Housing Boom and Non-housing Consumption: Evidence from Urban Households in China

Online Appendix

Dong Cheng

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A. Housing Markets and Land Supply in Urban China

Land supply by local governments has substantial impacts on housing markets in China. Formal housing markets were established in 1998. Though housing prices are market determined equilibrium prices after that, Chinese local governments could greatly affect local housing prices through the supply of land. In urban China, land is publicly owned, and only use rights of land is allowed for market transactions. Local governments control the supply of leases pertaining to land use rights, hence playing an important role in housing markets as well.

The typically procedure of land use rights trading is presented in **Figure F.1**. It displays a timeline for the trading of a representative piece of land in urban China. *Step 1*, local government prepares a piece of vacant land and sells the use rights of that land in the form of a lease to real estate developers. The lease has a maximum length of 70 years. It is generally sold via auctions (see, e.g. Cai et al., 2013, for more information on different types of auctions used by local governments). *Step 2*, real estate developers who win the auctions build houses (like multistory apartment buildings) on that land. It might take years before houses are built. The length of the lease pertaining to the land is depreciating during that period. *Step 3*, developers sell houses to households in housing markets. When selling houses, developers also need to transfer the land lease to households. The cost of land lease is already factored into housing prices. *Step 4*, households who own the houses might continue to hold them or sell them to new buyers. When homeowners sell their houses, the depreciation of land lease length is already factored into housing prices. *Step 5*, when land leases expire, households are probably allowed to renew them. Though it is unclear for now what homeowners could do when land leases expire, Chinese central government is formulating a new policy that allows households to renew leases, according to the reply to a reporter question by the current premier minister, Li Keqiang, in March 2017.

Aggregate data from the National Bureau of Statistics (NBS) and Ministry of Land and Resources of the People's Republic of China imply that land sales revenue is crucially important for local governments, and land costs take up a very large portion of housing prices.

Figure F.2 plots the contributions of land to local fiscal revenues and housing prices. It shows clearly that land sales are an important sources of fiscal revenues for local governments. Revenue from land sales accounted for around 40.4% of total fiscal revenues for local governments during 1998-2015. Over our sample period (2002-2009), the share reached 45.1%. Therefore, it is easy to infer that local governments have strong incentives to maintain (even raise) high land prices, in order to meet needs of various government expenditures. **Figure F.2** also exhibits that land prices are a major type of costs in equilibrium housing prices. Land prices took up 40.4% of housing prices over the period 1998-2015. The share even reached 45.2% between 2002 and 2009. Clearly, it means that local governments can significantly change housing prices by adjusting land prices.

B. Urban Household Survey

The Urban Household Survey (UHS) is conducted by the NBS on an annual basis. In accordance with the Statistics Law of People's Republic of China, the survey is designed to track the standard of living for urban households, which also meets the needs of central and local governments in formulating economic policy and making macroeconomic management.[1] We introduce the design, implementation, and wide academic use of the UHS first, then discuss the availability of data and representativeness of our sample.

B.1. Survey Design and Implementation

The NBS takes full responsibility in working out the survey and assigns uniform requirements to its local affiliates for reporting the survey data. All the UHS forms are made by the NBS and then distributed to local statistical survey departments, so there is no geographic variation in survey design or questionnaire. When the survey work is finished, local affiliates are required to report the data in a uniform and hierarchical way. To be specific, there are three layers of statistical departments in China. The NBS belongs to the central government and is at the very top, then comes the survey unit at the province level, which governs multiple city-level survey teams within the province. The reporting procedure for the UHS data is well established: city-level survey teams conduct the field investigation to collect first-hand data, then they report the household-level survey data to the survey unit at the province level; the provincial unit closely goes through the survey data to rule out errors, and then reports it to the Urban Bureau

[1] A special type of needs that UHS tries to meet is to provide reference information for adjusting annual Consumer Price Index (CPI). In specific, the NBS updates the weights applied to different items in the basket of goods when constructing CPI by taking into account changes in the distribution of consumption expenditure shares across categories of goods revealed in the UHS data.

of the NBS via a pre-assigned File-Transfer-Protocol (FTP) address. The provincial unit is scheduled to report the data by January 10 in the following year of the survey, and no delay is allowed. Taken altogether, the UHS is uniformly designed and conducted across cities, and of high quality that is guaranteed by the province-level scrutiny and timely reporting.

The subjects of the UHS are various households living in urban areas. To a large extent, it covers all potential types of urban households in China. This ensures the representativeness of the survey for the entire pool of urban families, without ignoring any fraction of households that might reside in the urban areas of a fast-growing developing economy. Urban households surveyed include, but not limited to, residents with non-agricultural household registration (i.e. non-agricultural "Hukou" in Chinese), residents with agricultural household registration at the local bureau, non-agricultural households that are registered in a different city yet have been living in the city for more than half a year, agricultural households that are registered in a different city yet have been living in the city for more than half a year, bachelor families, and mobile households that never stay for more than half a year yet own homes in the city.

The UHS surveys inclusive economic, demographic, and social characteristics for urban households in China. There are multiple questionnaires including forms for the general information of the household and its members, for the pecuniary income and expenditure of the household, for the non-pecuniary income of the household, and for the consumption expenditure of the household. Restated, the UHS provides information on demographic characteristics, employment, housing and other durable goods, income and expenditure, and detailed consumption expenditure. The abundance of variables enables us to explore household consumption behavior in diversified categories and with reasonable controls. Within a city, all the information above is recorded at the household level via a daily bookkeeping procedure before being aggregated at the city level for reporting to a higher affiliate, which substantially helps to maintain the accuracy of the survey data.

The UHS is based on a stratified sampling, which is advantageous to sample each stratum independently. A base stratum in the UHS is a community. Within the community, households are randomly selected by a systematic sampling with a equiprobability feature, which starts by randomly selecting an element and then every k^{th} element in the county is selected, where k is the sampling interval defined as the ratio of population size (N) to sample size (n), i.e. $k = \frac{N}{n}$. The stratum higher than a community is a county-level city. Within the county, communities are randomly selected in the same way as households are chosen within a community. The next stratum higher than a county is a prefecture-level city. Within the prefecture, counties are randomly chosen and the sample size assigned to a county is governed by the population share of the county in the prefecture. The next higher stratum is a province. Within the province, nearly all prefectures are selected. Only excluding prefectures that have a similar peer prefecture in the same province are excluded. And the sample size assigned to a prefecture is determined by the population share of the prefecture within the province. The highest stratum is the whole country. Almost all provinces are included in the UHS, with sample size assigned to a province determined by the population share of the province in China. To account for geographic variation in economic development, the sampling at the prefecture level is conducted over a population sorted by average wage per capita of employed workers. Thus, the stratified sampling puts massive emphasis on the representativeness of the survey. The UHS also rotates the sample every three years to increase the randomness, which means that a household in principle remains in the sample for three years.

Except for the feature embedded in the survey design to guarantee randomization, the NBS also formulates multiple examination procedures to insure the quality of UHS data. First, it requires the provincial statistic unit to evaluate the representativeness of the reported data from prefectures and counties. The UBS even enacts a decree for quality control of the data. Second, the NBS systematically evaluates the representativeness of the reported data from provinces by comparing the sample moments with aggregated data at the country level. Third, the sample variances of three key household variables, that is, disposable income, total consumption expenditure, and household size are routinely checked every year to closely track the change in sampling errors.

In the literature, a plenty of studies have employed the UHS data as a random and representative sample to explore economic issues related to China. Amongst them are, but not limited to, researches on the evolution of poverty and income inequality by Yang (1999), Meng et al. (2005), Wu and Perloff (2005), and Ravallion and Chen (2007); on income taxation reforms by Piketty and Qian (2009); on accounting for Chinese high household saving rates by Chamon and Prasad (2010), Chamon et al. (2013), and Curtis et al. (2015); on household food demand analysis by Fang and Beghin (2002); on economic returns to schooling by Zhang et al. (2005); on long run trends in unemployment and labor force participation in urban China by Feng et al. (2017), and on household-level welfare effects of globalization and trade liberalization by Han et al. (2012) and Han et al. (2016). The increasingly wide use of the UHS data in diversified fields of economics further demonstrates that the high quality and reliability of the data has enabled it to earn more and more recognition in academic studies.

B.2. Data Availability and Representativeness

The UHS data is not easily accessible and only a fraction of it can be obtained via research institutions, like research universities in China. When research institutions get the data from the NBS, it is required in principle that the data could be only used for academic researches, not for commercial use. The subset of UHS data that we have covers six provinces over the period 2002-2009, and shared for research use by one university located in Beijing. A similar subset of the UHS data for these provinces has been utilized by Zhang et al. (2005), yet they focus on the period from 1988 to 2001.[2] The six provinces included in our data are Beijing, Liaoning, Zhejiang, Sichuan, Guangdong, and Shaanxi. See Panel (A) of **Figure 3** in the paper for their locations.

In an administrative sense, the six provinces are broadly representative of rich regional variation in China. According to the NBS, China has 34 province-level regions, 334 prefecture-level city divisions, and 2862 county-level city divisions.[3] At the provincial level, the administrative regions are grouped into eight zones based on their geographical locations, namely North China, Northeast China, East China, Mid-south China, Southwest China, Northwest China, Taiwan, and Hong Kong and Macao. With the exception of Taiwan, Hong Kong and Macao, we have one province for each of the six zones, that is, Beijing in North China, Liaoning in Northeast China, Zhejiang in East China, Guangdong in Mid-south China, Sichuan in Southwest China, and Shaanxi in Northwest China. It means that we have a subset of UHS data for around 20% of the provinces in China and those provinces are equally distributed over the geographic zones that have been surveyed in the UHS, which also establishes the representativeness of our sample at the province level. Another piece of supportive evidence for the representativeness is revealed by Panel (A) of **Figure 3**. It shows that the six provinces are well divided and fairly dispersed. Except for the case of Sichuan and Shaanxi, they are not contiguous. The reasonable separation helps us to avoid the oversampling of areas that are geographically alike, in terms of natural resources, transportation accessibility, population density, etc. It also contributes to control for mutual spillover effects of economic activities, like housing demand and supply that interest us the most, in adjacent provinces.

At the city level, either a prefecture or a county, our data is also fairly representative administratively. **Table F.1** lists the number and share of prefecture- and county-level cities included in our sample. Three facts are readily observed. First, more cites are surveyed in later years. The number increases from 64 to 70 for prefectures, and 106 to 226 for counties. Second, the representatives of prefectures surveyed is comparable to that of provinces. Approximately 20% of all Chinese prefectures are covered by our data, and the share is highly stable

[2]A concern might arise with regard to the selection of sample period. We are assessing the real economic impacts of housing price movements, which requires sufficient variation in housing price changes across time and locations. The period 2002-2009 witnesses a dramatic change in the nascent Chinese housing market, mainly featuring steadily high and geographically uneven growth of house prices. Thus, the period suits the purpose of our study well.

[3]More details on the Chinese names and digital codes of administrative divisions can be found through the NBS website, http://www.stats.gov.cn/tjsj/tjbz/xzqhdm/201703/t20170310_1471429.html.

across years. It also echoes the stratified sampling procedure we state above that nearly all prefecture-level cites are surveyed if they do not find a similar peer city in the same province, because the average within-province share of prefectures is 80% or so. Third, the national share of counties surveyed, even though low, rises steadily, from 3.7% to 7.9% over the eight years. It is worthy to notice that the low share of counties does not truly reflect thus not undermine the representativeness of our sample. Within each province, the share of counties surveyed in that specific province is actually quite high. For instance, there are in total 141 county-level cities in Guangdong, and the number of counties surveyed in this province varies from 18 to 38 across years, which corresponds to a fraction varying between 13% and 27%. On average, the within-province share of counties included in our data lies between 21% and 35%, which is a fairly sound fraction. It is more reasonable for us to care about the share within each province because the UHS employs a stratified sampling method as discussed above. Panel (B) of **Figure 3** in the paper further exhibits the geographic dispersion of the county-level cities surveyed in our sample. To save space, we only plot the distribution in 2002. Compared to 2002, the later years witness an even larger number of surveyed counties, as implied by **Table F.1**. The takeaway from Panel (B) of **Figure 3** is twofold. One, the counties surveyed within each province are considerably scattered. They are not concentrated in any part of a province, but dispersed in every direction. This somehow ensures the randomness at the county level within each province. Two, the importance of a county in our sample is well informative of its demographic and economic importance in the province. The sample size are much larger in those populous and economically advanced counties, like a county in the metropolitan area of Chengdu has a sample size of 304 while a county in the remote city Guangyuan has a sample size of 100.

Our sample is representative in terms of sample distribution as well. The sample size and its distribution across six provinces are tabulated in **Table F.2**. Total observations are 10,710 households in 2002, and increase to 21,506 in 2009. It suggests in the table that the households surveyed are reasonably evenly distributed across provinces. The share of households for a province lies between 10% and 30% in general, with only a few exceptions. Provincial across-year average is 10% for the lowest and barely more than 25% for the highest. Also, provinces that are located in the more developed and populous eastern part of China have a higher share in the sample. For instance, Zhejiang in East China on average has a share that doubles that of Shaanxi in Northwest China. Furthermore, the distribution partially reveals that provinces that are losing economic importance are losing the share as well. Liaoning, which is a heavy industrial province in Northeast China that relies on its affluent natural resources like iron ore and coal, gradually loses the share from 30.6% to 20.4% when the economy is undergoing the transformation towards a structure favoring more labor- and capital-intensive industries and the service sector. **Table F.2** also demonstrates the representativeness of our sample through the lens of demographic and economic shares. As listed in column (9)-(11), the six provinces as a whole constantly account for around 25% of China's national population, 33% of national GDP, and 32% of national consumption. More importantly, **Table F.2** further provides us the support that the subset of the UHS data we have is representative of housing sector in China. Column (12)-(13) make it clear that the six provinces as a whole averagely take up 25% percent of national completed residential investment and 35% of competed residential space across our sample years. These figures, combined with the fraction of 20% in administrative division at the province level, suggest that a fairly important portion of China has been captured by the dataset we employ.

Since we are investigating the economic impacts of changes in housing market, we expressly argue that the subset of the UHS data we get is representative of cross-sectional variation in housing market. In China, multiple levels of cities including municipalities, prefectures, and some counties are typically divided into several tiers, mostly on the basis of economic importance. This grouping method has been widely applied to the studies on Chinese housing markets. A conventional application is to highlight the heterogeneity in house prices across cities, where the cities with a higher rank generally exhibit higher housing prices and stronger growth momentum, see Fang et al. (2015) and Glaeser et al. (2017) as recent examples. Following the categorization in Fang et al. (2015), all cities in China are separated into three tiers. The first tier includes the four most demographically and economically important cities, namely Beijing, Shanghai, Guangzhou, and Shenzhen. Our data cover three of these first-tier cities, only Shanghai is absent. The second tier consists of all the capital cities of the 24 provinces and the two municipalities other than Beijing and Shanghai, that is, Chongqing and Tianjin. Several other prefecture cities like Dalian, which are not capitals, are also included in this tier, due to their manufacturing, services (especially finance), or trade importance. Our data covers 9 of the 36 second-tier cities. The rest of cities are classified as the third tier. There is not a commonly used list for it, but the number of cities is believed to be more than hundreds. Most of prefectures and some counties in our sample belong to this tier. What is revealed in the classification of cities is that our data has a reasonable number of cities from all of the three tiers, thus it bears a great deal of cross-sectional variation in characteristics of Chinese housing markets, such as housing price and growth momentum of the local housing market.

To further assess the representativeness of our data, we also cross validate several variables that are recorded in our sample with the aggregated national counterparts published in the Statistical Yearbook of China, which is reported annually by the NBS. We focus on the starting and ending years of our sample, that is, the year of 2002 and 2009.[4] In 2002, our

[4]The Statistical Yearbook of China is publicly available online, one can download the annual publication via the website: http://www.stats.gov.cn/tjsj/ndsj/.

sample averages for household size, number of workers in a household, household per capita disposable income are 3, 1.6, and 8,943 *yuan* (approximately 1,079 USD when we use exchange rate in 2002 to exclude the effect of Renminbi appreciation against USD during 2002-2009), and the corresponding aggregated national counterparts are 3, 1.6, and 7,703 *yuan* (approximately 929 USD). What interests us more is that the sample averages for household per capita consumption and household per capita residential space are 7,092 *yuan* and 25.4 square meters, amazedly comparable to their national counterparts, 6,030 *yuan* and 22.8 square meters. Marginally higher disposable income and consumption in the sample could be ascribed to the fact that the six provinces in our data are relatively economically advanced in their own geographic zones. As for 2009, the comparison again generates a reassuring result. Average household size, number of workers in a household decrease to 2.8 and 1.5 in the sample, and decrease to 2.9 and 1.5 at the aggregated national level. Sample averages for household per capital income and consumption increase to 21,036 *yuan* and 15,021 *yuan*, while their national counterparts rise to 17,175 *yuan* and 12,265 *yuan*. Sample average for per capita residential space tracks closely the national average as well, 32.5 square meters versus an estimate of 30 square meters.

C. Variable Construction

We construct variables at both household-level and county-level (or prefecture-level) using microeconomic data from the UHS. In the paper, we briefly discuss the construction of variables at both levels. More detailed information on the construction of household-level consumption, household-level wealth, county-level housing leverage ratio, and county-level financial net worth shocks is provided here. We also talk about the deflation of nominal variables in this section of **Online Appendix**.

C.1. Household-level Consumption

At the household level, consumption variables can be obtained directly from the UHS data. The consumption expenditure data are recorded in over 180 detailed categories and eight broad categories. The eight sections are consumption on food, clothing, household appliances, medical and personal care, transportation and communication, education and recreation, housing, and miscellaneous goods. For most of our purposes, it is useful to allocate consumption to three broad measures, nondurables, durables and services. Toward this end, the 180+ items are individually allocated to either nondurables, durables or services in accordance with the methodology used by the Bureau of Economics Analysis (2015), U.S. Department of Commerce. To be specific, nondurables are composed of food and beverages, clothing and footwear, gasoline and other energy goods, and other nondurable goods. Durables include motor vehicles and parts, furnishings and durable household equipments, recreational goods and vehicles, and other durables. Services is an increasingly broad category in a transitional economy like China, covering housing, household utilities, electricity and gas, health care, transportation, communication, education, and recreation services.[5] To sum it up, our household consumption variables are total consumption (C_t^h), nondurable consumption ($C_{t,nd}^h$), durable consumption ($C_{t,d}^h$), and service consumption ($C_{t,s}^h$). Note t denotes a year, h denotes a household, $\{nd, d, s\}$ denote nondurables, durables, and services, respectively. Before we close the construction of consumption variables, it needs to emphasize that housing consumption is carefully taken care of in our study. We include housing consumption in household-level summary statistics to make sure that our results are comparable to existing studies that employ other sources of micro data and include housing when summarizing consumption. However, to avoid the endogeneity issue involved in housing consumption, we exclude housing from consumption in all household-level regressions.[6] We also exclude housing consumption when constructing city-level consumption variables, thus city-level regressions are automatically free of any endogeneity issue caused by housing consumption.

C.2. Household-level Wealth

The measurement of household wealth characteristics involves more efforts because the UHS focuses mainly on flow variables like income and expenditures thus does not provide a good recording of household asset information other than home values. We employ detailed household income information to recover its net worth (NW_t^h). Net worth is defined conventionally as $NW_t^h = F_t^h + HV_t^h - D_t^h$, where F_t^h is financial assets including cash holdings and bank de-

[5] It is worthy to mention that the UHS does not provide expenditure information on household financial or insurance services, such as financial charges, fees, and commissions. However, the underdevelopment of financial market in China tends to restrain the vehicles of investment for households and force them to manage assets mainly as banking deposits and cash holdings, thus diminishing the importance of financial services and rendering them to be minor items. For detailed documentation on the underdevelopment of financial market in China, see Allen et al. (2005) among many others. Gan (2012) finds that about 75% of Chinese household-level assets (excluding housing) are banking deposits and cash holdings in 2011. Provided that our sample period is prior to 2011, the financial services should be even less important for households surveyed then because there is deepening financial reform ever since the 1997 Asian Financial Crisis.

[6] When housing consumption is included in consumption, an endogeneity problem easily arises in the regression of consumption on housing shocks. There exist lots of unobserved factors that could affect both consumption of housing and housing prices. For instance, a negative permanent income shock tends to depress both consumption of housing and housing prices within a location.

posits, D_t^h is the outstanding debt.[7] As for financial assets, cash holdings are recorded in the data. Bank deposits can be estimated using household total interest income and bank deposit interest rate from the NBS, that is, dividing total interest income by average deposit interest rate. The interest rate is set by the People's Bank of China (PBC), central bank in China. Between 2002 and 2009, the average annual nominal deposit interest rate is 2.79%.[8] Debt can be also estimated using annual interest payments on outstanding debt and bank loan interest rate from the NBS, that is, dividing total debt payment by average loan interest rate. The average annual nominal loan interest rate is around 5.86% over the period 2002-2009. It is also set by the PBC, and shares the similar evolution pattern as the nominal deposit interest rate. After we recover net worth, we can calculate the share of housing wealth in total net worth, which demonstrates the importance of housing in household-level portfolio of investment.

C.3. County-level Housing Leverage Ratio

The construction of housing leverage ratio is quite different from that in Mian et al. (2013). They define housing leverage ratio as the ratio of mortgage plus home equity line of credit (HELOC) to home value. In our data, we only have new mortgages rather than all existing mortgages, which apparently underestimates the annual scale of county-level mortgage loans. We have no information on home equity line of credit either, which typically measures the line of credit that allows households to borrow money using home's equity as collateral. However, several studies suggest that homes are the dominant way of collateral borrowing for Chinese households.[9] Also, it is shown in the paper that the home is by far the largest asset of house-

[7]Since the return to bonds is recorded in a general entry as total interest income, it is impossible for us to distinguish it from interest income generated by bank deposits. As suggested by Fang et al. (2015), bond markets are much smaller than bank deposits and stock markets in terms of fund scale. Thus, out of a practical concern, we ignore bonds in financial assets. The issue of stocks is more tricky. We have data on annual dividend, yet it is zero for more than 96% of the households. Zero dividend does not naturally mean zero stock holdings because a household might hold a stock that rarely pays dividends. This is quite common in China where managers in listed firms have less incentive to pay dividends than their peers in developed countries, mainly caused by the agency problem that arises from the specific evaluation system in China which emphases total profits and taxes paid rather than the interest of outside investors (Zhang, 2008). Thus, it means that we cannot truly recover stocks using dividends and dividend yield ratios for most households. Due to this data limitation and also the fact that the size of stock market is substantially smaller than bank deposits (a stable ratio of $\frac{1}{5}$ over the sample period), we also ignore stocks in financial assets. It is worthy to mention that when we take a more aggressive approach by assuming that stocks are constantly one fifth of bank deposits for all households, our empirical results are barely changed.

[8]We use weighted average for the average annual deposit interest rate, where weights are the shares of value for deposits with different horizons. Constant weights from 2002 is applied to all successive years. The average annual loan interest rate is calculated in the same way.

[9]The collateral role of housing in China has been discussed in a growing body of literature. For instance, Fang et al. (2015) indicates that only houses can act as collateral for mortgage loans. Wu et al. (2015) employ firm building as a main property to investigate how changes in firm collateral value affect its investment.

holds. The ongoing boom in Chinese housing market further bolsters the liquidity of housing assets, which forges it into an ideal collateral for borrowing. These China-specific features strongly suggest that housing values (and housing equity) is the collateral for Chinese urban households. Since mortgage loans in general are much larger than other loans, and also Chinese households only borrow in situations of outlays beyond their precautionary expectations or excess of their own high savings, we expect the housing leverage ratio constructed in this paper is much lower than that in Mian et al. (2013). Yet, the measure is still informative about the degree of leverage that Chinese households incur when borrowing against housing.[10] Following Mian and Sufi (2011), we use housing leverage ratio as a proxy for credit constraints. When a county has a higher leverage ratio specific to housing, it implies that the county has a tighter constraint for future borrowing, thus being more credit constrained.

C.4. County-level Financial Net Worth Shocks

We are unable to construct a financial net worth shock as Mian et al. (2013), due to the limited recording of financial assets, and a lack of data on asset prices. Since we cannot accurately recover the holding of stocks for the reason we discussed in a previous footnote, we can alternatively take a more aggressive approach by assuming that stocks are constantly one fifth of bank deposits for all households, given the fact that the size of stock market is a stable one fifth of that of aggregate bank deposits over our sample period. The holding of bonds is ignored due to the trivial size of bond markets in China, when compared with the stock market and bank deposits. Even when we recover household-level stocks in this way, we still lack data on household-level stock price index. Mian et al. (2013) also face the problem of lacking stock and bond price index at the household level. Instead, they assume that all households hold the market portfolio for stocks and bonds, such that the their asset prices are market price indexes. That is to say, the asset prices are identical to all households, and of course, counties as well. This is problematic in the sense that it masks the geographic variation originated from heterogeneous asset holdings at the micro level. Given the mature financial markets throughout the United States, this problem might be mitigated. However, it could cause a big issue in China. Considering that the middle and western part of China are much more financially underdeveloped than the eastern or coastal area, households in the middle and western parts are more inclined to hold bank deposits rather than bonds or stocks. Moreover, another difference between China and the United States makes it difficult to construct a financial net worth

[10] To make the measure informative and reasonable, we need to rigorously make an assumption that the scale of existing mortgages/HELOC is positively correlated with that of new mortgages. This probably holds because the supply of loans is governed by local financial development, which tends to affect the stock/flow of mortgage loans and HELOC in a similar way.

shock for Chinese counties. In the United States, stocks and bonds are the primary financial assets, while Chinese households primarily hold bank deposits. Since there is no price index for bank deposits in China, even when a good stock price index is available for households, it is impossible to construct a reasonable financial net worth shock that bears the Chinese flavor in portfolios. As a consequence, we exclude financial net worth shock in this study. We further argue that the overlook of financial net worth shock should only generate a minor issue. It is presented in Fang et al. (2015) that the returns in Chinese stock market is highly volatile, in comparison with the housing market. The standard deviation of returns in the Shanghai Stock Market is in general fivefold larger than that of housing returns. When the stock market is risky, we should expect that a transitory increase in wealth may have only a minor impact on consumption, as argued by Lettau and Ludvigson (2004).

C.5. Deflating Nominal Variables

Variables with monetary value in the UHS data are recorded as nominal terms, to truly recover economic behaviors, we need to deflate them into real terms. Kaplan et al. (2016) show that the elasticity of real consumption to housing net worth shocks is around 20% lower than that of nominal spending, which clearly suggests there exists a significant response from consumer price as well. Stroebel and Vavra (2016) further reveal that retail prices respond to changes in local housing prices with a elasticity of 15%-20%, mainly arising from the change in homeowner demand elasticity and firm markup decision. We focus on real response of consumption to housing price movements in this study, so it is necessary to exclude the change in price index. Since China is a fast growing economy with multiple levels of development across geographic regions, it is also crucial to account for the dynamic evolution of price level and the spatial heterogeneity in the evolution paths. Toward this end, we collect annual prefecture-level CPI from the China City Statistical Yearbook, published by the NBS. The yearbook has information on CPI for around 660 cities (a very constant number over time) in China, including both county- and prefecture-level cities. The number of prefectures is variant across years in our sample, yet all of them are listed in the corresponding yearbook, so we can construct an unbalanced panel of CPI data for the prefectures over the period 2002-2009. As for the counties, the number of them is also time varying in our sample, and we only have a fraction of them listed in the corresponding yearbook. With that in mind, we conduct the deflation of household-level nominal variables using the finest level of CPI that we could obtain. We use county-level CPI to deflate them if we have CPI data for that county, otherwise we use the prefecture-level CPI.

To appreciate the geographic variation in price index, we plot prefecture-level inflation rates in Panel (A) and (B) of **Figure F.3**. We choose prefectures for the reason that the calculation of inflation requires comparing CPI over time and we have a good panel for prefecture-level CPI. For the purpose of comparing price difference in 2002 and 2009, we also focus the set of 59 prefectures that appear in both years. Panel (A) of **Figure F.3** is the average annual inflation rate for these 59 cities over the sample period. It shows that the inflation rate is highly dispersed across cities. The mean value is 2.7%, with a standard deviation around 0.9%. Around 36% of the 59 prefectures fall outside of the one-standard-deviation range. Guangyuan, a prefecture located in Sichuan province, exhibits an inflation rate as high as 5.8%. It could be ascribed to a big exogenous shock that causes a substantial shortage in supply, i.e. the Great Sichuan Earthquake. The earthquake occurred on May 12, 2008, and Guangyuan is close to the epicenter thus was heavily devastated. The unfriendly terrain in Guangyuan further restricts the supply of goods. In the same year, the annual inflation rate there rose to 15.1%, even much higher than the other prefectures in the same province that are geographically easier to reach. Our city-level key variables are defined as the growth rates or level changes between 2002 and 2009, to keep consistency, we also plot inflation rates between these two years in Panel (B) of **Figure F.3**. It further confirms that there is massive heterogeneity in consumer price movements across cities. The mean value for the price difference between 2002 and 2009 is 20.6%, with a standard deviation around 7.2%. 19 prefectures fall outside of the one-standard-deviation interval. Guangyuan, once again, shows the largest difference (47.2%) over the seven-year interval, probably due to the catastrophic earthquake shock.

D. Household-level Summary Statistics

Table F.3 presents annual summary statistics for our UHS data at the household level over the period 2002-2009. We start with household housing characteristics in Panel A. Average residential space per capita rises steadily over the sample period, from 25.4 square meters in 2002 to 32.5 square meters in 2009. The figures are not just close to national averages (22.8 square meters in 2002 and around 30 square meters in 2009), but also comparable to the number implied in Fang et al. (2015).[11] They take advantage of a comprehensive dataset of mortgage loans issued by a major Chinese commercial bank from 2003 to 2011, and find that the average home size for bottom-income mortgage borrowers in the first-tier cities lies between 72 and 80 square meters throughout the decade. For a typical family of three (based on the one-child policy in China), it implies that the average residential space per capita is around 24-26.7 square meters. The number is slightly smaller than ours because Fang et al. (2015) exclusively investigate mortgage borrowers who could generally afford less spacious homes on

[11]Our figures are also quite consistent with the number documented in Li and Wu (2017). Using data from the 2010 China Family Panel Studies (CFPS), which is similar to the Panel Study of Income Dynamics (PSID) in the U.S., they show that the average per capita floor space for urban residents is 31.2 square meters in 2010.

the one hand, and this number only applies to the first-tier cities that have more expensive homes than other areas on the other.

Average housing wealth per household increases dramatically, more than tripling from 88,294 *yuan* in 2002 to 398,202 *yuan* in 2009.[12] The fast-growing housing wealth mainly comes from soaring housing prices rather than more spacious homes. Housing price in 2009 is around 5,000 *yuan* per square meter on average, which is more than fourfold of that in 2001, merely higher than 1,200 *yuan*. We also observe substantial dispersion in housing wealth and housing prices throughout the sample period, which provides us reasonable variation to identify the effects of housing on household spending. In addition, it shows that dispersed housing prices contribute to most of the cross-sectional differences in housing wealth, because there is much less dispersion in the quantity of housing, as reveled by the small standard deviation of residential space per capita. **Figure F.4** further displays the substantial growth in real housing prices during 2002-2009. It plots provincial real housing prices for all the six provinces in our UHS data. All provinces exhibit strong growth in real housing prices during the eight years. However, the magnitude of housing price growth varies a lot across provinces. Shaanxi has a growth of 250%, while that of Beijing is around 500%.

The self-reported monthly housing rent rate by homeowners grows along with housing prices, from averagely less than 20 *yuan* per square meter in 2002 to around 150 *yuan* per square meter in 2009. A somewhat more rapidly increasing housing rent between 2002 and 2005 explains the concurrent decline in average price-to-rent ratio, from around 50 to 45 in five years. However, the mean ratio picks up quickly in 2007 and surpasses 53 in 2009. Wu et al. (2012) collect aggregate price-to-rent data for major cities in China, which tends to mask the massive heterogeneity across households and thus generates smaller figures than us. It turns out that their figure is slightly larger than 26 in 2007. Even that figure is much higher than the price-to-rent ratio in more mature housing markets. For instance, Zillow's Home Value Index for All Homes and Rent Index for All Homes indicate that the average price-to-rent ratio in the United States is well below 15 over the past two decades. In addition, we find that Chinese urban households maintain a rising average homeownership rate from 70% in 2002 to almost 85% in 2009. The figure is comparatively high throughout the world. Between 2002 and 2009, data from the U.S. Bureau of the Census suggest that the average homeownership rate is around 68% and on the decline. The high homeownership rate is in accordance with the argument proposed by Wei et al. (2017) that homeownership is a status for single men to demonstrate their competitiveness in the marriage market where there exists

[12] Li and Wu (2017) indicate that it further climbs to 459,800 *yuan* in 2010, which has not been CPI adjusted thus the real term should be smaller, yet it is still a strong growth when compared to our figure in 2009.

a shortage of women due to the widespread sex imbalance in China.[13] Among homeowners, the share of households that possess two or more homes is markedly ascending from under 10% to above 16% over the eight years. The average homes for these multiple-homeowners is quite stable, lying between 2.05 and 2.15. Thus, it means that multiple-homeowners generally hold two homes while rarely buy more than two. Since we have information on the amount of money paid to own the current homes, we can combine it with home values to define housing premium (i.e. the ratio between current home value and money paid to own the home), for the purpose of reflecting the returns to invest in housing market. It reveals that the profit is pretty high and still enlarging, with the average premium increasing from 4.4 in 2002 to 6.6 in 2009. This also provides support to explain the high homeownership rate because owning a home induces huge expected returns.

Next, we turn to summarizing household employment characteristics. As a result of one-child policy, the typical urban household size is close 3 in China. Mean household size mildly shrinks from 3 to 2.8 over the sample years, indicating that a decline in fertility rate and more aging population as a whole, probably triggered by higher cost in raising children and postponed childbearing from couples with more education (Morgan et al., 2009). The average number of wage earners falls in the interval of 1.3 and 1.6, and keeps considerably stable. With only one noticeable drop in 2008, partly reflecting the economic downturn in the Great Recession. The fraction of wage earners in state-owned enterprises averagely drops from almost 59% in 2002 to 43.6% in 2009. This decline dovetails nicely with the simultaneous reform of state-owned enterprises, which reduces the redundancy of inefficient labor as narrated by Berkowitz et al. (2016) and thus forces previous SOE employees to seek jobs in the domestic private sector.

Turning to average household total income in 2009, it exceeds 63,000 *yuan*, which is more than doubling of that in 2002. It evidently shows a continuous and stable growth over the sample period. The figure is fairly close to the national average, around 57,000 *yuan*. Disposable income rises from 25,570 *yuan* in 2002 to 56,644 *yuan* in 2009, exhibiting a similar growth

[13]Moreover, Painter et al. (2004) suggest that culture might contribute to the high homeownership rates of Chinese households. They document that Chinese homeownership rates in the Los Angeles Consolidated Metropolitan Statistical Area adjusted by socioeconomic and housing market characteristics are, on average, 18% higher than those of native white households. According to their empirical results, the presence of ethnic Chinese communities can partially explain why Chinese groups own homes at higher rates than the native white population. The operational channels could be the presence of shared resources in a social network or the strong peer influence of homeowning in Chinese culture. Shen and Turner (2015) argue that preferential admission policies from Chinese universities for local residents encourage households to purchase rather than rent local homes, on the condition that there are rising college premiums in China since 2003 (a vast number of studies have documented dramatically increased and large college premiums, see among many other, Han et al., 2012, Li et al., 2012, and Wang, 2012). In a broader sense, local residency also enjoys preferential treatment when it comes to other public services, like primary/secondary education and healthcare, among many other amenities and resources.

pattern as total income. Labor income is the primary source of income for Chinese households, with an average fraction of 66.3% in 2002 and mildly decreasing to 62.4% in 2009. The moderate decline can be ascribed to the fact that urban households in China accumulating more wealth like housing and stocks as the economic reform deepens, thus more property income is acquired. The average price-to-income ratio balloons from 3.75 in 2002 to 7.24 in 2009. We confirms the finding in Fang et al. (2015) that the price-to-income ratio on average increases drastically between 2003 and 2011. Since they use data on mortgage borrowers who tend to be low- or middle-income groups, they in general get larger price-to-income ratios than us, like a ratio around 6-8 for households in the first-tier cities in 2003. Compared to the U.S., our price-to-income ratio is substantially higher. For example, Cheng et al. (2014) documents a mean ratio of 3 for the U.S. during the first decade of the twenty-first century, though they investigate relatively high-income groups like lawyers. The high price-to-income ratio means heavy financial burdens for typical Chinese urban households despite the strong and steady income growth in China over the past three decades. It could also have contributed to China's high saving rates because low- and middle-income households need to save a large amount of income to cover the housing down payment, which is typically lies between 30% and 40% of home value.[14]

Finally, we switch to the stock variables accumulated from resource inflows, i.e. household wealth characteristics. The average household net worth in 2009 is more than 460,000 *yuan*, almost a quadruple of that in 2002, and a spectacular build-up at the microeconomic level, which is accompanied by China's speedy growth in macroeconomy.[15] Given the stringent capital controls, Chinese urban households cannot invest in international capital markets. As a result, they are forced to invest in domestic markets where only a few investment vehicles exist. The underdevelopment of financial markets further limits the opportunity to gain returns from stocks and bonds. Instead, households principally choose to invest in bank deposits and housing markets. Though bank deposits generate nearly zero or even negative real returns, the

[14]Household saving rate in China has risen dramatically since the early 1990s. The average saving rate of urban households, relative to their disposable income, reached 24% in 2005 (Chamon and Prasad, 2010). The upward trend continued throughout the first decade of the twenty-first century (Curtis et al., 2015). Many competing explanations have been proposed to unveil this multifaceted phenomenon. Notable amongst them are: Chamon and Prasad (2010) who ascribe the high household saving rate to the private burden of expenditures on housing, education, health care, and financial underdevelopment; Wei and Zhang (2011) who propose a new competitive saving motive that Chinese parents with a son raise their savings in a competitive manner in order to improve their son's relative attractiveness in the marriage market where sex imbalances have resulted in more males than females; and Curtis et al. (2015) who emphasized several channels through which demographic changes contribute to high household saving rate, including the decline in family size brought about by the one-child policy, growing working age population, and the projected decline in workers per retiree.

[15]We find that the average household net worth for urban Chinese households implies a quite comparable wealth/income ratio to that found in developed economies. Piketty (2014) finds that the wealth/income ratio stabilizes at around 4-7 in the long run for Europe and the United States. The wealth/income ration calculated from our data lies between 4.7 and 7.3 during 2002-2009, with an average of 5.98.

risk-free feature and strong precautionary saving motives of Chinese households (see Meng, 2003, and Chamon and Prasad, 2010, for the precautionary motives) make it a suitable choice. However, as emphasized by Fang et al. (2015), a better choice is housing due to its high returns and relatively mild risk when compared with stocks.[16] The average share of housing in household net worth rationalizes the choice. It rises from 55.8% in 2002 to 71.4% in 2009. Employing another microeconomic survey on Chinese urban households, the China Family Panel Studies (CFPS), Xie and Jin (2015) finds that the share has increased to 74% in 2012, consistent with the uninterrupted great housing boom in China after 2009.

E. Error in Variables

When constructing a pseudo panel out of time series of cross-sections, we suffer from the classic error-in-variable problem discussed by the seminal work of Deaton (1985). This specific type of measurement error shows up when we measure city-level variables in the panel data with corresponding sample averages from the household-level repeated cross-sections. Since we do not have household identifiers to track them over time, we resort to the pseudo-panel techniques by tracking "cohorts". Cohort here is a group with fixed membership, which means that individuals with a common time-invariant characteristic should be assigned to a unique cohort. Typically, it is an age cohort where individuals have the same range of birth years (see Browning et al., 1985, as a well-known example). In our case, the cohort is a geographic region, i.e. a city. That means individuals from the same city form a cohort in our study, like the regional cohorts defined by Campbell and Cocco (2007) who employs microeconomic data from the U.K. In this subsection, we describe how the measurement error emerges in our city-level regressions and how to correct city-level baseline regressions for this measurement error.

To discuss the issue of measurement error, it would be better for us to present it with mathematical notations. We start with a simple linear model of panel data for households. Let y_t^h denotes the dependent variable, which is consumption in our study. $\boldsymbol{X}_t^h$ is a k-dimensional vector of explanatory variables, which includes housing price or home value in our regressions and the constant term as well. The coefficient vector of interest is denoted as the $k \times 1$ vector $\boldsymbol{\beta}$. Household unobserved heterogeneity or individual fixed effect is captured by α^h. Hence, the simple household-level panel regression model is:

$$y_t^h = \boldsymbol{X}_t^h \cdot \boldsymbol{\beta} + \alpha^h + \epsilon_t^h \tag{1}$$

[16] A explanation for the low risk in housing investment, which is suggested by Glaeser et al. (2017), rests on the strong incentive of Chinese local governments to maintain steady growth in housing prices and avoids a housing crash, for the purpose of raising revenue from land sales.

where ϵ_t^h is idiosyncratic shocks to households. When a panel data of households are available, one can easily obtain a consistent estimate of $\boldsymbol{\beta}$ in equation (1) via fixed-effect estimation. However, in practice, household-level panel data is scarce and difficult to access. What is more commonly seen is a series of independent cross-sections, like the UHS sample we have or the BHPS data employed by Campbell and Cocco (2007). The panel nature is crucial for us to deal with the unobserved heterogeneity α^h. If the exogeneity condition $E[\alpha^h \boldsymbol{X}_t^h] = 0$ holds, we could still consistently estimate $\boldsymbol{\beta}$ using pooled OLS or random effect estimation. Yet, the exogeneity assumption is easily violated. For instance, the martial status of household head is missing in our data and could be largely treated as a time-invariant component. Since it tends to be positively correlated with household homeownership rate or home value as the fierce competition from the Chinese marriage market with an imbalanced sex ratio incentivizes males to possess homes or even large homes to attract females (see Wei and Zhang, 2011, and Wei et al., 2017, for more details), the pooled OLS or random-effect estimation will produce an overestimated coefficient for home value. In this case, Deaton (1985) suggests to construct a cohort-based panel out of the easier accessible repeated cross-sections, which is formally referred to as the pseudo-panel approach.

In our city-level regressions, a cohort is defined as a city so that households residing in the same city are assigned into a unique cohort. We choose defining a cohort in this way, rather than the frequently used age cohort, is to keep comparable with the studies on consumption response to housing shocks utilizing U.S. county-level data like Mian et al. (2013) on the one hand, and to compromise with the data limitation that we have no information on demographic or socioeconomic conditions of the household heads on the other. Using this cohort definition, we aggregate over households h belonging to cohort c that is observed in the UHS data at time t by taking sample averages within a cohort. We then obtain a cohort sample mean version of equation (1), which is deemed as the pseudo (or synthetic) panel model:

$$\widetilde{y}_t^c = \widetilde{\boldsymbol{X}}_t^c \cdot \boldsymbol{\beta} + \widetilde{\alpha}_t^c + \widetilde{\epsilon}_t^c \tag{2}$$

where variables with a tilde denotes simple sample average within the cohort c. Deaton (1985) notes that $\widetilde{\alpha}_t^c$, which is the sample average of the fixed effects for those members of cohort c that show up in the survey, is time-varying, unobserved, and generally correlated with $\widetilde{\boldsymbol{X}}_t^c$. Hence, equation (2) is not an appropriate basis for the consistent estimation of $\boldsymbol{\beta}$. Alternatively, Deaton (1985) proposes a cohort population mean version of equation (1) as:

$$y_t^{*,c} = \boldsymbol{X}_t^{*,c} \cdot \boldsymbol{\beta} + \alpha^c + \epsilon_t^c \tag{3}$$

where $y_t^{*,c}$ and $\boldsymbol{X}_t^{*,c}$ are the unobservable cohort population means, and α^c is the cohort fixed effect. α^c is time-invariant because the population of the cohort c is assumed to be fixed throughout time. Though $y_t^{*,c}$ and $\boldsymbol{X}_t^{*,c}$ are unobserved, we can proxy them with sample means $\widetilde{y}_t^c$ and $\widetilde{\boldsymbol{X}}_t^c$, respectively. However, sample means are error-ridden estimators of population means, as long as the sample size of cohorts is not large enough. There is no consensus in the literature as to what cohort size is considered sufficiently large. Verbeek and Nijman (1992) argue that 100 or 200 individuals are sufficiently large, while Devereux (2007) later find that the bias could be an order of 10% even with cohort sizes of 10,000 observations per cohort (which means that even 10,000 might not be enough). In our paper, **Table 1** reveals that the average cohort size is 93.7 with a median of 53, firmly below 100. Therefore, it would be quite necessary for us to address the error in variables, in accordance with the seminal idea proposed by Deaton (1985) .

To conveniently model the measurement error, we follow Deaton (1985) by rewriting equation (3) in a single index form:

$$y_t^* = \boldsymbol{X}_t^* \cdot \boldsymbol{\beta} + \epsilon_t \tag{4}$$

where the cohorts, i.e. cities in our case, and rounds of surveys have been stacked into a single index t, running from 1 to $T = C \times R$ where C is the number of cohorts in each round of survey and R is the total rounds of surveys. In our study, $T = 42 \times 8 = 336$ for counties and $T = 59 \times 8 = 472$ for prefectures. The time-invariant cohort dummies α^c are also included in $\boldsymbol{X}_t^*$ and can be treated as elements with a measurement error that has zero mean and variance, as well as other observed cohort-level constant characteristics if included. Deaton (1985) pays special attention to the context where the measurement error is the key problem, that is, the cohort size is fixed while the number of cohorts thus the total number of observations in equation (4), i.e. T, tends to infinity ($T \to \infty$). Other authors, like Moffitt (1993), Verbeek and Vella (2005), and Inoue (2008), instead have assumed that T is fixed while the cohort size tends to be sufficiently large, and concentrating on the issues involved in dynamic panel regression. In our study, it is easy to see that the measurement error or the errors-in-variables is the primary issue as we have relatively small cohort size. The focus on measurement error also encourages Deaton (1985) to assume for simplicity that the error term ϵ_t is normal, homoskedastic and independent over the index t. To make this assumption sensible, we need to weight all observations in equation (4) by the square root of the cohort size (i.e. $\sqrt{N^c}$, where N^c is the number of households surveyed in cohort c). Then, Deaton (1985) assumes that the measurement structure corresponding to the specific error-in-variable problem in equation (3) can be characterized by:

$$\begin{pmatrix} v_t^0 \\ \boldsymbol{\nu}_t \end{pmatrix} \equiv \begin{pmatrix} \widetilde{y}_t - y_t^* \\ \widetilde{\boldsymbol{X}}_t - \boldsymbol{X}_t^* \end{pmatrix} = \boldsymbol{N} \begin{pmatrix} 0; & \sigma_{00} & \boldsymbol{\sigma}' \\ 0; & \boldsymbol{\sigma} & \boldsymbol{\Sigma} \end{pmatrix} \tag{5}$$

where $\widetilde{y}_t$ and $\widetilde{\boldsymbol{X}}_t$ are simple sample averages of population values y_t^* and $\boldsymbol{X}_t^*$, respectively. v_t^0

and $\boldsymbol{\nu}_t$ are defined as corresponding measurement errors associated with y_t^* and $\boldsymbol{X}_t^*$. The normality of the multi-dimensional distribution finds plausible support from the random sampling structure of the UHS. As noted by Verbeek (2008), the true population values y_t^* and $\boldsymbol{X}_t^*$ can be interpreted as unknown but constant terms. Hence, the population moments of measurement errors in equation (5) are reduced to population moments of the respective sample averages. To be specific, we have $\sigma_{00} = Var(\widetilde{y}_t)$, $\boldsymbol{\sigma} = Cov(\widetilde{y}_t, \widetilde{\boldsymbol{X}}_t)$, and $\boldsymbol{\Sigma} = Cov(\widetilde{\boldsymbol{X}}_t, \widetilde{\boldsymbol{X}}_t) = Var(\widetilde{\boldsymbol{X}}_t)$. It further implies that we can consistently estimate the population moments of measurement error with sample counterparts of the population moments of the respective sample averages. With the assumed measurement structure in equation (5), Deaton (1985) derives a consistent estimator for $\boldsymbol{\beta}$ as:

$$\boldsymbol{\beta}^* = (\boldsymbol{M_{XX}} - \boldsymbol{\Sigma})^{-1}(\boldsymbol{m_{Xy}} - \boldsymbol{\sigma}) = (\mathbb{X}'\mathbb{X} - T\boldsymbol{\Sigma})^{-1}(\mathbb{X}'\boldsymbol{y} - T\boldsymbol{\sigma}) \tag{6}$$

where $\boldsymbol{M_{XX}} = \frac{1}{T}\mathbb{X}'\mathbb{X}$ and $\boldsymbol{m_{Xy}} = \frac{1}{T}\mathbb{X}'\boldsymbol{y}$ are the respective sample moments and cross product matrices of $\boldsymbol{X}_t$ and y_t. Since $\boldsymbol{\Sigma}$ and $\boldsymbol{\sigma}$ are unknown population moments of measurement errors, they can be replaced with their sample counterparts as we mentioned earlier. Denote the sample counterparts of $\boldsymbol{\Sigma}$ and $\boldsymbol{\sigma}$ as $\boldsymbol{S}$ and $\boldsymbol{s}$, respectively, then the estimator in equation (6) is rewritten as:

$$\widetilde{\boldsymbol{\beta}} = (\boldsymbol{M_{XX}} - \boldsymbol{S})^{-1}(\boldsymbol{m_{Xy}} - \boldsymbol{s}) = (\mathbb{X}'\mathbb{X} - T\boldsymbol{S})^{-1}(\mathbb{X}'\boldsymbol{y} - T\boldsymbol{s}) \tag{7}$$

The asymptotic variance of $\widetilde{\boldsymbol{\beta}}$ in equation (7) can also be straightforwardly derived and expressed in equation (8) as:

$$\boldsymbol{Avar}(\widetilde{\boldsymbol{\beta}}) = \boldsymbol{\Omega}^{-1}[\boldsymbol{\Sigma_{XX}}\boldsymbol{\omega^2} + (\boldsymbol{\sigma} - \boldsymbol{\Sigma\beta})(\boldsymbol{\sigma} - \boldsymbol{\Sigma\beta})']\boldsymbol{\Omega}^{-1} + \frac{1}{\bar{N}_c}\boldsymbol{\Omega}^{-1}\boldsymbol{Avar}(\boldsymbol{s} - \boldsymbol{S\beta})\boldsymbol{\Omega}^{-1} \tag{8}$$

where $\boldsymbol{\Omega} = \boldsymbol{\Sigma_{XX}} - \boldsymbol{\Sigma}$ with $\boldsymbol{\Sigma_{XX}} = E[\boldsymbol{M_{XX}}]$; $\boldsymbol{\omega^2} = \sigma_\epsilon^2 + \sigma_{00} + \boldsymbol{\beta}'\boldsymbol{\Sigma\beta} - 2\boldsymbol{\sigma}'\boldsymbol{\beta}$ with $\sigma_\epsilon^2 = Var(\epsilon_t)$; $\boldsymbol{Avar}(\boldsymbol{s} - \boldsymbol{S\beta}) = \boldsymbol{\Sigma}(\sigma_{00} + \boldsymbol{\beta}'\boldsymbol{\Sigma\beta} - 2\boldsymbol{\sigma}'\boldsymbol{\beta}) + (\boldsymbol{\sigma} - \boldsymbol{\Sigma\beta})(\boldsymbol{\sigma} - \boldsymbol{\Sigma\beta})'$; and $\bar{N}^c$ is the mean value of cohort size N^c, i.e. the average cohort size. It equals to 93.7 in our study. Similarly, using sample counterparts as consistent estimators of unknown population moments, we can get an estimate for $\boldsymbol{Avar}(\widetilde{\boldsymbol{\beta}})$.

Notice however that equation (4) is expressed as level values, while variables in regression equation (2) and (4) of the paper are differences between 2002 and 2009. Thus, we need resorting to the model in differences from Deaton (1985). Like equation (4), we write a model in the form of differences as:

$$\Delta_{2002-2009}y_t^* = \Delta_{2002-2009}\boldsymbol{X}_t^* \cdot \boldsymbol{\beta}_\Delta + \epsilon_t \tag{9}$$

where $\Delta_{2002-2009}y_t^*$ and $\Delta_{2002-2009}\boldsymbol{X}_t^*$ are the true unobservable differences between the two years, i.e. the true values in 2009 minus those in 2002. Since we only focus on the differences between 2009 and 2002, equation (9) is actually a cross-sectional regression. Yet, we can still use the method developed by Deaton (1985) to do estimation and inference for $\boldsymbol{\beta}_{\Delta}$ because the cross-section is essentially a specific type of panel data with observations appearing only once, i.e. $T = C$. Corresponding to equation (5), we assume the measurement structure for the model in differences as:

$$\begin{pmatrix} u_t^0 \\ \boldsymbol{u}_t \end{pmatrix} = \begin{pmatrix} \nu_{2009}^0 - \nu_{2002}^0 \\ \boldsymbol{\nu}_{2009} - \boldsymbol{\nu}_{2002} \end{pmatrix} \equiv \begin{pmatrix} \Delta_{2002-2009}\widetilde{y}_t - \Delta_{2002-2009}y_t^* \\ \Delta_{2002-2009}\widetilde{\boldsymbol{X}}_t - \Delta_{2002-2009}\boldsymbol{X}_t^* \end{pmatrix} = \boldsymbol{N}\begin{pmatrix} 0; & 2\sigma_{00} & 2\boldsymbol{\sigma}' \\ 0; & 2\boldsymbol{\sigma} & 2\boldsymbol{\Sigma} \end{pmatrix} \tag{10}$$

where u_t^0 and $\boldsymbol{u}_t$ are measurement errors associated with $\Delta_{2002-2009}y_t^*$ and $\Delta_{2002-2009}\boldsymbol{X}_t^*$, respectively. The doubled variance or covariance matrix in equation (10) primarily results from the linearity of u_t^0 or $\boldsymbol{u}_t$ in ν_t^0 and $\boldsymbol{\nu}_t$. Moreover, given the fairly long gap of years between 2002 and 2009, we should reasonably expect no autocorrelation between ν_{2009}^0 and ν_{2002}^0, or between $\boldsymbol{\nu}_{2009}$ and $\boldsymbol{\nu}_{2002}$. Then, it is quite straightforward for us to derive the estimator for $\boldsymbol{\beta}_{\Delta}$ in equation (9). For simplicity, we write $n_t = \Delta_{2002-2009}\widetilde{y}_t$ and $\boldsymbol{Z}_t = \Delta_{2002-2009}\widetilde{\boldsymbol{X}}_t$. As derived by Deaton (1985), a clearly consistent estimator for $\boldsymbol{\beta}_{\Delta}$ will be:

$$\boldsymbol{\beta}_{\Delta}^* = (\boldsymbol{M}_{\boldsymbol{ZZ}} - 2\boldsymbol{\Sigma})^{-1}(\boldsymbol{m}_{\boldsymbol{Z}n} - 2\boldsymbol{\sigma}) = (\mathbb{Z}'\mathbb{Z} - 2T\boldsymbol{\Sigma})^{-1}(\mathbb{Z}'\boldsymbol{n} - 2T\boldsymbol{\sigma}) \tag{11}$$

where $\boldsymbol{M}_{\boldsymbol{ZZ}} = \frac{1}{T}\mathbb{Z}'\mathbb{Z}$ and $\boldsymbol{m}_{\boldsymbol{Z}n} = \frac{1}{T}\mathbb{Z}'\boldsymbol{n}$ are the respective sample moments and cross product matrices of $\boldsymbol{Z}_t$ and n_t. Likewise, since $\boldsymbol{\Sigma}$ and $\boldsymbol{\sigma}$ are unknown population moments, they can be replaced with their sample counterparts $\boldsymbol{S}$ and $\boldsymbol{s}$, respectively, then the estimator in equation (11) is rewritten as:

$$\widetilde{\boldsymbol{\beta}}_{\Delta} = (\boldsymbol{M}_{\boldsymbol{ZZ}} - 2\boldsymbol{S})^{-1}(\boldsymbol{m}_{\boldsymbol{Z}n} - 2\boldsymbol{s}) = (\mathbb{Z}'\mathbb{Z} - 2T\boldsymbol{S})^{-1}(\mathbb{Z}'\boldsymbol{n} - 2T\boldsymbol{s}) \tag{12}$$

The asymptotic variance of $\widetilde{\boldsymbol{\beta}}_{\Delta}$ in equation (12) requires slightly more efforts for derivation and could be done in a similar way as we derive the asymptotic variance of $\widetilde{\boldsymbol{\beta}}$ in equation (8). However, in our study, a comparatively lower number of observations in equation (9) against that in equation (4), 42 versus 336 for counties and 59 versus 472 for prefectures, encourages us to employ bootstrapped standard errors rather than asymptotic ones when estimating equation (5), whereas we still use asymptotic standard errors for equation (4) when we estimate it for robustness checks.

To construct standard errors for equation (9), we adopt the following bootstrapping procedure: (i) draw random samples with replacement repeatedly from the sample dataset of counties or prefectures; (ii) estimate the desired statistic $\widetilde{\boldsymbol{\beta}}_{\Delta}$ corresponding to these bootstrap samples, which then forms the sampling distribution of $\widetilde{\boldsymbol{\beta}}_{\Delta}$; (iii) calculate the sample standard deviation of the sampling distribution as the bootstrapped standard errors. We also follow the suggestion by Verbeek and Nijman (1993), to correct the estimator in equation (7) or (12) for the limited rounds of surveys, which basically addresses the issue that only a very few number of repeated cross sections are available for estimation. In our case, the number of rounds is 8 for equation (7) and 2 for (12). Hence, the correction tends to be imperative. In specific, we premultiply $\tau = (R-1)/R$ with $\boldsymbol{S}$ and $\boldsymbol{s}$ to get the corrected estimators as $\widetilde{\boldsymbol{\beta}} = (\mathbb{X}'\mathbb{X} - T\tau\boldsymbol{S})^{-1}(\mathbb{X}'\boldsymbol{y} - T\tau\boldsymbol{s})$ or $\widetilde{\boldsymbol{\beta}}_{\Delta} = (\mathbb{Z}'\mathbb{Z} - 2T\tau\boldsymbol{S})^{-1}(\mathbb{Z}'\boldsymbol{n} - 2T\tau\boldsymbol{s})$, where R is the rounds of cross-sections.

Lastly, notice that in the baseline city-level regressions, we make a compromise between the issues of endogeneity and error in variables, as it involves much heavier computation for us to deal with them simultaneously on the one hand and it helps us quantitatively assess the severity of different issues on the other. We ignore the error-in-variable problem in those baseline regressions and simply estimate regression equation (2) and equation (4) in the paper with instruments for housing shocks as if there is no measurement error, that is, by estimating regression equations (5-6) and (7-8) in the paper. Then, we address the measurement error by estimating regression equation (2) and equation (4) in the paper without instruments and using the estimator in equation (12) in a robustness check. Finally, we add as another robustness check that considers both issues of endogeneity and measurement error. In this robustness check, we utilize an instrumental variable estimator similar as that developed by Deaton (1985). Mathematically, it could be presented as an expression comparable to equation (12):

$$\widetilde{\boldsymbol{\beta}}_{\Delta,IV} = [\mathbb{W}'\mathbb{Z}(\mathbb{W}'\mathbb{W} - 2T\tau\boldsymbol{S_W})^{-1}\mathbb{Z}'\mathbb{W}]^{-1}[\mathbb{W}'\mathbb{Z}(\mathbb{W}'\mathbb{W} - 2T\tau\boldsymbol{S_W})^{-1}\mathbb{W}'\boldsymbol{n}] \tag{13}$$

where the sample moment $\boldsymbol{S_W} \xrightarrow{d} \boldsymbol{\Sigma_W}$ and the latter is the variance covariance matrix of the vector of error-ridden explanatory variables, in which the endogenous variables have been replaced by the instrumental variables. Due to the same issue of limited observations, we use bootstrapped standard errors for $\widetilde{\boldsymbol{\beta}}_{\Delta,IV}$ in equation (13), in a similar way as what we do for $\widetilde{\boldsymbol{\beta}}_{\Delta}$ in equation (12).

Appendix References

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F. Additional Figures and Tables

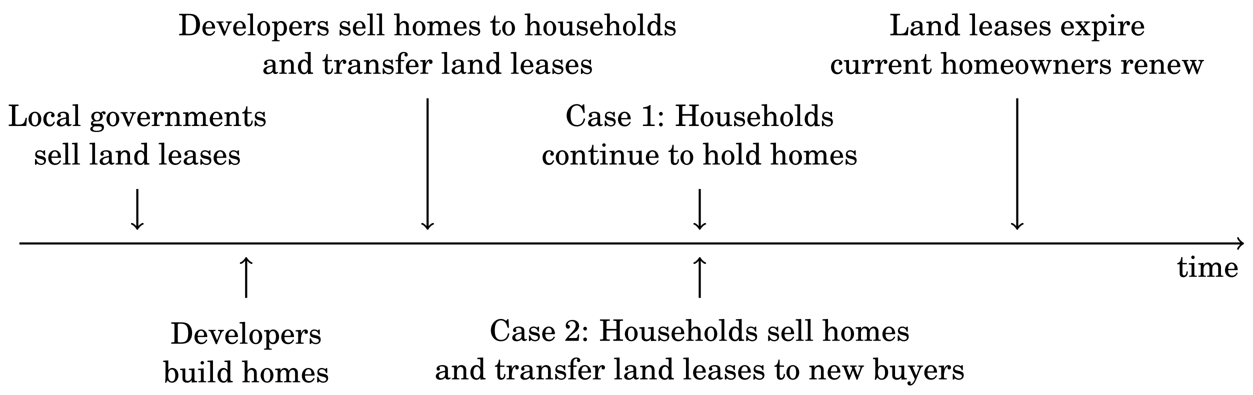

Figure F.1. Trading procedure of land use rights lease in urban China.

Notes. This figure plots the timeline of land use rights trading in urban China. Land leases are leases of land use rights, which have a maximum length of 70 years for residential use. Developers are real estate developers who supply a majority of housing for urban households in China.

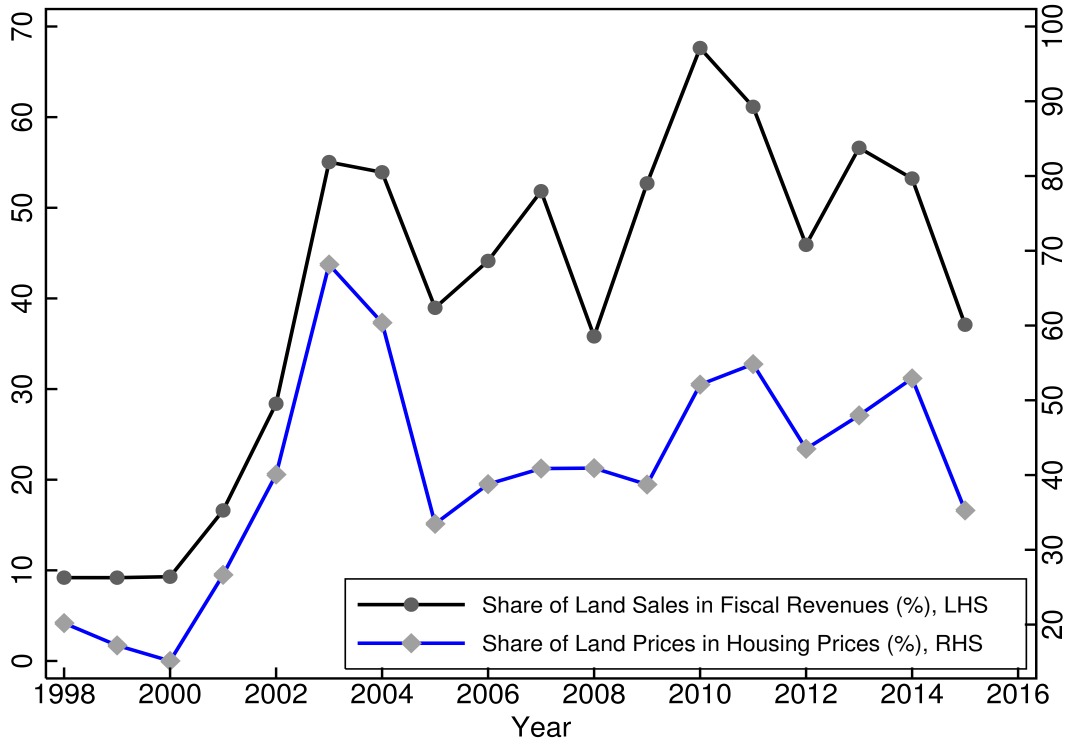

Figure F.2. Contributions of land to local fiscal revenues and housing prices.

Notes. This figure plots the share of land sales in total local fiscal revenues (on the left vertical axis) and the share of land prices in housing prices (on the right vertical axis) during 1998-2015. These shares are calculated using aggregate data from the NBS and Ministry of Land and Resources of the People's Republic of China.

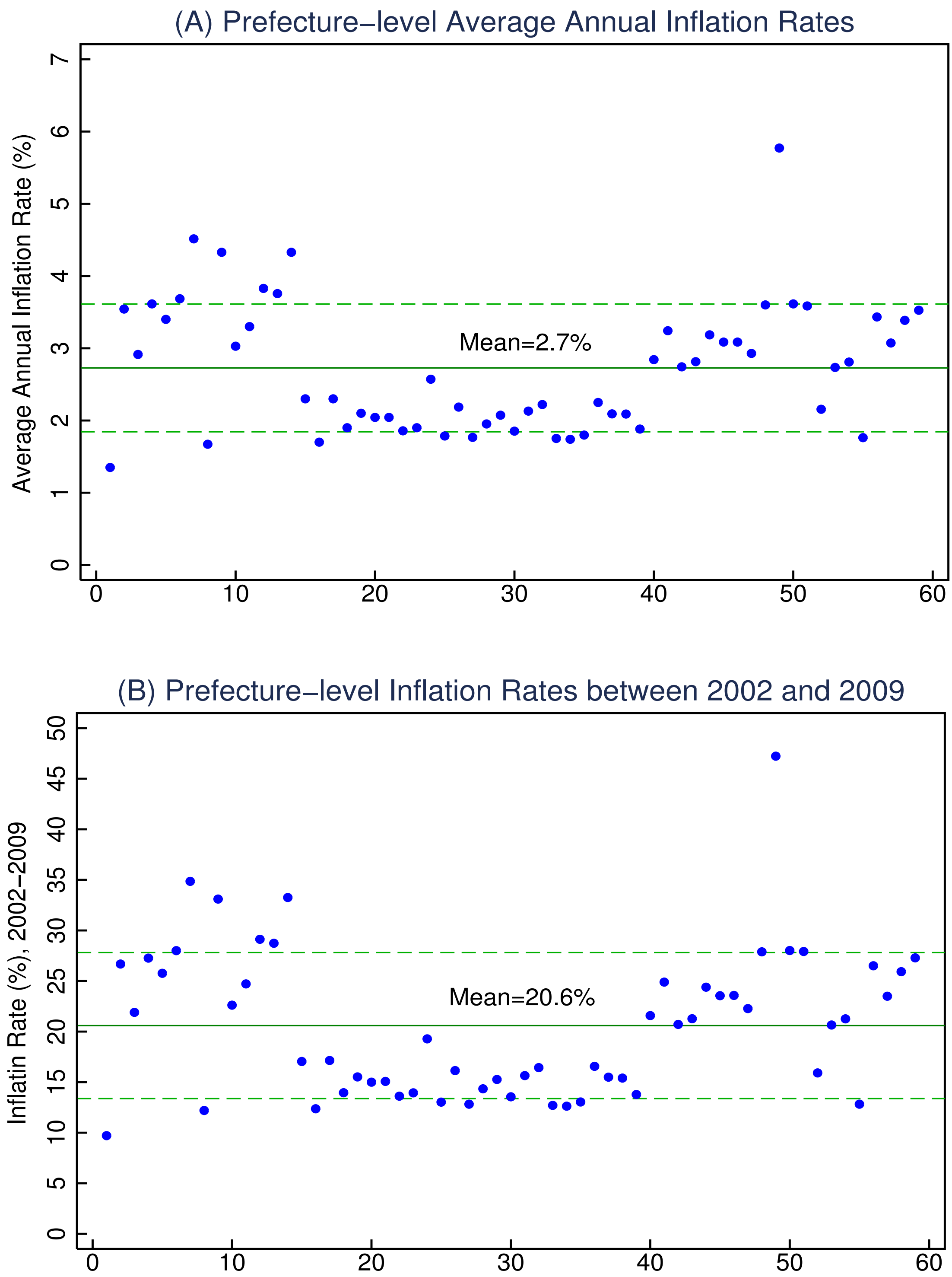

Figure F.3. Prefecture-level annual inflation and inflation between 2002 and 2009.

Notes. This figure plots the prefecture-level CPI data that are collected from the NBS. Average annual inflation rate is taken across all eight years during 2002-2009 for each prefecture. Inflation rate between 2002-2009 is the percentage change in CPI between the two years, 2002 and 2009. The green solid line shows the mean value across all prefectures, while the two green dash lines denote the band of one standard deviation relative to the mean value.

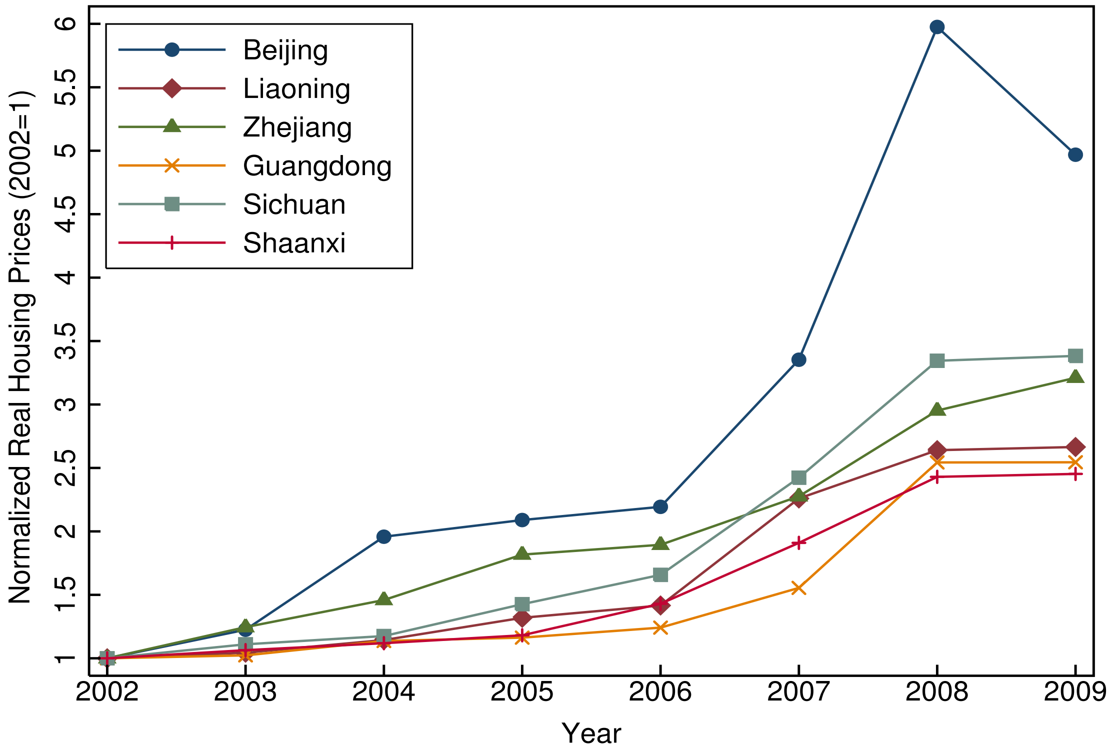

Figure F.4. Provincial real housing prices from the UHS data.

Notes. This figure plots provincial real housing prices constructed using our UHS data. We average real housing prices across all homeowners within each of the six provinces to measure provincial housing prices. Then, we normalize real housing prices to be 1 in 2002 for all six provinces.

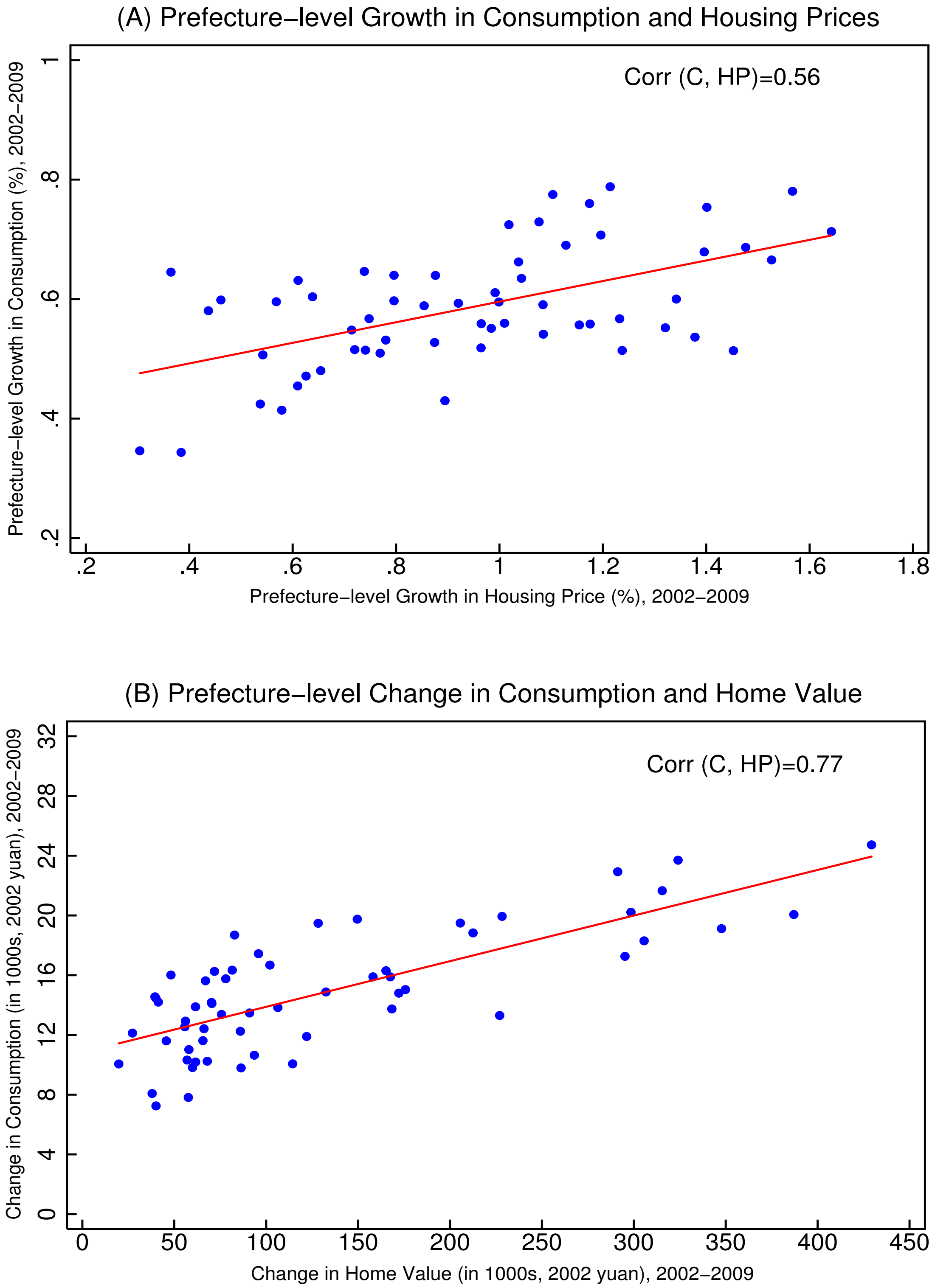

Figure F.5. Prefecture-level correlation patterns: consumption and housing.

Notes. This figure plots prefecture-level correlation between consumption and housing price/home value movements. The blue solid line is the linear fitted line. "$Corr(C,HP) = 0.56$" and "$Corr(C,HP) = 0.77$" indicate a coefficient of correlation equal to 0.56 and 0.77, respectively.

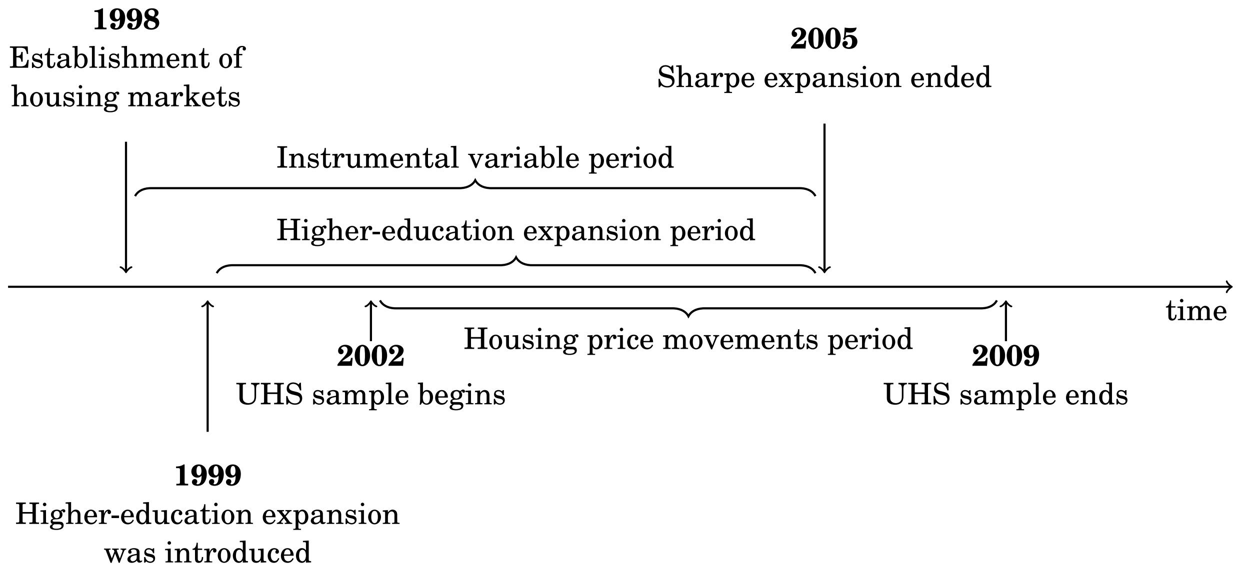

Figure F.6. Timeline of higher-education expansion in China.

Notes. This figure plots the timeline of higher-education expansion in China since 1999. The sharp expansion spanned from 1999 to 2005. We employ the college enrollment expansion between 1998 and 2005 to predict an exogenous source of housing price movements between 2002 and 2009. The four-year gap reflects the typical length of college study in China.

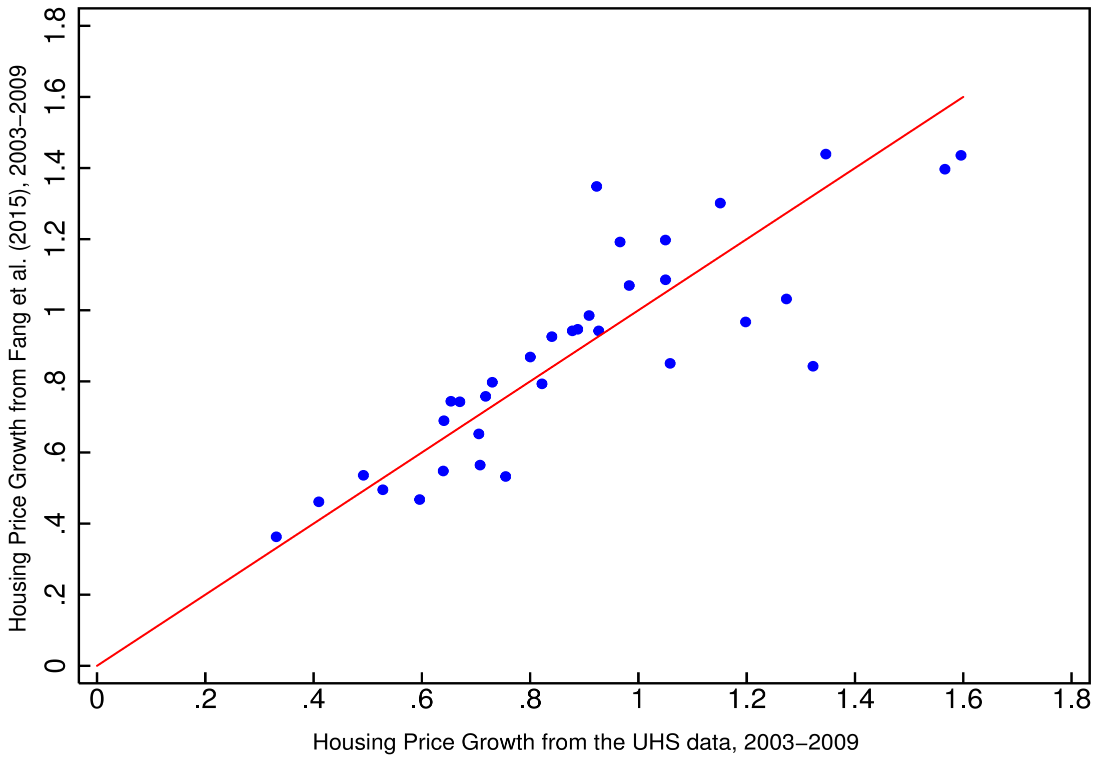

Figure F.7. Housing price growth from the UHS and Fang et al. (2015).

Notes. This figure plots housing price growth rate calculated using hedonic housing price index from Fang et al. (2015) and housing price growth rate calculated using real housing prices from our UHS data. Housing price growth is the growth rate of housing price or housing price index over the seven-year interval between 2003 and 2009. The red solid line is the 45-degree line. The two growth rates track each other closely, showing a coefficient of correlation equal to 0.85.

Table F.1. Summary statistics of prefectures and counties included in our UHS data, 2002-2009.

Year	Number of prefectures	National share (%)	Within-province share (%)	Number of counties	National share (%)	Within-province share (%)
2002	64	19.2	78.6	106	3.7	21.0
2003	64	19.2	78.6	117	4.1	21.5
2004	66	19.8	80.1	118	4.1	21.5
2005	66	19.8	80.1	124	4.3	22.5
2006	66	19.8	80.1	122	4.3	22.3
2007	66	19.8	80.1	207	7.2	33.0
2008	69	20.7	82.2	218	7.6	35.0
2009	70	21.0	82.2	226	7.9	34.7
Mean	66	19.9	80.3	155	5.4	26.5

Notes. This table presents the summary statistics of prefectures and counties included in our UHS sample. Prefectures are higher-level cities that constitutes provinces, like Chengdu in Sichuan province; counties cities are lower-level cities that constitutes prefectures, like Shuangliu in Chengdu. The national share denotes the fraction of cities that are included in our data in the total number of cities in China, whereas the within-province shares denotes the fraction in the total number of cities in a specific province.

Table F.2. Sample representativeness, size and distribution across six provinces in urban China, 2002-2009.

Year	N	Beijing (%)	Liaoning (%)	Zhejiang (%)	Guangdong (%)	Sichuan (%)	Shaanxi (%)	L (%)	Y (%)	C (%)	I_H (%)	H (%)
2002	10710	9.7	30.6	17.8	15.1	13.7	13.1	24.1	31.4	30.1	24.0	N/A
2003	12147	8.4	29.9	18.6	14.2	16.8	12.2	24.2	32.4	30.4	26.1	N/A
2004	13325	15.8	27.2	17.9	12.2	16.1	10.9	24.2	32.6	30.6	25.3	37.6
2005	15331	13.7	24.9	27.3	10.6	14.0	9.5	24.4	33.3	33.8	24.7	36.7
2006	15140	13.7	24.4	27.3	10.6	14.2	9.8	24.5	33.3	34.2	26.2	35.8
2007	16079	17.7	22.9	26.9	10.0	13.4	9.0	24.7	32.5	34.1	24.3	35.5
2008	20280	16.9	22.5	22.5	16.0	13.7	8.3	24.9	32.2	32.6	24.0	32.6
2009	21506	23.4	20.4	21.0	15.4	12.7	7.1	25.1	32.1	32.5	28.0	31.7
Mean	15565	14.9	25.3	22.4	13.0	14.3	10.0	24.5	32.5	32.3	25.3	35.0

Notes. This table presents the sample representativeness of our UHS data. N is the sample size. Annual share of sample size for each province is listed in column (3)-(8). Shares of population (L), GDP (Y), consumption (C), completed residential investment (I_H), and completed residential space (H) of the six provinces in China's corresponding totals are listed in column (9)-(13).

Table F.3. Household-level summary statistics for the UHS data, 2002-2009.

	2002	2003	2004	2005	2006	2007	2008	2009
Panel A: Household Housing Characteristics:								
Residential space per capita	25.4	26.0	26.7	29.2	29.9	30.6	31.8	32.5
(square meters)	[15.2]	[15.1]	[15.0]	[17.4]	[17.8]	[18.2]	[19.6]	[18.9]
Housing wealth	88294.3	96304.5	129837.7	172549.5	185907.6	257551.3	373997.1	398201.5
(2002 *yuan*)	[97527.0]	[110101.6]	[141856.0]	[223719.9]	[205728.2]	[270773.0]	[390923.2]	[380457.7]
Housing price	1205.1	1358.7	1773.4	2133.0	2272.4	3291.2	4746.3	4942.6
(2002 *yuan* per square meter)	[1225.6]	[1349.8]	[1817.0]	[2301.1]	[2276.0]	[3262.1]	[4473.0]	[4428.9]
Monthly housing rent rate	18.6	19.3	56.7	146.0	147.0	140.5	135.0	146.7
(2002 *yuan* per square meter)	[18.4]	[15.4]	[35.7]	[42.1]	[45.0]	[97.5]	[118.6]	[132.7]
Price-to-rent ratio	49.3	48.3	47.6	45.4	45.2	50.5	53.8	53.4
	[22.4]	[22.0]	[23.2]	[25.3]	[24.7]	[23.7]	[29.8]	[27.2]
Homeownership rate(%)	69.8	70.9	69.5	72.0	75.6	79.2	82.7	83.8
Multiple-homeownership rate	9.3	10.3	12.6	14.6	14.8	14.3	12.9	16.4
among homeowners (%)								
Number of homes	2.07	2.09	2.13	2.13	2.14	2.12	2.13	2.10
among multiple-homeowners	[0.36]	[0.35]	[0.90]	[0.78]	[0.85]	[0.53]	[0.48]	[0.40]
Housing premium	4.4	4.4	4.8	4.9	5.1	6.0	6.6	6.6
	[4.2]	[4.3]	[5.2]	[5.4]	[5.6]	[6.6]	[7.9]	[7.8]
Number of households	10710	12147	13325	15331	15140	16079	20280	21506

(*continued*)

Notes. This table presents household-level summary statistics of our UHS sample. We report means for each variable, corresponding standard deviations are in the parentheses. Price-to-rent ratio is the ratio of housing price to monthly rent. Multiple-homeowners are the households that own two or more homes. Housing premium is the ratio of current housing price to the amount that a household pays when it acquires the house.

Table F.3. Household-level summary statistics for the UHS data, 2002-2009 (*continued*).

	2002	2003	2004	2005	2006	2007	2008	2009
Panel B: Household Employment Characteristics:								
Household Size	2.98	2.82	2.94	2.90	2.88	2.85	2.85	2.83
	[0.85]	[1.01]	[0.80]	[0.84]	[0.83]	[0.82]	[0.91]	[0.88]
Number of wage earners	1.55	1.48	1.51	1.45	1.48	1.51	1.38	1.46
	[0.81]	[0.80]	[0.80]	[0.82]	[0.82]	[0.83]	[0.84]	[0.84]
Fraction of SOE	58.7	55.8	54.2	49.8	49.2	49.2	43.0	43.6
wage earners (%)								
Panel C: Household Income Characteristics:								
Total income	27332.3	28815.8	34158.8	38255.7	42958.6	50553.6	55186.7	63375.0
(2002 *yuan*)	[18697.9]	[21786.5]	[25316.4]	[28560.7]	[32176.4]	[37636.2]	[45081.1]	[51156.5]
Disposable income	25570.1	26669.1	31400.9	35060.3	39262.7	45840.9	50214.6	56643.9
(2002 *yuan*)	[17357.3]	[20060.7]	[23103.3]	[25828.9]	[29109.5]	[33226.8]	[41033.9]	[46671.3]
Fraction of labor income	66.3	66.4	65.7	63.4	62.9	63.3	61.9	62.4
(%)								
Price-to-income ratio	3.75	3.88	5.31	5.87	6.02	6.27	6.79	7.24
	[3.97]	[4.36]	[4.53]	[4.55]	[5.73]	[5.86]	[7.09]	[7.33]
Number of households	10710	12147	13325	15331	15140	16079	20280	21506

(*continued*)

Notes. We report means for each variable, corresponding standard deviations are in the parentheses. Price-to-income ratio is defined as the ratio between cost of the home owned by a household and household yearly disposable income.

Table F.3. Household-level summary statistics for the UHS data, 2002-2009 (*continued*).

	2002	2003	2004	2005	2006	2007	2008	2009
Panel D: Household Expenditure Characteristics:								
Total expenditure	26425.5	28419.7	33521.3	36067.1	40336.0	46027.2	47618.2	58123.1
(2002 *yuan*)	[26981.1]	[34338.8]	[41215.7]	[43282.4]	[53796.4]	[57701.6]	[53496.7]	[63043.9]
Consumption expenditure	20428.9	21091.4	24544.8	26996.9	29542.7	33417.4	36328.1	40615.3
(2002 *yuan*)	[15846.5]	[18098.6]	[20522.3]	[23857.0]	[26167.8]	[27797.4]	[32821.6]	[35367.1]
Nondurable expenditure	8559.5	8760.7	10094.9	10900.4	11794.0	13690.5	15461.9	16801.4
(2002 *yuan*)	[4497.2]	[4792.2]	[5305.2]	[6059.2]	[6618.1]	[7459.5]	[10050.4]	[9978.7]
Durable expenditure	3514.1	3729.1	4224.1	4680.0	5378.1	6018.6	5924.9	7562.0
(2002 *yuan*)	[9034.3]	[10910.1]	[12338.4]	[14822.8]	[16728.5]	[16984.0]	[17325.2]	[21438.8]
Service expenditure	8355.3	8601.7	10225.8	11416.5	12370.5	13706.6	14925.6	16250.5
(2002 *yuan*)	[7278.1]	[8086.5]	[19038.1]	[10098.1]	[10790.5]	[11845.3]	[14586.5]	[15014.1]
Panel E: Household Wealth Characteristics:								
Net worth	128930.4	139197.0	178831.2	227037.2	254099.6	312251.6	428269.0	460794.6
(2002 *yuan*)	[125553.7]	[149996.3]	[174549.0]	[255863.3]	[310306.8]	[312251.6]	[431505.8]	[434805.8]
Housing share in net worth (%)	55.8	58.7	63.1	65.7	65.9	66.5	67.8	71.4
Number of households	10710	12147	13325	15331	15140	16079	20280	21506

Notes. We report means for each variable, corresponding standard deviations are in the parentheses. The classification of nondurable, durable, and service consumption is from the Bureau of Economic Analysis (2015), U.S. Department of Commerce.

Table F.4. College enrollment expansion shock as a source of exogenous variation, at the prefecture level

Dependent Variable (vertical)	College enrollment expansion shock (in 1000s)	Constant	N	R^2
(1) Housing net worth shock	0.058***	-2.433***	59	0.279
	[0.012]	[0.870]		
(2) Housing price shock	0.039***	-2.242***	59	0.361
	[0.011]	[0.792]		
(3) Change in home value, 2002-9	0.146***	-0.929***	59	0.529
(in 1000s, 2002 *yuan*)	[0.028]	[0.321]		
(4) Change in land sales share, 2002-9	0.014	1.386***	59	0.002
	[0.046]	[0.434]		
(5) Permanent shock to wage growth,	0.048	1.015	59	0.003
2002-9	[0.233]	[1.597]		
(6) Change in DPS employment share,	0.120	1.071***	59	0.004
2002-9	[0.414]	[0.363]		
(7) DPS employment share in 2002	0.119	1.335	59	0.001
	[0.292]	[1.056]		
(8) Population growth, 2002-9	0.043**	-0.306***	59	0.218
	[0.021]	[0.111]		
(9) Disposable income per household	0.024**	-1.171	59	0.182
in 2002 (in 1000s, 2002 *yuan*)	[0.011]	[1.174]		
(10) Net worth per household	0.003***	-0.745	59	0.206
in 2002 (in 1000s, 2002 *yuan*)	[0.001]	[0.644]		

Notes. This table presents coefficient from prefecture-level univariate regressions which regress various dependent variables on college enrollment expansion shock. Each row represents a separate regression. The first three rows exhibit the first stage estimation of housing net worth shock, housing price shock, and change in home value on the instrumental variable, i.e. college enrollment expansion shock, respectively. Bootstrapped standard errors based on 1,000 repetitions are in parentheses. ***, ** indicates statistical significance at the 1% and 5% levels, respectively.