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Credit Constraints, Housing Finance and the Monetary Transmission to Consumption

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ABSTRACT OF THE DISSERTATION

Housing Finance, Credit Constraints and the Monetary Transmission to Consumption

by

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This dissertation is intended to study the effect of housing wealth on consumption. It first builds a panel of micro home prices in U.S. and evidences a credit channel that finances consumption by home equity withdrawals. More importantly, the size of the credit channel is found to be much bigger than the one in the literature with aggregate home prices. Next, it shows that the credit channel is also working in China but is enabled by private credits from relatives and friends, not by bank credits as in U.S., though it is neutralized by precautionary savings due to uncertainties out of bad health and raising children under the one-child policy. Moreover, this dissertation shows in aggregate data that a fall in monetary policy rate reduces the prime mortgage spread over safe rate and induces banks to increase the supply of risky high-yield mortgages. This process heats the housing market and home equity withdrawals, suggesting a monetary transmission to consumption via the housing sector.

Data in this dissertation is from the Consumer Expenditure Survey 2001-2006, the Survey of Consumer Finance 2004 and 2007, the China Household Finance Survey 2013, and the St. Louis Fed FRED 1992-2006. Strategies are an estimated representative agent model with housing wealth and varying MPC that views an excess consumption response to housing wealth growths by constrained households as evidence of a credit channel, and a Sequential VAR that first captures the response of the prime mortgage spread to monetary shocks, then that of risky mortgages to changes in the spread, and finally the response of housing sector to developments in risky mortgages.

This dissertation adds to the literature by building and utilizing micro home prices that produce new results on the housing wealth effect, by showing that home equity withdrawals for consumption are independent of specific housing finance institutions, and by proving that monetary policy shocks also transmit to consumption through the housing sector, in addition to the balance-sheet channel often found.

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Chapter 1: Micro House Prices and the Credit Effect of Housing Wealth

Preview of Chapter 1

This chapter examines how housing wealth affect household consumption through a credit channel that extracts home equities for consumption. To this end, it builds and feeds a true panel of U.S. individual house prices to an estimated representative agent model, which views an additional consumption response by constrained households to changes in housing wealth as a sign of a credit channel. The identification of constrained households is based on household self-revealed financial characteristics, not ages and/or balance-sheet indicators as in the literature. Results show that for a one-dollar anticipated increase in housing wealth, a constrained household extracts and spends 25-30 cents on consumption, much larger than the 2-10 centers often found in the literature that uses aggregate house prices. This chapter contributes by building and using individual house prices that yield new results on the housing wealth effect, and by measuring the degree of credit constraint with household self-revealed financial characteristics that carry fewer endogeneity issues and measurement errors.

1.1 Introduction to Channels of the Housing Wealth Effect on Consumption

During the pre-crisis period of 2001-2006, the United States experienced a significant boom in housing and expenditure, thus offering an interest on the link between housing wealth and consumption. While savings rates stayed about the same, the expenditure continued to grow at about 3% per year. This savings puzzle has been inspiring the search for a non-traditional engine for consumption. Given that house prices were growing at 10%-15% per year at the time, many studies view the increase in housing wealth as a source of consumption growth[1]. The canonical study by Case et al (2005) finds a strong effect of housing wealth on consumption. Many empirical studies follow up to examine the housing wealth effect on consumption and often find a 2%-10% MPC out of housing wealth (e.g. Bostic et al, 2007; Benjamin and Chinloy, 2008; Carroll, 2004; Carroll et al, 2011; Case et al, 2013, among others)

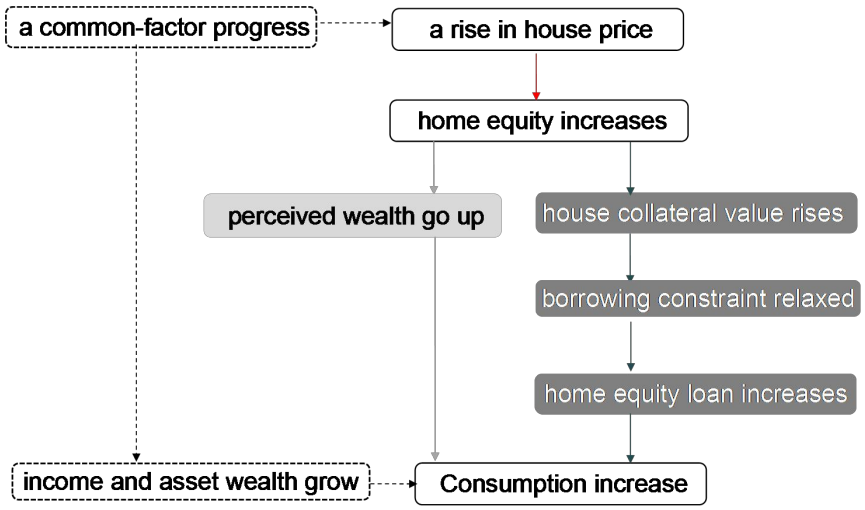
This paper goes further and asks through what exact channels housing wealth affect consumption, a question hardly answered before. An increase in housing wealth can add to consumption via a *wealth channel* in which a household increases its consumption as a direct result of higher perceived housing wealth, or via a *credit channel* that enables the household to borrow against its rising home equities to finance consumption growths[2] (see Figure 1.1 for a demonstration of different channels). Given that a wealth channel is

[1] Unless specified, this paper uses "housing wealth" and "house price" as interchangeably.
[2] A common 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 prices, presenting a spurious link from house prices to consumption (see Atlay et al, 2013 for details). Since it is spurious, this paper will not cover it. See Figure 1.1 for details.

ambiguous in theory (Sinai and Souleles, 2005; Buiter 2008), the question of this chapter is narrowed as: whether and (if any) by how much a credit channel contributes to the housing wealth effect on consumption[3].

Figure 1.1 Channels of the House Price Effect on Consumption

The literature often finds three channels through which a rise in house price contributes to consumption: a credit channel, a wealth channel and a common-factor channel. The dark-grey boxes indicate a credit channel and the light-grey box indicates a wealth channel. The solid-lined boxes are the steps that both the credit and the wealth channel go through. The dash-lined boxes indicate the often called "common-factor" channel, which increases both house prices and consumption at the same time and presents a spurious link from housing wealth to consumption.



Few studies try to identify a working channel but find divergent results. Attanasio et al (2009) find neither a credit channel nor a wealth one, while Campbell and Cocco (2007) evidence both channels using same data and a similar strategy. Interestingly, Browning et al (2013) observe a wealth channel but only for constrained households. More, Mian and Sufi (2011) and Mian et al (2013) both show a higher MPC out of housing wealth by

[3] This paper also tests a wealth channel but finds no empirical evidence of it. See Appendix D.

households with high debt leverages and low credit ratings, implying a credit channel. Likewise, Cooper (2013) finds a higher MPC for those with low asset holdings and high debt payments, also suggesting a credit channel.

The new features that separate this paper from the literature include: First, it builds a panel of micro house prices. Aggregate house prices that are often used in the literature are misleading if the growths of expenditure and of house prices do not match at household level[4]. Next, it measures the degree of credit constraint by household financial characteristics. In contrast, the literature often measures credit constraints by ages or balance-sheet indicators, both of which bear endogeneity issues and measurement errors and produce inaccurate results on a credit channel. Lastly, it controls for parts of income that might add to consumption as house prices do, while the literature rarely pays attention to this and might void any effect found for house prices.

The author identifies a credit channel by an estimated version of a representative agent model with the permanent income hypothesis, which views an excess consumption response by constrained households to a predicted rise in housing wealth as evidence of credit constraints (King, 1994; Carroll and Kimball, 2001; Carroll, 2001; Mian and Sufi, 2011). First, this paper derives house prices for a household from the expected rentals it reports quarterly. Next, an AR (1) is estimated to divide all house prices into a predicted and a surprise part. Then, households are grouped into the constrained and the non-constrained by a set of financial characteristics, e.g. a household in poverty is viewed

[4] For example, households that have a rise in housing wealth may not be those that increase expenditures.

constrained. Lastly, the paper investigates whether and (if any) by how much a credit constrained household displays an additional consumption response to an anticipated increase in housing wealth.

One feature of this paper is to tell if a household is credit constrained or not using its self-revealed financial characteristics, including: whether a household lives in poverty, receives supplemental security income, was rejected by banks on credit requests, lives in a rental unit, always pays full credit-card balance on time, and never cash-out refinanced on mortgages during 2001-2006[5]. The first three characteristics indicate if a household is constrained, while others detect if the household is non-constrained[6].

The data in this paper is built by matching the Consumer Expenditure Survey (CES) and the Survey of Consumer Finance (SCF). CES go from 2001-2006 and includes expenditure, income, wealth, demographics and house information (e.g. expected rental). SCF are of 2004 and 2007 and contains demographics, income and financial information. A household from SCF is matched to its CES counterpart by a distance function of age, income, family size and home tenure (see Appendix C). Results of this paper are robust to an alternative strategy that runs no data matching and uses only CES data.

The results show that a constrained household yields an additional consumption response of 19-26 percentage points to a predicted rise in housing wealth, suggesting a

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[5] Cash-out refinancing a mortgage refers to a situation in which a household takes out a new mortgage that is larger than the remaining balance on its current mortgage, and the household can withdraw the difference. This process is also called home equity withdrawal. See Greenspan and Kennedy (2008).

[6] Precisely, being a renter translates to having no access to a credit channel that uses houses as collateral.

credit channel of the housing wealth effect on consumption. Including the additional response, the MPC out of predicted housing wealth by a constrained household is 25%-30%, much higher than the 2%-10% often found in the literature. Thus, for every one-dollar predicted rise in housing wealth, a credit constrained household extracts and spends 25-30 cents on consumption. Furthermore, households without constraints or without access to a credit channel display no additional response, therefore justifying the credit channel found. In contrast, the author can not find evidence of a wealth channel. The results are robust to various data processing methods and different applied micro econometrics settings.

This paper adds to the literature in two ways: First, by building a panel of individual house prices, it not only rules out a spurious housing wealth effect that might arise in aggregate data, but also exploits both time series and cross-section co-movements of house prices and consumption at household level to precisely capture the housing wealth effect, which is under-estimated in the literature of aggregate data. Second, by the micro nature of the data, the paper employs a set of household financial characteristics that comprehensively measures the degree of credit constraint. In contrast, the literature often measures it by ages or balance-sheet indicators, both of which lack a diversified view and suffer endogeneity issues and measurement errors.

Note that this paper is close to Jappelli (1990) in measuring credit constraints but with two key differences: First, he uses only one financial characteristic, namely if a household was ever rejected by a bank on credit requests, to tell if it is constrained, while

this paper uses a much broader set of characteristics that yield consistent results. Second, he has only 300 observations on credit request rejection and needs to impute for others the probabilities of being constrained, which suffers potential biases. In contrast, this paper has over 7,000 observations on each characteristic and needs not do so.

The rest of the paper is structured as the following: Section 2 describes the data. Section 3 presents the strategy and the results. Section 4 conducts a series of robustness checks, and Section 5 concludes.

1.2 Data of Micro House Prices and Household Expenditure

This paper employs household data on consumption, income, financial asset holdings and demographics from the Consumer Expenditure Survey (CES) by the Bureau of Labor Statistics, together with information about household self-revealed financial characteristics from the Survey of Consumer Finance (SCF) by the Federal Reserve Banks. CES is a repeated panel that interviews a household every three month for a total of five interviews, and SCF is a repeated cross-section conducted every three years. This paper uses CES from 2001-2006 and SCF of 2004 and 2007. See Table 1.1 for details on the variables, measures and data sources.

A group of six financial characteristics is employed to provide a multi-dimension proxy for the degree of credit constraint of a household. These decisions include: if a household lives below the poverty line, receives supplemental security income, lives in a rental unit, always pays off full credit balances on time, never cash-out refinanced on

mortgage during 2001-2006, or was rejected by a bank on credit requests. Information on the first three come from CES while others are from SCF. Details on how they measure credit constraints are provided in Section 1.3.1.

Individual house prices for each house are derived from the expected rentals reported by households at each interview by CES. Then, this paper feeds the house prices in an AR (1) to derive the expected and the surprise house prices, which are defined as the explained and the error terms of the AR (1), respectively. Income will go through a similar process to yield expected and surprise income for each household. Please see Section 1.2.1 to Section 1.2.3 for details.

Table 1.1 Summary of Variables

The first Column describes the variables to be used in the estimation of the housing wealth effect on consumption. The second column introduces the proxy for each variable as well as the unit and frequency of the proxy. The last column is the data source for each proxy. "CES" is the Consumer Expenditure Survey by the Bureau of Labor Statistics; "Imputed" means the data of a proxy is calculated by the author based on information from the CES.

Variable	**Measure** (at quarterly frequency unless specified)	**Source**
1.Consumption	Expenditures by all household members	CES
2.Income	Household income of all sources, annual	CES
3.Predicted income	The expectation of income by an AR (1), annual,	Imputed
4.Surprise income	The error term of income by the AR (1), annual	Imputed
5.Wealth	Financial asset holdings, annual	CES
6.Age	Age of the household head	CES
7.Family size	Number of family members living in the household	CES
8.House price	Derived from expected rentals reported in CES	Imputed
9.Predicted housing wealth	The explained part of house price that is generated by an AR(1) on house prices	Imputed
10.Surprise housing wealth	The error term of house price that is generated by an AR(1) on house prices	Imputed
11.Education	1. Less than high school; 2. High school graduate; 3. Some college; 4. College degree; 5. Graduate school and above	CES

1.2.1 Individual House Prices

This part derives individual house prices using expected rentals reported by home owners in CES. First, the expected price of a house is calculated as the sum of present discounted values of all future rentals, augmented with a premium factor:

$$EP_i^t = \left[\frac{L_i^{yt} \times 12}{(1+r_y)} + \frac{L_i^{yt} \times 12}{(1+r_y)^2} + \frac{L_i^{yt} \times 12}{(1+r_y)^3} + \ldots \right] \times (1+r_y) \tag{1.1}$$

where y is the year of survey, t the order of interview and t=1 to 5, i household, L log expected monthly rental, r average weekly annualized rate on 30-year T-bond[7], the sum in the big bracket is the present discounted value of all future rentals, and the factor $1+r_y$ in the small bracket to the very right captures the premium of owning over renting[8].

By Equation (1.1), the growth of house price is realized through: 1) the variations in expected rentals across interviews for a household, who observes the market and then updates its rental expectations in the next interview 2) the variations in 30 year T-bond interest rates that capture economic fundamentals which drive the housing market.

Next, following Attanasio et al (2009) and Browning et al (2013), this paper imposes an AR (1) on house prices:

$$P_i^t = \rho_1 P_i^{t-1} + u_i^t \tag{1.2}$$

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[7] The expected rental in an interview is assumed constant over time, but since a household is interviewed for five times, it can update its expected rental according to the market, which offers time variations in expected rentals.

[8] Since time variations in house prices, captured by the superscripts y and t, already partly internalize the premium, the factor $(1+r)$ that links the premium to the return on a safe comparable asset (30 year T-bond) is appropriate.

where u is an idiosyncratic shock with $E(u_i^t \mid P_i^{t-1})=0$. By Equation (1.2), the expected house prices formed at time *t-1* and *t-2* are:

$$EP_i^t = \rho_1 P_i^{t-1}$$

$$EP_i^{t-1} = \rho_1 P_i^{t-2}$$

Then, the change in expected house prices can be derived as a function of the lag change in house prices:

$$EP_i^t - EP_i^{t-1} = \rho_1 (P_i^{t-1} - P_i^{t-2}) \tag{1.3}$$

Next, this paper also imposes an AR (1) process on expected house prices. It can be shown (see Appendix A) that it has a same auto-regressive coefficient as Equation (1.2):

$$EP_i^t = \rho_1 EP_i^{t-1} + v_i^t \tag{1.4}$$

Estimating Equation (1.4) with expected house prices by Equation (1.1) yields an estimate of ρ_1. Plugging that estimate, along with the expected house prices, back to Equation (1.3) and moving house prices to the left-side yields:

$$P_i^{t-1} - P_i^{t-2} = \frac{1}{\rho_1}(EP_i^t - EP_i^{t-1}) \tag{1.3.1}$$

Furthermore, extending Equation (1.3.1) from t=3 to 5 gives the following:

$$\begin{aligned}
P_i^2 - P_i^1 &= \frac{1}{\rho_1}(EP_i^3 - EP_i^2) \\
P_i^3 - P_i^2 &= \frac{1}{\rho_1}(EP_i^4 - EP_i^3) \\
P_i^4 - P_i^3 &= \frac{1}{\rho_1}(EP_i^5 - EP_i^4) \\
P_i^5 - P_i^4 &= \frac{1}{3}[(P_i^4 - P_i^3) + (P_i^3 - P_i^2) + (P_i^2 - P_i^1)]
\end{aligned} \tag{1.3.2}$$

Note that since there is no sixth interview of any household, the expected house price at the sixth interview, EP^6, is not observed, and the (P^5-P^4) can not be derived using Equation (1.3.1). The author proxies for it using the average of $(P^{t-1}-P^{t-2})$ from t=3 to 5, as shown in the bottom of Equation (1.3.2).

Since expected house prices EP are given by Equation (1.1) and the autoregressive coefficient ρ_1 is estimated by Equation (1.4), it is now clear that if any P^t from t=1 to 5 is observed, then all other P^t can be recovered by Equation (1.3.2).

The SCF asks a household its house value, which is assigned by this paper to its matched household in the CES as the observed house price at the 5th interview[9]. Then, all house prices P^t from t=1 to 4 are recovered using Equation (1.3.2) and the 5th house price observed.

The imputation of house prices for renters adopts a different approach because CES does not ask a renter its expected rentals. The author tries two ways to derive house prices for renters: 1) a renter is given an expected rental, which is the average of expected rentals of home owners living in a similar house as the renter does, and the imputation starts with that average expected rental. See Appendix B for details; 2) some renters in SCF report a value on their rental houses, which is taken as the observed price on the house where their matched CES renters live[10]. Estimations based on either ways yield similar results, and the analysis below goes with the first.

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[9] Because the 5th interview includes all updated consumption, income and financial asset holding and thus makes the matching more precise. For more details on the matching, please refer to Appendix C.

[10] The matching design ensures that a SCF renter is matched to a CES renter. See Appendix C.

1.2.2 Decompose House Prices to Predicted and Surprise Parts

The strategy of this paper, namely the representative agent framework augmented with the permanent income hypothesis, requires both the predicted and surprise parts of house prices, which are defined as $\rho_1 P^{e-1}_i$ and u^t_i in Equation (1.2), respectively, and can be derived using house prices P and the estimate of auto coefficient ρ_1.

The estimate of ρ_1 is in Column 2 of Table 1.2. As discussed, the autoregressive coefficients for house prices and for expected house prices are the same. Thus, their estimates in large sample should be close. The estimate by house prices is in Column 2 and the one by expected price in Column 1. As shown, they are very close, implying that the AR (1) imposed in Equation (1.2) is appropriate[11]. This paper uses the estimate by house prices to derive predicted and surprise parts of house prices.

Simple as it may seem, but the AR (1) in Equation (1.2) is the best for its consistency and parsimoniousness. Since CES also records house structures, such as numbers of bedroom and of bathroom, building type, age of house, state and region, it is tempting to include that information in the AR(1). The author chooses, however, not to do so because 1) the house structure does not vary during a household's life in the survey 2) including house structure makes the two auto coefficients in Table 1.2 differ a lot, but they should be close since their population values are the same[12].

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[11] ρ_1 is the unknown coefficient of the AR (1) for both the expected house price and the house price. Its estimate based on the expected house prices is in Column 1 of Table 1.2 while the one based on the house price is in Column 2. The two should be close to each other in large sample, as found in the study.

[12] State-year fixed effects are not included also because otherwise the two coefficients differ a lot.

Table 1.2 Estimating AR (1) for Expected and Actual House Prices

Households report expected rentals on their houses at each interview for a total of five interviews conducted by the Consumer Expenditure Survey (CES). Then, the expected price on a house is calculated as the sum of present discounted values of all future expected rentals on the house, assuming the house is leased out to infinity. Next, this paper imposes an AR (1) on the series of expected house prices and derives the autoregressive coefficient, as shown in Column 1. Moreover, since the series of houses price follow a same AR (1) as the series of expected house price does, the author derives house prices using the series of expected house prices and its autoregressive coefficient. Last, the paper auto-regresses house prices on its one-period lag and present the autoregressive coefficient in Column 2. Since expected house price and house prices follow a same AR (1) in population, the estimated values of their auto-regressive coefficients should be close. The two coefficients found by this paper are very close, implying that the AR (1) imposed are appropriate. *, **, and *** represent 5%, 1% and 0.1% significance level, respectively. Standard errors in brackets are heteroscedasticity-robust.

	(1) Expected house Price (in log dollar)	(2) House price (in log dollar)
Lag expected house price(in log dollar)	**0.718*****	
	(0.0184)	
Lag house price (in log dollar)		**0.727*****
		(0.0135)
N	43692	41502
adj. R^2	0.520	0.694

1.2.3 Decompose Household Income to Expected and Surprise Parts

To derive and control for parts of income so that any house price effect found does not carry an income effect that works via a same channel[13], the paper imposes:

$$Y_i^t = \rho_2 Y_i^{t-1} + \varepsilon_i^t \tag{1.5}$$

where Y is income, ϱ_2 auto coefficient, ε error term, and other notation same as above.

The result for Equation (1.5) is in Column 1 of Table 1.3. For robustness checks, the author then controls for state-year fixed effects in Column 2, and further adds age, ownership dummy, mortgage dummy, number of person younger than 18 in Column 3.

[13] Income can also transmit to consumption via a credit channel, in which households borrow against a predicted rise in income to finance consumption, or via a wealth channel, in which a surprise rise in income raises spending.

It turns out that none of these add-ons significantly improves the adjusted R^2. For parsimoniousness, the paper uses Column (1) to derive the predicted and the surprise income, which are defined as the explained and the error in Equation (1.5), respectively.

Table 1.3 Estimating the AR (1) for Household Income

This table introduces alternative autoregressive models that divide household income into a predicted and a surprise part, both of which are needed in the benchmark strategy of this paper. The AR (1) presented in Column 1 produces about the same explanatory power but is much more parsimonious than the AR (1) in the other two columns. Thus, this paper adopts it to derive predicted and surprise income. The predicted income is defined as the component of income that is explained by the AR (1) while the surprise income is the residual in the AR (1). The dependent variable is total household income. Standard errors in brackets are heteroscedasticity-robust and clustered at state-year level. *, ** and *** are 5%, 1% and 0.1% significance level, respectively.

	Household income (in log dollar)		
	(1)	(2)	(3)
lag household income (in log dollar)	**0.782*****	**0.776*****	**0.691*****
	(0.00660)	(0.00672)	(0.00914)
age			0.0134***
			(0.00120)
age^2/100			-0.0148***
			(0.00111)
education			0.0512***
			(0.00230)
white			0.0854***
			(0.00945)
female			-0.118***
			(0.00787)
number of persons younger than 18			-0.0789***
			(0.00555)
family size			0.0981***
			(0.00523)
state-year fixed effect	NO	YES	YES
N	51694	51694	51694
adj. R^2	**0.617**	**0.618**	**0.636**

1.3 Estimate the Credit Channel of Housing Wealth Effects on Consumption

This part investigates the consumption response to an increase in housing wealth under a representative agent model augmented by the permanent income hypothesis, and quantifies the credit channel using the differential in the consumption responses across constrained and non-constrained households. Being constrained or not is approximated by household self-revealed financial characteristics. To show that this measure of credit constraint is better than ages and balance-sheet indicators as used in the literature, the paper also estimates a credit channel using those two measures but finds ambiguous and inconsistent results, which are presented in Appendix D and Appendix E.

1.3.1 Measure Credit Constraints by Household Financial Characteristics

Financial characteristics that measure credit constraints include two groups: the first group identifies if a household is credit constrained and includes a poverty dummy and a dummy for receiving supplemental security income (SSI). The second group indicates if a household is non-constrained and includes a dummy for full credit-card payments, a renter dummy, and a dummy for no cash-out mortgage refinancing during 2001-2006. See Table 1.4 for details.

There are also two points to pick financial characteristics as constraint measures. First, they involve no numbers that require memories and thus suffer fewer measurement errors. Not like balance-sheet indicators, the answer to a characteristic is just *Yes or No* and involves no numbers. Second, they record outcomes, not causes, of constraints and

make endogeneity problems irrelevant. While ages can work as constraint measures because it's correlated with constraints[14], financial characteristics, e.g. poverty, do not assume why a household is constrained or not constrained, but just record facts.

Table 1.4 Household Financial Characteristics

The first column is the financial decisions that work as the measures of credit constraint. Information on "Poverty", "Social Security Income" and "Renter" is from the Consumer Expenditure Survey, while the data of "Full Credit Card Payment", "No Mortgage Refinancing" and "Credit Request Rejection" is from the Survey of Consumer Finance. While all other financial decisions are proposed by the author as measures of credit constraint, the "Credit Request Rejection" is proposed by Jappelli (1990). The author present the results derived under this measure so as to make this paper comparable to Jappelli (1990).

Dummy	Value	Code
1.Poverty	1 if a household lives below the poverty line and 0 otherwise	1-constrained
2.Supplemental security income	1 if a household receives supplemental security income and 0 otherwise	1-constrained
3. Renter	1 if a household lives in a rental unit and 0 otherwise	1-non constrained
4. Full credit-card payment	1 if a household pays off full credit card balance on time and 0 otherwise	1-non constrained
5. No mortgage refinancing	1 if a household has no cash-out mortgage refinancing 2001-2006 and 0 otherwise	1-non constrained
6.Credit request rejection	1 if a household was ever rejected on credit requests and 0 otherwise	1-constrained

Reasons that a financial characteristic can reveal constraints are intuitive. First, the income of households in poverty is insufficient for life necessities. That is why some of them apply for SSI to smooth consumption. Next, those who always pay off full credit-card balances on time use credit cards for convenience, not for credits. Moreover, renters have no house against which they can borrow and have no access to a credit

[14] By the life-cycle theory, the young are more credit constrained relative to the old since they are in an early stage of their life cycles. That is, ages can work as constraint measures because they are linked to the stages of life cycle.

channel. Lastly, since house prices grew fast and interest rates stayed very low during 2001-2006, mortgage refinancing offered easy and cheap credits. Hence, those who had mortgages but never cash-out refinanced at the time were not constrained.

1.3.2 an Estimated R.A. Model with Permanent Income and Housing Wealth

The strategy of this paper is guided by the representative agent framework and the permanent income hypothesis. By the representative agent framework, a response of household consumption to wealth changes implies households being credit constrained (King, 1994; Kimball and Carroll, 1996; Carroll, 2001). Likewise, the permanent income hypothesis argues that a response of household consumption to a predicted change in wealth implies an incomplete credit market and households being constrained (Flavin, 1980; Zeldes, 1989). In housing context, the consumption response by a representative household to a rise in housing wealth is evidenced and the response is stronger for those who are more constrained (Mian and Sufi, 2011; Mian et al, 2013). It is also found that the consumption response by constrained households to a predicted increase in housing wealth are much stronger than that by other households (Attanasio et al, 2009; Campbell and Cocco, 2007).

Inspired by the literature, the author incorporates the permanent income hypothesis and the housing wealth to an estimated framework of the representative agent model, and tests whether and how the MPC out of predicted housing wealth vary across households. The econometric representation of the strategy is:

$$C_i^t = C_0 + \beta_{PP} PP_i^t + \beta_{SP} SP_i^t + \beta_{PP}^N PP_i^t N_i^t + \beta_{SP}^N SP_i^t N_i^t + \beta_{PI} PI_i^t + \beta_{SI} SI_i^t + \beta_{PI}^N PI_i^t N_i^t + \beta_{SI}^N SI_i^t N_i^t + \beta_W W_i^t + \beta_X X_i^t + \eta_i^t \quad (1.6)$$

Where i denotes household and t is time, C_0 a constant, η the error term, PI predicted income, SI surprise income, PP predicted house price, SP surprise house price. W financial asset holding, X a vector of demographics, N a dummy for poverty, SSI, full credit-card payment, renter and no refinancing, equal to 1 if a household is in poverty, receives SSI, always pays off full credit-card balance on time, is a renter, or never cash-out refinanced on a mortgage in 2001-2006, respectively, and 0 otherwise. Lastly, β_{PP}^N is the additional consumption response by the corresponding household group to a predicted rise in housing wealth, and is the coefficient of interest.

One feature of this strategy is that it employs household self-revealed financial characteristics to measure the degree of credit constraint so as to identify the constrained households, while the literature either use ages (Attanasio et al, 2009; Campbell and Cocco, 2007*)* or balance-sheet indicators (Mian and Sufi, 2011; Mian et al, 2013) to do so. The other feature of the strategy is the use of individual house prices, while much of the literature uses aggregate house prices, either at a region level (Attanasio et al, 2009*;* Campbell and Cocco, 2007) or zip-code level(Mian and Sufi, 2011*;* Mian et al, 2013).

1.3.3 Results Support a Credit Channel of the Housing Wealth Effect

Results are shown in Table 1.5 and indicate that a credit-constrained household yields an excess consumption response to a predicted rise in housing wealth, implying a credit channel. In Column 1, a household in poverty carries an extra response of 26 percentage points to a rise in predicted house price. Since the average response is 4%, the overall MPC out of the predicted housing wealth is 30%. In Column 2, the additional response by a household with SSI is about 20 percentage points. Since the average response is 5%, the overall MPC out of predicted housing wealth is about 25%. In other words, a credit-constrained household extracts 25-30 cents out of every one-dollar predicted rise in housing wealth and spend on consumption.

Results also show that households that are non-constrained or have no access to a credit channel do not exhibit any additional consumption response to an anticipated increase in housing wealth, thus verifying the credit channel found. Column 4 in Table 1.5 presents the response to an anticipated rise in housing wealth by households who had a mortgage but never refinanced it during 2001-2006, and Column 5 for those who always pay-off full credit-card balances on time. These households self-reveal them as non-constrained and, as expected, they display no significant additional consumption response to the anticipated rise in housing wealth. Column 6 shows the result for a renter, who has no access to a credit channel that uses houses as collaterals, and finds no significant additional consumption response by a renter. All these findings justify the credit channel found above.

Table 1.5 Estimating the Credit Channel of Housing Wealth on Consumption

"poverty", "supplemental security income", "credit request rejected", "no cash-out refinancing", "full credit card payment" and "renter" equal to 1 for households who is below the poverty line, receive any supplemental security income, was rejected on credit requests, always pay-off full credit card balances on time, is a renter, and never cash-out refinanced on mortgages in 2001-2006, respectively, and 0 otherwise. Demographics and state–year fixed effects are also controlled but not listed. Surprise income and housing wealth and their interactions with all dummies are also included but not reported. *, ** and *** is 5%, 1% and 0.1% level. S.E. in brackets is heteroskedasticity-robust and clustered at state-year.

	Total Consumption					
	(1)	(2)	(3)	(4)	(5)	(6)
1. Financial wealth	0.0405***	0.0455***	0.0457***	0.0466***	0.0453***	0.0459***
	(0.00420)	(0.00428)	(0.00431)	(0.00437)	(0.00428)	(0.00432)
2. Predicted income	0.411***	0.340***	0.337***	0.340***	0.322***	0.337***
	(0.0145)	(0.0178)	(0.0175)	(0.0248)	(0.0261)	(0.0177)
3. Predicted housing wealth	0.0443***	0.0586***	0.0618***	0.0594**	0.0676***	0.0615***
	(0.00826)	(0.00867)	(0.00857)	(0.0181)	(0.0163)	(0.00852)
4. Predicted income*	-0.312***					
poverty	(0.0644)					
5. Predicted housing wealth*	**0.264*** **					
poverty	(0.0496)					
6. Predicted income*		-0.231**				
supplemental security income		(0.0831)				
7. Predicted housing wealth*		**0.197** **				
supplemental security income		(0.0717)				
8. Predicted income*			0.102			
credit request rejected			(0.0693)			
9. Predicted housing wealth*			**-0.0986**			
credit request rejected			(0.0652)			
10. Predicted income*				-0.00502		
no cash-out refinancing				(0.0230)		
11. Predicted housing wealth*				**0.000524**		
no cash-out refinancing				(0.0209)		
12. Predicted income*					0.0221	
full credit card payment					(0.0229)	
13. Predicted housing wealth*					**-0.0166**	
full credit card payment					(0.0207)	
14. Predicted income*						-0.0864
renter						(0.0620)
15. Predicted housing wealth*						**0.0537**
renter						(0.0470)
N	7621	7729	7729	7729	7729	7729
adj. R^2	0.586	0.567	0.566	0.567	0.567	0.566

Note that due to an average effect, non-constrained households still bear a response to predicted housing wealth, but much smaller than that by the constrained. They have an MPC of 5%-7% to anticipated changes in housing wealth, while the number is 25%-30% for constrained households. Note also that financial characteristics used in this paper are dummies and can not measure the incremental effect of the credit channel, which, is, however, a common issue in the literature.

Note that Jappelli (1990) also measures credit constraints by household financial decisions, but this paper differs in two significant ways: First, Jappelli uses only one decision, namely if a household was rejected by a bank on credit requests, to define if it is credit constrained. In contrast, this paper uses a much broader set of household financial characteristics that yield supporting and consistent results. Moreover, Jappelli has about 300 observations on credit request rejections and needs impute for others the probabilities of being constrained, which might incur biases. In contrast, this paper has over 7,000 observations on each characteristic and needs not do so.

Furthermore, to compare with Jappelli (1990), the author also inspects households that were rejected on credit request but finds no additional consumption response by them, as shown in Column 3 of Table 1.5. One possible reason is that credit requests can be rejected for reasons other than credit constraints, e.g. short credit history. Banks often base loan decisions on credit scores, which, however, hardly reflect changes in housing wealth and might give imprecise measures of credit constraints. In contrast, financial characteristics in this paper are more appropriate measures.

To sum, the excess consumption responses to an anticipated increase in housing wealth by constrained households suggest a credit channel of the housing wealth effect, which is further confirmed by non-constrained households that yield no excess response. More surprisingly, the MPC out of predicted housing wealth is found much larger than that in the literature. For each one-dollar rise in predicted housing wealth, a constrained household extracts and spends 25-30 cents on consumption, compared to 2-10 cents in the literature that uses aggregate house prices.

1.4 Robustness Checks on the Credit Channel Found

In this part, the paper re-estimates Equation (1.6) to see if results in Table 1.5 are sensitive to the strategies, data processing methods and econometric settings used.

The first check tests if the income adjustment in this paper biases the results. Since CES just copies income of the 2nd interview to the 3rd and 4th, there is a lack of time variation in income. To fix it, Equation (1.6) was run with an income adjustment that assumes income growths of same rates as consumption growths. This amounts to a constant MPC and is reasonable within a one-year period. To see if this adjustment drives the results, the paper re-runs Equation (1.6) with original non-adjusted income. Results are in Column 1 of Table 1.6, where the additional responses by households in poverty or with SSI are of same sizes and significances as those in Table 1.5, and household viewed non-constrained by other constraint measures still yield no additional response, same as before. Thus, Table 1.5 is not biased by the income adjustment.

Table 1.6 Robustness Checks I

Each column is a different robustness check. Within a column, Table 1.5 is re-run for the robustness check using dummies on the left, one dummy per time: 1) Because the original income in CES is not updated at each interview, Table 1.5 is run on adjusted income. Now, Column 1 tests if the results are robust to the original income. 2) Since CES does not ask renters expected rentals, the earlier strategy is to assign a renter the average of the expected rental by homeowners living in a similar house. Now, Column 2 drops this process and just assigns to renters house values reported by their SCF counterparts. 3) Home improvement expenditures improve housing wealth and rental income can attenuate the house price effect, thus Column 3 drops both of them. 4) To soothe feelings against the matching between CES and SCF, Column 4 skips the matching and uses only CES data. Demographics, income, financial wealth are included but not reported. Parts of income as well as their interactions with dummies are also controlled but not reported. Other settings are same as in Table 1.5.

	Total Consumption				
	(1)	(2)	(3)	(4)	Table 1.5
1. predicted housing wealth*	**0.332*****	**0.264*****	**0.251*****	**0.302*****	**0.264*****
poverty	(0.0571)	(0.0490)	(0.0447)	(0.0350)	(0.0496)
2. predicted housing wealth*	**0.183***	**0.197****	**0.169***	**0.124**	**0.197****
supplemental security income	(0.0719)	(0.0716)	(0.0801)	(0.0998)	(0.0717)
3. predicted housing wealth*	-0.0669	-0.0997	-0.108		-0.0986
credit request rejected	(0.0799)	(0.0652)	(0.0753)		(0.0652)
4. predicted housing wealth*	0.0168	0.000867	0.00469		0.000524
no cash-out refinance	(0.0266)	(0.0210)	(0.0213)		(0.0209)
5. predicted housing wealth*	-0.0166	-0.0161	0.00490		-0.0166
full credit card payment on time	(0.0235)	(0.0206)	(0.0204)		(0.0207)
6. predicted housing wealth*	-0.0112	0.295	0.0351	-0.00853	0.0537
renter	(0.0584)	(0.150)	(0.0440)	(0.0489)	(0.0470)

A second check sees if the imputation of house prices for renters drives the findings. Since the expected rentals are critical for deriving individual house prices but are not reported by renters in CES, this paper assigns each renter an expected rental on the houses they live. The earlier strategy was to assign the average expected rental of home owners to a renter living in a similar house, with similarity defined by the age, location and structure of the house. The paper now skips that process and just assigns to a renter the house value reported by its matched SCF renter. Equation (1.6) is re-estimated with

the new house prices for renters, and results are in shown Column 2 of Table 1.6. Again, households in poverty or with SSI display excess responses of similar sizes and significances as they do in Table 1.5, and those with credit requests rejected, with full credit-card payments, without cash-out mortgage refinancing, and renters still exhibit no excess response. This confirms that the results in Table 1.5 are free of possible biases resulted from the imputation of house prices for renters.

The third robustness check asks if the results in Table 1.5 are sensitive to the correlation between home improvements and house prices. Other things equal, well-maintained houses often have better values. Thus, the link between house prices and consumption may be two-way if the expenditure on home improvement is counted as consumption, which is just the case in CES. Also, some households own rental units and have rental income, and their consumption responses to income may carry the effect of house prices, which often move with rentals to a same direction. In that case, the house price effect on consumption is underestimated. To relieve the two concerns, the paper re-runs Equation (1.6) with non-housing expenditures and non-housing income, which equal to consumption net of home improvement expenditures and total income less rental income, respectively. Results, as in Column 3 of Table 1.6, are similar to those in Table 1.5. That is, a constrained household exhibits an additional response of same size and significance as in Table 1.5, while a non-constrained one still bears no additional response. This means that results in Table 1.5 carry no bias from the two concerns.

The fourth check is run for the concern that results in Table 1.5 are biased by the data matching that assigns a SCF household to a matched CES one[15]. To soothe feelings against the matching, the author instead uses a non-matching strategy that employs data only from the CES and features two revisions: 1) It no longer estimates responses by households with full credit-card payments, with credit requests rejected or without cash-out mortgage refinancing, since the information on those decisions is from SCF; 2) It uses expected house prices to proxy for actual house prices, which can no longer be derived by Section 1.2.1 since the necessary observation on house value is from SCF. The new results, as in Column 4 of Table 1.6, show that a constrained household[16] has an excess consumption response of same size and significance as in Table 1.5, while others still yield no additional response. This proves that Table 1.5 is not biased by the data matching and provides a confidence on the matching.

The last robustness check addresses the issues of fixed effects and clustered standard errors. Since consumption and house prices often move with state-specific factors, e.g. building regulations, and with time factors, e.g. monetary policy, this paper imposes fixed effects and clustered standard errors both at state-year level. Alternatively, given the household data in the paper, it is tempting to try them both at household-level. The author chooses, however, not to do so for two concerns: 1) some constraint measures, e.g. poverty and SSI, are time-invariant for a household within a year, and a

[15] See Appendix C for details on the matching between CES and SCF households.

[16] Except that now households with SSI no longer have additional responses to predicted house prices. The reason is that assigning to renters the average expected rental of similar home owners gives renters a same expected rental (and house price). This reduces the effective sample size of households with SSI and raises the standard errors.

fixed effect at household-level will invalidate point estimates on the two measures; 2) household-level fixed effects or clustered standard errors imply no correlations among households, which is arbitrary. To show the two concerns, the author tries both fixed effects and clustered errors at household-level in Table 1.7, where Column 1 tries both at household-level, Column 2 presents only household-level fixed effects and Column 3 shows household-level clustered standard errors alone.

It is clear from Table 1.7 that whenever household fixed effects are used, e.g. Column 1 and 2, point estimates on constraint measures, i.e. poverty and SSI, turn insignificant. This is expected and can hardly mitigate the credit channel[17]. When household-level clustered errors are imposed alone, as in Column 3, the point estimates on poverty and SSI shrink compared to those in Table 1.5 because the unobservable omitted factors bias the estimates due to the absence of fixed effects. This is confirmed by comparing Column 3 to Column 4, in which fixed effects are at state-year level[18] but clustered errors at household-level, and then point estimates get much closer to those in Table 1.5.

[17] The failure of Column 2 has another reason: the fixed effect itself can only remove part of the error correlations. See Cameron and Miller (2011).
[18] As stated, household is not a good unit for fixed effects, thus the author picks state-year fixed effects.

Table 1.7 Robustness Checks II

A different setting of fixed effects and clustered errors is used in each column. Within a column, Table 1.5 is re-run using a dummy on the left, one dummy per time. Demographics, income, financial wealth are also included but not reported. Parts of income as well as their interactions with dummies are also controlled but not reported. Other settings are same as in Table 1.5. Note that 1) the qualitatively different results in both Column 1 and 2 are expected and can hardly undermine results in Table 1.5. Since the status of "Poverty" and/or "Supplemental Security Income" hardly change within a household's life in the CES (one year), fixed effects at household level (Column 1 or 2) will invalidate the point estimate on the two measures. 2) The reason that the coefficient on "Supplemental Security Income" turns insignificant in Column 3 is because no fixed effect is controlled there. 3) Column 4 produces the same results as in Table 1.5. However, this paper chooses to impose both fixed effect and clustered errors at state-year level, as suggested by the micro econometric literature.

	Total Consumption (in log dollar)				
	(1)	(2)	(3)	(4)	Table 1.5
1. predicted housing wealth*	**-0.0228**	**-0.0228**	**0.128*****	**0.264*****	**0.264*****
poverty	(0.0190)	(0.0190)	(0.0267)	(0.0599)	(0.0496)
2. predicted housing wealth*	**-0.00354**	**-0.00354**	**0.0513**	**0.197****	**0.197****
supplemental security income	(0.0212)	(0.0212)	(0.0332)	(0.0700)	(0.0717)
3. predicted housing wealth *	-0.0140	-0.0140	0.0180	-0.0986	-0.0986
credit request rejected	(0.0560)	(0.0560)	(0.0769)	(0.0713)	(0.0652)
4. predicted housing wealth*	-0.00168	-0.00168	0.00746	0.000524	0.000524
no cash-out refinance	(0.0147)	(0.0147)	(0.0166)	(0.0212)	(0.0209)
5. predicted housing wealth*	-0.0150	-0.0150	-0.0171	-0.0166	-0.0166
full credit card payment on time	(0.0111)	(0.0111)	(0.0162)	(0.0205)	(0.0207)
6. predicted housing wealth*	-0.0173	-0.0173	-0.0214	0.0537	0.0537
renter	(0.0279)	(0.0279)	(0.0620)	(0.0653)	(0.0470)
Household Fixed Effects	YES	YES	NO	NO	NO
State-year Fixed Effect	NO	NO	NO	YES	YES
Household Clustered Errors	YES	NO	YES	YES	NO
State-year Clustered Errors	NO	NO	NO	NO	YES

Note that while Column 1 clusters standard errors at household-level and Column 2 does not, they produce the same results. The reason is that clustered standard errors increase with the size of a cluster (Cameron and Miller, 2010). When clustered at household level, each cluster has only five observations, making clustered standard errors not much different than those without clustering.

To sum, Table 1.7 implies that both fixed effects and clustered errors should be included but not at household-level. Since the two are better at a same level (Bertrand et al, 2006), it is suggested that they should be both imposed at state-year level even though a mixt of levels, as in Column 4, is feasible[19]. Hence, the applied micro-econometric settings in this paper are appropriate. Moreover, under all other settings, as in Table 1.7, households that are non-constrained or without access to a credit channel still yield no additional consumption response to predicted housing wealth, same as in Table 1.5. This further offers a confidence on the settings in this paper.

1.5 Summary of Chapter 1

This chapter feeds a panel of individual house prices and expenditures to an estimated representative agent model that incorporates the permanent income hypothesis and housing wealth, with a goal to investigate whether and by how much housing wealth contribute to consumption through a credit channel. Individual house prices are derived using expected rentals self-reported by households in the Consumer Expenditure Survey from 2001-2006.

Guided by the literature, the author considers an additional consumption response, by the credit constrained households over others, to a predicted rise in housing wealth as evidence of a credit channel. Predicted prices are derived by an AR (1) on individual house prices. Being constrained or not is judged by household self-revealed financial

[19] A combination of fixed effects and clustered errors in different levels, as in Column 4, does not deny a strategy that imposes them both at state-year level because the two strategies actually yield quantitatively similar results. The reason to pick the latter is of econometrics, not empirical (see Bertrand et al, 2006).

characteristics, with living in poverty and receiving supplemental social security income equal to being constrained, and with always paying off full credit card balances on time, no cash-out mortgage refinancing during 2001-2006, and living in a rental unit equal to being not constrained. Information on household self-revealed financial characteristics is from the Survey of Consumer Finance of 2004 and 2007.

Results indicate a 25-30% MPC out of predicted housing wealth for a constrained household, a response much larger than the 2%-10% found in the literature. Hence, for every one-dollar predicted rise in house price, a constrained household extracts and spends 25-30 cents on consumption. This finding implies that the monetary policy which calms a housing boom by rapid rises in interest rate, as the one in 2005, may not be appropriate since it might directly trigger a recession by cutting household consumption too fast and too sudden. Housing wealth add to consumption via a credit channel that extracts growing home equities to finance consumption. A rapid rise in interest rate reverses market expectations by force and house prices then drop. This stops constrained household from using rising home equities as liquidities to smooth their consumption. A better alternative is to smoothly adjust the interest rates and allow the credit channel of the housing wealth effect to fade away.

Results also indicate little evidence for a wealth channel of the housing wealth effect on consumption. In the Appendix D, the author follows the literature to investigate a wealth channel in an estimated life-cycle model with the permanent income argument that measures credit constraints by ages. Results show that the old have no additional

consumption response over the young to a rise in surprise housing wealth while they should, thus negating a wealth channel. The play of a credit channel and the absence of a wealth channel suggest that housing finance is a crucial factor behind the housing boom from 2001-2006 and deserves more academic and policy attentions.

This chapter adds to the emerging literature on the relation between housing wealth and consumption. By utilizing a micro-based strategy, the paper derives individual house prices and estimates the housing wealth effect on consumption at household level, thus providing new results. Furthermore, by utilizing household financial characteristics as measures of credit constraint, it offers fewer measurement errors and endogeneity issues, and confirms the existence of a credit channel, which cannot be seen when using ages or balance-sheet indicators as the measures[20]. Moreover, the paper includes the permanent income hypothesis into a representative agent framework, so a credit effect is identified by the consumption response by a constrained household to predicted housing wealth. Lastly, it explicitly controls for parts of income so any effect found for house prices carries no income effect that might work via a same channel.

[20] See Appendix D and E for results by ages and by balance-sheet indicators as the constraint measures.

Chapter 2: the Non-Bank Credit Market and Home Equity Withdrawals

Preview of Chapter 2

This chapter studies the housing wealth effect on consumption in China and explores the channel via which this effect works. To this end, it feeds a cross-section of individual house prices and expenditure to a representative agent framework with housing wealth, and examines the heterogeneity in the MPC out of housing wealth across households grouped by degrees of credit constraint. It finds that household consumption is sensitive to housing wealth with an MPC of 9-14% and the sensitivity increases with the degree of constraint, a result implying a credit channel. It further shows that the credit channel is enabled by non-bank private credits, not bank credits. This is partly due to the absence of a bank credit market for home equity withdrawals in China. The chapter also shows how precautionary savings motives of households, especially those with low income, lead to an under estimation of the credit channel. The chapter contributes to the literature by showing a credit channel of the housing wealth effect, which can work without bank credits and can work with precautionary savings motives.

2.1 Introduction to a Context without Bank Credits for Home Equity Withdrawals

A sub-prime mortgage crisis quickly turned into the Financial Crisis in 2007 and invited interests to explore effects of housing wealth on the economy, especially on consumption. Case et al (2005) evidence a strong effect of housing wealth on consumption, much stronger than that of stock. Afterwards, a pool of studies finds a 2-10% MPC out of housing wealth (Bostic et al, 2007; Carroll, 2004; Carroll et al, 2011; Case et al, 2013) and confirms the housing wealth effect on consumption.

Further studies wonder how housing wealth affect consumption. Campbell and Cocco (2007) find that rising house prices increase consumption via both a wealth channel, which increases perceived housing wealth of homeowners, and a credit channel that relaxes their borrowing constraints. In contrast, Attanasio et al (2009) use a same data set but find little evidence for the two channels. Moreover, Browning et al (2013) report a wealth channel but only for credit constrained households, and Cooper (2013) claims a credit channel since the consumption sensitivity to housing wealth increases with debt leverages.

Do housing wealth raise consumption in China where house price growths have been remarkable? If yes, what is the working channel? The answers are, however, not clear since few studies examine the effect of housing wealth on consumption in China. This is in part due to the unique institutional arrangements on the housing market in China, and is in part due to data and method issues in the literature that disable an extension of the common approach of housing wealth studies to the China context.

One feature of the housing market in China is the absence of a bank credit market for mortgage refinancing. In the last housing boom, the growing mortgage securitization enabled banks to provide home owners easy and cheap credits through mortgage refinancing (Kennedy and Greenspan, 2008). An increase in house price, along with mortgage refinancing, stimulated home equity withdrawals that were later spent on consumption, a process referred as a credit channel (Mian et al, 2013). The context is, however, different in China where a bank market for mortgage refinancing does not exist. Thus, the mechanism of a credit channel (if any) might be different in China.

Additionally, the housing market in China is a nascent market with limited repeated sales where the governments often interfere in the pricing of and demand for houses (Wu et al, 2014). Market incompleteness, together with regulations, distort market house prices and lead to officially published market prices that are often much lower than the actual ones (Deng et al, 2012). House prices, however, are key variables in estimating the housing wealth effect on consumption. So, studies that utilize officially published market house prices in China might yield biased results.

Furthermore, the literature on housing wealth effect is facing endogeneity and data issues that stop its extension to the China context. First of all, it often utilizes aggregate house prices, which is misleading if the distributions of house price growths and of consumption growths do not match at household level. Moreover, the literature views the excess consumption response to housing wealth by constrained households as a sign of a credit channel, and measures the degree of constraint by ages, with being young

equal to being constrained. But, age is not a good constraint measure in housing context since the young often face home tenure choices that endogenize their consumption responses to changes in housing wealth[21].

The housing market institutions in China, plus the issues in the literature on housing wealth effect, motivate this paper. First, it explores whether non-bank private credits assist the transmission of housing wealth to consumption. Second, it utilizes household self-reported house prices, instead of market house prices or aggregate house prices. Lastly, this paper resorts to household self-revealed financial characteristics, e.g. if a household lives in poverty, to identify constrained households and estimate the credit channel. Such measures have fewer endogeneity issues and measurement errors.

This paper utilizes a cross-section of individual house prices and expenditure to uncover the size and the channel of the housing wealth effect on consumption in China. First, it presents the housing wealth effect in an estimated representative agent model with housing, and shows that the effect is working through a credit channel. Then, it offers evidence that the credit channel is enabled by non-bank credits consisting of borrowings from relatives/friends, but not by bank credits. Lastly, the paper shows how precautionary savings motives of households hide the credit channel and lead to an under estimation of the housing wealth effect..

Results show that household consumption in China is sensitive to housing wealth and the sensitivity increases with the degree of credit constraint, implying a credit

[21] A young household that plans to trade up on housing (buy a house for the first time or buy a bigger house) may need to save more given a higher house price and thus cut consumption. In contrast, a young household that plans to trade down on housing may respond with a higher consumption. It is difficult to observe their plans.

channel of the housing wealth effect on consumption. An average household yields a 9-14% MPC out of housing wealth, higher than the 2-10% often found in the literature. For constrained households, the MPC goes up to 18-21%. That is, for a one-yuan increase in housing wealth, a constrained household extracts and spends 18-21 cents. Especially, the MPC increases with non-bank loan, implying that the credit channel is enabled by non-bank credits. Moreover, precautionary savings motives due to low income, bad heath conditions and additional kids reduce the propensity to consume out of housing wealth and neutralize the credit channel.

This paper is close to Mian and Sufi (2011) and Mian et al (2013), but with several contributions: First, it employs micro house prices and rules out a potential spurious housing wealth effect that might arise from aggregate house prices. Next, it shows how a credit channel works without bank credits, and how a precautionary savings motive can neutralize and under estimate the credit channel. Lastly, besides balance-sheet indicators as in the literature, this paper also uses household self-revealed financial characteristics as measures of credit constraint because they come with fewer endogeneity issues and measurement errors.

The rest of the paper is organized as below: Part II describes the data. Part III presents the strategy and the results. Part IV conducts a series of robustness checks, and Part V concludes.

2.2 Micro House Prices from Survey Data in China

The data is from the China Household Finance Survey (CHFS) biennially conducted by the Southwestern University of Finance and Economics in China. CHFS is a national representative survey that interviews random households about their demographics, jobs, income, assets and expenditure, among others. The survey used is of 2013 and is the latest one available. During the 2013 survey, 262 counties out of a total of 2,585 counties from 29 provinces are randomly selected, and a random set of 4 communities is picked in each county. This yields a total of 1,048 communities. Then, within each community, a group of around 28 households is randomly chosen, providing a total of around 29,000 households. For more details of the survey, please refer to Gan et al (2013).

Main variables to be used include: 1) Expenditure, including household spending of all categories in the past 12 months; 2) Income, of all sources by all family members in the past 12 months; 3) Financial Wealth, recording the current market value of all financial assets hold by all family members, excluding cash and demand deposits; 4) Housing Wealth, measuring the total value of all houses owned by a family, or the estimated value of a house where lives a renter; 5) Demographics, like education, age, gender and family size. Note that the housing market in rural China is, by law, illiquid and thus we focus on the urban market. This shrinks the size of the sample in this paper to around 6,000 households. Table 2.1 summarizes the data:

Table 2.1 Summary of Data

	Obs	Mean	S.D.	Min	Max
Expenditure	6081	6.79	10.03	0	310
Income	6081	4.95	8.32	0	223.96
Financial Wealth	6081	6.49	21.93	0	505.8
Housing Wealth	6081	92.41	107.29	0	950
Non-Bank Loan	6081	3.39	192.4	0	15000
Credit Card Utilization	6081	3.2%	12.7%	0	450%
Family Size	6081	1.7	1.20	0	12
Age	6081	50.17	15.98	21	111
Education	6078	11.19	3.96	0	21
Owner	6081	69.28%	46.13%	0	1
If with Home Loan from Relatives	6081	12.60%	33.19%	0	1

(Source: CHFS 2013, Southwestern University of Finance and Economics, CHINA)

2.3 Identify a Credit Channel of the Housing Wealth Effect in China

In this section, the author first shows a housing wealth effect on consumption, and then proceeds to examine if such an effect is working through a credit channel that enables households to borrow against their rising home equities to finance consumption.

2.3.1 Housing Wealth also Contribute to Consumption in China

First, this paper examines the overall housing wealth effect on consumption by:

$$E_i = a_1 + \beta_y Y_i + \beta_w W_i + \beta_h H_i + \beta_x X_i + \omega_i \tag{2.1}$$

Where i denotes household, E consumption, a_1 constant, Y household income, W financial wealth, H house value, X a vector of demographics, w the error term, and β_h the consumption response to changes in housing wealth.

Following the literature, a positive and significant β_h estimated from the data is a sign of housing wealth effects on consumption, and is a prerequisite to the identification of

working channels of the effects. While some argue that house price growths do not add to net housing wealth and there is no housing wealth effect on consumption (Sinai and Souleles, 2005; Buiter, 2010), most empirical studies still report a MPC of 2-10% out of housing wealth[22]. Hence, the author expects a β_h of this value.

Estimation results of Equation (2.1) are shown in Column 1 of Table 2.2 where a housing wealth effect on consumption is evidenced. The author finds an average MPC out of housing wealth at 14%, which is slightly higher than but not far from that in the literature. This gives us a motivation to proceed to the identification of working channels for the housing wealth effect.

Table 2.2 Housing Wealth Effects on Consumption

Income, financial wealth, housing wealth and housing debt are all in ten thousand yuan. Housing wealth is the self-reported value of a house. Housing debt is the sum of outstanding balances on all mortgages and non-bank loans for the house. A constant, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All variables except demographics are in log. Standard errors in the parenthesis are heteroscedasticity robust and clustered at state level. *, ** and *** is 0.1%, 1% and 5% significance level, respectively.

	Consumption	
	(1)	(2)
Income	0.125***	0.120***
	(0.0129)	(0.0298)
Financial wealth	0.0601***	0.0822***
	(0.00600)	(0.0118)
Housing wealth	**0.141*****	
	(0.0107)	
Housing debt		**0.0862*****
		(0.0155)
N	4524	665
adj. R^2	0.431	0.345

[22] Given a rise in house price, the increase in home equities offsets the growth in user costs, adding zero to wealth.

The author next follows Mian et al (2013) to estimate the effect of housing debts on consumption and finds results in favor of a credit channel. A credit channel is a process where home owners finance consumption by debts that use their rising home equities as collaterals. Hence, if a credit channel works, consumption should respond to housing debts. This paper relates consumption with housing debts and finds, as shown in Column 3, that the MPC out of housing debts is about 9%, again suggesting a credit channel[23].

To sum, the paper detects a housing wealth effect on consumption that seems to be working through a credit channel. The rest of this paper will go further to confirm the existence of the credit channel and investigate its working mechanism.

2.3.2 a Credit Channel Finances Excess Consumption out of Housing Wealth

Now that a housing wealth effect is observed, it becomes interesting to identify the working channels. Wealth is often found to transmit to consumption via two channels. One is a credit channel and the other is a wealth channel. In housing context, while empirical studies find that the two channels both facilitate the housing wealth effect on consumption (Campbell and Cocco, 2007), theoretical work is ambiguous about the wealth channel due to the dual natures of a house (Sinai and Souleles, 2005; Buiter, 2010)[24]. For this reason, this paper focuses on identifying a credit channel, with a

[23] Technically, it is the consumption response to home loans, not mortgages, that captures the credit channel. The problem is that, not like U.S., there are no home loans that use home equities as collaterals in China, however, since the mortgage underwriting standards on LTV is standard in China, a bigger housing debt (mortgage) is equivalent to bigger hosing wealth. Hence, given a same percentage rise in house price, households with a bigger housing debt will experience a higher increase in home equities and have a higher limit of home loan (if any).

[24] An owner-occupied house provides residential service to its owner and that service also appreciates given a higher house price. Hence, the dual nature of a house as both an asset and service actually balance the increases in its value and cost, thus adding zero increase to the wealth of its owner.

robustness check in Part 5 to show that the survey data deliver little evidence of a wealth channel of the housing wealth effect on consumption in China.

An implication by the theory of credit channel (Bernanke and Gertler, 1989; King, 1994; Kiyotaki and Moore, 1997) is that the MPC out of wealth increases with constraint degrees if wealth can be collateralized for borrowings. So, an empirical strategy to locate a credit channel is to find a MPC out of wealth that increases with the degree of constraint. This strategy has been well extended to the housing context by Mian and Sufi (2011) and Mian et al (2013).

In order to find out if the MPC out of housing wealth increase with constraint degrees, this paper captures constraint degrees with two groups of measures: the first group consists of various financial characteristics that are self-revealed by a household, e.g. whether it receives supplemental security income, and the second group consists of balance-sheet indicators that are often used in the literature as measures of constraint degree, e.g. Loan-to-Value ratio.

The paper first examines if households viewed as constrained by the self-revealed constraint measures yield excess consumption sensitivity to housing wealth growths. The strategy is an estimated representative agent model that allows financial frictions:

$$E_i = a_2 + \lambda_y Y_i + \lambda_w W_i + \lambda_h H_i + \lambda_{he}(H_i \times C_i) + \lambda_x X_i + \varepsilon_i \qquad (2.2)$$

where a_2 is a constant, C a self-revealed constraint measure equal to 1 if a household was rejected on requests for mortgages or credit cards, receives supplemental security income,

or lives in poverty, respectively, and zero otherwise, ε the error term, other notations same as above[25].

Equation (2.2) is built on the literature on consumption sensitivity to income. A standard representative agent model with a full risk-sharing assumption will yield an optimum consumption that is insensitive to changes in wealth. If, however, the estimated MPC varies with wealth, it is because the risk-sharing assumption fails, in which case arise credit constraints (King, 1994) and/or precautionary savings motives (Carroll and Kimball, 2001; Carroll, 2001). An implication for housing studies is that if households are credit constrained and a credit channel is in place, then a rise in house price can relax their constraints and enable them to withdraw home equities for consumption. This suggests that one way to prove a credit channel is to find a MPC out of housing wealth that increases with the degree of credit constraint.

Reasons to use the self-revealed credit constraint measures are two folds: First, self-revealed measures are binary and carry fewer measurement errors. No memory of numbers is needed when answering questions by those measures. Second, they come with fewer endogeneity issues often found in other measures. E.g. the literature often uses age as a constraint measure, assuming the young are constrained because they are at an early life-cycle stage. In contrast, using self-revealed measures can reduce endogeneity issues because one needs not assume reasons for credit constraints.

[25] Since different provinces have different nominal poverty line, we use the Engel poverty line.

Note that Jappelli (1990) also measures credit constraints by financial behaviors, but our approach is still different in several ways: 1) while Jappelli judges if a household is constrained by whether its credit request was rejected, this paper resorts to a broader set of measures that probes financial characteristics from comprehensive angles; 2) Jappelli has only 300 observations on credit request rejections and imputes probabilities of being constrained for others, while this paper has at least 4,000 observations on each measure and need not do so. This ensures that it doesn't catch imputation biases.

Results by the self-revealed constraint measures are in Table 2.3 where a credit channel is evidenced, though with concerns. If a credit channel exists, constrained households are expected to exhibit excess consumption response to a rise in housing wealth that relaxes their constraints. According to this standard, Column 1-3 reject a credit channel, while Column 4 shows that households in poverty and viewed as constrained show an excess MPC of 12 percentages points, implying a credit channel.

The conflicting results by the self-revealed constraint measures motivate us to turn to balance-sheet indicators that measure to what extent is a household constrained. The healthiness of balance sheets directly determines the availability and cost of external financing, hence a balance-sheet channel is considered the working horse of the credit channel in monetary transmission studies (Kiyotaki and Moore, 1997). Following that idea, housing studies often examine how the healthiness of balance-sheets help the transmission of housing wealth to consumption (Mian and Sufi, 2011; Mian et al, 2013), with healthiness measured by balance sheet indicators, e.g. Loan to Value ratio.

Table 2.3 Consumption Response to Housing Wealth by Constrained Households

Income, financial wealth, housing wealth and consumption are in ten thousand yuan "Mortgage rejected", "Credit card rejected", "SSI" and "Poverty" are dummies equal to 1 if a household's mortgage request was rejected, credit card request was rejected, receives supplemental security income, and lives in poverty, respectively, and zero otherwise. A constant term, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All variables except demographics are in log. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** stand for 0.1%, 1% and 5% significance level.

	Consumption			
	(1)	(2)	(3)	(4)
Income	0.125***	0.124***	0.123***	0.231***
	(0.0132)	(0.0135)	(0.0132)	(0.0197)
Financial wealth	0.0609***	0.0593***	0.0603***	0.0589***
	(0.00604)	(0.00610)	(0.00602)	(0.00547)
Housing wealth	0.140***	0.142***	0.142***	0.0902***
	(0.0106)	(0.0105)	(0.0107)	(0.00920)
Housing wealth*If Mortgage rejected	**-0.0221**			
	(0.0312)			
Housing wealth*If Credit card rejected		**-0.0267****		
		(0.00732)		
Housing wealth*If SSI			**-0.0429*****	
			(0.0105)	
Housing wealth*If Poverty				**0.121*****
				(0.00821)
N	4524	4524	4524	4524
adj. R^2	0.429	0.431	0.431	0.488

The paper utilizes two balance-sheet indicators to measure the degree of credit constraint and estimates the incremental effect of a credit channel. One indicator is LTV, which has been wide used in the literature. It reflects the extent to which a household relies on external financing in purchasing a house, and is a good proxy for the degree of credit constraint. The author replaces the dummy in the interaction term in Equation (2.2) with LTV so as to estimate how the MPC out of housing wealth varies with LTV. Results shown in Column 1 of Table 2.4 indicate that when LTV goes up by one percentage

point, the MPC out of housing wealth increases by 11 basis points. That is, the more constrained is a household, the bigger is its consumption response to housing wealth. This simply evidences a credit channel.

Table 2.4 Incremental Effects of the Credit Channel

Income, financial wealth and housing wealth are in ten thousand yuan. "LTV" is the loan-to-value ratio of mortgages. "Credit card utilization" is the ratio of total statement balance over total credit limit across all credit cards at last billing statement. A constant term, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All are in log except demographics, LTV and Credit Card Utilization. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** is 0.1%, 1% and 5% level.

	Consumption	
	(1)	(2)
Income	0.123***	0.122***
	(0.0129)	(0.0126)
Financial wealth	0.0610***	0.0585***
	(0.00597)	(0.00608)
Housing wealth	0.133***	0.134***
	(0.0107)	(0.0105)
Housing wealth*LTV	**0.111*** **	
	(0.0212)	
Housing wealth*Credit Card Utilization		**0.118*** **
		(0.0289)
N	4524	4524
adj. R^2	0.432	0.439

The utilization of credit card is the other balance-sheet indicator being used and it also yields results supportive of a credit channel. Credit card is an often means of debts and its utilization measures the extent to which one relies on debts for its consumption. Hence, the utilization is a good proxy for the degree of credit constraint. The utilization is defined as the ratio of total statement balances over total credit limits of all credit cards at last billing statement, and Equation (2) is revised to multiply housing wealth by

the utilization. Results are shown in Column 2 of Table 2.4, where a one percentage point increase in credit card utilization can raise the MPC out of housing wealth by about 12 basis points. This implies that a higher degree of credit constraint brings a stronger consumption response to housing wealth, and confirms the credit channel.

To sum, results by balance-sheet indicators and credit card data strongly evidence a credit channel, though whether the channel exits is ambiguous according to self-revealed constraint measures. Next, the paper further examines why self-revealed measures yield conflicting results on a credit channel. The answer is while a non-bank credit market enables a credit channel in China, precautionary savings and the absence of a bank market for home equity withdrawals hide it. This will be shown in the next two sections.

2.3.3 Private Credits Enable the Credit Channel of Housing Wealth in China

In this part, the author answers why households with credit requests rejected and viewed as constrained do not yield excess consumption response to housing wealth? This is equivalent to ask whether there exists a credit channel for the housing wealth effect. The strategy is to examine the non bank credit market since the bank market in China does not support home equity withdrawals.

The hidden assumption in the literature on credit channel is a functional credit market that is accessible to agents (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). In economies that legalize home equity withdrawals, e.g. U.S. and U.K., home owners have free access to bank markets for mortgage refinancing and thus the credit

channel for housing wealth effect works. The situation is, however, different in China where there is no bank market for any types of home equity withdrawals.

The absence of a bank credit market for home equity withdrawals in China explains why households with credit requests rejected by banks yield no excess consumption sensitivity to housing wealth. Those households are already credit constrained, and given no bank means to cash home equities, they could hardly afford consumption growths. Thus, results in both Column 1 and 2 of Table 2.3 can not deny a credit channel. Instead, they inspire the search for a credit channel that works without bank credits.

While a functional credit market is critical for a credit channel, there could be many ways to form the market and it needs not be run by banks. Besides traditional banks, non depository specialized mortgage originators also service home equity withdrawals, and besides mortgage refinancing, home equity lines of credits also arise as major tools for home equity withdrawals (Greenspan and Kennedy, 2008)[26].Furthermore, transfers from family members often form a major source of down payments on the first housing (Engelhardt and Mayer, 1998). These findings inspire this paper to show evidence that it is a non-bank credit market consisting of borrowings from relatives/friends that enables home equity withdrawals for consumption in China.

The first piece of evidence of the non-bank market for home equity withdrawal is that households with education loans from relatives/friends display excess consumption sensitivity to housing wealth. Education has been a priority of household expenditure.

[26] Explains what are specialized mortgage originators and HELOC

The left panel of Figure 2.1 shows that the share of education in total expenditure of an average household in China is much higher than that in U.S. Furthermore, the right panel shows that under most of the time, household education expenditure in China outgrow that in U.S.

The two findings evidence the commitment to education by China households. Hence, it is reasonable to argue that households that need borrow from relatives/friends to pay schools are truly constrained. The consumption response of such households is shown in Column 1 of Table 2.5, where they yield an additional MPC of 3.8 percentage points, a result suggesting a credit channel.

Figure 2.1 Shares and Growths of Education Expenditure in China and U.S.

The left panel presents shares of education expenditure in average household expenditure and the right panel presents growths of education expenditure. Both are in percentages. China data covers only urban residents while U.S. data covers all households. Data Source: China Statistical Year book 2004-2013 and The Consumer Expenditure Survey in U.S. 2002-2011.

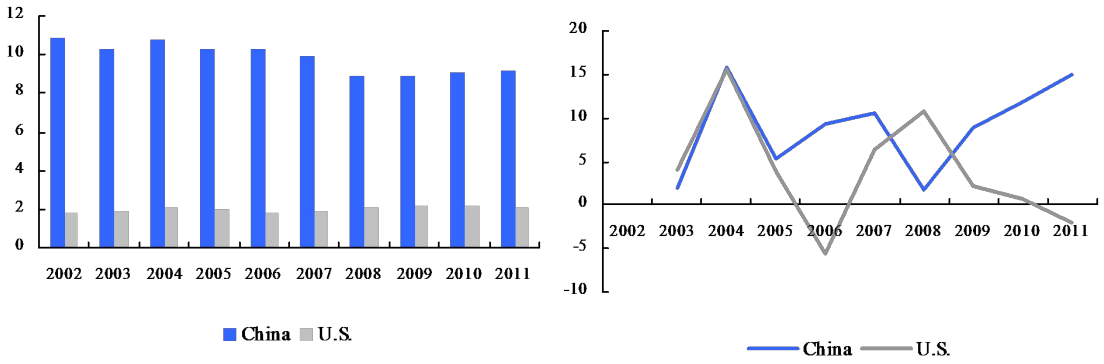


Table 2.5 the Private Credit Market and the Credit Channel

Income, financial wealth, housing wealth and non-bank loan are in ten thousand yuan. "If non bank education loan" is a dummy equal to one if a household has education loans from relatives/friends, and zero otherwise. A constant term, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All variables are in log except demographics. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** is 0.1%, 1% and 5% significance level. Non-bank loan in Column 2 cover all categories of loan while the one in Column 3 excludes non-bank home loan.

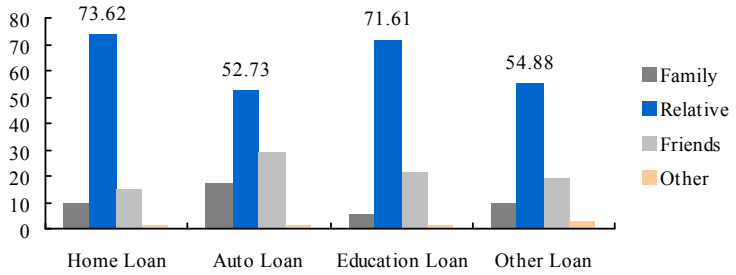
	Consumption		
	(1)	(2)	(3)
Income	0.126***	0.0831**	0.0518
	(0.0131)	(0.0277)	(0.0431)
Financial wealth	0.0616***	0.0558***	0.0382
	(0.00606)	(0.0104)	(0.0232)
Housing wealth	0.140***	0.0955***	0.0886*
	(0.0107)	(0.0211)	(0.0372)
Housing wealth*If Non-bank education loan	**0.0383***		
	(0.0152)		
Housing wealth*Balance of non-bank loan		**0.00767****	**0.0218***
		(0.00258)	(0.00807)
N	4524	880	202
adj. R^2	0.430	0.328	0.270

Some might ask why education loan by relatives? Why not loan by other agents and loan for other purposes? The answer is because relatives/friends are the most reliable non-bank lenders and education is the most frequent purpose of loan issued by them.

First of all, a major part of households resorts to relatives/friends for non-bank credits. Figure 2.2 shows the shares of households that turn to different agents when they need certain type of non-bank credits, e.g. 73.62% households choose to borrow non-bank home loan from relatives. It is obvious that a dominant share of households turns to relatives/friends when they need each type of non-bank loan. In contrast, the share of households that resort to other agents is much smaller under each loan type.

Figure 2.2 Sources of Non-Bank Loans for Various Purposes (in percentage)

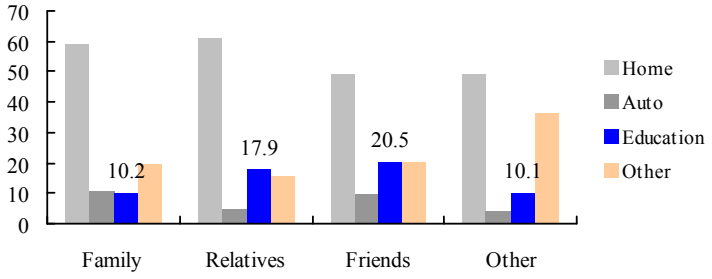
The figure tells the fractions of households that resort to different non-bank lenders for a certain type of loan. Loan types include home loan, auto loan, education loan and other loans. Types of non bank lenders include family, relatives, friends and other lenders. Only the values associated with relatives are shown explicitly.



Furthermore, except home loan, the most common type of loan by relatives/friends is education loan[27]. Figure 2.3 tells the purposes of loan issued by each non-bank agent, e.g. 17.9% households that borrow from relatives spend the loan on education and the number is 20.5% of those that borrow from friends. In contrast, education loan only account for a smaller share in the total lending by each other non-bank agent.

Figure 2.3 Purposes of Loan from Non-Bank Lenders (in Percentage)

The figure tells the fractions of households that borrow different loan from a certain type of non-bank lender. Loan types include home loan, auto loan, education loan and other loan. Types of non-bank lenders include family, relatives, friends and other lenders. Only the values associated with education loan are shown explicitly.



[27] We don't consider households with home loans from relatives/friends as necessarily constrained because the purchase of a house often involves a large amount of money and most households need borrow for that.

The second piece of evidence that non-bank credits enable the credit channel of the housing wealth effect in China is that the MPC out of housing wealth increases with non-bank loan. Instead of detecting excess consumption by constrained households, the author now tests if the MPC of a typical household increases with its debts. This strategy was introduced in Kimball and Carroll (1996) and Carroll (2001), and is extended to the housing context in Mian and Sufi (2011) and Mian et al (2013). To serve the purpose of this paper, a minor revision is that it now tests if the MPC out of housing wealth increases with non-bank debts. The strategy is to revise Equation (2.1) to include non-bank loan and interact it with housing wealth:

$$E_i = a_1 + \beta_y Y_i + \beta_w W_i + \beta_h H_i + \beta_{nb}(H_i \times NB_i) + \beta_x X_i + \omega_i \qquad (2.3)$$

Where *NB* is non-bank credit, β_h consumption sensitivity to housing wealth, β_{nb} tells how that sensitivity changes with non-bank debts and other notation same as above.

Results from the estimation of Equation (2.3) show that the MPC out of housing wealth by an average household increases with its non-bank debts, implying a credit channel. Column 2 of Table 2.5 includes all types of non-bank debts and finds that the MPC out of housing wealth increases by 0.7 percentage points for a ten-thousand yuan increase in non-bank debts. Since a major part of non-bank debts is home loan, the author next excludes home loan from non-bank debts to reduce potential biases, and finds an even larger effect: the MPC is now up by 2 percentage points for a ten-thousand Yuan increase in non-bank debts. This implies a credit channel of the housing wealth

effect on consumption in China that works through non-bank credits[28] consisting of borrowings from relatives/friends.

The results are similar to Mian and Sufi (2011) and Mian et al (2013) who also find a MPC that increases with debt leverages, but with two key differences: 1) this paper uses individual house prices while they both use aggregate house prices; 2) in addition to balance-sheet indicators, e.g. debts, this paper also utilizes other constraint measures that come with fewer endogeneity issues and measurement errors, e.g. poverty[29]; 3) this paper distinguishes between credit constraints and precautionary savings since they both yield a MPC that increases with housing wealth. This will be shown in the next section.

2.3.4 but Precautionary Savings Motives Hide the Credit Channel

As aforementioned, if a credit channel exists, then households that are constrained, e.g. those with credit requests rejected and/or those with supplemental security income, should exhibit excess consumption sensitivity to housing wealth, however, there are two factors that restrain them from doing so. The first factor, a missing bank market for home equity withdrawals, has been discussed above. Now, this paper turns to discuss on the second factor: a precautionary savings motive.

A precautionary savings motive is defined as a decreasing absolute risk aversion with a convex marginal utility, i.e. $U'''>0$, where U is the utility function of goods and services

[28] Households may not remember the exact amount of every single non-bank loan since such loans often come without contracts. To reduce measurement errors, we only count, for a certain loan category, the one with biggest value, and sum them up across different categories.

[29] A minor issue of balance-sheet indicators as measures of credit constraint is that they only apply to a part of the household sample, e.g. LTV only applies to households that bought households with mortgages.

(Kimball, 1990)[30]. While the presence of a precautionary savings motive has been shown theoretically (Aiyagari, 1994; Kimball, 1996; Lusardi, 1998), empirical evidence both confirm (Kantor and Fishback, 1996; Kazarosian, 1997; Kennickell and Lusardi, 2004) and deny (Guiso et al, 1992; Browning and Lusardi, 1996) it. One possible reason is the lack of suitable data and a good proxy for future income risks that trigger precautionary savings motives (Ventura and Eisenhauer, 2005).

Precautionary savings motives can confuse a credit channel since a non-constrained household with precautionary savings motives acts just like a constrained one without such motives (King, 1994; Kimball and Carroll, 2001; Carroll, 2001). An implication by precautionary savings motives is that households with such motives will excessively raise its current consumption (and/or holdings of risky assets) given a rise in its wealth. This imposes two issues on the credibility of a credit channel. First, for an average household, an increase in housing wealth may contribute to consumption by reducing precautionary savings motives, not by relaxing credit constraints, thus it is not clear whether a credit channel works. Moreover, for home owners with very low income, the precautionary savings motive may be strong and offset the propensity to consume out of housing wealth growths and hide a credit channel. Thus, their consumption responses to housing wealth might be under estimated.

The fist issue has been cleared in Column 2 of Table 2.6 where the MPC out of housing wealth by a typical household increases with non-bank loan, a result supportive

[30] See Leland (1968) and Kimball (1990) for details on the theoretical definition on and quantitative measures of precautionary savings motives.

of a credit channel. Hence, the rest of this section focuses on the second concern. In Table 2.3, households who earn low income and receive supplemental security income do not yield excess consumption sensitivity to housing wealth, which seems to reject a credit channel. It is, however, the rise of precautionary savings that restrains their consumption responses. The author presents two pieces of evidence for this.

First of all, households with more than one child yield significantly lower MPC out of housing wealth than others do, confirming a precautionary savings motive. Due to the one-child policy in China, kids other than the first one may not enjoy free schooling and healthcare[31]. This imposes future uncertainty on family expenditure and equals to an income shock, thus enhancing precautionary savings motives. Hence, the number of children is a good proxy for precautionary savings motives. Then, results in Column 1 of Table 2.6 show that each additional kid will reduce the MPC by 1.6 percentage points[32]. Though the average MPC is about 15% and it seems like having one or two more kids wouldn't drive the overall MPC down to an insignificant level, but there could be many other factors that also trigger precautionary savings.

[31] The variation in the execution of one-child policy across time and regions amounts to uncertainty.
[32] The strategy is the same as in Equation (2.3) except that we are now estimating the coefficient on the interaction term between housing wealth and kid sizes.

Table 2.6 Consumption Responses to Housing Wealth with Precautionary Savings

Income, financial wealth and housing wealth are in ten thousand yuan. "Kid size" is the number of children in a household. "If unhealthy" is a dummy equal to one if a household quitted a job last year due to health conditions, and zero otherwise. A constant term, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All variables except demographics are in log. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** is 0.1%, 1% and 5% significance level.

	Consumption	
	(1)	(2)
Income	0.148***	0.124***
	(0.0289)	(0.0134)
Financial wealth	0.0427***	0.0606***
	(0.00846)	(0.00605)
Housing wealth	0.153***	0.142***
	(0.0165)	(0.0106)
Housing wealth*Kid size	**-0.0160****	
	(0.00379)	
Housing wealth*If Unhealthy		**-0.0165****
		(0.00510)
N	1367	4524
adj. R^2	0.413	0.430

Furthermore, this paper shows that an unhealthy household head can also produce a reduction on the MPC out of housing wealth. Health is a good proxy for precautionary savings motives since bad heath conditions bring uncertainty to future labor income and amount to income shocks (Kimball and Carroll, 2001). Especially in China where the incomplete health insurance system often makes households overpay for excessive healthcares(Wagstaff and Lindelow, 2008), uncertainties out of bad health conditions further enhance precautionary savings motives that restrain them from consuming out of rising wealth. Results from the data, as shown in Column 2 of Table 2.6, suggest that households whose heads once quitted jobs in last year due to bad heath conditions yield

a MPC that is 1.6 percentage points below the average[33]. This again confirms the play of precautionary savings motives.

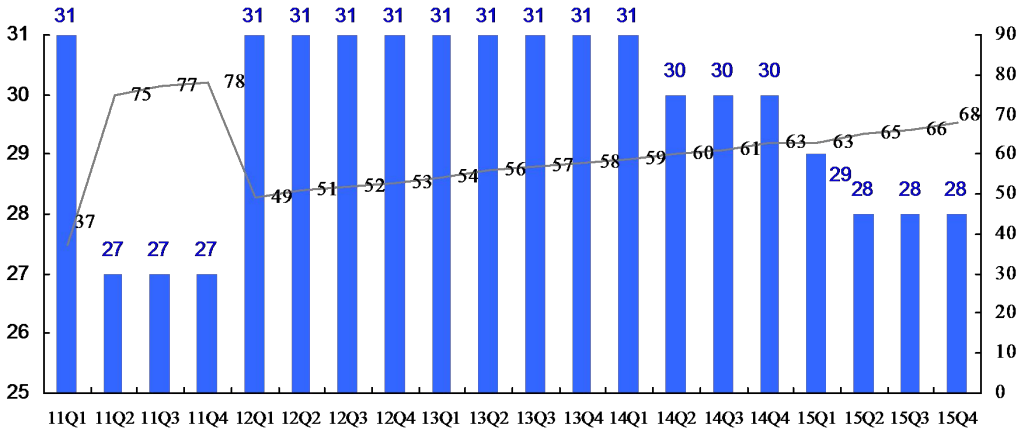
While the two findings evidence a precautionary saving motive, one concern still arise because households in poverty also live with low income and bear precautionary savings motives, but they still yield excess consumption responses. Hence, it is probably not precautionary savings motives that restrain the consumption response to housing wealth. To clear this concern, the author checks the identifications of households in poverty and with supplemental security income, and finds that the poverty line is much higher than supplemental security income lines in China (see Figure 2.4). This explains why households in poverty do not have strong precautionary savings motives.

Figure 2.4 shows that in the last five years, at least 27 out of 31 states in China on average set their supplemental security income lines at least 20% below the national poverty line. In other words, households eligible for supplemental security income often earn much less income and carry stronger precautionary savings motives than those in poverty do. Hence, it is not surprising that the former do not yield excess consumption sensitivity to housing wealth while the latter do. If taking into account the precautionary savings motive, this difference in consumption response by the two household groups actually confirms the credit channel, not rejects it,

[33] Column 2 is estimated by a strategy similar to Equation (2.2) except that we now focus on households who quit a job due to heath conditions and assign them a value of 1 on the dummy *C* while assign other households a zero.

Figure 2.4 Headcount of States with Poverty below Supplemental Income Line

The left axis measures numbers of states whose supplemental line is below the national poverty line, among a total of 31 states. The right axis measures ratios of national average supplemental income lines over the national poverty line, in percentage. Data (for urban residents) provided by the Ministry of Civil Affairs and the State Council Leading Group Office for Poverty Alleviation, and is calculated by the authors. See Appendix H for Details.



To conclude, empirical evidence by survey data is supportive of the conjecture that precautionary savings motives restrain low income households from consuming out of their increasing housing wealth. This may hide a credit channel that enables home equity withdrawals for consumption, but could hardly deny it.

2.4 the Credit Channel of Housing Wealth in China is Robust

This section conducts a series of robustness checks to clear several concerns that might arise when one tries to understand results found above.

The first robustness check is to show that the MPC out of housing wealth is not biased by a potential one-time expenditure shock. For instance, if a household bought lots of durable goods prior to the survey, its consumption response to housing wealth

may be biased. To rule out that possibility, consumption is divided into daily and non-daily parts. The former includes food, grocery and utility, while the latter includes durable goods. Equation (2.1) is re-run with the two types of expenditure and results are in Column 1 and 2 of Table 2.7. It is clear that the daily expenditure is also sensitive to housing wealth, though the MPC is about 6 percentage points below that of non-daily expenditure. The results comply with the literature and need no further explanations.

The second check confirms the credit channel by showing that home owners display an excess MPC out of housing wealth while renters don't. Since a credit channel works when home owners borrow against their home equities, it should not work for renters. A strategy to verify this is to see if home owners exhibit significantly more consumption responses to housing wealth than do others, and if renters display significantly fewer responses than do others. Equation (2.2) is revised to include dummies for owners and renters, and the results are shown in Column 3 and 4 of Table 2.7, where the additional MPC is about 2.8 percentage points for home owners and a negative 3.5 for renters[34]. This matches the ex-ante analysis and suggests that consumption responses to housing wealth work via a credit channel that uses homes as collaterals and excludes renters.

The third check further verifies the credit channel by showing that households that are not constrained display no excess consumption sensitivity to housing wealth. A credit channel transmits housing wealth to consumption by relaxing budgets constraints. Hence, it should not work for households not constrained and with few incentives to borrow

[34] Note that due to an average effect, renters still seem to display a consumption response to housing wealth, though their response is significantly lower than that by home owners.

against their home equities. In other words, such households are not expected to yield excess consumption sensitivity to housing wealth growths. Column 5 of Table 2.7 shows that consumption of a household that bought a house with no mortgage is insensitive to housing wealth growths. Given the value of a house, such a household can hardly be constrained and need not borrow for consumption, and their insignificant response justifies a credit channel.

Table 2.7 Robustness Checks on the Housing Wealth Effect

Dependent variable is daily expenditure in Column 1, non daily expenditure in Column 2, and total expenditure in all other columns. Income, financial wealth and housing wealth are in ten thousand yuan. "Owner", "Renter", "No mortgage" and "Retiree" are dummies equal to 1 if a household is an owner, renter, bought a house without a mortgage, and is retired, respectively, and zero otherwise. A constant term, age, age^2/100, gender, family size and state fixed effects are also controlled but not reported. All variables except demographics are in log. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** is 0.1%, 1% and 5% significance level.

	Daily Expenditure	Durable Goods	Total Consumption			
	(1)	(2)	(3)	(4)	(5)	(6)
1. Income	0.107***	0.234***	0.122***	0.124***	0.125***	0.126***
	(0.0113)	(0.0213)	(0.0135)	(0.0133)	(0.0132)	(0.0132)
2. Financial wealth	0.0434***	0.145***	0.0593***	0.0596***	0.0603***	0.0610***
	(0.00617)	(0.0120)	(0.00589)	(0.00613)	(0.00595)	(0.00601)
3. Housing wealth	**0.126****	**0.185****	0.115***	0.142***	0.136***	0.141***
	(0.0113)	(0.0280)	(0.0127)	(0.0107)	(0.0113)	(0.0109)
4. Housing wealth			**0.0272****			
*If Owner			(0.00650)			
5. Housing wealth				**-0.0350****		
*If Renter				(0.00779)		
6. Housing wealth					**0.00566**	
*If No Mortgage					(0.00337)	
7. Housing wealth						**-0.00190**
*If Retiree						(0.00498)
N	4307	4524	4524	4524	4524	4524
adj. R^2	0.308	0.365	0.433	0.431	0.429	0.429

The last robustness check is to rule out the possibility that the consumption response to housing wealth works through a wealth channel, not the credit channel as claimed. A home owner may perceive the growth of its housing wealth and raise consumption out of that while it needs not borrow for consumption. This process is often referred as a wealth channel of the housing wealth effect. Empirical studies that report a wealth channel (Campbell and Cocco, 2007; Browning et al, 2013) often follow the life-cycle theory to approximate that channel with additional consumption responses by the old to housing wealth. The argument is that the old are at a late stage of life-cycle and are not constrained, thus their responses are driven by a wealth channel.

The author adopts this idea but finds no excess consumption sensitivity by retirees to housing wealth, a result less supportive of a wealth channel. Retirees are at a late stage of their lives, and unlike the unemployed or self-employed, they have health insurance and pension, which means they are little constrained. Hence, if there is a wealth channel, they should exhibit a MPC out of housing wealth that is above the average. Equation (2.2) is revised to include the dummy of retiree, and results shown in Column 6 of Table 2.7 imply that retirees are not different from others in terms of consumption response to housing wealth. Hence, the data support no wealth channel. These findings support a credit channel as a working horse for the housing wealth effect, and confirm theoretical findings that deny a wealth channel (Sinai and Souleles, 2005; Buiter, 2010).

2.5 Summary of Chapter 2

This chapter investigates if there is a credit channel of the housing wealth effect on consumption in China, and explores how the channel works in a country where no bank credit market exists for home equity withdrawals. Empirical evidence supports a credit channel, and further suggests that households in China extract their increasing home equities to finance consumption via a non-bank credit market consisting of borrowings from relatives/friends. This finding somewhat implies the independence of home equity withdrawals from country-specific housing finance institutions.

By putting a cross-section of national representative household survey data in an estimated representative agent model that allows MPC to vary with wealth, this paper finds in China an average MPC out of housing wealth that ranges 9%-14%, higher than the 2%-10% found in the literature that uses aggregate house prices. The paper also finds an MPC of 18%-21% for households that are credit constrained, a result suggesting a credit channel. In order to identify constrained households, this paper utilizes not only popular balance-sheet indicators, more importantly, but also household self-revealed constraint measures that carry fewer endogeneity issues and measurement errors.

To confirm the credit channel, the author shows that it gets under estimated because it is turned off by households with precautionary savings motives that restrain them, especially those with low income, from consuming out of growing housing wealth. The paper captures precautionary savings motives by bad health conditions and the number of children. While the former proxy is usual, the latter is unique because the one-child

policy in China brings uncertainty to the cost of raising more than one child. Results indicate that households with bad health and/or more than one child are reluctant to consume out of housing wealth. This can hide the credit channel, but can not deny it.

To confirm that it is the non-bank credit market that enables the credit channel in China, this paper shows that those who borrow from relatives/friends to pay schools display excess consumption sensitivity to housing wealth. Such households are truly constrained and their accesses to the non-bank market help finance their consumption, including education expenditure. Another piece of evidence for the non-bank credit market is that the MPC out of housing wealth by an average household increases with its non-bank loan. Since a credit channel helps smoothie consumption by borrowings, if the MPC out of housing wealth goes up with non-bank loan, then non-bank loan is assisting the transmission of housing wealth to consumption. This verifies a credit channel that works via non-bank credits.

This paper contributes to the literature in several ways. First, it uses individual house prices to examine the housing wealth effect on consumption. Next, it identifies a credit channel of the housing wealth effect on consumption that works through a private credit market, instead of a bank credit market. Moreover, it captures a precautionary savings motive using the one-child policy in China, and shows how precautionary savings can neutralize a credit channel and lead to an under estimation of the channel.

Chapter 3: Housing Finance and the Monetary Transmission to Consumption

Preview of Chapter 3

This chapter examines the role of monetary policy on the U.S. housing and consumption sectors. In particular, it studies the channels through which monetary policy causes changes in sub-prime mortgages that impact these sectors. The method to be used is sequential vector auto regressive models at monthly frequency, which first capture the response of the spread of prime mortgage rate over T-bond rate to a monetary shock, and subsequently the response of housing sector to a credit spread shock. The results indicate that expansionary monetary policy shocks lead to a fall in the prime mortgage spread and a rise in sub-prime mortgage, which in turn increases house prices and consumption. This chapter contributes to the literature by showing that the monetary transmission to housing and consumption sectors also works via changes in sub-prime mortgage, by utilizing non-agency MBS and home equity lines of credit as new measures of sub-prime mortgages, and by investigating the simultaneous role of monetary shocks, capital inflows, and housing finance in an integrated analysis of recent developments in the housing sector.

3.1 Introduction to Three Factors Behind the Financial Crisis 2007

The recent financial crisis was associated with a rise in sub-prime mortgages, which led to an emerging literature aiming to understand how housing finance affects house prices and the aggregate economy. Green and Wachter (2007) and Favilukis et al (2010) find that deregulations in housing finance in the late 1990s and early 2000s substantially relaxed household credit constraints and fostered a housing surge. Taylor (2009) investigates the possibility that the prolonged phase of low interest rates prior to the crisis reduced the costs of external financing, including housing finance. Bernanke (2007) and Aizeman and Jinjarak (2009) study the role of the "global savings glut", that is, an increase in capital inflows that raised resources for housing finance and pushed up house prices. While these factors may all have played a role, to the author's knowledge, no studies have considered whether they jointly drive the market, or work separately. Future preemptive policies targeting a single factor may not work if these factors work together and can not be disentangled.

This paper estimates how a monetary shock transmits to housing and consumption sectors[35]. The question of interest is whether the fall in the spread of prime mortgage rate over safe rate and the subsequent rise in sub-prime mortgage during the recent housing boom contributed to the transmission. The interest is motivated by recent findings that risk-taking behaviors of financial intermediaries raise the demand for risky

[35] A monetary shock is defined as the exogenous part of a change in short-term interest rate that cannot be explained by monetary policy rules. The "housing sector" refers to house prices and housing finance.

asset (Rajan 2005; Borio and Zhu, 2008), and that mortgage derivatives facilitate capital inflows to the housing sector (Sá et al, 2014; Sá and Wieladek, 2014). Given these findings, a question of interest is whether loose money prior to the crisis led to a rise in the supply of risky sub-prime mortgages. If yes, how did the rise in sub-prime mortgages transmit to the housing sector? Did it interact with the rise in capital inflows at the time? What were the possible effects on the aggregate economy? Understanding these questions not only contributes to the literature but also helps policy makers to identify important factors of the boom-bust in the housing sector.

This paper constructs three sequential VARs to estimate the effects of monetary policy shocks on housing and consumption sectors[36]. The first VAR estimates the response of the prime mortgage spread to monetary shocks, and includes *consumption, inflation, short-term interest rate, credit spread,* and *house price*. The second VAR captures the response of housing sector to changes in the spread and includes *consumption, inflation, mortgage spread, house price,* and *home equity loan*. Implied by Iacoviello and Minetti (2008), a combination of the first and second VARs reveals if the monetary transmission to housing sector works via changes in sub-prime mortgages that are captured by the mortgage spread[37]. The last VAR, consisting of *consumption*, *inflation* and *home equity loan*, shows how consumption respond to changes in home equity loan, and completes the sequential VARs.

[36] The results obtained are insensitive to various orderings suggested in the literature.
[37] A lower credit spread can proxy for a rise in sub-prime mortgage because it reduces bank profits and encourages banks to issue high-yield sub-prime mortgage. See Section 3.5 for more.

The literature often suggests a balance-sheet channel in which a negative shock to short-term interest rate improves household balance sheets and reduces their mortgage rates (Iacoviello, 2005; Kiyotaki et al, 2011)[38]. In addition, this paper finds that that the monetary transmission to housing sector also works via changes in sub-prime mortgages. The paper shows that negative shocks to short-term interest rate reduce the spread of prime mortgage rate over safe rate and induce banks to issue more high-yield sub-prime mortgages. It also shows that a fall in the prime mortgage spread raises the supply of non-agency mortgage backed security (MBS), one major sub-prime mortgage derivative, and raises home equity withdrawals in the form of home equity line of credits, a housing finance tool like sub-prime mortgages. These findings reveal that sub-prime mortgages facilitate the monetary transmission to the housing sector.

The results also indicate that a negative shock to short-term interest rate boosts capital inflows to the housing sector, even though it is not a direct determinant of capital inflows[39]. In particular, this paper finds that capital inflows contribute to the rise in non-agency MBS and show that capital inflows are independent of U.S. monetary policy shocks. Taken together, the findings reveal that expansionary monetary policy raises the supply of sub-prime mortgage and provides destinations for excess capital inflows that seek high-yield assets. In this sense, monetary policy also facilitates the housing boom by attracting foreign capitals to the housing sector.

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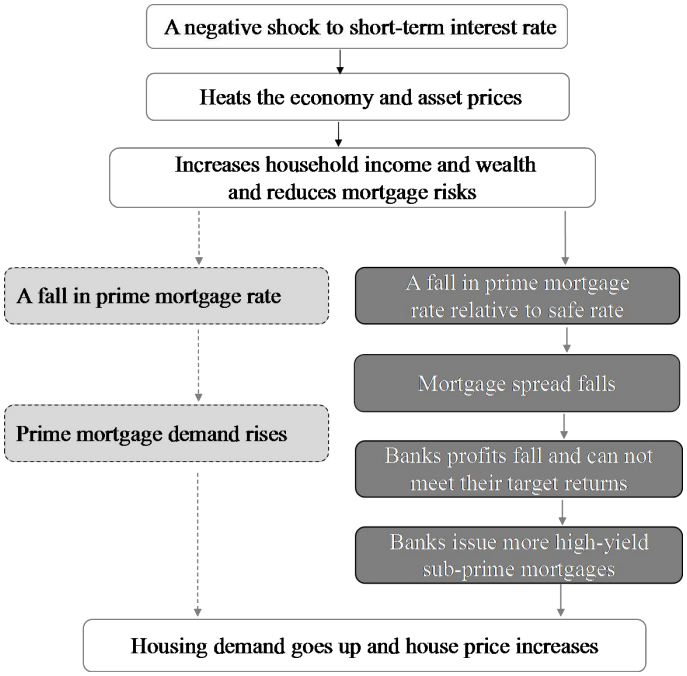
[38] This paper uses "monetary (policy) shock" and "shock to short-term interest rate" interchangeably since a negative shock to short-term interest rate equals a positive money shock.
[39] Capital inflows are modeled as pursuits of relative returns across major economies.

Figure 3.1 Findings in This Paper with Comparison to the Literature

Dash-line Light-grey boxes indicate the interest rate channel and Solid-line Dark-Grey boxes indicate the sub-prime mortgage channel found by this paper. Other boxes are the common steps that the two channels both go through.



This paper also proposes and estimates a Structural VAR (SVAR) to test for the robustness of the results and finds that it yields qualitatively similar findings. The author forms nested SVAR by picking alternative variables and restrictions as suggested in the literature, and estimates them using the *AB* model in Amisano and Giannini (1997). Results show that all responses to monetary shocks are not significantly different from those obtained under the sequential VARs, regardless of whether the SVAR is just or over identified.

The main contributions of this paper are: first, it shows that the monetary transmission to housing and consumption sectors also works via changes in sub-prime

mortgages, in addition to the balance-sheet channel often found in the literature. Second, it proposes innovative measures of sub-prime mortgages by non-agency MBS and home equity lines of credits. Finally, it integrates monetary shocks, capital inflows, and housing finance in an integrated framework to provide an overall assessment on how the housing boom evolved.

The rest of the chapter is structured as: Section 3.2 introduces the data. Section 3.3 specifies the sequential VAR models. Section 3.4 shows the recursive identification strategy. Section 3.5 gives the results. Section 3.6 tests if the results are robust to a SVAR that is an alternative identification strategy. Section 3.7 concludes.

3.2 Data: Aggregate Economy and Trends of Home Prices

The data in this paper all come from the FRED by the St. Louis Fed. Consumption is measured by retail sales that is the best available measurement at monthly frequency. Inflation is defined as Consumer Price Index (CPI). Short-term rate is just the Federal Funds Rate, and the prime mortgage spread is the spread of 30-year fixed mortgage rate over 30-year Treasury bond rate[40]. Capital inflow is simply defined as the net imports. Home equity loan is the outstanding balance on revolving home equity line of credits. Non-agency MBS is its dollar value share in all MBS. Prime mortgage is the outstanding balance of all traditional commercial and residential mortgages. This is the best available proxy for monthly residential mortgage. House price is measured by the Standard-Pool

[40] The 30-year T-bond is discontinued by the Treasury during 2002M3-2006M1. For that period, the author uses data from the Yahoo Finance that traces existing bonds and imputes the interest rates.

Case-Shiller National Home Price Index that traces the average market transaction price of single family houses. See Appendix I for a full description of terminologies to be used in the analysis below, and see Appendix J for a full description of the data.

All variables are in log except that short-term rate and prime mortgage spread are in percentage. Consumption, capital inflow, and home equity loan are all in log billion dollars while inflation and house price are indices. All series go from 1992M1 -2006M12. The start date is constrained by data availability, and the end date is chosen to exclude the recent financial crisis during which the quantitative easing policy may have contaminated the dynamics. Table 3.1 summarizes the variables of interest.

Table 3.1 Summary of Variables

Variable	**Measure** (all in monthly frequency)	**Source**
1.Consumption	Retail sales	Bureau of Census
2,Inflation	CPI	Bureau of Labor Statistics
3.Short-term interest rate	Federal Funds Rate (FFR)	The St. Louis Fed
4.Prime mortgage spread	30 year mortgage rate less 30 year T-bond rate	Freddie Mac
5.Home equity withdrawal	Ratio of home equity loans to prime mortgage	The St. Louis Fed
6.Capital inflow	Net import	Bureau of Economic Analysis
7.House price	Case-Shiller national home price index	Standard-Poor
8.Non-agency mortgage backed securities	Its dollar share in all mortgage-backed securities	The St. Louis Fed

All series appear to be I (1) by the augmented Dickey-Fuller test, but the author still builds the VAR in level since the paper focuses on a short-run dynamics. As suggested in Sims (1980) and Sims, Stock and Watson (1990), to difference or detrend the data so as to achieve stationarity throws away information on the co-movement of variables that is

critical to the identification of a short-run dynamics. Instead, they argue that an unrestricted VAR in level is capable to capture the dynamics. Plus, short-run responses derived using a VAR in differencing can be very sensitive to even small mis-specifications of the model (Faust and Leeper, 1997). Hence, to model the short-run dynamics under a VAR in level is at least safe.

3.3 a Sequential VAR for Monetary Transmission to Consumption via Housing

This part first defines the three VARs that form the sequential VARs, then explains the theory and empirical foundations, and last describes in a matrix form the restrictions on contemporaneous responses among variables in each VAR. Table 3.2 summarizes the strategies to be used in the estimation.

Table 3.2 Summary of the Sequential VARs

VAR	Shock to	Response of	Variables included
1	Monetary Policy	Prime Mortgage Spread	Consumption, Inflation, Short-term interest rate(FFR), Mortgage Spread, House Price
2	Credit Spread	Home Equity Loan	Consumption, Inflation, Mortgage Spread, House Price, Home equity Loan
3	Home Equity Loan	Consumption	Consumption, Inflation, Home equity loan

3.3.1 Monetary Shocks Drive the Prime Mortgage Spread over Safe Rate

Since the literature shares a standard approach to estimate monetary transmission in a VAR (Christiano et al, 1999), this paper simply follows that to model the monetary transmission to the housing sector. That approach is:

$$Y_t = C + A(L)Y_t + BU_t \tag{3.1}$$

Where *C* is a vector of constants and *Y* a vector of endogenous variables described as the following:

$$Y_t = \begin{bmatrix} y_t^1 \\ y_t^2 \\ y_t^3 \\ y_t^4 \\ y_t^5 \end{bmatrix} = \begin{bmatrix} \text{Cons}_t \\ \text{Infl}_t \\ \text{FFR}_t \\ \text{Spread}_t \\ \text{Hprice}_t \end{bmatrix}$$

Where "Cons" is consumption, "Infl" inflation, "FFR" short-term interest rate, "Spread" prime mortgage spread, and "Hprice" house price.

Next, *A(L)* is a matrix of polynomials in lag operator and contains two parts:

$$A(L) = A(0) + \overset{+}{A}(L) \tag{3.2}$$

Where *A(0)* is the part of *A (L)* with *L*=0, and $\overset{+}{A}(L)$ is the part of *A(L)* with $L > 0$. Note that *A(0)* contains the contemporaneous responses among endogenous variables:

$$A(0) = \begin{bmatrix} 0 & -a_{21} & -a_{31} & -a_{41} & -a_{51} \\ -a_{12} & 0 & -a_{32} & -a_{42} & -a_{52} \\ -a_{13} & -a_{23} & 0 & -a_{43} & -a_{53} \\ -a_{14} & -a_{24} & -a_{34} & 0 & -a_{54} \\ -a_{15} & -a_{25} & -a_{35} & -a_{45} & 0 \end{bmatrix}$$

Where a_{ij} is the contemporaneous response by variable *j* to a shock to variable *I,* for example, a_{34} is the contemporaneous response by mortgage spread to a monetary shock.

Moreover, *U* is a vector of structural shocks that are serially uncorrelated white noise disturbances with zero means and normalized variances:

$$U_t = \begin{bmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \\ u_t^4 \\ u_t^5 \end{bmatrix} - \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \right)$$

and B contains the *S.D.* of the structural shocks, with a diagonal variance-covariance matrix $\sum_B$ as below:

$$B = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{bmatrix} \text{ with } \sum_B = \begin{bmatrix} b_{11}^2 & 0 & 0 & 0 & 0 \\ 0 & b_{22}^2 & 0 & 0 & 0 \\ 0 & 0 & b_{33}^2 & 0 & 0 \\ 0 & 0 & 0 & b_{44}^2 & 0 \\ 0 & 0 & 0 & 0 & b_{55}^2 \end{bmatrix}$$

The choice of variables in Equation (3.1) is guided by the literature on monetary transmission to aggregate economy (Christiano et al, 1999) and to the housing market (Iacoviello and Minetti, 2008; Sá et al, 2014). The literature finds a balance-sheet channel of monetary transmission, via which a rise in short-term rate hurts a firm's balance sheet, increases its external financing cost, and persistently reduces its investment and income (Bernanke and Gertler, 1989). The adverse effects are amplified and accelerated if the firm is constrained and uses lands as borrowing collaterals (Kiyotaki and Moore, 1997). This balance-sheet channel also applies to the housing market where a rise in short-term interest rate reduces jobs and household income, hurts its balance-sheet, and raises the spread of mortgage rate over safe rate, which cuts the housing demand (Iacoviello, 2005). Hence, the strategy in Equation (3.1) has good economic and economics foundations.

For Equation (3.1) to be estimated, it needs to be converted to a reduced form model that gets rids of the contemporaneous response Matrix $A(0)$. First, plugging Equation (3.2) into Equation (3.1) and moving $A(0)$ to the left-hand side gives:

$$[1 - A(0)]Y_t = C + A(\overset{+}{L})Y_t + BU_t \tag{3.3}$$

Next defining [1-A (0)] as a Matrix A and it becomes:

$$AY_t = C + A(\overset{+}{L})Y_t + BU_t \tag{3.4}$$

Where

$$A = 1 - A(0) = \begin{bmatrix} 1 & a_{21} & a_{31} & a_{41} & a_{51} \\ a_{12} & 1 & a_{32} & a_{42} & a_{52} \\ a_{13} & a_{23} & 1 & a_{43} & a_{53} \\ a_{14} & a_{24} & a_{34} & 1 & a_{54} \\ a_{15} & a_{25} & a_{35} & a_{45} & 1 \end{bmatrix}$$

Further moving the Matrix A to the right-hand side of Equation (3.4) gives:

$$Y_t = A^{-1}C + A^{-1}A(\overset{+}{L})Y_t + A^{-1}BU_t \tag{3.5}$$

Defining E_t=$A^{-1}BU_t$ and rewriting Equation (5) as:

$$Y_t = A^{-1}C + A^{-1}A(\overset{+}{L})Y_t + E_t \tag{3.6}$$

Where it is now clear that E is just the vector of residuals when one estimates Equation (3.6), and further rearranging E_t=$A^{-1}BU_t$ yields:

$$AE_t = BU_t \tag{3.7}$$

This is the *AB* model as in Amisano and Giannini (1997). It is clear from Equation (3.5) that $A^{-1}B$ captures the response by Y to a structural shock u^i. To solve for $A^{-1}B$ that has a total of 25 unknowns, one needs to impose 10 restrictions on the off-diagonal elements of Matrix A since the variance-contrivance matrix of residuals from estimating Equation (3.6), Σ_E, only provides a total of 15 conditions. Given that Matrix A records contemporaneous responses among endogenous variables, restrictions on its off-diagonal elements is equal to restrictions on how those variables immediately react to each other.

The essential difference between the three common VAR strategies, including the recursive identification, the structural VAR, and sign restrictions, is that they restrict the Matrix A in different ways. This paper uses the recursive identification that assumes a lower diagonal Matrix A, but the results are also robust to a structural VAR.

3.3.2 Prime Mortgage Spreads Affect Risky Mortgage Supply and Home Prices

The 2nd VAR models the transmission of changes in the prime mortgage spread and is specified as:

$$\hat{Y}_t = \hat{C} + \hat{A}(L)\hat{Y}_t + \hat{B}\hat{U}_t \tag{3.8}$$

Where $\hat{Y}_t$ is a vector of endogenous variable as below (where "Hloan" is home equity loan), and other variables are likewise defined as in Section 3.3.1.

$$\hat{Y}_t = \begin{bmatrix} \hat{y}_t^1 \\ \hat{y}_t^2 \\ \hat{y}_t^3 \\ \hat{y}_t^4 \\ \hat{y}_t^5 \end{bmatrix} = \begin{bmatrix} \text{Cons}_t \\ \text{Infl}_t \\ \text{Spread}_t \\ \text{Hprice}_t \\ \text{Hloan}_t \end{bmatrix}$$

The goal of this strategy is to test if a change in prime mortgage spreads, resulted from a monetary policy shock, further transmits to consumption through home equity withdrawals, as what is often found in the micro literature (Greenspan and Kennedy, 2008; Mian and Sufi, 2011; Mian et al, 2013). Since the 1st VAR assumes that prime mortgage spreads respond to a monetary shock, following Iacoviello and Minetti (2008), the 2nd VAR does not include the spread otherwise the response by the housing market to a mortgage spread shock may carry effects beyond monetary policy shocks.

Similarly, the 3rd VAR captures how consumption respond to changes in home equity loan and is specified as:

$$\widetilde{Y}_t = \widetilde{C} + \widetilde{A}(L)\widetilde{Y}_t + \widetilde{B}\widetilde{U}_t \tag{3.9}$$

Where $\widetilde{Y}$ is a vector of endogenous variables defined as below, and other variables are similarly defined as in Section 3.3.1.

$$\widetilde{Y}_t = \begin{bmatrix} \widetilde{y}_t^1 \\ \widetilde{y}_t^2 \\ \widetilde{y}_t^3 \end{bmatrix} = \begin{bmatrix} \text{Cons}_t \\ \text{Infl}_t \\ \text{Hloan}_t \end{bmatrix}$$

The 3rd VAR, when combined with the 1st and the 2nd VAR, tells a full picture of how a monetary policy shock transmits to consumption via the housing market. Thus, it completes the sequential VARs. Note that it does not include any variable that is ordered before home equity loan in the 2nd VAR because otherwise the response of consumption will marginally carry effects beyond those of a monetary shock.

A similar AB model can be constructed for both the 2nd and 3rd VAR. Since the derivations are similar to that in Section 3.3.1, the author just provides the results:

$$\hat{A}=\begin{bmatrix} 1 & \hat{a}_{21} & \hat{a}_{31} & \hat{a}_{41} & \hat{a}_{51} \\ \hat{a}_{12} & 1 & \hat{a}_{32} & \hat{a}_{42} & \hat{a}_{52} \\ \hat{a}_{13} & \hat{a}_{23} & 1 & \hat{a}_{43} & \hat{a}_{53} \\ \hat{a}_{14} & \hat{a}_{24} & \hat{a}_{34} & 1 & \hat{a}_{54} \\ \hat{a}_{15} & \hat{a}_{25} & \hat{a}_{35} & \hat{a}_{45} & 1 \end{bmatrix} \quad \text{and} \quad \widetilde{A}=\begin{bmatrix} 1 & \widetilde{a}_{21} & \widetilde{a}_{31} \\ \widetilde{a}_{12} & 1 & \widetilde{a}_{32} \\ \widetilde{a}_{13} & \widetilde{a}_{23} & 1 \end{bmatrix}$$

Where $\hat{A}$ is the matrix of contemporaneous responses by $\hat{Y}_t$ to structural shocks in Equation (3.8) and $\widetilde{A}$ is that by $\widetilde{Y}_t$ to structural shocks in Equation (3.9).

3.4 How to Identify Monetary Shocks?

This paper identifies a monetary shock using a recursive scheme that restricts some of the contemporaneous responses in the Matrix A to be zero. The reason is that the recursive identification is easy to compute and yields a unique solution. Moreover, the recent housing boom-bust already demonstrated how a housing boom builds up and transmits to the economy, so the ordering of events is clear (Greenspan and Kennedy, 2008; Mian and Sufi, 2011). This rationalizes the use of recursive identification[41]. Table 3.3 summarizes the ordering in each VAR.

Table 3.3 Summary of Recursive Identifications of Shocks

VAR	Variable of interest	Is ordered before	Is ordered after
1	Short-term Interest Rate	Mortgage Spread and House price	Consumption, Inflation
2	Mortgage Spread	House Price and Home equity loan	Consumption, Inflation
3	Home Equity Loan		Consumption, Inflation

[41] A possible issue of the recursive identification is that its results might be sensitive to the ordering of variables, which is, however, not a problem in this paper.

Results from the recursive identification can be sensitive to the ordering of variables included, but our results are robust to various orderings suggested by the literature. Also, the recursive scheme executes partial identification and can only identify one shock per time, which is not a problem since this paper only identifies the monetary shock[42].

3.4.1 Monetary Shocks Are Ordered Before Prime Mortgage Spreads

A monetary shock is identified in a way such that that the short-term interest rate is ordered after consumption and inflation but before mortgage spreads and house prices. Hence, consumption is the least endogenous variable in the system while the house price is the most endogenous one. In a matrix view, the identification strategy for a monetary shock is to impose zero restrictions on coefficients above the diagonal in the Matrix A and convert it to a lower diagonal matrix denoted as A_r:

$$A_r = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{12} & 1 & 0 & 0 & 0 \\ a_{13} & a_{23} & 1 & 0 & 0 \\ a_{14} & a_{24} & a_{34} & 1 & 0 \\ a_{15} & a_{25} & a_{35} & a_{45} & 1 \end{bmatrix}$$

The 1st and 2nd rows in A_r say that consumption responds immediately to no shocks while inflation only to consumption shocks. This is common in the literature and can be theoretically achieved in a DSGE model with nominal rigidities (Iacoviello, 2005; Sims and Zha, 2006).

The 3rd row implies that monetary shocks do not immediately affect consumption and inflation but instantaneously impact mortgage spreads and house prices. This is just

[42] See Iacoviello and Minetti (2008) for the reason of and the solution to partial identification.

a representation of the Taylor Rule. Such an ordering is not new in the literature (see Christiano et al, 1999). The difference than in the monetary transmission literature is that this paper uses monthly data and makes it very much unlikely for short-term interest rates to contemporaneously affect consumption and inflation (see Sims and Zha, 1998, 2006). Note that the monetary shock can still affect consumption and inflation with lags.

Restrictions in the last two rows are appropriate since they deliver economics senses. The 4th row says that the mortgage spread, a risk premium, instantaneously responds to the fundamentals (consumption and inflation) and possible future risks as implied by the policy signal (short-term interest rates). The last row suggests that house prices, an asset price, immediately respond to the economic fundamentals and the housing sector risk that is captured by mortgage spreads.

By the Matrix A_r that puts 10 zero restrictions on the contemporaneous responses among variables, it is able to just identify Matrix A and B in Equation (3.7), then the responses of all endogenous variables to monetary shock can be traced by $E_t=A^{-1}BU_t$

3.4.2 Prime Mortgage Spreads Are Ordered Before Home Prices and Home Loan

The mortgage spread shock in the 2nd VAR is ordered after consumption and inflation but before house prices and home equity loan. So, a rise in the prime mortgage spread affects home prices and home equity loan immediately, but affects consumption and inflation with lags. In a matrix view, to identify a mortgage spread shock is to restrict the Matrix A *hat* as a lower diagonal matrix:

$$\hat{A}_r = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \hat{a}_{12} & 1 & 0 & 0 & 0 \\ \hat{a}_{13} & \hat{a}_{23} & 1 & 0 & 0 \\ \hat{a}_{14} & \hat{a}_{24} & \hat{a}_{34} & 1 & 0 \\ \hat{a}_{15} & \hat{a}_{25} & \hat{a}_{35} & \hat{a}_{45} & 1 \end{bmatrix}$$

It is consistent to order the mortgage spread after consumption and inflation because it responds to a monetary shock that is after consumption and inflation in the 1st VAR. The idea to order it before housing variables roots in the findings that financial intermediaries that seek high returns often take excess risky investments and raise the demand for risk assets (Rajan, 2005; Borio and Zhu, 2008), and that the risk premia of stock return over safe rate adversely affects residential investments (Lustig and Van Nieuwerburgh, 2005). A similar story happens in the housing market where a fall in the spread of prime mortgage rate over safe rate induces banks to offer risky but high-yield mortgages, otherwise capital escape to other assets, e.g. stocks.

If the 1st VAR yields a significant response of mortgage spread to monetary shocks and the 2nd VAR further shows that house prices actively respond to mortgage spread shocks, then it is legitimate to combine the two to study the monetary transmission to housing sector that works via risky mortgages, which are measured by mortgage spreads. Note that mortgage spreads can proxy for risky mortgages because a fall in the spread of prime mortgage rate over safe rate cuts bank revenues from prime mortgages and invites banks to increase the supply of risky but high-yield mortgages.

3.5 Results show Monetary Transmission to Consumption Works via Housing

This section first presents evidence that a fall in short-term interest rate reduces the prime mortgage spread over safe rate, which invites banks to increase the supply of high-yield risky mortgage. Then, the paper proceeds to show how the rise in risky mortgages heats the housing and consumption sectors. To verify the findings, the paper further uses non-agency mortgage backed security (MBS) and home equity line of credit (HELOC), two major risky housing finance derives in the last housing boom, to proxy for the risky mortgage supply. They both give similar results and offer a confidence.

3.5.1 a Fall in Short-Term Interest Rate Raises the Supply of Risky Mortgage

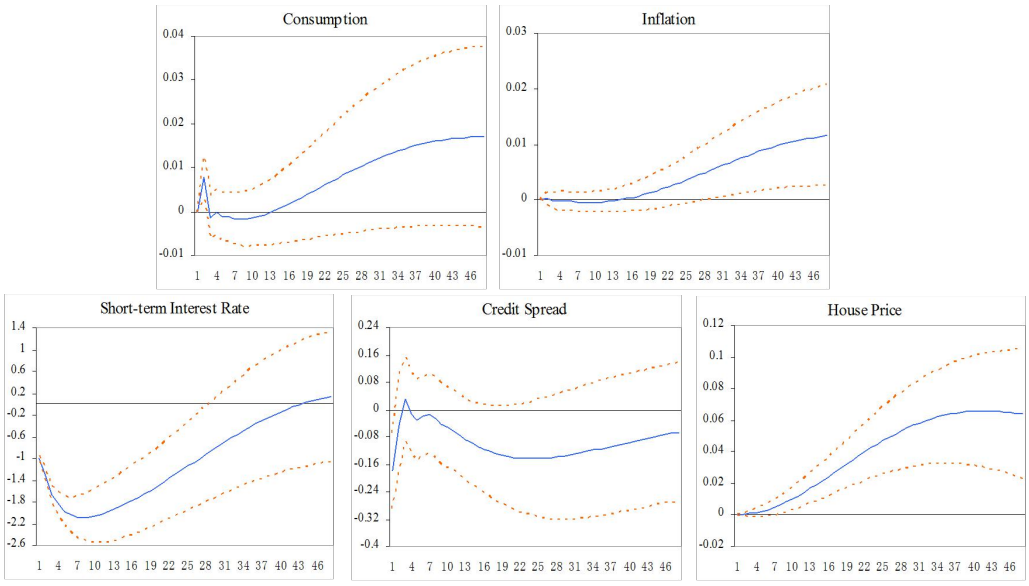
If a monetary shock transmits to housing and consumption sectors via changes in risky mortgages, then a decrease in short-term interest rate should cut the prime mortgage spread, raise the supply of risky mortgage, push up house prices, increase home equity loan, and add to consumption and inflation. It is expected that the 1st-3rd VAR that together complete the monetary transmission yield responses similar to these.

A fall in short-term interest rate indeed reduces the mortgage spread, as shown in Figure 3.2. First of all, consumption first stays inertial then begins rising in 12 months until a trough of about 1.7% in roughly 45 months. Inflation yields a similar pattern. This is qualitatively similar to results in the literature (Christiano et al, 1999). Next, mortgage spreads are first volatile until it starts a smooth falling in 7 months and finally hits a trough of about 14.5 basis points in about 24 months. This implies that overtime

prime mortgage rates decrease more than short-term rates do and confirms the play of financial accelerator in the housing finance. Furthermore, house prices grow fast, as what is found in the literature that empirically studies housing in the monetary transmission (Calza et al, 2011; Elbourne, 2008). While this may also work via a balance sheet channel, this paper will show that it is due to a rise in the supply of risky mortgage. The point of Figure 3.2 is to confirm that a fall in the short-term rate cuts the mortgage spread.

Figure 3.2 Responses to a 100 Basis Point Shock to Short-Term Rates ±one S.E.

Results derived under a recursive VAR that includes (in this order) consumption, inflation, short-term interest rate, mortgage spread and house price. The graphs below present the responses to a shock to the short-term interest rate (i.e. a monetary shock). Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sales in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Short-term interest rate is federal funds rate in percentage; Mortgage (credit) spread is the 30 year prime mortgage rate less 30 year T-bond rate and is in percentage; House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.



Results in Figure 3.2 are qualitatively robust to various orderings of the variables. For example, to order house prices before or after short-term interest rates, to order mortgage spreads before or after house prices, and to order short-term interest rates before or after consumption and inflation, all yield qualitatively similar results. This implies that the identification of monetary shock in this paper is not inappropriate, and confirms the finding that a fall in short-term interest rate indeed cuts mortgage spreads.

Next, the paper shows in Figure 3.3 that a fall in mortgage spread raises house prices and home equity loan. First of all, house prices rise immediately and keep growing until hitting a peak of 0.21% in about 27 months. Home equity loan that use home equities as collaterals also go up immediately and keep growing to 0.36% in 48 months. This implies that a rise in risky mortgage, resulted from the fall in prime mortgage spread, helps the loose monetary policy to boost the housing market. Next, consumption and inflation both increase moderately with a peak of 0.16% and 0.07%, respectively. This is reasonable given increasing home equity loan.

Results in Figure 3.3 are also qualitatively insensitive to various orderings of the variables. For instance, to order mortgage spreads before or after house prices, to order mortgage spreads before or after home equity loan, and to order home equity loan before or after consumption and inflation, all produce qualitatively similar results. This implies that identifying mortgage spread shocks in a recursive scheme, as in this paper, is at least not inappropriate. More importantly, it is confirmed that a fall in mortgage spread indeed increases home equity loan.

Figure 3.3 Responses to a one S.D Shock to Credit Spreads ± one S.E.

Results derived under a recursive VAR that includes (in this order) consumption, inflation, mortgage spread (credit spread), house price and home equity loan. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sales in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Credit spread is the 30 year prime mortgage rate less the 30 year T-bond rate and is in percentage; House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log; Home equity loan is the outstanding balance on revolving home equity line of credit and is in log billion dollars. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines are the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.

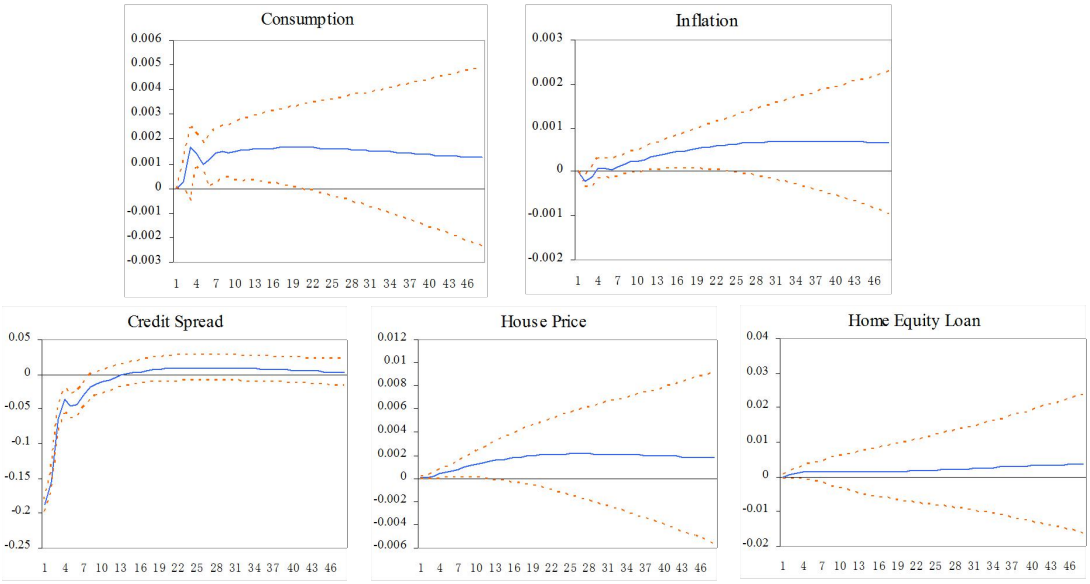


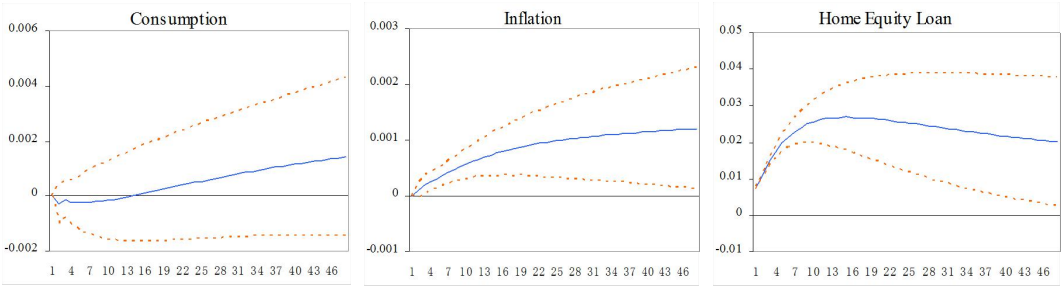
Figure 3.2 and 3.3 together show that a negative shock to short-term interest rate heats the housing market via a lower prime mortgage spread that raises the supply of risky mortgage. As mentioned earlier, a balance-sheet channel can do the same thing. To confirm the role of risky mortgage, this paper introduces the non-agency MBS, a major risky mortgage derivative, and show that a decrease in mortgage spread increases the issuance of non-agency MBS, which increases housing demands and house prices. This confirms the role of risky mortgage in the housing boom.

3.5.2 the Rise in Risky Mortgage Adds to Home Prices and Home Equity Loan

Now that the 1st-2ndVAR have been justified, the next is to justify the 3rd VAR that captures the response of consumption to changes in home equity loan and completes the monetary transmission to consumption via the housing market. As found in Greenspan and Kennedy (2008), a main source of expenditure growth prior to the crisis is a rapid rise in home equity withdrawals. Thus, given a rise in home equity loan, consumption is expected to increase. This is intuitive since home equity loan allow households to extract unused home equities to finance expenditures.

Figure 3.4 Responses to a one S.D Shock to Home Equity Loans ± one S.E.

Results derived under a recursive VAR that includes (in this order) consumption, inflation, and home equity loan. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sales in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Home equity loan is the outstanding balance on revolving home equity line of credit and is in log billion dollars. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.



The impulse responses to a rise in home equity loan are in Figure 3.4 where both consumption and inflation increase. Consumption first stays inertial but starts rising in 12 months and is up by 0.14% in 48 months. In contrast, Inflation is up much earlier and

increases by 0.12% in 48 months. One possibility is that it takes time for firms to adjust productions to demand shocks resulted from increasing home equities. Thus, price adjustments are more significant before output catches up. After that, the rise in price turns slower. To sum, the 3rd VAR is appropriate since it yields responses in line with both the literature and the reality.

Again, results in Figure 3.4 are insensitive to alternative orderings of the variables[43]. This means that the recursive identification of shocks to home equity loan, as in this paper, is at least safe and appropriate. It also confirms that an increase in home equity loan contributes to persistent consumption growths.

3.5.3 Non-Agency MBS and HELOC Both Evidence the Rise in Risky Mortgage

To ensure that the monetary transmission to housing and consumption sectors works through changes in risky mortgages, this part introduces the non-agency MBS and home equity lines of credits s as proxies for risky mortgages.

First, the paper includes non-agency MBS to the 2nd VAR and show that a fall in mortgage spread indeed increases non-agency MBS issuances. MBS include agency MBS backed by government agencies, e.g. Fannie Mae, and non-agency MBS. The government agencies measure mortgage risks by the Loan-to-Value and the Payment-to-Income ratios, among others, and decide whether to back a mortgage and its MBS. Non-agency MBS often securitizes mortgages that do not conform to the government agency underwriting

[43] E.g., to order home equity loans before or after consumption, and to order home equity loans before or after inflation, all produce qualitatively similar results.

standards and thus carry high probabilities of default but offer high returns. Thus, non-agency MBS is a good proxy for risky mortgages.

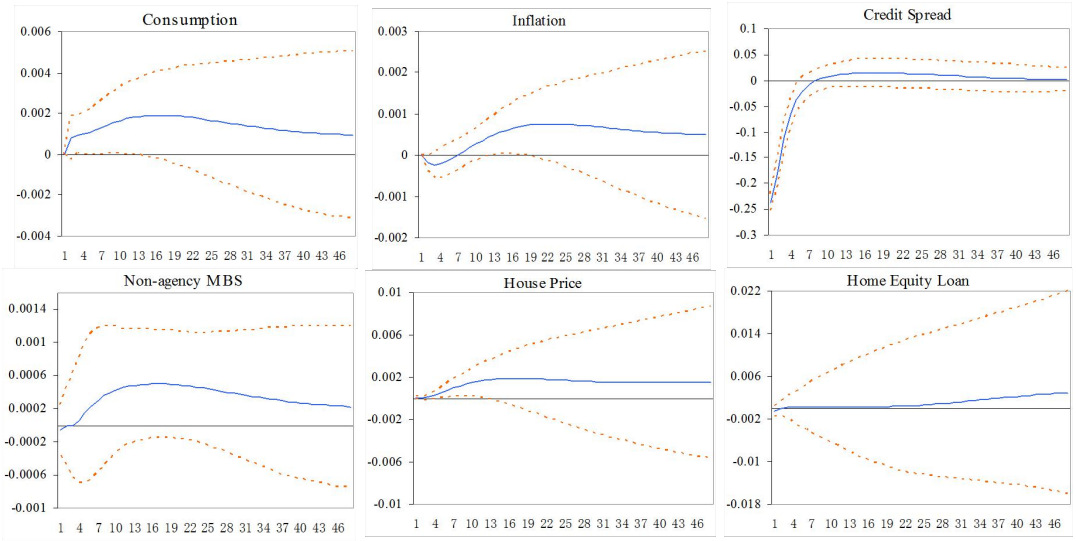
Figure 3.5 replicates Figure 3.3 but including non-agency MBS that is ordered after mortgage spreads and before house prices. The non-agency MBS is measured as its dollar value share in all MBS[44]. The non-agency MBS first stays inertial and then starts growing in 4 months until hitting a peak of 0.05% in about 16 months. This makes sense since the fall in interest rate reduces returns on prime mortgage and there are increasing needs for banks to supply high-yield risky mortgage products. The responses of non-agency MBS confirm that a monetary shock also transmits to the housing market through changes in risky mortgages.

Robustness checks that arrange variables in alternative orderings all yield results that are qualitatively similar to those in Figure 3.5. For example, to order non-agency MBS before or after mortgage spreads, to order house prices before or after mortgage spreads, and to order home equity loan before or after consumption and inflation, all yield qualitatively similar results. This suggests that non-agency MBS is a good proxy for risky mortgages and confirms the role of risky mortgages in facilitating monetary transmission to housing and consumption sectors.

[44] Including the share of non-agency MBS, not its volume, because agency MBS also increased at the same time.

Figure 3.5 A one S.D Mortgage Spread Shock and with Non-agency MBS

Results derived under a recursive VAR that includes (in this order) consumption, inflation, mortgage spread (credit spread), non-agency MBS, house price and home equity loan. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sale in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Mortgage spread (credit spread) is the 30 year prime mortgage rate less the 30 year T-bond rate and is in percentage; Non-agency MBS is the dollar value share of non-agency mortgage-backed securities (MBS) over all MBS and is in percentage. House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log; Home equity loan is the outstanding balance on revolving home equity line of credit and is in log billion dollars. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.

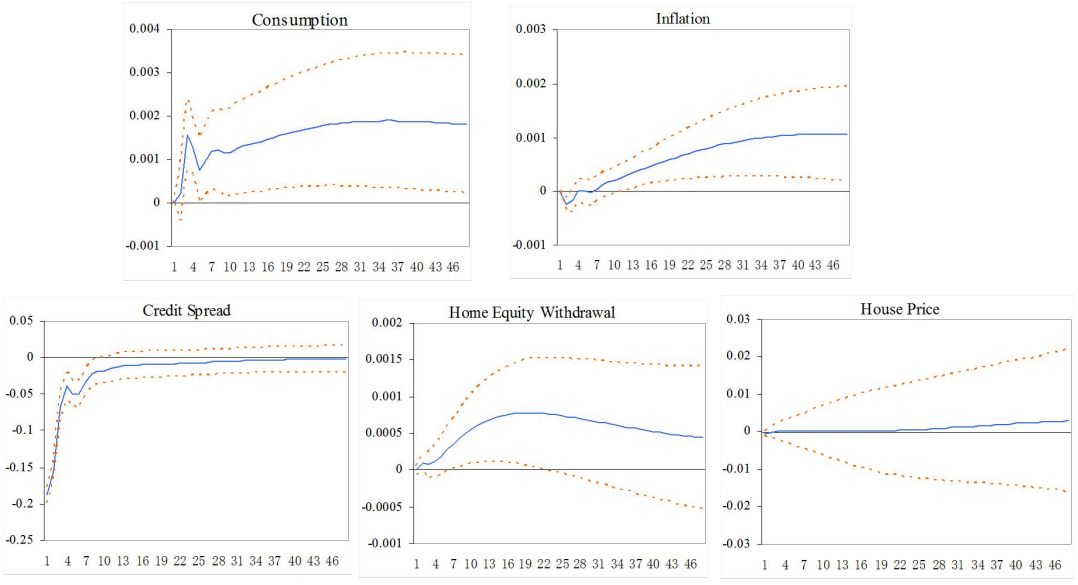


Next, this paper approximate risky mortgages with home equity lines of credits and examines if a decrease in prime mortgage spread boosts home equity withdrawals. Home equity withdrawals refer to the practice by which a household extracts its unused home equity, either by cash-out mortgage refinancing or home equity loans, both of which use home equities as collaterals just like prime mortgages do but with shorter terms, more rigorous underwriting standards and higher interest rates. Thus, home equity withdrawals can proxy for risky mortgages.

To test home equity withdrawals, the author includes it to the 2nd VAR and measures it by the ratio of home equity line of credits over prime mortgages. Since it plays as a proxy for risky mortgages that respond to mortgage spreads and transmit to the housing market, it is ordered after mortgage spreads and before house prices. Moreover, home equity loan is removed from the 2nd VAR to avoid co-linearity with home equity lines of credits, which measures home equity loan in this paper.

Figure 3.6 A one S.D. Credit Spread Shock and Home Equity Withdrawals

Results derived under a recursive VAR that includes (in this order) consumption, inflation, mortgage spread (credit spread), home equity withdrawal, and house price. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sale in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Mortgage spread (credit spread) is the 30 year prime mortgage rate less the 30 year T-bond rate and is in percentage; Home equity withdrawal is the ratio of home equity line of credit over prime mortgage and is in percentage. House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.



Results shown in Figure 3.6 indicate that given a fall in prime mortgage spread, home equity withdrawals increase and hit a peak of almost 0.08% in about 19 months. Translating to the housing boom, while low rates increase house prices and the demand for home equity withdrawals, the fall in mortgage spread invites banks to supply risky mortgage products in the form of home equity line of credits so as to meet that growing demand and to maintain revenues. Hence, the outcome is a rising housing market and consumption. This confirms the role of risky mortgages. Again, alternative orderings of the variables yield results that are qualitatively similar[45].

3.5.4 Capital Inflows also Assist Monetary Transmission to the Housing Sector

One concern on the role of risky mortgage is that if its growth not only raises bank returns, but also serves foreign investors who seek high-yield assets, then a rise in capital inflow, in addition to low rates, may also add to the housing boom. Simply put, banks provide the supply of risky mortgages, and capital inflows provide the demand. This concern is motivated by the fact that excess capital inflows co-existed with low rates during the housing boom and is found significant to the rise in housing market (Sá et al, 2014; Sá and Wieladeck, 2014).

To test this, the paper examines if a rise in capital inflow increases risky mortgages. Since foreign capital enter the housing market mainly by holding mortgage securities, this paper again measure risky mortgages by non-agency MBS. To be specific, it builds a

[45] For instance, to order house price before or after home equity withdrawals, and to order home equity withdrawals before or after consumption.

recursive VAR that includes *consumption, inflation, capital inflows, non-agency MBS, house price and home equity loan,* and estimates the responses of non-agency MBS to a rise in capital inflow. The choice of variables and the ordering of variables are inspired by few studies that explore the transmission of capital inflow to the housing sector (Aizenman and Jinzarak, 2009; Reinhat and Reinhart, 2008; Sá et al, 2014; Sá and Wieladeck, 2014). If foreign investors choose to buy risky high-yield mortgage assets, then an increase in capital inflow should raise the non-agency MBS.

Results in Figure 3.7 show that an increase in capital inflow raises the supply of non-agency MBS, implying that capital inflows also helped the housing boom. First, non-agency MBS first falls but recovers fast and starts rising in 6 months until it hits a peak of 0.12% in about 21 months. This evidences an increase in risky mortgages. Next, following the rise in non-agency MBS, what happens is straightforward. The growing risky mortgages raise the housing demand of owner self-occupying or for speculative investments, both of which increase house prices and enable growths in home equity loan. These results are insensitive to different orderings of the variables[46].

Since capital inflows also contribute to a rising housing market, just like a negative shock to short-term interest rate does, it is now ambiguous whether the rising housing market is resulted from a negative shock to short-term interest rate, or from an increase in capital inflow, or both. Thus, a next step is to investigate the link between the two.

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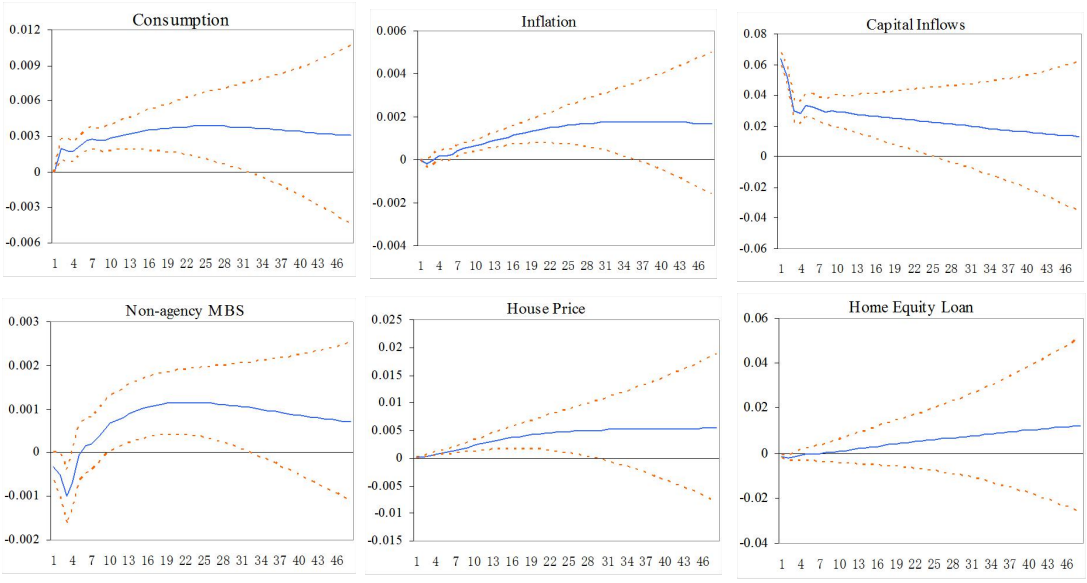
[46] E.g., to order non-agency MBS before or after capital inflows, to order capital inflows before or after house price, to order capital inflows before or after consumption and inflation, all yield qualitatively similar results.

The paper now investigates the link between monetary policy and capital inflows so as to identify the source of the rising housing market. This is done by modeling capital inflows as pursuits of relative interest rates across major economies that include U.S. and Europe. Since U.S. is often found as a leading economy followed by Europe, the premia of U.S. short-term interest rate over Europe's is defined as the determinant of capital inflow. Hence, the question is now whether a change in U.S. rate induces a same sign but unequal change in Europe's? If yes, the premia and capital inflows follow U.S. monetary policy. If no, then capital inflows are independent of the U.S. monetary policy.

Figure 3.7 Responses to a one S.D Shock to Capital Inflows ±one S.E.

Results derived under a recursive VAR that includes (in this order) consumption, inflation, capital inflow, non-agency MBS, house price and home equity loans. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. Consumption is retail sales in log billion dollars; Inflation in log CPI index with the CPI of 1982-1984=100; Capital inflow is net import and is in log billion dollars; Non-agency MBS is the dollar value share of over all MBS and is in percentage. House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log; Home equity loan is the outstanding balance on home equity line of credit and is in log billion dollars. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and two dashed lines the response -/+ one S.E.

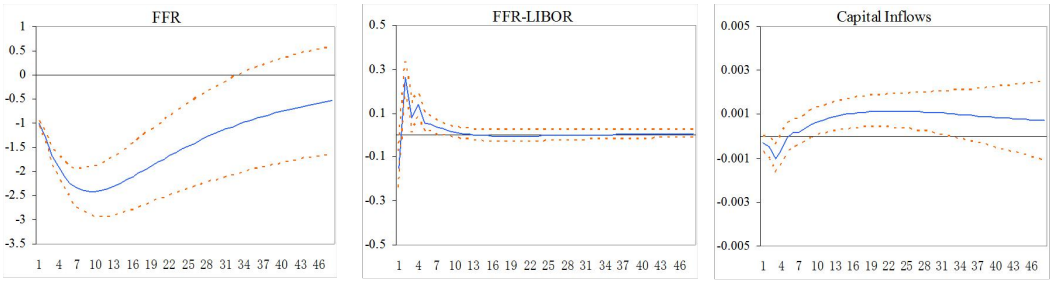


The paper measures the U.S and Europe rates by FFR and LIBOR, and builds a recursive VAR that include *FFR, the premia of FFR over LIBOR*, and *capital inflows* to test how the premia and capital inflows respond to a negative FFR shock. The intuition is: if the adjustment of LIBOR does not equal to the FFR shock, then the premia changes, so do the capital inflows to U.S.

Results in Figure 3.8 imply that capital inflows are independent of U.S. monetary policy. The premia first rises for about 12 months but then recovers fast and remains at its initial levels afterwards. This implies that U.S. monetary policy can hardly control the relative interest rates across economies and capital inflows to U.S. Changing the ordering of the variables will not produce significantly different results[47].

Figure 3.8 Response of Capital Inflows to a 100 Basis Point FFR Shock ±one S.E.

Results derived under a recursive VAR that includes (in this order) federal funds rate (FFR), federal funds rate less London inter-bank overnight offer rate (LIBOR), and capital inflow. Horizontal axis measures the number of months from the shock and vertical axis the level responses to the shock. FFR and (FFR-LIBOR) are both in percentage; Capital inflow is net import in log billion dollar. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.



[47] E.g. to order capital inflows before or after FFR both yields similar results

To summarize, since monetary policy and capital inflows do not depend on each other but both affect the housing market, the mechanism of the housing boom is clear: a fall in the short-term interest rate reduces the mortgage spread of prime mortgage rate over safe rate, and invites banks with a target return to issue more risky but high-yield mortgages, part of which are then purchased by excess capital inflows to U.S. that seek high-yield return assets. The coincidence of the rising supply of and the rising demand for risky mortgages drove the housing market into a boom.

3.6 Results are Robust to an Alternative Structural VAR

One concern on the recursive VAR is that its identification strategy may not have enough theory contents, just as the traditional large-scale macroeconomic equations do. Hence, a structural VAR (SVAR) that attempts to impose restrictions by economic theory often works as an alternative to a recursive VAR (Sims, 1986; Bernanke, 1986). The literature utilizes SVAR to study factors and effects of house prices and how they vary across countries (Tsatsaronis and Zhu, 2004; Chrinko, 2008). The role of housing sector in monetary transmission is also examined in a SVAR (Elbourne, 2008). The channels of the transmission are, however, rarely studied in a SVAR.

To justify the recursive VAR, this paper builds a SVAR of same purpose and tests if the results by the recursive sequential VAR are robust to the SVAR, which is specified as:

$$Y_t^S = C^S + A^S(L)Y_t^S + B^S U_t^S$$

Where all variables are similarly defined as their counterparts in Section 3.3.1 except that the superscript *s* denotes that a variable is now under the SVAR and Y^S is:

$$Y_t^S = \begin{bmatrix} y_t^{S1} \\ y_t^{S2} \\ y_t^{S3} \\ y_t^{S4} \\ y_t^{S5} \\ y_t^{S6} \end{bmatrix} = \begin{bmatrix} \text{Cons}_t \\ \text{Infl}_t \\ \text{FFR}_t \\ \text{NaMBS}_t \\ \text{CInflow}_t \\ \text{Hprice}_t \end{bmatrix}$$

Where "NaMBS" is non-agency MBS and "CInlfow" is capital inflow, other variables are likewise defined as in Section 3.3.1

The capital inflow is included because it also adds to a rising housing market and its interplay with monetary policy shocks is now interesting. The SVAR can be further decomposed to an *AB* model where the zero restrictions are again imposed on the contemporaneous responses, but now according to theories:

$$B^S U^S = A^S E^S$$

Where B^S, U^S and E^S are again similarly defined as in Section 3.3.1 while A^s carries different restrictions than A does:

$$A^S = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & a_{61} \\ a_{12} & 1 & 0 & 0 & 0 & 0 \\ a_{13} & a_{23} & 1 & 0 & 0 & 0 \\ a_{14} & 0 & a_{34} & 1 & a_{54} & a_{64} \\ 0 & a_{25} & a_{35} & a_{45} & 1 & a_{65} \\ 0 & 0 & a_{36} & a_{46} & a_{56} & 1 \end{bmatrix}$$

Rows 1-3 simply summarize implications from theory: First, consumption and inflation are exogenous. In most cases, they do not contemporaneously respond to but

immediately affect other variables. This can be theoretically realized in a DSGE model that assumes nominal rigidities (Iacoviello, 2005; Sims and Zha 2006). Second, FFR immediately responds to consumption and inflation, but not vice versa. This is just a simple idea of the Taylor Rule. Lastly, a difference from the literature is that now consumption is allowed to immediately respond to changes in house prices. This is inspired by the micro evidence (Case et al, 2005) and the theoretical work (Campbell and Cocco, 2007) which both find that a rise in house price adds to consumption. Elboune (2008) has a similar restriction in a SVAR of the U.K housing market and finds results supportive of a contemporaneous consumption response to housing wealth.

Rows 4-6 restrict how mortgage spreads, capital inflows and house prices respond to structural shocks. The author tries various scenarios since the theory is rather silent on this and presents the benchmark one: 1) non-agency MBS immediately responds to consumption that indicates system risks and to FFR that signals policy risks. Also, capital inflows may choose to buy non-agency MBS, and house prices signal the sector risks, hence they also affect non-agency MBS immediately; 2) capital inflows immediately respond to inflation and FRR that together decide the benchmark real asset return in U.S., and to non-agency MBS and house prices that signal the risk and returns of housing market, respectively; 3) house prices instantaneously respond to FFR and non-agency MBS that together determine the supply of risky mortgage, and to capital inflows that form the demand for risky mortgage.

Results of the SVAR, as shown in Figure 3.9, confirm that the monetary transmission to housing market also works via changes in risky mortgage, in addition to the balance-sheet channel. The model A^S is solved using the scoring algorithm in Amisano and Giannini (1997) and the computing of impulse responses in Figure 3.9 is executed by the *JMulti* package with a lag of 2 suggested by the Bayesian Information Criterion. The two one S.E. bands are computed under 100 bootstrap repetitions.

It is clear from Figure 3.9 that a negative shock to short-term interest rate raises the supply of risky mortgage and invites a rising demand for risky mortgage derivatives, e.g. non-agency MBS, that are financed by an increase in capital inflow. As a result, house prices persistently go up. This is not qualitatively different from what have been found by the recursive sequential VAR. Hence, results in this paper are insensitive to different identification strategies.

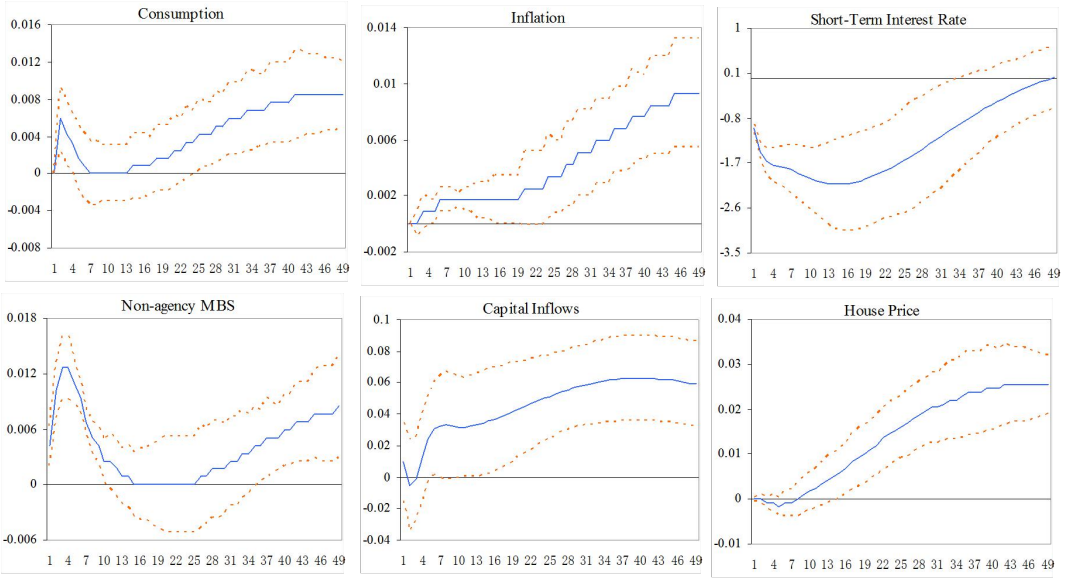
Results in Figure 3.9 are insensitive to various scenarios regarding how non-agency MBS, capital inflows and house prices should immediately respond to each other and to economy fundamentals. For example, whether non-agency MBS immediately respond to consumption or not, and whether to house prices or not, all yield results that are qualitatively similar to Figure 3.9. Also, to proxy for changes in risky mortgages with variations in mortgage spreads or with changes in non-agency MBS yield similar results.

Note that this paper does not use the SVAR as the benchmark strategy not because it is not as good as the recursive VAR in terms of methodology, but because the selling point of a SVAR is to restrict contemporaneous responses based on the economic theory,

which is, however, rather silent on how monetary shocks transmit to consumption through risky mortgages and capital inflows. Another concern on the SVAR is that the number of restrictions it imposes so as to just identify the monetary shock is also exogenously determined[48]. If instead switching to an over-identified SVAR, then the solution may not be unique. Hence, a structural VAR is not necessarily better than a recursive VAR given the context of this paper.

Figure 3.9 SVAR Responses to a 100 Basis Point Shock to FFR ± one S.E.

Results derived under a structural VAR that includes consumption, inflation, short-term interest rate, non-agency MBS, capital inflow, and house price. The graphs below present the responses to a shock to short-term interest rate. Horizontal axis measures the number of period (months) from the shock and vertical axis the level responses to the shock. Consumption is retail sales in real term deflated by CPI and is in log billion dollars; Inflation is log CPI index with the CPI of 1982-1984=100; Short-term interest rate is federal funds rate in percentage; Non-agency MBS is its dollar value share over all MBS and is in percentage. Capital inflow is net import in real term deflated by CPI and is in log billion dollar. House price is the Standard/Poor Case-Shiller National Home Price index with the house price in year 2000=100 and is in log real term deflated by CPI. Suggested by the Bayesian and/or the Hannan-Quinn information criterion, a lag of 3 is imposed on the VAR. The solid line presents the response and the two dashed lines the response -/+ one S.E., with S.E. calculated by Monte Carlo bootstrapping with 100 repetitions.



[48] As shown in the Matrix A from Section 3.3.1, the number of restrictions imposed equal to $(n^2-n)/2$ where n is the number of endogenous variables included in the VAR.

3.7 Summary of Chapter 3

This chapter investigates the role of monetary policy on the U.S. housing and consumption sectors. In particular, it studies how a monetary shock translates to changes in risky mortgage that affect house prices and aggregate consumption. The paper uses monthly sequential vector autoregressive models that first estimate the response of the spread of prime mortgage rate over safe rate to a monetary shock, and subsequently the response of housing sector to changes in the mortgage spread. It also examines if capital inflows facilitate the monetary transmission to housing and consumption sectors.

The results suggest that a negative shock to short-term interest rate reduces the prime mortgage spread and raises the supply of risky high-yield mortgage, which then boosts the housing market. Translating to the recent housing boom, the prolonged phase of low interest rates reduced the prime mortgage spread substantially, and induced banks to raise the supply of risky but high-yield mortgages so as to ensure target returns. This in turn boosted speculative housing demand and house prices. Additionally, the persistent rise in house price increased home equity loan and financed consumption growths. This also explains the savings puzzle during the time.

The results also show that the increase in capital inflow during the housing boom increased the non-agency MBS, although it did not depend on the low rates at the time. Hence, capital inflows also facilitate the monetary transmission to the housing sector. Since the decrease in interest rate and the rise in capital inflow independently boost the housing market, it is suggested that the former provides the supply of risky mortgage

while the latter provides the demand. In this sense, monetary policy is still a driving force of the housing boom.

The results obtained are insensitive to various orderings suggested in the literature. A structural VAR is also built as an alternative strategy to identify the monetary shock, but produces results qualitatively similar to those by the sequential VARs. In order to show that a monetary shock also affects housing and consumption sector via changes in risky mortgage, this paper proxies for risky mortgages by non-agency MBS and home equity lines of credits, and finds that a negative shock to short-term interest rate raises both of them. This confirms the role of risky mortgage in the monetary transmission to housing and consumption sectors.

The policy implications of this paper are threefold: First, since a monetary shock also affects the housing sector via risky mortgages, financial regulations on mortgage derivatives is an important preemptive policy. Second, since the rise in risky mortgage was rooted in a persistent fall in the prime mortgage spread, smooth monetary policy changes allow banks time to adjust their expectations on returns, rather than to resort to high yield but risky mortgages. Lastly, capital inflows that seek high-yield assets also heat the housing market but are independent of monetary policy. Thus, capital inflows should be closely observed.

Conclusion

This dissertation offers micro evidence to a credit channel of the housing wealth effect on consumption, which turns out to be much bigger than that in the literature with aggregate home prices. It further finds that the practice of extracting home equities to finance consumption is also prevailing in China, where a bank market for home equity withdrawals, such as the one in U.S., does not even exit and the credit channel is instead enabled by private credits. Lastly, it shows that the credit channel also transmits monetary policy shocks to aggregate economy because a decrease in FFR reduces returns to prime mortgage and invites banks to raise the supply of risky but high-yield mortgage.

A first implication by this study is that home equity withdrawals are independent of country-specific housing finance institutions. In other words, there could be countless housing finance derivatives to facilitate home equity withdrawals. Hence, the stabilization of housing market could hardly be achieved by regulating housing finance alone. Instead, attentions should also focus on how to improve the supply side of the hosing market so it can quickly cope with changes in demand. A good example is to allow housing supply elasticity to vary with home price index in a countercyclical way, though this still needs more rigorous academic evidence.

A second implication is that monetary policy needs to be executed in a smooth way that allows time for finance intermediaries to adjust their return expectations. A gradual fall in monetary policy rate, instead of a drastic one, would provide banks enough time to

realize the changing fundamentals of the economy, in which case they may settle down with a lower expectation, instead of taking excess risks to ensure returns as before. Less risk-taking behaviors by financial intermediaries would then reduce the funding for the speculative housing demand that is often found to drive the last housing boom.

A last implication is to include the housing wealth effect on consumption into the formulation of monetary policy. While the effect of home price on the economy is often found to work via residential investments, its transmission to consumption via home equity withdrawals is often ignored and under estimated. A fast increase in policy rate not only raises the cost of residential investments, more importantly, it also removes the conduit to finance consumption through home equity withdrawals and thus discourages consumption. Hence, the stabilization policy is accelerated by the housing wealth effect on consumption, which, if ignored, may lead the economy into a downturn much deeper than expected and necessary.

This dissertation is so far empirical and future extensions can include a theoretical work that provides further evidence to results found here. Moreover, improvements on the imputation of micro home prices that accommodate heterogeneous developments in regional housing markets, e.g. price to rent ratio and supply elasticity, are also desirable. Furthermore, the access to a wide-accepted measure of credit constraint, e.g. credit score, can better help identify a credit channel since whether and to what extent the MPC out of housing wealth varies with constraint degrees define the channel.

Reference

Aiyagari, R. 1994. Uninsured Idiosyncratic Risk and Aggregate Saving. The Quarterly Journal of Economics, 109(3): 659-684

Aizenman, J and Jinjarak, Y, 2009. Current Account Patterns and National Real Estate Markets. Journal of Urban Economics, 75-89.

Amisano, Gianni and Carlos Giannini. Topics in Structural VAR Econometrics (Second Edition), 1987, Springer.

Atalay, Kadir, Stephen Whelan and Judith Yates, 2013. Housing Wealth and Household Consumption: New Evidence from Australia and Canada. Economic Working Paper, Sydney University.

Attanasio, O. and Weber, G., 1994. The UK Consumption Boom of the Late 1980s: Aggregate Implications of Microeconomic Evidence. The Economics Journal, Vol. 104, Pages 1269–302.

Attanasio, O., Blow, L., Hamilton, R. and Leicester, A., 2009. Booms and Busts: Consumption, House Prices and Expectations. Economica, Vol. 71, Pages 20–50.

Benjamin, J., Chinloy, P. and Jud, G.D., 2004: Real Estate versus Financial Wealth in Consumption. Journal of Real Estate Finance and Economics, Vol. 29, Pages 341–354.

Benjamin, J.D., and Chinloy, P., 2008. Home Equity, Household Savings and Consumption. Journal of Real Estate Finance and Economics, Vol.37, Issue.1, Pages 21-32.

Bernanke, Ben, 1986. Alternative Explanations of Money-Income Correlation. Carnegie-Rochester Conference Series on Public Policy 25 (1986), Pages 49-100.

Bernanke, Ben, 2007. Global Imbalances: Recent Developments and Prospects. Bundesbank Lecture Speech.

Bernanke, B and Gertler, M, 1989. Agency costs, net worth, and business fluctuations. American Economic Review, Vol. 73, Pages 14-31.

Bernanke, Ben, Mark Gertler and Simon Gilchrist, 1999. The Financial Accelerator In A Quantitative Business Cycle Framework. Hand Book of Macroeconomics, Vol. 1, Part C, Pages 1341-1393.

Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan, 2004. How Much Should We Trust Differences-in-Differences Estimates? The Quarterly Journal of Economics, Vol. 119, Pages 249-275.

Borio, C and Haibin Zhu, 2008. Capital Regulation, Risk-Taking and Monetary Policy: a Missing Link in the Transmission Mechanism. BIS Working Paper No. 268

Bostic, Raphael, Stuart Gabriel and Gary Painter, 2007. Housing Wealth, Financial Wealth, and Consumption: New Evidence from Micro Data. Regional Science and Urban Economics, Vol. 39, Pages 79-89.

Browning, Matin, Mette Gørtz and Søren Leth-Petersen, 2013. Housing Wealth and Consumption: A Micro Panel Study. The Economic Journal, Vol.123, Pages 401–428.

Buiter, Willem, 2008. Housing Wealth Isn't Wealth, National Bureau of Economic Research, Work Paper, No. 14204

Calza, Alessandro, Tommaso Monacelli and Livio Stracca, 2013. Housing Finance and Monetary Policy. Journal of European Economics Association, 11 (1), 101-122.

Cameron, Colin and Douglas Miller, 2015. A Practitioner's Guide to Cluster-Robust Inference. Journal of Human Resources, Vol. 250, No.2, Pages 317-372.

Campbell, John and João Cocco, 2007: How Do House Prices Affect Consumption? Evidence from Micro Data. Journal of Monetary Economics, Vol. 54, Pages 591-621.

Carroll, C.D., 1997. Buffer-stock Saving and the Life-cycle/Permanent Income Hypothesis. Quarterly Journal of Economics, Vol. 114, Pages 433–495.

Carroll, C.D., 2004. Housing Wealth and Consumption Expenditure: Unpublished Paper. John Hopkins University.

Carroll, C.D., 2001. A Theory of the Consumption Function, with and without Liquidity Constraints. The Journal of Economic Perspectives, Vol. 15, No. 3, pp. 23-45

Carroll, C.D., and Miles Kimball. On the Concavity of the Consumption Function, Econometrica, 64 (1996), 981–992.

Carroll, C.D., and Miles Kimball, 2001. Liquidity Constraints and Precautionary Saving, NBER Working Papers No.8496

Carroll, C.D., Misuzu Otsuka, and Jiri Slacalek, 2011. How Large Are Housing and Financial Wealth Effects? A New Approach. Journal of Money, Credit and Banking, Vol.43, Issue.1, Pages 55-79.

Case, Karl, John Quigley, and Robert Shiller, 2005. Comparing Wealth Effects: The Stock Market versus the Housing Market. Advances in Macroeconomics, Vol. 5, No. 1, Pages 1235–1235.

Case, Karl, John Quigley, and Robert Shiller, 2013. Wealth Effects Revisited: 1975–2012. National Bureau of Economic Research, Working Paper, No. 18667.

Christiano, L., Eichenbaum, M., Evans, C., 1999. Monetary Policy Shocks: What Have We Learned, and to What End. In: Taylor, J.B.,Woodford,M. (Eds.), Handbook of Monetary Economics. North-Holland, Amsterdam, 65–148.

Cooper, Daniel, 2013. House Price Fluctuations: The Role of Housing Wealth as Borrowing Collateral. The Review of Economics and Statistics, Vol 95, Pages 1183-1197.

Cristini, Annalisa and Sevilla Almudena, 2014. Do House Price Affects Consumption? A Re-Assessment of Wealth Hypothesis. Economica, Vol.81, Issue 324, Pages 601-625.

Deng, Yongheng, Joseph Gyourko, Jing Wu. Land and House Price Measurement in China. NBER Working Paper No. 18403

Disney, R.J., Gathergood, J. and Henley, A., 2010. House Price Shocks, Negative Equity and Household Consumption in the United Kingdom. Journal of the European Economic Association, Vol. 8, Pages 1179–207.

D'Orazio, Marcello, 2014. Statistical Matching and Imputation of Survey Data with StatMatch. Unpublished working paper. Italian National Institute of Statistics.

Elbourne, Adam, 2008. The UK Housing Market and the Monetary Policy Transmission Mechanism: An SVAR approach. Journal of Housing Economics 17, Pages 65-87.

Engelhardt, Gary V., 1994. House Prices and the Decision to Save for Down Payments. Journal of Urban Economics, Vol. 36, Pages 209-237.

Engelhardt, Gary V. and Christopher J. Mayer, 1998. Intergenerational Transfers, Borrowing Constraints, and Savings Behavior: Evidence from the Housing Market. Journal of Urban Economics, Vol. 44, 1998: Pages 135-157.

Faust, J., Leeper, E., 1997. When do Long-Run Identifying Restrictions Give Reliable Results? Journal of Business, Economics and Statistics 15, 345–353.

Favilukis, Jack, Sydney C. Ludvigson and Stijn Van Nieuwerburgh, 2010. The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium. NBER Working Paper No. 15988, May 2010.

Flavin, M., 1981. The Adjustment of Consumption to Changing Expectations about Future Income. Journal of Political Economy, Vol. 89, Pages 974–1091.

Gan, Li, Zhichao Yin, Nan Jia, Shu Xu, Shuang Ma, 2013, Data you need to know about China, Springer.

Green, Richard and Susan. M. Wather. The Housing Finance Revolution. University of Pennsylvania Institute for Law and Economics, Research Paper Series No.09-37, August 2007.

Greenspan, Alan, James Kennedy, 2008. Uses and Sources of Equity Extracted from Homes. Oxford Review of Economic Policy, Vol.24, Issue 1, Pages 120-144.

Guiso, Luigi, Tullio Jappelli and Daniele Terlizzese. Earnings uncertainty and precautionary saving. Journal of Monetary Economics, Volume 30, Issue 2, November 1992, 307-337

Iacoviello, Matteo, 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. The American Economic Review, Vol. 95, No. 3 (Jun., 2005), Pages 739-764

Iacoviello, Matteo and Raoul Minetti, 2008. The Credit Channel of Monetary Policy: Evidence from the Housing Market. Journal of Macroeconomics 30, 69-96

Jappelli, Tulio, 1990. Who is Constrained in the U.S. Economy? The Quarterly Journal of Economics, Vol.105, No.1, Pages 219-243.

Kantor, S. and Fishback, V. 1996.Precautionary Saving, Insurance, and the Origins of Workers' Compensation. The Journal of Political Economy, 104(2): 419-442

Kazarosian, M. 1997. Precautionary Savings - A Panel Study. The Review of Economics and Statistics. 79(2): 241-247

Kennickell, A. and Lusardi, A. 2004. Disentangling the Importance of the Precautionary Saving Motive. NBER Working Paper No. 10888

Kimball, M. 1990. Precautionary Saving in the Small and in the Large, Econometrica, 58 (1): 53-73

King, Mervyn. Debt Deflation, 1994: Theory and Evidence. European Economic Review, Vol.38, Issue 3-4, Pages 419-445.

Kiyotaki, Nobuhiro and John Moore, 1997. Credit Cycles, Journal of Political Economy, Vol. 105, Pages 211-248.

Lusardi, Annamaria. On the Importance of the Precautionary Saving Motive. The American Economic Review, Vol. 88, No. 2, Papers and Proceedings of the 110th Meeting of the American Economic Association (May, 1998), pp. 449-453

Lusardi, Annamaria and Martin Browning. Household Saving: Micro Theories and Micro Facts. Journal of Economic Literature. Vol. 34, No. 4, 1797-1855

Lustig, Hannon and Stijn Van Nieuwerburgh. Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective. The Journal of Finance, Vol. 60, Issue 3, May 2005, Pages 1167-1219.

Maclennan, D., Muellbauer, J., Stephens, M., 1998. Asymmetries in Housing and Financial Market Institutions and EMU. Oxford Review of Economic Policy, Vol. 14, Issue 3, Pages 54–80.

Mian, Atif and Amir Sufi, 2011. House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis. American Economic Review, vol. 101, Pages 2132-2156.

Mian, Atif, Kamalesh Rao and Amir Sufi, 2013. Household Balance Sheet, Consumption and the Economic Slump. The Quarterly Journal of Economics, Vol.128, Issue.4, Pages 1687-1726.

Rajan, R, 2005. Has Financial development made the world riskier? NBER Working Paper No. 11728.

Reinhart, C and Reinhart, V, 2008. Capital Inflow Bonanzas: An Encompassing View of the Past and Present. NBER Working Papers No. 14321.

Sá, Filipa and Tomasz Wieladek, 2014. Capital Inflows and the U.S. Housing Boom. Journal of Money, Credit and Banking, 47(1), 221-256

Sá, Filipa, Pascal Towbin and Tomasz Wieladek, 2014. Capital Inflows, Financial Strcture and Housing Booms. Journal of European Economic Association, 12(2), 522-546

Sheiner, Louise, 1995. Housing Prices and the Savings of Renters. Journal of Urban Economics, Vol. 38, Pages 94-125.

S.Chrinko, Robert, Leo De Hann and Elmer Sterken, 2008. Asset Price Shocks, Real Expenditures, and Financial Structure: A Multi-Country Analysis. CESifo Working Paper No. 2342

Sinai, Todd and Nicholas S. Souleles, 2005. Owner-Occupied Housing As A Hedge Against Rent Risk, Quarterly Journal of Economics, Vol.120, Pages 763-789.

Singh, A.C., Mantel, H., Kinack, M., Rowe, G., 1993. Statistical Matching: Use of Auxiliary Information as an Alternative to the Conditional Independence Assumption. Survey Methodology, Vol. 19, Pages 59–79.

Sims, C.A., 1980. Macroeconomics and Reality. Econometrica 48 (1), Pages 1–48.

Sims, C.A., 1986. Are Forecasting Models Usable for Policy Analysis? Federal Reserve Bank of Minneapolis Quarterly Review (Winter 1986), Pages 3-16.

Sims, C.A, James Stock, and Mark W.Watson, 1990. Inference in Linear Time Series Models with Some Unit Roots. Econometrica 58, 113-144

Sims, C., Zha, T., 1998. Does Monetary Policy Generate Recessions? Federal Reverse Bank Atalanat Working Paper 98-12.

Sims, C., Zha, T., 2006. Does Monetary Policy Generate Recessions? Macroeconomic Dynamics Vol. 10 (2), 231–272.

Taylor, John,2007. Housing and monetary policy. Economic Policy Symposium Proceedings, Jackson Hole, Federal Reserve Bank of Kansas City, Pages 463-476.

Taylor, John, 2009. The Financial Crisis and the Policy Responses: an Empirical Analysis of What Went Wrong. NBER Working Paper No. 14631.

Tsatsaronis, Kostas and Haibin Zhu, 2004. What Drives Housing Price Dynamics: Cross-Country Evidence. BIS Quarterly Review, March, 65-78.

Ventura, L. and Eisenhauer, G. 2005. The Relevance of Precautionary Saving. German Economic Review, Blackwell Publishing 6(1): 23-35

Wagstaff, Adam and Magnus Lindelow. Can insurance increase financial risk?: The curious case of health insurance in China. Journal of Health Economics, Vol.27, Issue 4, July 2008, 990-1005.

Wu, Jing, Yongheng Deng, Hongyu Liu. House Price Index Construction in the Nascent Housing Market: The Case of China. The Journal of Real Estate Finance and Economics, April 2014, Vol.48, Issue 3, 522-545

Zeldes, S., 1989. Consumption and Liquidity Constraints: an Empirical Investigation. Journal of Political Economy, Vol. 97, Pages 305–346.

Yoshikawa, Hiroshi and Fumio Ohtake, 1989. An Analysis of Female Labor Supply, Housing Demand, and the Saving Rate in Japan. European Economic Review, Vol. 33, Pages 997-1030.

APPENDICES

Appendix A: Actual and Expected House Prices Have a Same AR coefficient

This appendix explains why the AR (1) for house price and for expected house prices have a same auto-regressive coefficient. If not, and instead assuming:

$$P_i^t = \rho_1 P_i^{t-1} + u_i^t \tag{A.1}$$

$$EP_i^t = \rho_3 EP_i^{t-1} + v_i^t \tag{A.2}$$

Where *EP* is expected house price, *P* house price, *i* household, *t* the order of interview, *u* and *v* are white noise error terms.

According to Equation (A.1), the expected house prices of time *t* and of *t-1* formed at time *t-1* and *t-2*, respectively, are :

$$EP_i^t = \rho_1 P_i^{t-1} \tag{A.3}$$

$$EP_i^{t-1} = \rho_1 P_i^{t-2} \tag{A.4}$$

Plugging Equations (A.3) and (A.4) into Equation (A.2) yields:

$$\begin{aligned} &\rho_1 P_i^{t-1} = \rho_3 \times (\rho_1 P_i^{t-2}) + v_i^t \\ &\Rightarrow P_i^{t-1} = \rho_3 \times P_i^{t-2} + \frac{1}{\rho_1} v_i^t \\ &\Rightarrow P_i^t = \rho_3 \times P_i^{t-1} + \frac{1}{\rho_1} v_i^{t+1} \end{aligned} \tag{A.5}$$

Assuming v^{t+1} and v^t follow the same distribution, as often assumed, and comparing Equation (A.5) with Equation (A.1) yields the following result that has to be true:

$$\rho_1 = \rho_3$$

That is, the AR (1) of house prices and the AR (1) of expected house prices have a same auto-regressive coefficient.

Appendix B: The Imputation of House Price for Renters

Since CES does not ask a renter its expected rentals, this paper assigns a renter the average of expected rentals reported by home owners who live in a similar house as the renter does. Below is the procedure:

First, the paper groups households by the structures of the houses 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

Then, within a same group, the author assigns the average expected rentals of home owners to renters, and makes it as the expected rental of a renter. For renters who don't report one or more house structures above, their expected rentals are not imputed.

Next, by Equation (1.3), the author calculates an expected house price for every household at each interview using their expected rentals.

Last, by the process in Section 1.2.1 and the expected house prices, the author further derives a house price for every household at each interview.

Appendix C: Data Matching between CES and SCF households

First, before CES and SCF households can be matched to each other, they both go through a data cleaning process in the order as below:

1) drop households living in neither a house nor an apartment
2) drop households with a negative consumption, income or financial wealth
3) drop those who report a negative expected rental
4) drop those with a negative demographics, e.g. age and schooling

Then, the paper groups both CES and SCF households based on an ownership dummy, a mortgage dummy and demographics as below:

a) Age : young (age $\leq$ 40), middle-aged(40<age$\leq$60), and old (age>60)
b) Marital status: married, and not
c) Race: white, black and others
d) Family size: 1 person, 2, 3, 4, and more than 4
e) Education: less than high school, high school graduate, some college, college degree, graduate school and above
f) Ownership: own a house (an apartment), or not
g) Mortgage: with a house mortgage, or not

By this process, a total of 1, 800 household groups are created in both CES and SCF, and the paper assigns a same and unique ID to the two groups (one from CES and the other from SCF) that are the same in each characteristics from a) to g).

Next, the paper deletes groups where the size of CES households is more than twice that of SCF households, and then doubles the size of a SCF group that remains to ensure that each CES household has a math from SCF.

Then, within the two groups with a same ID, a SCF household is assigned to a CES one that is in the closest distance, with distance defined as a Manhattan distance function of income, age and family size:

$$D_{ij} = \sum_{k=1}^{n} (X_i^k - X_j^k) \tag{C.1}$$

where *i* denotes a CES household and *j* a SCF one, *D* the distance, *X* the set of matching variables: income, age and family size, *n* the number of matching variables.

Finally, the paper assigns the information of a SCF household to its matched CES household and finishes the matching.

Appendix D: Using Ages as Measures of Credit Constraint

While the literature often uses ages to measure credit constraints, this paper proposes household financial characteristics as better measures of credit constraint. To show this, the author applies the strategy by the literature to data in this paper, and finds that it yields inconsistent results.

The literature strategy that measures credit constraints by ages, namely the life-cycle model with the permanent income hypothesis (see Attanasio and Weber, 1994; Carroll, 1997; Attansio et al, 2007, Campebell and Cocco, 2008), is specified as:

$$C_i^t = \beta_{10} + \beta_{PP} PP_i^t + \beta_{SP} SP_i^t + \sum_{J=Y,M} (\beta_{PP}^J PP_i^t J_i^t + \beta_{SP}^J SP_i^t J_i^t) + \beta_{PI} PI_i^t + \beta_{SI} SI_i^t + \sum_{J=Y,M} (\beta_{PI}^J PI_i^t J_i^t + \beta_{SI}^J SI_i^t J_i^t) + \beta_W W_i^t + \beta_X X_i^t + \eta_i^t \quad \text{(D.1)}$$

where J is Y or M, both of which are age-group dummies and equal 1 if a household is young or middle-aged, respectively, and 0 otherwise, and other notation same as in Equation (1.1.6).

According to the life-cycle model, the young is often more credit constrained than the old, while the old has a higher MPC out of unexpected increases in wealth since they have shorter life spans, thus: 1) if a credit channel works, the young respond more than the old to a rise in predicted housing wealth; 2) if a wealth channel works, the old respond more than the young to a rise in surprise housing wealth.

A wealth channel is rejected by the results in Table A1. Column 1 tests whether and (if so) how the housing wealth effect on consumption varies across age groups, but finds an additional response by the young, which denies a wealth channel. Column 2 includes surprise housing wealth that are interacted with the young and shows that the young does not display a significant lower response to surprise housing wealth than the old, negating a wealth channel. Column 3 further includes parts of income to control for any income effect, but still can not find a significant lower response by the young to surprise housing wealth. To sum, none of the results support a wealth channel.

The existence of a credit channel is, however, less clear. While Column 3 presents no additional consumption response by the young to predicted housing wealth and can not find a credit channel, both Column 1 and 2 support a credit channel. Column 1 shows that the young carry an additional response of about 1% to the overall housing wealth. Plus an average response of 5%, the total MPC out of housing wealth by the young is 6%, about the same size as in the literature. Column 2 indicates that the young display an additional response of 1% to predicted housing wealth, making the total MPC out of predicted housing wealth as about 6%. This is again in line with the literature.

There are three reasons why Column 3, the benchmark strategy by Equation (D.1), can not produce an additional response by the young to predicted housing wealth. First, there is indeed no credit channel. This is less likely given that a housing wealth effect is evidenced in Column 1 but a wealth channel is not found. Second, the income adjustment may bias the result. This is also less likely since the original income yield a

same result[49]. Lastly, ages are not good measures of credit constraints in the housing context because the young often face home tenure choices that are unobserved

Ages are not good measures of credit constraints in the housing context because the savings for down payments on a house bias the response of the young. For a young household, given a rise in house price, trading up on house requires more savings for down-payments, which reduces expenditures and hides a credit channel[50], while trading down needs fewer savings for down-payments and boosts expenditures, which highlights a credit channel (Sheiner, 1995; Maclennan et al, 1998; Case et al, 2005; Buiter, 2008). But, whether a household plans to trade up or down is unobserved[51]. If it trades up and saves for down-payments, the credit channel is under estimated.

[49] Please refer to the first robustness check in Section 1.1.4 for details.
[50] Trading up on houses refers to buying a house for the first time or buying a house bigger than the current one. Likewise, trading down refers to buying a smaller house or selling the current house and becoming a tenant.
[51] Campbell and Cocco (2007) solve the endogeneity problem of home tenure choice, but using cohort-level consumption data and regional house prices.

Table D Estimations using Ages as Credit Constraint Measures

Dependent variable is total expenditure in the past 3 months prior to the survey. Income is the total income in the past 12 months. Financial wealth includes savings bonds, savings accounts, and other securities on the last day of last month. Young is aged ≤ 40, Middle is 40<aged ≤60, and Old is aged > 60. Demographics and state-year fixed effect are also controlled but not listed. S.E. in brackets is heteroscedasticity robust and clustered at state-year level. *, ** and *** is 5%, 1% and 0.1%.

	Total Consumption		
	(1)	(2)	(3)
house price	0.0477***		
	(0.00696)		
Income	0.366***	0.376***	
	(0.0164)	(0.0162)	
financial wealth	0.0477***	0.0441***	0.0466***
	(0.00435)	(0.00428)	(0.00443)
house price*young	**0.00998****		
	(0.00380)		
house price*middle	**0.00643****		
	(0.00238)		
surprise housing wealth		0.0570***	0.0681***
		(0.0166)	(0.0167)
predicted housing wealth		0.0536***	0.0887***
		(0.00897)	(0.0145)
surprise housing wealth *young		**-0.0445**	**-0.0486**
		(0.0333)	(0.0341)
surprise housing wealth *middle		0.0173	0.0108
		(0.0237)	(0.0250)
predicted housing wealth *young		**0.0100***	**-0.0303**
		(0.00416)	(0.0274)
predicted housing wealth *middle		0.00589*	-0.0555*
		(0.00262)	(0.0219)
surprise income			0.393***
			(0.0225)
surprise income*young			0.0430
			(0.0516)
surprise income*middle			0.0494
			(0.0317)
predicted income			0.297***
			(0.0216)
predicted income*young			0.0478
			(0.0308)
predicted income*middle			0.0706**
			(0.0250)
N	10354	7782	7729
adj. R^2	0.540	0.561	0.568

Appendix E: Balance-Sheet Indicators as Measures of Credit Constraint

The literature also often measures credit constraints by balance-sheet indicators, which are also inappropriate since they yield inconsistent results on a credit channel, too. To show this, the author feeds the data of this paper to the strategy in that literature (King, 1994; Kimball and Carroll, 1996; Mian and Sufi, 2011), a revised representative agent framework with the permanent income hypothesis that is defined as:

$$C_i^t = \beta_{20} + \beta_{PP} PP_i^t + \beta_{SP} SP_i^t + \beta_{PP}^K PP_i^t K_i^t + \beta_{SP}^K SP_i^t K_i^t + \beta_{PI} PI_i^t + \beta_{SI} SI_i^t + \beta_{PI}^K PI_i^t K_i^t + \beta_{SI}^K SI_i^t K_i^t + \beta_W W_i^t + \beta_X X_i^t + \eta_i^t \quad \text{(E.1)}$$

where K is a dummy for balance-sheet indicators, equal to 1 if the indicator of a household is above the median (i.e. constrained), 0 otherwise, other notation same as in Equation (1.1.6). The choice of balance-sheet indicators are guided by the literature (Cooper, 2013; Mian and Sufi, 2011; Mian et al, 2013) and include: the *Loan to Value ratio* (LTV)[52], *Debt to Service Ratio* (DSR) and *Expenditure to Income ratio* (ETI).

By the representative agent framework, a household responds in consumption to a wealth change if it is borrowing constrained. Given that, a constrained household should display an additional consumption response to a predicted rise in its housing wealth, which can be used as collaterals for a higher borrowing to fuel consumption. Hence, if a balance-sheet indicator captures credit constraints, a household with an indicator above median should yield an additional response to predicted housing wealth.

[52] Slightly different from the literature, the LTV here is defined as the ratio of monthly mortgage interest payment over the house price. The traditional LTV is also used, but it yields the same pattern of results.

Results are shown in Table E.1 where a credit channel can only be weekly confirmed. In Column 2, a household with a DSR above median bears an additional response of 13 percentage points to a rise in predicted housing wealth. Given an average response of zero, its total MPC out of predicted housing wealth is 13%. In Column 3, a household with an ETI above median exhibits an additional response of 17 percentage points to a rise in predicted housing wealth. Given an average response of -4%, its total MPC out of predicted housing wealth is 13%. Both findings seem to suggest a credit channel, which is, however, not supported by results in Column 1, where households with a LTV above median and defined as constrained do not show a significant additional response to predicted housing wealth.

There are two possibilities why balance-sheet indicators yield inconsistent results; 1) some indicators, e.g. LTV and DSR, only apply to home owners with a mortgage and reduce the sample size[53]; 2) the construction of an indicator needs households to report numbers from long time ago and induces measurement errors[54]. Either possibility stops balance-sheet indicators from being a precise measure of credit constraints.

[53] E.g. Column 3 has a bigger sample size than Column 1 and 2 does.
[54] For LTV, one needs remember loan and house values at the time. For ETI, the expenditure last quarter.

Table E Balance-Sheet Indicator as Measures of Credit Constraint

Dependent variable is total expenditure in the past 3 months prior to the survey. Income is the total income in the past 12 months. Financial wealth includes savings bonds, savings accounts, and other securities on the last day of last month. High LTV, high DSR and high ETI equal to 1 if LTV, DSR and ETI is above its median, respectively, and 0 otherwise. Demographics and state-year fixed effects are also controlled but not reported. Standard errors in parentheses are heteroscedasticity-robust and clustered at state-year level. Surprise income and price as well as their interactions with LTV, DSR and ETI are also controlled but not reported. *, ** and *** stands for 5%, 1% and 0.1% significance level, respectively.

	Total Consumption		
	(1)	(2)	(3)
predicted income	0.325***	0.457***	0.582***
	(0.0276)	(0.0240)	(0.0160)
financial wealth	0.0459***	0.0445***	0.0318***
	(0.00537)	(0.00508)	(0.00361)
predicted housing wealth	**0.0696*** **	**-0.0227**	**-0.0456*** **
	(0.0153)	(0.0143)	(0.00779)
predicted income*high LTV	0.0450		
	(0.0268)		
predicted housing wealth *high LTV	**-0.0428**		
	(0.0246)		
predicted income*high DSR		-0.127***	
		(0.0208)	
predicted housing wealth *high DSR		**0.134*** **	
		(0.0189)	
predicted income*high ETI			-0.147***
			(0.0154)
predicted housing wealth *high ETI			**0.178*** **
			(0.0137)
N	5568	5559	7729
adj. R^2	0.516	0.568	0.732

Appendix F-1: Data Description and Summary of Variables in Chapter 2

Variable	Measurement	Description	Source
1. Income	Ten Thousand Yuan/Year	Annualized income of all household members in the past 12 months	China Household Finance Survey (CHFS) 2013
2. Financial Wealth	Ten Thousand Yuan/Year	Holding of Asset, including Savings, Stock, Bond, Fund, Derivatives, Managed Assets, Gold, and Foreign Currency	CHFS 2013
3. Housing Wealth	Ten Thousand Yuan/Year	Sum of self-reported values of all houses owned by a household	CHFS 2013
4. Housing Debts	Ten Thousand Yuan/Year	Debts for the purchase, decoration and renovation of a house, including bank and non bank loans	CHFS 2013 and Self Calculation
5. Non Bank Loans	Ten Thousand Yuan	Borrowings from family, relatives, friends and other non bank agents	CHFS 2013 and Self Calculation
6. Education Spending per capita to GDP per capita ratio	Percentage	The per capita Out-of-Pocket schooling expenditure over the per capita disposable income.	China Statistical Year Book 2004-2014; Consumer Expenditure Survey, 2002-2014 (US)
7. Supplemental Security Income Line	Yuan/Month	Monetary thresholds to determine if a household is eligible for supplemental security income	Ministry of Civil Affairs Data Base 2011-2015
8. Poverty Line	Yuan/month	Monetary thresholds to determine if a household is eligible for poverty alleviation aid	State Council Leading Group Office for Poverty Alleviation
9. Loan to Value Ratio	Percentage	The value of mortgage over the value of house when first bought	CHFS 2013 and Self Calculation
10. Expenditure to Income Ratio	Percentage	Annualized expenditure over annualized income in last year	CHFS 2013 and Self Calculation
11. Credit Card Utilization	Percentage	The ratio of statement balances across all credit cards over the total limits at last billing statement	CHFS 2013 and Self Calculation
12. If Unhealthy	Dummy, 1 or 0	Equal to 1 if household head quit a job due to health conditions last year, and 0 otherwise	CHFS 2013

Appendix F-1: Data Description and Summary of Variables (Continued)

Variable	Measurement	Description	Source
13. If SSI	Dummy, 1 or 0	Equal to 1 if a households receives any supplemental security income, and 0 otherwise	CHFS 2013
14. If Poverty	Dummy, 1 or 0	Equal to 1 if a household lives below poverty line, and 0 otherwise	CHFS 2013 and Self Calculation
15. If Owner	Dummy, 1 or 0	Equal to 1 if a household owns one or more houses, and 0 otherwise	CHFS 2013 and Self Calculation
16. If Renter	Dummy, 1 or 0	Equal to 1 if a household owns no houses and does not live in public housing or houses of its family/relatives, and 0 otherwise	CHFS 2013 and Self Calculation
17. If Mortgage rejected	Dummy, 1 or 0	Equal to 1 if one is rejected on mortgage application, or fears that it will get rejected and reluctant to apply one, and 0 otherwise	CHFS 2013 and Self Calculation
18. If Credit card rejected	Dummy, 1 or 0	Equal to 1 if one is rejected on credit card application, or worries that unable to pay and didn't apply, or has credit cards but can only make minimum payments or delay payments, and 0 otherwise.	CHFS 2013 and Self Calculation
19. If Non bank education loan	Dummy, 1 or 0	Equal to 1 if one borrows from non bank agents of any kind to pay for schooling of any kind	CHFS 2013
20. If No mortgage	Dummy, 1 or 0	Equal to 1 if one does not have a mortgage because needs no one to buy a house, and 0 otherwise	CHFS 2013
21. If Retiree	Dummy, 1 or 0	Equal to 1 if the households head is retired, and 0 otherwise	CHFS 2013
22. Age	Year	Age of the household head	CHFS 2013
23. Education	Year	Years of schooling received by the household head	CHFS 2013
24. Family Size	Persons	Number of family members living at the household	CHFS 2013
25. Kid Size	Persons	Number of persons younger than 18 living at the household	CHFS 2013

Appendix F-2: Detailed Summary of Data in Chapter 2

	Obs	Mean	S.D.	Min	Max
Expenditure	6081	6.79	10.03	0	310
Income	6081	4.95	8.32	0	223.96
Financial Wealth	6081	6.49	21.93	0	505.8
Housing Wealth	6081	92.41	107.29	0	950
Non-Bank Loan	6081	3.39	192.4	0	15000
Credit Card Utilization	6081	3.2%	12.7%	0	450%
Family Size	6081	1.7	1.20	0	12
Age	6081	50.17	15.98	21	111
Education	6078	11.19	3.96	0	21
Owner	6081	69.28%	46.13%	0	1
If with Home Loan from Relatives	6081	12.60%	33.19%	0	1

Appendix G: Other Balance-Sheet Indicators indicate a Credit Channel in China

In Table 2.4, two balance-sheet indicators, LTV and Credit Card Utilization work as proxies for constraint degrees. Results show that households that are more constrained yield more consumption response to housing wealth, implying a credit channel.

This appendix employs the other two usual balance-sheet indicators, Expenditure to Income ratio (ETI) and Asset to Income ratio (ATI), to verify the credit channel found. ETI is defined as the ratio of daily expenditure over total income and measures the extent to which one is constrained on its rigid spending, with a high ETI indicating a high degree of credit constraint. ATI is defined as the ratio of liquid financial wealth over total income and measures the likelihood that one can quickly convert its wealth to liquidity, with a high ATI standing for a low degree of credit constraint. Both ETI and ATI are usual proxies for degrees of constraint in the literature (Cooper, 2013; Browning et al, 2013; Mian et al, 2013)

The strategy is similar to Equation (2.3), except that the paper now replaces the dummy in the interaction term in Equation (2.3) with ETI and ATI, so as to estimate how the MPC out of housing wealth varies with ETI and ATI. Results shown in Table G indicate that households that are more constrained indeed yield more consumption response to housing wealth, though the incremental effects are small.

Table G: Credit Channel when Balance-Sheet Indicators as Constraint Measures

Income, financial wealth and housing wealth are in ten thousand yuan. ETI is expenditure to income ratio and ATI is asset to income ratio. A constant term, age, age^2/100, gender, family size and state fixed effects are also included but not reported. All variables except demographics are in log. Standard errors in the parenthesis are heteroskedasticity robust and clustered at state level. *, ** and *** stand for 0.1%, 1% and 5% significance level.

	Consumption	
	(1)	(2)
Income	0.132***	0.133***
	(0.0115)	(0.0117)
Financial wealth	0.0604***	0.0600***
	(0.00601)	(0.00601)
Housing wealth	0.139***	0.138***
	(0.0106)	(0.0106)
Housing wealth*ETI	**0.00000848*** **	
	(0.00000135)	
Housing wealth*ATI		**0.000158*** **
		(0.0000291)
N	4524	4524
adj. R^2	0.432	0.432

Appendix H: Supplemental Security Income and Poverty Lines in China

This appendix offers evidence that supplemental security income lines in China are much lower than the poverty lines. Table H.1 tells the urban poverty lines 2011-2015 and Table H.2 urban supplemental security income lines 2015Q1-Q4. For a full description of the supplemental security income lines in other years, please refer to the database of the Ministry of Civil Affairs of China http://www.mca.gov.cn/article/sj/

Since 2012, the rural poverty line in China is set at annual per capita income of 2,300 Yuan at 2010 prices, but that line is only for rural residents. This paper imputes urban poverty lines by the steps below: 1) assume rural and urban poverty lines having same percentiles in the distributions of rural and urban income in 2010; 2) recover the urban poverty lines of 2010 from the urban income distribution of 2010; 3) update the urban poverty lines of 2012-2015 by inflations between the year and 2010, just as the authority does for rural poverty lines. 4) For 2011, only executes Steps 1-2 but with income distributions of 2011 sine the new poverty line was not yet introduced in 2011.

Table H.1 Urban Poverty Lines in China 2011-2015 (Yuan/Month)

	2011	2012	2013	2014	2015
Poverty Line	390.7	651.4	668.9	686.4	700.8

(Source: State Council Lead Group Office for Poverty Alleviation, and self-calculations by authors)

Table H.2 China Supplemental Security Income Lines 2015Q1-Q4 (Yuan/Month)

Provinces	15Q1	15Q2	15Q3	15Q4	(contd)	15Q1	15Q2	15Q3	15Q4	Poverty
Beijing	706.25	710	710	710	Hubei	415.84	440	442.07	447.12	**700.8**
Tianjin	640	705	705	705	Hunan	353.59	355.59	357.13	359.78	**700.8**
Hebei	434.47	436.64	437.1	441.37	Guangdong	460.09	495.32	511.28	513.83	**700.8**
Shanxi	387.06	404.46	408.55	413.18	Guangxi	343.98	343.98	350.16	404.38	**700.8**
Inner Mongolia	496.67	502.04	504.93	508.01	Hainan	371.5	400.87	406.96	466.84	**700.8**
Liaoning	455.53	457.13	489.95	493.49	Chongqing	372.13	373.25	373.25	419.13	**700.8**
Jilin	371.54	372.35	375.53	401.59	Sichuan	345.01	346.09	355.75	367.03	**700.8**
Heilongjiang	455.16	452.91	498.33	506.35	Guizhou	403.5	420.99	438.92	453.42	**700.8**
Shanghai	710	790	790	790	Yunnan	368.93	377.88	389.19	395.85	**700.8**
Jiangsu	538.14	539.15	574.41	581.74	Tibet	554.05	583.38	589.32	589.32	**700.8**
Zhejiang	587.55	593.24	595.42	640.46	Shannxi	399.74	410.24	412.14	460.71	**700.8**
Anhui	440.92	447.66	453.54	455.04	Gansu	347.6	369.25	377.3	378.12	**700.8**
Fujian	421.05	423.34	444.63	478.14	Qinghai	356.63	361.85	370.39	370.39	**700.8**
Jiangxi	451.1	451.47	451.47	452.02	Ningxia	309.77	343.27	356.36	361.82	**700.8**
Shandong	455.89	462.19	465.07	470.12	Xinjiang	338.23	338.58	341.45	349.23	**700.8**
Henan	330.49	331.64	359.6	374.09						

(Source: Ministry of Civil Affairs, People's Republic of China, refer to its database for information on other years)

Appendix I Descriptions of Terminologies in Chapter 3

Terminology	Description	Example
1.Monetary policy	The adjustment of short-term interest rate by the central bank	Federal Funds Rate
2.Monetary shock	The change in short-term interest rate that can not explained by the monetary policy rule of the central bank	
3.Monetary Transmission	The process in which monetary policy affects the aggregate economy or affects a sector	
4.Risky mortgage	Mortgages that bear excess risks due to low down payment and low income to payment ratios. Target borrowers often have bad credit ratings and are not qualified for prime mortgage. Interest rates on such mortgages are often much higher than prime rates.	Balloon mortgage; Teaser mortgage;
5.Non-agency MBS	MBS that are not backed by government agencies because the mortgages do not meet the underwriting standards by the agencies. Major agencies are Fannie Mae and Freddie Mac. The underwriting standards restrict on down payment, payment to income ratios, and others.	Down payment less than 80%; Payment to income ratio larger than 28%
6.Home equity withdrawal	Households cash their unused home equities, by cash-out refinancing, in which the refinanced balance is more than the outstanding balance, or by home equity loans. It uses home equity as collateral, just like mortgage.	Home equity line of credit, allows uses of home equities as credit cards.
7. Balance sheet channel	A fall in FFR hurts the economy and asset prices, and reduces household income and wealth, which in turn hurts their balance-sheets and raise external financing costs.	
8.Impulse response	If a variable Y is Granger caused by X, then the change in Y as a result of a change in X is referred as the impulse response of Y to the shock to X	
9.Recursive identification	A restriction on the directions of contemporaneous effects among variables in a model. The idea is that a variable can instantaneously affect all variables ordered after it while none of those variables can immediately affect it.	Choleski decomposition

Appendix J Detailed Descriptions of Data in Chapter 3

Variable	Measure	Description	Source
Consumption	Retail sales	Monthly; 1992M1-2006M12; In log billion dollars; Seasonally adjusted	Bureau of Census;
Inflation	CPI	Monthly; 1992M1-2006M12; Index 1982-84=100; seasonally adjusted	Bureau of Labor Statistics
Short-term interest rate	Effective Federal funds rate	Monthly average of daily figures; 1992M1-2006M12; In percentage; Not seasonally adjusted.	Board of Governors of the Federal Reserve System
Mortgage spread	30 year mortgage rate less 30 year T-bond rate	Monthly; 1992M1-2006M12; in percentage; Not seasonally adjusted	Freddie Mac (mortgage rate); the Fed and Yahoo Finance(T-bond rate)
Non-agency MBS	Share of non-agency MBS in all MBS	Monthly; 1992M1-2006M12; In percentage; Agency MBS is defined as the dollar value of Treasury and Agency MBS hold by large domestic commercial banks; Non- agency MBS is the dollar value of other MBS hold by those banks. Seasonally adjusted.	Board of Governors of the Federal Reserve System
Home equity withdrawal	Ratio of home equity loan to all prime mortgage	Monthly; 1992M1-2006M12; In percentage; Home equity loans are revolving; Prime mortgages cover both commercial and residential; Seasonally adjusted;	Freddie Mac (mortgage rate); the Fed
Capital Inflow	Net import	Monthly; 1992M1-2006M12; In log billion dollars; Seasonally adjusted	Bureau of Economic Analysis; Bureau of the Census
LIBOR	London Inter bank Overnight Loan Offer Rate, based on Euro	Monthly average of daily figures; 1992M1-2006M12; In percentage; Not seasonally adjusted	Board of Governors of the Federal Reserve System