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Fundamentals and the Volatility of Real Estate Prices in China: A Sequential Modelling Strategy*

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Abstract

In a similar way to the stock market, the housing market in China has often been portrayed as highly speculative, giving rise to "bubble" concerns. Over the last decade, residential prices increased every year on average by double digits in Beijing or Shanghai (Deng, Gyourko and Wu, 2012). However many observers and researchers argue that the fundamentals of the housing sector, both sector-specific and macroeconomic, may have been the driving force behind housing price volatility. While existing empirical work exclusively relies on downward-biased official housing prices, this paper uses original high-frequency unit level residential price series for Beijing and Shanghai to test alternative hypotheses about the drivers of house price growth. We propose a sequential research strategy including the construction of hedonic prices, explosive unit root tests (Phillips, Shi and Yu, 2014), the filtering of microstructure noise (Bollerslev et al. 2015) and a Mixed Data Sampling (MIDAS) methodology (Ghysels et al, 2007; Engle et al., 2013) which enables us to document that fundamentals can indeed account for movements in housing price volatility, as well as transaction volume in first-tier cities such as Beijing and Shanghai.

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1. Introduction

The housing market in China has often been portrayed as highly speculative, giving rise to "bubble" concerns. Figure 1 shows a dramatic increase in discussion about "housing bubbles" in the Chinese media, based on a Google search. The search covers the period from 2005Q1 to 2013Q4, starting before the global financial crisis and ending with a recent housing market boom triggered by the huge monetary-fiscal reflation programme in China in 2009. Indeed the sharp rise in real estate prices in China has been similar to that experienced in the United States during the subprime decade (Deng, Gyourko and Wu, 2012; and Wu, Gyourko and Deng, 2012). For example, over the last decade, residential land prices increased on average by approximately 25% per annum in Beijing. A similar pattern of residential market volatility has been observed in other major housing markets, such as Shanghai and Hangzhou (see Deng, Gyourko and Wu, 2012). There is a presumption that such accelerated rises in prices are generated by a bubble. However, some observers and researchers argue that fundamentals in the housing sector, both sector-specific and macroeconomic, may have been the driving force behind housing price volatility (see, for example, Fu, Qian and Yeung, 2013). This paper tests these alternative hypotheses on original high-frequency hedonic residential housing data, which avoid the bias in official housing prices data. We find no statistical evidence that a bubble was driving the rise of real estate prices in China in the second half of the first decade of the new millennium. Rather price volatility seems to be well-explained by movements in classical fundamentals.

The real estate industry contributes greatly to Chinese economic growth. In 2009 it directly accounted for over one tenth of total national GDP growth, and therefore played a substantial part in the quick recovery of the Chinese economy from the global financial crisis (Deng, Morck, Wu and Yeung, 2011, 2015; Wu, Gyourko and Deng, 2012; and Wu, Deng, Huang, Morck and Yeung, 2014). The overall importance of this sector is even larger if indirect effects on the construction material industries are taken into account (possibly up to one third, Renmin, 2014). As reported by the People's Bank of China, at the end of 2010 the outstanding balance of developer plus residential mortgage loans represented around 6.28 trillion yuan RMB, over 18% of total loans.

We contribute to a literature trying to assess empirically sector-specific as well as macro-variables as potential determinants of long run asset market volatility, building on Schwert (1989). As stressed by Schwert (1989, p. 1116), if macroeconomic data "provide information about the volatility of either future expected cash flows or future discount rates, they can help explain why [asset] return volatility changes over time". Existing empirical work along such lines focuses almost exclusively on the stock market, both for large panels of countries (Diebold and Yilmaz, 2010; Engle and Rangel, 2008) and for China (Girardin and Joyeux, 2013). In the case of daily real estate data such an approach cannot be applied directly.

In order to address the challenges presented by the modelling of high-frequency real estate prices in an emerging market like China, we propose a sequential strategy in five steps integrating several techniques previously developed in a piecemeal and scattered way. The first issue concerns the

appropriate data to be used. Focusing on repeated-sales housing data has become standard practice for large advanced countries, like the US. By contrast, a lack of sufficient comparable transactions of repeated-sales in the housing market in China, a feature common with some other emerging economies, means that the hedonic method is the most commonly adopted house price index model among nascent housing markets (Wu, Deng and Liu, 2014). A major difficulty in studying the property market in China lies in the low quality of official price data due in particular to the underestimation of quality changes (Wu, Gyourko and Deng, 2015(b)). Our first contribution is the use of a unique data set including daily hedonic prices as well as transactions for the residential resale housing markets of Beijing and Shanghai between January 2005 and December 2010.

In a second step, while it is traditional in time-series analysis to conduct prior stationarity tests, this is not appropriate for real estate prices potentially subject to bubbles. We thus propose using recently developed tests (Phillips, Shi and Yu, 2014) with an explosive root as an alternative to the unit root hypothesis. The third step is generated by the necessity of handling microstructure noise present in daily real estate data. If we reject the explosive root in favour of the unit root, filtering the raw data with the extraction of a random walk component (as suggested recently for daily data by Bollerslev et al., 2015) seems all the more relevant. The fourth step aims at extracting a long run volatility component from the filtered daily hedonic real estate data. The GARCH-MIDAS procedure seems well adapted to this task in as much as it enables us to account for the heteroskedasticity in short run volatility as well as extracting a long-run volatility component via a beta-lag distribution on realized volatility. We apply the MIDAS methodology (developed by Engle, Ghysels and Sohn, 2013; and Engle and Rangel, 2008) to extract long-run volatility from Chinese residential housing market daily squared returns. The finding that bubbles do not characterize the residential housing market in first tier Chinese cities leads us in a fifth step to examine to what extent fundamentals are able to explain the long-run volatility of Chinese housing prices at a monthly frequency.

We study the influence of three types of control groups: sector-specific, and policy variables, as well as speculation-related variables. We consider the direct effect of fundamentals on real estate volatility and also the indirect effect through the impact of transaction volume on prices. Such an influence is well rationalized (in the non-rational expectations search model of Berkovec and Goodman, 1996, and the down payment model of Stein, 1995) and documented for the residential property market (e.g. for Hong Kong by Leung, Lau and Leong, 2002; for mainland China since its housing system reform by Deng, Zheng and Ling, 2005; and for Singapore by Deng, McMillen and Sing, 2012).

We find that the three types of variables are present, though in a contrasted way, in Beijing and Beijing and Shanghai combined. Among the first category, rent and land supply play a role; in the second, stock market returns and foreign currency reserve inflows are important; and among the last macroprudential, but not monetary, policy matters. Some of these influences impact prices indirectly via transaction volume.

To sum up, our analysis has three main contributions. First, we assemble the first dataset of high-frequency transactions in the Chinese urban real estate market. This data allow us to correct some important biases affecting existing studies. Second, to analyse this data, we propose a five-step strategy involving state-of-the-art econometric techniques. From a methodological point of view, we provide one of the first analysis using bubble detection techniques and mixed frequency data analysis for the real estate market. Third, we assess the determinants of the recent rise in both volume and volatility in housing prices in China. We show that concerns about a housing bubble are probably unfounded and that this rises are well-explained by changes in fundamentals.

The remainder of the paper is organized as follows. Existing evidence on the presence of bubbles in China's housing market, as well as empirical analyses of the effect of sector-specific, speculative and policy variables on real estate prices will be presented in section two. The bubble-detection, microstructure-noise filtering and MIDAS methodologies, as well as the unique hedonic residential resale-price data for major Chinese cities used in the present paper will be introduced in section three. Section four will discuss the results of the application of these techniques to real estate data in China, and provide an interpretation. Section five offers some conclusions.

2. Fundamentals, Speculation and the Real Estate Market

The difficulties associated with detecting a possible deviation of real estate prices from their fundamentals, and identifying the associated bubble component, are clearly illustrated by work on the US housing market prior to the subprime crisis (e.g. McCarthy and Peach, 2004; Cutts and Nothaft, 2005). The literature attempting in a similar way to detect deviations of China's real estate prices from their fundamentals will be presented first. We will then examine work on fundamentals, transactions and volatility.

2.1 Fundamentals and Real Estate Prices in China

Research has examined the determinants of, and evidence for, booms and busts in housing markets. A rich empirical literature has endeavoured to study the drivers of house prices in China, stressing the role of sector specific as well as speculative or policy factors.

2.1.1 Housing-Price Boom-Busts

In his famous book Irrational Exuberance (2005), Shiller argues that the feedback that creates bubbles has the primary effect of amplifying stories that justify the bubble. He points out that contagion tends to work through word of mouth and through the news media. From a theoretical perspective, the modelling of booms and busts in the housing market has increasingly relied on expectations-driven cycles introduced for example by Lambertini et al. (2013) using the model of the

housing market developed by Iacoviello and Neri (2010). News shocks1 generate common booms in house prices and credit to households. A macroeconomic bust takes place when expectations about future economic conditions are not matched by economic outcomes. Thus, unrealized news shocks distort borrowing above its equilibrium level. Their sudden reversal has negative effects on real and financial decisions. Similar cycles are generated in the models of Kermani (2013) and Kanik et al. (2014). Booms and busts can also occur when agents have heterogeneous expectations about long-run fundamentals but change their views because of social dynamics (Burnside et al., 2013). Agents with tighter priors are more likely to convert others to their beliefs. The booms that are not followed by busts typically occur when optimistic agents happen to be correct[2].

However, real estate cycles may be driven by factors other than "news shocks". Leung (2014) presents a simple dynamic stochastic general equilibrium model in which the reduced form dynamics are consistent with the error correction model estimated by Malpezzi (1999), and Capozza et al. (2004). In addition, the presence of collateral constraints and large shocks, modelled by Chen and Leung (2007), can generate large scale bankruptcy, leading to regime-switching dynamics in house prices, in line with the evidence presented by Chang et al. (2011). Since agents do not know the market perfectly, Kuang (2014) shows that the fact that agents learn on the one hand and trade on the other may induce cycles in both house prices and credit. Stressing the expectation formation process when the market displays regime-switching, Chen et al. (2015) find that the anticipation of possible regime change may impact agents' behavior, and hence aggregate output and house price dynamics.

The conditions for a bubble in the real estate market differ from those in stock markets in as much as the response of supply plays a major role in the former and not in the latter. Malpezzi and Wachter (2005) introduce a crucial distinction between short run and long run price-elasticities of supply. When the former is smaller than the latter a demand shock will generate price volatility.

In their empirical modelling of monthly Shanghai and Beijing house prices data from 1997 to 2003, Hui and Yue (2006) employ Granger causality tests and generalized impulse response analysis, and find evidence of speculative bubbles for Shanghai house prices in 2003 but not for Beijing. Hui and Ng (2009), using similar econometric techniques and quarterly data between 1996 and 2007, find some mild evidence of a bubble in Shenzhen house prices. Chen and Li (2011) detect some risk of speculative bubble in several regional housing markets, especially in the eastern area, in as much as the convergence rate of the housing price towards the long-term equilibrium price is relatively slow in such regions. However, in more recent work, Fang, Gu, Xiong and Zhou (2015) report that appreciation in China's housing markets has been mostly accompanied by equally impressive household income growth. In their study of 120 cities, they find that households from the lower end of

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1 According to Gomes and Mendicino (2015) news shocks explain a sizable fraction of the variation in house prices and other macroeconomic variables.

2 Ascari et al. (2013) propose a partial disequilibrium dynamic model of the housing market in which the rational-expectations hypothesis is also relaxed, this time in favour of chartist-fundamentalist mechanism to allow for the endogenous development of bubbles.

the income distribution are able to access financing and purchase homes, even in cities with high house price appreciation. Also, Ren, Xiong, and Yuan (2012), using panel-regression techniques on yearly house-price returns for 35 Chinese cities between 1999 and 2009, find no evidence to support the existence of rational expectations bubbles.

Ahuja et al. (2010) conclude that in China, while prices have run ahead of fundamentals in some market segments, nationally this does not seem to be the case. This assessment is based on a comparison of movements in China's residential property prices with those implied by market fundamentals, as measured with two different approaches. The first is based on a panel regression linking prices to long-term fundamentals and the second on the relationship between price, rent, and ownership cost. The paper finds that there is no significant price misalignment. Over the past decade, when misalignments in house prices have occurred, they have been corrected relatively quickly. Finally, the combination of restricted housing credit policy and purchase restriction policy measures taken by the Chinese government in April 2010 appears to have succeeded in reducing the gap between market and fundamentals-implied prices in some cities, but not in others (Guangzhou, Tianjin, and Shenzhen). Wang and Zhang (2012) document that, for most cities in their sample, housing price appreciation can be largely explained by changes in fundamentals between 2002 and 2008.

At the aggregate level, Liu and Yue (2005), conclude that market fundamentals, including mostly demand-side variables (unemployment rate, total population, and changes in the consumer price index) and some supply–side ones (changes in construction costs), could explain most of the variations in housing prices between 1986 and 2002. At a local level, Dreger and Zhang (2013) examine house-price developments using panel-cointegration techniques and data on 35 major cities. A long run relationship is detected between real house prices and a set of macroeconomic determinants. The national bubble component was estimated to be less than 15 per cent of the equilibrium value as implied by the fundamentals at the end of 2010, but the bubble was larger in the cities located in the south-east coastal areas and special economic zones. Using data from 35 metropolitan areas, Zhang, Weng, and Zhou (2007) find that equilibrium prices are determined by basic economic conditions in China and greatly affect fluctuations of actual prices, which return to their equilibrium level through self-adjustment.

Putting Chinese developments in an international perspective[3], Glindro, Subhanij, Szeto, and Zhu (2011) examine house price developments in eight economies in the Asia-Pacific area as well as China, using both panel data and country-specific regressions using quarterly data between 1993 and 2006. Following previous work on the U.S. (Capozza et al. 2002), they define a bubble as the component of price not explained by cyclical and fundamental factors. In Glindro et al.'s analysis, demand-side factors include real GDP, population, the real mortgage rate, and the mortgage credit-to-GDP ratio, while supply-side factors consist of the land supply index and real construction costs. The

[3] Ghysels et al. (2013) present an exhaustive survey of the principal methodologies used in constructing real estate price indices and of the main empirical findings on the determinants of price movements for the US residential and commercial real estate markets.

trend component of the mortgage credit-to-GDP ratio and equity prices is used to proxy long-run house price fundamentals. They conclude that the recent house price growth in China can be explained by macroeconomic fundamentals.

2.1.2 Housing-Market Specific Fundamentals

Some literature[4] has focused more specifically on housing-specific fundamentals. Wu, Gyourko, and Deng (2012) note that the price-to-rent ratio in Beijing, and seven other large markets across the country, has increased by 30% to 70% since the beginning of 2007. Current price-to-rent ratios imply a very low user cost of no more than 2%–3% of house value. Very high expected capital gains appear necessary to justify such a low user cost. Their calculations suggest that even modest declines in expected appreciation would lead to large price declines, of over 40% in markets such as Beijing, in the absence of offsetting rent increases or other countervailing factors. Using both national and province-level panel data, Chen and Li (2011) find that housing prices growth is closely related to demand-side variables, such as increases in household income.

Peng, Tam and Yu (2005) provide evidence that, over 1998-2004, a supply-side variable, *land price*, has a much larger 'multiplier' effect on property prices in coastal areas than in the interior provinces.

2.1.3 Speculative Forces

In the case of China, it is generally considered that speculative forces acting on the real estate market originate either in the stock market or in the provision of liquidity from hot money inflows.

As a by-product of the very successful reforms initiated in the late 1990s, home ownership in China is extremely widespread (87% of households in urban and 97% in rural areas) and substantially higher than stock ownership (only 6% in the late 2000s). However, households who buy new housing mainly do it (62% of them) for investment or speculative purposes, often in the form of a second or third housing unit. China's stock market is also often portrayed as highly speculative, as testified by the fact that the number of new household stock market accounts created every month often reaches several millions (households represent 80% of investors in China's stock market). Accordingly it is worth considering to what extent portfolio choice and wealth effects may be at work between the real estate and stock markets, particularly for households in China whose only alternative (until the very recent gradual capital account opening) store of wealth is a bank account.

It is noteworthy that developments in the real estate markets may not be independent from what happens in stock markets (Cocco, 2004; Campbell and Cocco, 2015) or possibly bond markets (Yao and Zhang, 2005). Indeed in as much as the portfolio of investors is composed of both types of assets,

[4] In addition, previous studies have mostly discussed the distribution of affordability, in particular for low income families (Sato, 2006; Wang, Yang and Liu, 2011; and Gan, Yin, and Zang, 2010). Shen (2012), defines housing affordability in terms of permanent income, and finds that housing is more affordable in China than in developed economies, although the ratio of housing prices to current income is much higher than in developed nations.

substitution between the two investments may lead to a negative correlation of their returns (Shiller, 2014), while wealth effects may lead to positive correlations (Gyourko and Keim, 1992). As distinct other financial assets, housing is both a durable consumption good, generating utility to its owner, and an investment vehicle that allows the investor to hold home equity. This is obviously true only for those households who are owner occupiers, while in China many derive housing services from renting their home and investing in a second home.

Huang and Ge (2009), find only weak correlation between stock and real estate markets in China, but their (monthly) sample is very short (26 months starting in April 2006). With a longer sample (2003-2012) but a lower frequency (quarterly) and with a regional panel, Yuan, Hamori and Chen (2014) contrast positive short-run with negative long-run effects of stock prices on housing prices. Guo and Huang (2010) find a positive effect of excess financial wealth on property prices as well as price volatility. By contrast Xu and Chen (2012) find such an impact insignificant when controlling for the effect of money supply growth.

The role of hot money inflows in driving housing market dynamics in China is potentially important given the spectacular accumulation of foreign currency reserves, representing an ever expanding source of liquidity if not fully sterilized. Such inflows can also affect stock market investment. Feng, Lin and Wang (2012) find that hot money inflows (immediately) impact stock but not housing returns, while foreign direct investment (FDI) impacts the latter (with a lag) and not the former. Guo and Huang (2010), with monthly data over 1997-2008, find that hot money does impact significantly on China's real estate, but not stock markets. Besides, while stock price shocks drive housing price movements, the reverse is not true. Xu and Chen (2012), over July 2005 to February 2010, find that a bullish stock market accelerates subsequent housing price growth, but, when controlling for money-supply growth, hot money inflows do not impact housing-price growth.

2.1.4 Monetary Versus Macroprudential Policy

Movements in bank credit are often responsible for overheating in real estate markets. The authorities' toolkit includes either price and quantity monetary instruments or macroprudential tools.

Households' income, representing one of the major fundamentals of housing prices, would represent a bound on the latter in an economy without financial markets. However, the presence of mortgage loans used to finance housing purchases may disconnect house prices from the household-income fundamental. As modelled by Hillebrand and Kikuchi (2013), with rational expectations, and neither heterogeneity nor financial frictions, a household may buy a house exceeding the discounted present value of its income, if it finances the purchase partly with a loan, which it will repay in the future by selling the house at a higher price. At the macro level, persistent income changes generate parallel large movements in credit volumes and housing prices[5].

[5] See Agnello et al. (2011) for a study of a sample of eighteen industrialised countries over the period 1980–2007.

Qi and Cao (2007) investigate the relationship between property prices and *bank lending* in China over the period 1999Q1–2006Q2. Using an autoregressive distributed lag framework, they find short- and long-run causality from bank lending to property prices. Using panel data models covering 31 Chinese provinces and major cities, Peng, Tam, and Yiu (2005), over 1998-2004, find that *credit expansion* by the four large state-owned banks does not feed property-price inflation.

Two studies consider a narrow or wide set of monetary policy instruments. Xu and Chen (2012) use quarterly (1998Q1 to 2009Q4) and monthly (July 2005 to February 2010) data, and document that key monetary policy variables (bank loan rate, money supply growth, and mortgage credit policy indicator) are the main driving forces behind real estate price growth dynamics in China. Zhang, Hua and Zhao (2012), using a non-linear modelling approach, enlarge the number of monetary and price variables (mortgage rate, producer price, broad money supply and real effective exchange rate) as significant determinants of housing prices in China over the period January 1999 to June 2010. Within a wider study of the transmission mechanism, Zhang (2013) finds that *monetary growth* is transmitted to the real economy via changes in house prices[6].

Given the role of the state in the Chinese economy and banking system, and the existence of direct controls on credit, Deng, Morck, Wu and Yeung (2011, 2015) provide evidence that China's monetary stimulation in 2009 and 2010 led to soaring house prices in major cities. They argue that such speed and efficacy of China's monetary policy derives from state control over its banking system and corporate sector. Beijing ordered state-owned banks to lend, and they lent. Beijing ordered centrally-controlled state-owned enterprises (SOEs) to invest, and they invested. Much of this investment was highly-leveraged purchases of real estate.

Macroprudential policy aimed at limiting the effect of credit expansion on real estate prices relies, in particular, on changing down-payment requirements, which in the Chinese case are differentiated between first, second and possibly third home purchases. Xu and Chen (2012) develop a five-pronged qualitative index of loan to value requirements for housing purchases of first and second homes. They find that restrictive (expansionary) movements in that index significantly curb (stimulate) house prices with monthly panel data, with a one month lag. Deng, Wachter and Zhu (2015) find that a combination of restricted housing credit policy and home purchase restriction policies implemented by the Chinese government around April 2010 effectively cooled down the housing booms through curbing transaction volumes in many markets.

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[6] Focusing on another key aspect of the transmission channels, Wu, Gyourko and Deng (2015(a)) study the dramatic swings in Chinese land markets in recent years and investigate the evidence of an economically meaningful real estate collateral channel effect on non-real estate listed firm investment. Their study indicates that since China's debt markets are not characterized by the frictions found in the U.S. and other developed countries there is no reason to expect a collateral channel effect as borrowers do not need to pledge property as collateral to fund investment programs.

2.2 Fundamentals, Transactions and Asset Price Volatility

In the context of the stock market Schwert (1989) suggests explaining asset market volatility by the time varying volatility of macroeconomic variables. More recently Engle and Rangel (2008) model high-frequency return volatility as the product of a slow-moving component and a GARCH process. The slow-moving component is then modelled as a function of macroeconomic and financial variables. Engle et al. (2013) introduce the GARCH-MIDAS approach to model simultaneously the GARCH component and the functional relationship between the long-run component with the volatility and the mean of macroeconomic variables. The GARCH-MIDAS component model uses a daily GARCH process and a MIDAS polynomial as proposed by Ghysels, Santa-Clara and Valkanov (2006). Such an approach is applied to China's stock market volatility by Girardin and Joyeux (2013), with both daily stock returns and monthly macroeconomic variables.

The impact of transactions volume on prices has been emphasized in the housing market literature. Stylized facts for the housing market are well described by Berkovec and Goodman (1996) who show that because housing supply is less than perfectly elastic, changes in turnover rates are positively correlated with changes in house prices (via a wealth effect working through the presence of down payments, Stein, 1995). In addition, such a relationship between price and turnover holds more strongly at low rather than at high frequencies (due to the time lag between the signing and closing of the contract). Finally the response to housing demand is quicker for turnover rates than for prices, which is in line with the search-theoretic cum informal friction model of Berkovec and Goodman (1996) but inconsistent with the rational expectations model. Subsequent research (Leung et al, 2002) has shown that, on disaggregated data (for 35 residential estates in Hong Kong over June 1991 through November 1998), the medium-run component of transaction volume (extracted with a band-pass filter) leads (and Granger causes) a similar component of the housing price (see also Leung and Feng, 2005; and Leung, Cheung and Ding, 2008, on the Hong Kong commercial property market).

Empirical evidence surveyed by Tu, Ong and Han (2009, p.2), leads them to conclude that "the fact that transactions lead to price changes after a demand shock is established" .Wheaton and Lee (2009), on panel data of US local housing markets showed that a large part of the variation in turnover is due to flows between rental and owner-occupied housing. In a search market context, there should be a connection between price volatility and turnover: the more uncertainty, the higher should be reservation prices and the longer houses should stay on the market before being sold. Consistent with this, Tu, Ong and Han (2009) document a negative correlation between volatility and turnover in their analysis of Singapore condominiums. In China a specific pattern may arise due to the particularities of housing policy (Huang and Yi, 2011), in which households living in public rental housing are more likely than homeowners to own a second home (in the mid 2000s around one quarter of renters owned second homes).

Bond and Hwang (2001) propose a fundamental measure of volatility for the commercial property market by using a stochastic volatility model (applied to the U.K. commercial property market) to filter

out the signal in the different sources of volatility. The different measures of volatility are decomposed into transitory noise and unobserved fundamental volatility. Several recent papers have investigated whether GARCH effects exist in the U.S. housing market (Dolde and Tirtiroglu, 1997; Crawford and Fratantoni, 2003; Miller and Peng, 2006; and Miles, 2008). Some research in finance indicates that the conditional variance of some assets exhibits far greater persistence, or even "long memory", than is accounted for in standard GARCH models. If house prices do indeed have this very persistent volatility, properly estimating the conditional variance to allow for such persistence is crucial for optimal portfolio management. Miles (2011) examines housing prices in a number of U.S. metropolitan areas, and finds that, for those with significant GARCH effects, more than half indeed exhibit the very high persistence found in other assets, such as equities.

3. Methodology and Data

3.1. Methodology

3.1.1 Explosive-Behaviour Test

Stationarity tests may not be appropriate when series are subject to bubbles, as in the case of real estate prices. In such cases the null of a unit root should be tested against the alternative of explosive roots. Phillips, Wu and Yu (2011), (PWY), develop such a test estimating the Augmented Dickey-Fuller (DF) statistics recursively and taking the supremum. Phillips, Shi and Yu (2014) (PSY) subsequently show that the PWY test may fail to reveal the existence of explosive behaviour in the presence of multiple explosive episodes, and construct a robust version of the test. PSY argue that bubbles arise from nonlinearities produced by multiple breaks. Their test, based on recursive/backward recursive ADF regressions, is designed to detect such breaks. PSY also show that their test can be used to date-stamp explosive periods.

The PSY test, denoted by generalized sup ADF (GSADF), is a right-tailed test. The ADF regression model with p lags can be written for each sample as:

$$\Delta y_t = \alpha_{f_1}^{f_2} + \beta_{f_1}^{f_2} y_{t-1} + \sum_{h=1}^{p} \phi_{h,f_1}^{f_2} \Delta y_{t-h} + \xi_t \quad (1)$$

where f_1 is the fractional starting point of the regression sample and f_2 the fractional ending point. The ADF t-ratio on the estimated $\hat{\beta}_{f_1}^{f_2}$ is denoted by $ADF_{f_1}^{f_2}$. The hypotheses are $H_0: \beta_{f_1}^{f_2} = 0$ (unit root dynamics), and $H_1: \beta_{f_1}^{f_2} > 0$ (explosive behaviour). The GSADF statistic is defined for each smallest feasible window size, f_0, as:

$$GSADF(f_0) = \sup_{f_2 \in [f_0,1], f_1 \in [0, f_2 - f_1]} \{ADF_{f_1}^{f_2}\}. \quad (2)$$

The regression sample size is $T_w = \lfloor T(f_2 - f_1) \rfloor$, where T is the total number of available observations and $\lfloor . \rfloor$ is the integer part of the argument.

PSY tabulate the asymptotic critical values of the GSADF statistic for different values of f_0. If the GSADF test statistic is found to be larger than the critical value then, for each sample point $\lfloor Tf_2 \rfloor$, a sequence of backward recursive tests is computed and a supremum taken:

$$BSADF_{f_2}(f_0) = \sup_{r_1 \in [0, r_2 - r_1]} \{ ADF_{f_1}^{f_2} \}. \quad (3)$$

The point $\lfloor Tf_2 \rfloor$ belongs to a bubble regime if:

$$BSADF_{f_2}(f_0) > CV(a, f_0) \quad (4)$$

where $CV(a, f_0)$ is the critical value for a given significance level a and window size range f_0.

3.1.2 Noise Filtering

Daily house prices are usually noisy, due to the small number of transactions on a daily basis. Corsi et al. (2015) develop techniques to extract the 'true' price process from high frequency data suffering from microstructure noise. If we do not reject the null of unit root in favour of explosive behaviour using the PSY test we follow Bollerslev et al. (2015) who employ these techniques for daily real estate data using a simple Kalman filter approach.[7] We denote by P_t the true price process at time t. The log of the 'raw' price, denoted by $\log P_t^*$, is presumed to be equal to the log of the true latent price plus an error term:

$$\log P_t^* = \log P_t + \varepsilon_t \quad (5)$$

where ε_t is serially uncorrelated. The 'true' log of price is assumed to follow a random walk with drift:

$$r_t = \Delta \log P_t = \mu + \eta_t \quad (6)$$

with ε_t and η_t mutually uncorrelated. We can then write the raw returns as

$$r_t^* = \Delta \log P_t^* = r_t + \varepsilon_t - \varepsilon_{t-1} = \mu + \eta_t + \varepsilon_t - \varepsilon_{t-1} \quad (7)$$

[7] Previously similar methods were used for low frequency real estate data by Engle, Lilien, and Watson (1985), and Brown, Song, and McGillivray (1997).

The true returns can be obtained from a Kalman-filter estimation assuming that the error terms are *i.i.d.* normally distributed. The normal assumption in our case cannot be justified and we can only interpret the filtered price series as best linear approximation.

3.1.3 MIDAS and GARCH-MIDAS

In order to model the volatility of the Chinese real estate (filtered) prices as a combination of sector-specific or macroeconomic effects and time series dynamics, we follow Engle et al. (2013) (EGS) and use a Mixed Data Sampling (MIDAS) methodology, as in Ghysels et al. (2005).

As in Engle and Rangel (ER) (2008) we assume that unexpected asset returns can be written as:

$$r_{i,t} - E_{i-1,t}\left(r_{i,t}\right) = \sqrt{\tau_t g_{i,t}}\,\zeta_{i,t} \tag{8}$$

where $r_{i,t}$ is the log asset return on day i during month t,[8] $E_{i-1,t}()$ is the conditional expectation given information up to time $i-1$. The high-frequency return volatility is assumed to be the product of a short run component, $g_{i,t}$, and a long-run component, τ_t. Macroeconomic and sector-specific variables can affect the low-frequency volatility but not the short-run component. Then, according to (8), the same news can affect returns differently depending on economic conditions.

In (6) we modelled the true daily prices as random walks and therefore it follows that $E_{i-1,t}\left(r_{i,t}\right) = \mu$. We re-write equation (8) as:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\,\zeta_{i,t} \tag{9}$$

where $\zeta_{i,t} \mid \Phi_{i-1,t} \sim N(0,1)$ and $\Phi_{i-1,t}$ is the information set up to day $(i-1)$ of period t. Note that μ in equation (9) should be the same as in equation (6).

We assume that $g_{i,t}$ follows a GARCH(1,1) process:

$$g_{i,t} = \left(1-\alpha-\beta\right) + \alpha\frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{10}$$

We can use a rolling window MIDAS filer to smooth realized volatility and obtain the long run component, $\tau_i^{(rw)}$, which can vary daily as:

[8] In theory t could be chosen to be monthly or quarterly. However, since our sample period spans only a small number of years we set t to be monthly.

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \tag{11}$$

where $RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2$ is the rolling window (*rw*) realized volatility, and *i* denotes the day of the period. For a monthly rolling-window *N'* is set to 30. $m^{(rw)}$ and $\theta^{(rw)}$ are the intercept and slope, respectively, of the rolling window MIDAS filter.

The function, $\varphi_k(\omega_1, \omega_2)$, can be chosen to be either a *Beta* or an *Exponentially-weighted* polynomial:

$$\begin{aligned} \varphi_k(\omega_1, \omega_2) &= \frac{(k/K)^{\omega_1 - 1}(1-k/K)^{\omega_2 - 1}}{\sum_{q=1}^{K} (q/K)^{\omega_1 - 1}(1-q/K)^{\omega_2 - 1}} \quad , \omega_1 + \omega_2 = 1, \text{ Beta} \\ \varphi_k(\omega) &= \frac{\omega^k}{\sum_{q=1}^{K} \omega^q} \quad , 0 < \omega < 1, \qquad \text{Exponentially weighted} \end{aligned} \tag{12}$$

A thorough analysis of the various shapes obtainable with Beta and exponentially weighted lags can be found in Ghysels, Sinko, and Valkanov (2007).

Equations (9)-(12) form a GARCH-MIDAS model for time-varying conditional variance with rolling-window realized volatility and parameter space $\Theta = \left\{ \mu, \alpha, \beta, m^{(rw)}, \theta^{(rw)}, \omega_1, \omega_2 \right\}$. *K* can be selected to minimise some information criterion such as the Bayesian one (BIC).

3.2 Data

Existing house price index construction methods, such as the repeated-sales index model which has been adopted in most of the developed markets, are not necessarily suitable for nascent housing markets. Using the booming market in China as an example, Deng, Gyourko and Wu (2012), Wu, Deng and Liu (2014), and Wu and Deng (2015) evaluate and compare the performance of three most common house price measurement methods, including the simple-average method without quality adjustment, the matching approach with the repeated-sales modelling framework, and the hedonic modelling approach. Their theoretical and empirical analyses suggest that the simple-average method and the matching approach both tend to produce a downward bias due to the complex- and unit-level quality changes over time of sales in these immature housing markets. The hedonic method seems to provide better control for these effects.

On the basis of this finding, we apply here the hedonic method to the housing market in two major Chinese cities, Beijing and Shanghai. Such daily detailed micro level housing transaction data were collected from multiple leading residential real estate agencies and local government authorities' websites. The sample covers the period from January 2005 to December 2010. For example, in the Beijing case, the daily data contain more than 360,000 transactions, which include 77,577 resale housing transactions from which our sample is extracted. Each record contains transaction information such as transaction date, transaction price (sale price), unit size, number of rooms, the floor level where the unit is located, and the total number of floors of the building. We then use the "Soufun Website-Based GIS" system [9] to match each transaction into more than 6,000 neighbourhoods[10], and compute the floor area ratio (FAR), distance to the city centre (Tiananmen Square), and the distance to the nearest subway station based on the neighbourhoods where the transacted units are located. Similar data are constructed for the Shanghai market. (See Ren, Wu and Deng, 2013, for a more detailed discussion on the compilation of the data set).

Properly measuring house prices requires disentangling observed movements in prices from the impact of quality changes on housing units sold in different periods (Wu, Deng and Liu, 2014; Malpezzi, 2002). In Chinese cities the housing sector is mostly composed of non-landed condominium units. It is usual for a condominium complex to be composed of hundreds or often thousands of units located in multiple high-rise residential buildings on a specific land parcel. Accordingly two groups of housing attributes should be distinguished: i) the complex-level attributes which include the locational characteristics and neighborhood amenities, plus some physical characteristics (building type and construction quality); ii) the unit-level attributes which refer to physical characteristics, usually unit size, floor level, and specific environmental attributes (for example, noise, view, accessibility to sunshine, *etc*.). Within the same complex, housing units share the former attributes, but differ in the latter.

Based on these features, the hedonic model in the Chinese *resale* housing market can be expressed as:

$$P_{vst} = \lambda U_{vt} + \gamma C_{st} + \delta_t D_{vst} + \upsilon_{vst} \tag{13}$$

where P_{vst} is the transaction price of unit v in complex s sold at time t; U_{vt} and C_{st} are sets of unit-level and complex-level housing characteristics, respectively, all in natural logarithm; and υ_{vst} is an *i.i.d.* error term.

[9] The system can be accessed at map.soufun.com.

[10] These 6,000 plus neighborhoods are located in eight urban districts in Beijing, namely, Chaoyang, Haidian, Fengtai, Xicheng, Xuanwu, Dongcheng, Chongwen and Shijingshan Districts. Among them, the Chaoyang District contains about 43% of the sample.

While other parameters might also be of interest, the key task of house price index construction is the accurate estimation of time dummies' coefficients δ_t . The hedonic method seeks to incorporate the quality adjustment, directly based on the estimation results of the hedonic model. In its most frequently used, time-dummy, specification, housing transactions from multiple periods are pooled into a single hedonic model to estimate the vector of time dummy coefficients δ_t, and subsequently the house price index can be computed on the basis of δ_t (Kain and Quigley, 1970; Gourieroux and Laferrere, 2010).

A major challenge for the hedonic method is the high data requirement, involving not only the transaction price, but also detailed housing-attribute information. Data on housing attributes has started becoming available recently in China, thanks to the required registration with local authorities of all housing transaction contracts. The electronic recording by municipal housing authorities in major cities of each transaction's key information ("Real Estate Market Information System") was initiated in 2003, and became compulsory in 2006 (as mandated by the Ministry of Housing and Urban-Rural Development of China: MOHURD). In April 2007, the MOHURD went as far as to prescribe the list, as well as to define the nature and format, of variables to be reported. Such official detailed recording is a natural data source for the implementation of the hedonic method, even though such data are unlikely to be exhaustive enough to encompass each and every complex- or unit-level attribute. However this does not affect the reliability of the hedonic method as long as the unobserved housing characteristics do not change monotonically over time (Wu, Deng and Liu, 2014).

Officially-published monthly data on housing prices suffer from two major weaknesses. First these ignore the fall in complex-level quality over time: rapid urbanization pushes new buildings to the periphery (Deng, Gyourko and Wu, 2012), and permitted floor-area ratios rise. Second, these suffer from a downward bias resulting from developers' opportunistic pricing strategy. The downward bias in both the level and rate of change of official prices is illustrated in Figure 2 which reports the monthly average prices in Beijing and a transaction-weighted average of Beijing and Shanghai (TWABS) both for official prices and our hedonic prices.

Since we are interested in testing whether economic fundamentals and their volatility have an influence on the volatility of Chinese housing prices we include a number of macroeconomic and sector-specific variables as suggested by previous literature (see Section 2.1). The sector-specific variables include the growth rate of the monthly land supply (ΔLland), the real rent (ΔLrent) in Beijing (sourced from multiple leading residential real estate data vendors in China, and local land resources authorities' websites, to collect data on all residential usage land sales to private parties for 2005-2010), the growth rate of the permanent or registered population (ΔLreg) in Beijing and Shanghai (sourced from China Data Online, and interpolated using the cubic match last option in Eviews), and proxies for construction costs (growth rates of cement, ΔLcem, and copper prices, ΔLcop). The macroeconomic variables include the (month-on-month) CPI national inflation rate extracted from the OECD's Main Economic Indicators (ΔLcpi), monthly industrial output growth (ΔLpi), and household

disposable income (ΔLdisp), from CEIC. Foreign currency reserves[11] in RMB (ΔLfxres) as well as the Shanghai stock market A-share index (ΔLstock) and transactions volume (Lstockvol) are also sourced from CEIC. The monetary variables include the growth rate of bank credit to the private sector (ΔLcredit), sourced from IMF's International Financial Statistics, the growth in broad and narrow (ΔLM2) and (ΔLM1) monetary aggregates, the one-year lending rate, and PBC credit refinancing (ΔLref) all from CEIC. We construct a five-pronged monthly index of the loan to value ratio (LTV) in the spirit of the quarterly index reported in the appendix of Xu and Chen (2005). A loosening (1, from Oct. 2008) corresponds to an LTV of 20% for a first and second home purchases, a moderate tightening (-0.5 from beginning of sample) is defined as an LTV above 20% for the second home, and a tightening (-1 from June 2006) is when the LTV is over 30% for a first home over 90 square meters (sqm), and a sharp tightening(-1.5, from September 2007 and May 2010) is defined as an LTV of over 20% for a first home below 90 sqm, over 30% for a first home over 90 sqm, and 40 % for a second home.

Our TWABS data for prices is the transaction-weighted average of Beijing and Shanghai. Table A.1 in the Appendix provides summary statistics for the monthly sector-specific, macroeconomic and policy series, as well as daily housing prices and transaction volumes. For the monthly sector-specific, macroeconomic and policy series we fit an AR(4) model to the first difference of the log of the variable and use the estimated squared residuals as proxies for the monthly volatility (as in Schwert, 1989). We denote the volatility of these variables by their name prefixed by R (RΔLland, etc…).

4. Results

In this section we initially test for the presence of explosive behaviour in daily Beijing and national (transaction-weighted) average (TWABS) hedonic resale price series. Subsequently, we filter out the microstructure noise and extract long run volatility from the daily series. Finally, with the monthly data we relate that long-run volatility to housing sector specific, monetary policy and speculative factors**.**

4.1 Detecting Explosive Behaviour

Figure 3 presents the evolution of the PSY test for explosive behaviour for the log of the "raw" national average and Beijing prices, including a constant and a trend in the ADF regression. As illustrated in the Beijing plot, the BSADF statistics remains well below the 10% significance threshold with a small peak on May 3rd 2010. For the TWABS data the BSADF statistics are also below the critical values but with a slightly earlier peak on April 29th 2010.

[11] We do not substract the trade surplus and net FDI inflows from currency reserves, since according to some survey data (reported by Martin and Morrison, 2008), the latter two items represent over two-thirds quarters of illicit capital inflows into China. It is thus inappropriate to exclude them from a measure of hot money.

4.2 Noise Filtering

Table 1 contains the noise-filter estimates and Figure 4 presents the sample autocorrelation for the raw daily hedonic housing returns (ΔLBeijing and ΔLTWABS). The noise to signal ratio $\sigma_\varepsilon/\sigma_\eta$ is estimated to be equal to 6.3408 and 4.8326 for TWABS and Beijing respectively, thus emphasizing the importance of filtering the data. The first order autocorrelation is estimated to be equal to -0.4209 and -0.4172 for TWABS and Beijing respectively, which is in line with comparable evidence for the US market (Bollerslev et al. 2015). According to equation (7) the first order auto-correlation should be equal to $-\frac{\sigma_\varepsilon^2}{\sigma_\eta^2+2\sigma_\varepsilon^2}$. Using the estimated values of σ_ε and σ_η from Table 1, the first order autocorrelation should be equal to -0.4939 and -0.4895 for TWABS and Beijing respectively, which is close to the estimated values.

4.3 Extracting Long-Run Volatility

We use the GARCH-MIDAS model described in Section 3 to model daily changes in the filtered log of Beijing and TWABS real estate prices between January 6th 2005 and December 31st 2010. We choose the Bayesian Information Criterion (BIC) to select the optimal number of lags necessary to smooth rolling-window realized volatility weighted by the beta lag function in equation (4). 300 lags were selected for Beijing and 380 for TWABS.

We extract the daily long run component of the conditional volatility for both indices, and aggregate them to a monthly frequency (as plotted with transaction volumes in logs in Figure 5). Generally speaking, volumes and long run volatility move in opposite directions during our sample period. The most striking episode of large long-run volatility takes place in Spring 2010 for both the Beijing and TWABS series. A similar, but lower-magnitude, occurrence of high volatility takes place for TWABS in Spring 2007, and for both series in Spring 2008.

The estimates of the GARCH-MIDAS parameters are presented in Table 2. Although the *Beta* weighting function in equation (12) includes two parameters ω_1 and ω_2, the optimal ω_1 is always unity such that the weights are monotonically decreasing over the lags. Therefore, we only report a single ω parameter. Except for μ all of the coefficients are statistically significant. The coefficient, θ, of the sum of the weighted rolling-window realized volatility in equation (11), is highly significant. The GARCH parameters, α and β, sum to 0.89 for TWABS and 0.92 for Beijing. Finally, as expected, the estimated μs in Table 2 are within two standard deviations of the estimated μs in Table 1.

4.4 Fundamentals and Long Run Volatility

We relate the long run volatility of residential prices to housing sector specific, speculative and policy or macroeconomic variables. We include a dummy variable for April 2010 which corresponds to a tightening of regulation policy by the Chinese government.[12] We also include a dummy variable for Chinese New Year and March. We follow Berkovec and Goodman (1996), who recommend using lagged values of independent variables due to the time required by housing search and marketing, so that sales lag behind the determinants of demand[13]. We initially estimated the long run volatility equation together with the volume equation using maximum likelihood but found no simultaneity. The results presented here are the OLS estimations of the individual equations.

As reported in Table 3, an autoregressive model of order two for the logarithm of long run volatility of real estate returns is necessary to eliminate residual autocorrelation. Among housing sector specific variables, the growth in rents and land supply in Beijing has a positive effect, both with a one-month lag, on Beijing long-run volatility (Table 3, column 2). Among macroeconomic variables, only national industrial output growth significantly affects long run volatility. We tested for the impact of proxies for construction costs, like the (filtered) growth in the Shanghai copper or cement price, but neither proved significant. By contrast the volatility of land supply in Beijing does impact positively on Beijing real estate price volatility. We detect an indirect volatility-enhancing effect from the growth of foreign currency reserves[14] through transaction volume. We did not find any evidence of an impact of monetary policy either in a narrow or broad sense (lending interest rate, broad and narrow monetary aggregates, or bank credit[15]) on either volatility or transaction volume. By contrast, transactions are an indirect channel through which macroprudential policy affects housing prices volatility. In addition Beijing real estate transaction volumes (Table 3, column 3) are sensitive to a Chinese-New-Year and a March effect, and contain a deterministic trend.

We find that, after controlling for macroeconomic effects (industrial output growth), transaction volumes impact negatively on price volatility (with a lag). Such an inverse relationship can be interpreted as follows: for a given supply of resale housing, a fall in demand (possibly caused by a

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[12] As a consequence of the stimulus measures in 2008, housing prices started to soar in early 2009 and continue to grow dramatically until 2010, which led to another round of regulation known as the strictest tightening regulation policy around April 2010. The key points of this new round of regulation included differentiated housing credit policy and home purchase restriction policy. Under the home purchase restriction policy, only local residents who had one housing unit and non-residents who had worked and lived in the city for more than one year were eligible for home purchase. Local residents with two or more housing units, or non-residents with one or more housing units, or non-residents who could not provide proof of living in the city for over one year, were all suspended from purchasing house in the city. After central government expressed its unprecedented dedication to curb surging property prices, many cities followed suit by issuing local packages limiting purchases on homes. (See Deng, Ren, and Wu, 2013 for more discussion.)

[13] "In addition, most existing home sales are recorded as of the 'closing date', which can lag behind the signing of the contract by a month or two. Terms of the sale are set at contract signing, not closing." (Berkovec and Goodman (1996) p. 424).

[14] We consider foreign currency reserve changes themselves and do not exclude the trade and FDI balance as is often done when trying to proxy hot money inflows. This choice is motivated by the observation that the majority (possibly three quarters) of underground capital inflows operate via misinvoicing, and FDI misreporting, i.e. precisely in the components which such measures exclude (Kar and Freitas, 2012).

[15] This is in line with the results of Huang et al. (2015) for housing prices in 35 Chinese cities after controlling for amenities.

rise in the loan to value ratio) leads to a fall in transaction volumes, which trigger a fall in housing prices, leading to a rise in price volatility as predicted by the financial markets literature. A standard result in the literature is indeed that volume and prices are positively correlated (see review in Section 2.2. above).

The volatility of the two-city weighted index (Table 3, column 2) responds positively to industrial growth volatility, and the April 2010 dummy and negatively to lagged volumes, as with the Beijing index though in a much milder (in absolute values) way. This implies that volatility responds less to these three variables in Shanghai than in Beijing. In addition, a direct effect of the growth in foreign currency reserves, as well as the volatility of stock returns and the LTV index, is significant for the two-city volatility, implying that such effects are entirely driven by a sensitivity of Shanghai's volatility to these variables.

The long-run effects are derived using the Beveridge-Nelson (1981) decomposition by re-parameterizing our model in error correction form. For Beijing an increase in volumes of 1% results in the long-run in a decrease in volatility of 0.57%, whereas the decrease is only 0.36% for TWABS. Although significant the macroeconomic variables and their volatility have only a limited impact in magnitude. Except for LTV, they have a positive effect on volatility as expected. An increase in LTV, i.e. a loosening of the loan to value ratio requirements, decreases long run volatility for TWABS. The long run volatility rises three-fold (TWABS) and six-fold (Beijing) in May 2010 implying a milder response in Shanghai than in Beijing.

Volumes decrease by around 70% in May 2010 for both Beijing and TWABS. An increase of 1% in foreign currency reserves increases volumes in Beijing by around 0.1% in the long-run. An increase in LTV increases volumes for both Beijing and TWABS but the effect is ten-fold for TWABS. An increase of 1% in Shanghai stock market transaction volumes increases volumes by 0.3% and 0.5% in Beijing and TWABS respectively. The Chinese New Year and the resulting March effects are similar for Beijing and TWABS: a decrease of 40% during Chinese New Year and an increase of over 100% in March.

5. Conclusion

The growing concerns of a “bubble” in Chinese real estate markets in the second part of the first decade of the new millennium imply that skyrocketing increases in housing prices in many major Chinese cities may have little relationship with economic fundamentals. We propose using a unique high frequency daily data set on residential housing prices and transactions in the Beijing and Shanghai resale real estate market, covering six years, to address such concerns. These data remedy the bias present in official housing prices. Our use of recently developed explosive versus unit-root tests imply that, contrary to such concerns, while near-explosive behaviour can be detected around June 2007 and February 2010, this is not statistically significant. In line with these results, we filter out microstructure noise by extracting a random walk component from raw hedonic housing prices. In a third step, using a Mixed Frequency Data Analysis (MIDAS) method, previously only applied to stock market data, we extract a long-run volatility component from the filtered daily real estate prices. At a monthly frequency this long-run component appears to relate significantly in China to fundamentals. Three series of factors appear to play a role. Among real estate specific variables, rent growth and land supply impact positively on volatility. Speculative elements seem to be present in the form of an impact of stock returns and foreign-currency-reserve inflows on volatility. Finally monetary policy seems unable to influence long run volatility, in contrast with the effectiveness of macroprudential policy (loan to value ratio regulation along with purchase restriction policy). Some of these effects operate only indirectly on housing prices, through transaction volumes.

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Table 1. Noise Filter Estimates

	Beijing	TWABS
μ	0.00075	0.00067
	(0.00045)	(0.00034)
C1	-4.69967	-4.59643
	(0.01438)	(0.01468)
C2	-7.85045	-8.29043
	(0.04268)	(0.07043)
σ_ε	0.0954	0.1004
σ_η	0.0197	0.0158
$\frac{\sigma_\varepsilon}{\sigma_\eta}$	4.8326	6.3408

Notes: 1. Standard errors are in brackets.

2. $\sigma_\varepsilon^2 = exp(C1)$ $\sigma_\eta^2 = exp(C2)$

Table 2. Parameter Estimates for GARCH-MIDAS with Realized Variance

GARCH-MIDAS Parameters	Beijing Estimates (t-stat)	TWABS Estimates (t-stat)
μ	0.0013**	0.0014**
	(5.127)	(6.478)
α	0.1651**	0.1837**
	(8.312)	(7.491)
β	0.7618**	0.7087**
	(16.224)	(20.928)
m	0.0089**	0.0081**
	(5.201)	(7.930)
θ	0.1726**	0.1503**
	(10.855)	(10.465)
ω	9.2656**	7.8594**
	(2.483)	(5.166)
LLF	5232.29	5435.90
BIC	-5.614	-6.086

GARCH-MIDAS models are fitted using QMLE.

The estimated parameters correspond to those of equations (10) to (11) in the text.

The ω in the table is ω_2 as the optimal ω_1, such that the optimal weights are monotonically decreasing over the lags, is 1.

The numbers in the parenthesis are robust t-stats computed with HAC standard errors.

LLF is the optimal log-likelihood function value and BIC is the Bayesian Information Criterion.

** Denotes significance at 5%.

Table 3. Fundamentals, Housing Volume and Long-Run Volatility

	Beijing		TWABS	
	Log τ (1)	Log Volume (2)	Log τ (3)	Log Volume (4)
Cst.	-0.37	1.99	-0.77	1.81
	(-2.70)***	(3.76)***	(-6.42)***	(3.56)***
	[0.012]	[0.001]	[0.000]	[0.002]
Log τ_{-1}	1.02		1.11	
	(28.14)***		(29.18)***	
	[0.000]		[0.000]	
Log τ_{-2}	-0.34		-0.36	
	(-8.55)***		(-10.20)***	
	[0.000]		[0.000]	
Log Volume$_{-1}$	-0.39	0.57	-0.09	0.59
	(-9.53)***	(6.04)***	(3.97)***	(5.53)***
	[0.000]	[0.000]	[0.000]	[0.000]
Log Volume$_{-2}$	0.208			
	(6.29)***			
	[0.000]			
ΔLrent$_{-1}$	0.008			
	(1.69)*			
	[0.109]			
RΔLland$_{-1}$	0.0008			
	(2.20)**			
	[0.031]			
ΔLfxres$_{-2}$		0.05	0.038	
		(1.93)*	(3.46)***	
		[0.062]	[0.002]	
RΔLpi$_{-2}$	0.028		0.012	
	(4.10)**		(3.70)***	
	[0.001]		[0.005]	
Lstockvol		0.13		0.20
		(1.66)*		(2.49)**
		[0.108]		[0.020]
RΔLstock$_{-2}$			0.00015	
			(2.55)**	
			[0.024]	
LTV		0.11	-0.02	0.93
		(2.87)***	(-2.04)**	(2.83)***
		[0.012]	[0.044]	[0.013]
Chinese New year		-0.55		-0.53
		(-11.05)***		(-7.64)***
		[0.000]		[0.000]
Dum042010$_{-1}$	1.924	-1.23	1.42	-1.23
	(53.33)***	(15.28)***	(47.20)***	(-17.39)***
	[0.000]	[0.000]	[0.000]	[0.000]
DumMarch		0.79		0.76
		(4.75)***		(4.09)***
		[0.000]		[0.000]
Trend		0.008		0.006
		(2.24)**		(1.87)*
		[0.035]		[0.081]
R2 Adj.	0.98	0.88	0.93	0.90
Q(4)	1.32	8.98	2.53	5.27
	[0.86]	[0.06]	[0.64]	[0.26]
BIC	-77.61	21.65	-46.38	14.94
J-B	0.633	2.506	77.15	3.28
	[0.73]	[0.29]	[0.00]	[0.19]

White HACE t-stat, ***1%, **5%; *10%; Sample : 2006M05 to 2010M12. *p*-values are in square brackets. For the regression coefficients the *p*-values are the OLS bootstrapped *p*-values.

Figure 1. Frequency Count of "China Housing Bubble" Mentioned in the Media

Note: Figure 1 reports the number of returns generated by the google search engine on the webpages of Chinese media, using the key words "china real estate bubble" OR "China estate bubble" OR "China housing bubble" by Chinese words in the region of China with Chinese language.

Figure 2. Official and Hedonic Housing Prices: Beijing and Shanghai Transaction-Weighted Average (TWABS): Jan 2005-Dec 2010.

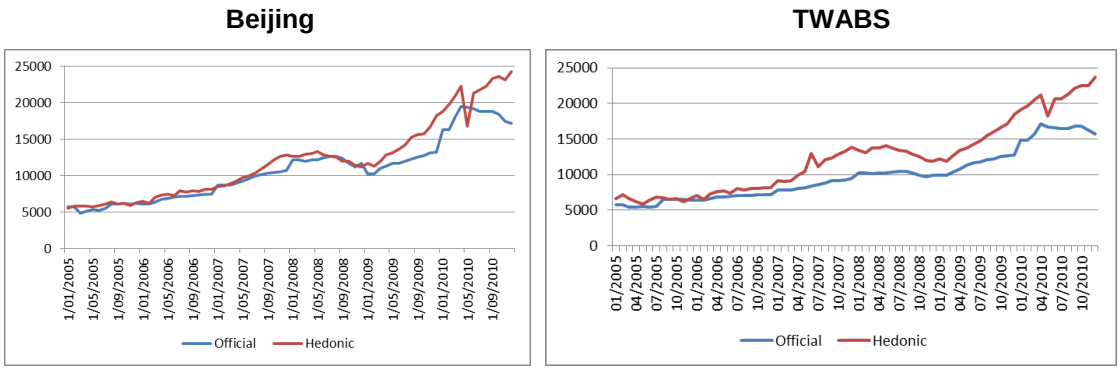


Figure 3. Backward SADFS Statistic (90% Critical Value in Red) Raw Prices (Trend and Constant Included in ADF Regressions)

Beijing **TWABS**

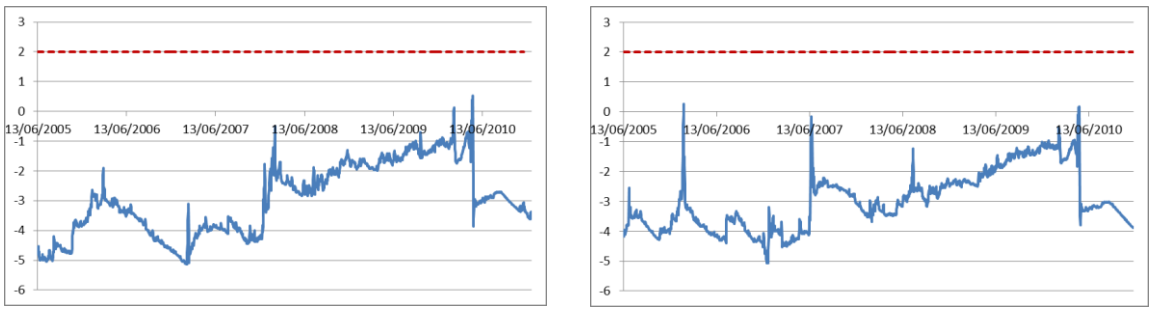


Figure 4. Sample Autocorrelation for Raw Daily Returns, with 95% Confidence Intervals

Beijing **TWABS**

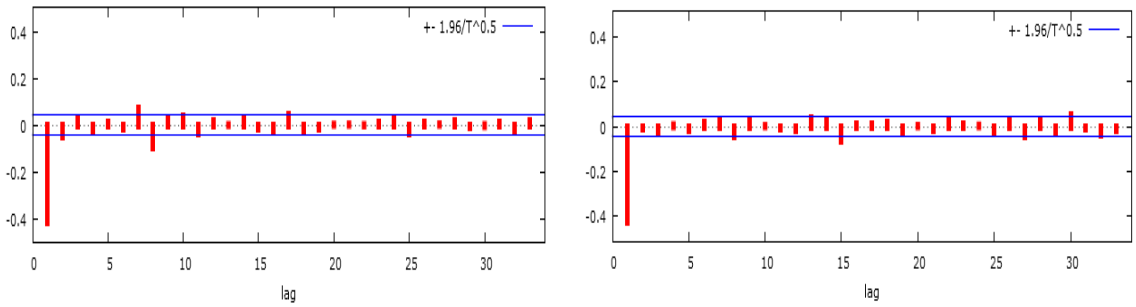
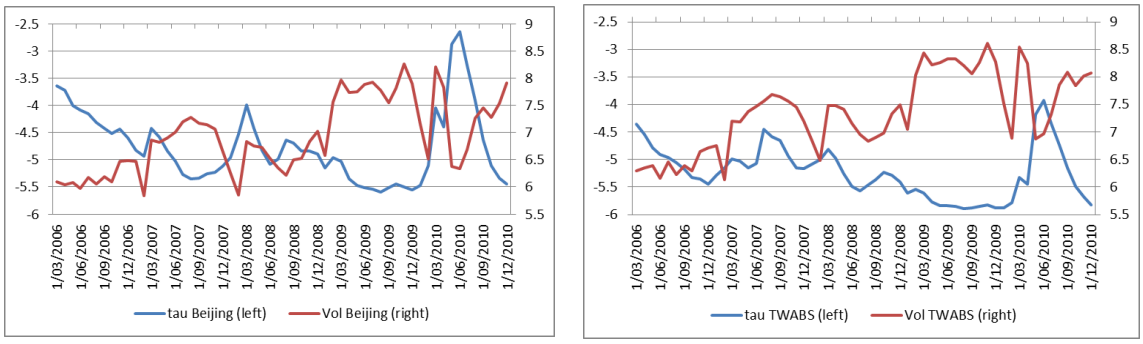


Figure 5. Logs of Monthly Long-run Components of Conditional Volatilities and Logs Transaction Volumes

Beijing **TWABS**



Appendix

Table A.1 Summary Statistics

Variable	Mean	Median	Std. Dev.	Skewness	Excess Kurtosis	Jarque-Bera: *P*-value
			Monthly Variables (2006:3 to 2010:12)			
ΔLrent	0.66	0.66	2.00	–0.06	–0.70	0.55
ΔLreg	0.08	0.08	0.01	–0.30	–1.21	0.00
ΔLcop	0.50	1.41	11.20	–2.33	10.66	0.00
ΔLcem	0.05	0.00	5.91	–0.30	0.51	0.46
ΔLdisp	1.76	1.71	1.70	–0.26	0.44	0.48
ΔLfxres	1.78	1.93	1.34	–0.82	0.76	0.02
ΔLM1	1.58	1.52	1.78	0.13	0.73	0.49
ΔLpi	1.57	1.89	20.50	–0.62	1.35	0.02
ΔLcredit	0.01	0.01	0.01	1.37	1.85	0.00
ΔLref	0.62	–1.52	17.60	0.16	–1.19	0.16
ΔLcpi	2.92	2.75	2.85	0.26	–0.69	0.42
ΔLstock	1.48	4.06	11.26	–0.82	0.38	0.04
Lstockvol	5.74	5.72	0.64	0.02	–0.82	0.44
Beijing Log volume	6.93	6.83	0.61	0.25	–1.07	0.18
TWABS Log volume	7.36	7.39	0.70	–0.02	–1.09	0.24
			Daily hedonic returns (Jan-7-2005 to Dec-31-2010)			
ΔLBeijing	0.0012	0.0025	0.1266	-0.1420	7.4669	0.00
ΔLTWABS	0.0001	0.0012	0.1319	-0.4001	7.4908	0.00
ΔLBeijing filtered	0.0008	0.0010	0.0207	-1.4458	17.9614	0.00
ΔLTWABS filtered	0.0007	0.0004	0.0164	0.0067	21.1087	0.00