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Tightening belts to buy a home: Consumption responses to rising housing prices in urban China[☆]

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ABSTRACT

This paper measures the impact of housing price changes on household consumption at the city level using the universe of credit and debit card transactions in China from 2011 to 2013. In sharp contrast to the literature on the US housing market, our analysis shows a large and negative housing price elasticity of consumption: a 10% increase in housing prices would lead to a 9% reduction in non-housing spending. We argue that the negative elasticity is driven by the combination of a strong investment incentive in housing and heavy borrowing constraints faced by households. This finding is corroborated by the fact that households increase their savings as housing prices increase. Our analysis suggests that the negative impact of housing price increases on consumption was an important factor behind the low growth rate in household consumption relative to the growth of disposal income during the sample period.

1. Introduction

How does household consumption respond to changes in housing prices? Sinai and Souleles (2005) argue that because housing is both an asset and a source of housing services, capital gains to homeowners will be exactly offset by future increases in the cost of housing services. Given household optimization over an infinite horizon, their model yields consumption smoothing that is consistent with the predictions of the Permanent Income Hypothesis. While this approach forms the basis of our understanding of the consumption and wealth effects of home ownership, the prediction of no consumption response to house prices may not accurately characterize the behavior of many households.[1] In particular, Campbell and Cocco (2007) show that with the addition of borrowing constraints, consumption responses are large and respond to the financial position of households. A number of recent US empirical studies identify meaningful positive consumption responses to housing appreciation (DeFusco 2018; Aladangady 2017; Mian et al. 2013).

While positive consumption responses to housing appreciation have been well established in the US context, there is a lack of evidence from other countries.[2] This gap matters especially in emerging markets, where the nature of household savings over the life cycle is likely to differ and has implications for a sustainable growth trajectory. In China, the contrast with the US is all the more conspicuous given the country's staggering income growth and persistent high savings rate: the annual income growth in urban China was 11% and savings rates averaged around 25% during 2006–10 (Curtis et al. 2015). The role of housing is no less important in urban China, where housing accounted for 40.7% of total household wealth in 2011 (Gan et al. 2013), compared to 30% for US households in the 2010 Census.

In this paper, we utilize the universe of credit and debit card (bank card) transactions in China from 2011 to 2013 to examine the relationship between housing price changes and household non-housing consumption on a monthly basis across cities in China during its most recent

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[1] With the addition of depreciation or substitution effects, the model predicts a non-zero but small consumption response.

[2] An exception is Campbell and Cocco (2007), who study this relationship in the UK.

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housing boom.[3] To the best of our knowledge, this is the most comprehensive city-level dataset on consumption and housing ever created for China. The bank card transaction dataset covers over 300 categories of consumption goods, which is complemented by urban monthly housing price indices at the city level.

This unique dataset allows us to account for an important margin of adjustment to housing price increases not fully captured in previous studies: a corresponding reduction of consumption driven by saving for housing investment. How can consumption fall amid dramatically rising income in urban China? The answer is that income growth is outstripped by housing price appreciation, which, in turn, is propelled by household demand and by private sector investment seeking stable returns.[4] For Chinese households, a lack of access to the credit market can mean that home-ownership creates considerable financial burdens on households. This challenge is exacerbated by restrictions on the use of current housing for collateral effectively, which in other contexts acts as a channel for consumption increases (Fang et al. 2016).

To illustrate the channels through which these effects play out, we develop an intertemporal model of household consumption over housing and non-housing goods. When households do not face borrowing constraints, consumption smoothing occurs. We document, however, that when households face constraints on their ability to borrow against future income or against current housing assets (as is the case in China), permanent housing price appreciation generates consumption reductions when investment incentives outweigh wealth effects. We illustrate these channels in the form of a version of a Slutsky decomposition applied to intertemporal housing consumption. We also extend the model to consider how these effects vary across the life cycle and with adjustment costs.

A major challenge to analyzing consumption responses to changes in housing prices is the likely correlation between prices and time-varying unobserved local economic factors that could also affect consumption. These unobservables cannot be adequately controlled for by fixed effects. Therefore, we use a set of instrumental variables (IVs) that act as plausibly exogenous shifters of local housing supply. Our main instrument is the lagged volume (in square kilometers) of cumulative land sales in each city. This instrument is valid because variation in land sales during the period we study is primarily driven by local governments' need to service debt incurred during the financial crisis, rather than in response to local housing or land market conditions (State Tax Administration 2013). To address concern about the validity of the strict exogeneity assumption, we apply a series of bounding exercises to our IV estimates, following Nevo and Rosen (2012).

Our analysis shows that the combination of borrowing constraints and a lack of investment opportunities leads to a *negative* consumption response to housing price increases across Chinese cities, implying an elasticity of -0.9. We document this pattern across several consumption categories: a 10% appreciation in housing price would result in a 7.4% reduction in automobile purchases and a 6.2% drop in spending at supermarkets and department stores. This provides, to the best of our knowledge, the first evidence of negative consumption responses to housing price increases. While the result is the opposite of what has been found in the US and EU, it is consistent with a large body of literature that documents restrained consumption growth and persistent high savings incentives among Chinese households despite dramatic rises in income. There is disagreement about the underlying causes of this behavior: Wei and Zhang (2011) argue it is due to competitive marriage market pressures, while Chamon et al. (2013) suggest that it is linked to income volatility. Regardless of the cause, consumption reductions in response to housing price appreciation are consistent with the stylized fact of the high savings rate in China.

Our analysis of city-level aggregate household savings indicates that a 10% increase in housing prices is associated with a 1.9% increase in savings deposits, corroborating the fact that households that face tight borrowing constraints are deferring consumption to save for home purchases. Our ability in the paper to fully measure all margins of households' adjustment is limited by not having household-level data; indeed, our unit of observation is limited to the city-month level. That said, our data is comparable to that of Mian et al. (2013), who estimate the elasticity of aggregate consumption for households that have different levels of wealth in the US.[5]

We do not observe demographic information for cardholders. Given the high penetration of bank cards (debit and credit cards) during our sample period and our ability to control for changes in card penetration, our estimates provide a reasonable measure of average spending patterns across cities. In terms of differential effects among social groups, we examine heterogeneity based on city-level demographics. In addition, we identify homeownership status through an adaptive learning algorithm and compare the responses of 'likely home owners' with those of 'likely renters.' In both cases, we document heterogenous effects that are consistent with a model of consumption reduction due to housing investment incentives and borrowing constraints.

Our paper contributes to the literature on housing and household consumption behavior along three dimensions. First, as previously mentioned, existing studies that try to understand the impact of housing price changes on consumption behavior focus predominantly on the US. Our paper documents patterns that are in sharp contrast to those in the existing literature, highlighting the importance of taking into consideration capital market imperfections faced by households in developing countries and emerging markets. Second, our paper helps to explain the role of the Chinese housing market in the recent economic boom. Our analysis shows a negative impact of the housing market boom on domestic non-housing consumption. This has important implications given that China is trying to make the transition from export-led economic growth to growth that relies on domestic demand. Third, our study sheds light on the microeconomic basis for and the implications of the persistently high savings rate in China. The existing literature attributes this phenomenon to several determinants, such as the weak social safety net and the marriage market competition due to sex ratio imbalances. Our findings suggest that housing market dynamics are another important set of factors to consider when examining household saving behavior.

Our paper proceeds as follows. Section 2 discusses the context of the Chinese housing market boom. Section 3 provides a theoretical model that illustrates how housing price spikes could reduce consumption. Section 4 presents our data, Section 5 our econometric framework, and Section 6 our results. Section 7 discusses differential responses to housing prices across cities and over time, and Section 8 concludes.

2. China's residential housing market

Starting in 2003, China's housing market experienced a boom that lasted for more than a decade. Fig. 1 shows that median housing prices in the four Tier-1 cities increased roughly five times from 2003 to 2013, while in Tier-2 and Tier-3 cities it more than tripled.[6] That said, during the period of our study, 2011–13, prices took a slight dip in the

[3] For brevity, we refer to non-housing consumption simply as consumption, which excludes consumption of housing services.

[4] Chen and Wen (2017) find that while income grew 11% annually from 2006 to 2010, housing prices grew by 17% per year.

[5] The effect found by Mian et al. (2013) is the opposite of the effect found by our study – a difference that probably is driven by positive wealth effects. Our data have a finer spatial resolution than Case et al. (2005), who, using data at the state- and international-level, find a sizable positive relationship between consumption and housing wealth.

[6] The Tier System was designed by the central government in the 1980s to prioritize development objectives by city type. The four tiers correspond to importance in relative GDP, political governance and population. In Appendix Table D.1, we list cities by tiers.

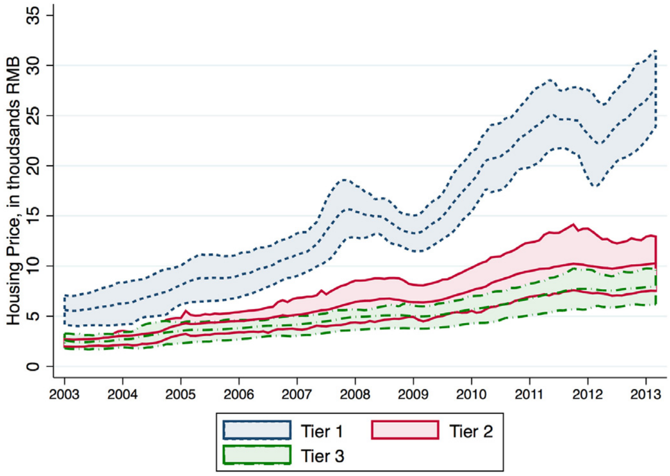

Fig. 1. Monthly average housing price index, 2003–13.
Note: Data come from the urban housing price index of 101 cities in Fang et al. (2016). The housing price index is normalized to 1 in January 2009 for each city.

Fig. 2. Housing price growth, deposit rate, and stock returns, 2003–13.
Note: The figure plots national annual average housing price growth, 1-year deposit rate, and Shanghai Stock Exchange Index returns. The shaded areas for the housing price growth are the inter-quartile range across cities for each year.

last quarter of 2011 in Tier-1 cities, with a corresponding leveling off in Tier-2 and Tier-3 cities. While this provides important variation in housing prices for our empirical model, which is discussed in Section 5, it means that we need to control for city and time effects to distinguish consumption responses from underlying macroeconomic trends.

As documented in Glaeser et al. (2017), these high housing prices have been chased by furious home building that is partially driven by government support. The annual growth of investment in real estate was 30.3% in 2003, and it has remained high since.[7] Chinese developers built 178 billion square feet of residential real estate from 2003 to 2013 (China Statistical Yearbook 2014). Despite this tremendous building and high vacancy rates in some cities, prices have continued to rise, in part because of residual demand from private investment that is searching for higher returns on capital. Whether or not this constitutes a bubble and whether the bubble is rational have been the focus of several papers (Wu et al. 2012, 2016).

A combination of several macroeconomic forces has led to the recent boom of the housing market in China. The Chinese Statistical Yearbook reports that from 2003 to 2012, income per capita has more than doubled in Tier-1 cities and experienced even more growth in Tier-2 and Tier-3 cities. This new wealth has been directed largely to savings rather than consumption for a variety of reasons, including inadequate public medical insurance programs and social security policies (Chamon and Prasad, 2010) and marriage market competition (Wei and Zhang, 2011). Few investment opportunities exist for households because of strict capital controls: savings in banks, the stock market, and the housing market constitute their primary investment options. Savings in bank deposits bear modest returns. Returns for equities are larger but highly volatile. For the past couple of decades, housing in most Chinese households has proven to be the most attractive vehicle for investing savings, as demonstrated by the comparison in Fig. 2.

Another unique feature of the Chinese housing market is the heavy involvement of the public sector, which began in earnest with the inclusion of real estate as a part of the national development strategy in 1998. Local governments are charged with regulating housing markets, including taking actions to insure real estate developers against investment risks.[8] In the aftermath of the global financial crisis of 2007–08, local governments took on close to four trillion RMB in debt to keep local economies stimulated. Much of the debt is repaid from revenues generated by local land sales, which made local land development an important policy instrument during the recovery. Our identification strategy (discussed below) is motivated by this unique feature of local government finances in China.

At the same time, having observed the consequences of housing bubbles in the US, China's central government is keen to keep the market from overheating. In 2006, down payment requirements on mortgages were raised to 30% for households' first homes and 40% for second homes. In 2007, the interest rate on mortgage repayment was raised by 10%, with a 50% cap on the ratio of monthly mortgage payments to income. Since 2010, various other restrictions have been imposed. Beijing, for example, raised the down payment to 50% for second homes. Finally, by law, current houses cannot be used as collateral for future home loans, making housing a far less liquid asset than in the US or EU. All of these factors have led to heavy financial burdens on households hoping to buy a home. Previous evidence from Singapore suggests that when restrictions limit the liquidity of existing housing assets, this can mitigate collateral effects and have negative impacts on non-housing consumption (Agarwal and Qian 2017).

We plot changes in log housing price against changes in log spending from 2011 to 2013 in Fig. 3. The red lines denote zero change over the period. A large number of cities (especially Tier-1 and Tier-2 cities) appear in the lower right quadrant, indicating that they experienced a substantial growth in housing prices but a reduction in consumer spending.[9] We investigate the relationship between housing price growth and consumption in Section 6 via formal econometric analysis. In the following section, we use a theoretical model to illustrate the mechanisms that lie behind this relationship.

[7] The annual growth of investment in real estate was 25% on average from 2003 to 2007, according to the China Statistical Yearbook (2007).

[8] This has fueled a common perception in China that housing prices are backed by the government and, thus, are unlikely to fall (Song and Xiong 2018). An added dimension to this phenomenon is that this policy is largely reactionary, resulting in uncertainty in the housing market about when and how far future government actions will occur (Zheng et al. 2016).

[9] The figure excludes two cities, Taizhou and Chengde, which experienced greater than 50% increases in housing prices during the sample period. To isolate the overall effects of this relationship in our sample these two Tier-3 cities are excluded from the subsequent analysis, but our results are not meaningfully affected by their inclusion.

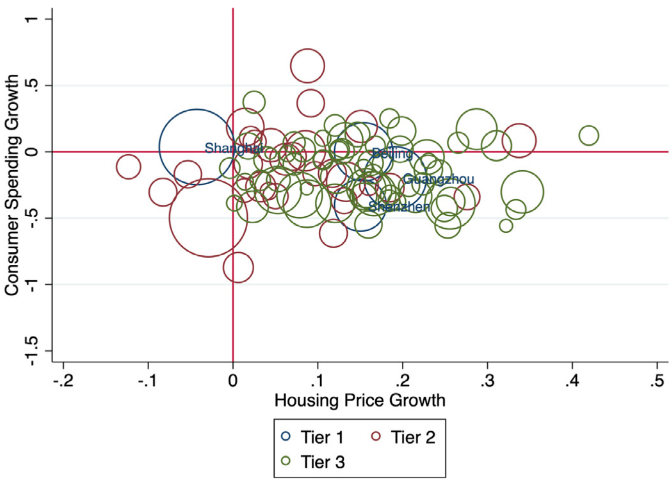

Fig. 3. Consumer spending growth versus housing price growth, 2011–13. *Note*: The figure plots changes in log consumer spending versus housing price by city over 2011–13 by three city tiers. "Log consumer spending" is the residual of the log of consumer spending regressed on a linear time trend. Circle size of each dot corresponds to the population size of each city.

3. An intertemporal model of home prices and consumption

Here we develop a partial equilibrium model of household consumption to illustrate possible channels for consumption responses to housing price changes.[10] The driving mechanism for our theoretical results are binding borrowing constraints that are expected to tighten over time due to stricter regulations on lending. The rationale for this mechanism, as discussed in Section 2, comes from the fact that it is illegal to use current housing assets as collateral for new home purchases. Mortgages in China are limited to a fixed proportion of income by law, and this proportion has been falling over time. This makes the framing of our theoretical model distinct from traditional treatments of borrowing constraints in the US and EU. We illustrate these effects and their relation to standard income and substitution effects via a version of a Slutsky decomposition applied to an intertemporal model of housing and non-housing consumption. The main result of the model suggests that households will reallocate greater housing consumption to the present in the face of permanent price increases and tightening borrowing constraints. While this constitutes an important mechanism for the patterns documented in our empirical results, we readily acknowledge that there are alternative explanations, some of which we explore in Section 6.

That said, our framework can accommodate some of these alternative explanations for consumption reductions. For example, while our model focuses on long-term price adjustments from one steady state to another, one can interpret our result as composed of short time periods during which borrowing constrained households save cash to cover the downpayment for their large housing investments. Another alternative explanation for our results are adjustment costs, which could also result in reallocation of housing accumulation towards the present. However, the suggestive evidence reported in Section 7.1 indicates that consumption reductions seem to be driven by renters rather than homeowners, so adjustment costs that are relevant for home owners may not be the main driver of our results. That said, we use our theoretical framework to fix ideas and acknowledge that consumption adjustment in reality is much more complicated with many potential explanations.

[10] The full intertemporal household utility maximization model and the derivation of its comparative statics are presented in Appendix A.

3.1. Model setup

We consider the household's utility maximization problem when housing and consumer goods are traded in competitive markets. In this model, household i maximizes utility by choosing non-housing consumption, c_t, and housing services, h_t, for each period t, subject to an inter-temporal budget constraint. The temporal dimension of the model captures the deviations from steady-state housing price levels by aggregating total price growth over the period into a single, permanent price change: dP. This framing may overstate the effects of housing price increases over short periods of time such as the monthly data considered in our empirical analysis. It also abstracts from short-run behavioral responses to expectations of future housing price increases. Additionally, borrowing constraints, which are important in explaining the key result of the model, are assumed to go up in every year of the model, whereas, in reality, they may go up in fits and starts. Nevertheless, the model provides a useful framework for understanding channels of consumption responses to housing price changes.

The price of non-housing consumption is normalized to one. The market price of a unit of housing is P_t. Expenditure on housing services at period t is denoted as $P_t h_t$. Because housing assets are durable, housing purchase at period t is valued at $P_{t+1} h_t$ in period $t+1$, which comprises part of the household's wealth in the same period. The rental rate of housing consumption, R_t, can be written in terms of the discounted difference in the housing price net of depreciation:

$$R_t = P_t - \frac{1-\delta}{1+r} P_{t+1},$$

where δ is depreciation and r is the discount rate.

3.2. Intertemporal utility maximization

An infinitely-lived representative household is faced with the following intertemporal utility maximization problem[11]:

$$\max_{\{c_t, h_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} U(c_t, h_t)$$
$$\text{s.t.} \quad \sum_{t=0}^{\infty} \frac{1}{(1+r)^t}(c_t + R_t h_t) = I$$
$$(1+m_t)y_t + (1-\delta)P_t h_{t-1} \geq (1+r)m_{t-1}y_{t-1} + c_t + P_t h_t,\ t = 1, 2, \ldots \quad (1)$$

where the first constraint requires the present discounted value of lifetime consumption from housing services and non-housing consumption to equate to permanent income I. We denote the Lagrange multiplier on this constraint as λ.

In the second constraint, y_t is exogenous labor income and m_t denotes the share of wage income the household may borrow during that period. $m_t y_t$ represents all the household can borrow to pay for housing during period t and m_t is set by the Chinese government in period t. $(1+m_t)y_t$ denotes period t's income plus borrowing. $(1-\delta)P_t h_{t-1}$ is the value of housing assets, and $(1+r)m_{t-1}y_{t-1}$ is repayment of the previous period's debt. The second constraint limits consumption in each period to wage income, borrowing, and the value of housing assets less repayment of the previous period's debt. The Lagrange multiplier on the second constraint (the shadow value of each period's borrowing constraint) is denoted as γ_t. This second constraint may or may not be binding depending upon a household's financial position.

Households in our model expect the borrowing constraint (the second constraint) to be more stringent over time because of the tightening of mortgage regulations discussed in Section 2. In our model, this is represented by the assumption of strict monotonicity of the borrowing limit

[11] For simplicity, we assume that households discount future utilities at the market interest rate, although it is straightforward to have the rate of time preference be different from the interest rate.

over time, $m_{t+1} < m_t$, which in turn means that $\gamma_{t+1} > \gamma_t$ from (1). This assumption, while strong, approximates the policy environment in urban China for the period considered. For example, in Beijing, the down payment requirement for second homes was raised from 30% in 2006 to 40% in 2007 and to 50% in 2010. The annual interest rate on mortgage repayment was raised five times in 2007 from 6.4% to 7.3%, and the monthly mortgage payment-to-income ratio was capped at 50%. In 2010, it was made explicit that no mortgage would be granted to buyers of third properties.

If the second constraint in Eq. (1) is non-binding, then households are able to fully draw on their existing assets to purchase homes both for the purpose of housing services and as investments. In this case, there may be full consumption smoothing, which is consistent with the classical Permanent Income Hypothesis model. Moreover, as shown in Appendix A, any permanent price increase in housing will both increase the value of the housing asset and the cost of future housing services. The attendant effect is that there is no change in consumption as a result of housing price increases, as in Sinai and Souleles (2005).

If, however, the second constraint in Eq. (1) is binding, then households may not be able to choose the bundle of consumption and housing that they would have preferred in the absence of borrowing constraints. In other words, households are constrained to purchase housing based on a limited amount of liquidity. Note that the borrowing constraint is different from the collateral constraints common in the US and EU markets (*inter alia*, Attanasio et al. 2011). In that literature, borrowing is tied to the value of household asset holdings rather than limited to a fixed share of income. Therefore, housing price increases could raise a household's liquidity as the value of pre-existent asset holdings rises. In our context, for a variety of reasons (e.g., lack of alternative investment opportunities, high housing price to income ratios), when housing prices increase, households may be forced to direct a large proportion of their savings towards housing rather than non-housing consumption. Below we show that when the budget constraint is binding for every period, households will spend more of their income on housing than on non-housing consumption when housing prices increase.

To simplify the exposition, we model housing price increases as occurring in a single period. This can be thought of as a single permanent deviation from a steady state where housing prices (and therefore rents) are constant over time: $P_t = P$.[12] In reality, housing prices go up continuously over time. Hence one should interpret the single price change dP in the model as representing the sum of price changes over time dP_t. With a Cobb–Douglas utility function $U(c_t, h_t) = c_t^{\alpha} h_t^{1-\alpha}$, it is easy to show that the first order conditions for optimal consumption are simplified to:

$$\frac{c_t}{Rh_t} = \frac{\alpha}{1-\alpha}\left[1 + \frac{(1-\delta)(\gamma_t - \gamma_{t+1})}{(r+\delta)\left(\lambda + \gamma_t\right)}\right], \tag{2}$$

where λ is the Lagrange multiplier on the first constraint that is related to lifetime income in Eq. (1) and γ_t is the Lagrange multiplier on the second constraint. Because the borrowing limits are expected to tighten with each successive period, we have that $\gamma_t < \gamma_{t+1}$.

If households are borrowing-constrained, the share of expenditures on consumption relative to housing in each period reflects changes in the tightness of the borrowing constraint relative to the shadow value of each constraint. On the other hand, if the borrowing constraint in Eq. (1) does not bind, the household will choose constant levels of housing and non-housing consumption, h and c, as can be intuited from Eq. (2)[13]:

$$\frac{c}{Rh} = \frac{\alpha}{1-\alpha}.$$

[12] This implies that $R_t = R = \left(1 - \frac{1}{1+r}(1-\delta)\right)P$.

[13] We prove this formally in Appendix A.

We frame our analysis below by comparing the behavior of a borrowing-constrained household to one for which this constraint does not bind. It is worth bearing in mind that while in reality both types of households exist, in the representative agent model considered here, we do not explicitly account for heterogeneity in endowments or preferences and so the comparison between these two types of households occurs across alternative states of the world. In the discussion below on how consumption responds to housing price changes, we use the perfectly smoothed level of housing asset accumulation from the unconstrained household, h, as a reference point for the constrained household's housing accumulation in each period, h_t.

3.3. Assumptions

Several assumptions are implicit in the model presented above. First, we assume that returns on non-housing assets evolve independently of household income, housing prices, and consumption. This assumption allows us to model the household's inter-temporal utility maximization problem over housing and non-housing consumption independently of non-housing investment choices. It is straightforward to incorporate the full portfolio choice problem into this framework, for which the additional choice of investment in other assets arises. While this margin is generally important, we abstract from it in this simple model because holdings of non-housing assets are negligible for most households in China, as discussed in Section 2. We also assume that borrowing limits (m_t) decrease over time and are set exogenously by the government.[14]

Second, we assume that the form of utility is such that the problem below results in interior solutions in each period so that $c_t > 0, h_t > 0, \forall t$. This means that households consume and hold some housing in their portfolio in each period. We relax this assumption in Section 3.4, when we extend the model to renters. Income is assumed to evolve in a deterministic manner, ignoring the important fact that, in reality, households save in part to insure against income uncertainty. In addition, we abstract from modeling supply side adjustments and assume that housing supply is elastic so that housing prices are bounded above (and do not approach infinity).

As discussed in Section 2 and shown in Fig. 2, returns from housing are high relative to alternative investment options. We assume that households have perfect foresight and do not face uncertainty in predicting future price movements.

3.4. Consumption responses to housing prices

To motivate our empirical framework, we decompose consumption responses for the constrained home buyer where the second constraint in Eq. (1) binds. The derivations below reflect the fact that a permanent change in house prices affects the relative price of housing services, the available income for non-housing services, the wealth of households from housing, and the shadow cost of future housing investments. We decompose responses into four effects and show how differential investment incentives for constrained households can lead to a deviation from perfect consumption smoothing.

Fixing utility at an initial level U, we describe the response of consumption to a permanent change in P using a Slutsky decomposition (where superscripts on consumption reflect either compensated (H for Hicksian) or uncompensated (M for Marshallian) demand):

$$\begin{aligned}\frac{dc_t^M(R,U)}{dP} &= \frac{\partial c_t^H(R,U)}{\partial P} - \frac{\partial c_t^M(R,I)}{\partial I}\frac{\partial I}{\partial P} \\ &= \underbrace{\left[\frac{r+\delta}{1+r}\right]\frac{\partial c_t^H(R,U)}{\partial R}}_{\text{substitution effect}} - \underbrace{\left[\frac{r+\delta}{1+r}\right]\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty}\frac{1}{(1+r)^t}h}_{\text{income effect}}\end{aligned}$$

[14] In reality, the Chinese government changes borrowing limits to stabilize the housing market. As a result, housing demand, housing prices and borrowing limits might respond to each other over time.

$$+\underbrace{\frac{\partial c_t^M(R,I)}{\partial I}(1-\delta)h_{-1}}_{\text{endowment effect}}$$
$$-\underbrace{\left[\frac{r+\delta}{1+r}\right]\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty}\left[\frac{1}{(1+r)^t}\left(h_t-h\right)\right]}_{\text{investment effect}}, \tag{3}$$

which has four principal effects. The first two are the standard income and substitution effects. The third, the endowment effect, incorporates changes in consumption that are driven by increases in housing wealth and depends on the level of the initial housing endowment, h_{-1}. This endowment effect features prominently in the US and EU when rising housing prices increase households' wealth and borrowing power and become a major driver of consumption increases. As discussed in Section 2, Chinese laws that prevent the use of existing housing as collateral severely limit the endowment effect in our case. These first three effects form the basis of the theoretical model in Berger et al. (2017) who provide a framework for empirical measurement of the marginal propensity to consume.

Finally, the investment effect, a novel component of our model, captures decreases in consumption that help to finance the present value of deviations in housing asset accumulation $(h_t - h)$ relative to the fully smoothed, unconstrained case. This component highlights the impact of tightening borrowing conditions on consumption. As shown in Lemma 1 in A.2, there is a direct relationship between changes in the level of borrowing limits, $m_{t+1} < m_t$, the tightening of the borrowing constraint, $\gamma_t < \gamma_{t+1}$, and the extent to which h_t is greater than h, which can be derived directly from the model's first order conditions. Therefore, while the expression for the investment effect does not explicitly include the borrowing limit, m_t, an increase in m_t loosens borrowing constraints and, therefore, decreases $\sum_{t=0}^{\infty}\frac{1}{1+r}\left(h_t-h\right)$.

It may seem curious that an increase in the price of a good would result in an increase in expenditure on that good for a borrowing-constrained household. This counter-intuitive result arises from the fact that with a permanent housing price increase and tightening budget constraints $\gamma_{t+1} > \gamma_t$, it is more burdensome to increase housing holdings in the future. As a result, households accumulate more housing assets in period *t*. In order to pay for this higher amount of housing, the household has to pull resources away from non-housing consumption.

3.5. Empirical predictions from the theoretical model

The theoretical model presented above describes one channel by which housing price increases may translate into non-housing consumption reductions in urban China. While the framework is not intended to perfectly describe reality in terms of all potential margins of adjustment and heterogeneity, it explains why several unique features of Chinese housing markets (no collateral channel, tightening borrowing constraints, and a lack of alternative household investment instruments), that are distinct from the US, might generate a different response. The model predicts that housing price increases will serve to shift the accumulation of housing assets toward the present which can generate decreases in contemporaneous non-housing consumption. In the short-run, this could reflect an increase in cash savings in order to pay for faster housing accumulation. It may also imply that renters and younger households (who have accumulated less or no housing assets to date) reduce consumption by more as they have a stronger incentive to speed up housing accumulation. Intuitively, borrowing-constrained consumers have to save more to finance the down payment. As the only way to save in our model is through housing assets, constrained households end up with more housing assets than unconstrained consumers.

Therefore, excess housing demand of borrowing-constrained households creates an additional force that lowers consumption. But is this force sufficient to dominate the other three? As the following Proposition states, the consumption response to a permanent house price increase can be shown to be negative when income and substitution effects cancel each other out and when the endowment effect is sufficiently small relative to the investment effect.

Proposition. *In a model with borrowing constraints, a household's non-housing consumption response to a permanent house price increase is negative if the value of the endowed housing asset* (h_{-1}) *is not sufficient to pay for the present discounted value of the entire stream of additional housing investments:* $\sum_{t=0}^{\infty}\frac{1}{(1+r)^t}R\left(h_t-h\right)$.

Proof. See Appendix A.2. □

An implication of this proposition is that while the lack of a collateral mechanism in China prevents households from borrowing against existing housing assets, it is the value of the initial housing endowment, which defines the available resources households have for additional housing investments above the unconstrained level. The following corollary connects the negative consumption response to the extent of tightening borrowing constraints.

Corollary. *Households facing tighter borrowing constraints over time may be expected to respond with greater consumption reductions.*

Proof. See Appendix A.4. □

This corollary provides the result that borrowing constrained households will want to consume more housing than they would have without constraints because it will be harder to borrow in the future. This result is useful when considering heterogeneity in household resources that may affect initial levels of housing, so that their current level of wealth and borrowing ability is limited.

Is this result likely to hold in urban China? The use of the Cobb–Douglas preferences (where income and substitution effects cancel each other out by construction) has been justified for the US based on micro-level evidence of an elasticity of substitution between durable and non-durable consumption close to one (Piazzesi et al. 2007, Davis and Ortalo-Magné 2011). We are not aware of studies that identify this elasticity in urban China, but an elasticity close to unity would seem plausible. Therefore, whether consumption responses to housing price increases are positive or negative depends on whether endowment effects outweigh investment effects, which is an empirical question we explore below. However, it is likely that investment effects dominate more in China than in the US or EU because existing housing assets in China cannot be used as collateral, and so their appreciation might be not be expected to drive consumption increases. The upshot of this is that housing price increases incentivize a bigger holding of housing assets, but this cannot be financed using collateral on current housing assets, and so, to the extent that households are borrowing-constrained, we may expect consumption reductions as a result. While our city-level data do not allow us to measure the exact fraction of households that are borrowing-constrained in urban China, our empirical results below provide suggestive evidence that it is non-negligible.

3.6. Life-cycle effects

Under a number of scenarios we may expect to see variations in the responses described above that are relevant to the empirical analysis below.[15] First, consumption responses to permanent housing price increases may vary over a household's life cycle. In a finite horizon version of our model with overlapping generations (A.3), we show that consumption responses can still be decomposed into the effects described above. We identify two mechanisms that vary among households over the life cycle that can mediate consumption responses: the level of a household's income and the relative magnitude of investment and endowment effects. The first mechanism simply reflects the fact that with

[15] We are thankful to the editor and an anonymous reviewer for pointing out the importance of this variation.

a lower income, younger households may have to curtail consumption more in the face of tightening borrowing constraints. The second mechanism reflects the fact that if bequested wealth has not yet been inherited, the endowment effect will likely be much smaller. We present suggestive evidence for this in Section 7.2.

3.7. Housing tenure

Second, current homeowners may respond differently to housing price increases relative to renters. In the model, consideration of home purchase at time t means that a renter would have holdings $h_{t-1} = 0$, while for a pre-existing homeowner they would be positive.[16] This would be possible if the optimal choice in period $t-1$ (and potentially prior) is a corner solution. Because asset holdings in our model are only comprised of housing, renters have no wealth beyond savings, and so the wealth equation for renters excludes period $t-1$ housing assets.[17]

As we demonstrate in A.5, if a renter does not have adequate savings, then a lack of housing assets could imply a more tightly binding borrowing constraint.[18] A related issue for renters may be the lack of sufficiently small units. A renter with binding borrowing constraints may wish to purchase a small quantity of housing, but there may not be units small enough for them to purchase. This would, again, likely make endowment effects smaller for renters and increase the magnitude of consumption reductions.

3.8. Adjustment costs

Homeowners might incur adjustment costs when changing their housing asset position. In Appendix A.6, we reformulate our model by incorporating adjustment costs that can reflect transaction costs, nonvariable costs of renovation, or moving costs. In the case of adjustment costs, it can be optimal for changes in housing asset accumulation to be zero in certain periods. Moreover, younger households may attempt to consume more housing earlier in the lifecycle to minimize adjustment costs in the future.

A point relevant for the empirical analysis presented below is that adjustment costs represent an additional burden for the budget of a household and therefore make the borrowing constraint more likely to be binding. While we do not observe adjustment costs or borrowing constraints, in Section 7.1 we show differential effects between likely homeowners and likely renters that are consistent with borrowing constraints instead of adjustment costs as the key driver of our results.

4. Data description

Our main econometric analysis utilizes a panel dataset of 101 Chinese cities at the monthly level over 2011–13. This panel is primarily constructed from two data sources: (1) the Constant Quality Housing Price Index developed by Fang et al. (2016); and (2) UnionPay credit and debit card transaction data. Because there are comparatively few repeat sales in the Chinese housing market, the Constant Quality Housing Price Index adjusts for quality variation in new houses by using sequential sales of new units in the same development.[19]

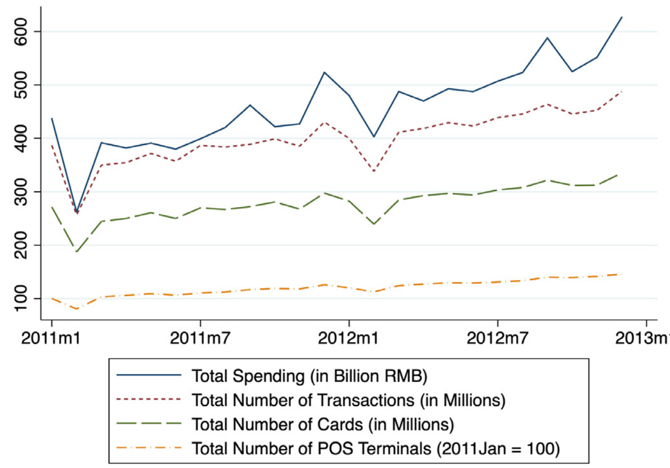

Fig. 4. UnionPay Data, 2011–13.
Note: This figure plots total consumption expenditure (“Total Spending”), the number of transactions (“Total Number of Transactions”), the number of cards in use (“Total Number of Cards”), and the number of Point of Sale (POS) terminals across all cities at the monthly level over 2011–13. The number of POS terminals is calculated from a 1% random card sample, and normalized to 100 in January 2011.

We obtained the universe of credit and debit card (bank card) transaction data from UnionPay and use it to measure consumer spending. UnionPay is the only interbank payment network in China. It intermediates all credit and debit card transactions, which account for more than 48% of national expenditures in 2015 (People’s Bank of China, 2015). The database covers transactions from 2.7 billion cards over 300 merchant categories.[20] Each observation records the location, time, and value of the transaction. We aggregate the data to the city-merchant category-month level. An important advantage of our data over consumer expenditure surveys is that transactions reflect real-time purchases as opposed to respondents’ recollection of their spending. Relevant to our procedure is Koijen et al. (2014), who examine observed auto sales data to document the extent of under-reporting from household expenditure surveys.

We summarize the key variables in Table 1, which yields a few useful observations. Housing prices, as measured by the index, vary considerably between 0.96 and 2.45. Monthly government revenue exhibits a large dispersion as well, between 0.08 and 43.3 billion RMB. There are on average 4.01 million transactions in our consumption data in a city-month, which corresponds to 4.61 billion RMB in non-housing expenditures. Cash withdrawals comprise a quarter of total non-housing consumption in UnionPay, and for this reason, we pay particular attention to the response of cash withdrawals in our results below. Fig. 4 shows steady growth in spending, the number of transactions, the number of cards and the number of Point of Sale terminals over 2011–13. Dips in the first quarter of each year correspond to the lunar new year holiday period. Finally, it is worth noting that although our theoretical model examines consumption responses to housing prices, our data are actually expenditures. As noted by Becker (1965), consumption reflects the output of household production that includes both expenditures and time inputs. Although our approach is widely used in the housing-macroeconomics literature, it implicitly ignores the role of time inputs.

We exclude wholesale and government expenditures and divide the remaining private spending categories into seven groups of expenditure:

[16] In Appendix, we show this for an finite-lived, overlapping-generation version of the model in which homeownership can be constrained by the combination of borrowing constraints and limited bequests.

[17] The exact formulation of the wealth equation for renters can be found in the Appendix.

[18] If households were able to borrow against current housing assets then this might loosen borrowing constraints, but as discussed above, this is not possible in China.

[19] That this index is a good metric for housing price variation relies largely on the assumption that within development, i.e., a complex, unobserved attributes do not vary in a meaningful way. We use the 101 Chinese cities in our sample that fall into the first three tiers, where this assumption is likely to hold. As noted earlier, we have removed two cities, Changde and Taizhou, from our sample, because of extreme housing price spikes.

[20] Merchant categories describe the principal goods or services provided by the seller. Examples include “Silverware shop,” “Bookstore,” and “Bakery.”

Table 1
Summary statistics.

Variable	Mean	SD	Min.	Max.
Constant Quality House Price Index	1.53	0.2	0.96	2.45
Standard Deviation of Elevation	0.17	0.17	0.002	1
Monthly Government Revenue (Billion RMB)	2.81	4.59	0.08	43.34
Saving Deposits (Billion RMB)	315.87	379.42	26.15	2229.86
Per Capita Disposable Income (RMB)	2102.66	855.42	698.97	11195.67
Cumulative Land Sales (in 1000 km^2)	0.01	0.01	0	0.07
Total Non-Housing Consumption (Billion RMB)	4.61	8.44	0.13	74.01
Total Number of Transactions (Million)	4.01	7.57	0.11	54.11
Number of Cards (Million)	2.8	5.34	0.08	39.7
Number of POS Terminals (10,000)	1.1	1.74	0.03	14.38
Cash Withdrawals (Billion RMB)	1.00	1.67	0.04	10.72

Note: All variables are at the city-month level. Units of the variables in the summary statistics are the same as those used in the regressions. “Total Number of Transactions” includes cash withdrawals. “Per capita Disposable Income” is household income after taxes at the monthly level reported quarterly. “Cumulative Land Sales” (1000 km^2) are calculated using land sold after January 2008. “Number of POS Terminals” is calculated using a 1% random card sample.

travel and restaurant, daily goods, automobile, supermarket, health, cash withdrawals, and others.[21] As noted in the household consumption literature, there is an inherent trade-off in using transaction-level data (such as scanner data or card transactions) and consumer expenditure surveys. The latter suffer from recall biases and sampling errors, whereas the former may not provide a representative sample of expenditures for households as a whole. In Appendix Table D.2, we assess the representativeness of our expenditure categories. To do this we compare shares in our data to those reported by the National Bureau of Statistics’ (NBS) Total Retail Sales of Consumer Goods.[22] While our categories are overall comparable to those in NBS, a few discrepancies are worth mentioning. Grocery and supermarket expenditures have a substantially larger share of purchases in our data, partly because supermarkets in China sell consumer durables and electronics in addition to groceries. This makes inference of categorical spending complicated, which is reflected in our discussions of heterogeneous consumption responses across categories in Section 6.1.

It is important to note that despite the general correspondence of expenditure category shares to national sales data and the growing penetration of UnionPay in urban China, our data do not represent the full universe of all transactions by urban households in China. It is likely that a non-negligible share of households spend a portion of their disposable income in cash. We observe and include cash withdrawals in our consumption data to maximize our coverage of private consumption.

Additional data used in our analysis include quarterly disposable income per capita, quarterly gross domestic product for each prefecture level city, land sales transaction volumes, and monthly bank savings deposits that are compiled from the National and City Bureau of Statistics and are available via the CEIC online database.[23] We also incorporate data on the age structure of city residents and the fraction of individuals who have residency permits (*Hukou*) – information that we gather from the 2005 National Census. The average number of rooms per household is compiled from the 2010 China Statistical Yearbook and the 2015 National Census. Data on firms come from the State Administration for Industry and Commerce. Tertiary sector data are from the census of new firm registrations compiled by the Chinese Ministry of Commerce. Data on topographical information and local government revenues come from each city’s Municipal Bureau of Statistics.

5. Econometric framework

We now present our empirical framework to estimate consumption responses to house price increases in urban China outlined in our model in Section 3. As discussed in that section, when households are borrowing constrained, they may be expected to reduce non-housing consumption in the face of housing price increases. We apply an econometric model across cities to test the predictions of the model. In our main specification, we regress the logarithm of total non-housing expenditures for city i in month t, c_{it}, on the logarithm of the monthly housing price index, p_{it}, and additional controls:

$$log(c_{it}) = \beta_1 \log(p_{it}) + X'_{it}\beta_2 + \eta_t + u_i + \epsilon_{it}, \quad (4)$$

where η_t is a year × month fixed effect, u_i is a city fixed effect, and ϵ_{it} is the error term. X_{it} includes the number of cards and sales terminals to control for the increasing penetration of bank cards during our sample period and a set of macroeconomic variables, including the city’s disposable income per capita. It also includes the logarithm of contemporaneous monthly local government revenue, which reflects the fact that local fiscal activity may have a direct effect on consumption. Controlling for contemporary effects of government revenue is important in our IV regressions, which try to isolate the effect of land supply on housing prices.

Behavior consistent with Section 3 would suggest $\beta_1 < 0$. The explanation posited there was that consumption reductions in the face of tightening future borrowing constraints result in a reallocation of housing accumulation from the future to the present at the expense of current non-housing consumption. Without a direct measurement of housing accumulation in our data, the empirical model in (4) does not directly account for changes in housing assets, but measures the reduced-form relationship between consumption and housing prices. In practice, a number of alternative mechanisms (savings in liquid assets such as cash rather than housing assets, adjustment costs, etc.) could also explain the value of β_1, and we explore these possibilities in Section 7 below.

The empirical analysis also departs from the theory in its treatment of time, where the former considers short-run (monthly) responses of consumption to housing prices rather than long-run changes, as in the

[21] The Travel and Restaurant category contains hotel, restaurant, entertainment, and travel expenditures. The automobile category contains automobile sales and repairs. Daily Goods include purchases of household staples. The supermarket category contains supermarket and department stores, which are grouped together because Chinese supermarkets often sell large durables and non-grocery consumer goods. The health category contains pharmacy and clinics and public hospitals. Cash Withdrawals contains ATM and bank counter withdrawals. Others include charity and social work expenditures.

[22] We reclassify categories reported in Total Retail Sales into the same six categories, according to the United Nations’ Classification of Individual Consumption According to Purpose (COICOP).

[23] The CEIC Data Company Ltd. provides an online subscription database that includes financial time series data in emerging market and developing countries. These data include prefecture city-level data on output, income, government finance, and consumer price indices. Disposable income is defined as total household income after taxes.

latter. That said, in order to capture potential lags in households' perception of housing price changes that evolve over time in a manner analogous to the aggregation of short-term price increases into a single *dP* as in Section 3, we use the average of the price index for a city during the preceding three months. In Appendix Tables D.3 and D.4, we confirm the robustness of this assumption and document a slight attenuation of our estimates with the use of earlier housing prices to construct our variable of interest. β_1 in Eq. (4), the coefficient of interest, is the elasticity of urban household consumption with respect to housing prices. As shown in Section 3, this elasticity captures substitution, income, endowment, and investment effects, all of which determine how household consumption responds to housing price changes.

5.1. Identification strategy

Identification of β_1 in Eq. (4) requires that $Cov[\epsilon_{it}, \log(p_{it})] = 0$. This condition will not hold if city-level consumption responds to time-varying demand factors that are correlated with housing prices not included in our covariates nor partialed out by our fixed effects. For example, consider the discovery of a silver mine in one municipality, which would not be directly observed in our data. As land becomes more valuable, local housing prices rise. If wages paid to miners and investments in local infrastructure rise, so would consumption. This effect would result in a positive correlation between the error term and housing prices, which would lead to an upward bias in the estimate of β_1. In basic terms, we are measuring the effects that changes of price in the housing market have on expenditures for non-housing goods, both of which reflect patterns of aggregate demand. Because this source of endogeneity arises via shifters in aggregate demand, we need an instrumental variable (IV) that captures supply-side shocks to the housing market.[24]

Our IV strategy therefore relies on exogenous shifts in housing supply that come from land markets to identify variation in housing prices. This instrument set takes advantage of three factors likely to affect the extent of a housing supply shift: volumes of land sales, the value of these land sales (as measured by changes in government revenue), and the cost of building on marginal units of land as reflected by variation in urban topography. Our first instrument for housing prices measures the volume in square meters of lagged cumulative local land sales for residential and all-purpose uses. Land sales increase the supply of land, which, in turn, would be expected to increase the supply of housing. For our IV strategy to be valid, changes in lagged land sales must be uncorrelated with unobserved determinants of contemporaneous consumption changes. In the US, this assumption would seem hard to defend given that increases in demand (from, say, population increases) increase housing prices, which, in turn, incentivize greater land sales for further development. In China, we do not believe this concern is warranted, and we now provide evidence for the assumption that lagged land sales are a valid instrument for housing prices in China. While we do not account for the adjustment of housing supply in the theoretical model presented in Section 3, our instrument helps to capture the extent to which variation in prices arising from changes in government land sales results in non-housing consumption reductions.

All land in China is owned by the central government, but local governments are authorized to sell usufructuary leases for up to 70 years. Real estate on developed land can then be resold in a secondary market (*tudi zhuanrang*) as residential or commercial property (Ho and Lin 2003). This means that expansion in the supply of land responds to local government policy agendas and fiscal incentives rather than directly to anticipated housing demand. Indeed, as demonstrated by Han and Kung (2015), there is clear evidence that as the central government took over authority of business taxation prior to the period we study, local governments increasingly shifted towards local land sales as the primary revenue source. To relieve heavy debt burdens incurred during the financial crisis, local governments leased away large quantities of land to developers, which comprised approximately 40% of their fiscal revenues (Wu 2015). As a result, past land supply is arguably uncorrelated with unobserved consumption shocks.[25] To address any remaining concerns about potential demand shocks, we include contemporaneous government revenue in our regressions, which would, in principle, account for correlation between, say, taxation and public good provision and consumer spending.

Appendix Fig. C.1 plots the relationship between land sales, government revenue, and housing prices for a few Tier 1 and 2 cities during our sample period. These figures demonstrate variation in the extent of land sales across cities, with a dramatic increase in Chongqing and less of an expansion in Guangzhou. Generally, land sales correspond to an increase in government revenues, although there is variation in how closely these two series move together.

As a second instrumental variable, we use lagged local government revenue interacted with a measure of land topography. Our topographical measure provides an indication of variability of elevation in an urban area. While this is not a measure of developable land or construction costs, it does serve as a proxy for the relative cost of developing the marginal unit of land. As shown in Panel A of Table 2, this instrument is positively correlated with housing prices. One might be concerned about the validity of this measure given that in the US, there is evidence that lower land availability is correlated with high housing demand in areas with growing incomes (Davidoff et al. 2016). The correlation with amenities in China is less clear. Consider, Urumqi, which has a great deal of developable land and relatively limited amenities (it is in the desert), but as shown in Appendix Fig. C.3, it has the most topographical variation in our data because it is flanked by mountains. In addition, sorting between cities based on amenities is slower in China than in the US because residency permit restrictions (*Hukou*) significantly limit mobility (Ngai et al. 2016).

Nevertheless, we test the hypothesis that amenity-based sorting undermines the topography instrument by considering potential impacts of the growth of the service sector. Services have been a driver of income growth in many cities that have a high variation in topography. If the correlation of tertiary sector growth with housing prices was a threat to the validity of our topography instrument, we might expect it to affect the sign of housing prices when included in our baseline regression. We include tertiary sector growth as an additional control in our analysis in Table 7 and find no meaningful effect on our results.[26]

The argument for the validity of lagged local government revenue is similar to that for land sales because we expect it to be driven by repayment of accumulated government debt during the period studied. However, these instruments are not perfectly correlated because local government revenue contains variations that are independent of land

[24] An important limitation to IV approaches in the current context pointed out by Piazzesi and Schneider (2016) is worth reiterating. While accounting for simultaneity and omitted variable bias is crucial, the relationship between consumption and housing prices reflects general equilibrium (GE) adjustments between the price of housing, other consumption goods, and interest rates. The use of an IV strategy effectively purges these GE effects from the estimates, which limits their applicability for policy or welfare analysis, but it results in partial equilibrium estimates that are valid.

[25] If debt was accumulated from past public spending that is correlated with contemporaneous consumption (e.g., via infrastructure), this would suggest that the negative consumption responses documented below may even be smaller in magnitude than the true effect because the positive correlation between land sales, unobserved infrastructure and consumption would bias our negative estimates upwards.

[26] Tertiary sector firms are those with principle operations in Wholesale and Retail; Transportation, Storage, and Postal Service; Lodging and Catering; Information Transfer, Software, and IT; Finance; Real Estate; Rental and Commercial Service; Scientific Research; Water, Environment and Public Infrastructure Management; Residential Service, Maintenance, and other service; Education; Health and Social work; Cultural, Sport and Entertainment; and Public Management, Social Security, and Organizations.

Table 2
The impact of housing price on consumer spending.

Panel A: First stage Dependent variable: log (Housing price)	I	II (IV 1)	III (IV 2)	IV (All IVs)
Land Sales (in 1000 km^2)		−5.27***		−2.99**
		(1.21)		(1.31)
S.D. of Elevation × Lagged Government Revenue			0.08***	0.07**
			(0.03)	(0.03)
Lagged Govt. Revenue			−0.05***	−0.04***
			(0.01)	(0.01)
log(No. of Cards)		0.06*	0.04	0.03
		(0.04)	(0.04)	(0.04)
log(No. of POS Terminals)		0.01	−0.00	−0.00
		(0.02)	(0.02)	(0.02)
log(Income per capita)		0.01	0.02	0.01
		(0.01)	(0.01)	(0.01)
log(Government Revenue)		0.01***	0.01**	0.01***
		(0.00)	(0.00)	(0.00)
Observations		2397	2397	2397
First Stage F-stat		18.83	18.29	12.58
Panel B: Second Stage	OLS	Land Sales	Slope × GovtRev	All IVs
Dependent Variable: log(Total Spending)		(in 1000 km^2)		
log(Housing Price)	−0.14*	−0.90**	−0.62***	−0.73***
	(0.08)	(0.43)	(0.21)	(0.26)
log(No. of Cards)	0.92***	0.99***	0.97***	0.98***
	(0.08)	(0.10)	(0.08)	(0.09)
log(No. of POS Terminals)	−0.02	−0.00	−0.01	−0.00
	(0.02)	(0.03)	(0.03)	(0.03)
log(Income per capita)	0.03*	0.04	0.04*	0.04
	(0.02)	(0.02)	(0.02)	(0.02)
log(Government Revenue)	0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2397	2397	2397	2397
First Stage F-stat		18.83	18.29	12.58
Over-identification Test (p-value)			0.33	0.49

Note: All specifications include city and year × month fixed effects. Standard errors are clustered at the city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. "First-Stage F stat" is the Kleibergen–Paap F-statistic. "log(Housing Price)" is the logarithm of lagged 3-month average housing price. "log(Income per capita)" is the logarithm of quarterly disposable income per capita. "log(Government Revenue)" is the logarithm of current month government revenue. IV results are estimated using 2-stage least squares. Column 2 uses Land Sales (in 1000 km^2) calculated as the volume of cumulative land area sold for both residential and all-purpose uses lagged by 18 months as the instrument. Column 3 uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue as the instruments. Column 4 uses both sets of instruments.

sales and are driven by movements in land prices.[27] Evidence during our sample period indicates that local governments were able to establish nominally independent financing vehicles to resell land to developers in secondary land markets (Huang and Du 2018). The varying extent to which these vehicles exist and dictate price levels across municipalities introduces additional useful variation in local government revenues. In Appendix Fig. C.2, we plot government revenue against real estate sector investment from 2008 to 2012. Revenues are higher when investment is growing the most. Also noteworthy is that the slope is steepest in Tier 2 and 3 cities, reflecting the larger impact of land sales on government revenue in these cities. Nevertheless, it is not possible to be certain that there is no correlation between lagged government revenues and contemporaneous consumption, and for this reason, we consider regressions with land sales as the only instrument as our preferred specification in the results below.

[27] We use the log of the average local government revenue during the previous 7 to 18 months. This long lag is preferred because there is at least a half year lag between the time of land sales and that of housing construction (which affects housing price).

6. Empirical results

In this section, we present our empirical estimates of the impact of housing price changes on consumption across cities in China. We begin our analysis by examining the effect for aggregate consumption and then decompose it across expenditure categories. We then corroborate these effects with what we expect the corresponding responses in savings would be across cities. Finally, we examine the robustness of our IV approach and the empirical model more generally.

6.1. The effect of housing prices on consumption

Panel B of Table 2 presents results from the baseline model of the total consumption response to housing prices. We begin by estimating an ordinary least square (OLS) model with city and year × month fixed effects in Column I, where the standard errors are clustered at the city level (as with all subsequent regression estimates). The OLS results suggest that a 10% increase in housing prices is associated with a 1.4% decrease in total non-housing spending. As described in Section 5, there is reason to believe that this estimate is biased upwards. Coefficients for the logarithm of the number of cards indicates that spending increases one-for-one with the number of cards; this is consistent with Fig. 4, which documents the parallel growth of card spending and card

Table 3
Impact of housing price on consumer spending by category.

Dependent variable: log(Spending)	I Travel & Restaurant	II Automobile	III Daily goods	IV Supermarket	V Health	VI Cash withdrawals	VII Others
Panel A (OLS)							
log(Housing Price)	0.13	−0.03	−0.03	−0.15	0.31	−0.10**	−0.47*
	(0.09)	(0.12)	(0.14)	(0.14)	(0.25)	(0.05)	(0.25)
Panel B (Land Sales (in 1000 km^2))							
log(Housing Price)	0.09	−0.43	0.49	−0.36	−0.51	−0.55***	−2.09*
	(0.29)	(0.41)	(0.43)	(0.36)	(0.87)	(0.19)	(1.16)
First-stage F statistic	20.59	17.77	20.58	17.09	17.70	21.20	20.45
Panel C (All IVs)							
log(Housing Price)	−0.12	−0.74**	0.33	−0.62	−1.23	−0.40***	−1.16
	(0.22)	(0.31)	(0.31)	(0.43)	(0.77)	(0.15)	(0.78)
First-stage F statistic	15.34	12.44	14.85	11.41	10.63	13.70	14.62
Observations	2397	2397	2397	2397	2397	2397	2397
Share of Total Consumption	6.2%	18.1%	7.1%	12.3%	4.0%	23.2%	29.1%
Average Value per Transaction (RMB)	818.57	23,890.67	696.35	408.53	934.57	1,121.88	2,340.59

Note: All regressions include log(No. of Cards), log(No. of POS Terminals), log(Income per capita), log(Government Revenue), and city and year × month fixed effects. Standard errors clustered at the city level are reported in parentheses. "First-Stage F stat" is the Kleibergen–Paap F-statistic. Panel B uses land sales as the instrument. Panel C uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue in addition to land sales as the instruments. Share of total consumption refers to the percentage of the value of spending in the respective category out of total spending. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

penetration. The coefficient on government revenue is small and statistically insignificant, suggesting that consumption and government fiscal positions are not strongly correlated.[28]

Columns II and III present estimates from our IV models: Column II uses past cumulative land sales (in square meters) as the IV, while Column III uses lagged government revenue and the interaction of land constraint and lagged government revenue as instruments. Column IV uses all three IVs together. Our preferred specification in Column II has a higher F-statistic, indicating a stronger first-stage when only using land sales. Over-identification tests in Columns III and IV do not reject the null hypothesis that the over-identifying restrictions are valid. First-stage results are reported in Panel A of Table 2.[29] The IV estimate suggests that a 10% increase in housing prices yields a 9.0% decrease in non-housing spending. According to the National Bureau of Statistics of China, the total value of national retail sales of consumer goods in 2010 was 15.5 trillion *Yuan* ($2.3 trillion). Therefore, the 15% increase in housing prices as observed during 2011–13 is associated with a 2.1 trillion *Yuan* ($312 billion) reduction in total consumer spending.

According to the Chinese National Bureau of Statistics, the average disposable income of urban households grew by 12.6% from 2011 to 2012. At the same time, the growth of per capita consumption expenditure in China was 2.1% (down from 4.9% in the previous year). The average housing price increased 7.5% in 2012, which, multiplied by our elasticity estimate of 0.9, corresponds to a 6.8% reduction in consumption. This back-of-envelope calculation suggests that consumption growth could have been closer to 8–9% in the absence of the negative consumption response from housing price appreciation. This is consistent with the theoretical model from Section 3, which describes a channel by which there is reallocation of household resources away from non-housing consumption and towards housing.

Is the estimated negative elasticity of consumption with respect to housing prices believable? Estimates for the US and Europe range from 0.02 to 1.7, and the two studies we are aware of in China, Painter et al. (2019) and Gan (2010), find effects of 0.13 and 0.17, respectively. To understand the discrepancy in findings it is important to keep a few distinctions in mind. First, we are measuring deviations from overall upward trends in consumption, which on average has increased roughly 50% over our sample (Fig. 3). Our results suggest that this overall increasing trend was dampened by growth in housing prices and that our findings may be specific to the post-crisis period studied. The other two studies in China consider pre-crisis periods when government restrictions on housing prices were less stringent and price-to-income ratios were lower. Another important distinction is that those studies rely exclusively on fixed effects/differenced models for which the bias discussed in Section 5.1 may also be of concern. In addition, there is reason to believe that effects in Hong Kong (Gan, 2010) differ from those across all Chinese cities because of the formers' special status and unique economic characteristics (we do not include Hong Kong in our sample).

Second, as we will substantiate below, the estimated negative elasticity reflects deferred consumption of households as they save to buy houses. Given the series of factors previously mentioned – tight mortgage restrictions, stringent down payment requirements, the inability to use housing as collateral, limited alternative investment opportunities, government backing of the housing sector, expectations of continued income growth, and continued high savings rates – this result is consistent with previous findings on household saving in China. The large burden of housing expenditure has caused households to raise their savings in order to cover the down payment of a house. It is important to reiterate that because home purchases remain common among low- and middle-income households, it is likely that many homebuyers are financially constrained in the short-run but expect to benefit from real wealth gains from house value appreciation in the long-run.

In Table 3, we decompose the aggregate consumption into seven categories to better understand how consumers reduce consumption in response to housing price changes. With a 10% increase in house price, households decrease consumption by 7.4% on automobile purchases and 4% on cash withdrawals, which may reflect reduced spending on smaller discretionary items. While we lack statistical power to make precise statements, reductions in more discretionary expenditures, such as Travel and Restaurants, and not in consumer staples, such as Daily

[28] In Appendix Tables D.7 and D.8, we show estimates from more parsimonious models than Table 2, which highlight the importance of controlling for city and year × month fixed effects.

[29] The first-stage F-statistics reported in our IV models are Kleibergen–Paap F-statistics although there is reason to prefer Montiel-Olea-Pflueger statistics when weak instruments are a concern in the presence of heteroskedasticity (Olea and Pflueger 2013). For our preferred specification, weak IVs are not a concern given that the test statistics is close to double the rule-of-thumb cutoff of 10 (Stock and Yogo 2005). In Appendix Table D.15, we calculate these statistics and find that they are not meaningfully different.

Table 4
Impact of housing price on savings.

Dependent variable: log(Saving Deposit)	I OLS	II Land sales	III Slope × GovtRev	IV All IVs
log(Housing Price)	0.11**	0.14	0.19**	0.19**
	(0.05)	(0.13)	(0.08)	(0.08)
log(Income per capita)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
log(Government Revenue)	0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1218	1218	1218	1218
First-stage F statistic		14.65	19.43	10.78
Over-identification Test (p-value)			0.28	0.51

Note: All specifications include city and year × month fixed effects. Standard errors are clustered at the city level and reported in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. "First-Stage F stat" is the Kleibergen–Paap F-statistic. "log(Saving Deposit)" is total saving deposits for each prefecture level city at month end. "log(Housing Price)" is the logarithm of lagged 3-month average housing price. "log(Income per capita)" is the logarithm of quarterly disposable income per capita. "log(Government Revenue)" is the logarithm of current month government revenue. IV results are estimated using 2-stage least squares. Column 2 uses Land Sales (in 1000 km^2) calculated as the volume of cumulative land area sold for both residential and all-purpose uses lagged by 18 months as the instrument. Column 3 uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue as the instruments. Column 4 uses both sets of instruments.

Goods, is indicative of what one might expect for responses of a typical household.[30]

6.2. Saving responses to housing price

If households reduce consumption in the face of an appreciating housing stock, we should expect to see a corresponding increase in household savings. To measure this, we utilize information on monthly savings deposit records for 62 prefecture-level cities that are received by the People's Bank of China from 2011 to 2013. Our econometric model to measure savings' responses is identical to that for consumption; that is, we regress the logarithm of total monthly savings deposits at the city level, $log(S_{it})$, on the logarithm of 3-month average housing prices, $log(p_{it})$, and other covariates:

$$log(S_{it}) = \alpha_1 \log(p_{it}) + X_{it}'\alpha_2 + \eta_t + u_i + \varepsilon_{it}$$

where X_{it} is the same as it is in Eq. (4). η_t is a year × month fixed effect and u_i is a city fixed effect.

Both the OLS and IV estimates are positive and statistically significant, suggesting a positive response of savings to housing price increases (Table 4). The F-statistics range between 11 and 19. Columns III and IV indicate that savings deposits increase by 1.9% for a 10% increase in housing prices.

To benchmark the magnitude of this adjustment relative to consumption, note that nationwide total savings deposits in 2010 were 71.8 trillion *Yuan* ($11 trillion). Therefore, the 15% increase in housing price during 2011–13 is associated with a 2.0 trillion *Yuan* ($320 billion) increase in saving deposits. The magnitude of the increase in savings deposits is remarkably similar to that of the reduction in consumer spending calculated above (2.1 trillion *Yuan*). Our finding of a positive savings response to housing price increases is consistent with the People's Bank of China (2015) report that households accumulate savings for future housing down payments.

[30] The negative coefficient on supermarket spending appears counter-intuitive given that one would expect it to reflect changes in food and necessities purchases, which should be more inelastic. However, supermarkets in China resemble department stores in the US in that they sell durables, luxury goods, and necessities, and other items that are discretionary.

6.3. Relaxing IV validity assumptions

In Section 5.1, we present arguments that the determinants of housing prices across Chinese cities modeled in the first stage of our IV model are plausibly exogenous. While it is not possible with our data to test that assumption, there is growing acknowledgment in the empirical microeconomics literature that greater caution in interpreting estimates from IV models is warranted (Young 2017). To test the robustness of our estimates when relaxing the strict exogeneity assumption, we perform a test that estimates the bounds of our IV estimates following Nevo and Rosen (2012).[31] The bounds include our IV estimates from the preferred specification in Table 2, and they exclude 0.

Panel I in Table 5 reports the point estimate and its standard error from our preferred baseline specification in Table 2. Nevo and Rosen (2012) propose a test of validity that relaxes the assumption that the instruments are exogenous to the second stage error term, ε_{it}. The intuition for this approach is that rather than assuming that the instrument set is uncorrelated with the second stage error term, we assume that it is correlated, but that it is not too strongly correlated, and we know the sign of their correlation. To be explicit, their paper demonstrates that rather than relying on the assumption that $E[Z\varepsilon]=0$, the restriction that

$$E\left[\left(\sigma_p Z - \frac{corr[Z\varepsilon]}{corr[p\varepsilon]}\sigma_Z p\right)\varepsilon\right] = 0$$

can be used to provide valid estimates, where σ_p and σ_Z are the standard deviations of p and Z, respectively. Though $\frac{corr[Z\varepsilon]}{corr[p\varepsilon]}$ is not known to the econometrician, its value can be bounded between 0 and 1 using straightforward and generally defensible assumptions about the correlations between ε, p and Z.[32]

[31] The calculation of these bounds, which are easily implementable in standard statistics packages (Clarke and Matta 2017), amount to making assumptions about the correlation of key variables of interest and are related to the approach developed by Imbens and Manski (2004) of constructing confidence intervals for partially identified parameters.

[32] These assumptions are that $corr[p\varepsilon]corr[Z_j\varepsilon] \geq 0$ and $|corr[p\varepsilon]| \geq |corr[Z_j\varepsilon]|$ for each instrument j. This amounts to assuming that the endogenous variable has the same direction of correlation with the error as the instrument and that the error term is more correlated with the endogenous variable than the instrument. Both assumptions are likely to hold in our case. Since our instruments

Table 5
Bounding IV estimates.

Dependent variable: log(Spending)	I Lower bound	II Point estimate	III Upper bound
Panel I: Instrument used: Land Sales (in 1000 km^2)			
log(Housing Price)	−1.72	−0.90**	−.07
		(0.43)	
Panel II: Instruments used: All IVs			
log(Housing Price)	−1.27	−0.73***	−.03
		(0.26)	

Note: The upper and lower bounds on the confidence interval using the identification assumptions of Nevo and Rosen (2012) is reported for both sets of IVs. Standard errors clustered at the city level and reported in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. 95% Confidence Interval is specified for calculating two-sided bounds.

Table 6
The impact of housing price on transaction volume.

Dependent Variable: log(No. of Transactions)	I OLS	II Land Sales (in 1000 km^2)	III Slope × GovtRev	IV All IVs
log(Housing Price)	−0.06**	−0.23**	−0.23**	−0.23**
	(0.03)	(0.10)	(0.10)	(0.09)
log(No. of Cards)	1.07***	1.09***	1.09***	1.09***
	(0.03)	(0.04)	(0.04)	(0.04)
log(No. of POS Terminals)	0.01	0.01*	0.01*	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
log(Income per capita)	0.003	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
log(Government Revenue)	0.002	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2397	2397	2397	2397
First Stage *F*-stat		21.56	18.29	12.58
Over-identification Test (*p*-value)			0.19	0.29

Note: All specifications include city and year × month fixed effects. Standard errors are clustered at the city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. "First-Stage *F* stat" is the Kleibergen–Paap *F*-statistic. "log(Housing Price)" is log of lagged 3-month average housing price. log(Income per capita) is the logarithm of quarterly disposable income per capita. "log(Government Revenue)" is the logarithm of current month government revenue. IV results are estimated using 2-stage least squares. Column 2 uses Land Sales (in 1000 km^2) calculated as the volume of cumulative land area sold for both residential and all-purpose uses lagged by 18 months as the instrument. Column 3 uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue as the instruments. Column 4 uses both sets of instruments.

We implement this test in Panels I & II of Table 5, where we report the bounds of our estimates using standard errors clustered at the city level. We note that this approach produces negative bounds of the coefficient estimate and includes our main IV estimates and as well as the OLS estimates.

6.4. Further robustness checks

We conduct several robustness checks. First, we estimate the impact of housing prices on the number of total non-cash transactions in Table 6. This measures an alternative margin of consumption: how many times consumers make purchases in a city. To the extent that households reduce expenditures by substituting cheaper for more expensive goods, these estimates should be interpreted as a lower bound on the true consumption effects. In our preferred IV model, consumers reduce the number of transactions by 2.3% for a 10% increase in housing prices. The estimated elasticity here is lower in magnitude than our main results, but it nonetheless supports our overall findings. Appendix Table D.10 analyzes transaction responses by expenditure category; it is analogous to Table 3 and demonstrates negative coefficients with statistical significance across a wide range of categories, including Automobiles, Daily Goods, Health, Cash Withdrawals and Other Expenditures.

are negatively correlated with housing prices and we would likely expect that cities with higher land supply see greater consumption growth, based on the background in Section 2.

Second, our instruments could be correlated with unobservables that also affect consumption. For example, in urban China, the growth of the service sector has been an important driver of income growth in cities with modestly developable land. In Table 7, we directly control for the growth of the tertiary sector, which is the ratio of new to incumbent firms and the registered capital of new firms relative to that of incumbents in this sector.[33] Our key coefficient estimates are not statistically distinguishable.

Third, we vary the number of lags of local government revenue used in our instrument set. In our main specification, we assume that it takes half a year for land sales to affect housing prices and that the impact can persist for roughly a year. In Appendix Tables D.11 and D.12, we compare instruments with different lengths of lagged cumulative land sales and local government revenue. Changing the lag structure does not affect the coefficients in a statistically meaningful manner.

7. Heterogeneity in consumption responses

The previous section provides strong evidence for negative consumption responses to housing price increases across Chinese cities from 2011 to 2013, but this leaves open the questions: who is responding, and what

[33] Entrants are firms newly registered in a given month, while incumbents are previously registered firms. Registered capital is the initial investment dedicated by the shareholder(s) that is registered with China's Administration for Industry and Commerce (AIC).

Table 7
Impact of housing prices on consumer spending: controlling for industrial activities.

Dependent variable:	Controlling no. of firms			Controlling registered capital		
	I	II	III	IV	V	VI
log(Total Spending)	OLS	Land Sales IV	All IVs	OLS	Land Sales IV	All IVs
log(Housing Price)	−0.13	−1.08*	−0.85***	−0.13	−1.05*	−0.83***
	(0.09)	(0.56)	(0.30)	(0.08)	(0.55)	(0.30)
log(No. of Cards)	0.91***	1.02***	0.99***	0.91***	1.01***	0.99***
	(0.09)	(0.12)	(0.10)	(0.09)	(0.12)	(0.10)
log(No. of POS Terminals)	−0.01	0.01	0.00	−0.01	0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
log(Income per capita)	0.03	0.04	0.04	0.03	0.04	0.03
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
log(Government Revenue)	0.00	0.01	0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No. of Entrants over Incumbents	0.26	1.18	0.96			
	(0.70)	(0.91)	(0.77)			
Registered Capital of Entrants over Incumbents				−0.32	−0.28	−0.29
				(0.29)	(0.30)	(0.29)
Observations	2185	2185	2185	2185	2185	2185
First-stage *F* statistic		13.57	9.53		13.63	9.72
Overidentification Test (*p*-value)			0.59			0.61

Note: Same specification as in Table 2, with additional controls for the development of the tertiary sector. There are 92 city clusters in all estimation samples. Standard errors are clustered at city level in parentheses. “First-Stage *F* stat” is the Kleibergen–Paap *F*-statistic. “No. of Entrants over Incumbents” is measured by the ratio of number of entrants over incumbents in the tertiary sector. “Registered Capital of Entrants over Incumbents” is the registered capital of all entrants over incumbents in the tertiary sector. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

are the long-run implications for the Chinese economy? While a formal answer to these questions is beyond the scope of this study, we document some suggestive evidence in this section to help place our results within the broader literature on housing markets in China.

7.1. Homeownership

A critical dimension of heterogeneity in consumption responses highlighted in Section 3 is the extent to which appreciation of existing holdings of housing assets (the endowment effect) offsets investment incentives. As discussed there, renters who have no housing assets may be expected to demonstrate larger consumption reductions because they do not experience a contemporaneous wealth increase from housing price appreciation.

The card transactions data do not include any demographic information about cardholders. Identifying home owners accurately is a difficult task. We observe transaction categories but not specific items that consumers purchased with their bank cards and few categories are exclusive to home owners. In addition, because rental and owner-occupied housing is co-located geographically, we could not use the locations of transactions within cities to distinguish likely from unlikely homeowners. We take advantage of three categories suggestive of homeownership (sales of residential and commercial buildings, brokers' fees, and real estate management) as well as merchants whose name contains ‘real estate tax’ to identify a core group of home owners and end up with 6.5% of the card users. This is significantly lower than the existing literature's estimates of 90% home ownership in China (Glaeser et al. 2017).

To identify potential homeowners in our data, we use an algorithm described in Appendix B to predict cardholders likely to be homeowners based on their purchasing patterns. First, we characterize the expenditure pattern (spending shares across all categories) by our core group of home owners as the ‘benchmark’ purchase pattern. For each card, we calculate the mean squared error (MSE) between its spending pattern and the benchmark pattern, and we rank cards by MSE. Cards with small MSEs are ‘likely homeowners’ while cards with large errors are ‘likely renters’. We adjust MSE cutoffs such that ‘likely homeowners’ account for between 30% and 89% of card users and we run separate regressions.

Appendix Fig. C.5 shows IV estimates for ‘likely homeowners’ that account for 30%, 47%, 60%, 69%, 78%, 84%, and 89% of card users, with 95% confidence intervals plotted. Consumption elasticity with respect to housing prices for home owners is not statistically different from zero except when they account for 89% of the card users (solid red line). For predicted renters (i.e., the remainder of the sample), the estimates are negative, statistically different from zero, and different from those for the homeowner sample in all cases, with the effect ranging between −1 and −3 (the dashed black line).[34] These results are consistent with our theoretical exposition that homeowners are less likely to reduce consumption because endowment effects on existing housing assets counteract investment incentives. These results also suggest that adjustment costs (which are mostly borne by homeowners) may not explain the aggregate consumption reduction we observe. Instead, it may be the case that it is the behavior of renters, modeled in Section 3.4 that best describe the behavior observed here.

In Panel D of Table 8, we present regression estimates for the predicted homeowner and renter sample; homeowners account for 89% of card users. IV estimates suggest an elasticity of non-housing consumption for renters to be as high as −2.30, which is substantially larger than our baseline estimates. We interpret this as reflecting more extreme consumption reductions by those less likely to own homes.[35]

7.2. Heterogeneous effects by city characteristics

Given the different trends in housing prices in Fig. 1, one might expect the consumption elasticity to differ across city tiers. In Panel A of Table 8, we add an interaction between Tier 1 and 2 cities and housing prices to our baseline model. Both the OLS and the IV estimates suggest that Tier 1 and 2 cities exhibit a larger negative response to housing price changes. This could be driven by the faster price growth in those cities, more stringent purchase restrictions, or the high price levels, all of which lead to both stronger investment incentives and tighter budget

[34] The confidence intervals on renters widen as that sample shrinks, which is intuitive.

[35] Full regression results with over- and under-identification test statistics are reported in Appendix Table D.14.

Table 8
Impact of housing price on consumer spending: heterogeneity.

Dependent Variable: log(Total Spending)	I OLS	II Land Sales (in 1000 km^2)	III All IVs
Panel A: City Tier			
log(Housing Price)	−0.10	−0.54	−0.60**
	(0.10)	(0.63)	(0.27)
Tier 1&2 × log(Housing Price)	−0.15	−2.50	−0.51
	(0.17)	(1.98)	(0.61)
Under-identification Test (p-value)		0.02	0.03
Over-identification Test (p-value)			0.77
Panel B: "Young" Cities			
log(Housing Price)	0.12	1.00	0.17
	(0.21)	(1.01)	(0.52)
Pct of 25–40 × log(Housing Price)	−0.01	−0.08	−0.03
	(0.008)	(0.05)	(0.02)
Under-identification Test (p-value)		0.001	0.01
Over-identification Test (p-value)			0.21
Panel C: Share of Local Residents			
log(Housing Price)	−0.26***	−3.00**	−1.26***
	(0.09)	(1.45)	(0.45)
Higher Pct of Locals × log(Housing Price)	0.23*	3.30**	1.06**
	(0.13)	(1.61)	(0.44)
Under-identification Test (p-value)		0.001	0.02
Over-identification Test (p-value)			0.39
Panel D: Likely Housing Tenure			
log(Housing Price) [*likely homeowners*]	−0.06	−0.44	−0.58*
	(0.13)	(0.44)	(0.33)
log(Housing Price) [*likely renters*]	−0.23	−2.30**	−2.36***
	(0.41)	(1.05)	(0.83)

Note: Same specification as in Table 2, with interactions of log housing price and city characteristics. Standard errors are clustered at city level in parentheses. "Under-identification Test" is the Kleibergen–Paap rk LM statistic. "Tier 1&2" is an indicator variable equal to 1 if the city is in Tier 1 or 2. "Pct of 25–40" is the percentage of the city's population between age 25 to 40. "Higher Pct of Locals" is an indicator that equals 1 if a city's fraction of residents with a residential permit (*Hukou*) is higher than the median of all cities in our sample, and equals 0 otherwise. Panel D displays results from six separate regressions for cards identified as likely homeowners (89% of cards) and likely renters (11% of cards) following the algorithm described in the Appendix. Under- and over-identification test results for each regression are reported in Appendix Table D.14 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

constraints. The evidence from all three panels in this table should be viewed as only suggestive because the estimates tend to be imprecise.

Demand for housing probably differs across the age cohorts. A strand in the housing literature highlights the differential effects of house price increases over the life cycle: older households that have more housing-related assets exhibit stronger consumption responses to house prices, while younger households have stronger consumption responses to income changes (Attanasio et al. 2011). While we are not able to test these theories directly, we add to our baseline model the interaction between the logarithm of housing prices and the share of the population aged 25 to 40 years, as shown in Panel B of Table 8. This captures differences in city residents' life cycles. The negative though statistically insignificant coefficient on the interaction term suggests that cities that have a younger population may be more likely to reduce consumption in the face of higher housing prices.

In Panel C of Table 8, we include the interaction of the share of individuals with a residency permit (*Hukou*) with the logarithm of the housing price. For a number of reasons, having a local *Hukou* may be important. Economic (and earning) opportunities are fewer for individuals without a *Hukou* for the city in which they are living. A *Hukou* is also harder to obtain for larger, faster growing cities like Beijing and Shanghai, whereas smaller, more remote cities often have a larger share of established residents with local *Hukou*s. Our results suggest that cities with larger shares of residents with local *Hukous* restrict consumption less, which is indicative of cities with greater non-residents facing greater financial burdens to acquire a home.

One caveat to the interpretation of our results is the relatively narrow time window covered: 2011 to 2013. While we report robust findings of negative consumption responses to housing price increases, it is clear that housing prices are projected to grow at a solid pace for the medium-term and Chinese consumers can afford to cut back on non-housing expenditures only so far. Fig. 5 plots changes in the number of rooms per person for homeowners over 2010–15 versus growth in home prices over the same period. A 10% increase in prices is associated with a decrease in the rooms per person of 0.42. The largest declines are for the cities with the greatest price growth, Beijing and Shanghai. This suggests that, in addition to reducing consumption, households adjust to rising housing prices by consuming less housing. This trend may continue when consumption reductions are no longer able to fully offset housing price increases.[36]

[36] We note that decreases in unit sizes also emerge in equilibrium out of housing supply constraints, but given the pace of home building in urban China, this trend towards smaller units is more likely to be driven by housing demand.

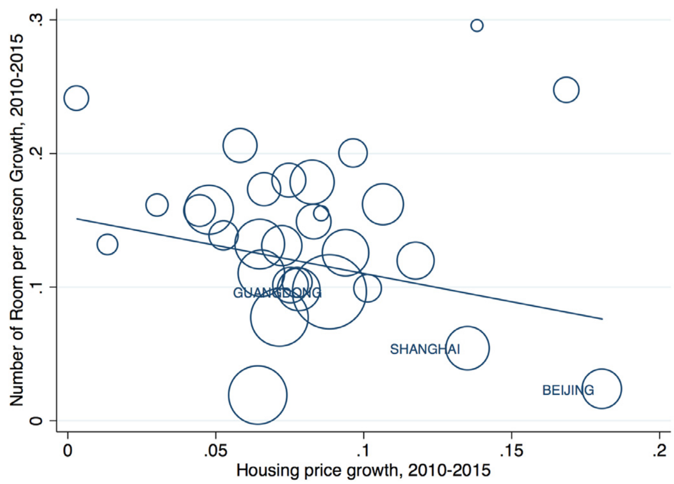

Fig. 5. Housing price growth and average number of rooms.
Note: This figure plots the average number of rooms per person in a household against the growth rate of housing price. Each circle corresponds to a province in our sample, and there are 30 provinces in our sample. The circle size of each dot corresponds to the population size of each city. The slope for the population weighted linear fitted line is −0.42, and is statistically significant at the 1% level.

8. Conclusion

The real estate market in China has been booming for over a decade, with real housing prices growing at an annual average rate of 10% since 2004. An important dimension of the boom is the extent to which it coincides with a rise in household income and a large supply of household savings that is chasing an underdeveloped investment market. Few studies have looked at the impact of the housing boom on household wealth accumulation.

In this paper we construct a novel transaction-level dataset of consumer spending during 2011 to 2013 across 101 cities to document, to the best of our knowledge, the first evidence of a negative housing price elasticity of consumption. We first develop a theoretical model to demonstrate how severe borrowing constraints create a channel that induces households to defer current consumption in the midst of property value appreciation. Our instruments capture plausibly exogenous variation in housing prices through changes in local land supply that are driven by the fiscal concerns of the local government. While the size of the reduction in consumption differs across spending categories, we document that for a 10% rise in housing prices, consumption decreases on average by 9.0%. In addition, a 10% rise in housing price increases household savings by 1.9%.

Our findings have implications for sustaining long-run economic growth in the context of China's demographic transition, and they are relevant to concerns about potential future housing market crises. First, as China makes its transition from an export-driven growth model to one that relies more on domestic consumption, our finding implies that the rapid rise in housing prices may have hindered this transition and that the slowdown of the housing market in recent years could paradoxically boost domestic consumption.

Second, our estimated elasticities are short-run in nature. As long as housing prices continue to grow and borrowing constraints continue to tighten in the future, low- and middle-class households will at some point be unable to continue reducing consumption to pay for housing. Without further government intervention, market corrections, or alternative investment instruments, lower income households probably will be priced out of the housing market eventually. We provide suggestive evidence that there already has been some adjustment. Third, while the central government has taken substantial steps to limit overheating in the real estate sector, our paper suggests that to cope with rising housing prices, households are still tightening their belts and directing savings into housing. As argued by Wu et al. (2012), this could represent a substantial misallocation of resources and potentially lead to a less-than-rational bubble.

Appendix A. Theoretical model

We present a household consumption model to illustrate the channels through which housing prices affect consumption.[37] We use the model to demonstrate the possibility that under certain conditions, when housing prices increase, the total consumption response could be negative. We decompose the consumption response into the income and substitution effect, the endowment effect, and the investment effect. This decomposition allows us to identify conditions when we may expect to see negative non-housing consumption responses to housing price increases.

We distinguish between two types of households: First, there are those that are able to draw on their existing assets to purchase homes, so their consumption response from house price changes follows the prediction of the permanent income hypothesis. The second type of households are subject to a binding borrowing constraint. There is a maximum level of mortgage that these households can obtain, which is in proportion to their labor income. Therefore, when their stock of liquid (non-housing) wealth is insufficient, they have to sacrifice current consumption in order to purchase a home.

We consider the household's decision problem when housing as well as other consumer goods are traded in competitive markets. In this model, households maximize utility by choosing non-housing consumption and housing consumption, subject to an inter-temporal budget constraint.

For an infinitely-lived representative household, the optimization problem is[38]:

$$\begin{aligned} &\max_{\{c_t, h_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} q^t U\left(c_t, h_t\right) \\ &\text{s.t.} \quad \sum_{t=0}^{\infty} \frac{1}{(1+r)^t}\left(c_t + R_t h_t\right) = I \\ &\left(1+m_t\right) y_t + (1-\delta) P_t h_{t-1} \geq (1+r) m_{t-1} y_{t-1} + c_t + P_t h_t, t = 1, 2, \ldots, \end{aligned} \tag{A.1}$$

where h_t denotes housing services, c_t is the value of non-housing consumption, r is the interest rate, y_t is exogenous labor income, w_t is total wealth, $m_t y_t$ denotes the maximum borrowing that households can obtain, and $q = \frac{1}{1+r}$, where r is the interest rate.[39] Conceptually, $m_t y_t$ can be thought of as embedding asset holdings of each period reflecting the household's flow of savings deposit or mortgage borrowing in the current period.

Total wealth is defined as

$$w_t = (1+r)[w_{t-1} + y_{t-1} - c_{t-1} - P_{t-1} h_{t-1}] + (1-\delta) P_t h_{t-1}, \quad t = 1, 2, \ldots,$$

which is the present value of last period's savings (or borrowing) at an arbitrary interest rate r and housing asset after depreciation; and

[37] We consider the effect of a permanent price change on consumption. A transitory shock to prices will have a larger short-run impact on consumption than a permanent one, however this impact would be expected to diminish more quickly as housing prices revert to previous levels. For the reasons discussed in Section 2, it seems plausible that most households during our sample would behave as though observed price increases are permanent.

[38] Households in the model behave the same as the finite-lived overlapping generations of households with friction-less bequests. We will reformulate the model this way in the next section.

[39] We assume that households discount future utilities at the interest rate.

$P_0 h_0$ for $t = 0$. Borrowing or savings from the preceding period, $m_{t-1} y_{t-1}$, accrue at interest rate r, and enter in the form of the preceding period's wealth w_{t-1}.

The budget constraint in (A.1) describes the trade-off households face each period between consumption and housing: in each period, households have wealth w_t, labor income y_t, and borrowing up to $m_t y_t$, and choose to spend on non-housing consumption c_t and housing h_t at price P_t. The borrowing constraint restricts a household's maximum borrowing up to a fraction m_t of their per-period labor income y_t: $c_t + P_t h_t - w_t - y_t \leq m_t y_t$. We assume (following the exposition about urban China in Section 2) that borrowing limits fall in each period $m_{t+1} < m_t$, decreasing the amount that households can borrow against current income.[40]

The per-period budget constraint can be aggregated into an intertemporal budget constraint at date 0:[41]

$$\sum_{t=0}^{\infty} q^t \left[c_t + [P_t - q(1-\delta)P_{t+1}]h_t - y_t\right] = (1-\delta)P_0 h_{-1}. \tag{A.2}$$

Define the implicit rental rate $R_t \equiv P_t - q(1-\delta)P_{t+1}$.[42] To make explicit the effects of a permanent change to housing prices, we assume that the house price is initially constant at P so that the implicit rental rate is then $R = (1 - q(1-\delta))P$.

We then want to decompose the response of c_t to a permanent change in P and highlight differential effects for borrowing constrained households. Define Marshallian demand $c_t = c_t^M(R, I)$, which comes from maximizing $\sum_{t=0}^{\infty} q^t U(c_t, h_t)$ subject to $\sum_{t=0}^{\infty} q^t (c_t + Rh_t) = I$, where I is lifetime income. Similarly, define Hicksian demand $c_t = c_t^H(R, U)$, which comes from minimizing $\sum_{t=0}^{\infty} q^t (c_t + Rh_t)$ subject to $\sum_{t=0}^{\infty} q^t U(c_t, h_t) \geq U$, where U is the maximum level utility achievable with I. From the household's Slutsky equation, we can decompose the total response of consumption to a change in P into

$$\begin{aligned}\frac{\mathrm{d}c_t}{\mathrm{d}P} &= \frac{\partial c_t^H(R,U)}{\partial P} - \frac{\partial c_t^M(R,I)}{\partial I}\frac{\partial I}{\partial P} \\ &= \underbrace{[1 - q(1-\delta)]\frac{\partial c_t^H(R,U)}{\partial R}}_{\text{substitution effect}} \underbrace{-[1 - q(1-\delta)]\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty} q^t h_t}_{\text{income effect}} \\ &\quad + \underbrace{\frac{\partial c_t^M(R,I)}{\partial I}(1-\delta)h_{-1}}_{\text{endowment effect}}\end{aligned} \tag{A.3}$$

A1. Unconstrained households

We proceed by considering two cases, first, where the representative household in our model is not constrained in borrowing and, second, where she is. To derive clearer comparative statics, we assume that the household's per period utility function is Cobb–Douglas: $U(c_t, h_t) = c_t^{\alpha} h_t^{1-\alpha}$. If $c_t + Ph_t - w_t - y_t < m_t y_t$, households are not financially constrained. These households have enough savings or endowed housing assets to cover the down payment on a house.

Therefore, we can express (A.1) using the Lagrangian equation:

$$L = \sum_{t=0}^{\infty} q^t c_t^{\alpha} h_t^{1-\alpha} + \lambda \left[I - \sum_{t=0}^{\infty} q^t (c_t + Rh_t) \right]$$

First order conditions are

$$\frac{\partial L}{\partial c_t} = q^t \alpha c_t^{\alpha-1} h_t^{1-\alpha} - \lambda q^t = 0 \tag{A.4}$$

$$\frac{\partial L}{\partial h_t} = q^t (1-\alpha) c_t^{\alpha} h_t^{-\alpha} - \lambda q^t R = 0 \tag{A.5}$$

$$\frac{\partial L}{\partial \lambda} = I - \sum_{t=0}^{\infty} q^t (c_t + Rh_t) = 0. \tag{A.6}$$

From Eqs. (A.4) and (A.5), we get that the solution to the household problem gives a constant level of housing $h_t = h$ and of consumption $c_t = c$, where

$$\frac{c}{Rh} = \frac{\alpha}{1-\alpha}. \tag{A.7}$$

Therefore, substituting in (A.6):

$$c = \alpha \frac{r}{1+r}\left[(1-\delta)Ph_{-1} + \sum_{t=0}^{\infty} q^t y_t\right].$$

The effect of a permanent change in P would lead to

$$\frac{\mathrm{d}c}{\mathrm{d}P} = \alpha \frac{r}{1+r}(1-\delta)h_{-1}. \tag{A.8}$$

Because of our assumption of Cobb–Douglas preferences, income and substitution effects exactly cancel and only the endowment effect remains and full consumption smoothing will be possible. In this situation, although high housing appreciation attracts investment, the lack of binding borrowing constraints means that households can increase their leverage as needed to adjust holdings of housing.

A2. Constrained households

If $c_t + Ph_t - w_t - y_t = m_t y_t$, households are borrowing constrained, and will borrow at the maximum level allowed. We now more closely consider the behavior of these constrained households.

The new Lagrangian equation is

$$\begin{aligned}L' &= \sum_{t=0}^{\infty} q^t c_t^{\alpha} h_t^{1-\alpha} + \lambda\Big[I - \sum_{t=0}^{\infty} q^t (c_t + Rh_t)\Big] \\ &\quad + \sum_{t=0}^{\infty} q^t \gamma_t [(1-\delta)Ph_{t-1} - q^{-1} m_{t-1} y_{t-1} + (1+m_t)y_t - c_t - Ph_t].\end{aligned}$$

First order conditions are

$$\frac{\partial L'}{\partial c_t} = q^t \alpha c_t^{\alpha-1} h_t^{1-\alpha} - \lambda q^t - \gamma_t q^t = 0 \tag{A.9}$$

$$\frac{\partial L'}{\partial h_t} = q^t (1-\alpha) c_t^{\alpha} h_t^{-\alpha} - \lambda q^t R - \gamma_t q^t P + q^{t+1} \gamma_{t+1} (1-\delta) P = 0 \tag{A.10}$$

$$\frac{\partial L'}{\partial \lambda} = I - \sum_{t=0}^{\infty} q^t (c_t + Rh_t) = 0 \tag{A.11}$$

$$\frac{\partial L'}{\partial \gamma_t} = (1-\delta)Ph_{t-1} - q^{-1} m_{t-1} y_{t-1} + (1+m_t)y_t - c_t - Ph_t = 0. \tag{A.12}$$

[40] However, $m_t - m_{t+1} > m_{t+1} - m_{t+2}$, so that $\lim_{t\to\infty} m_t$ is defined and approaches a value between 0 and 1.

[41] Here we assume inter-temporal risk neutrality. It is possible to show the same results with more general CRRA utility function incorporating relative risk aversion. CES preferences are also, in principle, possible.

[42] The budget constraint at period 0 is $c_0 + p_0 h_0 = y_0 + w_0 = y_0 + (1-\delta)p_0 h_{-1}$, where $m_{-1} y_{-1} = 0$.

Hence, combining Eq. (A.9) and (A.10), we have

$$\begin{aligned}\frac{c_t}{Rh_t} &= \frac{\alpha}{1-\alpha}\frac{\lambda R + \left[\gamma_t - q\gamma_{t+1}(1-\delta)\right]P}{(\lambda+\gamma_t)R} \\ &= \frac{\alpha}{1-\alpha}\left[1 + \frac{(1-\delta)(\gamma_t - \gamma_{t+1})}{(r+\delta)\left(\lambda+\gamma_t\right)}\right].\end{aligned} \tag{A.13}$$

Comparing Eq. (A.13) to Eq. (A.7), we can see that if $\gamma_t < \gamma_{t+1}$, then $\frac{c_t}{Rh_t} < \frac{c}{Rh}$, otherwise, $\frac{c_t}{Rh_t} > \frac{c}{Rh}$. Since γ_t is the shadow value of borrowing constraint, whether γ_t is smaller than γ_{t+1} depends on the strictness of the borrowing constraint (specifically that $m_t > m_{t+1}$). This tightening of the borrowing constraint reflects the fact that Chinese households expect legal and financial constraints on borrowing to be tighter in the future as discussed in Section 3. This fact allows us to state the following lemma about constrained housing asset accumulation that will allow us to explain responses of non-housing consumption to housing price increases.

Lemma 1. *Constrained households facing borrowing constraints will have a higher lifetime present discounted value of housing asset accumulation than unconstrained households.*

Proof. From Eqs. (A.7) and (A.13), if $\gamma_t < \gamma_{t+1}$, then

$$\begin{aligned}&\frac{c_t}{Rh_t} < \frac{\alpha}{1-\alpha} = \frac{c}{Rh}, \text{ for all } t \\ \Rightarrow &\frac{\sum_{t=0}^{\infty} q^t c_t}{\sum_{t=0}^{\infty} q^t Rh_t} < \frac{\sum_{t=0}^{\infty} q^t c}{\sum_{t=0}^{\infty} q^t Rh}.\end{aligned}$$

From Eqs. (A.6) and (A.11), we know that $I = \sum_{t=0}^{\infty} q^t(c_t + Rh_t) = \sum_{t=0}^{\infty} q^t(c + Rh)$. It follows that $\sum_{t=0}^{\infty} q^t Rh_t > \sum_{t=0}^{\infty} q^t Rh$, which is equivalent to $\sum_{t=0}^{\infty} q^t h_t > \sum_{t=0}^{\infty} q^t h$ because R is constant. h_t is housing accumulation of the constrained households, while h is housing accumulation of the unconstrained households. So the present discounted value of lifetime housing accumulation is greater for constrained households. □

We can then decompose the response of consumption to a change in P into

$$\begin{aligned}\frac{\mathrm{d}c_t}{\mathrm{d}P} &= \frac{\partial c_t^H(R,U)}{\partial P} - \frac{\partial c_t^M(R,I)}{\partial I}\frac{\partial I}{\partial P} \\ &= \underbrace{\frac{r+\delta}{1+r}\frac{\partial c_t^H(R,U)}{\partial R}}_{\text{substitution effect}} - \underbrace{\frac{r+\delta}{1+r}\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty} q^t h}_{\text{income effect}} \\ &\quad \underbrace{\frac{\partial c_t^M(R,I)}{\partial I}(1-\delta)h_{-1}}_{\text{endowment effect}} - \underbrace{\frac{r+\delta}{1+r}\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty} q^t \tilde{h}_t}_{\text{investment effect}}\end{aligned} \tag{A.14}$$

where from Lemma 1, $\sum_{t=0}^{\infty} \tilde{h}_t = \sum_{t=0}^{\infty} q^t\left(h_t - h\right)$ is positive, reflecting incentives to invest more in housing for constrained households during the current period.

Definition. The **housing investment effect** is one component of the consumption response from a permanent house price increase that comes from an increase in the present value of housing investment made by borrowing-constrained households relative to unconstrained households. This additional investment is the direct effect of tightening borrowing constraints in the future.

From Eq. (A.14) we know that the investment effect is negative while the endowment effect is positive. Therefore, if the investment effect outweighs the endowment effect, the consumption response to housing price increase would be negative.

Proposition. *In a model with borrowing constraints, a household's non-housing consumption response to a permanent house price increase is negative if the value of the endowed housing asset (h_{-1}) is not sufficient to pay for the present discounted value of the entire stream of additional housing investments: $\sum_{t=0}^{\infty} q^t R\tilde{h}_t$.*

Proof. Recall that in Eq. (A.8), for unconstrained households, the only consumption response from a permanent housing price increase comes from the endowment effect. The first two terms, which are the substitution and income effect cancel each other out since they are exactly the same as those for the unconstrained households. The other two terms left in Eq. (A.14) determine the sign of $\frac{\mathrm{d}c_t}{\mathrm{d}P}$. The sum of the two terms is

$$\begin{aligned}&-[1-q(1-\delta)]\frac{\partial c_t^M(R,I)}{\partial I}\sum_{t=0}^{\infty} q^t \tilde{h}_t + \frac{\partial c_t^M(R,I)}{\partial I}(1-\delta)h_{-1} \\ &= \frac{\partial c_{t,m}(R,I)}{\partial I}\left[(1-\delta)h_{-1} - [1-q(1-\delta)]\sum_{t=0}^{\infty} q^t \tilde{h}_t\right],\end{aligned}$$

where $\sum_{t=0}^{\infty} q^t \tilde{h}_t > 0$ from Lemma 1. Therefore, if

$$\begin{aligned}&(1-\delta)h_{-1} < [1-q(1-\delta)]\sum_{t=0}^{\infty} q^t \tilde{h}_t \\ \Rightarrow &(1-\delta)Ph_{-1} < [1-q(1-\delta)]P\sum_{t=0}^{\infty} q^t \tilde{h}_t \\ \Rightarrow &(1-\delta)Ph_{-1} < \sum_{t=0}^{\infty} q^t R\tilde{h}_t\end{aligned} \tag{A.15}$$

then $\frac{\mathrm{d}c_t}{\mathrm{d}P} < 0$. Intuitively, Eq. (A.15) provides an upper bound on the depreciated value of the initial housing endowment, h_{-1} for consumption responses to be negative: they must be below the present discounted rental value of the borrowing constrained household's lifetime excess housing accumulation above the unconstrained household $\left(\sum_{t=0}^{\infty} q^t R\left(h_t - h\right)\right)$. If the value of endowed housing asset after being depreciated one period is not enough to cover the entire life-time present discounted value of housing needed for this additional investment, then households need to sacrifice current period consumption. □

A3. Life cycle effects

As documented by Campbell and Cocco (2007) and Attanasio et al. (2009), housing price effects on consumption are likely to vary over the life cycle, however how they vary has not been agreed upon. The first paper suggests the effects are stronger for older households, while the second suggests they are stronger for younger ones. Theoretically, the effect is ambiguous as will be shown in the following discussion. Consider two households at different points in the life cycle, say 25 years old and 65 years old. To start, we begin by rewriting the utility maximization problem from (1) as a finite-lived problem, where households born at time t living for J years maximize lifetime utility:

$$\max_{\{c_{t+j},h_{t+j}\}_{j=1}^{J}} \sum_{j=1}^{J} q^j U(h_{t+j}, c_{t+j}) + q^{J+1} B(\hat{\omega}_{t+J+1})$$
$$\text{s.t. } \sum_{j=1}^{J} q^j \left(c_{t+j} + R_{t+j} h_{t+j}\right) = I$$
$$\left(1+m_{t+j}\right) y_{t+j} + (1-\delta) P_t h_{t+j-1} \geq q^{-1} m_{t+j-1} y_{t+j-1} + c_{t+j} + P_{t+j} h_{t+j}.$$
$$j = 1, 2, \ldots, J \tag{A.16}$$

In order to incorporate intergenerational transmission of wealth, the term $B(\hat{\omega}_{t+J+1})$ accounts for bequests from parents to offspring, which, because the only form of asset holdings in our model is housing, results in the transfer of housing wealth. The bequest function is specified as:

$$B(\hat{\omega}_{t+J+1}) = \frac{1-\delta}{1-\sigma}\left[P_{t+J+1} h_{t+J}\right]^{1-\sigma}. \tag{A.17}$$

We assume again Cobb–Douglas preferences, where now $U(c_t, h_t) = \frac{1}{1-\sigma}\left[c_t^{\alpha} h_t^{1-\alpha}\right]^{1-\sigma}$.

It is instructive to rewrite (A.2) to reflect the new date 0 (birth) intertemporal budget constraint, which now incorporates housing wealth bequests ($h^b_{t+j'}$) inherited from parents at age j':

$$\sum_{j=1}^{J} q^j \left[c_{t+j} + [P_{t+j} - q(1-\delta)P_{t+j+1}]h_{t+j} - y_{t+j}\right] = q^{j'+1} P_{t+j'+1} h^b_{t+j'}. \tag{A.18}$$

The First Order Conditions are similar to that for the infinitely lived case, except at death, when $j = J$, (A.9) becomes:

$$\frac{\partial L''}{\partial h_{t+J}} = q^J \left(c^{\alpha}_{t+J} h^{1-\alpha}_{t+J}\right)^{-\sigma} (1-\alpha) c^{\alpha}_{t+J} h^{-\alpha}_{t+J} + q^{J+1} \omega (1-\delta)(P h_{t+J})^{-\sigma} P -$$
$$q^J \lambda R - q^J \gamma_{t+J} P = 0. \tag{A.19}$$

It is helpful to compare this to the same First Order Condition from the previous period:

$$\frac{\partial L''}{\partial h_{t+J-1}} = q^{J-1} \left(c^{\alpha}_{t+J-1} h^{1-\alpha}_{t+J-1}\right)^{-\sigma} (1-\alpha) c^{\alpha}_{t+J-1} h^{-\alpha}_{t+J-1} - \tag{A.20}$$
$$q^{J-1} \lambda R - q^{J-1} \gamma_{t+J-1} P + q^J \gamma_{t+J} (1-\delta) P = 0.$$

indicating that in the final period of life, the term that corresponds to the marginal value of housing wealth in the next period is replaced with a term equal to the marginal bequest value of that housing wealth. For a permanent increase in the price of housing, this has the effect of also increasing the value of bequests. Substituting in (A.18), we can solve for equilibrium consumption when the borrowing constraint is relaxed:

$$c = \alpha \frac{r}{1+r}\left[q^j P_{t+j} h^b_{t+j} + \sum_{j=1}^{J} q^{t+j} y_{t+j}\right].$$

Finally, we can rewrite Eq. (A.13) for the case with a finite-lived household facing borrowing constraints, where (as with the unconstrained household), the endowment effect now can be written in terms of initial inherited housing wealth rather than period 0 housing wealth, h_{-1}:

$$\begin{aligned}\frac{\mathrm{d}c_{t+j}}{\mathrm{d}P} &= \frac{\partial c^H_{t+j}(R,U)}{\partial P} - \frac{\partial c^M_{t+j}(R,I)}{\partial I}\frac{\partial I}{\partial P} \\ &= \underbrace{\frac{r+\delta}{1+r}\frac{\partial c^H_{t+j}(R,U)}{\partial R}}_{\text{substitution effect}} \underbrace{-\frac{r+\delta}{1+r}\frac{\partial c^H_{t+j}(R,I)}{\partial I}\sum_{j=1}^{J} q^{t+j} h}_{\text{income effect}} \\ &\quad \underbrace{-\frac{r+\delta}{1+r}\frac{\partial c^M_{t+j}(R,I)}{\partial I}\sum_{j=1}^{J} q^{t+j}\tilde{h}_{t+j}}_{\text{investment effect}} + \underbrace{\frac{\partial c^M_{t+j}(R,I)}{\partial I} q^{j'}(1-\delta) h^b_{t+j'}}_{\text{endowment effect}}.\end{aligned} \tag{A.21}$$

Eq. (A.21) makes clear that two scenarios are possible based on when the bequest is transferred: the household receives a bequest at age $j' < j$, in which case the inherited wealth increases in value from the price increase in the same manner as the effect in the infinitely-lived case. Alternatively, when $j' > j$, the bequest has not yet been inherited, but represents future wealth that can be borrowed against. Mechanically, the difference has no bearing on the derivation of (A.21), but, as will be explored in the next section, it likely matters for its interpretation.

A4. Adjustments over the life cycle

How consumption responses to housing price changes vary over the life cycle is a reflection of changes in asset holdings (here housing wealth) of households, preferences between housing and non-housing consumption, and expected future income growth.[43] These responses are clearly manifested in two features of the present model: the extent to which a household is borrowing constrained in the first place, and the relative magnitudes of investment versus endowment effects. The following corollary demonstrates that to the extent that borrowing constraints bind more tightly for younger households, they may be expected to reduce consumption more. How tightly the borrowing constraint is expected to bind in the near future can be seen from rewriting it as

$$\left(1+m_{t+j}\right) y_{t+j} + q^{-1} m_{t+j-1} y_{t+j-1} \geq c_{t+j} + P_{t+j} h_{t+j} - (1-\delta) P_t h_{t+j-1} :$$

it depends on income growth, borrowing limits and changes in the household's housing asset position. Households earlier in the life-cycle may expect future income growth, but may face constraints on their ability to borrow against that future income.

Corollary. *Households facing tighter borrowing constraints over time may be expected to respond with greater consumption reductions.*

Proof. From Lemma 1, we know that tighter borrowing constraints imply a larger value of $\gamma_{t+j+1} - \gamma_{t+j}$, which, in turn, means a larger value of $\sum_{j=0}^{\infty} q^{t+j}\tilde{h}_{t+j}$. This means a larger investment effect from (A.14) and therefore larger consumption reductions. □

It is important to put this Corollary in context: younger households might consume less housing if they are more borrowing constrained in the short-run because of limited near-term income growth. They will want to consume more housing than they would have without constraints because it will be harder to borrow in the future. The second mechanism that the borrowing constraint makes clear is that younger households may have lower initial levels of housing, so that their current level of wealth and borrowing ability is limited.

A5. Housing tenure

Because asset holdings in our model are only comprised of housing, renters have no wealth beyond savings, so that $w^{renter}_{t+j} = (1+r)[w^{renter}_{t+j-1} + y_{t+j-1} - c_{t+j-1}]$.[44] For a household buying a house in period $t+j$, the borrowing constraint becomes:

$$\left(1+m_{t+j}\right) y_{t+j} \geq (1+r) m_{t+j-1} y_{t+j-1} + c_{t+j} + P_{t+j} h_{t+j}, \tag{A.22}$$

[43] Another important aspect is uncertainty, which is not captured in our deterministic model presented here. The ability for households to self-insure against income fluctuations in order to smooth consumption depends upon the completeness of markets, which seems unlikely given limitations of investment vehicles for savings discussed in Section 3. For older households income volatility may be expected to decline, with uncertainty effectively zero at retirement, while for younger households, precautionary savings may help to smooth consumption in the face of uncertainty. These patterns will tend to exacerbate the differentiated responses we describe in this section.

[44] As noted in Section 2, given the lack of alternative investment options, the assumption of no alternative investment assets, while strong, is not without basis in reality.

from which it is clear that renters deciding to purchase housing assets in period $t+j$ face potentially tighter borrowing constraints because of a lack of existing assets. One difference unlikely to matter in urban China as discussed in Section 2 is the ability of owners to use housing as collateral. To understand the differential effects on renters, it is helpful to think about the three possibilities of inheriting housing in the finite-lived model. A renting household could be renting because they have received their housing bequest but liquidated it to cash to spend on consumption or savings. With Cobb–Douglas utility, convexity of preferences is going to preclude this possibility and in reality it seems unlikely that a forward-looking household would liquidate an appreciating asset with search costs except under extreme circumstances.

Alternatively, a renting household could have received no bequest, however, given the preferences of parents in the model, this too is unlikely. Practically speaking, the bequest may be too small to increase housing purchases. Here we have abstracted from non-divisibility issues with housing and in the next section we will consider adjustment costs. In practice both of these factors may mean that bequest wealth is too small to be converted into housing for the young household. If this is the case, it will shut down the endowment effect, making the investment effect dominant. A final possibility is that the household is expecting the bequest in the future. In this case, note that the endowment effect will remain as the expected future bequest rises in value. To the extent that future bequests are large, this may increase the size of the endowment effect, making consumption reductions smaller or even increasing consumption. In summary, the magnitude of consumption responses by renters relative to owner-occupiers is ambiguous although to the extent that it reflects lack of wealth to borrow against, we would expect this to increase the magnitude of negative consumption adjustment.

A6. Adjustment costs

Adjusting housing asset holdings is not a cost-less activity as on the intensive margin it involves time-consuming renovations and on the extensive margin it requires moving altogether. Denoting adjustment costs as the fixed cost when housing assets are changed, $K_{t+J} = \theta \cdot 1\left[h_{t+j} \neq h_{t+j-1}\right]$, we can rewrite (A.16) as

$$\max_{\{c_{t+j}, h_{t+j}\}_{j=1}^{J}} \sum_{j=1}^{J} q^j U(h_{t+j}, c_{t+j}) + q^{J+1} B\left(\hat{\omega}_{t+J+1}\right)$$

$$\text{s.t.} \sum_{j=1}^{J} q^j \left(c_{t+j} + (1+K_{t+j}) R_{t+j} h_{t+j}\right) = I$$

$$\left(1+m_{t+j}\right) y_{t+j} + (1-\delta)(1+K_{t+j-1}) P_t h_{t+j-1}$$
$$\geq (1+r) m_{t+j-1} y_{t+j-1} + c_{t+j} + (1+K_{t+j}) P_{t+j} h_{t+j} \quad j = 1, 2, \ldots J \tag{A.23}$$

With adjustment costs, a household may be more likely to wait to change their holdings of housing assets until the marginal benefit of changing their position is at least as large as the level of adjustment costs. One complication is that the presence of adjustment costs may incentivize faster accumulation of housing assets earlier in the life cycle rather than a more gradual accumulation without.

Appendix B. Home owner prediction algorithm

As discussed in Section 4, our UnionPay data do not provide an explicit or even indicative measure of individual homeownership. In order to gauge the extent of differential non-housing consumption responses to housing price increases between renters and owner-occupiers, we develop and algorithm to classify a subset of cardholders in our data as homeowners based upon their pattern of expenditure. Specifically, we observe a small (6.5%) share of households that purchase services classified as sales of residential and commercial buildings, paid broker's fee, and/or real estate tax in the UnionPay transactions, which we will call "identified homeowners." Assuming that these represent true homeowners, the share (6.5%) is far less than the actual homeownership rate across urban China, which is closer to 90% (Glaeser et al. 2017). Because UnionPay cards are so prevalent among urban Chinese households, there is a strong reason to believe that a much larger share of our cardholders own homes, but remain unidentified. There are many potential explanations for the under-representation of these type of transactions in the data (households having multiple cards, use of cash to pay for housing services, etc.).

To better identify a larger potential subset of homeowner cards in our data, we characterize the spending patterns of households based on the 6.5% of "identified homeowner" cardholders and then use this to identify similar households from those that did not spend on residential and commercial buildings, paid broker's fee, and/or real estate tax (i.e., non-"identified homeowners"). We call these "predicted renters." The algorithm for classifying these "predicted homeowners" is performed as follows:

1. Add up "identified homeowner" spending by category, and sort categories by total expenditures.
2. Select the top 32 merchant categories (excluding housing related categories–residential and commercial buildings, paid broker's fee, and/or real estate tax). These 32 categories account for 87% of total non-housing spending for "identified homeowner" cards.
3. Calculate the average share of spending in each of the top 32 categories for "identified homeowner" cards: $\bar{e}^h_c, \quad c = 1, \ldots, 32$.
4. Similarly calculate expenditure shares across the same 32 categories for each i non-"identified homeowner" cards: $e^n_{i,c}$.
5. Calculate the mean squared error for every card (including "identified homeowners": $MSE_i = \frac{1}{32} \sum_{c=1}^{32} \left(\bar{e}^h_c - e^n_{i,c}\right)^2$.
6. Rank all cards ("identified homeowner" and otherwise) $i = 1, \ldots$ from lowest to highest MSE_i. Define $M\tilde{S}E$ such that $\theta = \frac{\#(MSE_i < M\tilde{S}E)}{\#(Allcards)}$, where θ is the target number of homeowners in the sample, #() is an operator counting the UnionPay card accounts. The sub-sample of cards for which $MSE_i < M\tilde{S}E$ then becomes the "likely homeowner" group and the remainder becomes the "likely renter" group.

Fig. C.4 provides an illustrative example of what the algorithm does. Each horizontal bar in the diagram represents the distribution of *MSE* across cards in the sample, with the far left side representing $MSE = 0$ and the far right with the highest values of MSE. The red lines correspond to the *MSE* for "identified homeowners" with expenditures on residential and commercial buildings, paid broker's fee, and/or real estate tax. If the pattern of spending on the top 32 categories perfectly predicted homeownership, we would expect the distribution *MSE* to look like the pattern in the top bar, with all "identified homeowners" concentrating on the far left side. Alternatively, if these spending categories provided as good a prediction as random selection, we would expect the pattern of *MSE* for "identified homeowners" to look something like the pattern for the middle bar. In reality, our own prediction produce a pattern like that in the third bar so a large mass of "identified homeowners" fall to the far left side of the *MSE* distribution, and a smaller mass with decreasing frequency have higher MSEs to the right of the bar.

Based on our algorithm, setting $\theta = 0.9$ means that the top 90% of all cards contain 95% of "identified homeowner" cards, while using the "perfect" algorithm, the top 90% of all cards would contain 100% of "identified homeowner" cards, and for the "random" prediction algorithm, the top 90% of all cards contain only 90% of "identified homeowner" cards. Appendix Table D.13 reports spending shares for the top 14 spending categories for both homeowners (i.e. "identified" and "predicted" homeowners and non-homeowners). Appendix Table D.14 reports regression estimates using our prediction algorithm for the top 89% of cards, while Appendix Fig. C.5 reports estimates for the top 30–89% of cards.

Appendix C. Appendix Figures

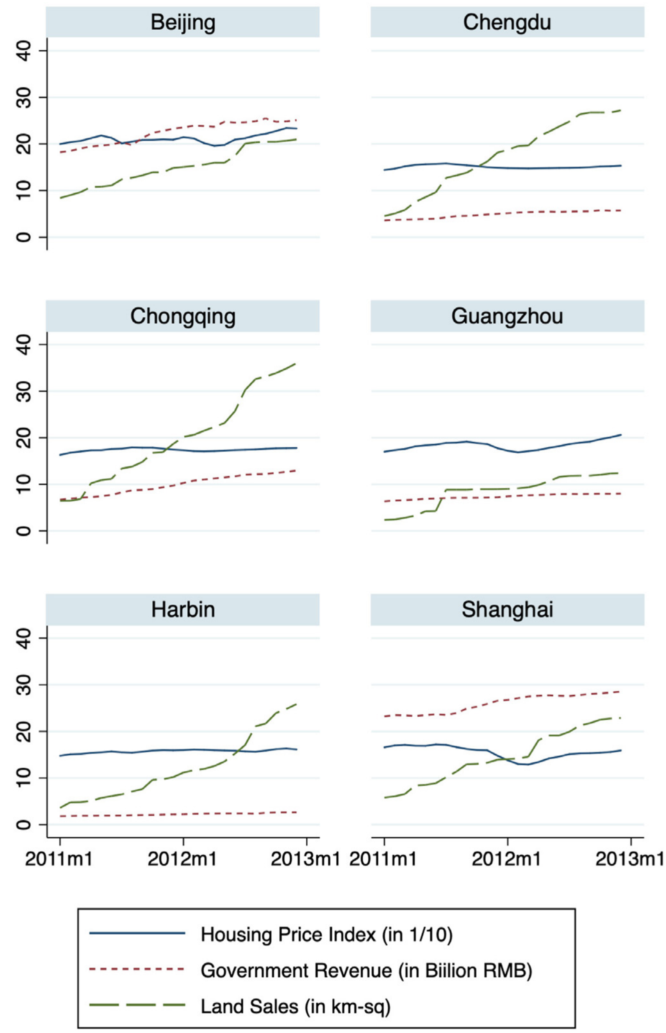

Fig. C.1. Land supply and housing prices for 9 Chinese cities.
Note: Fig. C.1 plots housing prices, government revenue and land sales for six tier 1 and 2 cities over the sample period.

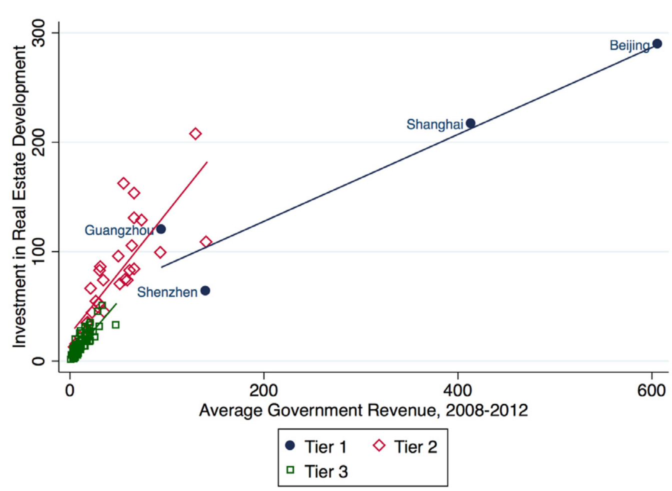

Fig. C.2. Housing investment and government revenue.
Note: Fig. C.2 plots the 5-year average investment in real estate development against each city's government revenue by three tiers in our sample. Both investment in real estate development and government revenue are in billion RMB. Investment in real estate includes investment by the real estate development companies, commercial buildings construction companies and other real estate development units of various types of ownership in the construction of residential buildings.

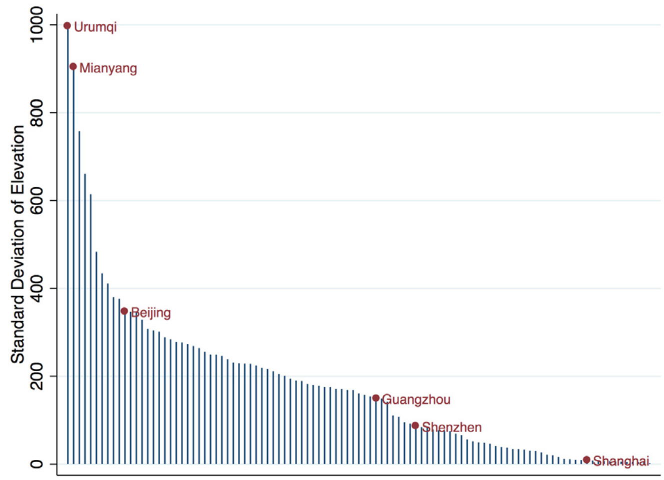

Fig. C.3. Standard deviation of elevation across Cities.
Note: Fig. C.3 plots the standard deviation of elevation for all 101 cities in our sample from high to low. The standard deviation of elevation for each city is the standard deviation of a city's altitude in kilometers across a grid of one kilometer squares.

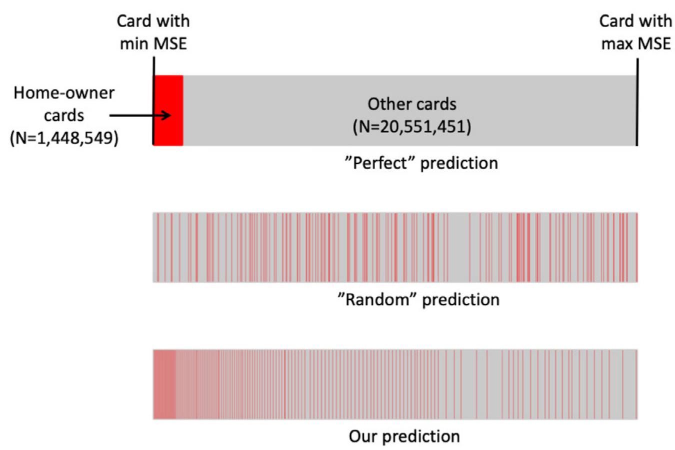

Fig. C.4. Home owner prediction.
Note: This figure illustrates the approach of our homeowner prediction methodology described in Appendix B. The horizontal bars present cards in our dataset ranked by the mean squared error (MSE) of expenditure shares relative to the average expenditures shares for the top 32 categories in cards that spend on sales of residential and commercial buildings, paid broker's fee, and/or real estate tax. The red lines indicate the rank of the 6.5% of cards that spend in those three categories. The top bar reflects the ranking that would result from a random prediction of homeownership, the middle bar reflects that from a random prediction, and the last from our prediction based on MSE.

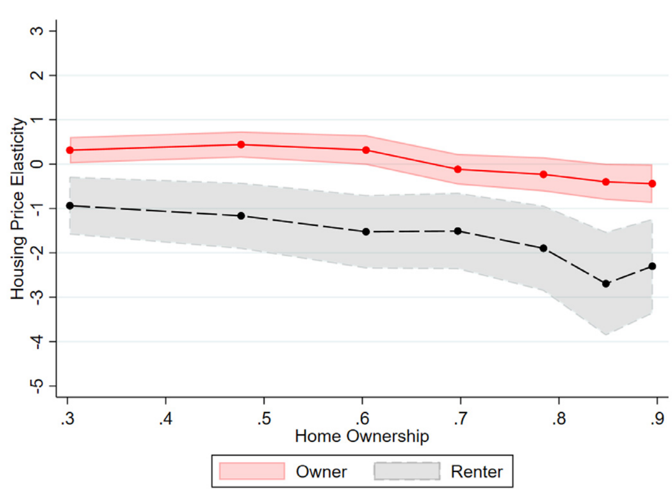

Fig. C.5. Impact of housing price on home owner versus non-home owner's spending.
Note: This figure plots coefficients from 7 IV regressions of non-housing consumption on housing prices using land sales (in 1000 km^2) as the instrument. Each regression varies by the sample allocated to homeowners (solid red line) or renters (dark dashed line) following the algorithm outlined in Appendix B. The shaded regions correspond to the 95% confidence intervals of each estimate.

Appendix D. Appendix Tables

Table D.1
City list by tier.

Tier	City name
Tier 1 (4 cities)	Beijing, Guangzhou, Shanghai, Shenzhen
Tier 2 (31 cities)	Changchun, Changsha, Chengdu, Chongqing, Dalian, Fuzhou, Haikou, Hangzhou, Harbin Hefei, Hohhot, Jinan, Kunming Nanchang, Nanjing, Nanning, Ningbo, Qingdao, Shenyang Shijiazhuang, Suzhou, Tianjin, Urumqi, Wenzhou, Wuhan, Wuxi, Xiamen, Xian, Xining, Yinchuan, Zhengzhou
Tier 3 (66 cities)	Anqing, Anshan, Baoding, Baotou, Bengbu, Changzhou, Chuzhou, Dazhou, Dezhou, Dongguan, Foshan, Fuyang, Heyuan, Huaian, Huangshan, Huizhou, Huludao, Huzhou, Jiangmen, Jiaxing, Jinhua, Jiujiang, Kaifeng, Langfang, Leshan, Lianyungang, Liaocheng, Luoyang, Mianyang, Nanchong, Nantong, Nanyang, Ningde, Panjin, Puyang, Qingyuan, Qinhuangdao, Quanzhou, Rizhao, Shangrao, Shantou, Shanwei, Shaoguan, Shaoxing, Suqian, Taiizhou, Tangshan, Wuhu, Xingtai, Xinxiang, Xinyu, Xuancheng, Xuchang, Xuzhou, Yancheng, Yangjiang, Yangzhou, Yiichun, Yingkou, Yuncheng, Zaozhuang, Zhangjiakou, Zhangzhou, Zhaoqing, Zhenjiang, Zhongshan

Note: Cities listed in alphabetical order.

Table D.2
Comparison of UnionPay and total retail sales, by category.

Category	UnionPay	NBS retail sales
Daily consumption	28.04%	29.95%
Grocery and Supermarket	17.47%	5.03%
Clothing and Footwear	3.74%	10.17%
Consumer Goods	6.83%	13.26%
Health	5.81%	4.98%
Recreation and Culture	11.64%	3.69%
Automobile	21.96%	26.15%
Jewelry	4.87%	2.30%
Raw Material & Construction	Not Applicable	20.31%
Total Percentage Covered (in volume)	72.32%	83.96%

Note: UnionPay categories reorganized to correspond to retail data. "NBS Retail Sales" is the National Bureau of Statistics' Total Retail Sales of Consumer Goods obtained from the CEIC database. The categories are organized according to the United Nations' Classification of Individual Consumption According to Purpose (COICOP).

Table D.3
Housing price lag robustness: OLS.

Dependent variable: log(Total Spending)						
log(Current Housing Price)	−0.155**					
	(0.076)					
log(Lagged 3-month Housing Price)		−0.144*				
		(0.080)				
log(Lagged 6-month Housing Price)			−0.139			
			(0.084)			
log(Lagged 9-month Housing Price)				−0.114		
				(0.082)		
log(Lagged 12-month Housing Price)					−0.079	
					(0.063)	
log(Lagged 15-month Housing Price)						−0.054
						(0.055)
Observations	2397	2397	2394	2391	2390	2390

Note: Standard errors are clustered at city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The only difference between the columns is the lag structure of housing price. Column I uses the contemporary one period housing price. Column II is the preferred specification that uses the lagged 3-month average housing price (the previous 1 to 3 month). Column III uses the lagged 6-month average housing price (the previous 1 to 6 month). Column IV uses the lagged 9-month average housing price (the previous 1 to 9 month). Column V uses the lagged 12-month average housing price (the previous 1 year). Column VI uses the lagged 15-month average housing price (the previous 1 to 15 month). City and year × month fixed effects are included in all specifications. A constant, log(No. of Cards), log(No. of POS Terminals), log(Income per capita), and log(Government Revenue) are included in the regressions but not reported here in the table. There are 101 prefecture city level clusters.

Table D.4
Housing price lag robustness: land sales (in 1000 km^2) as IV.

Dependent variable: log(Total Spending)						
log(Current Housing Price)	−0.96** (0.46)					
log(Lagged 3-month Housing Price)		−0.90** (0.43)				
log(Lagged 6-month Housing Price)			−0.89** (0.42)			
log(Lagged 9-month Housing Price)				−0.85** (0.41)		
log(Lagged 12-month Housing Price)					−0.74** (0.37)	
log(Lagged 15-month Housing Price)						−0.81* (0.45)
Observations	2397	2397	2394	2391	2390	2390
F-statistics	20.06	18.83	16.88	13.54	9.56	5.61

Note: Standard errors are clustered at city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. All columns use the IV specification which is the same as Table 2 column 2. The only difference between the columns is the lag structure of housing price. Column I uses the contemporary one period housing price. Column II is the preferred specification that uses the lagged 3-month average housing price (the previous 1 to 3 month). Column III uses the lagged 6-month average housing price (the previous 1 to 6 month). Column IV uses the lagged 9-month average housing price (the previous 1 to 9 month). Column V uses the lagged 12-month average housing price (the previous 1 year). Column VI uses the lagged 15-month average housing price (the previous 1 to 15 month). City and year × month fixed effects are included in all specifications. A constant, log(No. of Cards), log(No. of POS Terminals), log(Income per capita), and current government revenue are included in the regressions but not reported here in the table. There are 101 prefecture city level clusters.

Table D.5
Housing price lag robustness: All IVs.

Dependent variable: log(Total Spending)						
log(Current Housing Price)	−0.83*** (0.30)					
log(Lagged 3-month Housing Price)		−0.73*** (0.26)				
log(Lagged 6-month Housing Price)			−0.74*** (0.26)			
log(Lagged 9-month Housing Price)				−0.67*** (0.23)		
log(Lagged 12-month Housing Price)					−0.52*** (0.18)	
log(Lagged 15-month Housing Price)						−0.45*** (0.17)
Observations	2397	2397	2394	2391	2390	2390
F-statistics	10.85	12.58	12.01	11.38	10.67	8.89
Over-identification Test (*p*-value)	0.48	0.49	0.74	0.71	0.58	0.44

Note: Standard errors are clustered at city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. All columns use the IV specification which is the same as Table 2 column 4. The only difference between the columns is the lag structure of housing price. Column I uses the contemporary one period housing price. Column II is the preferred specification that uses the lagged 3-month average housing price (the previous 1 to 3 month). Column III uses the lagged 6-month average housing price (the previous 1 to 6 month). Column IV uses the lagged 9-month average housing price (the previous 1 to 9 month). Column V uses the lagged 12-month average housing price (the previous 1 year). Column VI uses the lagged 15-month average housing price (the previous 1 to 15 month). City and year × month fixed effects are included in all specifications. A constant, log(No. of Cards), log(No. of POS Terminals), log(Income per capita), and current government revenue are included in the regressions but not reported here in the table. There are 101 prefecture city level clusters.

Table D.6
Impact of housing price on savings: first stage estimates.

Dependent variable: log(Housing Price)	I Land Sales (in 1000 km^2)	II Slope × GovtRev	III All IVs
Land Sales (in 1000 km^2)	−5.63***		−3.18*
	(1.47)		(1.66)
S.D. of Elevation × Lagged Government Revenue		0.09***	0.08***
		(0.03)	(0.03)
Lagged Government Revenue		−0.05***	−0.04***
		(0.01)	(0.01)
log(Income per capita)	0.01	0.02	0.02
	(0.02)	(0.02)	(0.02)
log(Government Revenue)	0.01***	0.01*	0.01*
	(0.01)	(0.01)	(0.01)
Observations	1218	1218	1218
First Stage *F*-stat	14.65	19.43	10.78

Note: All specifications include city and year × month fixed effects. Standard errors are clustered at the city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. "First-Stage *F* stat" is the Kleibergen–Paap *F*-statistic. log(Housing Price) is log of lagged 3-month average housing price. Land Sales (in 1000 km^2) is the cumulative land area sold of both residential and all-purpose land 1.5 years ago. log(Income per capita) is the logarithm of quarterly disposable income per capita. log(Government Revenue) is the logarithm of current month government revenue. IV results are estimated using 2-stage least squares. Column 1 uses the volume of cumulative land sales from 18 months prior as the instrument. Column 2 uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue as the instruments. Column 3 uses both sets of instruments.

Table D.7
Impact of housing price on consumer spending, OLS.

Dependent variable: log(Total Spending)	I	II	III	IV	V
log(Housing Price)	0.44*	−0.03	−0.10	−0.14*	−0.14*
	(0.24)	(0.07)	(0.08)	(0.08)	(0.08)
log(No. of Cards)	0.76***	1.13***	1.09***	0.92***	0.92***
	(0.07)	(0.05)	(0.05)	(0.08)	(0.08)
log(No. of POS Terminals)	0.11	0.06*	−0.02	−0.02	−0.02
	(0.07)	(0.03)	(0.02)	(0.02)	(0.02)
log(Government Revenue)	0.10***	0.01	0.01	0.00	0.00
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Time Trend			0.00***		
			(0.00)		
log(Income per capita)					0.03*
					(0.02)
City FE		Yes	Yes	Yes	Yes
Year × Month FE				Yes	Yes
Observations	2397	2397	2397	2397	2397

Note: Standard errors are clustered at city level in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. There are 101 prefecture city level clusters. "log(Housing Price)" is the logarithm of lagged 3-month average housing price. "log(Income per capita)" is the logarithm of quarterly disposable income per capita. "log(Government Revenue)" is the logarithm of current month government revenue.

Table D.8
Impact of housing price on consumer spending, using land sales (in 1000 km^2) as IV.

Dependent variable: log(Total Spending)	I	II	III	IV	V
log(Housing Price)	2.03	−3.46*	−1.07**	−0.90**	−0.90**
	(3.79)	(1.95)	(0.42)	(0.43)	(0.43)
log(No. of Cards)	0.78***	1.38***	1.12***	1.00***	0.99***
	(0.10)	(0.19)	(0.05)	(0.10)	(0.10)
log(No. of POS Terminals)	0.05	0.47*	0.04	−0.00	−0.00
	(0.21)	(0.24)	(0.03)	(0.03)	(0.03)
log(Government Revenue)	0.10**	−0.01	0.01	0.01	0.01
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
Time Trend			0.01***		
			(0.00)		
log(Income per capita)					0.04
					(0.02)
City FE		Yes	Yes	Yes	Yes
Year × Month FE				Yes	Yes
First Stage *F*-stat	0.48	3.37	19.85	18.83	18.83
Observations	2397	2397	2397	2397	2397

Note: Standard errors are clustered at city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. There are 101 prefecture city level clusters. “log(Housing Price)” is the logarithm of lagged 3-month average housing price. “log(Income per capita)” is the logarithm of quarterly disposable income per capita. “log(Government Revenue)” is the logarithm of current month government revenue.

Table D.9
Impact of housing price on consumer spending, using all IVs.

Dependent Variable: log(Total Spending)	I	II	III	IV	V
log(Housing Price)	0.87	−2.99*	−1.03***	−0.76***	−0.73***
	(0.54)	(1.65)	(0.31)	(0.27)	(0.26)
log(No. of Cards)	0.77***	1.35***	1.12***	0.98***	0.98***
	(0.06)	(0.16)	(0.05)	(0.09)	(0.09)
log(No. of POS Terminals)	0.10	0.41**	0.04	−0.00	−0.00
	(0.08)	(0.21)	(0.03)	(0.03)	(0.03)
log(Government Revenue)	0.10***	−0.01	0.01	0.01	0.01
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Time Trend			0.01***		
			(0.00)		
log(Income per capita)					0.04
					(0.02)
City FE		Yes	Yes	Yes	Yes
Year × Month FE				Yes	Yes
First Stage *F*-stat	8.57	1.35	10.48	11.83	12.58
Over-identification Test (*p*-value)	0.14	0.89	0.68	0.45	0.49
Observations	2397	2397	2397	2397	2397

Note: Standard errors are clustered at city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. There are 101 prefecture city level clusters. “log(Housing Price)” is the logarithm of lagged 3-month average housing price. “log(Income per capita)” is the logarithm of quarterly disposable income per capita. e “log(Government Revenue)” is the logarithm of current month government revenue.

Table D.10
Impact of housing price on transaction volume by category.

Dependent variable: log(No. of Transactions)	I Travel & Restaurant	II Automobile	III Daily goods	IV Supermarket	V Health	VI Cash withdrawals	VII Others
Panel A (OLS)							
log(Housing Price)	−0.01	−0.03**	0.02	−0.03**	−0.05	−0.04*	−0.26**
	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)	(0.02)	(0.12)
Panel B (Land Sales (in 1000 km^2))							
log(Housing Price)	0.03	−0.12**	−0.13	−0.01	−0.32*	−0.19**	−0.33
	(0.05)	(0.05)	(0.13)	(0.05)	(0.17)	(0.07)	(0.25)
First-stage *F* statistic	20.59	17.77	20.58	17.09	17.70	21.20	20.45
Panel C (All IVs)							
log(Housing Price)	0.02	−0.09**	−0.15*	−0.03	−0.39***	−0.14**	−0.63***
	(0.04)	(0.04)	(0.08)	(0.04)	(0.13)	(0.07)	(0.20)
First-stage *F* statistic	15.34	12.44	14.85	11.41	10.63	13.70	14.62
Observations	2397	2397	2397	2397	2397	2397	2397
Share of Total No. of Transactions	9.0%	0.9%	11.9%	35.4%	5.0%	24.1%	13.6%
Average Value per Transaction (RMB)	818.57	23,890.67	696.35	408.53	934.57	1121.88	2340.59

Note: All regressions include log(No. of Cards), log(No. of POS Terminals), log(Income per capita), log(Government Revenue), and city and year × month fixed effects. Standard errors clustered at the city level are reported in parentheses. Panel B uses the volume of cumulative land sales from 18 months prior as the instrument. Panel C uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue in addition to the land sales as the instruments. Share of total No. of transactions refers to the percentage of the number of transactions in the respective category out of total number of transactions. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table D.11
Varying lag structure of land sales (in 1000 km^2) as IV.

	I	II	III	IV	V
Panel A: Second Stage: Dependent Variable: log(Total Spending)					
log(Housing Price)	−1.15**	−1.02*	−0.92*	−0.90**	−0.82**
	(0.54)	(0.58)	(0.52)	(0.43)	(0.39)
Panel B: First Stage: Dependent Variable: log(Housing Price)					
Cumulative Land Sales Up Until Current Month	−3.87***				
	(1.47)				
Cumulative Land Sales Up Until 6-Month Ago		−4.27***			
		(1.25)			
Cumulative Land Sales Up Until 12-Month Ago			−5.05***		
			(1.30)		
Cumulative Land Sales Up Until 18-Month Ago				−5.27***	
				(1.21)	
Cumulative Land Sales Up Until 24-Month Ago					−5.75***
					(1.36)
Observations	2397	2397	2397	2397	2397
F_stat	6.94	11.69	14.96	18.83	17.87

Note: Standard errors are clustered at city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. City and year × month fixed effects are included in all specifications. All columns use the same regression specification as Table 2, column 2, except for the instruments used. A log(No. of Cards), log(No. of POS Terminals), and log(Income per capita) are included in the regressions but not reported here in the table. There are 101 prefecture city level clusters.

Table D.12
Varying lags of government revenue in All IVs.

	I	II	III
Panel A: Second Stage: Dependent Variable: log(Total Spending)			
log(Housing Price)	−0.86**	−0.73***	−0.76***
	(0.37)	(0.26)	(0.27)
Panel B: First Stage: Dependent Variable: log(Housing Price)			
Land Sales (in 1000 km^2)	−4.62***	−2.99**	−3.16**
	(1.29)	(1.31)	(1.25)
S.D. of Elevation × Lagged Government Revenue (7–12 month)	0.03**		
	(0.01)		
Lagged Government Revenue (7–12 month)	−0.01***		
	(0.00)		
S.D. of Elevation × Lagged Government Revenue (7–18 month)		0.07**	
		(0.03)	
Lagged Government Revenue (7–18 month)		−0.04***	
		(0.01)	
S.D. of Elevation × Lagged Government Revenue (7–24 month)			0.05***
			(0.02)
Lagged Government Revenue (7–24 month)			−0.03***
			(0.01)
Observations	2397	2397	2397
F-statistics	17.89	12.58	14.84
Over-identification Test (*p*-value)	0.73	0.49	0.53

Note: Standard errors are clustered at city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. City and year × month fixed effects are included in all specifications. All three columns use the same regression specification as Table 2, column 4, except for the lags in the instruments used. A log(No. of Cards), log(No. of POS Terminals), and log(Income per capita) are included in the regressions but not reported here in the table. There are 101 prefecture city level clusters.

Table D.13
Comparison of homeowners' versus renters' top spending categories.

Homeowners		Renters	
Spending ategory	Spending share	Spending category	Spending share
Automobile	19.29%	Third-Party Payment (Alipay, etc.)	19.48%
Supermarkets	9.16%	Automobile	13.30%
Department Store	7.92%	Auction	13.12%
Third-Party Payment(Alipay, etc)	6.16%	Utilities	6.95%
Electronics	5.44%	Recreational Vehicle	6.54%
Recreational Vehicle	4.02%	Public Hospital	6.14%
Restaurant	3.71%	Insurance	5.15%
Insurance	3.45%	Public University	4.74%
Public Hospital	3.31%	Electronics	2.17%
Hotel	3.01%	Department Store	1.96%
Clothes	2.87%	Phone Services	1.44%
Utilities	2.52%	Self-Service Station	1.17%
Auction	2.15%	Airline	1.17%
Airline	1.64%	Clothes	0.72%
Total Percentage Covered	74.65%	Total Percentage Covered	84.07%

Note: Homeowners are defined as cardholders falling within the lowest 89% MSE rank according to the algorithm described in the Appendix. Renters are cardholders with MSE above this cutoff. Within each consumer group, the spending categories from top to bottom are ranked from the highest spending share to the 14th in rank. The spending shares are the share of spending in a given category with respect to the total spending within each consumer group.

Table D.14
Impact of housing price on consumer spending: homeowners versus renters.

Dependent variable: log(Total Spending)		
Underlying sample:	Likely homeowners	Likely renters
Panel A: OLS		
log(Housing Price)	−0.06	−0.23
	(0.13)	(0.41)
Panel B: Land Sales (in 1000 km^2) IV		
log(Housing Price)	−0.44	−2.30**
	(0.44)	(1.05)
F-stat	21.01	19.44
Panel C: All IVs		
log(Housing Price)	−0.58*	−2.36***
	(0.33)	(0.83)
F-stat	14.96	13.10
Over-identification Test (*p*-value)	0.17	0.18
Observations	2397	2397
Share of Spending (in RMB)	78%	22%
Share of Cards	89%	11%

Note: Homeowners are defined as cardholders falling within the lowest 89% MSE rank according to the algorithm described in the Appendix. Renters are cardholders with MSE above this cutoff. Standard errors are clustered at the city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. City and year × month fixed effects are included in all specifications. First-stage *F* statistics is the Kleibergen–Paap rk Wald*F* statistics.

Table D.15
Comparing different *F*-statistics of first stage regressions.

Dependent variable: log(Housing Price)	I Land sales (in 1000 km^2)	II Slope × GovtRev	III All IVs
Panel A: First Stage for Table 2			
Kleibergen–Paap rk Wald*F* statistic	18.83	18.29	12.58
Montiel-Olea-Pflueger Effective*F* statistics	18.04	15.94	13.41
Panel B: First Stage for Table 4			
Kleibergen–Paap rk Wald*F* statistic	14.65	19.43	10.78
Montiel-Olea-Pflueger Effective*F* statistics	13.59	15.58	11.37
Panel C: First Stage for Table 6			
Kleibergen–Paap rk Wald*F* statistic	21.56	18.29	12.58
Montiel-Olea-Pflueger Effective*F* statistics	18.04	15.94	13.41

Note: "log(Housing Price)" is the logarithm of lagged 3-month average housing price. All specifications include city and year × month fixed effects, cumulative land sales (in 1000 km^2), current government revenue, and log(Income per capita). IV results are estimated using 2-stage least squares. Column 1 uses the cumulative volume land sales from 18 months before as the instrument. Column 2 uses lagged government revenue, and the slope (standard deviation of elevation) interacted with lagged government revenue as the instruments. Column 3 uses both sets of instruments.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2019.103190.

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