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Long-Run Relationship and Causality between Credit Default, Banks' Lending and Property Prices: Evidence from Hong Kong SAR

Dr Fawaz Khaled
BA, PGDip MSc, PhD, AFHEA
Department of International Relations
School of Economics
University of Reading
Postcode: RG6 6UR, United Kingdom
E-mail: F.khaled@reading.ac.uk
E-mail:Fawazkhaled1983@yahoo.co.uk.
Tel: 0(044)7574051753

ABSTRACT

Using the Autoregressive Distributed Lag technique, the paper looks for the presence of cointegrating relationships between mortgage defaults, property prices and bank lending in Hong Kong. In addition to the short-term dynamics among these variables, our findings reveal evidence of cointegrating relationships between bank lending, property prices and mortgage defaults in the long term, which governs the correction mechanism between these indicators. More importantly, loan-to-value is found to play the most effective role in curbing mortgage default risk in the loan portfolios of the Hong Kong banking sector. The findings urge the need for a multifunctional toolkit allows managing the interdependence between the banking industry and the real estate market to achieve a stable relationship between bank lending, property prices, and bank performance, hence maintaining sustainable banking soundness.

Key words: Default; Housing Market; Residential Mortgage; Bank Lending; Autoregressive Distributed Lag; Hong Kong.

***JEL Classification Numbers:* G21, G28, G32, H31**

1. INTRODUCTION

Nearly a decade on from the latest global financial crisis, its repercussions still ripple through the world' economies, evoking bitter memories of multifaceted interactions between macroeconomic fundamentals, financial market and real estate market developments. The repeated occurrence of financial and banking crises has led to increasing attention being paid to devising prudential policies to minimize their financial distress and mitigate exposure to real estate circumstances. Numerous theories propose significant interactive relationships between asset prices, credit developments and banking stability (see, for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Salas and Suarina (2002), among others).

Among the sources of banking instability, mortgage delinquency constitutes a major concern for banks due to the high cost of managing mortgages and the associated burdens when selling properties in cases of foreclosure, as these properties are usually valued at 5-10% less than neighbouring properties (see for instance Nang et al. (2003) and Capone (2003)). Mortgage delinquency is the first step towards foreclosure or default; therefore, investigating its determinants is of great importance in order to track risky loans at earlier stages and allow timely intervention before a default becomes inevitable (Capone, 2003). Ambrose and Capone (1998) argue that whether the final status of a loan will be a foreclosure is strongly determined by the reason the mortgage became delinquent in the first place. Default behavior studies are also appreciated by policymakers as they help to foresee the consequences of any strategy on the evolution of credit defaults and the construction of policies to effectively increase homeownership (see, for example, Nang et al. (2003)).

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The nexus between the real estate market and the banking industry is justifiably the focus of much attention in existing literature and has been widely investigated in policy-oriented studies, such as by the IMF (2000) and BIS (2001). However, the perspective that seems to grab much of the academic researchers' attention appears to concentrate on one of the causality directions between the two markets, using a single equation setup, rather than dynamic models that are able to account for the interaction between the markets (if any exists). Keeping the framework of these studies confined to a single equation exposes them to so-called "simultaneity problems" and ensures they lack a focus on the magnitude of causality between the variables of interest. From a theoretical point of view, the interdependence between property price cycle, credit aggregate cycle and credit default suggests a high association between the three; however, what needs more investigation is the direction of causality between them. Numerous works on credit default have been conducted at the financial institution level, using data from bank balance sheets or sometimes from only one originator. Instead of considering a loan-by-loan analysis to check the performance of each individual loan, this paper concentrates on the broader market trend, using aggregated data on the country level, from Hong Kong, which allows the argument to focus on country-specific factors, such as the country's policies and its regulation of the mortgage market.

The main purpose of this study is filling this gap by testing the existence of possible long-term dynamics and short-term effects that result from the relationships between bank lending, residential property prices and mortgage defaults in Hong Kong by using an error correction model specification. Assuming the presence of unidirectional effects between property prices, credit availability and credit defaults, a multifunctional toolkit of financial, monetary and macroprudential methods is required to govern the multidirectional effects and the interaction between these cycles in order to maintain balanced relationships between them, particularly when this interaction contributes to an increase in banks' credit risk. Therefore, understanding the mechanism that governs the relationships between these factors helps in the planning of the right policy to govern all of them jointly in the best interests of the entire economy.

The real estate market occupies a crucial position in the Hong Kong economy, with a house being the preferable sort of investment for the majority of the population. As observed by Zhu (2006), households' housing mortgage loans constitute the main bulk of banks' loan portfolios. For example, in 1991 residential mortgage lending comprised around 20% of banks' lending portfolios to local borrowers, and reached a peak of around 37% at the end of the third quarter of 2002; the volume then declined to around 24% of the total issued loans for use in Hong Kong later in 2007. In light of these figures, it is not surprising that residential mortgage loans in the Hong Kong banking sector have always been looked at as one of the largest sources of risk exposure for the banking sector. The high concentration of mortgage loans in Hong Kong banks' loan portfolios provides an important case study that focuses on residential mortgage loan delinquency rather than other types of loans.

An arsenal of fiscal and monetary tools is used to fight against the build-up of systemic risk in financial institutions, such as control of interest rates. However, due to the Currency Board regime, according to which the Hong Kong dollar is pegged to the US dollar, interest rates, one of the most efficient monetary tools, cannot be operated to safeguard macroeconomic stability against swings in property prices.[1] More importantly, successive financial crises have provided evidence that monetary policy and banking regulations are not sufficient to prevent the build-up of systemic risk. In the same vein, these tools may be interact with other monetary and fiscal policy tools in many situations, which raises fundamental questions concerning cooperation with wider policy frameworks to provide a firewall that offers an additional pre-emptive barrier against economic fragility. In an attempt to counteract banks' exposure to swings in real estate prices, many macro prudential policies are designed to provide banks with sufficient cushioning to resist shocks triggered by real estate market disturbances or any undue risks.

As one of the pioneer developers and users of prudential tools, Hong Kong has devised various macro prudential tools over the past two decades in an attempt

[1] To guard against the severe financial turmoil resulting from the Sino-British parleys addressing the future of Hong Kong, the Linked Exchange Rate System (LERS) or Currency Board regime was established in October 1983, when the Hong Kong dollar linked to the US dollar (USD) at a fixed rate.

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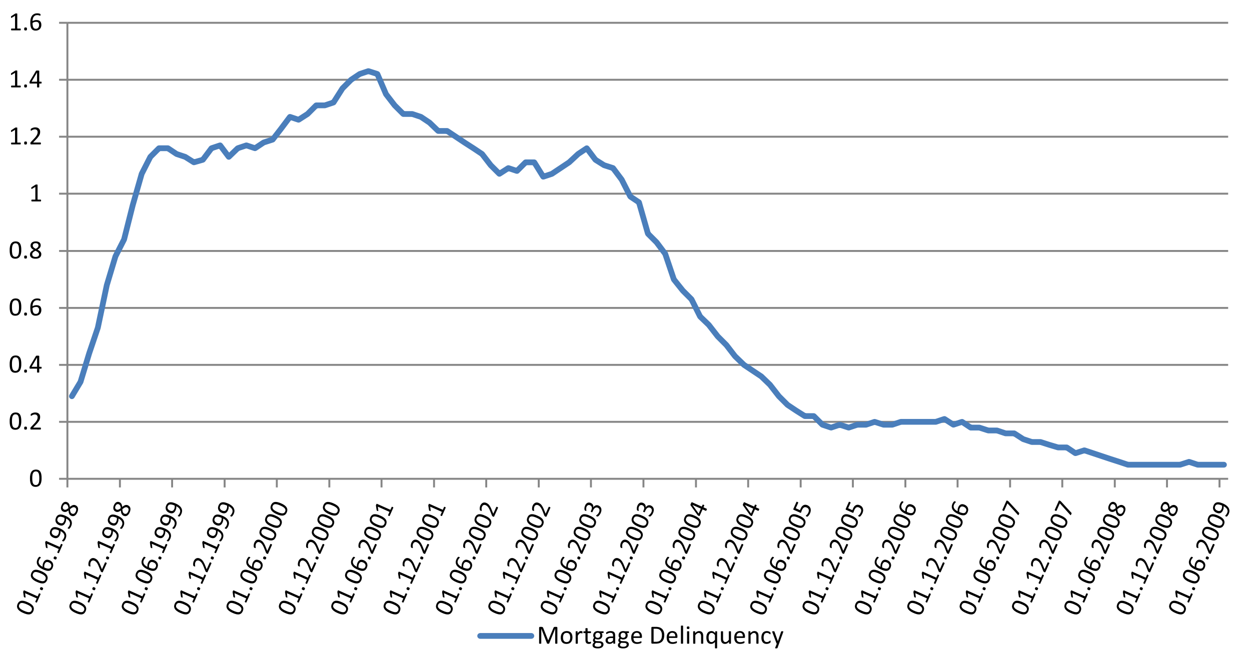
to safeguard the stability of its banking system. Among other macro prudential tools, the Hong Kong Monetary Authority (HKMA) started imposing loan-to-value (LTV) caps in 1991 to control the exposure of financial institutions to swings in real estate market prices. Moreover, the Hong Kong Mortgage Corporation (HKMC) launched the Mortgage Insurance Programme (MIP) in 1999 in an attempt to increase home ownership[2]. The MIP played a key role in developing tools for homebuyers to avoid the liquidity constraints imposed by LTV without incurring higher credit risk exposure for banks. Undeniably, devising and employing LTV and MIP techniques have played a key role in improving the resilience and stability of the banking sector, by bringing down the percentage of NPLs and delinquency ratios in the banks' loan portfolios (see, for example, Wong *et al*. (2011)). Remarkably, the LTV tool showed efficient performance during the Asian crisis, a period that was characterized by significant downturns in the property market of around 30-40%.

Despite the growing consensus on the importance of using macro prudential policy alongside monetary policy and a wider recognition within the policy-making community of its effectiveness, empirical evidence on the impact of this tool on mitigating credit risk remains scarce. Hence, in order to assess how effective the LTV policy is at reducing banks' exposure to the risk associated with the boom-and-bust cycle of property markets, the impact of LTV on the evolution of mortgage defaults is considered in this work.

What is distinctive in the experience of the Hong Kong real estate market is the unique behaviour of house prices in comparison to other markets. Tracing the history of private property prices in Hong Kong over the past two decades, high volatility with several episodes of boom and bust, associated with extraordinary swings in house prices, can be observed. This is in sharp contrast to other real estate markets where episodes of boom and bust were usually a single episode of large price swings, ending up with collapse in house prices (see, for example, Fan and Peng (2003) and Gerlach and Peng (2005)). In other words, the peculiarity of the Hong Kong real estate experience is that the property price fluctuations were as vigorous as in other countries, but with a higher frequency of occurrence.

Figure 1 Mortgage Delinquency Ratio in Hong Kong



[2] The HKMC is a Hong Kong government corporation established in 1997 to support bank stability through: (*i*) functioning as a source of liquidity for borrowers, contributing to a reduction in mortgage risk accumulation, (*ii*) propagating home ownership and (*iii*) facilitating the growth and development of debt and mortgage-backed securities in Hong Kong.

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Given that bank lending in Hong Kong is largely driven by variations in property prices and the overall condition of the entire real estate market (Gerlach and Peng, 2005), bank lending also experienced high volatility, although less extreme than with property prices. Moreover, financial indicators show a rapid deterioration in banks' balance sheets and a decrease in their profitability. These events were associated with a large increase in the unemployment rate, which negatively impacted household income and cash flows, resulting in higher ratios of delinquency and non-performance within mortgage loans. Mortgage delinquency, for example, underwent an increase from 0.3% in 1998 to more than 1.4% in 2001, after which it started to decline, reaching 1% in 2003 (see Figure 1).

In the present paper, the Autoregressive Distributed Lag (ARDL) model is employed to assess the dynamic long-term and short-term relationships between mortgage defaults, property prices, banks' lending behavior and LTV. Our findings indicate the presence of cointegrating relationships between bank lending, property prices and credit defaults, which drive the correction mechanism between the three cycles in the long term. Also, we find evidence of a short-run dynamic between these cycles.

The remainder of this paper is organized as follows. The following section provides a brief overview of the literature on mortgage delinquency, property prices and bank lending, and their implications. Section 3 clarifies the methodology and the econometric model that is used to address the research questions. In Section 4 data sources and the characteristics and construction of some variables that are used in the empirical analysis are presented. Section 5 presents the empirical results of the analyses and their inferences. Finally, Section 6 provides some concluding remarks along with their implications with regards to policy.

2. LITERATURE REVIEW

A typical mortgage contract requires the borrower (mortgagor) to pay back both the principle and the loan interests in payments at an agreed regular interval. However, when three consecutive payments have been missed and the following payment is due, the borrower is classified as having defaulted on their mortgage contract (see, for example, Capone (2002)). In this case, the lender has the right to claim ownership of the pledged property and offer it for sale in the open market as a "foreclosure", in order to fulfill the mortgagor's debt.

As far as the relationship between lending and property prices is concerned, the interaction between banks' lending behaviour and real estate prices has been described in an influential paper by Hott (2011). In his paper, Hott attributes the willingness of the banking sector to finance house purchases to the creditworthiness of the customers, which in turn is highly influenced by their expectations of house price increases. In terms of the feedback effect, the author suggests that housing demand is mainly influenced by the availability of credit, which is subject to banks' willingness to supply mortgages. More importantly, he proposes a model demonstrating how swings in real estate prices can be triggered by irrational participant expectations, contributing to higher fluctuations in the real estate prices and playing a crucial role in the formation of boom and bust cycles in the real estate market. Mora (2008) carried out a similar exercise and provides evidence that bank lending greatly influences the property market, while Gerlach and Peng (2005) show that banks' lending behaviour for house purchases is, to a great extent, governed by house price increases. Lawless and McCann (2012) provide evidence for the impact of flexible credit standards during a boom period on crisis-era loan delinquency.

An upswing in house prices provides further leverage to borrowers via the *wealth effect* stimulated by increased property valuations, offering higher borrowing capacity (see, for instance, Collyns and Senhadji (2002)), particularly in the case of collateralized loans, by activating the so-called *financial accelerator* mechanism (see, for instance, Bernanke *et al.* (1999) and Kiyotaki and Moore (1997)). Hence, an increase in property prices is supposed to result in higher demand for credit, encouraging banks to excessive lending behaviour with more relaxed borrowing conditions, leading to rapid credit growth, which is identified in the existing literature as one of the causes of the recent financial crisis (see, for instance, Borio and Lowe (2002) and Hofmann (2004)). Similarly, the depreciation of property undermines borrowers' capacity, and, furthermore, seriously worsens the quality of banks' loan portfolios and negatively influences their profitability through increasing the expense of their loans. Gerlach and Peng (2005) identify two additional impacts that changes in property prices have on the credit cycle through worsening banks' capital position, either through the revaluation of their real estate holdings, or through the influence that changes in property prices have on NPLs (see also Michael *et al.* (2006) and Karim *et al.* (2010)).

In light of this relationship, and due to the systemic risk that might arise between mortgage loans and the housing market, the Hong Kong Banking Commissioner in 1991 advised banks to cap mortgage loans at 70% of the value of the property. Since then, this cap has been voluntarily adopted by banks and officially authorized by the Hong Kong government. In 1995, the government enacted the 70% LTV ratio as a long-term regulatory policy. In 1996, residential property underwent sharp price increases, associated with a rapid increase in residential mortgage loans. As a result of this, the HKMA reduced the threshold of LTV for properties worth more than HK$ 12 million to 60% in January 1997.

A considerable number of studies on the determinants of credit risk confirmed the impact of using LTV caps in Hong Kong to control the increase of credit risk. However, the LTV ratio could be looked at as a mixed blessing. On one hand, it increases credit risk by acting through the wealth channel and resulting in negative equity, which in turn is widely accepted as a major determinant of mortgage defaulting (see, for example, Lydon and McCarthy (2011)). On the other hand, the adoption of a high LTV ratio by banks exposes them to greater credit risk and incurs a higher level of loss in the event of a default. In addition, high LTV ratios at origination have been found to be associated with a greater probability of mortgage delinquency and foreclosure. In return, LTV caps have also been found to reduce the sensitivity of mortgage defaults to fluctuations in property price (see, for example, Wong *et al.* (2011)). The MIP policy, on the other hand, was found to safeguard banks against additional exposure of losing the amounts of loans that are not secured by the 70% cap, in the event that the borrowers default, which assists banks to avoid incurring additional credit risk. More importantly, the use of the MIP policy was found to work well with the LTV policy and contribute to a more stable banking sector in Hong Kong (see, for example, Wong *et al.* (2011)).

Mortgage default events, according to Jackson and Kasserman (1980), can be explained in the light of two theories, the *equity theory* and the *ability-to-pay theory*. The former assumes that mortgagors' willingness to pay or default is decided by a wise comparison between the returns that might be gained from carrying on or terminating the obligated mortgage payments and the financial costs associated with each scenario.[3] Thus, the LTV ratio under the assumptions of the *equity theory* is supposed to play a key role in triggering conclusive default decisions (Wong *et al.*, 2004). From the latter theory's perspective, however, mortgagors do their best to avoid default as far as they can, by ensuring they can afford to pay their obligations and have sufficient income to settle their periodic payments. Thus, debt service ratio (DSR) is regarded as the critical factor impacting default decisions under the assumptions of the *ability-to-pay theory* (Wong, *et al.*, 2004). As demonstrated by Quercia and Stegman (1992), and later by Tam, *et al.* (2010), empirical studies that investigated the determinants of mortgage defaults explained these determinants in light of these two theories.

In early studies, mortgage defaults were attributed to loan-related factors, such as initial LTV and household income in Furstenberg (1969), payment-to-income in Williams *et al.* (1974) and mortgage interest rates in Vandell (1978). One of the most important studies to deal with mortgage delinquency is by Earley and Herzog (1970), in which they found loan-to-value ratio to be positively and significantly related to the probability of a loan being in delinquency status. Investigating factors that drive decisions to default on a mortgage, Campbell and Cocco (2011) suggested that such a decision is driven by negative home equity resulting from depreciation in house prices in a low inflation environment, accompanied by a large outstanding mortgage. They further find that high loan-to-value ratios at mortgage origination increase the probability of negative home equity and consequently the probability of a default. Later on, investigations into mortgage defaults were extended to account for macroeconomic factors, such as property price changes in Ambrose *et al.* (2001) and stock price variations in Fong *et al.* (2004). A recent strand of the literature attributed mortgage defaults to borrower-related factors.

[3] *Mortgagors are supposed to continue their payments for the collateralized mortgages as far as the market value of the mortgaged property exceeds the outstanding instalments and might terminate*
the payments at point of time when the value of the mortgaged property declines below the outstanding instalments

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This stream of studies included factors that reflect the borrowers' ability to pay their obligated debts, such as debt-to-income ratio (DTI) in Campbell and Dietrich (1983) and Consumer Price Index (CPI) in Nang *et al.* (2003).

There is a general consensus in the literature that advocates the notion that the use of LTV caps helps to control credit supply and credit demand. With credit demand, LTV limits help forcing some house-buyers out of the real estate market due to liquidity shortage or unprofitable investment in the property market. On the other hand, it influences credit supply by constraining lending behaviour by the financial and monetary authorities. Finally, the use of an LTV ratio is found to have a significant effect on decelerating the rapid growth of house prices during boom episodes, by means of dampening and controlling speculative activity that drives property prices up (see, for example, Craig and Hua, 2011).

More directly related to our case study, Tam, *et al.* (2010) find mortgage loans in Hong Kong to be less sensitive to changes in economic fundamentals than other types of loan. They reported that residential mortgage loan default rates in Hong Kong were not as high as total loan default rates, even after the Asian financial crisis of 1997. Their findings encourage us to concentrate our study on mortgage delinquency rather than delinquency on other types of loan, as it might provide a more stable relationship with property prices and bank lending, especially in the long run. Moreover, the findings of Tam, *et al.* encourage us to avoid including macroeconomic factors in our estimation, as they are supposed to show low significance.

As far as house prices are concerned, an important channel for the impact of property prices on banking stability is through the use of collateralized loans, where borrowers use the value of their property against their debts.[4] A bank's exposure credit risk caused by fluctuations in house prices becomes greater according to the degree of the bank's involvement in housing-related activities. In our particular case study, banks' exposure to the real estate market has grown considerably over the past two decades; this can be attributed to the heavy involvement of Hong Kong's banks in housing-related lending. As documented by Zhu (2006), Hong Kong is the second of two frontrunners in Asia, following Singapore, in terms of mortgage market share, with outstanding mortgages accounting for 44% of GDP.

Using a vector error-correction model, Gimeno and Martínez-Carrascal (2010) examined the interactive relationship between house prices and housing loans. They reached the conclusion that housing loans are positively influenced by house prices in the long term, and the latter participates in the adjustment process when the former deviates from their long-term equilibrium, while the correction process for house prices to return to the long-term level in cases of disequilibria is solely driven by house prices. In the short term, however, a positive contemporaneous effect between the two variables has been detected.

3. MODEL SPECIFICATION

Long-term and short-term relationships can be estimated and tested using different cointegration models. Two widely used methods of testing for cointegration among a set of variables are the Engle and Granger approach (1987) and the Johansen approach (1988, 1991). While the former is proposed to test for cointegration between two random walks, each of which is integrated of first order (*i.e.* $I(1)$), the latter allows examining the existence of multiple cointegrating relationships between two or more non-stationary processes (see, for instance, Asteriou and Hall, 2011).

Asteriou and Hall (2011) point out various deficiencies in the Engle and Granger approach. First, the dependence on a single-equation setup may result in misleading inferences, particularly in the presence of two or more cointegrated relationships, due to the inability of this methodology to capture more than a single cointegrating relationship. The second limitation of the Engle and Granger approach concerns the two-step procedure, which involves the inclusion of the estimated residual produced in the first step in the second step

4.The study provides an overview of changes in Hong Kong property prices and their effects on the banking sector and the ultimate economy.

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regression, which in turn might result in transferring any errors introduced in the first step to the second step. Moreover, as suggested by Banerjee *et al.* (1986), this procedure might result in substantially biased estimated parameters, which in turn can undermine the ability of the estimator.

The procedure suggested by Johansen, the so-called system-based approach to cointegration, addresses some of the Engle and Granger approach's shortcomings. It provides a multivariate approach that accommodates multiple cointegrating relationships between the variables of interest. It also helps to overcome the bias that might be triggered by the omitted lags in the Engle and Granger approach, by allowing the inclusion of lags in the specification. Moreover, it provides a framework to impose restrictions on the cointegrating relationships and the adjustment speed in the vector error correction model. Nevertheless, estimations using the Johansen method are still subject to criticism for being overly sensitive to the included number of lags, as suggested by Gonzalo (1994). More importantly, a common criticism leveled at both these approaches is the requirement that the variables included in the estimation have to be non-stationary. In the presence of variables that are stationary in levels, use of the Johansen procedure would deliver biased estimators.

In order to address this issue, Pesaran *et al.* (2001) proposed the Autoregressive Distributed Lags ($ARDL$) model or Bounds testing approach to investigate the long-term dynamics and short-term relationships between a set of variables. One of the main advantages of this procedure is that no restrictive assumptions need to be imposed in terms of the variables' order of integration when estimating $ARDL$. The suggested inference procedure can be applied whether the variables are entirely integrated of order one $I(1)$, entirely integrated of order zero $I(0)$, or fractionally integrated (see for instance Atif *et al.* (2010)). Although it has been widely argued in empirical research that pre-testing the variables' order of integration is not a binding condition to apply $ARDL$, it is asserted that stationarity testing should be performed to avoid including variables that are integrated of order two or higher. This is done in order to obtain accurate estimates. Furthermore, in contrast to the Johansen testing procedure, which suffers from severe size distortion problems in finite samples, Bounds testing is less prone to small sample size distortion (see Peseran *et al.*, 2001). In our case, this is a crucial issue as our time series is limited, owing to the lack of availability of the data; thus, employing $ARDL$ technique is supposed to appropriately fit our data. In this respect, the $ARDL$ model is less affected by nuisance parameters and allows for adding a sufficient number of lags to capture the data generation process (DGP) properly in a general-to-specific modelling context, which helps to overcome problems related to omitted variables and autocorrelations. It further allows flexibility in the structure of the variables' lags, as opposed to the VAR models of cointegration, where all the variables in the system have the same number of lags (see, for example, Pesaran *et al.* (2001)).

The $ARDL\ (p, q1, q2, q3)$ model estimates $(p+1)^k$ number of regressions to achieve the optimal lag length for each variable, where p refers to the maximum number of lags included in the estimation, while k denotes the number of variables included in the estimation and $q1, q2, q3$ are the optimal number of lags of the regressors X_{1t} , X_{2t} and X_{3t}, respectively. Eq. (1) represents the long-term equilibrium relationship for a dependent variable Y_t and three independent variables X_{1t} , X_{2t} and X_{3t}, as follows:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_t, \qquad (1)$$

where α is a constant, and β_1, β_2 and β_3 are coefficients of the long-term equilibrium relationship.
Following Pesaran *et al.* (2001), we apply the bounds test procedure by modelling the long-term relationship shown in Eq. (1) as a general vector autoregressive model of order p, in $\mathcal{Z}_t$:

$$\mathcal{Z}_t = c_0 + \beta t + \sum_{i=1}^{p} \emptyset_i \mathcal{Z}_{t-i} + \varepsilon_t \, , t = 1,2,3, \cdots\cdots, T \qquad (2)$$

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where c_0 denotes a $(k+1)$ vector of constants , β is a $(k+1)$ vector of trend coefficients and $\mathcal{Z}_t$ is the vector of the variables Y_t and X_t, respectively. However, as suggested by Pesaran *et al.* (2001), the vector equilibrium correction model (VECM) formulated in Eq. (3) can be derived to correspond to the representation in Eq. (2):

$$\Delta\mathcal{Z}_t = c_0 + \beta t + \prod\mathcal{Z}_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta\mathcal{Z}_{t-i} + \varepsilon_t \,, t = 1,2,3,\cdots\cdots,T \qquad (3)$$

where $\Pi = I_{k+1} + \sum_{i=1}^{p} \Psi_i$ and $\Gamma_i = -\sum_{j=1+i}^{p} \Psi_j$, $i = 1,2,\cdots\cdots,p-1$ represent $(k+1)\text{x}(k+1)$ matrices, containing the long-term multipliers and short-term parameters of the vector error correction model. In the presence of a unique long-term relationship between the variables of interest, the conditional VECM formulated in Eq. (3) can be converted to the following representation:

$$Y_t = c_{y0} + \beta t + \delta_{yy}Y_{t-1} + \delta_{xx}X_{t-1} + \sum_{i=1}^{p-1} \lambda_i \Delta Y_{t-i} + \sum_{i=0}^{p-1} \xi_i \Delta X_{t-i} + \varepsilon_{yt} \,,$$

$$t = 1,2,3,\cdots,T \qquad (4)$$

Following Liang and Cao (2007), Whyte (2010) and Adebola *et al.* (2011), and based on the foundation of Eq. (4), assuming the existence of a unique long-term relationship between the variables, the $ARDL$ model of the conditional VECM in a multivariate setting can be formulated as shown in Eq. (5):

$$\Delta Y_t = \alpha_1 + \beta_1 Y_{t-1} + \beta_2 X_{1t-1} + \beta_3 X_{2t-1} + \beta_4 X_{3t-1} + \sum_i^p \gamma_i \Delta Y_{t-i} + \sum_j^{q1} \delta_j \Delta X_{1t-j} + \sum_l^{q2} \varphi_l \Delta X_{2t-l} + \sum_m^{q3} \eta_m \Delta X_{3t-m} + \varepsilon_t, \qquad (5)$$

where $\alpha_1, \beta_1, \cdots\cdots, \beta_4, \gamma_i, \delta_j, \varphi_l$ and η_m denote the coefficients to be estimated and $|\beta_1| < 1$, ε_t refers to the white noise error terms of the equations that are assumed to be uncorrelated. Δ Denotes the first difference operator. By construction ΔX_t are not correlated with the error terms ε_t. Due to the unrestricted structure of the lag distribution, Eq. (5) is well-identified and can be reliably estimated using the ordinary least square (OLS) method. However, as suggested by Pesaran and Shin (1999), a parsimonious specification is appreciated in the $ARDL$ approach.

The estimation procedure of the $ARDL$ model can be formulated as follows:

Step 1:

Estimate a set of equations, as shown in Eq. (5), for the variables of interest by employing the simple OLS method for mortgage delinquency, property price, bank lending and loan-to-value as dependent variables in turn, each of which is a function of the other three variables.

Step 2:

Calculate the F-test for joint significance of the coefficients of variables' lags to test the presence of a long-term association between the variables. More specifically, we test the significance of the variables' lags by performing a test to examine the null hypothesis of no cointegration between the variables, that is:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0,$$

Against the alternative that there exists a cointegrated relationship between the stochastic processes of interest, that is:

$$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0.$$

Based on the Wald test, in which the asymptotic distribution is non-standard under the null hypothesis of no cointegration between the variables, the resulting F-statistics are to be compared with the critical upper and lower bounds values reported by Pesaran *et al.* (2001) for the cointegration test. While the lower critical value implies no cointegration between the variables, and that all the variables are $I(0)$, the upper critical value suggests the existence of a cointegration between the variables and that the variables are $I(1)$. The criteria for taking the decision consider three situations: (i) the existence of cointegration between the variables when the computed F-statistic is greater than the upper critical value, in which case the null hypothesis of no cointegration is rejected; (ii) inconclusive presence of cointegration between the variables when the computed F-statistic lies between the lower and the upper critical values; and (iii) no cointegration between the variables when the computed F-statistic is less than the lower critical value. When a long-term relationship between the variables in Eq. (5) is confirmed, the F-statistics refer to the variables that normalisation should depend on.

Step 3

After finding the presence of possible cointegration between the variables, the coefficients of the long-term dynamic of the $ARDL$ model have to be estimated. Hence, multivariate level long-term estimations of the $ARDL\ (p, q_1, q_2, q_3)$ models are formulated as shown in Eq. (6):

$$Y_t = \alpha_1 + \sum_{i=1}^{p} \gamma_i\, Y_{t-i} + \sum_{j=0}^{q1} \delta_J\, X_{1t-j} + \sum_{l=0}^{q2} \varphi_l X_{2t-l} + \sum_{m=0}^{q3} \eta_m\, \Delta X_{3t-m} + v_{yt}. \quad (6)$$

In this step, a variety of information criteria can be used for optimal lag order selection. Some of the most used tests to estimate the lag order include the log likelihood ($LOG\ L$), the likelihood ratio (LR), the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion ($SBIC$), and the Hannan and Quinn information criterion ($HQIC$). However, for a small sample, Pesaran and Shin (1999) found $SBIC$ to be a consistent selection criterion that slightly outperformedAIC. Hence, we use $SBIC$ to select the optimal lag order for all variables under consideration in the $ARDL$ model.

Step 4:

Investigate the short-run dynamics by estimating the error correction models shown in Eq. (7):

$$\Delta Y_t = \alpha_1 + \sum_{i}^{p} \gamma_i \Delta\, Y_{t-i} + \sum_{j}^{q1} \delta_j \Delta\, X_{1t-j} + \sum_{l}^{q2} \varphi_l \Delta X_{2t-l} + \sum_{m}^{q3} \eta_m \Delta X_{3t-m} + \vartheta\, ecm_{t-1} + v_{\Delta yt}, \quad (7)$$

where ecm_{t-1} denotes the lagged error correction terms, while ϑ is the corresponding coefficient. For detailed representations of the equations that are estimated in the $ARDL$ model see the explanation provided in APPENDIX 8.

As a post-estimation check, several diagnostic tests are performed, namely normality tests of the estimated residuals, homoscedasticity tests of the residuals and tests of the functional form. Furthermore, as recommended by Pesaran (1997), both the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests proposed by Brown *et al.* (1975) are considered to test for the stability of the long-term parameters, along with the short-term dynamics of the residuals of the estimated ECMs.

4. DATA AND UNIT ROOT TESTS

Some data issues will be highlighted in this section. Monthly time series data for Hong Kong, spanning the period from June 1998 to June 2009, are used in the empirical analyses. The rationale behind confining the data to this period is twofold: first, we are performing this research to concentrate on the troubled period in which the Asian financial crisis took place, rather than

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on stable periods, and second, because the observed mortgage delinquency after June 2009 shows no material change, and stays at the same rate of 0.01 until the end of the available data.

Using monthly data enriches the analyses with more rigorous intra-year dynamics, since loan performance assessments and decisions on delinquency and lending behaviour are usually performed on a monthly basis. From a practical perspective, the advantage of monthly reviews of mortgage delinquency is that they offer an early warning that helps to avoid high levels of delinquency by estimating the expected number of delinquency or default loans at the end of the period, in order to gain more time to negotiate with borrowers. Similar to loan delinquency, monthly review of banks' lending behaviour help banks to amend their lending, taking into consideration the outcomes from the probabilities of default risk obtained from the previous process. The data relate to:

D: *Residential Mortgage Loans Delinquency Ratio.* The series is supplied by the Hong Kong Monetary Authority (HKMA) in the Monthly Residential Mortgage Survey (RMS).[5]

HP: *Propriety Price Index.* The property price index has been constructed by calculating a compound property price index using different types of property. To calculate the index, principal component analysis has been used. The rationale for this approach is based on two considerations: first, tracking the history of price indices for all types of property (residential, private offices, private retail and flatted factories) revealed that the prices for all these types of property evolved in a similar manner over the period under scrutiny, with slight differences in price levels according to the type of property (see Figure 5 in APPENDIX 9). Hence, adopting this approach helps overcome Multicollinearity problems triggered by the high correlation between these indicators. Second, a property ownership often involves demand for credit by engaging in mortgage agreements, and these loans are exposed to delinquency or default, whether for residential or commercial, and whether used for a house purchase or rental.

Evidence from Hong Kong shows that during the expansion period that preceded the Asian financial crisis, a large proportion of all types of loan to the private sector was used for property-related investment rather than for house purchases.[6] Therefore, using a summary measure that includes the development in real estate property prices, comprising all relevant property prices, would deliver better information in this regard.

Principle component analysis has been conducted on both prices and rentals of residential, private offices, private retail and flatted factories offered by the Rating and Valuation Department (RVD) of the Hong Kong government to extract the property price index.[7] Table 8 in APPENDIX 7 shows the outcomes of the principal component analysis. From Table 8 it appears that the eigenvalue associated with the first component is significantly higher than one and represents more than 96% of the standardized variance in the prices and rentals of these types of property, while the rest of the components represent only around 3% of these variations. Therefore, the first principle component has been constructed and used as a summary indicator for property prices.[8] Figure 5 in APPENDIX 9 shows the fluctuations in price of all types of property included in the principle component analysis, along with the first component summary indicator for the property prices denoted below as ($\boldsymbol{HP}$).

L: *Bank Lending.* As far as banks' lending behaviour is concerned, data on gross loans made in Hong Kong obtained from the HKMA has been used as a proxy for bank lending. This variable is preferred to other proxies, such as mortgages for house purchasing, because evidence shows that in addition to residential mortgage lending, banks in Hong Kong make loans to institutions for which construction and property development are their main activity. Furthermore, the use of gross loans made in Hong Kong is more consistent with our choice of property price proxy mentioned above.

5. The variable refers to ratios of delinquency among residential mortgage loans (including refinancing loans) to private individuals to purchase residential properties, but doesn't include properties under the Home Ownership Scheme, Private Sector Participation Scheme, Tenants' Purchase Scheme and mortgage loans to corporates. The authorized institutions included in this survey account for over 95% of the total residential mortgage lending business.
6. Due to this concern, the HKMA includes more constrains on bank lending guidelines, in an attempt to account for the use of other loans – rather than residential loans – by borrowers to enhance their access to credit in the property sector (For more information, see HKMA (1997)).
7. These indexes are compiled by the Rating and Valuation Department of the Hong Kong government, based on market transaction data and reflect changes in prices and rents per square foot of the properties with comparable building and location qualities.
8. To check robustness, we re-estimated the empirical model using some property prices mentioned above, and the results, which in the interest of brevity are not reported, confirmed no material difference in the dynamic relationships either in the long term or the short term.

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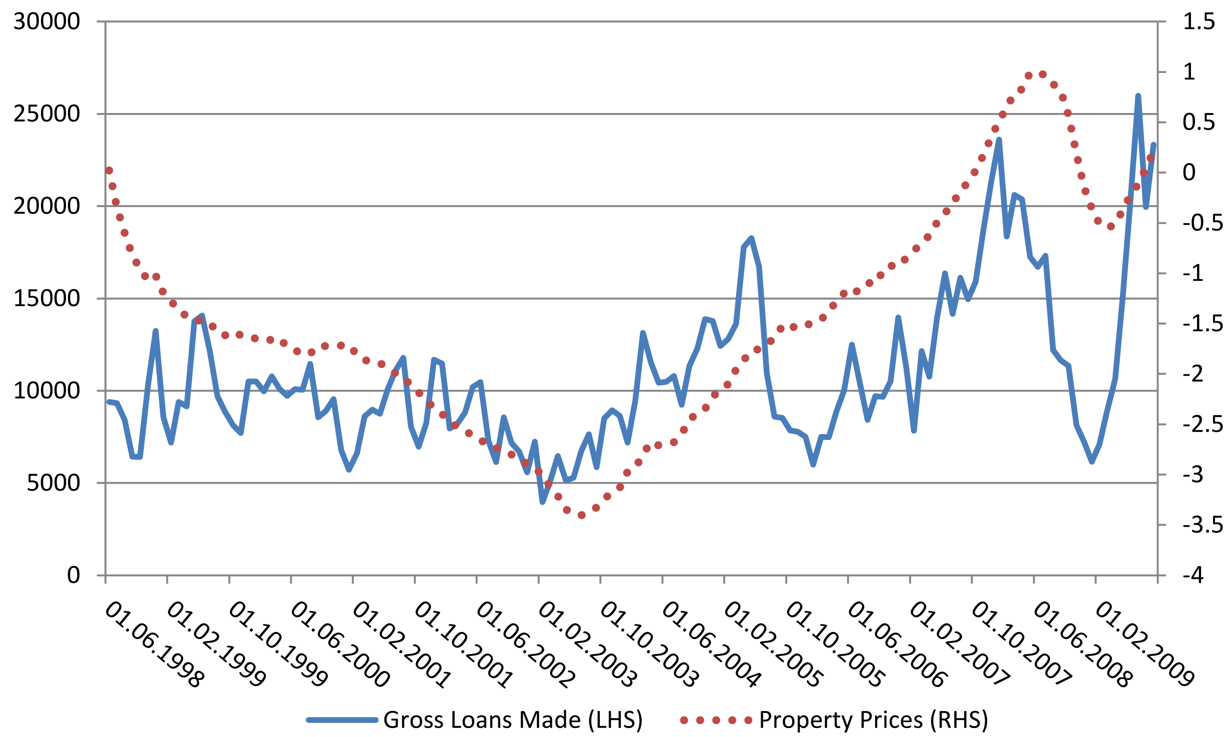
LTV: *Current Loan-To-Value*. This variable has been used to capture the impact of macroprudential tools on protecting bank loan portfolios against shocks in the real estate market. The data for loan-to-value were collected from Bloomberg. However, data for LTV usually refer to the relative size of the loan to the value of the pledged property at mortgage origination. Fan and Peng (2003) and Gerlach and Peng (2005) assert that current loan-to-value is highly correlated to default probability. Thus, in order to capture the actual influence of loan-to-value on the level of mortgage default, current loan-to-value, denoted as ($\boldsymbol{LTV}$), is used. Since the HKMA does not provide much data about current loan-to-value $CLTV$, it is derived from loan-to-value at mortgage origination by dividing the LTV value of a particular month by the same month's reported value in the Hong Kong Midland Property Price 100 Index (see, for example, Clapp *et al.*, 2001).[9]

Figure 2 plots banks' lending (scaled on the left-hand side axis) and property prices (scaled on the right-hand side axis). The chart demonstrates that banks' lending reveals frequent bumps and wiggles that correspond to periods of expansionary and contractionary lending policy by the Hong Kong banks. In terms of the peculiarity of property price developments in the experience of Hong Kong, the chart shows that the fluctuations in property prices are not smooth, with a repeated peaks and troughs during the period under consideration. That is, property prices are characterized by the high frequency of occurrence of episodes of increases or decreases in prices. More importantly, Figure 2 clearly displays a high correlation between the two variables, which suggests a long-term association between bank lending and property prices. The behaviour of these two indicators proposes a possible cointegration between them; the long-term behaviour could be better scrutinized using an error correction model specification.

Figure 2 Gross Loans Made and Property Prices



Note: Gross loans made are scaled on the left-hand side axis, whereas the property price indicator is scaled on the right-hand side axis.

9.The Hong Kong Midland Property Price 100 Index is compiled from the transaction records of the 100 most popular housing estates in Hong Kong and has been used to reflect the latest price trend in the residential market.

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Table 1 reports some descriptive statistic of the abovementioned variables. Clearly, house prices show the highest standard deviation among the variables, which reflects the high and frequent fluctuations in property prices, as can be seen in Figure 2.

Table 1 Descriptive Statistics of the Selected Variables

Statistics	D_t	HP_t	LTV_t	L_t
Mean	0.672	-1.525	2.117	9.204
Median	0.660	-1.643	1.904	9.181
Std. Dev.	0.491	1.114	0.495	0.339
Skewness	0.034	0.435	1.050	0.232
Kurtosis	1.281	2.578	3.209	2.897
Jarque-Bera	16.403	5.174	24.673	1.257
Probability	0.000	0.075	0.000	0.533
No. of Observations	133	133	133	133

In the light of theoretical remarks stated in Section 3 the stationarity of the series under scrutiny needs to be investigated in order to rule out the presence of $I(2)$ stochastic processes prior to estimating the $ARDL$ model. However, before undertaking the stationarity tests of the variables, some caveats regarding their behaviour, in particular mortgage delinquency, during the sample period are discussed.

The history of mortgage delinquency in Hong Kong shows that the mortgage delinquency ratio remained low, fluctuating around 0.3%, in the second half of 1998, but rose substantially after that to reach more than 1.4% in 2001, before dropping gradually to less than 1% in the last quarter of 2003 and continued with moderate fluctuations until the end of the sample (see Figure 1).[10] This time series behaviour suggests a potential presence of structural break(s) in the time series caused by the Asian financial crisis, which is crucial to correctly specify the model, and might undermine the reliability of the estimated parameters if not accounted for properly.

In the light of these arguments, the Bai and Perron (1998, 2003) test that allows detection of multiple structural breakpoints in a long-term relationship has been applied to test the existence of (l) breakpoints against $(l+1)$ breakpoints. The Bai and Perron test is conducted based on the estimation of Eq. $(1.B)$, which is provided in APPENDIX8, to examine the existence of up to a maximum of five breakpoints, and the outcome of the test is provided in Table 2.[11]

Evidently, the results of the sequential test highlight the existence of two structural breakpoints with the rejection of the null hypotheses of 0 and 1 breakpoints, in favour of the alternatives 1 and 2 breakpoints; however, the test of 3 breakpoints versus 2 breakpoints does

10 In contrast to the experience of Hong Kong, house prices in other countries declined less sharply but caused higher ratios of mortgage delinquency. For example, when house prices dropped by 30% in the United States, mortgage delinquency ratio increased by more than 10%, also when house prices declined by 50% in Ireland, the 90-day mortgage arrears ratio climbed to around 11%.

11 Eq. $(1.B)$ in APPENDIX8corresponds to Eq. (5) presented in Section 3.

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not reject the null. Therefore, a suitable dummy variable, denoted below as $\boldsymbol{DV}$, has been constructed and included in the estimation of the $ARDL$ model for mortgage delinquency, in order to capture the impact of the Asian financial crisis on the evolution of mortgage delinquency. Furthermore, the exclusion of the dummy from the estimation is found to result in non-normally-distributed residuals, which violates a fundamental *priori* assumption of the $ARDL$ approach and might result in misleading statistical inferences and consequently drawing wrong conclusions.

Table 2 Bai-Perron Tests of L+1 vs. L Sequentially Determined Breakpoints

Sequential ***F*-statistic determined breaks: 2**			
Break Test	***F*-statistic**	**Scaled *F*-statistic**	**Critical Value****
0 vs. 1 *	14.68	117.43	23.70
1 vs. 2 *	6.82	54.58	25.75
2 vs. 3	2.09	16.73	26.81

*Note: * Significant at the 0.05 level, ** Bai-Perron (Econometric Journal, 2003) critical values.*

Estimators of ordinary unit root tests such as Augmented Dickey-Fuller (ADF, 1979, 1981), Phillips and Perron (PP, 1988), Elliott *et al.* (1996), Kwiatkowski *et al.* (1992) and Ng and Perron (2001) are biased and suffer low power to capture the existence of the unit root in the presence of structural break(s). Hence, they are not reliable for reaching coherent conclusions about the stationarity of series that have structural break(s) (Baum, 2004).

To overcome this problem, Clemente, Montañés and Reyes (1998) suggested a test that allows for two breaks in the mean. The test offers a major advantage by providing information about two different forms of structural break points, namely the Additive Outliers (AO) and the Innovational Outliers (IO) models. While in the former (AO), changes are supposed to take place suddenly, allowing for a shift in the slope of a time series, in the latter (IO), changes are supposed to occur gradually. The IO model seems to better capture the breaks in mortgage delinquency, as the time series shows gradual changes, while the AO models are found to be appropriate for the bank lending, property prices and loan-to-value variables, which experienced a sudden structural change as a result of the Asian financial crisis. The Clemente, Montañés and Reyes (1998) unit root tests have been conducted both at levels and first differences and the results are reported in Table 3.

The results in Table 3 show that mortgage delinquency and loan-to-value suffer two structural breaks in the mean, while property prices and bank lending have one structural break in the mean (see $TB1$ and $TB2$ Table 3 for the dates of breaks). As far as unit root is concerned, the results reveal that, with the exception of bank lending, which is integrated of order zero at the 5% significance level, mortgage delinquency, property prices and loan-to-value seem to be integrated of order one at the 5% significance level. Therefore, the outcomes of the Clemente, Montañés and Reyes (1998) unit root tests indicate a mix of $I(1)$ and $I(0)$ stochastic processes. In light of these findings, the $ARDL$ model is supposed to be a suitable approach to capture the data generation process (DGP) of our series.

Table 3 Clemente-Montañés-Reyes (1998) Unit Root Tests[12]

Variable	Level			First difference			Decision
	T-Statistic	$TB1$	$TB2$	T-Statistic	$TB1$	$TB2$	
D_t^{IO}	-5.20 (4)	2001m4	2003m8	-5.95 (6)**	2003m4	2005m3	$I(1)$
HP_t^{AO}	-2.68 (1)	2008m4	-	-4.13 (1)**	2003m3	-	$I(1)$
L_t^{AO}	-4.03 (0)**	2007m2	-	-10.37 (1)**	2002m12	-	$I(0)$
LTV_t^{AO}	-3.66 (1)	2001m12	2004m4	-10.92 (0)**	2003m6	2004m3	$I(1)$

*Note: T-Statistics refer to the minimum test statistics. Asterisks ** refers to the significance at 5% significance level. Lag order is in the parentheses. AO refers to Additive Outliers models, while IO refers to Innovational Outliers models. $TB1$ and $TB2$ indicate the dates of breaks.*

5. EMPIRICAL RESULTS AND DISCUSSION

In this section, the Bounds test for the $ARDL\ (p, q1, q2, q3)$ model is used to examine the long-term relationships and dynamic interactions between mortgage delinquency, property prices, and banks' lending behaviour. Furthermore, to scrutinize the effect of macroprudential policy on mortgage defaults, loan-to-value is also considered. Estimations of Eq. (5) are considered for mortgage delinquency $\boldsymbol{D}$, banks' lending $\boldsymbol{L}$, property price $\boldsymbol{HP}$ and loan-to-value $\boldsymbol{LTV}$, respectively, to check the existence of cointegration between the variables. Table 4 presents the outcomes of the calculated F-statistics when each variable is dealt with as a function of the other variables of interest in the $ARDL - OLS$ estimations.

Table 4 Results of the Bound Tests at 5% and 10% Significance Levels[13]

Equations	SIC Lag	F-statistic	Outcomes 5%	Outcomes 10%
$F_D(D\|LTV, HP, L)$	4	11.6727 ***	Cointegration	Cointegration
$F_L(L\|LTV, D, HP)$	1	11.9045***	Cointegration	Cointegration
$F_{HP}(HP\|LTV, D, L)$	3	1.7164	No Cointegration	No Cointegration
$F_{LTV}(LTV\|HP, D, L)$	1	2.6229	No Cointegration	No Cointegration

Note: Asymptotic critical value bounds are obtained from Pesaran and Pesaran (1997).

12To examine the null hypothesis of the unit root, the asymptotic critical values for AO and IO models at the 5% significance level are -5.490 for two structural breaks, while the critical values at the 5% significance level for single structural breaks are -3.560 and -4.270 for AO and IO models, respectively.

13 For mortgage delinquency estimation, the Lower Bound $I(0)$ and Upper Bound $I(1)$ critical values are 4.55 and 5.65 at 95% and 3.90 and 4.94 at 90%, respectively. For bank lending and property price estimations, the Lower Bound $I(0)$ and Upper Bound $I(1)$ critical values are 3.30 and 4.44 at 95% and 2.77 and 3.80 at 90%, respectively. Finally, for loan-to-value estimations, the Lower Bound $I(0)$ and Upper Bound $I(1)$ critical values are 4.10 and 5.17 at 95% and 3.52 and 4.52 at 90%, respectively.

Looking at Table 4, the normalized F-statistic for mortgage delinquency model, denoted below as $F_D(D|LTV, HP, L) = 11.67$, is higher than the upper bound and lower bound critical values at both 5 and 10% significance levels, with trend and intercept included in the estimations. This means for the mortgage delinquency model, at the 5% significance level, there is cointegration between the variables. The normalized F-statistic for bank lending estimation produced F-statistic, denoted below as $F_L(L|LTV, D, HP) = 11.90$, is greater than the upper critical values at both the 5 and 10% levels of significance, with only intercept included in the estimations. Similarly, this result suggests the rejection of the null hypothesis of no cointegration, inferring a cointegrating relationship between the included variables.

From the property prices and loan-to-value estimations, the F-statistics, denoted below as $F_{HP}(HP|LTV, D, L) = 1.72$ and $F_{LTV}(LTV|HP, D, L) = 2.62$, respectively, are both lower than both the upper and lower corresponding bound critical values at both 5 and 10% significance levels, with only intercept included in the estimations. The above two F-statistics indicate that the null hypothesis of no cointegration relationship cannot be rejected for property prices and loan-to-value models.

To sum up, the overall results of the F-tests imply that causality runs not only from bank lending towards mortgage default, but also in the opposite way, *i.e.* from mortgage default towards bank lending, when the regressions are normalized on the related variables. Therefore, the findings confirm a unidirectional effect between mortgage default and banks' lending behaviour.

Once we established that a long-run cointegration relationship exists, the $ARDL$ (4,0,0,0) specification is estimated. Since our main focus in this paper is to investigate causality between mortgage delinquency, property prices and bank lending, the cointegration relationship is assessed by normalising on mortgage delinquency.

5.1THE LONG-TERM RELATIONSHIP

Estimation of Eq. (6) is conducted to find the long-term parameters and the results reported in Table 5 are obtained by normalizing on mortgage delinquency $\boldsymbol{D}$. Overall, the results presented in Table 5 reveal that mortgage delinquency is highly influenced by loan-to-value caps, banks' lending behaviour and fluctuations in property prices in the long term.

Table 5 Estimated Long-term Coefficients Using the ARDL Approach

$ARDL$ (4, 0, 0, 0) Selected Based on Schwarz Bayesian Criterion				
Dependent variable is D_t				
Repressors	**Coefficient**	**Standard Error**	**T-ratio**	**Probability**
HP_t	-0.279***	0. 0541	- 5.157	0.000
L_t	0.354***	0.0919	3.851	0.000
LTV_t	0.469***	0.0823	5.698	0.000
DV_t	0.127***	0.0585	2.166	0.032
C	4.332***	0.9377	4.620	0.000
$Trend$	-0.015***	0.0011	-12.838	0.000

*Note: The asterisks refer to coefficient significance at: * at 10%, ** at 5% and ***at 1%.*

As far as property prices are concerned, the coefficient ***HP*** is statistically significant with a negative sign (see Table 5). The coefficient of property prices reveals that a 1% increase in property prices would lead to an approximate 28% drop in the ratio of mortgage delinquency in the long-run, which can be explained in

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light of a financial accelerator. On one hand, an increase in property prices provides borrowers with supplemental privileges, enhancing their ability to satisfy their committed debts through appreciation in collateral values, which is called the "*net wealth channel*". Given the dominant use of collateralized loans in Hong Kong, the increase in collateral values contributes to a decline in the probability credit defaults (see, for example, Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)). On the other hand, the appreciation in property prices helps boost banks' accumulated capital positions due to the increase in the values of properties held by the banks contributing to greater lending capacity.

Furthermore, this finding is consistent with the view provided by Koetter and Poghosyan (2010) regarding the impact of deviations in property prices from their fundamental values on the evolution of credit defaults. However, as the real estate market goes into reverse, this behaviour is rapidly translated into a growth in the mortgage delinquency ratio and NPLs in banks' loan portfolios, resulting in higher negative home equity. This is particularly true in the case of Hong Kong, given the heavy involvement of Hong Kong banks in property-related lending activities.

Bank lending is another factor that is found to influence mortgage delinquency evolution in the long term. The bank lending coefficient is highly significant at the 1% significance level and carries a positive sign, highlighting that a 1% expansion in bank lending is expected to expose 35% of these loans to the risk of defaulting, contributing to a higher probability of loan delinquency in the long term.

This outcome is consistent with empirical evidence in the related literature, which suggests that an increase in banks' lending exposes banks to a higher probability of mortgage default (see, for example, Gerlach and Peng (2005)). However, as stated above, the exposure to such a risk is highly influenced by the extent to which banks are involved in property-related lending activities, such as mortgage loans and lending for construction and housing developments. In the case of Hong Kong, banks' exposure to the real estate market is high, given that, for example, 24% of the total loans issued for use in Hong Kong at the end of 2007 were residential mortgage loans. Driven by an increasing demand for credit as a result of the increase in collateral values, excessive lending behaviour with lax lending conditions resulted in a rapid credit boom, which is considered a key indicator of an increased probability of defaulting and is therefore supposed to contribute to higher ratios of mortgage delinquency and bad loans (see, for example, Hofmann, 2004).

The results in Table 5 reveal that loan-to-value has the highest coefficient, highlighting the essential importance of this tool in reducing the rate of mortgage defaults. Furthermore, the positive sign of this coefficient is implies that higher loan-to-value limits expose higher proportions of mortgage loans to default, resulting in an increase in the credit default attached to banks' loan portfolios. In other words, it implies an expected increase of around 47% in mortgage delinquency would be associated with a 1% rise in LTV caps in the long term. Indeed, the LTV data used in these analyses refer to the loan-to-value at origination, adjusted for market prices, and evidence from the literature advocates the idea that a greater probability of mortgage delinquency can be triggered by high LTV ratios at origination.

Our findings regarding the impact of LTV on the rate of mortgage defaults are consistent with the literature, since many studies reached the same conclusion. For example, an influential paper by Earley and Herzog (1970) found that the probability of a loan being in delinquency in the U.S.A. is positively and significantly influenced by loan-to-value ratio. Furthermore, Campbell and Cocco (2011) attributed the impact of loan-to-value on the evolution of mortgage delinquency to the role that higher ratios of this factor play in producing negative equities, which in turn increase the probability of default. Also, our result is in line with the notion of the *"equity theory of default"* according to which, the LTV ratio plays a key role in triggering default decisions (see, for example, Wong, *et al*. (2004)).

Finally, the dummy variable, which was included to identify the impact of the Asian financial crisis on the evolution of mortgage delinquency, is highly significant at the 1% significance level. The positive sign confirms the fundamental and unsurprising role that the Asian financial crisis played in driving up the rate of mortgage delinquency. In other words, periods of financial turmoil are thought to increase the credit default risk through rapid growth in mortgage delinquency in banks' loan portfolios, accelerated by a sharp plunge in collateral values, followed by vigorous growth in negative equity.

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5.2 SHORT-TERM ESTIMATION AND ADJUSTMENT

Estimation of Eq. (7) has been conducted to investigate the short-term dynamic and the speed of adjustment to equilibrium. The estimation results are reported in Table 6. Mortgage delinquency shows some persistence with one out of three included lags being significant at the 1% confidence level, indicating the impact of previous values of mortgage delinquency on driving up their current values. As for property prices, bank lending and loan-to-value, they are highly significant in the short term and carry the same signs confirming the conclusions reached in the long-term estimations.

Table 6 Error Correction Representation for the Selected ARDL Model

$ARDL\ (4,0,0,0)$ Selected Based on Schwarz Bayesian Criterion				
Dependent variable is ΔD_t				
Repressors	**Coefficient**	**Standard Error**	**T-Ratio**	**Probability**
$\Delta\ D_{-1}$	0.131	0.078	1.677	0.096
$\Delta\ D_{-2}$	-0.007	0.077	-0.095	0.924
$\Delta\ D_{-3}$	0.214***	0.071	3.026	0.003
$\Delta\ HP$	-0.025***	0.005	-5.442	0.000
$\Delta\ L$	0.032***	0.007	4.666	0.000
$\Delta\ LTV$	0.042***	0.010	4.373	0.000
$\Delta\ DV$	0.011**	0.006	1.958	0.053
$\Delta Trend$	-0.001***	0.000	-6.940	0.000
ecm_{-1}	-0.090***	0.014	-6.425	0.000

*Note: The asterisks refer to coefficient significance at: * at 10%, ** at 5% and ***at 1%.*

The coefficient of the lagged error correction term ($\boldsymbol{ecm_{t-1}}$) for the mortgage delinquency *ARDL* model is highly significant and occurs in the negative direction. This finding confirms the long-term relationship between mortgage delinquency and the other variables included in the estimation, and further indicates that any disequilibrium that occurred due to previous shocks is corrected to converge back to the long-term equilibrium. However, the magnitude of the error correction term is to some extent small, suggesting a fairly slow adjustment process. That is, around 9% of the disequilibria of the previous month's shock adjust back to the long-term equilibrium in the current month. A representation of the estimated error correction term for mortgage delinquency is shown in Eq. (8):

$$ecm = D - 0.35 * L + 0.28 * HP - 0.47 * LTV + 0.01 * TREND - 4.33 * C - 0.13 * DV. \quad (8)$$

Following the establishment of the cointegration between the variables, a dynamic error correction model has been estimated and Cholesky impulse response functions are plotted in Figure 3. The chart shows the different directions of responses between mortgage delinquency, banks' lending, property prices and loan-to-value. As far as mortgage delinquency is concerned, the upper row of charts in Figure 3 is in line with our findings obtained from the *ARDL* estimation. In other words, the positive impact of bank lending and loan-to-value on NPLs can be inferred while the negative effect of property prices on the escalation of mortgage defaults is detected. Notably, the first chart in the upper row shown in Figure 3 also confirms the persistence of mortgage delinquency.

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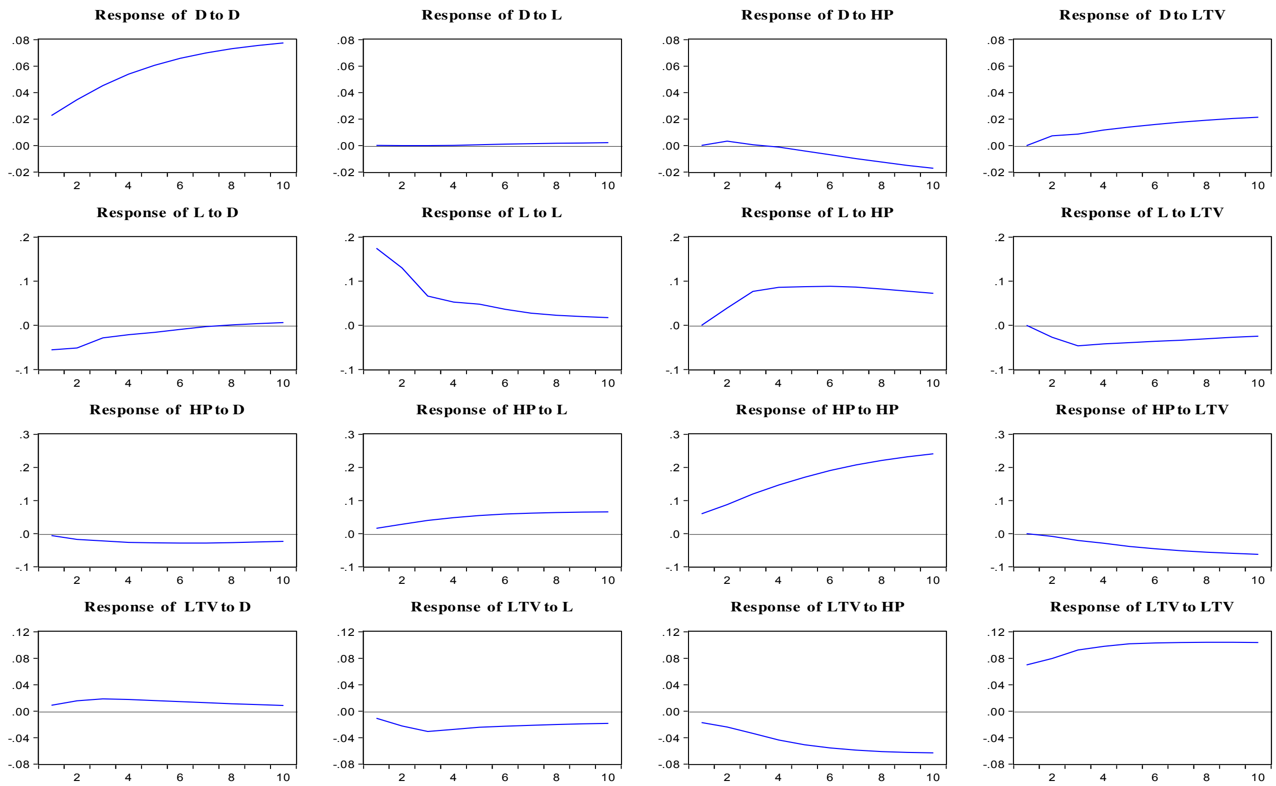
Figure 3 Impulse Response Functions to Cholesky One S.D. Innovations



Note: The chart is produced from vector error correction estimation (VECM).

5.3 MISSPECIFICATION AND DIAGNOSTIC TESTS

The *ARDL* estimation of mortgage delinquency has a high adjusted R^2, revealing the favourable goodness of fit of the model. Diagnostic tests were employed to check the validity of the *ARDL* estimation, normalised on mortgage delinquency, and the results of the tests are shown in Table 7. The misspecification tests show that the residuals have no serial correlation, the correct functional form and normally distributed residuals. Unfortunately, the null hypothesis of homoscedasticity error cannot be accepted, indicating heteroscedasticity residuals. However, as demonstrated by Shrestha and Chowdhury (2005), Fosu and Magnus (2006) and later by Rafindadi and Yusof (2013), detecting heteroscedasticity in residuals generated by an *ADRL* approach is not surprising since the variables constituting the equations of the *ARDL* model combine time series that are integrated of different orders, and this does not undermine the estimate's validity.

Table 7 Diagnostic Tests of ARDL VECM Model of Mortgage Delinquency

R^2 = 0.9986		Adjusted R^2 = 0.99853	
Serial Correlation: $x^2(12)$ = 20.27	[0.062]	F(12,107) = 1.66	[0.086]
Functional Form: $x^2(1)$ = 0.32	[0.574]	F(1,118) = 0.29	[0.591]
Normality $x^2(2)$ = 5.79	[0.055]	Not applicable	
Heteroscedasticity $x^2(1)$ = 6.45	[0.017]	F(1,127) = 6.69	[0.011]

Note: R_1^2 and its adjusted value were determined based on the estimation of Eq. (5). The serial correlation test was based on Lagrange multiplier test of residual serial correlation. The functional form test was based on Ramsey's RESET test using the square of the fitted values. The normality test was based on a test of skewness and kurtosis of residuals. The heteroscedasticity test was based on the regression of squared residuals on squared fitted values.

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Figure 4 CUSUM and CUSUMQ Coefficient Stability in the ECM

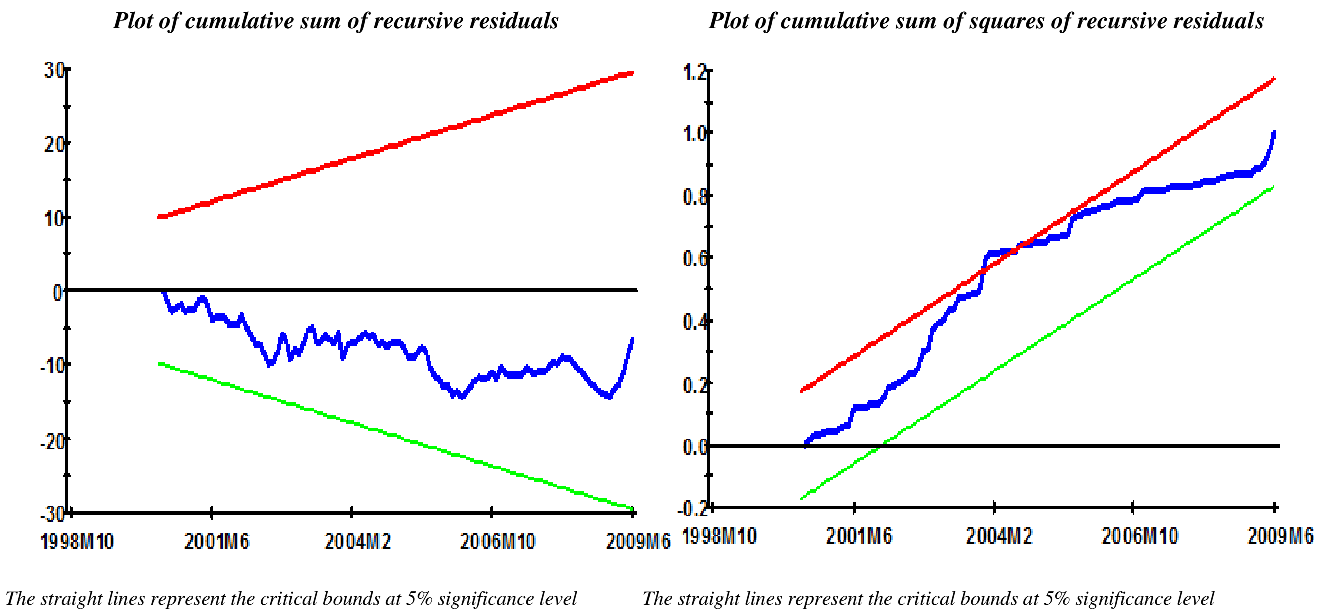

Figure 4 plots the CUSUM and the CUSUMSQ stability test of the estimated coefficients of the residuals of Eq. (6). The result of the stability test suggests no evidence of instability of the coefficients with the CUSUM, and the CUSUMSQ lies within the critical bands of the 5% confidence interval of parameter stability. This confirms the global stability of both the long-term and all short-term coefficients in the ECM.

6. CONCLUSION

This paper investigated the long-term equilibrium relationship and short-term dynamic between mortgage default, property prices and banks' lending behaviour in Hong Kong, taking into account the impact of loan-to-value. The autoregressive distributed lag (*ARDL*) or Bounds testing technique has been employed for cointegration on monthly time series data for Hong Kong, over the period from June 1998 to June 2009. Due to the Asian financial crisis, which led to structural break(s) in the time series under consideration, a suitable dummy variable has been constructed and included in the estimation to capture the impact of the financial crisis on the evolution of mortgage defaults.

Overall, the findings of *ARDL* estimations reveal that mortgage defaults are highly influenced by loan-to value caps, banks' lending behaviour and variations in property prices. In addition to the short-term dynamic between these variables, the analyses provide evidence of a cointegrating relationship that governs the correction mechanism between bank lending, property prices and mortgage defaults in the long term to guarantee that any disequilibrium in the relation between these variables converges back to the long-term equilibrium.

Consistent with other empirical works (see, for example, Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)), property prices are found to be highly significant in explaining the evolution of mortgage defaults. Furthermore, the analysis reveals the negative impact of property prices on mortgage defaults, implying that an appreciation in property prices would enhance borrowers' ability to service their scheduled debts through the "*net wealth channel*", contributing to a lower probability of default.

As far as banks' lending behaviour is concerned, a positive influence has been detected on the magnitude of mortgage delinquency, signifying that an expansion in bank lending paves the way for a higher amount of mortgage defaults, by increasing the exposure of larger amounts of loans to the risk of defaulting. The impact of banks' lending behaviour is in agreement with expectations and empirical evidence found in the related literature (see, for example, Gerlach and Peng, 2005). Given that residential mortgages comprise approximately 24% of the total loans issued for use in Hong Kong at the end of 2007, banks' exposure to perturbations in the real estate market is particularly high in the case of Hong Kong.

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Various macroprudential policy tools have been devised and employed in Hong Kong over the past two decades to safeguard the stability of the banking system against real estate market disturbances. As one the most effective tools, loan-to-value has exhibited the highest impact on mortgage defaults, highlighting the crucial importance of this tool in reducing the exposure of the banking industry to housing market disturbances.

The presence of cointegrating relationships between mortgage delinquency, property prices and banks' lending behaviour has remarkable practical implications, as it implies unidirectional effects between the three cycles. It suggests the need for a range of financial, monetary and macroprudential tools that are able to effectively control the multifaceted interactions between the banking sector and the real estate market segments in a manner that contributes to the stability of the banking system and the entire economy. Although challenging, this finding suggests planning the policies that govern these indicators in wider policy frameworks, through continuous cooperation between policymakers in the real estate market and the banking industry, in order to ensure a sustainable and sound banking system.

7. APPENDIX

Principal component analyses have been carried out over prices and rentals of residential properties, private offices, private retail, and flatted factories in an attempt to construct a compound property price index that is able to capture the impact of property prices and rents on the evolution of mortgage delinquency. Therefore, the principal analysis is employed over the eight variables shown in Figure 5 in APPENDIX 9, and the results of the analysis are shown in Table 8.

Table 8 Principal Components Analysis for Property Price

Component	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
Comp 1	7.727125	7.556405	0.9659	7.727125	0.9659
Comp 2	0.170720	0.115303	0.0213	7.897844	0.9872
Comp 3	0.055417	0.029166	0.0069	7.953261	0.9942
Comp 4	0.026251	0.015871	0.0033	7.979511	0.9974
Comp 5	0.010380	0.005163	0.0013	7.989891	0.9987
Comp 6	0.005216	0.001837	0.0007	7.995107	0.9994
Comp 7	0.003379	0.001866	0.0004	7.998487	0.9998
Comp 8	0.001513	---	0.0002	8.000000	1.0000

No. of observations included: 133; No. of components: 8

The first principal of the components can explain more than 96% of the standardized variance in the prices and rentals of these types of property. Hence, the first principal, denoted below as $\boldsymbol{HP}$, is generated and used as a summary measure to represent changes in real estate property prices.

1. APPENDIX

In the first step, the representations shown in Eq. (1.B), Eq. (2.B), Eq. (3.B) and Eq. (4.B) are estimated for mortgage delinquency $\boldsymbol{D}$, bank lending $\boldsymbol{L}$, property prices $\boldsymbol{HP}$ and loan-to-value $(\boldsymbol{LTV})$ respectively, by employing simple ordinary least squares (OLS):

$$\Delta D_t = \alpha_{1,1} + \beta_{1,1} D_{-1} + \beta_{2,1} HP_{-1} + \beta_{3,1} L_{-1} + \beta_{4,1} LTV_{-1} + \sum_{i1}^{p} \gamma_{i1} \Delta D_{t-i1} + \sum_{j1}^{q1} \delta_{j1} \Delta HP_{t-j1} + \sum_{l1}^{q2} \varphi_{l1} \Delta L_{t-l1} + \sum_{s1}^{q3} \Phi_{s1} \Delta LTV_{t-s1} + \varepsilon_{t1}, \quad (1.B)$$

$$\Delta HP_t = \alpha_{1,2} + \beta_{1,2} D_{-1} + \beta_{2,2} HP_{-1} + \beta_{3,2} L_{-1} + \beta_{4,2} LTV_{-1} + \sum_{i2}^{q1} \gamma_{i2} \Delta D_{t-i2} + \sum_{j2}^{p} \delta_{j2} \Delta HP_{t-j2} + \sum_{l2}^{q2} \varphi_{l2} \Delta L_{t-l2} + \sum_{s2}^{q3} \Phi_{s2} \Delta LTV_{t-s2} + \varepsilon_{t2}, \quad (2.B)$$

$$\Delta L_t = \alpha_{1,3} + \beta_{1,3} D_{-1} + \beta_{2,3} HP_{-1} + \beta_{3,3} L_{-1} + \beta_{4,3} LTV_{-1} + \sum_{i3}^{q1} \gamma_{i3} \Delta D_{t-i3} + \sum_{j3}^{q2} \delta_{j3} \Delta HP_{t-j3} + \sum_{l3}^{p} \varphi_{l3} \Delta L_{t-l2} + \sum_{s3}^{q3} \Phi_{s3} \Delta LTV_{t-s3} + \varepsilon_{t3}, \quad (3.B)$$

$$\Delta LTV_t = \alpha_{1,4} + \beta_{1,4} D_{-1} + \beta_{2,4} HP_{-1} + \beta_{3,4} L_{-1} + \beta_{4,4} LTV_{-1} + \sum_{i4}^{q1} \gamma_{i4} \Delta D_{t-i4} + \sum_{j4}^{q2} \delta_{j4} \Delta HP_{t-j4} + \sum_{l4}^{q3} \varphi_{l4} \Delta L_{t-l2} + \sum_{s4}^{p} \Phi_{s4} \Delta LTV_{t-s4} + \varepsilon_{t4}, \quad (4.B)$$

where $\alpha_{1,1}, \beta_{1,1}, \cdots\cdots, \beta_{4,1}, \gamma_{i1}, \delta_{j1}, \varphi_{l1}$ and Φ_{s1}refer to the coefficients of the right-hand side variables in Eq. (1.B); $\alpha_{1,2}, \beta_{1,2}, \cdots\cdots, \beta_{4,2}, \gamma_{i2}, \delta_{j2}, \varphi_{l2}$ and Φ_{s2} refer to the coefficients of the right-hand side variables in Eq. (2.B); $\alpha_{1,3}, \beta_{1,3}, \cdots\cdots, \beta_{4,3}, \gamma_{i3}, \delta_{j3}, \varphi_{l3}$ and Φ_{s3} refer to the coefficients of the right-hand side variables in Eq. (3.B); and $\alpha_{1,4}, \beta_{1,4}, \cdots\cdots, \beta_{4,4}, \gamma_{i4}, \delta_{j4}, \varphi_{l4}$ and Φ_{s4} refer to the coefficients of the right-hand side variables in Eq. (4.B). Finally, $\varepsilon_{t1}, \varepsilon_{t2}, \varepsilon_{t3}$ and ε_{t4} are the error terms of Eq. (1.B), Eq. (2.B), Eq. (3.B) and Eq. (4.B) respectively.

Following the estimations, F-tests for joint significance of the coefficients of the variables' lags have been calculated and compared with the critical upper and lower bounds values reported by Pesaran *et al.* (2001), to check the presence of a long-term association between the included variables. More specifically, we examine the null hypothesis of no cointegration between the variables: $H_0: \beta_{1,n} = \beta_{2,n} = \beta_{3,n} = \beta_{4,n} = 0$, against the alternative of the existence of cointegrating variables, $H_a: \beta_{1,n} \neq \beta_{2,n} \neq \beta_{3,n} \neq \beta_{4,n} \neq 0$, where $n = 1, \cdots\cdots, 4$ correspond to Eq. (1.B), Eq. (2.B), Eq. (3.B) and Eq. (4.B), respectively.

In the second step, the coefficients of the long-run equations are estimated through normalizing on mortgage delinquency, as shown in Eq. (5.B):

$$D_t = \alpha_{1,1} + \sum_{i1=1}^{p} \gamma_{i1} D_{t-i1} + \sum_{j1=0}^{q1} \delta_{j1} HP_{t-j1} + \sum_{l1=0}^{q2} \varphi_{l1} L_{t-l1} + \sum_{s1=0}^{q3} \Phi_{s1} LTV_{t-s1} + \varepsilon_{t1}. \quad (5.B)$$

As the final step, the error correction models along with the short-term dynamic coefficients are estimated as shown in Eq. (6.B):

$$\Delta D_t = \alpha_{1,1} + \sum_{i1}^{p} \gamma_{i1} \Delta D_{t-i1} + \sum_{j1}^{q1} \delta_{j1} \Delta HP_{t-j1} + \sum_{l1}^{q2} \varphi_{l1} \Delta L_{t-l1} + \sum_{s1}^{q3} \Phi_{s1} \Delta LTV_{t-s1} + \vartheta_1 ecm_{t-1} + \varepsilon_{t1}. \quad (6.B)$$

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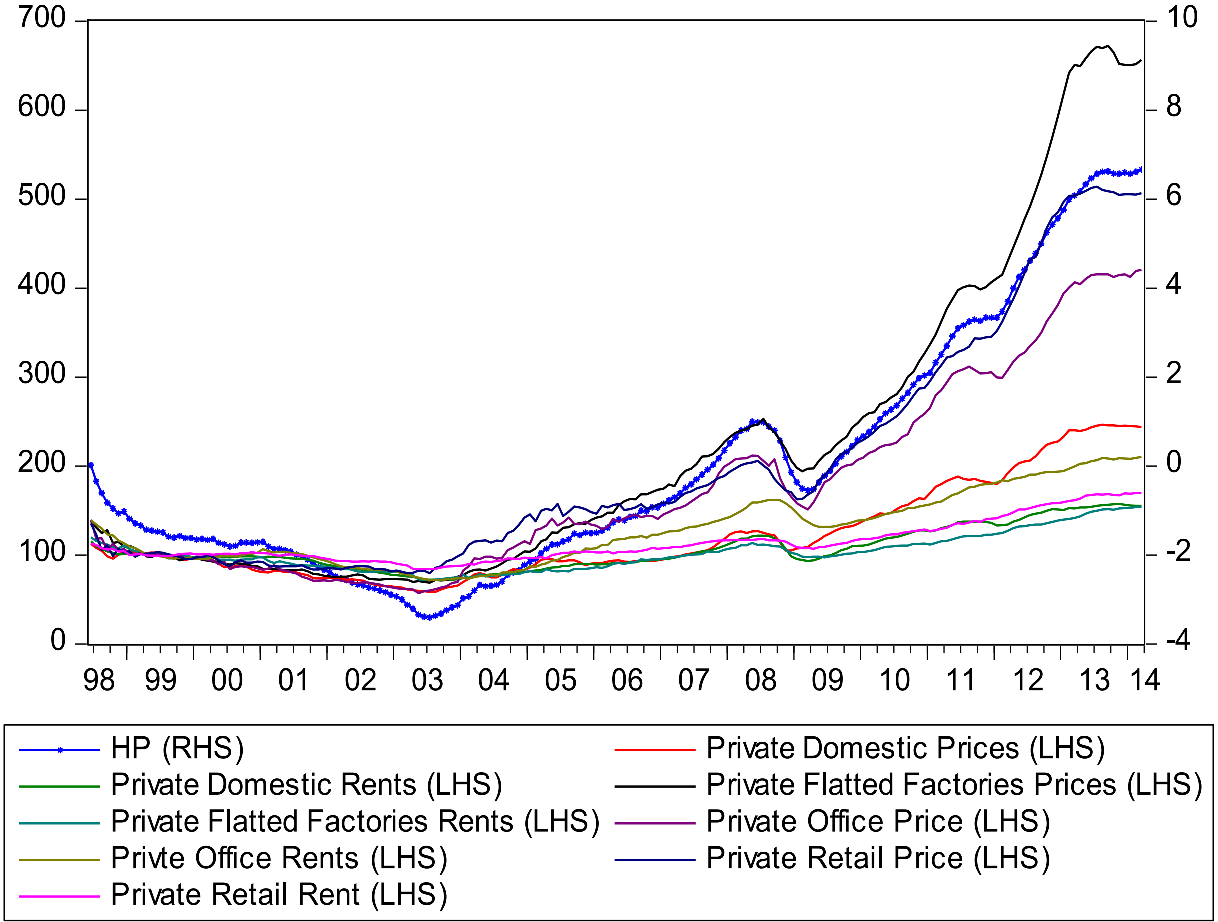
9. APPENDIX

Figure 5 depicts the fluctuations in prices of all types of property included in the principle component analysis (residential, private offices, private retail, and flatted factories are scaled on the left-hand side axis) along with the first component summary indicator for the property prices (scaled on the right-hand side axis) denoted below as (***HP***). It should be noted that the prices and rents of all types of property mentioned above are observed to behave in the same manner over the time period under study, as shown in this figure.

Figure 5 Hong Kong Property Prices and the other Four Types of Property



Note: The summary indicator for the property prices (HP) is scaled on the right-hand axis, while the indicators for the other property price indices (residential, private offices, private retail and flatted factories) are scaled on the left-hand axis.

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