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Anticipating critical transitions of the housing market: new evidence from China

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ABSTRACT

We introduce a novel quantitative methodology to detect real estate bubbles and forecast their critical end time, which we apply to the housing markets of China's metropolises. Building on the Log-Periodic Power Law Singularity (LPPLS) model of self-reinforcing feedback loops, we use the quantile regression calibration approach recently introduced by two of us to build confidence intervals and explore possible distinct scenarios. We propose to consolidate the quantile regressions into the arithmetic average of the quantile-based LPPLS Confidence indicator, which accounts for the robustness of the calibration with respect to bootstrapped residuals. We make three main contributions to the literature of real estate bubbles. First, we verify the validity of the arithmetic average of the quantile-based LPPLS Confidence indicator by studying the critical times of historical housing price bubbles in the U.S., Hong Kong, U.K. and Canada. Second, the LPPLS detection methods are applied to provide early warning signals of the housing markets in some metropolises in China. Third, we determine the possible turning points of the markets in Beijing, Shanghai, Shenzhen, Guangzhou, Tianjin and Chengdu and anticipate critical transitions of China's housing markets via our multi-scales and multi-quantiles analyses. Finally, given these projections performed in February 2017, the price trajectories from March 2017 to January 2018 that became available from the time of submission to the time of revision of the present article offer quite unique genuine out-of-sample tests of the performances of our indicators.

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1. Introduction

Real estate markets are prone to excesses with large impact on economies, as witnessed by the stupendous repercussions of the slowdown in 2006 and progressive correction of real estate prices in the U.S. that triggered the 2008 financial crisis and the 'great recession' (Sornette and Cauwels 2014). Real estate development has been arguably the main driver of the Chinese growth miracle in the last two decades (Case, Quigley, and Shiller 2005), fueled by the fiscal stimulus orchestrated by the Chinese government and massive credit expansion. In the last few years, there has been growing concerns that the real estate markets in China have been over-heating (Zhang, Huang, and Yao 2016), with bubble-like behaviors (with a high vacancy rate, see Glaeser et al. 2017), and increasing dangers of bursting that could drag along the Chinese economy. So, evaluating the risk of Chinese housing markets, detecting real estate bubbles early enough and forecasting their burst are extremely important issues (Wu, Gyourko, and Deng 2016). These investigations could guide the People's Bank of China (the Central Bank of China) to improve its monetary policies, and help the Chinese government to prepare against or deal with

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the economic risks caused by housing prices sharp falling. Thus, China could avoid the occurrence of financial crises such as the American subprime mortgage crisis in 2008.

But how to detect housing bubbles? The first influential studies on real estate bubbles, which tested the efficiency of real estate markets, can be dated back to the 1980s and 1990s (Hamilton and Schwab 1985; Case and Shiller 1990). At that time, the presence of some skills to forecast returns was interpreted as the evidence of market inefficiencies (Malkiel and Fama 1970). As a consensus concerning market inefficiencies has built up, a number of studies have rather focused on the detection of bubbles, and the identification of their turning points.

Ghysels et al. (2013) review the literatures on real estate price forecasting, putting it in perspective with respect to predictive regressions. It is useful to divide predictive regressions into three categories based on the predictors and proposed hypotheses. The first one uses lagged returns as the inputs for prediction. Several studies (Rayburn, Devaney, and Evans 1987; Case and Shiller 1989; Knight, Hill, and Sirmans 1997; Hill, Sirmans, and Knight 1999; Schindler 2013) find that housing price changes exhibit positive serial correlation. However, simple serial dependence tests on housing price are complicated by the fact that the price changes of some indices are serially correlated by construction, making it difficult to disentangle spurious correlations from actual market inefficiencies (see Ghysels et al. 2013 for a review).

The second category of predictive regressions uses valuation ratios as the inputs for predictions, such as the rent-price ratio (Himmelberg, Mayer, and Sinai 2005; Gallin 2008; Plazzi, Torous, and Valkanov 2010) or price-income ratio (Malpezzi 1990). The economic reason for the use of analogous ratios as predictors of future returns is straightforward and hinges on the plausible assumption that the variables used to form the ratios are co-integrated in logs. And a similar logic can be applied to most of the valuation ratios. However, an obvious drawback of these ratios is that a given predictive ratio might not be able to capture fully the time variations in the conditioning set.

The third one accounts for the considerable evidence of the relevance of property, and/or region-specific, economic variables. Its aim is to proxy for demand and supply shocks in the real estate market associated with future appreciations, other than past returns or valuation ratios. There are many such predictors, such as demography, income, construction costs, and zoning restrictions, as shown in many studies (Rosen 1984; Case and Shiller 1990; Pace et al. 2000; MacKinnon and Zaman 2009; Plazzi, Torous, and Valkanov 2010). However, the corresponding regressions only account mainly for the heterogeneity observed in the real estate investments.

Our research presented here is mostly related to the recent theoretical literature on financial bubbles that can be seen as attempts to formalize Minsky's characterization of financial markets and their instabilities (Minsky 1992) and to explore the underlying mechanisms. The Log Periodic Power Law Singularity (LPPLS) model (Johansen, Sornette, and Ledoit 1999; Johansen, Ledoit, and Sornette 2000) is a non-linear model that embodies the effect of positive feedback loops between economic agents, which may lead to unsustainable price developments with predictable critical times. The LPPLS model has been widely used to detect bubbles and crashes with advanced documented notice in real time in various kinds of markets, such as the real estate market in Las Vegas (Zhou and Sornette 2008), the real estate bubbles in the United Kingdom (Zhou and Sornette 2003) and the United State (Zhou and Sornette 2006). These analyses confirm the existence of real estate bubbles that can be detected by the LPPLS model, whose signature is the existence of a transient faster-than-exponential price growth. The LPPLS model is a simple generic parameterization to describe endogenous bubbles that are often followed by crashes or corrections. It especially captures such super-exponential behavior, together with the simplest analytical formulation of time series that possess a discrete regular hierarchy of time scales (Sornette 2009). Ardila et al. (2017) combine the LPPLS model with a diffusion index based on a sparse composition of many macroeconomic time series. They provide a robust interval estimation method to identify turning points, which improves on the standard point-estimations and shows that the interval estimation width depends on the time scale of analysis of the data. Complementing this literature, we extend the LPPLS model by including quantile regressions to construct robust early warning signals. We introduce systemic indicators and show that they exhibit significant predictive ability around the real critical time when the burst/rally occurs (Zhang, Zhang, and Sornette 2016).

Building on the Log-Periodic Power Law Singularity model of self-reinforcing feedback loops, we implement the quantile regression calibration approach to explore possible distinct scenarios of real estate market prices. We aggregate these calibrations into the so-called quantile-based LPPLS Confidence indicator, with the goal of characterizing the states in different cities in China and especially of diagnosing the possible existence of real estate bubble as well as forecasting their turning points, in the form of soft landing or large crash. Our underlying hypothesis is that the super-exponential growth mechanisms embodied in the LPPLS model can capture the occurrence of anomalies developing in housing markets. We propose to conduct a complementary post-mortem analysis on some historical housing bubbles in the United States, Hong Kong, United Kingdom and Canada. The reason for choosing these four economics is that they all have experienced a complete cycle of real-estate fluctuation, and the analysis can help us assess the effectiveness of our metrics and methodology. Then we apply the metrics and methodology in some metropolises in China.

We make three main contributions to the literature. First, we verify the validity of the arithmetic average of the quantile-based LPPLS Confidence indicator by checking its power in determining the critical times of past historical housing price bubbles of the U.S., Hong Kong, U.K. and Canada. Second, we adapt the LPPLS methodology to the housing markets in some metropolises in China to explore the applicability of this method. Third, we provide novel diagnostics of the possible future turning points of the housing markets in Beijing, Shanghai, Shenzhen, Guangzhou, Tianjin and Chengdu and anticipate critical transitions of China's housing markets via multi-scales and multi-quantiles analyses. The synthetic dt-Violin plot allows us to identify the genuine LPPLS signals from spurious ones. The arithmetic average of the quantile-based LPPLS Confidence indicator provides an efficient aggregator of the wealth of information generated by our multi-scales and multi-quantiles analyses and consolidates the obtained ensembles of scenarios.

Our study suggests that housing prices in Beijing, Tianjin and Chengdu are at high risks to meet a turning point or correction in 2017, while the turning point is likely to be in 2018 for Shanghai and Shenzhen. Although there is no obvious warning signals for Guangzhou, the dt-Violin plot and quantile-based calibrations suggest that the turning point would occur in 2018. Thus, the risk of a significant correction is relatively smaller in Guangzhou in the short term, but the market still requires continuous attention.

The rest of this article is organized as follows. Section 2 describes the development and status of the housing market in China. Section 3 lays out the basic building blocks of the LPPLS model. Section 4 describes the data and how the arithmetic average of the LPPLS Confidence indicator is constructed. Section 5 assesses the forecasting performance of our methods on four countries' or region's historical housing bubbles. Section 6 analyzes the empirical results and the present situations of six housing markets in China's metropolises. Section 7 summarizes the results and concludes.

2. The housing market in China

Since 1998, the Chinese housing sector has evolved from a welfare-oriented public housing distribution system to a fully commercialized market. The government explored how to establish a new housing supply system with commercial and socialized housing stocks. The housing reform achieved gradual housing privatization, and encouraged the simultaneous development of the housing finance system. Mortgage loans were introduced and provided to house buyers in 1994, however the housing market was still stagnant before 1998. Only 13% of the 264 billion Yuan (about 32 billion US Dollar) real estate loans from Chinese commercial banks were mortgage in 1998. Thereon, the mortgage market in China developed as the largest mortgage market in Asia, with an outstanding balance of more than 2 trillion Yuan (about 242 billion US Dollar) in 2005 (Deng and Liu 2009).

In 2003, the real estate industry was confirmed as the pillar industry for the national economic development of China. The growing liberalized housing market led to a period of prosperity. As a response to the American subprime crisis and in order to fight its negative global impact, the central government of China implemented the '4-Trillion Investment Plan' in 2009, which generated rapid growth of housing markets in major cities of China. As a consequence, housing has become an essential asset for urban residents in China and for regional governments across the country. The total value of real estate assets in China was about 200 trillion Yuan (about 30.8 trillion US Dollar) at the end of 2015, which can be compared with the capitalization of the Chinese stock market near 53 trillion Yuan and the accumulated deposits in commercial banks at 136 trillion Yuan. For comparison, according to the Zillow report, the total value of real estate market in the United States was about 29.6 trillion US Dollars at the end of 2016, the capitalization of the stock market was about 23.8 trillion US Dollar, and the accumulated deposits was 10.9 trillion US Dollar. In addition, according to the China Household Finance Survey

Report, housing expenditures amounted to 69.2% of the household income of urban residents in 2015, while the ratio was 25%, 44% and 24% in the United States, United Kingdom and Japan, respectively.[1] According to the report of the Bank of Japan on capital flows in Japan, the United States and the Eurozone, the assets of Japanese households are mainly allocated to bonds, mutual funds, cash, savings, insurance and pension reserves. The preferred households' asset allocation in the Eurozone is similar to that of Japanese households for their strong propensity in saving, however, with stronger private savings in Japan and stronger pension savings in Eurozone. Meanwhile, American households have also been investing in pension plans but with a lower saving propensity, with a keener perception of high-risk assets and low-risk aversion. Compared with these developed countries, asset allocations of Chinese households are relatively simpler, with a preference for cash savings and real estate over other assets. In particular, there seems to be a wide-spread anticipation among Chinese households[2] that housing prices can only move upwards, supporting their over-concentration on real estate investments.

Given these anticipations, the Chinese housing market suffers from a number of problems, such as rapid price growth, large price fluctuations, excessive speculation, and increasing unaffordability (Zhang and Li 2014; Fang et al. 2016; Fan et al. 2018). Note that the instability of the U.S. housing price has been widely regarded as one of the chief culprits that triggered the subprime mortgage crisis in 2008. Similarly, China's economic development is strongly underpinned and influenced by the development of its real estate markets. To respond to the possible destabilizing role of real estate markets, the central government in China has frequently applied monetary policy, fiscal policy and industrial policy to regulate the real estate markets. The government has promulgated restriction policies for the housing market, such as restrictions on mortgage loans and home purchase qualifications. But the housing prices have still been rising continuously in some major cities, especially in the first-tier cities.[3]

In fact, by the end of January 2018, the housing prices in most of China's first-tier cities have doubled compared with that at the end of February 2007, with especially large fluctuations of housing prices in Beijing, Shanghai and Shenzhen. It may be explained by the strong willingness of Chinese households to save in the real estate sector, as mentioned above. The Chinese real estate property market has been the largest proportion (at 60%) of Chinese households' investments (especially for urban households), according to the data provided by Southwestern University of Finance and Economics. The high demand of Chinese households has contributed to the continuous growth of China's house prices,[4] even if strict regulations were in place. There is then the concern that this strong demand may fuel a bubble. And if the real-estate bubble would burst, the remarkable Chinese economic growth of the last two decades might be stopped and financial instabilities with negative impact on employment and social stability might follow (Case, Quigley, and Shiller 2005). Moreover, history tells us that volatility of housing prices, whether in bubble or burst mode, have the potential to buoy up or wreak havoc on the financial sectors and the economy.

Notwithstanding these analyses, real estate is generally perceived as a good, reliable and easy-to-assess investment for households. This explains the large number of mortgages held by Chinese households. The data from the People's Bank of China indicate that, at the end of 2015, the total loan balance for real estate was 21 trillion Yuan, accounting for 22.4% of the total balance of RMB loans from commercial banks. The personal housing mortgage loans totaled 14.2 trillion Yuan, accounting for 15.1%. The real estate development loans was 6.6 trillion Yuan, corresponding to 7%. Moreover, taking into account the local financing platform and related industrial chain loans, large real estate price variations would be expected to have a negative impact on the financial sector. The bursting of a real estate bubble would bring huge harm to China's developing economy, justifying the importance of early warning of the potential for a real estate housing bubble burst.

3. Log-periodic power law singularity (LPPLS) model

In this section, in order to be self-contained, we briefly summarize the model used for our analyses. The Johansen-Ledoit-Sornette (JLS) model (Johansen, Sornette, and Ledoit 1999; Johansen, Ledoit, and Sornette 2000) assumes that the asset price $p(t)$ follows a standard diffusive dynamics with varying drift (or conditional expected return) $\mu(t)$ in the presence of discontinuous jumps:

$$\frac{\mathrm{d}p}{p} = \mu(t)\,\mathrm{d}t + \sigma(t)\,\mathrm{d}W - \kappa\,\mathrm{d}j, \tag{1}$$

where $\sigma(t)$ is the volatility and $\mathrm{d}W$ is the increment of a Wiener process (with zero mean and variance equal to $\mathrm{d}t$). The term $\mathrm{d}j$ represents a discontinuous jump such that $j = 0$ before the crash and $j = 1$ after the crash occurs. The loss amplitude associated with the occurrence of a crash is determined by the parameter κ. Each successive crash corresponds to a jump of j by one unit. The dynamics of the jumps is governed by a crash hazard rate $h(t)$. Since $h(t)\,\mathrm{d}t$ is the probability that the crash occurs between t and $t + \mathrm{d}t$ conditional on the fact that it has not yet happened, we therefore have the expectation conditional on the history up to time t, that is, $E_t[\mathrm{d}j] = 1 \times h(t)\mathrm{d}t + 0 \times (1 - h(t))\,\mathrm{d}t = h(t)\,\mathrm{d}t$. By the no-arbitrage condition leading to the condition that the price process is a martingale ($E_t[\mathrm{d}p/p] = 0$, neglecting the risk free rate), it leads to $\mu(t) = \kappa h(t)$.

Under the assumptions of the JLS model that a crash may be caused by local self-reinforcing imitation processes between noise traders (Johansen, Sornette, and Ledoit 1999; Johansen, Ledoit, and Sornette 2000), the aggregate effect of noise traders can be accounted for by the following dynamics of the crash hazard rate (Seyrich and Sornette 2016):

$$h(t) \approx B_0|t_c - t|^{m-1} + C_0|t_c - t|^{m-1}\cos(\omega \ln|t_c - t| + \phi'), \tag{2}$$

where B_0 and C_0 are two positive constants of the first order expansion of the general solution for the hazard rate. And the cosine part of the second term takes into account the existence of possible hierarchical cascades of accelerating panic punctuating the growth of the bubble, resulting from a preexisting hierarchy in noise trader sizes and/or the interplay between market price impact inertia and nonlinear fundamental value investing.

Using $\mu(t) = \kappa h(t)$, we obtain the dynamics of the expectation of the logarithm of the price in the form of the Log-Periodic Power Law Singularity (LPPLS) model:

$$E[\ln p(t)] = A + B|t_c - t|^m + C|t_c - t|^m \cos(\omega \ln|t_c - t| + \phi), \tag{3}$$

where t_c denotes the critical time for the burst of the bubble, in the form of a crash for example. The constant $A = \ln[p(t_c)]$ gives the terminal log-price at t_c. $B = sgn(t - t_c)(\kappa B_0/m)$ and $C = \mathrm{sgn}(t - t_c)(\kappa C_0/\sqrt{m^2 + \omega^2})$ respectively control the amplitude of the power law acceleration and of the log-periodic oscillations. The exponent m quantifies the hyperbolic power law describing the degree of super-exponential growth. The log-periodic angular frequency ω is related to a scaling ratio $\lambda = \exp(2\pi/\omega)$ of the temporal hierarchy of accelerating oscillations converging to t_c. Finally, $\phi \in (0, 2\pi)$ is a phase embodying a characteristic time scale of the oscillations. Equation (3) is the first-order log-periodic correction to a pure power law for an observable exhibiting a singularity at t_c (Gluzman and Sornette 2002; Sornette 2009). Because of its structure with a power law singularity at t_c and the presence of log-periodic oscillations, the model (3) is referred to as the Log-Periodic Power Law Singularity model.

Given the starting and ending dates t_{start} and t_{end} of the fitting window, we define the time scale $\mathrm{d}t \triangleq t_{end} - t_{start}$ as the duration of the fitting window. The critical time t_c is searched in the interval $[t_{end} - \eta\,\mathrm{d}t, t_{end} + \eta\,\mathrm{d}t]$. Previous calibrations of the LPPLS specification (3) to the log-price development during a number of historical financial bubbles have suggested to qualify fits based on the parameters of the LPPLS model belonging to the following intervals (Jiang et al. 2010; Johansen and Sornette 2010; Filimonov and Sornette 2013): $m \in [0.1, 0.9]$, $\omega \in [6, 13]$, $B < 0$, $|C| \leq 1$. The results we report below have been obtained without imposing conditions on B and C and with $\eta = 0.3$.

The implementation of the quantile regression method to the calibration of the LPPLS model described by Zhang, Zhang, and Sornette (2016) has the following main properties: (i) It generalizes the minimization of the L^1 norm (corresponding to the quantile confidence level $q = 0.50$) and provides a bundle of scenarios that should be considered conceptually to occur over many realisations of the noise decorating the supposed theoretical generating process in Equation (3); (ii) It allows us to discover more complete structures that avoids global distributional assumptions on the residuals, and to exploit the specification of multiple super-exponential accelerated upward (resp. downward) rates of change in the quantiles of the distributions of log-price conditional at the current time with different time scales. Thus, the exploration of the heterogeneous residuals with the quantile regressions can be implemented as a function of time and presents many new possibilities for the statistical analysis and interpretation of observational data. Besides, due to the significant variability of the estimations (or predictions), with the implementation of ensemble forecasting that combines a grid of quantile-based estimators into a final aggregated predictor, the quantile regression method contributes to disentangle (at least partially) a priori unknown complicated residuals and the genuine LPPLS signals. For example, the averaged estimator is a representative sample of the possible future states, which is usually better than any of the single base estimator since the variance is reduced, while the median of individual estimates is more accurate than at least half of the individual forecasts (Mcnees 2010; Zhang, Zhang, and Sornette 2016).

To significantly decrease the complexity of the search and provide an intuitive representation of the results of the calibration, a two-stage fitting procedure is developed according to the special structure of the LPPLS model (Filimonov and Sornette 2013). In essence, for minimizing the objective function of the quantile regressions, the four linear parameters $\{A(q), B(q), C_1(q), C_2(q)\}$, where q is the probability level of one of the quantile regressions, are determined using the LU decomposition algorithm through a linear regression model, while the three nonlinear parameters $\{t_c(q), m(q), \omega(q)\}$ are searched globally through the Taboo search (Cvijovic and Klinowski 1995) followed by the Quasi-Newton method with line search. The two linear parameters $\{C_1(q), C_2(q)\}$ are defined by expanding the cosine in expression (3), yielding $\{C_1(q) = C(q)\cos(\phi(q)), C_2(q) = C(q)\sin(\phi(q))\}$.

4. Data and indicator definition

4.1. Data

This study first investigates the typical historical real estate bubbles in four economies therein. To gain monthly data time series that are as long as possible, we choose the S&P/Case Shiller Composite Index of 10 metropolitan areas of the United State as the measures of the U.S. real estate prices. January 2000 is used as the base period at which the index is set to 100.

The housing price data for Hong Kong is the Centa-City Index (CCI), which is jointly issued by the Centaline Group and the University of Hong Kong. It is a monthly index based on all transaction records registered with the Land Registry to reflect property price movements in previous months. July 1997 is the base period at which the index is set to 100. The price index can be calculated by aggregating the prices of the constituent estates using the formula:

$$CCI \text{ for a month} = \frac{\text{Total market value of the constituent estates in this month}}{\text{Total market value of the constituent estates in last month}} * CCI \text{ for last month.}$$

We use the Halifax House Price as the measure of housing price for the United Kingdom, which covers the whole country and is the U.K.'s longest running monthly house price series since January 1983. This 'standardized' house price is calculated and property price movements on a like-for-like basis (including seasonal adjustments) are analyzed over time. The unit of the data is the British Pound.

The housing price data for Canada is from the Canada Mortgage and Housing Corporation (CMHC). The average price is equal to the total value divided by total number sold, and the unit of the data is in thousands of Canadian Dollars.

From the statistical descriptions of housing prices data of four economies in Table 1, it can be seen that, during the sample period, the highest housing prices of the U.S., Hong Kong, U.K. and Canada are 3.60, 4.58, 4.08 and 2.20 times that of the lowest, respectively.

In addition, in order to study the real estate markets in China's first-tier and second-tier cities, we complement our dataset with the sample of Beijing (BJ), Shanghai (SH), Shenzhen (SZ), Guangzhou (GZ), Tianjin (TJ) and

Table 1. Four countries' or region's housing price data and statistical descriptions.

Market	Data range	Number of data points	Min	Max	Mean	Standard deviation
United States	1987.01–2016.09	357	62.82	226.29	130.11	51.40
Hong Kong	1994.01–2016.09	273	31.34	143.46	72.91	29.90
United Kingdom	1994.01–2016.11	275	50,520.51	206,144.96	129,218.30	51,491.30
Canada	2004.09–2016.10	146	225.50	495.70	347.75	67.85

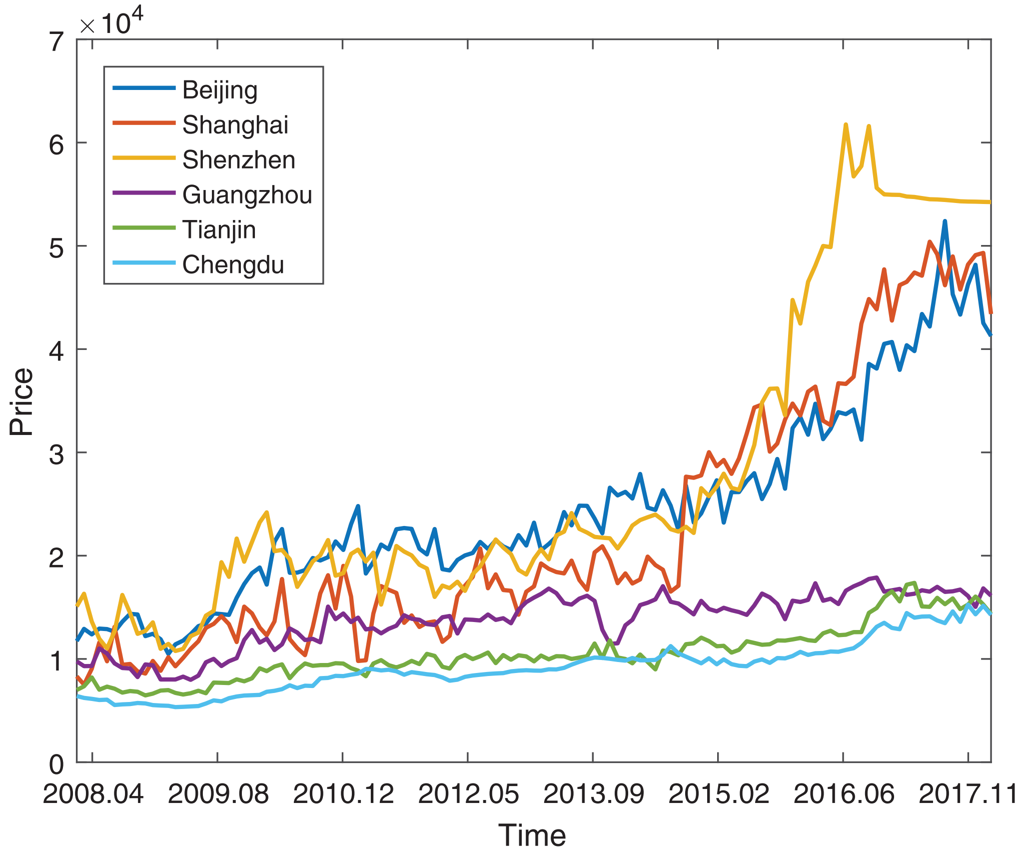

Figure 1. Housing price time series of the six cities in China.

Chengdu (CD). The data is from January 2008 to January 2018, and the unit of the data is Yuan per square meter. All the data are from the Real Estate Trading Center of each city.[5] Among these cities, Beijing, Shanghai, Guangzhou and Shenzhen are recognized as four first-tier cities in China, while Tianjin and Chengdu are two very promising second-tier cities in the north and southwest of China, respectively. As shown in Figure 1, before 2014, except for the slightly lower house prices in Guangzhou, the housing price trends are almost the same among the four first-tier cities. However, since the second half of 2014, the sharp rise of housing prices in Beijing, Shanghai and Shenzhen has led to an increasing gap with Guangzhou. From the perspective of housing price level, Guangzhou has moved away from the first-tier cities, and now is closer to the two second-tier cities.

The statistical descriptions of housing prices in these six cities in Table 2 show that the mean values of properties in Beijing, Shanghai and Shenzhen are significantly higher than in other cities, and the gap is more obvious when comparing their own maximum over the whole sample with their minimum. It can be seen that the maximum housing prices in Beijing, Shanghai and Shenzhen are 5.00, 6.71 and 5.73 times their minimal values, respectively, while the corresponding ratio for Guangzhou, Tianjin and Chengdu is less than 3 times. The standard deviation of the data in Beijing, Shanghai and Shenzhen are also significantly greater than the other three cities. Therefore, according to the value of housing price and standard deviation, Beijing, Shanghai and Shenzhen are more likely to be one group, while Guangzhou, Tianjin and Chengdu belong to another.

4.2. Consolidated arithmetic average of the quantile-based LPPLS confidence indicator

In order to provide a more extensive test of the LPPLS quantile regression approach, we use the arithmetic average of the quantile-based LPPLS Confidence indicator defined by Zhang, Zhang, and Sornette (2016) that can

Table 2. Six cities' housing price data in China and statistical descriptions.

Market	Data range	Number of data points	Min	Max	Mean	Standard deviation
Beijing (BJ)	2008.01–2018.01	121	10,486.38	52,405.00	24,528.56	9356.24
Shanghai (SH)	2008.01–2018.01	121	7510.87	50,401.00	22,676.30	12,596.63
Shenzhen (SZ)	2008.01–2018.01	121	10,770.00	61,756.00	27,593.81	14,937.54
Guangzhou (GZ)	2008.01–2018.01	121	7978.11	17,884.00	13,717.15	2652.16
Tianjin (TJ)	2008.01–2018.01	121	6470.76	17,366.00	10,493.07	2618.68
Chengdu (CD)	2008.01–2018.01	121	5336.63	15,258.00	9189.51	2502.19

be compared with the price time series to allow a judgement of bubbles' terminations. Although the significant predictive ability of this indicator around the real critical time of historical bubbles has been established for financial stock markets, we must examine it for the case of historical housing bubbles, since housing markets are quite different from stock markets in terms of the liquidity, maturity, frictions and regulations.

Here are the precise definitions of the indicators used in this work.

(1) The *LPPLS Confidence* indicator is the fraction of fitting windows whose calibrations meet the filtering condition used in Zhang, Zhang, and Sornette (2016): within the JLS framework, the condition that the crash hazard rate $h(t)$ is non-negative by definition (Bothmer and Meister 2003) translates into the value of $|Bm/C\omega|$ (where the parameters B, C, m and ω are defined by the expression (3)) being larger than or equal to 1. The LPPLS Confidence indicator thus measures the sensitivity of the observed bubble pattern to the choice of the time window length used for analysis. A large value of this indicator indicates that the LPPLS pattern has been found at most time scales and is thus more reliable. A small value of the indicator signals a possible fragility of the signal and/or overfitting since the LPPLS structure is found only in a few fitting windows.

(2) The *arithmetic average of the quantile-based LPPLS Confidence indicator* is the sum of the LPPLS Confidence indices obtained for a number of quantile levels, for instance q is from 0.10 to 0.90 in intervals of 0.10, divided by the total number of quantile levels, 9 in this example.

5. Empirical validation of historical bubbles

Motivated by the fact that housing prices in China's metropolises have risen rapidly without any 'corrections' since 2004, this study will aim at detecting real estate bubbles and forecast their critical end time. Although the application of the LPPLS model to many financial markets has been demonstrated in the relevant recent literature (Ardila and Sornette 2016; Zhang, Zhang, and Sornette 2016), we now apply it to the four economies of the United States, Hong Kong, United Kingdom and Canada, in order to further illustrate the relevance of the recently introduced quantile regression calibration approach (Zhang, Zhang, and Sornette 2016) to real estate markets.

5.1. Real-time diagnostics associated with quantile regressions

Figures 2–5 show, as a function of t_{end}, the dependence of the calibrated critical time $\widehat{t_c}(q, \mathrm{d}t)$ averaged over the 5 quantile regressions with the 5 quantile levels $\{q = 0.10, 0.30, 0.50, 0.70, 0.90\}$, for time windows of duration dt months. The time windows are sliding in steps of 3 months. From the definition of the horizontal blue line and associated blue dashed lines described in the caption of Figure 2, the values of $\widehat{t_c}(q, \mathrm{d}t)$ located above the red dashed diagonal line within the band defined by two blue dashed lines correspond to critical time estimates at times $t_{end} < \widehat{t_c}(q, \mathrm{d}t)$ that are close to the true maximum of the price, and can thus be considered as good predictions, if they are obtained by skill and not luck. The values of $\widehat{t_c}(q, \mathrm{d}t)$ located below the red dashed diagonal line within the band defined by two blue dashed lines corresponding to correct ex-post diagnostics that there has been a bubble ending at the calibrated $\widehat{t_c}(q, \mathrm{d}t) < t_{end}$. The main criterion for the existence of diagnostic and predictive skills is the existence of plateaus of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}, which represent the fact that the calibration 'synchronises' on a critical time t_c that does not change appreciably when changing t_{end}, at least over a sufficiently large interval. We thus focus on the appearance of these 'plateaus' and interpret their meaning.

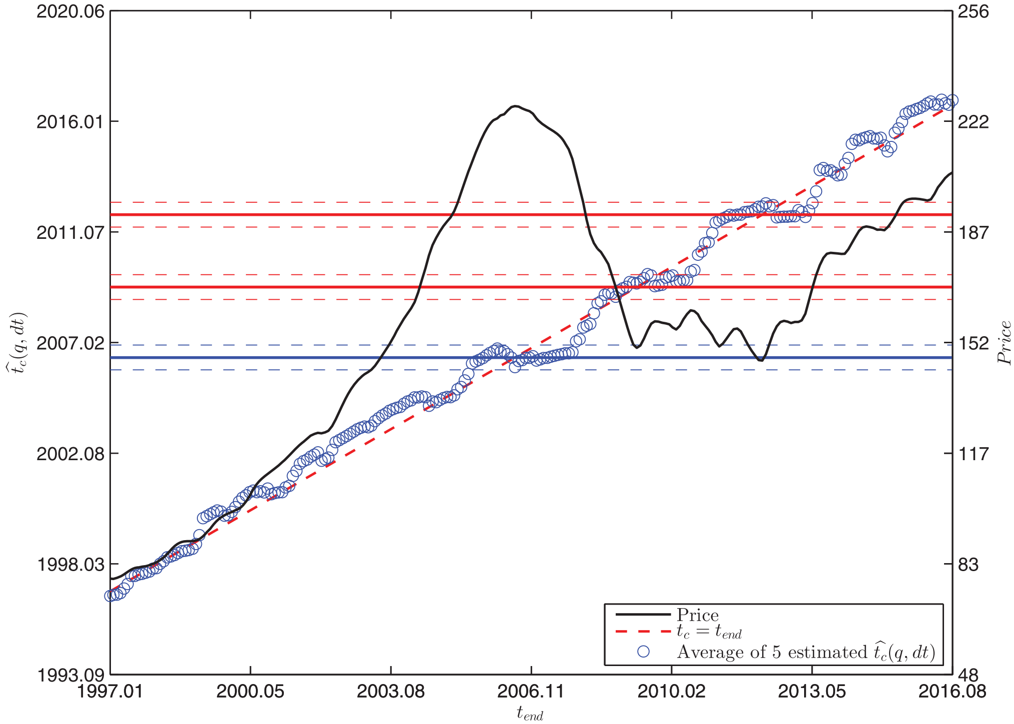

Figure 2. The price time series of the U.S. housing market is shown with the black solid line (right vertical axis). The blue circles (corresponding to the left vertical axis) represent the calibrated critical time $\widehat{t_c}(q, \mathrm{d}t)$ obtained by averaging over the 5 quantile regressions with the 5 quantile levels $\{q = 0.10, 0.30, 0.50, 0.70, 0.90\}$, for time windows of duration $\mathrm{d}t = 48$ months. $\widehat{t_c}(q, \mathrm{d}t)$ is shown as a function of t_{end}, the right end time of the analysing window. The horizontal blue line indicates the date of a large price peak in June 2006, as represented along the vertical axis. The two blue dashed lines around the blue continuous line delineate a six-month band around the peak date. Besides, two horizontal continuous red lines indicate the positions of the large troughs in March 2009 and January 2012. The two red dashed lines around each red continuous line delineate a six-month band around the individual trough date. The red tilted straight dashed line represents the equation $t_c = t_{end}$, i.e. diagonal.

In Figure 2, with the size of windows $\mathrm{d}t = 48$ months, one can observe that, for t_{end} lying in the first half of 2006, the obtained estimates of $\widehat{t_c}(q, \mathrm{d}t)$ are located within the interval around the peak date in June 2006. Moreover, as the 'present' time t_{end} moves forward, the corresponding $\widehat{t_c}(q, \mathrm{d}t)$ remains close to June 2006, confirming that the bubble was ending and there was a high-risk for a change of regime. The subsequent very strong decline of the house prices from June 2006 to 2009 supports the value of our prediction. This confirms and extends the previous real-time analysis of Zhou and Sornette (2006), which also used the LPPLS model, but without the novel sophistication of the quantile regressions and LPPLS Confidence indicators. Moreover, we see two clearly defined plateaus in $\widehat{t_c}(q, \mathrm{d}t)$ along the horizontal continuous red lines, corresponding to two main pronounced minima of the price. This further shows that our LPPLS model can diagnose/predict the end of negative bubbles.

Figure 3 shows the results obtained by the same method applied to the Hong Kong housing market with time windows of size $\mathrm{d}t = 36$ months. The four main peaks indicated by the four horizontal blue lines and a trough indicated by the horizontal red line, located on March 2008, October 2008, June 2011, March 2013 and August 2015, are each associated with a plateau in the behavior of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}, confirming the good diagnostic power of our approach. Even the less pronounced peak and large price plateau in 2005 is associated with a nice predictive plateau of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}. Except for the second price peak, the first and the last two peaks can be diagnosed in advance since the plateau of $\widehat{t_c}(q, \mathrm{d}t)$ is clearly visible already for t_{end} significantly earlier than the time of the price peak. Note that, for the first bubble ending in 2008, Hong Kong's housing price (black solid line and right vertical axis) had experienced a 30% fall from the second quarter of 2008 to the first quarter of 2009, which is the greatest decline in 12 months since the Asian financial crisis happened

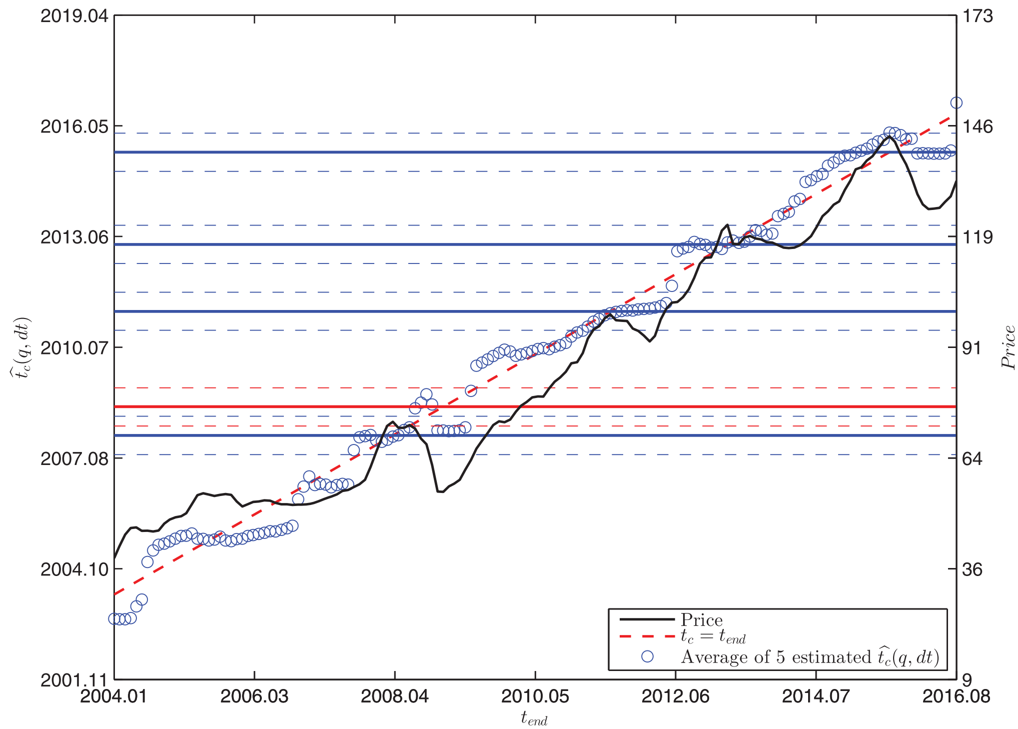

Figure 3. Same as Figure 2 for the Hong Kong housing market.

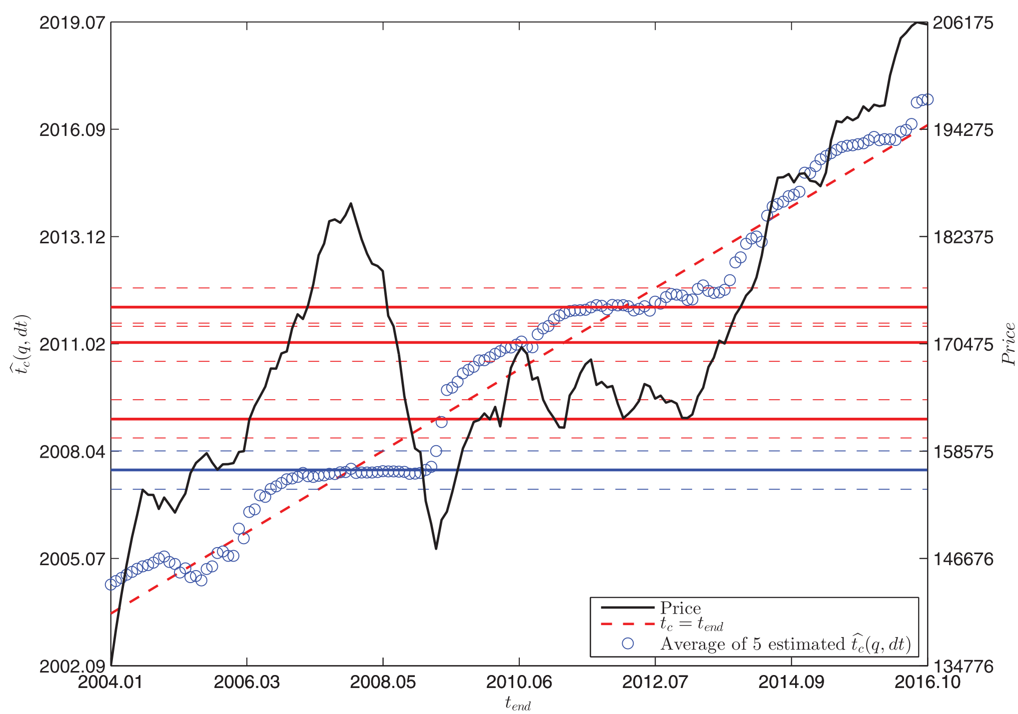

Figure 4. Same as Figure 2 for U.K. housing market.

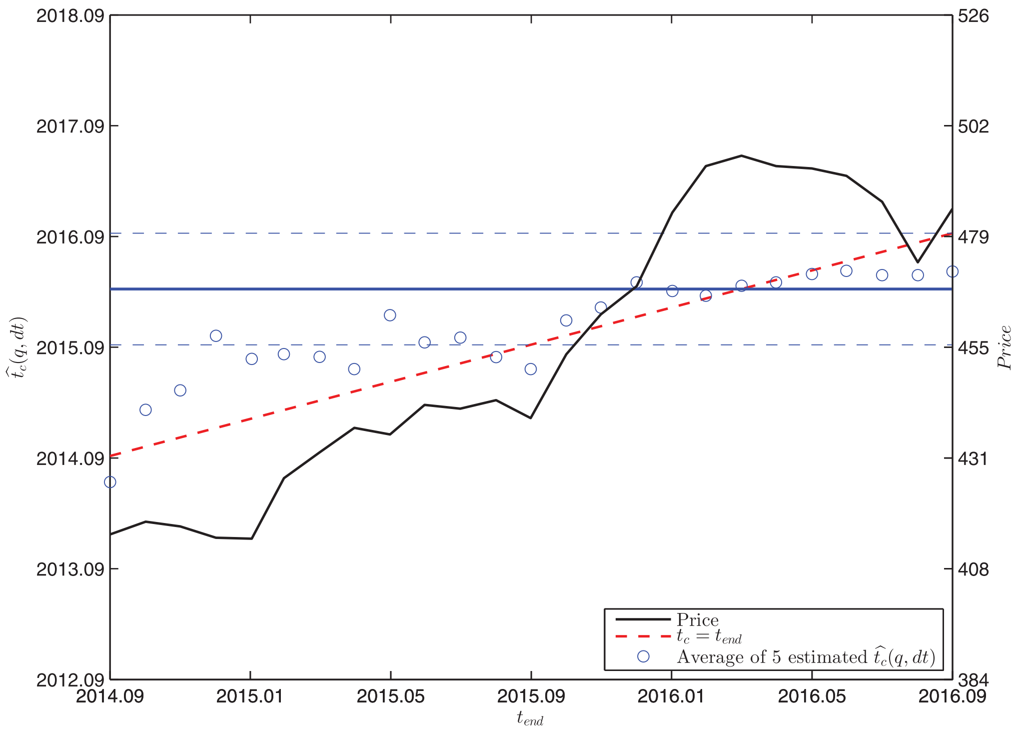

Figure 5. Same as Figure 2 for the Canadian housing market.

in 1997. These findings support the prediction ability of our technology in detecting the rapid declines in the Hong Kong housing market.

Figure 4 shows the results obtained by the same method applied to the housing prices in the U.K. with windows' size of $\mathrm{d}t = 48$ months. One can observe a remarkable long and narrow plateau of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}, which extends from t_{end} equal to the second half of 2006 to 2008 and it is located at $\widehat{t_c}(q, \mathrm{d}t)$ very close to the realized peak of the house prices in October 2007. Indeed, the housing prices in the U.K. began to decline in January 2008 until early 2009. Our methodology provides consistent estimates of the price peak in advance and then confirms this peak systematically as the price fall develops. In other words, our method not only has a forward-looking mechanism, but also exhibits a dynamic adjustment mechanism to confirm the diagnostic after the peak has been reached. Moreover, the last two main troughs indicated by the two horizontal red lines, located on February 2011 and January 2012, are respectively associated with an individual plateau in the behavior of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}, confirming the power of our approach in diagnosing negative bubbles.

In Figure 5, due to the small number of data points, the results seems more noisy than for the three previous cases. Here, we use a rather larger time windows of $\mathrm{d}t = 108$ months in order to decrease the influence of noise. One can observe that, from the beginning of Q4 of 2014, there is a plateau of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end} that is forming. This plateau forecasts correctly the timing of a coming peak in the Canadian housing price, and indeed the house price started to decline since early 2016.

The results in Figures 2–5 show that the aggregated estimator associated with the quantile regressions can detect the critical time of the phase transition for these real estate markets in real time. Real time means that the estimator would adjust its judgement dynamically when additional market information is made available as time passes. With the benefit of hindsight on these historical bubbles, the estimator has provided rather accurate predictions of their decline/rebound in advance. This means that our method not only has a forward-looking mechanism, but also exhibits a dynamic adjustment mechanism to confirm the diagnostic after the peak/trough has been reached.

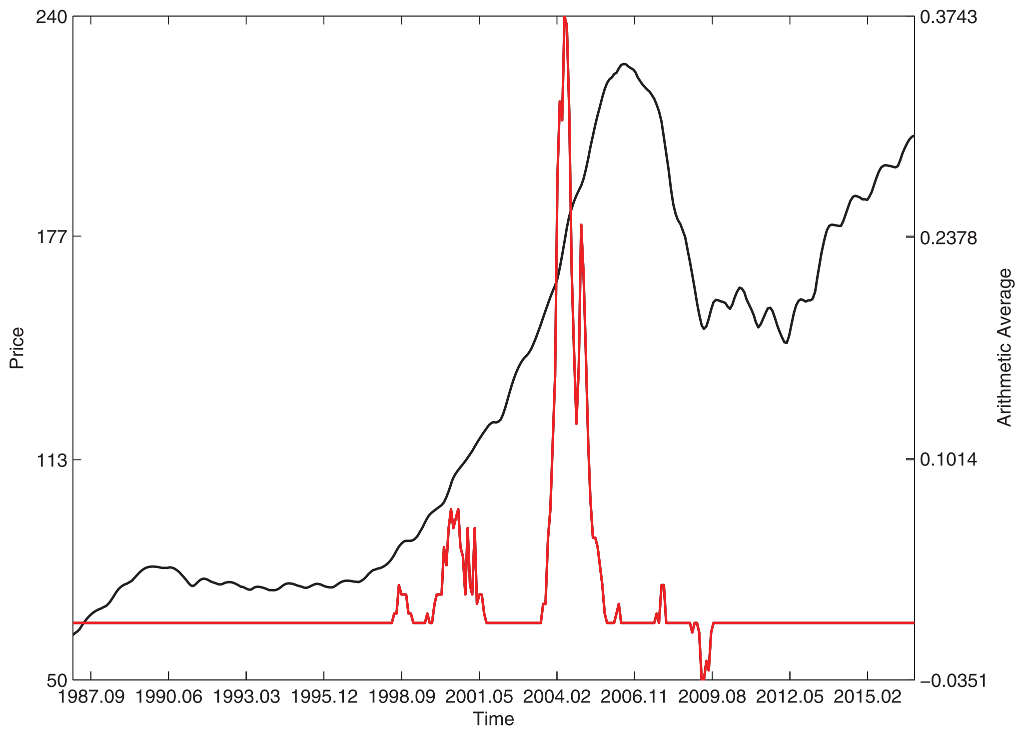

Figure 6. Arithmetic average (red curve and right vertical axis) over the 9 quantile probability levels $\{q = 0.10, 0.20, \ldots, 0.90\}$ of the LPPLS Confidence indicator for the U.S. housing market. The U.S. house price index is also shown with the black line (left vertical axis).

5.2. Early warning signals of LPPLS confidence indicator

In this section, we complement the analysis of the previous subsection by presenting a more quantitative assessment of the predictive skills of our methodology. This is done by using the LPPLS Confidence indicator, constructed for a number of quantile probability level and then averaging over their obtained values. We refer to the definitions given in subsection 4.2. The LPPLS Confidence indicator measures the sensitivity of the observed bubble pattern with respect to the position of the 49 time windows of duration from 60 to 12 months sliding in steps of 1 month. In our analysis, we use the 9 quantile probability levels $\{q = 0.10, 0.20, \ldots, 0.90\}$. Figures 6–9 present the house price time series of four countries or region together with the arithmetic average of the quantile-based LPPLS Confidence indicator.

Figure 6 shows that the arithmetic averaged LPPLS Confidence indicator pinpointed quite well the beginning of the large price appreciation in 2000-2001. Then, the very large peak of the indicator in 2004 diagnosed the approach to the end of the bubble, about two years in advance. In the first half of 2009, the LPPLS Confidence indicator turned negative, indicating the approach to the end of a 'negative' bubble (see Figure 4 in Sornette and Cauwels 2015), i.e. the approach to a rebound. Thus, the LPPLS Confidence indicator revealed the presence of a housing bubble and exhibited a sound ability to predict the decline and then, later, the subsequent recovery of the U.S. housing price index.

For the Hong Kong housing market, except for the fall in 1997 within the in-sample window, Figure 7 shows that the LPPLS Confidence indicator provides strong early warning signals in the early 2008 and at the end of 2010, which successfully predicted a subsequent sharp fall in the second half of 2008 and 2011. There is also a smaller early warning signal in the early 2005, also correctly associated with a peak of the house price followed by a mild correction. The two latest peaks of the housing price are not detected, due to the choice of the window sizes $\{dt = 60, 59, \ldots, 12 \text{ months}\}$, which cannot resolve their presence so close to each other.

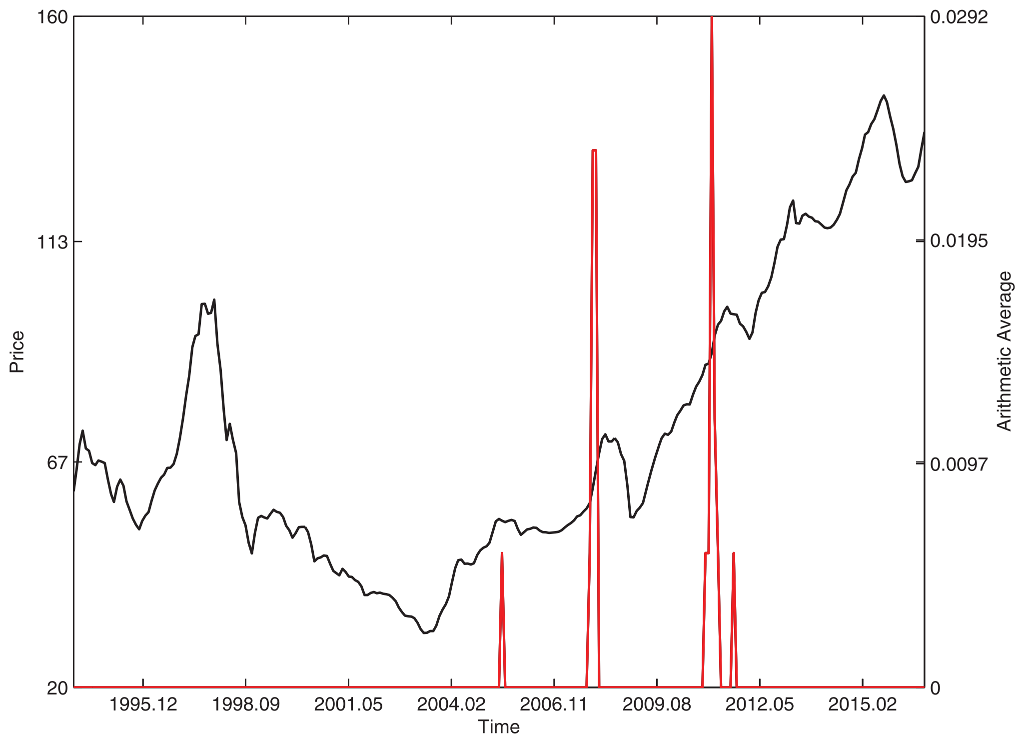

Figure 7. Same as Figure 6 for Hong Kong housing market.

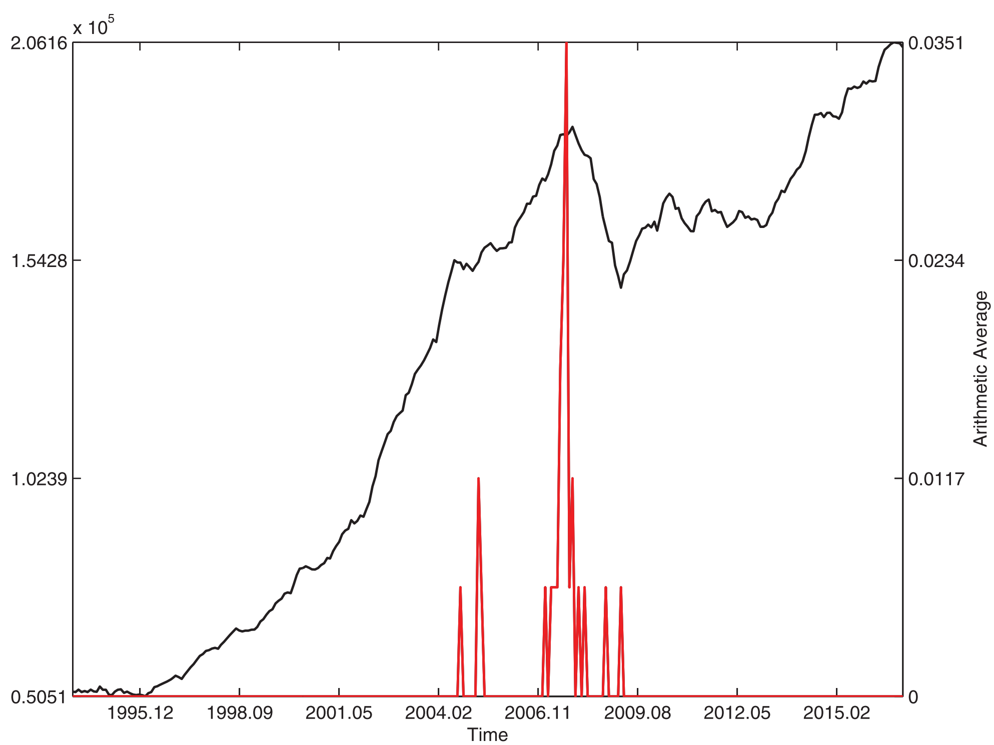

Figure 8. Same as Figure 6 for the U.K. housing market.

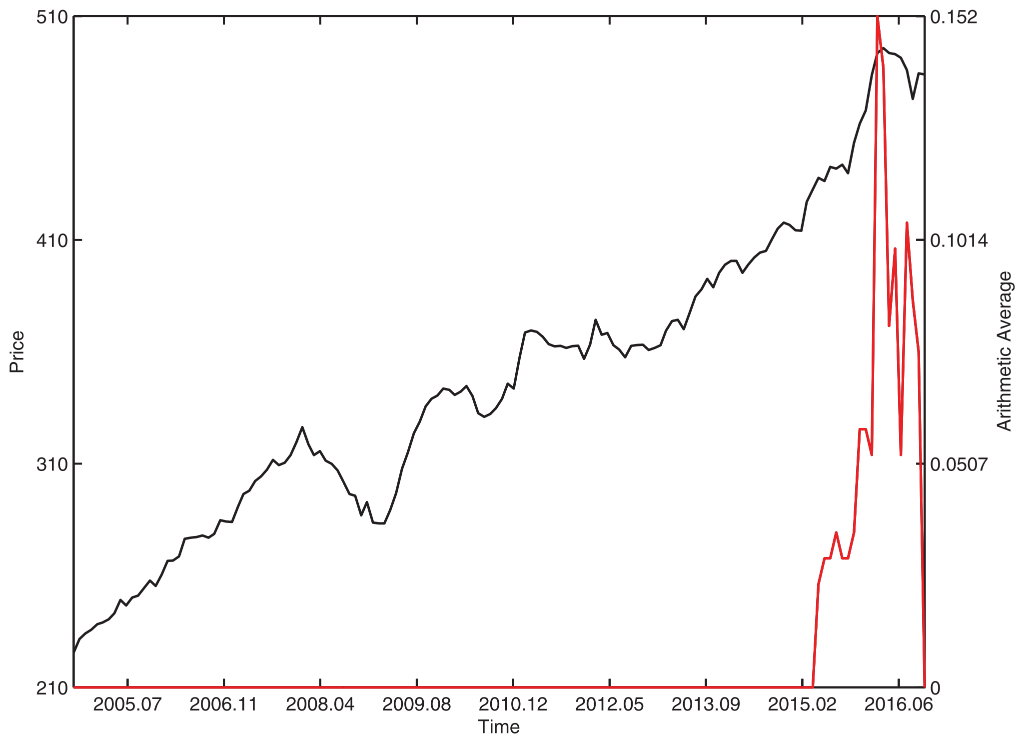

Figure 9. Same as Figure 6 for Canadian housing market.

For the U.K. housing market, Figure 8 shows two main peak clusters of the arithmetic averaged LPPLS Confidence indicator. The first one can be associated with a change of regime from an accelerated price to a transient volatility price plateau. The second peak is almost perfectly coincident with the house price peak, which was followed by a price correction of nearly 30% over the following 20 months.

For the Canadian housing market, Figure 9 shows that the LPPLS Confidence indicator has started to flash warning signals since 2015, with increasing intensity. The peak of the indicator occurred right at the house price peak, confirming the transition from a regime with a strong accelerated price increase to a more volatile price dynamics going sideway. Given the present analysis, we can surmise that the Canadian housing market is going to continue its volatile correction, with the risk of more losses.

Regarding the above results for the four economies' housing markets, we must stress that we are presenting the diagnostics as if in real-time, as done below for the Chinese market (see also Zhou and Sornette 2008 for the real estate market in Las Vegas, Zhou and Sornette 2003 for the real estate bubbles in the United Kingdom, Zhou and Sornette 2006 for the real estate bubbles in the United Kingdom). The analysis for the Chinese real-estate markets presented below is ex-ante, as genuine real-time forecasts for each date t_{end}, whose validity will be determined by comparison with the future (unknown at the time of the forecast) evolution of the time series. This is different from the more standard ex-post approach in academic publications reporting forecast tests in delayed time, or ex-post.

From the current application of quantile regression methods for investigating the behavior of $\widehat{t_c}(q, \mathrm{d}t)$ as a function of t_{end}, the introduction of our metrics and methodology contributes a real-time aggregated predictor when an ensemble of scenarios are exploited by quantile regressions. From the performance of the arithmetic averaged quantile-based LPPLS Confidence indicator that was compared with the real data, we provide a useful precursor for early warning of the critical transitions of these housing markets when they have developed a propensity for instability and a potential for predictability. In summary, these metrics and methodology have

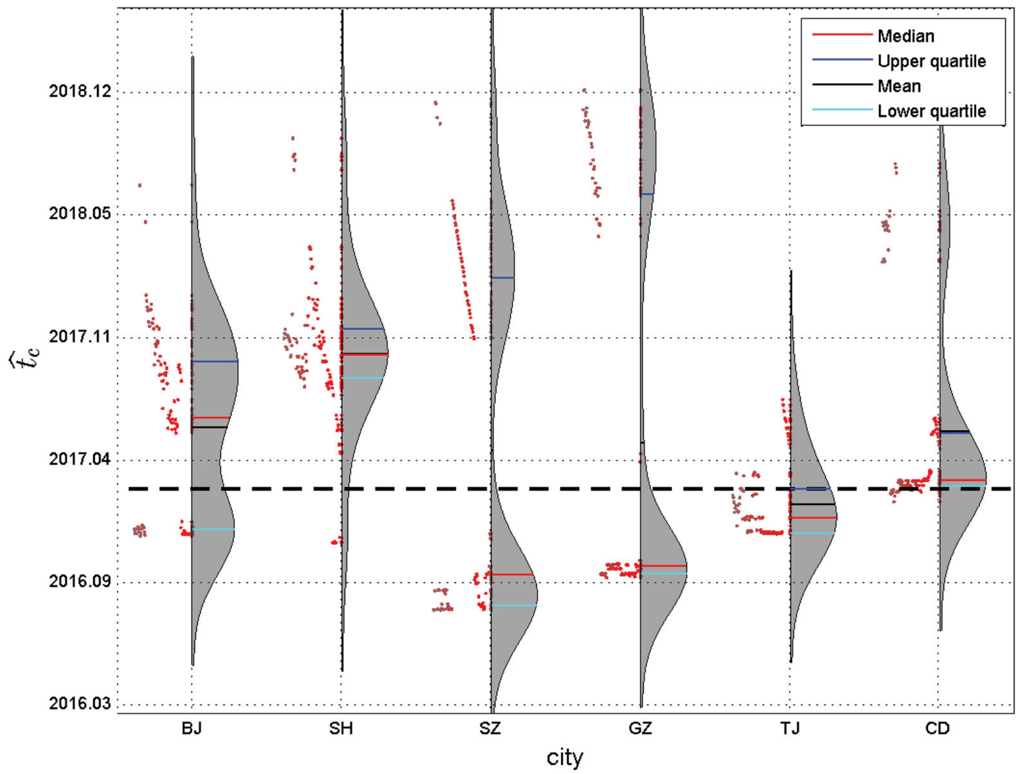

Figure 10. Six dt-Violin plots of $\widehat{t_c}$ for the six Chinese cities: Beijing (BJ), Shanghai (SH), Shenzhen (SZ), Guangzhou (GZ), Tianjin (TJ) and Chengdu (CD). For each of these six cities, the left side of the dt-Violin plots provides the values of dt that contribute to a given $\widehat{t_c}$ among the 99 time windows. The smallest window length of $dt = 12$ months corresponds to the central vertical axis of each dt-Violin plot while the largest window length of $dt = 110$ months corresponds to the position of the point that is at the maximum distance to the left. The right side of each dt-Violin plot gives the rotated kernel estimation of the probability density function of the critical times $\widehat{t_c}$, over the set of 99 time window sizes. These estimates have been obtained for the fixed t_{end} = February 2017, whose value is shown as the horizontal black dashed line. The following descriptive statistics of each distribution of $\widehat{t_c}$ are indicated: median (red line), upper quartile (blue line), mean (black line) and lower quartile (brilliant blue line).

been able to successfully diagnosed the large bubbles and their subsequent change of regimes. These give us some confidence to apply them for the forward analysis of China's housing markets and the diagnostics of bubbles.

6. Application to the housing markets in China's metropolises

The goal of this section is to diagnose the potential existence of bubbles systematically and to forecast the possible turning points of six housing price in China's metropolises listed in Table 2. We first estimate the critical time t_c within a group of time windows with different window lengths and given quantile levels. This multi-scales and multi-quantiles analysis allows us to effectively integrate the information and detect the LPPLS patterns from the data, providing a broader perspective for systematically disentangling the transient accelerating trends and noises in these housing markets. We present the evidence for the existence of bubbles and the forecast of their future likely turning points, using a number of graphical representations that complement each other to provide sound forecasts.

6.1. *Multi-scales analysis from the dt-violin representation* $\mathrm{dt}(\widehat{t_c}) - pdf(\widehat{t_c}(\mathrm{dt}))$

The importance of multi-scales analysis has been documented, for instance by Sornette and Zhou (2006) and Ardila and Sornette (2016). In our case, for a fixed t_{end}, this amounts to scan the time t_{start} of the beginning of the time window ending at t_{end}, and perform the analysis for each window. Specifically, we shift t_{start}

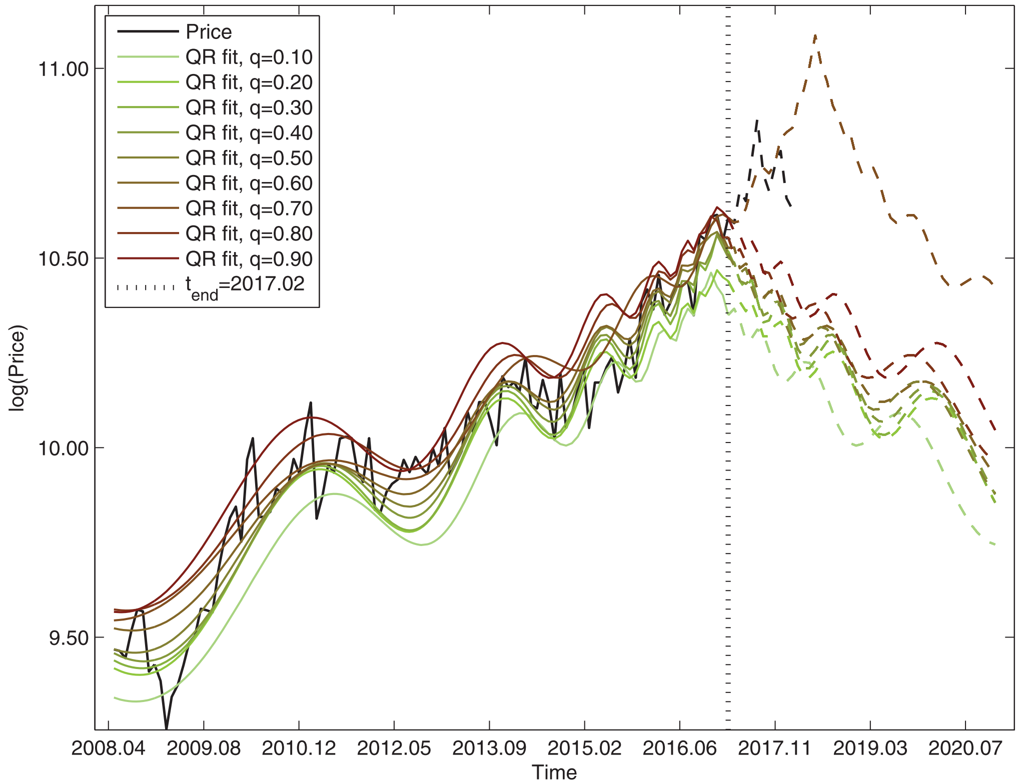

Figure 11. Nine colored calibrated LPPLS curves obtained by quantile regression for the nine different $\{q = 0.10, 0.20, \ldots, 0.90\}$ of Beijing's housing market in the time window [2008.05, 2017.02]. The in-sample continuous curves are extended by dashed out-of-sample lines with the same colors. The noisy black line is the in-sample empirical price time series. The consequent black dashed line is the realized price in the out-of-sample window [2017.03, 2018.01]. The black dashed vertical line shows the value of t_{end} = February 2017 used in the calibration.

(and thus the window size $\mathrm{d}t = t_{end} - t_{start}$) in steps of 1 month, obtaining 99 windows of lengths $\{\mathrm{d}t = 110, 109, \ldots, 12$ months$\}$. For each window $[t_{start}, t_{end}]$, we perform the quantile regression of the LPPLS model on the six metropolises with quantile probability level $q = 0.50$, corresponding to using the L^1-norm for the calibration. This kind of multi-scales analysis thus explores the ensemble behavior of transition times $\widehat{t_c}$ over a large set of different time scales.

Six $\mathrm{d}t$-Violin plots for the six cities are shown in Figure 10. These plots present the influence of the time scale $\mathrm{d}t$ on the t_c-estimates when t_{end} = February 2017. Introduced by Zhang, Zhang, and Sornette (2016), these $\mathrm{d}t$-Violin plots are constructed with the statistics obtained over the set $\{\mathrm{d}t = 110, 109, \ldots, 12$ months$\}$, and for the fixed quantile level $q = 0.50$, as already mentioned. The left side of these $\mathrm{d}t$-Violin plots provides the values of $\mathrm{d}t$ that contribute to a given $\widehat{t_c}$. In other words, the left side of a $\mathrm{d}t$-Violin plot shows the dependence of $\widehat{t_c}$ as a function of time scale $\mathrm{d}t$ of analysis. Since we use 99 time windows, there are 99 points on this left side graph. The kernel estimation of the density distribution of the variable $\widehat{t_c}$ over these 99 values gives the right side of the $\mathrm{d}t$-Violin plot in the form of rotated mono-modal or multi-modal functions. These functions directly quantify the probability that the critical time t_c is at a given value. The following descriptive statistics are added: the median (red line), the upper quartile (blue line), the mean (black line) and the lower quartile (brilliant blue line).

For Beijing, the smallest windows tend to give a $\widehat{t_c}$ close to (and earlier than) t_{end} and contribute to the first mode of the bimodal distribution. Most of the 99 other windows provide the estimates $\widehat{t_c}$ that fall in Q2 and Q3 2017 (second larger and wider mode). This suggests that the Beijing's housing price may reach its peak and change regime during that time. As this analysis was finalized in February 2017.[6] Figure 11 shows that indeed

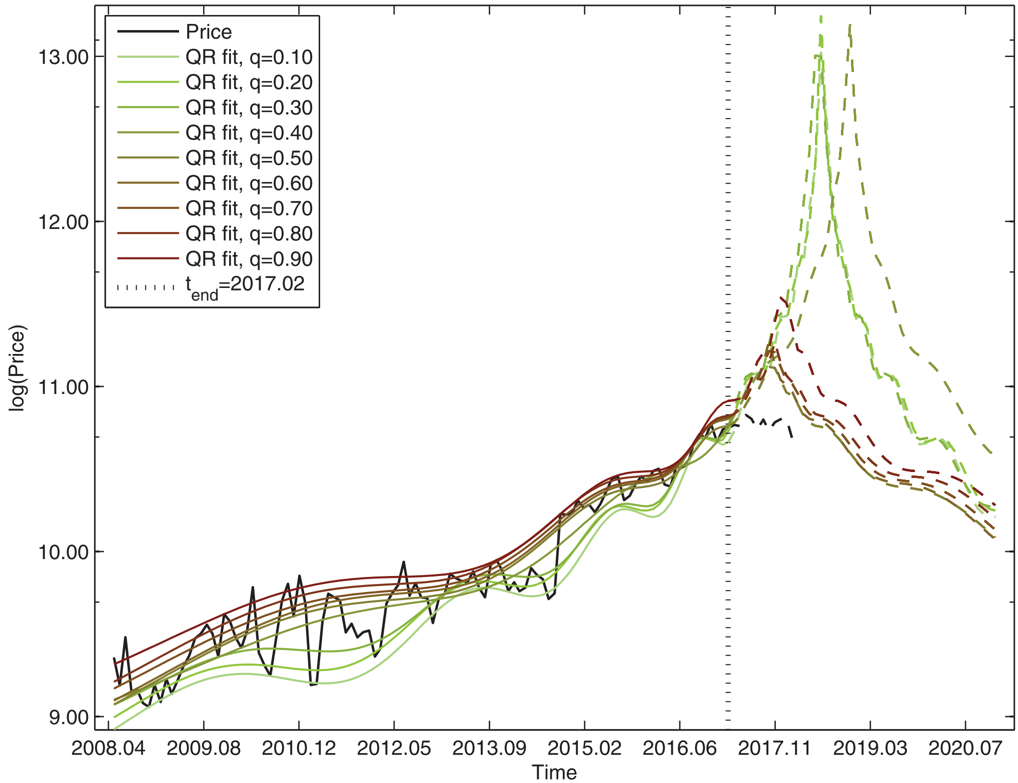

Figure 12. Same as Figure 11 but for Shanghai housing market.

the peak for Beijing was reached towards the end of Q3 2017, and the price has since then moved sideway and slightly down with significant volatility.

For Shanghai, the distribution of $\widehat{t_c}$ is mono-modal and peaked approximately in the same time interval as the second largest mode of the Beijing's housing market, i.e. in Q3 2017. The quasi-synchronous most probable t_c's for these two first-tier cities strengthen somewhat the credibility of these two predictions. Figure 12 shows that the price for Shanghai has exhibited a broad peak over Q1 and Q2 2017, with the beginning of a slow descent or plateau becoming visible. After an impressive ascent from 8314.66 Yuan/square meter in January 2008 to 46,513.00 Yuan/square meter in February 2017, the price has receded to 43,399.00 Yuan/square meter in January 2018.

For Shenzhen and Guangzhou, there are a bimodal probability distribution of $\widehat{t_c}$. The first mode is in the past (before t_{end}) and the second one is in the first half of 2018 for the former and second half of 2018 for the later. But the probability weights are smaller than for Beijing and Shanghai. Figures 13 and 14 show that the price has indeed plateaued before the date t_{end} = February 2017 of the analysis, confirming the relevance of the first mode of the predictions. For Shenzhen, the price was 15,082.21 Yuan/square meter in January 2008, 54,778.00 Yuan/square meter in February 2017, and 54,240.00 Yuan/square meter in January 2018. For Guangzhou, the price was 9765.72 Yuan/square meter in January 2008, 16,211.00 Yuan/square meter in February 2017, and 16,124.00 Yuan/square meter in January 2018.

For Tianjin and Chengdu, the peak of the housing price is imminent or has already occurred in the recent past, since the distributions of $\widehat{t_c}$ exhibit their main modes close to t_{end}. For Tianjin, the recent price development in Figure 15 compared with the prediction of the unimodal distribution shows an almost perfect agreement: the peak of the price indeed occurred in Q1 2017, as expected from our analysis. The price went from 6995.59 Yuan/square meter in January 2008, to peak around 17,186.00 Yuan/square meter in February 2017, and then decreased to 14,368.00 Yuan/square meter in January 2018. For Chengdu, the distribution of critical time spreads

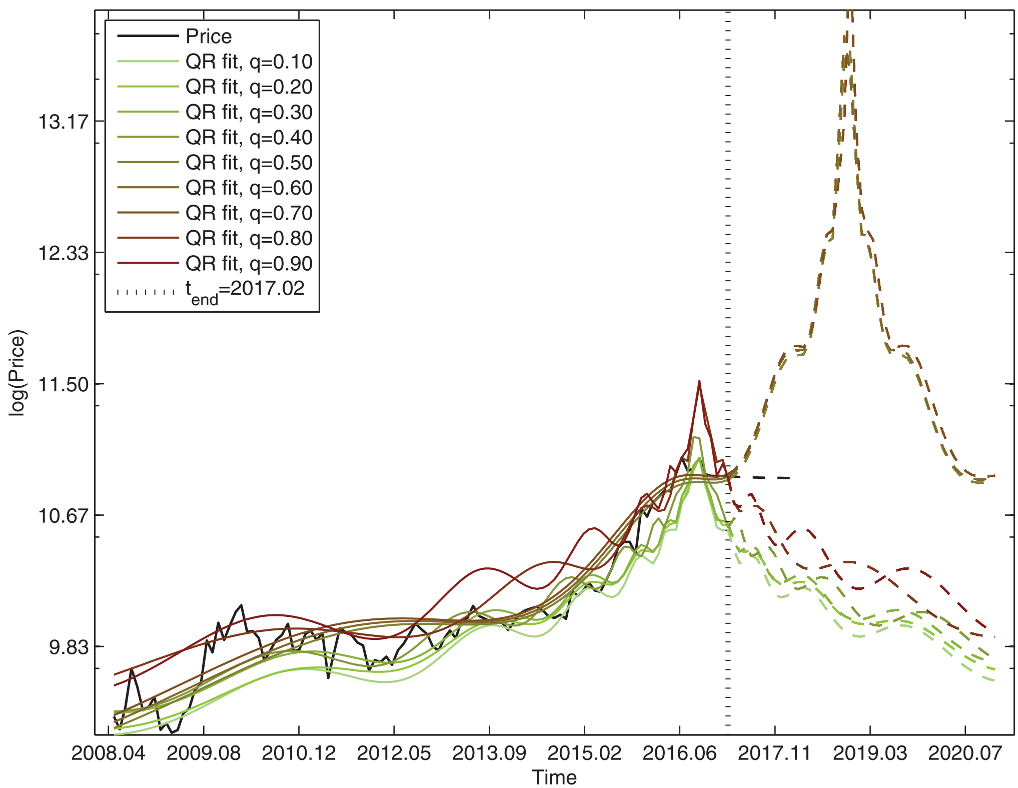

Figure 13. Same as Figure 11 but for Shenzhen housing market.

over Q2 and Q3 2017, while the recent price development shown in Figure 16 suggests that the peak has occurred in Q4 2017. Indeed, the price was 6409.63 Yuan/square meter in January 2008, it passed 14,447.00 Yuan/square meter in February 2017, peaked in Q4 2017 before going down to 14,264.00 Yuan/square meter in January 2018.

6.2. Prediction of the critical time at different quantile probability level q

We complement the multi-scales analysis of the previous section with a study of multiple quantile probability levels, i.e. by fixing the window length dt and varying the quantile level q. Changing q amounts to vary the sampling of the residuals that are not described by the LPPLS model. Thus, it allows us to construct different scenarios corresponding to different sensitivities to the noise realization.

Figures 11–16 show the results of the calibrations of the LPPLS model at nine different quantile levels $\{q = 0.10, 0.20, \ldots, 0.90\}$ in the fixed window [2008.05, 2017.02] of the housing price of the six metropolises in China: Beijing, Shanghai, Shenzhen, Guangzhou, Tianjin and Chengdu.

Figure 11 shows, for Beijing's housing price, that 8 out of 9 quantile regressions pinpoint the critical time of the end of the present bubble regime in the first half of 2017. Only the quantile regression with $q = 0.70$ provides a different scenario with the critical time found much later in the second half of 2018. It is interesting to note that these two scenarios coincide with those contributing to the double-peak shape of the distribution of t_c obtained in the dt-Violin plot in Figure 10. The black dashed line shows the realized price from the time of the analysis in March 2017 to January 2018, and thus corresponds to a true out-of-sample. One can observe that it has followed the scenario outlined by the $q = 0.70$ regression and recently shows signs of starting its correction, bracketed between the two sets of scenarios.

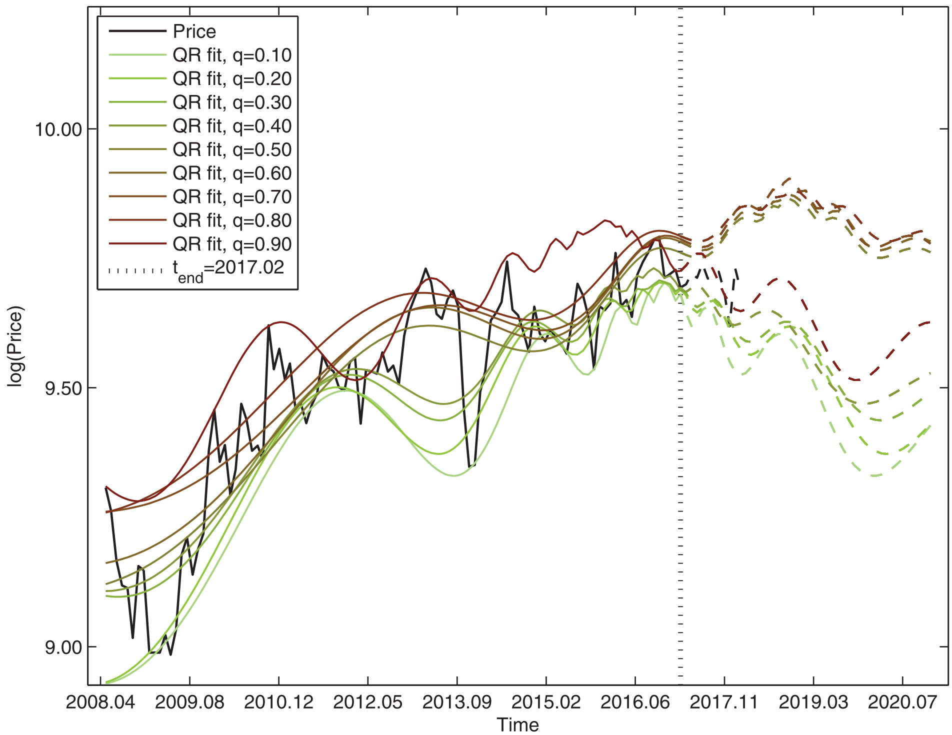

Figure 14. Same as Figure 11 but for Guangzhou housing market.

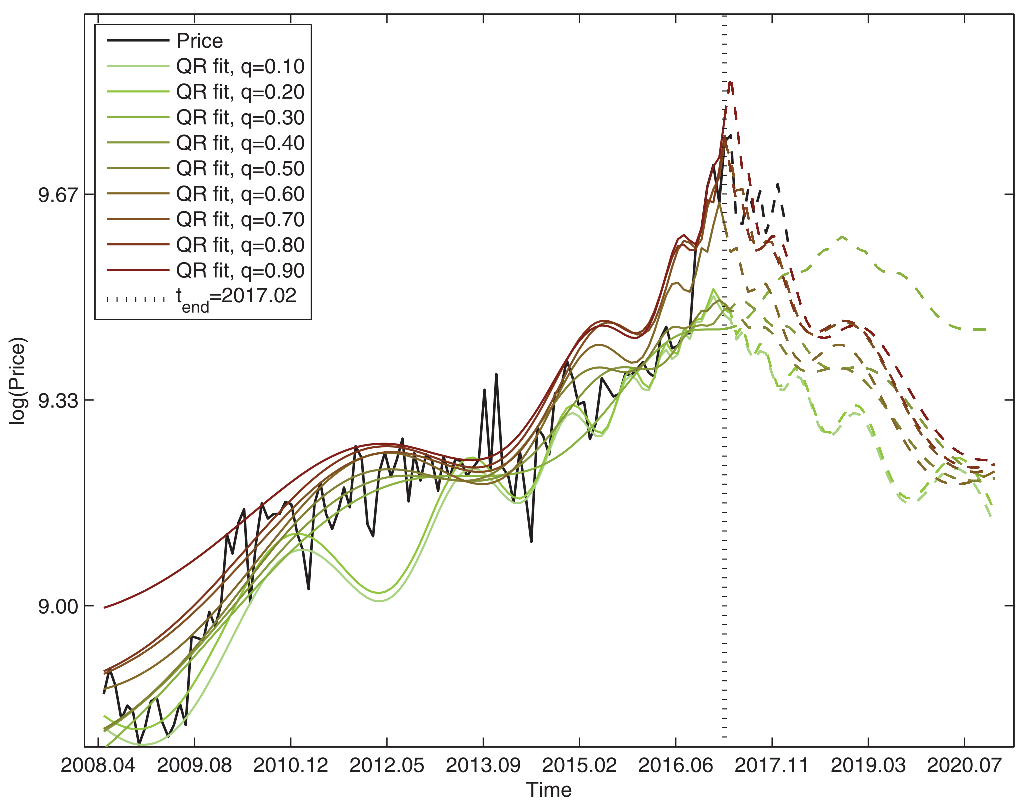

Figure 15. Same as Figure 11 but for Tianjin housing market.

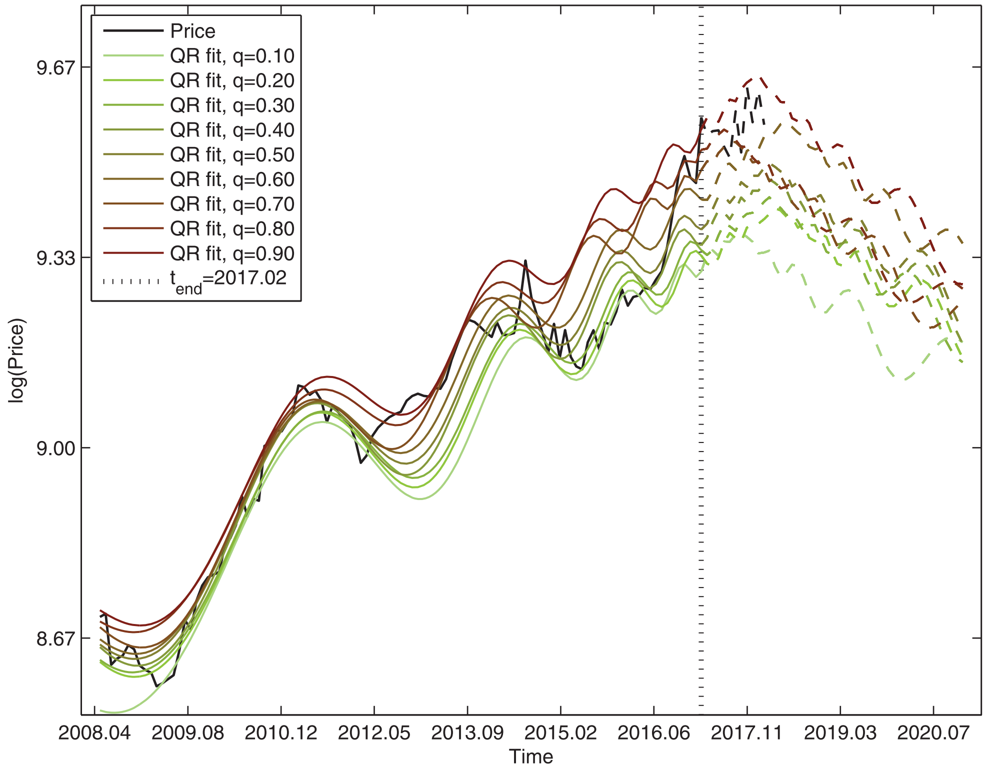

Figure 16. Same as Figure 11 but for Chengdu housing market.

Figure 12 shows that Shanghai's housing price has been growing super-exponentially since at least 2010. Different from Beijing, the predicting t_c's at different quantile levels is not imminent, spanning from the second half of 2017 to the first half of 2018. The black dashed line of the true out-of-sample price trajectory from March 2017 to January 2018 shows a reasonable agreement with the high-quantile scenarios, notwithstanding the absence of the sharp predicted peak which is replaced by a flat truncation.

Figure 13 shows scenarios for Shenzhen's housing price that are similar to those found in Figure 11 for Beijing's. The scenarios obtained for $\{q = 0.50, 0.60, 0.70\}$ suggest that t_c is at the end of 2018. On the other hand, the other quantile levels diagnose that the change of regime has already occurred and is unfolding. From Figure 1, Shenzhen's housing price has peaked in the second half of 2016, and started a decline. It is possible that this is the beginning of a significant correction, following the accelerated decrease of the preceding year. But one should not exclude the possibility identified by the three other quantile levels that this could just be a short-lived correction ending with a rebound until a later peak towards the end of 2018. The black dashed line of the true out-of-sample price trajectory from March 2017 to January 2018 now informs that the price has plateaued, following a trajectory bracketed by the two sets of scenarios decreased above.

Figure 14 suggests that Guangzhou's housing price is not in a bubble, as the calibrations do not exhibit their characteristic super-exponential accelerations. While, the Tianjin's housing market is at or close to the turning point t_c from the Figure 15. For Guangzhou, the black dashed line of the true out-of-sample price trajectory from March 2017 to January 2018 is quite in agreement with the set of scenarios obtained for the lower half of the quantiles. For Tianjin, the black dashed line of the true out-of-sample price trajectory from March 2017 to January 2018 is very well described by the scenarios obtained for the upper half of the quantiles.

Figure 16 also suggests that Chengdu's housing price may reach its change of regime in the second half of 2017 to the first half of 2018. Similarly to Tianjin, the black dashed line of the true out-of-sample price trajectory from March 2017 to January 2018 is very well described by the scenarios obtained for the upper half of the quantiles.

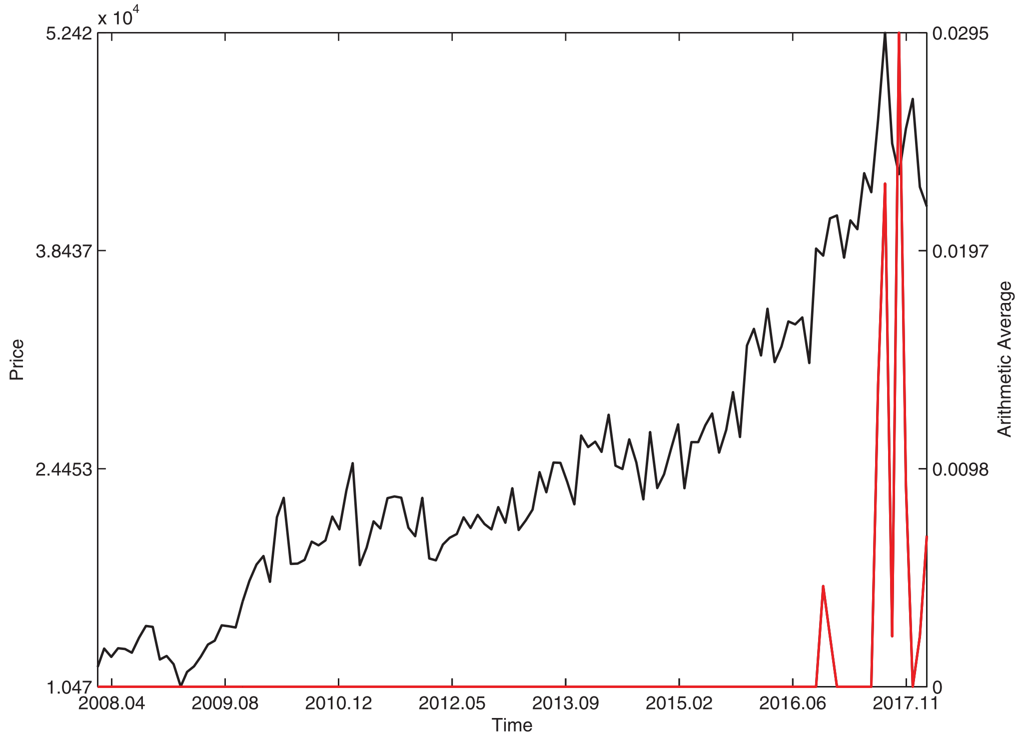

Figure 17. Arithmetic average over the 9 deciles $\{q = 0.10, 0.20, \ldots, 0.90\}$ of LPPLS Confidence indicator for housing market in Beijing.

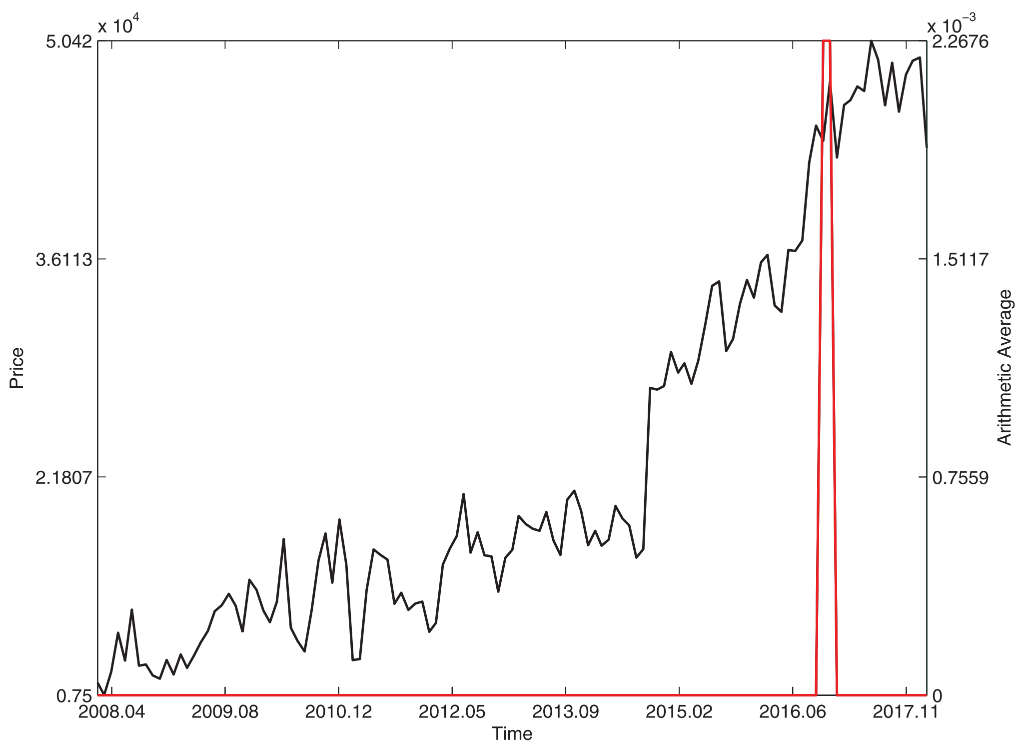

Figure 18. Same as Figure 17 for Shanghai housing market.

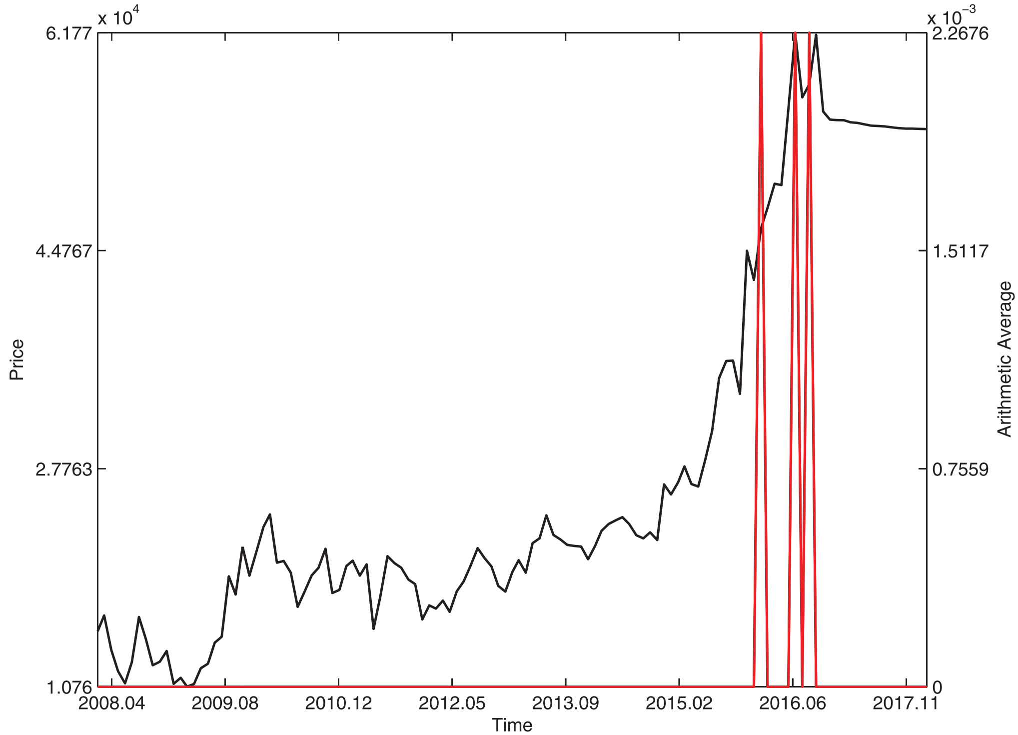

Figure 19. Same as Figure 17 for Shenzhen housing market.

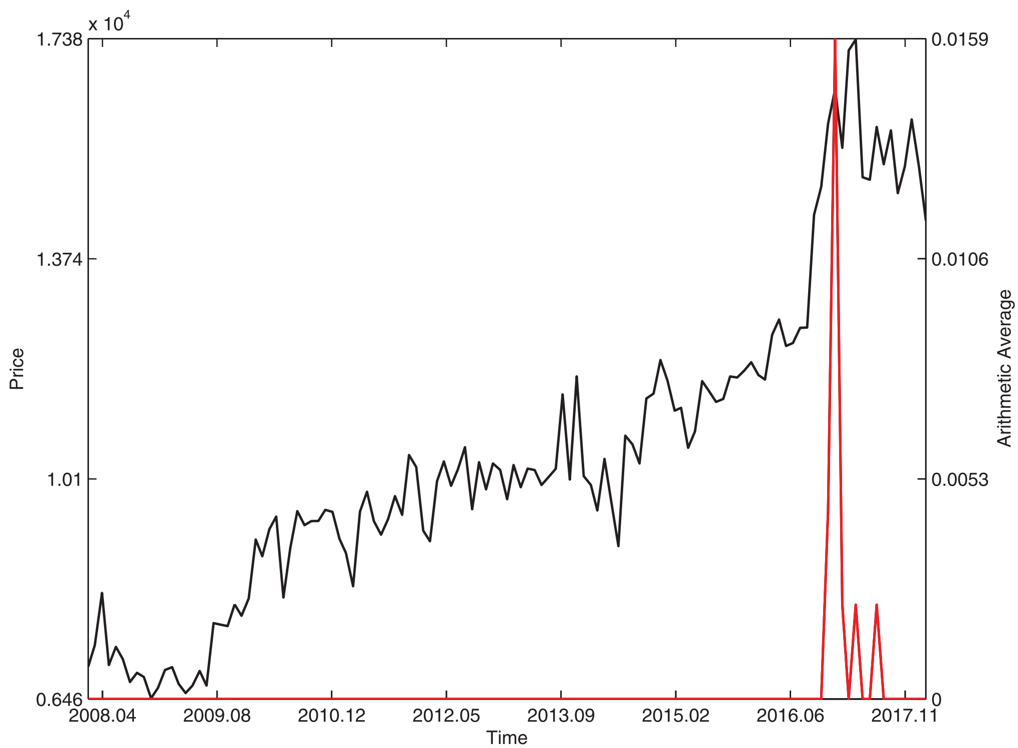

Figure 20. Same as Figure 17 but for Tianjin housing market.

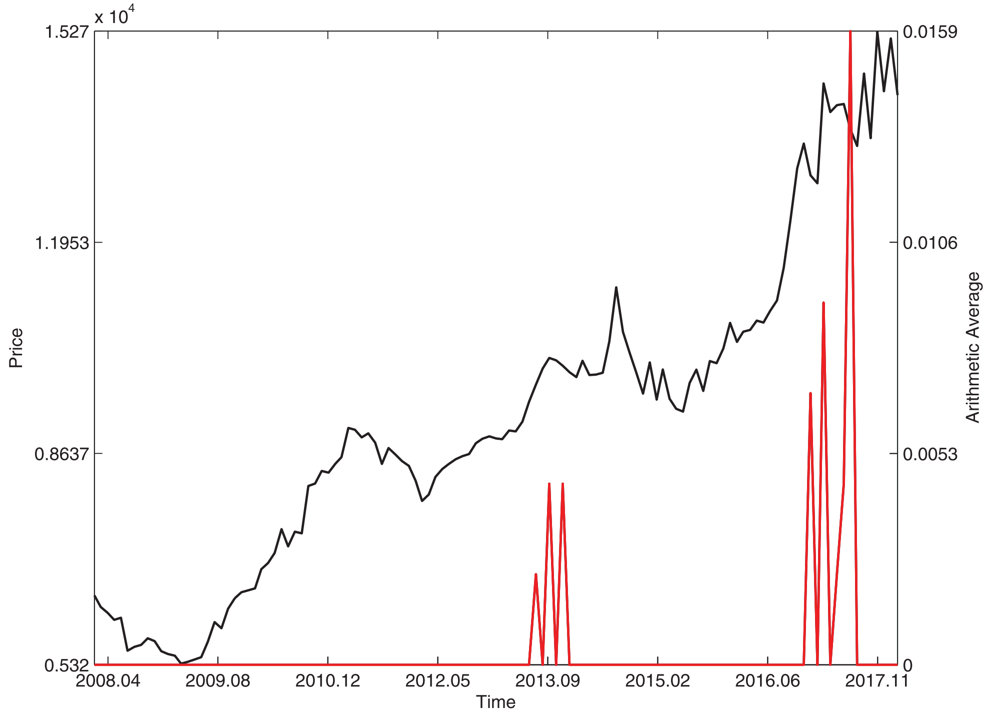

Figure 21. Same as Figure 17 but for Chengdu housing market.

6.3. Early warning signals based on the arithmetic average of the quantile-based LPPLS confidence indicator

In the preceding sections, we have found that the arithmetic average of the quantile-based LPPLS Confidence indicator provided useful warning signals of future declines in the housing markets of the U.S., Hong Kong, U.K. and Canada. This indicator aggregates the information at different quantile levels within a group of different time windows. Here, we apply this indicator to further assess the likely future evolution of the house prices in Beijing, Shanghai, Shenzhen, Guangzhou, Tianjin and Chengdu.

Figure 17 shows the changes in housing prices in Beijing (the Capital of China) since 2008, together with the warning signal given by the arithmetic average of the quantile-based LPPLS Confidence indicator. Although Beijing's housing price did not rise as rapidly as Shenzhen's price (see Figure 1), its price appreciation also reached nearly 300% over the past eight years. The LPPLS Confidence indicator gives a clear warning signal in October and November 2016, which anticipates the change of regime likely to be in the first half of 2017 according to the above multi-scales and multi-quantiles analyses. Similar results are observed for the Shanghai market in Figure 18 with a single clear warning signal in November 2016, as well as for the housing market in Tianjin in Figure 20 with its continuous signals from October 2016 to January 2017.

Figure 19 presents the change of housing prices in Shenzhen since 2008, together with the warning signals obtained from the arithmetic average of the quantile-based LPPLS Confidence indicator. Given the very strong increase from the low price of 10,770.00 Yuan/square meter to the 61,756.00 Yuan/square meter within eight years, the first early warning signal occurred in July 2015. Since that date, the LPPLS Confidence indicator has provided further warning signals. This evidence is in line with the previous multi-scales and multi-quantiles analyses, suggesting that Shenzhen's market has started its correction.

From Figure 21, Chengdu is also characterized by clear early warning signals for corrections. The first warning signal occurred in the second half of 2013, while the second batch starts in December 2016 and continues till the end of the sample (February 2017).

For Guangzhou, there are no early warning signals, confirming the conclusion based on the multi-quantiles analysis.

Combining all the above results for these metropolises, we can summarize as follows. At the time of analysis (February 2017), the China's housing markets were breeding some potential 'turmoils' with downward risks. Especially in China's metropolises, the significant rise of housing prices in the earlier stages boosted our concerns about the major potential risk of collapse that may induce a financial crisis. The warning signals of the LPPLS Confidence indicator suggest a significant risk of a large decline or even a phase change in the near future. Moreover, the multi-scales and multi-quantiles analyses suggest that the housing markets may experience a large decline developing over 2017 or 2018. Adding on these Figures 17–21 the true out-of-sample price trajectories from March 2017 to January 2018, one can observe the quite remarkable performance of the LPPLS Confidence indicator in picking out almost eerily the peaks and change of regimes of these housing markets.

7. Concluding remarks

This study has provided multiple pieces of evidence showing that the LPPLS detection technology can be used to diagnose real estate bubbles and to forecast their critical times. We have advocated the use of quantile regressions of the LPPLS model because this method provides ensemble estimates, which can be further consolidated in ensembles of scenarios as well as aggregated into an early warning signal, the arithmetic average of the quantile-based LPPLS Confidence indicator. This consolidated indicator gives useful early warning signals that can be compared with the price time series to allow a judgment of bubbles' terminations. The obtained LPPLS signals exhibit significant predictive ability to detect the real critical time at which the historical bubbles burst. The super-exponential growth mechanisms embodied in the LPPLS model capture the particularities of these real estate markets.

The results of the paper show that: (1) From the studies of housing prices in the U.S., Hong Kong, the U.K. and Canada, the arithmetic average of the quantile-based LPPLS Confidence indicator has successfully diagnosed the large crashes and rebounds in advance. (2) The dt-Violin plot based on a multi-scales approach allows us to disentangle the genuine LPPLS signals for the residuals in a series of potential scenarios. The arithmetic average of the quantile-based LPPLS Confidence indicator combines the many quantile regressions with a multi-scales analysis, which consolidates the obtained ensembles of scenarios. (3) From the prediction of the critical time at nine quantile levels, Beijing, Tianjin and Chengdu are diagnosed to be at a high risk of approaching a turning point or correction in 2017. The change of regime is likely to be in 2018 for Shanghai and Shenzhen. Guangzhou does not seem to be in a bubble. (4) For Beijing, Shanghai, Shenzhen, Tianjin and Chengdu, the warning signals of the arithmetic average of the quantile-based LPPLS Confidence indicator provide good evidences that significant decline or even a phase change is likely to occur in the near future. Adding the price trajectories from March 2017 to January 2018 that became available from the time of submission to the time of revision of the present article, we have offered true out-of-sample tests of the performances of our indicators.

From a broader scientific and societal perspective, our empirical results suggest that the quantile-based multi-scales LPPLS calibration method is able to diagnose the existence of real estate bubbles and to forecast their ends. We hope that this study will contribute to the development of an operational implementation of the real-time diagnostic in real estate bubbles, with the ultimate goal of improving financial regulation.

Notes

1. The data are from the Federal Reserve, Bank of England and Bank of Japan.
2. This is similar to the belief of U.S. households before the 2008 crisis.
3. In China, the first-tier cities include Beijing, Shanghai, Guangzhou and Shenzhen. The second-tier cities include the capital cities of eastern and central provinces and other Municipalities with Independent Planning Status under the National Social and Economic Development. The third-tier cities include the capital cities of western provinces and some developed medium and small-sized cities in eastern and central provinces.
4. The relationship of supply and demand always affects the housing market. Before the housing supply-side structural reform achieved substantial progress in China, due to the rigidity of housing supply, house price has been mainly determined by the demand side. See e.g. Chow and Niu (2015) and Bian and Gete (2015).

5. Just as Wu, Deng, and Liu (2014) said, the official government (housing) price series are of lower quality. Thus, to address the concerns regarding the quality of the Chinese house prices, the data used in our study are the price from the local Real Estate Trading Centers, rather than use 'the average selling price of new properties in the cities'. This kind of transaction data, which are the total amount of housing sold for the current month, divided by the area of the housing, show the overall level of housing turnover in the city (including the new properties and the repeated housing sale) over a period of time (within 1 month).
6. See posted version on May 20, 2017, on the SSRN archive https://papers.ssrn.com/sol3/papers.cfm?abstract_id = 2969801, we are in a position to evaluate this prediction.

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