Household-Specific Housing Wealth and Consumption: Evidence from U.S. Micro Data

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Abstract

This paper examines whether housing wealth transmit to household consumption via a credit channel. To this end, we augment home rents with time and spatial variations in home price growth to build a panel of U.S. individual home price from 2001-2006, and test if household consumption respond to housing wealth growth in a way violating the permanent income hypothesis. Results show that households in poverty, with welfare income or a high credit card utilization rate, who self-reveal them as credit constrained, all yield an excess MPC out of anticipated housing wealth, which implies a credit channel but is still under estimated due to adverse effects of home purchase and precautionary saving on consumption. An investigation into home equity-based borrowing verifies the credit channel found in that it doesn't serve not credit constrained households.

JEL codes: D12; E21; G21; R21

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1 Introduction

The simultaneity of fast consumption growth and flat savings rates in U.S. during 2001-2006 often raises the question of what finances the consumption growth? Personal consumption increased more than disposable income at most of the time while personal savings rates stayed about the same, leading to a savings puzzle that motivates the search for a non traditional engine of the consumption growth. Since home price kept growing at 7%-15% per year at the time, many studies view the persistent rise in housing wealth as a source of consumption growth[1].

Empirical studies prove a significant correlation between consumption growth and housing wealth growth. The canonical study by Case *et al* (2005) evidences a strong effect of housing wealth on consumption, much stronger than that of stock wealth. A wave of empirical studies follows to examine the housing wealth effect on consumption and often find a 2%-10% MPC out of housing wealth growth (Aladangy, 2017; Browning *et al*, 2013; Carroll *et al*, 2011; Disney *et al*, 2010; Bostic *et al*, 2007).

Given the empirical finding of the housing wealth effect on consumption, a next question is how can housing wealth transmit to consumption? A rise in housing wealth can add to consumption via a *wealth channel* in which a household raises its consumption as a direct result of higher perceived housing wealth, or via a *credit channel* that enables the household to borrow against its growing home equity to finance consumption growth[2] (see Figure 1 for a demonstration of the two channels).

[1] Unless specified, we use "housing wealth", "house price" and "home price" as interchangeably.
[2] A common-factor channel is also proposed in which a common factor (e.g. technology progress) raises income and consumption of goods, including houses, and pushes up house price, showing a spurious link from house price to consumption . This paper won't discuss it.

Few studies try to identify the working channel of the housing wealth effect but find divergent results. Attanasio *et al* (2009) find neither a credit channel nor a wealth channel, while Campbell and Cocco (2007) discover both channels using the same data set and a similar strategy. Interestingly, Browning *et al* (2013) find a weak wealth channel, but only for credit constrained households. Moreover, Bhutta and Keys (2016), Mian *et al* (2013) and Mian and Sufi (2011) all reveal stronger home equity borrowing for households with low credit scores or high debt leverages, and Cooper (2013) uncovers a high MPC for those with low asset holding or high debt payments, all implying a credit channel.

Reasons why the literature can't agree on the working channel of the housing wealth effect are threefold. First, the use of aggregate house price restricts variations in housing wealth and biases the correlation of housing wealth and consumption, e.g. while zip-code level home price yield a 25% MPC out of housing wealth growth (Mian and Sufi, 2011), state/city home price yield a 2%-10% one. Moreover, the literature often views the young and those with a high LTV as credit constrained[3], which incurs endogeneity issues and measurement errors since the young's consumption responses to housing wealth growth depend on their home purchase plans (Sheiner, 1995) and LTV involves numbers from a long time ago. Furthermore, income uncertainty incur precautionary saving that restrain households from consuming housing wealth and hide the true housing wealth effect on consumption, but the literature rarely discusses this.

With several new motivations, this paper studies whether housing wealth transmit to household consumption via a credit channel. The first motivation is to employ individual

[3] The terminology "credit constraint" in this paper can be interpreted as having the same definition as "liquidity constraint" and "borrowing constraint" that are often used in the consumer study literature.

house price. Along a growing effort to utilize micro home price in housing wealth studies (Aladangady, 2017; Bhutta and Keys, 2016; Bhatia and Mitchell, 2016), we construct the baseline price of a home as the present discounted sum of its rents over infinity, and augment that price with home supply elasticity and the Case-Shiller National Home Price index to absorb spatial and time variations in home price growth, respectively. Besides home supply elasticity, alternative spatial factors significant in home price formation, e.g. crime (Pope, 2008) and employment (Nieuwerburgh and Weill, 2010), are also tested.

A second motivation is that we exploit behavior-based credit constraint measures to capture constrained households that can help identify a credit channel. These measures indicate: whether a household lives in poverty, receives welfare income, or carries a high credit card utilization rate. Relative to ordinary measures like balance-sheet indicators/age, they involve few numbers a long time ago and reasons why they reflect credit constraints are obvious, so they incur few measurement errors and endogeneity issues. Also, in light of rising attentions to home equity borrowing (Mian and Sufi, 2011; Bhutta and Keys, 2016; Greenspan and Kennedy, 2008), we examine mortgage refinancing behaviors that were popular during 2001-2006 and define those who reject a mortgage refinancing with benefits greater than costs as truly not credit constrained.

The third motivation of this paper is to recover the true housing wealth effect by isolating the adverse effects of precautionary saving and home purchase on consumption. By factors behind precautionary saving motive (Kennickell and Lusardi, 2004), this paper further groups credit constrained households into the precautionary and the not, so the consumption response by the latter is free of precautionary effects and captures the true housing wealth effect on consumption. Also, in consistent with Sheiner (1995), we find that renters with a home buying plan cut consumption in response to home price growth while other renters increase it.

The strategy in this paper is to examine whether household consumption respond to housing wealth growth in a way violating the permanent income hypothesis since the rejection of which implies a credit channel (Zeldes, 1989). This strategy is similar to Mian *et al* (2013) except that we test the MPC out of anticipated housing wealth, not net housing wealth as they do. First, we build a home price for each household using the expected rents it reports quarterly on its house. Next, an AR (1) is estimated to divide home price to anticipated and surprise parts. Then, households are grouped into the constrained and the not by credit constraint measures. Lastly, we estimate if constrained households yield an excess MPC out of anticipated housing wealth.

Much of the data in this paper is from the Consumer Expenditure Survey (CEX) , a national representative survey that quarterly interviews a household for five times and records expenditure, income, assets, housing and demographics, among others. The CEX in this paper goes from Year 2001-2006.

Results show that a credit constrained household yields a MPC of 13%-23% out of anticipated housing wealth growth, implying a credit channel via which housing wealth add to consumption. The size of this MPC for constrained households is in line with Mian and Sufi (2011) that uses zip-code level home price, but higher than what's found in Aladangady (2017) and Bhatiaa and Mitchell (2016) that also use micro home price, and is much bigger than the 2%-10% in the literature using aggregate home price. Hence, for every one-dollar anticipated increase in housing wealth, a credit constrained household extracts and spends 13-23 cents on consumption. After isolating the adverse effect of precautionary saving, the MPC by constrained people can even reach 55%.

Results also show that households that are not credit constrained exhibit no excess consumption response to anticipated housing wealth growth, verifying the credit channel. Households that self-reveal them as not credit constrained by refusing lucrative mortgage refinancing are found insensitive to anticipate housing wealth growth. This verifies the credit channel in that it does not serve those not credit constrained. Moreover, renters with a home purchase plan cut consumption gin response to home price growth while other renters don't. Since renters are often the young, this heterogeneity within a same age group implies that age is not a good credit constraint measure in housing context.

This paper adds to the literature in several ways. First, it constructs a panel of U.S. household-specific home price that yields new results[4]. Moreover, it uses behavior-based credit constraint measures to identify constrained households and so relieves endogeneity issues and measurement errors. Lastly, it isolates adverse effects of precautionary saving and home purchase on consumption and restores the true housing wealth effect.

Since housing is, by nature, both consumption and asset, a rise in home price raises both living costs and housing wealth and it is hard to tell how would household wealth change, so the wealth channel of housing wealth effect is ambiguous in theory (Sinai and Souleles, 2005). Also, recent studies on housing wealth effects often proceed in a credit view (Aladangady, 2017; Bhutta and Keys, 2016; Favara and Imbs, 2015). For the reasons,

[4] We use "household-specific", "individual" and "micro" home price as interchangeably in this paper.

this paper focuses on a credit channel, though it also tests but finds no wealth channel.

The rest of the paper is organized as: Section 2 reviews the data, builds individual home price, and divides both home price and income into anticipated and surprise parts. Section 3 studies how credit constrained households respond in consumption to housing wealth growth and discusses why the response is under estimated by precautionary saving and home purchase. Section 4 conducts robustness checks and Section 5 concludes.

2 Data

We extract household data on expenditure, income, assets, housing (including rents and house structure), credit constraint measures and demographics from the Consumer Expenditure Survey (CEX), a repeated panel that quarterly traces a same household for five times. The CEX in this paper spans from the year 2001-2006. Table 1 summarizes the main variables to be used. Now, we briefly review the processing on these variables, and the details will be discussed in Section 2.1-2.3.

Home price is constructed from the expected rent on a house reported quarterly by its owner. With a series of home price on every house, an AR (1) is then estimated to decompose home price to an anticipated and a surprise part, for each household at each interview. Two alternative AR (1) are examined based on theory and econometric merits before a simple AR (1) that relates the current home price to its one-period lag and an error term is chosen. See Section 2.1 and 2.2 for details.

Income also go through an AR (1) process before decomposed to an anticipated and a surprise part. This is to control for the anticipated income that can also work via a credit channel to finance consumption as anticipated housing wealth do. See Section 2.2

for details on the AR (1) of income.

Behavior-based credit constraint measures identify not only the credit constrained households but also the not since the two are not an either/or. A first set of behaviors, namely living in poverty, receiving social welfare income, or carrying a high credit card utilization rate, decodes as being credit constrained while a second set, including: never refinancing a mortgage or never extracting home equities during the low interest period of 2001-2006, translates to being not credit constrained.

For comparison, we also review ordinary credit constraint measures, most of which are balance-sheet indicators, such as the Loan to Value ratio (LTV) and the Debt Service Ratio (DSR), a.k.a. the Debt Payment-to-Income ratio.

Table 1 presents a summary of main variables and data to be used in this paper. To remove significant outliers, the sample is truncated at the two 1 percentiles of each of expenditure, income, financial wealth and housing Wealth.

2.1 Factors of House Price Determination

This part examines the time and spatial variations in macro home price growth that should enter the construction of individual house price, which starts with expected rents.

Home supply elasticity is a often proxy for the spatial variation in home price growth. During the last housing boom, while the fast growth of house price is a national trend, the growth rates vary significantly across states. Home supply elasticity is often proposed as a source of home price growth variation at MSA level (Glaeser *et al,* 2008; Saiz, 2010), with a lower supply elasticity leading to a higher home price growth. We now test if this holds at state level since the most micro geographic unit at which the CEX public data trace a household is state.

Home price growth rise as home supply elasticity fall across states. Since population is an important factor of home supply elasticity variation (Green *et al,* 2005), we weight MSA home supply elasticity by population to yield state elasticity, and define home price growth as the growth of the Federal Housing Finance Agency(FHFA) House Price index between Jan 2001 and Dec 2006. We then plot the two variables by state at Figure 2, where it is obvious that home price growth is negatively linked to home supply elasticity at state level, suggesting that the home price construction should absorb the effect of home supply elasticity. This pattern still holds after excluding outliers. See *Appendix A* for a full list of home supply elasticity and home price growth at state level.

Alternative proxy for the spatial variation in home price growth, including crime and employment, are also reviewed but give similar results as home supply elasticity do[5]. Pope (2008) find that fears of crime significantly decrease the house prices of a neighborhood, and Nieuwerburgh and Weill (2010) show that productivity differentials across cities lead to spatial variations in home price growth. Inspired by these findings, we proxy for the spatial variation in home price growth by cross-state variations in crime intensity and in employment. Crime intensity is the crime rate of a state relative to the national one, and employment share is its share in total national non-farm employee. Home price built with crime intensity/employment share to reflect the spatial variation support a credit channel as do home price built with supply elasticity. See details in *Appendix B*.

[5] Except crime, other aspects of community quality, including schooling, waste disposal and air quality are also found to drive spatial variations in home price growth (Collins and Kaplan, AER 2014; Greenstone and Gallagher, QJE 2008; Chay and Greenstone, JPE 2005). Due to data availability, we don't review these aspects here.

Home supply elasticity carry no effects of these home price fundamentals. Instead, known relationships between home price and such fundamentals change if missing home supply elasticity. Figure 3 depicts states with employment share<5% and home price growth<100%. Surprisingly, home price growth now fall as employment rise. This is because increases in housing demand due to job growth only lead to home price growth when home supply elasticity is low, but now many states with low elasticity are excluded. Of these states, five are in the Top 10 states with least home supply elasticity. Likewise, it is often thought that home price fall as crime rates rise, but in the left of Figure 4 they are positively linked. The reason is that populated cities often carry both high crime rates and low home supply elasticity, presenting a positive link from crime rates to home price. Removing such outliers, then home price fall as expected when crime rise (in the right).

The construction of house price needs also incorporate the time variation in home price growth. While fast home price growth is a lasting trend during the housing boom, growth rates change over time. The reasons are probably that a rising home ownership premium encourages a growing number of people to buy their own houses, and that the expansion of credit supply that finances this rising demand changes in magnitude over time. Though different in nature, both the reasons can be captured by the Case-Shiller National Home Price index that records home price growth over time.

Changes in home ownership premium lead to time-varying home price growth and are measured by the Case-Shiller Price index in this paper. Tax deductions on mortgage interest, property tax payments and housing capital gains explain the ownership premium (Poterba and Sinai, 2008), and a rise in rent risk also adds to it (Sinai and Souleles, 2005).

Tax deductions usually increase with home price, and so do rent risks since rents often move with home price. Given persistent home price growth during the boom, these two factors of home ownership premium build up, resulting in a home ownership premium that grows over time. As in the left of Figure 5, the home ownership premium, defined as Home Price Growth less Rent Growth, begun increasing in early 2002 and didn't calm down until early 2006. This trending of home ownership premium, plus its timing, is well traced and captured by the growth of the Case-Shiller index.

Changes in the magnitude of credit supply expansion that result in time variations in home price growth are also well captured by the Case-Shiller index. The expansion of credit supply often drives home price growth by providing otherwise credit constrained households mortgage credits (Greenspan and Kennedy, 2008; Favara and Imbs, 2015), so changes in the size of credit supply over time help result in time variations in home price growth. Given the overall flat rates during the boom, we turn to quantitative tools and use the growth of *Home Mortgage by Households* from the Fed to reflect changes in the size of mortgage supply. Again, as shown in the right of Figure 5, this measure can also be well traced by the Case-Shiller index under most of the time.

Other home price indexes alternative to the Case-Shiller index are also reviewed and yield similar results. Despite differences in computing methodology, the FHFA National House Price index and the FNC Residential Price index perform the same job as the Case-Shiller index does in capturing the time variation in home price growth. This is not surprising since they all display a same trending over time, as shown in Figure 6.

Note that another reason why we use home ownership premiums to explain the time variation in home price growth is that by definition it represents the deviation of home price from its fundamental, a closely-watched indicator of housing market conditions. As will be discussed, the home price constructed in this paper is in fact a discounted sum of rents, but rents usually move milder than home price do, so it is necessary to capture and account for their deviations over time. Defined as the growth differential between home price and rent, the home ownership premium in this paper well performs that job.

2.2 The Construction of Individual House Price

Individual home price is built as the present discounted sum of expected rents to infinity, augmented by home supply elasticity and the Case-Shiller National Home Price index, which accounts for spatial and time variations in home price growth, respectively.

$$P_t^i = (6 - E^s) \times CS_t \times \left(\frac{12 \times ER_t^i}{1+r} + \frac{12 \times ER_t^i}{(1+r)^2} \cdots \frac{12 \times ER_t^i}{(1+r)^\infty} \right) \tag{1}$$

p is house price, *s* state, *i* household, *t* the time of survey and t=2001Q1 to 2006Q4, *e* home supply elasticity scaled from 0 to 6, *cs* the Case-Shiller National Home Price index, *er* expected monthly rents asked by households on their houses, *r* the annualized return of Real Estate Investment Trust Funds (REITS).

The choice of REITS return as the discounting rate is motivated by several concerns: First, building home price by User Cost theory treats homes as assets, so it is good to use REITS returns as the discounting rate. Second, REITS has influential impacts on home price via direct housing investments and portfolio holding of mortgage-backed securities that replenish bank credits. Last, since REITS offers ordinary people an easy access to housing investments, its returns better reflect the housing market conditions.

By Equation (1), house price is composed of three parts: (1) the fundamental value, determined by the User Cost Theory claiming that the price of a home equal the present discounted sum of its rents assuming that it is rented out to infinity; (2) the deviation from the fundamental value due to nationwide housing demand shocks, e.g. a mortgage supply expansion (Favara and Imbs, 2015; Mian and Sufi, 2011). Results of such shocks are mostly fast home price growth, so it is appropriate to capture these shocks using the Case-Shiller National Price index; (3) the deviation from the fundamental value due to local home supply factors, e.g. geographic and regulatory land constraints (Glaeser *et al*, 2008; Saiz, 2010). The speed and the timing of home supply response to demand shocks decide the size of home price growth, and we follow Saiz (2010) to reflect home supply responses by supply elasticity, among other factors of local housing market.

By Equation (1), the time variation in house price is realized through: 1) the change in expected rents asked by a same household, who observes the market and updates its rent expectation at next interview; 2) the variation in REITS return that reflects changes in the finance side of the housing market; 3) the trending of the Case-Shiller Price index that reflects the tightness of the housing market over time.

Alternative price factors are also tested to ensure the robustness of the constructed house price and they all yield similar results. First, in discounting expected rents, we try 30-year Fixed Mortgage rate and 30-year T-bond rate as alternatives to the REITS return. Moreover, in capturing time variations in home price growth, FHFA House Price index and FNC Residential Price index both work as alternatives to Case-Shiller index. Last, in reflecting spatial variations in home price growth,employment share and crime rates are also tried as alternatives to home supply elasticity. See *Appendix B* for details.

We now illustrate how the home price construction successfully reproduces both the time and spatial variation of actual aggregate home price. Since the exact sensitivity of home price to the Case-Shiller index and to home supply elasticity can hardly be known, the scale of constructed home price isn't comparable to actual ones, but our construction replicates both the time and spatial patterns of actual ones.

The constructed individual home price reproduce the time trend of Price-Rent ratio found in actual aggregate home price. First, define the Price-Rent ratio of a state as the median Price-Rent ratio of all houses in that state, and aggregate state Price-Rent ratios into a national one with state population as weight. Repeat this process for each quarter from 2001-2006 to form a time series of the national Price-Rent ratio and its growth. Meanwhile, since FHFA quarterly publishes the National House Price index and the Rent CPI index, we generate the growth of FHFA Price-Rent ratio as its Home Price index growth less the Rent CPI index growth. Now we have two series of Price-Rent ratios, one by constructed individual price and the other by actual aggregate price. In Figure 7, the two series yield a similar time trend, though the constructed one is a bit lagged and volatile (See *Appendix C* for more on the Price-Rent ratios).

The constructed home price also replicate the spatial variation in actual aggregate home price. The left panel of Figure 8 plots the growth of the FHFA House Price index against the growth of the constructed home price at state level, with the growth defined as the point change in home price between 2001Q1 and 2006Q4. Clearly, the two growth indexes are positively correlated at state level, suggesting that the construction of home price successfully reproduces the spatial variation in actual home price growth[6].

Note that the left of Figure 8 excludes states where the median constructed home price increase by about or over 400%, including Tennessee, New Jersey, Kentucky and Louisiana. As in the right of Figure 8, these states are the Top 4 in median rent growth. This is why their median constructed home price increase so much. The problem is that their rent growth are even higher than major states that have a bigger population and should yield higher rent growth, e.g. CA an TX. A possible reason is that the median rent is reported by one single household and faces idiosyncratic shocks. So, it is proper not to reflect these states in the graph, though they are included in the main estimation.

2.3 Anticipated and Surprise House Price

With a series of home price generated by Equation (1), we need decompose home price into an anticipated and surprise part so as to enable the strategy of this paper that examines how household consumption respond to anticipated home price growth.

We follow Attanasio *et al* (2009), Campbell and Coco (2007) and Browning *et al* (2013) to decompose house price using an AR(1) process:

$$p_q^{di} = \partial^d p_{q\text{-}1}^{di} + u_q^{di} \tag{2}$$

Where d is one of the nine census divisions defined by the Bureau of Census, the auto-correlation coefficient ∂ is called home price persistence, u is an idiosyncratic home

[6] For reasons aforementioned, the scale of constructed individual home price is not comparable to actual aggregate home price, hence the two growth indexes will not show a 1:1 relation.

price shock with $E\ (u_q |\ P_{q-1})=0$, other notation same as above.

The home price persistence ∂, together with the one-period lag home price P_{q-1}, would decompose the current home price P_q into $\partial\, P_{q-1}$ and u_q, which are defined as the anticipated house price formed at the start of time q and the surprise house price that is observed at the end of time q, respectively.

Obviously, home price is set to evolve independently cross states. This is a reflection of the earlier finding that home price growth vary with local factors, e.g. home supply elasticity. In Figure 2, low home supply elasticity often result in high home price growth and since high home price growth, within a fixed time frame, lead to low home price persistence, it is then straightforward to assume that home price persistence is positively linked to home supply elasticity. This forms a testable foundation for Equation (2).

Data support a positive correlation between home supply elasticity and home price persistence at both division and state levels. As in Figure 9, home price persistence rise as home supply elasticity go up, so it is proper to allow home price to evolve independently cross regions that differ in home supply elasticity. For comparability, when showing the correlation at state level, Figure 9 exclude states with less than 300 interviewees, though Equation (2) is run at division level in the rest of this paper to ensure coverage.

Simple as it may seem, the AR(1) in Equation (2) is actually the best of its kind for two reasons. First, it yields realistic home price persistence while its alternatives can't. The price on a house shouldn't vary a lot within a year, but alternative AR(1) that includes house structure, e.g. number of bedroom and bathroom, yield persistence too low to be true. Moreover, it yields results consistent cross divisions while its alternatives can't. No other factors added to Equation (2) stay significant cross divisions except for the number of bathroom, which, if included, yields persistence that is too low.

Results of Equation (2) are shown in Table 2, where home price persistence vary a lot across census divisions. This empirically justifies Equation (2) that runs house price auto regression by division. An alternative AR(1) that runs Equation (2) by 25 percentile of state home supply elasticity also confirms the variation in home price persistence.

2.4 Anticipated and Surprise Income

Same as anticipated housing wealth growth do, anticipated income growth can also relax household credit constraints and spur expenditure by credits, so the identification of a credit channel of the housing wealth effect needs remove the income effect.

To identify and control for anticipated income growth, we impose the following AR (1) on income to decompose it into an anticipated and a surprise part:

$$y_q^i = \beta y_{q-1}^i + X_q^i + \varepsilon_q^i \tag{3}$$

where y is income, X a vector recording job hours, number of earners and a set of household demographics, β the auto coefficient of income process, ε error term and other notation same as above.

Note that the anticipated income is $\rho y_{q-1}+X_q$, which is formed at the start of time q, while the surprise income, ε_q, is observed only when the actual income of time q, y_q, is realized at the end of time q.

The income strategy in Equation (3) is guided by theory more than by econometrics. The affluent literature on income studies has evidenced the effects of labor participation and socio-demographics on income determination. So, the priority in specifying an AR (1) on income is to include all known income factors while parsimoniousness comes second. More compact AR (1) are also tried but are found not much different than Equation (3) in explaining anticipated income while short on theory foundation.

Results of Equation (3) shown in Regression 3 of Table 3 suggest that Equation (3) is in fact a proper income dynamics strategy that balances theory and econometrics. Two things are worthy noting in Table 3: First, while a simpler AR(1) on income in Regression 1 yields both higher income persistence and adjusted R^2, it misses theory-proven income factors, e.g. number of earners and job hours, both of which are significant in the other two specifications. Second, the AR(1) in Regression 2 gives similar income persistence and adjusted R^2 as Equation (3) does, but it excludes demographics that are proven in the literature as significant in income determination, e.g. education, age, race and gender of the household head. All these factors are significant in Regression 3.

3. Credit Constrained Households and Housing Wealth Growth

With anticipated and surprise parts of both housing wealth and income, we now can study the consumption response to anticipated housing wealth growth while controlling for income effects. This part is to investigate if credit constrained households are excess consumption sensitive to anticipated housing wealth growth. First, a group of behavior based credit constraint measures are proposed to tell credit constrained households from those not. Then, an estimated framework of the representative agent model augmented with the permanent income hypothesis and housing wealth is introduced to test if credit constrained households yield an excess MPC out of housing wealth growth.

3.1 Who are Credit Constrained Households?

A growing literature has been trying to identify credit constrained households based on their financing behaviors. Credit card use behaviors, such as credit limits, credit scores, and credit card utilization rates, are increasingly used to tell credit constrained households from others (Agarwal *et al*, 2007;Gross and Souleles, 2002; Bhutta and Keys, 2016). Other financing behaviors, such as rejections by banks on credit requests (e.g. loan/credit card applications) and borrowings on bank cards, are also tried as credit constraint measures (Jappelli, 1990; Gross and Souleles, 2002).

We extend this literature for three improvements on the measure of credit constraint. First, while the literature often utilizes one financing behavior, e.g. credit usage, we resort to a broader set of behaviors that goes beyond credit card usage. Moreover, this paper examines in details home equity withdrawals during the housing boom since they can tell the true degree of credit constraint. Lastly, we also identify households that are not credit constrained and test whether their responses justify a credit constraint channel.

Behavior-based credit constraint measures in this paper consist of two groups: one identifying credit constrained households and the other capturing those not constrained. The former includes dummies for living under the poverty line, receiving welfare income, and carrying a high credit card utilization rate, and the latter includes dummies for no mortgage refinancing and no home equity withdrawal (e.g. home equity loan/HELOC) during the low interest rate period 2001-2006[7]. Table 4 sums these behaviors, along with balance-sheet indicators that often measure credit constraint in the literature.

[7] Welfare income in this paper refers to public welfare income, including supplemental security income, food stamps and other income that is documented as "welfare income" in CEX.

Reasons why these behaviors can reflect credit constraints are threefold. First of all, it is intuitive. Income of households in poverty is insufficient for life necessities. That is why some of them apply for welfare income to smooth consumption. Moreover, it is in line with the literature. Mian and Sufi (2011) and Mian *et al*(2013) illustrate the credit card utilization rate as a good credit constraint measure in housing context. Furthermore, it is based on facts. The housing boom in 2001-2006 helped offer easy and cheap credits via home equity withdrawals, and those who could but chose not to refinance mortgages or take out home equity loan/HELOC are actually not credit constrained.

These behavior-based credit constraint measures are independent of ordinary credit constraint measures in the literature. Table 5 summarizes the correlations between the behavior-based credit constraint measures and the two balance-sheet indicators that often work as constraint measures, LTV and DSR. No significant correlation is found, implying that behavior-based constraint measures are not agents of the usual ones.

A first merit of behavior-based credit constraint measures is that they can precisely capture households that are credit constrained. In Column 3 of Table 6, those in poverty, with welfare income or a high credit card utilization rate all yield an average propensity to consume (APC) out of income that is well above the one by others, meaning that their credit constraints are more binding. The same is true for the APC out of liquid wealth.

Moreover, behavior-based credit constraint measures incur few endogeneity issues. First, sorting households by such measures rules out the possibility that spending habits drive consumption responses to housing wealth growth. As shown in Column 5 of Table 6, households in poverty, with welfare income or a high credit card utilization rate all yield a lower APC out of housing wealth than others do, hence their excess consumption response to housing wealth growth, if any, is not because of aggressive spending habits. Second, behavior-based measures record outcomes, not causes, of credit constraints. The literature often assumes that the young are more constrained than others and takes age as a credit constraint measure (Parker *et al*, 2013; Johnson *et al*, 2006, among others). This invites endogeneity issues since given home price growth, the young, contingent on their home buying plans, differ in consumption/saving choices and thus the degree of credit constraint (Sheiner, 1995; Skinner, 1989)[8]. In contrast, behavior-based measures, e.g. in poverty, assume no reason but just record the fact of being constrained.

Furthermore, behavior-based constraint measures incur few measurement errors. Constraint measures like balance-sheet indicators often require memories of numbers from a long time ago and suffer measurement errors, e.g. LTV involves information on both home price and loan principal when a house was purchased. In contrast, answers to most behavior-based measures are *Yes/No* and involve few numbers.

Note that being credit constrained or not are not necessarily mutually exclusive. For example, while it makes sense to view households without home equity withdrawals during 2001-2006 as not credit constrained, it is unreasonable to assume that those who extract home equities are credit constrained since it is rational to do so given the low interest rates at the time. Hence, while it is a priority to illustrate a credit channel with evidence that constrained households display an excess MPC out of anticipated housing wealth growth, it is also critical to verify the channel by showing that it does not serve

[8] Young households with a home buying plan need save for down payment and choose to spend little and thus may be more credit constrained than other young people.

those not constrained. This is why we adopt both groups of constraint measures.

Note also that behavior-based measures may incur precautionary saving motives that work exactly like a credit channel. Low income/wealth often incur precautionary motives that restrain spending but can be relieved by wealth growth, so housing wealth growth can also spur consumption by relieving precautionary motives, not necessarily by relaxing credit constraints. If constrained households bear strong precautionary motives, their excess MPC out of housing wealth growth may come from the decline in precautionary motive, not necessarily from a credit channel. Table 7 shows that indeed households in poverty, with welfare income or with a high credit card utilization rate are more likely to suffer bad health and income shocks, both of which induce precautionary saving motives (Kennickell and Lusardi, 2004). Hence, in identifying the credit channel, we need isolate precautionary saving motives from credit constraints.

3.2 How Can Housing Wealth Affect Constrained Households' Consumption?

The empirical strategy that identifies and quantifies the consumption response by a credit constrained household to anticipated housing wealth growth is:

$$e_q^i = e^0 + \eta_{\hat{p}} \hat{p}_q^i + \eta_c c_q^i + \eta_{\hat{p}}^c (c_q^i \times \hat{p}_q^i) + \kappa_l w_q^i + \lambda_z Z_q^i + \lambda_x X_q^i + \phi_q^i \qquad (4)$$

Where i denotes household and q time, e consumption, e^0 a constant, ϕ error term, *p hat* anticipated housing wealth, c a dummy equal to 1 if a household lives in poverty, receives welfare income, carries a high credit card utilization rate, respectively, and 0 otherwise, W financial wealth, Z a vector of anticipated income, surprise income and surprise housing wealth as well as their interactions with c, X a vector of demographics.

Note that *hat c* is the excess consumption response by credit constrained households to an anticipated rise in housing wealth, and is the coefficient of interest.

This strategy is guided by the literature on inter-temporal consumption optimization under credit constraints. The marginal utility of credit constrained agents is everywhere higher than the one when absent credit constraints (Zeldes, 1989) and leads to an excess MPC out of income/wealth in relative to agents not constrained (Lusardi, 1996; Souleles, 1999; Kimball, 1990). This violates the life-cycle/permanent income hypothesis that allows borrowings and predicts an insensitive MPC. In housing context, a representative agent carries a significant MPC out of net housing wealth that rises as the agent becomes more credit constrained (Mian *et al*, 2013). Moreover, the part of housing wealth growth that can be anticipated also encourages credit constrained households to yield a non-zero consumption response(Campbell and Cocco, 2007).

We follow Mian *et al* (2013) to detect a credit channel by testing whether household consumption respond to to housing wealth growth in a way violating the LC/PIH that allows borrowings and assumes no credit constraints. If the LC/PIH holds, agents can borrow to insure consumption against income shocks and need no wealth growth to smooth consumption, leading to a MPC that is insensitive to wealth growth. If, however, household consumption behaviors violate this pattern, the LC/PIC is rejected and its assumption of borrowing fails, leading to a credit channel that fuels consumption growth by wealth growth which relax credit constraints. Equation(4) is built to perform this test and if gamma is positive and significant, then a credit channel is found.

We differ, however, from Mian *et al* (2013) in several aspects: First, we test the MPC out of anticipated housing wealth, not net housing wealth, as it is more consistent with the LC/PIH that claims a MPC insensitive to anticipated wealth changes. Second, while they use zip-code level home price, we use individual ones to avoid spurious regressions brought by a mismatch of micro distributions of aggregate spending and housing wealth. This practice is inspired by a growing effort in the literature to exploit micro home price (Alagangady, 2017; Bhatia and Mitchell, 2016). Last, we run a panel with five consecutive quarters of home price for a same household while they execute a differencing strategy on two periods.

3.3 A Credit Channel via Which Housing Wealth Growth Finance Consumption

Results of Equation (4) are shown in Table 8, where credit constraints are measured by both behavior-based credit constraint measures and balance-sheet indicators to ensure comparability. Regression 1-2 run Equation (4) with the Loan to Value ratio (LTV) and the Debt to Service ratio (DSR) as constraint measures, respectively, and Regression 3-6 with dummies of a high credit card utilization rate, in poverty and with welfare income as constraint measures, respectively.

Results show that households with a high credit card utilization rate display an excess MPC out of anticipated housing wealth growth that increases as credit card utilization rates rise. We define a credit card utilization rate above the median as high and find in Regression 3-4 that households with a high utilization rate yield an excess MPC of 13.7 percentage points over others, and that their responses go up by 23.1 percentage points if the utilization rate increases by 100%. In dollar term, for a one-dollar anticipated home price growth, an average household with a credit card utilization rate above the median extracts and spends 13.7 cents, and spends an extra 2.3 cents if its credit card utilization rate increases by 10 percentage points. By the theory behind our strategy, this suggests a credit channel of the housing wealth effect on consumption.

Results also show that households with high DSR exhibit an excess MPC out of anticipated housing wealth growth. We define a DSR above the median as high and find, as shown in Regression 2, that an average household with a high DSR exhibits an excess MPC of 8.3 percentage points over others, though there is no evidence that this response increases with the level of DSR, which is, however, the often case in studies with DSR as the constraint measure. In dollar term, it means a household with an above-the-median DSR, who is defined credit constrained, extracts and spends 8.3 cents given a one-dollar anticipated increase in its home price.

The findings above together evidence a credit channel of the housing wealth effect that provides credit constrained households a 13%-23% MPC out of anticipated housing wealth growth. That is, if a credit constrained household anticipates a one-dollar rise in its housing wealth, it extracts and spends 13-23 cents on consumption.

The rest of balance-sheet indicators and behavior-based credit constraint measures yield results that are, however, less supportive of a credit channel. Households with high LTV, in poverty and with welfare income are viewed credit constrained and are supposed to yield an excess MPC out of anticipated housing wealth. This is, however, not the case in Regression 1 and 5-6, where such households just act like the average. These mixed results call for further investigations into the credit channel found and motivate the next section of this paper.

3.4 The Credit Channel is Under Estimated due to Precautionary Saving

This section investigates why households in poverty/with welfare income and thus viewed credit constrained are, however, not excess consumption sensitive to anticipated housing wealth growth as expected.

The main reason is that being in poverty/with welfare income triggers precautionary saving that restrain consumption out of housing wealth growth. In an incomplete market with uninsurable income shocks, agents often hold precautionary savings as buffer stock against income risks (Carroll, 1997). Such precautionary saving motives work like credit constraints in that they both restrain spending but decline as wealth grow (Carroll, 2001; Guerrieri and Lorenzoni, 2017). Hence, they can offset each other if, however, moving in opposite directions. When precautionary motives are strong enough to withstand wealth growth and overturn the uptrend in consumption fueled by the relaxation of credit constraint, consumption may stay the same while savings build up (Carroll, 2001). In housing context, given home price growth, the build-up in precautionary saving by households in poverty/with welfare income, who often need trade up on housing in future, may outweigh the relaxation of credit constraints and restrain consumption out of housing wealth. This can explain why they don't yield the excess MPC in Table 8.

We follow the literature to capture precautionary motives by health risks and income risks. While the theoretical measure for precautionary motives is well developed (Kimball, 1990), empirical measures are diversified and often include income variance (Carroll and Samwick, 1998), probability distribution of future income (Guiso *et al*, 1992), job loss probability (Lusardi, 1998) and out-of-pocket health care expenditure (Palumbo, 1999). These measures are intended to capture income risks or health risks, both of which are main causes of precautionary saving (Kennickell and Lusardi, 2004). In line of this spirit, we propose income shocks and bad health as the two measures of precautionary motives, and view a household as precautionary if its average income growth rate or the ratio of its health care expenditure over income is above the median[9], respectively.

A review of the data shows that a significant fraction of households in poverty/with welfare income carry precautionary saving motives. As shown in Figure 10, at least 39% of these households suffer bad heath/income shocks and would build up precautionary saving against income/health uncertainty. This justifies out earlier statement that the arise of precautionary saving motives may have restrained credit constrained households from consuming their housing wealth growth.

We first show the effect of precautionary saving by the differential in the MPC out of income between precautionary households and the not. To avoid the effect of credit constraints, we only look at not credit constrained households who are further grouped by bad health and income shocks in Figure 11. For households NOT in poverty, income shocks bring much (6%) lower income but just a slightly higher MPC. Also, among households WITHOUT welfare income, income shocks bring about the same income but a lower MPC. The same pattern holds when sorting households by bad health. Those with bad health all have dramatically (as high as 25%) lower income but report a MPC that is only modest higher. This proves that households with income shocks/bad health

[9] Since health conditions often fall as people age, it is not surprising to see that an old household displays a share of health care spending in income that is above the median.

restrain spending to accumulate precautionary savings against risks.

We then isolate precautionary motives and find an excess MPC out of housing wealth for households in poverty, proving the credit channel. The idea is to examine if credit constrained but NOT precautionary households yield, as expected, an excess MPC out of anticipated housing wealth growth. We sort households by bad health and income shocks in Table 9 and re-run Equation (4) for each group. Clearly, households in poverty that are not precautionary (no bad health/income shock) now exhibit an excess MPC out of housing wealth, proving a credit channel of the housing wealth effect. Moreover, that excess MPC is greater than the one by households both in poverty and precautionary, suggesting that precautionary motives restrain consumption out of housing wealth. This explains why households in poverty have no excess MPC in Table 8 since a significant fraction of them carry precautionary motives.

For households with welfare income, the MPC out of housing wealth growth also varies with precautionary motives, though results are mixed. If a credit channel exists and welfare income reflect credit constraints, then households with welfare income but not precautionary should yield an excess MPC out of housing wealth, but this is not true in Table 9 (Regression 4 and 8) and the precautionary even cut their spending (Regression 3 and 7). This is because wealth growth impose two competing effects on precautionary saving: 1) relive it via wealth effects, and 2) enhance it via the concern of losing eligibility for welfare programs (Hubbard *et al*, 1999). Since welfare income is often a major income for these households, the concern offsets the wealth effect and consumption hardly grow. Still, households with welfare income but not precautionary cut consumption to a lesser extent than the precautionary, proving that precautionary motives reduce consumption.

The fact that precautionary saving motives cut the MPC out of anticipated housing wealth suggests that the credit channel is under estimated. Earlier in Table 8, households in poverty exhibit no excess MPC, but after isolating precautionary motives, households in poverty but not precautionary yield an excess MPC of 53%-268% (Regression 2 and 6 of Table 9). Yet, it is still hard to tell by how much the credit channel is under estimated since the literature rarely studies the simultaneity of credit constraints and precautionary motives and it is not clear how to separate them, hence a good practice is to view the 13%-23% MPC out of anticipated housing wealth in Table 8 as a base.

3.5 Home Buying Plans also Bias the Credit Channel

We don't tell home owners from renters in Equation (4), so all the excess MPC out of anticipated housing wealth in Table 8, which evidence the credit channel, also carry renters' consumption responses that do not, however, work via the credit channel since renters have no home equities. That is, renters' consumption responses to home price growth bias the credit channel found, though not dominate it (see Section 4). Hence, in order to restore the true credit channel, we need identify renters' consumption responses to anticipated housing wealth.

Renters' consumption responses to home price growth are contingent on their home buying plans that are unobserved in the data. Renters that plan to buy a home in the near future may cut spending to save for it given home price growth, but those without a home plan may be consumption insensitive to the same home price growth, or even turn aggressive if they further give up the plan. Renters' home purchase plans are, however, unobserved in the data and may even be time variant too.

To proxy for home purchase plans, we follow U.S. mortgage practice to define home buying eligibility for renters. Assuming that a renter targets a median value home among owners from a same group of age, income, state and family size as she, we view a renter as eligible for a home buying if 1) her family income is no less than 2.5 times her target home value, and 2) her expected mortgage payment after buying a home is no more than 28% of family income or total debt payment is no more than 36% of family income.

Results suggest that renters eligible for a home purchase plan cut consumption given home price growth while the ineligible don't. It seems in Regression 1-2 of Table 10 that both eligible and ineligible renters' consumption are not related to housing wealth, but this hardly means that they are consumption insensitive to home price growth since their responses work via an income channel given that they have no housing wealth. This is confirmed by the fact that those ineligible for home buying yield a MPC out of income about 10 percentage points above the one by the eligible. That is, eligible renters restrain consumption to save for a home that is now more expensive.

Relaxing the eligibility to reflect the looseness in mortgage underwriting standards during 2001-2006 yields similar results. Now, as long as a renter's family income is no less than 2.5 times its target home value, it is eligible for a home buying. Results in Regression 3-4 of Table 10 show that the MPC out of income by eligible renters is still much lower than that by the ineligible, implying that eligible renters restrain consumption to save for a home given home price growth while the ineligible don't.

Findings above suggest that in response to home price growth, renters with a home buying plan increase savings and so cut the MPC out of housing wealth in the economy. Although their consumption response does not work via a credit channel as owners do, it still enters the housing wealth effect on consumption. While a simpler strategy that tests only owners' responses may capture the credit channel more precisely, it is inconvenient for the policy to ignore how renters respond to housing wealth since they account for a significant share of of all households in the data from a national representative survey.

Admittedly, the strategy in Table 10 is a bit intuitive and can be more precise given a bigger sample size. Anyway, the results still send out a message that renters' consumption responses to home price growth may bias the credit channel downward.

Note that results in Table 10 also imply that age is not a proper constraint measure. Renters in this paper are aged at or below 40, an age range that is viewed as young in the literature. Given home price growth, renters with a home buying plan need save more for down payment and are more credit constrained while renters without such a plan are not. This heterogeneity within a same age group means that age can not consistently measure the degree of credit constraint. We go further to test if another ordinary credit constraint measure, balance-sheet, can consistently measure the degree of credit constraint. Results in *Appendix G* show that LTV, a typical balance-sheet indicator, fails to do so, too.

3.6 Home Equity Withdrawals Verify the Credit Channel

This section verifies the credit channel by showing that it does not serve households that are not credit constrained. For that, we examine home equity withdrawal behaviors, which, when free of endogeneity issues, reveal the true degree of credit constraint.

The investigation into home equity withdrawals is motivated by a growing literature that studies how developments in housing finance fuel the housing boom. In addition to banks' policy of credit supply and its effects (Hurst *et al*, 2016; Favara and Imbs, 2015), household responses to credit supply expansion, e.g. home equity withdrawals and home buying, are also examined (Bhutta and Keys, 2016; Fuster and Zafar, 2016). Home equity withdrawals should interest housing wealth studies because its nature can help smooth consumption and offer insurance against labor income shocks. So, whether and by how much to withdraw home equities reveal the degree of credit constraint. To answer the question, we study the three major types of home equity withdrawals, including mortgage refinancing, home equity loan and home equity line of credit (HELOC).

Mortgage refinancing behaviors that capture households who self-reveal them as not credit constrained prove the credit channel. From 2001-2006, the persistent rise in home price, along with the loose monetary policy and mortgage derivative innovations, offers easy and cheap credits via mortgage refinancing. Households that had a mortgage but chose not to refinance it in fact reveal themselves as not credit constrained, hence the credit channel shouldn't work for them. As shown in Regression 1 of Table 11, they have no excess MPC out of anticipated housing wealth, verifying the credit channel. But, this is not convincing enough since no refinancing may be an endogenous choice, e.g. when the the cost of refinancing exceeds the benefit. So, need remove endogeneity issues.

The behavior of refusing lucrative mortgage refinancing precisely captures the truly not credit constrained households and further confirms the credit channel. A refinancing is viewed lucrative if 1) the expected monthly payment ex-post refinancing is lower than the ex-ante one, and 2) the total saving exceeds the fees of refinancing, a standard called the *Break Even Point* in the mortgage business. While taking a lucrative refinancing or refusing a profitless one is natural and can not tell much about whether a household is credit constrained, to refuse a lucrative one makes irrelevant the cost-benefit accounting and reveals, with few endogeneity, that the household is truly not credit constrained since it needs no credits. For a credit channel to be credible, it shouldn't serve such households. Results in Regression 2 of Table 11 find no excess MPC out of anticipated housing wealth for these households, implying that the credit channel indeed does not serve not constrained households. This verifies the credit channel. See *Appendix D* for more.

Other home equity withdrawal behaviors that can also capture not credit constrained households, i.e. home equity loan/HELOC, justify the credit channel, too. Home equity loan is a second mortgage used for consumption and HELOC works like credit cards with credit limits linked to home equities. For the low costs and popularity of these two derivatives during 2001-2006, if one ignores them, it can hardly be credit constrained. As shown in Regression 3 of Table 11, such a household displays no excess MPC out of anticipated housing wealth, justifying the credit channel. This is, however, not convincing either since not everyone has vacant home equities to access these derivatives which use home equities as collateral. So, need first identify accessibility.

The behavior of rejecting accessible home equity loan/HELOC accurately capture the truly not credit constrained households and further verifies the credit channel, too. While the absence of home equity withdrawal can be a result of insufficient home equities, those with low LTV and sufficient home equities but still rejecting home equity withdrawals in fact reveal them as truly not credit constrained since they need no credits. For a credit channel to be credible, it should not serve such households either. As shown in Regression 4 of Table 11, these households yield no excess MPC out of anticipated housing wealth, implying that indeed the credit channel does not serve households that are not credit constrained. This verifies the credit channel, again.

To sum, this section removes endogeneity issues behind the behavior of no home equity withdrawal and uses it as a proxy for being not constrained. Results show that the credit channel serves no one that are truly not credit constrained, verifying itself.

4 Robustness Checks

In this section, Equation (4) is re-run under alternative identification strategies, data processing, and econometric settings to ensure the robustness of the credit channel.

The first robustness check examines if the excess MPC out of anticipated housing wealth growth is instead driven by a wealth channel. Anticipated housing wealth growth certainly add to the perceived wealth that could also fuel up household consumption, in which case, the wealth channel kicks in. According to the life-cycle theory, if there exists a wealth channel, the old should yield a higher MPC out of surprise wealth growth than others do since they have a shorter life span to consume that wealth. Following this idea, we replace credit constraint measures in Equation (4) with the dummy of being old, and see if the old yield any excess consumption response to surprise housing wealth growth. Results find no excess MPC out of surprise housing wealth. So, the housing wealth effect on consumption found could hardly work via a wealth channel.

A second check aims to clear the concern that results of Table 8 are driven by a lack of income variation due to the survey design. CEX surveys record household income at the 2nd interview and carry over that information to the 3rd and the 4th before updating it at the 5th. Convenient as it may be, this process may force house price to pick up income effects that would otherwise work via an income channel To resolve this issue, income is now adjusted by expenditure growth in Column (1) of Table 12, where all results are qualitatively similar as in Table 8[10]. Alternatively, to adjust income by job hours produce similar results, too. So, the lack of income variation could hardly drive the results. Details of income adjustments are revealed in *Appendix F.*

The next robustness check is intended to exclude the possibility that the home price imputation for renters biases the results. The home price construction by Equation (2) utilizes expected rents that are not reported by renters in CEX, so we define a renter's expected rent as the median of expected rents asked on owner-occupied houses with a same structure as the one where the renter lives (See *Appendix H for details*). Now, to see whether this process drives the results, we exclude renters and test only the consumption response by home owners to housing wealth growth. Results in Regression 2 of Table 12 show that credit constrained households still exhibit an excess MPC out of anticipated housing wealth, similar to what is found in Table 8. Thus, the home price imputation for renters could hardly bias the results.

The fourth robustness check investigates if the results are sensitive to the correlation between home improvement expenditures and home price growth. All other things equal,

[10] Except that now High DSR is no longer significant. This just illustrates the point that balance-sheet indicators as credit constraint measures can be inconsistent in the housing context.

well-maintained homes have better values. Thus, consumption also affect housing wealth if home improvement expenditures are counted as consumption, which is just the case in CEX. This may lead to a two-way link between home price and consumption and bias the results. Moreover, if households own rental units for which they receive rent income, their consumption responses to income may carry the effect of home price, which often move with rents. In that case, the housing wealth effect is under estimated. To clear these concerns, Equation (4) are re-run with non-housing expenditures and income, which is consumption net of home improvement expenditure and total income less rent income, respectively. Results in Regression 3 of Table 12 are qualitatively similar to what is in the Table 8, again confirming the robustness of the credit channel.

The last robustness check addresses the issue of fixed effects. Since house price often move with state specific factors, e.g. building regulations, and with time factors, e.g. monetary policy, fixed effects in this paper are imposed at state-year level. Alternatively, it is tempting to try fixed effects at household level since household data is employed. We choose, however, not to do so because: 1) some credit constraint measures, e.g. poverty, are often time invariant for a household within one year, and fixed effects at household level shall invalidate point estimates on these measures; 2) household fixed effects come with a presumption that no consumption correlations exists among households, which is questionable given the wide-spread of home equity withdrawals during 2001-2006 (See *Appendix I* for why). To illustrate these two concerns, household fixed effects are tried in Regression 4 of Table 12, where no credit constrained households that yield an excess MPC before now stay excess consumption sensitive to anticipated housing wealth. This is expected and can hardly evidence against the credit channel found.

Conclusion

We investigate whether and how a change in housing wealth transmits to household consumption in an estimated framework of the representative agent model that includes the permanent income hypothesis and housing wealth, with a panel of household level home price and expenditure data.

Results show that for each one-dollar anticipated increase in housing wealth, a credit constrained households extracts and spends 13-23 cents on consumption, suggesting a credit channel. A policy implication is that a rapid increase in interest rate may trigger a recession since home price growth that could finance consumption growth would vanish amid the adverse market expectation on housing that is induced by the rate rise.

This paper adds to the literature in several aspects: First, it builds household-specific home price that replicate both the time and spatial variations in actual aggregate home price. Next, it proposes behavior-based credit constraint measures to identify the credit channel in a way with few endogeneity issues and measurement errors. Lastly, it isolates adverse effects of precautionary saving and home buying on consumption and recovers the true housing wealth effect that works via a credit channel.

Further efforts on this topic may work to improve on the incremental measurement of credit constraint so that the consumption elasticity to credit constraint can be known. Also, a longer panel on individual home price and consumption can better help identify anticipated and surprise home price, both of which are critical in identifying the working channels of the housing wealth effect on consumption.

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Figure 1 Channels of the Housing Wealth Effect on Consumption

The literature often finds three channels via which a rise in housing wealth adds to consumption: a credit channel, a wealth channel and a common-factor channel. The dark gray boxes indicate a credit channel and the light gray box indicates a wealth channel. The solid-lined boxes are the steps that both the credit and the wealth channel go through. The dashed lines demonstrate the often called "common-factor" channel, in which a progress on common factors, e.g. technology, brings higher income that raise both home price and consumption at the same time, thus presenting a spurious link from home price to consumption.

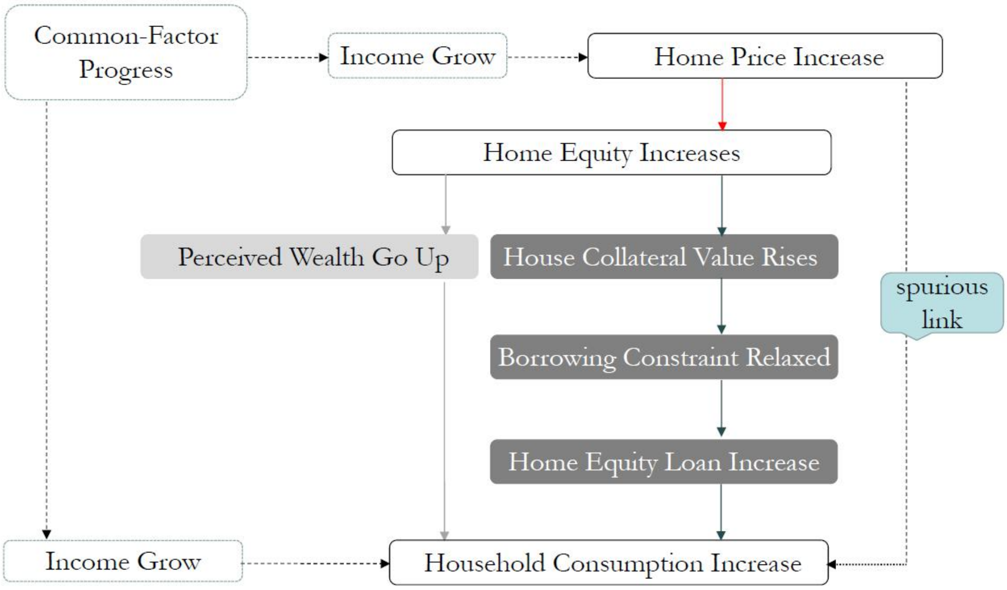
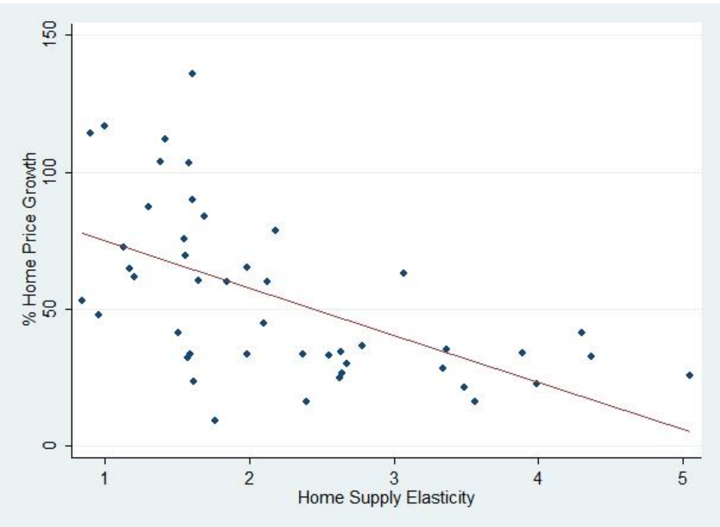


Figure 2 Home Supply Elasticity and Home Price Growth by States 2001-2006

Home price growth is the growth of FHFA Home Price Index between Jan 2001 and Dec 2006. Home supply elasticity is measured on a scale of 0-6, with a higher elasticity implying a bigger change in home supply in response to one unit change in home price.



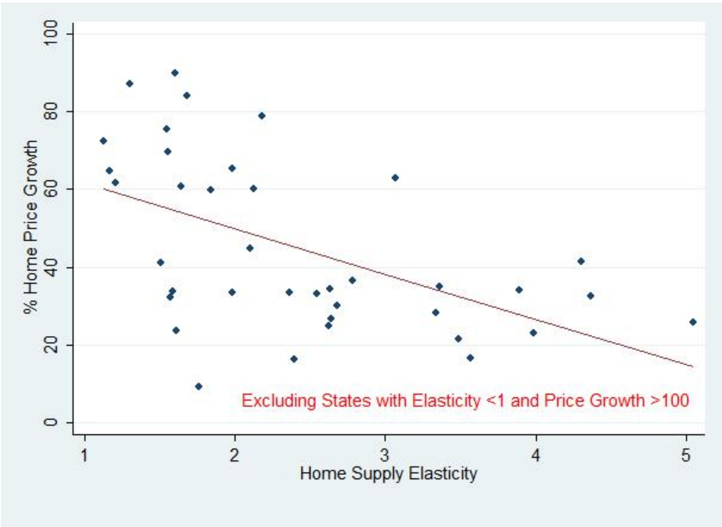


Figure 3 Home Price, Employment and Home Supply Elasticity

The left panel excludes states with price growth>100% or an employment share>5%, and the right panel lists these states with their home supply elasticity. Home price growth is the growth of FHFA Home Price index between Jan 2001 and Dec2006. Employment share is the share of a state in national non-farm employees and is averaged over 2001-2006.

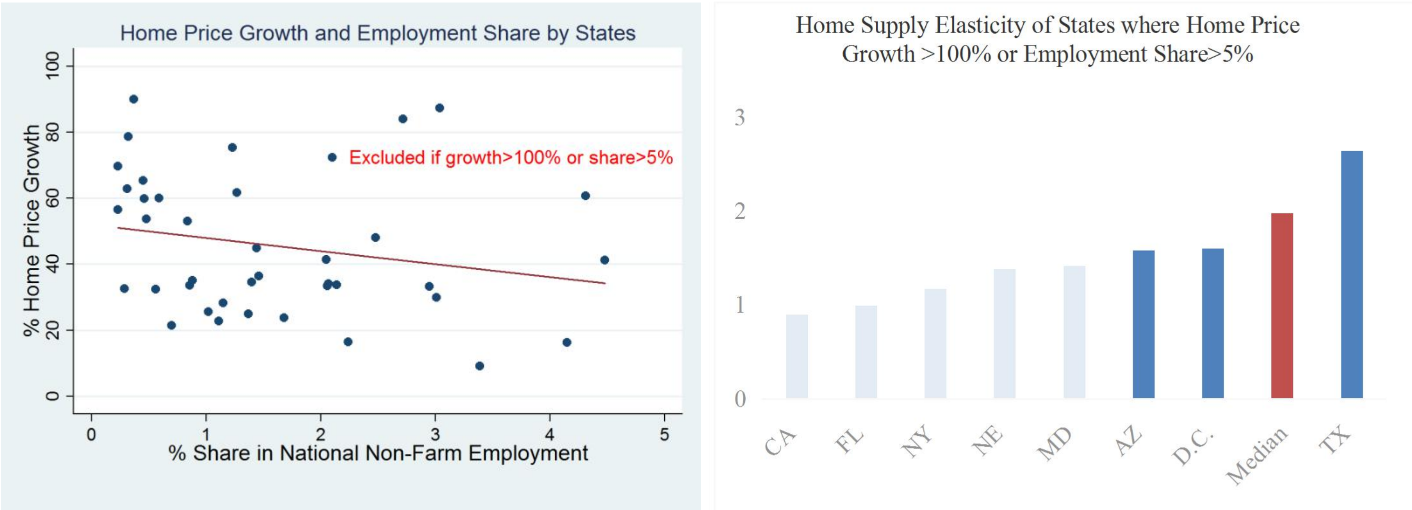


Figure 4 Home Price , Crime Intensity and Home Supply Elasticity

The left panel plots home price growth against crime intensity by states and the right panel does the same but excluding states with home price growth>100% or crime intensity>1.4. Home price growth is the growth of FHFA Home Price index between Jan 2001 and Dec2006. Crime intensity is the crime rate of a state over the national crime rate and is averaged over 2001-2006.

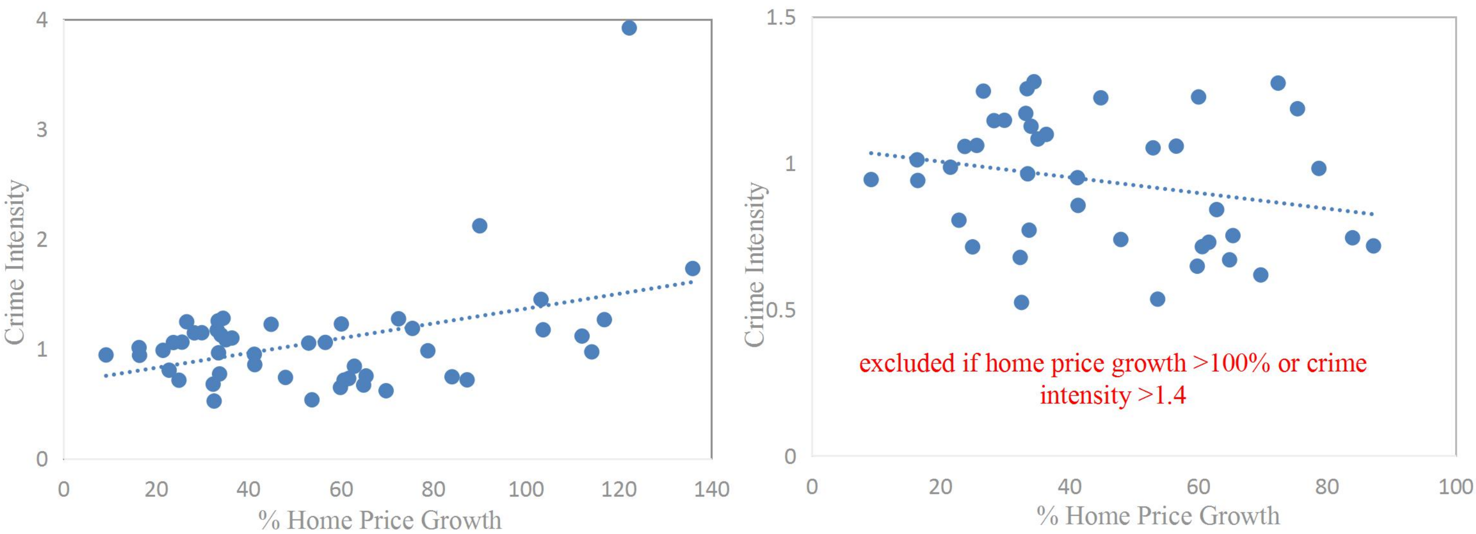


Figure 5 National Home Price and Rent Growth 2001-2006

The left panel plots the FHFA Home Price Index growth less FHFA Rent CPI growth, and the growth of Case-Shiller National Home Price index. The Right panel depicts the growth of the Case-Shiller index and the growth of Mortgage Balance held by households. Frequency is month and growth is from one year go.

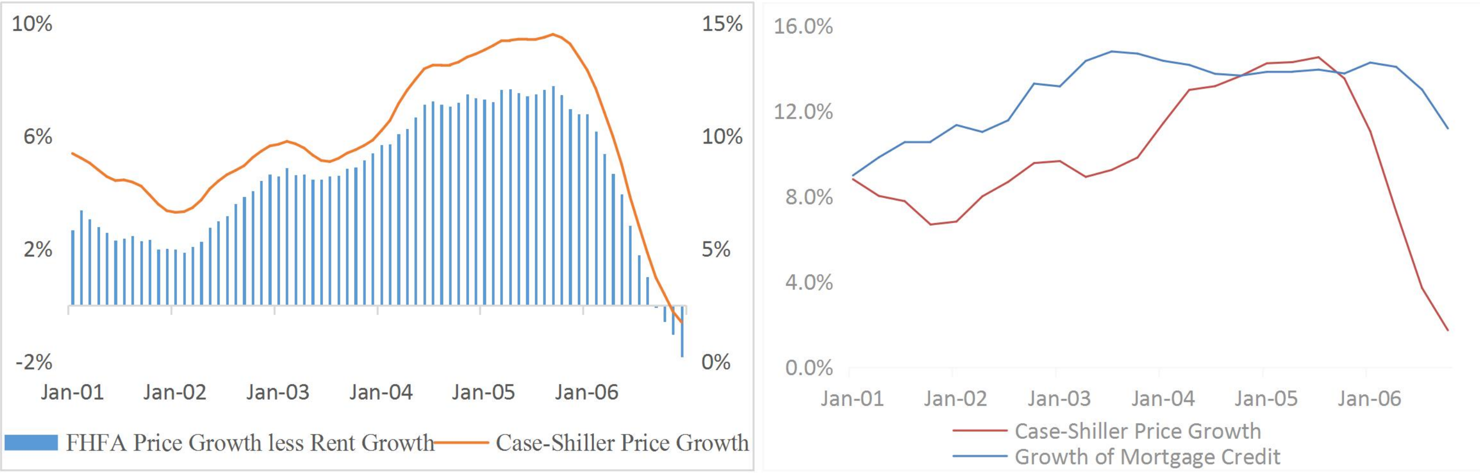


Figure 6 National Home Price Growth 2001-2006

Case-Shiller index refers to the Case-Shiller National Home Price index. FHFA index refers to the Federal Housing Financing Agency Home Price index at state level. FNC index is the Residential Price index released by the mortgage technology company FNC.

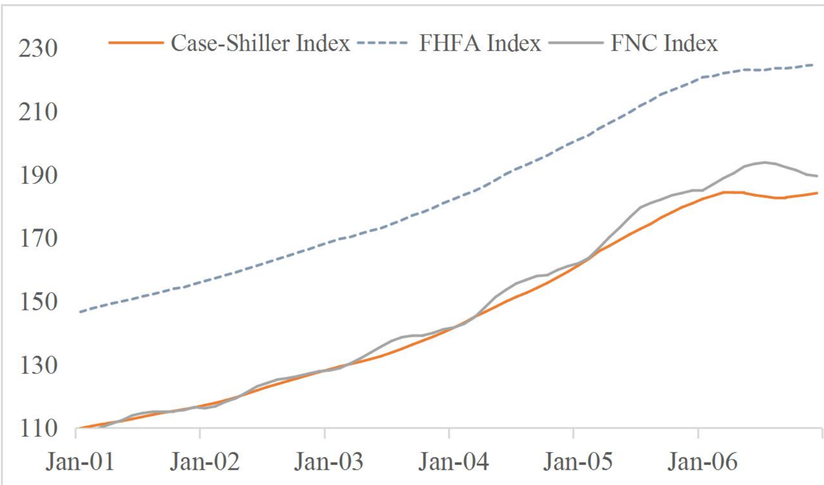
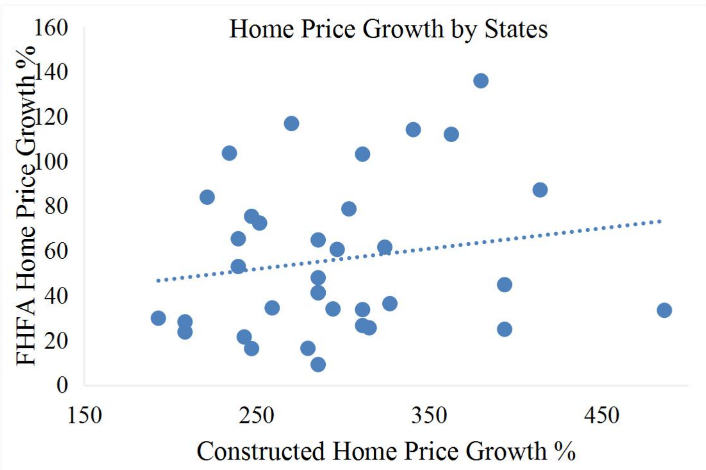


Figure 7 Growth of the two Price/Rent Ratios

The % change in the constructed Price/Rent ratio, measured on the left axis, is based on individual home price constructed from expected rents reported in CEX. The % change in the FHFA Price/Rent ratio, measured on the right axis, is based on the FHFA National Home Price index and the FHFA Rent CPI index. Date frequency is month and the % change is from one year go.

Figure 8 FHFA Home Price Growth and Constructed Home Price Growth

Home price growth is the growth of constructed home price and of the FHFA Home Price index between 2001Q1 and 2006Q4, respectively, excluding states with constructed home price growth near or above 400%, namely TN, NJ, KY and LA. Their rent growth is shown at the right with that of major states.



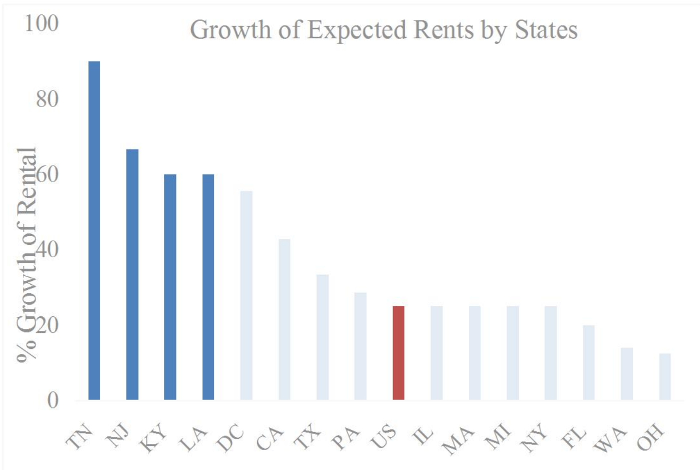
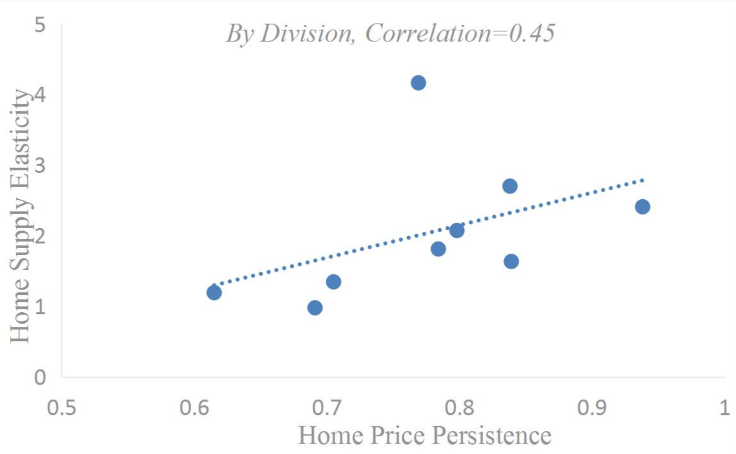


Figure 9 Home Price Persistence and Home Supply Elasticity

Home price persistence is the auto-correlation coefficient in an AR (1) process of constructed home price. Home supply elasticity is measured on a scale from 0 to 6, with a higher elasticity implying a bigger change in home supply in response to one unit change in home price. Division is by the Bureau of Census.



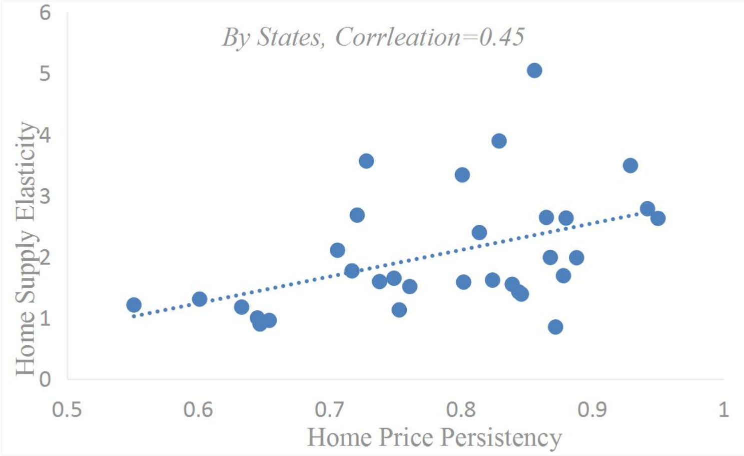
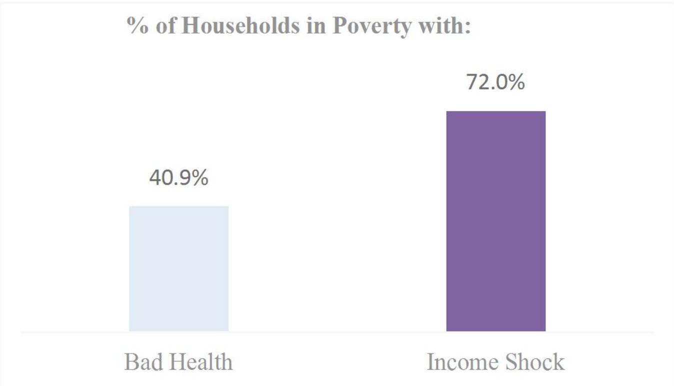


Figure 10 Fractions of Constrained Households with Precautionary Motives

Bad Health and Income Shock equals to 1 if the ratio of health care expenditure over income of a non-old household and the average income growth rate is above the median, respectively, and 0 otherwise.



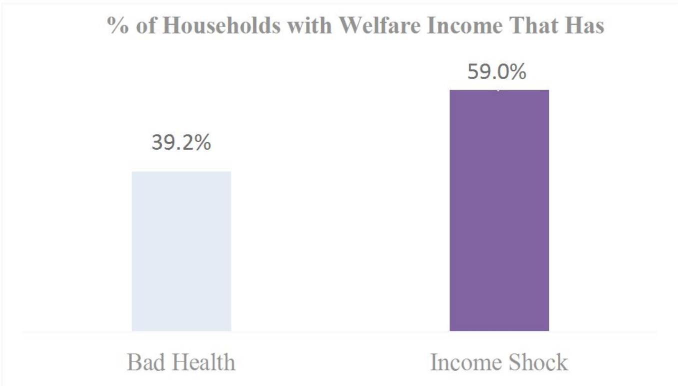


Figure 11 Precautionary Motives and the MPC out of Income

The two figures plot income and the MPC out of income for not credit constrained households that are further grouped into the precautionary and the not. The light bar plots income and the dark bar the MPC out of income. Income shock and Bad Health equal to 1 if the average income growth rate of a household and the ratio of health care expenditure over income is above the median, respectively, and 0 otherwise.

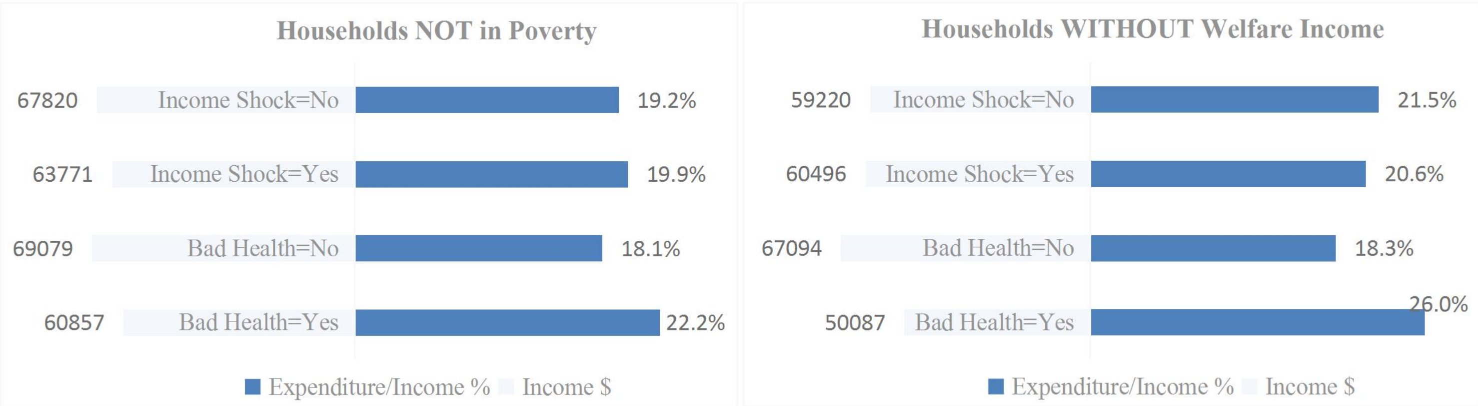


Table 1 Summary of Data

Variable	Definition	Unit	Obs	Mean	Min	Max
1. Consumption	Total expenditure in last 3 months	$	45,728	12,456	2,266	50,650
2. Income	Total income in last 12 months	$	45,728	58,827	0	284,123
3. Liquid Financial Wealth	Checking+Savings+U.S. bonds	$	43,811	8,400	0	280,286
4. Expected Rent	Monthly rent asked on the house	$	40,306	1,281	150	5,070
5. Housing Wealth	Adjusted PV of all future rents to infinity	1, 000 $	40,306	1,645	218	7,823
6. Credit Card Utilization	Total balance over total limit	%	28,258	22.5	0	503
7. LTV	Remaining mortgage balances over home price	%	32,387	10.1	0	87.4
8. DSR	Mortgage payment over income	%	30,007	6.3	0	190
9 .Renter	If live in a rental unit	1(yes) or 0(no)	45,728	14.7%	0	1
10. Young	If household head aged below 40	1(yes) or 0(no)	45,728	32.4%	0	1
11. Age	Of the household head	Year	45,728	47.9	14	86
12 .Family size	# of people in the household	Person	45,728	2.9	1	16
13. Education	Of the household head	Year	45,728	13.5	0	17

Table 2 Home Price Dynamics

Division is one of the nine divisions defined by the Bureau of Census. States Included are states included in a division, and ∂ is the auto coefficient in the AR (1) of constructed home price. Divisio^2, ∂^2, and States Included^2 have similar definitions, except that now the division system is by the 25 percentile of state-level home supply elasticity, with Division^2=1 including states at the bottom 25% of home supply elasticity.

Division	∂	States Included
1	0.643	CT, ME, MA, NH, RI, VT
2	0.705	NJ, NY, PA
3	0.798	IL, IN, MI, OH, WI
4	0.769	IA, KS, MN, MO, NE, SD
5	0.785	DE, FL, GA, MD, NC, SC, VA, DC, WV
6	0.938	AL, KY, MS, TN
7	0.838	AR, LA, OK, TX
8	0.839	AZ, CO, ID, MT, NV, NM, UT
9	0.691	AK, CA, HI, OR, WA

Divisio^2	∂^2	States Included^2
1	0.696	UT, CA, MA, FL, WA, NY, CT, NJ, NV, MD, IL
2	0.787	AZ, CO, DC, ME, MI, OR, PA, RI, VT, VA, WV, WI
3	0.850	ID, TN, LA, NM, DE, MS, OH, NC, KY, SC, TX
4	0.799	GA, AL, MT, OK, AR, NE, IN, MO, IA, MN, SD, KS

Table 3 Household Income Dynamics

This table runs auto regressive models that divide income into an anticipated part and a surprise part. Regression 3 presents the income auto-regression strategy in this paper, while Regression 2 and 1 introduce two alternative strategies that are more compact but less charming in theory. All in log except for sex and race, both of which are categorical variables.

	Household income		
	(1)	(2)	(3)
Lag income	0.823***	0.744***	0.721***
	(0.0112)	(0.0207)	(0.0310)
Job hours		0.0863***	0.109***
		(0.00870)	(0.0163)
Number of Earners		0.0770***	0.0800***
		(0.0131)	(0.0182)
Years of Schooling			0.488***
			(0.0751)
Age			√
Race			√
Sex			√
Family size			√
# of Persons Aged Below 18			√
State and Year Fixed effects	YES	YES	YES
N	35620	21048	12000
adj. R^2	0.687	0.613	0.621

Table 4 Credit Constraint Measures

The top panel describes all behavior-based credit constraint measures that can be decoded as either credit constrained or not credit constrained. For comparability, the bottom panel lists the balance-sheet indicators that often work as constraint measures in the literature, e.g. LTV and DSR, which is the Loan-to-Value ratio and the Debt-to-Service ratio, respectively.

Behavior-based Measure	**Definition**	**Unit**	**Coding**	**Obs**	**Mean**
1. Poverty	If live below the poverty income line	1(yes) or 0(no)	1-constrained	42,110	4.6%
2. Welfare Income	If receive social welfare income	1(yes) or 0(no)	1-constrained	45,728	3.9%
3. Credit Card Utilization	Ratio of total balance over total limit	Percentage	%	28,258	22.5%
4. High Credit Card Utilization	If Credit card utilization above median	1(yes) or 0(no)	1-constrained	28,258	49.9%
5. No Mortgage Refinancing	If no mortgage refinance 2001-2006	1(yes) or 0(no)	1-not constrained	24,809	66.6%
6. No Home Equity Withdrawal	If no home equity loan or HELOC	1(yes) or 0(no)	1-not constrained	45,728	72.0%
Balance-Sheet Indicators					
High LTV	If the LTV ratio is above median	1(yes) or 0(no)	1-constrained	32,787	49.9%
High DSR	If the DSR ratio is above median	1(yes) or 0(no)	1-constrained	30,007	49.9%

Table 5 Correlations of the Two Types of Credit Constraint Measures

Poverty, Welfare Income, High Credit Card Utilization, No Mortgage Refinancing and No Home Equity Withdrawal are dummies equal to 1 if a household lives in poverty, receives social welfare income, carries a credit card utilization rate above the median, never refinanced its mortgage during 2001-2006, and never took out home equity loan and home equity line of credit during 2001-2006, and 0 otherwise. High LTV and High DSR equals to 1 if a household bears a Loan-to-Value ratio and a Debt-to-Service ratio that is above the median, respectively, and 0 otherwise.

	High LTV	**High DSR**
Poverty	-0.0334	0.1476
Welfare Income	-0.0344	0.0342
Credit Card Utilization	0.0419	0.1721
High Credit Card Utilization	0.0457	0.1444
No Mortgage Refinancing	0.0925	0.0452
No Home Equity Withdrawal	-0.0044	0.0455

Table 6 Consumption as Percentage of Income and Wealth

This table sorts households into the credit constrained and the not by the behavior-based credit constraint measures at the 1st column and compares their propensity to consume out of income, liquid wealth and housing wealth. Consumption, income, liquid wealth and housing wealth have the same definitions as in Table 1, and all the credit constraint measures at the 1st column have the same definitions as in Table 4.

	Answer	**Consumption as % of Income**	**Consumption as % of Liquid Wealth**	**Consumption as % of Housing Wealth**
Poverty	Yes	55.0%	647.3%	0.5%
	No	19.6%	141.3%	0.8%
Welfare Income	Yes	24.5%	388.6%	0.6%
	No	21.1%	145.7%	0.8%
High Credit Card Utilization	Yes	22.7%	219.6%	0.8%
	No	19.2%	118.0%	0.8%
No Mortgage Refinancing	Yes	21.0%	165.8%	0.8%
	No	20.6%	137.3%	0.8%
No Home Withdrawal	Yes	20.8%	153.3%	0.8%
	No	21.2%	159.3%	0.9%

Table 7 Fraction of Constrained Households with Precautionary Motives

This table groups households into the constrained and the not by behavior-based measures in Column 1 (Yes=constrained, No=not constrained), and lists the percentage of household in each group that carries precautionary saving motives. Precautionary motives are measured by Bad Health and Income Shocks, which equals to 1 if the ratio of health care spending over income for a not-old household and the average income growth rate is above the median, respectively, and 0 otherwise.

	Answer	**Bad Health**	**Income Shocks**
In Poverty	Yes	40.9%	72.0%
	No	38.8%	47.7%
With Welfare Income	Yes	39.2%	59.0%
	No	42.9%	45.8%
High Credit Card Utilization	Yes	44.6%	49.7%
	No	36.1%	46.1%

Table 8 The Excess MPC out of Housing Wealth for Constrained Households

The * sign in the 1st column is the interplay between anticipated housing wealth and the variable of interest. Poverty, With Welfare Income and High Credit Card Utilization are dummies equals to 1 if a household lives below the poverty line, receives social welfare income, and carries a credit card utilization rate above median, respectively, and 0 otherwise. High LTV and High DSR are dummies equal to 1 when the LTV and DSR of a household exceeds its median, respectively, and 0 otherwise. All in log except for gender and race. *, ** and *** in Regression 1-6 is 5%, 1% and 0.1% significance level. S.E. in the brackets is heteroskedasticity robust and clustered at state-year level.

	Total Consumption					
	(1)	(2)	(3)	(4)	(5)	(6)
Anticipated Housing Wealth	0.134***	0.0292	0.0374	0.0610	0.113***	0.117***
	(0.0270)	(0.0299)	(0.0344)	(0.0373)	(0.0217)	(0.0217)
* High LTV	-0.00245					
	(0.0375)					
* High DSR		0.0833*				
		(0.0377)				
* High Credit Card Utilization			0.137**			
			(0.0430)			
* Credit Card Utilization Rate				0.231*		
				(0.0986)		
* In Poverty					0.169	
					(0.181)	
* With Welfare Income						-0.109
						(0.0634)
N	2069	2069	1454	1454	2248	2270
adj. R^2	0.403	0.409	0.355	0.355	0.385	0.379

Other RHS Variables Controlled in EACH Column:

Anticipated, Surprise income, Surprise Housing Wealth and their interactions with constraint measures
Liquid and Non-Liquid Financial Asset Holdings
Demographics (Age, Education, Family Size, Race and Gender of the Household Head)
State and Year Fixed Effects

Table 9 Precautionary Motives Bias the Credit Channel of Housing Wealth Effect

This table sorts households by precautionary motives and tests, for credit constrained households only, if precautionary motives lead to differentials in the MPC out of anticipated housing wealth growth. Measures of precautionary motives include Bad Health and Income Shock, which is a dummy equal to 1 if the ratio of health care expenditure over income by a non-old household and the average income growth rate is above the the median, respectively, and 0 otherwise. All in log except for gender and race. The * sign in the 1st column is the interplay between anticipated housing wealth and the variable of interest, while *, **, *** in Regression 1-8 are 5%, 1% and 0.1% significance level. S.E. in the brackets is heteroskedasticity robust and clustered at state-year level.

	Total Household Consumption							
	Bad Health				Income Shock			
	(1)Yes	(2) No	(3) Yes	(4) No	(5) Yes	(6) No	(7) Yes	(8) No
Anticipated Housing Wealth	0.158***	0.0602	0.165***	0.0582	0.140**	0.0885***	0.145***	0.0942***
	(0.0254)	(0.0307)	(0.0243)	(0.0315)	(0.0402)	(0.0235)	(0.0405)	(0.0234)
* In Poverty	0.00825	0.536***			-0.0484	2.684***		
	(0.233)	(0.103)			(0.223)	(0.401)		
* With Welfare Income			-0.155*	-0.190			-0.308*	-0.0248
			(0.0607)	(0.127)			(0.142)	(0.0395)
N	1068	1180	1085	1185	852	1396	868	1402
adj. R^2	0.353	0.457	0.349	0.457	0.388	0.396	0.388	0.384

Other RHS variables Controlled:

Anticipated, Surprise income, Surprise Housing Wealth and their interactions with the two dummies

Liquid and Non-Liquid Financial Asset Holdings

Demographics (Age, Squared Age, Education, Family Size, Race and Sex)

State and Year Fixed Effects

Table 10 Home Buying Plans Bias the Credit Channel

Loose Eligible is a dummy equal to 1 if a young (aged<=40) renter's family income is no less than two and half times the median value of homes where live home owners in a same group of age, income, state and family size as the renter, and 0 otherwise. Eligible is a dummy equal to 1 if a young renter is loose eligible and its expected mortgage payment is less than 28% of its family income or its total debt payment is less than 36% of its family income, and 0 otherwise. All in log except for sex and race. *, ** and *** is 5%, 1% and 0.1% significance level. S.E. in the brackets is heteroskedasticity robust and clustered at state-year level.

	Young Renters' Consumption			
	(1) Eligible=Yes	(2) Eligible=No	(3) Loose Eligible=Yes	(4) Loose Eligible=No
Income	0.380***	0.471***	0.366***	0.481***
	(0.0606)	(0.0816)	(0.0546)	(0.114)
Housing Wealth	0.0362	-0.112	0.0400	-0.115
	(0.0635)	(0.0870)	(0.0621)	(0.0856)
N	388	213	391	210
adj. R2	0.492	0.361	0.492	0.351

Other RHS Variables Controlled in EACH Column:
Liquid and Non-Liquid Financial Asset Holdings
Demographics (Age, Education, Family Size, Race and Sex)
State and Year Fixed Effects

Table 11 Home Equity Withdrawals Verify the Credit Channel

The * in the 1st column is the interplay between anticipated housing wealth and the variable of interest. No Mortgage Refinancing, Rejecting Lucrative Mortgage Refinancing, No Home Equity Withdrawal and Rejecting Feasible Home Equity Withdrawal is a dummy equal to 1 if a home owner had a mortgage but never refinanced it during 2001-2006, chose not to refinance mortgages during 2001-2006 even though it was profitable, has neither home equity loan nor outstanding home equity line of credit (HELOC), bears a low Loan-to-Value ratio but has no home equity loan and HELOC, respectively, and 0 otherwise. All in log except for sex and race. *, ** and *** in Regression 1-4 is 5%, 1% and 0.1% significance level, respectively. S.E. in the brackets is heteroskedasticity robust and clustered at state-year level.

	Total Consumption			
	(1)	(2)	(3)	(4)
Anticipated Housing Wealth	0.128***	0.121***	0.110*	0.130***
	(0.0324)	(0.0298)	(0.0503)	(0.0346)
*No Mortgage Refinancing	-0.0236			
	(0.0365)			
*Rejecting Lucrative Mortgage Refinancing		-0.00792		
		(0.0633)		
*No Home Equity Withdrawal			0.00870	
			(0.0502)	
*Rejecting Feasible Home Equity Withdrawal				0.0160
				(0.0477)
N	1554	1554	2270	1554
adj. R^2	0.385	0.386	0.381	0.394

Other RHS variables Controlled in EACH Column:

Surprise housing wealth, Anticipated/Surprise income and their interactions with the dummies

Liquid and Non-Liquid Financial Asset Holdings

Demographics (Age, Education, Family Size, Race and Sex), and State and Year Fixed Effects.

Table 12 Robustness Checks

The * in Column (0) is the interplay between anticipated housing wealth and the variable of interests. Each of Column (1)-(4) corresponds to a purpose of robustness checks while each of Row 1-5 contains a set of robustness checks that is run with a same credit constraint measure, e.g. the cell where the Column "*Adjusted Income*" and the Row "*Credit Card Utilization*" cross represents a robustness check that tests how the consumption response to anticipated housing wealth varies with credit card utilization rates, using "*Adjusted Income*" that adjust household income in the 3rd and 4th interview by expenditure growth. Column (5) lists the results in Table 8 that correspond to each credit constraint measure. *, ** and *** in Column (1)-(5) is 5%, 1% and 0.1% significance level. S.E. in the brackets is heteroskedasticity robust and clustered at state-year level. Other notation same as above.

(0)	(1) Adjusted Income	(2) Renters Excluded	(3) Non-Housing Spending/Income	(4) Household Fixed Effects	(5) Table 8
Anticipated Housing Wealth					
1. *Credit Card Utilization	0.265**	0.241*	0.234*	0.0445	0.231*
	(0.0973)	(0.100)	(0.109)	(0.0942)	(0.0986)
2. *High Credit Card Utilization	0.112**	0.137**	0.139*	0.0193	0.137**
	(0.0366)	(0.0450)	(0.0621)	(0.0739)	(0.0430)
3. * High DSR	0.0482	0.0830*	0.0836	0.0265	0.0833*
	(0.0340)	(0.0377)	(0.0429)	(0.0483)	(0.0377)
4. * No Profitable Mortgage Refinance	-0.0134	-0.00868	-0.107	0.0290	-0.00792
	(0.0562)	(0.0630)	(0.0719)	(0.0929)	(0.0633)
5. * No Feasible Home Equity Withdrawal	-0.0138	0.0167	0.00678	0.0463	0.0160
	(0.0390)	(0.0480)	(0.0655)	(0.0644)	(0.0477)

Appendix A: Home Supply Elasticity and Home Price Growth 2001-2006

This table lists the home supply elasticity and home price growth for all the states covered in the Consumer Expenditure Survey during the Year 2001-2006. MSA-level home supply elasticity is provided by Saiz (2010) and we weight the MSA elasticity by MSA populations to generate the state-level home supply elasticity that is measured on a scale from 0-6 with a bigger number implying a higher elasticity. Home price growth is the point growth of the Federal Housing Financing Agency House Price index (state level) between Jan 2001 and Dec 2006.

States	FHFA Price Growth	Home Supply Elasticity	States	FHFA Price Growth	Home Supply Elasticity
Utah	53.0%	0.84773585	Louisiana	44.9%	2.1036036
California	114.2%	0.8975563	New Mexico	60.0%	2.1258014
Massachusetts	48.0%	0.95575938	Delaware	78.7%	2.181916
Florida	116.9%	0.99568327	Mississippi	33.5%	2.3687069
Washington	72.4%	1.1274772	Ohio	16.3%	2.3933719
New York	64.9%	1.1734051	North Carolina	33.2%	2.5477507
Connecticut	61.6%	1.2080689	Kentucky	24.9%	2.625581
New Jersey	87.2%	1.3039111	South Carolina	34.5%	2.6304121
Nevada	103.6%	1.386464	Texas	26.6%	2.6407503
Maryland	112.0%	1.4214086	Georgia	29.9%	2.6783578
Illinois	41.2%	1.5091023	Alabama	36.4%	2.7833732
Oregon	75.4%	1.5463852	Montana	62.9%	3.066104
Vermont	69.7%	1.561844	Oklahoma	28.3%	3.3373974
West Virginia	32.3%	1.571845	Arkansas	35.1%	3.3619351
Arizona	103.2%	1.5825828	Nebraska	21.5%	3.4900744
Wisconsin	33.7%	1.5911804	Indiana	16.4%	3.5640224
Rhode Island	89.9%	1.605547	Missouri	34.0%	3.8922454
D.C.	136.0%	1.605827	Iowa	22.8%	3.9906476
Colorado	23.7%	1.6150121	Minnesota	41.3%	4.3016279
Pennsylvania	60.6%	1.6455856	South Dakota	32.6%	4.3666974
Virginia	84.0%	1.6869764	Kansas	25.6%	5.0459535
Michigan	9.2%	1.7663736	Alaska	56.6%	
Maine	59.8%	1.8420442	Hawaii	122.3%	
Idaho	65.4%	1.9817327	New Hampshire	53.7%	
Tennessee	33.4%	1.9859363			

Appendix B: Employment and Crime as Alternative Spatial Home Price Factors

Home price is built as the discounted sum of rents to infinity, adjusted by time and spatial variations in home price growth. The baseline measure of the spatial variation is home supply elasticity. This appendix details alternative measures, including employment share and crime rates.

Employment Share is the share of a state in the U.S. national non-farm employees. When a state is in an economy boom, labor flows in and housing demand increases, and both the employment share and home price rise. This qualifies employment share as a measure of the spatial variation in home price growth. Employment data is released by the Department of Labor each year and we simple average the shares of all years from 2001-2006 to get the overall employment share of a state. For convenience, we normalize all employment shares by adding 1 to them.

Crime Rate is the number of all crimes per 100,000 people. Home price often vary a lot across communities and crime rate is a key measure of community quality. Given a home demand shock, states with a high crime rate tends to see a low rise in home price. This qualifies crime rate as a measure of the spatial variations in home price growth. Crime data is released by the Department of Justice each year and we simple average the crime rate of all years from 2001-2006 to form the overall crime rate of a state before we normalize it by its ratio over the nationwide level, which is then called crime intensity.

Appendix C: The Price-Rent ratio and the Choice of Discounting Rate

Home price in this paper is built as the discounted sum of rents, thus the choice of discounting rate is critical to the price-rent ratio, a critical index in assessing the quality of the constructed home price since it reflects not only the affordability and tightness of the housing market, but also the time variation in home price growth. The Price-Rent ratio and its growth are formulated as:

$$PR \equiv \frac{P}{R}$$

$$\frac{\Delta PR}{PR} = \frac{\Delta P}{P} - \frac{\Delta R}{R}$$

where *PR* is the Price-Rent ratio, *R* rents and *P* individual home price built as:

$$P = (6 - E) \times CS \times \frac{R \times 12}{i}$$

where *E* is Home Supply Elasticity, *CS* Case-Shiller index, *R* rents and *i* discounting rate. Since *E* is fixed, *P* grows at:

$$\frac{\Delta P}{P} = \frac{\Delta CS}{CS} + \frac{\Delta R}{R} - \frac{\Delta i}{i}$$

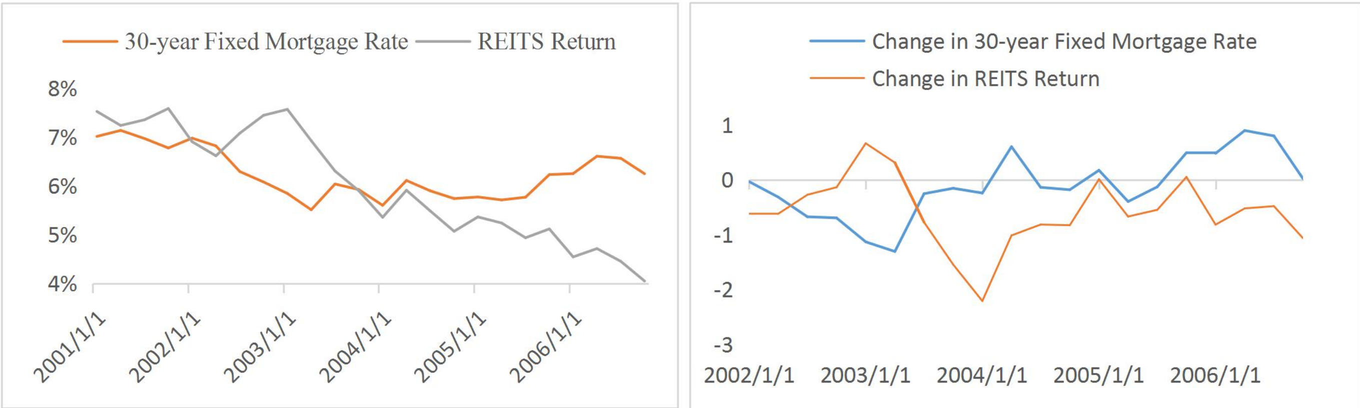
So the Price-Rent ratio grows as:

$$\frac{\Delta PR}{PR} = \frac{\Delta CS}{CS} - \frac{\Delta i}{i}$$

The two competing discounting rates in this paper are the 30-year fixed mortgage rate and the REITS return. While the 30-year T-bond rate can also work as a discounting rate, it is a benchmark rate and could be less than precise for certain markets. Hence, we compare results based on 30-year fixed mortgage rates and on the REITS return.

The REITS return often moves together with the 30-year fixed mortgage rate over time, but in a lagged and volatile way. The reason it is lagged is that it reflects the profits of the real estates it invests in, which is decided by the overall wellness of the real estate market that is in turn affected by the 30-year fixed mortgage rate. The reason it is more volatile is that REITS is, by nature, a trust fund and its return is sensitive to financial market conditions that are frequently changing. Being lagged and volatile, REITS returns may look different than 30-year fixed mortgage rates despite a similar trending, e.g. their changes from year ago, as in the right of Figure C, often differ at a given time point.

Figure C 30-yr Fixed Mortgage Rates, REITS Returns and their % Change



We choose to work with the REITS return because 1) REITS is more accessible to regular investors like households than is mortgage investment 2) the REIT return is more sensitive to the market while 30-year fixed mortgage rates often depend on idiosyncratic non-market factors, e.g. credit scores.

Results in this paper are, however, robust to either discounting rates and support a credit channel of the housing wealth effect anyway. So, it doesn't matter that much which discounting rate to use. In fact, when plotting the Price-Rent ratio in Figure 5, we work with 30-year fixed mortgage rates to yield a more smooth series of Price-Rent ratio, but switch to the REITS return when running regressions to get results of this paper.

Appendix D: Costs and Benefits of Mortgage Refinancing

This appendix details the cost-benefit accounting that plays as a key reference when a household considers whether or not to refinance its outstanding mortgages.

First, the **new monthly payment** after planned mortgage refinancing is calculated by the following equation that is wide used in the mortgage business:

$$NewPay = \frac{r_{30} * 0.8 * Balance * (1 + r_{30})^{360}}{(1 + r_{30})^{360} - 1} \quad \text{if the remaining term > 15 year}$$

-where r_{30} is 30-year fixed mortgage rate, *Balance* the remaining balance of current mortgage, *360* the total months in 30 years, 0.8 is the fraction of current balance to be refinanced. A new term of 30 years is assumed if the the remaining term>15 years, or a 15 year term otherwise.

Then, the **monthly savings** after planned refinancing is defined as:

$$MonSav = NewPay - LastPay$$

-where *LastPay* the last regular monthly payment made on the mortgage.

Next, the **Break Even Point** is defined as the number of months in which the total saving from refinancing exceeds the cost of refinancing:

$$BEP = \frac{Balance * 0.03}{MonSav}$$

-where *0.03* is the refinancing fee charged as a fraction of the balance.

Finally, **a mortgage refinancing is defined as lucrative** if the break even point is no more than 72 months, which is how long a typical American stays at a house:

Lucrative if BEP<=72

Appendix E: Renters' Home Buying Eligibility

Renters' home purchase plans are often unobserved and thus we assume a home purchase plan for a renter if she is eligible, with the eligibility decided by three rules that are popular in mortgage business.

Rule 1: $FamInc >= 2.5 * HomeValue$

-where *FamInc* is the family income of the renter, *HomeValue* is the price of the target home, assuming the renter targets a median-value home among all home owners from a same group of income, age, family size and state as she is.

Rule 2: $MgtPay <= 0.28 * FamInc$

-where *MgtPay* is the expected monthly mortgage payment after the renter buys her target house with a mortgage and it is calculated using the equation in *Appendix D*.

Rule 3: $TotPay <= 0.36 * FamInc$

-where *TotPay* is the total monthly payment of all kinds, including mortgage payment, after the renter purchases the target house with a mortgage.

While a bank often reviews all three rules on a mortgage request, relaxations on one or more of the rules were often made during the housing boom in 2001-2006, hence we follow the mortgage business to define **two sets of home buying eligibility**:

1）***Eligible*** if Rule 1 AND either Rule 2 OR Rule 3 are true for a renter

Or

2) ***Loose Eligible*** if Rule 1 is TRUE for a renter

Appendix F: Income Adjustments by Expenditure and by Job Hours

The income at the 2nd interview is carried over to the 3rd and 4th and is not updated until the 5th, leading to a possible lack of income variation. This appendix explains how to adjust income by expenditure and by job hours as described in the second robustness check in Part 5, though results are both similar to the one with unadjusted income.

1. Income Adjustment by Expenditure

1) First, assume income increase at same rates as expenditure do. This is to assume a constant MPC out of income and is reasonable within a period of one year.
2) Then, calculate the expenditure growth between two consecutive interviews using the expenditure reported by a household at each interview.
3) Next, project the expenditure growth between the 2nd and 3rd interview to income growth at the same time, and repeat the process between the 4th and 5th interview.
4) Now, the 3rd income can be adjusted using the 2nd income and the income growth between the 2nd and 3rd interview.
5) Last, the 4th income can also be known using the 5th income and the income growth between the 4th and 5th interview.

2. Income Adjustment by Job Hours

1) First, assume income grow at same rates as job hours do. This is to assume a fixed hourly wage, which is reasonable since unions often negotiate wages every year.
2) Next, repeat Steps 2-5 in the *Income Adjustment by Expenditure* outlined above, except that now expenditure is replaced with job hours.

Appendix G: Why Balance-Sheets not Proper Credit Constraint Measures

A high LTV may imply credit constraints, but not necessarily the access to a credit channel since few home equity is vacant, though those who can still refinance mortgages shall see a rise in LTV. In light of this, we define the starting and ending LTV as the LTV when a mortgage was issued and the current LTV, so an ending LTV above the starting one captures a household that gains access to the credit channel via mortgage refinancing. Hence, it should respond to housing wealth growth that enable more refinancing.

Results show that a rise in LTV leads to, however, no excess MPC out of anticipated housing wealth, implying that LTV is not a proper credit constraint measure. As shown in Table G, a rise in LTV instead cuts consumption, which is certainly not supportive of a credit channel. Also, a high starting/ending LTV brings no excess MPC either. Since a credit channel is already evidenced by trusted measures, e.g. credit card usage, the chance is that LTV fails to capture credit constraints in housing context.

Table G LTV is not a Good Measure of Credit Constraint

	Total Consumption		
	(1)	(2)	(3)
Anticipated Housing Wealth	-0.0563	0.134***	0.0562
	(0.112)	(0.0270)	(0.0943)
*High Starting LTV	0.177		
	(0.139)		
*High Ending LTV		-0.00245	
		(0.0375)	
*Rises in LTV			-0.550**
			(0.184)
N	121	2069	121
adj. R^2	0.385	0.403	0.409

Other RHS Variables Controlled in EACH Column:
Surprise housing wealth, Anticipated/Surprise income and their interactions with the three LTV
Liquid and Non-Liquid Financial Asset Holdings
Demographics (Age, Education, Family Size, Race and Sex) and State-Year Fixed Effects

Appendix H: Home Price Construction for Renters

Home price in this paper is built as the discounted sum of rents, but CEX asks no renters their expected rents, so we assign a renter the average of expected rents reported by home owners living in a similar house as the renter does. Below is the procedure:

First, group households by the structure of the house where they live:

1) State: in which state is the house located.
2) Year: the year of the survey, from 2001-2006
3) Location: urban, or rural
4) House age: <= 25% percentile, 25%-50%, 50%-75%, others
5) Building type: single-family house, or others
6) Off-street-park space: yes, or no
7) Swim pool: yes, or no.
8) Number of bedrooms: 1, 2, 3, 4, 5 and above
9) Number of bathrooms: 1, 2, 3, 4 and above

Next, within a same group, assign the average expected rents asked by home owners to renters and make it as the expected rent of those renters. For renters who don't report one or more aspects of house structure, their expected rents will not be imputed.

Last, by Equation (1), calculate a house price for every renter at each interview using their expected rents.

Appendix I: State-Year Fixed Effects and Household Fixed Effects

This appendix explains why we imposes state-year fixed effects, not household fixed effects that might seem natural given that we are using household data.

Fixed effects capture unobserved time-invariant factors and the unit of fixed effect restrict these factors to be different across units. For this paper, state fixed effects assert that unobserved time-invariant consumption factors vary across states, while household fixed effects posit that they need also be different at household level.

Household fixed effects is inappropriate in this paper since holidays/races may invite many households to raise their expenditure at the same time. For household fixed effects to work, unexplained consumption, the part of consumption due to unobserved factors, need to be uncorrelated among households. So, if one family's consumption is related to holidays, another family's can't be affected by the same holidays. Obviously, this will not hold, e.g. most people do more shopping and travelling during Christmas while Asians often raise food/dinning expenditure for the Lunar New Year. Since holiday shopping, traveling and dinning plans are often unobserved and heterogeneous, it is hard to ensure such a zero consumption correlation. SO\o, household fixed effects is inappropriate.

Instead, state-year fixed effects imposes few restrictions on household consumption correlation and catches more unobserved consumption factors. The transmission from housing wealth to consumption is different cross states and over time e.g. in states where banks were loosely regulated, home equity loan grew a lot relative to other states. Also, the relaxation of home equity borrowing varied over time with changing monetary policy. State-year fixed effects is better at capturing these unobserved state factors.