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Shadow Banking and the Property Market in China

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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 2007-2016, define the "fundamentals" of housing prices with the Gordon dividend discount model, and use lagged rents, prices, real and 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 house prices rapidly chasing growing rents. More importantly, we find that house prices increase more quickly with the availability of shadow banking funds, which have grown rapidly.

Keywords

Chinese Housing Market, Shadow Banking, Pooled Mean Group Estimation

1. Introduction

Property values have increased rapidly in China in the last decade, and one of the contributing factors have been public policy changes. The Chinese government claimed that a housing bubble had been successfully “deflated” at the end of 2014, and subsequently relaxed restrictions on second-home purchases upon the emergence of an economic slowdown in 2015, with the aim to boost the property market as a means of supporting the dampened economy. Chinese households have been since 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 and Van Order (2017), one of the ways to study the dynamics of house prices is to apply the Gordon dividend discount model, which makes use of rental and interest rates to explain for long run house prices, to which actual prices adjust over time. This leads to a well- defined long run equilibrium, but with a less restrictive adjustment process. 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. We exploit the fact that shadow banking policies are made at the national level, but we use them to estimate the determinants of city by city price changes, as a way of avoiding endogeneity problems and suggesting causality from shadow banking to price changes.

To the best of our knowledge, we are the first to formally test the effects of shadow banking on the property markets in China and model Chinese house prices by decomposing the effects into long run fundamentals and short run adjustments. 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 housing growth in the short run is related to the availability of shadow banking funds, which have also grown rapidly. A policy suggestion 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 regular banking system is the absence of deposit insurance coverage. The 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 non-bank 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 (WMPs), and interbank market activities (see Elliott *et al*. (2015) for detailed descriptions of each of these sources of shadow banking). Some of the non-bank channels, such as bond markets and interbank market activities, should not be classified as shadow banking. For instance, the bonds here refer to corporate bonds, which are not generally traded in the bond markets like those in the US, whereas interbank market activities are really large corporations that are 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 WMPs that pool assets together. Most of the assets are loans. Sharma (2014) and Hsu and Li (2015) are some examples of the literature on shadow banking in China.

In response to the Global Financial Crisis, the Chinese central government initiated a stimulus package in 2009, which was followed by unprecedented growth in fixed asset investments that were 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 was from local governments.[2] Funding was also available to riskier borrowers, typically real estate developers and local government financing vehicles, the corporate arm of local governments, which helped local governments generate their high GDPs through infrastructure construction.

The growth of shadow banking has been fueled by the fact that the five largest banks in China, all state-owned, are only allowed to lend to the large state-owned enterprises (SOEs) but not corporates and small and medium sized enterprises (SMEs). Hence, the shadow banking sector provides lending needs outside regulations. On the supply side, the lack of investment opportunities (made up of only 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) deposit rates. Furthermore, average investors are under the impression that these products are

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

[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 at http://thediplomat.com/2015/11/the-rise-and-fall-of-shadow-banking-in-china/

safe because they are mostly sold by big banks, which supposedly have implicit guarantees from the People's Bank of China (the Chinese central bank), ignoring the fact that these big banks are only intermediaries and do not provide any guarantees.

While boosting local incomes, over-investment in infrastructure has generated "ghost towns", with roads and bridges that very few people use. It is reported that shadow banking makes up 20%-41% of on-balance bank lending, without which total lending would have declined by 16-29%.[3] The downturn of the Chinese property market resulted in the 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 is only 26% of the GDP in China, which ranks 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 US (Figure 1) where funding comes from various sources, (with "Other Financial Institutions" as 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 in Table 2, shadow banking in China has grown very rapidly, from 1.6% of all assets in financial intermediation to 7.7%, thus becoming the third largest sector in terms of size. Along with that, according to Elliott 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 prospered from profitable SMEs and was able to obtain financing through various channels of shadow banking, 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 of 2013, which is 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 (USD1 ≈ RMB7 as at mid-2019) 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 at the end of 2016.[5] It seems that even though the central government is willing to stabilize the market through intervention,

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[3] *Ibid*.

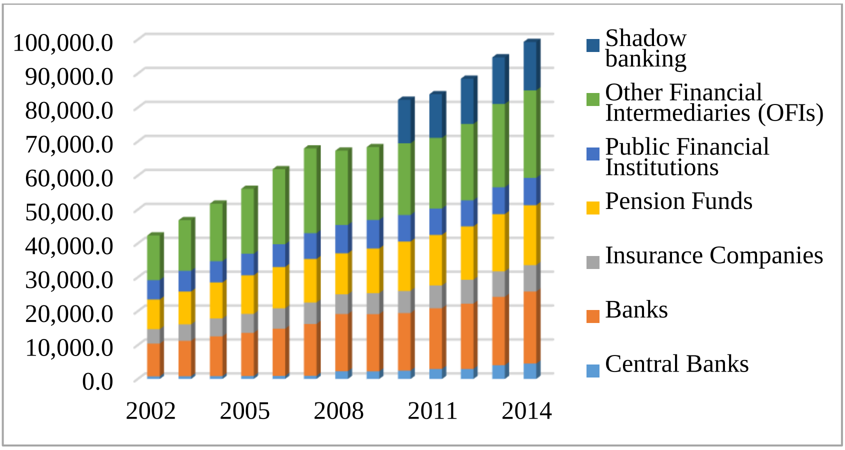
[4] "China's December New Bank Loans Miss Expectations", MarketWatch, January 15, 2016.

[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.

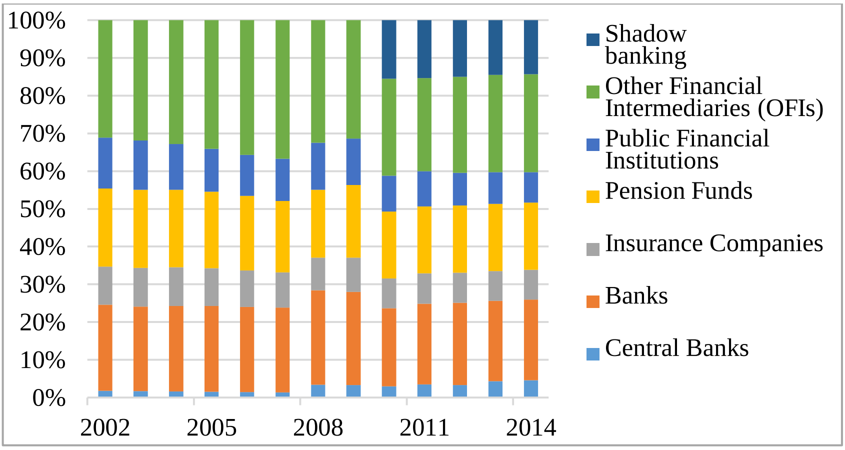
there is still the risk of bad-debt that leads to contagion throughout the financial sector.[6]

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

Panel A: In Billions USD



Panel B: In Percentage

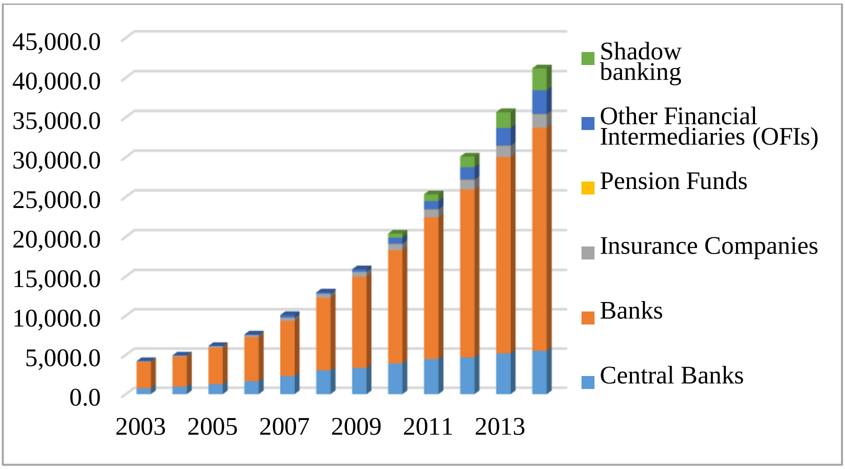


Source: Financial Stability Board (2015)

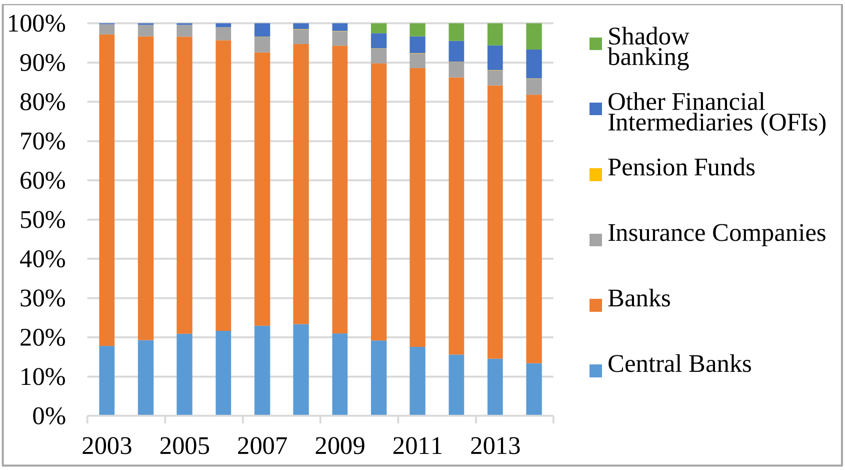
[6] See, for example, the Bloomberg reports in "Be Scared of China's Debt, Not Its Stocks" on January 7, 2016, available at http://www.bloombergview.com/articles/20160107/bescaredofchinasdebtnotitscrashingstocks, and "Mid-tier Chinese banks piling up trillions of dollars in shadow loans" of Thomson Reuters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

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

Panel A: In Billions USD



Panel B: In Percentage



Source: Financial Stability Board (2015) and Lai and Van Order (2017)

Table 1 Shadow Banking, Other Financial Intermediaries (OFIs) and Banks as Percentage of GDP of 26 Jurisdictions: 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
The Netherlands	74	838	326
United States	82	148	122
Switzerland	90	277	364
United Kingdom	147	326	601
Ireland	1190	1551	363

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

Source: Financial Stability Board (2015)

Table 2 **Share of Shadow Banking Assets as Percentage of All Financial Intermediations of 26 Jurisdictions: End of 2010 and 2014**

	End of 2010	End of 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
The 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 an economic function-based measure.
Source: Financial Stability Board (2015)

3. The Chinese Housing Market

There have been many studies on the US housing bubble. Examples include Black and Hoesli (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 *et al.* (2009) and Yang and Chen (2014), among others, focus on the Chinese housing policy reform. Others such as Wu *et al.* (2012) discuss the sustainability of its boom. The links between house prices and land policies are studied in Cai *et al.* (2013), and Peng and Thibodeau (2009). Ren *et al.* (2012) are one of the few to explicitly measure the extent of the Chinese house price run up. A very recent study is Glaeser *et al.* (2017). Lai and Van Order (2018) compare the housing bubbles between China and the US. To the best of our knowledge, there is no study on the effect of shadow banking as a source of funding on Chinese house prices.

This paper studies the property markets in China over the past decade. We use a variation of the Gordon dividend discount model as the common representation of long run fundamentals, but the model allows a 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 an estimation of how fast deviations from the long run are corrected. For further analysis, we also classify cities into Tier 1 and Tier 2 cities (which are official classifications based on size and speed of development) and coastal versus inland (because coastal cities are those that have had more advanced development for a longer period of time). Our prior is that the housing bubble would be larger in Tier 1 and/or coastal cities.

3.1 Data

We use monthly house price and rental series for 65 cities over the period of 2005 – 2014 obtained from CityRE Data Technology Co. Ltd,[7] which is the first to compile comprehensive data on housing for sale and lease for over 290 cities and areas in China starting from 2003. Numerous studies such as Ren *et al.* (2012) use house price and rental indices from the CEIC Data. However, the CEIC database only covers 35 cities. Monthly data on the 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; however, the data were no longer collected after 2010. The property price index of the China Real Estate Index System (CREIS) can also be used, especially after the termination of the housing index in 2010. Note that it might be a challenge to compare house price and rent series if the underlying representative housing units are not comparable, for instance, due to improved quality over time. Fortunately, such an effect is not likely to have significant impact on the empirical results due to the relatively large volume of transactions, and the relative homogeneity of housing within cities in China.

We use the 5-year Chinese government bond rates obtained from the National Interbank Funding Center as a proxy of nominal long-term risk-free rate, and from which we also obtain real interest rates by using the consumer price index (CPI) from the NBS of China. We also proxy risk relative to government bonds with the 5 year AAA corporate bond yields (obtained from the China Central

[7] Details of CityRE Data Technology Co., Ltd. can be obtained from http://www.cityre.cn/en/ or http://www.cityhouse.cn. They claim to operate the largest real estate data set in China.

Depository & Clearing Co., Ltd.), so that the yield spread is the 5-year corporate bond yields minus the 5-year Chinese government bond yields.

3.2 Impact from Shadow Banking

The shadow banking data, classified as "loans from non-banking financial institutions", are reported by the NBS, with a monthly frequency that spans the period of January 2006 to December 2015. These are nationwide data, and the only public source of data on shadow banking. We cannot rule out the existence of a significant amount of funds from informal banking via many informal channels that are unfortunately not systematically and officially recorded. To control for the basic factors in the real estate sector, we also include the house price and the rental indexes from the CPI series published by the NBS as well as interest rate, 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" and "housing starts", and land purchases and investment. All are aggregate monthly data from the NBS, some of which start as early as March 1998, while data that start 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" is 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" is proxied by "Land Area Purchased", "Real Estate Investments: Residential", "Real Estate Investments: New Increase", "Real Estate Investments", "Real Estate Investments: Land Transactions", "Land Area Purchased: 40 cities" and "Real Estate Investments: Residential: 40 cities".

All of the variables are presented in percentage changes. We perform unit root tests and cannot reject that the log differenced (percentage change) data are stationary. As expected, the rental rates do not have much influence on the demand and supply measures of real estate because the rental market is very small, and hence, we rerun the regressions without rental rates on the right-hand side. The signs of the explanatory variables are mostly as expected. That is, interest rates have negative effects while funds from shadow banks have positive effects on the housing market. Other variables that do not seem to have the expected signs are not significant anyway. Table 3 shows the results with various proxies of real estate demand and supply.

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

Panel A: Buildings and Floor Space Sold

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

Panel B: On Floor Space Started and Completed

	Floor Space Started	
	Proxy 1	Proxy 2
Housing Price	1.813***	2.776***
Shadow Banking	1.095***	1.275***
Interest rates	-0.169***	-0.218**
Constant	-0.003	-0.024
Observations	72	100
Adjusted R-squared	0.653	0.744

	Floor Space Completed			
	Proxy 1	Proxy 2	Proxy 3	Proxy 4
Housing Price	-1.652	-2.062**	-1.961*	-3.424***
Shadow Banking	1.012***	0.878***	0.937***	0.373**
Interest rates	0.059	0.107	0.076	0.222**
Constant	0.106***	0.086***	0.094***	0.146***
Observations	100	100	100	72
Adjusted R-squared	0.552	0.509	0.534	0.195

Panel C: On Land Purchases and Real Estate Investments

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

It can be seen from Panel A of Table 3 that high housing prices and availability of shadow banking funds can increase the volume of buildings and floor space sold, while interest rates have negative effects as expected. In particular, an increase of 1% in the shadow banking funds increase, say, the floor space of existing units (Proxy 2) by 1.426%, or the floor space of presale units (Proxy 3) by 1.277%. Similarly, available funds and surging house prices can encourage construction, as demonstrated by Floor Space Started in Panel B. While the variables also exert effects on Floor Space Completed, they are 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 taken place. Panel C also shows interesting results in that there will be real estate investments and land purchases as long as there is funding and housing price continues to increase; therefore, 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 beforehand in order for units to be completed and sold . 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 attributed to observations of a good market over the past period. The rationale of the latter is that construction decisions are often made beforehand, while funding is needed immediately to stimulate purchases. The results are shown in Table 4 (tests with various lags generate similar results and therefore not all are provided). Interestingly, shadow banking funds are the most significant explanatory variable, regardless whether we use no lags, six-month, 1-year, 18-month, or two year lags. Moreover, when shadow banking is considered, even a dominating factor such as housing price index sometimes shows a negligible influence.

From Panels A and B of Table 4, it is clear that real estate investments and land purchases are affected by the 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 become favorable. Panel C shows that the property sales market is affected by house price and interest rate variables lagged by six months, while shadow banking funds are not lagged; that is, testing whether past information on house prices and interest rates trigger more purchases if funds are available today. Again, while the variables are correctly signed, only current funding availability is important. In terms of the decisions of the developers, 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 a market boom period when investors and developers were optimistic about the market, but also when there were government restrictions and policies that curbed the market, and the housing prices were once affected. Developers were apparently willing to invest as long as there was funding.

We also study if there is an increased demand from shadow banking because of increased demand and supply of real estate investments. The results are shown in Table 5. All of the variables that represent real estate investments, building and development, and housing completed and sold exert significant and positive effects on shadow banking. In other words, both demand and supply of real estate trigger demand for more shadow banking funds. While it is logical that higher interest rates also attract a larger supply of shadow banking funds, it is also logical to interpret that lower housing prices attract more buying and therefore increase the demand for shadow banking funds.

In general, the results confirm that shadow banking might be an important, although perhaps endogenous, factor in real estate investment in China. To check for robustness, we also test for the presence of autocorrelation of the regression residuals in the above tests. All of the regression results show no autocorrelation. Next, we include shadow banking funds as a short term variable that affects the model for the pricing of housing units across cities in China.

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

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

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

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

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

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

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

4. Modeling House Price Growth via Pooled Mean Group

This section follows Lai and Van Order (2017) in developing a model for property value changes over time. In equilibrium, rent, which is essentially the current dividend from the property, should equal the risk-adjusted interest rate and expected capital gains over the period. Then, given an information set, Ω_t, the equilibrium condition for holding the property at time t is given by[8]

[8] See Lai and Van Order (2010).

$$R_t / P_t = i_t + \alpha - E\left(\left(P_{t+1} / P_t\right) - 1 \mid \Omega_t\right) \equiv i_t + \alpha - \pi_{ht} \tag{1}$$

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 conduct the estimation later.

House price can thus be found from Equation (1) given expected future house prices. Since future prices depend on future rents, current price depends on future prices, which in turn depends on future rents through the expected present value:

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

where the discount factor is $I_t = 1 + i_t$, such that 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, the expected present value formulation becomes:

$$P_t / R_t = \sum_{i=0}^{\infty} E(1 / D_{t+i} \mid \Omega_t) \tag{2'}$$

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 growth rate of rent are constant in the long run, then the reciprocal of Equation (2') will converge to (1), which gives the long run fundamentals.

The advantage of this approach is that it does not require the development of a housing demand and supply model, but only a model of how the expectations are formed. In other words, the model must allow transaction costs to facilitate gradual adjustments of Equation (2'). In general, house prices adjust to shocks slowly, and therefore are less efficient. Glaeser and Nathanson (2017) develop a house pricing model in which traders are "almost" rational. That is, small mistakes can lead to large forecasting errors, such that forecasted prices based on past prices have short run momentum (positive feedback), long run mean reversion, and excess volatility. Our estimated models generate all of these phenomena, with the long run model being the Gordon dividend model.

4.1 Long Run Specification

Theory suggests that in the long run, prices and rents are expected to move together and depend on real interest rates, which, according to the Gordon model, should be:

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

where r_t is the real rate. This suggests a coefficient of unity for the real rate. It is possible that for tax reasons, money illusion or inability to borrow against human capital that a coefficient of unity for the real rate is unlikely. Hence, we consider a more general formula:

$$\frac{R_t}{P_t} = c_t \tag{4}$$

where $c_t = \alpha_i i_t - \alpha_\pi \pi_t + \alpha \equiv \gamma_i i_t + \gamma_r r_t + \alpha$ is the "cap rate" for housing.

Our tests include both long-run and short-run behaviors. The long-run tests are to check whether property prices converge to rent divided by the cap rate as in Equation (4), and, if so, the speed of convergence. For the short-run, the tests are about the nature of the deviations from the long-run phenomenon, and whether the coefficients make sense. We use long run risk free rates for i; α represents depreciation and long run expected future rent growth; and risk adjustments with one for each city, which are assumed to be invariant over time.

We take Equation (4) as 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, γ_r is expected to be close to 1, and α to be around 2%. We have no presuppositions 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 by using the PMG and MG estimation models developed in Pesaran *et al.* (1997, 1999).[9] Our hypothesis is that Ω_t contains only past rents, prices, interest rates and shadow banking indicators, and that prices ultimately adjust to fundamentals.

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.

[9] See Ott (2014) for a study that uses PMG on house price dynamics in the Euro area.

Our model can be represented by:

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

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

δ_c captures the city specific fixed effects
$x^k_{c,t\text{-}j}$ is the kth of n regressors for city c
$\delta^k_{c,j}$ is the coefficient of the kth regressor for city c
$\lambda_{c,j}$ are scalars
$\varepsilon_{c,t}$ are 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 $\rho = \frac{R}{P}$, Equation (5) can be written as:

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

which when written in error correction form, yields:

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

where $\phi_c = -(1-\lambda_c)$, $\beta_c^k = \frac{\delta_{c,0}^k}{(1-\lambda_t)}$.

Equation (7) is used for the MG estimation model, which allows us to restrict some of the parameters inside the brackets to be zero — so that we can obtain a long run specification that looks like the Gordon model, as given in Equation (4), but with fewer restrictions on the short run adjustment parameters across cities. Among the items inside the brackets in Equation (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 the reversion to the long run, after short run deviations. The adjustment outside the brackets is the momentum (or mean reversion), which will disappear if the model is not explosive.

For the 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:

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

The double summation term in Equations (7) and (8) can include lagged changes in the dependent variable, that is, in *R/P*. We measure the level of momentum with the sum of these coefficients. If there is momentum, we expect the sums of the coefficients to be positive; a negative sum implies 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[10], but δ_c 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. The 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 Equation (9), which is the negative of the ratio of the constant term in Equation (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.

Since the PMG and MG estimations are autoregressive distributed lag (ARDL) models, the series in the models must be stationary or cointegrated. Hence, we run unit root tests on our time series.

We perform cointegration analysis tests developed by Westerlund (2007) to confirm the presence of long-run relationships among the time series. If long run cointegration exists, then we can find the long-run and short-run effects among the variables by using the MG and PMG models. All of the variables pass the tests (lengthy results are omitted). The Hausman test can be used to check if a common long run coefficient is present (that is, if the null hypothesis of the common coefficients between the MG and PMG is not rejected, then the common coefficients should be adopted).

4.3 Specifics of Data and Models

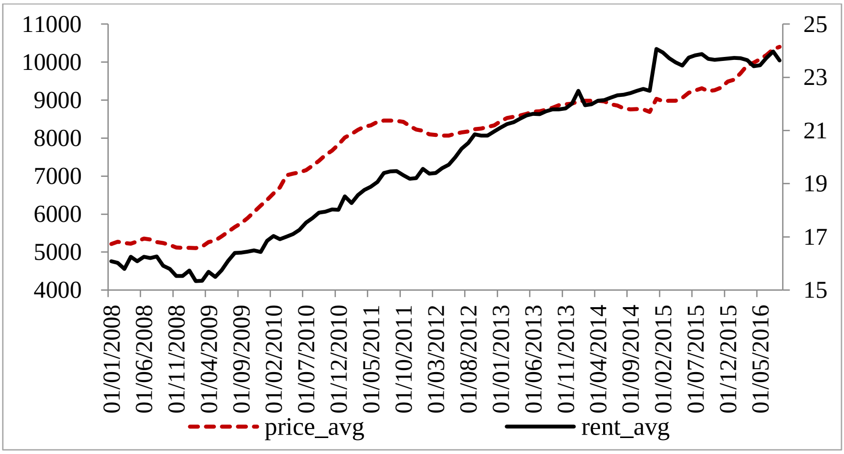
Before discussing the tests, we provide some observations of the data and an explanation of the tests. Figure 3 shows the average rent and house price across

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

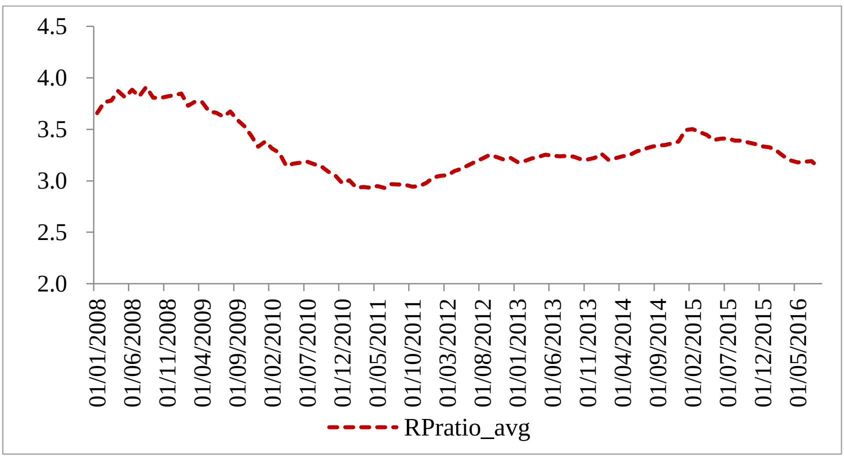
cities over time. A key observation from Figure 3A is that in the aggregate, the slopes of the two series are close to each other, which means that despite rapid growth, there might not be a bubble. Figure 3B shows the rent divided by house price, which is placed on the left side of our regression. The plotted curve does fluctuate but not nearly as much as in the US, which is plotted in Figure 3C, and shows a large departure of the house price from rent during the upswings and downturns around the Great Recession. Note in Figure 3B that the raw data have rents relative to prices as values like 0.003, which means 30 basis points per month (data are in monthly frequency). In our regressions, we multiply the rent to house price by 1200, so that the above is now 3.60 (% per year). This makes those return data comparable to our interest rate data, and we can test for whether the coefficient of the real or nominal interest rate is equal to one.

Figure 3 Aggregate Prices and Rents

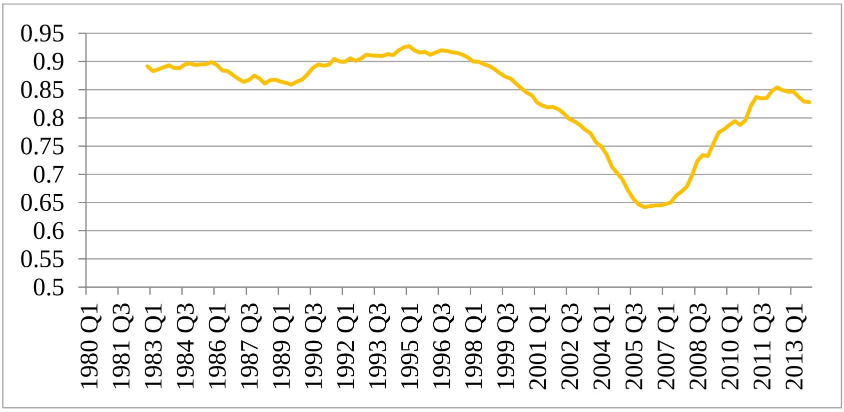
Panel 3A: Averages of Monthly Rent and Average Price



Panel 3B: Ratio of Average Monthly Rent to Average Price (in %)



Panel 3C: Rent to House Price in the US



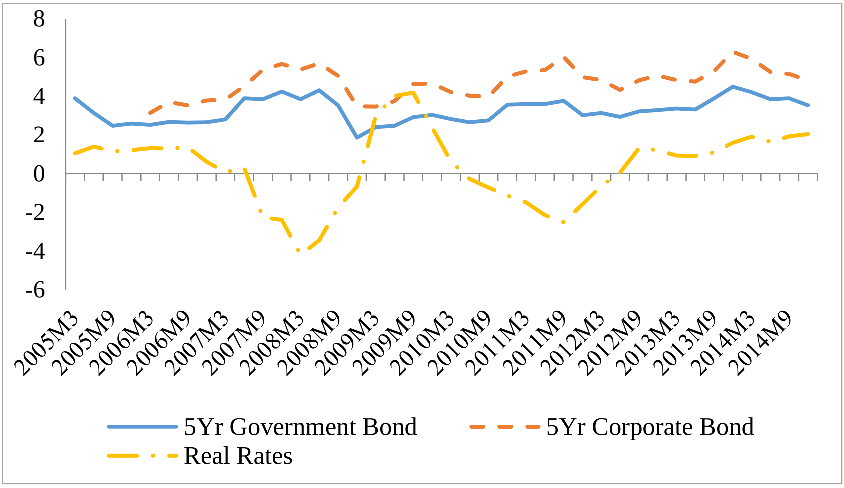
We group the cities in our sample into different categories ─ bubble versus non-bubble, coastal versus inland, and Tier 1 versus Tier 2 versus Other Tiers. Bubble cities are those with a price growth over rent growth that is higher than the 65-city average (2.59% for the 78-city average, and 2.75% for 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 the 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 try two sets of long run fundamental models. Model A includes various combinations of real interest rates, 5-year bonds, and 5-year bonds minus rent growth rates. Model B uses real interest rates as the only long run variable, which forces the 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 rates are shown in Figure 4.

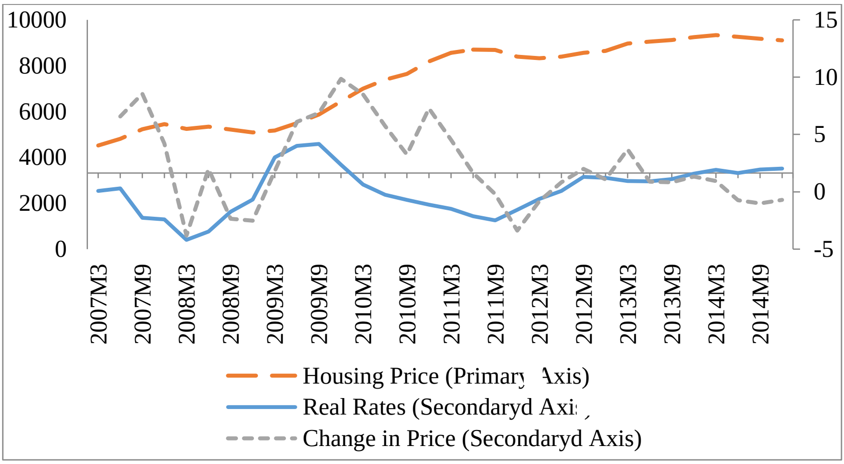
Other variables used in the models are the lagged shadow banking funds and the lagged yield spread. Lagged 5-year bonds, and 5-year bonds minus rent growth rates alternate in different models. We use both monthly and quarterly data. With our monthly data, we use up to six lags, a maximum of half a year.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

Figure 4 Movement of Interest Rates and Housing Prices

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



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



One of the concerns is that shadow banking is endogenous. In our model, the dependent variables are by city, but the shadow banking variable is nationwide. Hence, while the shadow banking variable might be influenced by national data, it is unlikely that individual cities (65 to 78 of them) have influenced the national level of shadow banking. As a result, we feel justified in assuming that shadow banking is exogenous in the city-by-city equations.

5. Results

The results of Model A are shown in Panel A of Table 5, while those of Model B are in Panel B. All of the variables, both long term and short term, have coefficients with the correct signs as expected. All of the long term variables are significant, thus implying that the proposed fundamental model works in the case of the 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 return to a long run relationship. Short term lagged yield spreads do not show a very strong and persistent effect, while 5-year bonds and 5-year bonds minus rent growth are mostly significant. Lagged rent to price ratios actually have negative effects which not only suggest that there is no bubble but many mean reversions during the short run. 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 house prices are stable; the stability depends on the variations in rents.

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

We next compare and contrast how different cities react to the availability of shadow banking funds. In particular, we group cities into bubble versus non-bubble cities, coastal versus inland cities, as well as Tiers 1, 2, and others (see Appendix A for the list of cities with various classifications). 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 cities in which housing price growth minus rent growth rates are above the mean for the period of 2007-2014. These three categories overlap in that many bubble cities are also coastal cities, and the Tier 1 cities fall in the former two groups. The sum of the coefficients of three lags of change in shadow banking funds as the short run variables for different city classifications is 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.

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

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

It can be seen from all three PMG models with the best explanatory power (i.e. highest likelihood) that shadow banking has its largest 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, which can nevertheless be ignored. This is because "bubble" cities (defined as cities with a house price growth minus rent growth that is greater than the mean) would be more meaningful since the rental markets in major cities are much larger, and therefore rents tend to grow faster. Another observation is that the variations of the sums of coefficients (i.e. maximum minus minimum) are in general larger 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", coastal, or Tier 1 cities is mostly due to more investments drawn into those cities, where normal banking funds would be available to only very large developers or State Owned Enterprises. That is why other developers and investors have to rely on shadow banking. As a result, more shadow banking funds of all forms would be available in those cities, which subsequently push up housing prices. The sum of all short run coefficients are provided in the Appendix B for reference.

Lai and Van Order (2017) mainly focus on testing whether the bubbles of the housing markets in the US were explosive by checking if the residuals from the regression estimates are highly autocorrelated, and the variances of the residual autoregression equations differ between bubble and non-bubble cities. Since the Chinese housing markets have also been described as having large bubbles that have not exploded yet, we repeat their tests. In particular, we refer to PMG Models A3, A4, and B3 as reported in Table 6, and attempt the autoregressive modeling of the residuals with various lags. None of the equations show much autocorrelation in the residuals (results are shown in Panel A of Table 8). This and the low sums of the coefficients of lagged rent to price mean that bubbles are not evident in the Chinese housing markets. Rather, there is momentum in the short run that is nowhere near explosive. It should be noted that the Chinese government has undertaken several policy changes to boost and curb the markets at different stages of the market boom and bust. Such effects on housing markets have been studied by, for instance, Cao *et al.* (2018). They could be largely responsible for the lack of observed bubbles. Since we test the effects of shadow banking on housing markets, and not the overall stabilization policy, we do not try to separate stabilization policy from stabilization due to the underlying market structure.

We further test if the variances of these models are different. Note that since the residuals are not autocorrelated, the variances of these autoregressive models are really the variances of the PMG models. We show the sums of the 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 large residual variances might be sources of bubbles in housing markets, their 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 cities have larger variances than inland cities, and Tier 1 cities have smaller variances than Tier 2 cites which are in turn smaller than the other tier cities. This shows that our models are able to explain those major cities (bubble and Tier 1 cities) with higher precision. To further test if the variances from the models with different lags are indeed different, we run the Goldfeld-Quandt test as shown in Panel D. Finally, we check the differences in variances across city classifications with the Goldfeld-Quandt test again, and the results are also shown in Panel D. Both show that these models are different both across lags and cities, which imply that cities in different categories do possess unique characteristics.

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 Interest 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 Interest 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**	
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal
Mean	-0.0106	-0.0063	-0.0066	-0.0109	-0.0080	-0.0105
Maximum	0.0224	0.0204	0.0205	0.0224	0.0224	0.0205
Minimum	-0.0606	-0.0498	-0.0606	-0.0498	-0.0474	-0.0606
No. of cities	37	28	32	33	44	21

(***Continued…***)

(Panel A Continued)

	Tier		
	Tier 1	Tier 2	Other Tiers
Mean	-0.0117	-0.0063	-0.0110
Maximum	-0.0022	0.0224	0.0186
Minimum	-0.0202	-0.0474	-0.0606
No. of cities	4	31	30

Panel B: Model A4

	Bubble Price		**Bubble Price-Rent**		**Coastal City**	
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal
Mean	-0.0115	-0.0067	-0.0075	-0.0112	-0.0082	-0.0120
Maximum	0.0222	0.0197	0.0197	0.0222	0.0222	0.0174
Minimum	-0.0610	-0.0499	-0.0610	-0.0499	-0.0480	-0.0610
No. of cities	37	28	32	33	44	21

	Tier		
	Tier 1	Tier 2	Other Tiers
Mean	-0.0121	-0.0070	-0.0115
Maximum	-0.0032	0.0222	0.0170
Minimum	-0.0200	-0.0480	-0.0610
No. of cities	4	31	30

Panel C: Model B3

	Bubble Price		**Bubble Price-Rent**		**Coastal City**	
	Non-bubble	Bubble	Non-bubble	Bubble	Non-coastal	Coastal
Mean	-0.0087	-0.0060	-0.0051	-0.0099	-0.0071	-0.0085
Maximum	0.0274	0.0273	0.0274	0.0228	0.0273	0.0274
Minimum	-0.0536	-0.0478	-0.0536	-0.0490	-0.0490	-0.0536
No. of cities	37	28	32	33	44	21

	Tier		
	Tier 1	Tier 2	Other Tiers
Mean	-0.0112	-0.0058	-0.0089
Maximum	-0.0001	0.0228	0.0274
Minimum	-0.0199	-0.0490	-0.0536
No. of cities	4	31	30

Notes: "Bubble" cities are those with price growth greater than the mean during 2007-2014.
"Bubble Price-Rent" cities are those with price growth minus rent growth greater than the mean during 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**			**Other Tiers**		
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)		
Sum	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**			**Other Tiers**		
Sum	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**					
Sum	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			

Notes: “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	Other Tiers
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) vs. non-Bubble (p-r)	Coastal vs. non-Coastal	Tier 1 vs. Tier 2	Tier 1 vs. Other Tiers	Tier 2 vs. Other Tiers
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

Notes: The Goldfeld-Quandt Test is a test for statistical differences between two fundamental equations.
*, ** and *** denote significance at the 10%, 5% and 1% levels respectively (compared to an F-value of 1.3).

6. 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 PMG estimations of house price dynamics to analyze the role of fundamentals and adjustment to them. The question lies in determining their causality. The issue is similar to the case in the US on whether the increase in private label securities is the cause, or result, of the house price bubble. That we use aggregate shadow banking data but local house prices is an attempt to manage the endogeneity of shadow banking policy with respect to economy-wide variables. The strong link between shadow banking and housing price movements suggests important implications for the effects of a collapse in the shadow banking market.

We further analyze pricing dynamics by classifying cities into bubble versus non-bubble, coastal versus inland, and Tier 1 versus Tier 2 and other tier cities. We find that shadow banking indeed helps to 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. This is particularly remarkable as anecdotal evidence suggests that shadow banking is an essential source of funding in second tier cities. As for the long run, we find that housing in China is priced like a growth stock (high P/E ratio) with different expected growth rates across cities, as in Lai and Van Order (2018), and cities tend to share common long run fundamentals and adjust relatively quickly to deviations from them, without bubbles. Prices appear to be rapidly chasing growing rents. Indicators of shadow banking activity have a positive effect on house price growth. The data are consistent with the notion that a one-percentage point increase 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 argument seriously.

That there is no evidence of bubbles does not mean Chinese property is not risky. Growth stocks are risky because small changes in expected growth of earnings (in this case rents) can lead to large changes in value. Alternatively, one might argue that there is a rent bubble, or perhaps a lending bubble, that is causing high prices. However, rents and lending activity are not prices of traded assets; they are at best considered as factors in risk assessment. Fear of shadow banking collapse is reasonable; nevertheless, the property market in China is risky but not doomed to crash.

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Appendices

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 missing data, our tests are also based on 65 cities, which do not include the 13 cities on the bottom right of the table. Shaded are the four Tier 1 cities.

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