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A dynamic mathematical test of international property securities bubbles and crashes

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A B S T R A C T

This study investigates property securities bubbles and crashes by using a dynamic mathematical methodology developed from the previous research (Watanabe et al. 2007a, b [31,32]). The improved model is used to detect the bubble and crash periods in five international countries/cities (namely, United States, United Kingdom, Japan, Hong Kong and Singapore) from Jan, 2000 to Oct, 2008. By this model definition, we are able to detect the beginning of each bubble period even before it bursts. Meanwhile, the empirical results show that most of property securities markets experienced bubble periods between 2003 and 2007, and crashes happened in Apr 2008 triggered by the Subprime Mortgage Crisis of US. In contrast, Japan suffered the shortest bubble period and no evidence has documented the existence of crash there.

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1. Introduction

In recent years the existence of bubbles and crashes in the world’s property markets has become the main focus for both policy makers and investors. From a macroeconomic point of view, the property sector is an aspect of paramount importance of the holistic performance of economy. In fact, over the past few decades the real estate industry has been a target of government fiscal and monetary policies aimed at achieving balanced economic growth, low inflation, and low unemployment. However, policy makers seem to have no way in restraining bubbles in real estate markets; indeed, their adherence to orthodox policies (e.g. easy monetary policy or low interest rates to avoid recession) may be making the problems worse [1].

The definition of “bubble” given by Kindleberger [2] is widely accepted, which is “A bubble may be defined loosely as a sharp rise in price of an asset… in a continuous process, with the initial rise generating expectations of further rises and attracting new buyers—generally speculators interested in profits from trading in the asset rather than its use of earning capacity. The rise is usually followed by a reversal of expectations and a sharp decline in price often resulting in financial crisis”. In other words, bubble is a huge rise in prices followed by a crash. Speculative bubbles have the special characteristics that they are persistent, systematic and exhibit increasing deviations of prices from their fundamental values [3].

The worst episode of bubble in recent times happened in Japan following the collapse of its stock and property bubbles. After the peak in 1991, land prices fell by more than 90% while stock prices slumped badly by 80%, which led to much lower economic growth ratio and a sharp rise in unemployment in the following decades. In August 1997 the Asian Tigers suffered a similar crisis, after asset price bubbles collapsed. While the trigger was the collapse of the currency, it was the massive rise and subsequent fall of property and stock prices that made the aftermath so painful [1]. Most recently, the Subprime Mortgage Crisis that began in August 2007 lies at the center of recent turmoil in housing and credit markets. A number of studies have examined the Subprime Mortgage Crisis and its tremendous effect to the real economy (see Refs. [4,5] for a survey).

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Some articles document that real estate markets could be related to financial crises. For instance, Edelstein and Paul [6] and Mera [7,8] argue that several “urban economic policies”, such as land use regulation, are partially responsible for the formation of the land price bubble in Japan, which led to the financial crisis later. Renaud [9] connects the real estate cycles and banking crises in Asia. Zhou [10] finds that the 1997 financial crisis in Thailand is related to the real estate bubble.

There are also some relevant studies that examine the property bubbles across the world, see Fernández-Kranz and Hon [11] for Spain, Fraser et al. [12] for New Zealand, Cameron et al. [13] for Britain, Hui and Shen [14] for Hong Kong and so on. These works provide important insights. However, most of the empirical studies rely on accurately defining the fundamental value and fail to detect the beginning of a bubble period.

The main objective of this study is to introduce an improved mathematical model which could detect bubble and crash period directly without assessment of fundamental value and discover bubbles even before they burst. The structure of this paper is laid out as follows: Section 1 provides the background for the study. Section 2 presents a review of previous studies on property bubble. The mathematical models used in this study are described in Section 3. Section 4 presents the data and Section 5 detects the bubbles and crashes. The last section concludes the paper.

2. Literature review

A large and growing number of papers propose methods to detect asset bubbles. Debate on house price bubbles mostly focuses on charts of house prices to income or rent ratios, or mortgage payment to income ratios (see Refs. [15–17] for examples), because it seems reasonable to cite the currently low level of the rent–price ratio as a sign that we are in a housing price bubble. However, Meen [18] argues that there is no stable relationship between house prices and rents or between house prices and income. The main reason is that the discount factor of future rents or income is not stable over time. Therefore, evaluations of house prices have to consider a discount factor as well.

There has been a long tradition of studying the theory and models of price bubbles in the general stock markets, and these models are also utilized to detect bubbles in the property markets. According to Yuen and Chu [19], the bubble detection methodologies can be divided into two generations.

The first generation bubble tests are volatility tests such as Variance-bound tests (e.g. [20–24]) and Newey–West’s Two-Step Test [34]. Basically the specification of these methods is developed to compare the volatility between the assumed fundamental housing price and the actual housing price. If the volatility of the actual housing price is significantly larger than that of the assumed fundamental housing price, the test will claim that housing price bubbles are being detected indirectly. However, Marsh and Merton [25] provide a striking example which provides evidence that variance bounds test fails when dividends and stock prices are non-stationary (see also Ref. [26]). Furthermore, these tests have other problems (e.g. model mis-specification, omission of important variables) with implementation that makes them unsuitable for bubble detection.

The second generation bubble tests are direct tests for the no-bubble hypothesis by econometrics method (e.g. unit root test or cointegration test). If house price to income or rent ratio is stationary or the house price is cointegrated with the fundamental price, the no-bubble hypothesis cannot be rejected. Kim and Lee [27] employ the cointegration test to examine the existence of real estate price bubbles in Korea. More recently, Hui and Shen [14] incorporate econometrical methodologies into a Reduced Form Equations structure to study housing price bubbles in Shanghai and Beijing. Taipalus [17] develops a rolling sub-sample Augmented Dickey Fuller (ADF) indicator to test log rent–price ratio for the existence of real estate bubbles for Finland, USA, UK, Spain and Germany, and the results suggest bubbles exist in nearly all of these countries. However, these direct tests can only provide necessary, but not sufficient, evidence of bubbles existing because rejecting the no-bubble hypothesis is not the same as detecting a bubble. As Gurkaynak [24] argues, econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty despite recent advances, especially when dealing with small sample econometrics problems.

These empirical studies can provide an integrated conclusion regarding the presence of property bubbles to some extent. The difficulty of accepting a bubble lies in the specification of the underlying fundamental economic models. As Flood and Garber [28] argue that any bubble detected suffers from the problem of model mis-specification or regime switch processing without any universally accepted fundamental model.

As discussed above, the usual definition of a bubble is a deviation of the property price from its fundamental value. However this definition is generally thought to be not very practical, because it is very difficult to definitively identify a bubble until after the fact—that is, when it is bursting we confirm its existence (see Ref. [29]). Zhou and Sornette [30] give a mathematical description of the end of the bubbles as the spontaneous singularity assuming that a crash follows after rapid growth of economic indicators faster than an exponential function. Although their method is practically useful for prediction of the end of a bubble, it says nothing about the start of a bubble. There is little mathematical definition or criterion formula to identify the start of the bubble period. Recently, Watanabe et al. [31,32] introduce a mathematical definition of bubbles and crashes by exponential behaviors detected in the systematic data analysis. Their mathematical model could identify the whole period of a bubble or a crash determined purely from past data, and the start of a bubble can be identified even before its burst. However, there are still some limitations in practice. Firstly, they fix the optimal time scale $T_i$ for observing the exponential behaviors to be constant, e.g. 100 days. Secondly, the coarse-graining scale of data $\Delta t$ needs to be very small, like 30 s around in order to derive reasonable results. Unfortunately, we can just get monthly or daily data in some certain
markets (e.g. real estate markets) due to the limitation of data frequency. Therefore, we will improve this model in this paper so that it can be used in the real estate market reasonably.

3. Methodology

3.1. Mathematical definition of the bubbles and crashes

The mathematical definition of bubbles and crashes by exponential behaviors detected in the systematic data analysis is first introduced by Watanabe et al. [31,32]. The definitions of the bubbles and crashes in the financial time series:

\[ P(t) - P(t - 1) = (\omega_1(i; T_i) - 1) [P(t - 1) - P_0(i; T_i)] + F(t). \] (1)

In this formula, \( P(t) \) is the price at time \( t \) and \( F(t) \) is the residual noise term. The parameters \( \omega_1(i; T_i) \) and \( P_0(i; T_i) \) are uniquely determined from the past \( T_i \) data points by the condition that minimizes the root-mean-square of \( F(t) \). From this formula, we have three kinds of behavior.

1. \( \omega_1(i; T) > 1.0 \); the price is either exponentially increasing or decreasing and \( P_0(i; T_i) \) gives the base line of the exponential divergence. Watanabe et al. [31,32] define such behavior as a bubble or crash. In this case, the positive feedback from the past price change becomes larger as time passes.
2. \( \omega_1(i; T) = 1.0 \); the price follows a random walk.
3. \( \omega_1(i; T) < 1.0 \); the price is convergent to \( P_0(i; T_i) \).

When fixing the optimal observation period \( T_i \), an ordinary AR model is introduced with the number of terms \( N = 5 \) as suggested by Watanabe et al. [31,32].

\[ P(t) - P(t - 1) = \sum_{j=1}^{N-1} b_j \Delta P(t - j) + f(t) \] (2)

\[ \Delta P(t) = P(t) - P(t - 1). \] (3)

Then the optimal time scale \( T_i \) is given by the minimum time scale in which we cannot observe \( \omega_1(i; T) > 1.0 \) in Eq. (1) for this artificial AR time series.

3.2. Bubbles and crashes trend approximation

Using Eq. (1), we calculate \( \omega_1(i; T_i) \) and \( P_0(i; T_i) \) from the past \( T_i \) steps, and if \( \omega_1(i; T_i) \) is larger than 1.0, we assign all time steps in the observing box of size \( T_i \) steps as exponential divergence. If \( \omega_1(i; T_i) \) is one or less, only the latest time step in the box is assigned as convergence. Then, we shift the box by one step, and calculate two parameters for the new box, and repeat the above procedures. After finishing assignment of divergence and convergence, we connect neighboring divergent time steps to define connected divergent periods. Then we draw a trend curve for each connected divergent period by approximating the price fluctuation in each period by one exponential function of Eq. (3). The remaining convergent time steps are also connected to make convergent period and a trend curve is drawn in the same way by an exponential function of Eq. (3) for each period.

\[ P_{\text{trend}}(t) = \omega_1(i; T_i)P_{\text{trend}}(t - 1) + (1 - \omega_1(i; T_i))P_0(i; T_i). \] (4)

3.3. Model improvement

Watanabe et al. [31,32] use the above method to explore the Internet bubble and crash, YHOO, SUNW and CSCO in NASDAQ from 1998 to 2001, and they fix the optimal time scale \( T_i \) for observing the exponential behaviors to be constant, namely 100 days. However, in practical sense, \( T_i \) follows the rule above is hard to find out. The reason is that the coarse-graining scale of data (\( \Delta t \)) should be very small, like 30 s around in order to derive reasonable results. Unfortunately, we can just get monthly or daily data in some certain markets (e.g. real estate markets or some property securities index) due to the limitation of data frequency. For instance, if only daily data is available, which means the minimum coarse-graining scale of data is 1 day, no matter how large \( T_i \) is, like 100 days, 200 days or above, \( \omega_1(i; T_i) \) would always be found larger than 1.0 (see Appendix for details). In this instance, we can hardly find out accurate bubble periods when \( T_i \) is determined as a constant.

It is very necessary to apply another rule of \( T_i \) in financial bubbles and crashes modeling. In this study, hereby we propose a dynamic process to derive the time scale \( T_i \), which can almost uniquely determine the period of bubbles and crashes independent of the coarse-graining scale of data. In our model, we define the scale of \( T_i \) from 50 days to 600 days. For each time step, \( T_i \) is determined by the condition that minimizes the errors \( \sigma \).

\[ \sigma = \sum_{j=0}^{T_i - 1} F(t_j)^2. \] (5)
By repeating for each point at time $t$, $\omega_1(i; T_i)$ is obtained for different $T_i$ diversified from 50 to 600, which means that the time scale $T_i$ used is dynamic and determined by historical data. After $T_i$ are obtained for each point, we introduce the following formula defining bubbles and crashes, adding $P(t-2)$ into the autoregressive model.

$$P(t) = \omega_1(i; T_i)P(t-1) + \omega_2(i; T_i)P(t-2) + P_0(i; T_i) + F(t).$$

(6)

$P(t)$ is the price at time $t$ and $F(t)$ is the residual noise term. The parameters $\omega_1(i; T_i)$, $\omega_2(i; T_i)$ and $P_0(i; T_i)$ are uniquely determined from the past $T_i$ data points by the condition that minimizes the root-mean-square of $F(t)$. Similar to the AR(1) Model, we propose a new definition for bubbles and crashes as below:

1. $\omega = \omega_1(i; T_i) + \omega_2(i; T_i) > 1.0$: the price is either exponentially increasing or decreasing and $P_0(i; T_i)$ gives the baseline of the exponential divergence. We define such behavior as a bubble or crash. In this case, the positive feedback from the past price change becomes larger as time passes.

2. $\omega = \omega_1(i; T_i) + \omega_2(i; T_i) = 1.0$: the price follows a random walk.

3. $\omega = \omega_1(i; T_i) + \omega_2(i; T_i) < 1.0$: the price is convergent to $P_0(i; T_i)$.

The trend for each bubbles or crashes period follows an exponential function:

$$P_{\text{trend}}(t) = \omega_1(i; T_i)P_{\text{trend}}(t-1) + \omega_2(i; T_i)P_{\text{trend}}(t-2) + P_0(i; T_i).$$

(7)

4. Data

The daily property securities indices data used in our study are obtained from the Global Property Research (GPR) database (GPR 250 Property Securities Index) via Bloomberg data system on five national markets, namely, the United States (USA), the United Kingdom (UK), Japan (JP), Hong Kong (HK) and Singapore (SG).

The GPR 250 Property Securities Index is especially designed in such a way that tracking it with an investment portfolio is easy: it consists of the 250 most liquid property companies worldwide, and only uses the tradable market capitalization of these companies as index weights. This makes the index very well suited for practical portfolio and performance measurement. The GPR 250 Index is available on a daily basis, and is divided into various sub-indices. The standard GPR 250 REIT Index is calculated in three currencies: local, euro and US dollar, and we use the US dollar currency in this paper.

Fig. 1 provides an overview of the movements of GPR 250 Property Securities Index for 5 international countries (cities) over the last 9 years. As can be seen from Fig. 1, after several years’ fluctuations, price indices of the countries (cities) run up extraordinarily since 2003 except for Japan, which fluctuated moderately between around 61 and 163. In contrast, Hong Kong Property Securities market enjoyed the most remarkable rapid growth. USA, United Kingdom and Singapore also fluctuated with a similarly overall upward trend. All five property securities indices plunge after the Subprime Mortgage Crisis happened. It is interesting that the index of Hong Kong Property Securities market culminated in Jan, 2008, about one year later than the average of other countries studied in this paper.

Table 1 provides the mean and standard deviation and other statistic parameters for all index series. The mean of daily property securities indices vary from 72.48 (Japan) to 582.57 (Hong Kong), and the standard deviations range from 35.57 for Japan to 274.43 for Hong Kong.
Table 1
Summary statistics.

|       | Mean   | Median | Maximum | Minimum | Std. dev. | Skewness | Kurtosis | Observations |
|-------|--------|--------|---------|---------|-----------|----------|----------|--------------|
| USA   | 492.96 | 447.15 | 972.23  | 196.14  | 215.32    | 0.36     | 1.75     | 2304         |
| UK    | 342.61 | 304.73 | 767.44  | 136.05  | 177.40    | 0.66     | 2.24     | 2304         |
| Japan | 72.48  | 61.24  | 162.92  | 28.39   | 35.72     | 0.78     | 2.34     | 2304         |
| HK    | 582.57 | 492.53 | 1394.15 | 232.86  | 274.43    | 1.00     | 3.08     | 2304         |
| SG    | 335.78 | 222.00 | 855.08  | 106.65  | 223.74    | 1.02     | 2.60     | 2304         |

Source: GPR 250 Property Securities Index via Bloomberg data system.

5. Empirical analysis

The preceding model results of USA, United Kingdom, Japan, Hong Kong and Singapore property securities markets are given by Figs. 2a–2e respectively. In each figure, $\omega_1(i; T_i)$ (left scale) is shown as a thin orange line, property securities indices data (right scale) of each market are shown as blue line, meanwhile, these figures also illustrate the convergence periods (heavy dotted line, gray), the bubble periods (heavy line, gray) and the crash periods (heavy line, red).

The optimal dynamic time scales $T_i$ are showing in the Table 2, which reveals that the average of time scale $T_i$ is about 118 days and varies from 101–120 days.

After analysis of $\omega_1(i; T_i)$, either exponential or convergent behaviors (bubble or crash) could be assigned to each time step (one time step is one day) as we defined above. We could see most of property securities markets in different countries...
Fig. 2c. The time series of property securities index and $\omega(i; T_i)$ of Japan.

Fig. 2d. The time series of property securities index and $\omega(i; T_i)$ of Hong Kong.

Fig. 2e. The time series of property securities index and $\omega(i; T_i)$ of Singapore.
Table 2
Summary statistics of time scale $T_i$.

|            | Mean | Max  | Min  | Std. dev. | Ske.  | Kurtosis |
|------------|------|------|------|-----------|-------|----------|
| USA        | 118.76 | 120  | 101  | 3.32      | −3.49 | 15.33    |
| United Kingdom | 118.74 | 120  | 101  | 3.28      | −3.57 | 15.95    |
| Japan      | 118.14 | 120  | 101  | 3.68      | −2.55 | 9.50     |
| Hong Kong  | 117.88 | 120  | 101  | 4.00      | −2.20 | 7.27     |
| Singapore  | 118.09 | 120  | 101  | 3.75      | −2.46 | 8.79     |

Fig. 3. Comparison of bubble and crash periods among the five places.

experience bubbles during 2003 to 2007 (see Fig. 3 for comparison). Among these countries, the USA property securities market which is the world’s largest, most mature and transparent securitized real estate market suffers the longest period of bubbles, from around Jan 2003 to Mar 2007 approximately. European largest property market, the United Kingdom market and one of the Asian Tigers Singapore market experience the similar bubble epidemic as the USA. In contrast, the results of Hong Kong seems different to some extent, as the trend and fluctuation of index is much more moderate between Mar 2004 and Sep 2005 (the test result is convergence), when the real estate market of Hong Kong was hit by the SARS (Severe Acute Respiratory Syndrome) Crisis. Furthermore, Japan, another major world economy country, still has not recovered from the episode of Land Crisis in the 1990s.

The results suggest that the first crash in recent years present in USA on March 31st 2008, triggered by the Subprime Mortgage Crisis, which spreads to other counties quickly. Crashes of the Property Securities markets persist until the end of sample period. Distinguished from other countries, Japan Property Securities market experienced the shortest bubble period and no evidence indicates that crash has ever happened in Japan during the sample period.

Comparing the five figures above, we can find that, the Property Securities booms took place between March and April 2003. The property securities indices escalated dramatically during the past five years, and the recent boom of the real estate market seems unique in its pervasiveness. According to the tendency of property securities indices, we document that USA and Singapore suffer the exponential crashes recently. Other countries (the United Kingdom and Hong Kong), however, undertake different level of crashes. In other words, the collapses of property securities markets in the USA and Singapore are more seriously than other countries in our study.

6. Conclusions

Distinguished from previous literature (e.g. [33,13,14,16,12]), this paper uses a dynamic mathematical method to test bubbles and crashes of international Property Securities markets, namely, the United States, the United Kingdom, Japan, Hong Kong and Singapore. Due to the difficulties of assessing the fundamental value of the property markets, the purpose of this paper is to contribute the literature on the definition and detect property bubbles by exponential fitting of the lower frequency historical data (e.g. real estate or property securities markets) without the presence of fundamental value.

Our study produces a number of valuable and statistically significant findings, notably (a) we can detect the beginning of property securities bubble directly even before it bursts; (b) we can derive the persistent periods of bubble and crash; (c) our dynamic process in deriving time scale $T_i$ can provide us more reasonable results when data frequency is limited. This method is powerful in detecting bubbles and crashes in the financial markets; though it cannot be used to predict the end of either bubble or crash [31,32], which would be focused on in our further study.
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Appendix. Comparisons between the original model and improved model

Using YHOO stocks price data from Jan 07, 1998 to Dec 28, 2001, the results of $\omega_t$ for original model are shown in Fig. A.1 (source Watanabe et al., [32], Fig. 1(a)).

When the coarse-graining scale of data ($\Delta t$) comes to 1 day instead of 30 s, the results of $\omega_t$ could not fall under 1 no matter how large $T_i$ is. Therefore, the choice rule of $T_i$ in original model could hardly be satisfied when $\Delta t$ is much larger than 30 s. If we fixed the $T_i$ as 100 days, the graph of $\omega_t$ (see Fig. A.2) looks similar to the one when $\Delta t$ is 30 s but the scale of $\omega_t$ fluctuates much larger than Fig. A.1. The bubbles and crashes period might be inaccurate.

In order to apply the model when $\Delta t$ is 1 day, we improve the fixed $T_i$ to be dynamic $T_i$, fitting by regression model. The result of the improvement model is shown by Fig. A.3.

Here we could see that $\omega_t$ stays close to 1 and seems more stable. As a result, we could get bubble and crash periods more reasonable in our improved model.

In the previous study by Watanabe et al. [31,32], which proved that $\Delta t$ is independent to the model result, in the scale from 30 s to 300 s. However, when $\Delta t$ comes to 1 day, it is much more related to the model performance. According to the original model, we test YHOO data as $\Delta t = 1$ day, the result is shown in Fig. A.4, and the improved model is shown in Fig. A.5.

Comparing Figs. A.4 and A.5, it is obviously that the original model result is not as reasonable as the model we improved. Such as no crashes are detected after Jan, 2000 by the original model, which obeys the situation we observed.
Fig. A.3. $\omega_t$ with $T_i$ dynamic, $\Delta t = 1$ day.

Fig. A.4. The time series of price and $\omega(i; T_i)$ of YHOO ($T_i = 100$ day).

Fig. A.5. The time series of price and $\omega(i; T_i)$ of YHOO ($T_i$ dynamic).
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