Internet Search as Social Learning: Implications for China's Housing Market Dynamics

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March 25th 2014

Abstract

Over the last decade, China's home prices have soared. Young people, especially young men, continue to want to buy homes and must choose whether and when and where to buy. Due to fundamental uncertainty about one's labor income path, future real estate price growth and government policy, potential real estate buyers have an incentive to seek out Internet information about evolving market sentiment. Following a recent U.S literature, we build a 35 Chinese city real estate sentiment index that measures the degree of optimism in a local market at a point in time. All else equal, this index predicts several important real estate phenomena and its effects differ depending on local demand side and supply side conditions. Our findings suggest that this sentiment index proxies for a time varying housing demand shifter. We use a household expectations survey covering seven cities to further explore the underpinnings of the empirical relationships we document.

Introduction

Urban housing in China is a multi-trillion dollar industry. In recent years, the rate of return on Chinese housing assets has been phenomenal. Figure 1 shows quality adjusted hedonic housing price indices for 35 major Chinese cities from 2006 to 2013. These 35 major cities represent all municipalities directly under the federal government, provincial capital cities, and quasi provincial capital cities in China. They account for one quarter of the total urban population in more than 600 Chinese cities. For this subset of cities, we have access to a high quality transaction based hedonic home price index by city and quarter.[1] Beijing has an annual average appreciation rate of 27.4%. The average annual appreciation rate is 14.3% for these 35 cities during 2006 and 2013. One co-author of this paper bought her first apartment near Tsinghua campus in Beijing by 0.5 million RMB in late 2003 and this apartment is worth 5 million now. This extremely high price appreciation has led some leading real estate scholars to conclude that the very high price-to-income and price-to-rent ratios in Chinese urban housing markets is a sign of a housing market bubble (Wu, Gyourko and Deng, 2012).

*** Insert Figure 1 here ***

Owning an apartment offers access to a flow of housing and local amenity services and the option to sell at a higher price in the future. In a traditional housing demand model, the key determinants of a household's demand for housing include its wealth, the hedonic pricing gradient, expectations of future price appreciation and the interest

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[1] The construction of this city housing price index is based on the real transaction prices of all newly-constructed housing units in a city. The municipal housing authority keeps all the transaction contracts of these units in a database. The contract contains the information on the transaction price (Yuan/square meter), the dwelling's physical attributes (unit size, floor number, building structure type, decoration status, etc.) and its detailed address, from which locational attributes (distance to the city center, distance to the closest subway stop, etc.) can be derived. A standard hedonic model is used to compute the quarterly price index, using all the transaction observations. Every municipal housing authority then reports the index to the State's Ministry of Housing and Urban-Rural Development. This set of hedonic housing price indices is proprietary data and has not been publicly published. Two co-authors of this paper are on this housing price index team.

rate that households can borrow at. Households will also consider the opportunity cost of investing their down payment in alternative assets.

Our study focuses on the urban Chinese housing market where several additional demand factors emerge. Chinese households have fewer alternative assets to invest in because they have limited access to invest in foreign assets. The domestic stock market is viewed as a very risky investment – a common belief is that only those who can access inside information are able to earn money, and most small investors are losing money there.

In China today, demographics also play an important role in determining housing demand. The combination of the nation's one-child policy and the high male to female ratios in big cities provide strong social incentives for young men and their parents to save up money to pay the down payment for apartments in order to raise the likelihood that the young man can get married (Wei and Zhang, 2011). If parents and their children believe that housing price will keep rising, these young people will transition to home ownership at an earlier age. Such young men seek a home because of their demand for status and the belief that that increased status raises their marriage prospects. Investing in the housing market can be viewed as a lottery that allows young men to move up in the relative income distribution. In this sense housing is an input in the production of status that increases a young man's marriage prospects (for a hedonic model of status see Becker, Murphy and Werning 2005).

Potential investors are also well aware that there are deep uncertainties about China's urban housing market. Such uncertainties come from several sources. With the absence of publicly-available accurate market indicators (such as high-quality Case-Shiller housing price indices), people have to rely on scattered pieces of news from here and there.[2] Since China's urban housing market has a short history of less than twenty

[2] Few people trust the official price index released by the National Bureau of Statistics of China which is almost flat and has an annual growth rate of less than 5% even in the recent soaring period (Guo, Zheng, Geltner and Liu, 2014).

years, many homebuyers are inexperienced and face the challenge of predicting future price dynamics.[3] In addition, Chinese central and local governments heavily intervene in housing markets. They sometimes seek to stimulate the housing sector to achieve economic growth, while at other times they seek to regulate the market to slow price appreciation in order to appease the poor and middle class who are angry about soaring housing costs. Such high-frequent interventions cause considerable uncertainty about the government's future policies.[4]

Chinese real estate investors face a high degree of uncertainty about future price dynamics, due to their inexperience in the market, limited knowledge about past housing price trends, and uncertainty over future macro-economic trends and government policies. In this setting, Internet search offers such potential investors valuable insights into what other potential buyers are thinking. Potential purchasers "know that they do not know" what is taking place in the Chinese housing markets. This provides them with strong incentives to seek out additional information and to learn from the experience of others. The rise of access to the Internet in China provides a cheap source for this social learning process as potential Chinese buyers tap into the "collective wisdom". As discussed by Keynes in his example of the beauty contest, households will seek to learn what others think about emerging trends in the asset market (Allen, Morris and Shin 2006). The literature on herding also states that investors are more likely to buy (sell) the same assets at the same time as other investors buy (sell). In doing this, they give more weight to a decision that imitates what other investors are thinking and doing, at the expense of a decision based on their own

[3] Chinco and Mayer (2014) document that in the United States that out of town second home buyers made systematic mistakes in their real estate investing.

[4] Some recent policy uncertainties come from whether the central or local governments will stick to the current heavy market interventions such as purchase restriction; the possible introduction of property tax legislation in more cities to cool down the speculative demand; the possible launch of a national system for tracking real estate ownership to precede the roll out of the property tax, as well as to help CCP rooting out corruption; the vast but uncertain amount of the supply of subsidized cheaper apartments by local governments. For more information, see http://blogs.wsj.com/five-things/2014/02/06/5-things-to-watch-in-chinas-housing-market-in-the-year-of-the-horse/

evaluation of available information (Ro and Gallimore, 2014).

Internet search activity represents a costly choice (in terms of time invested) and is unlikely to suffer from the cheap talk critique that arises in surveys. Such Internet searches yield valuable data for researchers searching to learn about household's interests and priorities (see Kahn and Kotchen 2011). Following the approach introduced by Chauvet, Gabriel, and Lutz (2012) and Soo (2013), we construct our local real estate market sentiment index measure of the optimistic view (versus pessimistic view) about future housing market trend by city/quarter using Internet search data. Our approach also builds on the approach of Baker, Bloom and Davis (2012) who use newspaper coverage of policy-related economic uncertainty (a normalized index of the volume of news articles discussing economic policy uncertainty) as a component of their policy uncertainty index. In this paper we will apply their approach but use the Internet to construct our sentiment index.

Our sentiment index is an aggregate measure of people's expectations about real estate market trend at the city/quarter level. Ideally, we could observe each household's evolving expectation over time. In a diverse society, the marginal buyer's expectations will play a key role as a demand shifter in setting the market price. We acknowledge that our sentiment index aggregates such expectations across the population distribution. As we discuss below, in seven of the 35 cities in our study we have conducted a household level expectations study. We use the results from our survey to measure the dispersion of beliefs within a specific market at a point in time.

We examine how our new sentiment index performs in explaining a variety of housing market outcomes in China's emerging housing market. In particular, we study how new housing prices, units sold, land sales and land prices are associated with our sentiment index. We document the predictive power of this variable even controlling for a set of "fundamental factors". We interpret our expectations index as proxying for local expectations of short term demand. We document that this index has a heterogeneous impact on local real estate outcomes depending on both demand side and supply side factors. We find that this optimism index's correlation is further amplified in cities featuring a larger share of young men. We also find that supply side limits to new housing and thus an inelastic housing supply lead to a larger positive correlation between our sentiment index and local price increases (see Saiz 2009, Fu, Zheng and Liu, 2008). In the second to last section of the paper, we discuss whether the associations we document could represent causal effects and sketch a future research agenda for studying the role that market expectations play in determining real estate market dynamics.

The Market for Information Related to China's Housing Market

Real estate is a hot topic among Chinese urbanites. To attract readers, Internet media companies and newspapers allocate considerable space for real estate news and commentary. Journalists, correspondents and specialists write about this topic intensively. Internet searches by households point them to these articles. The original articles are copied by other news and forum websites and blogs, and can be further copied and commented upon.

Each individual who engages in this behavior is providing some public goods both for researchers such as ourselves but also for other interested parties eager to learn more about the Chinese real estate market. We conjecture that such individuals do not have a strategic intent but instead devote their time to linking to such stories because they enjoy being engaged about this issue. This behavior creates a detectable signal that we researchers use to detect relevant and salient information.

Real estate information in China is especially demanded because market instruments such as an ability to buy and sell future Case-Shiller style price indices by city do not exist. If such futures markets existed then the price of futures contracts would already incorporate investor's current beliefs.

A growing body of work started by Harrison and Kreps (1978) on heterogeneous beliefs states that in a market in which agents disagree about an asset's fundamental and short sales are constrained, an asset owner is willing to pay a price higher than his own expectation of the asset's fundamental because he expects to resell the asset to a future optimist at an even higher price (Xiong, 2013). Short-sales constraints can cause stocks to be overpriced when investors have heterogeneous beliefs about stock fundamentals (Scheinkman and Xiong 2003). Since the pessimistic investors are not allowed to short sell, prices in general will be higher than what would prevail in the absence of short-sale constraints (Xiong 2013). In fact, the housing market is a market where short-selling houses is impractical.[5]

To test whether heterogeneous beliefs lead to higher prices, we also introduce our new micro household level survey of expectations in seven cities and document that the larger dispersion of this expectation measure within a city amplifies the positive effect of our sentiment index on future housing price appreciation.

Constructing Our Sentiment Index

We construct our sentiment index by city/quarter by counting the total entries of the key words describing housing price trend in Google search[6]. For each of the 35 major cities, we type in its name, plus "housing price" and the mostly popular positive key words ("rising" or "increasing", in Chinese), and restrict the search in a specific quarter. Google Search reports back the total number of entries by quarter ($Positive_{it}$). These entries include the original articles with the optimistic views, and also the cross-pastes of those articles, and the comments about those articles in all kinds of websites.

[5] This is because different people claim ownership of the same house at the same time often results in legal disputes (e.g. multiple people use the same house as the collateral to borrow money from banks).

[6] Google's China Office closed in April 2010, but Chinese Internet users can still use Google search by linking to Google's website based in Hong Kong. Nevertheless this closing event caused a drop in the number of Google users in Mainland China. However, we believe that this does not bias our sentiment index. This is because our index counts the number of articles with the key words appearing in the three major local newspapers' websites and all kinds of online forums, blogs and micro-blogs. As long as people discuss those articles in those places, the Google search will find those webpages and return the number of total entries. Micro-blogs are a popular online social discussion forum nowadays in China. But it only exists for a very short existence period (from 2010) and it does not have a good built-in search engine, which prevents us from directly using it.

Therefore this count reflects the approximate size of the Internet chatters who share the common view of the optimistic housing price trend. We repeat this process but replace the positive key words with negative ones ("falling" or "decreasing") and obtain the total count by city/quarter ($Negative_{it}$). Our sentiment index is then calculated as the ratio of the count of positive entries to the total count of both positive and negative entries (Equation (1)).

$$Sentiment\ Index_{i,t} = \frac{Positive_{i,t}}{Positive_{i,t} + Negative_{i,t}} \tag{1}$$

This index reflects the relative degree of optimism for future price growth reflected in the Internet chatter. Investors in the market should have a qualitative sense of this ratio (more optimistic or less optimistic) though they may not know the exact number. The index captures the intensity that people are talking about those real estate articles and linking to them. If sentiment is high today then this means that people believe that home prices in the city will be higher next year and this should induce people to buy now.

Our sentiment index can also be observed by real estate developers. If a city's developers anticipate a rise in market sentiment and respond quickly by building more apartments, the supply curve will shift and the equilibrium price would rise by less even if the demand curve shifts out. However, housing supply responds much slower than demand to market sentiment due to several reasons in Chinese cities. First, urban land supply is controlled by city governments and is sluggish in responding to market signals. Second, it takes developers about two to three years to build after they buy land parcels from city governments. Third, most real estate developers in Chinese cities face a very tight financing constraint (with the average debt ratio over 60%), so in most situations they always choose to sell their apartments very fast to receive cash back. Therefore we view our sentiment index to be a demand shifter rather than a supply shifter.

Figure 2 shows the quarterly sentiment indices for the 35 Chinese cities. In our sample by city/quarter, 91.5% of all the sentiment index values are larger than 0.5 (positive entries more than negative ones). This means that in most time people are quite optimistic about future price appreciation.

*** Insert Table 2 here ***

To learn more about our sentiment index, we calculate its temporal autocorrelation within a city and its cross-city correlation. Similar to some macro-economic variables, such as GDP and housing price, the sentiment index is also highly auto-correlated based on our estimates of AR(1) models. Therefore in the empirical section, we follow Soo (2013) and first difference this index in all equations.

We examine market sentiment's effect on the price and quantity outcomes in the market for newly-built housing units in 35 Chinese major cities. The resale market is closely related to the new housing market through the filtering process. In a hot market with high sentiment index, rich households who own relatively higher quality and newer units in the existing stock (at the top of the filtering ladder) will sell their existing homes to the second-tier buyers at higher prices in order to finance their new purchases. Those second-tier buyers (renters or owners of relatively lower quality houses) are willing to move up along the ladder by paying higher prices if they also believe that housing prices will continue to rise. Therefore we believe that the positive associations between our sentiment index and housing price/quantity will also exist in the resale market. Here we implicitly assume that there is only a small number of people who will migrate to other cities during housing booms.

Other Variables

We study 35 major Chinese cities during 2006 and 2013. We focus on these cities because we can access high-quality housing price indices (*Housing Price*), price-to-rent ratios (*Price-to-rent Ratio*), land sale prices (*Land Price*), and the quantities of housing sales and land sales (*New Housing Sales* and *New Land Sales*, respectively) for them. These variables measure the price and quantity outcomes in the housing and land markets and they will be the dependent variables in our empirical equations.

Using data from the year 2000 Census we calculate the sex ratio (male to female ratio, *Male_Ratio*), the share of young people (20-35 years old, *Young%*), and the share of young males in each city (*Young_Male%*). We use the housing supply elasticity (*Supply Elasticity*) estimates from Wang et. al. (2012) as a measure of land scarcity in a city. In those cities where land supply is scarcer, an increase in the sentiment index (a demand shifter) is likely to increase local home prices. We are interested in the sentiment's heterogeneous effect in different cities, and the above city attributes will be interacted with our sentiment index in our empirical equations.

We include three variables to control for market fundamentals, city average household income (*Income*), interest rate in real term (*Interest*), and the exogenous demand shock in local labor market (*Labor Demand*). This last variable measures whether given a city's industrial composition and the nation's overall industrial growth whether a specific city's labor demand is rising. For example, if steel production at the national level is rising and a specific city is a center of steel production then this index predicts that this city will be booming. We follow Bartik (1991) and Blanchard and Katz (1992) to construct this exogenous labor demand variable where we weight national industry growth by the city's base year share of employment in that industry:

$$Labor\ Demand_{it} = \sum_{j=1}^{J} Employment_{ij,base} \cdot Growth_{jt} \qquad (2)$$

Where, $Labor\ Demand_{it}$ is the labor demand index for city i in year t; $Employment_{ij,base}$ is the employment share of industry j in city i in the base year (year 2006); $Growth_{jt}$ is the national employment growth rate of industry j in year t.

Table 1 provides the variable definitions and summary statistics.

*** Insert Table 1 here ***

Main Hypotheses

Within a given Chinese city in a given quarter, there are a large number of people considering purchasing an apartment. These people will differ with respect to their willingness to pay as a function of their demographics, income, access to capital and their beliefs about the likely future price appreciation. The marginal purchasers are likely to be the most optimistic among the group.

When an individual makes his home purchase decision now, he predicts how housing prices would change in the future. The prediction is based on the information from two main sources. One is the public available information which is observed by all market participants. This information composes of observable market fundamentals. The other source is social learning. Access to the Internet allows those who recognize their ignorance about the true model of price discovery for these assets to learn other people' belief about next year's price growth, and then approximate an empirical conditional distribution function of home price growth beliefs. Internet search is a low cost way of social learning. If such individuals act "as if" they know the sentiment index reported in equation (1), then this evolving state variable is likely to influence their bidding strategy. For example, if the city's population is optimistic about housing trends then this suggests that housing prices will be bid up. A renter who is intent on owning would be more likely to buy now before prices rise.

In the Appendix, building on the work by Wei et. al. (2012), we present a two-period choice model to describe people's decision between housing investment and saving. In Wei et. al. (2012) model, they mainly consider the "emotional utility" an individual can gain from marriage market by owning housing wealth as the major factor determining the individual's choice of the investments in housing market and non-housing market. They set housing price and rent to be stable in two periods, so the main factor affecting an individual's choice in the first period is the "emotional utility" he will gain from the status competition in the second period. Here, we include the individual's expectation of future housing price appreciation as the second factor influencing his housing investment decision. The intuition is that, if an individual expects that housing price will increase in the second period based on the information he obtains from both observing market fundamentals and social learning, he will have a higher probability to buy a house in the first period, and the marginal increase in this probability is positively correlated with the additional "emotional utility" derived from the marriage market. Our model yields the hypotheses H1-H2 below.

We test the following several hypotheses in our empirical work.

H1: Controlling for the fundamentals in the housing market, our sentiment index is positively correlated with future housing price appreciation, land price appreciation, the quantity of new housing sales, and the quality of land sales.

While we discuss alternative explanations below, our favorite explanation for these associations focuses on the claim that this index captures households' housing investment demand derived from their social learning on the Internet.

To test H1, we will estimate the following empirical equations (Equation (3)-(6)):

$$\Delta Housing\ Price_{i,t} = \alpha_0^{HP} + \beta^{HP} \cdot \Delta Sentiment_{i,t-1} + \gamma^{HP} \cdot Fundamentals$$
$$+\theta^{HP} \cdot Housing\ Price_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \qquad (3)$$

$$New\ Housing\ Sales_{i,t} = \alpha_0^{HS} + \beta^{HS} \cdot \Delta Sentiment_{i,t-1} + \gamma^{HS} \cdot Fundamentals$$
$$+\theta^{HS} \cdot New\ Housing\ Sales_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \quad (4)$$

$$\Delta Land\ Price_{i,t} = \alpha_0^{LP} + \beta^{LP} \cdot \Delta Sentiment_{i,t-1} + \gamma^{LP} \cdot Fundamentals$$
$$+\theta^{LP} \cdot Land\ Price_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \qquad (5)$$

$$New\ Land\ Sales_{i,t} = \alpha_0^{LS} + \beta^{LS} \cdot \Delta Sentiment_{i,t-1} + \gamma^{LS} \cdot Fundamentals$$

$$+\theta^{LS} \cdot New\ Land\ Sales_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \qquad (6)$$

Where Δ denotes the first difference by quarter. *Fundamentals* include the changes in observable fundamentals that drive housing price change over time, including the exogenous labor demand shock, log(*Labor Demand*), city average household income change, log(*Income*), and the lagged interest rate change in real term (we use the lagged term here to mitigate the endogenous problem due to interest regulation), *Interest*.

To control for the potential omitted variables we also include a set of city fixed effects, c_i. Housing price growth may bear a seasonal pattern so we also include a set of quarterly fixed effects, w_t. The standard errors are clustered by city. In estimating these regressions using OLS panel estimators, we are implicitly assume that the error term $\varepsilon_{i,t}$ is uncorrelated with the independent variables. This may not be true if the error term contains some unobservables that affect both housing price and market sentiment, such as unobserved market fundamentals and government interventions.

H2: The sentiment index is more positively correlated with price growth in the cities whose demographics predict higher home ownership demand.

The magnitude of the β coefficients in the above Equation (3) – (6) may vary across cities. First, given the demand shock caused by the increase in our sentiment index, cities with smaller housing supply elasticity (*Supply Elasticity*) will see a larger price appreciation and a smaller quantity of new construction.

Second, we have a direct measure of the heterogeneity in households' expectation towards future price change in our 7-city survey (*Std.Dev._expectation*). This survey was conducted in 2012 by the National Bureau of Statistics of China.[7] Each city survey

[7] The National Bureau of Statistics of China (NBSC) conducted this survey for us. Three first-tier cities (Beijing, Shanghai, Tianjin) and four second-tier cities (Chengdu, Xi'an, Wuhan, Shenyang) were selected. Each city's sample includes roughly 500 respondents. Households were randomly selected from each city. NBSC officials came to those respondents' home and assisted them to fill in the questionnaire.

yielded roughly 500 respondents. In the survey we asked the respondents "By what percentage do you think the housing price in your city will grow in the next year?" (*Expectation*). We compute the standard deviation of *Expectation* and call it *Std.Dev._Expectation*. A larger deviation means more people in the market are in the fat right tail so the marginal buyer will have a higher bidding price. Figure 3 shows the distributions of this expectation variable in those seven cities and the mean and standard deviation statistics. We can see that the first-tier cities, such as Beijing and Shanghai, have a larger dispersion, maybe due to the more dispersed demographics and higher uncertainty in such superstar cities. With short-sales constraint in the housing market, housing asset will be more likely to be overpriced to a larger extent in the cities where investors have a higher degree of heterogeneous beliefs (a larger *Std.Dev._expectation*). We will test if this heterogeneity in people's beliefs amplifies the positive effect of our sentiment index on future housing price appreciation.

We test the above heterogeneous effects of sentiment on market outcomes by estimating subsample regressions or interacting our sentiment index with those variables (Equation (7)).

$$\Delta Housing\ Price_{i,t} = \alpha_0^{HP} + \beta^{HP} \cdot \Delta Sentiment_{i,t-1} + \lambda^{HP} \cdot (Z_i \cdot \Delta Sentiment_{i,t}) + \gamma^{HP} \cdot \Delta Fundamentals_{i,t} + \theta^{HP} \cdot Housing\ Price_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \quad (7)$$

H3: By shifting home purchase to an earlier stage in one's life-cycle, optimistic sentiment towards future housing price appreciation pushes more renters into the homeownership, and therefore leads to a higher price-to-rent ratio.

Wei and Zhang (2011) state that Chinese parents with a son raise their savings in a competitive manner in order to improve their son's relative attractiveness for marriage. A large share of such savings will be used to buy a house which is regarded in China as a “necessity” a man needs to marry a woman. If the parents and their children believe that housing price in Chinese cities will keep rising, these young people will leave the rental market and transition to home ownership at an earlier age. We test this by interacting our sentiment index with several demographic variables, including the sex ratio (*Male_ratio*), the share of young people (*Young%*), and the share of young males (*Young_male%*).

We test this hypothesis by estimating Equation (8). During our study period our sentiment index keeps high (91% of the index values are larger than 0.5). This provides a possible explanation for the high price-to-rent ratio in Chinese cities found in Wu et. al. (2012).

$$\Delta Price-to-rent\ ratio_{i,t} = \alpha_0^{prr} + \beta^{prr} \cdot \Delta Sentiment_{i,t-1} + \lambda^{prr} \cdot (Z_i \cdot \Delta Sentiment_{i,t-1})$$

$$+\gamma^{prr} \cdot \Delta X_{i,t} + \theta^{prr} \cdot Price-to-rent\ ratio_{i,t-1} + \omega_t + c_i + \varepsilon_{i,t} \quad (8)$$

H4. Our sentiment index does not purely represent general “animal spirits”.

We argue that our sentiment index measures people’s optimistic view towards future housing price through social learning. But an alternative possibility is that this index only represents pure “animal spirits” – when people are generally excited about everything this index will be higher. We run a placebo test to see if this possibility is true. We create another sentiment index by searching for “food safety” (another hot topic in recent years in China) in Google Search (*Food Safety Sentiment Index*) in the largest eight cities among the 35 major cities. We include this variable in placebo regressions to see if it also has some effect on housing market outcomes.

Results

Table 2 presents the associations between our sentiment index and the price and quantity outcomes in the housing and land markets. Our basic market fundamentals are income change (*Δlog(Income)*), one quarter lagged real interest rate change (*ΔInterest_lag1*), and labor market demand shock (log(*Labor Demand)*). In all regressions we include the lagged term of the dependent variable (in level, to account for mean reversion), and control for city fixed effects. Standard errors are clustered by city. For housing price regressions, in column (1) we include our housing price sentiment index (one quarter lagged) and the fundamental variables. This sentiment index is statistically significant at 1% level. Among the three fundamentals, only labor market demand is statistically significant. Housing price shows a clear mean reversion pattern. This regression can explain 12.8% of the housing price variation. As a placebo test, in column (2) we augment the regression by adding our "food safety" sentiment index and this regression is constrained in the eight cities with this food safety index. It is not significant at all. This is not surprising because these two sentiment indices have a very weak correlation of 0.05. So our Hypothesis 4 is true – our housing price sentiment index does not purely represent "animal spirits". Column (3) and (4) show the quantity regressions. The dependent variable is how many units were sold in that quarter (in log). Higher housing price sentiment index in the previous quarter significantly push up transactions in the quarter after. It seems that the sentiment has a larger effect on quantity than on price. Rising Interest rate will significantly discourage market transactions. Again the food safety sentiment does not matter at all.

Columns (5) and (6) show that optimistic sentiment in the housing market also predicts higher land price and greater land sales in the later quarter.

*** Insert Table 2 here ***

In Table 3 we examine the heterogeneous effects of our sentiment index on market outcomes. The marginal housing investors in the cities with more constrained supply will be more anxious to buy and be willing to pay a higher price if they search online to find that others also think housing price will continue to rise. Here our sentiment index proxies for a type of demand shock. To test this, in column (1) and (2) we interact our sentiment index with a city's housing supply elasticity. Given a unit increase of the sentiment index, a city with more constrained supply will face a larger pressure on price appreciation, and a smaller amount of quantity change. With the same sentiment index mean, the marginal investor in the cities with a larger standard deviation of this index (*Std.Dev._Expectation*, more dispersed attitudes towards future market trend) should be willing to pay a higher bidding price. The significant and positive interaction term (*⊿Sentiment Index*_lag1**Std.Dev._Expectation*) in column (3) supports this claim. Such markets also have more new sales (see column (4)).

*** Insert Table 3 here ***

To test how demographics affect the role of social learning (Hypothesis 2), we interact our sentiment index with three demographic variables in Table 4. 91% of our sentiment index numbers (by city/quarter) have their values larger than 0.5, so in most time people are quite optimistic of future price growth. Our argument is that, when Chinese parents of boys and their children believe housing price will continue to rise, they will have more incentive to buy now rather than later (to avoid higher cost) because owning a house will raise the likelihood that the young man can marry (Wei and Zhang, 2011). In Table 4 we do see that in the cities with more males (*Male_ratio*), larger share of young people (*Young%*), especially young males(*Young_male%*), our optimistic sentiment measure significantly pushes up both housing price appreciation and transaction volumes.

*** Insert Table 4 here ***

If these young people leave the rental market and transition to home ownership at an earlier age in their life cycle, we will observe a higher price-to-rent ratio when or where the optimistic sentiment is strong. We regress price-to-rent ratio on our sentiment index and the fundamentals in Table 5. The increase in sentiment index will push up price-to-rent ratio (significant at 10%) level, and it has a larger role in cities with higher degree of heterogeneous beliefs, smaller supply elasticity, more anxious parents and their young boy children. This finding provides a possible explanation to the puzzle that Wu et. al. (2012) find that the every high price-to-rent ratio lacks the support of fundamentals in Chinese residential property market.

*** Insert Table 5 here ***

Robustness Checks

The positive associations between our sentiment index and market outcomes we reported above may be driven by market fundamentals if the sentiment index proxies for some fundamentals that market participants are aware of but we researchers have trouble quantifying. Following the method of Baker and Wurgler (2006) and Chauvet et. al. (2014) we develop an orthogonalized sentiment index (in first difference), $\Delta Sentiment\ index_o$. $\Delta Sentiment\ index_o$ is the residual from a regression of $\Delta Sentiment\ index$ on key fundamental variables. The regression result is provided in Table 7, where we can see there is a very small correlation between fundamentals (and also the lagged housing price change) and our sentiment index. All explanatory variables are insignificant, and the R square is very small. Overall, the correlation between the orthogonalized sentiment index and the original sentiment index (both in first difference) is 0.98, suggesting that the observed market fundamentals have a weak relationship with our sentiment index. Nevertheless we still cannot rule out the possibility that our sentiment index proxies for unobserved fundamentals.

We re-estimate Equation (3)-(6) with $\Delta Sentiment\ index$ replaced by $\Delta Sentiment\ index_o$ and all other variables unchanged (Table 7). The results are similar to those showed in Table 2 that the change in sentiment is positively correlated with housing price appreciation, land price appreciation, the quantity of new housing sales, and the quality of land sales.

*** Insert Table 6 here ***

*** Insert Table 7 here ***

Within City Variation in Housing Expectations, New Survey Evidence

We recognize that our empirical work has focused on a city panel data set measuring how average sentiment evolves over time. Ideally, we would observe each potential apartment buyer's and seller's expectations at each point in time. In this sub-section, we report results from a recent survey we conducted in seven Chinese cities. We use the results from this expectations survey to re-examine some of the relationships we reported above.

In this seven city survey, at the end of each quarter, our household survey asks the respondent about his/her expectation about price growth rate (in percentage) in the next 12 months (*Expectation*), and when he/her plans to buy a housing unit – "When do you plan to buy a house in the future?" (*Purchase_plan*, from 1 to 4, indicating "will buy a house 5 years or even longer years later", "will buy a house around 4-5 years from now", "will buy a house around 2-3 years from now", "will buy a house in this year"). This is a panel data set with only four quarters. These two questions allow us to test the implicit assumption we have made throughout this paper that our city/quarter sentiment index is positively correlated with average household optimism about future real estate price appreciation. Such optimists should be more likely to buy a home earlier.

Using this household survey, we first examine whether city i's sentiment index in quarter t is positively correlated with the housing price expectation of the individuals in that city. We regress individual k's expectation on his/her city i's sentiment index in that quarter (t), the lagged housing price and interest rate, and a bundle of household attributes (X) including household annual income, the household's gender, age and education attainment (Equation (9)). City fixed effects are controlled for and the standard errors are clustered by city. In the second step we further test that, if an individual expects that housing price will appreciate more, will he/she plan to buy a house earlier (Equation (10)). We estimate an ordered logit model in which we include the same control variables as those included in Equation (9).

$$Expectation_{kjt} = \alpha_0^e + \beta^e \cdot Sentiment_{kjt} + \lambda^e \cdot \log(Housing\ Price)_{j,t-1} + \eta^e \cdot \log(Interest)_{j,t-1} + \gamma^e \cdot X_{kj} + c_j + \varepsilon_{kjt} \quad (9)$$

$$Purchase\_Plan_{kjt} = \alpha_0^p + \beta^p \cdot Expectation_{kjt} + \lambda^p \cdot \log(Housing\ Price)_{j,t-1} + \eta^p \cdot \log(Interest)_{j,t-1} + \gamma^p \cdot X_{kj} + c_j + \varepsilon_{kjt} \quad (10)$$

Results are shown in Table 8. In the OLS regression in column (1), the respondent's expectation is positively associated with his/her city's sentiment index in that quarter at a very high statistic significant level. When they see the Central Bank increased interest rate, they expect that their city's housing market will cool down. Richer households are more optimistic, but other households' attributes do not matter much. In the ordered logistic regression in column (2), households with higher expectation do have a plan to buy homes much earlier.

*** Insert Table 8 here ***

The evidence reported in Table 8 increases our confidence that the city-level regression results that our sentiment captures a cross-elasticity in the sense that when households believe that future price increases will accelerate they are more likely to buy now.

Causal Effects?

We have argued that an unobservable (expectations and investor sentiment) plays an important role in Chinese real estate market dynamics. We recognize that serious concerns can be raised concerning whether the robust correlations we have documented truly represent causal effects. In this section, we lay out a possible research agenda that would further raise our confidence in this nascent literature's contribution.

In applied micro economics today, many studies rely on a field experiment design to guarantee that key explanatory variables are exogenously determined at the baseline. One way that the expectations literature could make progress on this front would be if certain influential people in Chinese society (a Chinese "Robert Shiller") could make statements whose content is determined at random to see how such influential speeches impact people's expectations. In a similar spirit as Manski's work on subjective expectations (Manski, 2004; Dominitz and Manski, 1997), one could combine our panel survey expectations design with an event study determined at random to see how expectations evolve as a function of the actions of influential people. This would be a direct test of "learning from others", though it is difficult to actually implement such a field experiment.

Does our sentiment index proxy for unobserved fundamentals that investors know but we do not? In this case, we would face a serious omitted variables problem. If unobserved (to the econometrician) fundamentals are common knowledge, the mood and optimism in a city reflects fundamentals that have already been recognized to cause real estate outcomes rather than it being the case that the mood and optimism themselves have a causal effect. One way to study this would be if there is a major policy regime change in China such that the government reduces political business cycle uncertainty about its housing policies. In that case we predict that the coefficient on sentiment should shrink close to zero. If such shrinkage did not occur then this would suggest that our model suffers from omitted variables bias.

Another concern with our empirical approach is reverse causality. We acknowledge that our sentiment index may be caused by past housing price dynamics. In this "adaptive expectations" case, we would misinterpret the causal effect of city wide optimism when in fact the price series simply reflects auto-correlation. However, our empirical results in Table 6 show that the lagged housing price change has a very weak prediction power on the change in the sentiment index. This discussion does highlight the point that we do not have a very strong grasp for why the city sentiment index evolves over time. Given the growth in the number of studies examining market sentiment in the United States and China, future research should be able to make progress on this topic.

Conclusion

In China's emerging housing market, many market participants recognize that they "know that they do not know" the main factors determining pricing dynamics. Such individuals have strong incentives to seek out additional information related to the house price appreciation expectations of others. The Internet offers such information.

Building on a recent U.S literature, we have shown how to use Google searches to create a city panel data set on evolving net optimism about real estate trends in China. Based on a series of regressions, we have reported that this sentiment index acts as if it is a demand shifter. When optimism is higher in a market, prices rise, property sales increase and land auction prices increase. We have also documented that we can explain heterogeneity in the effect of this index using simple demand side and supply side explanations.

While it is intuitive that different people may hold different views of the future, the challenge remains how to elicit such initial views (as we have done through our new micro survey) and to understand how different people update their beliefs as new information becomes available and to study how people act upon such beliefs. In ongoing research, we are investigating whether the most optimistic households in our seven city survey are more likely to buy apartments. Do people act upon their optimism? Panel data at the household level will help to provide microfoundations for the city aggregate patterns we have documented.

References

Allen F, Morris S, Shin H S. Beauty contests and iterated expectations in asset markets. Review of Financial Studies, 2006, 19(3): 719-752.

Baker, Scott, Nick Bloom, and Steven Davis. "Has Economic Policy Uncertainty Hampered the Recovery?." Chicago Booth Research Paper 12-06 (2012).

Baker M, Wurgler J. Investor sentiment and the cross‐section of stock returns[J]. The Journal of Finance, 2006, 61(4): 1645-1680.

Bartik T J. Who benefits from state and local economic development policies?. Books from Upjohn Press, 1991.

Becker, Gary S., Kevin M. Murphy, and Ivan Werning. "The equilibrium distribution of income and the market for status." Journal of Political Economy113.2 (2005): 282-310.

Blanchard O J, Katz L F, Hall R E, et al. Regional evolutions. Brookings papers on economic activity, 1992, 1992(1): 1-75.

Chauvet M, Gabriel S, Lutz C. Fear and Loathing in the Housing Market: Evidence from Search Query Data. Available at SSRN, 2012.

Chinco, Alex and Christopher Mayer, Misinformed Speculators and Mispricing in the Housing Market, 2014 Columbia Working Paper.

Dominitz, Jeff, and Charles F. Manski. "Using expectations data to study subjective income expectations." Journal of the American Statistical Association 92.439 (1997): 855-867.

Guo X, Zheng S, Geltner D, Liu H. A New Approach for Constructing Home Price Indices in China: The Pseudo Repeat Sales Model. Journal of Housing Economics, 2014. Forthcoming.

Han, Lu, and William C. Strange. "Bidding Wars for Houses." Real Estate Economics (2013).

Kahn, Matthew E., and Matthew J. Kotchen. "Business cycle effects on concern about climate change: the chilling effect of recession." Climate Change Economics 2, no. 03 (2011): 257-273.

Manski, Charles F. "Measuring expectations." Econometrica 72.5 (2004): 1329-1376.

Ro, SeungHan, and Paul Gallimore. "Real Estate Mutual Funds: Herding, Momentum Trading and Performance." Real Estate Economics (2013).

Saiz, Albert. "The geographic determinants of housing supply." *The Quarterly Journal of Economics* 125, no. 3 (2010): 1253-1296.

Scheinkman, Jose A., and Wei Xiong. "Overconfidence and speculative bubbles." *Journal of political Economy* 111, no. 6 (2003): 1183-1220.

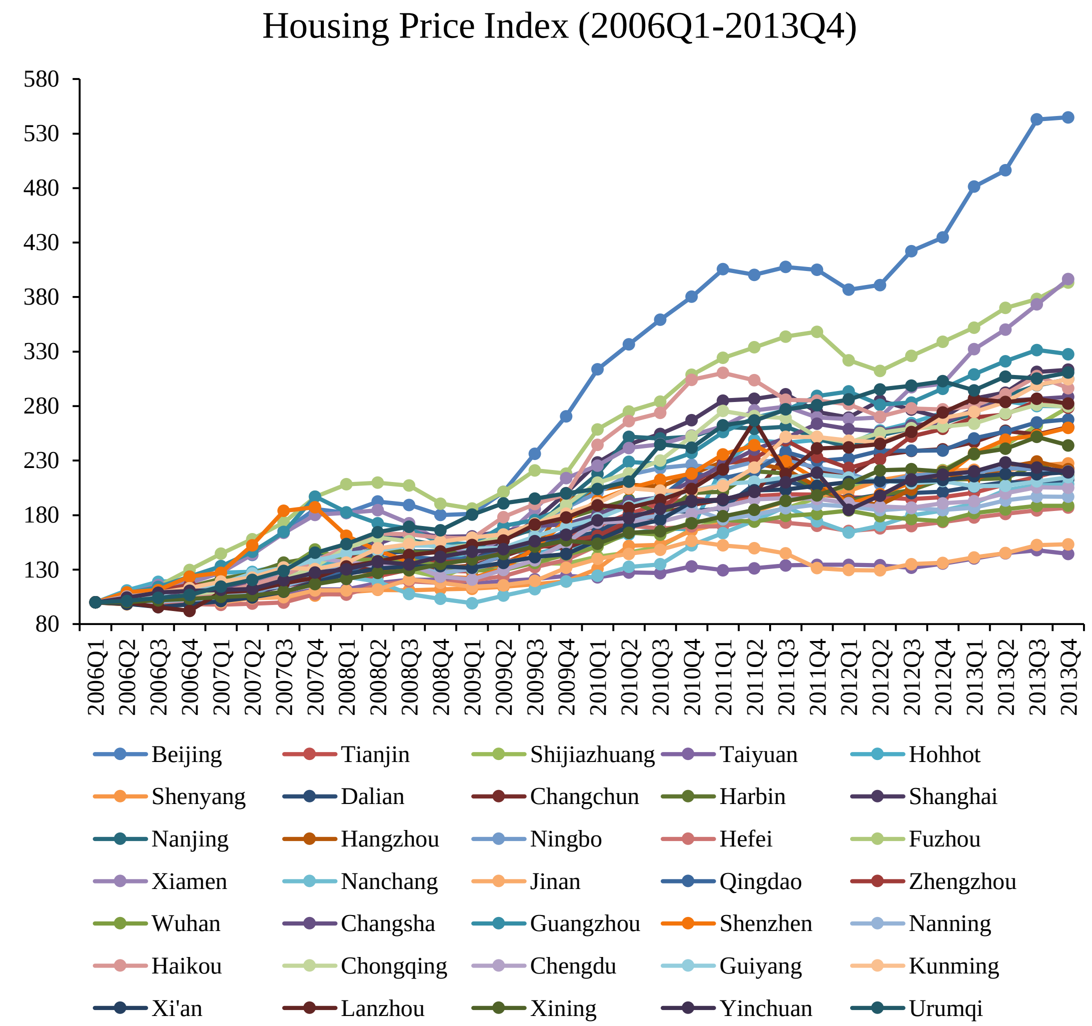
Soo C. Quantifying animal spirits: news media and sentiment in the housing market. Working paper, Wharton School, University of Pennsylvania, 2013.

Wang S, Chan S H, Xu B. The estimation and determinants of the price elasticity of housing supply: Evidence from China. Journal of Real Estate Research, 2012, 34(3): 311-344.

Wei S J, Zhang X. Sex ratios, entrepreneurship, and economic growth in the People’s Republic of China. National Bureau of Economic Research, 2011.

Wu J, Gyourko J, Deng Y. Evaluating conditions in major Chinese housing markets. Regional Science and Urban Economics, 2012, 42(3): 531-543.

Xiong, Wei. Bubbles, Crises, and Heterogeneous Beliefs. No. w18905. National Bureau of Economic Research, 2013.



First-tier Cities: Beijing, Shanghai, Shenzhen

Figure 1 Hedonic Housing Price Indices in 35 Major Chinese Cities

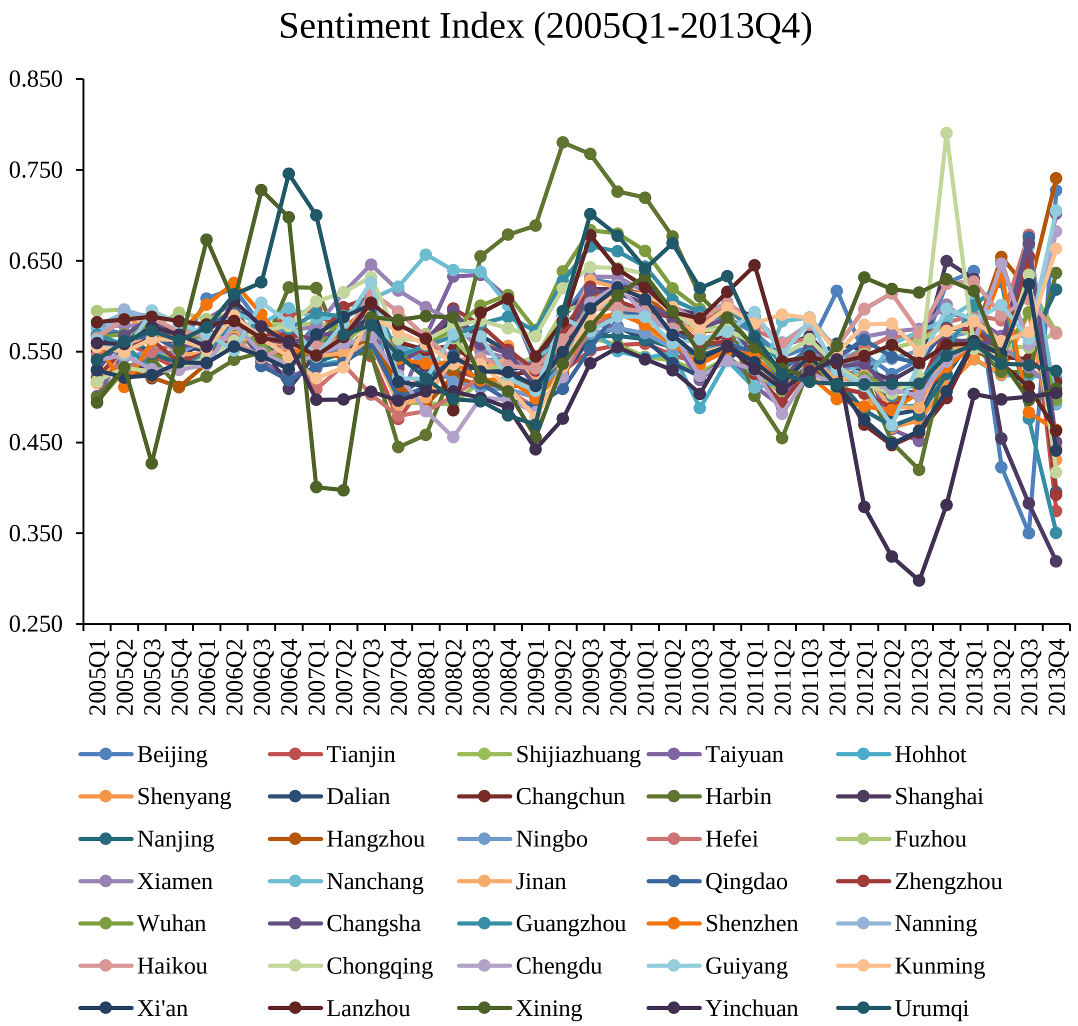
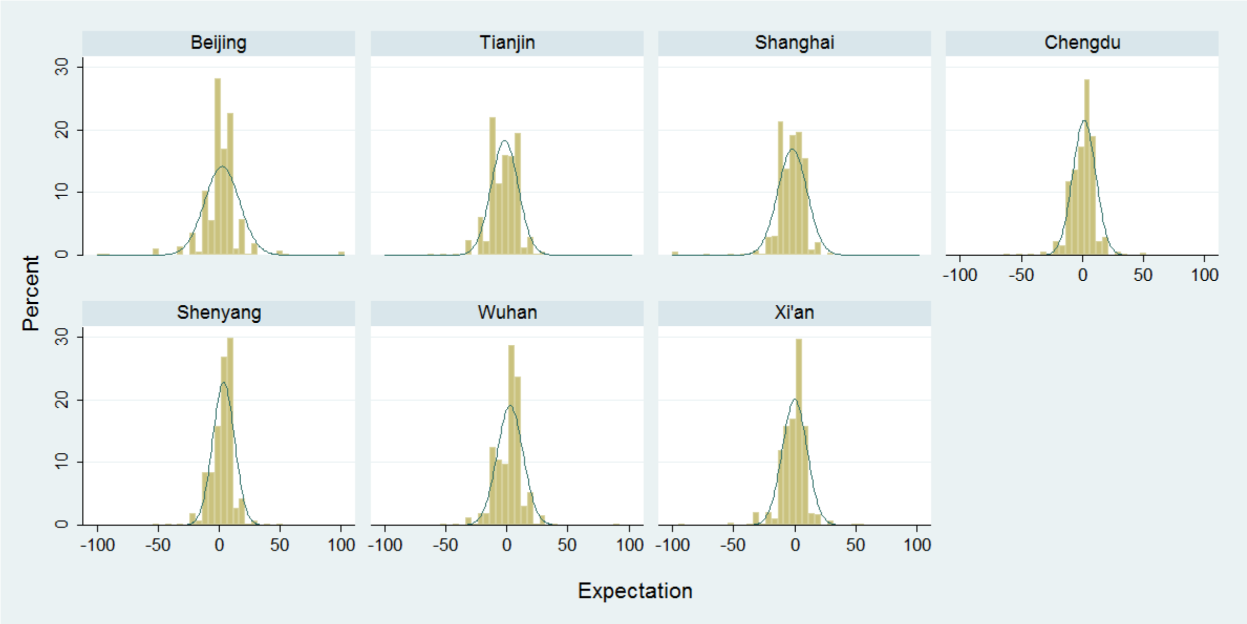


Figure 2 Housing Sentiment Indices in 35 Major Chinese Cities



City	Mean (%)	Standard Deviation (%)
Beijing	2.447	14.272
Tianjin	-1.815	11.030
Shanghai	-1.832	11.931
Chengdu	1.502	9.859
Shenyang	3.667	8.859
Wuhan	2.635	10.604
Xi'an	0.076	10.084

Figure 3 Dispersion of People's Expectation of Future Housing Price Appreciation in the Next Year in Seven Chinese Cities

Table 1 Variable Definitions and Summary Statistics

		Obs.	Mean	Std. Dev.	Min	Max
Sentiment Indices:						
Sentiment index	Housing price sentiment index	1120	0.56	0.05	0.30	0.79
Food Safety Sentiment index	Food safety sentiment index	256				
Housing Market Indicators:						
Housing Price	Quality-controlled hedonic housing price index (2006Q1-2013Q4, 2006Q1=100)	1116	179.52	67.04	92.18	544.95
New Housing Sales	Number of apartment units sold	1116	12185.11	10009.73	305	74711
Land Price	City average land auction price	1031	2606.22	2522.09	122	16882.5
New Land Sales	Number of the sold land parcels	1120	14.41	15.51	0	126
Price-to-rent Ratio	Price-to-rent ratio (2009Q1-2013Q4)	698	26.95	8.13	10.71	63.51
Fundamentals:						
Labor Demand	Bartik index measuring exogenous demand shock in local labor market	1120	0.04	0.04	-0.05	0.14
Income	City average household income	1120	5987.22	2315.77	2210.94	15274.64
Interest	Interest rate in real term	1120	0.00	0.02	-0.05	0.05
Supply Elasticity	Land supply elasticity (Data source: Wang S, Chan S H, Xu B (2012))	35	0.85	0.11	0.57	0.99
Std.Dev._expectation	Standard deviation of respondents' expectation for housing price appreciation (%) in the city, from the small survey.	7	10.88	1.81	8.86	14.27
Male_Ratio	The ratio of males to females in the city (2000 census)	35	1.07	0.03	0.97	1.13
Young%	The share of young people (20-35y) in the city (2000 census)	35	0.30	0.06	0.24	0.59
Young_Male%	The share of young males (20-35y) in the city (2000 census)	35	0.16	0.03	0.12	0.29

Table 2 The Sentiment Index Predicts Price and Quantity Outcomes in the Housing and Land Market (Panel, all cities, 2006Q1-2013Q4)

Dependent Variable	⊿log(*Housing Price*)		log(*New Housing Sales*)		⊿log(*Land Price*)	log(*New Land Sales*)
	(1)	(2)	(3)	(4)	(5)	(6)
⊿*Sentiment index*_lag1	0.0776***	0.00890*	0.936***	0.0320**	0.352*	0.904***
	(2.79)	(2.01)	(3.79)	(2.96)	(1.98)	(3.03)
⊿log(*Food safety sentiment index*)_lag1		0.00230		-0.0132		
		(0.49)		(-0.38)		
log(*Labor Demand*)	0.0124***	0.0301**	0.138**	-0.0560	0.145***	0.274***
	(3.17)	(2.61)	(2.72)	(-0.55)	(6.23)	(4.01)
Lagged Price (in level)	-0.0620***	-0.0922***	-	0.502***	-0.667***	-
	(-8.45)	(-3.60)	-	(4.93)	(-11.34)	-
⊿log(*Income*)	0.00939	0.0402	0.117	0.354	0.0795	-0.0195
	(0.62)	(1.36)	(0.94)	(1.18)	(0.52)	(-0.09)
⊿*Interest_lag1*	-0.0846	-0.0164	-0.373***	-0.334***	0.0129	-0.154*
	(-1.53)	(-1.46)	(-7.40)	(-5.67)	(0.30)	(-1.85)
Constant	0.385***	0.560***	9.618***	4.165***	5.472***	3.318***
	(8.01)	(3.60)	(59.97)	(3.85)	(11.64)	(15.00)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	945	248	979	248	905	961
Adjusted R^2	0.128	0.216	0.702	0.497	0.325	0.423

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 3 The Heterogeneous Effects of the Sentiment Index on Market Outcomes with Respect to Different Market Attributes.

Dependent Variable	⊿log(*Housing Price*)	log(*New Housing Sales*)	⊿log(*HP*)	log(*SALE*)
	Sentiment Index interacted with *Supply Elasticity*		*Sentiment Index* interacted with *Std.Dev._Expectation*	
	(1)	(2)	(3)	(4)
⊿*Sentiment index*_lag1	0.443**	0.0269	0.0492	0.596
	(2.15)	(0.13)	(1.27)	(1.90)
⊿*Sentiment index*_lag1* *Supply Elasticity*	-0.435*	1.171***		
	(-1.88)	(4.65)		
⊿*Sentiment index*_lag1* *Std.Dev._expectation*			0.00997***	0.0971***
			(5.06)	(5.88)
log(*Labor Demand*)	0.0121***	0.138**	0.00812	0.0340
	(3.08)	(2.69)	(1.42)	(0.42)
Lagged Price (in level)	-0.0611***	-	-0.0447***	-
	(-8.31)	-	(-3.77)	-
⊿log(*Income*)	0.00805	0.123	0.0238	0.206
	(0.55)	(0.97)	(1.24)	(0.77)
⊿*Interest_lag1*	-0.0884	-0.372***	0.00364	-0.283***
	(-1.57)	(-7.32)	(0.55)	(-4.36)
Constant	0.379***	9.617***	0.288**	10.14***
	(7.89)	(59.33)	(3.66)	(38.86)
City fixed effect	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Observations	945	979	189	196
Adjusted R^2	0.134	0.703	0.175	0.252

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 4 The Heterogeneous Effects of the Sentiment Index on Market Outcomes with Respect to Demographic Variation.

Dependent Variable	⊿log(*Housing Price*)			⊿log(*New Housing Sales*)		
	(1)	(2)	(3)	(4)	(5)	(6)
⊿*Sentiment index*_lag1	0.0312	0.0309	0.0308	0.0420	0.0383	0.0371
	(1.22)	(1.19)	(1.19)	(0.19)	(0.18)	(0.17)
⊿*Sentiment index*_lag1**Male_Ratio*	0.0723***			0.876***		
	(2.80)			(3.77)		
⊿*Sentiment index*_lag1**Young%*		0.290***			3.005***	
		(2.97)			(3.65)	
⊿*Sentiment index*_lag1**Young_Male%*			0.555***			5.789***
			(2.98)			(3.67)
log(*Labor Demand*)	0.0120***	0.0120***	0.0120***	0.138**	0.137**	0.137**
	(3.12)	(3.14)	(3.14)	(2.69)	(2.68)	(2.68)
Lagged Price (in level)	-0.0615***	-0.0613***	-0.0612***	-	-	-
	(-8.47)	(-8.54)	(-8.52)	-	-	-
⊿log(*Income*)	0.0103	0.0107	0.0107	0.119	0.116	0.116
	(0.68)	(0.70)	(0.70)	(0.94)	(0.93)	(0.93)
⊿*Interest_lag1*	-0.0936	-0.0960*	-0.0959*	-0.373***	-0.373***	-0.373***
	(-1.66)	(-1.70)	(-1.71)	(-7.35)	(-7.36)	(-7.36)
Constant	0.381***	0.380***	0.379***	9.618***	9.619***	9.619***
	(8.04)	(8.12)	(8.11)	(59.33)	(59.45)	(59.45)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	945	945	945	979	979	979
Adjusted R^2	0.129	0.134	0.134	0.702	0.702	0.702

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 5 The Sentiment Index Pushes up the Price-to-Rent Ratio.

The Dependent Variable: Is the change in the Price to Rent Ratio *⊿Price-to-rent Ratio*

	(1)	(2)	(3)	(4)	(5)	(6)
*⊿Sentiment index*_lag1	0.0573*	-0.0304	0.857**	0.0352	0.0364	0.0361
	(1.76)	(-0.49)	(2.45)	(1.02)	(1.13)	(1.13)
*⊿Sentiment index*_lag1 **Std.Dev._Expectation*		0.00345*				
		(2.28)				
*⊿Sentiment index*_lag1**Supply Elasticity*			-0.996**			
			(-2.50)			
*⊿Sentiment index*_lag1 **Male_Ratio*				0.0561*		
				(1.84)		
*⊿Sentiment index*_lag1**Young%*					0.224*	
					(2.00)	
*⊿Sentiment index*_lag1 **Young_Male%*						0.428*
						(1.95)
*Price-to-rent Ratio*_lag1(*100)	-0.827***	-0.816***	-0.777***	-0.824***	-0.821***	-0.821***
	(-8.88)	(-12.47)	(-8.77)	(-8.82)	(-7.92)	(-7.91)
Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	133	662	662	662	662
AdjustedR^2	0.209	0.358	0.200	0.209	0.210	0.210

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 6 The Correlation between Sentiment Index and Fundamentals

The Dependent Variable: *⊿Sentiment index*

	(1)
log(*Labor Demand*)	-0.00749
	(-1.53)
⊿log(*Housing Price*)	-0.0606
	(-0.94)
⊿log(*Income*)	0.0374
	(1.27)
⊿*Interest*	0.0413
	(0.22)
Quarter Fixed Effects	YES
City Fixed Effects	YES
Observations	978
Adjusted R^2	0.040

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 7 The Orthogonalized Sentiment Index Predicts Price and Quantity Outcomes in the Housing and Land Market (Panel, all cities, 2006Q1-2013Q4)

Dependent Variable	⊿log(*Housing Price*)	Log(*New Housing Sales*)	⊿log(*Land Price*)	log(*New Land Sales*)
	(1)	(2)	(3)	(4)
⊿*Sentiment index*$_0$_lag1	0.0812***	0.875***	0.367**	0.845***
	(2.88)	(4.14)	(2.11)	(2.73)
log(*Labor Demand*)	0.0118***	0.132**	0.174***	0.271***
	(3.10)	(2.58)	(7.20)	(3.90)
Lagged Housing Price (in level)	-0.0622***		-0.775***	
	(-8.46)		(-15.03)	
⊿log(*Income*)	0.00819	0.0743	0.0213	-0.182
	(0.53)	(0.65)	(0.16)	(-0.82)
⊿*Interest_lag1*	-0.0785	-0.373***	-0.00586	-0.167*
	(-1.43)	(-7.26)	(-0.13)	(-1.96)
Constant	0.386***	9.626***	6.448***	3.428***
	(8.03)	(60.27)	(15.48)	(15.25)
City fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Observations	943	943	834	886
Adjusted R^2	0.129	0.712	0.389	0.474

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.

Table 8 Sentiment Influences Individuals' Expectations (Survey Sample Evidence)

Dependent Variables: The respondent's expectation about housing price appreciation rate in the next 12 months (%) and the demand for buying a house

Dependent Variable	*Expectation*	*Purchase Plan*
	OLS	Ordered Logistic Regression
	(1)	(2)
Sentiment index	47.81***	
	(5.42)	
Expectation		0.0142***
		(2.92)
Lagged housing price (log(*HP*)_lag1)	-51.13***	-1.112
	(-5.22)	(-0.46)
Lagged Interest rate in real term (INTEREST_lag1)	-3.415***	-4.235
	(-2.64)	(-0.92)
Whether the household owns a house now	0.228	-0.0860
	(0.66)	(-0.81)
log(*Household annual income*)	0.249	0.287***
	(0.97)	(2.82)
Household head's age	0.192**	0.0317
	(2.35)	(1.12)
Household head's age Square	-0.00181**	-0.000286
	(-2.31)	(-1.01)
Household head's gender (male=1)	0.237	0.124
	(0.84)	(1.34)
Whether the household head holds a graduate degree (yes=1)	0.214	0.102
	(0.53)	(0.80)
Constant	259.4***	
	(5.12)	
City fixed effect	Yes	Yes
Observations	5218	1747
Adjusted R^2/ chi2	0.109	55.63

Notes: (1) t-statistics are reported in parentheses. (2) ***: significant at the 1% level; **: significant at the 5% level;*: significant at the 10% level. (3) Standard errors are clustered by city.