A Tale of Two Countries: Comparing the US and Chinese Bubble Housing Markets

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Abstract

This paper compares the recent evolution of property values in the U.S. and China across cities and time by estimating similar models for the two countries to compare price dynamics. We find little in common between the two countries. While there are some similarities in terms of long run fundamentals, there are major differences in adjustment. In particular, the U.S. adjustment process appears prone to "bubbles" in the sense of strong momentum from past prices. However, Chinese prices have been strongly mean reverting, with nothing like momentum. In short, our results suggest that the U.S. house prices have tended to chase past house prices; whereas in China house prices have tended to chase past rents, suggesting that the rise in China has had more to do with scarcity than exuberance. We find differences across cities, especially in China, but differences within countries are smaller than differences between them.

Keywords: Chinese housing market, US housing market, Bubbles, Momentum, (Pooled) Mean Group Estimation

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1. Introduction

This paper compares the recent evolution of property values in the United States and China, both because they are the two largest economies and because they have had periods of similarly sharp increases in house prices, earlier in the U.S. and later in China. In the case of the U.S., a strong increase until around 2006, something like a bubble, was then followed by a sharp decline. A major question in this paper is whether or not China today is like the U.S. in 2006, and therefore could learn from the U.S. lessons. We estimate similar models for the two countries, across cities and time, to compare long run trends and short run dynamics. Because the time period allowed for our analysis is short, we view the results as essentially descriptive, albeit applied to important time periods.

It has been widely agreed that the Great Recession in 2008 was triggered by a bursting of the U.S. housing bubble that was built up from around 2000 until about 2006. During this period, the securitized mortgage market, particularly the "private label" market, experienced an unprecedented boom, which, however, collapsed once the housing market collapsed, followed by many financial institutions that held the securities. The housing market has largely recovered over the past six years, although price fluctuations have varied widely across cities.

On the other side of the globe, China as the second largest economy, has experienced rapidly-increasing house prices since 2009, in a way that looks somewhat like the U.S. housing market up to 2006. As a result "Bubble" has been used to describe the Chinese housing market. The longer it takes for the seeming housing bubble in China to burst, the more concern there is over implications of a burst. After decades of strong growth in China, cash-rich households, finding very limited channels for investment, have poured their savings into the housing market. In some cities infamous “ghost towns” have been created from empty investor-held units due to lack of rental demand (although there is also anecdotal evidence that many owners simply do not like to rent their vacant housing units). Despite this, local municipal governments have continued to encourage more construction because land sales revenue is the major source of funds for their operations, and also because boosting the construction industry boosts their local GDP, a “report card” to be submitted to the Central government.

The Chinese government also effects property values. The Central government has attempted to impose policies to curb market prices in some years, and has relaxed policies in others, upon seeing the markets being over-cooled and economic growth slowing down. For instance, releasing second-home purchase restrictions in 2014 is claimed to have “deflated” a bubble safely. There appears to be a perception that investors’ demand and local governments’ needs for funding supported house prices, despite the Central government policies, which were nevertheless frequently tightened and loosened depending on the level economic growth.

A key question then is whether the rise in house prices is reasonable and fundamentally supported. In other words, is there really a housing bubble that has not yet been burst, or have growing house prices simply reflected economic scarcity? Or is there something else, like better stabilization policy being implemented?

There have been numerous studies on housing bubbles since the Great Recessions, such as Chan *et al.* (2001), Chang *et al.* (2005), Black *et al*. (2006), Coleman et al (2008), Hwang *et al.* (2006), Lai and Van Order (2010, 2017), Ling *et. al*. (2015), Nneji et.al. (2012), Taipalus (2006), and Wheaton and Nechayef (2008). However, in-depth studies of existence of a Chinese housing market bubble are scant. Studies on Chinese housing markets, policies, and reforms include, among others, Cai and Zhang (2013), Deng, Sheng and Wang (2009), Peng and Thibodeau (2009), Ren, Xiong, and Yuan (2012), Wu, Gyourko and Deng (2010), and Yang and Chen (2014).

We analyze house prices in cities in China from 2009-2016 and the U.S. from 1999-2016. Our main result is that China and the U.S. have had somewhat similar long run price trends, but quite different adjustment processes in their booms. U.S. house prices have tended to chase past house prices (strong momentum, maybe a bubble); whereas in China they have tended to chase past rents (weak or negative momentum; i.e. no evidence of bubble). A summary of this for aggregate rents and prices can be seen in Figure 1. Panel A of the Figure shows U.S. prices and rents, and Panel B shows prices and rents in China.

From Panel C, which compresses Panels A and B, it is obvious that in the seven (different) years of upward movements, both countries experienced a doubling of house prices. Figures 2 and 3 show rates of change and ratios of these variables. The U.S. shows a clear tendency, leading up to 2006, for prices to grow much faster than is justified by past or subsequent rents; whereas, Chinese prices, in the aggregate, look much more like they are chasing past rents and anticipating future rents.

We also analyze differences across sub-periods and by city types. We find some differences, but they are not big enough to change our main results. Differences between the two countries appear to be more pronounced than differences within them. In any event, it appears that the experience of boom-bubbles-bust in the US market cannot not be directly applied to China. To the best of our knowledge we are the first to study and compare the housing market "run-ups" of the two biggest economies in the world, both in the short run and long run.

2. Model and Estimation

Following Lai and Van Order (2017), the "fundamental" value of a housing unit is the present value of the flow of expected (net) rent. We focus on the inverse of the price to rent ratio (like the inverse P/E ratio for stocks; see for example Clark (1995), Ayuso and Restoy (2006), Lai and Van Order (2010, 2017) and Sommer *et al* (2011)) as our dependent variable. Our preferred model is an asset pricing model that is forced to obey a simple version of the Gordon dividend discount model in the long run, while allowing for considerable variation in short run adjustment to the long run equilibrium.

2.1 Equilibrium

The dividend discount model implies that in a steady state equilibrium holding a property should mean that rent relative to price is equal to the user cost of capital, which is the appropriate (risk adjusted) interest rate net of expected capital gains. That is,

$$\frac{R_t}{P_t} = i_t - \pi_t + \alpha \equiv r_t + \alpha \tag{1}$$

where P_t is the price of a representative housing unit, R_t is net rental income (or the imputed net rent of an owner-occupied housing unit, which we take to be proportional to measured rent, and should reflect much of the political and/or economic impacts in the same ways as price), i_t is the risk-adjusted, nominal, hurdle rate for housing, π_t is expected house price growth, α is a constant that includes depreciation and other factors like (long run stationary) risk premiums, and r_t is the real rate. We expect expression (1) to determine the long run level of prices relative to rents, although we also expect significant variation from the long run as prices adjust over time.

User cost for housing should, in principle, allow for tax and other effects. For instance, if the focus is on the tax break for not paying tax on imputed rent for owner-occupied housing and not taxing capital gains on housing, then

$$\frac{R_t}{P_t} = (1-\theta)i_t - \pi_t + \alpha \equiv -\theta i + r + \alpha \tag{1'}$$

where θ is the marginal tax rate for the homeowner who is indifferent between owning and renting. However, it may be the case that high nominal interest rates provide a cash-flow problem for home buyers (even if real rates are constant), who cannot draw down savings or borrow against human capital. This can induce a "shadow price" on nominal interest rates, which has a positive effect on user cost.

We formulate the long run in general as:

$$\frac{R_t}{P_t} = c_t \tag{2}$$

where $c_t = \alpha_i i_t - \alpha_\pi \pi_t + \alpha \equiv \gamma_i i_t + \gamma_r r_t + \alpha$ so that user cost, c, represents the "cap rate" for housing. Our preferred expectation is for γ_r to be unity or less, and γ_i be zero. The effects mentioned above may alter this, but they do have offsetting expected signs, and measurement error in real rates may bias coefficients downward. We test if property values converge to rent divided by cap rate (i.e. $P_t = \frac{R_t}{c_t}$ as in (2)), and estimate convergence rates and the nature of short run deviations across cities. Our paper can be thought of as comparing estimates of the dynamics of cap rates in China versus the U.S..

Our panel data sets for both the U.S. and China are short in the dimension of time series, but wide in cross sectional terms (including 44 US Metropolitan Statistical Areas, MSAs, and 80 Chinese cities). Our China data cover less than one boom-bust cycle. This suggests that we might have trouble obtaining correct long run coefficients. However, we may be able to exploit cross sectional differences to shed light on short run adjustment.

2.2 Adjustment

We set up our models so that the economies in both countries eventually adjust to the long run fundamental equilibrium.[1] The adjustment to the long run can be quite complicated. For instance, adjustment paths will be different in economies where governments pursue strong stabilization policies, versus more *Laissez Faire* policies, or where investors and/or financial markets have different structures. Getting a strong handle on this requires building a structural model, which we do not attempt. Rather our goal is to see if the two countries share similar adjustments to fundamental equilibria. We study a set of dynamic reduced form models, whose long run properties are tightly constrained, but whose adjustments are not. Policy regimes as well as underlying market structures are buried in the parameters.

2.3 Estimation Procedure

[1] We do not completely take this for granted. Instead, we checked to see if the model explodes, which is not the case for any of our estimates of residuals.

We use Pooled Mean Group (PMG) and Mean Group (MG) estimation models developed in Pesaran, Shin and Smith (1997, 1999) to estimate dynamics of price to rent ratios in a way that forces the long run properties discussed above. The MG and PMG models are restricted maximum likelihood estimations, based on an autoregressive distributed lag (ARDL) model (see Pesaran and Shin (1997)), with coefficient restrictions that allow easy identification of long run relationships and short run dynamics separately. The intercepts for the estimation are fixed effects. Short run coefficients and the error adjustments are allowed to differ across cities. In the case of MG estimation, the long run coefficients are also allowed to vary across cities (we present averages of these estimates in our Tables); they are forced to be identical in the case of PMG estimation.

The adjustment to the model in (2) can be represented by:

$$\Delta \frac{R_{c,t}}{P_{c,t}} = \sum_{j=1}^{l} \lambda_{c,j,} \Delta \frac{R_{c,t-j}}{P_{c,t-j}} + \sum_{j=0}^{q} \sum_{k=1}^{n} \delta^{k}{}_{c,j} x^{k}{}_{c,t-j} + \delta_{c} + \varepsilon_{c,t} \tag{3}$$

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 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 the city specific errors

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

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

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 $\rho = \frac{R}{P}$, (3) can be written as:

$$\Delta\rho_{ct} = \lambda_c \rho_{c,t-1} + \sum_{j=0}^{q}\sum_{k=1}^{n} \delta^k{}_{c,j} \Delta x^k{}_{c,t-j} + \delta_c + \varepsilon_{c,t} \tag{4}$$

which when written in error correction form, yields:

$$\Delta\rho_{ct} = \phi_c \left\{ \rho_{c,t-1} - \sum_{k=1}^{n} \beta_c{}^k x^k_{c,t} \right\} - \sum_{j=0}^{q}\sum_{k=1}^{n} \delta^k_{c,j} \Delta x^k{}_{c,t-j} + \delta_c + \varepsilon_{c,t} \tag{5}$$

where

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

Adjustment of the rent to price ratio is divided into two parts: one is a gradual adjustment to the difference between the long run given by the Gordon model and the current level, and the other is a loosely specified reaction to past changes. The terms within the brackets in expression (5) form the long run specification, which, because all other effects are first differences, is forced to go to zero as the model approaches a steady state, if the model converges. The other terms outside the parentheses provide the short run adjustment parameters across cities.

Expression (5) is for the MG estimation model. In the case of PMG all cities are forced to share the same long run coefficients, i.e., $\beta_c{}^k = \beta^k$ for all cities, then:

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

The key restrictions in the MG/PMG models are that the variables inside the brackets must only be those in the Gordon model and whether the coefficients are the same or different across cities. In the case of MG estimation we report averages of relevant coefficients across cities. We also report averages for other short run parameters that are always allowed to vary across cities.

The double summation terms in expressions (5) and (6) allow inclusion of lagged changes in the dependent variable, which capture short run effects of house price changes (relative to rent) based on past changes. The sum of the coefficients of past rent to price changes is our measure of momentum. We expect the error correction term, ϕ_c , to be negative and the sums of the coefficients of lagged changes in *R/P* (momentum) to be positive but less than 1 (in order that the model converge), or to have a negative sum if the model is strongly mean reverting (negative momentum), beyond that given by ϕ_c .

The model can have the properties of short run momentum and long run mean reversion. We use rent as a sort of summary statistic rather than using a complicated vector of factors that affect housing demand and supply, which makes modeling relatively easy, and is particularly useful for our short data period. This is consistent with the “almost-rational” model in Glaeser and Nathanson (2015). We force the long run (terms inside the bracket) to be very simple, depending only on real or nominal rates, even though the adjustment can be more complicated. We try a range of specifications to test for whether dynamics (momentum) results are sensitive to different specifications.

3. Data for the Two Markets

3.1 Data for the US Housing Market

We use monthly house price indices from Freddie Mac (FMHPI) for Metropolitan Statistical Areas (MSAs). The corresponding rent series are monthly Owners'

Equivalent Rent of Primary Residence (OER) from the Bureau of Labor Statistics. Nominal and real interest rates are respectively proxied by 5-year Treasury bonds and 5-year Treasury Inflation-Protected Securities (TIPS). Credit spread, which may affect the short-run adjustment in housing market, is measured as difference in Merrill Lynch US Corporate AA Effective Yield and 1-year Treasury rate.

We include 44 MSAs (listed in Appendix A) with all data available between January 1999 and August 2016. We also use subperiods: January 1999 to December 2006 and January 2009 to August 2016. The first subperiod captures the beginning and almost end of the boom period of the US housing market. The second subperiod captures the recovery period. We separate the MSAs into groups based on location and supply elasticity.

Figure 2A shows that FMHPI for national prices is highly seasonal. Hence, we seasonally adjust the FMHPI with the Census Bureau's multiplicative X-12 ARIMA method. Figure 1B depicts the seasonally adjusted house price index.

3.2 Data for the Chinese Housing Market

Although the National Bureau of Statistics (NBS) of China provides monthly data on sales price indices of newly constructed residential buildings for 70 cities from 1997 onwards, it stops providing rental indices in 2010, and the rental series before 2010 are published quarterly. Our house price and rental series are monthly data obtained from the CityRE Data Technology Co. Ltd,[2] which compiles comprehensive data on housing

[2] 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.

for sale and lease for over 290 cities and areas in China starting from 2003. Prices and rents are per square meter for relatively homogeneous units.

Nominal long term interest rates are the rates on 5-year Chinese government bonds, obtained from the National Interbank Funding Center, from which real interest rates are then obtained by deducting CPI growth, from the National Bureau of Statistics of China. We also proxy risk relative to government bonds with the 5-year AAA corporate bond yields (from the China Central Depository & Clearing Co., Ltd.).

Chinese cities are usually grouped into three or four tiers. Tier 1 cities consist of the four cities with the largest population and economic importance in China — Beijing, Shanghai, Guangzhou, and Shenzhen. Tier 2 cities include capital cities of the 24 provinces, 2 autonomous municipalities (Tianjing and Chongqing) and 10 other cities, which are typically industrial or commercial centers (Fang et. al. (2016)). The third or fourth tier cities are commonly not distinguished. Our sample covers all Tier 1 cities, all 36 Tier 2 cities, and 40 other cities.

We also group the 80 Chinese cities into other categories: Coastal versus Inland, and regions (Eastern/Central/Western). We classify Coastal/Inland cities according to Yang and Chen (2014), and Eastern, Western and Central cities, as there is a lower ownership rate in the Eastern regions (most of which are also coastal cities) because of more expensive housing. This means that these groups of cities might be subject to different regimes. Appendix B provides a list of all cities in our sample, and a list of provinces by regions.

A majority of the current literature on the Chinese housing market has focused on 35 major cities, all included in our sample. Some offer different grouping criteria. For instance, Wu *et al*. (2016) estimate supply and demand parameters and find that, using their particular definitions, housing demand in most of the 35 major cities is higher than supply. As a robustness check, we run our models on the same 35 under-supply and over-supply cities. In our case the mean supply elasticity of 7.657 cuts off the cities into two groups. We also repeat the calculations following the classification by Wang *et al.* (2008), namely, Tier-1, Eastern, Middle Southern, Northern, Western.

4. Estimation Results

We ran Dicky-Fuller unit root tests, and cointegration tests developed by Westerlund (2007) to confirm the existence of long-run relationships among the series. All variables passed the tests (lengthy results omitted here). We then ran the MG/PMG estimations and use the Hausman test to confirm whether MG or PMG is more suitable for each of the models we tested.

4.1 Modeling

In running models for both countries we use versions of expressions (5) and (6) above. While our model is simpler than many others, it necessitates modeling expected future rents in order to use real interest rates. Nonetheless, as discussed in Glaeser and Nathanson (2015), we can do this (i.e. using current and past rents) in a way that reflects somewhat rational expectations, with limited information. In the U.S. we exploit data on indexed bonds (5 years or 10 year TIPs), which take account of market expectations of general inflation, as proxies for long term real rates; and noting that rents and general prices have grown in a similar manner, the TIPs real rate is similar to the real rate net of rent growth.

There is no instrument similar to TIPs for China, though there are long term nominal bonds. We observe from Figure 3 that rent growth nationwide in China did not have a trend during the period in question and deviations from average rent growth were strongly mean reverting. This implies rational forecasts for long term rent growth were likely to be constant[3]. In our model this means we cannot separately identify rent trends from the constant term. Hence, we simply ignore expectations and use long term nominal rate, with expected rent growth assumed to be part of the constant term.

With these two assumptions (using TIPs in the U.S. and nominal rates in China) we can estimate similar models for the two countries and compare coefficients. We are also interested in the US model during the run up to the sharp price decline, because it is more likely to be comparable to China from 2009-2016. We run a range of variations, especially on the adjustment factors, of up to 12 lags (i.e. one year), and find that in both countries the long run factors are sensitive to specification (though they work well in the one we think makes the most sense). However, differences in dynamics of adjustment back to the long run and in momentum look about the same across specifications within countries; so our main points about differences between the two countries hold up.

[3] We tried various Autoregressive models for the Chinese rent series, and both AIC and SC indicate a lag of 7 is the best. Yet, none of the lags is statistically significant. Hence, with the significant constant in this AR(7) process, we can safely conclude that the long term rent growth is constant.

4.2 Results for the US Market

For the U.S. we follow Lai and Van Order (2017), whose PMG estimation covers a similar sample period, but with different data sources and frequencies. We replicate their estimation with our sample period to cross check if the data sources are comparable, especially because their data are quarterly and seasonally adjusted (estimates from their Model A with 3 and 6 lags are shown in Appendix C, results with other lags and those following their Models B and C are omitted). We find that the estimates are comparable, although our data have different frequencies (monthly) and this paper covers a more recent period. Given that the data generate results comparable to Lai and Van Order (2017), we proceed to a simpler model that is also used for the case of China. Results are presented in Table 1. Our preferred model uses real rates taken from the TIPs market.

Calibration of Returns

It should be noted that, unlike the China data, our series for the US markets are indices and not actual prices and rents. Hence, the rent to price ratio is only *proportional* to the actual rental yield. Note from Figure 2 that our rent to price index ratio is roughly around 2.0, and the mean value for TIPs in our data, representing long run rental yield, is also around 2.0%. Hence the numbers are within the same range of estimates. However, 2.0% is too low for a cap rate. Therefore, the coefficients for the long run variables inside the brackets in expressions (5) and (6) should be interpreted with caution. It is necessary to multiply the coefficient by some factor greater than one in order for it to be meaningful in magnitude. Nevertheless, this does not affect the signs of the coefficients or test statistics, or the size of momentum coefficients, which are our primary concern.[4]

Estimation Results

In Table 1 long run real rate coefficients tend to be within the 0.1 to 0.2 range. The exception is in the final two columns where the coefficients are slightly negative, but lagged TIPs has a strong positive effect outside the brackets. This inconsistency suggests difficulty in identifying long run effects from momentum in a short sample. However, terms outside the long run in the parentheses are informative. Note the relatively low reversion speeds to long-run of well below 1% per month (except in Panel A2). There is also strong momentum, robust across lags and specification structures: the sum of coefficients of lagged rent to price ratio is between 0.7 and 0.9 across all the estimates from the three models shown in Panels A to C. As can be seen from Panels B and C of the Table, which show results for similar models with more variables as robustness checks, estimates inside the brackets for the long run effect are quite different, even though the momentum and slow adjustment speed are about the same.

Panels A1 and A2 of Table 1 repeat the above for the subsample period of January 1999 – December 2006, a run-up period before the crash, similar to that in China over the past few years, and January 2009 – August 2016, the period that allows comparison for both countries. Basic results hold in both subsamples, especially in terms of strong momentum, although the adjustment speed back to long run equilibrium during the post-crisis recovery period can be as big as five times that of the pre-crisis boom period

[4] An example of calibration is to multiply the coefficient for the real rate by 4 if the perceived market average cap rate is 8%, i.e. 4 times of the 2% that we see from Figure 2.

(though still just a bit above 1% per month), while the long run real rate coefficients during the pre-crisis boom period are also high across columns. Perhaps the post-crisis recovery period was more revealing of the long run than was the pre-crash period. Not surprisingly, it does look like there was a regime shift around or after 2006.

Panel D shows the maxima and minima of the sums of the coefficients across all MSAs. The results discussed above generally hold for all MSAs except for some specific cases. For example, a few MSAs generate insignificant, albeit positive, error correction coefficients. Furthermore, a few MSAs have small to negative momentum in some cases with long lags.

4.3 Results for the Chinese Market

Because of limitations on data availability, we can only run the estimations for China for the period of January 2009 to August 2016, which is a period of constant rise in house prices in China. Unfortunately, not all the tests generate valid results. The good news though is that the signs of the coefficients, whenever available, are consistent. More importantly, models with backward-looking determinants of real rates are the most unreliable ones, which leads us to being skeptical about modeling real rates. We do not calibrate rent to price as we did above because we have actual rent estimates. We do note that we do not have *net* rent; so our rents probably overstate net rents, which would affect the coefficients for long rates, albeit not by much.

In general, PMG estimation works better for all four variations of the model, although the MG estimation results are similar. This means that all 80 cities share the same long run coefficients, but deviate in short run dynamics. All long run coefficients of real rates are significant, ranging from 0.4802 to 0.6545 from PMG. The error correction terms are also significant, ranging from -0.075 to -0.0962 (and -0.0957 to -0.1169 from MG), showing that there is correction from short run deviation back to the long run at a pace of about slightly less than 10% per month, for a half-life of about 7 months. Short term effects from interest rates are also significant and with correct signs. It is interesting that the momentum variables, i.e. the coefficients of lagged differenced dependent variables, are all negative (and significant only up to one quarter), implying that there is negative momentum in Chinese house prices.

We also included yield spreads (i.e. 5-year corporate bond yields minus the 5-year Chinese government bond yields) as short run variables. The results are similar and therefore omitted here.

5. Comparisons

The purpose of this paper is to compare house price dynamics between the US and the Chinese housing markets. However, we do not use exactly the same models for the two countries because of differences in how the real interest rates are interpreted. For purposes of comparison, we also used models for the US with only nominal interest rates, like that for the Chinese markets. Depending on the sample period used, PMG estimation may not be valid for the US market data. Even for those valid results, the long run coefficients can vary a lot. Hence, the model with only nominal interest rates is not suitable for representing the long run house price dynamics of the US market. However, the momentum coefficients were still similar.

We compare results from the models in which the long term variable is TIP rates in the case of the US market and long term nominal rate for China, and focus on the short run variables. Note that the error correction terms for the US, ranging from -0.0022 (for the whole period) to -0.0159 (for the post-crisis period), are much smaller than those for the Chinese market (ranging from -0.075 to -0.1169), while the first lagged momentum coefficients are significantly positive, ranging from 0.7139 (for the post-crisis period) to 0.9037 (for the whole period), compared to the negative ones for China; the short run coefficients for lagged interest rates are about one-tenth of those of the Chinese market. Even though some other lagged momentum coefficients are significant and negative, their magnitudes tend to be much smaller.

These results imply that, both because of smaller adjustment coefficients and more momentum, US house prices correct from short term deviations back to the long term fundamentals much slower than Chinese prices, with deviation-amplifying changes at first; whereas China has mostly quick mean reversion.

5.1. Differences across US MSAs

Cities can behave very differently from one another in terms of momentum and other factors. We look at differences across U.S. cities by exploiting two exogenous factors. One is distance to either the east or west coasts on the grounds that these are desirable locations (comparable to a similar classification, "Coastal cities", for China), and the other is on local supply elasticity, as given by Saiz (2010), on the grounds that low elasticities will lead to more momentum. In general, coastal MSAs are also those with lower supply elasticities. In the case of China, Tier 1 cities also have housing markets that are different from other cities. It would therefore be interesting to compare specifically the speed of long run adjustments and momentum across different MSAs and cities in various classifications, as discussed in the following.

Coastal & Inland MSAs

Panel A of Table 3 shows that US Coastal MSAs correct faster toward the long run equilibrium, but not by much. Momentum of these Coastal MSAs also tends to be bigger than those of Inland MSAs, again not by much. It is interesting to note that the constant term, representing either a risk premium on top of the theoretical Gordon model or an exogenous deduction from expected growth, is bigger in Coastal MSAs, although very small in both differences and in magnitudes. Clearly the two MSA groups are not all the same, but patterns are not obvious. However, when the estimations are run on subperiods, both types of MSAs adjust faster to the long run, have very similar momentum and bigger constant terms in post-crisis period than in the pre-crisis period when Coastal MSAs generated much bigger momentum than the Inland counterparts. It seems, therefore, that differences in the MSAs appeared only before the crisis; MSAs did not behave too differently upon recovering from the crisis.

MSAs with High and Low Supply Elasticity

According to Saiz (2010), cities with low supply elasticities have higher house price growth. We group 24 MSAs that match the list in Saiz (2010), with average supply elasticity of 1.3503 as cutoff. There are 8 MSAs in the "High" elasticity group, and 16 in the "Low" group. Panel B of Table 3 shows the sums of coefficients. MSAs with low supply elasticities revert back to the long run faster, but also have higher momentum, although not much bigger than those with high elasticities, and have higher constant terms. In the subperiods, however, the differences are obvious only in the pre-crisis periods, when constant terms were even negative. These findings mirror those with Coastal and Inland classifications.

We also regress our measure of momentum, the sums of coefficients of lagged rent to price ratio, on the corresponding supply elasticities of the 24 MSAs. Results are depicted in Panel C of Table 3 (results with both sums of significant coefficients and sums of all coefficients are regressed), and graphs shown in Figure 4. As expected, the regression is downward sloping, with coastal cities, which tend to be less supply elastic, having higher momentum (sums of coefficients are higher). Also seen from both the Table and the Figure is that this relationship is more pronounced in the pre-crisis period (and stronger, in terms of higher R-squared), and much flatter during the crisis-recovery.

MSAs with High and Low Property Tax Rates

MSAs also differ in property tax rates, which is a component of user cost. Himmelberg *et al*. (2005) demonstrates that heterogeneous changes in user cost (our cap rates) help explain the heterogeneity of price and price-to-rent growth across cities. Diverse levels of property tax rates might generate different adjustment speeds to long-run equilibrium and different momentum effects. We use average effective property tax rates of the States as an alternative classification criterion. Those tax rates are calculated by the Tax Foundation based on data of American Community Survey, which are released by the U.S. Census Bureau. The two groups of MSAs, below (23 MSAs) and above (21 MSAs) mean "Average Effective Property Tax Rate (2010-2014)" of 0.0128, do not show significant differences, and results are therefore omitted here.

5.2. Differences across Chinese Cities

Panel B of Table 2 shows summary statistics across individual cities. The error correction terms are mostly significant, ranging from -0.3911 in the 3-lag model to -0.0003 in the 9-lag model. Sums of the coefficients of the momentum variables are generally negative, except for a few "outlier" cities where these sums are unreasonably big (this, however, is due to adding the sum of all coefficients, including those that are insignificant). The following is a breakdown into different city classifications from the same PMG models. Summaries of sums of coefficients are shown in different Panels of Table 4.

Cities in Tiers

For all four PMG models, with different lags, the mean error correction coefficients of the four Tier 1 cities in Panel A of Table 4 are all smaller in absolute value when compared to other Tiers, implying that house prices of Tier 1 cities tend to take longer to adjust back to long run equilibrium, followed by Tier 2 Cities (36 in total) adjusting slower than the other lower tier (the remaining 40) counterparts. Furthermore, even though coefficients of lagged differenced rent to price ratios are all negative (and significant only up to one quarter) in the overall models, sums of these coefficients of Tier 1 cities are positive, albeit not especially large, in all four models; those of Tier 2 are positive in two models (with 6 lags and 12 lags), and those in Other Tier are relatively much more negative in all four models. This shows that there is indeed some momentum in Tier 1 cities, and moderate momentum in Tier 2 cities. Also, while the short run nominal interest rates exhibit correct signs, their magnitudes vary by Tiers; changes in interest rates affect housing prices the least for Tier 1 cities. Finally, while all the constants are positive, those of the Tier 1 cities are smallest and Other Tier the largest, suggesting less perceived risk and/or more expected growth in the big Tier 1 cities.

Hence, even though the PMG results including all 80 cities do not seem to support momentum in the cities, when breaking down the cities into tiers, there are differences: Tier 1 cities do exhibit some momentum, and are slower in adjusting back to long run equilibrium, and they less affected by interest rate movements, and housing in those cities generates smaller constant terms.

Coastal versus Inland Cities in Tiers

All Tier 1 cities except Beijing are by the coast. Also the huge migration from the west to the eastern coastal cities for more job opportunities has been a major cause of high demand in housing. Hence, it is not surprising for coastal cities to have housing markets that behave more like Tier 1 and 2 cities. The sums of coefficients in Panel B of Table 4 show confirming results. First, the error correction coefficients are smaller for Coastal cities (23) than those the Inland cities (57), and although momentum is not seen anymore, the coefficients of coastal cities are still smaller in absolute value than the inland counterparts. They are also less affected by interest rate changes. The constant terms are also smaller than those of the inland ones. All these results are different from those found for the US Coastal & Inland MSAs.

By Regions

As mentioned above, Coastal cities are hotter housing markets. Most of these are also on the Eastern side. We further classify them as Central (19), Eastern (43) and Western (14) and compare them with the 4 Tier 1 cities. Again, from Panel C, the Tier 1 Cities correct slowest to the long run equilibrium, followed by Eastern cities, while the Central cities tend to be the fastest. Tier 1 cities also show momentum, while all the others do not, with the Central having the most serious price-chasing-rent phenomenon. Interest rate effects and constant terms do not have very clear patterns.

As a robustness check, we also employ the classification due to Wang *et al*. (2008), which includes the 4 Tier 1 cities, 7 Eastern cities, 7 Middle Southern cities, 8 Northern cities and 9 Western cities, making up a total of 35 cities. The orders of magnitude of the coefficients in Panel E are the same as above, again with Tier 1 cities slowest to adjust to long run equilibrium, prone to momentum, least effects from interest rates, and smallest constant terms, followed by Eastern and Northern (which take turns with different lags used in the PMG models), and then Middle Southern and Western (also taking turns depending on the models). Momentum exists not only in Tier 1 cities, but also in other cities except the Western cities. In any case the momentum is not large relative to that for US counterparts.

By Over- and Under-Supply

Finally, in Wu *et. al*. (2016), cities are also classified according to whether there is undersupply or oversupply of housing units. Following their study, we calculated the ratio of supply to demand (so that a ratio smaller than 1 is undersupply, and oversupply if it is greater than 1) for the whole period of 2001-2014 (with 8 undersupplied cities and 27 oversupplied cities), and subperiods 2001-2010 (with 12 undersupplied and 23 oversupplied) and 2011-2014 (with 10 undersupplied and 25 oversupplied), to separate the cities into two groups for each period and run the PMG estimations for the whole sample period as in our other tests. Since the results are similar, we show results from the 2011-2014 classification, particularly because this period is closer to our sample period, and also because this is the period with most frequent changes in government policies to curb the market, showing that this period is in a frenetic period.

Tier 1 cities are likely to be the ones with undersupply because they are the most heated markets. Other cities that experienced undersupply should have similar PMG results as those of Tier 1 cities, versus other less popular cities. Panel E of Table 4 shows results in line with our expectation; undersupplied cities correct slowly toward equilibrium, exhibit momentum, react less to interest rate chances, and have smaller constant terms. What is interesting is that even oversupplied cities are prone to price momentum. In addition, Wang *et. al*. (2012) use supply elasticity to cut 35 cities into 21 low elasticity cities and 14 high elasticity cities. We follow their classification and obtain estimates that are in line with the oversupplied/undersupplied classifications. Panel F shows that cities with low supply elasticity tend to be undersupply cities. These findings contrast with those of the US MSAs, with low supply elasticities that revert back to the long run faster and have higher constant terms.

As a final check, we repeat the regressions of the sums of coefficients of lagged changes for rent to price ratio (momentum) on supply elasticities, as with the US MSAs. Results are depicted in Panel G of Table 4 and Figure 5. The negative slope is as expected, although the cities seem to cluster together, meaning the relation is not really strong (at least not as strong as that for the US).[5]

[5] As yet another variation of low versus high supply elasticity, we also classified the 34 cities with data on "developable land shares", in percentages, and perform analysis that generates similar conclusion.

A point worth noting is that although momentum is found in the big four Tier 1 cities, it does not indicate existence of bubbles because the sums of the coefficients of the rent to price ratios are way smaller than 1. Furthermore, there has been debate that housing units in the rental market in China are distinctively different (usually inferior) from those in the sales market, which implies that the housing units underlying the rental series and the price series in our models are not comparable. Nonetheless, the fact that the corrections back to the long run fundamental are similar shows that this data limitation is not a big issue, even though the hottest cities (Tier 1 and Coastal cities), where such housing differences on average should be biggest, do tend to show slightly slower adjustment speeds.

5.3. Estimation of Residuals and Explanatory Powers

Our goal is to suggest a simple model that could represent the housing price mechanisms in both countries without encountering more variables than the basic rent to price ratio and cap rates. One question is how well this model can explain the two markets. Another is how the residuals behave if the model omits a lot of information. Both questions are addressed in this subsection.

Autoregression Results of Residuals

To begin, we check the autoregressive processes of the residuals. Residuals represent effects from omitted variables. They work like temporary changes in the constant term. A possibility is that they represent government policies that affect the price adjustment (but not rent, and therefore cannot be fully reflected by the short run rent to price ratio variable), or they could be random changes in expectations of either perceived risk or expected appreciation. They work outside the momentum factors given by lagged rent to price ratio. The autoregressive representation of the residuals, estimated from regressing current residuals on past residuals, tells us how permanent these changes are. We interpret the sum of coefficients of past residuals being equal to one as indicating random permanent changes in the constant term that in turn effect long run rent to price ratios. If the sum is less than one, it is interpreted as indicating eventual mean reversion.

Table 5 summarizes the sum of significant coefficients of the autoregression on the residuals from the PMG results explained in the previous section. Given that our data set is of monthly frequency, we use different lags for the AR(lag) autoregression tests, illustrating the results with 6, 12, and 18 lags[6] in the Table. Panel A shows the results of the US MSAs, while Panel B shows those of the Chinese cities, which are grouped according to the classifications used in the previous section. Empty cells imply no significant coefficients. In the case of the US (Panel A), the sums of the coefficients are in general very small in magnitude; a lot are negative, meaning there is a lot of oscillation in the residuals between being positive and negative. The largest value is only 0.2967 for non-bubble (i.e. low momentum) MSAs in AR(18).

The situation is very different in the case of Chinese cities (Panel B). Most of the sums are not only positive, but are large, albeit less than one; those that are negative are small in magnitude. It looks like the residuals from the PMG estimations for Chinese cities contain important information about omitted variables that is not explained by the model. This is particularly the case for coastal cities and Eastern cities (with sums of the autoregression coefficients greater than 0.8, and highlighted in bold), which are in

[6] We do not attempt to find the best fit of residual process by trying different lags for individual MSAs or cities because our goal is not to find the best model for forecasting; rather, results from comparable models will be preferred.

general cities with relatively higher demand. Interestingly, the four hottest Tier 1 cities do not show much sign of autocorrelation in the residuals.

Explanatory Powers

Given the results from the autoregression tests from the residuals, it seems that a lot of the rent to price series of the Chinese cities could be explained by the residuals' processes. We therefore compare the explanatory powers (partial R^2s) of the models of the two countries. Results are depicted in Table 6. Panel A is for the U.S. MSAs, while Panels B1 and B2 are for the Chinese cities. It should be noted that the numbers shown in the Table are averages across the MSAs and cities in the various classifications. Hence, for instance, the Long Run Partial R^{2}'s are the average of those of all cities, and therefore do not come from the same cities that generate the short run Partial R^{2}'s. Likewise, the explanatory powers from the PMG estimation and the residual autoregression are also averages.

In the case of the U.S. (Panel A of Table 6), the PMG estimation together with the residual autoregression model can explain about 70% to 80% of the rent to price ratio, with the residual regression explaining less than 5%. The simple long run model contributes roughly one-quarter of the rent to price dynamics, while most explanatory power comes from the short run mechanism. Moreover, the models tend to work better for coastal MSAs than inland MSAs, and better for bubble MSAs relative to non-bubble MSAs.

On the other hand, for Chinese cities, even though the residual autoregressions can explain the rent to price ratio only up to 10% (mostly below 10%, except for a few cases), they still tend to explain more than the 5% in the U.S. On the other hand, the overall explanatory powers are on the low side, mostly below 50%, and mostly in the 20th percentile (some of these numbers are above 1, which are a result of high mean PMG R^2 plus a high mean autoregression R^2). Comparing across different city classifications generates inconclusive results. For instance, "Eastern" cities generate different explanatory powers in the two classifications (Easter/Central/Western versus Eastern/Middle Southern/Norther/Western). Hence, the results are apparently very sensitive to the mix of the cities.

In sum, the explanatory power from PMG estimation on the U.S. MSAs is much more consistent across different model settings and different MSA classifications than for the Chinese counterparts, even though the time series are of the same length (except for the whole sample of the U.S. MSAs). A possible explanation is that the U.S. MSAs experience similar market forces and can therefore be represented with the same fundamentals and short run dynamics. On the other hand, there may be more diverse market mechanisms across the different cities in China, together with differences in the kinds and magnitudes of the policies implemented by the government, both of which might be contained in the residuals of the PMG estimations.

In any event, short run adjustment in the U.S. is apparently best explained by momentum from past prices. However, adjustment in China is best explained by random shocks (being contained in the residuals) outside of momentum. There is also momentum in these random shocks, albeit not permanent; this is not the case for the U.S.. The shocks could be, for instance, from random changes in appreciation expectations or changes in government policy.

6. Conclusions

Both the U.S. and China have had periods of sharp increases in house prices. The major question in this paper is whether or not China today is like the U.S. in 2006. We use the inverse of the ratio of prices to rents (like the inverse P/E ratio for stocks) as our dependent variable and force it to obey a simple version of the Gordon Dividend Discount model in the long run (effects of all possible exogenous factors on house price reflected by rent alone), while allowing for considerable variation in short run adjustment. Using almost identical models and comparable data, we analyze whether the price adjustments are similar between the US and Chinese housing markets, and whether the fundamental structures of the two markets are similar. We use Pooled Mean Group and Mean Group Estimation, which provides an easy way to separate short run movements from the long run fundamentals. We also analyze differences across sub-periods and by city types.

We find important differences between China and the U.S. markets. In particular, the U.S. going in to the crash from 1999-2006 had strong momentum and stable rent growth — prices were chasing prices. However, in China there was quick mean reversion to long run price to rent ratios, more like prices chasing rents. We also tested for differences inside the two countries and found some differences by location and city type. However, these differences were small compared to the differences in adjustment between countries.

Not only do we not find evidence of bubbles in China, we find quick reversion to equilibrium for both property values and rent growth, suggesting less risk in China. We should, however, note in terms of recent data that (see Figure 1 Panel C) from 2014 to 2016 prices did increase rapidly while rents did not change much. While there are not enough data to extrapolate, this does suggest caution, particularly since our model also shows a lower, and less consistent, explanatory power on the Chinese markets relative to that of the U.S. counterparts.

Our model, particularly the adjustment to long run, is a reduced form model that could be generated from a variety of structural models, which we cannot identify. It cannot tell if the Chinese economy is structured in a way that is less prone to bubbles than the U.S., or if different results reflect policy in the U.S. that destabilized housing markets versus policy in China that was more stabilizing. If that is the case, then there is risk that these different policy regimes might change. In any event the boom-bubbles-bust cycle that the US housing market experienced does not seem to be a lesson for the Chinese counterpart to learn.

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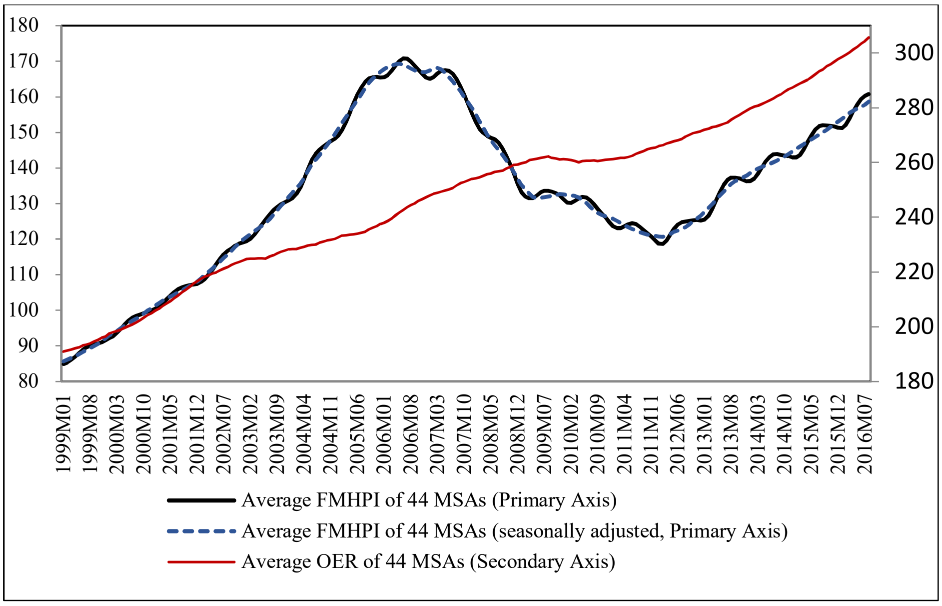
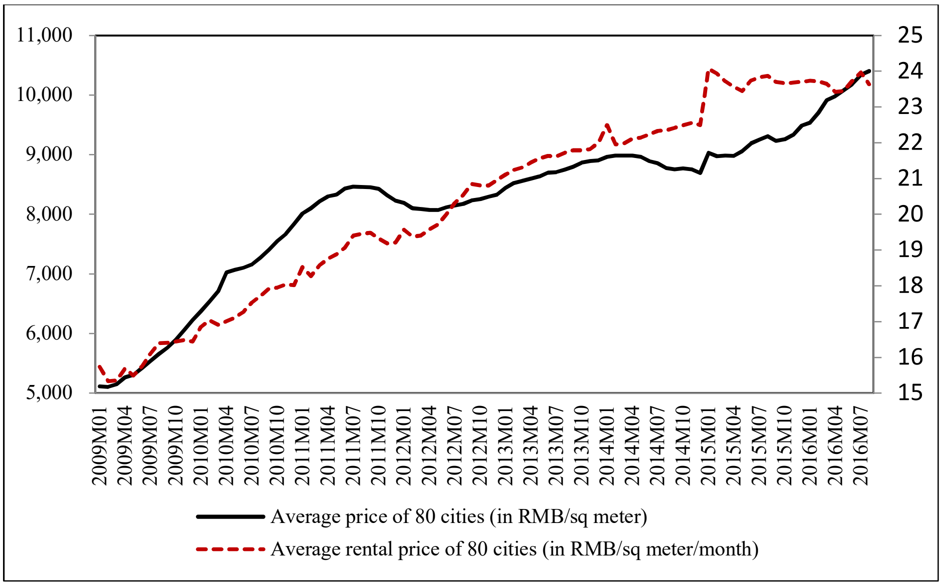
Figure 1   House Price and Rent Series

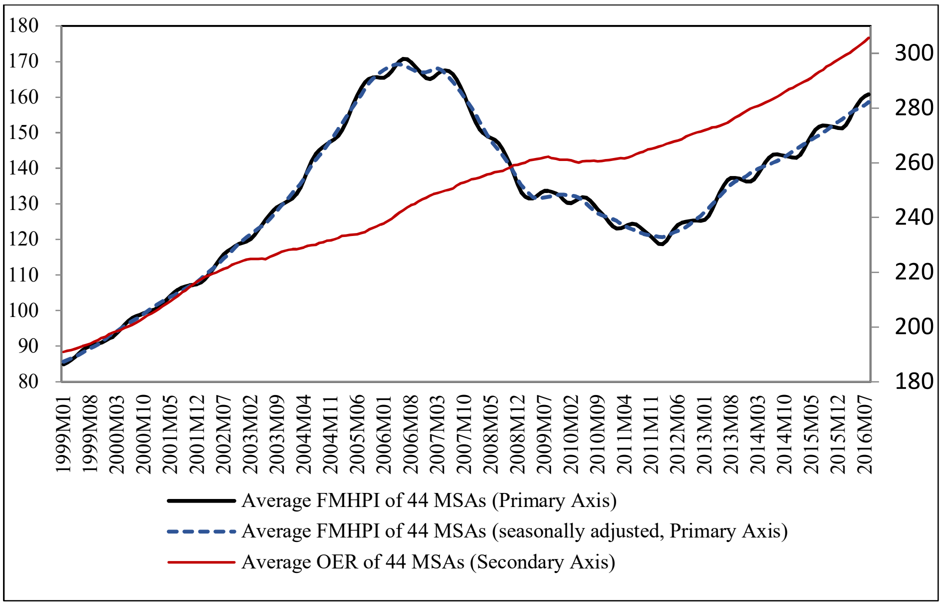
Panel A   44 US MSAs



Panel B   80 Chinese cities



Panel C Visual Comparison of Housing Prices of Both Countries



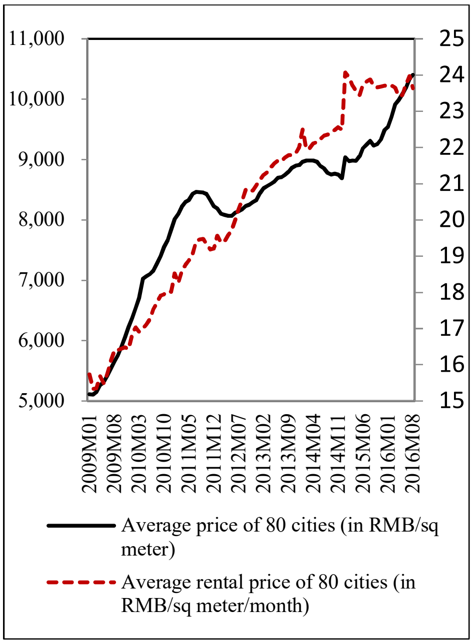
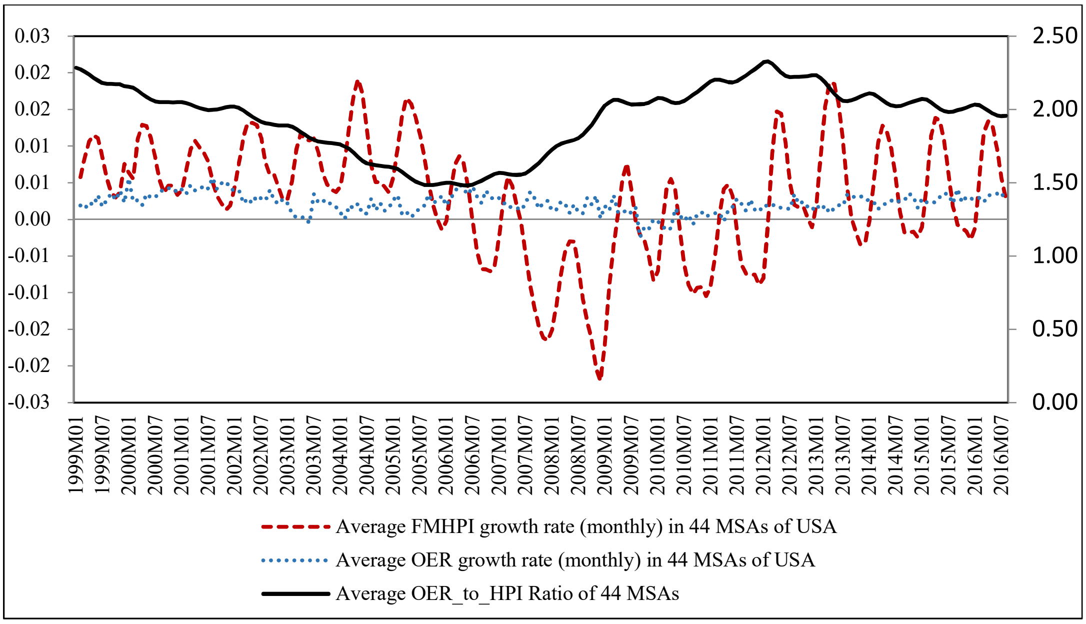


Figure 2 Average Rent-to-Price Ratio, Price Growth Rate, and Rent Growth Rate of US MSAs

Panel A Original Data



Panel B Seasonally Adjusted Data

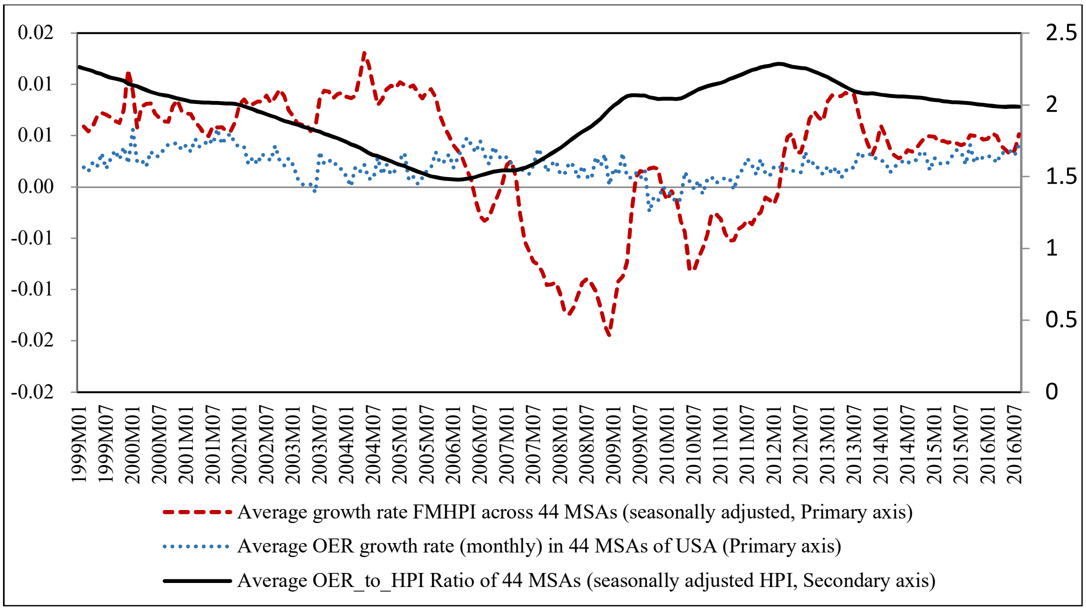


Figure 3　Average Rent-to-Price Ratio, Price Growth Rate, and Rent Growth Rate of Chinese Cities

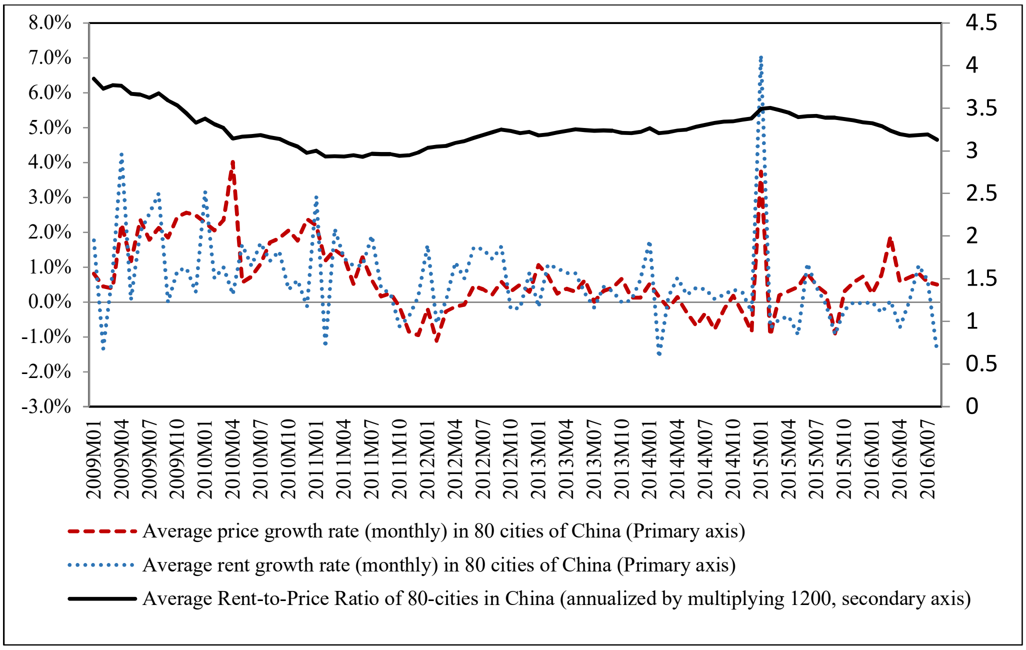
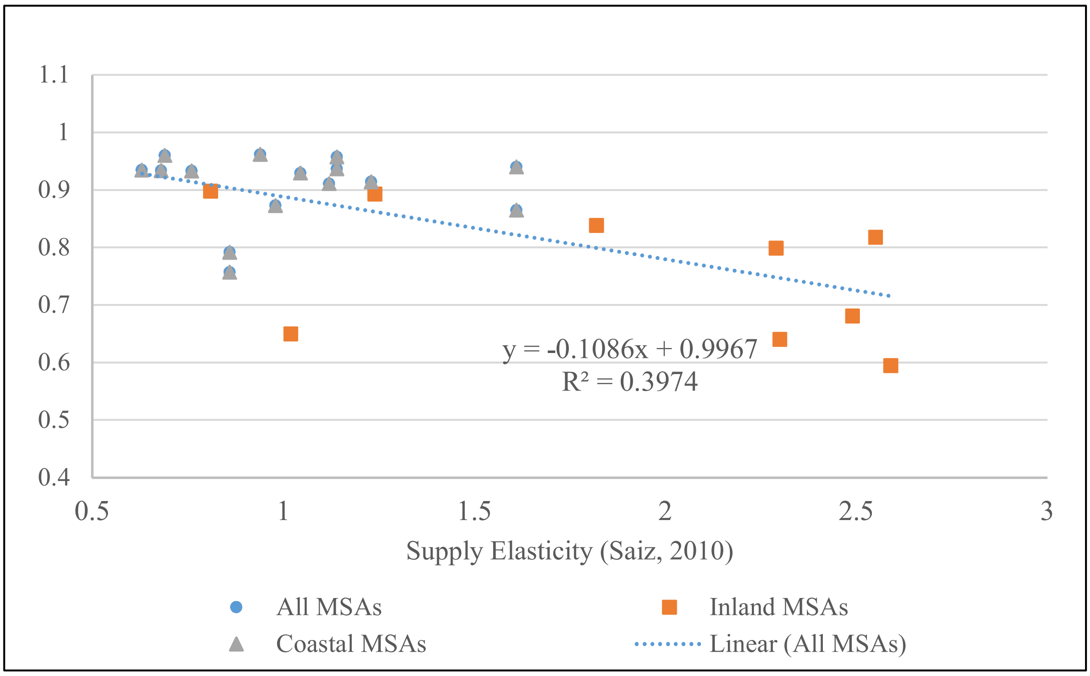


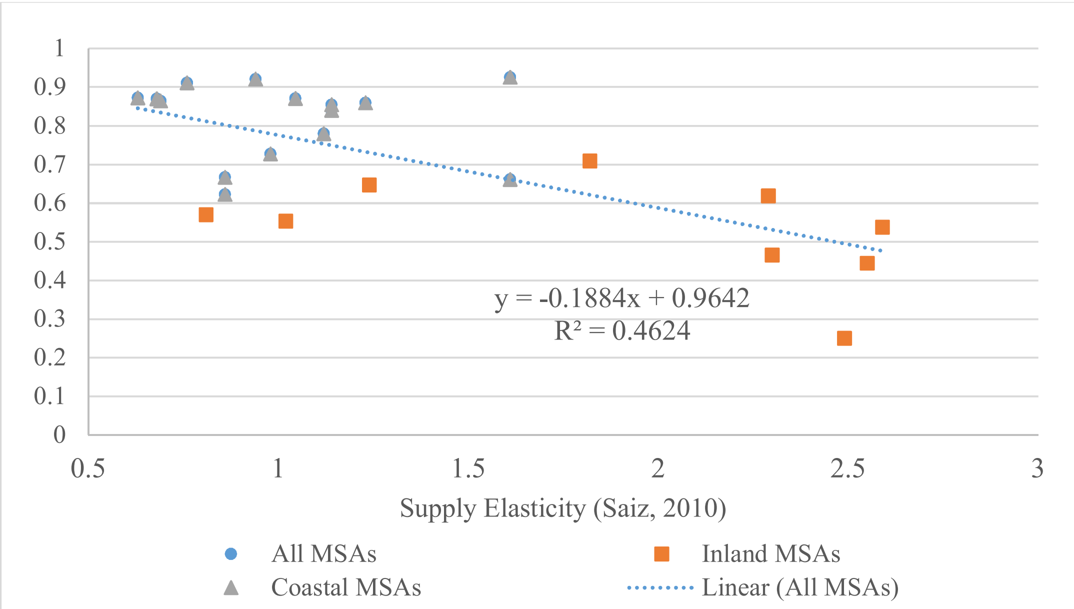
Figure 4 Regression of Sum of Coefficients of Changes in Rent-to-price Ratios on Supply Elasticity for 24 MSAs in US

***Note**: The sum of coefficients of changes in Rent-to-Price ratio are based on the Model A PMG results with 3 lags*

Whole Sample Period, 1999-2016



Pre-Crisis Period, 1999-2006



Post-Crisis Recovery Period, 2009-2016

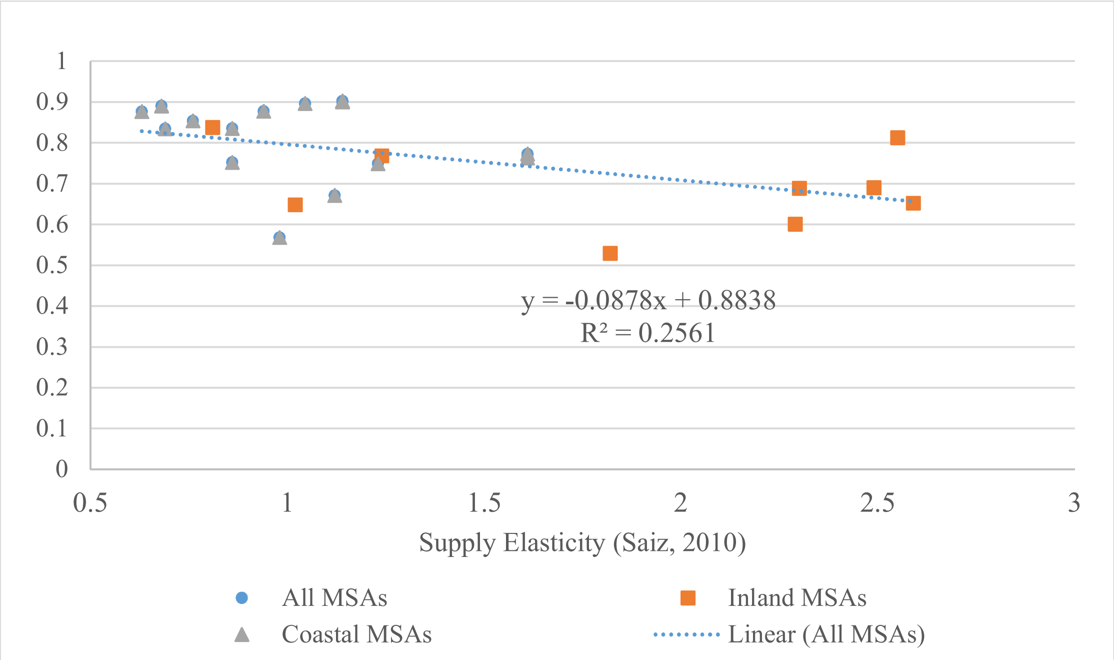
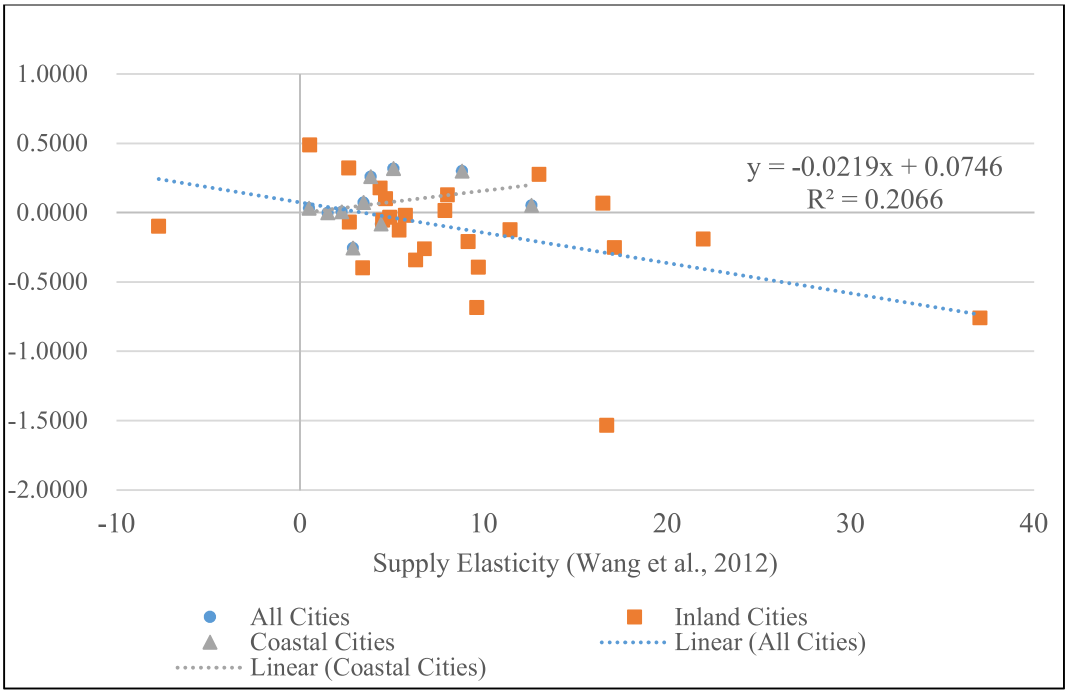


Figure 5 Regression of Sum of Coefficients of Changes in Rent-to-price Ratios on Supply Elasticity for 35 Chinese Cities

***Note**: The sum of coefficients of changes in Rent-to-Price ratio are based on the Model A PMG results with 3 lags*

Coastal Versus Inland Cities



Tier 1 versus Others

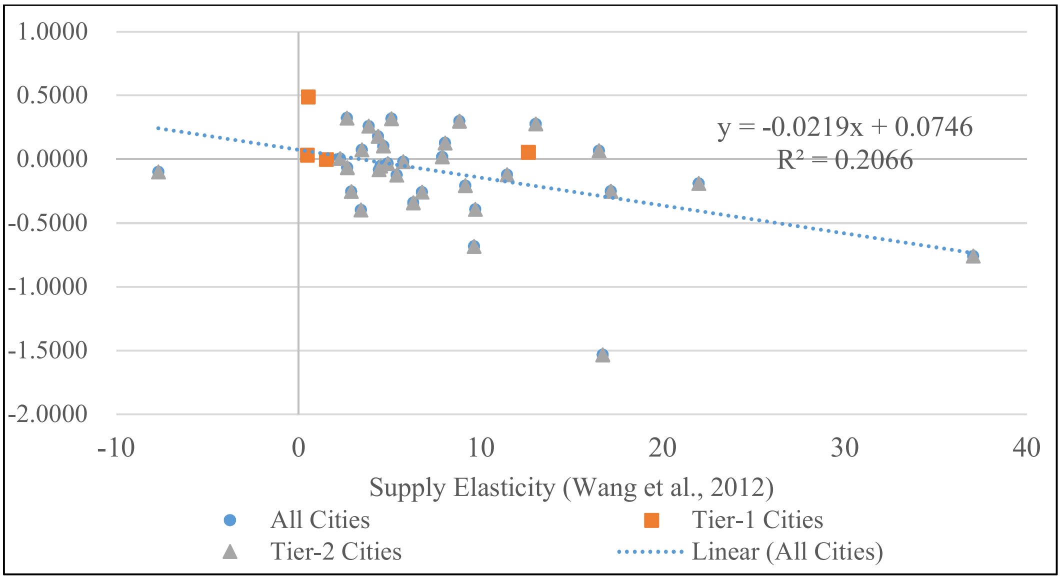


Table 1 PMG & MG Estimation for Rent-To-Price Ratio For US Markets

Panel A Model A (Sample Period is 1999 Jan - 2016 Aug)

	Model A1		**Model A2**		**Model A3**		**Model A4**	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates$_{t-1}$	0.2004***	-0.0092	0.1877***	0.095	0.1431***	0.1875***	-0.0736**	-0.0555*
Short-run variables								
Error Correction	-0.0022***	-0.0030***	-0.0023***	-0.0031***	-0.0032***	-0.0037***	-0.0043***	-0.0041***
$\Delta R/P_{t-1}$	0.5951***	0.5926***	0.5803***	0.5784***	0.5874***	0.5859***	0.6012***	0.6000***
$\Delta R/P_{t-2}$	0.1162***	0.1161***	0.0996***	0.0992***	0.0743***	0.0735***	0.0627***	0.0610***
$\Delta R/P_{t-3}$	0.1259***	0.1251***	0.0728***	0.0729***	0.0767***	0.0767***	0.0833***	0.0829***
$\Delta R/P_{t-4}$			0.0563***	0.0557***	0.0476***	0.0474***	0.0441***	0.0441***
$\Delta R/P_{t-5}$			0.1496***	0.1500***	0.1321***	0.1326***	0.1268***	0.1264***
$\Delta R/P_{t-6}$			-0.1010***	-0.1010***	-0.1890***	-0.1886***	-0.1841***	-0.1846***
$\Delta R/P_{t-7}$					0.1221***	0.1226***	0.1268***	0.1272***
$\Delta R/P_{t-8}$					0.0064	0.0062	0.0058	0.0051
$\Delta R/P_{t-9}$					0.0290***	0.0297***	0.0413***	0.0408***
$\Delta R/P_{t-10}$							0.0212*	0.0213*
$\Delta R/P_{t-11}$							-0.0166	-0.0157
$\Delta R/P_{t-12}$							-0.0088	-0.0077
ΔReal Rates$_{t-1}$	-0.0024***	-0.0024***	-0.0024***	-0.0023***	-0.0026***	-0.0026***	-0.0020***	-0.0020***
ΔReal Rates$_{t-2}$	-0.0009**	-0.0009**	-0.0009**	-0.0008**	-0.0009***	-0.0009***	-0.0002	-0.0002
ΔReal Rates$_{t-3}$	-0.0007*	-0.0006	-0.0007**	-0.0006*	-0.0006*	-0.0006*	0.0001	0.0001
ΔReal Rates$_{t-4}$			-0.0008**	-0.0007*	-0.0010***	-0.0010***	-0.0001	0
ΔReal Rates$_{t-5}$			0	0.0001	-0.0003	-0.0003	0.0007**	0.0007**
ΔReal Rates$_{t-6}$			0.0017***	0.0018***	0.0012***	0.0012***	0.0023***	0.0023***
ΔReal Rates$_{t-7}$					0.0007*	0.0007*	0.0015***	0.0015***
ΔReal Rates$_{t-8}$					0.0014***	0.0015***	0.0019***	0.0019***
ΔReal Rates$_{t-9}$					-0.0010***	-0.0009***	0.0002	0.0002
ΔReal Rates$_{t-10}$							0.0016***	0.0016***
ΔReal Rates$_{t-11}$							0.0010**	0.0010**
ΔReal Rates$_{t-12}$							0.0023***	0.0023***
Constant	0.0035***	0.0050***	0.0036***	0.0053***	0.0054***	0.0064***	0.0086***	0.0084***
Obs	9,152	9,152	9,020	9,020	8,888	8,888	8,756	8,756
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	30639	30655	30411	30429	30666	30677	31156	31176
Hausman test	**Invalid**		0.74		3.16		3	
p-value			0.3905		**0.0756**		**0.0833**	

Panel A1 Model A (Subsample Period is 1999 Jan - 2006 Dec)

	Model A1		Model A2		Model A3		Model A4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates$_{t-1}$	0.4698***	0.3833	0.5283***	1.0680*	0.5907***	0.6224**	0.4673***	0.2513
Short-run variables								
Error Correction	-0.0023***	-0.0056***	-0.0021***	-0.0058***	-0.0026***	-0.0064***	-0.0026***	-0.0053**
$\Delta R/P_{t-1}$	0.4601***	0.4566***	0.4395***	0.4359***	0.4239***	0.4198***	0.4515***	0.4457***
$\Delta R/P_{t-2}$	0.0751***	0.0758***	0.0569***	0.0583***	0.0339**	0.0355**	0.0316*	0.0334**
$\Delta R/P_{t-3}$	0.1944***	0.1927***	0.1556***	0.1572***	0.1632***	0.1645***	0.1774***	0.1780***
$\Delta R/P_{t-4}$			0.0697***	0.0707***	0.0594***	0.0599***	0.0327	0.0348
$\Delta R/P_{t-5}$			0.1592***	0.1602***	0.1543***	0.1549***	0.1455***	0.1459***
$\Delta R/P_{t-6}$			-0.1294***	-0.1282***	-0.1576***	-0.1542***	-0.1707***	-0.1675***
$\Delta R/P_{t-7}$					0.0866***	0.0871***	0.0622***	0.0606***
$\Delta R/P_{t-8}$					-0.0402**	-0.0372**	-0.0377*	-0.0371*
$\Delta R/P_{t-9}$					0.0399**	0.0411**	0.0334*	0.0342**
$\Delta R/P_{t-10}$							0.0201	0.0217
$\Delta R/P_{t-11}$							0.0015	0.0036
$\Delta R/P_{t-12}$							-0.0308	-0.0292
ΔReal Rates$_{t-1}$	-0.0024***	-0.0024***	-0.0029***	-0.0027***	-0.0040***	-0.0037***	-0.0028***	-0.0028***
ΔReal Rates$_{t-2}$	-0.0006	-0.0006	-0.0001	0	-0.0009	-0.0007	-0.0006	-0.0006
ΔReal Rates$_{t-3}$	-0.0008	-0.0007	-0.0006	-0.0005	-0.0023***	-0.0021***	-0.0018***	-0.0018**
ΔReal Rates$_{t-4}$			0	0.0001	-0.0014**	-0.0012*	-0.0007	-0.0007
ΔReal Rates$_{t-5}$			0.0005	0.0006	-0.0002	-0.0001	-0.0007	-0.0007
ΔReal Rates$_{t-6}$			-0.0007**	-0.0006*	-0.0017***	-0.0016***	-0.0013**	-0.0013**
ΔReal Rates$_{t-7}$					-0.0018***	-0.0017***	-0.0015***	-0.0015***
ΔReal Rates$_{t-8}$					-0.0005	-0.0004	-0.0009*	-0.0009*
ΔReal Rates$_{t-9}$					-0.0031***	-0.0030***	-0.0016***	-0.0016***
ΔReal Rates$_{t-10}$							-0.0014***	-0.0014***
ΔReal Rates$_{t-11}$							-0.0011**	-0.0011**
ΔReal Rates$_{t-12}$							0.0002	0.0002
Constant	0.0009***	0.0067*	0.0007**	0.0078**	0.0008**	0.0085*	0.0013*	0.0063
Obs	4,048	4,048	3,916	3,916	3,784	3,784	3,652	3,652
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	14923	14942	14669	14686	14397	14415	14303	14319
Hausman test	0.24		0.9		0.02		0.2	
p-value	0.6222		0.3423		0.8856		0.6541	

Panel A2 Model A (Subsample Period is 2009 Jan - 2016 Aug)

	Model A1		**Model A2**		**Model A3**		**Model A4**	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates$_{t-1}$	0.1324***	0.3204***	0.1672***	0.1026	0.1817***	0.1829***	0.1163***	0.0333
Short-run variables								
Error Correction	-0.0107***	-0.0120***	-0.0123***	-0.0135***	-0.0145***	-0.0159***	-0.0156***	-0.0158***
$\Delta R/P_{t-1}$	0.5866***	0.5798***	0.5792***	0.5747***	0.5685***	0.5639***	0.5687***	0.5646***
$\Delta R/P_{t-2}$	0.0959***	0.0926***	0.1012***	0.0979***	0.1017***	0.0993***	0.0831***	0.0785***
$\Delta R/P_{t-3}$	0.0392***	0.0415***	-0.0047	-0.0052	-0.0028	-0.0026	0.0042	-0.0005
$\Delta R/P_{t-4}$			0.0269**	0.0294**	0.0528***	0.0563***	0.0544***	0.0567***
$\Delta R/P_{t-5}$			0.1396***	0.1394***	0.1206***	0.1201***	0.1340***	0.1301***
$\Delta R/P_{t-6}$			-0.1104***	-0.1118***	-0.1806***	-0.1813***	-0.1681***	-0.1723***
$\Delta R/P_{t-7}$					0.1371***	0.1371***	0.1705***	0.1691***
$\Delta R/P_{t-8}$					-0.0082	-0.0065	-0.0238	-0.0227
$\Delta R/P_{t-9}$					-0.0319**	-0.0331**	0.0289	0.0255
$\Delta R/P_{t-10}$							-0.0191	-0.0184
$\Delta R/P_{t-11}$							-0.0264	-0.0252
$\Delta R/P_{t-12}$							-0.0459***	-0.0521***
ΔReal Rates$_{t-1}$	-0.0002	-0.0002	-0.0006	-0.0007	-0.0011	-0.0014	-0.001	-0.001
ΔReal Rates$_{t-2}$	-0.0012**	-0.0013**	-0.0012*	-0.0013**	-0.0017**	-0.0020**	-0.0008	-0.0008
ΔReal Rates$_{t-3}$	-0.0017***	-0.0018***	-0.0014***	-0.0015***	-0.0011***	-0.0013***	0.0001	0
ΔReal Rates$_{t-4}$			-0.0030***	-0.0030***	-0.0028***	-0.0030***	-0.0021***	-0.0021***
ΔReal Rates$_{t-5}$			-0.0015***	-0.0016***	-0.0016***	-0.0018***	-0.0006*	-0.0006
ΔReal Rates$_{t-6}$			0.0030***	0.0029***	0.0025***	0.0023***	0.0034***	0.0034***
ΔReal Rates$_{t-7}$					0.0011	0.001	0.0023***	0.0022***
ΔReal Rates$_{t-8}$					0.0012**	0.0011**	0.0021***	0.0020***
ΔReal Rates$_{t-9}$					0.0001	0	0.0009*	0.0008
ΔReal Rates$_{t-10}$							0.0026***	0.0025***
ΔReal Rates$_{t-11}$							0.0011***	0.0010**
ΔReal Rates$_{t-12}$							0.0019***	0.0018***
Constant	0.0199***	0.0213***	0.0224***	0.0240***	0.0260***	0.0275***	0.0290***	0.0297***
Obs	4,048	4,048	4,048	4,048	4,048	4,048	4,048	4,048
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	14617	14646	14931	14948	15200	15220	15388	15408
Hausman test	5.8		0.19		0		0.34	
p-value	0.016		0.6589		0.9721		0.5595	

Panel B Model B (Sample Period is 1999 Jan - 2016 Aug)

	Model B1		Model B2		Model B3		Model B4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates$_{t-1}$	0.1777***	0.0782	0.1774***	0.0954	0.0992**	0.1457***	-0.0767**	-0.0868***
Short-run variables								
Error Correction	-0.0023***	-0.0030***	-0.0023***	-0.0030***	-0.0035***	-0.0038***	-0.0043***	-0.0043***
$\Delta R/P_{t-1}$	0.5967***	0.5942***	0.5829***	0.5809***	0.5897***	0.5878***	0.6028***	0.6018***
$\Delta R/P_{t-2}$	0.1179***	0.1179***	0.0954***	0.0950***	0.0700***	0.0694***	0.0594***	0.0584***
$\Delta R/P_{t-3}$	0.1262***	0.1256***	0.0760***	0.0761***	0.0772***	0.0769***	0.0766***	0.0765***
$\Delta R/P_{t-4}$			0.0595***	0.0589***	0.0549***	0.0546***	0.0550***	0.0555***
$\Delta R/P_{t-5}$			0.1492***	0.1495***	0.1276***	0.1280***	0.1237***	0.1233***
$\Delta R/P_{t-6}$			-0.0961***	-0.0959***	-0.1827***	-0.1819***	-0.1730***	-0.1732***
$\Delta R/P_{t-7}$					0.1243***	0.1243***	0.1277***	0.1280***
$\Delta R/P_{t-8}$					0.0127	0.0128	0.0122	0.0121
$\Delta R/P_{t-9}$					0.0183	0.0194*	0.0261**	0.0256*
$\Delta R/P_{t-10}$							0.0153	0.0155
$\Delta R/P_{t-11}$							-0.0006	0.0005
$\Delta R/P_{t-12}$							-0.0158	-0.0152
ΔReal Rates$_{t-1}$	-0.0024***	-0.0023***	-0.0025***	-0.0023***	-0.0027***	-0.0027***	-0.0020***	-0.0019***
ΔReal Rates$_{t-2}$	-0.0013***	-0.0013***	-0.0014***	-0.0013***	-0.0013***	-0.0013***	-0.0007**	-0.0007*
ΔReal Rates$_{t-3}$	-0.0009**	-0.0009**	-0.0012***	-0.0011***	-0.0011***	-0.0011***	-0.0005	-0.0004
ΔReal Rates$_{t-4}$			-0.0016***	-0.0015***	-0.0019***	-0.0019***	-0.0011***	-0.0010***
ΔReal Rates$_{t-5}$			-0.0008**	-0.0008**	-0.0010***	-0.0010***	-0.0002	-0.0002
ΔReal Rates$_{t-6}$			0.0017***	0.0018***	0.0012***	0.0012***	0.0022***	0.0022***
ΔReal Rates$_{t-7}$					0.0006	0.0006	0.0014***	0.0015***
ΔReal Rates$_{t-8}$					0.0018***	0.0018***	0.0022***	0.0023***
ΔReal Rates$_{t-9}$					-0.0004	-0.0004	0.0007*	0.0007*
ΔReal Rates$_{t-10}$							0.0019***	0.0019***
ΔReal Rates$_{t-11}$							0.0013***	0.0013***
ΔReal Rates$_{t-12}$							0.0025***	0.0025***
ΔNom Rates$_{t-1}$	-0.0002	-0.0001	-0.0002	-0.0002	0.0001	0.0001	0.0001	0.0001
ΔNom Rates$_{t-2}$	0.0010***	0.0010***	0.0015***	0.0014***	0.0014***	0.0014***	0.0012***	0.0012***
ΔNom Rates$_{t-3}$	0.0004	0.0004*	0.0011***	0.0011***	0.0007**	0.0007**	0.0010***	0.0010***
ΔNom Rates$_{t-4}$			0.0008***	0.0008***	0.0010***	0.0010***	0.0013***	0.0013***
ΔNom Rates$_{t-5}$			0.0016***	0.0016***	0.0014***	0.0014***	0.0016***	0.0016***
ΔNom Rates$_{t-6}$			-0.0006*	-0.0006**	-0.0008**	-0.0008**	-0.0002	-0.0002
ΔNom Rates$_{t-7}$					-0.0003	-0.0003	-0.0006*	-0.0005*
ΔNom Rates$_{t-8}$					-0.0002	-0.0002	-0.0004*	-0.0004*
ΔNom Rates$_{t-9}$					-0.0009***	-0.0009***	-0.0005	-0.0005
ΔNom Rates$_{t-10}$							-0.0009***	-0.0009***
ΔNom Rates$_{t-11}$							0.0002	0.0003
ΔNom Rates$_{t-12}$							0.0000	0.0000
Constant	0.0037***	0.0051***	0.0037***	0.0054***	0.0061***	0.0068***	0.0087***	0.0089***
Obs	9,152	9,152	9,020	9,020	8,888	8,888	8,756	8,756
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	32874	32888	32793	32805	32680	32690	32680	32689
Hausman test	3.44		**Invalid**		**Invalid**		**Invalid**	
p-value	0.0637							

Note: Real Rates are represented by the 5-year TIPs, "Nom Rates" are nominal rates represented by 5-year Treasuries.

Panel C Model C (Sample Period is 1999 Jan - 2016 Aug)

	Model C1		Model C2		Model C3		Model C4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates$_{t-1}$	0.1830***	0.1341**	0.1977***	-0.0155	0.0908*	0.544	-0.1044***	-0.0367
Nom Rates$_{t-1}$	-0.0048	0.0328	-0.0144	-0.2786	0.0042	-0.7126	0.0270***	-0.037
Short-run variables								
Error Correction	-0.0023***	-0.0033***	-0.0022***	-0.0032***	-0.0035***	-0.0039***	-0.0042***	-0.0043***
$\Delta R/P_{t-1}$	0.5966***	0.5909***	0.5828***	0.5790***	0.5898***	0.5863***	0.6024***	0.5989***
$\Delta R/P_{t-2}$	0.1179***	0.1158***	0.0954***	0.0935***	0.0700***	0.0685***	0.0598***	0.0584***
$\Delta R/P_{t-3}$	0.1261***	0.1228***	0.0759***	0.0758***	0.0773***	0.0768***	0.0771***	0.0771***
$\Delta R/P_{t-4}$			0.0594***	0.0583***	0.0549***	0.0543***	0.0553***	0.0559***
$\Delta R/P_{t-5}$			0.1490***	0.1483***	0.1276***	0.1269***	0.1237***	0.1225***
$\Delta R/P_{t-6}$			-0.0965***	-0.0974***	-0.1826***	-0.1823***	-0.1725***	-0.1733***
$\Delta R/P_{t-7}$					0.1244***	0.1237***	0.1275***	0.1270***
$\Delta R/P_{t-8}$					0.0127	0.0123	0.0121	0.0113
$\Delta R/P_{t-9}$					0.0185	0.0185	0.0263**	0.0253*
$\Delta R/P_{t-10}$							0.0155	0.016
$\Delta R/P_{t-11}$							-0.0003	0.0006
$\Delta R/P_{t-12}$							-0.0145	-0.0148
ΔReal Rates$_{t-1}$	-0.0024***	-0.0023***	-0.0025***	-0.0023***	-0.0027***	-0.0027***	-0.0019***	-0.0019***
ΔReal Rates$_{t-2}$	-0.0013***	-0.0013***	-0.0014***	-0.0013***	-0.0013***	-0.0013***	-0.0007**	-0.0007*
ΔReal Rates$_{t-3}$	-0.0009**	-0.0009**	-0.0012***	-0.0011***	-0.0011***	-0.0011***	-0.0004	-0.0004
ΔReal Rates$_{t-4}$			-0.0016***	-0.0015***	-0.0019***	-0.0019***	-0.0011***	-0.0010**
ΔReal Rates$_{t-5}$			-0.0008**	-0.0008**	-0.0010***	-0.0010***	-0.0002	-0.0002
ΔReal Rates$_{t-6}$			0.0017***	0.0018***	0.0012***	0.0012***	0.0022***	0.0022***
ΔReal Rates$_{t-7}$					0.0006	0.0006	0.0015***	0.0015***
ΔReal Rates$_{t-8}$					0.0018***	0.0018***	0.0023***	0.0023***
ΔReal Rates$_{t-9}$					-0.0004	-0.0004	0.0007*	0.0007*
ΔReal Rates$_{t-10}$							0.0020***	0.0019***
ΔReal Rates$_{t-11}$							0.0013***	0.0013***
ΔReal Rates$_{t-12}$							0.0025***	0.0025***
ΔNom Rates$_{t-1}$	-0.0002	-0.0001	-0.0002	-0.0002	0.0001	0.0001	0.0001	0.0001
ΔNom Rates$_{t-2}$	0.0010***	0.0010***	0.0015***	0.0014***	0.0014***	0.0014***	0.0012***	0.0012***
ΔNom Rates$_{t-3}$	0.0004	0.0004	0.0011***	0.0011***	0.0007**	0.0007**	0.0010***	0.0010***
ΔNom Rates$_{t-4}$			0.0008***	0.0008***	0.0010***	0.0010***	0.0012***	0.0013***
ΔNom Rates$_{t-5}$			0.0016***	0.0015***	0.0014***	0.0014***	0.0016***	0.0016***
ΔNom Rates$_{t-6}$			-0.0005*	-0.0006**	-0.0008**	-0.0008**	-0.0002	-0.0003
ΔNom Rates$_{t-7}$					-0.0003	-0.0004	-0.0005*	-0.0006*
ΔNom Rates$_{t-8}$					-0.0002	-0.0002	-0.0004*	-0.0004**
ΔNom Rates$_{t-9}$					-0.0009***	-0.0009**	-0.0005	-0.0005
ΔNom Rates$_{t-10}$							-0.0009***	-0.0009***
ΔNom Rates$_{t-11}$							0.0002	0.0003
ΔNom Rates$_{t-12}$							-0.0001	0
Constant	0.0037***	0.0057***	0.0037***	0.0058***	0.0062***	0.0070***	0.0083***	0.0089***
Obs	9,152	9,152	9,020	9,020	8,888	8,888	8,756	8,756
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	32874	32906	32794	32817	32680	32700	32683	32704
Hausman test p-value	**Invalid**		**Invalid**		**Invalid**		**Invalid**	

Panel D Summary Statistics of Sum of Short-run Coefficients from Model A

		Error Correction coefficient		Sum of Δ*R/P*		Sum of Δ5Y		Constant	
PMGs									
		Max	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**
Whole period (1999-2016)	**3 lags**	0.0005	-0.0035	0.9612	0.3299	0.0002	-0.0137	0.0030	-0.0012
	6 lags	0.0013	-0.0033	0.9566	0.2262	0.0034	-0.0197	0.0030	-0.0013
	9 lags	-0.0006	-0.0044	0.9721	0.1995	0.0096	-0.0272	0.0045	-0.0009
	12 lags	-0.0002	-0.0054	0.9885	0.1942	0.0274	-0.0249	0.0080	-0.0001
Sub-period (1999-2006)	**3 lags**	0.0010	-0.0034	0.9552	0.2496	0.0080	-0.0188	0.0007	-0.0028
	6 lags	0.0030	-0.0039	1.1259	0.0972	0.0233	-0.0223	0.0014	-0.0027
	9 lags	0.0031	-0.0048	1.2014	-0.2747	0.0192	-0.0632	0.0025	-0.0057
	12 lags	0.0045	-0.0050	1.1591	-0.7572	0.0198	-0.0699	0.0020	-0.0084
Sub-period (2009-2016)	**3 lags**	0.0047	-0.0281	0.9204	0.2588	0.0056	-0.0198	0.0594	-0.0119
	6 lags	0.0119	-0.0446	1.0649	0.3284	0.0186	-0.0393	0.0893	-0.0175
	9 lags	0.0125	-0.0771	1.1756	0.2261	0.0536	-0.0820	0.1449	-0.0182
	12 lags	0.0011	-0.1194	1.1741	-0.0046	0.0770	-0.1247	0.2293	-0.0023
MGs									
Whole period (1999-2016)	**3 lags**	0.0004	-0.0083	0.9621	-0.0096	0.0022	-0.0144	0.0142	-0.0035
	6 lags	0.0003	-0.0089	0.9572	-0.0110	0.0052	-0.0240	0.0159	-0.0032
	9 lags	0.0003	-0.0087	0.9717	-0.0080	0.0073	-0.0401	0.0149	-0.0051
	12 lags	0.0000	-0.0125	0.9885	-0.0019	0.0267	-0.0254	0.0221	-0.0043
Sub-period (2009-2016)	**3 lags**	0.0083	-0.0324	0.9675	-0.0188	0.0715	-0.0193	0.0706	-0.0345

Note: The selected MGs outperform corresponding PMGs, according to Hausman test.

Table 2 PMG & MG Estimation for Rent-To-Price Ratio For Chinese Markets

Panel A Model A (Sample Period is 2009 Jan - 2016 Aug)

	Model A1		**Model A2**		**Model A3**		**Model A4**	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Nom Rates$_{t-1}$	0.4802***	0.5791**	0.5312***	0.7814**	0.5958***	0.4104***	0.6545***	0.5607***
Short-run variables								
Error Correction	-0.0750***	-0.0962***	-0.0779***	-0.0957***	-0.0877***	-0.1039***	-0.0962***	-0.1169***
$\Delta R/P_{t-1}$	-0.1974***	-0.1900***	-0.1853***	-0.1833***	-0.1739***	-0.1769***	-0.1851***	-0.1858***
$\Delta R/P_{t-2}$	-0.0701***	-0.0672***	-0.0736***	-0.0743***	-0.0644***	-0.0690***	-0.0591***	-0.0634***
$\Delta R/P_{t-3}$	-0.0303*	-0.0292*	-0.0550***	-0.0551***	-0.0632***	-0.0673***	-0.0436***	-0.0475***
$\Delta R/P_{t-4}$			-0.0189	-0.0181	-0.0217	-0.0262	-0.0342*	-0.0402**
$\Delta R/P_{t-5}$			0.0241	0.0241	0.0117	0.0076	0.0008	-0.0039
$\Delta R/P_{t-6}$			0.0115	0.0107	0.0062	0.0033	-0.0058	-0.0092
$\Delta R/P_{t-7}$					0.0182	0.0174	0.0095	0.008
$\Delta R/P_{t-8}$					0.0089	0.0082	-0.0017	-0.004
$\Delta R/P_{t-9}$					0.0186	0.0166	0.004	0.0034
$\Delta R/P_{t-10}$							0.0209	0.0224
$\Delta R/P_{t-11}$							0.0238*	0.0256*
$\Delta R/P_{t-12}$							0.0521***	0.0532***
ΔNom Rates$_{t-1}$	-0.0490***	-0.0458***	-0.0541***	-0.0538***	-0.0683***	-0.0714***	-0.0640***	-0.0698***
ΔNom Rates$_{t-2}$	-0.0786***	-0.0751***	-0.0815***	-0.0824***	-0.0925***	-0.0973***	-0.0932***	-0.0998***
ΔNom Rates$_{t-3}$	-0.0678***	-0.0657***	-0.0661***	-0.0672***	-0.0701***	-0.0756***	-0.0762***	-0.0833***
ΔNom Rates$_{t-4}$			-0.0491***	-0.0500***	-0.0530***	-0.0587***	-0.0568***	-0.0652***
ΔNom Rates$_{t-5}$			0.0034	0.0023	-0.006	-0.0116	-0.0212**	-0.0301**
ΔNom Rates$_{t-6}$			-0.0265*	-0.0271*	-0.0369***	-0.0417***	-0.0529***	-0.0607***
ΔNom Rates$_{t-7}$					-0.0310**	-0.0352***	-0.0285**	-0.0359***
ΔNom Rates$_{t-8}$					-0.0571***	-0.0601***	-0.0659***	-0.0721***
ΔNom Rates$_{t-9}$					-0.0048	-0.0095	-0.0219**	-0.0288***
ΔNom Rates$_{t-10}$							-0.0183**	-0.0240***
ΔNom Rates$_{t-11}$							-0.0257***	-0.0304***
ΔNom Rates$_{t-12}$							0.0034	-0.0012
Constant	0.1268***	0.2210***	0.1174***	0.1747***	0.1142***	0.1444***	0.1125***	0.1460***
Obs	7,032	7,032	6,790	6,790	6,550	6,550	6,310	6,310
No. of groups	80	80	80	80	80	80	80	80
Log likelihood	6252	6308	6982	7045	7583	7647	8110	8184
Hausman test	0.16		0.49		1.5		0.84	
p-value	0.6905		0.4834		0.2202		0.3585	

Panel B Summary Statistics of Coefficients from PMG for Individual Cities

PMG		**3 lags**	**6 lags**	**9 lags**	**12 lags**
Error Correction coefficient	**Max**	-0.0067	-0.0057	-0.0003	-0.0040
	Min	-0.3911	-0.3216	-0.2494	-0.3771
Sum of $\Delta R/P_t$	**Max**	0.4877	0.6000	0.9948	1.7170
	Min	-1.5341	-2.6669	-3.4056	-3.1771
Sum of Δ5Y	**Max**	0.2034	0.2642	0.2064	0.5381
	Min	-0.5922	-1.3790	-1.7749	-2.7572
Constant	**Max**	0.8208	0.4776	0.4759	0.5488
	Min	-0.0065	-0.0136	-0.0282	-0.0689

Table 3 Sum of Short-run Coefficients for Individual US MSAs from PMG/MG Estimation with Model A

Panel A Coastal & Inland MSAs

		PMG				MG			
		Error Correction coefficient	**Sum of Δ*R/P***	**Sum of ΔTIPS_5Y**	**Constant**	**Error Correction coefficient**	**Sum of Δ*R/P***	**Sum of ΔTIPS_5Y**	**Constant**
Whole Sample Period 1999 Jan - 2016 Aug									
3 lags	Inland	-0.0009	0.7205	-0.0042	0.0005	-0.0019	0.8055	-0.0040	0.0016
	Coastal	-0.0019	0.9052	-0.0057	0.0009	-0.0027	0.8366	-0.0052	0.0025
	Total	-0.0015	0.8422	-0.0052	0.0007	-0.0024	0.8260	-0.0048	0.0022
6 lags	Inland	-0.0012	0.7537	-0.0072	0.0008	-0.0020	0.8278	-0.0082	0.0009
	Coastal	-0.0019	0.9175	-0.0055	0.0007	-0.0026	0.8539	-0.0043	0.0024
	Total	-0.0017	0.8616	-0.0061	0.0007	-0.0024	0.8450	-0.0057	0.0019
9 lags	Inland	-0.0020	0.7945	-0.0123	0.0015	-0.0026	0.8548	-0.0127	0.0012
	Coastal	-0.0026	0.9408	-0.0073	0.0016	-0.0032	0.8839	-0.0068	0.0031
	Total	-0.0024	0.8909	-0.0090	0.0016	-0.0030	0.8740	-0.0088	0.0025
12 lags	Inland	-0.0026	0.8175	-0.0028	0.0035	-0.0031	0.8701	-0.0016	0.0033
	Coastal	-0.0030	0.9495	0.0031	0.0038	-0.0036	0.8972	0.0021	0.0047
	Total	-0.0028	0.9045	0.0011	0.0037	-0.0034	0.8880	0.0008	0.0042
Subsample Periods									
		1999 Jan - 2006 Dec				**2009 Jan - 2016 Aug**			
3 lags	Inland	-0.0010	0.5235	-0.0039	-0.0011	-0.0095	0.6361	-0.0019	0.0189
	Coastal	-0.0019	0.8311	-0.0049	-0.0013	-0.0135	0.7389	-0.0014	0.0207
	Total	-0.0016	0.7263	-0.0046	-0.0012	-0.0121	0.7038	-0.0016	0.0201
6 lags	Inland	-0.0009	0.5078	-0.0056	-0.0008	-0.0120	0.7034	-0.0097	0.0236
	Coastal	-0.0022	0.8679	-0.0059	-0.0009	-0.0142	0.7623	-0.0055	0.0249
	Total	-0.0018	0.7451	-0.0058	-0.0009	-0.0134	0.7422	-0.0069	0.0245
9 lags	Inland	-0.0009	0.5124	-0.0089	-0.0010	-0.0201	0.7488	-0.0229	0.0377
	Coastal	-0.0028	0.8726	-0.0257	-0.0016	-0.0181	0.7864	-0.0064	0.0304
	Total	-0.0021	0.7498	-0.0199	-0.0014	-0.0188	0.7736	-0.0120	0.0329
12 lags	Inland	-0.0008	0.4085	-0.0102	-0.0011	-0.0256	0.7609	-0.0196	0.0481
	Coastal	-0.0025	0.8497	-0.0257	-0.0019	-0.0175	0.7812	0.0062	0.0308
	Total	-0.0019	0.6993	-0.0204	-0.0017	-0.0203	0.7743	-0.0026	0.0367

Note: For subsample period 2009 Jan - 2016 Aug, coefficients of MG instead of PMG is presented here, since MG outperform PMG in this case.

Panel B 24 MSAs by Supply Elasticity (Saiz, 2010)

		PMG				MG			
		Error Correction coefficient	**Sum of Δ*R/P***	**Sum of ΔTIPS_5Y**	**Constant**	**Error Correction coefficient**	**Sum of Δ*R/P***	**Sum of ΔTIPS_5Y**	**Constant**
Whole Sample Period 1999 Jan - 2016 Aug									
3 lags	Low	-0.0020	0.8893	-0.0074	0.0011	-0.0025	0.7712	-0.0058	0.0027
	High	-0.0012	0.7715	-0.0041	0.0002	-0.0021	0.8337	-0.0032	0.0029
	Total	-0.0017	0.8500	-0.0063	0.0008	-0.0023	0.7920	-0.0049	0.0027
6 lags	Low	-0.0020	0.9055	-0.0066	0.0010	-0.0026	0.7972	-0.0063	0.0026
	High	-0.0014	0.7965	-0.0061	0.0004	-0.0024	0.8774	-0.0080	0.0022
	Total	-0.0018	0.8692	-0.0065	0.0008	-0.0025	0.8240	-0.0069	0.0024
9 lags	Low	-0.0025	0.9291	-0.0070	0.0019	-0.0032	0.8267	-0.0109	0.0030
	High	-0.0023	0.8474	-0.0109	0.0012	-0.0030	0.9117	-0.0150	0.0022
	Total	-0.0025	0.9019	-0.0083	0.0017	-0.0031	0.8550	-0.0123	0.0028
12 lags	Low	-0.0027	0.9349	0.0046	0.0038	-0.0036	0.8469	-0.0024	0.0046
	High	-0.0031	0.8708	-0.0018	0.0035	-0.0035	0.9293	-0.0037	0.0044
	Total	-0.0028	0.9135	0.0025	0.0037	-0.0036	0.8744	-0.0028	0.0045
Subsample Periods									
		1999 Jan - 2006 Dec				**2009 Jan - 2016 Aug**			
3 lags	Low	-0.0020	0.7766	-0.0066	-0.0012	-0.0115	0.6753	0.0007	0.0190
	High	-0.0012	0.5762	-0.0034	-0.0015	-0.0099	0.6182	-0.0003	0.0218
	Total	-0.0017	0.7098	-0.0056	-0.0013	-0.0109	0.6563	0.0004	0.0200
6 lags	Low	-0.0022	0.8083	-0.0080	-0.0009	-0.0129	0.8230	-0.0043	0.0241
	High	-0.0010	0.5428	-0.0051	-0.0012	-0.0111	0.7208	-0.0076	0.0206
	Total	-0.0018	0.7198	-0.0070	-0.0010	-0.0123	0.7889	-0.0054	0.0229
9 lags	Low	-0.0026	0.8061	-0.0272	-0.0018	-0.0162	0.8553	-0.0002	0.0301
	High	-0.0011	0.5506	-0.0126	-0.0011	-0.0206	0.8023	-0.0186	0.0356
	Total	-0.0021	0.7210	-0.0223	-0.0016	-0.0177	0.8376	-0.0063	0.0319
12 lags	Low	-0.0023	0.7887	-0.0261	-0.0019	-0.0175	0.8473	0.0111	0.0335
	High	-0.0010	0.4367	-0.0127	-0.0011	-0.0271	0.8409	-0.0193	0.0486
	Total	-0.0019	0.6713	-0.0216	-0.0016	-0.0207	0.8451	0.0010	0.0385

Note: For subsample period 2009 Jan - 2016 Aug, coefficients of MG instead of PMG is presented here, since MG outperform PMG in this case.

Panel C Regression of Sum of Coefficients of Changes in Rent-to-price Ratio on Supply Elasticities

		Sum of All Coefficients			Sum of Significant Coefficients		
		Supply Elasticity	**Constant**	**R-squared**	**Supply Elasticity**	**Constant**	**R-squared**
PMG Estimation							
Whole period 1999-2016	**3 lags**	-0.1086***	0.9967***	0.397	-0.1263***	0.9934***	0.438
	6 lags	-0.0996***	1.0036***	0.423	-0.0942*	0.9305***	0.171
	9 lags	-0.0755***	1.0038***	0.427	-0.1187**	0.9323***	0.283
	12 lags	-0.0602**	0.9947***	0.295	-0.1565**	1.0634***	0.214
1999-2006	**3 lags**	-0.1884***	0.9642***	0.462	-0.1574***	0.8962***	0.254
	6 lags	-0.2416***	1.0461***	0.439	-0.1328	0.8238***	0.118
	9 lags	-0.2523**	1.0616***	0.312	-0.3324**	1.0857***	0.329
	12 lags	-0.3662**	1.1658***	0.272	-0.3770***	1.1580***	0.334
2009-2016	**3 lags**	-0.0878***	0.8838***	0.256	-0.1291**	0.9177***	0.185
	6 lags	-0.0632	0.8742***	0.080	-0.0861	0.8737***	0.046
	9 lags	-0.0210	0.8660***	0.008	-0.0758	0.8724***	0.089
	12 lags	0.02700	0.8087***	0.008	-0.0483	0.7917***	0.027
MG Estimation							
Whole period 1999-2016	**3 lags**	0.0536	0.7197***	0.031	0.0223	0.7283***	0.005
	6 lags	0.0627	0.7394***	0.044	0.0346	0.7088***	0.011
	9 lags	0.0627	0.7704***	0.043	0.0122	0.6842***	0.002
	12 lags	0.0617	0.7911***	0.042	0.0497	0.6320***	0.025
2009-2016	**3 lags**	-0.0607	0.7382***	0.037	0.0040	0.5923***	0.000

Table 4 Sum of Short-run Coefficients for Individual Chinese Cities from PMG Estimation

Panel A By Tiers

PMG		Error Correction Coefficient	Sum of Δ*R/P*	Sum of Δ5Y	Constant
3 lags	Tier 1	-0.0247	0.1431	-0.1017	0.0100
	Tier 2	-0.0643	-0.1083	-0.1817	0.1143
	Others	-0.0896	-0.5123	-0.2172	0.1497
	Total	-0.0750	-0.2977	-0.1954	0.1268
6 lags	Tier 1	-0.0398	0.0591	-0.1609	0.0138
	Tier 2	-0.0648	0.0119	-0.2002	0.1041
	Others	-0.0934	-0.6110	-0.3513	0.1397
	Total	-0.0779	-0.2972	-0.2738	0.1174
9 lags	Tier 1	-0.0403	0.0789	-0.1822	0.0088
	Tier 2	-0.0752	-0.0031	-0.3382	0.1039
	Others	-0.1037	-0.5245	-0.5172	0.1340
	Total	-0.0877	-0.2597	-0.4199	0.1142
12 lags	Tier 1	-0.0294	0.0810	-0.0812	-0.0002
	Tier 2	-0.0878	0.1646	-0.4607	0.1086
	Others	-0.1105	-0.5928	-0.6200	0.1274
	Total	-0.0962	-0.2183	-0.5214	0.1125

Panel B By Coastal versus Inland

PMG		Error Correction Coefficient	Sum of Δ*R/P*	Sum of Δ5Y	Constant
3 lags	Inland	-0.0783	-0.3226	-0.2033	0.1370
	Coastal	-0.0668	-0.2361	-0.1760	0.1015
	Total	-0.0750	-0.2977	-0.1954	0.1268
6 lags	Inland	-0.0836	-0.3201	-0.3094	0.1291
	Coastal	-0.0637	-0.2405	-0.1855	0.0886
	Total	-0.0779	-0.2972	-0.2738	0.1174
9 lags	Inland	-0.0917	-0.2715	-0.4483	0.1227
	Coastal	-0.0776	-0.2302	-0.3494	0.0931
	Total	-0.0877	-0.2597	-0.4199	0.1142
12 lags	Inland	-0.1027	-0.1908	-0.5665	0.1239
	Coastal	-0.0801	-0.2864	-0.4095	0.0844
	Total	-0.0962	-0.2183	-0.5214	0.1125

Panel C By Regions & Tier-1

PMG		Error Correction coefficient	Sum of $\Delta R/P$	Sum of $\Delta 5Y$	Constant
3 lags	Tier 1	-0.0247	0.1431	-0.1017	0.0100
	Eastern	-0.0640	-0.3054	-0.1770	0.0877
	Central	-0.0967	-0.3890	-0.1920	0.1892
	Western	-0.0935	-0.2764	-0.2835	0.1957
	Total	-0.0750	-0.2977	-0.1954	0.1268
6 lags	Tier 1	-0.0398	0.0591	-0.1609	0.0138
	Eastern	-0.0688	-0.2874	-0.2293	0.0847
	Central	-0.0999	-0.3907	-0.3642	0.1760
	Western	-0.0867	-0.3024	-0.3201	0.1681
	Total	-0.0779	-0.2972	-0.2738	0.1174
9 lags	Tier 1	-0.0403	0.0789	-0.1822	0.0088
	Eastern	-0.0813	-0.3003	-0.3851	0.0824
	Central	-0.1085	-0.1616	-0.5247	0.1682
	Western	-0.0926	-0.3647	-0.4523	0.1687
	Total	-0.0877	-0.2597	-0.4199	0.1142
12 lags	Tier 1	-0.0294	0.0810	-0.0812	-0.0002
	Eastern	-0.0849	-0.2801	-0.4255	0.0766
	Central	-0.1250	-0.1686	-0.7309	0.1724
	Western	-0.1110	-0.1816	-0.6572	0.1739
	Total	-0.0962	-0.2183	-0.5214	0.1125

Panel D 35 Chinese Cities by Area & Tier-1 (Wang et al. 2008)

PMG		Error Correction coefficient	Sum of $\Delta R/P$	Sum of $\Delta 5Y$	Constant
3 lags	Tier-1	-0.0247	0.1431	-0.1017	0.0100
	Eastern	-0.0468	-0.0079	-0.1530	0.0400
	Northern	-0.0495	-0.1408	-0.2178	0.1011
	Middle Southern	-0.0614	0.0164	-0.1377	0.1158
	Western	-0.0721	-0.3058	-0.2578	0.1626
	Total	-0.0543	-0.0928	-0.1859	0.0972
6 lags	Tier-1	-0.0398	0.0591	-0.1609	0.0138
	Eastern	-0.0529	0.0515	-0.2054	0.0400
	Northern	-0.0479	0.0721	-0.1999	0.0910
	Middle Southern	-0.0684	0.3107	-0.2384	0.1221
	Western	-0.0635	-0.3675	-0.2759	0.1360
	Total	-0.0561	0.0011	-0.2238	0.0898
9 lags	Tier-1	-0.0403	0.0789	-0.1822	0.0088
	Eastern	-0.0656	0.0599	-0.2831	0.0378
	Northern	-0.0398	-0.0356	-0.2353	0.0689
	Middle Southern	-0.0876	0.3893	-0.3992	0.1368
	Western	-0.0844	-0.3552	-0.4735	0.1616
	Total	-0.0660	-0.0006	-0.3328	0.0932
12 lags	Tier-1 1	-0.0294	0.0810	-0.0812	-0.0002
	Eastern	-0.0483	0.0733	-0.1837	0.0194
	Northern	-0.0563	0.1238	-0.3617	0.0887
	Middle Southern	-0.1052	0.5330	-0.5679	0.1406
	Western	-0.1046	-0.0140	-0.6253	0.1740
	Total	-0.0738	0.1552	-0.4031	0.0970

Panel E By Supply-to-Demand Ratio for (2011 – 2014) (Wu et al., 2016)

PMG		Error Correction coefficient	Sum of Δ*R/P*	Sum of Δ5Y	Constant
3 lags	Undersupplied	-0.0415	0.0283	-0.1238	0.0385
	Oversupplied	-0.0594	-0.1412	-0.2107	0.1207
	Total	-0.0543	-0.0928	-0.1859	0.0972
6 lags	Undersupplied	-0.0484	0.1001	-0.1817	0.0356
	Oversupplied	-0.0592	-0.0384	-0.2407	0.1114
	Total	-0.0561	0.0011	-0.2238	0.0898
9 lags	Undersupplied	-0.0529	0.1409	-0.2342	0.0298
	Oversupplied	-0.0713	-0.0572	-0.3723	0.1186
	Total	-0.0660	-0.0006	-0.3328	0.0932
12 lags	Undersupplied	-0.0437	0.1532	-0.1861	0.0188
	Oversupplied	-0.0858	0.1560	-0.4899	0.1283
	Total	-0.0738	0.1552	-0.4031	0.0970

Panel F By Supply Elasticity (Wang et al., 2016)

PMG		Error Correction coefficient	Sum of Δ*R/P*	Sum of Δ5Y	Constant
3 lags	Low	-0.0437	0.0024	-0.1611	0.0626
	High	-0.0702	-0.2355	-0.2230	0.1492
	Total	-0.0543	-0.0928	-0.1859	0.0972
3 lags	Low	-0.0503	0.1481	-0.2062	0.0640
	High	-0.0648	-0.2193	-0.2502	0.1284
	Total	-0.0561	0.0011	-0.2238	0.0898
9 lags	Low	-0.0587	0.1555	-0.2859	0.0635
	High	-0.0771	-0.2349	-0.4032	0.1378
	Total	-0.0660	-0.0006	-0.3328	0.0932
12 lags	Low	-0.0568	0.1457	-0.2846	0.0583
	High	-0.0993	0.1695	-0.5808	0.1551
	Total	-0.0738	0.1552	-0.4031	0.0970

Panel G Regression of Sum of Coefficients of Changes in Rent-to-price Ratio on Supply Elasticities

	Sum of All Coefficients			Sum of Significant Coefficients		
PMG	**Supply Elasticity**	**Constant**	**R-squared**	**Supply Elasticity**	**Constant**	**R-squared**
3 lags	-0.0219***	0.0746	0.207	-0.0225**	0.0457	0.236
6 lags	-0.0543***	0.4172***	0.431	-0.0566***	0.3840***	0.440
9 lags	-0.0610**	0.4667***	0.429	-0.0485*	0.3613*	0.382
12 lags	-0.0345*	0.4195***	0.202	-0.0340*	0.4008***	0.246

Table 5 Sum of Significant Coefficients of Residual Autoregression Estimation

Panel A US MSAs

	PMG — 3 lags			PMG — 6 lags			PMG — 9 lags			PMG — 12 lags		
	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)
Whole Sample	-0.0998	0.0481	0.1399	-0.1253	-0.0636	0.0167	0.0520	-0.0413	-0.0789	0.0060	-0.0512	-0.0779
Pre-Crisis Period	-0.1484	0.1026	0.2663	-0.1849	0.0020	0.1407	-0.0082	0.0171	0.0553	-0.0115	0.0054	-0.0520
Post-Crisis Period	-0.0906	-0.0810	-0.0911	-0.1478	-0.1426	-0.0993	0.0670	-0.0453	-0.1131	-0.0425	-0.1532	-0.2776
Coastal	-0.0488	-0.0130	0.0081	-0.0969	-0.0273	-0.0140	0.0833	-0.0090	-0.1082	0.0082	-0.0580	-0.0990
Inland	-0.1084	0.0955	0.2812	-0.1253	-0.0706	0.1090		-0.1035	-0.0114		-0.0809	0.0593
High Supply Elasticity	-0.0970	0.0115	0.1285	-0.1035	-0.0656	0.0339		-0.1202	-0.1158		-0.0599	-0.0171
Low Supply Elasticity	0.0456	0.0818	0.0169	-0.0836	0.0095	0.0664	0.0563	0.0888	-0.0539	0.0436	0.0484	-0.0416
Bubble (high momentum) MSA	0.0595	0.1281	0.1255	-0.0579	0.0751	0.1161	0.1132	0.1180	0.0685	0.0189	0.0123	-0.0346
Non-Bubble (low momentum) MSA	-0.2056	0.0582	0.2967	-0.1781	-0.2060	-0.0291		-0.1343	-0.0606		-0.0912	-0.0564

Panel B ***Chinese Cities***

	PMG — 3 lags			PMG — 6 lags			PMG — 9 lags			PMG — 12 lags		
	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)	AR(6)	AR(12)	AR(18)
All Cities	0.4819	0.7508	0.7107	0.2824	0.4793	0.5192	0.3097	0.5331	0.6120	0.6683	0.7953	0.7752
Coastal	0.7729	**0.8572**	**0.8190**	0.4377	0.6658	0.7096	0.4802	**0.8014**	0.7101	**0.8726**	**0.9019**	0.6753
Inland		-0.0324	0.1433		0.0814	0.0852	-0.0034	-0.0028	0.0109		-0.0047	0.1016
High Supply Elasticity	-0.0877	0.0773	0.1318		0.1067	0.1010	0.0662	0.1500	0.0423		-0.1261	-0.0071
Low Supply Elasticity	0.0680	0.1315	0.1745		0.0035	-0.0884		-0.0592	-0.1900		-0.0609	-0.1455
Tier 1	0.0933	0.1977	0.2030	0.0984	0.3826	0.1742					-0.1340	-0.1394
Tier 2		0.2122	0.1583	-0.0502	0.1913	0.1197		0.1460	0.0204			
Others	0.5867	0.8126	0.8430	0.3449	0.4644	0.5488	0.3670	0.6535	0.7052	0.7678	0.7872	**0.8278**
Tier 1	0.0933	0.1977	0.2030	0.0984	0.3826	0.1742					-0.1340	-0.1394
Eastern	0.7047	**0.8429**	0.7348	0.4535	0.5474	0.5203	0.5634	0.6836	0.7073	**0.8268**	**0.9101**	0.7337
Central		0.0716	0.1882	-0.1136	0.1232	0.2198	-0.0740	-0.0877	0.0195	0.0707	0.0974	0.2984
Western	0.1228	0.1367	0.0954	-0.0714	0.0726	0.0973	0.0152	-0.0817	-0.0656	-0.0682	-0.1153	-0.2050
Tier-1	0.0933	0.1977	0.2030	0.0984	0.3826	0.1742					-0.1340	-0.1394
Eastern	0.0884	0.2813	0.3057	0.0840	0.0074	0.1251		0.1589	0.1782			
Middle Southern	0.0747	0.0709	0.0292	-0.0877				0.0780	-0.0034		-0.0809	
Northern		0.0995			0.0865			-0.1074	0.1018			
Western	-0.0284	0.1092	0.0777		0.1921	0.1800		-0.0740	-0.0740		-0.1794	-0.0401

Table 6 Explanatory Power of Various Models: Partial R^2s

Panel A US MSAs

	Overall	Low Supply Elasticity	High Supply Elasticity	Coastal	Inland	Bubble (high momentum) MSAs	Non-bubble MSAs
Subpanel A1: PMG with 3 lags in short run							
Long Run Partial R^2	0.1713	0.2368	0.1636	0.2175	0.0820	0.2386	0.1099
Short Run Partial R^2	0.8087	0.8819	0.7906	0.8786	0.6737	0.8718	0.7512
PMG Model	0.6695	0.6575	0.7483	0.7669	0.4813	0.7629	0.5843
Residual Autoregression	0.0367	0.0421	0.0342	0.0298	0.0500	0.0416	0.0323
Total = PMG + Residual	**0.7062**	**0.6996**	**0.7825**	**0.7967**	**0.5313**	**0.8044**	**0.6165**
Subpanel A2: PMG with 6 lags in short run							
Long Run Partial R^2	0.2131	0.2652	0.2102	0.2632	0.1162	0.2741	0.1573
Short Run Partial R^2	0.8255	0.8946	0.8071	0.8896	0.7014	0.8832	0.7727
PMG Model	0.6833	0.6718	0.7579	0.7725	0.5109	0.7684	0.6056
Residual Autoregression	0.0293	0.0343	0.0287	0.0246	0.0385	0.0360	0.0233
Total = PMG + Residual	**0.7126**	**0.7060**	**0.7866**	**0.7971**	**0.5494**	**0.8043**	**0.6289**
Subpanel A3: PMG with 9 lags in short run							
Long Run Partial R^2	0.2709	0.3206	0.2656	0.3282	0.1602	0.3378	0.2098
Short Run Partial R^2	0.8421	0.9042	0.8286	0.9004	0.7294	0.8955	0.7933
PMG Model	0.6990	0.6866	0.7791	0.7812	0.5400	0.7773	0.6274
Residual Autoregression	0.0254	0.0302	0.0256	0.0219	0.0321	0.0331	0.0183
Total = PMG + Residual	**0.7243**	**0.7169**	**0.8047**	**0.8031**	**0.5720**	**0.8104**	**0.6458**
Subpanel A4: PMG with 12 lags in short run							
Long Run Partial R^2	0.2773	0.3448	0.2629	0.3459	0.1447	0.3617	0.2002
Short Run Partial R^2	0.8533	0.9148	0.8391	0.9099	0.7439	0.9071	0.8042
PMG Model	0.7009	0.6860	0.7809	0.7772	0.5534	0.7736	0.6346
Residual Autoregression	0.0244	0.0292	0.0247	0.0211	0.0308	0.0322	0.0174
Total = PMG + Residual	**0.7254**	**0.7153**	**0.8055**	**0.7984**	**0.5842**	**0.8058**	**0.6520**

Panel B Chinese Cities

	Overall	Low Supply Elasticity	High Supply Elasticity	Coastal	Inland	Tier 1	Tier 2	Others
Subpanel B1: PMG with 3 lags in short run								
Long Run Partial R^2	-0.0249	0.1206	-0.0014	0.0149	-0.0410	0.2515	0.0526	-0.1223
Short Run Partial R^2	0.4048	0.3810	0.3656	0.4260	0.3963	0.4139	0.3584	0.4458
PMG Model	0.4586	0.1682	0.1541	1.1443	0.1819	0.1658	0.1585	0.7579
Residual Autoregression	0.1518	0.0595	0.0374	0.4390	0.0359	0.1023	0.0439	0.2537
Total = PMG + Residual	**0.6104**	**0.2277**	**0.1915**	**1.5833**	**0.2178**	**0.2682**	**0.2025**	**1.0117**
Subpanel B2: PMG with 6 lags in short run								
Long Run Partial R^2	0.0635	0.0347	0.1350	0.1229	0.0042	0.3535	0.1147	-0.0115
Short Run Partial R^2	0.4946	0.4823	0.5251	0.4748	0.5143	0.5791	0.4783	0.5008
PMG Model	0.3057	0.2157	0.5286	0.3851	0.2262	0.2342	0.1940	0.4134
Residual Autoregression	0.0388	0.0188	0.0883	0.0647	0.0129	0.0859	0.0225	0.0487
Total = PMG + Residual	**0.3445**	**0.2345**	**0.6169**	**0.4498**	**0.2391**	**0.3201**	**0.2165**	**0.4621**
Subpanel B3: PMG with 9 lags in short run								
Long Run Partial R^2	0.2709	0.3206	0.2656	0.3282	0.2124	0.3777	0.2357	0.0684
Short Run Partial R^2	0.8421	0.9042	0.8286	0.9004	0.6124	0.6397	0.5501	0.5600
PMG Model	0.6990	0.6866	0.7791	0.7812	0.2483	0.2374	0.2126	0.4242
Residual Autoregression	0.0254	0.0302	0.0256	0.0219	0.0129	0.0784	0.0205	0.0549
Total = PMG + Residual	**0.7243**	**0.7169**	**0.8047**	**0.8031**	**0.2611**	**0.3158**	**0.2331**	**0.4791**
Subpanel B4: PMG with 12 lags in short run								
Long Run Partial R^2	0.3150	0.2347	0.3202	0.3062	0.1447	0.4444	0.3109	0.1944
Short Run Partial R^2	0.6243	0.6111	0.6744	0.6462	0.7439	0.7093	0.6188	0.6307
PMG Model	0.2228	0.2304	0.9046	0.6001	0.5534	0.2168	0.2332	0.6169
Residual Autoregression	0.0286	0.0183	0.3792	0.2312	0.0308	0.0768	0.0224	0.2162
Total = PMG + Residual	**0.2514**	**0.2486**	**1.2837**	**0.8313**	**0.5842**	**0.2936**	**0.2556**	**0.8331**

Panel B *Chinese Cities (Continued)*

	Eastern	Central	Western	Eastern	Middle Southern	Northern	Western
Subpanel B1: PMG with 3 lags in short run							
Long Run Partial R^2	0.0014	-0.1337	-0.0370	0.1516	0.1225	-0.0089	-0.0381
Short Run Partial R^2	0.4020	0.4476	0.3529	0.3773	0.3056	0.4121	0.3763
PMG Model	0.6884	0.2037	0.1826	0.1379	0.1319	0.1854	0.1838
Residual Autoregression	0.2446	0.0311	0.0445	0.0424	0.0443	0.0482	0.0413
Total = PMG + Residual	**0.9329**	**0.2348**	**0.2271**	**0.1804**	**0.1762**	**0.2337**	**0.2251**
Subpanel B2: PMG with 6 lags in short run							
Long Run Partial R^2	0.0896	-0.0345	0.0335	0.2313	0.2138	-0.0099	0.0270
Short Run Partial R^2	0.4829	0.5070	0.4894	0.4721	0.4802	0.4841	0.4812
PMG Model	0.3718	0.2214	0.2374	0.1736	0.1856	0.1812	0.2218
Residual Autoregression	0.0511	0.0157	0.0188	0.0256	0.0208	0.0283	0.0177
Total = PMG + Residual	**0.4230**	**0.2370**	**0.2562**	**0.1992**	**0.2065**	**0.2095**	**0.2395**
Subpanel B3: PMG with 9 lags in short run							
Long Run Partial R^2	0.1727	0.1038	0.1302	0.3426	0.3227	0.1585	0.1517
Short Run Partial R^2	0.5419	0.5773	0.5665	0.5495	0.5430	0.5519	0.5521
PMG Model	0.3930	0.2239	0.2479	0.1854	0.1948	0.1987	0.2369
Residual Autoregression	0.0571	0.0130	0.0167	0.0244	0.0199	0.0252	0.0148
Total = PMG + Residual	**0.4500**	**0.2369**	**0.2645**	**0.2099**	**0.2146**	**0.2239**	**0.2517**
Subpanel B4: PMG with 12 lags in short run							
Long Run Partial R^2	0.2768	0.1754	0.2666	0.3017	0.4525	0.1719	0.2881
Short Run Partial R^2	0.6377	0.6192	0.5943	0.6431	0.6330	0.6040	0.5833
PMG Model	0.5900	0.2174	0.2547	0.1997	0.1951	0.2289	0.2595
Residual Autoregression	0.2066	0.0174	0.0171	0.0256	0.0228	0.0270	0.0154
Total = PMG + Residual	**0.7967**	**0.2348**	**0.2718**	**0.2254**	**0.2179**	**0.2559**	**0.2749**

Appendix A: List of MSAs

MSA	Coastal	Supply Elasticity	MSA	Coastal	Supply Elasticity
Akron, OH	0	2.59	Mount Vernon-Anacortes, WA	1	
Ann Arbor, MI	0	2.29	Napa, CA	1	1.14
Atlanta-Sandy Springs-Roswell, GA	0	2.55	New Haven-Milford, CT	1	0.98
Atlantic City-Hammonton, NJ	1		New York-Newark-Jersey City, NY-NJ-PA	1	1.12
Baltimore-Columbia-Towson, MD	1	1.23	Olympia-Tumwater, WA	1	
Boston-Cambridge-Newton, MA-NH	1	0.86	Oxnard-Thousand Oaks-Ventura, CA	1	
Bremerton-Silverdale, WA	1		Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0	1.82
Bridgeport-Stamford-Norwalk, CT	1		Providence-Warwick, RI-MA	1	1.61
Chicago-Naperville-Elgin, IL-IN-WI	0	0.81	Reading, PA	0	
Cleveland-Elyria, OH	0	1.02	Riverside-San Bernardino-Ontario, CA	1	0.94
Dallas-Fort Worth-Arlington, TX	0	2.49	San Francisco-Oakland-Hayward, CA	1	0.68
Detroit-Warren-Dearborn, MI	0	1.24	San Jose-Sunnyvale-Santa Clara, CA	1	0.76
Flint, MI	0		Santa Cruz-Watsonville, CA	1	
Gainesville, FL	1		Santa Rosa, CA	1	
Houston-The Woodlands-Sugar Land, TX	0	2.3	Seattle-Tacoma-Bellevue, WA	1	1.045
Kankakee, IL	0		Sherman-Denison, TX	0	
Kingston, NY	1		Trenton, NJ	1	
Los Angeles-Long Beach-Anaheim, CA	1	0.63	Vallejo-Fairfield, CA	1	1.14
Manchester-Nashua, NH	1		Vineland-Bridgeton, NJ	1	
Miami-Fort Lauderdale-West Palm Beach, FL	1	0.69	Washington-Arlington-Alexandria, DC-VA-MD-WV	1	1.61
Michigan City-La Porte, IN	0		Winchester, VA-WV	1	
Monroe, LA	0		Worcester, MA-CT	1	0.86

Note: 1 Coastal (1) vs noncoastal (0). Definition: In a state that is on either the east coast or west coast=1.
2. Supply Elasticity is from Saiz (2010). By matching MSAs to Saiz (2010), when more than one match occur, we take average of the supply elasticity. For example, both "Dallas, TX"(with supply elasticity 2.18) and "Fort Worth–Arlington, TX"(2.8) in Saiz (2010) is matched to "Dallas-Fort Worth-Arlington, TX" in our sample, then the average supply elasticity is adopted.

Appendix B: List of Chinese Cities

City	Province	Tiers	Coastal	Supply Elasticity	City	Province	Tiers	Coastal	Supply Elasticity
Beijing	Beijing	Tier 1		0.53	Guangzhou	Guangdong	Tier 1	*	12.62
Shanghai	Shanghai	Tier 1	*	1.52	Shenzhen	Guangdong	Tier 1	*	0.49
Hefei	Anhui	Tier 2		13.03	Wuxi	Jiangsu	Tier 2		
Chongqing	Chongqing	Tier 2		4.51	Nanchang	Jiangxi	Tier 2		6.78
Xiamen	Fujian	Tier 2	*	3.47	Changchun	Jilin	Tier 2		5.4
Fuzhou	Fujian	Tier 2	*	3.85	Dalian	Liaoning	Tier 2	*	4.41
Lanzhou	Gansu	Tier 2		4.9	Shenyang	Liaoning	Tier 2		5.75
Beihai	Guangxi	Tier 2	*		Yinchuan	Ningxia	Tier 2		21.98
Nanning	Guangxi	Tier 2		11.45	Xining	Qinghai	Tier 2		37.05
Guiyang	Guizhou	Tier 2		9.71	Xian	Shaanxi	Tier 2		8.04
Haikou	Hainan	Tier 2	*	8.83	Qingdao	Shandong	Tier 2	*	2.89
Sanya	Hainan	Tier 2	*		Jinan	Shandong	Tier 2		2.68
Shijiazhuang	Hebei	Tier 2		7.89	Taiyuan	Shanxi	Tier 2		9.16
Harbin	Heilongjiang	Tier 2		6.3	Chengdu	Sichuan	Tier 2		4.36
Zhengzhou	Henan	Tier 2		16.5	Tianjin	Tianjin	Tier 2	*	5.1
Wuhan	Hubei	Tier 2		4.66	Urumqi	Xinjiang	Tier 2		16.71
Changsha	Hunan	Tier 2		17.14	Kunming	Yunnan	Tier 2		-7.7
Hohhot	Inner Mongolia	Tier 2		9.63	Ningbo	Zhejiang	Tier 2	*	2.27
Suzhou	Jiangsu	Tier 2			Wenzhou	Zhejiang	Tier 2	*	
Nanjing	Jiangsu	Tier 2		3.42	Hangzhou	Zhejiang	Tier 2		2.65
Bengbu	Anhui				Xuzhou	Jiangsu			
Anqing	Anhui				Changzhou	Jiangsu			
Tongling	Anhui				Yancheng	Jiangsu		*	
Wuhu	Anhui				Yangzhou	Jiangsu			
Quanzhou	Fujian		*		Ganzhou	Jiangxi			
Shantou	Guangdong		*		Jiujiang	Jiangxi			
Dongguan	Guangdong		*		Jilin	Jilin			
Foshan	Guangdong				Weifang	Shandong			
Huizhou	Guangdong				Yantai	Shandong		*	
Shaoguan	Guangdong				Weihai	Shandong		*	
Zhanjiang	Guangdong		*		Zibo	Shandong			
Zhuhai	Guangdong		*		Linyi	Shandong			
Qinhuangdao	Hebei		*		Rizhao	Shandong			
Tangshan	Hebei				Nanchong	Sichuan			
Baoding	Hebei				Mianyang	Sichuan			
Pingdingshan	Henan				Jinhua	Zhejiang			
Luoyang	Henan				Huzhou	Zhejiang			
Changde	Hunan				Jiaxing	Zhejiang			
Yueyang	Hunan				Shaoxing	Zhejiang			
Nantong	Jiangsu		*		Taizhou	Zhejiang			

Note: Supply Elasticity is from Wang et al. (2016)

List of Province by Regions

Eastern region (11 provinces): Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan;
Central region (8 provinces): Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan;
Western region (12 provinces): Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang.

Appendix C: Replication of Model A of Lai and Van Order (2016)

Panel C-1 Whole Sample Period (1999 Jan - 2016 Aug) with 3 lags in short-run

	Model A1		Model A2		Model A3		Model A4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates	0.4729***	-0.1126	0.4273***	0.6602**	0.4129***	0.3842***	0.3479***	0.2735***
Nom Rates	-0.0383	-0.4479	-0.0124	0.2294	-0.0136	0.0633	-0.0311*	-0.0318
Nom Rates – RentG							0.0320***	0.0366**
Short-run variables								
Error Correction	-0.0021***	-0.0031***	-0.0015***	-0.0018***	-0.0015***	-0.0019***	-0.0016***	-0.0022***
$\Delta R/P_{t-1}$	0.5646***	0.5574***	1.0904***	1.0852***	1.0847***	1.0796***	1.0837***	1.0731***
$\Delta R/P_{t-2}$	0.1194***	0.1164***	-0.4306***	-0.4294***	-0.4254***	-0.4244***	-0.4252***	-0.4226***
$\Delta R/P_{t-3}$	0.1334***	0.1307***	0.2618***	0.2616***	0.2671***	0.2669***	0.2672***	0.2658***
Δspread_t	0.0045***	0.0046***	0.0026***	0.0026***	0.0031***	0.0031***	0.0032***	0.0031***
$\Delta \text{spread}_{t-1}$	0.0029***	0.0029***	0.0021***	0.0021***	0.0021***	0.0021***	0.0021***	0.0021***
$\Delta \text{spread}_{t-2}$	0.0012***	0.0013***	0.0011***	0.0011***	0.0006***	0.0006***	0.0006***	0.0006***
$\Delta \text{spread}_{t-3}$	0.0012***	0.0012***	0.0004	0.0004	0.0004	0.0004	0.0005	0.0005
Δ Nom Rates $_t$	-0.0028***	-0.0027***			-0.0011***	-0.0012***	-0.0011***	-0.0012***
Δ Nom Rates $_{t-1}$	-0.0012***	-0.0011***			0.0001	0.0000	0.0001	0.0000
Δ Nom Rates $_{t-2}$	0.0003	0.0004			0.0009***	0.0008***	0.0009***	0.0008***
Δ Nom Rates $_{t-3}$	0.0001	0.0001			0.0006***	0.0006***	0.0006***	0.0005***
$\Delta \text{NomRate}_t$ - RentG_t			-0.0015***	-0.0015***	-0.0016***	-0.0015***	-0.0016***	-0.0016***
$\Delta \text{NomRate}_{t-1}$-$\text{RentG}_{t-1}$			0.0002***	0.0002***	0.0002***	0.0002***	0.0001***	0.0001***
$\Delta \text{NomRate}_{t-2}$-$\text{RentG}_{t-2}$			-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
$\Delta \text{NomRate}_{t-3}$-$\text{RentG}_{t-3}$			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Constant	0.0022***	0.0045***	0.0017***	0.0019***	0.0017***	0.0021***	0.0020***	0.0026***
Obs	9,152	9,152	9,108	9,108	9,108	9,108	9,108	9,108
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	33073	33110	38376	38406	38557	38588	38561	38617
Hausman test	**Invalid**		8.59		**Invalid**		**Invalid**	
p-value			0.0136					

Note: Real Rates are represented by the 10-year TIPs, "Nom Rates" are nominal rates represented by 10-year Treasuries.

Panel C-2 Whole Sample Period (1999 Jan - 2016 Aug) with 6 lags in short-run

	Model A1		Model A2		Model A3		Model A4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates	0.2889***	0.5939	0.3491***	0.2502***	0.2653***	-2.1835	0.1780***	0.1264
Nom Rates	-0.0558***	0.0194	-0.0044	-0.0139	-0.0244	-2.2710	-0.0437***	-0.0399
Nom Rates – RentG							0.0558***	0.0494***
Short-run variables								
Error Correction	-0.0022***	-0.0031***	-0.0016***	-0.0019***	-0.0016***	-0.0021***	-0.0018***	-0.0025***
$\Delta R/P_{t-1}$	0.5504***	0.5444***	1.0687***	1.0629***	1.0558***	1.0497***	1.0532***	1.0421***
$\Delta R/P_{t-2}$	0.0996***	0.0970***	-0.4174***	-0.4163***	-0.4105***	-0.4092***	-0.4101***	-0.4075***
$\Delta R/P_{t-3}$	0.0777***	0.0770***	0.2264***	0.2242***	0.2322***	0.2296***	0.2319***	0.2278***
$\Delta R/P_{t-4}$	0.0566***	0.0558***	-0.0107	-0.0092	-0.0053	-0.0037	-0.0056	-0.0039
$\Delta R/P_{t-5}$	0.1547***	0.1540***	0.0713***	0.0707***	0.0704***	0.0698***	0.0704***	0.0690***
$\Delta R/P_{t-6}$	-0.0974***	-0.0971***	-0.0086	-0.0054	-0.0030	0.0011	-0.0019	0.0018
Δspread_t	0.0043***	0.0044***	0.0025***	0.0025***	0.0030***	0.0030***	0.0031***	0.0031***
$\Delta \text{spread}_{t-1}$	0.0029***	0.0029***	0.0021***	0.0020***	0.0020***	0.0020***	0.0021***	0.0021***
$\Delta \text{spread}_{t-2}$	0.0017***	0.0017***	0.0012***	0.0012***	0.0008***	0.0007***	0.0008***	0.0008***
$\Delta \text{spread}_{t-3}$	0.0009**	0.0009***	0.0003	0.0003	0.0004*	0.0004*	0.0004*	0.0004*
$\Delta \text{spread}_{t-4}$	0.0022***	0.0022***	0.0007***	0.0007***	0.0012***	0.0012***	0.0012***	0.0012***
$\Delta \text{spread}_{t-5}$	-0.0003	-0.0002	0.0000	0.0000	-0.0001	-0.0001	-0.0001	0.0000
$\Delta \text{spread}_{t-6}$	-0.0020***	-0.0020***	-0.0012***	-0.0012***	-0.0015***	-0.0015***	-0.0014***	-0.0014***
Δ Nom Rates $_t$	-0.0024***	-0.0023***			-0.0010***	-0.0010***	-0.0010***	-0.0010***
Δ Nom Rates $_t$	-0.0011***	-0.0010***			0.0001	0.0001	0.0001	0.0001
Δ Nom Rates $_{t-1}$	0.0012***	0.0012***			0.0012***	0.0012***	0.0013***	0.0012***
Δ Nom Rates $_{t-2}$	0.0006**	0.0007***			0.0010***	0.0010***	0.0010***	0.0010***
Δ Nom Rates $_{t-4}$	0.0008***	0.0008***			0.0005***	0.0005***	0.0005***	0.0005***
Δ Nom Rates $_{t-5}$	0.0010***	0.0010***			0.0008***	0.0008***	0.0007***	0.0007***
Δ Nom Rates $_{t-6}$	0.0015***	0.0015***			0.0008***	0.0009***	0.0008***	0.0008***
ΔNom Rates_t-RentG_t			-0.0015***	-0.0015***	-0.0016***	-0.0016***	-0.0016***	-0.0017***
$\Delta\text{NomRate}_{t-1}$-$\text{RentG}_{t-1}$			0.0002***	0.0002***	0.0001***	0.0001***	0.0001*	0.0000
$\Delta\text{NomRate}_{t-2}$-$\text{RentG}_{t-2}$			-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0005***	-0.0005***
$\Delta\text{NomRate}_{t-3}$-$\text{RentG}_{t-3}$			-0.0001**	-0.0001**	-0.0001***	-0.0001***	-0.0002***	-0.0002***
$\Delta\text{NomRate}_{t-4}$-$\text{RentG}_{t-4}$			-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0003***
$\Delta\text{NomRate}_{t-5}$-$\text{RentG}_{t-5}$			-0.0001**	-0.0001**	-0.0001***	-0.0001***	-0.0001***	-0.0001***
$\Delta\text{NomRate}_{t-6}$-$\text{RentG}_{t-6}$			-0.0001**	-0.0001**	-0.0001***	-0.0001***	-0.0001***	-0.0001***
Constant	0.0033***	0.0057***	0.0019***	0.0025***	0.0024***	0.0035***	0.0030***	0.0045***
Obs	9,020	9,020	8,976	8,976	8,976	8,976	8,976	8,976
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	32981	33011	38168	38198	38449	38482	38457	38516
Hausman test	1		**Invalid**		17.29		5.57	
p-value	0.6063				0.0002		0.1342	

Panel C-3 Whole Sample Period (1999 Jan - 2016 Aug) with 9 lags in short-run

	Model A1		Model A2		Model A3		Model A4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates	-0.0269	0.0011	-0.0264	0.0327	-0.1154***	-0.1245**	-0.1376***	-0.1299
Nom Rates	-0.0306**	-0.0373**	0.0504***	0.0251	0.0365***	0.0458**	0.0083	0.0329
Nom Rates – RentG							0.0274***	0.0412***
Short-run variables								
Error Correction	-0.0033***	-0.0040***	-0.0025***	-0.0024***	-0.0024***	-0.0026***	-0.0025***	-0.0031***
$\Delta R/P_{t-1}$	0.5398***	0.5343***	1.0558***	1.0492***	1.0434***	1.0362***	1.0415***	1.0278***
$\Delta R/P_{t-2}$	0.0857***	0.0840***	-0.4278***	-0.4266***	-0.4156***	-0.4142***	-0.4158***	-0.4131***
$\Delta R/P_{t-3}$	0.0728***	0.0724***	0.2366***	0.2344***	0.2322***	0.2298***	0.2318***	0.2269***
$\Delta R/P_{t-4}$	0.0608***	0.0607***	-0.0191	-0.0189	-0.0075	-0.0072	-0.0079	-0.0080
$\Delta R/P_{t-5}$	0.1424***	0.1416***	0.1032***	0.1029***	0.1021***	0.1018***	0.1018***	0.1008***
$\Delta R/P_{t-6}$	-0.1717***	-0.1705***	-0.0719***	-0.0715***	-0.0758***	-0.0747***	-0.0758***	-0.0745***
$\Delta R/P_{t-7}$	0.1162***	0.1164***	0.0535**	0.0537**	0.0816***	0.0820***	0.0815***	0.0808***
$\Delta R/P_{t-8}$	0.0138	0.0144	-0.0095	-0.0100	-0.0091	-0.0088	-0.0087	-0.0087
$\Delta R/P_{t-9}$	0.0192	0.0205*	0.0324**	0.0351**	0.0146	0.0183	0.0147	0.0185
$\Delta spread_{t}$	0.0047***	0.0048***	0.0028***	0.0027***	0.0032***	0.0032***	0.0032***	0.0032***
$\Delta spread_{t-1}$	0.0034***	0.0034***	0.0024***	0.0024***	0.0025***	0.0026***	0.0026***	0.0026***
$\Delta spread_{t-2}$	0.0016***	0.0016***	0.0013***	0.0013***	0.0006**	0.0006**	0.0006**	0.0006**
$\Delta spread_{t-3}$	0.0005	0.0005	0.0002	0.0003	0.0002	0.0003	0.0003	0.0003
$\Delta spread_{t-4}$	0.0026***	0.0026***	0.0007***	0.0007***	0.0013***	0.0013***	0.0014***	0.0014***
$\Delta spread_{t-5}$	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
$\Delta spread_{t-6}$	-0.0016***	-0.0015***	-0.0010***	-0.0010***	-0.0012***	-0.0012***	-0.0011***	-0.0011***
$\Delta spread_{t-7}$	-0.0011	-0.0011	-0.0017***	-0.0017***	-0.0018***	-0.0018***	-0.0017***	-0.0017***
$\Delta spread_{t-8}$	-0.0016***	-0.0016***	-0.0011***	-0.0011***	-0.0011***	-0.0011***	-0.0010***	-0.0010***
$\Delta spread_{t-9}$	-0.0019***	-0.0019***	-0.0019***	-0.0019***	-0.0017***	-0.0018***	-0.0017***	-0.0017***
Δ Nom Rates $_{t}$	-0.0022***	-0.0022***			-0.0006***	-0.0006***	-0.0005**	-0.0005**
Δ Nom Rates $_{t}$	-0.0008**	-0.0007**			0.0002	0.0003	0.0003	0.0003
Δ Nom Rates $_{t-1}$	0.0017***	0.0017***			0.0018***	0.0018***	0.0018***	0.0018***
Δ Nom Rates $_{t-2}$	0.0009***	0.0010***			0.0013***	0.0014***	0.0014***	0.0014***
Δ Nom Rates $_{t-4}$	0.0010***	0.0010***			0.0007***	0.0008***	0.0008***	0.0008***
Δ Nom Rates $_{t-5}$	0.0011***	0.0011***			0.0009***	0.0010***	0.0009***	0.0009***
Δ Nom Rates $_{t-6}$	0.0013***	0.0013***			0.0006***	0.0007***	0.0007***	0.0006***
Δ Nom Rates $_{t-7}$	0.0010***	0.0010***			0.0015***	0.0015***	0.0015***	0.0015***
Δ Nom Rates $_{t-8}$	0.0017***	0.0017***			0.0004***	0.0005***	0.0004***	0.0004***
Δ Nom Rates $_{t-9}$	-0.0002	-0.0001			-0.0004	-0.0003	-0.0003	-0.0003
$\Delta NomRates_{t}\text{-}RentG_{t}$			-0.0015***	-0.0016***	-0.0016***	-0.0016***	-0.0016***	-0.0017***
$\Delta NomRate_{t-1}\text{-}RentG_{t-1}$			0.0001***	0.0001***	0.0001***	0.0001**	0.0000	0.0000
$\Delta NomRate_{t-2}\text{-}RentG_{t-2}$			-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0006***	-0.0006***
$\Delta NomRate_{t-3}\text{-}RentG_{t-3}$			-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0003***
$\Delta NomRate_{t-4}\text{-}RentG_{t-4}$			-0.0002***	-0.0002***	-0.0003***	-0.0003***	-0.0003***	-0.0004***
$\Delta NomRate_{t-5}\text{-}RentG_{t-5}$			-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***
$\Delta NomRate_{t-6}\text{-}RentG_{t-6}$			-0.0002***	-0.0002***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
$\Delta NomRate_{t-7}\text{-}RentG_{t-7}$			-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0001***	-0.0001***
$\Delta NomRate_{t-8}\text{-}RentG_{t-8}$			-0.0001***	-0.0001***	-0.0001**	-0.0001**	-0.0001***	-0.0001***
$\Delta NomRate_{t-9}\text{-}RentG_{t-9}$			-0.0000**	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0001***
Constant	0.0071***	0.0087***	0.0043***	0.0040***	0.0049***	0.0055***	0.0054***	0.0066***
Obs	8,888	8,888	8,844	8,844	8,844	8,844	8,844	8,844
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	32947	32977	38030	38066	38447	38486	38453	38524
Hausman test	**Invalid**		3.4		0.2		4.4	
p-value			0.1823		0.9048		0.2211	

Panel C-4 Whole Sample Period (1999 Jan - 2016 Aug) with 12 lags in short-run

	Model A1		Model A2		Model A3		Model A4	
	PMG	MG	PMG	MG	PMG	MG	PMG	MG
Long-run variables								
Real Rates	-0.2789***	-0.2493***	-0.0820***	-0.0392	-0.2334***	-0.2478***	-0.2366***	-0.2348***
Nom Rates	-0.0352**	-0.0337*	0.0353***	-0.0052	0.0156*	-0.0137	0.0003	-0.0257
Nom Rates – RentG							0.0159***	0.0269**
Short-run variables								
Error Correction	-0.0040***	-0.0047***	-0.0025***	-0.0024***	-0.0026***	-0.0032***	-0.0027***	-0.0036***
$\Delta R/P_{t-1}$	0.5326***	0.5258***	1.0770***	1.0708***	1.0527***	1.0419***	1.0519***	1.0336***
$\Delta R/P_{t-2}$	0.0814***	0.0798***	-0.4218***	-0.4195***	-0.4096***	-0.4068***	-0.4099***	-0.4040***
$\Delta R/P_{t-3}$	0.0680***	0.0682***	0.2229***	0.2202***	0.2153***	0.2118***	0.2149***	0.2078***
$\Delta R/P_{t-4}$	0.0576***	0.0585***	-0.0240	-0.0234	-0.0145	-0.0137	-0.0149	-0.0132
$\Delta R/P_{t-5}$	0.1371***	0.1371***	0.1017***	0.1015***	0.1046***	0.1047***	0.1038***	0.1026***
$\Delta R/P_{t-6}$	-0.1603***	-0.1585***	-0.0712***	-0.0713***	-0.0707***	-0.0694***	-0.0708***	-0.0686***
$\Delta R/P_{t-7}$	0.1197***	0.1201***	0.0639**	0.0635**	0.0844***	0.0848***	0.0842***	0.0839***
$\Delta R/P_{t-8}$	0.0210	0.0216	-0.0237	-0.0232	-0.0284	-0.0269	-0.0281	-0.0266
$\Delta R/P_{t-9}$	0.0327***	0.0338***	0.0506***	0.0498***	0.0353**	0.0362**	0.0354**	0.0368**
$\Delta R/P_{t-10}$	0.0266*	0.0284**	0.0907***	0.0923***	0.1006***	0.1037***	0.1008***	0.1025***
$\Delta R/P_{t-11}$	0.0008	0.0015	-0.2161***	-0.2163***	-0.2067***	-0.2043***	-0.2067***	-0.2029***
$\Delta R/P_{t-12}$	-0.0045	-0.0032	0.1121***	0.1136***	0.1172***	0.1182***	0.1172***	0.1167***
Δspread$_t$	0.0045***	0.0046***	0.0026***	0.0026***	0.0030***	0.0031***	0.0030***	0.0031***
Δspread$_{t-1}$	0.0031***	0.0031***	0.0021***	0.0021***	0.0024***	0.0024***	0.0024***	0.0024***
Δspread$_{t-2}$	0.0018***	0.0018***	0.0011***	0.0011***	0.0005*	0.0005**	0.0005*	0.0005**
Δspread$_{t-3}$	0.0008**	0.0008**	0.0006***	0.0006***	0.0008***	0.0008***	0.0008***	0.0008***
Δspread$_{t-4}$	0.0031***	0.0032***	0.0008***	0.0008***	0.0013***	0.0014***	0.0013***	0.0014***
Δspread$_{t-5}$	0.0002	0.0002	-0.0003	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001
Δspread$_{t-6}$	-0.0016***	-0.0016***	-0.0009***	-0.0009***	-0.0012***	-0.0012***	-0.0012***	-0.0012***
Δspread$_{t-7}$	-0.0017**	-0.0017**	-0.0019***	-0.0019***	-0.0020***	-0.0020***	-0.0020***	-0.0020***
Δspread$_{t-8}$	-0.0009**	-0.0010**	-0.0009***	-0.0009***	-0.0006***	-0.0007***	-0.0006***	-0.0007***
Δspread$_{t-9}$	-0.0011***	-0.0012***	-0.0015***	-0.0014***	-0.0012***	-0.0012***	-0.0011***	-0.0012***
Δspread$_{t-10}$	-0.0029***	-0.0029***	-0.0008***	-0.0008***	-0.0010***	-0.0011***	-0.0010***	-0.0011***
Δspread$_{t-11}$	-0.0020***	-0.0022***	-0.0009***	-0.0009***	-0.0015***	-0.0016***	-0.0015***	-0.0016***
Δspread$_{t-12}$	-0.0011**	-0.0013**	0.0005***	0.0005***	0.0008***	0.0007***	0.0008***	0.0008***
Δ Nom Rates $_t$	-0.0019***	-0.0018***			-0.0004**	-0.0003	-0.0004*	-0.0003
Δ Nom Rates $_t$	-0.0006*	-0.0005			0.0000	0.0002	0.0001	0.0001
Δ Nom Rates $_{t-1}$	0.0013***	0.0014***			0.0015***	0.0016***	0.0015***	0.0016***
Δ Nom Rates $_{t-2}$	0.0015***	0.0016***			0.0014***	0.0015***	0.0014***	0.0015***
Δ Nom Rates $_{t-4}$	0.0016***	0.0017***			0.0013***	0.0015***	0.0014***	0.0014***
Δ Nom Rates $_{t-5}$	0.0012***	0.0013***			0.0010***	0.0011***	0.0010***	0.0011***
Δ Nom Rates $_{t-6}$	0.0021***	0.0022***			0.0009***	0.0010***	0.0009***	0.0009***
Δ Nom Rates $_{t-7}$	0.0016***	0.0017***			0.0015***	0.0016***	0.0015***	0.0016***
Δ Nom Rates $_{t-8}$	0.0012***	0.0012***			0.0000	0.0001	0.0001	0.0001
Δ Nom Rates $_{t-9}$	0.0001	0.0002			-0.0001	0.0000	-0.0001	0.0000
Δ Nom Rates $_{t-10}$	0.0003	0.0004			0.0009***	0.0010***	0.0009***	0.0009***
Δ Nom Rates $_{t-11}$	0.0015***	0.0017***			0.0011***	0.0013***	0.0011***	0.0012***
Δ Nom Rates $_{t-12}$	0.0013***	0.0014***			0.0005**	0.0006***	0.0005**	0.0006**
ΔNomRates$_t$-RentG$_t$			-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0016***	-0.0016***
ΔNomRate$_{t-1}$-RentG$_{t-1}$			0.0002***	0.0002***	0.0001***	0.0001***	0.0001**	0.0000
ΔNomRate$_{t-2}$-RentG$_{t-2}$			-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0005***	-0.0006***
ΔNomRate$_{t-3}$-RentG$_{t-3}$			-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0003***
ΔNomRate$_{t-4}$-RentG$_{t-4}$			-0.0002***	-0.0002***	-0.0002***	-0.0003***	-0.0003***	-0.0003***
ΔNomRate$_{t-5}$-RentG$_{t-5}$			0.0000	0.0000	-0.0001**	-0.0001***	-0.0001***	-0.0002***
ΔNomRate$_{t-6}$-RentG$_{t-6}$			-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0003***
ΔNomRate$_{t-7}$-RentG$_{t-7}$			0.0000	0.0000	-0.0001**	-0.0001***	-0.0001***	-0.0001***
ΔNomRate$_{t-8}$-RentG$_{t-8}$			0.0000	0.0000	-0.0001***	-0.0001***	-0.0001***	-0.0001***

ΔNomRate$_{t-9}$-RentG$_{t-9}$			0.0001***	0.0001***	0.0000	0.0000	0.0000	0.0000
ΔNomRate$_{t-10}$-RentG$_{t-10}$			0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***
ΔNomRate$_{t-11}$-RentG$_{t-11}$			-0.0001*	-0.0001**	-0.0001*	-0.0001**	-0.0001**	-0.0001**
ΔNomRate$_{t-12}$-RentG$_{t-12}$			0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
Constant	0.0107***	0.0129***	0.0048***	0.0046***	0.0063***	0.0083***	0.0066***	0.0090***
Obs	8,756	8,756	8,712	8,712	8,712	8,712	8,712	8,712
No. of groups	44	44	44	44	44	44	44	44
Log likelihood	32,975	33,012	38,195	38,229	38,758	38,814	38,761	38849
Hausman test	**Invalid**		4.12		6.29		4.78	
p-value			0.1277		0.0431		0.1883	