House Price Bubbles in China*

Yu Ren Yufei Yuan† Cong Xiong

The Wang Yanan Institute for Studies in Economics

Xiamen University, Fujian, China, 361005

December 17, 2011

Abstract

In this paper, we apply the theory of rational expectation bubbles to the Chinese housing market. Rational expectation bubbles imply that negative returns on house prices are, theoretically, less likely to occur if the bubbles exist and persist. Based on data from 35 cities in China, we find no evidence to support the existence of bubbles in the housing market.

JEL classification: R31; E31

Keywords: China house price; Rational expectation bubble; Hazard rate

*Yufei Yuan is an Assistant Professor at Xiamen University. Yuan's research was supported, in part, by Xiamen University. Yu Ren is an Associate Professor at Xiamen University. Ren's research was supported by Xiamen University, the Natural Science Foundation of Fujian Province of China (No.2011J01384), the Natural Science Foundation of China (No.71131008 and No.70971113). We thank the co-editor, Professor Yi Wen, and the anonymous referee for insightful comments that greatly improved this paper. We also thank Seonghoon Kim, Shihe Fu, Ying Shang, Ying Fang, Renshui Wu and the participants in the annual meeting of China Economics Society 2010, Peking University and Shanghai University of Finance and Economics.

†Corresponding Author. Corresponding address: The Wang Yanan Institute for Studies in Economics, Xiamen University, Fujian, China 361005. Email: yyuanwise@gmail.com. Phone: 86-592-218-1782. Fax: 86-592-218-7708.

1 Introduction

In the past 20 years, housing prices in China have risen rapidly. From 2003 to 2007, the average price increase reached as high as 14% per year. For some cities, such as Beijing, the increase in house prices reached 22% annually during that period. If we consider rental income and capital income, then the return on housing capital exceeds that of business sectors,[1] which understandably attracts substantial concern regarding the existence of price bubbles. This has become one of the major concerns of policymakers in China because a bubble burst would lead to serious consequences for China's economy. Thus, it is important to determine whether housing price bubbles actually exist in China. The major contribution of this paper is to provide a new method for answering this question.

Most related literature tests for house price bubbles by comparing the present value of houses with housing market prices. The main debate in the literature concerns how to calculate present value. One of the most popular methods is to discount future cash flows (rental income), but this approach is not reliable. Future rental income in China is difficult to predict because rental income is affected by GDP, population density, and other economic variables, and those economic variables continue to change over time. Furthermore, it is difficult to choose the appropriate discount rate for housing assets.

Alternatively, other contributions to the literature consider that house price increases can be explained by changes in economic fundamentals, such as income, construction costs, population and interest rates. House price bubbles are then defined as deviations from those fundamentals. For example, Mikhed and Zemcik (2009) suggest the oversized house price increases in the US cannot be explained by the changes in these fundamentals between 1997 and 2006, in distinction to McCarthy and Peach (2004), who at the

[1] Xin, Lin and Yang (2007) estimate the average return rate of the listed companies in Chinese stock markets. They display that the average return rate is around 2.6%. CCER (2007) displays that capital returns in China have been increasing since 1998. The capital return of state-owned companies is 8% on average from 2003 to 2006. And the capital return of the private sectors is 17% on average from 2003 to 2006. Because the private sectors are financially constrained, the high return can be explained by their insufficient capital. The literature, such like Cagetti and Nardi (2006), has shown that when financially constrained, the companies have higher capital returns in equilibrium.

time of their publication found that there was no bubble in the US housing market and that changes in house prices reflected movements in the fundamentals, such as income and interest rates[2]. However, this approach heavily depends on the choice of economic fundamentals, and the results are quite sensitive to the perspective from which these fundamentals are considered.

As for the housing market in China, many researchers set up demand and supply functions for housing and use market equilibrium conditions to test for house price bubbles, but the definition of a bubble is vague in their papers. Moreover, Montrucchio and Privileggi (2001) and Santos and Woodford (1997) among others have already proved that rational expectation bubbles are marginal and fragile in the general equilibrium of efficient markets. Hence, solid theoretical support does not exist for applying the equilibrium model to this area.

In this paper, we provide a new method to test the existence of the rational expectation bubbles in China housing market. The rational expectation bubbles are proposed by Blanchard and Watson (1983). These bubbles bring the returns comparative to the average returns of other assets in order to compensate the opportunity costs of holding such assets. Moreover, rational expectation bubbles are characterized by asset prices that continue to grow over time and returns that surpass the average capital return in the economy. These features match the dynamic path of China's house prices quite well during the past ten years.

While there is another kind of bubbles, static bubbles, which could possibly exist in China. If the economy has incomplete financial markets, the static bubbles can exist in competitive equilibrium. Here we refer to incomplete financial markets following the paper by Kiyotaki and Moore (2004). In incomplete financial markets, firms have borrowing constraints against their future flows of profits and liquidity constraints against their capital holding. Hence they choose to save in the forms of liquid assets in order to

[2]This literature also includes Shiller (1990), Clapp and Giaccotto (1994), Abraham and Hendershott (1996), Capozza et al.(2002), Case and Shiller (2003), and Gallin (2006).

fund the possible future demand for investment. Some of the recent literature, such like Kocherlakota (2009) and Wang and Wen (2009), points out that in such economies of incomplete financial markets, the static bubbles can exist as a form of liquid assets in one of the multiple general equilibria. The static bubbles allow entrepreneurs to re-allocate physical capital more efficiently and hence lead to higher wages and consumption.

The distinguished feature between these two bubbles are that before they burst, the rational expectation bubbles are growing while the static bubbles are not. By comparing the growing bubbles (the rational expectation bubbles) with the static bubbles, we can see some interesting and important differences on the consequences of their collapses. If people hold bubble assets just to capture the future high returns, the bubbles must grow over time and hence yield the high returns to compensate investors for the probability of a crash. In this case, the burst of the growing bubbles will not affect liquidity or capital allocation. While, if people hold the bubbles for liquidity demand in the future, the bubbles may have returns lower than the average returns of the economy and hence might not grow over time. The benefits of facilitating liquidity will compensate the probability of bubble crash and the low returns. Therefore, the collapse of static bubbles will let the entrepreneurs lose liquidity value and have to self-finance their investment, which lead to the inefficient usage of the physical capital.

Hence, if we could exclude the existence of the growing bubbles in China housing market, then the only possible bubble is the static one. And the bursting of static bubbles can generate large adverse welfare effects. As we know, Chinese government recently makes a series of policies to cool down the real estate markets. One of the policies is to directly freeze the market by restricting the purchases of residential real estate. Our work can shed some light on the aftermath of the possible bubbles bursting of house prices under these policies.

Unlike most literature studying China housing market, such as Dreger and Zhang (2010), Han (2010) and Wang et al. (2011), this paper tests for housing price bubbles by adopting the method in McQueen and Thorley (1994) originally proposed to find stock market bubbles. Because the theory of rational expectation bubbles can be applied to any risky asset and McQueen and Thorley (1994) derive their method based on this theory, their method can also be applied to house prices. To the best of our knowledge, we are the first to introduce this method into the housing literature. However, the method in McQueen and Thorley (1994) cannot be implemented directly. In the empirical analysis, we find that annual data only exists for eleven years, which is too limited to conduct the same application of time series as McQueen and Thorley (1994) did. This limitation also makes it difficult to apply the method of cointegration or unit root tests, as applied in Mikhed and Zemcik (2009). We circumvent this problem by extending the method into the panel data analysis for metropolitan areas since the housing returns in those areas are highly correlated [3]. The method we use bypasses the arbitrary estimation of fundamental house values and avoids the theoretical weakness of general equilibrium models in the current literature. The basic idea behind our methodology is that the theory of rational expectation bubbles implies that negative returns on house prices are less likely to occur, theoretically, if bubbles exist and persist. However, based on data from 35 cities in China, we find the hazard rate of positive returns is not a decreasing function of duration. Thus, we suggest that there are no rational expectation bubbles in the housing market of China.

The remainder of this paper is organized as follows. In Section 2, we display the model to test for house price bubbles. In Section 3, we illustrate the empirical results, and Section 4 provides a conclusion.

[3] We conduct the cross-section correlation test with the null hypothesis that all the housing returns are uncorrelated against the alternative that the correlation is nonzero for some of them. We use the statistic in Frees (1995) and find that the null hypothesis is rejected at the significant level of 1%.

2 Model

2.1 Theoretical Model

Blanchard and Watson (1983) propose the definition of the rational expectation bubbles based on a simple efficient market condition, which states the expected return of a house is equal to the required return:

$$E_t[R_{t+1}] = r_t.$$

Here E_t denotes the expectation conditional on the information set of time t. And r_t is the required return on this asset at period t. R_{t+1} can be regarded as the return of owning house from period t to period $t+1$. Specifically,

$$R_{t+1} \equiv \frac{p^*_{t+1} - p^*_t + d_{t+1}}{p^*_t}.$$

Here p^*_t and p^*_{t+1} are the unobservable true values of housing at periods t and $t+1$. d_{t+1} is the rental income of the house at period $t+1$. By holding a house from period t to period $t+1$, the investor can have two sources of revenues: the capital gain from the variation of the house prices and the rental income. After some rearrangement, the condition for a competitive equilibrium is equivalent to

$$p^*_t = \frac{E_t[p^*_{t+1} + d_{t+1}]}{1 + r_t}. \tag{1}$$

By repeatedly imposing the above conditions, we can get the expression defining the fundamental values of the house as

$$p^*_t \equiv E_t \sum_{i=1}^{\infty} \frac{d_{t+i}}{\prod_{j=0}^{i-1}(1 + r_{t+j})}. \tag{2}$$

We assume the market house prices, p_t, contain two components: the true value and the bubble as $p_t = p_t^* + b_t$. Here b_t is denoted as the bubble. While as long as b_t satisfies

$$E_t[b_{t+1}] = (1 + r_t)b_t, \tag{3}$$

the condition (1) also holds for the market prices. It suggests that the market price can deviate from the fundamental value by a rational speculative bubble factor b_t. Equation (3) is the necessary condition of the bubbles existing in the competitive equilibrium. It implies that as long as the bubble component b_t grows over time and provides the required return r_t, the agents in the economy would like to hold the houses with price bubbles.

Following McQueen and Thorley (1994), we use ϵ_{t+1} to define the unexpected price changes of the houses. Since $p_{t+1} = p_{t+1}^* + b_{t+1}$, both the unexpected changes in the true value and the unexpected changes in the bubble components can affect ϵ_{t+1}. That means $\epsilon_{t+1} = \mu_{t+1} + \eta_{t+1}$, where μ_{t+1}, η_{t+1} are the unexpected changes for the true value and the bubbles respectively. The unexpected change in the true value is defined by

$$\mu_{t+1} = p_{t+1}^* + d_{t+1} - (1 + r_t)p_t^*.$$

And the unexpected change in the bubble is defined by

$$\eta_{t+1} = b_{t+1} - (1 + r_t)b_t.$$

We assume that μ_{t+1} satisfies a symmetric distribution with mean 0. The symmetric assumption on the distribution of μ_{t+1} is made based on the fact that the true value is usually believed to have mean-reversion property. In addition, we assume that b_t follows a two-point discrete distribution. With a probability of π, the bubble component b_t can persist and stay in the house price for the next period. With a probability of $1 - \pi$, the bubble component b_t will burst and the left-over value is a_0. In order to make the equilibrium condition (Equation (3)) hold, b_{t+1} must satisfy the following condition

$$b_{t+1} = \begin{cases} \frac{(1+r_t)b_t}{\pi} - \frac{1-\pi}{\pi}a_0 & \text{with probability } \pi \\ a_0 & \text{with probability } 1-\pi \end{cases}. \tag{4}$$

Here, we assume $\pi > 1 - \pi$, which implies $\pi > 1/2$. This assumption is reasonable because, empirically, the probability for a bubble, no matter what the underlying asset is, to burst is smaller than to persist. We can observe this stylized fact from stock markets, housing markets around the world. Furthermore, intuitively

$$\frac{(1+r_t)b_t}{\pi} - \frac{1-\pi}{\pi}a_0 > a_0 \geq 0. \tag{5}$$

This means if the bubble persists, its realized value is larger than the value when it bursts.

By plugging the equation (4), we can transform the equation $\epsilon_{t+1} = \mu_{t+1} + \eta_{t+1}$ into

$$\epsilon_{t+1} = \begin{cases} \mu_{t+1} + \frac{(1-\pi)}{\pi}\left[(1+r_t)b_t - a_0\right] & \text{with probability } \pi \\ \mu_{t+1} - (1+r_t)b_t + a_0 & \text{with probability 1-}\pi \end{cases} \tag{6}$$

We define the probability of observing the negative abnormal return as the following

$$\lambda_{t+1} \equiv \text{Prob}[\epsilon_{t+1} < 0],$$

which can be expressed as

$$\lambda_{t+1} = \pi F\left[-\frac{(1-\pi)}{\pi}((1+r_t)b_t - a_0)\right] + (1-\pi)F\left[(1+r_t)b_t - a_0\right].$$

Here $F(\cdot)$ is the cumulative density function of the unexpected changes of the fundamental value μ_{t+1}. Let us look at the first order partial derivative of λ_{t+1} with respective to b_t,

$$\frac{\partial \lambda_{t+1}}{\partial b_t} = -(1-\pi)(1+r_t)\left[f(-\frac{(1-\pi)}{\pi}((1+r_t)b_t - a_0)) - f((1+r_t)b_t - a_0)\right].$$

Since $\pi > 1/2$ and f is symmetric around 0, $\frac{\partial \lambda_{t+1}}{\partial b_t} < 0$. That means the probability of observing negative unexpected price changes will become less likely as the bubble grows. Just as stated by McQueen and Thorley (1994), when the bubble component grows, it starts to dominate the fundamental values. The negative unexpected price changes are less likely to happen and happen primarily when the bubbles crash.

Usually, we care the returns much more than the price changes. If the return is

$$e_{t+1} \equiv \frac{\epsilon_{t+1}}{p_t},$$

then $\text{Prob}[e_{t+1} < 0] = \text{Prob}[\epsilon_{t+1} < 0]$. So the previous argument can apply to the return as well, namely

$$\frac{\partial \text{Prob}[e_{t+1} < 0]}{\partial b_t} < 0.$$

The theoretical model demonstrates that if the prices contain bubbles and we observe a sequence of positive abnormal returns, it is highly possible that the bubble components exist, persist and grow over time. And growing bubble components leads to smaller probability of observing negative abnormal returns. Therefore, we can get the necessary condition for the existence of the bubbles: the probability of negative abnormal returns will decrease as the length of the existence of the bubbles. If we use $h(T)$ to denote the hazard rate of *positive* abnormal returns and T to denote the number of periods of *positive* abnormal returns (run length), the necessary condition for the bubbles existing is

$$\frac{\partial h(T)}{\partial T} < 0, \tag{7}$$

where $h(T) = \text{Prob}(e_t < 0 | e_{t-1} > 0, e_{t-2} > 0, \cdots, e_{t-T} > 0, e_{t-T-1} < 0)$.

2.2 Model Implementation

McQueen and Thorley (1994) apply Equation (7) to test for bubbles in the US stock market. They use the monthly returns of portfolios (equally weighted or value-weighted) of all New York Stock Exchange (NYSE) stocks from 1927 to 1991. They compute the time series of unexpected returns and, hence, the hazard rates $h(T)$ under the assumption that abnormal return is independent and identically distributed($i.i.d$) over the time horizon. Then, they test whether or not $h(T)$ satisfies Equation (7).

However, this method cannot work in the housing market of China. China started the commercialization of houses in the middle of the 1990s, and only annual data are available. Therefore, there are no more than 15 data points in the time series. The problem of small samples will generate large errors when computing hazard rates. To alleviate this problem, we propose to use the panel data of 35 cities.

As discussed in Equation (6) of section 2, the unexpected house price changes of city i at period t, ϵ_t^i satisfies

$$\epsilon_t^i = \begin{cases} \mu_t^i + \frac{(1-\pi)}{\pi}\left[(1+r_{t-1}^i)b_{t-1}^i - a_0^i\right] & \text{with probability } \pi \\ \mu_t^i - (1+r_{t-1}^i)b_{t-1}^i + a_0^i & \text{with probability 1-}\pi \end{cases}$$

We compute the real house return of city i at period t as follows

$$R_t^i = \frac{(p_t^i + d_t^i)}{p_{t-1}^i} - 1,$$

where p_t^i denotes the price in city i at time t. In order to perform the test, we need to compute the unexpected returns. The unexpected return is the difference of the realized return and the expected return. Hence, if we denote e_t^i as the unexpected returns of city i at period t, then

$$e_t^i = R_t^i - E_{t-1}(R_t^i).$$

$E_{t-1}(R_t^i)$ means the expected housing return at time t by using the information up to time $t-1$. We can run a predictive regression to obtain this value. As we are studying 35 different cities, some idiosyncratic factors may exist, which are not time-varying for each city. Therefore, we employ the fixed-effect model to forecast the house returns

$$R_t^i = \beta_0 + f_i + \sum_{j=1}^{k} \beta_j x_{j,t-1}^i + e_t^i, \tag{8}$$

where f_i is unobservable city characteristics; $x_{j,t-1}^i$ is the j-th factor in the i-th city at time $t-1$. The residual of the regression, e_t^i, is treated as the unexpected return.

As for the explanatory variables $\{x_{j,t-1}^i\}$, we may choose them as follows. House returns consist of two components: rental income d_t^i and capital income from house price variations $p_t^i - p_{t-1}^i$. Thus, we focus on the variations of these two components to forecast returns. We add the lagged rent-price ratio rp_{t-1}^i into the list of explanatory variables to capture the effects of expected rental income on the expected house returns. Gallin (2006) suggests that the changes of fundamentals, such as personal income, population, construction costs, usage costs of housing and interest rates, reflect house price variations $p_t^i - p_{t-1}^i$. Hence, we include the growth rates of GDP per capita gdp_{t-1}^i and population pop_{t-1}^i to capture the effects of expected income growth and population growth on the expected house price changes. Moreover, the expected returns depend on the required rates for future cash flows, which fluctuate with the business cycle: low in peaks and high in troughs. Fama and French (1989), among others, confirm this point by checking stock returns. Their explanation is that, in economic recessions, people require high expected returns to compensate for risks brought by macroeconomic uncertainty. Here, we regard the unemployment rate $unem_{t-1}^i$ as a measurement for economic conditions. By adding it to the explanatory variables of the regression, we can reveal how macroeconomic risks affect expected returns in the housing market. In addition to the above fundamental factors, we also include the variables implying the opportunity costs of holding houses.

The increase of opportunity costs should lead to the decrease of house prices and hence generate lower expected returns. The rate rr^i_{t-1} denotes the interest rates of one-year bank deposits. The rate sr^i_{t-1} denotes the returns from China stock market. The former displays the returns of risk-free assets while the latter displays the returns of risky and less liquid assets.

After we obtain the unexpected returns, we count the positive run lengths of 35 cities and mix them together to estimate the hazard rate [4]. We assume that the hazard rate takes a linear-logistic function as

$$h_t \equiv h(t) = \frac{1}{1 + e^{-\alpha - \beta t}}, \tag{9}$$

and maximize the log-likelihood function

$$L(\theta) = \sum_{t=1}^{\infty} N_t \ln h_t + M_t \ln(1 - h_t) + Q_t \ln(1 - h_t), \tag{10}$$

where N_t is the count of completed runs of length t in the sample, and M_t and Q_t are the count of completed and partial runs of length greater than t.

As we explain earlier, the necessary condition for the bubbles to exist is

$$\frac{\partial h_t}{\partial t} < 0, \tag{11}$$

which implies β should be negative, so we can perform the likelihood ratio test on this data.

[4] We need an assumption that the abnormal return is *i.i.d.* across time and cities here. Although it is hard to justify this *i.i.d.* assumption because of short time series data, we circumvent the potential pitfalls of this assumption by studying different model settings. This is reasonable because the lack of *i.i.d.* can be explained as 'indicating that there is still something there.' For example, cross-sectional dependence in the residuals implies that the model may miss some common factors, so we can add more factors to the model. If there is a serial correlation, then adding a lagged dependent variable into the right-hand side of the regression is a usual treatment. This kind of approach is not uncommon (see Willcocks (2009) and Al-Loughani and Chappell (1997), for examples). Since model specification is not the main goal of this paper, we simply study all the potential models with different sets of regressors.

3 Empirical Analysis

3.1 Data

We focus on explaining the yearly house returns between 1999 and 2009. Appendix A displays all the data used in this paper collected from 35 cities. Figure 1 displays the names and the locations of the 35 cities. All of the cities but one are located in the east and central areas of China. The selected cities are consistent with the population distribution: around 70 percent of the population is concentrated in these areas, which represents only 30 percent of China's land area.[5] As local goods, houses are difficult to trade across different places. The changes of house prices therefore reflect the variations of the local fundamental factors and opportunity costs. Hence, we use the CPI of each city instead of the national level to transfer all the nominal variables into real ones[6], including stock returns and one-year deposit rates. The transformed data, which are used in our empirical analysis, are summarized in Table 1. By following Breitung (2000), we do the unit-root test for these variables one by one, and find the rejection of the unit-root hypothesis at 10% significance level for each of them. Figures 2 and 3 display the nominal GDP and the house prices averaged cross all the 35 cities. These two figures show that from 1999 to 2009, the nominal GDP increases to more than 400 % and the house prices increase to around 300 %.

[Figure 1 around here]

[Figure 2 around here]

[Figure 3 around here]

[Table 1 around here]

[5]Resources: National Bureau of Statistics of China.

[6]We also use the GDP deflator to transfer the nominal values into the real ones. The results will be shown in Section 3.3.

3.2 Empirical Results

We first analyze the benchmark model specified by Equation (8). In this experiment, we study four different sets of regressors.

Table 2 displays the empirical results based on the benchmark models. In the first panel, the first column lists all the variables, and the other four columns display the regressors for the models studied. For each variable, the corresponding row indicates the estimators for its coefficients, followed by the $p-$value in the next row.

[Table 2 around here]

The estimation results are very interesting. First, the coefficient for the rent-price ratio rp is positive and significant at the level of 10% (Thereafter, the significance level is set at 10%). The high value of the rent-price ratio implies that the cash flow from owning a house is high. Thus, investors are more likely to increase their investments in houses, so house prices will increase in the future, which leads to an increase in capital income from price changes in the future. Therefore, the lagged rental-price ratio is positively related to the rate of future house returns, as suggested by our regression results.

Second, the coefficient for the growth rate of GDP per capita is only significant in Model I and Model II, and insignificant in the other two models. Other fundamental factors, population growth rate and unemployment rate, are not significant in the models. As we know, regional development in China is quite unbalanced. The differences of real GDP growth rates (per capita) reflect the differences of the income growth of each city. The unemployment rate reflects the conditions of the business cycles and is high when the local economy is in recession; the population growth rates reflect the increase of local consumption demands for houses. However, the empirical results show that these variables do not significantly affect the expected returns on housing assets. One possible explanation is that housing capital can flow freely across the different cities of China so as to completely eliminate the influence of local economic fundamentals.

Third, the coefficients for the real deposit rates and the real stock returns are significant and negative. According to the theory of asset pricing specified by Equation (2), the house prices satisfy the following

$$p_t^* \equiv E_t \sum_{i=1}^{\infty} \frac{d_{t+i}}{\prod_{j=0}^{i-1}(1 + rf_{t+j} + df_{t+j})}. \tag{12}$$

where rf_{t+j} is the risk-free rate, and df_{t+j} is the interest rate compensating the risks of liquidity and price variations. The sum of them is equal to r_{t+j} in Equation (2). Equation (12) shows that house prices decrease with the increase of rf and df. Real deposit rates rr are the benchmark for risk-free rates rf. When the real deposit rates increase suddenly, house prices will decrease. The decrease of house prices will make house transactions shrink, and hence increase liquidity costs and df[7]. In addition, real stock returns measure the prices of risks. The increase of stock returns displays that market requires higher compensations for risks and hence implies that the market is more risk averse and puts higher values for df. Hence the increase of these two variables leads to the future decrease of house prices and hence the decrease of expected house returns.

Our results reveal that Chinese houses are mainly used as investment goods instead of consumption goods, and hence the opportunity costs of capital become the major influencing powers. This phenomenon may be explained by the institutional features of Chinese financial markets. China is still in the process of gradual transitions; in particular, the nominal deposit rates of Chinese commercial banks have not been liberalized. As capped by the government, the nominal deposit rates in China have been experiencing very slow adjustments[8]. This leads to negative real deposit rates when volatile inflation is

[7] liquidity risk is the risk that a given asset cannot be traded quickly enough in the market to prevent a loss (or make the required profit). A large literature, both empirically and theoretically, has shown that house transactions and prices are significantly positive correlated. This literature includes Stein (1995) and Genesove and Mayer (2001) among others. When house transactions increase, the time spent on liquidizing house assets decreases and so do the risks brought by the variations of house prices. Hence there are smaller liquidity risks when house transactions boom.

[8] Many papers described and analyzed this special feature of Chinese financial markets including Wang (2001), Burdekin and Siklos (2008) and Porter et al. (2009) among others. Hence our paper will not develop the discussions related to this point.

high. From 2000 to 2011, as Figure 5 displays, China spent around half of the past decade in a state of negative real deposit rates. This experience keeps enforcing the expectations that negative real deposit rates are persistent, and that house prices in China are supposed to be high. Equation (12) tells us that house prices increase with the decreases of real deposit rates. The extreme case is that house prices may converge to infinity when rf_{t+j} keeps negative and df_{t+j} is close to zero if rental income d_t does not converge to zero.

[Figure 5 around here]

The popular indicators used to measure house price bubbles, including rental/price and income/price ratios, can not apply to our cases because those comparative numbers are from developed countries where real risk-free rates are mostly positive. Similarly, Himmelberg et al. (2005) also held this idea: when the long-term real interest rates are low, house prices are sensitive to changes in fundamentals; hence these fundamentals cannot be used to measure the existence of bubbles. Lacking safe channels for investment, Chinese hold houses to protect their wealth from losses due to inflation. For houses, the role of investment therefore dominates that of consumption in China as displayed by our empirical results.

The first panel of Table 2 gives us the estimation results. Based on these, we collect the residuals of the regressions, counting the numbers of the partial and the completed run lengths on 35 cities individually. Then we apply MLE to get the estimators for α and β in Equation (9) and Equation (10). The second panel of Table 2 reports the estimation results. Figure 4 displays the estimators of the hazard rates with their 90% confidence intervals. The confidence intervals are based on the likelihood ratio test, which insures that they conform to the zero to one probability space and allows them to be asymmetric.

We can see that the estimator for β is positive in all the models. This means the hazard rate increases with duration. In addition, we cannot reject the null hypothesis that $\beta = 0$ in any of the four models, so the hazard rate at least does not depend on duration. Neither of these results satisfies the necessary condition for the existence of growing price bubbles. Therefore, we may conclude that there is no growing bubbles of rational expectations in the Chinese housing market.

[Figure 4 around here]

3.3 Robustness Check

In order to check the robustness of our results, we consider different models and regressions.

3.3.1 Subsamples

We use the subsample of all the cities between 2003 and 2007 to analysis the benchmark models described in the previous section. As we know, the housing prices grow most rapidly during 2003 and 2007. Higher growth rates of house prices are supposed to generate higher abnormal returns. Hence this turns out to be the period with the high probability of the existence of the growing rational expectation bubbles. In order to check the robustness of our results, we test this subsample. The estimation results are summarized by Table 3.

[Table 3 around here]

By comparing the coefficients of the regressions with the whole sample, we can see the following differences. The rent-price ratio rp is not significant in subsamples. This implies a further deviations of house returns from the economic fundamentals. Second, the coefficient of real risk-free rates is around 5 times higher than that of the whole sample. Hence the house returns are much more sensitive to the real risk-free rates in subsamples. These two points imply that the role of investment in housing market gets stronger but the role of consumption gets weaker. At last, the coefficient of stock return is still significant but changes the sign completely, which implies the structural difference between the subsample and the whole sample. Although there exists the structural difference, we can see that the $p-$values of the estimated β are all higher than 10%. This suggests that the hazard function does not dependent on duration, and thus there is no evidence supporting the existence of growing rational expectation bubbles in this sub-period.

Then, we move back to the whole sample between 1999 and 2009, but decompose them into two groups based on the average levels of the cities' GDP per capita and make separate empirical analyses. GDP per capita varies greatly across the provinces of China. In the previous analysis, we did not control for this variable because of its non-stationarity. Here, we divide the 35 cities into two groups in terms of their average GDP per capita from 1999 to 2009 [9]. Appendix B displays the names of the cities in each group. Most high-GDP cites are located in the coastal areas while low-GDP cities are located in the interior. Table 4 and Table 5 summarize the empirical results. An interesting difference is that the growth rate of GDP per capita is significant and positive for the high-GDP cities in all of the models, but not significant for the low-GDP cities in any of the models studied. This finding indicates that expected house returns depend on the growth of the local economy in the rich regions, whereas they do not in the poor regions. Hence the local economies of the poor regions do not affect the expected returns of their housing asset holders. One possible explanation is that the majority of the housing assets in the poor regions may be held by people from the rich regions. Furthermore, the second panels of Table 4 and Table 5 display that in all the models of each group, the estimators of β are positive and the hypothesis of $\beta = 0$ cannot be rejected. Hence, we have not yet found any evidence to support the decreasing hazard rates for each group, which implies that there is no growing rational expectation bubble in the housing market of China after controlling for the effect of GDP per capita.

[Table 4 around here]

[Table 5 around here]

[9] We sort 35 cities based on the average GDP per capita and pick the leading 18 cities as the high-GDP cities, the remaining 17 cities as the low-GDP cities.

3.3.2 Dynamic Model

Following McQueen and Thorley (1994), we include the lagged housing returns as the explanatory variables in the model and apply the dynamic panel estimation method, proposed by Arellano and Bond (1991), to obtain the residuals. The regression model is

$$R_t^i = \beta_0 + f_i + \gamma R_{t-1}^i + \sum_{j=1}^{k} \beta_j x_{j,t-1}^i + e_t^i. \tag{13}$$

Table 6 displays the results of the regressions. We notice that, in all the models, the estimated coefficient for the lagged house returns is negative. This implies that as a form of assets, houses have the feature of mean-reverting in returns, which is also shared by the other ordinary assets like stocks.[10] The second panel of Table 6 shows that the estimators of β are positive, and we cannot reject the null hypothesis that $\beta = 0$. The existence of growing rational expectation bubbles is not supported in this scenario.

[Table 6 around here]

3.3.3 Different Measures of Variables

We also consider the potential consequences of different measures on some variables. First, we use nominal variables, instead of the real variables, to repeat the benchmark analyses. Table 7 summarizes the results.

[Table 7 around here]

Then, we switch back to the real values of our sample, but we use the GDP deflator to obtain these real values. Table 8 displays the estimating results.

[Table 8 around here]

[10] See Fama (1970), Samuelson (1991)

We can see that the patterns of the hazard functions in these two settings are very similar with the ones in the original benchmark models. And again, the existence of growing rational expectation bubbles is not supported even if we use different measures on the variables.

3.3.4 Hazard Rate Functions

All the previous analyzes are based on the linear-logistic function of the hazard rate. We try a simple linear function as

$$h(t) = \alpha + \beta t. \tag{14}$$

We apply this hazard function to the benchmark models and compare the estimation results with the original ones. Table 9 reports this comparison.

[Table 9 around here]

We find that the estimated β is not significant in any of the four models no matter which hazard function is employed in the estimation. This implies that it is hard to believe the existence of growing rational expectation bubbles.

In summary, although we adjust the model and the data, in all the experiments we have studied, the necessary condition that hazard rate decreases with duration does not hold in any scenario, which implies the robustness our result that there is no growing rational expectation bubbles in the housing market of China.

4 Conclusion

This paper tests the existence of the growing rational expectation bubbles in China housing market. We find that the house returns in Chinese cities do not satisfy the necessary conditions for the existence of such kind of bubbles. We also reveal that our result is quite robust to the model and the data that we use. This finding means that the growing rational expectation bubbles are not a solid reason for the rapid growth of China's house prices.

In addition, we also find two interesting results. First, local fundamentals such like the GDP growth rate, unemployment, and population growth, cannot significantly affect the local expected returns of houses. As we have discussed in the previous sections, house capital flows freely across different regions, and hence eliminates the influence of the local economy on the expected rate of house returns. Cash flow from the rich regions in particular becomes the major reason for the high rate of increase for house prices in poor regions. Given the rapid rise in house prices, the government now is confronted with the pressure to lower the rate of increase for house prices in certain cities and make house prices consistent with income growth. Thus, this result implies that to fulfill this purpose, it is necessary to block the free flow of the capital between the housing markets of different cities and especially from rich to poor regions, such that the expected house returns will vary with the local growth rate of income. Policies such as placing restraints on the purchases of houses by non-locals can work in this direction.

Second, the real deposit rates significantly negatively affects expected house returns. As the opportunity cost of capital, this variable influences the expectations of house returns mainly through affecting the expectations of future house prices. It also shows that the role of investment dominates that of consumption for Chinese houses. The long-term official control of nominal deposit rates may be responsible for this phenomenon. According to this result, any policy targeting the elimination of 'investment demand' for Chinese houses should generate significant results for the price control of Chinese houses. We also have to understand that the distortion of Chinese financial markets is the basic reason behind this phenomenon. If the financial market goes through further reform and liberalization in the future, the current high prices of Chinese houses may be unsustainable.

To explore the mechanisms behind the rapid increase of house prices further, we need to carefully examine demand and supply in the China housing market. China has been experiencing a period of extraordinary changes, both in income growth and urbanization. We also know that the government is the dominant power in terms of land supply in China. Do these special features of the housing market affect the dynamics of China's house prices? These questions are left for future research.

References

Abraham, J., Hendershott, P., 1996. Bubbles in metropolitan housing markets. Journal of Housing Research 7, 191-207.

Al-Loughani, N., Chappell, D., 1997. On the validity of the weak-form efficient markets hypothesis applied to the London stock exchange. Applied Financial Economics 7, 173-176.

Arellano, N., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297.

Blanchard, O., Watson, M., 1983. Bubbles, rational expectations and financial markets. NBER working papers 1983.

Breitung, J. 2000. The local power of some unit root tests for panel data. Advances in Econometrics Volume 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels, ed. B. H. Baltagi, 161-178. Amsterdam: JAI Press.

Burdekin, R., Siklos, P., 2008. What has driven Chinese monetary policy since 1990? Investigating the People's Bank's policy rule. Journal of International Money and Finance 27(5), 847-859.

Cagetti, M., Nardi, D., 2006. Entrepreneurship, frictions, and wealth. Journal of Political Economy 114(5), 835-870.

Capozza, D., Hendershott. P., Mack, C., Mayer, C., 2002. Determinants of real house price dynamics. NBER Working Papers.

Case, K., Shiller, R., 2003. Is there a bubble in the housing market? Brookings Papers on Economic Activity 34(2), 299-362.

CCER, 2007. Measurements of China's capital return (1978-2006): Microeconomic underpinnings for the recent economic boom In China. China Economic Quarterly 6(3); 723-758.

Clapp, J., Giaccotto C., 1994. The influence of economic variables on local house price dynamics. Journal of Urban Economics 36(2), 161-183.

Dreger C., Zhang Y., 2010. Is there a bubble in the Chinese housing market? DIW Discussion Papers No. 1081.

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 25, 383-417.

Fama, E., French, K., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25(1), 23-49.

Feyzioglu, T., Porter, N., Takáts, E., 2009. Interest rate liberalization in China. IMF Working Papers 09(171), 1-28.

Frees, E., 1995. Assessing cross-sectional correlation in panel data. Journal of Econometrics 69, 393-414.

Gallin, J., 2006. The long-run relationship between house prices and income: Evidence from local housing markets. Real Estate Economics 34(3), 417-438.

Genesove, D., Mayer, C., 2001. Loss aversion and seller behavior: Evidence from the housing market. The Quarterly Journal of Economics 116(4), 1233-1260.

Han, X., 2010. Housing demand in Shanghai: A discrete choice approach. China Economic Review 21, 355-376.

Himmelberg, C., Mayer, C., Sinai, T., 2005. Assessing high house prices: Bubbles, fundamentals and misperceptions. Journal of Economic Perspectives 19(4), 67-92.

Kiyotaki, N., Moore, J., 2004. Liquidity, Business Cycles and Monetary Policy (Clarendon Lectures 2). ESE Discussion Papers 111, Edinburgh School of Economics, University of Edinburgh.

Kocherlakota, N., 2009. Bursting Bubbles, Consequences and Cures. Federal Reserve Bank of Minneapolis Mimeo

McCarthy, J., Peach, R., 2004. Are home prices the next bubble? Economic Policy Review (Dec), 1-17.

McQueen, G., Thorley, S., 1994. Bubbles, stock returns, and duration dependence. Journal of Financial and Quantitative Analysis 29(03), 379-401.

Mikhed, V., Zemcik, P., 2009. Do house prices reflect fundamentals? Aggregate and panel data evidence. Journal of Housing Economics 18 (2), 140-149.

Montrucchio, L., Privileggi, F., 2001. On fragility of bubbles in equilibrium asset pricing models of Lucas type. Journal of Economic Theory 101 (1), 158-188.

Samuelson, P. A., 1991. Long-run risk tolerance when equity returns are mean regressing: Pseudoparadoxes and vindication of 'business man's risk'," in money, macroeconomics, and economic policy: Essays in Honor of James Tobin, W. C. Brainard, W. D. Nordhaus, and H. W.Watts eds., Cambridge, MA: MIT Press.

Santos, M., and Woodford, M., 1997. Rational asset pricing bubbles. Econometrica 65(1), 19-58.

Shiller, R., 1990. Speculative prices and popular models. Journal of Economic Perspectives 4(2), 55-65.

Stein, J., 1995. Prices and trading volume in the housing market: A model with down-payment effects. The Quarterly Journal of Economics 110(2), 379-406.

Wang, G., 2001. Interest rate control and market-oriented interest rate in China. Economic Research Journal 6(1), 13-20.

Wang, P., Wen, Y., 2009. Speculative bubbles and financial crisis. American Economic Journal: Macroeconomics, 2011, forthcoming.

Wang, S., Yang, Z., Liu, H., 2011. Impact of urban economic openness on real estate prices: Evidence from thirty-five cities in China. China Economic Review 22, 42-54.

Willcocks, G., 2009. UK housing market: time series processes with independent and identically distributed residuals. Journal of Real Estate Finance and Economics 39, 403-414.

Xin, Q., Lin, B., Yang, D., 2007. Return to capital investment and its determinants in China: Evidence from listed companies. China Economic Quarterly 6(4), 1143-1154.

Appendices

A Data Description

This section describes the data in this paper. All the data, unless specified, are collected from CEIC Data (http://www.ceicdata.com).

1. House price (hp): average market price of newly built houses within one city.

2. Rental price (hr): we can only obtain rental index, which is an index regarding the nominal rental price of the previous year as 100. We back out the rental price from this index by assuming that the ratio of rental price over housing price in 1997 is equal to the nominal deposit rate at that time.

3. Nominal aggregate gross domestic product (ngdp).

4. Unemployed population (upop): the population of registered unemployed people.

5. Working population (wpop): the population of registered working people includes both the industries and the governments of the corresponding city. [Source: China City Statistical Yearbook]

6. Self-employed population (spop): the population of registered self-employed population. [Source: China City Statistical Yearbook]

7. Consumer Price Index (cpi): the price level in 1997 is the base year.

8. Aggregate population (apop): the population of the permanent residents (Hukou holders) within one city including rural areas.

9. Nominal stock return (nsr): the value-weighted returns for Shanghai and Shenzhen stock exchanges

10. Nominal deposit rate (dr): one-year deposit rate of China's commercial banks

11. Real house return: $\mathrm{R}_t = \frac{(\mathrm{hp}_t + \mathrm{hr}_t)\mathrm{cpi}_{t-1}}{\mathrm{hp}_{t-1}\mathrm{cpi}_t} - 1$. Real house return includes the summations of rental income and capital income from price changes adjusted by inflation.

12. Rent-price ratio: $\mathrm{rp}_t = \frac{\mathrm{hr}_t}{\mathrm{hp}_t}$

13. Growth rates of real GDP per capita: $\mathrm{gdp}_t = \frac{\mathrm{ngdp}_t \mathrm{cpi}_{t-1} \mathrm{apop}_{t-1}}{\mathrm{ngdp}_{t-1} \mathrm{cpi}_t \mathrm{apop}_t} - 1$

14. Real deposit rate: $\mathrm{rr}_t = \mathrm{dr}_t - \frac{\mathrm{cpi}_t - \mathrm{cpi}_{t-1}}{\mathrm{cpi}_{t-1}}$.

15. Real stock return: $\mathrm{sr}_t = \mathrm{nsr}_t - \frac{\mathrm{cpi}_t - \mathrm{cpi}_{t-1}}{\mathrm{cpi}_{t-1}}$.

16. Population growth rate: $\mathrm{pop}_t = \frac{\mathrm{apop}_t}{\mathrm{apop}_{t-1}} - 1$

17. Unemployment rate: $\mathrm{unem}_t = \frac{\mathrm{upop}_t}{\mathrm{wpop}_t + \mathrm{spop}_t + \mathrm{upop}_t}$

B Cities' Locations

High GDP Cities: Shanghai, Beijing, Tianjin, Hangzhou, Guangzhou, Nanjing, Fuzhou, Shenyang, Jinan, Urumqi, Dalian, Qingdao, Ningbo, Xiamen, Shenzhen, Hohhot, Wuhan, and Haikou.

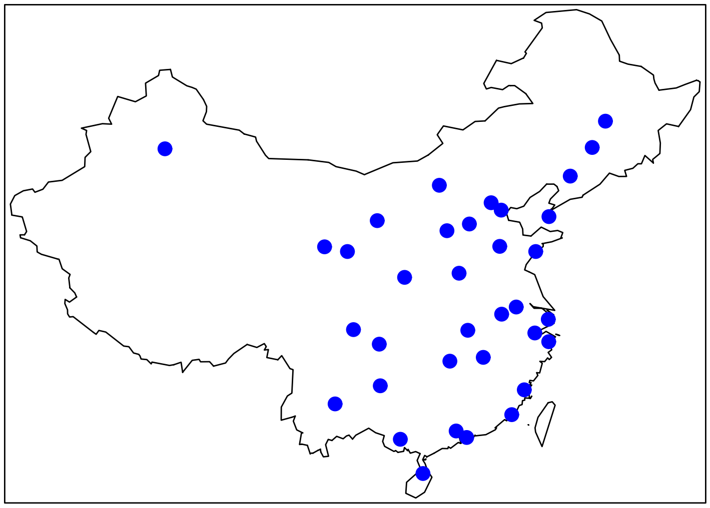
Low GDP Cities: Xining, Chongqing, Nanning, Guiyang, Hefei, Yinchuan, Xi'an, Lanzhou, Nanchang, Shijiazhuang, Kunming, Haerbin, Changchun, Chengdu, Changsha, Taiyuan, and Zhengzhou.

C Tables and Figures

Table 1: Data used in Regression

Item	Variables	Notation	Year
1	House return	R	1999-2009
2	Rent-price ration	rp	1998-2008
3	Growth rate of GDP per capita	gdp	1998-2008
4	Real deposit rate	rr	1998-2008
5	Real stock return	sr	1998-2008
6	Population growth Rate	pop	1998-2008
7	Unemployment rate	unem	1998-2008

Figure 1: Cities and Locations



This figure displays the locations of the 35 cities studied in our paper. They are Shanghai, Beijing, Tianjin, Hangzhou, Guangzhou, Nanjing, Fuzhou, Shenyang, Jinan, Haerbin, Shijiazhuang, Urumqi, Changchun, Haikou, Hohhot, Wuhan, Taiyuan, Chongqing, Changsha, Zhengzhou, Yinchuan, Xining, Nanning, Chengdu, Hefei, Nanchang, Xi'an, Lanzhou, Guiyang, Kunming, Dalian, Qingdao, Shenzhen, Ningbo, and Xiamen.

Table 2: Benchmark Models

Regressors	Model I	Model II	Model III	Model IV
rp	1.46	1.51	1.52	1.52
	0.00	0.00	0.00	0.00
gdp	0.13	0.14	0.16	0.16
	0.05	0.03	0.13	0.14
rr	-0.01	-0.01	-0.01	-0.01
	0.00	0.01	0.01	0.01
sr		-0.01	-0.01	-0.01
		0.10	0.09	0.09
pop			0.02	0.02
			0.72	0.72
unem				0.00
				0.99
cons	0.07	0.05	0.05	0.05
	0.00	0.03	0.07	0.07
linear-logistic hazard function	$h_i = 1/(1+\exp(-\alpha - \beta i))$			
α	-0.55	-0.45	-0.51	-0.48
β	0.25	0.23	0.26	0.25
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.14	0.17	0.13	0.14

This table summarizes the estimation results for four different models. 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the real stock return, 'rr' denotes the real deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 3: Benchmark Models for Subsample: 2003-2007

Regressors	Model I	Model II	Model III	Model IV
rp	-0.96	0.60	0.61	0.73
	0.41	0.66	0.65	0.62
gdp	0.03	0.05	0.06	0.06
	0.70	0.45	0.62	0.64
rr	-0.02	-0.05	-0.51	-0.05
	0.00	0.00	0.00	0.00
sr		0.03	0.03	0.03
		0.01	0.01	0.01
pop			0.01	0.01
			0.87	0.88
unem				-0.01
				0.67
cons	0.23	0.20	0.20	0.22
	0.00	0.03	0.00	0.00
linear-logistic hazard function	$h_i = 1/(1+\exp(-\alpha-\beta i))$			
α	-0.32	-0.56	-0.68	-1.02
β	-0.04	0.19	0.31	0.51
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.95	0.75	0.60	0.33

This table summarizes the estimation results for the subsample between 2003 and 2007. 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the real stock return, 'rr' denotes the real deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 4: Benchmark Models for High-GDP Cities

Regressors	Model I	Model II	Model III	Model IV
rp	1.02	1.07	1.10	1.07
	0.09	0.10	0.08	0.09
gdp	0.24	0.26	0.32	0.33
	0.04	0.04	0.05	0.05
rr	-0.02	-0.01	-0.01	-0.01
	0.00	0.02	0.03	0.03
sr		-0.01	-0.01	-0.01
		0.22	0.19	0.19
pop			0.08	0.09
			0.33	0.32
unem				0.00
				0.77
cons	0.09	0.07	0.06	0.05
	0.00	0.05	0.14	0.18
linear-logistic hazard function	$h_i = 1/(1 + \exp(-\alpha - \beta i))$			
α	-0.71	-0.61	-0.49	-0.49
β	0.40	0.29	0.24	0.24
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.15	0.22	0.31	0.31

This table summarizes the estimation results for high GDP cities. ‘rp’ denotes the ratio of rental over price; ‘gdp’ denotes the growth rate of GDP per capita; ‘sr’ denotes the real stock return, ‘rr’ denotes the real deposit rate; ‘pop’ denotes the growth rate of population; ‘unem’ denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 5: Benchmark Models for Low-GDP Cities

Regressors	Model I	Model II	Model III	Model IV
rp	2.69	2.77	2.79	2.74
	0.02	0.01	0.01	0.01
gdp	0.06	0.07	0.08	0.07
	0.43	0.36	0.49	0.55
rr	-0.01	-0.01	-0.01	-0.01
	0.00	0.15	0.16	0.16
sr		-0.01	-0.01	-0.01
		0.20	0.19	0.19
pop			0.01	0.01
			0.86	0.89
unem				0.00
				0.59
cons	0.00	-0.02	-0.02	-0.03
	0.92	0.68	0.64	0.52
linear-logistic hazard function	$h_i = 1/(1+\exp(-\alpha-\beta i))$			
α	-0.05	-0.17	-0.17	-0.17
β	0.17	0.21	0.21	0.21
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.54	0.43	0.43	0.43

This table summarizes the estimation results for low GDP cities. 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the real stock return, 'rr' denotes the real deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 6: Dynamic Models

Regressors	Model I	Model II	Model III	Model IV
R_{-1}	-0.14	-0.08	-0.09	-0.10
	0.08	0.50	0.37	0.29
rp	3.88	4.17	3.86	3.76
	0.00	0.00	0.00	0.00
gdp	0.18	0.22	0.25	0.26
	0.07	0.02	0.07	0.06
rr	-0.02	-0.01	-0.01	-0.01
	0.00	0.04	0.09	0.05
sr		-0.01	-0.01	-0.01
		0.10	0.08	0.20
pop			0.08	0.08
			0.45	0.36
unemp				0.01
				0.56
cons	-0.02	-0.07	-0.07	-0.07
	0.66	0.23	0.24	0.26
linear-logistic hazard function	$h_i = 1/(1 + \exp(-\alpha - \beta i))$			
α	-1.23	-1.05	-1.19	-1.16
β	0.21	0.16	0.20	0.21
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.11	0.23	0.13	0.13

This table summarizes the estimation results for four dynamic panel models. 'R_{-1}' denotes the lagged housing return; 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the real stock return, 'rr' denotes the real deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 7: Benchmark Models with Nominal Variables

Regressors	Model I	Model II	Model III	Model IV
rp	-0.85	-0.91	-0.83	-0.89
	0.16	0.22	0.29	0.31
gdp	0.23	0.23	0.26	0.26
	0.00	0.00	0.02	0.02
rr	-0.02	-0.02	-0.02	-0.02
	0.00	0.00	0.00	0.00
sr		-0.00	-0.00	-0.00
		0.76	0.78	0.79
pop			0.05	0.04
			0.60	0.44
unem				-0.00
				0.44
cons	0.23	0.23	0.22	0.23
	0.00	0.00	0.00	0.00
linear-logistic hazard function	$h_i = 1/(1+\exp(-\alpha-\beta i))$			
α	-0.02	-0.10	-0.10	0.01
β	0.02	0.04	0.04	0.01
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.90	0.83	0.83	0.97

This table summarizes the estimation results for four different models. 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the stock return, 'rr' denotes the deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. All the variables are in their nominal values. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 8: Benchmark Models with GDP Deflator

Regressors	Model I	Model II	Model III	Model IV
rp	0.14	0.14	-0.22	-0.19
	0.75	0.77	0.69	0.74
gdp	0.16	0.16	-0.24	-0.23
	0.18	0.18	0.33	0.35
rr	-0.00	-0.00	-0.01	-0.01
	0.26	0.66	0.18	0.18
sr		-0.00	-0.00	-0.00
		0.93	0.95	0.95
pop			-0.32	-0.32
			0.04	0.05
unem				-0.00
				0.61
cons	0.10	0.10	0.18	0.18
	0.00	0.00	0.00	0.00
linear-logistic hazard function	$h_i = 1/(1 + \exp(-\alpha - \beta i))$			
α	-0.29	-0.29	-0.51	-0.41
β	0.14	0.14	0.23	0.17
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.42	0.42	0.20	0.34

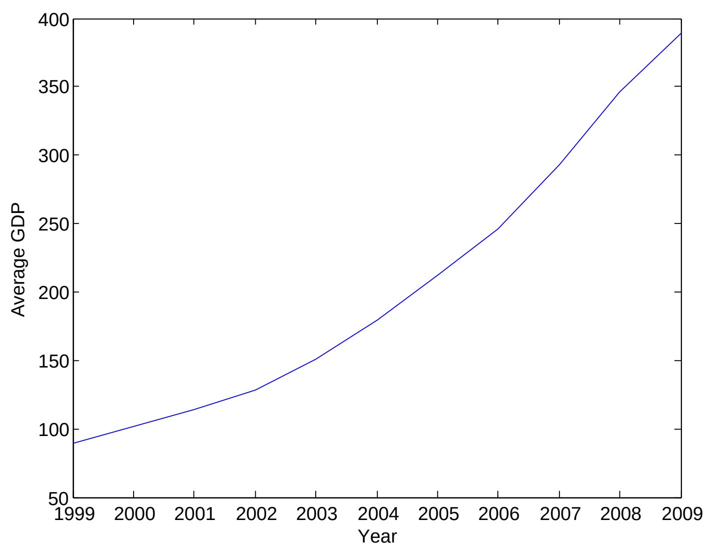
This table summarizes the estimation results when we use the GDP deflator, instead of the CPI, to transfer the nominal values into the real ones. 'rp' denotes the ratio of rental over price; 'gdp' denotes the growth rate of GDP per capita; 'sr' denotes the real stock return, 'rr' denotes the real deposit rate; 'pop' denotes the growth rate of population; 'unem' denotes the unemployment rate. For each regressor, the first row reports the estimator of the corresponding coefficient, and the second row is its associated $p-$value. The estimators of the hazard functions are derived based on the run length of the residuals of the regressions.

Table 9: Estimation of Hazard Functions

	Model I	Model II	Model III	Model IV
	Linear hazard function			
α	0.36	0.38	0.37	0.38
β	0.06	0.06	0.07	0.07
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.14	0.16	0.12	0.14
	Linear-logistic hazard function			
α	-0.55	-0.45	-0.51	-0.48
β	0.25	0.23	0.26	0.25
likelihood ratio test	$H_0 : \beta = 0$			
$p-$value	0.14	0.17	0.13	0.14

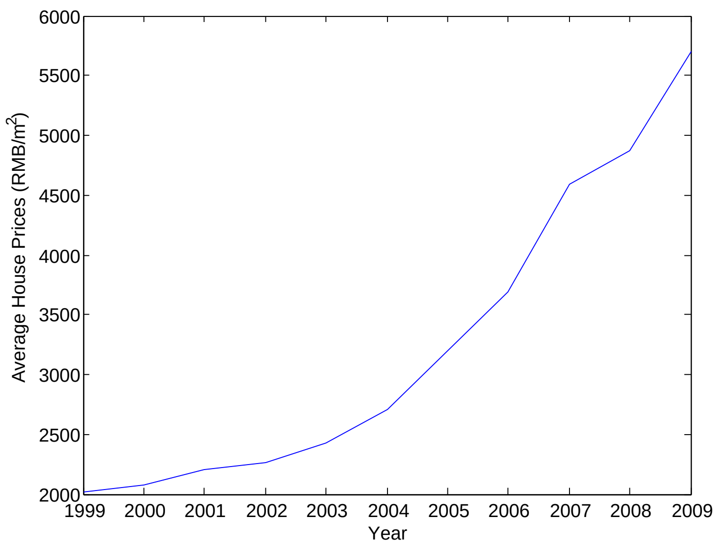
This table summarizes the estimation results for the hazard rates in the benchmark models. In the first panel, the linear hazard function is employed in the estimation, compared with the linear-logistic hazard function in the second panel.

Figure 2: GDP



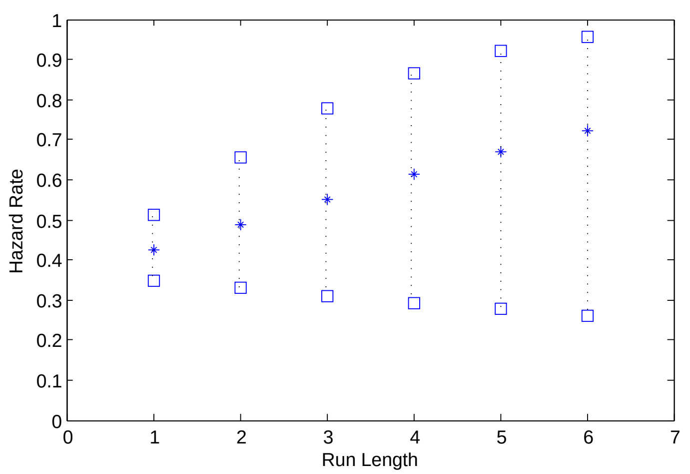
This figure shows the average GDP (billion RMB) between 1999 and 2009 for the 35 cities.

Figure 3: House Prices



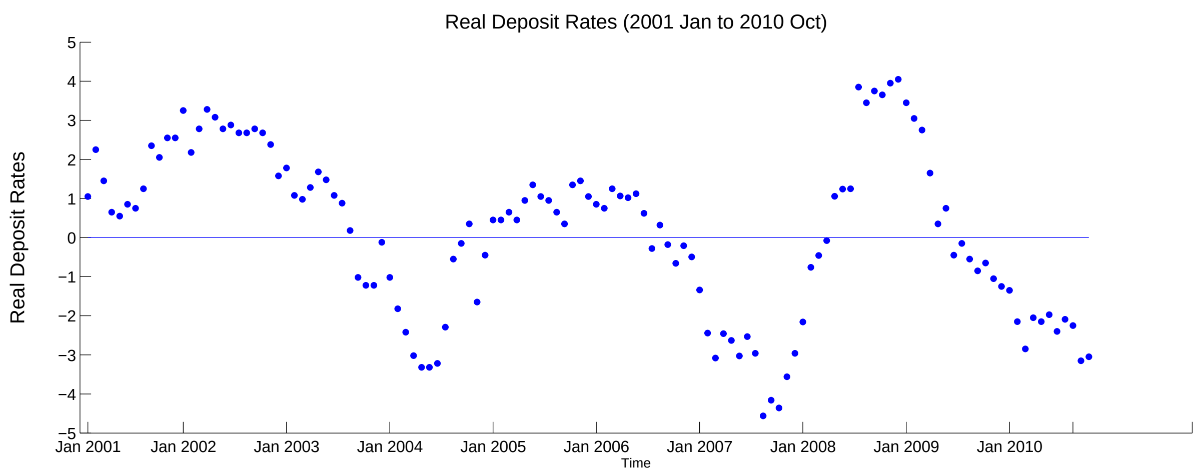
This figure shows the average house prices (RMB per square meter) between 1999 and 2009 for the 35 cities.

Figure 4: Hazard Rates



This figure shows the hazard rate and 90% confidence intervals for runs of unexpected returns in China housing market. The stars denote the estimated hazard rates and the squares denote the corresponding confidence intervals.

Figure 5: Monthly One-year Real Deposit Rates



This figure shows the one-year real deposit rates (in percentage) which are computed by subtracting the CPI from the one-year nominal deposit rates.