Risk appetite of real estate and property security markets: an empirical study of Hong Kong

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Abstract
Purpose – The purpose of this paper is to investigate the risk appetite in Hong Kong real estate and property security markets in the recent episode of global financial crisis.

Design/methodology/approach – An advanced methodology developed from the previous risk appetite measurement and Markov Chain Monte Carlo simulation is used. Traditional research on risk appetite had never been applied to the real estate market before because no options underlying properties exist. However, this paper makes a contribution that in the absence of options, risk appetite indicators are derived for the real estate and property security markets.

Findings – The empirical results show that the risk appetite for the real estate market started to fall markedly in the third quarter of 2008, matching the very period of the Sub-prime Mortgage Crisis in the USA. By contrast, those for the property security index were stabilizing in that period. This implies that investors’ risk attitude to the real estate market differs from that to the property security market. Furthermore, the correlations between the index prices and the corresponding risk appetite in each market suggest that investors are “risk neutral” in the real estate market, while they are “risk lovers” in the property security market.

Originality/value – This paper, to the authors’ best knowledge, is the first study to explore the risk appetite indicator in the real estate market, which could enable us to shed new light on the market price movement from the perspective of investors’ market sentiment.

Keywords Risk management, Real estate, Property, Securities, Hong Kong

Paper type Research paper

1. Introduction
It is now generally accepted that the efficient market theory and the standard asset pricing model are not enough to account for the real price of risky assets, which contain uncertainty. More specifically, if the market is fully efficient and the investors are all unemotional and fully informed, then it is hard to explain the dramatic fluctuation occurred in the financial tsunami of 1997 Asian Financial Crisis and 2007 US Sub-prime Mortgage Crisis by fundamental economic factors, and even more difficult to explain the contagion or spillover phenomenon in different countries and markets (Gai and Vause, 2006; Kim, 2007). As Eichengreen and Mody (1998) contend that shifts

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in the market’s attitude towards risk might be able to explain a crisis in one country may trigger a crisis elsewhere.

Indeed, investors’ sentiment is believed to be a key factor driving broad trends in property prices and clause the co-movement of property prices in different and even un-correlative markets. The terms risk aversion, risk appetite and risk premium are frequently used to refer to sentiment in asset markets. However, these concepts are conceptually distinct. Risk aversion measures the subjective attitude and underlying preferences of investors with regard to uncertainty. It is usually assumed to be constant or expected to change infrequently over time. In contrast, risk appetite is likely to varying over time in terms of investors responding to the changing levels of uncertainty in macroeconomic environments. Risk premium, which can be defined as the extra yield gained for holding a risky asset (Kanli, 2008), is the additional sum payable or return to compensate investors for adopting a particular risk. Generally speaking, risk premium is calculated by taking into account the price and the quantity of the risk inherent in underlying assets. In other words, the increase of risk premium in financial crises could be illustrated by the rising price of risk. The risk premium in asset prices is influenced by both risk aversion and the riskiness of the asset (see Gai and Vause (2006) and Hermosillo (2008) for more details). In prosperous circumstances, investors hold optimistic market sentiment. Therefore, there will be more investments under-going and the expected returns will be lower. On the contrary, in adverse circumstances, investors will require higher excess expected returns to hold each unit of risk which seems to be more likely taken place (Gai and Vause, 2006). In addition, as Pericoli and Sbracia (2006) note that, an increase in either risk or risk aversion will cause asset prices to decline and risk premiums to increase, in other words, the financial market falls down.

Risk appetite is the investors’ tolerance for financial risk and frequently used throughout the risk management community among others. It depends on investors’ willingness to bear uncertainty and on the overall level of uncertainty about the fundamental factors which drive asset prices. In the financial market, some investors prefer safe assets, for example, Ten-year treasures, bills or other kinds of bonds in fixed income markets, while others are willing to buy higher-return assets like stocks, foreign exchange, or derivatives. When the investor gambles on the financial market, he/she shows his/her preference and willingness to bear risks, which is the so-called risk appetite. The level of the investors’ risk appetite depends on many factors, for example, the uncertainty of the underlying assets and how investors dislike bearing that uncertainty. The degree of uncertainty is related to the feature of underlying assets and macroeconomic factors at work (e.g. interest rate level, production index, and price index and inflation rate, etc.).

Risk appetite analysis could help portfolio managers and individual investors to understand the general investors’ attitude to risk in the whole market as well as the potential market movement within different market sentiments. To quantify risk appetite not only gives the information about how market sentiment changes, but also the level of it. Market sentiment acts as an important role when forecasting the future financial market. There have been discussions over different methods in risk appetite modeling (e.g. Bandopadhyaya and Jones, 2005; Gai and Vause, 2006; Kim, 2007; González-Hermosillo, 2008; Kanli, 2008). Some applications are sensible to apply in financial stock markets. Previous studies were able to measure the risk appetite in the stock market, in an attempt to explain the contagion phenomenon during the adverse economic circumstances. Their approaches depend primarily on the information of the underlying options of the respective stocks in the markets. However, such options data
are not available in the stock markets of emerging economies, nor is in the context of the real estate markets particularly. This makes evaluations impossible. As a result, no understanding has been provided. Risk appetite clearly is an important issue in the real estate field for investors, academics and governments. Hence, our study attempts to investigate risk appetite in Hong Kong real estate and property security markets within the recent episode of global financial crisis. It is this risk appetite issue that this study provides added knowledge. Specifically, the paper provides an extension/addition to knowledge twofold. First, this study provides a new approach to measuring the investor’s risk appetite without underlying options. Second, it is the first study to explore the risk appetite indicator in the real estate market, which could shed new light on the market price movement from the perspective of investors’ market sentiment. Hence, this paper is adding value to the topic, making contributions to the existing literature.

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 risk appetite. The models used in this study are described in Section 3. Section 4 presents the data and the empirical results of our improvement model in the Hong Kong properties and property security market. The last section concludes the paper.

2. Literature review
In the context of this study, three related bodies of empirical literature are reviewed. The first group of research involves examining the relationship between market sentiment and price movement.

Given the important role of market sentiment in explaining the price movement, several studies have discussed the measurement of market sentiment in order to explain the abnormal occurrence in the financial market with sentiment. For instance, De Long et al. (1990) note that many investors do not follow economists’ advice to purchase their market portfolio. And they divide investors into two types: rational arbitrageurs and irrational traders who are subject to sentiment. Furthermore, they argue that irrational traders affect market price much more than the rational arbitrageurs. Keep in all the above in mind, Kumar and Persaud (2002) develop a new measurement of risk aversion based on changes in excess returns of assets. They argue that investor risk appetite plays an important role in explaining developments in global financial markets including financial crisis. It assumes that no arbitrage opportunities exist. Hence, same level risky assets should share same excess returns. Meanwhile, risk appetite increases when excess returns of very risky assets increase by more than less-risky assets. The correlations between change excess returns on risky assets and the level of risk in a number of assets should be normally followed by risk appetite. Time-lags are expected especially during financial crisis. There are some difficulties with this approach to measure risk appetite. First, this measure only tracks the changes of risk aversion, rather than the level of changes. Second, the portfolio asset is measured as a unity. A rank correlation could be detected even if no change happens to risk appetite of this portfolio. As Kumar and Persaud (2002) point out that the degree of correlation between changes in excess returns and the level of risk across a number of assets should indicate any change in the willingness to bear risk.

A comparison of the risk-neutral and subjective probability density functions is first used by Tarashev et al. (2003). The shortcoming of this measure technique is quite obvious that the information of the risk free rate is not regarded as important as that of risk-neutral and subjective probability density functions. Hayes et al. (2003) suggest that
movements in the ratio of risk-neutral probability to investors’ subjective probability might reflect investors’ concerns about liquidity- risk free interest rate. However, this approach puts much attention on the liquidity factors that do not always affect risk appetite. Bollerslev et al. (2004) use a model-free computation for the implied volatility by option prices and high-frequency historical data for subjective volatility. Beak et al. (2005) examines the determinants of the market-assessed sovereign risk premium, measured by the Brady bond stripped yield spread. Hermosillo (2008) uses a structural vector auto-regression to analyze the dynamics of bond spreads among a sample of mature and developing countries during periods of financial stress in the last decade. He identifies idiosyncratic factors and introduces global market risk factors as fundamental driving forces. Similar to that approach, Gai and Vause (2006) discuss a new measurement technique by comparing the variance ratio of risk-neutral density and subjective density. In their studies, an indicator of risk appetite is established with regard to risk-free interest rate to reflect the money liquidity. More recently, Kanli (2008) analyzes the impact of global risk appetite on the risk premium in Turkey. He finds that the risk premium volatility responds only to a worsening in the risk appetite for the Turkish economy. The empirical results provide supporting evidence for the role of current account dynamics in the estimated asymmetry.

Within real estate research, in contrast, only a little literature focuses on market sentiment. For example, Clayton (1996) studies the real estate investment risk and its implications for real estate valuation. He shows that the risk premium on un-securitized commercial real estate varies over time and is strongly related to general economic conditions. The author also suggests that changing expected returns might reflect rational revisions of real estate investment risk, or alternatively investor psychology or sentiment. To our best knowledge, however, no such studies have been conducted for the property market. The reason is that the “model-free” risk neutral density is used to measures risk appetite, and it is derived from the comparison between traditional Black-Sholes option pricing modeling and option prices observed in the real market. Unfortunately, we could not find any options whose underlying assets are properties. Hence, traditional models for risk appetite are not competent in the property market. Besides, no existing study explores the role of the investors’ attitude towards risk in explaining risk embedded in the property markets.

In order to fill this gap, we contribute to the previous literature with a new approach to measure the investor’s risk appetite in markets without underlying options. Our new approach is built on the previous risk appetite modeling (see Kim, 1992; Gai and Vause, 2006, among others) and could be applied to some markets if no options underlying that certain asset exist in the world. Specifically, we propose a measure based on the MCMC simulation, and it could be a reasonable alternative approach to obtain the risk neutral density without options.

3. Methodology and the models
The general measurements of risk appetite indicator in the previous studies on risk appetite involve the historical density by the generalized autoregressive conditional heteroskedasticity (GARCH) model and the risk neutral density by the options prices. Nevertheless, such options are absent in some markets, for instance the property market in Hong Kong. In this paper, we employ the Markov chain Monte Carlo (MCMC) simulation to find the risk neutral density instead of the underlying options prices. It is a significant improvement of the risk appetite measurement approach in application.
3.1 Previous studies

3.1.1 Calculating the risk appetite indicator: the definition. As Kim (1992) shows, the preference of market participants is projected to the market price of options. Following this viewpoint, Gai and Vause (2006) suggest a creative method which stands on the implied information in the option price. They propose that a measure of risk appetite may be derived by computing the variation in the ratio of risk-neutral to the subjective probabilities used by investors in evaluating the expected pay-off of an asset, and calculate a price of risk and interpret its reverse as a risk appetite. This method enables investors to identify the expected price of risk which is formed by the investors’ sentiment. According to Gai and Vause (2006), the risk appetite indicator is shown by the following (please refer to Gai and Vause (2006) for more details about the derivation of equation 3.1.1):

\[ \lambda_t = \frac{1}{R_{t+1}^f} \text{var} \left( \frac{f^*(X_{t+1})}{f(X_{t+1})} \right) \]  

(3.1.1)

where \( \lambda_t \) is the unit price of risk, \( R_{t+1}^f \) is the gross risk-free rate at time \( t+1 \) (in application, the composite interest rate is widely used as the risk-free rate), var(\( ^* \)) is the variance operator, \( f^*(X_{t+1}) \) is the risk-neutral density at time \( t+1 \) and \( f(X_{t+1}) \) is the historical density at time \( t+1 \). In particular, a high value of price of risk (\( \lambda_t \)) is corresponding to a low risk appetite of investors in the investment and vice versa. When an investor’s risk appetite falls, they require larger expected excess returns to hold risky assets. Risk appetite, therefore, can be defined as the inverse of the price of risk.

3.1.2 Finding historical density \( f(X_{t+1}) \) by GARCH model. Historical density function could be found from the statistical probability distribution of log returns (see Hayes et al., 2003, Gai and Vause, 2006). It is based on the following Threshold-GARCH (T-GARCH) model of returns on log returns \( r_t \):

\[ r_t = \beta_0 + \varepsilon_t \]

\[ \sigma_t^2 = \beta_1 + \beta_2 \varepsilon_{t-1}^2 + \beta_3 \varepsilon_{t-1}^2 d_{t-1} + \beta_4 \sigma_{t-1}^2 \]  

(3.1.2)

where \( \sigma_t^2 \) is the variance of the residuals.

3.1.3 Finding risk neutral density \( f^*(X_{t+1}) \) by fitting the two-lognormal mixture distribution. According to Yu and Tam (2007), the prices of European call and put options at time \( t \) can be written as the discounted sums of expected future payoffs:

\[ c(X, \tau) = e^{-rt} \int_X^{\infty} f^*(S_T)(S_T - X) dS_T \]

\[ p(X, \tau) = e^{-rt} \int_0^X f^*(S_T)(X - S_T) dS_T \]  

(3.1.3)

where \( c(X, \tau) \) and \( p(X, \tau) \) are the call and put prices respectively. The option prices are functions of the strike price \( X \), the time to maturity \( \tau \), the asset price at the expiry \( (S_T) \), the risk free interest rate \( (r) \) and the density function of the asset price as at expiry \( (f^*(S_T)) \). Assuming that the density function is as two-lognormal mixture, \( f^*(S_T) \) at time \( t \) can be expressed as:
\[ f(S_T) = \sum_{i=1}^{2} \theta_i L(a_i, b_i; S_T) \]  

where:
\[ a_i = \ln S_i + \left( \mu_i - \frac{\sigma_i^2}{2} \right) \tau \]
\[ b_i = \sigma_i \sqrt{\tau} \]  

\( L(a_i, b_i; S_T) \) is the \( i \)th lognormal density function with parameters \( a_i \) and \( b_i \), \( \theta_i \) is the weight of the \( i \)th density in the mixture and the mixtures are summed to unity, \( \mu_i \) and \( \sigma_i \) are the mean and volatility of asset return respectively. At any time \( t \), five parameters \((a_1, b_1, a_2, b_2, \theta_i)\) in the two lognormal density functions are estimated by solving the following minimization problem:
\[ \min_{a_1, b_1, a_2, b_2, \theta} \left\{ \sum_{n=1}^{N} [c(X, \tau) - c_{obs}]^2 + \sum_{n=1}^{N} [p(X, \tau) - p_{obs}]^2 \right\} \]  

where \( N \) is the number of possible expiry asset price, \( c_{obs} \) and \( p_{obs} \) are the observed call and put prices at \( t \) respectively. By substituting the estimated parameters into Equation (3.1.3), the probability density at different prices can be calculated accordingly (please refer to Yu and Tam (2007) for more details).

### 3.1.4 Comparison between two densities

In the calculation of var(\( f^*(X_{t+1})/f(X_{t+1}) \)) in equation (3.1.1), a restriction is set in our paper. Only ratios for \( f^*/f \leq 10 \) are available in the empirical studies. Any ratios for which \( f^*/f > 10 \) are dropped.

### 3.2 Improvement: finding risk neutral density by MCMC simulation

The above model provides an effective method to measure risk appetite in some certain markets. However, it is impossible to derive a risk-neutral density \( (f^*(X_{t+1})) \) by option prices if such financial products are not available. For example, we could not apply it to the property market since we have no options underlying properties. In order to fill this gap, we propose to obtain the risk neutral density by MCMC simulation, instead of two mixtures log-normal density. The method and procedures are introduced briefly as follows.

#### 3.2.1 Gibbs sampling

Before the MCMC simulation, we should first find out a sequence of Monte Carlo samples \( X_0, X_1, \ldots, X_n \), which follows the diffusion like this:
\[ dX^{(h)} = \mu(X^{(h)}) dt + \sigma(X^{(h)}) dW \]  

where \( h \) is the \( h \)th iteration in our simulation.

The simplest and most popular MCMC algorithm is called the Gibbs sampling, a label often attributed to the paper of Geman and Geman (1984). Gibbs sampling is introduced for all missing observations to obtain enough amounts of data.

Assuming that \( X^{(h)} \) is the missing data and both \( X^{(h-1)}, X^{(h-1)} \) and parameter vector \( \theta = (\mu(X^{(h)}), \sigma(X^{(h)})) \) are known. We can simulate the missing data \( X^{(h)} \) by the conditional distribution as follows:
\[ X_i | X_{i-1}^{(h)}, X_{i+1}^{(h)}, \theta \sim N \left( \frac{1}{2} \left( \hat{Y}_{i-1} + \hat{Y}_{i+1} \right), \frac{1}{2} \sigma_i^2 \Delta t \right) \]
The procedures of Gibbs sampling are explained by three steps ($h$ means the $h$th iteration):

1. Use linear interpolation to get one initialized value of the simulated stock prices between the two observed data. Here starts from $h = 1$.

2. Draw $X_i^{(h)}$ for all $i = 0, 1, 2, \ldots, n$ except for the number which are multiples of 2 by applying the Hybrid rejection Metropolis-Hastings algorithm. (The detailed procedures of drawing samples by the Metropolis Hastings algorithm are shown in the Appendix.)

3.2.2 MCMC simulation. Let $X$ be a diffusion solving the following equation under risk neutral measure, under the log-normal return rate assumption, we have:

$$dX(t) = k(t)X(t) + \sigma(t)X(t)dW(t)$$  \hspace{1cm} (3.2.3)

It is a simple stochastic diffusion equation, which $k(t)$ can be interpreted as the mean of $X(t)$ and $\sigma(t)$ can be interpreted as the standard variance of $X(t)$.

According to the MCMC analysis of diffusion model by Eraker (2001), we get a joint conditional distribution of the parameter vector $\theta$, which is $(k, \sigma)$ as follows:

$$
\pi(\theta|\hat{X}) \propto \prod_{i=1}^{n} \frac{1}{\sigma(t)\hat{X}_{i-1}} \times \exp\left\{-\frac{1}{2} \frac{(\hat{X}_i - \hat{X}_{i-1} - k(t)\hat{X}_{i-1}\Delta t)^2}{\sigma^2(t)\hat{X}_{i-1}}\right\} \hspace{1cm} (3.2.4)
$$

Let $Y$ is obtained by stacking $(\hat{X}_i - \hat{X}_{i-1})/\hat{X}_{i-1}\sqrt{t}$ and $y$ is obtained by stacking $[\sqrt{\Delta t}\hat{X}_{i-1}\sqrt{t}]$ and rewrite the likelihood function, we have:

$$k|\sigma, \hat{Y} \sim N(\bar{\theta}, \sigma^2(Y'|Y)^{-1})$$ \hspace{1cm} (3.2.5)

and

$$\sigma^{-2}|\hat{Y} \sim IG(n-2, \bar{s}^2)$$ \hspace{1cm} (3.2.6)

where $\bar{\theta} = (Y'|Y)^{-1}(Y'|y)$ and $\bar{s}^2 = 1/n\sum_i(y_i - X_i\bar{\theta})^2$.

By drawing from the distribution of equations (3.2.3) and (3.2.4) above, we could obtain the parameter values, means and variances, by the conditional distribution, not by the options information anymore.

To sum up, sampling recipe for this model is briefly shown as follows ($h$ means the $h$th iteration):

1. Initialize all unknowns. For instance, one might use linear interpolation between observed values of $X_i$ to initialize $\hat{X}_i$. Set $h = 1$.

2. For all $i = 0, 1, \ldots, n$, draw $\hat{X}_i|\hat{X}_i^{(h-1)}$, $\theta$ using hybrid rejection Metropolis-Hastings algorithm with proposal density $N(1/2(\hat{X}_{i-1}^{(h)} + \hat{X}_{i+1}^{(h-1)}), 1/2[\sigma_{i-1}^{(h)}]^2\Delta t)$.

3. Draw $k^{(h)}$ using equation (3.2.5).

4. Draw $\sigma^{(h)}$ using equation (3.2.6).

5. Increase $h$ by 1 and return to step 2.
4 Empirical studies

4.1 Data description

4.1.1 Centa-City Leading Index and Hang Seng Property Index. This section measures the risk appetite using the weekly Centa-City Leading Index (CCL Index) and Hang Seng Property Index (HSPI) from January 1994 to January 2009. The CCL index is one of the most popular indexes in Hong Kong. It is a weekly housing price index based on the current preliminary contract prices in Centaline Property Agency Limited transactions that monitors the up-to-date property price variations. The CCL index has been provided by Centaline since 1992. The methodology of constructing the CCL Index is purely transaction-based and quality adjusted by Hedonic Pricing Model. And it covers housing units in large-scale residential developments in Hong Kong. In this study, we employed the CCL Index (a sub-index provided by Centaline), because it is the only index that provides weekly data and could reflect market information faster than others. On the other hand, the HSPI includes stocks that are related to the property sector from the Hang Seng Index. Generally speaking, CCL index reflects the price movement of direct real estate market investment, while HKPI reflects of indirect real estate investment.

The two indices show a similar trend over the period but HSPI keeps a little ahead of CCL Index, which is widely accepted that the security market could serve as a leading indicator to the real estate market. Both of the real estate and property security markets suffer a sudden decline in 1998 and 2008, which correspond to the 1997 Asian Financial Crisis and the 2007 Subprime Mortgage Crisis, respectively (please refer to Wong et al. (2005), Wong and Hui (2008), Hui et al. (2010a, b) for more details about the 1997 and 2007 crisis and their impact on the Hong Kong property security market).

4.1.2 Gross risk-free rate. The Hong Kong Composite Interest Rate (HKCIR) is used as the risk-free interest rate for the Hong Kong Financial Market. The HKCIR peaked at 3.34 percent in September 2007. Then it decreased substantially to only 0.8 percent by December 2008.

4.2 Results

4.2.1 Historical sigma. In this study, the historical sigma for both indexes is obtained by using T-GARCH model. We concentrate on the comparison of expected variance in order to find the different performances in the property security market and the real property market. The estimations of the variance of returns in the T-GARCH model in this period are based on a rolling window of equation (3.1.1) starting from January 1994. Figures 1 and 2 illustrate the historical sigma of CCL and HSPI respectively. Generally speaking, HSPI fluctuates stronger and moves in much higher levels of variance compared to that of CCL. The expected variance of CCL stays low when the CCL is stably climbing to the peak. Then it could be seen that the expected variance of CCL becomes larger and larger as the CCL declines to the bottom. In early 2009, the CCL becomes steadily low again but the expected variance decreases substantially.

The relationship between the expected variance of HSPI and the property security market is distinct from that between the expected variance of CCL and the real estate market, which reveals the investment types of real estate market and property security market are different. Therefore, we will discuss the risk appetite for these two indexes separately as follows.

4.2.2 Risk appetite indicator. Assuming that the index prices $X(t)$ for CCL and HSPI are both following the diffusion equation (3.2.3), from which we can obtain the risk neutral density. $k(t)$ means the expected mean and $\sigma(t)$ means the expected standard
variance. Therefore, combining them with the CIR and the historical density, we get the risk appetite indicator for CCL and HSPI using equation (3.1.1). It should be noted that the risk appetite indicator in this paper was measured with the data from December 2006 to January 2009. We used the T-GARCH model to calibrate variance in our model, and the weekly data from 1994 to 2006 (around number of 700) is used as historical data only. This makes sure that the one-step forecast on variance starts from December 2006 is accurate enough. Therefore, the estimation of the risk appetite indicators that are shown in Figures 3 and 4, starts from the end of 2006.
In general, when investors' risk appetite falls, they would immediately reduce their exposure to risky assets, which, consequently, fall in value together. When investors' risk appetite rises, risky assets are in increased demand and rise in value together (Kumar and Persaud, 2002). However, the same trend for both value and risk appetite might exist. It could be interpreted as the self-reinforcing effect, which triggers the bubbles or crashes in the property markets.

Figure 3 depicts the investors' risk appetite indicator for the real estate market of Hong Kong from December 2006 to January 2009. It is important to note that a high value of indicator (unit price of risk shown in left scale) indicates a low appetite of investors for risk in the investment and vice versa. Therefore, values of risk appetite indicator are shown in reverse order in the figure for the sake of simplicity, and the investor's risk appetite increases vertically upward. By the first quarter of 2007, risk...
appetite indicator moved close to zero and stayed around there for about eight months, which denotes that the risk appetite was comparatively high during this period, resulting in a marked increase of CCL index. Then risk appetite indicator fluctuates with a downward trend since November 2007, when the US Sub-prime Mortgage Crisis became apparent. It is plausible to argue that the risk appetite can serve as a leading indicator of the price movement, since it turned down five months before the CCL did, which implies that the investors’ sentiment has been adversely affected by the cross-border tsunami. In September 2008, the risk appetite “dropped” significantly to its bottom (since the risk appetite indicator increased substantially). In other words, the willingness of investors to bear risk dropped substantially, due to the global financial recession or macroeconomic uncertainty. They reduce their exposure to risky assets, which, consequently, fall in value of asset price.

Figure 4 shows the risk appetite indicator of investors for HSPI. Similar to Figure 3, we should interpret the high-risk appetite indicator value as a low appetite of investors for risk in the investment and vice versa. Values of risk appetite indicator are also in reverse order. As shown in Figure 4, the risk appetite stayed at its high level till around August 2007[1] and fell down to the bottom at late 2007 when the US Sub-prime Mortgage Crisis broke out, while the HKPI reached its peak. Then the risk appetite moved up and down slightly around its average level, but it headed down in October 2008. In general, the HSPI and its corresponding risk appetite moved in opposite trend most of the time, which is similar to the case of CCL index.

4.2.3 The correlations between the risk appetite indicators and their markets. In order to explore the relationships between the real estate market and the property security market, the correlation coefficients table is shown in Table I.

As shown in Table I, the correlation coefficients between the two different markets and their corresponding risk appetite indicators are both positive at 1 percent significant level (noting that the risk appetite move in reverse direction of risk appetite indicator, hence, the correlation between risk appetite and property price is negative). It is worth pointing out that the correlation between the property security market and its investors’ risk appetite indicator (i.e. 0.75999) is much higher than the one between the real estate market and its investors’ risk appetite indicator (i.e. 0.19954). This implies that the real estate investors are much less sensitive to inherent risk of assets than the property security investors. In other words, the property security market is more likely or/and quickly to get contagion when the external financial crisis happens, this is also confirmed by our empirical results that the crash in property security market happened about half year early than that of real estate market did. It could be also interpreted as the type of investors in the real estate market is relatively “risk neutral”, while another type of investors in the property security market is “risk-loving”.

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<th>HSPI</th>
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<th>Price_CCL</th>
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Table I. Correlations between real estate market and property security market

Note: *Denotes 1 percent significant level; risk appetite indicator (RAI)
5. Conclusions
Risk appetite indicator can serve as a compass for the investors’ preference to risk and the level of which they would like to take. It can catch the market sentiment as to whether the prospect of investors is optimistic or pessimistic. A low index value indicates a strong appetite for risk and vice versa. When the market crashes, the risk appetite would show a dip and fluctuate much more sharply than before.

This paper focuses on the risk appetite in the Hong Kong real estate market and property security market with a new methodology in measuring risk appetite. Such methodology could also be applied to other countries or markets in absence of options information. This model proves to be sensible in empirical studies of CCL and HSPI with the case of Hong Kong. Risk appetite for CCL index had markedly declined after September, 2008, which coincides with the US Sub-prime Mortgage Crisis. On the contrary, the risk preference in the property security market was not affected as much. Although the property security index price dropped sharply after May 2008, the HSPI stabilized towards the end of 2008. This phenomenon can be reasonably explained that the type of investor is “risk-loving” in property security market while the type of investor is “risk neutral” in the real estate market in terms of the risk appetite movement. It has also been proved by the correlations analysis between these two markets and their risk appetite indicators.

This research study is meaningful but it does have its limitations. First, the investor’s risk appetite is measured indirectly in terms of price of risk. Secondly, we only focus on two different property markets in a solely region, whether the contagion phenomenon exit in different countries should be addressed in the further research. Nevertheless, this study is first of its kind to the best of our knowledge. It develops a new method to quantify the risk appetite in property markets without the information of options transactions. Indeed, our model is not only a good alternative to the one proposed by Gai and Vause (2006) and Yu and Tam (2007), but is also proved to be a reasonable methodology for risk analysis for the property market, and could be further applied to more widely transaction markets.

Note
1. The change point here in HSPI appeared about three-months earlier than that of CCL, because the property security market is more liquid than the real estate market and the investors in the property security market are better informed.

References


Further reading

Appendix
Gibbs sampling of Geman and Geman (1984) and Gelfand and Smith (1990) is one of the most popular MCMC method. It is a special case of Metropolis-Hastings algorithm. The point of Gibbs sampling is that given a multivariate distribution, it can sample from a conditional distribution then to integrate over a joint distribution. For the simulation in Markov Chain, the procedures of Gibbs sampling are comprised of two main steps.

If there is a sequence data $Y_0, Y_1, Y_2, ..., Y_n$ missing $Y_i$ and

$$dY = \mu(Y)dt + \sigma(Y)dW.$$ (A1)

The conditional density is defined by:

$$\pi(\hat{Y}_i | \hat{Y}_i, \theta) \propto \rho(\hat{Y}_i | \hat{Y}_{i-1}, \hat{Y}_{i+1}, \theta)$$ (A2)

where:

$$\rho(\hat{Y}_i | \hat{Y}_{i-1}, \hat{Y}_{i+1}, \theta) = |\sigma_{i-2}^{-1}|^{1/2}|\sigma_{i-1}^{-2}|^{1/2}$$

$$\times \exp \left\{ -\frac{1}{2} \left\| \left( \Delta \hat{Y}_i - \mu_{i-1} \Delta t \right) \sigma_{i-1}^{-1}(\Delta t)^{-1/2} \right\|^2 - \frac{1}{2} \left\| \left( \Delta \hat{Y}_{i+1} - \mu_i \Delta t \right) \sigma_i^{-1}(\Delta t)^{-1/2} \right\|^2 \right\}$$

Set $q(\hat{Y}_i | \hat{Y}_{i-1}, \hat{Y}_{i+1}, \theta) \propto N(\frac{1}{2} (\hat{Y}_{i-1}, \hat{Y}_{i+1}), \frac{1}{2} \sigma_i^2 \Delta t)$, now we get $c$ which is defined by:

$$c = \frac{\rho(\hat{Y}_i | \hat{Y}_{i-1}, \hat{Y}_{i+1}, \theta)}{q(\hat{Y}_i | \hat{Y}_{i-1}, \hat{Y}_{i+1}, \theta)}.$$ (A3)

Using the Hybrid Accept/Reject Metropolis-Hastings Algorithm, we make the choice of missing data $Y_i$ by the known joint conditional density.

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