Shadow Banking and the Property Market in China

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Abstract

This paper studies the evolution of property values and the connections between shadow banking and property markets in China. We use Pooled Mean Group estimation to analyze Chinese house prices in 65 cities from 2007-2014, defining the "fundamentals" of housing prices with the Gordon dividend discount model, and using lagged rents, prices, real, nominal interest rates, and shadow banking activity as short term explanatory factors. We find that the cities tend to share long run fundamentals and adjust relatively quickly to deviations from the fundamentals. We do not find bubbles; rather houses are like growth stocks with prices chasing rapidly growing rents. We also find that house prices grow more rapidly with availability of shadow banking funds, which have grown rapidly.

Keywords: Chinese housing market, shadow banking, pooled mean group estimation

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1. Introduction

Property values have increased rapidly in China in the last decade, and public policy changes have been a factor. Fueled by an over-supply of housing in the first- and second-tier cities, the Chinese government has relaxed restrictions on second-home purchases, after claiming that the housing bubble was "deflated" safely by the end of 2014. However, because of the slowdown of the economy in 2015, the central government once again relaxed different sorts of restrictions with the aim of boosting the property market, as a means of supporting the dampened economy. Chinese households have been buying more apartments, and developers have been borrowing more to fund their construction projects. The ensuing demand for funding has boosted the expansion of the shadow banking system. Our interest in this paper is the role of that system in the growth of property values.

As in Lai & Van Order (2016), a way to study the dynamics of house prices is to apply the Gordon dividend discount model, making use of the rental rates and interest rates in explaining long run house prices, to which actual prices adjust over time-leading to well-defined long run equilibrium with a less restrictive adjustment process. To do this we use Pooled Mean Group (PMG) (and Mean Group (MG)) estimation to separate long run from short run. We study the Chinese housing market with a focus on shadow banking as the source of funding. Our specification forces shadow banking to only affect short run property value adjustment (momentum), but not long run fundamentals. An issue, not resolved here, is causation-if (as is the case in our regressions) there is a relationship between shadow banking and property values, it is not clear which is causal (if either).

To the best of our knowledge, we are the first to formally test the effects of shadow banking on property markets in China and to model China house prices via PMG. We find that the cities tend to share long run fundamentals and adjust relatively quickly to deviations from the fundamentals, and we do not find bubbles. We also find that that house growth is related to the availability of shadow banking funds, which have grown rapidly. A policy implication for the Chinese government is to focus on regulatory monitoring in this funding sector. Not only can its contraction hurt property markets, its non-performing loans can trigger contagion to the main banking system and therefore the economy as a whole.

2. Shadow Banking in China

The Financial Stability Board (FSB) (2015) defines shadow banking as "credit intermediation involving entities and activities outside of the regular banking system". An important element of being outside the system is not being covered by deposit insurance. FSB points out that non-bank credits contribute to financing the real economy, simultaneously becoming a source of systemic risk when they are highly interconnected with the regular banking system.[1]

In China shadow banking can be broadly defined as nonbank financing such as trust and entrusted loans, bankers' acceptances, interbank entrusted loan payments, microfinance companies, financial leasing, special purpose finance companies associated with e-commerce, guarantees, pawn shops and unofficial lenders, bond markets, trust beneficiary rights, and wealth management products, and interbank market activities (see Elliot *et al*. (2015) for detailed descriptions of each of these sources of shadow banking).

Some of the nonbank channels, such as bond markets and interbank market activities should not be classified as shadow banking. For instance, the bonds here are referred to corporate bonds, which are not broadly traded in bond markets like those in the US; whereas the interbank market activities are really large corporations using finance company subsidiaries to act like banks. The most common source of shadow banking funds that is collected from the general public comes from the wealth management products (WMPs) that pool assets together. Most of the assets are loans. Sharma (2014) and Hsu and Li (2015) are some examples of literature on shadow banking in China.

In response to the Global Financial Crisis, the Chinese Central government initiated a stimulus package in 2009, which stimulated unprecedented growth in fixed asset

[1] Various issues of the "Global Shadow Banking Monitoring Report" by the Financial Stability Board.

investments, which was increasingly funded by shadow banking. Infrastructure projects constituted 72% of the stimulus package, of which 30% was funded by the Central government, while the rest from local governments.[2] Funding was also available to riskier borrowers, typically to real estate developers and local government financing vehicles, the corporate arm of local governments, which helped local governments to generate their high GDPs through infrastructure construction.

The growth of shadow banking has been fueled by the fact that the five biggest banks in China, all state-owned, are not allowed to lend to corporates and small and medium sized enterprises (SMEs), other than the big State-Owned Enterprises (SOEs). Hence, the shadow banking sector provides lending needs outside regulations. On the supply side, the lack of investment opportunities (other than the stock markets, the very small bond market, and the very hot real estate market) stimulates all sorts of WMPs that can generate returns higher than the very low (sometimes even negative in real terms, given the high inflation rate) deposit rates. Furthermore, average investors are under the impression that these products are safe because they are mostly sold by big banks, which therefore have implicit guarantees from the People's Bank of China (the Chinese Central Bank).

Over-investment in infrastructure, while boosting local incomes, has generated "ghost towns", roads and bridges that very few people would use. It is reported that shadow banking made up 20%-41% of on-balance bank lending, without which total lending would decline by 16-29%.[3] The downturn of the Chinese property market resulted in lack of liquidity for developers. Yet, the Chinese government is still optimistic that the shadow banking sector in China is only a small problem.

Table 1 shows that shadow banking as a percentage of GDP in China is only 26%, ranking only 13th among the 26 jurisdictions according to the Financial Stability Board (2015), relative to 82% in the US. A comparison between Figures 1 and 2 shows that, unlike the

[2] Reported by Sarah Hsu in "The Rise and Fall of Shadow Banking in China – How shadow banking became the catch-all for riskier" *The Diplomat*, 2015 11 09, available from http://thediplomat.com/2015/11/the-rise-and-fall-of-shadow-banking-in-china/
[3] *Ibid*.

US (Figure 1) where funding comes from various sources, and with "Other Financial Institutions" being the dominant sector, banks in China (Figure 2) dominate funding supply. It should be noted, however, that by referring to only the economic function-based measures of shadow banking, the FSB might have underestimated the proportion of loans in the total loan system.

As shown from Table 2, shadow banking in China has grown very rapidly, from 1.6% of all assets in financial intermediation to 7.7%, becoming the third largest sector in terms of size. Along with that, according to Elliotte and Yan (2013), there are large pools of bad loans that are not acknowledged by banks. An example is the situation in Wenzhou, a small city that eventually got rich from profitable SMEs and that was able to obtain financing through various channels of shadow banks, subsequently followed by widespread defaults after 2012 because of the economic slowdown. Sheng *et. al*. (2015) report that the real estate sector makes up 18% of shadow banking assets as at 2013%, being the third largest industry. Also based on their calculations, an estimate of 22% to 44% of the non-performing loans in shadow banking will be brought back to the banking system. In fact, it is also reported that there are RMB1.19 trillion bad loans at the end of September 2015, up from RMB842.6 billion at the end of 2014[4], and a 22% non-performing loan rate in the whole financial system by the end of 2016.[5] It seems that even though the central government is willing to stabilize the market through intervention, there is still a danger of bad-debt leading to contagion throughout the financial sector.[6]

3. A Model for the Chinese Housing Market

[4] "China's December New Bank Loans Miss Expectations", MarketWatch, January 15, 2016.

[5] As reported by Peter Eavis in "Toxic Loans Around the World Weigh on Global Growth" in The New York Times on February 3, 2016.

[6] See, for example, the reports from "Be Scared of China's Debt, Not Its Stocks" of Bloomberg on January 7, 2016, available from http://www.bloombergview.com/articles/20160107/ bescaredofchinasdebtnotitscrashingstocks, and "Mid-tier Chinese banks piling up trillions of dollars in shadow loans" of Thomson Reuters on January 31, 2016, available from http://www.reuters.com/article/china-banks-investment-idUSL8N 156053.

Studies of the US housing bubble by now have become abundant. Examples are Black et al. (2006), Chan et al. (2001), Chang et al. (2005), Coleman et al. (2008), Hwang et al. (2006), and Wheaton and Nechayev (2008). However, studies on the Chinese house price movements are scant, although studies on the housing markets themselves are extensive. Deng, Sheng and Wang (2009) and Yang and Chen (2014), among others, focus on the Chinese housing policy reform. Others such as Wu, Gyourko and Deng (2010) discuss the sustainability of its boom. The links between house prices and land policies are studied in Cai and Zhang (2009), and Peng and Thibodeau (2009). Ren, Xiong, and Yuan (2012) is one of the few to explicitly measure the extent of the Chinese house price run up. A very recent study is and Glaeser *et al* (2016). To our knowledge, effects on the Chinese house prices have not been separated into long run and short run factors.

This paper studies property markets in China over the past decade. We use rental and house price data from 65 cities over the period of 2005 – 2014, and a version of the Gordon dividend discount model as the common representation of long run fundamentals, but the model allows short run momentum that can vary across cities. We are able to test and estimate a long run fundamental model, as well as the short run adjustments and momentum across cities. Associated with this is estimation of how fast the deviation from the long run is corrected. For further analysis, we also classify cities into Tier 1 and Tier 2 cities (which are classifications in terms of size and speed of development) and coastal versus inland cities (because coastal cities are those that have more advanced development for longer period). Our prior is that a housing bubble would be bigger in Tier 1 and/or coastal cities.

3. 1. Impact from Shadow Banking

The shadow banking data, classified as "Loans from non-banking financial institutions", are reported by the National Bureau of Statistics, with a monthly frequency spanning the period of January 2006 to December 2015. To control for the basic factors in the real estate sector, we also include the house price index and the rental index from the Consumer Price Index series published by the National Bureau of Statistics as well as interest rates, proxied by nominal lending rates for housing loans issued by the People's Bank of China.

In order to study how shadow banking affects investments in the real estate sector in China, we include data on housing completed, housing sold, housing starts, and land purchases and investment. All are monthly data are from the National Bureau of Statistics, some of which starting as early as March 1998; while data starting as late as March 2007 and March 2008 are on land purchases and investment. The "Housing completed" category is proxied by "Floor space completed", "Floor space completed: commodity building – residential", "Floor space completed – residential", and "Floor space completed: 40 cities – residential". "Housing sold" are proxied by "Floor space sold: residential: presale", "Floor space sold: residential: existing units", "Floor space sold: residential", "Building sold: residential", "Building sold: residential: presale", and "Building sold: residential: existing units". "Housing starts" are proxied by "Floor space started: commodity building: residential" and "Floor space started: 40 cities: residential". Finally, "Land purchases and investment" are proxied by "Land area purchased", "Real estate investment" residential", "Real estate investment" new increase", "Real estate investment", "Real estate investment: land transaction account", "Land area purchased: 40 cities" and "Real estate investment" residential: 40 cities".

All variables are percentage changes. We performed unit root tests and cannot reject that the log differenced (percentage change) data are stationary. As expected, because the rental market is very small, and hence the rental rates do not exert much influence on demand and supply measures of real estate, we rerun the regressions without rental rates on the right-hand side. The signs of the explanatory variables are mostly correct (i.e. negative coefficients for interest rates and positive coefficients for shadow banks); otherwise they are not significant anyway. Table 3 shows the results with various proxies of real estate demand and supply.

It can be seen from Panel A of Table 3 that high housing prices and availability of shadow banking funds can boost up buildings sold and floor space sold, while interest rates exert negative effects as expected. In particular, an increase of 1% in the measure of shadow banking fund can increase, say, floor space of existing units (Proxy 2) by 1.426%, or floor space of presale units (Proxy 3) by 1.277%. Similarly, available funds and surging house prices can encourage construction, as represented by Floor Space Started in Panel B. While the variables also exert effects on Floor Space Completed, it should be noted that it is negatively affected by housing price, which is not reasonable. Nevertheless, note first that they are mostly not significant, and more importantly, the house price variable is not lagged, and therefore should not be a factor that would deter construction which has already been taken place. Panel C also show the interesting results that there will be real estate investments and land purchases as long as there is funding and housing price continues increasing; interest rates do not seem to be very important when considering investments by developers.

We use lagged shadow banking variables to represent situations where funding was needed for construction one or two years before, in order for units to be completed and sold now. Alternatively, funds from shadow banking might be needed immediately for purchases of housing units, the completion of which would be triggered by high property prices one or two years ago. We repeat the regression in two sets of tests with six-month, 1-year, 18-month, and 2-year lags, given that most housing buildings can be completed in around two years. Similar lags are applied to all explanatory variables. The first set includes lags for all variables, while the second set includes lags for all variables except shadow banking funds. The rationale for the former is that current investment decisions can be due to observing a good market over the past period. The rationale of the latter is that construction decisions are often made before, while funding is needed now to stimulate purchases. Results are shown in Table 4 (tests with various lags generate similar results and therefore are not all depicted). Interestingly, shadow banking funds are always the most significant explanatory variable, no matter whether we use no lags, six-month, 1-year, 18-month, or two year lags. And once shadow banking is considered, even the dominating factor as housing price index sometimes shows negligible influence.

From Panels A and B of Table 4, it is clear that the motivation for real estate investments and land purchases is affected by lagged availability of funds. Interestingly, housing price is not a strong consideration for land purchases, probably because developers always favor stacking up land banks for any option for construction whenever housing prices turn out to be favorable. Panel C shows effects of house price and interest rate variables lagged by six months, while shadow banking funds are not lagged, on the property sales market, testing whether past information on house prices and interest rates trigger more purchases if funds today are available. Again, while the variables are correctly signed, only current funding availability is important. In terms of developers' decisions, commencement of construction (i.e. Floor Space Started) and land purchases are mostly based on availability of funding. While this is not very convincing, it should be noted that our sample period covers the period of market boom when investors and developers are optimistic about the market. It is doubtless the case that the period also covers the time when there were government restrictions and policies to curb the market, and the housing prices were once affected. However, developers were apparently willing to invest as long as there was funding.

We also study if there was increased demand from shadow banking because of increased demand and supply of real estate investments. The results are depicted in Table 5. It is obvious that all the variables representing real estate investments, building and development, and completed and sold exert significant and positive effect on shadow banking. In other words, both demand and supply of real estate trigger demand for more shadow banking funds. While it is logical to consider that higher interest rates also attract more shadow banking funds, it is also logical to interpret the mostly negative effect from house price as that lower prices attract more buying and therefore more demand for funds.

In general, the results confirm that shadow banking might be an important factor in real estate investment in China. Hence, we include shadow banking funds as a short term variable that could affect the model for pricing of housing units in China. To check for robustness, we also test for existence of autocorrelation of the regression residuals in the above tests. All regression results show no existence of autocorrelation.

4. Modeling House Price Growth via Pooled Mean Group

This section follows Lai and Van order (2016) in developing a model for property value changes over time. The equilibrium condition for holding property is that the current dividend, or rent, from the property equal the appropriate (risk adjusted) interest rate plus expected capital gains over the period. Then, given an information set, Ω_t , the equilibrium condition for holding property at time t is given by[7]

$$R_t / P_t = i_t + \alpha - E((P_{t+1} / P_t) - 1 | \Omega_t) \equiv i_t + \alpha - \pi_{ht} \quad (1)$$

where P_t is the price of a constant quality house, R_t is net rental income, which is the imputed net rent of the property in the case of owner-occupied housing, i_t is the risk-adjusted hurdle rate, which can be thought of as a long term nominal rate, α is constant depreciation, and π_{ht} is expected house price growth. Equation (1) applies to a particular location. We suppress location notation until we get to estimation later.

Equation (1) can be used to determine house prices given expected future prices. Because future prices depend on future rents, current price depends on future rents via the expected present value relationship:

$$P_t = \sum_{i=0}^{\infty} E(R_{t+i} / I_{t+i} | \Omega_t) + \lim E(1 / I_{t+i} | \Omega_t) \quad (2)$$

where the discount factor is given by I_t = 1+ i_t, and therefore I_{t+i} is the discount rate for an i-period loan at time t. Assuming that the second term approaches zero and dividing through by R_t, gives the usual expected present value formulation:

$$P_t / R_t = \sum_{i=0}^{\infty} E\left(1 / D_{t+i} | \Omega_t\right). \quad (2')$$

where $D_{t+i} = (1 + i_{t+i}) / (1 + \pi_{t+i}*)$, and $\pi_{t+i}*$ is the expected rate of growth of rent from period t to period i. If D and the rate of growth of rents are constant in the long run, then the reciprocal of (2') will converge to (1), which gives the long run fundamentals.

The advantage of this approach is that it does not require development of a model of housing demand and supply. The model requires a model of how expectations are formed.

[7] See Lai and Van Order (2010)

More broadly, it needs to acknowledge transaction costs that can make adjustment to (2') gradual. It has been well known at least since Case and Shiller (1989) that house prices adjust slowly to shocks, making house prices more predictable than is consistent with standard notions of market efficiency. We take Glaeser and Nathanson (2015) as our point of departure. They develop a pricing model for house prices where traders are "almost" rational. The "almost" is because rational expectation models are subject to big errors for small mistakes; as a result their optimal forecasting procedure uses past prices to forecast housing in a way that allows short run momentum (positive feedback), long run mean reversion, and excess volatility. Our estimation allows for all of these properties. We add the model the requirement that the long run mean is given by the Gordon dividend model.

4.1 Long Run Specification

Theory suggests that we should expect prices and rents to move together in the long run, in a way that depends on real interest rates. In the long run, the Gordon model implies

$$\frac{R_t}{P_t} = i_t - \pi_t + \alpha \equiv r_t + \alpha \qquad (3)$$

where r_t is the real rate. This suggests a coefficient of unity for real rate. It is possible that for reasons of taxes or money illusion or inability to borrow against human capital that it is not. Hence we consider a more general formula:

$$\frac{R_t}{P_t} = c_t \qquad (4)$$

where $c_t = \alpha_i i_t - \alpha_\pi \pi_t + \alpha \equiv \gamma_i i_t + \gamma_r r_t + \alpha$.

Then c is the "cap rate" for housing. Our tests are of whether property values converge to rent divided by cap rate, how fast they converge, the nature of short run deviations, and whether coefficients make sense. We use long run risk free rates for i, so that estimates of α contain risk adjustments that vary across cities but (we assume) do not change over time, as well as depreciation and long run expected future rent growth.

We take (4) to be our representation of long run fundamentals. We do not define short run fundamentals; rather we analyze how short run deviations move over time. In general, we expect γ_r to be close to 1, α to be a number of around 2% and not sure about γ_i.

4.2 *Dynamic Heterogeneous Panel Estimation*

We assume that *R/P* depends on a complicated lagged function of past levels of *R, P* and *i*. We decompose the relationship into long-run and short-run effects using the Pooled Mean Group (PMG) and Mean Group (MG) estimation models developed in Pesaran, Shin and Smith (1997, 1999).[8] Our hypothesis is that Ω_t contains only past rents, prices, interest rates and shadow banking indicators, and that prices ultimately adjust to fundamentals.

The MG and PMG models are restricted maximum likelihood estimations, based on an autoregressive distributed lag (ARDL) model (see Pesaran and Shin (1997)). Traditionally economic analysis has focused on long run relationships among the dependent variables and the regressors. PMG estimation allows us to identify long run relationships (equation (4)) and short run dynamics separately; the intercepts that reflect the fixed effect, short run coefficients and error variances are allowed to differ across cities, but long run coefficients are constrained to be the same. MG estimation is different in that the long run coefficients are also allowed to vary across cities.

Our model can be represented by:

$$\Delta \frac{R_{c,t}}{P_{c,t}} = \sum_{j=1}^{l} \lambda_{c,j,} \Delta \frac{R_{c,t-j}}{P_{c,t-j}} + \sum_{j=0}^{q} \sum_{k=1}^{n} \delta^k{}_{c,j} x^k{}_{c,t-j} + \delta_c + \varepsilon_{c,t} \tag{5}$$

where $\frac{R_{c,t}}{P_{c,t}}$ is property rent to price ratio in city *c* at time *t*

δ_c captures city specific fixed effects

$x^k_{c,t-j}$ is the *k*th of *n* regressors for city *c*

$\delta^k_{c,j}$ is the coefficient of the *k*th regressor for city *c*

[8] Ott (2014) uses PMG to study the house price dynamics in the Euro area.

$\lambda_{c,j}$ are scalars

$\varepsilon_{c,t}$ are the city specific errors

c represents panels or cities, $i = 1,2,\ldots,N$

t represents time in quarters, $t = 1,2,\ldots,T$

j is an indicator of lags;

$j = 0,1,2,\ldots,l$ for lagged dependent variable

$j = 0,1,2,\ldots,q$ lags for regressors

Letting $\rho = \dfrac{R}{P}$, (5) can be written as:

$$\Delta\rho_{ct} = \lambda_c \rho_{c,t-1} + \sum_{j=0}^{q}\sum_{k=1}^{n} \delta^k{}_{c,j} \Delta x^k{}_{c,t-j} + \delta_c + \varepsilon_{c,t} \tag{6}$$

which when written in error correction form, yields:

$$\Delta\rho_{ct} = \phi_c \left\{ \rho_{c,t-1} - \sum_{k=1}^{n} \beta_c{}^k x^k_{c,t} \right\} - \sum_{j=0}^{q}\sum_{k=1}^{n} \delta^k_{c,j} \Delta x^k{}_{c,t-j} + \delta_c + \varepsilon_{c,t} \tag{7}$$

where

$$\phi_c = -(1-\lambda_c) \ , \quad \beta^k_c = \frac{\delta^k{}_{c,0}}{(1-\lambda_c)} .$$

Expression (7) is used for the MG estimation model. It allows us to restrict some of the parameters inside the brackets to be zero — so we can get to a long run specification that looks like the Gordon model, as given in (4), but with fewer restrictions on short run adjustment parameters across cities. Among the items inside the bracket in (7) are long run fixed effects, α_c, and note that $\alpha_c = \delta_c / \phi_c$.

The coefficients (one for each city) before the brackets, ϕ_c, denote the speed of reversion to the long run, after short run deviations. The adjustment outside the brackets is momentum (or mean reversion), which will disappear if the model is not explosive.

For PMG we assume homogeneous long run relations; i.e., $\beta_c{}^k = \beta^k$ for all cities, but we continue to allow long run adjustment speeds and constant terms to vary across cities. Then:

$$\Delta\rho_{ct} = \phi_c \left\{ \rho_{c,t-1} - \sum_{k=1}^{n} \beta^k x_{c,t}^k \right\} - \sum_{j=0}^{q} \sum_{k=1}^{n} \delta_{c,j}^k \Delta x^k{}_{c,t-j} + \delta_c + \varepsilon_{ct} \tag{8}$$

The double summation term in (7) and (8) can have lagged values of changes in the dependent variable, which is our measure of momentum. We measure the level of momentum by the sum of these coefficients. If there is momentum we expect the sums of the coefficients of lagged changes in *R/P* to be positive; if they are negative we have short run mean reversion.

Note that the model requires long run rents and prices to grow at a constant rate within each city in the long run[9], but that δ_c can vary across allows the growth rates to vary across cities in the long run, which in turn causes the long run level of *R*/*P* to differ across cities. Long run equilibrium is given by:

$$\rho_c = \sum_{k=1}^{n} \beta^k x_c^k - \delta_c / \phi_c \tag{9}$$

Recall that the last term in (9), which is the negative of the ratio of the constant term in (8) (short run constant term) divided by the correction speed (which is negative), is the long run constant term, α_c. This allows for differences in risk premia and growth.

Before testing for the existence of a long run relationship, however, we need to check if the series are stationary. If some or all the rental income, house prices and interest rates are non-stationary and are integrated of the same order we can check for their long run relationship with cointegration tests. Hence, the first step is to test if these series are unit roots.

We perform cointegration analysis tests developed by Westerlund (2007) to confirm the existence of long-run relationships among the series. If long run cointegration exists, we can then find the long-run and short-run effects among variables using the MG and PMG

[9] We also tried to relax this condition by adding a linear time trend, common to all cities inside the brackets in (8). Results are similar, and therefore are omitted here.

models. All variables passed the tests (lengthy results omitted). The Hausman test can be used to check if a common long run coefficient exists (that is, not rejecting the null hypothesis of common coefficients between the MG and PMG means common coefficients should be adopted).

4.3. Data

Our house price and rental series are monthly data obtained from the CityRE Data Technology Co,.Ltd,[10] which compiles comprehensive data on housing for sale and lease for the first time for over 290 cities and areas in China starting from 2003. Numerous studies such as Wang *et al* (2011) and Ren *et al* (2012) use house price and rental indices from CEIC Data. The data from CEIC only cover 35 cities. Monthly data on sales price indices of newly constructed residential buildings for 70 cities from 1997 onwards can be obtained from the National Bureau of Statistics (NBS) of China, which however stopped in 2010. The property price index from the China Real Estate Index System (CREIS) can also be used, especially after the termination of housing index in 2010.

Figure 3 shows averages of rents and prices across cities over time. 3A shows the two series separately. A key observation is that in the aggregate the two series do not stay apart too long, indicating despite rapid growth there may not be a "bubble." Figure 3B shows rent divided by price, which is what we put on the left hand side of our regression. It does fluctuate but not nearly as much as in the U.S., which is depicted in 3C, showing a large departure of price from rent during the upswings and downturns around the Great Recession. Note in 3B the raw data have rents relative to prices as numbers like .003, which because the data are monthly means 30 basis points per month. In our regressions we multiply rent to price by 1200, so that the above is now 3.60 (% per year). This makes those return data comparable to our interest rate data, so that we can test for whether or not the coefficient of real or nominal rate is equal to one.

[10] Details of CityRE Data Technology Co., Ltd. can be obtained from http://www.cityre.cn/en/ or http://www.cityhouse.cn. It is claimed as operating the biggest real estate data set in China.

We group the cities in our sample into different categories ─ bubble versus non-bubble, coastal versus inland, and Tier 1 versus Tier 2 versus Other Tiers. Bubble cities are those with the price growth over rent growth higher than the 65-city average (2.59% for the 78-city average, and 2.75% for the 65-city average). We classify coastal/inland cities because, according to Yang and Chen (2014), for instance, there is a lower ownership rate in the eastern regions (i.e. the coastal cities) because of more expensive housing. This means that the two groups of cities might be subject to different regimes. Lastly, Tier 1 cities are made up of the four largest cities ─ Beijing, Shanghai, Guangzhou, and Shenzhen. Other smaller and more remote cities are classified as other tier cities.

We use rates on 5-year Chinese government bonds, obtained from the National Interbank Funding Center, as a measure of nominal long term risk-free rate. From this we also obtain real interest rates using the CPI from the National Bureau of Statistics of China. We also proxy risk relative to government bonds with the 5 year AAA corporate bond yields (obtained from the China Central Depository & Clearing Co., Ltd.), so that yield spread is the 5-year corporate bond yields minus the 5-year Chinese government bond yields.

We tried two sets of long run fundamental models. Model A includes various combinations of real interest rates, 5-year Bonds, and 5-year bond minus rent growth rates. Model B uses real interest rates as the only long run variable, forcing model to converge to a strong (no money illusion) version of the Gordon Model). In both Models, the lagged dependent variables are included to capture momentum. Interest rate variables are shown in Figure 4.

Other variables used in the models are the lagged shadow banking funds and the lagged yield spread. Lagged 5-year Bonds, and 5-year bond minus rent growth rates alternate in different models. We tried with monthly and quarterly data. With our monthly data, we used up to six lags, a maximum of half year. We also try to omit shorter lags for shadow banking funds to omit immediate funding effects. For quarterly data, we include up to four lags, representing one whole year. We also try to omit shorter lags for shadow banking funds. All tests show that PMG outperforms MG results, implying that all the cities share the same coefficients for the long run fundamental variables. Hence, we show only the

PMG results here (MG results are available upon request). The models that work best are those with monthly data with three lags, that is, lags from one month up to one quarter.

4.4 Results

Results from Model A are shown in Panel A of Table 5, while those from Model B are in Panel B. All variables, both long term and short term, have coefficients with the correct signs, as far as we can sign them. All long term variables are significant, implying that the proposed fundamental model works in the case of Chinese housing markets. The error correction coefficients, which show the speed of reverting to the long term fundamental from the short term deviation range between about -0.16 and -0.21. This is very fast. Since this is monthly data, the coefficients imply correction from short term deviation takes about 5 to 6 months to get back to the long run relationship. Short term lagged yield spreads do not show very strong and persistent effect, while 5-year bonds and 5-year bond minus rent growth are mostly significant. Lagged rent to price ratios actually have negative effects suggests ono only not bubble but a lot of short run mean reversion. Hence, our model is not one of bubbles; rather it appears that prices chase rents and adjust rather quickly. Note that this does not mean that prices are stable-that depends on how rents vary.

All models show significant short run effects of shadow banks on price changes.[11] We can also test whether or not long run effects of real rates on rent to price is unity. For instance in Model A effects are around 1.2 and in model B close to one in the first two panels and in the third panel around a half. We note however the very strong long run effects of nominal rates in Model A. Hence, while our model is sort of consistent with the Gordon Model and long run dependence on real rates, it is too ambiguous to take seriously now. Perhaps this is because while data set has a lot of cities it does not cover a very long time period

We next compare and contrast how different cities react to availability of shadow banking funds. In particular, we group cities into bubble versus non-bubble cities, coastal versus

[11] Notice that because the dependent variable is the *reciprocal* of price to rent ratio, negative shadow banking effect means increasing effects on house price growth.

inland cities, as well as Tiers 1, 2, and others (see Appendix A for the list of cities with various classifications). These three categories overlap, in that many bubble cities are also coastal cities; and the Tier 1 cities fall in the former two groups. We identify bubble cities in two ways. First, they have to have housing price growth rates higher than the mean growth rate for the period of 2007-2014 (the housing boom period). Second, they are the ones with which housing price growth minus rent growth rates are above the mean for the period of 2007-2014. The sum of the coefficients of three lags of change in shadow banking funds as the short run variables for different city classifications are shown in Table 7. Note that negative coefficients imply positive effects on price relative to rent, as the dependent variables in the PMG estimations are rent to price ratios.

It can be seen from all three of the PMG models with the best explanatory power (i.e. highest likelihood) that shadow banking has its biggest impacts in the coastal and Tier 1 cities. Exceptions are the results from the "bubble" cities defined as price growth rates higher than mean growth rates. Since the rental markets in major cities are much bigger, and therefore rents tend to grow faster, "bubble" cities defined as those cities with price growth minus rent growth greater than the mean would be more meaningful. Another observation is that the variations of these sum of coefficients (i.e. maximum minus minimum) are in general bigger in non-bubble cities as well as non-Tier cities. This implies that shadow banking as a source of investment funds in these cities tends to vary a lot. The fact that the means are generally higher in "bubble" cities, or coastal cities, or Tier 1 cities is mostly due to more investments drawn into these cities. And yet normal banking funds would be available only to very large developers or State Owned Enterprises. That is why the other developers and investors would have to rely on shadow banking. As a result, more shadow banking funds of all forms would be available in these cities, which subsequently push up housing prices. The sum of all short run coefficients are depicted in the Appendix B for reference.

A major part of Lai and Van Order (2016) is to test if the bubbles of the housing markets in the US were explosive by checking if the residuals from the regression estimates were highly autocorrelated, and whether the variances of the residual autoregression equations were different between bubble and non-bubble cities. Since the Chinese housing markets have also been described as having big bubbles that have not exploded yet, we repeat their tests. In particular, taking reference to PMG Models A3, A4, and B3 as reported in Table 6, we try the autoregressive residual equations with various lags. None of the equations shows much autocorrelation in the residuals (results shown in Panel A of Table 8). This and the low sums of coefficients of lagged rent to price, means that there do not appear bubbles in Chinese housing markets. Rather, there is momentum in the short run that is nowhere near explosive.

We further test to see if the variances of these models are different. Notice that since the residuals are not autocorrelated, the variances of these autoregressive models are really the variances of the PMG models. We show sums of coefficients of the lagged error terms in Panel B of Table 8. Also listed in the same Panel are the variances of the residuals from these autoregressive equations. While big residual variances might be sources of bubbles in housing markets, the small magnitudes show that there are no such sources of bubbles in our sample cities. Nevertheless, bubble cities have smaller variances than non-bubble cities, coastal bigger than inland, and Tier 1 smaller than Tier 2 which are in turn smaller than other tiers. This shows that our models are able to explain those major cities (bubble cities, Tier 1 cities) with higher precision. To test further if the variances from models with different lags are indeed different, we run the Goldfeld-Quandt test as shown in Panel D. Finally, we check differences in variances across city classifications, again by the Goldfeld-Quandt test, with results shown in Panel D. Both these last panels show that these models are different both across lags and across cities.

5. Conclusions

This is perhaps the first study that incorporates the availability of shadow banking funds on real estate prices in China, as well as using Pooled Mean Group estimation of house price dynamics to analyze the role of fundamentals and adjustment to them. We find that shadow banking appears to be an important factor in explaining property price dynamics in China. How causal this was remains to be explored. The issue is similar the U.S. one of whether the growth of private label securities caused the house price bubble or was the result of it. That the data suggest a strong link suggests worrying about implications of a collapse in shadow banking

We further analyze the pricing dynamics by classifying the cities into bubble versus non-bubble cities, coastal versus inland cities, and Tier 1 versus Tier 2 and Others. We find that shadow banking does help improve the liquidity of developers who cannot easily borrow from the major banking channels, particularly in non-bubble cities, which are mostly also inland cities/non-Tier 1 cities.

We can summarize our main other results as:

1. Housing in China is priced like a growth stock (high P/E ratio) with different expected growth rates across cities
2. Cities tend to share common long run fundamentals and adjust relatively quickly to deviations from them, without bubbles. Prices appear to be chasing rapidly growing rents.
3. Indicators of shadow banking activity have a positive effect on house price growth.
4. The data are consistent with the notion that a one percentage point rise in the real rate leads to approximately a one percentage point change in the rent to price ratio, but the data are too thin to take this too seriously.

That there is not evidence of bubbles does not mean property is not risky. Growth stocks are risky because small changes in expected growth of earnings (in this case rents) can lead to big changes in value. Alternatively one might are that there is a rent bubble or perhaps a lending "bubble" that are inducing high prices. But rents and lending activity are not prices of traded assets. They are best thought of as separate things, but are factors in risk assessment. Fear of shadow banking collapse is appropriate, and property in China is risky but not doomed.

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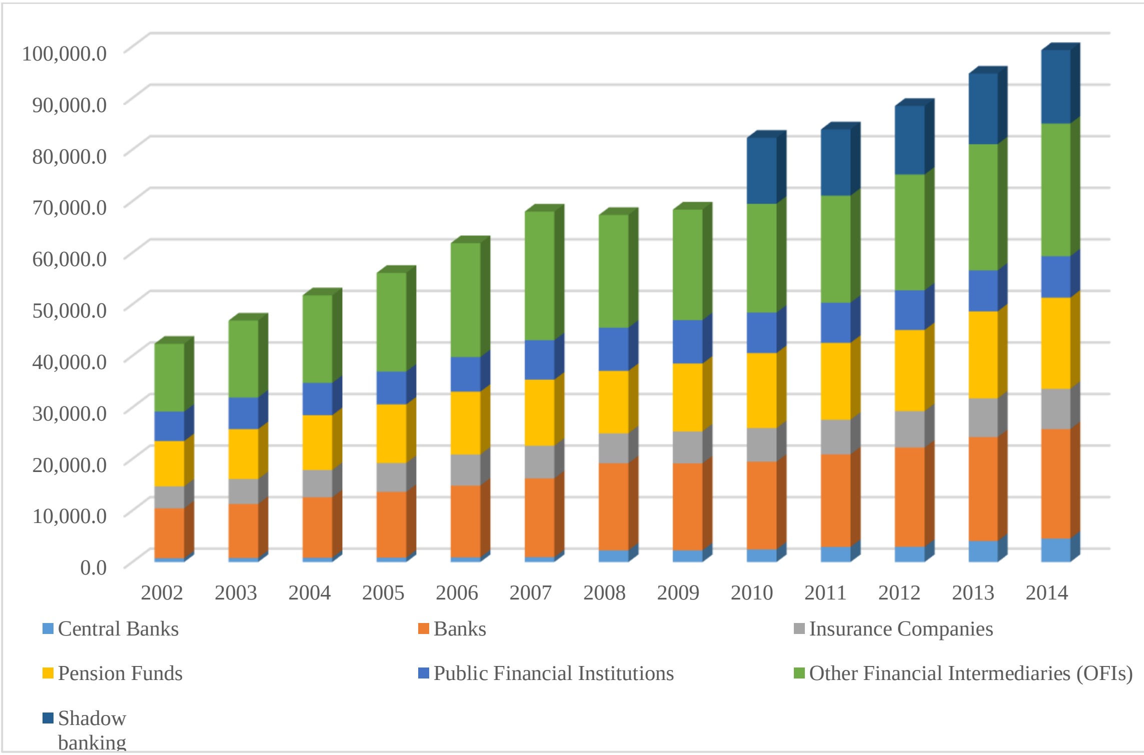
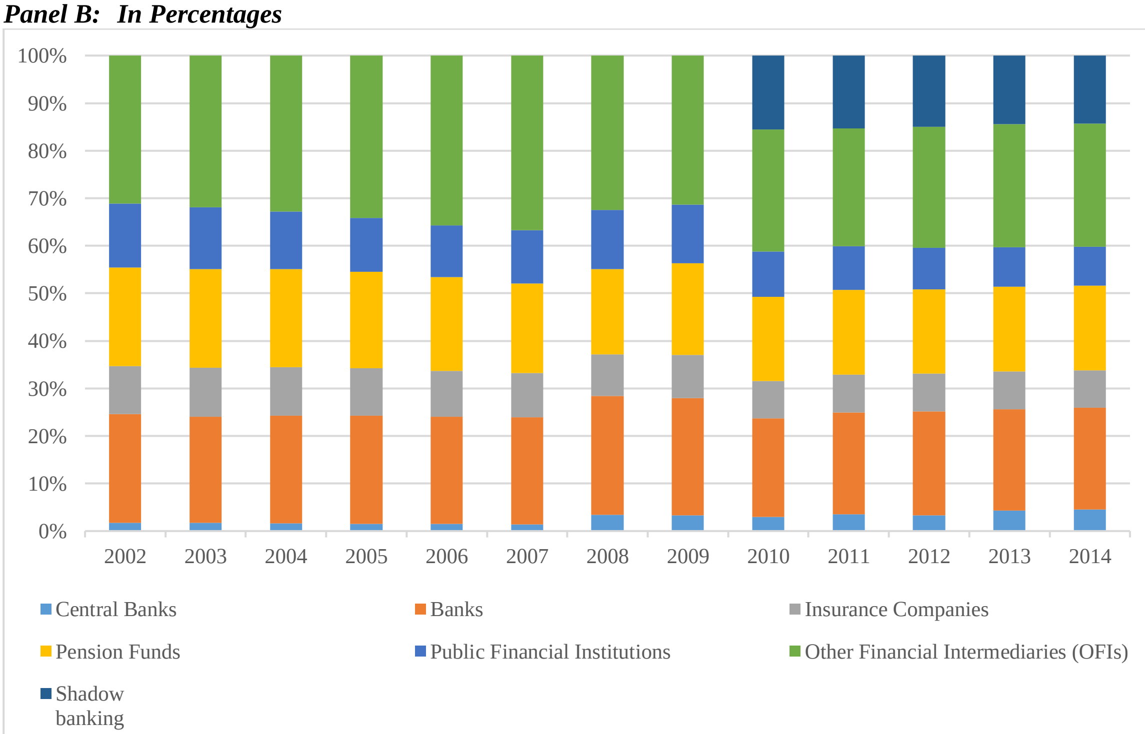
Figure 1 FSB Assets of Financial Institutions and Economic Function-Based Shadow Banking Measure – USA

Panel A: In Billions



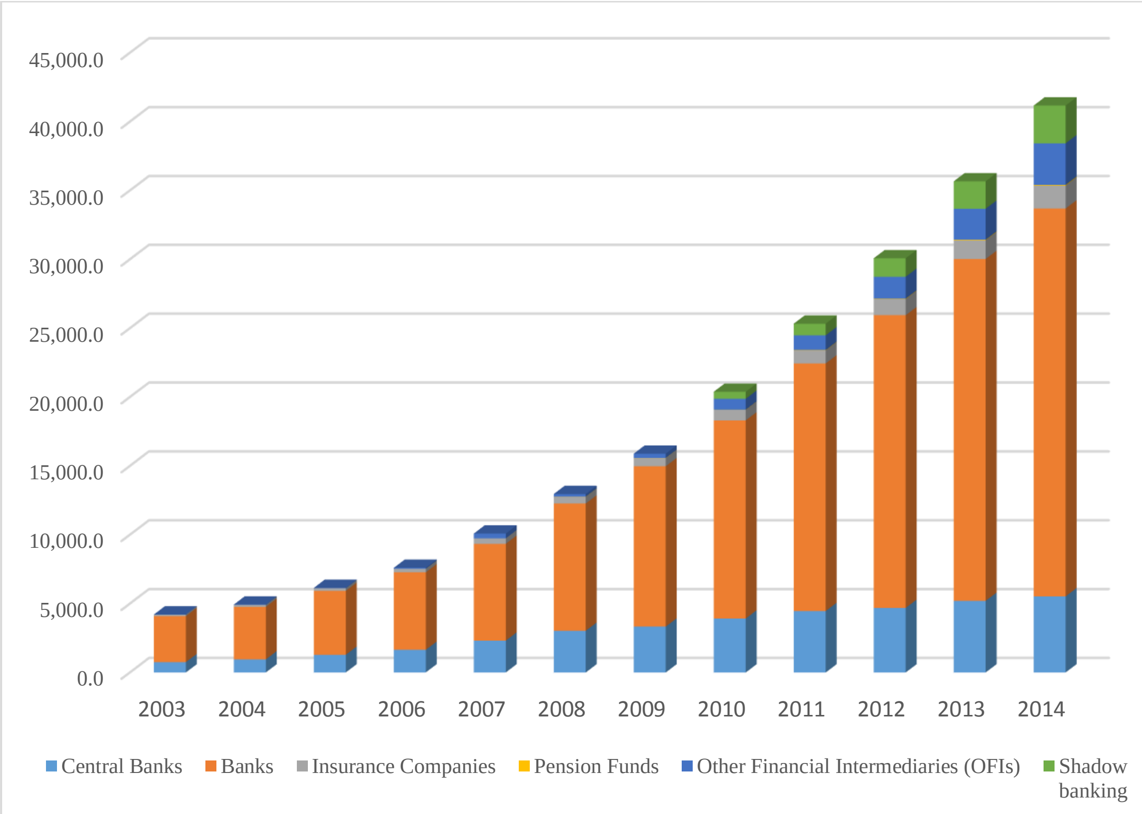
Panel B: In Percentages



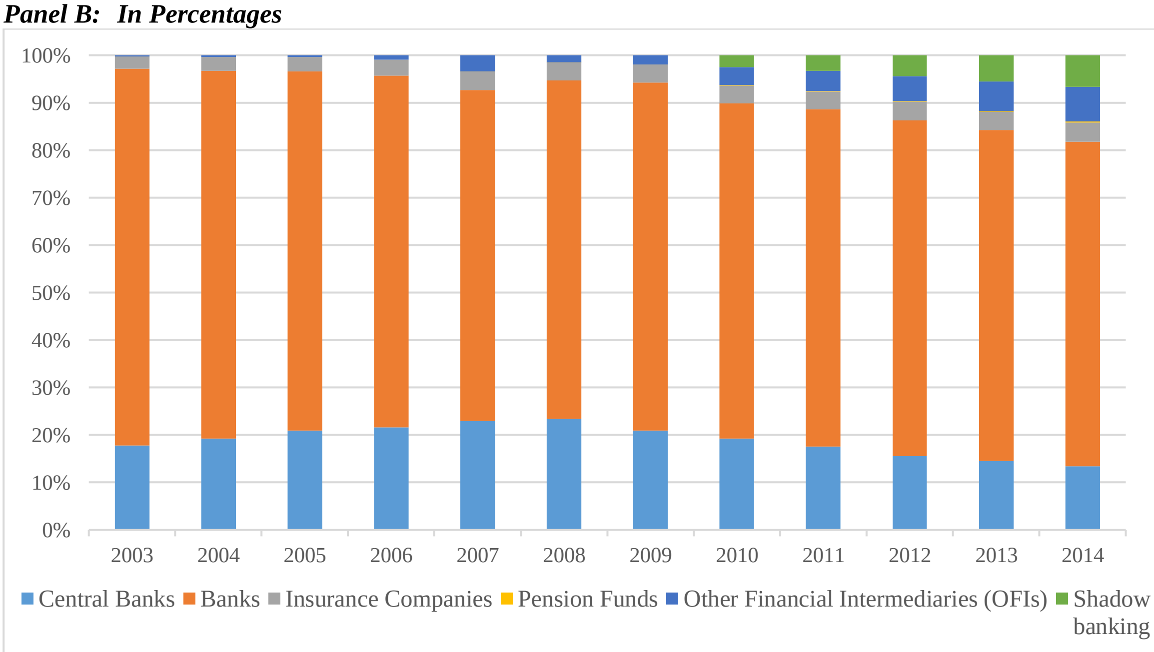
Source: Financial Stability Board (2015)

Figure 2 FSB Assets of Financial Institutions and Economic Function-Based Shadow Banking Measure – China

Panel A: In Billions



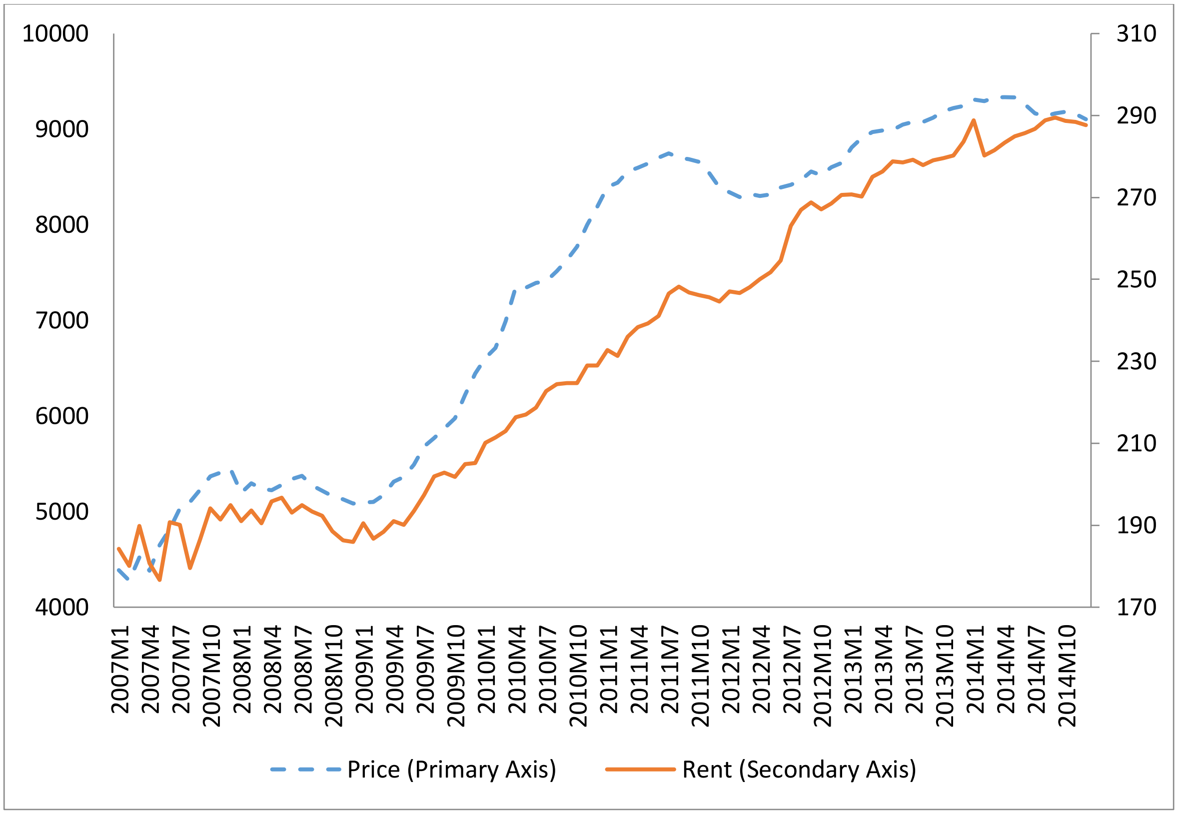
Panel B: In Percentages



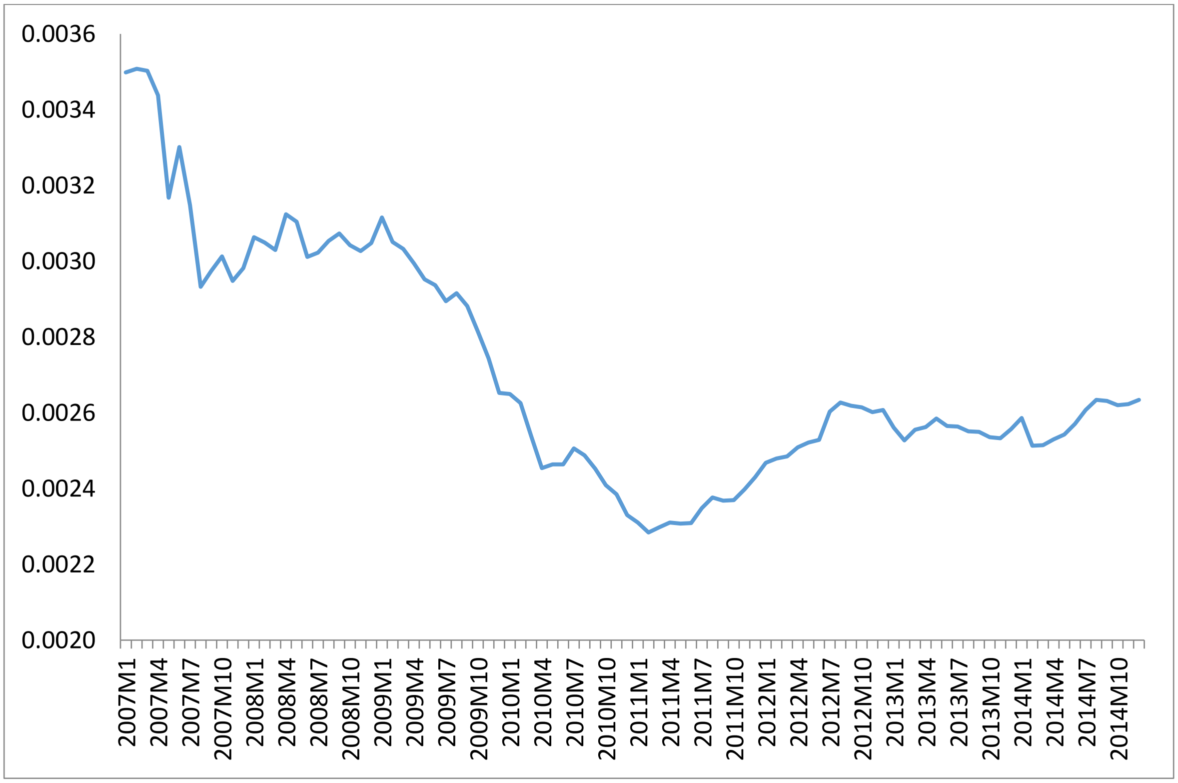
Source: Financial Stability Board (2015) and Lai and Van Order (2016)

Figure 3 Aggregate Prices and Rents

Panel 3A: Averages of *Monthly Rent and Average Price*



Panel 3B Ratio of Average Monthly Rent to Average Price



Panel 3C: Rent to price in the U.S.

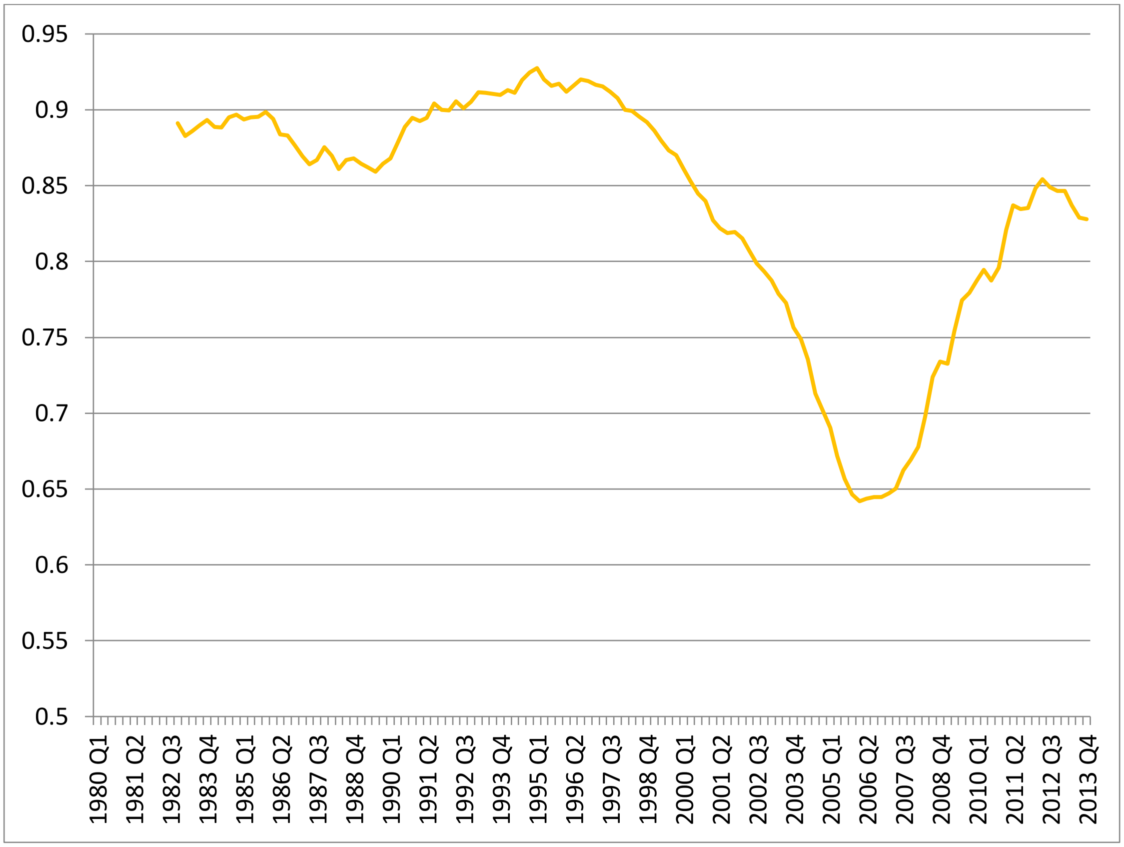
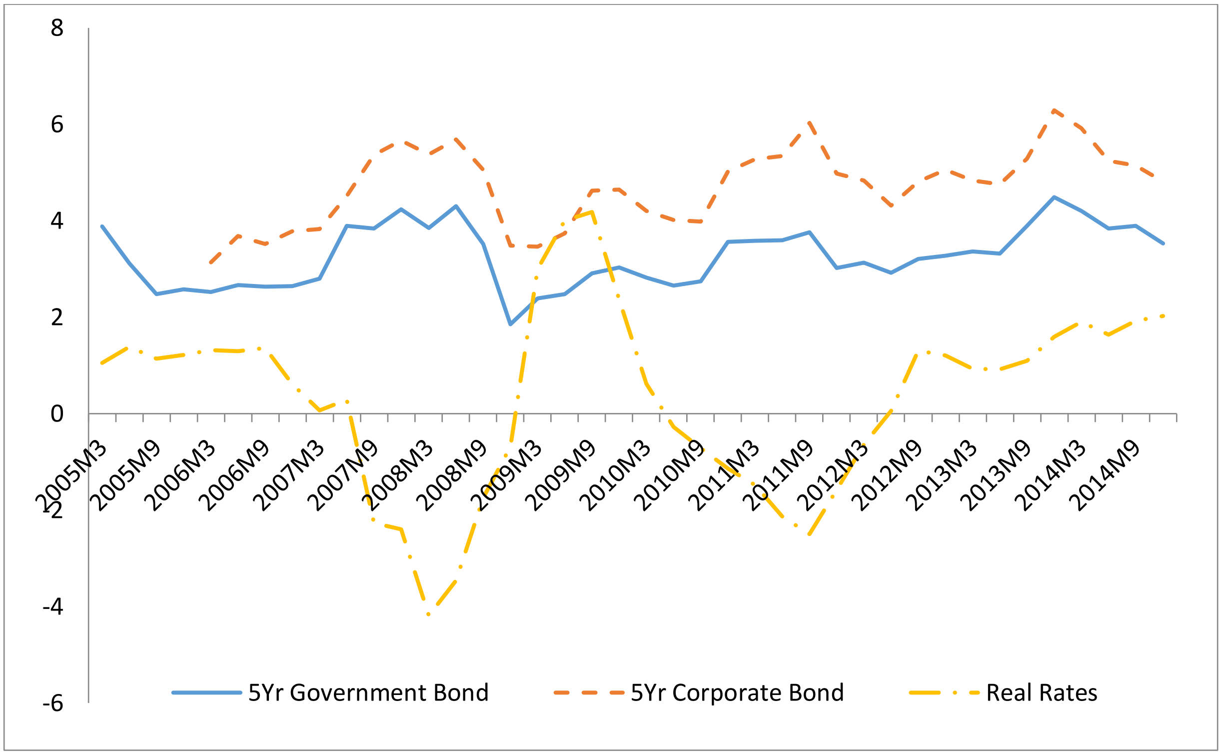


Figure 4 **Movements of Interest Rates and Housing Prices**

Panel 4A ***Various Rates (in %) Used for the Tests***



Panel 4B *Plot of Real Rates (in %), Housing Price (in RMB), and Change in Housing Price (in %)*

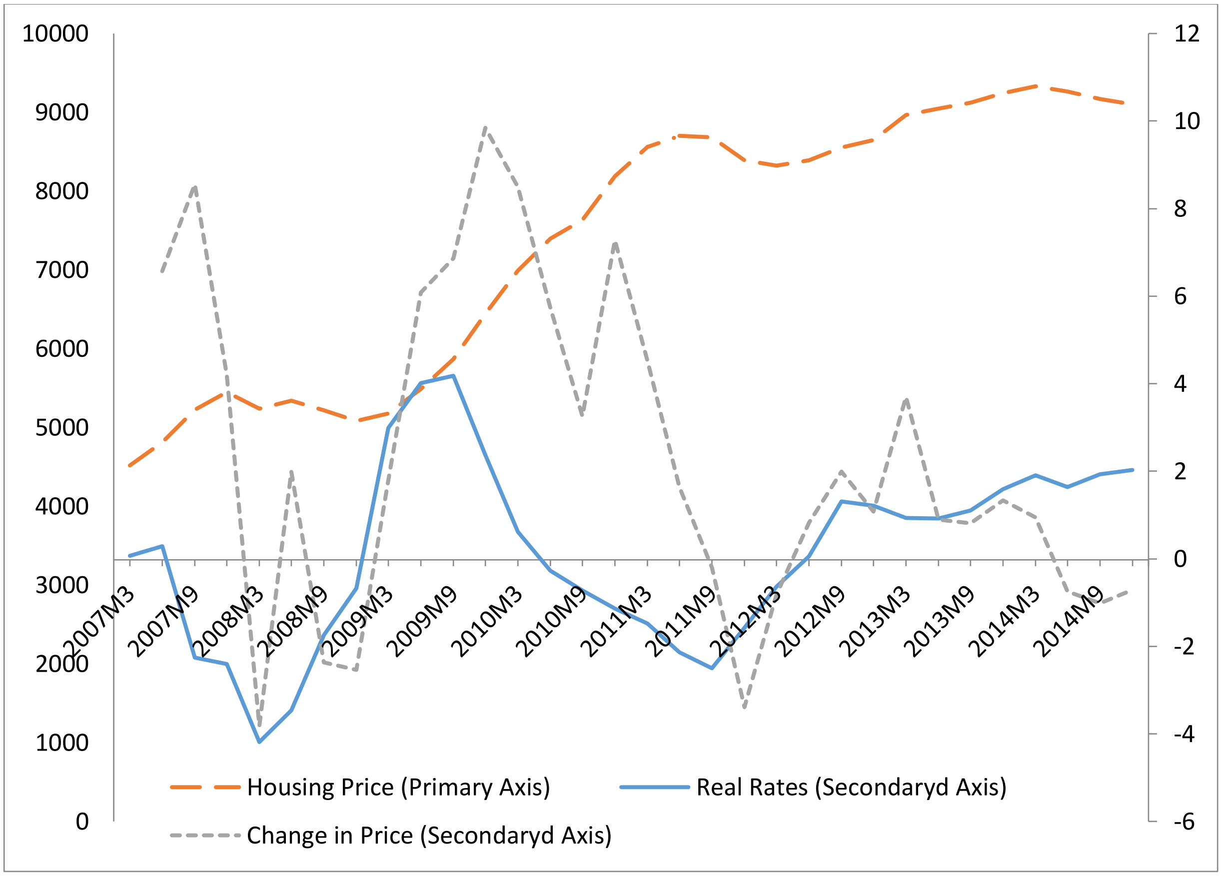


Table 1 Shadow banking, Other Financial Intermediaries (OFIs) and Banks as a Percentage of GDP of 26 Jurisdictions as at End of 2014

	Shadow banking	OFIs	Banks
Indonesia	1	8	54
Russia	4	5	109
Saudi Arabia	5	5	74
Argentina	6	6	30
Turkey	6	11	108
Singapore	10	90	607
Mexico	16	23	40
Italy	17	38	223
India	19	17	95
Hong Kong	20	85	817
Spain	21	69	267
Chile	23	31	106
China	26	29	271
South Africa	27	61	108
Australia	27	64	211
Brazil	33	60	91
Korea	48	100	205
Canada	58	147	228
Total	59	112	223
Japan	60	87	374
France	61	96	370
Germany	73	81	241
Netherlands	74	838	326
United States	82	148	122
Switzerland	90	277	364
United Kingdom	147	326	601
Ireland	1190	1551	363

Note: Banks = broader category of 'deposit-taking institutions'; OFIs = Other Financial Intermediaries; Shadow Banking = economic function-based measure of shadow banking.

Source: Financial Stability Board (2015)

Table 2 Share of Shadow banking Assets as a Percentage of All Financial Intermediations of 26 Jurisdictions as at End of 2010 and 2014

	At end-2010	At end-2014
United States	40.9	39.7
United Kingdom	13.0	11.4
China	1.6	7.7
Ireland	6.9	7.6
Germany	7.1	7.2
Japan	9.5	6.8
France	6.1	4.4
Canada	2.4	2.8
Brazil	2.0	1.9
Korea	1.3	1.8
Netherlands	1.8	1.7
Switzerland	1.5	1.6
India	0.9	1.1
Australia	1.3	1.0
Italy	1.2	0.9
Spain	1.0	0.7
Mexico	0.5	0.5
South Africa	0.3	0.2
Hong Kong	0.1	0.2
Chile	0.1	0.2
Russia	0.1	0.1
Turkey	0.1	0.1
Saudi Arabia	0.1	0.1
Argentina	0.0	0.1
Singapore	0.2	0.1
Indonesia	0.0	0.0

Note: Shadow banking is based on the economic function-based measure.

Source: Financial Stability Board (2015)

Table 3 Regression of Measures of Real Estate Supply and Demand on Shadow Banking Loans

Panel A On Buildings Sold and Floor Space Sold

	Buildings Sold			Floor Space Sold		
	Proxy 1	**Proxy 2**	**Proxy 3**	**Proxy 1**	**Proxy 2**	**Proxy 3**
Housing Price	2.819***	4.79	8.443**	2.731***	1.516	3.206***
Shadow Banking	1.185***	1.361***	1.250***	1.312***	1.426***	1.277***
Interest rates	-0.242**	-0.372**	-0.420***	-0.248**	-0.192*	-0.268***
Constant	0.022	-0.009	-0.008	0.005	0.003	0.005
Observations	100	70	70	100	100	100
Adjusted R-squared	0.664	0.638	0.689	0.69	0.662	0.691

Panel B On Floor Space Started and Completed

	Floor Space Started		Floor Space Completed			
	Proxy 1	**Proxy 2**	**Proxy 1**	**Proxy 2**	**Proxy 3**	**Proxy 4**
Housing Price	1.813***	2.776***	-1.652	-2.062**	-1.961*	-3.424***
Shadow Banking	1.095***	1.275***	1.012***	0.878***	0.937***	0.373**
Interest rates	-0.169***	-0.218**	0.059	0.107	0.076	0.222**
Constant	-0.003	-0.024	0.106***	0.086***	0.094***	0.146***
Observations	72	100	100	100	100	72
Adjusted R-squared	0.653	0.744	0.552	0.509	0.534	0.195

Panel C On Land Purchases and Real Estate Investments

	Land Purchases		Real Estate Investments				
	Proxy 1	**Proxy 2**	**Proxy 1**	**Proxy 2**	**Proxy 3**	**Proxy 4**	**Proxy 5**
Housing Price	2.338***	2.264***	3.320***	1.868**	-2.214**	3.387***	2.278***
Shadow Banking	1.404***	1.090***	1.313***	1.298***	0.668***	1.292***	1.032***
Interest rates	-0.117	-0.157**	-0.248**	-0.202**	0.118	-0.245**	-0.164**
Constant	-0.033*	0.019	0.002	-0.008	0.108***	0.006	0.035*
Observations	100	81	100	79	100	100	81
Adjusted R-squared	0.779	0.558	0.713	0.739	0.42	0.707	0.593

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
All variables except interest rates are differenced log values to obtain percentage changes of the values. Interest rates are differenced values.

Table 4 Regression of Measures of Real Estate Supply and Demand on *Lagged* Explanatory Variables, including Shadow Banking Loans

Panel A On Land Purchases and Real Estate Investments with 1-year Lag Variables

	Land Purchases		**Real Estate Investments**				
	Proxy 1	**Proxy 2**	**Proxy 1**	**Proxy 2**	**Proxy 3**	**Proxy 4**	**Proxy 5**
Housing Price	1.943	1.618*	3.050***	1.146	-1.943*	3.010***	2.256***
Shadow Banking	1.218***	0.968***	1.296***	0.994***	0.632***	1.284***	0.960***
Interest rates	-0.186	-0.202**	-0.225**	-0.213	0.136	-0.216*	-0.161*
Constant	-0.001	0.038*	0.004	0.049*	0.108***	0.006	0.045**
Observations	90	81	90	79	90	90	81
Adjusted R^2	0.57	0.435	0.699	0.483	0.4	0.702	0.535

Panel B On Land Purchases and Real Estate Investments with 2-year Lag Variables

	Land Purchases		**Real Estate Investments**				
	Proxy 1	**Proxy 2**	**Proxy 1**	**Proxy 2**	**Proxy 3**	**Proxy 4**	**Proxy 5**
Housing Price	1.959	1.182	2.926***	1.879	-2.245**	2.902***	2.369***
Shadow Banking	1.100***	0.814***	1.253***	0.930***	0.595***	1.246***	0.932***
Interest rates	-0.12	-0.052	-0.206*	-0.064	0.138	-0.204*	-0.167*
Constant	0.015	0.062**	0.009	0.058**	0.110***	0.011	0.048**
Observations	80	72	80	79	80	80	72
Adjusted R^2	0.576	0.336	0.707	0.509	0.41	0.708	0.531

Panel C On Buildings Sold and Floor Space Sold with 6-month Lag in Price Index and Lending Rates but No Lag for Shadow Banking Funds

	Buildings Sold			**Floor Space Sold**		
	Proxy 1	**Proxy 2**	**Proxy 3**	**Proxy 1**	**Proxy 2**	**Proxy 3**
Housing Price	0.217	0.591	0.094	0.536	1.091	0.356
Shadow Banking	1.153***	1.335***	1.221***	1.282***	1.404***	1.244***
Interest rates	-0.169	-0.206*	-0.173	-0.155	-0.187	-0.146
Constant	0.034*	0.007	0.019	0.016	0.009	0.018
Observations	100	70	70	100	100	100
Adjusted R^2	0.642	0.611	0.624	0.669	0.66	0.659

Panel D ***On Floor Space Started and Land Purchases with 6-month Lag in Price Index and Lending Rates but No Lag for Shadow Banking Funds***

	Floor Space Started		**Land Purchases**	
	Proxy 1	**Proxy 2**	**Proxy 1**	**Proxy 2**
Housing Price	0.207	0.561	0.801	0.031
Shadow Banking	1.022***	1.251***	1.397***	1.017***
Interest rates	-0.031	-0.079	-0.119	-0.157*
Constant	0.013	-0.014	-0.029*	0.033
Observations	72	100	100	81
Adjusted R^2	0.597	0.715	0.767	0.538

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
All variables except interest rates are differenced log values to obtain percentage changes of the values. Interest rates are differenced values.

Table 5 Regression of Shadow Banking on Various Independent Variables

Part A

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
House Price	-1.801	-1.485	-3.906*	0.615	0.859	0.81	-0.111	-1.640**	-0.923	-1.936***
Interest Rate	0.198	0.219	0.267	0.051	0.032	0.045	0.144*	0.188***	0.152**	0.203***
Building Sold										
Total Residential	0.564***									
Existing units		0.473***								
Presale			0.545***							
Floor Space Completed										
Total				0.545***						
Residential & Commercial					0.571***					
Residential						0.566***				
40-city Residential							0.186**			
Floor Space Sold										
Total Residential								0.529***		
Existing units									0.470***	
Presale										0.543***
Constant	0.052***	0.071***	0.064***	0.029*	0.048***	0.038**	0.133***	0.056***	0.062***	0.056***
Observations	100	70	70	100	100	100	72	100	100	100
Adj. R-Squared	0.667	0.633	0.672	0.551	0.5	0.529	0.125	0.694	0.67	0.693

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
All variables except interest rates are differenced log values to obtain percentage changes of the values. Interest rates are differenced values.

Part B

	Model 11	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**	**Model 17**	**Model 18**	**Model 19**
House Price	-1.363***	-1.787***	-1.439**	-1.540***	-1.988***	-1.125**	0.957	-2.041***	-1.659***
Interest Rate	0.170***	0.175***	0.106**	0.154***	0.188***	0.160***	0.040	0.189***	0.162***
Floor Space Started									
40-city Residential	0.600***								
Residential & Commercial		0.585***							
Land Area Purchased									
Total			0.555***						
40-Cities				0.516***					
Real Estate Investments									
Total					0.544***				
Land Transactions						0.573***			
New Increase							0.604***		
Residential-Total								0.548***	
Residential-40 Cities							0.604***		0.577***
Constant	0.052***	0.071***	0.064***	0.029*	0.048***	0.038**	0.133***	0.056***	0.056***
Observations	100	70	70	100	100	100	72	100	100
Adj. R-Squared	0.667	0.633	0.672	0.551	0.5	0.529	0.125	0.694	0.693

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
All variables except interest rates are differenced log values to obtain percentage changes of the values. Interest rates are differenced values.

Table 6 Pooled Mean Group Estimation for Rent to Price Ratio

Panel A Model A

	Model A1	**Model A2**	**Model A3**	**Model A4**
Long run variables				
Real Rates	1.20***	1.20***	0.96***	1.20***
Tbond_5y	2.88***	31.2***	3.62***	15.7***
T5y_rentg				-10.68***
Short run variables				
Error Correction	-0.17***	-0.17***	-0.14***	-0.14***
$\Delta R/P_{t-1}$	-0.25***	-0.21***	-0.24***	-0.23***
$\Delta R/P_{t-2}$	-0.17***	-0.15***	-0.15***	-0.153***
$\Delta R/P_{t-3}$	0.015	-0.02	0.003	-0.00
Δ *Shadow Bank*$_t$	***-3.48****	***-2.26****	***-0.60***	***-0.60***
Δ *Shadow Bank*$_{t-1}$	***-3.73****	***-4.56*****	***-3.72*****	***-0.4.08*****
Δ *Shadow Bank*$_{t-2}$	***-4.80*****	***-5.04*****	***-4.20*****	***-4.32*****
Δ *Shadow Bank*$_{t-3}$	***-1.68****	***-2.04*****	***-2.04*****	***-2.26*****
ΔYield Spread $_t$	0.48	0.36	-0.12	-0.12
ΔYield Spread $_{t-1}$	0.48	0.36	-0.48	-0.48
ΔYield Spread $_{t-2}$	-0.60	-0.96***	-1.32***	-1.32***
ΔYield Spread $_{t-3}$	-1.32**	-1.32***	-1.32***	-1.32***
$\Delta 5Y_t$	-1.68***		9.00***	7.68***
$\Delta 5Y_{t-1}$	0.24		3.48***	2.64**
$\Delta 5Y_{t-2}$	-0.84**		2.64**	1.80
$\Delta 5Y_{t-3}$	-1.08***		-0.24	-0.72
$\Delta 5Y_t$ - $RentG_t$		-2.26***	-10.2***	-9.12***
$\Delta 5Y_{t-1}$ - $RentG_{t-1}$		0.24	-3.48***	-2.64**
$\Delta 5Y_{t-2}$ - $RentG_{t-2}$		-0.84***	-3.48***	-2.76***
$\Delta 5Y_{t-3}$ - $RentG_{t-3}$		-0.72***	-0.72	-0.24
Constant	0. 37***	0. 35***	0. 27***	0. 22***
Observations	3,113	3,007	3,007	3,007
Number of groups	65	65	65	65
Log likelihood	16111	15980	16603	16606
Hausman Test	0.19	1.08	1.01	2.32
p-value	0.9102	0.5831	0.6022	0.5078

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Panel B ***Model B***

	Model B1	**Model B2**	**Model B3**
Long run variables			
Real Rates	0.96***	0.96***	0.48***
Short run variables			
Error Correction	-0.16***	-0.16***	-0.13***
$\Delta R/P_{t-1}$	-0.21***	-0.24***	-0.22***
$\Delta R/P_{t-2}$	-0.15***	-0.16***	-0.15***
$\Delta R/P_{t-3}$	-0.01	0.01	0.02
Δ *Shadow Bank*$_{t}$	***-2.16****	***-3.48*****	***-0.60***
Δ *Shadow Bank*$_{t-1}$	***-4.08******	***-3.48****	***-3.12*****
Δ *Shadow Bank*$_{t-2}$	***-4.92******	***-4.56******	***-3.84******
Δ *Shadow Bank*$_{t-3}$	***-1.56******	***-1.32****	***-1.44*****
ΔYield Spread $_{t}$	0.24	0.38	-0.24
ΔYield Spread $_{t-1}$	0.48	0.60	-0.36
ΔYield Spread $_{t-2}$	-0.84**	-0.48	-1.08***
ΔYield Spread $_{t-3}$	-1.44***	-1.32**	-1.44***
$\Delta 5Y_{t}$		-1.44***	9.00***
$\Delta 5Y_{t-1}$		0.48	3.36***
$\Delta 5Y_{t-2}$		-0.60	2.76**
$\Delta 5Y_{t-3}$		-0.84***	-0.36
$\Delta 5Y_{t}$ - $RentG_{t}$	-2.04***		-10.08***
$\Delta 5Y_{t-1}$ - $RentG_{t-1}$	0.48*		-0.3.12***
$\Delta 5Y_{t-2}$ - $RentG_{t-2}$	-0.48**		-3.24***
$\Delta 5Y_{t-3}$ - $RentG_{t-3}$	-0.60***		-0.36
Constant	0. 47***	0. 49***	0. 40***
Observations	3,007	3,113	3,007
Number of groups	65	65	65
Log likelihood	15945	16092	16562
Hausman Test	1.13	0.07	0.24
p-value	0.2876	0.7973	0.622

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 7 Sum of Short Run Coefficients for Shadow Banking Loans from PMG Three-lag Model (without adjustment rent to price units)

Panel A Model A3

	Bubble Price		**Bubble Price-Rent**		**Coastal City**		**Tiers**		
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal	Tier 1	Tier 2	Others
Mean	-0.0106	-0.0063	-0.0066	-0.0109	-0.0080	-0.0105	-0.0117	-0.0063	-0.0110
Maximum	0.0224	0.0204	0.0205	0.0224	0.0224	0.0205	-0.0022	0.0224	0.0186
Minimum	-0.0606	-0.0498	-0.0606	-0.0498	-0.0474	-0.0606	-0.0202	-0.0474	-0.0606
No. of cities	37	28	32	33	44	21	4	31	30

Panel B Model A4

	Bubble Price		**Bubble Price-Rent**		**Coastal City**		**Tiers**		
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal	Tier 1	Tier 2	Others
Mean	-0.0115	-0.0067	-0.0075	-0.0112	-0.0082	-0.0120	-0.0121	-0.0070	-0.0115
Maximum	0.0222	0.0197	0.0197	0.0222	0.0222	0.0174	-0.0032	0.0222	0.0170
Minimum	-0.0610	-0.0499	-0.0610	-0.0499	-0.0480	-0.0610	-0.0200	-0.0480	-0.0610
No. of cities	37	28	32	33	44	21	4	31	30

Panel C Model B3

	Bubble Price		**Bubble Price-Rent**		**Coastal City**		**Tiers**		
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal	Tier 1	Tier 2	Others
Mean	-0.0087	-0.0060	-0.0051	-0.0099	-0.0071	-0.0085	-0.0112	-0.0058	-0.0089
Maximum	0.0274	0.0273	0.0274	0.0228	0.0273	0.0274	-0.0001	0.0228	0.0274
Minimum	-0.0536	-0.0478	-0.0536	-0.0490	-0.0490	-0.0536	-0.0199	-0.0490	-0.0536
No. of cities	37	28	32	33	44	21	4	31	30

Note: "Bubble" cities are those with price growth greater than the mean during the period of 2007-2014.
"Bubble Price-Rent" cities are those with price growth minus rent growth greater than the mean during the period of 2007-2014.

Table 8 Residual Autoregressive Models from Model A4

Panel A Coefficients of the Autoregressive Models

	Overall			**Bubble (Price-Rent)**			**Non-Bubble (Price-Rent)**		
Residual	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
1 Lag	0.0176	0	-0.0099	0.0464*	-0.0178	-0.0629	-0.0078	0.015	0.0231
2 Lags		0.0293	0.0303		0.0251	0.0942		0.0371	-0.03
3 Lags		-0.0367	0.0018		-0.0633*	-0.1175*		-0.0123	0.1046*
4 Lags			0.0247			0.0009			0.0971
5 Lags			0.1249**			-0.0022			0.2860***
Obs	2,501	1,493	495	1,287	769	255	1,214	724	240
Adj. R^2	-9.74E-05	0.000181	0.0051	0.00134	0.000642	0.0075	-0.00077	-0.00222	0.0696

	Tier 1			**Tier 2**			**Others**		
Residual	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
1 Lag	0.0358	-0.0094	0.1399	0.0500*	0.0192	-0.0935	-0.0113	-0.0158	0.0255
2 Lags		-0.0736	0.0115		0.0587*	0.0772		0.0132	0.003
3 Lags		-0.0236	0.1371		-0.0188	-0.0457		-0.0583	0.0439
4 Lags			-0.480**			0.1473**			-0.0514
5 Lags			0.0285			0.0135			0.220***
Obs	158	94	31	1,227	735	244	1,116	664	220
Adj. R^2	-0.00513	-0.0279	0.0737	0.00162	0.000441	0.0197	-0.00077	-0.00089	0.0283

	Coastal			**Non- Coastal**		
Residual	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
1 Lag	-0.005	-0.046	-0.103	0.0294	0.0213	0.0573
2 Lags		-0.0332	0.1175		0.0591**	-0.0305
3 Lags		-0.0897*	-0.0766		-0.0137	0.0225
4 Lags			0.0112			0.0463
5 Lags			0.0838			0.158***
Obs	824	492	163	1,677	1,001	332
Adj. R^2	-0.00119	0.00337	0.00228	0.000248	0.00182	0.015

Note : *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Panel B Sum of Coefficients and Variances of the Autoregressive Models

	Overall			**Bubble (Price-Rent)**			**Non-Bubble (Price-Rent)**		
Sums	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
Coeff.	0.0176	-0.0074	0.1718	0.0464	-0.056	-0.0875	-0.0078	0.0398	0.4808
Sig. Coef	0	0	0.1249	0.0464	-0.0633	-0.1175	0	0	0.1046
Variance	1.24E-06	1.22E-06	1.12E-06	1.12E-06	1.12E-06	1.06E-06	1.37E-06	1.33E-06	1.10E-06

	Tier 1			**Tier 2**			**Others**		
Sums	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
Coeff.	0.0358	-0.1066	-0.1631	0.05	0.0591	0.0988	-0.0113	-0.0609	0.2411
Sig. Coef	0	0	-0.4801	0.05	0.0587	0.1473	0	0	0
Variance	1.05E-06	1.35E-06	6.56E-07	1.09E-06	1.01E-06	1.08E-06	1.43E-06	1.44E-06	1.17E-06

	Coastal			**Non- Coastal**		
Sums	1 lag	3 lags	5 lags	1 lag	3 lags	5 lags
Coeff.	-0.005	-0.1689	0.0329	0.0294	0.0667	0.2538
Sig. Coef	0	-0.0897	0	0	0.0591	0
Variance	1.30E-06	1.39E-06	1.29E-06	1.21E-06	1.13E-06	1.02E-06

Note: "Coeff." means sum of coefficients; "Sig. Coef" means sum of significant coefficients.

Panel C Goldfeld-Quandt Tests of Variance of Residuals from Autoregression Models

	Overall	**Bubble (Price-Rent)**	**Non-Bubble (Price-Rent)**	**Coastal**	**Non-Coastal**	**Tier 1**	**Tier 2**	**Others**
Model A4								
1 & 5 lags	1.646***	1.678***	1.627***	1.789***	1.568***	2.205***	1.550***	1.6907
3 & 5 lags	4.584***	4.853***	4.143***	5.151***	4.324***	3.758***	5.063***	4.236***
1 & 3 lags	2.786***	2.892***	2.546***	2.879***	2.757***	1.705***	3.267***	2.506
Model B3								
1 & 5 lags	1.677***	1.742***	1.630***	1.796***	1.616***	2.223***	1.584***	1.724
3 & 5 lags	4.626***	5.023***	4.071***	4.973***	4.484***	3.647***	5.224***	4.210***
1 & 3 lags	2.758***	2.884***	2.498***	2.769***	2.775***	1.641***	3.299***	2.442
Model A3								
1 & 5 lags	1.660***	1.703***	1.634***	1.801***	1.584***	2.217***	1.565***	1.705
3 & 5 lags	4.551***	4.750***	4.148***	5.107***	4.296***	3.746***	4.999***	4.240***
1 & 3 lags	2.741***	2.790***	2.539***	2.837***	2.713***	1.690***	3.194***	2.488

Panel D Goldfeld-Quandt Tests of Variance of Residuals of Different City Classifications

	Bubble (p-r) v.s. non-Bubble (p-r)	**Coastal v.s. non-Coastal**	**Tier 1 v.s. Tier 2**	**Tier 1 v.s. Others**	**Tier 2 v.s. Others**
Model A3					

1 lag	1.3135***	2.1625***	7.4781***	5.2374***	1.4278***
3 lags	1.2602***	2.4586***	10.5935***	6.8152***	1.5544***
5 lags	1.1471	2.5708***	5.6036***	4.6272***	1.211
Model A4					
1 lag	1.2959***	2.1877***	7.5468***	5.2216***	1.4453***
3 lags	1.2569***	2.4957***	10.7368***	6.8087***	1.5769***
5 lags	1.1064	2.6060***	5.6016***	4.6322***	1.2093*
Model B3					
1 lag	1.3369***	2.1429***	7.3524***	5.0559***	1.4542***
3 lags	1.2511***	2.3823***	10.3197***	6.5190***	1.5830***
5 lags	1.0836	2.3769***	5.1327***	4.3800***	1.1718

Note: The Goldfeld-Quandt Test is test for statistical difference between two fundamental equations.

*, ** and *** denote significance at the 10%, 5% and 1% levels respectively (compared to an *F*-value of 1.3).

Appendix A List of 78 Cities in the Sample

City	Bubble	Coastal	Tier	City	Bubble	Coastal	Tier
Anqing				Shantou	*	*	
Baoding	*			Shaoxing			
Beihai		*	2	Shenyang	*		2
Beijing	*		1	Shenzhen	*	*	1
Bengbu				Shijiazhuang			2
Changchun	*		2	Suzhou	*		
Changde				Taiyuan			2
Changsha			2	Taizhou			
Changzhou				Tangshan	*		
Chengdu			2	Tianjin	*	*	2
Chongqing	*		2	Urumqi	*		
Dalian		*	2	Weifang	*		
Dongguan	*	*		Weihai		*	
Foshan	*			Wenzhou	*	*	2
Fuzhou	*	*	2	Wuhan	*		2
Guangzhou	*	*	1	Wuxi	*		2
Guiyang			2	Xiamen	*	*	2
Haikou	*	*	2	Xi'an	*		2
Hangzhou			2	Xining			2
Harbin			2	Xuzhou	*		
Hefei	*		2	Yancheng	*	*	
Huzhou				Yangzhou	*		
Jiaxing				Yantai		*	
Jilin	*			Zhengzhou	*		2
Jinan	*		2	Zhuhai		*	
Jinhua				Zibo			
Kunming			2	Shantou			
Lanzhou			2	Shaoxing	*		
Nanchang			2	Shenyang			
Nanchong				Shenzhen			
Nanjing	*		2	Shijiazhuang			
Nanning			2	Suzhou			
Nantong		*		Taiyuan		*	2
Ningbo	*	*	2	Taizhou	*		
Qingdao	*	*	2	Tangshan			
Qinhuangdao		*		Tianjin			
Quanzhou		*		Urumqi	*		2
Rizhao				Weifang			
Shanghai	*	*	1	Weihai	*	*	

Note: Due to the problem of missing data, our tests are also based on 65 cities, which do not include the 13 cities on the bottom right of the table.

Appendix B Sum of *Significant* Short-run Coefficients for Individual Cities from PMG Estimation of Model A4

Bubble versus Non-bubble Cities (classified by price growth minus rent growth)

Panel A Non-bubble Cities

City	Error Correct-ion	Sum of Δ(R/P)	Sum of Δ Shadow Bank	Sum of Δ Spread	Sum of Δ5Y rate	Sum of Δ (5Y Rate – Rent Growth)	Constant
Changsha	-0.1126	-0.7644	-0.0063	-0.0015	0.0024	-0.0078	0.0029
Guiyang	-0.1466	-1.3375	-0.0095	-0.0217	0.0643	-0.0651	0.0046
Yantai	-0.2121	-0.7142	-0.0105	-0.0073	-0.0014	-0.0006	0.0025
Beihai	-0.0096	0.2451	-0.0275	-0.0012	0.0271	-0.0297	-0.0012
Bengbu	-0.2321	-0.429	0.0151	-0.0043	0.0104	-0.0159	0.004
Chengdu	-0.0903	-0.0528	-0.0199	0.0013	0.0033	-0.0073	0.0013
Dalian	-0.2779	0.0789	0.0174	-0.0006	0.0095	-0.011	0.0065
Harbin	-0.3119	-0.7486	-0.0094	-0.0193	0.0174	-0.0195	0.0091
Jinhua	-0.1282	-0.8079	-0.0232	0.0041	0.0055	-0.0124	0.0005
Kunming	-0.2546	-0.9534	-0.0107	-0.0037	0.0144	-0.0159	0.0044
Lanzhou	-0.0256	-0.1349	-0.006	-0.0035	0.014	-0.0164	0.0002
Nanchang	-0.0742	-0.7484	0.0036	0.0075	0.0127	-0.0182	0.0011
Nanchong	-0.2512	-0.0579	0.017	-0.0013	0.007	-0.0136	0.0037
Nanning	-0.0902	-0.2988	0.0002	-0.0082	0.0062	-0.0094	0.0023
Nantong	-0.0352	-1.1987	-0.0099	-0.0015	0.0139	-0.013	0.0005
Qinhuangdao	-0.5426	0.0583	0.0005	-0.0011	-0.0195	0.018	0.0054
Quanzhou	-0.0601	-1.2077	-0.0090	-0.0081	0.0258	-0.0268	0.0016
Shijiazhuang	0.0099	-0.6356	0.0197	-0.0096	0.0042	-0.0041	-0.0003
Weihai	-0.2452	0.0892	-0.061	0.0027	0.0158	-0.0173	0.0015
Zibo	-0.2032	-0.4254	-0.0021	0.0014	0.0026	-0.0067	0.0022
Anqing	-0.0725	0.4811	-0.0084	-0.0006	-0.0085	0.009	0.0007
Changde	-0.2479	0.3327	-0.0024	0.0002	0.0112	-0.0162	0.0058
Changzhou	-0.0948	-0.8634	-0.0270	0.0019	0.0161	-0.0228	0.0021
Hangzhou	-0.2147	0.9152	-0.0244	0.0015	0.0007	-0.0075	0.0014
Huzhou	-0.1731	0.0787	-0.0254	-0.0034	0.0005	-0.0006	0.0021
Jiaxing	-0.0796	-0.3421	-0.0099	-0.0028	-0.0109	0.0048	0.0015
Rizhao	-0.1669	-0.4414	-0.0233	-0.0016	0.001	-0.0031	0.0006
Shaoxing	-0.4128	-0.6861	0.0025	-0.0044	-0.0038	-0.003	0.0036
Taiyuan	-0.1203	-0.1278	0.0055	-0.0023	0.0107	-0.0118	0.0022
Taizhou	-0.1686	-1.3656	0.0123	-0.0105	0.021	-0.0195	0.0016
Xining	-0.4072	-0.358	0.0161	-0.0144	0.0128	-0.0154	0.0114
Zhuhai	-0.0418	-0.6482	-0.0243	-0.0012	-0.0178	0.0157	0.0004

Panel B Bubble Cities

City	Error Correct-ion	Sum of Δ(R/P)	Sum of Δ Shadow Bank	Sum of Δ Spread	Sum of Δ5Y rate	Sum of Δ (5Y Rate – Rent Growth)	Constant
Qingdao	-0.0560	0.1124	-0.0010	0.0018	0.0033	-0.0070	0.0005
Changchun	-0.0395	-0.3366	-0.0152	-0.0011	0.0072	-0.0105	0.0002
Jinan	-0.1337	-0.1401	-0.0204	0.0011	0.0169	-0.0194	0.0013
Shantou	-0.1559	-1.8098	-0.0499	0.0072	0.0363	-0.0476	0.0036
Suzhou	-0.0422	-0.3962	-0.018	-0.0109	0.0301	-0.0286	0.0005
Weifang	-0.0718	-0.7851	-0.0162	-0.0002	0.0024	-0.0065	0.0008
Xiamen	-0.0322	-0.3512	-0.012	-0.0049	-0.0077	0.0050	-0.0001
Xi'an	-0.0685	-0.6129	-0.0073	-0.0032	0.0346	-0.0354	0.0014
Chongqing	-0.3375	-1.4195	-0.0228	-0.0083	0.0803	-0.0849	0.0076
Dongguan	-0.0893	-0.5404	0.0161	-0.0071	0.0207	-0.0277	0.0025
Foshan	-0.2111	-0.7477	-0.0293	-0.0023	-0.0305	0.0275	0.0042
Fuzhou	-0.1081	-0.3706	-0.0164	-0.0004	0.0074	-0.0092	0.0011
Guangzhou	-0.0185	-0.0815	-0.0032	-0.0022	0.0107	-0.0072	-0.0002
Haikou	-0.0304	-0.4868	0.0077	-0.0081	0.0292	-0.0291	0.0013
Jilin	-0.1305	-0.3070	-0.0055	0.0027	0.0052	-0.0091	0.0025
Nanjing	-0.2480	-0.6407	0.0050	-0.0126	0.0224	-0.0221	0.0026
Ningbo	-0.0664	0.4866	-0.0137	0.0029	0.0007	-0.0038	0.0005
Shanghai	-0.0495	-0.4857	-0.0200	-0.0028	0.0068	-0.0093	0.0000
Shenyang	-0.0415	-1.1229	0.0222	-0.0077	0.0262	-0.0272	0.0016
Shenzhen	-0.0101	0.5447	-0.0166	0.0096	-0.0343	0.0323	-0.0002
Tangshan	0.0073	0.1926	0.0164	-0.0059	0.0138	-0.0148	-0.0004
Tianjin	-0.0133	-0.2947	-0.0196	0.0079	0.0115	-0.0160	-0.0003
Wenzhou	-0.1267	0.0563	-0.0043	-0.0020	-0.0088	0.0066	0.0003
Wuhan	-0.2260	-0.1896	-0.0100	0.0000	0.0016	-0.0078	0.0046
Urumqi	-0.1436	-0.7475	-0.0387	-0.0027	0.0122	-0.0159	0.0018
Wuxi	-0.2133	-0.4083	-0.0078	-0.0070	0.0172	-0.0169	0.0033
Xuzhou	-0.1794	-0.6709	-0.0101	-0.0068	0.0214	-0.0213	0.0023
Zhengzhou	-0.0961	-0.1679	-0.0018	-0.0050	0.0167	-0.0175	0.0016
Baoding	-0.2461	-0.2766	-0.0362	0.0078	-0.0069	1E-04	0.0021
Beijing	-0.0725	0.4200	-0.0087	0.0012	0.0090	-0.0127	0.0004
Hefei	-0.1805	-0.7416	-0.0480	0.0005	0.0308	-0.0293	0.002
Yancheng	-0.2243	-0.1542	0.0059	-0.0024	0.0116	-0.0141	0.0037
Yangzhou	-0.1106	0.3070	0.0088	-0.0015	-0.0515	0.0459	0.0014