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EXAMINING THE RELATIONSHIP BETWEEN REAL ESTATE AND STOCK MARKETS IN HONG KONG AND THE UNITED KINGDOM THROUGH DATAMINING

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ABSTRACT. This paper aims to examine the relationship between real estate market and stock market in the United Kingdom and in Hong Kong, from 1993 to 2007, using the method of datamining. The results provide evidence for the existence of not only a positive correlation, but also a co-movement, between the two markets. Such interactions reflect the similarities among these two regions, which can be explained by two transmission mechanisms: wealth effect and credit-price effect. However, the two real estate markets respond differently upon similar adjustments of the respective stock markets. Such dissimilarity is attributed to their respective local factors. It is shown in the paper that datamining could be an appropriate option for studying this kind of relationships.

KEYWORDS: Real estate market; Stock market; Frequent pattern; Datamining; Hong Kong; the United Kingdom

1. INTRODUCTION

Stock market and real estate market behaviors attribute significantly to the business cycle. These two markets have been of great academic interest (for instance, Ibbotson and Siegel, 1984; Eichholtz and Hartzell, 1996; Okunev et al., 2000; Fu and Ng, 2001; Sim and Chang, 2006). There are two views to explain the relationship between real estate price and stock price. The first one is wealth effect, regarded as the transmission channel from stock market to real estate market. As Kapopoulos and Siokis (2005) propose, this view points out that households with unanticipated gains in share prices tend to increasing housing transactions. Real estate is considered both a consumption good and an investment good. Because of a 'portfolio adjustment' effect, the relationship between stock price and real estate price could be stronger. Investors tend to shift their capital from stock market to other asset markets (i.e. real property) when stock prices rise (Markowitz, 1952; Kapopoulos and Siokis, 2005). Granger causality tests have been conducted to test whether or not wealth effect can explain the relationship between the two markets (see Shon et al., 2003; Sim and Chang, 2006 for examples).

The second view is credit-price effect. It is that changes in real estate prices are important for firms' financial position and collateral value. When real estate prices rise, the collateral value of these firms follows. Consequently, the cost of borrowing for investment will be reduced. By the time when the expected returns from such new investment are realized, the equity value of the firm will rise. This provides additional capital for further investments. This kind of interaction between these two markets leads to a spiraling upturn in both prices and explains why an exogenous shock causes persistent effects (Chen, 2001; Kapopoulos and Siokis, 2005).

A vast amount of papers have used econometric methods to explore the relationship between the real estate and stock markets (see Okunev and Wilson, 1997; Tse, 2001; Sim and Chang, 2006 among others), when the Engle and Granger (1987) and Johansen (1988) cointegration methodologies have been established and widely applied in economics research. However, both stock market and real estate market are becoming much more fluctuant and might deviate from each other due to other conditions (e.g. financial crisis, interest rate or policy change). Consequently, the traditional cointegration test alone might not be able to confirm the hypothesis that cointegration exists between the two markets. Besides, it has been widely accepted that non-linearity might exist between stock market and real estate market (see Ambrose et al., 1992; Baek and Brock, 1992; Okunev et al., 2000 for examples), and datamining could be an effective method to locate such relationship. In this study, a pattern-based mining approach is employed. The structure of this paper is laid out as follows: Section 1 provides the background for the study. Section 2 gives a brief review of previous studies on the relationship between stock market and real estate market. Section 3 presents the data and brief description. The methodologies used in this study are detailed in Section 4. The last section concludes the paper.

2. LITERATURE REVIEW

There is a considerable amount of research which has studied the relationship between stock market and real estate market. For instance, Worzala and Vandell (1993) document a positive correlation between these two markets in the U.K. Newell and Chau (1996) also show that a low positive correlation exists between stock market and real estate market, particularly for office and retail sectors. However, simple correlation method is not enough to address the issue. Furthermore, Quan and Titman (1999), using data from 17 different countries over 14 years, have found that a significant positive relation between stock returns and changes in commercial real estate values. On the other hand, some other scholars find that the correlation between these two markets is negative, see Ibbotson and Siegel (1984) and Eichholtz and Hartzell (1996) among others. Recently, econometric methods, such as cointegration test and Granger casualty test, have been used in studies regarding this topic. For example, Okunev and Wilson (1997) test whether or not there exists a relationship of co-integration between the REIT indices and the Standard and Poor's composite price index (S&P 500), from January 1979 to December 1993. The results indicate that there is a nonlinear and cointegrated, albeit weak, relationship between stock market and real estate market. Gyourko and Keim (1992), using regression of Equity REITs returns against S&P 500 returns, prove that the stock market contains important and timely information about real estate fundamentals. Okunev et al. (2000) conduct both linear and nonlinear causality tests on the US real estate and S&P 500 stock markets and conclude that there exists unidirectional relationship from real estate to stock market, when using linear causality test. Yet, a strong unidirectional relationship from stock market to real estate market is found when a nonlinear test is conducted. Tse (2001) argue that a good deal of stock market volatility can be attributed to the real estate market. Fu and Ng (2001) have found the correlation between returns on property and that on stock index is as large as 0.44. Sim and Chang (2006) explain such relationship in Korea using vector autoregression (VAR). Likewise, Hui and Shen (2006) examine the house price bubbles in Hong Kong, Beijing and Shanghai. More recently, Hui and Gu (2009) study the Guangzhou market based on state space model. Hui and Ng (2009) examine the price discovery of the two neighboring markets: Shenzhen and Hong Kong.

As discussed above, econometric methods have been prevalently used in this research area. However, as both markets have been very volatile during the past decades (especially during the 1997 Asian Finance Crisis and 2007 U.S. Subprime Mortgage Crisis), traditional cointegration tests might not be able to find evidence for a long-run equilibrium of stock and real estate prices (see Hui et al., 2009). Under this circumstance, another method that can explore the linkage between these two markets, is introduced. In this study, we contribute to the literature by using the datamining method, as an alternative, to explore the relationship between the two markets, if traditional econometric methods yield no significant results.

3. DATA SOURCES

In this paper, we choose two regions: the United Kingdom (U.K.) and Hong Kong as an example to examine the relationship between stock market and real estate market.

The U.K. and Hong Kong are very similar in market structures and operations for both real estate and stocks. Hong Kong had been one of the British colonies. The two markets still bear similarities even today. Some of companies listed on the London Stock Exchange are also listed on the HK Stock Exchange. Thus, it would be much interesting to investigate the relationship between the two markets – as a starting point here in this paper. The research has also provided a good comparison between Asia and Europe, two developed markets. Of course, the current research could well be extended to cover other countries in future studies.

Monthly data of house price indices and stock price indices in both the UK and HK, from January 1993 through December 2007, are employed. The data includes:

S_1: *FTSE 100 Index (FTSE), short for a share index of the 100 most highly capitalized UK companies listed on the London Stock Exchange (source: Bloomberg);*

S_2: *UKHP, short for the house price indices of the United Kingdom (source: www.nationwide.co.uk/hpi/historical.htm);*

S_3: *HSI, short for Hang Seng Index (source: Bloomberg);*

S_4: *HKHP, short for the residential house price indices of Hong Kong which is compiled by the Rating and Valuation Department (RVD) of Hong Kong Special Administrative Region (source: www.rvd.gov.hk).*

Figures 1 and 2 illustrate the movements of stock price index and housing price index in the U.K. and in Hong Kong over the last 15 years.

4. METHODOLOGY AND EMPIRICAL RESULTS

4.1. Instruction of datamining method

Datamining is a confluence of multiple disciplines, including database technology, statistics, machine learning, visualization and information science. Compared to traditional statistical methods, usually regarded as confirmatory analysis, using model fitting technology to explain the observed data, the process of datamining is essentially exploratory.

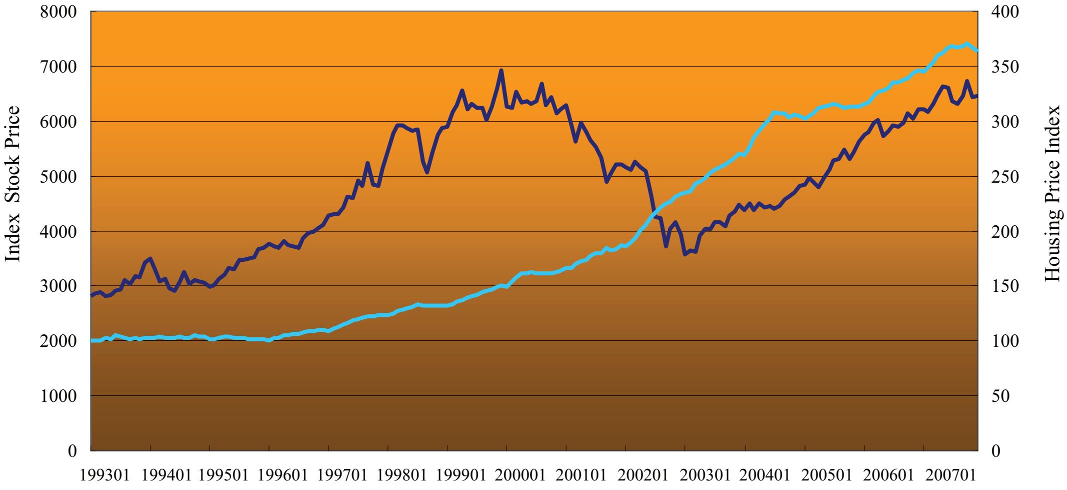

Figure 1. Time series plots for UK FTSE and UKHP, Jan, 1993 to Dec, 2007

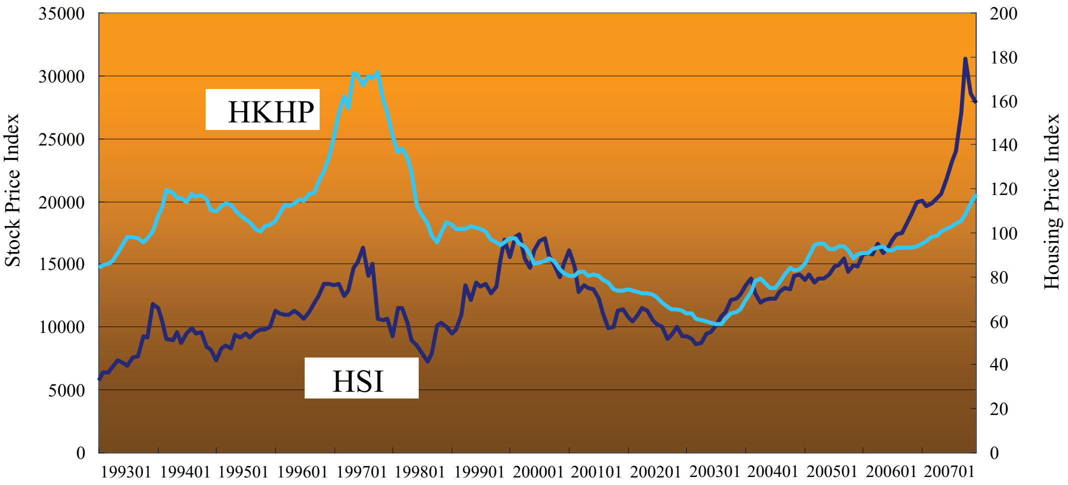

Figure 2. Time series plots for HSI and HKPI, Jan, 1993 to Dec, 2007

The target of datamining is to find new, interesting, previously unknown, potentially useful and ultimately understandable patterns from very large volumes of data (Nigro et al., 2007). The patterns hidden in data are some distinctive arrangements of structural elements and with the assistance of those discovered patterns, which are superior than their peers based on the selection criterion set in advance, researchers can retrieve some useful information which is not easily found by human within a vast amount of data. For instance, simply given a sequence S = *"AACBCAACABAAC"* and using the number of occurrences and pattern length as the selection criterion, we can get "*AAC*" as the frequent pattern by watching the sequence S.

4.2. Frequent pattern discovery

Datamining method can be applied to discover frequent patterns we are interested in among the dataset objectively. Time-series data should be converted to symbolic data (e.g. A, B, C *etc.*) that is useable for datamining method, which is detailed in the next section. With those symbolic data, algorithms of datamining can find patterns which are interpretable. A pattern-based mining approach is introduced in this paper, to disclose the frequent patterns in data, which is a combination of several atomic elements in sequential order with higher occurrences. We can benefit from the discovery of frequent patterns a lot, as they are in accordance with the intrinsic and important regularities of the data, rather than with personal experience and assumptions. In short, it is comparative objective than traditional statistical models.

Figure 3 shows a flowchart of the approach. The support of a candidate is defined as $sup = \frac{o}{s}$, where o is the occurrences of the candidate and s is the size of the sample data.

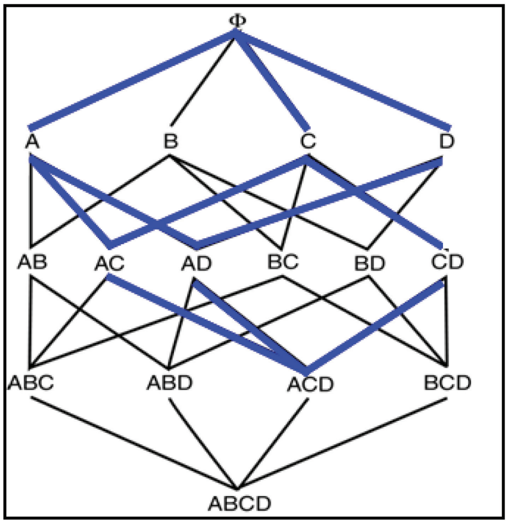

Figure 3. A flowchart of finding frequent patterns

In Figure 1, the dataset $\varnothing$ has been classified into four categories $\{A, B, C, D\}$. From top to bottom, candidates at each level are generated by candidates from the preceding level with right-joining and left-joining others; and the evolution between two levels is to eliminate unqualified candidates whose supports are less than a predefined minimum support and pass qualified candidates, which are highlighted by blue lines in the figure. This process continues until no qualified candidates are found for the following loop. Hence those qualified candidates at each level are the relatively frequent patterns of the data set and, to some extent, can be used to represent the data set for further research. The corresponding pseudo code is in Figure 4.

4.3. Introduction to data pre-processing

Data pre-processing is used to convert original raw data to a specified format which is easier to interpret. In order to identify patterns in time-series data, some meaningful symbols are suggested to be assigned to them. This numeric-to-symbolic conversion transforms some available features of those data to a sequence of symbols. Obviously, these symbols are dependent on the properties of data and patterns we expect to get. In our research, since we focus on the analysis of influence imposed on the real estate market by the stock market both in Hong Kong and in the United Kingdom, symbols which are better to describe the trend have been chosen. Another key point should be taken into consideration is to determine the appropriate number of symbols adaptable to describe different time series. For a given data set, the more symbols we adopt, the fewer patterns we retrieve from the data with the same requirement of minimum support; and another concern is the size of data set, which hosts the balance between the number of patterns and the reasonably predefined minimum support. Hence we use three symbols (Up: A, Level: B and Down: C) to compose the converted sequence in this research. The definition is that, assuming $S = \{s_1, s_2, \dots, s_n\}$ as a sequence of time series data, $thre_1$ and $thre_2$ ($thre_1 < thre_2$) as thresholds to categorize the sequence, we have:

Table 1. The definition of symbols

Symbol	Definition
Down	$\frac{s_{i+1} - s_i}{s_i} < thre_1$
Level	$thre_1 \le \frac{s_{i+1} - s_i}{s_i} \le thre_2$
Up	$\frac{s_{i+1} - s_i}{s_i} > thre_2$

Hence according to the definition of symbols in Table 1, we can get a converted sequence $C = \{c_1, c_2, \dots, c_{n-1}\}$ $(c_i \in \{Up, Level, Down\})$ for further research. In this experiment, the values of thre1 and thre2 are defined as –2% and 4.5% respectively.

4.4. Empirical results of datamining method

With the converted sequence C from the data pre-processing, we apply the pattern-based approach to the sequence in order to find frequent patterns.

For the implementation, a key issue is how to organize the format input data so that the result can simultaneously reflect the similarity and dissimilarity between two regions referring to the price performance of stock and real estate exchange markets. As the result of economy globalization, stock exchange markets in different countries would share some common features.

```
1.  Input:   E and C;
             Let E be a set of elements (e.g., E = {UP, LEVEL, DOWN})
             Let C be the sequence given for implementation
2.  Definition: |X| returns the cardinality of a set X
                sup(e) returns the support of element e in data set
3.  F ← ∅, N ← ∅, T ← E and min_sup = 0.02
4.  do {
    (1) for i ← 1 to |T| {
            (a) for j ← 1 to |E| {
                    (i)   if ( t_i e_j not exists in N) then put t_i e_j in N;
                    (ii)  if ( e_j t_i not exists in N) then put e_j t_i in N;
                }
        }
    (2) T ← ∅;
    (3) for k ← 1 to |N| {
            if ( sup(n_k) >= min_sup ) then put n_k in both T and F;
        }
    (4) N ← ∅;
5.  } while ( T ≠ ∅)
6.  return F;
```

Figure 4. The pseudo code of implementation

Changes in stock prices can be transmitted to other countries by their effect on the aggregate demand and balance of payments (Tse, 2001). However, there are still some particular features that are dominated by the local economy. That is to say, if we analyze two markets separately, unavoidably some indirect factors relevant to the local aspect could be introduced and have their special influence on the results. Thus in order to eliminate irrelevant factors as much as possible, we put the four kinds of data under the same timeline. In other words, the input vector has four elements in accordance with these four kinds of data for implementation. We expect to find out the similarity and dissimilarity of the interaction behavior of these two markets in two different regions. After choosing the format of input factors and defining the minimum support as 0.02, we use the pattern-based approach compiled by *JAVA* to mine the data and the analytical results are presented in the next section.

The analytical results of the pattern-based mining approach

The Table 2 is our result and lists all the frequent patterns resulted from the implementation.

Table 2. Frequent patterns resulted from the implementation

Indices	Frequent patterns	
FTSE	C	C
UKHP	B	C
HSI	C	C
HKHP	A	B

Note: A, B and C denote “Down”, “Level”, “Up” respectively.

From the Table 2 we can see that the frequent patterns discovered by the implementation describe the *simultaneous* movements of the four indices (S_1, S_2, S_3 and S_4) in two successive months. The frequent pattern indicates that the FTSE 100 index and HSI are rising continuously (denoted by ‘C-C’). For the housing price indices, however, the frequent patterns are different as UKHP is first stable and then goes up (‘B-C’) while HKHP remains stable after rebounding from a downtrend at the beginning (‘A-B’). That is to say, as the stock markets move in the same way, the upward trend in the two real estate markets is roughly similar. This relationship illustrates the ‘wealth effect’, from the stock market to the real estate market, as demand for real estate increases, due to unexpected stock market returns. From another perspective, when house price indices have the tendency of rising, such as the pattern ‘B-C’ of house price indices in the UK and ‘A-B’ in Hong Kong, both stock prices are showing sustainable increases with pattern ‘C-C’. This behavior could be interpreted as ‘credit-price effect’. The rise of real estate prices would both stimulate the economy from a macro perspective and raise firms’ collateral value from a micro perspective. Such an effect gives firms or households an easier access to financing or investment. Following the expansion of investment is the increase in real estate prices. The interaction between these two markets causes a spiraling upturn in both prices. However, dissimilarity is found in the results, which is that when the stock exchange markets of both regions have the same patterns found “C-C”, the corresponding real estate markets behave differently. The pattern of house price indices in Hong Kong is “A-B”, comparable to “B-C” in UK. This can be attributed to the two crises that Hong Kong had been through during the sample period, i) the Asian financial crisis and ii) the outbreak of SARS in 2003. Besides, the impact of stock prices on real estate prices is much lower than that of real estate prices on stock prices. For instance, when the pattern of HSI is “C-C”, the pattern of house price indices in Hong Kong is “A-B”.

Because we compare the two markets by putting them under the same timeline, the positive correlation between stock and real estate markets in both the United Kingdom and Hong Kong is simultaneous. This would add some limitations on discovering the frequent patterns which are unique to the single market. However, since frequent patterns found represent characteristic features of the data, the motivation behind those patterns is in accordance with existing theories such as wealth effect or credit-price effect.

5. CONCLUSION

Many previous studies have attempted to explore the relationship between stock market and real estate market, using traditional econometric methods. However, it is shown in this study that traditional cointegration test does not find evidence for a long-run equilibrium between the two markets in two different regions (i.e. the United Kingdom and Hong Kong). There are two possible reasons. Firstly, stock price and real estate price deviate from each other, due to temporary external shocks. And secondly, the relationship between these two markets might be nonlinear. Therefore, we employ datamining as an alternative method to discover useful information from large volumes of data and to analyze real estate market behaviors.

In this paper, we have applied a pattern-based mining approach in order to examine how these two markets interact with one another. The results indicate that both similarity and dissimilarity exist. Similar positive correlations are found between stock market and real estate market in both the United Kingdom and Hong Kong. It seems that the spiraling upturn or co-movement of both prices in these two regions happens in the two successive phases. This can be attributed to two transmission mechanisms, namely wealth effect and credit-price effect. This study also illustrates that datamining methodologies can be a reasonable alternative, when traditional econometric methods are not suitable for studying some markets due to their unique conditions.

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SANTRAUKA

RYŠIO TARP HONKONGO IR JUNGTINĖS KARALYSTĖS NEKILNOJAMOJO TURTO BEI AKCIJŲ RINKŲ NAGRINĖJIMAS ANALIZUOJANT DUOMENIS

Eddie C. M. HUI, Wenjuan ZUO, Lun HU

Šiame darbe siekiama duomenų analizės metodu išnagrinėti ryšį tarp Jungtinės Karalystės ir Honkongo nekilnojamojo turto rinkų ir akcijų rinkų nuo 1993 iki 2007 m. Remiantis gautais rezultatais matyti, kad tarp minėtų dviejų rinkų egzistuoja ne tik teigiama koreliacija, bet ir kovariacija. Tokios sąveikos rodo panašumus tarp šių dviejų regionų, o tai paaiškinama dviem perdavimo mechanizmais: turto poveikiu ir kredito bei kainos poveikiu. Tačiau dvi nekilnojamojo turto rinkos skirtingai reaguoja į panašų akcijų rinkų reguliavimą. Taip vyksta dėl jų vietinių veiksnių įtakos. Duomenų analizė galėtų būti tinkama alternatyva tiriant tokius ryšius.