This is the Pre-Published Version.
This is an Accepted Manuscript of an article published by Taylor & Francis in Housing, Theory and Society on 2016-06-23 (published online), available at: http://www.tandfonline.com/10.1080/14036096.2016.1196240.

Fundamentals and Market Sentiment in Housing Market

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ABSTRACT The primary purpose of this study was to explore the predictive power of sentiment on three market indicators (price, rent and transaction volume) in the housing market. Using an advanced causality analysis called Integrated Renormalized Partial Directed Coherence, the study focuses on the private housing market in Hong Kong during 1993–2012. The findings suggest that sentiment not only is a prominent indicator of price and liquidity (volume), but also provides an indirect linkage between rent and house prices in the short run. Armed with causality results, this paper further examines the effect of sentiment on the long run trend of housing market. The results explore different roles of sentiment in rent and transaction markets: sentiment affects housing price and its lagged term has an important bearing on rent.

KEY WORDS: Housing market, Market fundamentals, Market sentiment, Transaction volume

1. Introduction

Dynamics of housing prices have always drawn the most attention. Since house is a durable product and its price is fully determined as an asset, classic theory believes that equilibrium between demand and supply determines the price in the housing market (DiPasquale and Wheaton 1996). Case and Shiller (2003) suggest that other than some market fundamentals, excessive market expectation also plays an important role in rapid appreciation of housing price. The expectation affects prospective housing demand and then affects the price. Irrational expectations can even lead to fluctuations that drive the price away from market fundamentals in property markets (Jin, Soydemir, and Tidwell 2014).

Behavioural economics leads to studies aiming at theoretical modifications for asset pricing based on new assumptions. Sentiment, as an indispensable part of those assumptions, reflects a reference of psychology in modern economics and finance (De Long et al. 1990). Given the definition, sentiment is the belief of an investor in relation to the expectation on price movement, and market sentiment is the aggregate attitude of investors. Sentiment, as a non-fundamental factor, cannot be justified by market fundamentals (Baker and Wurgler 2007). Some previous efforts have attached great importance to sentiment. For instance, Baker and Wurgler (2006, 2007) discuss the relationship between investor sentiment and return rate of asset in the stock market; Clayton, MacKinnon, and Peng (2008) suggest that sentiment could cause divergence of property price from its fundamental value. Hui, Zheng, and Wang (2013) adds to their findings that sentiment is even responsible for some of the property mispricing. Sentiment acts a more persistent role in driving price away from fundamental value in private markets (Ling, Naranjo, and Scheick 2014). Freybote and Seagraves (2016) find that the institutional investors refer their investment decisions to the sentiment of specialized real estate investors.

As the housing market rides the cycle, the variation in housing price cannot be fully explained by fundamentals (Jin, Soydemir, and Tidwell 2014), and some models appeal to autoregressive pattern. Previous literature devote to the investigation on the effect of non-fundamental factors in housing market. It arouses the authors' interest in exploring whether sentiment (and its past value) contains informative content to explain the non-fundamental movements of housing market.

Differences between investor's expectations on housing price and rent are identified in Wong et al. (2005). As the rent is more "fundamental" than housing price, the degrees of effect of sentiment on the transaction market and the rental market should be different. In addition, due to the limitation of short-selling, switching between renting and owning a house is the only method to hedge the future risk in housing price for a household. Thus, this paper intends to examine whether there is a linkage by which sentiment effect in transaction market can be transmitted into rental market.

This paper begins with an analysis of statistical causality between market sentiment and three other market indicators: price, rent and trading volume. By taking advantage of the IRPDC method (developed by Hui and Chen 2012), the tests provide evidence showing the predictability of sentiment in the dynamics of housing market. This paper further investigates the explanatory power of market sentiment in the long-term trends for both sectors of housing market, i.e. the transaction and rental markets.

This study has meaningful implications in two ways. First, if sentiment has a power to predict other market indicators, the results can offer a better understanding of how sentiment, as a non-fundamental factor, drives fluctuations in the housing market. Conversely, if is the market indicators are found to have impacts on sentiment, this should help identify the causal factor for the formation of market expectation and explain the phenomenon of "herding" behaviour. Second, sentiment should have different roles in the transaction and rental markets as housing prices are observed to be more volatile than rents. This paper not only sheds light on the relationship between sentiment and market movements, but also supplies insights into how the market actually works with sentiment's influence. These implications can benefit not only investors in investment decision-making but also housing authorities in policy-making.

The paper proceeds as follows: Section 2 discusses the role of market sentiment and the sentiment index (SI) used in this paper. Section 3 reviews some related literature. Section 4 outlines the IRPDC method and theoretical model for, as well as the data description. Section 5 elaborates the results and implications of causality. Section 6 elaborates the effect of sentiment in long term trend of housing market. The paper concludes in the last section.

2. The Market Sentiment

This study intends to detect the causal relationships between sentiment and market indicators and further investigates the role of market sentiment in the long-term movement of housing market. The definition of market sentiment and the related index used in this paper is introduced as follows.

2.1. The Role of Market Sentiment

According to Baker and Wurgler (2007), sentiment is the belief of an investor in relation to the expectation of the price movement in a market that cannot be justified by market fundamentals. Generally, market sentiment is the aggregate attitude of investors towards the future trend of asset prices in a market.

Since housing market is characterized with heterogeneity, illiquidity and high transaction cost, the market is less efficient, and housing prices cannot respond quickly to all arrival of information. A class of assets with limit to arbitrage is more likely to be affected by sentiment (Baker and Wurgler 2006). Limitation of shortselling, as a well-known feature of housing market, confines the ability of market regulation to eliminate mispricing. This could eventually render unusual deviation of asset pricing in the real estate market caused by sentiment (Clayton et al. 2009). Moreover, information asymmetry and incompleteness could put investors at a disadvantage and make people behave in herding. As a result, asymmetric and incomplete information mislead them into improper expectations, which could also cause a huge shock to transaction volume. Therefore, we hypothesize that housing price and volume are affected by market sentiment in the transaction market.

Investors in the transaction market may have various purposes including home ownership, investment for rent and price appreciation, or even speculation. In comparison, the rental market is simpler: tenants consume housing service through renting rather than owning. Landlords (investors) provide units to let and expect for reasonable and stable cash flows, i.e. rental income. As such, the demand side has less critical determinants in decision-making and, thus, the rental market reaches a new equilibrium point faster than the transaction market. This implies less fluctuations of rent comparing with that of housing prices. In reality, it can be observed that price fluctuations always exceed rental ones (Wong et al. 2005). The subsequent hypothesis is that sentiment could render more profound impacts on the transaction market than on the rental market. Since little research has addressed such issue, this paper attempts to reveal whether the degrees of impact of sentiment on the rental and transaction markets are different.

To summarize, this paper has several research objectives regarding the role of sentiment in housing market: (1) to find out whether the three indicators, i.e. house price, rent and liquidity (trading volume) can be predicted by market sentiment; (2) to measure the explore the differences in the direction and relative strength of statistical causality of sentiment; and (3) to study the long run effect of sentiment in the rental and transaction sector of housing market.

2.2. The Sentiment Index

In this paper, market sentiment is captured and proxied by a SI published in Hui and Wang (2014a). This index starting from 1991 contains monthly and quarterly indices for the private housing market in Hong Kong. The index is transaction-based, and its construction framework is shown as follows[1]. Assume that some investors are sentiment-driven in housing transactions, while the rest are neutral. Sentiment would reduce the waiting time that the sentiment-based investors would take to reach a deal, compared to the time that the neutral ones would take. In other words, investor with bullish (bearish) sentiment will have a buy (sell) more quickly. The index measures market sentiment based on the trading intensity derived from the transactions in housing market.

Firstly, the expectation of the inter-arrival time between every two transactions is estimated using autoregressive conditional duration model. Then, the inter-arrival time can be transformed into the different intensities of buying and selling orders in a unit period and based on that, the probability of a transaction being driven by positive or negative sentiment is calculated. For every month (or quarter, as for the quarterly index), two aggregate probabilities (i.e. for positive and negative sentiment) of sentiment-based transactions are summarized to reveal the monthly market sentiment. The SI used in this paper is based on the detailed data of over 2 million records in Hong Kong which cover almost all sale and purchase agreements for private residential units registered in the Land Registry[2].

Marcato and Nanda (2016) summarize two prevailing methods to construct an index for sentiment in the real estate market: one is direct measurement based on survey and the other is to form an indirect index by selecting some underlying proxies to conduct principal component analysis. There are a few disadvantages embedded in these two methods which lead to inadequate measure of SI. Firstly, usually a survey is conducted online and respondents in such surveys are more likely to be certain kinds of individuals. This implies that the samples are not randomly selected and that bias might exist in the index derived from survey data which cannot fully reflect the average of market expectations. Besides, respondent in such survey may come from either supply side or demand side. Due to the information asymmetry in housing market, it indicates that the sample heterogeneity may cause bias in index compilation.

On the other hand, for indirect indices, the contingent events, which may have a considerable and instant shock to proxies but obscure impacts on sentiment or in the other way round, could lead to misestimation of indices. For instance, Hui and Liang (2015) examine the impacts of tax policy (Special Stamp Duty, SSD) on housing transactions and find that the policy caused a venturi effect and immediately shrank the transaction volume of the entire market but intensified the transaction in the transaction clustering area. Due to the hidden biases in the house price index (see Hui and Liang 2015), the SSD policy took an instant shock to the house price index but a vague effect on sentiment in the short term. In addition, the composite measure using underlying proxies (e.g. Baker and Wurgler 2006, 2007) is inclined to find out which kind of asset is more likely to be affected by sentiment rather than to measure sentiment.

By contrast, the transaction-based SI employed in this paper avoids the disadvantages above-mentioned. Noises could be embedded in survey-based data, but not in transactions as transactions are factual deals and every transaction reveals the participant′s decision which indeed affects the spot prices of house. As sentiment is unobserved and difficult to measure directly, transactions are observable and contain the information regarding the current (rather than underlying) participants′ attitude towards housing market. On the other hand, market liquidity is often considered as an indicator of sentiment (e.g. Clayton et al. 2009). Among the indirect measures, the trade-based index explores the changes in probability of whether a transaction is driven by positive or negative sentiment rather than to gauge the degree of sentiment, which makes this index more feasible to represent the changes in sentiment.

As strike price and trading volume are not directly involved in the construction of the index, we take this advantage to avoid co-linearity between SI and market indicators, i.e. price, rent and trading volume. Additionally, the empirical data only shows a slight correlation between sentiment and price. The detail results are displayed in panel B in Table 1. Thus, this index is more preferable than the traditional SI.

3. Literature Review

Changes in the performance of housing market have great impacts on the financial well-being of institutions and households (Hui et al. 2012). The three market factors, i.e. house price, rent and volume, in this study are conventional and important indicators that reflect housing market performance.

As the most prominent market indicator, housing prices is always affected by various fundamentals. Using cross-sectional regressions, Case and Shiller (1990) find that construction cost, changes in population and in real income are the efficient determinants of the housing price. Quigley (1999) studies the roles of fundamentals in the US property markets and finds that the supply and demand of the property market are subject to specific economic factors, so as price movements. At the macro level, mutual effects between GDP and new residential projects are endogenously linked up by the price (Crosthwaite 2000). However, some other findings challenge this orthodox: Clayton (1997) suggests that sharp appreciation of housing prices can partly be attributed to investors′ psychology, It is echoed with Case and Shiller (2003), in which they find that the rapid appreciation of housing price can be attributed in part to excessive expectation. Wong et al. (2005) point out that overconfidence can lead to biased assessment in evaluation of transactions.

Baker and Wurgler (2006) carry out a classic research on how investor sentiment affects the returns in the US stock market based on a unique SI established in their paper. There is a noticeable trend that the doctrine of psychology is adopted in economic studies in recent two decades. This implies that sentiment plays an important role in explaining the future movement of asset price (Farmer and Guo 1994; Hirshleifer 2001; Baker and Wurgler 2006). Hirshleifer (2001) argues that it is reasonable to attach investors′ psychology to the pricing theory. Tam, Hui, and Zheng (2010) suggest that changes in stock market, especially in the real estate securities, can be considered as a reflection of sentiment in the real estate market. Recently, an increasing amount of studies (e.g. Clayton et al. 2009; Ling, Naranjo, and Scheick 2014; Marcato and Nanda 2016) concentrates on effect of sentiment on return rate of the property market. Most of them find significant relationship between sentiment and market return.

Stein (1995) develops the down payment model to study the relationship between price and transaction volume. Clayton, MacKinnon, and Peng (2008) provide an important finding that housing price and volume are positively correlated. They

Table 1. Summary statistics of four variables and market fundamentals.

Statistics	PI	RI	Vol	SI
Panel A: Price Index (PI), Rental Index (RI), Trading Volume (Vol) and Sentiment Index (SI): 1993–2012 (monthly data with obs. = 237)				
Mean	111.5	105.6	9912.5	0.5542
Std.D.	35.3	18.8	3642.5	0.1195

Min	58.4	71.3	3786	0.2955
Max	217.8	147.5	25572	0.8404

Panel B: The correlation analysis of variables in Panel A: monthly data with obs. = 237

	PI	RI	Vol	SI
PI	1.000			
	–			
RI	0.446*	1.000		
	[7.65]	–		
Vol	0.260*	0.061	1.000	
	[4.13]	[0.94]	–	
SI	−0.189*	−0.059	−0.057	1.000
	[−2.95]	[−0.91]	[−0.88]	–

Panel C: Market fundamentals: 1993–2012 (quarterly data with obs. = 80).

Statistics	Household Income	GDP (million)	New completed flats	Real interest rate
Mean	16927.5	356493	4931.5	0.0627
Std.D.	1905.7	73570.7	2933.7	0.0216
Min	12300	209714	632	0.0115
Max	21100	557236	13425	0.1217

Panel D: The correlation analysis of variables in Panel C: quarterly data with obs. = 80

	INC	GDP	New	r	SI
Household Income (INC)	1.000				
	–				
GDP	−0.199	1.000			
	[−1.773]	–			
New completed flats (New)	−0.098	−0.027	1.000		
	[−0.859]	[−0.238]	–		
Real interest rate (r)	−0.014	−0.040	0.428*	1.000	
	[−0.118]	[−0.349]	[4.127]	–	
Sentiment (SI)	0.100	0.193	−0.073	0.033	1.000
	[0.873]	[1.712]	[–0.640]	[0.285]	–

Notes: t-statistics are reported in brackets.

(*) denotes the significance at confidence level 5%.

mention that investor sentiment affects market-wide liquidity, causing property prices to deviate from their fundamental values. In addition, Clayton et al. (2009) find that high segmentation of private commercial real estate markets, accompanied with an asymmetry of information caused by the liquidity of the markets, has a substantial disparity from that of public stock markets. Therefore, sentiment may somehow take part in forecasting the trading volume. However, these hypotheses are yet to be proven because there is still no direct conclusion on this issue. This paper shall attempt to fill this (the second) research gap by studying the relationship between market sentiment and liquidity. This paper further compares the degrees of impact of sentiment on housing price and volume.

The relationship between rent and price has been widely discussed (e.g. Henderson and Ioannides 1983; Poterba 1992 and Gallin 2008), and the rental market shows some specific feature different from the transaction market. Campbell and Cocco (2007) state that rental price is a crucial factor in household's decision on housing or non-housing consumption. Some studies employ the rent–price ratio to study the dynamics and trends of housing markets. Wong et al. (2005) reveal that participants in housing markets show significant different expectations on housing price and rent. Since market sentiment arises from different factors including irrational expectations and limits of the market (such as limits to arbitrage), the degrees of impact of sentiment on housing transaction and rental markets would probably be different. It is justified to incorporate rent as a variable in our study with the purpose of examining whether the rental market is affected by sentiment. As Gallin (2008) admits the inefficiency of rent–price ratio in predicting changes in rents, this paper aims to investigate the forecasting power of sentiment to future changes in rents.

4. Methods and Data

The research framework consists of two stages. In the first stage, the causality analysis is adopted to investigate statistical causality between market sentiment and the three market indicators (price, rent and trading volume). Superior to the Granger causality test (GCT), the integrated renormalized PDC method is employed in this paper. This method is advanced to provide detailed and rigorous inference to the formation of hypotheses. In the second stage, this paper moves further to study the long-term effect of market sentiment in the movements of house price and rent. The data for market indicators and fundamentals employed in this study are described in the following subsection.

4.1. The Method of Causality Analysis

The GCT, first introduced by Granger (1969), is a widely used tool which establishes a quantitative model (based on the vector autoregressive model) for analysis of causal relationships. The variables are pair wisely structured and are performed in estimated VAR models. GCT fails to obtain an accurate structure of covariance. That is, the causality of X to Y may also take the indirect effect (X to Z then to Y, where X, Y, Z are in multivariate process) into account. To overcome this drawback, new methods are developed to improve the ability of capturing multivariate process. One of those is the directed transfer function (DTF) introduced by Kaminski and Blinowska (1991). DTF introduces a more convenient process as it only requires one VAR model to identify the direct causal relationships among variables and is compatible to the GCT (Kaminski et al. 2001). DTF, however, may incorporate indirect relationship[3] into direct causality among variables.

The deficiency in DTF is resolved by the partial directed coherence (PDC) method introduced in Sameshima and Baccalá (1999). Its statistical properties are summarized by Schelter et al. (2005). The PDC method only detects and presents direct impacts.

Similar to DTF and GCT, the PDC method has different statistic distributions for different relationships. In the early stage, PDC is used to examine the significance of a relationship and fails to further discuss the strength of any causality relationship. This limitation has been overcome by the renormalized PDC introduced by Schelter, Timmer, and Eichler (2009). RPDC renormalizes the statistics with the same distribution, whereas the critical value depends only on the number of observations, which is constant for a fixed data set (Hui et al. 2012). Hui and Chen (2012) further improve the model by introducing integrated RPDC (IRPDC), which allows more explicit viewing of the statistics.

This paper employs the IRPDC method to achieve our research objectives, which is to identify the casual relationship of sentiment to price, rent and volume in the housing market. It quantifies the degrees of pairwise causality between any two of four variables and thus the results become comparable such that one can distinct the most influencing factor for a certain variable from others. The framework of IRPDC following Hui and Chen (2012) is presented in Appendix.

4.2. Dynamic Equilibrium Model

With statistical causality of sentiment, this paper moves further to investigate the role of sentiment in the evolution of housing price and rent. The traditional notion holds that prices in housing market are well explained by market fundamentals, and that relationship between prices and fundamentals is established based on the intersection of market supply and demand under the local economy. Following the framework of Quigley (1999) and Hui and Wang (2014b), housing price (P) can be represented by

$$P = f\left(H^{D}; H^{S}\right)$$

where H^D and H^S are housing demand and supply, respectively. The demand of housing market is a function of housing price, household affordability (household income[4] as a proxy) and local economy (denoted by Eco), that is

$$H^{D} = D(P; INC; Eco)$$

The supply of housing market is formulated by a function involving housing price, new completed flat[5] and local economy, and is shown as

$$H^{S} = S(P; New; Eco)$$

In this paper, GDP and real interest rate (denoted by r) are selected to represent the development of local economy. Derived from the demand and supply equations, the basic reduced form of price function associated with market sentiment (S) is

$$P = f(INC; New; GDP; r; S)$$

Additionally, if the causality results suggest endogeneity between price and sentiment, it is necessary to extend the above model into an autocorrelated structure. A modified model can be expressed as

$$L(P, S) = f(INC, New, GDP, r) \tag{1}$$

where L() is the lag operator. The model also will be enhanced by modification based on the causality results. We will discuss this in Section 6.

4.3. Market and Data Description

Despite the slowdown[6] of economy recovery in 2012, Hong Kong's housing price recorded an increase of 24%. Fuelled by low interest rates and strong non-local demand, property prices have surged by 63.6% during 2011–2013. In comparison, increases in rent have been milder at 36.8% (see Figure 1). However, there is an obvious decline in transaction volume, possibly due to government interventions such as the SSD[7] introduced in November 2010. The housing price departs from the trend of economy, indicating that conventional economic fundamentals are not effective enough to explain the dynamics of housing price in Hong Kong (Case and Shiller 2003; Hui and Wang 2014a).

The data contain two sets. Four variables in the first set for the causality tests are collected monthly. Apart from the aforementioned SI compiled by Hui and Wang (2014a), the price and rental indices, as well as trading volume, are collected over a span of twenty years during 1993–2012. The pricing index (PI) and rental index (RI) of private domestics are issued by Rating and Valuation Department (RVD), which is affiliated to the government of the Hong Kong Special Administrative Region (HKSAR). These two indices measure the changes in value to reflect the integral level of performance of housing market at a time. Trading Volume (Vol), defined as the aggregate number of sale and purchase agreements of residential units in a month, is also issued by RVD and announced by Land Registry. The data of the three variables (price, rent and trading volume) are open source and available from the official website of RVD since 1990. Figure 1 shows the price index of private domestics.

The original SI (provided in Hui and Wang, 2014a) consists of pairwise sentiment measures (i.e. positive % vs. negative %). In this paper, the index is transformed into a ratio of positive sentiment to total sentiment. Index value equal to 0.5 describes a neutral market sentiment where half of sentiment is bullish and the other half is bearish. Value of index above 0.5 indicates that positive sentiment dominates the housing market, and vice versa. The monthly data of the SI from 1993 to 2012 are displayed in Figure 2, and the descriptive statistics of the SI are given in Panel A of Table 1.

Second set includes the data for household income (INC), GDP, New completed flats (New) and real interest rate (r)[8]. All these data are quarterly basis from

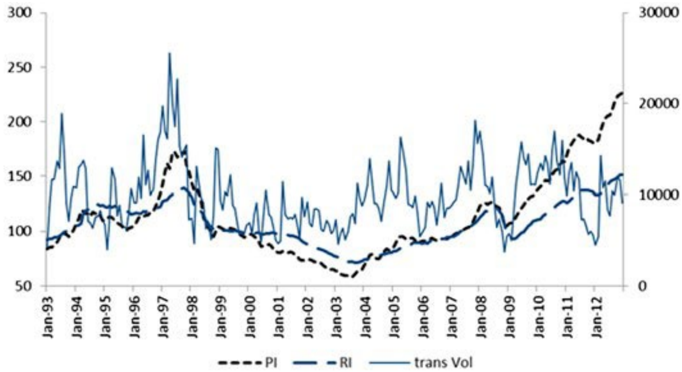

Figure 1. The chart of three monthly indices: Price Index (PI), Rental Index (RI) and Trading Volume (Vol) during 1993–2012.

1993–2012 and collected from Census and Statistics Department, HKSAR. Prior to econometric analysis, the stationarity of variables has been verified in order to avoid misestimating. The non-stationary raw data are transformed by first-order differencing as $y(i,t) = \ln y_{i,t} - \ln y_{i,t-1}$. The purpose is to transform the sample data into return rate such that the mean of the transformed series is approximately zero. Four (PI, RI, INC and GDP) of the six variables are identified to be non-stationary and thus processed with this transformation. The new completed flats show an obvious pattern of seasonal fluctuations and thus are treated with de-trend adjustment[9].

Panel A in Table 1 is a summary of the descriptive statistics of the four variables. With reference to the standard deviation in Table 1, it is obvious that the volatilities of price are significantly greater than those of rent, which coheres with the findings of Hui and Zheng (2012). Panel B shows the correlation analysis of four variables in the first data-set. For the second data-set, Panel C in Table 1 summarizes the descriptive statistics of the market fundamentals, followed by correlation analysis among sentiment and the four exogenous variables as shown in Panel D.

5. Statistical Causality

This section gives insight into the statistical causality among market sentiment (SI) and the other three variables – house price, rental and trading volume in the housing market of Hong Kong. A series of statistic tests have been performed and the empirical findings are discussed below. Initially, the unit root test is adopted to verify the stationarity of data as it is essential for the construction of the VAR model. The tests for lag selection according to several criteria are then carried out to determine the lag order in VAR model. Afterwards, the VAR model of the four variables is estimated to fit the data. Both the GCT and integrated renormalized PDC (IRPDC) are conducted. The latter explores more informative findings, compared to the GCT's results.

5.1. Unit Root Test

To identify the stationarity of variables through the unit root test is a preliminary step in econometric analysis. If the data are not stationary, the VAR model would be inefficient and then the IRPDC approach would be invalid. The unit root test based on Schwarz Bayesian Criterion has been employed, and the results are shown below in

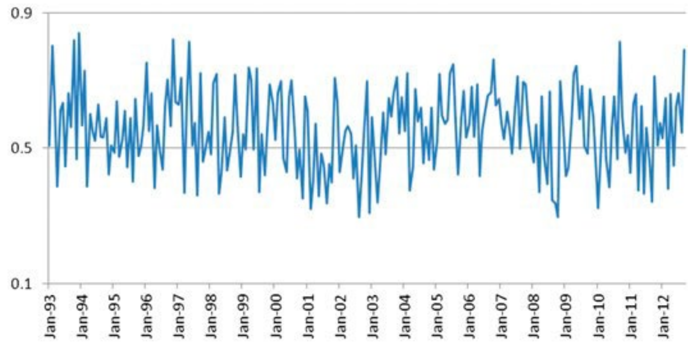

Figure 2. The chart of monthly sentiment index during 1993–2012. When curve is above (below) line 0.5, it indicates positive (negative) sentiment dominates the market.

Table 2. Summary of unit root tests on PI, RI, Vol and SI.

Method	Statistic	Prob.	Cross sections	Obs.
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chu t-test	−15.1872	0.0000	4	940
Null: Unit root (assumes individual unit root process)				
ADF – Fisher chi-square	354.474	0.0000	4	940
PP – Fisher chi-square	296.307	0.0000	4	944

Notes: Probabilities for Fisher tests are computed using an asymptotic chi-square distribution. All other tests assume asymptotic normality.

Table 2: The tests reject the null hypothesis that unit root exists, implying that multidimensional time series data are stationary to construct the VAR model.

5.2. Lag Selection

Table 3 shows the results of lag selection based on several criteria. Two options for lag orders are found acceptable, i.e. lag = 2 or 4. In general, it is better to follow the principle of parsimony in lag selection in VAR model. In other words, the structure with lag 2 is much simpler than that with lag 4 (twice as many parameters in VAR [2] to estimate as those in VAR[4]). Thus, VAR[2] is preferable in this case when all these factors are considered.

5.3. Traditional Granger Causality

The results generated by the traditional GCT are provided in comparison with the IRPDC results. Table 4 exhibits the results of GCT with lag 2. Nine statistics are found significant to reject the null hypothesis of no causality. The results indicate that the PI and SI Granger-cause other variables respectively. In other words, PI and SI

Table 3. VAR lag Selection based on several criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
1	1245.173	NA	2.56e−10	−10.73513	−10.49522	−10.63835
2	1293.518	93.31357	1.93e−10	−11.01763	−10.53781*	−10.82405*
3	1315.724	42.08474	1.83e−10	−11.07183	−10.35210	−10.78147
4	1346.442	57.14266*	1.61e−10*	−11.20036*	−10.24072	−10.81322
5	1358.422	21.86840	1.67e−10	−11.16526	−9.965707	−10.68133
6	1369.553	19.92900	1.74e−10	−11.12274	−9.683273	−10.54202
7	1383.686	24.80907	1.77e−10	−11.10643	−9.427052	−10.42893
8	1398.405	25.32477	1.80e−10	−11.09524	−9.175956	−10.32095

Notes: *indicates lag order selected by the criterion.

LR: sequential modified LR test statistic (each test at 5% level).

FPE: Final prediction error.

AIC: Akaike information criterion.

SC: Schwarz information criterion.

HQ: Hannan–Quinn information criterion.

Table 4. Pairwise Granger Causality Tests (Lags: 2).

Null hypothesis	Obs.	F-statistic	Prob.
RI does not Granger cause PI	235	0.80472	0.4485
PI does not Granger cause RI		55.1233	0.0000*
Vol does not Granger cause PI	235	2.74942	0.0661
PI does not Granger cause Vol		10.2650	0.0000*
SI does not Granger cause PI	235	11.4791	0.0000*
PI does not Granger cause SI		4.68517	0.0101*
Vol does not Granger cause RI	235	7.28119	0.0009*
RI does not Granger cause Vol		5.07206	0.0070*
SI does not Granger cause RI	235	3.37529	0.0359*
RI does not Granger cause SI		3.51382	0.0314*
SI does not Granger cause Vol	235	8.24022	0.0003*
Vol does not Granger cause SI		2.08484	0.1267

Note: *denotes the significance at confidence level 5%.

show the predictabilities to other variables with lead lag of no more than 2 months. Meanwhile, the results reveal the predictability of RI to Vol and SI, i.e. changes in Vol and SI can be linked to the former terms of RI. However, no feedback from Vol to RI has been found, implying that the changes in Vol might not necessarily cause significant impact to the performance of rental market. Indeed, Vol only Granger-cause sentiment, which is partly consistent with the findings in Clayton, MacKinnon, and Peng (2008) on the linkage between market liquidity and sentiment.

As GCT may cause a possibility of failing to capture the whole information of covariance structure in VAR model (Schelter, Timmer, and Eichler 2009), GCT can hardly reveal more useful and direct information for causality relationships between multidimensional data. Therefore, the more advanced method, IRPDC is adopted to conduct a more precise investigation on causal relationships and quantify the strengths of such relationships.

5.4. Estimated VAR Model

Consequently, the estimated VAR model with lag 2 to fit the data of the four variables is shown as

PI 1 2 0:5149 0:1968 0:0112 0:0284 30 PI 1

0:2738 0:0020

0:0028 RI

0:9466 0:2901

BBB@VolRISI CCCAt ¼ 2:1417 0:0035

00:1267:77037775BBB@VolSI

6664031::22282362:3612

CCCAt1

0:0381 0:0420 0:0087 0:0151 30 PI 1 0 PI 1

0:1493 0:0005 0:0060 RI RI

þ 666 4:5265 0:2558 7

00::63151074

0:2049 77BBBVolCCC þBBBVol

CCC

40:0932 2:2284 0:0536 0:38465@ SI At2 @ SI A

where the VAR[2] structure provides two coefficient matrices for further step, i.e. the Fourier transformation (refer to equation of A(ω) in Appendix). The error vector of ðtÞ is a 4-dimensional white noise or innovation process with covariance matrix Σ. The IRPDC method will then be adopted based on this VAR model.

5.5. Integrated RPDC

Figure 3 shows the graph matrix for the results of renormalized PDC derived from the estimated VAR[2] process. The sub-graph in the i-th row and the j-th column displays the impact of process j on process i. The confidence interval at 95% level for each RPDC in the sub-graph is highlighted by the shaded area. If the confidence interval is squeezed to an approximate zero width, the directed causal relationship does not exist. Since the self-influenced causality is trivial and invalid under the Granger causality framework, the four sub-graphs in the diagonal are omitted in Figure 3. There are eight sub-graphs showing significant causality: PI to RI, PI to Vol; RI to SI, RI to Vol; SI to

PI, SI to RI, SI to Vol and Vol to PI. These eight causal relationships are summarized in Figure 4(a). Interestingly, we find three disparities in comparison between the GCT results and IRPDC results. The causalities of Vol to RI and of PI to SI have been denied by the RPDC method while recognized by the traditional GCT. These three disparities might be due to the potential defect

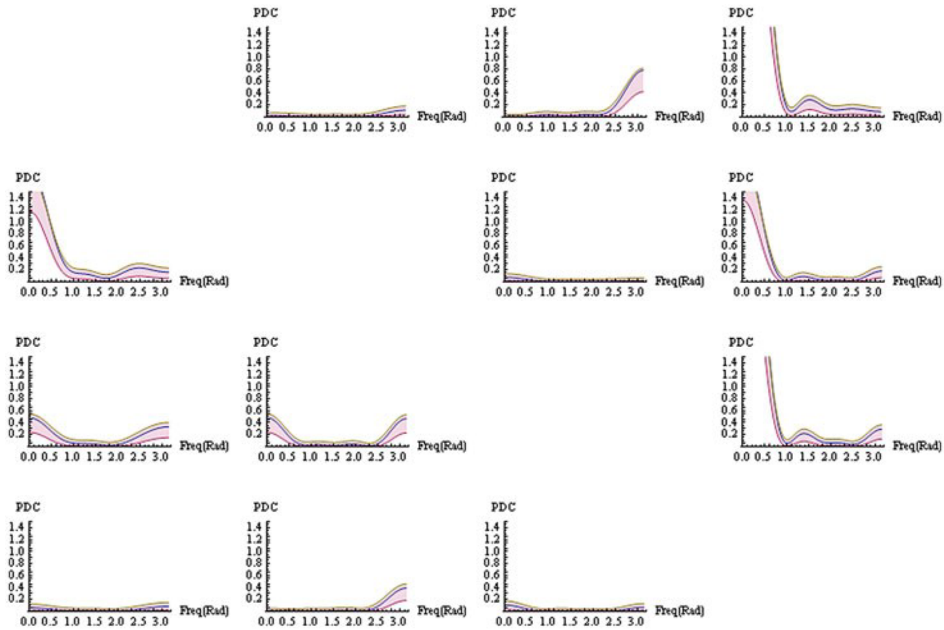

Figure 3. The graph matrix of causal relationships by using RPDC method based on the estimated VAR[2] model.

Notes: Sub-graph in i-th row and j-th column represents the RPDC causality of variable of X_j to X_i where i,j = 1,...4 representing price index (PI), rent index (RI), trading volume (Vol) and sentiment index (SI). The confidence interval at 95% level for each RPDC in sub-graph is highlighted by shaded area. There are 8 significant influenced patterns of causal relationships among four variables, which are corresponding to Table 5.

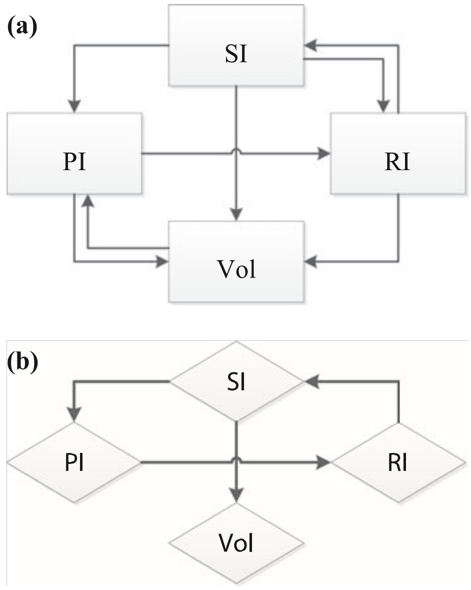

Figure 4. The most significant causal relationships among four variables. (a) The significant causal relationships among four variables. (b) The most influential factor for a specific factor among four variables.

of GCT while GCT has a chance to inadequately capture the covariance among the multidimensional data.

IRPDC is able to offer quantified measure of causality strengths among the four variables. These results (shown in Table 5) echo with the sub-graphs in Figure 3. The figures in the table can only be interpreted in two ways: (i) identify the significance of the predictability and (ii) screen out the most important factor predicting the specific variable by comparing the results of IPRDC in the same row. The significance of statistics can be identified by comparing the statistics with critical value given as $\theta_{0.05} = 0.1046$. When IRPDC > $\theta_{0.005}$ (0.1849), the predictability can be regarded as a strong level (see Hui et al. 2012). All of the 8 significant relationships are identified to exceed the threshold value of strong level.

In the last column of Table 5, three statistics are significant, suggesting that all of the three market indicators are affected by market sentiment. In other words, the private housing market in Hong Kong is significantly affected by market sentiment. By comparing the values in this column, the strength of predictability of SI to PI (4.6454) is higher than the other two, i.e. SI to RI (1.0805) and SI to Vol (3.0045), indicating that SI has greater impact on PI than on others. Furthermore, this indicates that the transaction market is more likely to be affected by sentiment than the rental market. Such implication can be attributed to the multiple demands including demand for investment and speculation in the transaction market. This could contribute to the knowledge gap as no previous literature has ever addressed the difference in causal strengths of sentiment on the rental and transaction markets.

Table 5. Test statistics of integrated renormalized PDC.

IRPDC	PI	RI	Vol	SI
PI	–	0.0699	0.4067*	4.6454*
RI	1.2619*	–	0.0451	1.0805*
Vol	0.5066*	0.4075*	–	3.0045*
SI	0.0815	0.1876*	0.0702	–

Notes: Statistic in i-th row and j-th volume represents the IRPDC causality of variable of X_j to X_i. Critical values are given as: $\theta_{0.05} = 0.1046$; $\theta_{0.01} = 0.1068$; $\theta_{0.005} = 0.1849$.

*denotes the significant statistics. Number in bold indicates the biggest value in the same row.

Furthermore, through comparison among the four rows, it is found that the strongest levels of causality to a specific variable are SI to PI, PI to RI, SI to Vol and RI to SI. These four causalities are stronger than others and are summarized in Figure 4(b).

Not surprisingly, the PI has the strongest power to predict the performance of RI in the short term. As classical theory suggests that the housing price is fundamentally determined as the present value of future rental income (Case and Shiller 1989; Gallin 2008), changes in price can predict future changes in rent. The first interesting finding for PI is that price and trading volume can predict each other in the short term though there is no agreement about the relationship between these two variables across the global markets. By comparing values in the first row of Table 5, the causal strength of SI to PI (4.6454) is higher than that of Vol to PI (0.4067), while the statistic of RI to PI (0.0699) is insignificant. This indicates that PI is more likely to be affected by sentiment (SI) than by trading volume (Vol). Meanwhile, sentiment is found to be the strongest factor to predict volume, which is widely considered as a proxy of market liquidity. The above results suggest that sentiment is the most significant factor to predict price and volume in the short term for the housing market of Hong Kong and supports the findings of sentiment in Clayton, MacKinnon, and Peng (2008). Therefore, sentiment should be recognized as a significant variable in modelling the trend of housing transaction market.

RI is the only factor found to be predictable to sentiment. In addition, RI is capable to forecast volume. These may give an insight into the household's tenure choice in the housing market of Hong Kong. The renters, as the most rational participants in housing market, are sensitive to changes in rent. Renters may choose to hedge the future risk of rent/ownership by switching their tenure choice, especially in the presence of a low mortgage rate. Thus, household's tenure switch, i.e. renting to owning or owning to renting, is subject to rent and reflects their expectation on future market trend. As such, RI shows its power to predict trading volume and market sentiment.

Three causalities among PI, SI and RI form a one-way cycle as shown in Figure 4(b). This cycle reveals the indirect impact of rent to price and sheds light on how the rental market transmits its feedback indirectly towards the transaction market.

5.6. Indirect Impact of Rent on Price

DiPasquale and Wheaton (1996) suggest a short run linkage between rent and price through a consistent channel (P ¼ R=i) given a constant return rate (i). In this study, the empirical results of short run predictability of RI show that RI is not a prominent indicator of forecasting PI. However, the one-way cycle provides a possible explanation for how rent indirectly affects price in the short term.

Tenants in the rental market consider housing services as a consumable product, and landlords invest in future cash flow due to property leasing. In the rental market, if the property price rises, the supply curve would shift towards the left which causes a rise in rent. When changes in rent are observed, tenant households may switch their housing tenure choices between renting and owning. As a result, a shock to the market sentiment and such impact is embedded in the housing transaction. With contagious effect of sentiment through herding in the housing market, market expectations are affected by those switchers. This is justified by the predictability of RI to SI. Then, the changes in market sentiment affect the housing prices, which can be justified by the predictability of SI to PI. In this study, we consider market sentiment an indicating variable to bridge the indirect linkage from RI to PI.

5.7. Asymmetry in Causality Strengths

Taking advantage of the IRPDC method, the findings also suggest asymmetries in pairs of causality between the two variables. In Table 5, different strengths of predictabilities are found between PI and Vol: Vol to PI is 0.4067 and PI to Vol is
0.5066. Another pairwise causality between SI and RI shows much more disparity at 1.0805 vs. 0.1876. Such difference between the pairwise causality reflects the market mechanism. Once the pairwise causalities are significant, the traditional GCT cannot capture the exact strengths of causality, but IRPDC can. Hence, the IRPDC results can provide more focused implications and important references to facilitate policymakers or investors in their decision-making.

6. Using Sentiment to Explain House Prices and Rents

This section discusses the role of sentiment in the dynamics of transaction market (housing price) and rental market (rent) in Hong Kong. Several models are established for these two sectors. Primarily, a number of studies suggest controlling the effect of financial crisis in modelling Asian housing markets. Hence, we employ a dummy variable (denoted by Fd[10]) to proxy the crisis effect on Hong Kong's housing market.

Based on the IRPDC causality results of sentiment, the theoretical model suggested in Section 4 is specified. As the results of IRPDC causality of SI to PI is monolateral, which indicates the lag term of price shows trivial power to predict sentiment. Based on equation 1, the VAR model is reduced to

P ¼ f L Pð ð Þ;SI;INC;New;GDP;r;FdÞ (2)

where the operator L Pð Þ[ ] indicates a significant autocorrelation. More generally, to compare with model (2), we establish a general VAR model as

½P;SI⁰¼ VARL P½ ;SI⁰;INC;New;GDP;r;Fd (2′)

Model (2′) aims to seek for evidence to show whether the housing price contributes little explanation to the changes in sentiment, which is to verify the monolateral causality of SI to PI.

Second, in the light of the causality between sentiment and rent, we also study the role of sentiment in the movement of rent. As mentioned, housing price affects rent and rent is also determined by the interactions between supply and demand. Similar to housing price, rent can be formulated by

$$RI = f\left(L(RI), P, INC, New, GDP, SI, r, Fd\right) \tag{3}$$

Based on the pairwise causality between sentiment and rent, we establish a VAR model associated with sentiment to capture the dynamics of rent, which is expressed as

$$[RI, SI]' = VAR\left(L[RI, SI]', P, INC, New, GDP, r, Fd\right) \tag{4}$$

Table 6 presents the model estimations on the returns of housing prices in the transaction market. The benchmark model in Table 6 excludes the sentiment variable in comparison with the sentiment models (2) and (2′). Firstly, the lagged term of price is insignificant in these three models, which implies a weak power of autocorrelation in explaining housing price in Hong Kong. For the role of sentiment, the coefficient of the sentiment variable is significant in model (2), which indicates that sentiment affects changes in housing prices. As the coefficient of the sentiment

Table 6. Estimation of models for transaction market.

	Benchmark model	Model 2	Model 2′	
Dependent variable	PI	PI	PI	SI
Lagged price index	0.128	0.093	0.072	0.176
(PI_{-1})	[1.279]	[0.990]	[0.663]	[0.675]
Sentiment index		0.159*		
(SI)		[3.396]		
Lagged sentiment index			0.074	0.060
(SI_{-1})			[1.362]	[0.455]
Household income	0.604*	0.530*	0.536*	0.412
(INC)	[3.127]	[2.922]	[2.699]	[0.859]
New completed flats	−0.033*	−0.027*	−0.032*	−0.034
(New)	[−2.038]	[−1.906]	[−2.008]	[−0.891]
GDP	−0.142	−0.202*	−0.134	0.388
	[−1.399]	[−2.105]	[−1.327]	[1.595]

Financial crisis	−0.133*	−0.119*	−0.131*	−0.086
(Fd)	[−5.485]	[−5.191]	[−5.459]	[−1.473]
Real interest rate	−0.261	−0.437	−0.356	1.032
(r)	[−0.752]	[−1.332]	[−1.011]	[1.213]
Intercept	0.304*	0.365*	0.350*	−0.348
(C)	[2.415]	[3.075]	[2.701]	[−1.111]
R_2	0.506	0.577	0.519	0.124
Log likelihood	122.108	128.060	123.130	55.217
Schwarz criterion (SC)	−2.777	−2.875	−2.747	−0.983

Note: t-statistics are reported in brackets.

*denotes the significance at confidence level 5%.

variable in model (2) is positive, an increase in sentiment leads to a positive change in housing price. Meanwhile, when introducing sentiment into the benchmark model, the term "GDP" becomes significant. It indicates a bias of estimation induced by the lack of variables in the benchmark model, and the sentiment improves the model performance (measured by R^2) compared to the benchmark model.

Furthermore, the VAR model (2′) reveals that the lagged term of sentiment variable plays a dispensable role in explaining housing prices. It indicates that only current sentiment affects the price return. In addition, model (2′) offers no evidence to support that either the sentiment variable is autoregressive or the sentiment is affected by the lagged price term. Thus, model (2) is preferred to capture the price movement for Hong Kong as it has a higher R^2 and a lower value of Schwarz criterion.

Surprisingly, the coefficient of the term GDP in model (2) is negative, implying that the local economy inhibits the housing price. Such a counter-intuitive situation can be explained by extraneous housing demand. The private housing market in Hong Kong features a combination of local demand and foreign demand. The inflow of demand (from mainland and overseas) takes a large proportion of total housing demand, and the local economy has slight impact on this extraneous demand. Besides, as the local real interest rate is identified as an insignificant indicator of housing price. It implies the investors are mildly subject to the local capital cost. This implicitly supports the above finding that a substantial proportion of housing demand is not indigenous. Thus, the negative correlation of GDP with housing prices and insignificant coefficient of real interest rate indicate the weakness of local housing demand.

Similarly, Table 7 reports the model estimations on rental return for the benchmark model, the linear model (3) and the VAR model (4). The benchmark model excludes the effect of sentiment, while the other two investigates the relationship of sentiment or the lagged term with rent. In contrast to price, the rent reveals the feature of autocorrelation as the coefficient of the lagged term of rent is significant among the three models. Note that the effect of sentiment in the linear model is identified to be trivial and the sentiment variable does not help improve the model performance. By contrary, the coefficient of the lagged sentiment variable in the VAR model is significant. The positive correlation reveals that the sentiment elasticity of rent is 0.093.

The finding is interesting that the lagged term rather than current term of sentiment plays a prominent role in the dynamics of rent, which is different from the effect of sentiment on price. The lagged sentiment affects the previous housing price and the change in price has a shock to rent which lasts more than one period. It takes a period to transmit the effect of sentiment into the rental market. In addition, the coefficient of price in the sentiment equation in model (4) illustrates the significant impacts of price on sentiment in the long run. This finding is consistent with the findings regarding the relationship between sentiment and price in model (2).

7. Conclusions

The first stage of this study is to examine the causal relationships among four indicators (price, rent, trading volume and sentiment) in Hong Kong′s housing market. The causality results provide implications to show the predictability of sentiment on other market indicators in the short run. With these implications, the second stage of this paper investigates the roles of market sentiment in the transaction market and the rental market. The empirical study spans over two decades: 1993–2012.

Table 7. Estimation of models for rental market.

	Benchmark model	Model 3	Model 4	
Dependent variable	RI	RI	RI	SI
Rent index	0.299*	0.301*	0.242*	0.162
(RI_{-1})	[3.322]	[3.321]	[2.836]	[0.436]
Sentiment index		−0.013		
(SI)		[−0.432]		
Lagged sentiment index			0.093*	0.003
(SI_{-1})			[3.415]	[0.028]
Price index	0.193*	0.204*	0.152*	0.908*
(PI)	[2.917]	[2.845]	[2.435]	[3.346]
Household income	0.099	0.098	0.040	−0.110
(INC)	[0.852]	[0.835]	[0.365]	[−0.229]
New completed flats	−0.009	−0.009	−0.009	−0.005
(New)	[−0.999]	[−1.000]	[−1.081]	[−0.137]
GDP	0.082	0.088	0.088	0.486
	[1.329]	[1.386]	[1.542]	[1.957]
Dummy variable	−0.058*	−0.058*	−0.058*	0.030
(Fd)	[−3.686]	[−3.634]	[−3.958]	[0.466]
Real interest rate	−0.006	0.011	−0.090	1.305
(r)	[−0.032]	[0.056]	[−0.505]	[1.694]
Intercept	0.081	0.072	0.144*	−0.657*
(C)	[1.114]	[0.955]	[2.051]	[−2.157]

R_2	0.615	0.616	0.672	0.247
Log likelihood	167.936	168.042	174.031	61.047
Schwarz criterion (SC)	−3.911	−3.857	−4.013	−1.078

t-statistics are reported in brackets.

*denotes the significance at confidence level 5%.

The causality analysis adopted in our empirical study, known as IRPDC, captures the predictability and the corresponding strength of economic factors. In the short run, market sentiment is a prominent indicator of forecasting price and trading volume. Compared to other factors, sentiment has overwhelming power to predict housing prices, which implies that the private housing market in Hong Kong is significantly affected by sentiment. The findings also show that rent is a significant predictor of sentiment. In addition, the one-way cycle of price, rent and sentiment implies that sentiment is an indicating factor in the indirect linkage of rent to price (see Figure 4(b)). Moreover, the asymmetry of causality strength between the four indicators can be verified by IRPDC method. The analysis fills the gap as Granger causality is incapable to handle causality strength.

Looking forward, with the preliminary implications of sentiment's causality, this paper outlines the role of sentiment in the transaction market and the rental market. The findings show that sentiment has significant effect on housing price and rent, but plays different roles in these two market sectors. The current house price is attributed to sentiment in part, while the rent is affected by the lagged term of sentiment. This result in return provides some indirect evidence to support the implication of one-way cycle in causality investigation. These new findings shall contribute to the knowledge of housing studies.

This paper benefits investors who are concerned with the predictability of market indicators and dynamics of housing market, as well as help households in their housing choices. On the other hand, the implication of this study may serve as a useful reference for relevant authorities when they make policies to stabilize and improve the functioning of the housing market.

Acknowledgements

We thank the editors and four anonymous referees for comments that greatly improved this paper. We are grateful for the financial support from the Hong Kong RGC GRF (B-Q42Q/PolyU 152059/14E) and the Hong Kong Polytechnic University Research Grants (G-UA6V and G-YBJL).

Funding

This work was supported by the HKUGC GRF.

Notes

1. For more details of index construction, please see Hui and Wang (2014a).

2. Land Registry is an affiliated to government of HKSAR and has a duty of maintaining an efficient and effective land registration system to facilitate the orderly conduct of land transactions. Every transaction happened in HKSAR has to register the document of agreement at Land Registry.
3. For instance, variable A has influence on B and B has influence on C. Then, the result by DTF may imply that variable A has a causal relationship with C, which is away from the truth. Therefore, it is difficult to observe all the true relationships among variables.
4. Housing demand at any time is always subject to household income (INC) (Quigley 1999). Besides, a long-term correlation between house price and income is widely found (e.g. Holly, Pesaran, and Yamagata 2010).
5. New completed flat (New) is a significant indicator of housing supply in Hong Kong (Hui 2003).
6. Referring to the figures issued by International Monetary Fund, GDP growth in Hong Kong slides sharply to 1.25% in 2012, compared with 5% in 2011 and 7.1% in 2010.
7. The Stamp Duty (Amendment) Ordinance 2011 imposes SSD on top of the ad valorem stamp duty on the disposal of residential properties with effect from 20 November 2010. Unless the transaction is exempted from SSD or SSD is not applicable, any residential property acquired on or after 20 November 2010, either by an individual or a company (regardless of where it is incorporated), and resold within 24 months, will be subject to SSD. (Source: http://www.ird.gov.hk/eng/faq/index.htm#01).
8. Real interest rate used in this paper is the mortgage rate that has been adjusted to remove the effects of inflation.
9. We use Hodrick-Prescott filter (Hodrick and Prescott 1980) to de-trend the data.
10. The dummy variable Fd indicates the effect of last two financial crises (i.e. two crises happened in 1997 and 2008, respectively). The two periods of taking effect are 1997Q4–1998Q3 and 2008Q3–2008Q4.

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