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WHAT DRIVES URBAN CONSUMPTION IN MAINLAND CHINA? THE ROLE OF PROPERTY PRICE DYNAMICS

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What Drives Urban Consumption in Mainland China?
The Role of Property Price Dynamics

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Abstract

This paper adds to the literature on wealth effects on consumption by disentangling house price effects on consumption for mainland China. In a stochastic modelling framework, the riskiness, rate of increase and persistence of house price movements have different implications for the consumption/housing ratio. We exploit the geographical variation in property prices by using a quarterly city-level panel dataset for the period 1998Q1 – 2009Q4 and rely on a panel error correction model. Overall, the results suggest a significant long run impact of property prices on consumption. They also broadly confirm the predictions from the theoretical model.

1.   Introduction

It is by now common knowledge that the housing bubble was the major, if not the only, cause of the subprime crisis and worldwide economic and financial crisis of 2007-2009. Just as the preceding property bubble had created dynamics that tended to be self-perpetuating, the dynamics of the broader economic crisis were also self-perpetuating, albeit in the opposite direction. Despite its importance, mainstream macroeconomics either treats housing as one of many consumption goods, or ignores the housing market altogether. On the other hand, conventional housing economics research for its part virtually ignores interactions with the macroeconomy.

With property prices soaring in China due to rapid economic growth, rising family incomes, accommodative monetary policy during the financial crisis, and continued migration to the cities, many economists worry that China risks being host to the next great property bubble set to burst. Housing affordability in some of the larger cities such as Beijing, Hangzhou, Nanjing, Ningbo, Qingdao, and Shanghai has also become an increasingly prominent political issue. Being aware of the risk of derailing the housing market, the Chinese government has begun to lean against the wind, making an effort in Spring 2010 to gradually halt the climb in house prices.[1] In particular, down-payment requirements were raised across the country as a whole. For the second home, buyers must make a 50 percent down payment, even if it is their first mortgage. Minimum mortgage interest rates have also been increased. In property hot-spots like Beijing, buying a 3rd home is prohibited.[2] Finally, out-of-towners have to prepay local taxes for a year. However, it remains an open question as to how effective these measures will be in quantitative terms. Based on early evidence, the measures seem to have succeeded in cooling the market, as the rise in housing prices flattened out in the summer of 2010. A further measure to clamp down on the housing market is the possible introduction of a property tax throughout the country based on the value of housing.

Several papers have analysed the impact of housing wealth on consumption. Most of these studies, however, focus on the Anglo-Saxon or euro area countries. In contrast, the house price – consumption

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[1]   Some observers argue that China´s inflated property prices are reminiscent of Japan's real estate bubble in the latter half of the 1980s, and believe the Chinese authorities, via accommodative monetary policy and a quasi-fixed exchange rate, are in danger of repeating the mistakes of their Japanese neighbours. The upward trajectory in Chinese housing prices, however, does not necessarily represent a bubble. Structural factors, including favourable demographics, increased urbanisation, rapid income growth and high household saving rates, have underpinned the buoyant demand. Any risk to financial stability due to falling housing prices is mitigated by the relatively low level of household indebtedness in China.

[2]   From the start of October 2010, bank loans were suspended for third home purchases. Down payments for all first home buyers were set at a minimum of 30% of the purchase price.

nexus in Asia is far less researched than in Europe and the US due to the paucity of disaggregated data.[3] This paper adds to the literature on house price effects on consumption by disentangling property price effects for mainland China. In a stochastic modelling framework, the riskiness, speed and persistence of house price movements have different implications for the consumption/housing ratio. We apply panel data techniques to a city-level dataset for mainland China. The heterogeneity present in the city-level data allows us to test whether the predictions from the theoretical model hold in the data, in addition to examining whether there is a significant overall impact of house prices on consumption in China.

The rest of the paper is organised as follows. Section 2 starts by looking at the impact of house prices on consumption from a theoretical perspective. Section 3 describes the data, outlines the econometric methodology and presents the empirical results. Section 4 concludes and the data are explained in appendices.

2.   Housing-Consumption Model Setup

How are property prices and consumption interrelated? To what extent do house prices influence consumption? Which mechanism underlies the link between property prices and consumption?[4] To assess the importance of these and other factors, we construct a simple model along the lines of the work by Piazzesi *et al*. (2007) and Flavin and Nakagawa (2008), which incorporates an explicit role for housing.[5] A representative consumer's utility is a function of housing services and consumption of ordinary goods.[6] The consumer maximises his intertemporal utility by choosing his optimal consumption paths for non-housing goods and housing services (thus the stock of housing), applying a constant discount factor. Other durable goods are ignored here. The intertemporal utility V of the consumer is expressed as

$$V_t = E_t\left[\sum_{s=t}^{T} \beta^{s-t} u_s\left(c_s, h_s\right)\right] \tag{1}$$

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[3]   Ahuja et al. (2010) have recently investigated house price misalignments in China using alternative empirical approaches. They find a small and insignificant impact of property prices on Chinese consumption. However, this may be driven by the fact that the authors match city-level data for housing prices with provincial-level macro variables, whereas our study uses city-level data for both. Another difference between their study and ours is that the models estimated in Ahuja et al. (2010) are in first differences, not considering long-run relationships. Koivu (2010) has also provided evidence on the impact of equity and residential property prices on consumption in Mainland China using a structural vector autoregression, but finds that the link between asset prices and consumption is not robust.

[4]   The terms "house prices" and "property prices" will be used interchangeably in this paper.

[5]   There is no commonly accepted theory that explicitly models consumption with uncertain housing returns, because housing is both an investment good and a consumption good, which imposes great challenges to modelling.

[6]   We deliberately adopted a modelling approach that neglects other assets for expositional reasons. We think that this simplification allows some transparent insights that can be obscured by more complicated dynamic models. Furthermore, this modelling strategy is particularly appealing in China because the limited financial sector offers few other investment options. People buy homes as a way of saving for the future. This is particularly important in China, where the population cannot rely on state pensions and other social security benefits.

where c_s denotes consumption in period s, h_s is housing stock, $E_t[\cdot]$ is the expectation operator based on information available at period t, and β^{s-t} is the discount factor for the future utility stream, $u_s(c_s, h_s)$.

The consumption/housing budget constraint incorporates differences in house asset values/payoffs over periods, nonfinancial income y_t and consumption c_t:

$$c_t + p_t h_t \leq \left(1 + r_t - \delta\right) p_{t-1} h_{t-1} + y_t \tag{2}$$

The meaning of equation (2) is straightforward. Each period, the consumer must decide on consumption c_t and housing stock h_t. The housing stock in the previous period is denoted by h_{t-1} and house price by p_{t-1}. The difference between h_t and h_{t-1} is the net change in housing stock for the consumer, so that in the current period, determining h_t is equivalent to determining housing investment. The housing depreciation rate δ is constant. House prices p_t and returns r_t are stochastic, adding a source of uncertainty to the household´s decision problem. The net growth of housing wealth is $(r_t - \delta)(p_{t-1}h_{t-1})$.[7] Non-housing income is denoted by y_t. If the consumer remains in the same house, the budget constraint $c_t \leq y_t$ applies. If the consumer plans to trade down to a cheaper home, or to sell for the last time, $h_t < h_{t-1}$ and higher consumption spending c_t occurs. By contrast, homeowners who trade up are characterised by $h_t > h_{t-1}$ leading to lower c_t. The optimal allocation of consumption and housing is given by the Bellman equation:

$$\begin{aligned} V_t\left(p_{t-1}\right) &= \max_{c_t, h_t} E_t\left[u_t\left(c_t, h_t\right) + \beta V_{t+1}\left(p_t\right)\right] \\ &= \max_{c_t, h_t} E_t\left[u_t\left(c_t, h_t\right) + \beta V_{t+1}\left(\left(1 + g_t - \delta\right)\frac{p_{t-1}h_{t-1}}{h_t} + \frac{y_t - c_t}{h_t}\right)\right]. \end{aligned} \tag{3}$$

V_t is a function of p_{t-1}, which is given and known for all subsequent decisions on h_t and c_t. The corresponding two first order conditions with respect to c_t and h_t are

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[7]   The term $1 + r_t - \delta$ is approximated by $\left(1 + r_t\right)p_{t-1}\left(1 - \delta\right)h_{t-1} \cong \left(1 + r_t - \delta\right)p_{t-1}h_{t-1}$.

$$\frac{\partial u_t}{\partial c_t} = \beta E_t \left[\frac{1}{h_t} \frac{dV_{t+1}}{dp_t} \right] \tag{4}$$

and

$$\frac{\partial u_t}{\partial h_t} = \beta E_t \left[\left(\left(1 + r_t - \delta\right) \frac{p_{t-1} h_{t-1}}{h_t} + \frac{y_t - c_t}{h_t} \right) \frac{1}{h_t} \frac{dV_{t+1}}{dp_t} \right] = \beta E_t \left[\frac{p_t}{h_t} \frac{dV_{t+1}}{dp_t} \right] \tag{5}$$

Note that the envelope theorem yields

$$\frac{dV_t}{dp_{t-1}} = \beta E_t \left[\left(1 + r_t - \delta\right) \frac{h_{t-1}}{h_t} \frac{dV_{t+1}}{dp_t} \right] \tag{6}$$

Simple algebraic manipulation leads to

$$\frac{\partial u_t}{\partial c_t} = \beta E_t \left[\left(1 + r_{t+1} - \delta\right) \frac{\partial u_{t+1}}{\partial c_{t+1}} \right] \tag{7}$$

and

$$1 = p_t \frac{\partial u_t / \partial c_t}{\partial u_t / \partial h_t} \tag{8}$$

To close our model, we assume standard *CES* preferences:

$$u(c_t, h_t) = \frac{\left(\gamma h_t^{\alpha} + c_t^{\alpha} \right)^{\frac{1-\rho}{\alpha}}}{1-\rho}, \ \alpha \le 1, \ \gamma \ge 0, \ 0 < \rho \ne 1, \tag{9}$$

where ρ is related to substitution within the consumption basket over time, and α denotes "intratemporal" substitution between consumption and housing at *t* [see Piazzesi et al (2007) and Flavin and Nakagawa (2008)]. $\alpha \to 1$ signifies perfect substitutes, $\alpha \to -\infty$ perfect complements, and $\alpha \to 0$ Cobb-Douglas utility. Solving for the equilibrium, equation (9) yields

$$\frac{c_t}{h_t} = \left(\frac{1}{\gamma} p_t \right)^{\frac{1}{1-\alpha}} \tag{10}$$

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Three properties of equation (10) are noteworthy. First, for reasonable values of α, higher housing prices lead to a higher consumption/housing ratio. Second, if consumption and housing are perfect complements $(\alpha \rightarrow -\infty)$, house prices have little impact on the ratio c_t/h_t. Third, if consumption and housing are close substitutes $(\alpha \rightarrow 1)$, house prices will raise the ratio c_t/h_t.

So far we have attempted to keep our theoretical model as simple and straightforward as possible. In particular, for the sake of generality, no specific stochastic process for house prices has been assumed. Next, we dig deeper into the microfoundations and suggest two particular versions of the model through which risky house prices and capital gains may affect consumption.[8] We begin with a setting in which agents consider stochastic capital gains as permanent. We assume that housing prices p_t have an independent log-normal distribution over time such that $\ln p \sim N\left(g, \sigma^2\right)$, where g is the expected capital gain rate. Any shocks drawn from such a distribution are permanent, as they are equivalent to geometrical Brownian motion for housing prices. By Ito's Lemma and an approximation of the exponential function via Taylor's expansions, we obtain

$$E_t\left[\frac{c_{t+1}}{h_{t+1}}\right] = \left(\frac{1}{\gamma} p_t\right)^{\frac{1}{1-\alpha}} e^{\frac{g}{1-\alpha} + \frac{1}{2}\frac{\alpha}{(1-\alpha)^2}\sigma^2} \cong \left(\frac{1}{\gamma} p_t\right)^{\frac{1}{1-\alpha}} \left(1 + \frac{g}{1-\alpha} + \frac{1}{2}\frac{\alpha}{(1-\alpha)^2}\sigma^2\right). \tag{11}$$

Equation (11) shows that uncertainty about future housing prices has a positive impact on the future consumption/housing ratio for $0 < \alpha < 1$, while uncertainty has a negative impact on the ratio for complements, $-\infty < \alpha < 0$.[9]

An important implication of the permanent income hypothesis is that households are likely to make smaller changes in consumption when they face (unexpected) transitory house price shocks than when they face permanent house price shocks. This implies that the relationship between consumer spending and house prices is more subtle than that reflected in equation (11).[10] In order to depict temporary vs.

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[8]   Needless to say, things are not so simple. One caveat regarding the modelling framework is that the relationship between asset prices and borrowing constraints, which is at the core of the financial accelerator model, is not included in the model. On the household side, increasing house prices may allow homeowners to borrow against the value of housing collateral, which can boost spending. Due to the growing importance of financial products that allow for mortgage equity withdrawal, this effect has recently attracted a lot of attention in the literature. In Gan (2010), the consumption sensitivity of the majority of households in Hong Kong was not driven by credit constraints. The alleged reason is that refinancing is not as common in Hong Kong than in other countries. By way of comparison, this collateral channel can be expected to be even less important in mainland China.

[9]   The dangers of basing risk on average long-term house price volatility are that volatility can change very quickly, that extreme but infrequent house price declines tend to be discounted, and that possible future volatility may be overlooked. Furthermore, standard deviations based on past house price data ignore cross-correlations and systemic risk. It is clear that in the recent financial crisis 2008-2009 all four occurred.

[10]   The dramatic rise in Chinese house prices has prompted questions about whether there is a bubble in China´s housing market. According to the evidence from eight large cities in Wu et al. (2010), housing markets look rather risky based on the affordability price-to-rent and price-to-income ratio measures.

permanent changes in house prices, we use the mean-reverting Ornstein-Uhlenbeck given by the stochastic differential equation

$$dp = \mu\left(\bar{p}_0 e^{gt} - p\right)p\,dt + \sigma p\,dW \tag{12}$$

where μ is the speed of mean-reversion, σ is the risk parameter, W is a standard Wiener process, the housing price trend has an expected growth rate g, and $\bar{p}_0$ is the initial price level of the mean/trend at $t = 0$.[11] The parameter μ determines the rate at which house price shocks dissipate and house prices revert to the mean/trend. In other words, the size of the parameter μ determines the perceived permanent-transitory decomposition of house price shocks.[12] This illustrates, in broad brushstrokes, how different types of shocks affect consumption.

It should be emphasized that the modelling setup incorporates an asymmetric treatment of income and house prices. Since China has not experienced typical business cycles, we assume that Chinese households´ perceptions are that GDP growth rates are not flashes in the pan. As a result, income shocks are considered permanent and expected future income prospects depend on current income.[13] This simplification does not change the nature of our modelling results below.

As the consumption-housing ratio takes the functional form $(p/\gamma)^{1/1-\alpha}$, it is not possible to obtain closed-form solutions for the consumption responses of equation (12). To tackle this problem, discrete-time numerical simulations are used to study households´ responses to perceived transitory and permanent shocks on c/h. In order to get a clear "feel" for the dynamics of the model, we must first specify a solution method that will lead to discrete realizations of housing prices, given the chosen levels of parameters. Several options are available at this point, but the structure of the model points to use of a sequential iterations method. It works as follows. Equation (12) is proxied by the discrete stochastic differential equation (Euler scheme)

$$p_{t+\Delta t} = p_t + \mu\left(\bar{p}_t - p_t\right)p_t\Delta t + \sigma p_t\sqrt{\Delta t}\,\varepsilon_t, \quad \varepsilon_t \sim N(0,1), \tag{13}$$

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[11]   Even equation (12) amounts to assuming that agents are perfectly certain that future market conditions are governed by this particular stochastic process. However, this assumption may be farfetched. Agents may think that other stochastic processes are also likely and may have no idea of the relative plausibility of these stochastic processes.

[12]   The approach here draws inspiration from the empirical analysis in Lettau and Ludvigson (2004), a widely cited and influential study. They show that aggregate consumption responds to permanent shocks but not to transitory shocks in aggregate wealth. They also found that most of the variation in housing wealth was transitory. This is a point that will be elaborated further in the next section.

[13]   In the study of business cycles, semantics are important. According to the NBER, a business cycle features a period of positive growth in aggregate economic activity, labelled the expansion phase, followed by a period of negative growth, the contraction or recession phase. By this definition, and judging by year-on-year growth rates, China has yet to experience a business cycle during the reform period; although the growth rate in real GDP has not been smooth, it has never been negative. China does not publish quarter-on-quarter changes in real GDP.

and

$$\overline{p}_{t+\Delta t} = \overline{p}_t + g\overline{p}_t \Delta t \tag{14}$$

where the normal random variables, ε_t, are generated via the central limit theorem and the Box-Muller (1958) method for transforming a uniformly distributed random variable to a normally distributed one with given mean and variance, and Δt represents a small change in *t*.

In the calibration exercise below, we illustrate the model's properties, in particular the impact of different values of *μ* on the degree of mean reversion.[14] Our base parameters, chosen for realism, are $p_0 = 0.65$, $\overline{p}_0 = 0.65$, $\Delta t = 0.01$. The baseline growth rate *g* = 0.03 is set in line with the trend growth rate of Beijing´s quarterly real house price index.

We set $\sigma = 0.2$ and depict the results using values of μ ranging from 0.25 to 1.0 in the four panels of Figure 1 (the shock series and baseline specification are otherwise identical). We have computed high-frequency realisations of the stochastic process and then changed the frequency to a lower quarterly one, using one realization only. The deterministic trend line in the figure is the trend value for $\overline{p}_0 e^{gt}$. The graphs show that larger values for *μ* imply less persistent shocks, i.e. there is a higher degree of mean-reversion to the deterministic trend line.

To further highlight the properties of the model, Figure 2 provides the risk-return trade-off surface between the *c/h*-ratio, the standard deviation σ, and the permanent-transitory decomposition of house price shocks μ. Note that $\alpha = 0.5$, $\gamma = 1$, *g* = 0.03, with one million Monte Carlo simulations.

The graph indicates that the house price – consumption nexus varies in response to changes in perceived uncertainty about the sustainability of house price gains/losses. An increase in σ renders housing more risky, which tends to reduce consumers´ willingness to invest in housing.

Figure 3 displays a sensitivity analysis of the optimal *c/h* ratio vis-à-vis *g* and μ. Households will run down *c/h* if house price shocks are more temporary (higher μ) and raise *c/h* for higher growth rates of house prices *g*. This is a reminiscent of Lettau and Ludvigson (2004).

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[14]   An important point to stress is that the calibration exercise focuses on conceptual issues in the interpretation of the model sketched above. In other words, the calibration exercise should be viewed as theory with numbers, not empirical analysis.

The foregoing analysis provides a theoretical underpinning for the house price shock – consumption nexus. The next section offers descriptive evidence of the data used and presents the econometric methodology in some detail.

3.   Empirical Application

3.1   Data

Prior to the econometric analysis, we describe the data set. Our panel dataset covers 35 major Chinese cities over the time period 1998Q1 to 2009Q4.[15] This 12-year period coincides with China's peak phase of urbanization and private housing market boom. The 35 major cities account for one quarter of the total urban population residing in more than 600 Chinese cities. These 35 major cities represent all municipalities directly under the federal government, provincial capital cities, and quasi provincial capital cities in China (see Figure 4). For each city, we use data on consumption expenditure per capita, income per capita, and housing prices, the latter covering both residential and commercial property.[16] All city-level data are from the CEIC database, transformed into real terms by deflating by the consumer price index.[17] The property price indices used in our study are compiled by the National Bureau of Statistics and are based on sample surveys. Our sample includes more than 10,000 units since July 2005. The data were collected via reporting forms and interviews, for a total of 70 large and medium-sized cities. We use housing price data for those cities where income and consumption data are available for model estimation.[18] Details on data construction are given in Appendix 1.

Housing price developments in the cities have been quite heterogeneous, as is clear from Figures of the series in Appendix 2. This heterogeneity allows us to split the sample in terms of the parameters of interest in Figures 2 and 3 – riskiness (σ) and growth rate (g) of housing prices. Similarly, we investigate

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[15]   For Guangzhou and Shenzhen, the dataset covers the period 1998Q2-2009Q4. The dataset allows us to take advantage of the significant variation in shocks to housing prices within and between markets. On the other hand, the house price data have certain limitations. The available time series are relatively short and cover only the post-Asian crisis period in the 1990s. However, longer time series of house price data may not improve the results since China has experienced a regime-shift in the housing market in 1998, which can be regarded as a milestone in housing reform and can be taken as the start of the private housing market in China. Indeed, until the late-1990s, the allocation of apartment units to most urban households was determined by employers, primarily government institutions and state-owned enterprises. The government initiated a market-oriented housing market in 1998 via the privatisation of the existing urban housing stock to current occupants at sharply discounted prices.

[16]   Most of the fluctuations in housing wealth are attributable to house price movements. Therefore we can focus on the latter variable to capture housing wealth fluctuations in Chinese cities.

[17]   The advantage of our city-level panel dataset is that the returns to housing differ greatly across cities. In areas with high growth and significant constraints on the supply of housing, as e.g. in several coastal cities, positive house price shocks are more likely to result in higher permanent prices, while in Chinese cities with fewer constraints such a house price shock would be largely transitory, as supply increases over time.

[18]   It is important to note that there are differences in the path of Chinese property prices depending on the reporting authority. Data published by the National Bureau of Statistics suggest that after April 2010, when the Chinese government introduced measures to cool the property market, a fall in prices (average price per square meter) occurred, whereas data from the National Development and Reform Commission indicate that prices continued to increase.

the importance of the persistence (μ) of property price shocks using filtering techniques. The lowest growth in real housing prices was experienced in Kunming, a fall of 0.2% during our sample period. The highest growth was for Ningbo, 70.5%. Other cities with significant growth in housing prices include Qingdao and Hangzhou. The riskiness of housing prices – measured by their standard deviation – was similarly highest in Ningbo and Qingdao and lowest in Changchun and Xining. The considerable cross-city heterogeneity in housing dynamics enables an examination of the effects of property price movements across cities but also provides useful information on the property price – consumption nexus for the economy as a whole.

3.2   Econometric Methodology

Panel methods are now widely used in cross sectional macro data sets, since they provide greater power than individual time series studies and hence greater efficiency. Empirical analysis of such datasets generally involves a system of $N \times T$ equations (N cities and T time observations) that can be estimated in different ways. The choice of the pooled cross-section time-series approach depends on the size of N and T. Pesaran et al. (1999) emphasized that there are two traditional methods for estimating panel models: averaging and pooling. The former involves running N separate regressions and calculating coefficient means.[19] A drawback to averaging is that it does not account for the fact that certain parameters may be equal over cross sections. Alternatively, pooling the data typically assumes that the slope coefficients and error variances are identical. This is unlikely to be valid for short-run dynamics and error variances, although it could be appropriate for the long run. Pesaran et al. (1999) proposed the PMG method, which is an intermediate case between the averaging and pooling methods of estimation, including aspects of both. The Pooled Mean Group Estimation (PMG) method restricts the long-run coefficients to be equal over the cross-section, but allows for the short-run coefficients and error variances to differ across groups on the cross-section. Given their shared institutional framework and common market, the assumption of common long-run parameters for all Chinese cities is a reasonable assumption.[20] In contrast, it is more difficult to assume homogeneity in the short-run dynamics. Formally, the PMG estimator is based on an Autoregressive Distributive Lag ARDL(p,q) model:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij}\, y_{it-j} + \sum_{j=0}^{q} \delta'_{ij} \mathbf{x}_{it-j} + \mu_i + \varepsilon_{it} \qquad (15)$$

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[19]   See, for example, the Mean Group (MG) estimator method suggested by Pesaran and Smith (1995).

[20]   There are numerous cross-country studies investigating the role of housing wealth in consumption [see e.g. Hiebert and Roma (2010)]. In these studies (albeit fruitful ones) it is difficult to circumvent the omitted variable bias. Substantial unobservable and/or immeasurable differences in institutions and policies make cross-country results problematic. This disadvantage of cross-country research can certainly be mitigated by using a within-country dataset with greater homogeneity. In this respect, studies of China have a unique advantage. On the one hand, China is a rather centralised country with a unified administrative and political system. On the other hand, there are substantial cross-city differences in terms of GDP per capita.

where $\boldsymbol{x}_{it}$ ($k{\times}1$) is the vector of explanatory variables for city i, μ_i represents the fixed effects, the coefficients of the lagged dependent variables (λ_{ij}) are scalars, δ_{ij} are ($k{\times}1$) coefficient vectors, and ε_{it} is the usual error term. T must be large enough so that the model can be estimated for each cross section.[21] In our empirical model, y_{it} denotes the property price index, and x_{it} includes per capita consumption and income per capita. Equation (15) can be re-parameterized:

$$\Delta y_{it} = \phi_i\, y_{it-1} + \beta'_i\, x_{it} + \sum_{j=1}^{p-1} \tilde{\lambda}_{ij}\, \Delta y_{it-j} + \sum_{j=0}^{q-1} \tilde{\delta}'_{ij}\, \Delta \mathbf{x}_{it-j} + \mu_i + \varepsilon_{it} \tag{16}$$

where $\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right)$, $\beta_i = \sum_{j=0}^{q} \delta_{ij}$, $\tilde{\lambda}_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}$, and $\tilde{\delta}_{ij} = -\sum_{m=j+1}^{q} \delta_{im}$. In addition, we assume that the residuals in (16) are *i.i.d.* with zero mean, variance greater than zero and finite fourth moments. Secondly, the roots of equation (16) must lie outside the unit circle. The latter assumption ensures that ϕ_i < 0, and hence that there exist a long-run relationship between y_{it} and $\boldsymbol{x}_{it}$ defined by

$$y_{it} = -\left(\frac{\beta'_i}{\phi_i}\right) \mathbf{x}_{it} + \eta_{it} \tag{17}$$

The long-run homogeneous coefficient is equal to $\theta = \theta_i = -\left(\beta'_i / \phi_i\right)$, which is the same across groups. The PMG uses a maximum likelihood approach to estimate the model and a Newton-Raphson algorithm. The lag length for the model can be determined using, for instance, the Schwarz Bayesian Information Criteria. The estimated coefficients in the model do not depend on whether the variables are $I(1)$ or $I(0)$.[22] The key feature of the PMG is to make the long-run relationships homogeneous while allowing for heterogeneous dynamics and error variances.[23] We test for long-run homogeneity using a joint Hausman

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[21]   Under large N and fixed T dynamic panel models with fixed effects imply a small-sample downward lagged dependent variable bias that has been shown analytically by Nickell (1981). In order to avoid this bias the literature has focussed on instrumental variable estimation (GMM) applied to first differences. Examples include Arellano and Bond (1991) and Holtz-Eakin et al. (1988). Unfortunately, the asymptotically efficient GMM estimator obtained after first-differencing has been found to suffer from substantial finite sample bias due to weak instruments.

[22]   The Hadri panel unit root test, allowing for heterogeneity in the series, suggests that the series are likely to be integrated of order 1, $I(1)$. In the testing procedure, a constant and trend are included as deterministic terms for the series in levels, and a constant is therefore only included for the series in first differences. The null hypothesis of stationarity can be rejected for both housing prices and consumption in levels at 5 percent level. In contrast, for the same series in first differences, the null hypothesis of stationarity cannot be rejected. For income, we reject the null of stationarity in levels at 5 percent level. For the series in first differences, stationarity is still rejected at 5% level (*p*-value 0.03) but not at 1% level. We therefore continue with the assumption that the series are integrated of order one, which makes it possible that the series are cointegrated.

[23]   On the contrary, dynamic fixed-effects GMM estimators generally impose homogeneity of all slope coefficients, allowing only the intercepts to vary across cities. At the other extreme is the mean-group approach (MG) that consists of estimating separate regressions for each city and calculating averages of the city-specific coefficients.

test based on the null of equivalence between the PMG and Mean Group estimation.[24] Under the null hypothesis, the difference in estimated coefficients for the Mean Group and the PMG is not statistically different, and for PMG the estimate is more efficient.

3.3   Empirical Results

Our analysis is conducted in two stages. First, we examine whether there is any significant effect of housing prices on consumption. Second, exploiting the cross-sectional heterogeneity in housing price movements and the theoretical model specified above, we split the sample and examine whether there are differences between the consumption-response to the average rate of increase in house prices versus the riskiness of prices. The importance of persistence in house price shocks is analyzed using filtering techniques. We emphasize that while the theoretical model includes the consumption/housing ratio and the empirical analysis considers the response of consumption to housing price movements, the approaches are consistent with each other. A major motivation for buying a house in China is to save for the future. If higher housing prices lead to higher consumption, less money is available for housing purchases and saving (ceteris paribus); therefore the consumption/housing ratio should also increase.

Contrary to equations (10) and (11), we included income as an explanatory variable in (16). Essentially any estimate of the property price effect on consumption is to some extent subject to endogeneity and may be due to a third common factor such as expected permanent income. We follow previous work in assuming that a large part of the house price dynamics is exogenous [Ho and Wong (2008)]. More practically, we have included per capita income in the x_{it} vector of explanatory variables to filter out any remaining endogeneity. In order to determine the lag length of the error correction model, we apply the conventional Akaike and Schwarz Bayesian information criteria. Assuming a maximum lag length of 4 lags in levels for our quarterly data – allowing for one year of dynamics - both criteria suggest that three lags in first differences is indeed the optimal lag length for our model. Table 1 presents the results for this lag length, with standard errors in parentheses.

Our benchmark system, including all cities and all time periods, is shown in column (1). The adjustment coefficient is statistically significant and negative, and the estimated speed of adjustment is -0.502. The negative and statistically significant coefficient suggests that there is indeed cointegration between the variables, and the estimated consumption relation returns to long-run equilibrium. As the data are in logarithms, we can simply interpret the estimates as elasticities. The long-run income elasticity after consumption completely adjusts is estimated at 0.802, with a high statistical significance. Clearly, an income elasticity below one is feasible only if the saving rate is increasing over time. Our estimate for 35

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[24]   As shown by Nickell (1981), the downward lagged dependent variable bias depends on $1/T$ and is much less of a concern when T is large and of the same order of magnitude as N. In this latter case, heterogeneity of cities is a more serious problem, so that imposing homogeneity of all short and long run parameters could lead to inconsistent results [see e.g. Lee et al. (1996)].

large cities is in line with the empirical fact that the gross saving rate was increasing as a ratio to GDP in China during the time sample, from 40.2 percent to 52.3 percent of GDP.[25] Moreover, we find a statistically significant long-run impact of housing prices on consumption.[26] This fact is in line with findings of a number of empirical papers using datasets from various countries.

Under long-run slope homogeneity, the pooled estimators are consistent and efficient. However, the (non-pooled) Mean Group estimator would provide consistent estimates as well, but these are inefficient if slope homogeneity holds. Therefore, we can test the effect of heterogeneity on the means of the slope coefficients by applying a Hausman-type test (see Pesaran et al. 1999). In our case, for the benchmark model (1), the Hausman test suggests that there is no systematic difference between the Mean Group and Pooled Mean Group estimates (*p*-value 0.15).

We additionally estimated the benchmark model, column 1, by including annual time dummies. These may capture time-varying precautionary saving motives such as healthcare expenditures and/or pension provisions, particularly by elderly households.[27] This "self-insurance" of Chinese households reflects saving as a response to uncertainty as to one's future financial situation and unanticipated future events. Furthermore, stock market wealth gains may affect the results, and returns from this market are also subsumed in the time dummies. However, none of the included time dummies were statistically significant.

Next, to link the empirical framework more closely to the predictions by the theoretical model, we split the sample according to average growth rates in housing prices and their riskiness. Finally, using filtering techniques, we explore the impacts of different types of housing price movements, i.e. permanent vs. transitory movements.

The theoretical model predicts that households raise consumption for higher growth rates of housing prices. We split the sample into the 17 cities with the highest average rates of increase in house prices during the estimation period and the 18 cities with the lowest average rates of increase. The results, presented in columns (2) and (3), respectively, confirm the predictions from the theoretical model: the long-run house price elasticity is high and statistically significant for the cities that experienced strong growth in house prices and statistically insignificant in the rest.

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[25]   Using data from World Bank Development Indicators Database.

[26]   We also consider a robustness test whereby we shorten the sample by two years, first from the start of the sample period and secondly from the end. The results for the long-run importance of income and housing prices remain robust for these alternative samples. Interestingly, when the last two years are omitted - years when China experienced a rapid increase in housing prices and the government was concerned about real estate sector developments – the long run impact of housing prices on consumption becomes larger in magnitude.

[27]   Chamon and Prasad (2008) have shown that it is the elderly that save the most in China, contrary to the typical lifecycle pattern.

Another prediction from the theoretical model is that more risky housing prices lower consumers' willingness to invest in housing (and should increase the consumption/housing ratio accordingly). The results from splitting the sample in terms of house price volatility (standard deviation) into the 17 cities with highest volatility and the 18 with the lowest, are presented in columns (4) and (5). Again, the results confirm the suggestion from the theoretical model: in the cities with the riskiest housing price movements, consumption reacts more strongly to house price developments (column 4). In contrast, where housing price volatility is low (column 5), the reaction of consumption to housing price movements is not significantly different from zero.

Finally, we evaluate the response of consumption to permanent and temporary house price shocks. We use a structural time series model and Kalman filter to extract households´ perceptions about which parts of property price shocks are permanent or transitory.[28] The local level state space model used to identify the permanent and transitory components consists of a measurement equation, describing how observations are related to the state variable, and a transition equation describing the evolution of the state variable.[29] Maximum likelihood estimation by numerical optimization is carried out using computed estimates of the hyperparameters, i.e. most non-zero values of the error matrices of the measurement and transition equations, which govern the movement of the components. After estimation, the filtered states are calculated using the Kalman filter. The filtered estimators are, by definition, the expected values conditional on the observations.

In our local level model, using a trend-cycle decomposition, we have a time-varying trend component and a cyclical component at a short business cycle frequency (5 years).[30] We interpret the stochastic trend component obtained from the state space model by filtering as the perceived permanent component of housing prices and the cyclical component as the perceived temporary component. The perceived permanent component is shown in Appendix 2.

The results for Kalman-filtered housing price data are presented in column (6) for the permanent component and column (7) for the temporary component. As suggested by the theoretical model,

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[28]   Structural time series models are now quite widely used, and a full description can be found in Harvey (1989). The Kalman filter is the optimal filter for a linear model subject to Gaussian noise and therefore an indispensable tool for modelling information and learning. It also allows for the derivation of time-dependent coefficients in agents' optimal decision rules, and permits a neat application of Bayesian learning to updating optimal forecasting rules from period to period as new information becomes available.

[29]   For a thorough exposition of the state space methodology, the reader may refer to Harvey (1989). From the state space form, the Kalman filter and the associated smoothing algorithm enable maximum likelihood estimation of the model parameters and signal extraction of the unobserved components, conditional on a set of initial parameters and the appropriate information set.

[30]   Estimation was carried out using the STAMP 6.0 software. Model selection criteria are based on Koopman et al. (1999). First and foremost, it is suggested that the convergence of the numerical maximum likelihood estimation be examined. Koopman et al. (1999) suggest that strong convergence is a necessary condition for the models to be suitably specified and that failure to satisfy this condition could be a symptom of misspecification. Further goodness of fit statistics and diagnostics using the innovations, i.e. the one-step-ahead prediction errors, are provided in Appendix 3. In most cases, the disturbances display the ideal conditions. Harvey et al. (1998) have stressed that time series models based on unobserved components are effective even in the presence of messy features such as outliers, structural breaks and non-Gaussian errors.

permanent shocks in housing prices have a statistically significant impact on consumption. Further, our analysis suggests that the impact of temporary shocks on consumption is statistically significant and negative, which is in line with the prediction from our theoretical model that households run down the consumption-housing ratio if house price shocks are of the more temporary variety.[31] Using one standard error, the marginal propensity to consume out of permanent house price shocks is between 0.03 and 0.09.

Our estimates are relatively high, given that a conventional estimate of house price effects for the US is that an increase in house prices of $1 leads to an increase in consumption of 5 cents (Lettau and Ludvigson, 2004).[32] Using US data at the state and national level, Case et al. (2005) and Benjamin et al. (2004) report estimates ranging from 0.05 to 0.09. Microstudies, such as Bostic et al. (2009) and Lehnert (2004) have found the elasticities to be between 0.04 and 0.06. The international evidence is more mixed: it ranges from 0.03 for Australia to 0.11 – 0.17 for US regions (Case et al., 2005). The marginal propensity to consume out of housing wealth in Slacalek (2009) is 0.04 – 0.06 for countries with developed mortgage markets. Furthermore, the housing wealth effect has risen substantially since 1998. Two studies for Hong Kong covering the period 1982 – 2001 report elasticities of 0.07 – 0.14 (Lai, 2002; Cutler, 2004). For China, the relatively large impact of house price changes on consumption can be understood in light of the fact that in an underdeveloped financial system with a limited number of assets, house ownership constitutes a major share of household wealth.

It is interesting to apply our estimate of 0.064 in column 1 of Table 2 to the Chinese economy in 2009. In 2009, based on the property price index for 70 cities, real estate prices in China increased on average at an annualised rate of 5.8% in nominal terms. Deflated by CPI inflation, real estate prices increased by 2.3%, which translates to a 2.3×0.064 = 0.15% increase in consumption. Over the same period, the growth of consumption in real terms was 9.9%. Thus, 1.5% of Chinese real consumption growth in 2009 was driven by the property price increase. Using property price data for Beijing and Shanghai, and the evolution of *per capita* consumption in these cities in 2009, 6.5% of real consumption growth in Beijing and 3.5% in Shanghai were driven by the property price increase.

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[31]   While the negative coefficient is quite large in magnitude, this is justified by the fact that the movements of the permanent component of housing prices are much larger than those of the temporary component (standard deviation of 0.145 for the former versus 0.018 for the latter).

[32]   In a recent study exploiting stickiness in consumption growth to distinguish between immediate and eventual wealth effects, Carroll et al. (2010) find that the immediate marginal propensity to consume from a $1 change in housing wealth in the US is about 2 cents, and the final eventual effect is about 9 cents.

4.   Conclusions

The aim of this paper is to shed light on the interplay between house prices and consumption in mainland China. In a stochastic modelling framework, the riskiness, speed and persistence of house price shocks have different implications for the consumption/housing ratio. Using available city-level house price panel data, we evaluate the link between property prices, income and consumption by estimating consumption equations. Data for 35 large cities indicate that during the time period of the analysis, 1998Q1 – 2009Q4, the developments in housing prices have been quite heterogeneous across geographic regions. This heterogeneity allows us to test the predictions from the theoretical model regarding the impacts of different factors – the volatility and growth rate of house prices and their persistence – on consumption. The benchmark results, obtained by the pooled mean group estimator, show that there is a significant impact of overall housing price movements on consumption. Splitting the sample in terms of riskiness of housing prices and speed of asset price growth, we find that the cities with faster growth in housing prices and higher volatility show the strongest links between housing prices and consumption, in line with the theoretical model. Similarly, permanent shocks to housing prices have a positive and statistically significant impact on consumption, in stark contrast to temporary house price shocks. Summarizing, the results suggest a significant long run impact of property prices on consumption. Thus, we conclude that the strong rise in property prices over the past decade has had a significant effect on consumption spending in China.

An interesting cross-check of the results would be to use Chinese microcensus data if such data were to become available. This would allow us to shed further light on the mechanisms underlying the link between consumption and property prices, such as the impact of high vs. low incomes, the different behaviour of renters vs. homeowners and the like.

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Table 1. Long-Run Estimates of Consumption Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Speed of	-0.502	-0.646	-0.371	-0.591	-0.419	-0.500	-0.304
adjustment	(0.062)	(0.095)	(0.073)	(0.098)	(0.077)	(0.031)	(0.118)
Long-run	0.802	0.775	0.884	0.779	0.804	0.807	0.845
income elasticity	(0.013)	(0.017)	(0.024)	(0.020)	(0.029)	(0.013)	(0.006)
Long-run house	0.081	0.129	0.047	0.122	0.136	0.064	-0.304
price elasticity	(0.029)	(0.034)	(0.118)	(0.038)	(0.138)	(0.031)	(0.118)
Log-likelihood	2769.99	1353.65	1419.62	1348.09	1422.76	2716.14	2708.54
N x T	1538	748	790	747	791	1502	1504

Notes: Standard errors in parentheses. Column (1) gives Pooled Mean Group estimates for full sample. Column (2) omits 18 cities with the lowest average housing price growth rates and column (3) the 17 cities with the highest. Column (4) omits 18 cities with the lowest volatility in house price developments and column (5) the 17 cities with the highest. Column (6) gives the responses to permanent house price shocks and (7) to temporary house price shocks.

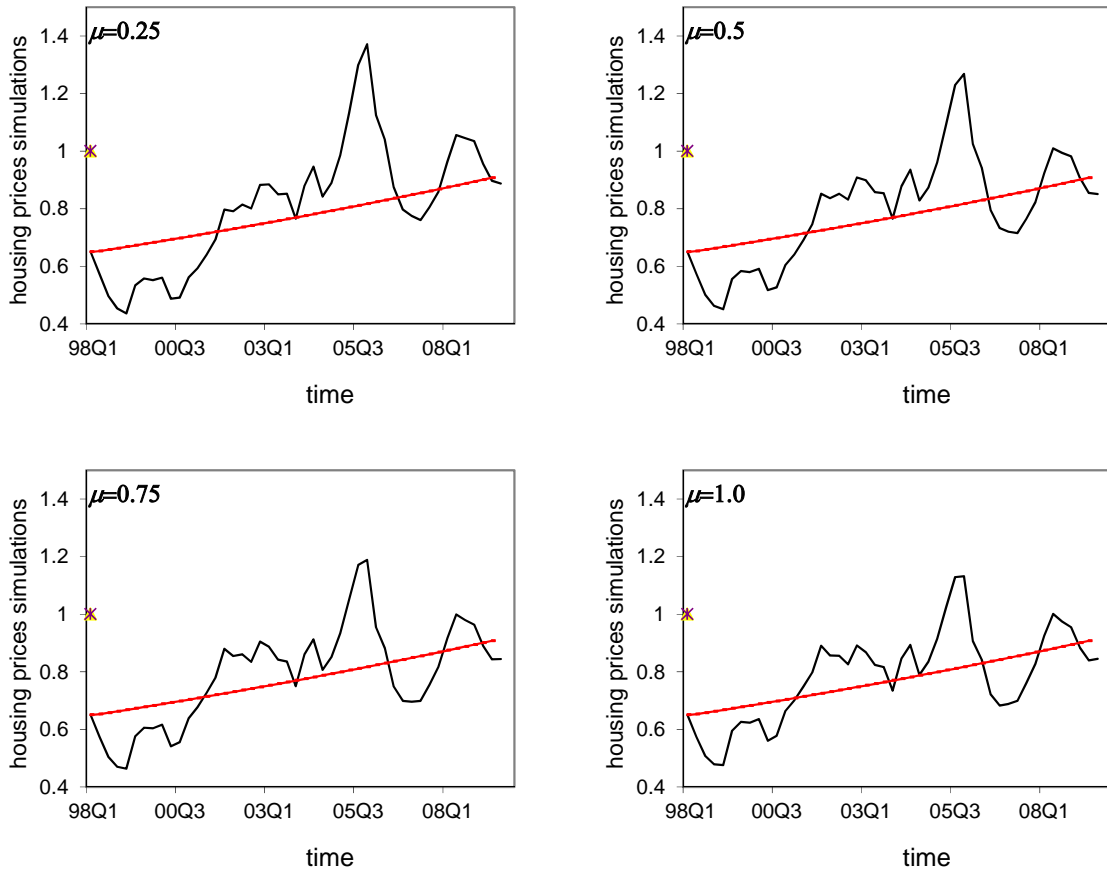**Figure 1. Characterising House Price Dynamics**
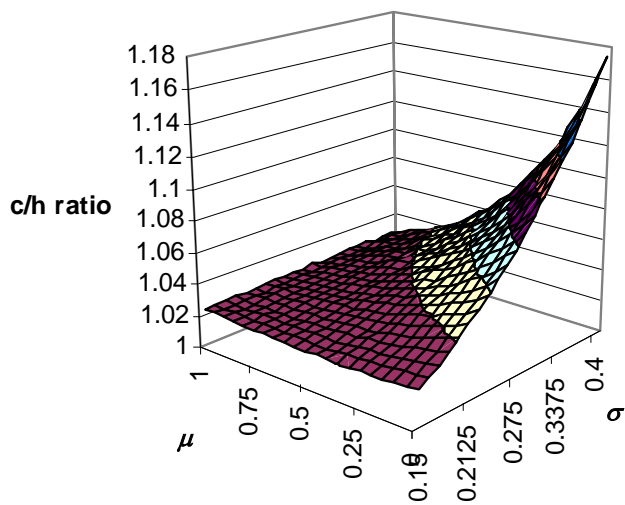

Figure 2. Optimal *c/h*-Ratio Depending on σ and μ

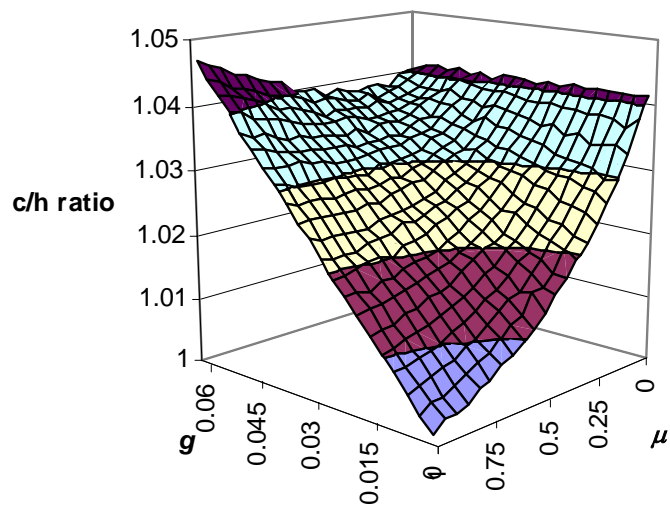**Figure 3. Optimal *c*/*h*-Ratio Depending on *g* and *μ***

Figure 4. Thirty-Five Major Chinese Housing Markets

Appendix 1. Data Construction

For income, we use quarterly data on disposable income per capita for 2007Q1-2009Q4. For 1998Q1-2006Q4, a monthly series for disposable income (discontinued from 2007Q1 onwards) is used to construct quarterly observations.

For consumption, we use quarterly data on consumption expenditure per capita for 2007Q1-2009Q4. Prior to this, we use monthly data on living expenditure per capita (discontinued in 2007Q1) to construct quarterly observations for this variable.

For housing prices, we use month-on-month changes for 2009 to build an index for house prices, setting 2009M1=100. Then, quarterly year-on-year growth rates are used to construct the series back to 1998Q1.

All series are transformed into real terms by deflating by the quarterly city consumer price index (CPI). A quarterly CPI for the cities is constructed as follows. We use annual data on CPI growth for the 35 cities in order to construct an annual CPI index for each city. Then, a proportional Denton method is applied to interpolate annual to quarterly observations using a quarterly indicator series (in our case the national CPI where quarterly data are available), imposing the condition that the interpolated quarterly series matches the annual totals.

All series are seasonally adjusted using the X-12 procedure.

Appendix 2. Figures of Series

Real Consumption
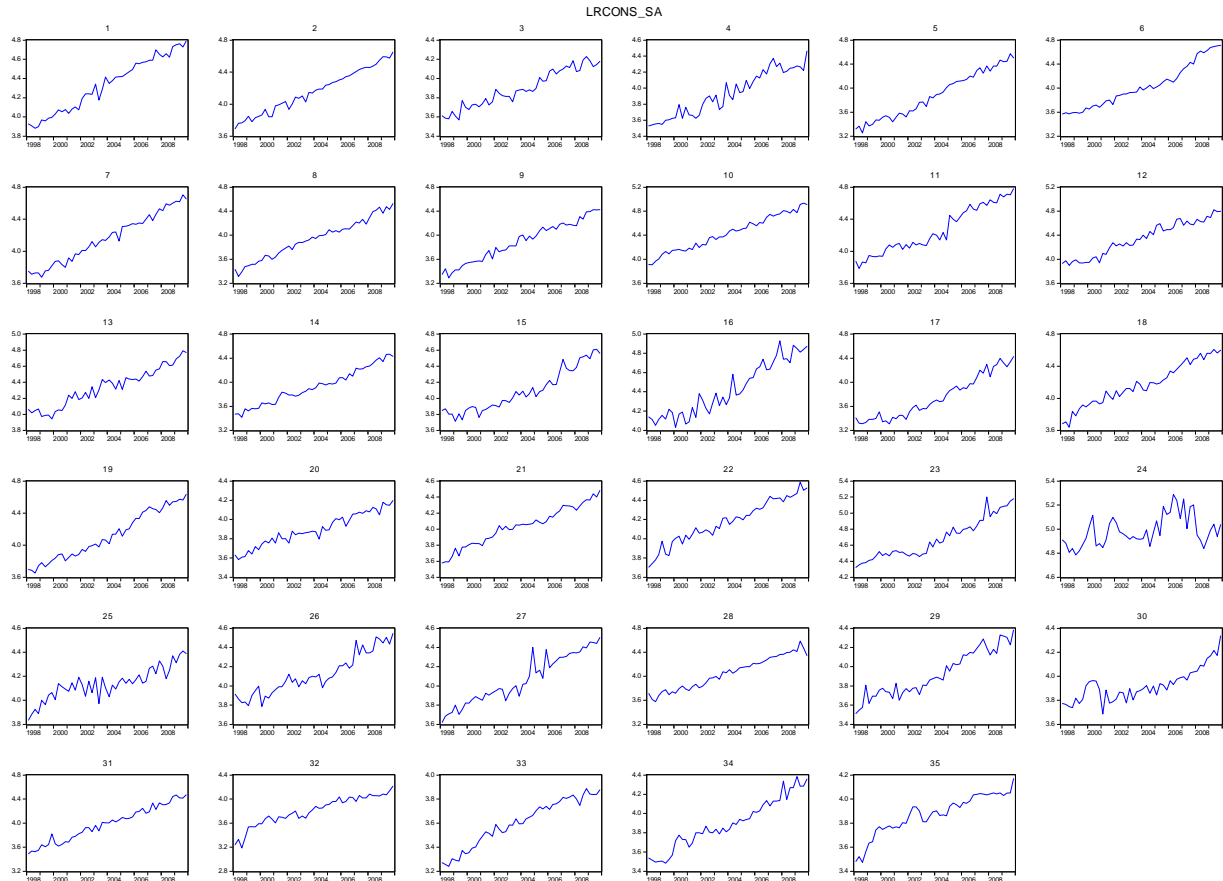
LRCONS_SA

Cities: (1) Beijing, (2) Tianjin, (3) Shijiazhuang, (4) Taiyuan, (5) Hohhot, (6) Shenyang, (7) Dalian, (8) Changchun, (9) Harbin, (10) Shanghai, (11) Nanjing, (12) Hangzhou, (13) Ningbo, (14) Hefei, (15) Fuzhou, (16) Xiamen, (17) Nanchang, (18) Jinan, (19) Qingdao, (20) Zhengzhou, (21) Wuhan, (22) Changsha, (23) Guangzhou, (24) Shenzhen, (25) Nanning, (26) Haikou, (27) Chengdu, (28) Chongqing, (29) Guiyang, (30) Kunming, (31) Xian, (32) Lanzhou, (33) Xining, (34) Yinchuan, (35) Urumqi.
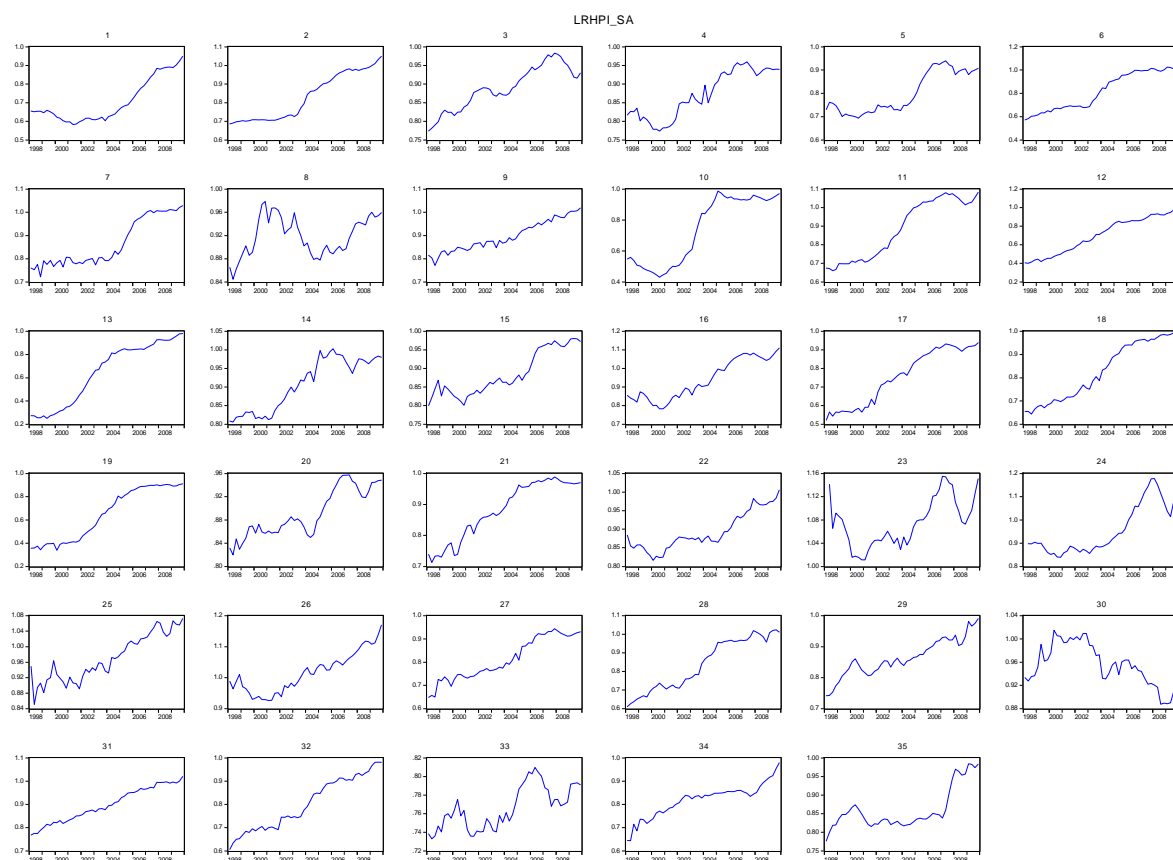
Real Income
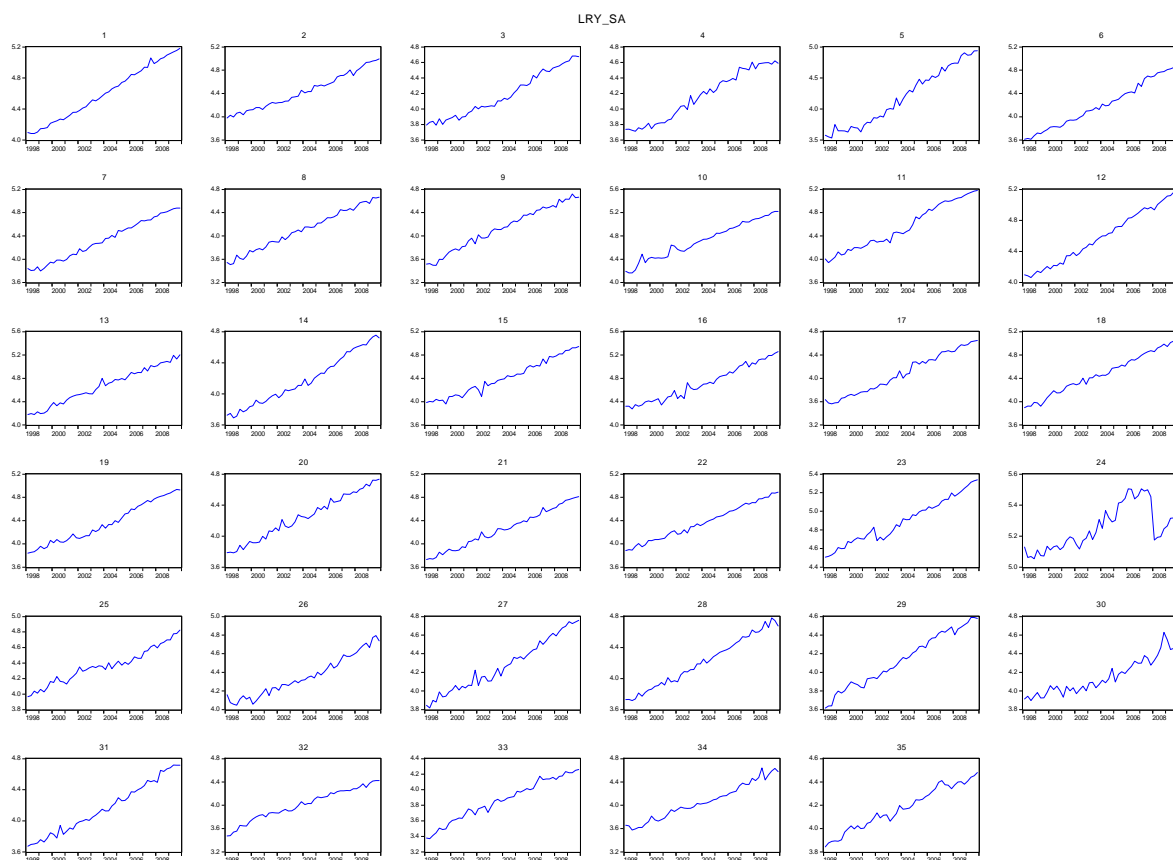
Cities: (1) Beijing, (2) Tianjin, (3) Shijiazhuang, (4) Taiyuan, (5) Hohhot, (6) Shenyang, (7) Dalian, (8) Changchun, (9) Harbin, (10) Shanghai, (11) Nanjing, (12) Hangzhou, (13) Ningbo, (14) Hefei, (15) Fuzhou, (16) Xiamen, (17) Nanchang, (18) Jinan, (19) Qingdao, (20) Zhengzhou, (21) Wuhan, (22) Changsha, (23) Guangzhou, (24) Shenzhen, (25) Nanning, (26) Haikou, (27) Chengdu, (28) Chongqing, (29) Guiyang, (30) Kunming, (31) Xian, (32) Lanzhou, (33) Xining, (34) Yinchuan, (35) Urumqi.
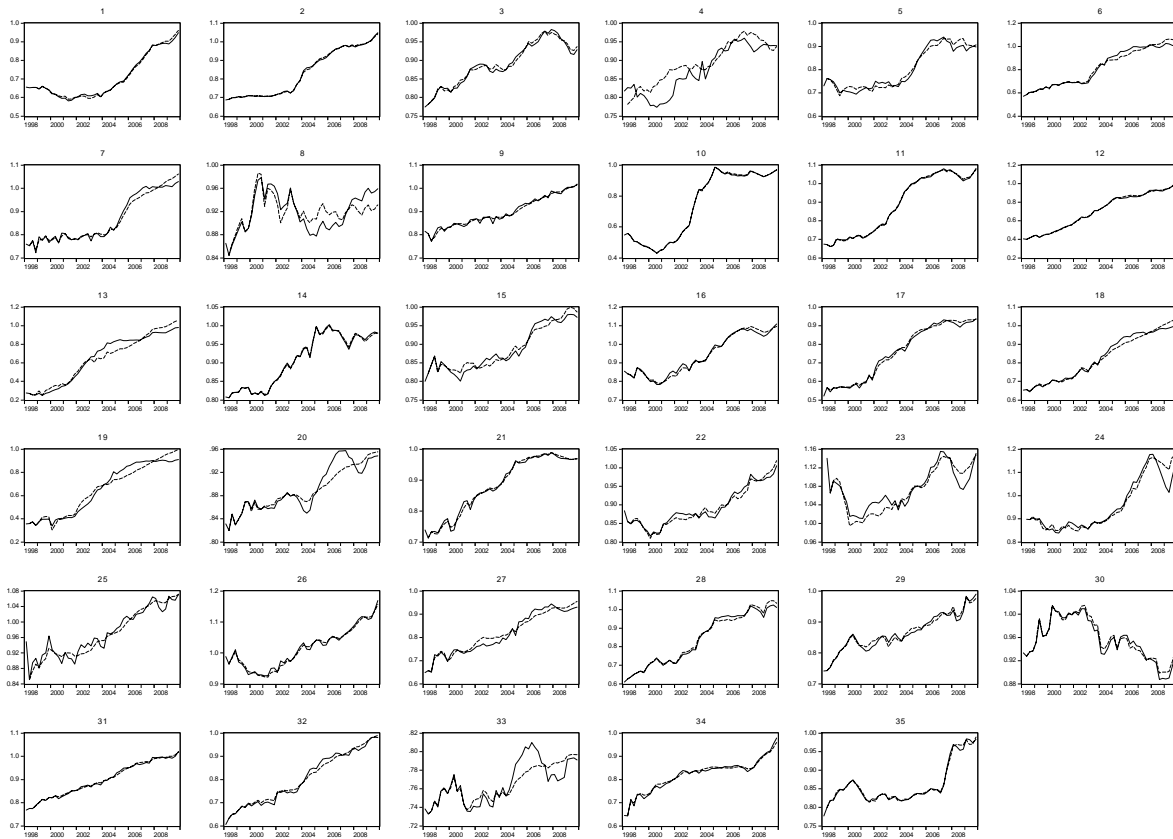
Real House Prices

Cities: (1) Beijing, (2) Tianjin, (3) Shijiazhuang, (4) Taiyuan, (5) Hohhot, (6) Shenyang, (7) Dalian, (8) Changchun, (9) Harbin, (10) Shanghai, (11) Nanjing, (12) Hangzhou, (13) Ningbo, (14) Hefei, (15) Fuzhou, (16) Xiamen, (17) Nanchang, (18) Jinan, (19) Qingdao, (20) Zhengzhou, (21) Wuhan, (22) Changsha, (23) Guangzhou, (24) Shenzhen, (25) Nanning, (26) Haikou, (27) Chengdu, (28) Chongqing, (29) Guiyang, (30) Kunming, (31) Xian, (32) Lanzhou, (33) Xining, (34) Yinchuan, (35) Urumqi.

Real House Prices (solid lines) and their Kalman-Filtered Permanent Component (dotted lines)

Cities: (1) Beijing, (2) Tianjin, (3) Shijiazhuang, (4) Taiyuan, (5) Hohhot, (6) Shenyang, (7) Dalian, (8) Changchun, (9) Harbin, (10) Shanghai, (11) Nanjing, (12) Hangzhou, (13) Ningbo, (14) Hefei, (15) Fuzhou, (16) Xiamen, (17) Nanchang, (18) Jinan, (19) Qingdao, (20) Zhengzhou, (21) Wuhan, (22) Changsha, (23) Guangzhou, (24) Shenzhen, (25) Nanning, (26) Haikou, (27) Chengdu, (28) Chongqing, (29) Guiyang, (30) Kunming, (31) Xian, (32) Lanzhou, (33) Xining, (34) Yinchuan, (35) Urumqi.

Appendix 3. Goodness-of-Fit and Diagnostic Tests for Maximum Likelihood Estimation

Beijing	Changchun	Changsha	Chengdu	Chongqing	Dalian
R^2 0.993	R^2 0.828	R^2 0.963	R^2 0.973	R^2: 0.986	R^2: 0.969
q-ratio 0.344	q-ratio 1.000	q-ratio 1.000	q-ratio 0.290	q-ratio 1.000	q-ratio 0.019
BS 1.121 [0.571]	BS 3.267 [0.195]	BS 1.834 [0.399]	BS13.488 [0.001]	BS 6.117 [0.047]	BS 1.156 [0.561]
Q 7.438 [0.592]	Q 27.678 [0.001]	Q 11.998 [0.213]	Q 8.127 [0.521]	Q 12.874 [0.168]	Q 12.251 [0.200]

Fuzhou	Guangzhou	Guiyang	Haikou	Hangzhou	Harbin
R^2:0.963	R^2 0.838	R^2 0.956	R^2 0.946	R^2 0.995	R^2: 0.962
q-ratio 1.000	q-ratio 0.068	q-ratio 1.000	q-ratio 0.011	q-ratio 0.102 BS	q-ratio 0.297
BS 86.82 [0.000]	BS 34.995[0.000]	BS 5.220 [0.074]	BS 0.561 [0.755]	1.829 [0.401]	BS 0.592 [0.744]
Q 8.663 [0.469]	Q 9.536 [0.389]	Q 11.002 [0.276]	Q 11.173 [0.264]	Q 4.690 [0.861]	Q 13.095 [0.158]

Hefei	Hohhot	Jinan	Kunming	Lanzhou	Nanchang
R^2: 0.961	R^2: 0.976	R^2: 0.994	R^2: 0.839	R^2: 0.989	R^2: 0.988
q-ratio 1.000	q-ratio 1.000	q-ratio 0.094	q-ratio 1.000	q-ratio 1.000	q-ratio 0.428
BS 0.321 [0.852]	BS 0.785 [0.675]	BS 0.629 [0.730]	BS 1.354 [0.508]	BS 15.491[0.000]	BS 3.848 [0.146]
Q 12.508 [0.186]	Q 8.231 [0.551]	Q 14.677 [0.100]	Q 11.151 [0.266]	Q 5.593 [0.780]	Q 8.395 [0.495]

Nanjing	Nanning	Ningbo	Qingdao	Shanghai	Shenyang
R^2: 0.994	R^2: 0.900	R^2: 0.997	R^2: 0.995	R^2: 0.991	R^2: 0.992
q-ratio 1.000	q-ratio 0.003	q-ratio 1.000	q-ratio 0.133	q-ratio 0.325	q-ratio 0.393
BS 4.696 [0.096]	BS 8.625 [0.013]	BS 0.416 [0.812]	BS 12.574[0.002]	BS 15.288[0.001]	BS 3.808 [0.149]
Q 17.722 [0.039]	Q 18.193 [0.033]	Q 8.296 [0.505]	Q 10.446 [0.316]	Q 17.109 [0.047]	Q 4.087 [0.906]

Shenzhen	Shijiazhuang	Taiyuan	Tianjin	Urumqi	Wuhan
R^2: 0.972	R^2: 0.982	R^2: 0.948	R^2: 0.995	R^2: 0.960	R^2: 0.979
q-ratio 0.058	q-ratio 1.000	q-ratio 0.055	q-ratio 0.662	q-ratio 1.000	q-ratio 0.948
BS 2.501 [0.286]	BS 0.843 [0.656]	BS 11.048[0.004]	BS 18.713[0.000]	BS 0.227 [0.893]	BS 0.809 [0.667]
Q 7.635 [0.571]	Q 6.955 [0.642]	Q 6.082 [0.732]	Q 2.549 [0.980]	Q 9.281 [0.412]	Q 4.798 [0.852]

Xiamen	Xian	Xining	Yinchuan	Zhengzhou	
R^2: 0.970	R^2: 0.993	R^2: 0.878	R^2: 0.961	R^2: 0.949	
q-ratio 1.000	q-ratio 0.796	q-ratio 1.000	q-ratio 0.06	q-ratio 0.039	
BS 4.408[0.110]	BS 0.895 [0.639]	BS 0.753 [0.686]	BS 4.891 [0.087]	BS 0.254 [0.881]	
Q 11.192 [0.263]	Q 6.377 [0.702]	Q 6.818 [0.656]	Q 8.391 [0.495]	Q 8.339 [0.500]	

Notes: R^2 is the coefficient of determination. q-ratio refers to the signal-to-noise ratio for the level (slope in the case of Beijing, Dalian, Hangzhou, Shenzhen and Yinchuan; cycle in the case of Jinan, Lanzhou, Ningbo, Xiamen and Xining; for the mentioned cities the relative variance of the level or slope is zero). BS is the Bowman-Shenton test statistic for non-normality. Q is the Box-Ljung test statistic for residual autocorrelation. *p*-values are in brackets.