CREDIT DEFAULT AND THE REAL ESTATE MARKET

A Thesis Submitted for the Degree of Doctor of Philosophy

By

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ABSTRACT

Evidence from various countries over the past two decades proves that swings in house prices have been concomitant with financial instability. The history of financial crises shows that the six biggest banking crises in advanced economies were accompanied by housing busts. Despite the abundance of literature on the forces behind the financial crisis, and in particular studies investigating the connections between financial stability and disturbances in the real estate market, fundamental questions still wait for convincing answers, such as: (i) To what extent is regional heterogeneity in property price increases reflected in dissimilarity in the evolution of credit default? (ii) What role do borrower-related factors such as housing affordability and household indebtedness, and financial market-related factors such as financial developments, play on the growth of bad loans as a main concern for banking sector? (iii) To which extent do banks' lending behaviour and property prices undermine the stability of the banking sector, and what are the directions of causality between credit defaults, property prices and banks' lending behaviour? The goal of this thesis is to investigate these issues and explain the practical implications of the findings.

This thesis contains three empirical essays. The first essay explores the nexus between house prices and non-performing loans (NPLs), concentrating on the extent to which geographical variations in house prices are translated into regional variations in credit defaults. The stochastic dominance approach has been used for this purpose, with 372 individual US banks. The stochastic dominance analyses disclose symmetric behaviour between NPLs and the scale of house price increments. The essay is further extended by employing Arellano and Bond's (1991) GMM model to explore the effect of GDP, unemployment rates, lending interest rates and house prices on the growth of NPLs. The outcomes of the GMM estimations reveal a high explanatory power of economic growth, unemployment and lending interest rates on NPLs. In an additional analysis, a generalised panel threshold model is estimated to check for the presence of a threshold point, above

which different impacts of house prices might be found. The threshold model specifications provide a threshold point, in relation to which two different impacts of house prices on the evolution of NPLs are estimated.

A general consensus in the literature attributes credit defaults to a wide-ranging spectrum of drivers that take into consideration borrower-related factor, lender-related factors and factors related to financial and real estate markets. The second essay attempts to answer the second question mentioned above, by investigating the impact of borrower-related factors, lender-related factors and financial market-related factors in driving NPLs. The impact of these factors on the evolution of impaired loans is explored by estimating fixed effect models then the analysis is extended to dynamic models using the GMM procedure on an annual balanced panel dataset. Household vulnerability, financial developments and housing affordability are found to be significant contributors to the growth of NPLs.

The interaction mechanism between the real estate market and the financial system has often been blamed for being the root of financial crises, through the accumulation of housing market bubbles that leads to the ultimate collapse of the financial markets. The third essay, using the Autoregressive Distributed Lag technique, looks for the presence of cointegrating relationships between mortgage defaults, property prices and bank lending in Hong Kong.

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 variables. These outcomes call for more effort to be devoted to maintaining a balanced relationship between these factors. The essay also finds evidence of short-term dynamics between these variables. Importantly, loan-to-value is found to play the most effective role in curbing mortgage default risk in the portfolios of the Hong Kong banking sector.

Dedicated to My Family

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Fawaz Khaled

July 2016

DECLARATION OF AUTHORSHIP

I, Fawaz Khaled, declare that this thesis, titled “Credit Default and the Real Estate Market”, is my own and the included works are done wholly while a candidate for a research degree at Brunel University. I confirm that:

No part of this thesis has been formerly submitted for a degree, award or any other qualification at Brunel University or any other institution, other than that of PhD; this has been clearly stated. This work is entirely my own investigations and I have not plagiarised the work of others, and when others works are consulted, the source is always given and the published works of others are clearly stated by acknowledging the references. Also, all main sources of help have been acknowledged in this work.

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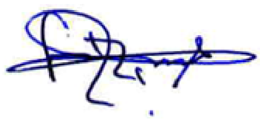

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1. CHAPTER ONE

FINANCIAL STABILITY AND THE REAL ESTATE MARKET

1.1. INTRODUCTION

Over the last two decades, the world has witnessed many financial and economic crises that have curbed the momentum of economic growth. The devastation caused by financial turmoil varies from country to country in several respects, which make it a tough task to talk in general terms about these crises. In some countries, the turmoil has led to complete destruction of the economy, or at least of their financial systems. These crises revealed several characteristics of financial system dysfunction that destabilise the financial markets and undermine their key role in channelling the available economic resources efficiently towards more prosperous economic growth.

The literature related to financial crises discriminates various shapes and forms of financial crisis in terms of classification. Reinhart and Rogoff (2009a) classified two groups of financial crises according to the theoretical framework behind the explanation of each crisis. The first group is categorised under strictly quantitative definitions and discriminates between currency and sudden stop crises. The second group relies mainly on qualitative definitions and distinguishes between two types of financial crises, debt and banking crises. In general, the group under which a crisis is categorised is strongly influenced by the theoretical framework used to explain crises.

By definition, a currency crisis refers to speculative activities that involve the national currency in such a way that they lead to a sharp depreciation in the purchase value of that currency. These activities put heavy pressure on governments to consume larger amounts of their international reserves in an attempt to safeguard their national currency, or increase interest rates. In an influential study, Kaminsky and Reinhart (1999) found currency crises to be often preceded by or associated with banking crises, providing evidence of an overlap between the two crises and referring to this concurrence as “twin crises”. They further found that banking crises occur as a result of various events, including recessions, a worsening of the terms of trade, slumps in the stock market, an overvalued real exchange rate and lending booms with an increase in the cost of credit and real interest rates.

The second type of financial crisis, sudden stop, is associated with banking system turmoil and refers to a situation of severe decline in international capital inflows, or a sharp reduction in national capital flows, often associated with a rigorous increase in credit spreads. A foreign debt crisis in a country represents the case of suspending or stopping its foreign debt service (intentionally or unintentionally). On the other hand, a domestic public debt crisis happens when countries stop performing their domestic fiscal responsibilities, by defaulting or exposing their currency to high rates of inflation, or by engaging in other types of financial repression that help reduce the burden of loan repayments.

Generally speaking, a banking crisis is a type of financial crisis that influences the behaviour of banks in managing their assets and liabilities, and their holding of equities. In the wake of a financial crisis, lending institutions are more likely to be exposed to a so-called “*bank run or bank panic*”, in which, almost simultaneously, sudden heavy cash withdrawals are performed by depositors as a result of a loss of confidence in the viability of the bank, due to an expectation that it may become insolvent, or when depositors foresee a slowing down or dramatic collapse of the local economy (Fratianni and Marchionne, 2009).

The phenomenon starts as a panic due to the fears of some of the bank’s depositors. With more people prompted by others to withdraw their funds, the phenomenon rapidly changes to become more real, rather than a true insolvency of the bank. The occurrence of this phenomenon results in a higher probability of the bank defaulting or going bankrupt, in particular if they keep insufficient reserves to fulfil their depositors’ withdrawals. Due to systematic risk factors, the banking industry in a nation is exposed to financial problems in fulfilling their payments if withdrawals are required suddenly by depositors. This in turn triggers various problems concerning banks' loans in the sense that it eats into the banks' accumulated capital due to increases in interest rates, a slowdown of capital flows and depreciation in asset prices, where real estate assets have the highest share of their loan portfolio (see, for example, Laeven and Valencia, (2008)).

As a matter of fact, the history of financial crises provides evidence of bank runs, such as the Bank of America in 1931 and the British bank Northern Rock in 2007 (see, for example, Shin, 2009). Owing to bank runs, around twenty-five US banks went bankrupt during the financial crisis in 2008 causing a severe drop in their stock prices and the instant downgrading of their assets by credit rating agencies such as Standard & Poor's (S & P), Fitch Group and Moody's (see, for instance, Fernando *et al*., 2012).

According to Cameron *et al*. (1967), banks, as providers of funds and intermediaries between depositors and borrowers, have been often regarded as "*the lubricant of the economy*", which justifies the heavy regulation governing this sector. Banks channel credit from depositors to borrowers who have investment opportunities, including owning property. They do so by engaging in borrowing and lending activities with large groups of participants, taking advantage of diversified loan portfolios and sharing their credit risk with their depositors (Allen *et al*., 2009). Working as intermediaries, it is reasonably acceptable that banks are exposed to risk attached to the two parties that banks mediate between.

Indeed, a general consensus in the literature identifies the essential role that significant changes in the composition of banks' funding resources and banks' lending concentrations played in the financial instability of banking systems during the past few decades. This has led to a strong interconnection between financial markets and banking systems (see, for example, Borio (2009), Boot and Thakor (2010) and Song and Thakor (2010)). In light of this interdependence, banks developed highly sophisticated means of risk hedging in order to ensure their stability. To avoid problems on the depositors' side, financial institutions first tried to develop new opportunities to raise their capital resources, such as the originate-todistribute securitisation model as opposed to the originate-to-hold model. Second, banks rapidly started to engage in investment activities by using wholesale funding with a particular interest in short maturities funds (see, for example, Martel *et al*., (2012)). Third, financial globalisation allowed banks to obtain funding from international markets, which has led to the heavy dependence of banks of many nationalities on international interbank US dollar markets (see, for example, Fender and McGuire (2010a and 2010b)).

Tracing the history of banking crises, it can be easily noted that most of the crises have been exacerbated by the excessive dependence of banks on particular sources of funding. Bank disproportionately diversified the composition of their financial instruments, in terms of maturity and currency of banks’ portfolios, which paved the way for additional sources of financial risk accumulation that may have negatively contributed to the creation of banking crises. The most severe global banking crisis, which rocked the world in 2007-2009, demonstrated the deficiencies of financial systems that relied excessively on short-term wholesale financing in a disproportionate manner. Evident examples of that behaviour could be seen in the policies adopted by Lehman Brothers and Bear Stearns in the United States, among others.

On the other hand, to overcome troubles associated with borrowers’ activities, banks developed many tools, such as provisions, to hedge themselves against credit risk. They use macroprudential tools such as loan-to-value (LTV) to dampen the impact of fluctuations in property prices and housing cycles on their financial stability. The LTV ratio is defined as the ratio of the maximum allowed loan to a borrower compared to the value of their house.

The experience of Hong Kong’s LTV policy in this regard is widely investigated in the literature and the effectiveness of using the tool is highly appreciated in reducing systemic risk accompanied with cycles of boom and bust in real estate markets.[1] Empirical evidence

[1] According to Caruana (2010a), “systemic risk is a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy”.

shows that the use of an LTV cap in Hong Kong helped control both borrower leverage and credit growth. This in return has played a key role in strengthening banks' resilience to risks associated with credit-property price spirals, by encouraging banks to keep higher amounts of provisions at origination, in order to achieve a lower probability of negative equity and defaulting (see, for example, Wong *et al*. (2004) and Wong *et al*. (2011)). Caps on LTV could help manage credit supply as well as credit demand. From the demand side, caps on LTV might result in kicking some house-buyers out of the market, owing to liquidity shortages or lower profits from investing in the property market. Similarly, LTV caps influence credit supply through imposing restrictions on lending policy by the national authority. For example, Thailand introduced an LTV policy for residential property in 2003, followed by procedures for computing risk weights on lending for house purchases, alongside the use of a specific ratio of LTV, in order to hedge risks that stem from excessive supply in particular sectors of the residential property market. Many other examples from the literature and empirical analyses show the role of using LTV limits in softening the exposure of banks to fluctuations in property prices.

There is a growing consensus that the majority of banking crises have been instigated by property price boom and bust cycles induced themselves by credit cycles. During property price booms, banks' appetite for risk grows, fostered by competition with other peer banks, resulting in them building up excessive exposure to real estate prices. When the boom period finishes and the bust period starts, property prices start to decline, resulting in high amounts of negative equity in the banks' holdings and a severe upsurge in the volume of NPLs, which undermines the stability of the banking sector.[2] Herring and Wachter (2003) assert that financial crises have often been outcomes of boom and bust episodes in real estate markets.

The history of financial crises presents a lot of evidence supporting the notion that banking crises such as the 2007-2009 global crisis originated in the real estate market.

[2] According to Bexley and Nenninger (2012), non-performing loans are loans that are ninety days or more delinquent in payments of interest and/or principal, and are considered bad or toxic assets in banks' accounts.

Furthermore, well-supported literature concerning financial crises around the world has confirmed the key role that fluctuations in real residential and commercial property prices play in igniting banking and financial crises. The link between real estate prices and banking crises has been widely investigated in the literature. In their seminal study, Kaminsky and Reinhart (1999) empirically established a connection between asset prices and banking crises. Although their main concern is on equity prices, their work has sparked numerous empirical studies investigating the correlation between house price dynamics and banking crises.

In an attempt to analyse the dynamics of residential property prices in sixteen of the countries rocked by the global banking crisis, Reinhart and Rogoff (2008) reported significant growth in residential property prices in the period preceding the sub-prime crisis, with the USA being the most obvious case of this behaviour. Later, in their comprehensive series of studies, Reinhart and Rogoff (2008a, 2008b and 2009) revealed that systemic crises in the banking industry are characteristically preceded by credit amplification and asset price surges. Furthermore, they document the negative consequences of the crisis resulted in a significant depreciation in house prices of around 35% over a time period of 6 years, a decline in equity prices of about 55% and a drop in GDP of 9%. These events were found to be associated with a huge increase in government debt, of approximately 86% in comparison to the period before the crisis, as well as an increase in unemployment rates of about 7% over 4 years.[3]

In his review of regulatory responses to the global banking crisis, Turner (2009) tries to draw attention to the impact of housing markets, with special emphasis on the role of house price swings in destabilising banking systems, and in the light of the events of the sub-prime crisis that took place in 2007-2008.[4] He suggests that credit expansion, stimulated by

[3] For further reading on the results of the financial and banking crisis, see Allen et al. (2009). Additionally, for an overview of the recent financial pre-crisis and post-crisis events, see Brunnermeier (2009).

[4] See FSA (2009). “The Turner Review: A Regulatory Response to the Global Banking Crisis”. Financial Services Authority, March 2009.

historically low interest rates during the sub-prime period, followed by property price appreciation, resulted in an increase in the value of households' assets, leading to crisis in the US and UK. In addition, Turner (2009) revealed that the crisis in the UK was highly aggravated by an increasing demand for housing with low responsiveness of the physical supply in a sense that boosted the total mortgage debt to GDP from 50% to more than 80% over a period of a decade, starting from 1997.

The history of the recent financial crisis provides evidence of the low lending interest rate policies of central banks, which helped to increase the appetite for excessive bank lending to expand market shares, leading to higher increases in credit growth. These events resulted in a dramatic increase in property prices, which reached their peak in 2006 in a majority of countries, including the US, UK, Ireland and Spain (see, for example, Allen *et al*., 2009). At the end of 2006, house prices underwent a dramatic depreciation, which resulted in considerable growth in the volume of negative equities held by banks. These events put tremendous pressure on financial institutions, forcing banks to consider high haircuts in the light of the poor quality of their held collaterals. These burdens became unaffordable in the second half of 2008 with the collapse of Lehman Brothers, which caused banks to incur sizeable financial losses. This distortion in their financial position led to a loss of confidence in financial institutions, resulting in a rush by investors to withdraw their deposits, which was mirrored by liquidity drying up. Later, these events translated into decelerated economic growth in the majority of developed countries, with dramatic upsurges in unemployment in March 2009 (see, for example, Allen *et al*., 2009).

Against this backdrop, profound understanding of housing market dynamics, and more importantly the mechanism that governs house price evolution, on the part of regulators is crucial to avoid the high costs of banking or financial crises. Given the mutable nature of financial markets in an environment of competition between banking intermediaries, the need for more detailed data resources on residential property price-related factors is an extremely urgent issue.

From the practical perspective of macroprudential development, there have been numerous suggestions to accommodate real estate-related factors when considering models to scrutinise the drivers of banking and financial crises (see, for example, BIS (2001)). As indicated above, these suggestions have been built on the premise of controlling house prices within a reasonable range, due to the negative consequences of their oscillation on banks' stability. There is a general consensus that these consequences are mostly stimulated by the highly disproportionate concentration of banks' loan portfolios in this sector (IMF, 2000), which jeopardises banking stability and exacerbates their exposure to boom and bust cycles in the housing market.

Generally speaking, academic researchers often look at the incidence of banking crises as a function of excessive accumulation of NPLs that might comprise, particularly during periods of banking crisis, a sizeable share of loan portfolios in some insolvent banks (see, for example, Fofack (2005)). As stated in the Basel II accord in 1999, a loan is conceptually classified as non-performing when any of the following events take place: a borrower is 90 days late on repayment of either the principal or its interest, a borrower's repayment changes to being improbable, the bank keeps provision of a loan, the liabilities are restructured as part of the losses of the bank, the bank claims or sells the loan at a loss and finally the bank writes off the loan.

A high ratio of NPLs is one of the main drivers of bank insolvency that may undermine the stability of the whole economy (Hou, 2007). For instance, the banking crisis that affected a considerable number of sub-Saharan African countries in the 1990s was also associated with a massive growth in the ratio of NPLs (Fofack, 2005). Furthermore, around 70 Indonesian banks collapsed and 13 were nationalised in the wake of the Asian financial crisis between 1997 and 2002, in which the ratio of NPLs comprised about 75 per cent of banks' loan portfolios. In the case of the US, more than 1400 savings and loan institutions and 300 banks failed between 1984 and 1991 (for a full review of episodes of systemic financial crisis, see Caprio and Klingebiel (2002)).

The repeated occurrence of these events in various banks around the world poses many questions concerning the nexus between real estate markets and financial stability. Among other questions, what are the main drivers of impaired loans? To what extent does an upsurge in the level of bad loans in banks' loan portfolios indicate the onset of a banking crisis, or at least the failure of these banks? To what extent is banks' loan performance exposed to housing market factors such as property prices and macroeconomic fundamentals? What are the consequences of increasing NPL ratios on the development of real estate markets? And, more importantly, what tools can be developed to insulate the stability of the banking system from perturbations in the real estate market? Actually, many of these questions have been addressed in scholarly research to investigate factors that can systematically lead to adverse shocks and failure in the banking sector (see, for example, Allen *et al*. (1995), Barr and Siems (1994) and Kaminsky and Reinhart (1999), among others).

To address the problem of credit defaults from a wider perspective, a suitable metaphor may help to convey the idea. A chain is only as strong as its weakest link. However, that does not necessarily imply that the deficiencies in the weakest link comprehensively explain why the chain breaks at that link. Rather, understanding the reasons behind the tension that caused the break in the chain is crucial, because strengthening the weak links is only useful if we can determine these links before the chain breaks. Furthermore, even if we aimed to strengthen these links, what will be achieved is the exposure of other links in the chain to breaking when the tension on the chain becomes considerably greater.

Credit defaults are regarded in the literature on financial crises as one of the most destabilising factors in the banking sector. Therefore, the weak links in the credit default chain refers to factors identified in the literature to be among the drivers of credit defaulting and banking instability. These links have been developed in the existing literature over time and can be categorised in three generations (see, for example, Quercia and Stegman (1992)). Below, we consider these generations in turn.

The first identifiable weak link is attributed to loan characteristics, such as loan-to-value at origination, debt-to-income, mortgage interest rate and payment-to-income. Each of these factors has been addressed in many empirical works, while some studies went even further to differentiate between several mortgage products, since each product implies a different level of risk exposure. The second weak link is expanded to account for macroeconomic fundamentals in addition to real estate factors. Unemployment rate, GDP growth rate, property price changes, stock price fluctuations and current loan-to-value are among the explanatory variables that are recognised in this generation of credit default models. The final generation of credit default models looked at borrower-related factors as the weakest links in the credit default chain. In this generation, factors such as income and consumer price index, in addition to borrowers' education, ethnicity, age, occupation and other borrower-related factors, were considered by researchers as the weakest links of the credit default chain.

Each of the generations mentioned above focus on a different aspect, but looking at the weakness in individual links helps to strengthen the identified link only, rather than the entire chain, and hence does not seem to be sufficient to maintain sound and reliable banking systems. This is particularly true if we assume the existence of other omitted factors that might play roles in undermining the stability of the banking sector, such as the regulatory framework. Based on this argument, developing models for credit defaults must account for the effects of specific factors, controlling for the impact of the other identified factors recognised in the established literature.

Numerous studies have been conducted to assess the drivers of NPLs. Some of these works looked at macroeconomic variables as key determinants of the level of NPLs. The macroeconomic variables that have been identified as drivers of NPLs include lending interest rates, unemployment rates, growth in gross domestic product (GDP), inflation rates and exchange rates. For example, Louzis *et al*. (2010), Salas and Suarina (2002), Fofack

(2005) and Jimenez and Saurina (2005) analysed the role of growth in GDP and found NPLs to be negatively influenced by GDP growth. This relationship has been justified on the basis of income growth, which is assumed to be associated with an increase in GDP, leading to higher repayment capacity by borrowers, contributing to a lower volume of NPLs. Unemployment rates, on the other hand, have been found to have a positive relationship with NPLs. The explanation of this relationship relies on the fact that an increase in the unemployment rate negatively impacts borrowers' incomes, leading to higher debt burdens and consequently a higher probability of default (see, for example, Nkusu (2011), Bofondi and Ropele (2011) and Rinaldi and Arellano (2006)). As for lending interest rates, empirical evidence shows a positive correlation between the interest rate and impaired loans, since an increase in the interest rate is supposed to result in higher debt costs, which implies greater burdens on the borrowers, reducing their repayment ability (see, for example, Nkusu (2011) and Louzis *et al*. (2010)).

NPLs may have a catastrophic impact on banks' survival and the entire economy, leading to banking failures and financial meltdown if not governed appropriately. It has been emphasised in the literature that a high ratio of NPLs in banks' loan portfolios can badly influence the profitability, liquidity and solvency position of financial institutions (see, for example, Michael *et al*. (2006)). Determinants of banks' credit defaults have been widely debated in the literature and empirical studies; however, exploring borrowers' defaulting behaviour in relation to the real estate market is of high importance, in order to measure and mitigate banks' exposure to real estate market imperfections. It also helps to notify borrowers of the penalties of withholding contractual payments, providing them with plenty of time to develop effective tactics for homeownership. Default behaviour studies are also valued by policymakers due to their importance for assessing the feasibility and efficiency of strategies to enhance homeownership, without exposing banks to a higher volume of credit defaults (see, for instance, Nang *et al.* (2003)).

Therefore, the main goal of this thesis is to investigate the determinants of default risk, whether it is NPLs or loan delinquency, and look at the connection between default risk and some housing-related proxies and borrower-related factors, taking into account the impact of the macroeconomic fundamentals that are identified in the established literature on the development of default risk.

CHAPTER TWO explores the nexus between house prices and NPLs using balanced panel data for US metropolitan areas. Holly *et al.* (2010) argues that the dynamics of house prices differs remarkably across time as well as across geographical dimensions. Based on Holly's suggestion, we use a stochastic dominance approach to examine the presence of regional disparities across 372 individual US banks, located in 47 states. In other words, we examine the extent to which regional variations in the origin of credit defaults, proxied by the ratio of NPLs as an indicator of ex-post credit risk, are in line with geographical variations in house prices across US metropolitan areas.

To capture the impact of the financial crisis, we select a subsample to reflect the pre-crisis housing boom period, during the crisis when the build-up of the house price bubble took place, and post-crisis bust period, to examine the relationship between NPLs and house prices during the different phases of the financial crisis. Furthermore, the US states have been divided into four groups according to fluctuations in the house prices projected in these states prior to the onset of the financial crisis in 2006. As a non-parametric procedure, stochastic dominance offers a framework based on the actual data distribution, using the entire data set in order to overcome the problem of being driven by randomly selected statistics. This feature of the stochastic dominance method is of high importance in our case, as it appropriately accommodates the asymmetric regional behaviour of the variable of interest (NPLs). In the second step of the analysis, we use Arellano and Bond's (1991) GMM model to check the effect of some macroeconomic fundamentals, including GDP, unemployment rates and lending interest rates, on the growth of NPLs; then in an additional analysis, we account for the impact of property prices. In the final step of our analysis, we utilise a generalised panel threshold model, allowing for regime intercepts suggested by Bick (2010), to test for the existence of a threshold point at which different impacts of house prices might be found. To this end, house price index returns serve as a threshold parameter, while macroeconomic fundamentals are included as control variables.

The outcome of the stochastic dominance procedure reveals a hierarchical ranking of NPL distributions, which starts with the states where house prices increased by less than 20%, and moves progressively through 40% to end up with the states where house prices underwent increases of more than 80%. This means the highest volume of NPLs is found in states that experienced house price upsurge of more than 80%, and the volume decreases steadily in states with lower house price increases. Therefore, this ranking of NPL distributions implies a symmetric relationship between NPLs and the level of house price increments observed. The implications of these findings are that plans to guard against banks' exposure to fluctuations in the real estate market should be: (i) designed locally, taking into consideration the regional heterogeneity and idiosyncratic factors of each states, rather than designed at the national level, (ii) consistent with the economic phase under consideration.

The results of the GMM model suggest that the rate of NPLs is mainly driven by economic growth, unemployment and lending interest rates. Particularly, increasing GDP and decreasing unemployment and lending interest rates play fundamental roles in reducing the rate of NPLs. Furthermore, the second GMM model reveals that house prices are negatively related to growth in NPLs, which is consistent with many studies in the related literature.

Finally, threshold specifications with regime intercepts deliver a threshold point, beyond which different impacts of house price index returns are inferred. This means that regime-dependent regressors specify two different effects of house prices on the evolution of NPLs, according to the relative position of house prices to the estimated threshold point. Furthermore, the detrimental impact of house prices on NPLs seems to be less pronounced when the house prices fluctuate below the threshold value, and become greater when house prices exceed the threshold point. Therefore, keeping house prices below the threshold point should be an indispensable aim of real estate policymakers, in order to maintain sustainable low ratios of NPLs. Interestingly, the history of house price development over the period under scrutiny is highly consistent with the estimated threshold point. In other words, the development of house prices during the period reveals that house prices was fluctuating close to the threshold point from 1999 to 2004, after which they started to increase progressively, above the threshold point, and the destructive effect of house price changes on banks' stability increased accordingly.

CHAPTER THREE investigates the factors driving NPLs, with special emphasis on house price fluctuations, housing affordability, household vulnerability and financial developments. This chapter is based on various arguments highlighting the key roles that the real estate market, the financial market and the financial status of the players in these markets play in driving credit defaults and creating banking and financial crises.

The collapse of real estate markets in several countries led to the recent financial crisis, which created pervasive economic and financial fallout. On one hand, banks suffered from a sharp increase in NPLs triggered by episodes of boom and bust in the real estate market. On the other hand, the same financial institutions have been blamed as some of the main contributors to the formation of residential property price bubbles, by means of their lending behaviour over the period preceding the crisis. This clearly explains the key role that swings in house prices play in systemically undermining the stability of the banking structure as a whole. These events pose the question of whether banks' stability is connected to changes in real estate market conditions, and whether loan performance is greatly affected by fluctuations in house prices. This belief can be attributed to the fact that loans for house purchases constitute the main bulk of bank loans in the majority of the world's countries, while the impact of house price changes increases in the case of collateralised loans that use property to guarantee loan repayments (see, for example, Davis and Zhu (2010)). The impact of the banking industry on real estate has been extensively investigated, however, the reverse impact of property prices on bank credit is not clear (see, for instance, Hofmann (2001) or Davis and Zhu (2004)). This urges the need to investigate the destabilising impact of the real estate market on the banking industry, with special attention to its impact on banks' loan performance.

As house purchases imply access to credit, this in turn implies a strong correlation between the real estate cycle and the credit cycle (Beckett, 2014). Indeed, both financial development and lending behaviour have been identified in the literature on credit defaults to be a crucial driver of the ratio of NPLs (see, for example, Jimenez and Saurina (2005), Sinkey and Greenwalt (1991) and Keeton (1999)). For example, Salas and Saurina (2002) identified rapid credit growth as one of the factors that help explain changes in NPL ratios. Aggressive lending behaviour was seen to be associated with an increase in housing demand in most OECD countries, which resulted in an upsurge in real house prices. Appreciation in house prices encouraged investors to become involved in borrow-to-buy homes and other speculative activities, leading to highly volatile house prices and consequently a high probability of defaults. This link poses other important questions concerning the impact of credit availability and financial development on the evolution of credit defaults. The impact of NPL growth on the credit cycle has been examined by Caporale *et al*. (2009), who reported a negative effect of NPLs on credit to the private sector, as a proxy for financial development. However, a possible reverse impact of financial development on the volume of NPLs has not been tested. Hence, using a more sophisticated measure of financial development, we try to fill the gap by testing the influence of this factor on the level of NPLs.

Owning a house is a major investment that many people wish to make; however, the affordability of owning a house is the most vexing problem for households, as well as for financial institutions. It refers to the ability to access housing of an acceptable standard, at a cost that does not overburden a household in each income class. That means an unaffordable house would expose the borrowers to additional encumbrances that reduce their ability to pay back their debts, resulting in a higher probability of defaulting and a higher rate of NPLs. Therefore, housing affordability is expected to have an important impact on the growth of bad loans. Closely related to housing affordability, household indebtedness essentially influences default decisions according to the "*ability-to-pay default theory*", and hence could be another candidate as a driver of NPLs. Since household fragility is accounted for when lenders assess loans' demanders to get loans, this lends legitimacy to the inclusion of this factor in our analyses as a driver of NPLs (see, for example, Salas and Saurina (2002) and Jappelli, Pagano and Maggio (2008)).

We used a balanced panel dataset of 23 countries with fundamental heterogeneity in the scales of house price evolution, household indebtedness, house affordability and financial development to scrutinise the impact of these factors on the evolution of impaired loans. To this end, we employed both static models and dynamic panel data models over an annual balanced panel dataset to examine the impact of the abovementioned factors, as well as control for the effect of some widely tested financial and macroeconomic variables on the growth of NPLs.

The chapter contributes to the existing literature of NPLs in combining borrower-related factors, bank-related factors and market-related factors by developing indicators to link households' financial status, house affordability and financial development to examine their contribution to the performance of bank loans. The empirical investigation is, to the best of the author's knowledge, one of the rare studies that use country-level data to investigate impaired loan determinants. Furthermore, in contrast to many previous studies, the empirical work accounts for drivers of housing supply and demand, by including indicators for household financial status, financial development and credit availability, housing affordability and household vulnerability. In comparison to many other empirical studies, which were limited to fixed effects models that ignore major differences in the dynamics of house prices, as asserted by Holly *et al.* (2010), we account for heterogeneity between the countries by extending our analyses and employing Arellano and Bond's (1991) two-step difference GMM dynamic models.

Overall, the estimated models are able to explain the variations in NPL ratios in the selected economies reasonably well, and the models are consistent with the findings provided by the related literature. According to the fixed effects model, economic growth reveals a negative association with the evolution of NPLs, while unemployment rates and interest rates have been found to have a positive impact on the level of NPLs. Real residential property price fluctuations are found to be negatively correlated with the volume of NPLs, revealing the high sensitivity of loan performance to fluctuations in real residential house prices. Household vulnerability shows a positive association with the level of NPLs, indicating that higher household indebtedness implies a higher default probability by undermining borrowers' ability to pay back their obligated debts. As for the financial development indicator, the overall effect of financial development is highly significant, with the positive sign indicating that easier access to credit and a relaxation in lending standards would result in an increase in the scale of NPLs. Finally, housing affordability seems to have a positive significant association with NPLs, meaning that when the affordability of the houses in a country decreases (increases) so the level of NPLs does. However, more mixed results have been detected when dynamic models are employed, which will be addressed later in CHAPTER THREE.

CHAPTER FOUR inspects the long-term equilibrium relationship and short-term dynamic between mortgage defaults, property prices and bank lending in Hong Kong, controlling for the impact of loan-to-value. Investigating mortgage delinquency can deliver an important advantage, since delinquency is the first step towards foreclosure or defaulting, according to Ambrose and Capone (1998). Detecting cointegration between mortgage delinquency, property prices, lending behaviour and loan-to-value has considerable practical implications. In other words, it indicates a persistent need for additional efforts to control the balance between these multidirectional effects, by utilising a multifunctional toolkit of financial, monetary and macroprudential methods, in order to plan the right policy to ensure financial stability. The choice of Hong Kong is based on various considerations that make it an interesting case study, such as it being an externally-oriented country, the Currency Board regime that links the Hong Kong dollar to the US dollar, the high level of government intervention in the residential market, its history of mortgage delinquency, residential property prices and bank lending.

Empirical studies on the link between banks' lending behaviour, property prices and banks' credit risk have often been conducted using a single equation setup, focusing on the impact of one of these factors on the others, rather than the interaction and the magnitude of the effects between them, as a "*simultaneity problem*". The main purpose of this study is filling this gap by testing the presence of possible long-term dynamics and short-term effects between bank lending, residential property prices and mortgage defaults in a multivariate cointegration framework. An Autoregressive Distributed Lag ($ARDL$) bounds test for cointegration on time series is used to test the plausible existence of long-term dynamics and short-term relationships between the abovementioned variables, in light of the mortgage default literature, which provides theoretical explanations for the interaction between these three variables.

Evidence of cointegrating relationships between these variables has been found. Our findings indicate the existence of cointegrating relationships that govern the correction mechanism between bank lending, property prices and mortgage defaults in the long term. These findings confirm that any disequilibrium in the relationship between these variables is corrected and converges back, with a moderately good speed of adjustment, to its long-term equilibrium. Also, we find evidence of short-term dynamics between these variables. A negative impact of property price changes on the growth of mortgage defaults has been detected, while the role that banks' lending behaviour plays on the evolution of mortgage defaults is found to be positive. Loan-to-value, as one of the most popular macroprudential tools, seems to have the most influential role in reducing mortgage defaults in the Hong Kong banking system.

CHAPTER FIVE summarises the main questions addressed in this thesis, along with the most important results and the conclusions drawn from the empirical analyses. It also provides some recommendations to avoid the perils that stem from the interaction between real estate markets and credit defaults. Moreover, it recognises some limitations in this study and delivers thoughts on potential future studies.

2. CHAPTER TWO

REAL ESTATE PRICES AND CREDIT RISK: AN INVESTIGATION INTO NON-PERFORMING LOANS IN THE US

2.1. INTRODUCTION

The real estate market plays an important role in the US economy, as developments in the housing market indicate the prosperity of the whole country. Since the onset of the subprime mortgage crisis, ignited by the bursting of the housing bubble in 2007, the world's economic growth has been sluggish. Episodes of real estate boom and bust have been found to contribute to financial instability in different countries over the last few decades. Nevertheless, the extent to which sustained imbalances in the housing market undermine financial stability and banking soundness is not yet well understood.

Holly *et al.* (2010) observed that the dynamics of house prices varied markedly both over time and across countries. The increase in real estate prices prior to 2006 was far from uniformly distributed across all US metropolitan areas. Rather, real estate markets witnessed substantial heterogeneity in the magnitudes of their house price fluctuations, which seemed to be geographically clustered across US metropolitan areas (see, for example, Sinai (2012)).[5] While house prices underwent unprecedented booms in some states, others were barely influenced at all.[6] For example, house prices in markets located in cities on the East and West coasts, including Los Angeles and Miami, underwent a twofold upsurge on the average between 1998 and 2006. However, much smaller house price growth was witnessed

[5] Sinai (2012) documented that the 75th percentile MSA observed to have 111% trough-to-peak growth in real house prices between 1990s and 2000s, whereas only 32% trough-to-peak real house price growth was detected at the 25th percentile.

[6] Greenspan asserted that housing bubble in the US in 2005 was local bubbles rather than one nationwide bubble, although these bubbles integrated later, in 2007, to create a bubble on a larger scale (see "Greenspan Alert on US House Prices". Financial Times, September 17, 2007).

over the same time period in several interior metropolises, such as Dallas and Denver. Regional disparities in the impact of house prices on the growth of bad loans have been neglected in empirical works, and a definite answer as to whether NPLs and house prices evolve in a symmetrical manner across geographical regions is still to be found.

The present study attempts to address the question of whether regional differences in the escalation of house prices reflect similar behaviour in the evolution of NPLs, by using non-parametric and parametric models. Investigating the impact of house prices on impaired loans at the state level provides a great advantage, since restricting the analyses to an aggregated perspective at the country level might omit fundamental variations in the dynamics of this relationship. Moreover, geographical heterogeneity in real estate prices and NPLs in the US can be better captured by using disaggregated data for NPLs and house prices. Hence, a yearly balanced panel dataset for individual banks across US states has been used to address the regional heterogeneity in the scales of non-performing loans in light of the geographical disparities in house price developments.[7]

As for property prices, we focus on residential property prices rather than other types of property in the real estate markets of the US. Our choice rests on the consideration that residential property comprises more than 76% of total mortgage loans, while all other types of property, including commercial properties, constitute on average only 24% of mortgage debt for all holders over the period 2000-2010.[8] Therefore, residential properties play a key role in fostering instability in the financial sector.

A mainstream of empirical works has been conducted on the relationship between NPLs and house price developments. Although some studies accounted for the origin of the financial crisis at the international level by investigating the contagion effect across countries, local disparities in the origins of credit defaults, which were triggered by local swings in house prices (within a country) have been ignored in these works. In other words, many

[7] A detailed description of the data and the sampling procedure is provided in Section 2.4.
[8] These figures were obtained from the Federal Reserve Board.

empirical works addressed the transmission mechanism of credit defaults across countries, in which house price developments play the key role. However, to the best of the author's knowledge, no efforts have been made to investigate the heterogeneity in the effects of house prices in driving credit defaults at the local level.

We conjecture that the behaviour of NPLs is closely related to that of property prices, which varies geographically, as observed by Sinai (2012). To test our hypothesis, states in the US have been divided into four categories according to their house price trajectories. Stochastic dominance (SD) tests have been employed to investigate the presence of regional dissimilarities in the impact of house prices on the volume of impaired loans. Stochastic dominance is a nonparametric method that offers a framework based on the entire empirical distribution of NPLs, rather than a few arbitrary moments. This feature makes the SD framework particularly attractive due to asymmetric developments in our variable of interest (NPLs) within the chosen sample.

The disproportionate exposure of banks' stability to changes in house prices is not only limited to the cross-sectional dimension, rather, there is general consensus that it varies over time, between episodes of house price booms and busts. In light of this argument, the impact of property prices on the evolution of NPLs is likely to be different in a period of a booming real estate market than in a period when the market is going bust. In order to examine the different levels of exposure of loan performance to house price changes during episodes of market boom and bust, we undertake a stochastic dominance analysis for selected years that can reflect the relationship between house prices and bad loans over periods of house price booms and periods of house price busts.

The responsiveness of NPLs to fluctuations in house prices presumably depends on the scale of house price deviations from their fundamental values. In other words, the impact of house prices on the escalation of NPLs is supposed to be driven by the magnitude of departure of the former from their long-term values; different impacts of property prices are expected when house prices depart from their fundamental values by different amounts. We intend to investigate the nexus between NPLs and house prices to check for the presence of a threshold point, above which house prices become severely detrimental to banks' loan portfolios.

For this purpose, we estimate a panel threshold model, allowing for regime intercept estimates, as proposed by Bick (2010), which is a generalisation of the threshold model proposed by Hansen (1999), to determine the existence of a threshold point endogenously instead of splitting our data depending on an exogenous criterion. Estimating this point is of high importance and has essential policy-related implications. These implications are twofold. First, the threshold point, as well as the lower bound of the corresponding confidence interval, designates the point at which increase in house prices becomes perilous to the stability of the banking industry. Second, a slight departure of house prices from the threshold point is amplified and translated into a considerably larger-scale exposure of banks to house price fluctuations. Therefore, keeping house prices around the threshold point contributes to a sustainable protection for the banking sector against house price shocks, and helps the former to achieve better loan performance ratios.

A substantial group of empirical works support the robust existence of the high association between NPLs and macroeconomic fundamentals, such as GDP growth, unemployment and inflation, in addition to bank-related factors such as lending interest rates (see, for example, Nkusu (2011), Rinaldi and Arellano (2006), Collins and Wanjau (2011), Bofondi and Ropele (2011), Louzis *et al*. (2010) and Salas and Saurina (2002), among others). A general explanation for the effects of these factors on NPLs relies on the argument that changes in any of these factors undermines borrowers' ability to service their debts through their income channel, exposing them to higher financial burdens, translated later into a higher probability of defaulting. NPLs are supposed to have relationships with macroeconomic fundamentals, financial indicators and house prices. Therefore, in addition to estimating the direction and magnitude of the impact of house prices on NPLs, the effects of unemployment rates, economic growth and lending interest rates are quantified in a nonlinear dynamic context by employing robust Arellano-Bond GMM estimation.

Stochastic dominance analyses reveal that, in general, the ranking of the distribution of NPLs in the states where house prices underwent low increases stochastically dominate their corresponding levels in states characterised by moderate and high house price changes. This suggests that the performance of banks' loans is highly driven by house price developments. Furthermore, we find that real estate prices and macroeconomic fundamentals have a pronounced influence on the quality of individual banks' loan portfolios, with a negative impact of house prices on the volume of NPLs. Finally, the threshold analyses provide evidence of the presence of a threshold point, at which two different possible impacts of house prices on the scale of NPLs may take place. More importantly, the departure of house prices from this threshold point causes house prices to have a detrimental effect on the performance of banks' loans and this detrimental impact becomes more harmful with increasing distance between house prices and the threshold point.

The following section highlights studies that investigate the determinants of NPLs, paying special attention to those that address this issue in light of regional differences in the evolution of NPLs. Section 2.3 provides the theoretical background and the test procedure for the stochastic dominance analysis. Section 2.4 presents sources of data, along with some descriptive statistics and sampling procedures. Section 2.5 presents the results and discussion of the stochastic dominance analysis, GMM and threshold models. Finally, concluding remarks are provided in Section 2.6.

2.2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Over the period 2006-2010, the US housing market underwent a dramatic bust with national house prices recording a historical decline of around 31 per cent, following an astonishing period of increases that began in the 1990s and continued with a speed boom over the period between 1997 and 2005. However, the appreciation of house prices during the boom period and depreciation during the bust period were not uniform across US metropolitan areas.[9] In particular, property prices recorded increases of around 60 to 80 per cent in the East and West coastal areas, while less vigorous increases were observed in the Mideast and Midwest. This asymmetry in the recent boom and bust episode in the US can be easily recognised by taking a closer look at state-level data for US house prices during the period under consideration. It can be noted that states such as Florida and California present considerable swings in property prices during the boom and bust episodes, whereas rapid house price growth during the boom period, which was not followed by a bust episode, was limited to other states such as Montana and Vermont. By contrast, house prices underwent vigorous depreciation during the bust period in states such as Michigan and Georgia.

Understanding the transmission channels between the financial industry and real estate sector in an economy is crucial when addressing financial stability.[10] Numerous studies have investigated the interdependence of the real estate market and banks' credit default exposure, particularly in the US, where the financial crisis originated. Hilbers, Lei and Zacho (2001) examined the role of real estate booms and busts in threatening financial system stability. According to their study, unbalanced developments in the real estate market and especially house prices are among the main drivers of financial distress. Despite the abundance of literature on credit risk that empirically investigated the connection between real estate market conditions and impaired loans (see, for example, Davis and Zhu (2010)), the effect of regional dissimilarities in house price developments on the evolution of credit risk has been generally ignored in empirical works, while studies on their impact on NPL accumulation is also lacking.

[9] Regional heterogeneity in house price dynamics in the US mirrors fundamental variations in housing market elements, demographic and sociocultural aspects, macroeconomics and financial system-related factors.

[10] See, for example, Basel Committee on Banking Supervision. (2011). "The transmission channels between the financial and real sectors: a critical survey of the literature". Basel, Bank for International Settlements.

According to economic theory, small (positive or negative) shocks to borrowers' incomes are found to be greatly magnified by endogenous developments in the economy (see, for instance, Almeida *et al.,* 2006). In their seminal paper, Bernanke *et al*. (1996) referred to the mechanism that lies behind the amplified impact of borrowers' income shocks as a "*financial accelerator*" or "*credit multiplier*". The financial accelerator mechanism suggests that under a specific leverage ratio, positive shocks to borrowers' incomes (individuals and institutions) contribute to a procyclical influence on their borrowing capacity, driving up housing prices and paving the way for the creation of housing booms. However, when the boom episode is over and the bust episode starts, expectations turn gloomy and an accelerating depreciation of asset prices and collateral values takes place, resulting in numerous instances of negative equity that expose banks' loan portfolios to high quantities of NPLs. In a similar way, Kiyotaki and Moore (1997) established that increasing asset prices may instigate a credit boom through the overvaluation of collateral values during the boom period, which results in increasing loan default rates when the market reverts and a bust period begins.

In principle, if house prices affect loan performance, one should expect NPLs to be higher in the States, where house price appreciation is greater, than in other countries. When house prices fall, homeowners with low or negative equity mortgages are less able to refinance, as lending standards for new loans become tighter. As a result, the owners will be presumably unable to repay their loans and increasingly be driven to default. A question of interest is, therefore, given the regional differences in house price behaviour during both boom and bust episodes, do NPLs follow a similar pattern? In other words, is it actually the case that NPLs are strongly related to house prices? And to what extent is geographical heterogeneity in house price changes translated into regional variation in the escalation of NPLs? These empirical questions can be formulated as a pair comparison between the distributions of bank's NPLs corresponding to different house price change groups across states in the US. Our procedure for testing differences between distribution functions relies on the concept of first and second order stochastic dominance to scrutinise the extent to which recent bubbles in the US housing market contributed to the build-up of NPLs in the banking sector. Therefore, by carrying out a stochastic dominance analysis, we attempt to deduce whether or not regional variations in the dynamics of house prices match a similar pattern in the behaviour of NPLs.

Koetter and Poghosyan (2010) looked at the impact of the deviations of property prices from their fundamental values, which are triggered by market imperfections, on financial stability from two contrasting points of view. The first assumption suggests that an increase in house prices results in higher values for the real estate holdings of the bank, as well as collateral values by subsidising the net wealth of the borrowers with additional privileges, contributing to a reduction in the probability of credit defaults (see also Bernanke and Gertler (1989) and Kiyotaki and Moore (1997)). By contrast, the second hypothesis assumes that the accumulative impact of these deviations might propagate moral hazards and adverse selection problems, by motivating banks to engage in irrational lending to risky mortgagors in an attempt to expand their market share, thereby exposing themselves to greater financial distress. Ultimately, Koetter and Poghosyan (2010) concluded that the deviation of house prices from their fundamental values exposes banks to a greater likelihood of defaults (see also Allen and Gale (2001)).

In light of these arguments, we test the hypothesis that states where large deviations in house prices from their fundamental values occurred before the financial meltdown also experienced greater bank instability, triggered by a sharp increase in loan defaults. The justification for this proposal relies on the notion that increasing house prices would be associated with excessive lending by banks, stimulated by high credit demand from risky investors who are driven by optimistic expectations about the future of house prices. Disproportionate risk accumulation then leaves banks greatly exposed to real estate market developments and likely high loan losses when house prices start to depreciate.

Moreover, the relationship between NPLs and the housing market cannot be disentangled from local business cycles, with empirical works and academic literature confirming the crucial role that the macroeconomic environment plays in influencing banks' loan performance. A general consensus between studies is that the quality of loan portfolios is strongly related to the business cycle. Bofondi and Ropele (2011) reported that the quality of loans to individuals and corporates varies negatively with real GDP and house prices, and positively with unemployment rates and short-term interest rates.[11]

Furthermore, the argument provided by Koetter and Poghosyan (2010) concerning the impact of the departure of house prices from their fundamental values on the evolution of credit risk suggests the existence of a threshold point, beyond which the detrimental impact of house prices starts to have a greater effect on NPLs. To investigate the presence of a threshold point, beyond which changes in house prices become serious, we attempted to expand our analyses by examining the hypothesis that the impact of real estate prices depends on departure from a threshold point, which may indicate substantially different effects of house prices on the evolution of bad loans for individual banks.

2.3. METHODOLOGY

The non-parametric stochastic dominance (SD) procedure aims at partitioning a set of prospects into two subgroups, with efficient prospects set against an inefficient set. While the latter set of prospects are not appealing to any profit maximising player, the former set comprises all prospects that are never stochastically dominated by any other prospect, from which individuals select their optimal opportunities. Different stochastic dominance orders can be defined, depending on the number of required characteristics. However, all forms of SD assume the maximisation of expected Von Neumann-Morgenstern utility functions

[11] Other studies that have explored the effect of the macroeconomic environment on NPLs include Rinaldi and Arellano (2006), Beck, Jakubik and Piloiu (2013), Vogiazas and Nikolaidu (2011), Espinoza and Prasad (2010), Bercoff *et al*. (2002), Warue (2013) and Dash and Kabra (2010).

attached to each individual.[12] Before describing the hypotheses of interest, we briefly review below the principles of stochastic dominance.

Statistical theories for "population ranking" have developed rapidly over the last few decades.[13] The development of ranking populations started with likelihood ratios and Wald-type tests, followed by the one-sided Wilcoxon rank and the multivariate forms of the Kolmogorov-Smirnov (KS) test. More recently, several nonparametric tests for stochastic dominance of first order (FSD) and second order (SSD) have been developed by McFadden (1989), Klecan *et al*. (1991) and Kaur *et al*. (1994).

McFadden (1989), and later Klecan *et al*. (1991), suggested procedures for first and second order stochastic dominance, each of which is built on the basis of the Kolmogorov-Smirnov statistic. While the former assumes $i.i.d.$ observations and independent variates, allowing the derivation of the asymptotic distribution of this test, and the exact distribution in some cases (Durbin, 1973 and 1985),[14] the latter is more general and allows for weak dependence in the processes across observations, and exchangeability among the variables.

Let X and Y be two stochastic processes for the NPLs at two different points in time, or for different states in the US. Let $U1$ represent the class of all Von Neumann-Morgenstern type utility functions u, such that $u' \geq 0$ (non-decreasing); also let $U2$ denote the set of all utility functions included in $U1$ that satisfy $u'' \leq 0$ (strict concavity); and $U3$ denotes a subset of U_2 that satisfies $u''' \leq 0$. Let $X_1, X_2, \cdots\cdots, X_n$ be n observations of X, while $Y_1, Y_2, \cdots\cdots, Y_m$ represent the m observation in Y, and let $F_1(x)$ and $F_2(x)$ be their corresponding continuous

[12] See Von Neumann, J., & Morgenstern, O. (1953). "Theory of games and economic behaviour". Princeton, Princeton University Press.

[13] For a review of the history of population ranking, see Maasoumi, E. (2000). "Parametric and Nonparametric Tests of Limited Domain and Ordered Hypotheses in Economics". In Baltagi, B. H. (ed.), A Companion to Econometric Theory; Basil Blackwell publishers.

[14] For further reading, see: Durbin, J. (1973). "Distribution theory for tests based on the sample distribution function". SIAM, Philadelphia.

Durbin, J. (1985). "The first passage density of a continuous Gaussian process to a general boundary". Journal of Applied Probability, 22, 99-122.

and monotonic cumulative distribution functions (CDF), respectively. Then we define first and second order stochastic dominance as follows:

Definition 1: *X first order stochastically dominates (FSD) Y,* denoted as $X \succeq_1 Y$, if and only if any of the following two equivalent conditions hold:

i) $E[u(X)] \geq E[u(Y)]$ for all $u \in \mathcal{U}_1$ with strict inequality for some u.

ii) $F_1(x) \leq F_2(x)$ $\forall x$ with strict inequality for some x.

According to Definition 1, banks would prefer lower non-performing to higher NPLs, which implies the utility function has a non-negative first derivative. Evidence of first order stochastic dominance in the analyses is informative and indicates that all banks would prefer X to Y, irrespective of their risk appetite, *i.e.* whether they are risk neutral, risk-averse or risk-seeking.

Second order stochastic dominance (SSD), on the other hand, accounts for risk aversion and postulates a negative second derivative, implying the diminishing marginal utility of the banks' utility function, which can be formally expressed as shown in Definition 2:

Definition 2: *X second order stochastically dominates (SSD) Y,* denoted as $X \succeq_2 Y$, if and only if any of the following two equivalent conditions hold:

i) $E[u(X)] \geq E[u(Y)]$ for all $u \in \mathcal{U}_2$ with strict inequality for some u.

ii) $\int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{x} F_2(t)dt$ $\forall\, x$ with strict inequality for some x.

Whitmore (1970) suggests the notion of third order stochastic dominance assumes decreasing absolute risk (see, for example, Whitmore and Findley (1978)).[15] However, in this chapter we are only interested in ranking distributions of NPLs, therefore, third order stochastic dominance is not considered.

[15] For a review of third order stochastic dominance and its implications, see Atkinson (2007), Shorrocks and Foster (1987) and Davies and Hoy (1995), among others.

Empirical implementation of FSD and SSD can be done by evaluating the conditions (ii) in Definitions 1 and 2.[16] That is, the stochastic dominance test can be carried out by multiple comparisons of the cumulative distribution functions (CDF) of the banks' NPLs; however, due to the fact that the underlying true $CDFs$ are unknown, SD can be implemented in practice on the empirical cumulative distribution functions ($ECDF$) (see, for example, Davidson and Duclos, 2000). It is worth noting that stochastic dominance outcomes suggest hierarchy, that is, FSD implies SSD. However, detecting SSD does not imply the existence of FSD.

In this chapter, we use the inference procedure suggested by Linton *et al*. (2005). In their paper, the authors propose a generalisation of the Kolmogorov-Smirnov test for stochastic dominance between different prospects. The test procedure is consistent under general conditions and allows for the existence of serial dependence between the prospects to be ranked, which is the case in the distributions of interest in this study.

As far as the stochastic dominance test procedure is concerned, let Ξ represents the support of X_k, where $k = 1,2,\cdots\cdots,K$ is the observed data for NPLs, which are assumed to be strictly stationary, and α-mixing with $\alpha(j) = O(j^{-\delta})$ for some $\delta > 1$. Furthermore, let $s = 1,2$ indicate the order of the stochastic dominance and refer to $X_i \geq_s Y_j$ for $i, j \in n$ as the stochastic dominance at order s. We also assume that the random variables in the set $\theta = \{X_1, X_2, \cdots\cdots, X_k\}$ are exchangeable random variables.

Let $D_i^s(x)$ and $D_j^s(x)$ denote the CDF defined as:

$$F_i(x,\theta) = P(X_{it}(\theta) \leq x), \tag{2.1}$$

and define the empirical distribution function $\widehat{F_{iN}}(x,\theta)$ as follows:

$$\widehat{F_{iN}}(x,\theta) = D_i^s(x; F_i) = \frac{1}{N(s-1)!}\sum_{t=1}^{N} 1\,(X_{it}(\theta) \leq x)\,(x - X_{it})^{s-1} \tag{2.2}$$

[16] For a practical characterisation of any order of stochastic dominance, see Davidson and Duclos (2000).

where $t = 1, \cdots\cdots, N$. The empirical distribution function $\widehat{F_{JN}}(x, \theta)$ of $D_j^s(x)$ is formulated similarly.

To test the null hypothesis that $\mathcal{H}_0^s: X_i \succeq_s Y_j$, we examine the following analogous hypothesis:

$$D_i^s(x; F_i) \leq D_j^s\big(x; F_j\big) \qquad \forall\, x \in \mathbb{R}, \qquad s = 1,2,$$

versus the alternative hypothesis:

$$D_i^s(x; F_i) > D_j^s\big(x; F_j\big) \qquad \forall\, x \in \mathbb{R}, \qquad s = 1,2.$$

For first order stochastic dominance, we define the functional of the joint distribution for $s = 1$ such that:

$$H = \min_{i \neq j} \sup_{x \in \chi} (F_i(x; \theta_{k0}) - F_j(x; \theta_{k0})), \tag{2.3}$$

then we test the null hypothesis of $\mathcal{H}_0^H: H \leq 0, \forall\, x \in \mathbb{R}$ against the alternative hypothesis of $\mathcal{H}_1^H: H > 0, \forall\, x \in \mathbb{R}$.

Similarly, for second order stochastic dominance, let $s = 2$ and we define:

$$G = \min_{i \neq j} \sup_{x \in \chi} \int_{-\infty}^{\infty} (F_i(\varpi) - F_j(\varpi))\, d\varpi\ , \tag{2.4}$$

then we test the null hypothesis of $\mathcal{H}_0^G: G \leq 0, \forall\, x \in \mathbb{R}$ versus the alternative hypothesis of $\mathcal{H}_1^G: G > 0, \forall\, x \in \mathbb{R}$.

According to the hypotheses stated above, the null hypothesis $\mathcal{H}_0^s$ (for $s = 1,2$) implies that X_i stochastically dominates X_j (for $i \neq j$). The alternative hypothesis is that stochastic dominance fails at some point. Then, we introduce the hypotheses of interest as follows:

i) $\mathcal{H}_0^s$: X_i stochastically dominates X_j, *i.e.* $X_i \succeq_s X_j$.

ii) $\mathcal{H}_0^s$: X_j stochastically dominates X_i, *i.e.* $X_j \succeq_s X_i$.

iii) $\mathcal{H}_0^s$: X_i and X_j have the same distribution, *i.e.* $X_i \sim X_j$.

Under hypothesis (i), we test that X_i stochastically dominates X_j, whereas under (ii), the converse is examined.[17] Finally, under (iii), the equality of the distributions X_i and X_j is tested, which is used as a further check since it has the attractive property that acceptance of this hypothesis is inconsistent with the acceptance of (i) and (ii) and infers that no evidence of the dominance of either of the distributions over the other has been detected.

To test the hypotheses stated above, we follow Linton *et al.* (2005), consider the Kolmogorov-Smirnov distance between the empirical distribution functions of the NPLs under consideration and define the analogous test statistics:

for FSD $(i.e.\ s = 1)$:

$$\widehat{H} = \min_{i \neq j} \sup_{x \in \chi} \sqrt{N} \left[\widehat{D}_i^s \left(x; \widehat{F}_i\right) - \widehat{D}_j^s \left(x; \widehat{F}_j\right)\right], \tag{2.5}$$

for SSD $(i.e.\ s = 2)$:

$$\widehat{G} = \min_{i \neq j} \sup_{x \in \chi} \sqrt{N} \int_{-\infty}^{x} \left[\widehat{D}_i^s \left(x; \widehat{F}_i\right) - \widehat{D}_j^s \left(x; \widehat{F}_j\right)\right] dt\,. \tag{2.6}$$

Under appropriate regularity conditions, $\widehat{H}$ and $\widehat{G}$ converge to a functional of a Gaussian process.

To estimate the empirical distribution functions, we use the overlapping moving block bootstrap (MBB) method, in which $\widehat{H}$ and $\widehat{G}$ are initially estimated over the original sample, followed by the generation of a number of subsamples by sampling the overlapping data blocks. Under this procedure, after obtaining the bootstrap subsample, we estimate the analogous bootstrap of $\widehat{H}$ and $\widehat{G}$ respectively. In a formal formulation, we allow Q to represent the number of bootstrap replications, and then we generate $N - q + 1$ overlapping blocks of equal length q. Once the bootstrap subsample is created, the bootstrap analogues of $\widehat{H}$ and $\widehat{G}$ can be calculated as:

$$\widehat{H^*} = \min_{i \neq j} \sup_{x \in \chi} \sqrt{N} \left[\widehat{D}_i^{s*} \left(x; \widehat{F}_i\right) - \widehat{D}_j^{s*} \left(x; \widehat{F}_j\right)\right], \tag{2.7}$$

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[17] Note that acceptance of first order also implies second order stochastic dominance, while the opposite is not true.

$$\widehat{G^*} = \min_{i \neq j} \sup_{x \in \chi} \sqrt{N} \int_{-\infty}^{x} \left[\widehat{D}_i^{s*}\left(x; \widehat{F}_i\right) - \widehat{D}_j^{s*}\left(x; \widehat{F}_j\right)\right] dt, \tag{2.8}$$

where:

$$\widehat{D^*}\left(x; \widehat{F_k}\right) = \frac{1}{N(s-1)!} \sum_{t=1}^{N} \{1(X_{2i}^* \leq x)(x - X_{2i}^*)^{s-1} - \omega(i,q,N) 1(X_{2i}^* \leq x)(x - X_{2i}^*)^{s-1}\} \tag{2.9}$$

and:

$$\omega(i,q,N) = \begin{cases} i/q & if\ i \in [1, q-1] \\ 1 & if\ i \in [1, N-q+1] \\ (N-i+1)/b & if\ i \in [N-q+2, N]. \end{cases}$$

Finally, p-value functions of the estimated bootstrap can be defined as follows:

$$p^*\left(\widehat{H}\right) = \frac{1}{N-q+1} \sum_{i=1}^{N-q+1} 1\left(H^* \geq \widehat{H}\right). \tag{2.10}$$

When $Q \to \infty$ the expressions in $\widehat{H^*}$ and $\widehat{G^*}$ converge to $\widehat{H}$ and $\widehat{G}$, respectively, given the stochastic processes X_i and X_j meet the stationary and α-mixing assumptions mentioned above. Furthermore, the asymptotic theory conditions of $q \to \infty$ and $q/N \to 0$ as $N \to \infty$ need to be satisfied.

After addressing the existence of a stochastic dominance between the states' NPL distributions, the second step of the analyses concerns estimating an Arellano-Bond GMM model with robust standard errors to investigate the effects of GDP, unemployment rates, lending interest rates and house prices on the evolution of NPLs.[18] The final part of the statistical analyses addresses a possible threshold point in the house price index returns, while the theoretical framework of the threshold model used is provided in APPENDIX 2.7.

2.4. DATA DESCRIPTION

The panel structure of the sample allows an analysis of non-performing bank loans according to the house price trajectories over a given period of time. We design different

[18] For the theoretical framework of the Arellano-Bond generalised method of moments (GMM), see Section 3.4 in the Chapter Three.

tests to explore whether the house price inflation that occurred between 2002 and 2005 affected banks' NPLs. This study is based on a panel dataset composed of yearly data from US banking institutions in 47 states as well as Washington D.C. and excluding Idaho, Kentucky and Wyoming due to the unavailability of their data. Data were collected over the time span 1999-2009, which therefore enables us to investigate the dynamics of NPL evolution during the critical period of financial turbulence that took place in 2007-2009.

The dataset is constructed by merging information from three separate databases. Banks' balance sheet-related and income statements-related data are extracted from the Bureau Van Dijk's Bankscope Database, which supplies in-depth comprehensive bank statistics. As a proxy for real estate prices, a state-level residential house price index (HPI) is obtained from the Database of the Federal Housing Finance Agency (FHFA) on loans issued by the GSEs Fannie Mae and Freddie Mac.[19] While state-level unemployment rate data are retrieved from the Bureau of Labour Statistics (BLS) which provides labour data, data on the growth of GDP at the state level is accessed from the Bureau of Economic Analysis (BEA) to serve as a proxy for macroeconomic and business cycles. Finally, lending interest rate data are accessed from the Federal Reserve Economic Data (FRED). Notably, all the aforementioned indicators are transformed into real terms.

The data were then refined by imposing some filtering restrictions regarding the specialisation of sample banks, in order to meet some considerations such as: (i) to avoid functional heterogeneity, we limit banks to commercial, savings and co-operative banks, as their main function is accepting deposits and making loans to maximise their profits as the primary objective of these activities; (ii) banks are required to have a minimum of 10 consecutive observations to provide good coverage of the recent financial crisis; (iii) we

[19] Headquartered in Washington D.C., the Federal Housing Finance Agency (FHFA) is a US independent federal agency founded by the Housing and Economic Recovery Act of 2008 in the aftermath of the most recent financial crisis. The main authority attached to this agency is regulating the secondary mortgage market and supervising the activities of Fannie Mae, Freddie Mac and the major Federal Home Loan Banks (FHLBs) to ensure sound government-sponsored housing enterprises and to guarantee a stable housing system. The data are provided at a quarterly frequency and the annual data are estimated through taking the averages of the quarterly data.

exclude banks that showed doubtful data caused by measurement errors, which are identified by eccentric values. Following these three refinements, the final sample is a balanced panel that comprises 372 individual US banks, with a total of 4092 annual observations over the sample period 1999-2009.

The US states that are considered in the comparison are grouped into four $codes$ according to the behaviour of house price evolution in the states under scrutiny between 1998 and 2006. In other words, in order to test whether NPLs in states with greater house price appreciation stochastically dominate their peers in states characterised by a lower house price increase, the selected states are divided into four categorical regions according to the corresponding degree of house appreciation they underwent between 1999 and 2006. In particular, with respect to the base year of 1999, $code\ 1$ is associated with the states where house prices underwent an increase greater than 80%, $code\ 2$ is for the states that witnessed house price increments between 40% and 80%, $code\ 3$ is for the states in which house price appreciation was observed to be between 20% and 40% and $code\ 4$ is for the states with detected house price changes of less than 20%. It is worth mentioning here that the initially considered procedure for division into quintiles was eventually abandoned, because a preliminary investigation revealed no substantial difference between the third and fourth quintiles.

Moreover, since the time period of the sample under scrutiny includes the financial meltdown that took place in 2006, the years used to carry out the stochastic dominance analyses are selected to reflect the pre-crisis housing boom period by including 2002 and 2004; during the crisis by considering the year 2006, when the house price bubble peaked; and post-crisis by analysing 2008, when the bust period began. By adopting this methodology, we were able to account for the differences in the impact of house prices on NPLs by providing comprehensive comparisons between all phases of the troubled period surrounding the financial crisis. Table 2.4.1 presents the geographical distribution of the sample banks among the US States categorised within the four $codes$, between which we are interested in comparing the distributions of their NPLs.

Table 2.4.1 US Sample Banks' Classification into the Four Codes

$Code\ 1$	Abb.	No. of Banks	$Code\ 2$	Abb.	No. of Banks	$Code\ 3$	Abb.	No. of Banks	$Code\ 4$	Abb.	No. of Banks
Arizona	AZ	2	Connecticut	CT	4	Colorado	CO	2	Alabama	AL	9
California	CA	26	Delaware	DE	8	Georgia	GA	18	Arkansas	AR	1
Florida	FL	19	Maine	ME	4	Illinois	IL	14	Indiana	IN	2
Hawaii	HI	5	Minnesota	MN	9	Louisiana	LA	7	Iowa	IA	7
Maryland	MD	7	Montana	MT	2	Michigan	MI	8	Kansas	KS	3
Massachusetts	MA	6	New York	NY	25	Missouri	MO	8	Mississippi	MS	5
Nevada	NV	6	Oregon	OR	2	New Mexico	NM	6	Nebraska	NE	3
New Hampshire	NH	3	Pennsylvania	PA	23	North Dakota	ND	5	North Carolina	NC	19
New Jersey	NJ	12	Vermont	VT	3	South Carolina	SC	8	Ohio	OH	13
Rhode Island	RI	4	Virginia	VA	4	South Dakota	SD	4	Oklahoma	OK	2
D.C.	DC	3	Washington	WA	9	West Virginia	WV	3	Tennessee	TN	4
-			-			Wisconsin	WI	10	Texas	TX	16
-			-			-			Utah	UT	9
Total		93			93			93			93

Note: $Code\ 1$: house price appreciation greater than 80%, $Code\ 2$: house price appreciation 40%-80%, $Code\ 3$: house price appreciation 20-40% and $Code\ 4$: house price appreciation less than 20%.[20]

As can be seen in Table 2.4.1, states such as California, Nevada and Arizona were hardly hit by appreciation in the housing market. Notably, many cities in the inland area of California were the epicentre of the 2000 boom-bust cycle in the housing market. Similarly, most of the large cities in Florida, New Hampshire and Massachusetts, along with many other states on the East coast, reported a large jump in house price returns. By contrast, real

[20] Note that the four $codes$ have the same sample size.

estate markets in states such as Nebraska and Kansas along with many other states in the Midwest and Mideast hardly experienced any price inflation in the period under consideration. Table 2.4.2 reports some essential univariate descriptive statistics for non-performing loans (NPL) and house prices returns ($\boldsymbol{HPR_{i,t}}$), calculated as ($HPR_{i,t} = \frac{HPI_{i,t} - HPI_{i,t-1}}{HPI_{i,t-1}}$) and categorised within the corresponding $codes$ presented in Table 2.4.1.

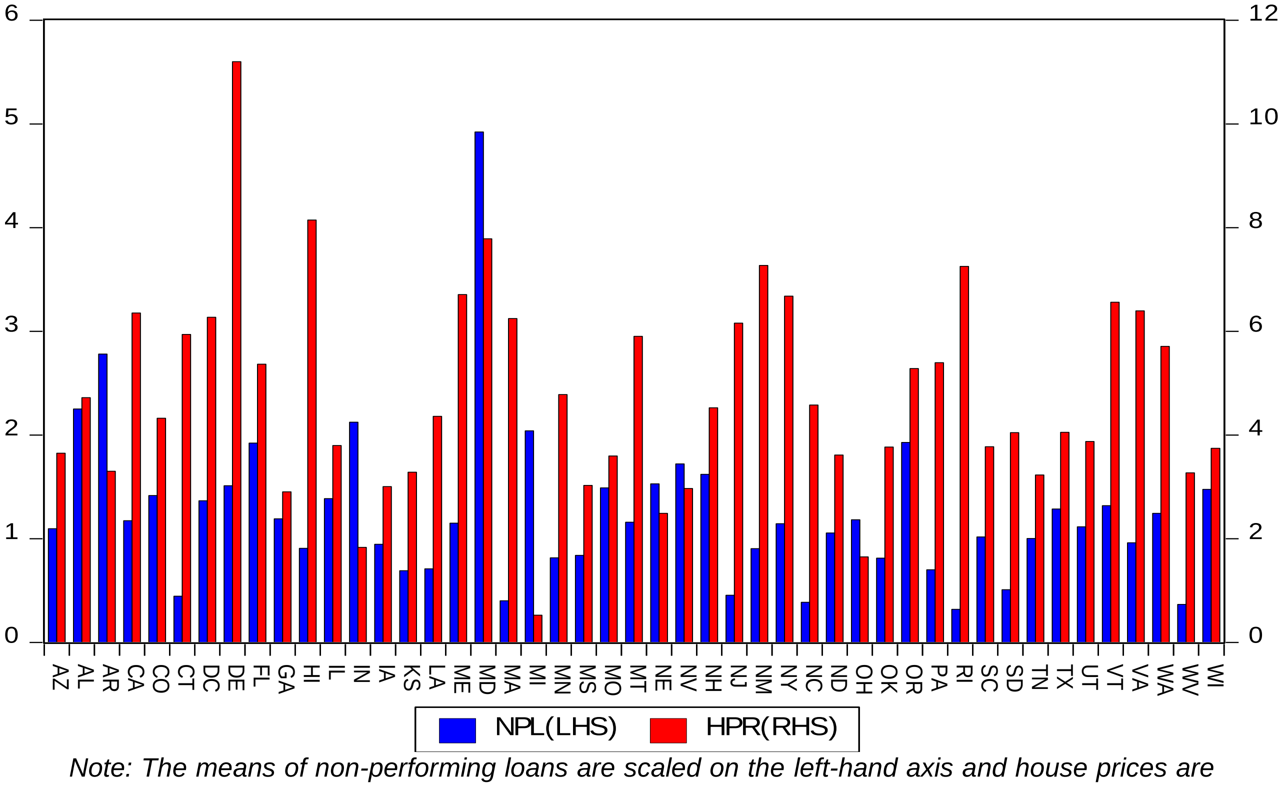
Table 2.4.2 Descriptive Statistics for Non-performing Loans and House Prices

Statistics	$\boldsymbol{Code\ 1}$	$\boldsymbol{Code\ 2}$	$\boldsymbol{Code\ 3}$	$\boldsymbol{Code\ 4}$
	Non-performing Loans ($\boldsymbol{NPL}$)			
Mean	1.61	1.01	1.28	1.13
Median	0.47	0.48	0.58	0.56
Std. Dev.	3.90	1.95	2.38	1.83
Skewness	6.14	6.80	6.46	4.84
Kurtosis	55.62	69.63	72.72	36.78
	House Prices Index Returns ($\boldsymbol{HPR}$)			
Mean	6.18	5.96	3.58	3.53
Median	10.13	7.42	5.08	3.63
Std. Dev.	12.46	5.54	4.53	4.28
Skewness	-0.90	-0.67	-0.54	0.80
Kurtosis	3.21	2.58	4.83	9.94

From Table 2.4.2, the overall mean of NPL ratios for the four $codes$ are positive, ranging from a maximum of 1.61 for the states where house prices underwent an increase of higher than 80%, to a minimum of 1.01 for the states that witnessed house price increments between 40% and 80%. States grouped in $codes$ 3 and 4 recorded overall mean NPL ratios of around 1.28 and 1.13, respectively. It's worth noting that the positive signs of the NPLs' means indicate a history of growth in NPLs during the period under scrutiny which is reasonable, given the financial turmoil that took place in 2007-2009. It is of interest to note that the NPLs in $code$ 1, where house price appreciation and standard deviation are detected to be the highest, have the highest standard deviation in NPLs of the four $codes$ under consideration. On the other hand, $code$ 4, which contains the states with the lowest mean and standard deviation in house prices of the four *codes*, also has the lowest standard deviation in NPLs. These findings seem to support the hypothesis that loan performance is highly influenced by fluctuations in house prices. In essence, the preliminary investigation suggests that the magnitude of changes in house prices often translates into changes in the scale of NPLs.

For a visual inspection of the evolution of NPLs and house prices at state-level, Figure 2.4.1 plots the means of NPLs (scaled on the left-hand axis) and house prices (scaled on the right-hand axis) in the states under investigation. It suggests considerable geographical differences in the means of the two indicators between different US metropolitan areas.

Figure 2.4.1 Mean of Non-performing Loans and House Prices



Note: The means of non-performing loans are scaled on the left-hand axis and house prices are scaled on the right-hand axis.

In order to further explore this issue, the stochastic dominance test is used to compare the distribution of NPLs among the four groups of US metropolitan areas. With respect to the simple use of the mean-variance procedure, stochastic dominance uses the information embedded in the whole distribution, rather than the first two moments of the distribution.

2.5. RESULTS AND DISCUSSIONS

In this section, the results of stochastic dominance, Arellano-Bond (1991) GMM estimation and the generalised panel threshold model are presented and discussed, allowing for regime intercepts.

2.5.1. STOCHASTIC DOMINANCE ANALYSIS

Table 2.5.1 and Table 2.5.2 report p-values of the test statistics for selected years. Note that similar analyses of the other years follow a similar pattern and are not reported, in the interest of brevity.

We use X and Y to denote the $CDFs$ of the regions corresponding to the different $codes$ reported in Table 2.4.1. The left half of Table 2.5.1 reports the results of the analyses of 2002, while the right half reports the results of the analyses of 2004. Similarly, Table 2.5.2 presents the results of the analyses of 2006 in the left half and the results of the analyses of 2008 in the right half. In each half of these tables, we carry out a paired comparison for two related $codes$. In essence, from the left half of Table 2.5.1, the null hypothesis $\mathcal{H}_0\colon X \succeq Y$ is tested in the first column to examine the dominance of X over Y, followed by a test for the null hypothesis of $\mathcal{H}_0\colon Y \succeq X$ to examine the reverse stochastic dominance relationship (*i.e.* Y over X) in the second column, and finally a test for the equality of the distributions is considered in the third column.[21]

The notation " $\succeq$ " is used to indicate the dominance relationship in the first and second columns, whereas the notation "$\sim$" is used to indicate the equality of distribution in the third column. In all cases, the alternative hypothesis is the opposite Boolean argument of the null, *i.e.* the negation of the null hypotheses. To get stochastic dominance of X over Y, the null hypothesis $\mathcal{H}_0\colon X \succeq Y$ has to be accepted, *i.e.* the corresponding p-value must be greater than 5%. Simultaneously, both null hypotheses, that $\mathcal{H}_0\colon Y \succeq X$ and $\mathcal{H}_0\colon Y \sim X$, have to be

[21] A similar procedure has been followed in the right half of Table 2.5.1 as well as the left and right halves of Table 2.5.2.

rejected, *i.e.* the corresponding p-values ought to be lower than 5%. Otherwise, the dominance of X over Y is inconclusive.

Table 2.5.1 Hypotheses and P-values of First and Second Order Stochastic Dominance for 2002 and 2004

SD	2002			2004		
	$\mathcal{H}_0: X \geq Y$	$\mathcal{H}_0: Y \geq X$	$\mathcal{H}_0: Y \sim X$	$\mathcal{H}_0: X \geq Y$	$\mathcal{H}_0: Y \geq X$	$\mathcal{H}_0: Y \sim X$
$C_1 \& C_2$	$\mathcal{H}_0: C_1 \geq C_2$	$\mathcal{H}_0: C_2 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_2$	$\mathcal{H}_0: C_1 \geq C_2$	$\mathcal{H}_0: C_2 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_2$
FSD	0.040	0.016	0.042	0.007	0.028	0.051
SSD	0.007	0.349	0.045	0.008	0.973	0.025
$C_1 \& C_3$	$\mathcal{H}_0: C_1 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_3$	$\mathcal{H}_0: C_1 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_3$
FSD	0.027	0.942	0.003	0.039	0.019	0.028
SSD	0.004	0.731	0.004	0.005	0.657	0.008
$C_1 \& C_4$	$\mathcal{H}_0: C_1 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_4$	$\mathcal{H}_0: C_1 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_4$
FSD	0.064	0.265	0.013	0.028	0.782	0.068
SSD	0.004	0.886	0.014	0.009	0.867	0.004
$C_2 \& C_3$	$\mathcal{H}_0: C_2 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_3$	$\mathcal{H}_0: C_2 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_3$
FSD	0.034	0.305	0.043	0.045	0.254	0.079
SSD	0.009	0.869	0.005	0.041	0.694	0.036
$C_2 \& C_4$	$\mathcal{H}_0: C_2 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_4$	$\mathcal{H}_0: C_2 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_4$
FSD	0.027	0.727	0.090	0.062	0.780	0.009
SSD	0.007	0.986	0.015	0.008	0.386	0.008
$C_3 \& C_4$	$\mathcal{H}_0: C_3 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_3$	$\mathcal{H}_0: C_3 \sim C_4$	$\mathcal{H}_0: C_3 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_3$	$\mathcal{H}_0: C_3 \sim C_4$
FSD	0.143	0.964	0.274	0.652	0.780	0.883
SSD	0.039	0.834	0.214	0.835	0.386	0.387

Note: C_s in the hypotheses refers to the code s.

At first glance, with few exceptions, the results of stochastic dominance analyses indicate the stochastic dominance of $code$ 4 over $codes$ 1, 2 and 3, the stochastic dominance of $code$ 3 over $codes$ 1 and $codes$ 2 and stochastic dominance of $code$ 2 over $code$ 1. This suggests that the ranking of the quantities of NPLs starts from the lowest of the states grouped in $code\,4$ (house prices increased by less than 20%) and increases gradually in states grouped in $code\,3$ (house prices increased between 20% and 40%), followed by states grouped in $code\,2$ (house prices increased between 40% and 80%) and ends up with the highest volume of NPLs in states grouped in $code\,1$ (house prices increased by more than 80%). Although the stochastic dominance analysis showed no material difference between $code\,3$ and $code\;4$ in 2002 and 2004, and mixed outcomes in 2006, the impact of house prices on the increase in NPLs became more conclusive in 2008, with the dominance of the $CDFs$ going respectively from $C4$ to $C1$. These preliminary findings suggest that the magnitude of NPLs is consistent with the sampling procedure used in Table 2.4.1, where the states have been categorised according to the level of house prices increases observed. However, the responsiveness of impaired loans to fluctuations in house prices was not uniform over the different phases of the financial crisis.

Starting from the year 2002 in Table 2.5.1, it appears that $C_2\,SSD\,C_1$ as the null hypothesis $\mathcal{H}_0\colon C_2 \succeq C_1$ was not rejected (the p-value 0.349 is greater than 5%), while the null of C_1 dominance $\mathcal{H}_0\colon C_1 \succeq C_2$, as well as the null of the equality of distributions, $\mathcal{H}_0\colon C_1 \sim C_2$ were both rejected at the 5% significance level, with all corresponding p-values less than 5%. The findings of these tests indicate that the amounts of NPLs in region C_1, where observed house price growth was higher than 80%, was higher than their amounts in region C_2, where house prices increased between 40% and 80%.

The results of the following hypotheses in 2002 seem to follow a similar pattern in terms of stochastic dominance, in a manner consistent with the behaviour of house price evolution. More specifically, the null hypotheses that $C_1\,FSD\,C_3$ and $C_1\,SSD\,C_3$, as well as the null of the equality of distributions $\mathcal{H}_0\colon C_1 \sim C_3$, were all rejected in favour of the corresponding alternative hypotheses, while the hypotheses $C_3\,FSD\,C_1$ and $C_3\,SSD\,C_1$ were both accepted with high significance, providing evidence that NPLs in region C_1, where house prices underwent growth of more than 80%, were higher than NPLs in region C_3, where house price increases were considerably lower (between 20% and 40%). A similar pattern of dominance relationships was detected in the cases of C_1 with C_4 (*i.e.* the acceptance of $\mathcal{H}_0: C_4 \succeq C_1$ against the alternative hypothesis and the rejection of both $\mathcal{H}_0: C_1 \succeq C_4$ and $\mathcal{H}_0: C_1 \sim C_4$), C_2 with C_3 (*i.e.* the acceptance of $\mathcal{H}_0: C_3 \succeq C_2$ against the alternative hypothesis and the rejection of both $\mathcal{H}_0: C_2 \succeq C_3$ and $\mathcal{H}_0: C_2 \sim C_3$) and C_2 with C_4 (*i.e.* the acceptance of $\mathcal{H}_0: C_4 \succeq C_2$ against the alternative hypothesis and the rejection of both $\mathcal{H}_0: C_2 \succeq C_4$ and $\mathcal{H}_0: C_2 \sim C_4$). These results reveal that the scale of NPLs in region C_1 is higher than in C_4, and the scale of NPLs in region C_2 is higher than in regions C_3 and C_4. However, it appears that there is no evidence of significant differences between the cumulative distribution functions of region C_3 and region C_4 in terms of NPL growth, as the test of the equality of distribution does not reject the null hypothesis of $\mathcal{H}_0: C_3 \sim C_4$.

From the right-hand panel of Table 2.5.1, it appears that the stochastic dominance in 2004 follows the same behaviour found in 2002. In particular, the null hypotheses $\mathcal{H}_0: C_2 \succeq C_1$, $\mathcal{H}_0: C_3 \succeq C_1$ and $\mathcal{H}_0: C_4 \succeq C_1$ were all accepted at the 10% significance level, indicating that NPLs in region C_1 were stochastically dominated by NPLs in regions C_2, C_3 and C_4, while the null hypotheses of C_1 dominance (*i.e.* $\mathcal{H}_0: C_1 \succeq C_2, \mathcal{H}_0: C_1 \succeq C_3, \mathcal{H}_0: C_1 \succeq C_4$), as well as the equality of distributions (*i.e.* $\mathcal{H}_0: C_1 \sim C_2, \mathcal{H}_0: C_1 \sim C_3, \mathcal{H}_0: C_1 \sim C_4$), were rejected at the 10% significance level. In the same way, C_2 was stochastically dominated by C_3 and C_4, with the acceptance of $\mathcal{H}_0: C_3 \succeq C_2$ and $\mathcal{H}_0: C_4 \succeq C_2$, against the alternative hypotheses and the rejection of the null hypotheses that $\mathcal{H}_0: C_2 \succeq C_3$, $\mathcal{H}_0: C_2 \succeq C_4$, $\mathcal{H}_0: C_2 \sim C_3$ and $\mathcal{H}_0: C_2 \sim C_4$. Similar to our findings for 2002, no evidence of significant differences between the $CDFs$ of states in C_3 and states in C_4 has been found in 2004, due to failing to reject the null hypothesis of distribution equality $\mathcal{H}_0: C_3 \sim C_4$.

In a slight contrast to the previous findings, in 2006 states in C_4 SSD states in C_1, states in C_3 and C_4 SSD states in C_2 and states in C_3 SSD states in C_1, whereas no significant difference was detected between the $CDFs$ of C_1 with C_2 and C_3 with C_4, as the null hypotheses of equality $\mathcal{H}_0: C_1 \sim C_2$ and $\mathcal{H}_0: C_3 \sim C_4$ were not rejected (see the left half of Table 2.5.2). Therefore, the behaviour of NPLs for 2006 is, to a large extent, in agreement with our previous outcomes for the years 2002 and 2004, as well as in line with the mapping of house price increases shown in Table 2.4.1.

Table 2.5.2 Hypotheses and P-values of First and Second Order Stochastic Dominance for 2006 and 2008

SD	2006			2008		
	$\mathcal{H}_0: X \geq Y$	$\mathcal{H}_0: Y \geq X$	$\mathcal{H}_0: Y \sim X$	$\mathcal{H}_0: X \geq Y$	$\mathcal{H}_0: Y \geq X$	$\mathcal{H}_0: Y \sim X$
$C_1 \& C_2$	$\mathcal{H}_0: C_1 \geq C_2$	$\mathcal{H}_0: C_2 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_2$	$\mathcal{H}_0: C_1 \geq C_2$	$\mathcal{H}_0: C_2 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_2$
FSD	0.574	0.969	0.473	0.060	0.833	0.046
SSD	0.063	0.541	0.087	0.061	0.530	0.011
$C_1 \& C_3$	$\mathcal{H}_0: C_1 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_3$	$\mathcal{H}_0: C_1 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_3$
FSD	0.051	0.994	0.026	0.040	0.948	0.011
SSD	0.064	0.447	0.093	0.045	0.630	0.019
$C_1 \& C_4$	$\mathcal{H}_0: C_1 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_4$	$\mathcal{H}_0: C_1 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_1$	$\mathcal{H}_0: C_1 \sim C_4$
FSD	0.092	0.973	0.003	0.063	0.907	0.033
SSD	0.026	0.827	0.004	0.039	0.857	0.022
$C_2 \& C_3$	$\mathcal{H}_0: C_2 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_3$	$\mathcal{H}_0: C_2 \geq C_3$	$\mathcal{H}_0: C_3 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_3$
FSD	0.052	0.856	0.090	0.098	0.769	0.023
SSD	0.004	0.568	0.006	0.081	0.352	0.063
$C_2 \& C_4$	$\mathcal{H}_0: C_2 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_4$	$\mathcal{H}_0: C_2 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_2$	$\mathcal{H}_0: C_2 \sim C_4$
FSD	0.104	0.890	0.007	0.007	0.915	0.005
SSD	0.059	0.721	0.005	0.008	0.303	0.004
$C_3 \& C_4$	$\mathcal{H}_0: C_3 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_3$	$\mathcal{H}_0: C_3 \sim C_4$	$\mathcal{H}_0: C_3 \geq C_4$	$\mathcal{H}_0: C_4 \geq C_3$	$\mathcal{H}_0: C_3 \sim C_4$
FSD	0.021	0.051	0.903	0.091	0.775	0.071
SSD	0.096	0.080	0.537	0.074	0.456	0.030

For 2008, the results of the stochastic dominance reveal a high consistency between the evolution of bad loans and the fluctuations that house prices underwent over the period under consideration (see the right half of Table 2.5.2). The outcomes of the tests clearly demonstrate the acceptance of C_2 dominance over C_1, C_3 dominance over C_1 and C_2 and finally C_4 dominance over C_1, C_2 and C_3, at the 10% significance level. Looking at the p-

values for the other null hypotheses in the same year, the rejection frequencies at the 10% significance level follow a similar, but more conspicuous, pattern with respect to previous years. Findings from 2008 indicate that the impact of house price fluctuations on the increase in NPLs became more powerful during the house price bust period at the onset of the financial crisis.

The p-values, although informative, do not give any idea of the magnitude of the NPL differential across different regions and different years. Hence, it is of interest to graphically represent the empirical $CDFs$ to provide a visual representation of the differentials between various distributions of NPLs in an endeavour to detect any influence of house price developments. Figure 2.5.1 shows the $CDFs$ of the NPL for the four codes in each year considered in the stochastic dominance analysis, while Figure 2.5.2 presents the empirical $CDFs$ of the NPLs for the four years considered in each region.[22]

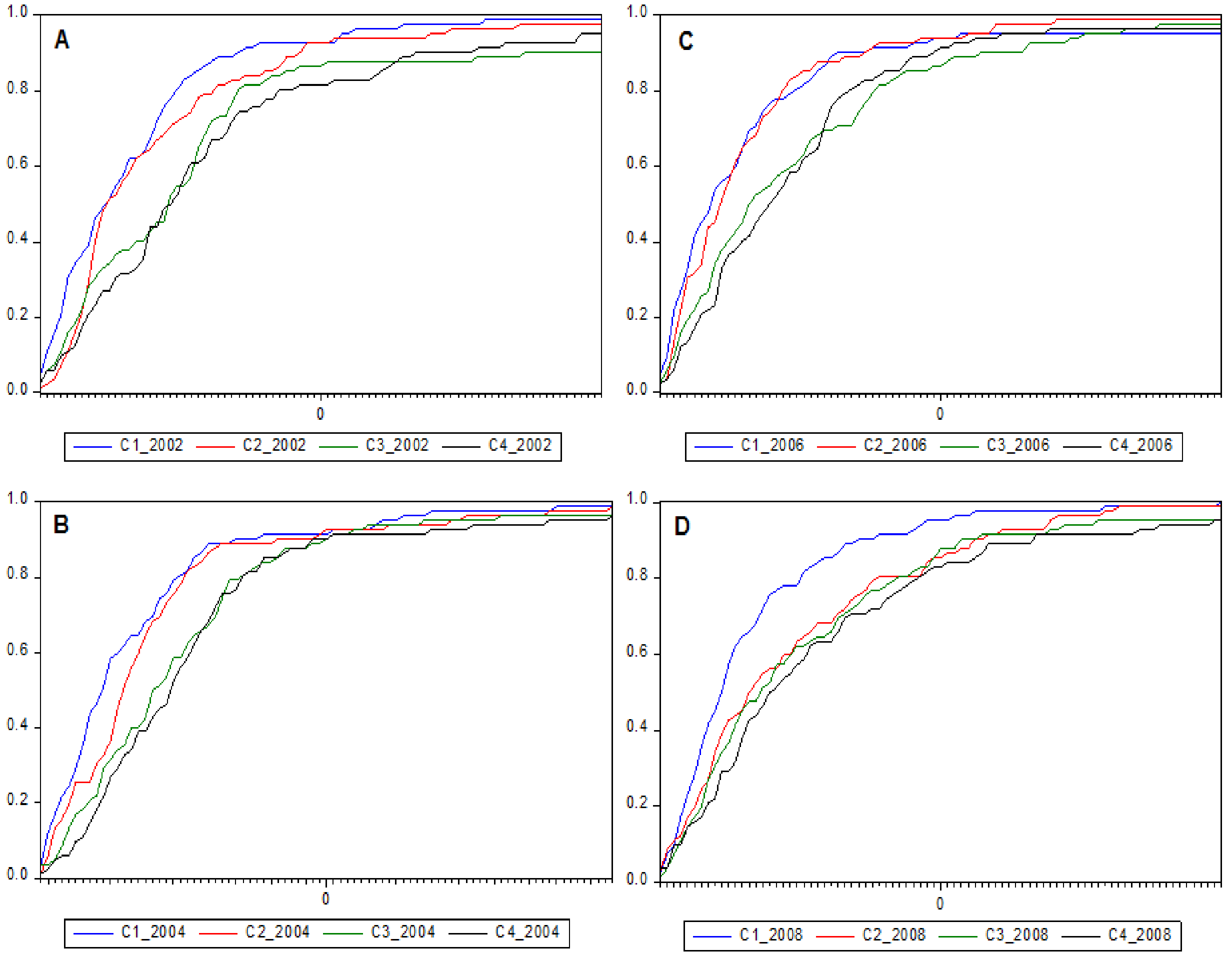
From the figures A, B, C and D displayed in Figure 2.5.1, it can be seen that, with few exceptions, the ranking of the empirical $CDFs$ starts from the curve of C_1, which lies on the left, followed by the curves of C_2, C_3 and C_4, respectively. This implies that the scale of house price increases can heavily influence the evolution of bad loans. The magnitude of the difference, as measured by the horizontal distance between the distribution functions, is more pronounced in 2006 and 2008, *i.e.* during and after the inception of the financial crisis.

Generally speaking, for a particular argument, the estimation of $\widehat{F_{iN}}(x, \theta)$ shown in Eq. (2.2) can be assessed by the usual geometric interpretation of the Riemann integral, as the area beneath the empirical CDF (Davidson, 2006). In light of Definition 2, second order stochastic dominance allows $CDFs$ to intersect, as long as the space under the dominating distribution curve does not exceed the space under the dominated distribution curve. From Figure 2.5.1, although the empirical $CDFs$ sometimes cross each other in the charts

[22] In the left chart of Figure 2.5.1, the label $C1\_2002$ denotes the distribution function for NPLs in the C_1 region in 2002. The other distribution functions are defined in a similar fashion.

mentioned above, the area between the $CDFs$ does not violate the condition for second order stochastic dominance.

Figure 2.5.1 Empirical CDFs of the NPLs for the Four Codes in Each Year



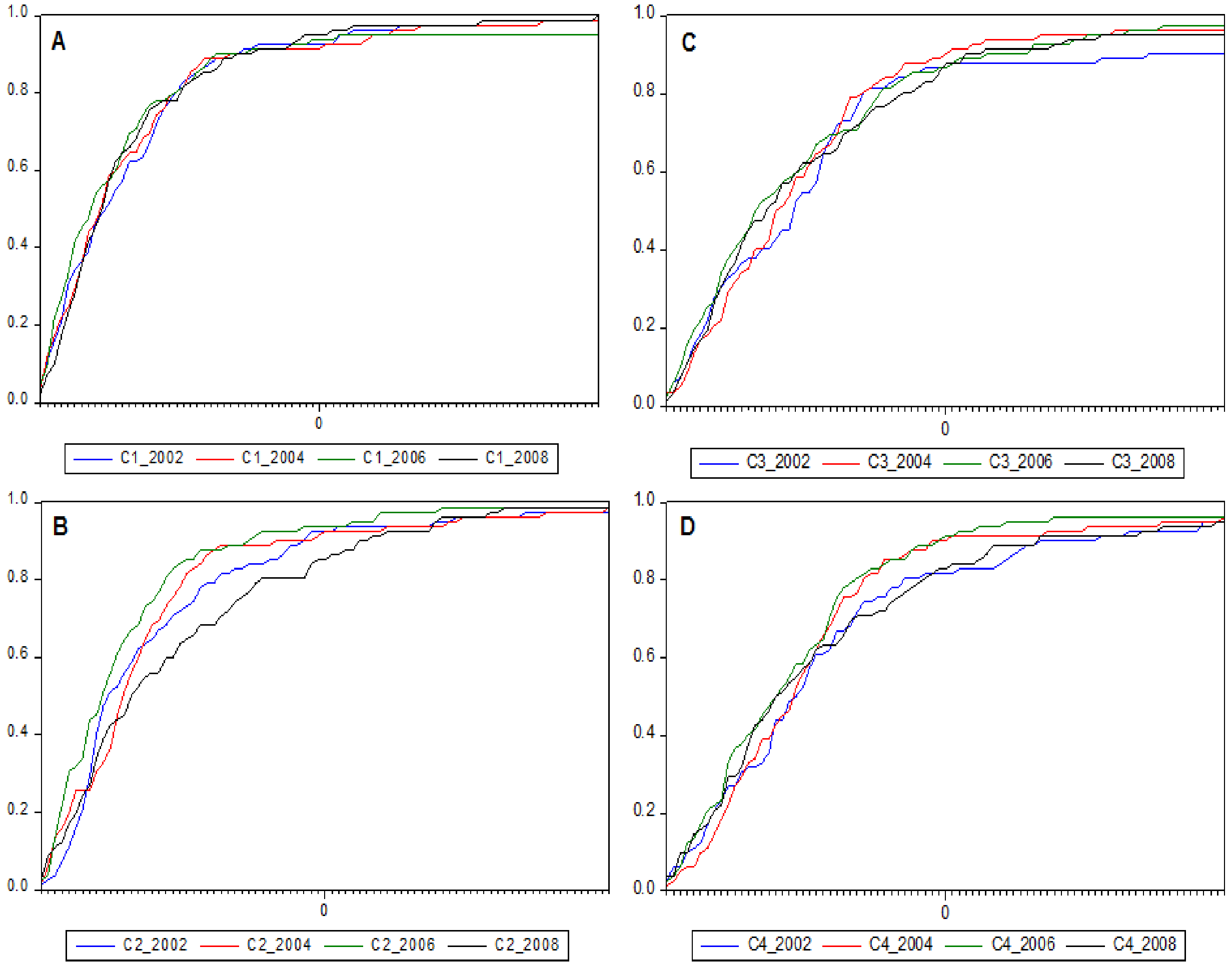
The scale of the NPL differential can be approximated by the locus of the quartiles on the vertical axis. Looking at Figure 2.5.1, it can be seen that all quartiles of the NPL distributions are higher for C_1 and C_2 than for C_3 and C_4. In particular, the difference in NPL median between banks in region C_2 and the corresponding banks in region C_4 is around 11% in 2002, while this difference is approximately 5% between banks in region C_3 and banks in region C_4 in the same year.

Similarly, in 2008 the estimated difference in NPL median between banks in region C_1 and banks in region C_4 is around 13%, which suggests remarkable differences in the evolution of NPLs between these regions. Furthermore, high differences have been found between the quartiles of the distribution of NPLs within the same region over different years. For example, a difference of about 14% is estimated between the lower quartile and the upper quartile of the NPL distributions for banks in region C_2 in 2006, while this difference is found to be approximately 32% in 2008.

On the other hand, the NPL differences are greater in the lower parts of the distributions. For example, a difference of around 27% in the lower quartile against a difference of roughly 1% in the upper quartile of the NPL distributions has been estimated between banks in C_1 and banks in C_3 in 2002. Similarly, this difference is around 20% in the lower quartile, against 2% in the upper quartile, between banks in C_1 and banks in C_3 in 2004.

To give an idea of the evolution of NPLs for each region over time, rather than across space, the empirical $CDFs$ in the same region are plotted by year in Figure 2.5.2.

Figure 2.5.2 Empirical CDFs of the NPLs for Each Code in the Selected Years



It is interesting to note that the positions of the $CDFs$ in 2006 of most regions under consideration shift to the left of the empirical $CDFs$ of 2002 and 2004. This indicates that NPL was higher in 2006 when the house price bubble started to bust. However, looking at the distribution functions of C_1, it appears that the recovery in these states after the turbulence of 2006 was much faster than the states in regions C_2, C_3 and C_4. Moreover, comparing the $CDFs$ for C_1 and C_2, it appears that the distribution functions of the latter are much closer together than the $CDFs$ of the former. Given the results in Table 2.5.1 and Table 2.5.2, this implies that the credit risk for states in the C_2 region is more structural than cyclical.

To summarise our results, the stochastic dominance analysis reveals that there is a strong relationship between housing market behaviour and credit risk exposure. States in the US that experienced a large real estate market boom, followed by a bust, also experienced greater financial instability. On the other hand, in states where housing market jumps were not so prominent, financial instability also occurred, but in this case the undermining impact of house price changes came as a result of the contagion effect of the recession initiated on the East and West coasts, rather than as an endogenous matter. The inferences from the stochastic dominance analysis are in line with the deviation hypothesis proposed by Koetter and Poghosyan (2010), as well as Borio and Lowe (2002), which suggests that risk builds up during booms and materialises itself during periods of economic recession. The findings also convey important policy implications, suggesting that proposals for curbing the impact of house price fluctuations on destabilising banking systems should be designed at the regional level, rather than at the nationwide level, which would help to take into account fundamental idiosyncratic factors of the individual states. Furthermore, these strategies must be consistent with the current phase of the economy since this exposure varies geographically and between economic phases.

The stochastic dominance method allows the analysis of possible differentials between the $CDFs$ of NPLs; however, it does not provide a justification and interpretation of the determinants behind these differences. In our case, stochastic dominance provides no information about the contributors to the differences in the scale of NPLs between states, with different scales in house price fluctuations, neither does it provide information concerning other possible factors that may influence changes in the ratio of NPLs. To gain further insight into this issue, we developed additional analysis to examine the impact of macroeconomic fundamentals and to quantify the impact and the magnitude of house price effects on the evolution of NPLs. In the following section, we consider the impact of gross domestic product $\boldsymbol{GDP}$, unemployment $\boldsymbol{UR}$, lending interest rate $\boldsymbol{IR}$ and return on house price index $\boldsymbol{HPR}$ on the behaviour of NPLs using an Arellano-Bond (1991) generalised method of moments (GMM) estimation followed by a generalised panel threshold model.

2.5.2. ARELLANO-BOND GMM ESTIMATIONS AND GENERALISED PANEL THRESHOLD MODEL

In this section, we estimate the Arellano-Bond (1991) GMM model to examine the impact of macroeconomic fundamentals, as well as house price index returns $\boldsymbol{HPR_{i,t}}$, on the volume of NPLs.[23] In the second step, we estimate a generalised panel threshold model, allowing for regime intercepts developed by Bick (2010) to assess the nexus between house price index returns and NPLs, controlling for the impact of macroeconomic fundamentals. Adopting the use of house price returns, rather than the house price index, is based on a lot of empirical evidence showing that the impact of house prices on the escalation of NPLs ratios is triggered by changes in house prices and their departure from their fundamental values.

Estimations of the GMM have been employed over the period under scrutiny to estimate two models, in particular NPL as a function of NPL lags, $\boldsymbol{GDP}$, unemployment rate $\boldsymbol{UR}$ and lending interest rate $\boldsymbol{IR}$ to form a baseline model, as shown in Eq. (2.11):

$$NPL_{i,t} = \alpha NPL_{i,t-1} + \sum_{j=1}^{2} \beta_{1j} GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} UR_{t-j} + \sum_{j=1}^{2} \beta_{3j} IR_{t-j} + \varepsilon_{i,t}, \qquad (2.11)$$

[23] For the theoretical framework of the Arellano-Bond generalised method of moments (GMM), see section 3.5 in Chapter Three.

where $\varepsilon_{i,t} = \mu_i + v_{i,t}$, $|\alpha| < 1,$ i denotes banks and $t = 1,\ldots,11$.

In the second step, we include house price index returns $\boldsymbol{HPR}$ to capture the impact of changes in house prices on the growth of NPLs, and to quantify the additional explanatory power of this variable, as shown in Eq. (2.12):

$$NPL_{i,t} = \alpha NPL_{i,t-1} + \sum_{j=1}^{2} \beta_{1j} GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} UR_{t-j} + \sum_{j=1}^{2} \beta_{3j} IR_{t-j} + \sum_{j=1}^{2} \beta_{4j} HPR_{i,t} + \varepsilon_{i,t}, \tag{2.12}$$

where $\varepsilon_{i,t} = \mu_i + v_{i,t}$, $|\alpha| < 1,$ i denotes banks and $t = 1,\ldots,11$.

Dynamic specifications allow including lags of the dependent variable which helps to account for autocorrelation. Furthermore, some of our regressors, such as interest rates, need to be dealt with as endogenous because causality might run in both directions, while other variables might have significant correlation with the error term. The GMM with instrumental variables helps to overcome problems of correlation in the errors. In particular, the Arellano-Bond two-step difference GMM estimation with robust standard errors is used to explore the effect of the macroeconomic factors and house price returns on the growth of bad loans in banks' loan portfolios. The instruments are selected from the explanatory variables, while their total number is restricted to be lower than the number of cross-sectional individuals. Eq. (2.11) and Eq. (2.12) have been estimated and the results are reported in Table 2.5.3.

The coefficients of the lagged NPLs in both estimations are statistically significant, with the positive sign suggesting that current NPL ratios are positively driven by their previous values. As far as economic growth is concerned, GDP reveals a high statistical significance with the negative sign, indicating that when the economy enjoys high economic growth, a lower volume of NPLs can be achieved. This is highly consistent with numerous previous studies that explored the determinants of NPLs, such as Louzis *et al*. (2010), Salas and Suarina (2002), Fofack (2005) and Jimenez and Saurina (2005). Each of these studies analysed the role of GDP growth on the evolution of NPLs, and found NPLs to be negatively influenced by the GDP growth, justifying that impact through the income growth that is associated with an increase in GDP, which is supposed to result in increasing borrowers' repayment capacity and thereby contributing to a lower scale of NPLs.

Table 2.5.3 Results of GMM Estimation for Macroeconomic factors and House Prices

Variables	**Baseline model**	**Model with house prices**
	Coefficients	**Coefficients**
NPL_{t-1}	0.935^{***}	0.897^{***}
	(0.065)	(0.062)
GDP_t	-0.317^{***}	-0.235^{***}
	(0.034)	(0.039)
UR_t	0.410^{***}	0.345^{***}
	(0.081)	(0.071)
IR_t	0.217^{***}	0.171^{***}
	(0.055)	(0.044)
HPR_t	-	-0.052^{***}
	-	(0.014)
$Constant$	-2.642^{***}	-1.791^{***}
	(0.603)	(0.606)
Arellano-Bond test for $AR(1)$ p-value	0.000^{***}	0.000^{***}
Arellano-Bond test for $AR(2)$ p-value	0.736	0.931
Sargan test of overid. restrictions p-value	0.875	0.955

*Note: Coefficients from the Arellano-Bond GMM estimation, with robust standard errors in parentheses and finite sample correction (xtabond2 in Stata). * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.*

As for the unemployment rate, the coefficients of UR in Table 2.5.3 are highly significant in both estimated models. Furthermore, the positive sign is indicative and implies that an increase in the unemployment rate negatively influences borrowers' incomes, undermining their borrowing capacity, and exposing them to higher debt burdens and consequently a higher probability of default (see, for example, Nkusu (2011), Bofondi and Ropele (2011) and Rinaldi and Arellano (2006)).

An equally important determinant of NPLs is lending interest rates. Empirical analyses in the two GMM models presented in Table 2.5.3 show high significance, with a positive correlation between the interest rate and impaired loans. This finding provides evidence that an increase in the interest rate would lead to a higher ratio of NPLs by forcing borrowers to incur higher costs on the debts, which might encourage them to default as these costs become unaffordable. This outcome is in agreement with the works surveyed in the literature review (see, for example, Nkusu (2011) and Louzis *et al.* (2010)).

Finally, the estimated coefficient of house price index returns reveals the high statistical significance of this variable. The negative sign associated with the coefficient indicates that an increase in the house price returns contributes to the reduction in the ratios of NPLs in banks' loan portfolios through the channel of households' net wealth, given the predominance of collateralised loans in the US (see, for example, Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)). This finding is in line with the view provided by Koetter and Poghosyan (2010) regarding the impact of property price deviations from their fundamental values on the evolution of credit defaults. On the other hand, property price appreciation helps enhancing banks' capital positions through the increase in the value of properties held by the banks, increasing their lending capacity. It is worth mentioning that when the real estate market turns, house prices start to depreciate, resulting in a high volume of negative home equity, which is rapidly translated into a high growth in non-performing loans in banks' loan portfolios.

As far as the robustness and validity of the estimation are concerned, the selection of the instruments used in the estimation and the serial uncorrelated error term are essential conditions to achieve consistent estimators of the GMM. To address this issue, the Sargan test suggested by Arellano and Bond (1991) to assess the joint validity of the instruments and over-identification restrictions has been employed for the two GMM estimations, in order to examine the validity of the selected instruments. Moreover, since the validity of the included instruments can be inferred from the structure of the errors, p-values for the statistical significance of the first order $AR(1)$ and second order $AR(2)$ of error autocorrelation, proposed by Arellano and Bond (1991), are provided in Table 2.5.3. For the best specifications, the null hypothesis of no first order serial correlation in the residuals should be rejected, and the null hypothesis of no second order serial correlation in the residuals should be accepted.

Our tests indicate the GMM models achieved good specifications. The p-value of the Sargan test reported in Table 2.5.3 does not reject the null hypothesis, suggesting that the chosen instruments are valid, exogenous and not correlated with the error term. On the other hand, p-values for the statistical significance of $AR(1)$ and $AR(2)$ reveal no evidence of first order serial correlation, but evidence of second order serial correlation in the residuals with the rejection of the first order null hypothesis and the acceptance of the second order null hypothesis. These findings confirm the robustness of the estimation and support the validity of the instruments, although they become weaker when a higher number of instruments are included.

To investigate the nexus between NPLs and house price index returns defined above, we adopt the methodology provided by Bick (2010) to estimate a generalised panel threshold model, allowing for regime intercepts.[24] To this end, the computational code provided by Bick (2010) has been utilised to satisfy our objectives (see APPENDIX 2.7 for the theoretical background). The generalised threshold model for a single threshold model with regime intercept is employed to estimate the following equation of interest, which corresponds to Eq. (2.B) provided in APPENDIX 2.7:

$$NPL_{it} = \mu_i + \beta_1 \widehat{HPR}_{it} I\left(\widehat{HPR}_{it} \leq \gamma\right) + \delta_1 I\left(\widehat{HPR}_{it} \leq \gamma\right) + \beta_2 \widehat{HPR}_{it} I\left(\widehat{HPR}_{it} > \gamma\right) + \varphi Z_{it} + \varepsilon_{it}, \tag{2.13}$$

where i denotes banks and $t = 1, \dots, 11$.

[24] Note that the generalized panel threshold model allowing for regime intercepts developed by Bick (2010) was implemented on a balanced panel dataset, and our panel dataset is also a balanced panel dataset.

In Eq. (2.13), non-performing loans NPL_{it} is the dependent variable of interest, while house price index returns $\widehat{HPR}_{it}$ plays the roles of the threshold variable and the regime-dependent variable. Z_{it} is a vector of control variables that are included consistently with the theoretical background highlighted in APPENDIX 2.7, and in light of our findings from the GMM estimation. Specifically, the term Z_{it} includes gross domestic product GDP, unemployment UR and lending interest rate IR. Table 2.5.4 presents the results for threshold specifications with regime intercepts.

The upper panel of Table 2.5.4 shows the regime-dependent coefficients, while the lower panel represents the regime independent coefficients. The threshold coefficient, -3.17, is highly significant with the inclusion of a regime intercept helping to decrease the threshold and the lower bound of the 95% confidence interval to -3.679.

With regards to regime-dependent regressors, the most remarkable point in this estimation is that, with the existence of a regime intercept, two different impacts of house price index returns on the evolution of NPLs have been detected. In particular, the results reveal that when the house price returns index is below -3.17, a 1% increase in house price index returns helps to reduce NPLs by 0.043%, holding other things equal. On the other hand, when the house price returns index fluctuates over -3.17, a 1% increase in house price index returns helps to reduce NPLs by only 0.01%, holding other things equal. This means that when house price index returns are below the threshold point of -3.17, house price index returns have a highly significant negative influence on NPLs of around 0.043% at the 1% significance level, while this negative influence declines to 0.01% when house price index returns fluctuate above the threshold point and are still highly significant.[25] Therefore, the impact of house price index returns on the evolution of NPLs is higher when the house price index exceeds the threshold value, while it is weaker below the threshold point.

[25] Note that the impact of house price index returns, as a threshold variable, conserves its negative sign, consistent with our finding from the second GMM model in Table 2.5.3.

Table 2.5.4 Threshold Results for Models with Macroeconomic Variables

Variables	Coefficients
Threshold estimates and confidence intervals	
$\hat{\gamma}$	-3.17***
95% confidence interval	[−3.679 , − 2.700]
Regime-dependent regressors	
$\hat{\beta}_1$	−0.043*** (0.020)
$\hat{\beta}_2$	−0.01*** (0.004)
$\hat{\delta}_1$	0.942** (0.453)
Regime-independent regressors	
NPL_{t-1}	1.094*** (0.355)
GDP_t	−0.735*** (0.293)
UR_t	0.123 (0.137)
IR_t	0.454*** (0.079)

*Notes: γ denotes threshold estimates. Robust standard errors are in parentheses. * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.*

As far as the regime intercept is concerned, the coefficient of regime intercept $\hat{\delta}_1$ reveals high statistical significance at 5% significance level. Moving on to the regime-independent regressors, with the exception of unemployment UR, which shows no evidence of statistical significance, the coefficients of gross domestic product GDP and lending interest rate IR, which are included in the vector of control variables Z_{it} in Eq. (2.13), confirm our findings in the Arellano-Bond (1991) GMM model. More importantly, these outcomes are consistent and in line with the empirical studies included in the literature review in Section 2.2.

According to Bick (2010), accounting for differences in the regime intercepts in the threshold effect model has important policy-related implications. First, the threshold value and the lower bound of the confidence interval refer to the point from which the impact of house prices starts to be highly influential on the growth of NPLs. Second, when house price index returns slightly exceed the threshold point, the negative impact of house price index returns on NPLs increases considerably. Finally, maintaining house price index returns close to or below the threshold point has a vigorous and advantageous impact on achieving low ratios of NPLs.

Tracing the history of house prices in the US during the period under scrutiny, it can be seen that, with few exceptions, house price growth in most of the states considered fluctuated below the threshold point from 1999 to 2004, when the rapid increase in house prices took place, leading to a more harmful impact of house prices on the evolution of bad loans. Furthermore, threshold point was exceeded to differing degrees in different states. That is, the magnitude of the departure of house prices from their fundamental values in states grouped in $code\ 1$ and $code\ 2$ was significantly less than their peers in states grouped in $code\ 3$ and $code\ 4$, which resulted in the more pronounced impact of house prices on the level of NPLs in the latter states. However, the threshold point seems to have been exceeded in all states, without exception, during the build-up of the housing price bubble, which lasted until the start of the financial crisis, when the house price bust took place and negative growth in house prices began to be witnessed. Consistent with our previous findings, the threshold analysis again proves that the escalation of NPLs is highly driven by changes in house prices, and more precisely by the departure of real estate prices from their fundamental values.

2.6. CONCLUSION

This chapter investigated the dynamic between real estate prices and credit default risk attached to financial institutions. Considering balanced panel data from individual US banks at the bank level, we used a stochastic dominance test to examine the presence of regional differences in the growth of non-performing loans.

US states were categorised into four groups according to the trajectories of the house prices observed in these states. The results of the stochastic dominance analysis indicate that the stochastic dominance of NPL distributions moves gradually from the states where house price increases were less than 20% to states where house prices underwent growth of more than 80%. This proposes that NPL ranking is the lowest in states where house prices increased by less than 20% and rises progressively in states where house prices increased by between 20% and 40%, followed by states where house prices increased by between 40% and 80%, to reach its peak in states where the appreciation in house prices was observed to be higher than 80%. Therefore, the outcomes of stochastic dominance show a symmetric behaviour between NPLs and the level of observed house price growth.

To account for the impact of macroeconomic factors and the business cycle on the growth of NPLs, we estimate the Arellano and Bond (1991) GMM model with robust standard errors to examine the effect of GDP, unemployment rate and lending interest rate in the first GMM model, and add house prices in the second model to check the additional explanatory power of house prices on the evolution of NPLs. The estimation of the first GMM model reveals that NPLs are, to a large extent, driven by economic growth, unemployment rates and lending interest rates. Particularly, economic growth proxied by GDP is found to negatively impact the growth of NPLs, while unemployment and lending interest rates contribute to the increase of NPLs through increasing the debt cost and increasing the risk that borrowers will default on their debt obligations.

The second GMM model, accounting for the impact of house prices, confirms the results of the first GMM model and reveals that house prices are negatively associated with the growth of NPLs. That is, an increase in house prices leads to a lower ratio of NPLs, which can be attributed to appreciation in the collateral values, providing additional scope for borrowers to service their debts and enhancing their ability to access credit. It is worth mentioning that our findings are consistent with various works covered in the literature review in Section 2.2 (such as Rinaldi and Arellano (2006)), and more importantly in line with the notion of a "*financial accelerator*" or "*credit multiplier*" provided by Bernanke *et al.* (1996). On the other hand, an increase in collateral values is supposed to encourage banks to boost their lending in order to achieve higher market share, leading in the long term to a credit boom, which is considered a key driver of credit defaults, as demonstrated by Kiyotaki and Moore (1997).

To explore the connection between NPLs and house prices, we implement a generalised panel threshold model allowing for regime intercepts, proposed by Bick (2010), allowing house price index returns to play the role of threshold parameter and accounting for the impact of the control variables considered in GMM estimation. The results of the threshold specifications with regime intercepts produce a threshold coefficient of -3.17, in relation to which different impacts of house price index returns on the evolution of NPLs are implied. In other words, the regime-dependent regressors indicate two different influences of house price index returns on the escalation of NPLs, according to the magnitude of house price index returns compared to the threshold point of -3.17. The harmful impact of house price index returns on the growth of NPLs is weak when the house price index fluctuates beneath the threshold value of -3.17, while it becomes greater when the threshold point is exceeded. As far as the regime-independent regressors are concerned, the results confirm our findings from the Arellano-Bond (1991) GMM model and are in line with the conclusions drawn from the stochastic dominance analyses, except for the unemployment rate, which is not significant in the threshold analyses.

The regime intercepts and threshold value in the threshold effect estimations are highly important due to their policy-related implications. Specifically, the threshold value refers to the point at which the dangerous effects of house prices on the performance of bank loans starts to be highly influential. Based on this finding, ensuring that house price index returns remain as close as possible to the threshold point is a vital task to be achieved by real estate policymakers, in order to maintain low ratios of NPLs.

Looking back at the house prices in the US over the investigated period, it can be verified that house price growth fluctuated below the threshold point from the beginning of our time period up to 2004, over almost the whole of the US. However, house price growth started to exceed the threshold point after 2004, resulting in a highly detrimental impact on the growth of impaired loans. More importantly, the amplitude of the departure of house prices from the threshold point was far from symmetrical, leading to differences in the scale of banks’ exposure to changes in real estate markets.

2.7. APPENDIX

A static panel threshold model, allowing regression parameters to take different values governed by an exogenous stationary variable, was developed by Hansen (1999). Later, in an attempt to generalise Hansen' approach, Gonzalez *et al*. (2005) proposed a panel smooth transition regression ($PSTR$) model to allow a gradual change of regression coefficients between regimes. Although the static models mentioned above are panel methods, and allow for the random variation of the regression coefficients over time, as well as cross-sectional unit dimensions, their validity in a dynamic panel context has not yet been rigorously proved (Hsiao, 2003).

Starting from Hansen's (1999) proposal, the estimation for balanced panels with individual-specific effects and observations defined as $\{y_{it}, q_{it}, x_{it}; 1 \leq i \leq N, 1 \leq t \leq T\}$, where the subscript i refers to the cross-section dimension, while subscript t denotes the time dimensions. The equation of interest with one potential threshold γ is given by Eq. (2.A), formulated as follows:

$$y_{it} = \mu_i + \beta_1' x_{it} I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + \varepsilon_{it} \quad \text{with} \quad \varepsilon_{it} \overset{iid}{\sim} (0, \sigma^2). \qquad (2.A)$$

The elements of Eq. (2.A) are defined as follows: y_{it} is the scalar stochastic variable of interest, x_{it} is a k-dimensional vector of exogenous regressors, $I(\cdot)$ is the indicator function, γ is the threshold parameter, q_{it} is the threshold (transition) scalar variable that separates the sample into two distinct regimes (however, it should not be included in x_{it}), β_1 and β_2 are the regression slope parameters associated with the two respective regimes, and finally ε_{it} is the independent and identically distributed error term.

As far as individual-specific effects are concerned, they could be estranged by performing fixed-effect transformations. However, Bick (2010) proposed a generalised panel threshold model allowing for regime intercepts, in which he confirmed that even with the presence of fixed effects, we can govern differences between the intercepts of the regimes through including them in all but one regime; therefore, Bick (2010) suggested an extension of Eq. (2.A) to be as follows:

$$y_{it} = \mu_i + \beta_1' x_{it} I(q_{it} \leq \gamma) + \delta_1 I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + \varepsilon_{it}. \qquad (2.B)$$

According to Eq. (2.B), the difference in regime intercepts, denoted as δ_1, are the same for all individuals rather than individual-specific.[26]

Given a specific threshold, the regression slope parameters β_1 and β_2 can be calculated by employing simple ordinary least squares (OLS) over the data produced from the fixed-effect transformation.[27] Importantly, ignoring variables correlated with any of the regressor and dependent variable might results in biased results. The reason for the bias is that limiting our estimation to the formulation in Eq. (2.A), rather than Eq. (2.B), with the existence of a regime intercept in the data generating process (DGP), exposes $\hat{\delta}_1$ to major proportional bias by violating the orthogonality condition of the regressors (Bick, 2010). In return, obtaining biased estimates of the slopes leads to added concerns in the panel threshold model, since the threshold coefficients are also produced by the least squares, as follows:

$$\hat{\gamma} = \underset{\gamma}{argmin}\ S_1(\gamma), \qquad (2.C)$$

where $S_1(\gamma)$ is the sum of squared residuals resulted from estimating either Eq. (2.A) or Eq. (2.B) for a specific threshold. In a special case, where a regime intercept exists in the DGP, estimating either the Eq. (2.A) or Eq. (2.B) specifications is presumed to deliver identical findings to the other. According to Bick (2010), biased estimates of β_1 and β_2 result in misleading statistical inferences that undermine the threshold significance test. Therefore, the following linear constraint should be satisfied:

$$\mathcal{H}_0\colon \beta_1 = \beta_2. \qquad (2.D)$$

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[26] Hansen (1999) provides a thorough overview framework of the estimation and inference strategy in dealing with multiple (single, double and triple) thresholds.

[27] For the mathematical formulation and estimation of the coefficient and the modifications introduced to the models by Hansen (1999) to allow for regime intercepts, see Bick (2010).

3. CHAPTER THREE

WHAT DRIVES NON-PERFORMING LOANS IN ADDITION TO THE ECONOMIC CYCLE? HOUSING AFFORDABILITY, HOUSEHOLD FRAGILITY AND FINANCIAL DEVELOPMENTS

3.1. INTRODUCTION

Sound banking and financial systems are essential for any economy to flourish. The banking industry is an indispensable service, enhancing economic plans through governing fund channels for economic stability purposes and supporting the financial and monetary policies of the government. One of the major concerns for any financial institution is non-performing loans (NPLs) since these, if not managed properly, can lead to a banking collapse. A financial crisis, in return, can have catastrophic consequences at both microeconomic and macroeconomic levels. In this respect, the great efforts devoted by academics to investigate the determinants of increases in impaired loans in banks' loan portfolios, and the negative consequences of this, are understandable. On the other hand, housing, as asserted by many researchers, is the spirit of any economy and plays an intrinsic role in stimulating and revitalising economic growth, particularly with shelter being a key indicator of development in a country (Njiru and Moronge, 2013).

Assuming a high correlation between the real estate market and the stability of the banking sector is reasonable in light of the following two considerations. First, loans to real estate markets comprise somewhere between one third and more than half of bank loan portfolios in most developed countries. Second, the prevailing uses of property for collateral-based loans forms an important channel between the two markets. Indeed, the collapse of several banks whose primary activity was real estate financing raises the question of whether the stability of banks is connected to changes in real estate market conditions and suggests the need for more efforts to quantify the actual impact of the real estate market on the quality of banks' loan portfolios.

The impact of the banking industry on the real estate market has been extensively scrutinised (see, for example, Hofmann (2001) and later Davis and Zhu (2004)); however, the reverse impact of the real estate market on banks' credit defaults remains neglected. In fact, the impact of some housing market factors on financial stability have been investigated (see, for instance, Ferguson and Navarrete (2003)); however, there is a general consensus that factors such as (i) the development of the financial system of the country, (ii) the level of house affordability and (iii) household indebtedness, in addition to the general macroeconomic environment, have important roles in the evolution of NPLs. Below, we analyse these factors in turn.

This chapter contributes to the existing literature on NPLs by providing evidence for the impact of housing-related factors, borrower-related factors and financial development factors on the evolution of impaired loans, which helps to capture the actual exposure of the banking sector to deficiencies in the real estate market. Different to previous studies that were limited to a sample of countries with similar characteristics in terms of financial development and housing markets, our sample has been chosen to reflect considerable differences in financial systems, housing market characteristics and household vulnerability, which imposes essential empirical implications in terms of model selection.

As house purchases involve access to credit, the strong link between real estate cycle and domestic financial development is not surprising (see, for example, IMF (2011) and Beckett (2014)). Financial development and banks' lending behaviour have been identified in the literature to be crucial drivers of credit risk. Aggressive lending behaviour has been found in many works to be a potential cause of increasing NPLs. Salas and Saurina (2002), for example, find rapid credit expansion to be one of the factors that explain variation in NPL rates (see also Jimenez and Saurina (2005), Keeton and Morris (1987), Sinkey and Greenwalt (1991) and Keeton (1999)). Hott (2011) suggests that housing demand is highly driven by credit availability, which in turn is subject to the supply of mortgages by banks. This link poses interesting questions regarding the impact of credit availability, and financial development in a broader context, on the evolution of credit defaults. In fact, the effect of NPLs on the credit cycle has been investigated in various works, including Caporale *et al*. (2009). The authors found negative effects of NPLs on credit to the private sector, due to the undermining role that growth in NPLs has with regard to banks' financial positions, leading to a deceleration in credit growth. However, the feedback effect, investigating the impact of financial development and lending behaviour on the evolution of NPLs, has not been examined. To address this issue, we generate a composite indicator that reflects the role of financial development and banks' lending behaviour on the growth of NPLs.

Owning a house is a common investment that many people wish to make in their lifetime. However, as with any investment opportunity, it must be affordable; in this case it requires households to afford the house price or rent. According to Andrews (1998), an affordable house is one that costs no more than 30 per cent of the income of the occupant household, implying buying or renting a house with acceptable standards at a cost that does not overburden households incomes for each income class.[28] This means that a change in housing affordability due to house price changes implies difficulties in affording necessities, which undermines borrowers' ability to pay their obligations, resulting in a higher probability of default. In light of this argument, housing affordability is regarded as one of the core issues for players in the housing market and a legitimate source of concern regarding bank's loan performance. As for measuring affordability, there are two widely used proxies to indicate affordability of housing, specifically, the price-to-income (PTI) ratio and the price-to-rent (PTR) ratio.[29] According to these two indicators, housing affordability is principally affected by house prices or rents and household income. Thus, changes in housing

[28] She also referred to housing costs that are higher than 30 per cent of income as cost burdened, and those that are 50 per cent or more as severe housing burdens (HUD, 2005). See US Department of Housing and Urban Development.

[29] Price-to-income is defined as nominal house prices divided by nominal disposable income per head, while price-to-rent is the ratio of nominal house prices to rent prices. Both ratios use the year 2010 as the base year.

affordability might be a result of changes in one or more of these components, and consequently the ultimate impact of affordability on NPLs depends on the source of change in these factors.

As a fundamental player in shaping and determining housing affordability and household creditworthiness, household fragility and indebtedness essentially influence the probability of defaulting under the *"ability-to-pay theory"* (see, for example, Gadanecz and Jayaram, 2008)). Furthermore, household indebtedness is an essential factor for lenders when assessing borrowers' eligibility to get loans, since it indicates the ability of the latter to service their obligated debts. In an influential study by Hott (2011), banks' willingness to fund house purchases is attributed to the creditworthiness of the borrowers, which is found to be mainly driven by the development of house prices. Based on this argument, household indebtedness is supposed to play a key role in determining credit default probability. Thus, household indebtedness is expected to affect the growth of bad loans in financial institutions, since an increase in this factor refers to a weaker ability to repay debts (see, for example, Salas and Saurina (2002) and Jappelli, Pagano and Maggio (2008)).

The link between housing system and financial system requires a profound understanding of the mechanism that governs house price changes across nations, because the literature concerning the financial crisis documents that episodes of boom and bust in real estate markets have often been associated with rapid growth in the ratio of impaired loans. However, the extent to which booms and busts in property prices foster instability in financial systems varies between countries, due to the heterogeneity in their housing finance systems and the degree of government involvement in this market. Therefore, the impact of house prices is scrutinised in this study in an attempt to quantify the impact of growth in residential property prices on the growth of NPLs.

The literature is rich with studies investigating the role of house prices and macroeconomic variables in undermining the stability of the banking system; however, macroeconomic factors and house prices tell only one side of the story. Hence, investigating the impact of housing affordability, household indebtedness and financial development on the increase in NPLs could produce important policy implications, because borrower-related factors, housing market factors and financial market factors are the main sources of credit risk. Since any of these factors might play the role of the weakest link in the lending chain, identifying these weaknesses constitutes a fundamental step towards strengthening vulnerable links in the banking sector.

After highlighting the studies that investigated the determinants of NPLs, the theoretical framework will be described in the next section, and then the empirical framework of the study will be considered, followed by the analyses of the estimated models. Finally, a summary and the conclusions of the empirical analyses will be provided in the last section.

3.2. LITERATURE REVIEW

High ratios of NPLs in banks' loan portfolios have been identified in the literature as the major cause of economic meltdown. It undermines confidence and increases uncertainty in the banking and financial system, in addition to adding the high costs of managing large volumes of NPLs, and the lower capital resulting from provisioning.[30] The overall effect of these events is slower credit growth, which has serious ramifications for economic activity as the future profits from investments will be shared with the financial institutions that provide funds (see, for example Myers (1977)).[31] In their study, Greenidge and Grosvenor (2010) found that the magnitude of NPLs is a key factor in triggering financial and banking crises; therefore, investigating their determinants is an indispensable approach.

Rinaldi and Arellano (2006) found that house prices are negatively related to NPLs in the short term, which supports the view that wealth could be used as a buffer against unexpected shocks or as collateral to facilitate access to credit. During periods of boom and bust, the appetite of banks to issue risky loans is justified by their expected profitability. In other words, markets often release expectations during boom periods that house values will

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[30] For further reading on the consequences of NPLs, the reader is referred to Karim *et al.* (2010).
[31] See, for example, Meltzer, B. (2010). "Mortgage Debt Overhang: Reduced Investment by Homeowners with Negative Equity". Kellogg School of Management.

continue to rise, adding that to the availability of liquid assets in businesses, which in turn affects the behaviour of the players in the market, who expect higher returns from using debt to finance house purchases. On the other hand, banks become motivated to lend with lax conditions to expand their market share, driven by the spurious and amplified borrowing capacity of loan demanders, which results in rapid credit growth with numerous low quality loans issued to less creditworthy borrowers. All these factors go into reverse when the borrowers' expectations vanish and asset prices, including banks' collateral, start to depreciate, resulting in large amounts of NPLs (see, for instance, Ahuja *et al*. (2010)).

Bearing the above arguments in mind, banks' lending behaviour, and financial developments in a wider context, seems to be fundamental drivers of NPLs through their influence on house prices and owing to the fact that house ownership implies borrowing. Within the related literature, a mainstream of works shows that financial crises are often preceded by domestic credit booms, demonstrating that an increase in providing credit to the private sector is a powerful predictor of banking instability and financial crises (see, for example, Schularick and Taylor (2012) and Gourinchas and Obstfeld (2012)). Among others, Gavin and Hausmann (1998) find excessive credit growth to be a key driver of banking crises. In his recent study, Nkusu (2011) finds that adverse shocks to the supply of credit to the private sector, as a widely used indicator of financial development, decrease the quality of loans.[32] In the same vein, Büyükkarabacak and Valev (2006) conducted a study over a sample of 45 emerging and developed markets and found that the proportion of domestic credit provided to households, rather than to enterprises, to be the only driving force with a positive link between banking instability and credit expansions. These findings constitute a source of motivation to scrutinise the impact of domestic credit provided to the private sector, rather than to enterprise, on the evolution of NPLs.

[32] According to the World Bank, "domestic credit provided to the private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable".

From a theoretical perspective, dealing with demand for durable goods as similar to demand for non-durable goods is acceptable among economists (Chow, 1957). Thus, demand for houses requires essentially both willingness to purchase (or rent) a house and housing affordability. Bogdon, Silver and Turner (1994) found that housing affordability is the most severe problem in most parts of the United States. In addition to work as a shield against the weather elements, affordable housing affects the stability and performance of the economy and financial system; therefore, it has a fundamental influence on the economic growth pursuit of the whole country.[33] Specifically, housing affordability means households' ability to reasonably meet their mortgage obligations in a way that does not prevent them from accessing the basic necessities of life.[34] This raises a question concerning the effect of changes in housing affordability on the ability of borrowers to fulfil their obligations, and consequently on the likelihood of them becoming defaulters. In terms of measuring affordability, the affordability of housing is measured by the ratio of a selected definition of household costs to a selected measure of household income in a given period (see, for example, Maclennan and Williams (1990)). Widely used proxies for housing affordability among scholarly researchers include price-to-income and price-to-rent, both of which indicate the ability of households to fulfil their mortgage obligations without encumbering them. To sum up, since changes in house prices and rents have been identified as a fundamental driver of NPLs and simultaneously as a determinant of housing affordability, housing affordability is expected to influence the level of NPLs in an economy.

From the lenders' point of view, issuing a loan depends primarily on the borrower's ability to pay back their debts, which is highly influenced by the borrower's fragility. Indeed, borrower vulnerability is used by banks when assessing loan demanders' qualifications for a loan. Jappelli, Pagano and Maggio (2008) used fixed effects to analyse household fragility and ability to service debts, focusing on mortgage arrears, and revealed a positive correlation between credit risk "insolvencies" and unemployment during periods of high indebtedness.

[33] See, for example, Boamah, N.A. (2010). "Housing Affordability in Ghana: A focus on Kumasi and Tamale". Ethiopian Journal of Environmental Studies and Management .Vol.3 No.3, 2010.

[34] See CHF International (2004). "Strategic Assessment of the Affordable Housing Sector in Ghana".

Similarly, Rinaldi and Arellano (2006) showed a high association between indebtedness, proxied by debt-to-income ratio, and the performance of banks' loans. In their study at the bank level, Salas and Saurina (2002) found family indebtedness, rapid past credit expansion and net interest margin, among other variables, to have a high influence on banks' credit risks.

3.3. EMPIRICAL FRAMEWORK

This section describes the procedure that is used to construct proxies for financial development, housing affordability and household indebtedness to be used in the empirical investigations. Due to limited data availability and structural breaks, mainly in emerging markets, developing a robust estimation at the country level is challenging. It is, therefore, suitable to depend on a panel data-based estimation for considerably different economies.

As far as financial development is concerned, related empirical literature in this regard advocates the use of monetary aggregates to reflect both the size and depth of the financial sector. However, this indicator has been widely criticised for being a poor measure in the case of underdeveloped financial systems (see, for example, Khan and Senhadji (2003)). Furthermore, this indicator has been subject to criticism for reflecting the magnitude of transactional services delivered by the financial sector, rather than its efficiency in channelling funds from depositors to borrowers (see, for instance, Fry (1997)). As an alternative measure of financial development, the ratio of domestic credit provided to the private sector to GDP has been widely advocated in empirical studies to reflect financial development (see, for example, King and Levine (1993a)). For example, Gourinchas and Obstfeld (2012) found domestic credit expansion to be the most robust and significant predictors of financial crises. The usefulness of this indicator is of twofold: first, it is limited to credit allocated to the private sector that allows the efficient use of funds; second, it is an accurate indicator of the financial institutions' savings prepared to the private sector, since it does not account for the proportion of credit assigned by the central banks.

However, since housing loan shares constitute between one third and more than half of bank loan portfolios in most developed countries, it is useful to represent this fact in our financial development indicator to reflect banks' lending behaviour for housing-related activities. Hence, the ratio of mortgages to GDP is used to represent the role of mortgages in the financial system. The selection of this variable is based on the fundamental consideration that a country's mortgage system generally reflects the supply and demand for housing as well as the political and regulatory environment. Therefore, we employ principal component analysis (PCA) for the ratio of domestic credit provided to the private sector to GDP, and the ratio of mortgages to GDP, to generate a summary measure of the financial development and mortgage lending behaviour, owing to the relative importance of these two financial indicators on the evolution of NPLs.

The effect of household indebtedness and fragility on the progress of NPLs ratio is also investigated in this work. We use two variables to reflect the level of household indebtedness, namely the ratio of household debt to net disposable income, and relative household housing consumption to household housing disposable income. The former indicator has been used in many empirical works as a proxy for household debts, such as the study by Rinaldi and Arellano (2006), who reported a high correlation between debt-to-income ratio and NPL ratio, while the latter indicator has been included to reflect household housing expenditure. An important channel for the impact of property prices on the economy is through consumption, due to the fact that spending on consumption relies, among other things, on households' financial capacity, while housing ownership constitutes the most preferable sort of saving in the majority of the world's economies (see, for instance, Peng *et al.* (2001)). Furthermore, property price fluctuations are found to affect consumption through credit availability, in which lending policy plays the most fundamental role (see, for example, Bernanke and Gertler (1995)). Therefore, depreciation in consumption driven by a decline in property prices is assumed to influence households' default decisions.

Consistent with the definition of housing affordability proposed by Maclennan and Williams (1990), we use two widely used proxies to indicate the affordability of housing, specifically price-to-income (PTI) ratio and price-to-rent (PTR) to capture the impact of housing affordability on the growth of NPLs. Although the term "housing affordability" seems to refer to the cost of buying a house, as noted in many empirical studies, housing affordability indicates the ability to both buy and rent houses, due to the high association between the two indicators. However, to reduce the number of regressors in the estimation, we employ principal component analyses (PCA) over the two affordability indicators mentioned above to construct a single summary measure of housing affordability. The resulting housing affordability indicator is expected to be significant in explaining NPLs, although the signs of their coefficients are not clear. Specifically, price-to-income is mainly driven by house prices and household income, while price-to-rent is driven by house prices and house rents; therefore, the overall impact of the affordability measure is mainly subject to the source of changes in affordability indicator components.

Finally, the academic literature on NPLs provides evidence that suggests a robust link between the growth in NPLs and some macroeconomic variables. Generally speaking, fundamental macroeconomic determinants of NPLs include the real interest rate, GDP growth, unemployment rate, inflation rate and loan growth, among others. Using a dynamic panel data method for the nine largest banks in Greece, Louzis *et al.* (2010) found that NPL growth is mainly driven by macroeconomic fundamentals. Similarly, Bofondi and Ropele (2011) found that loans to both households and corporates can be explained by macroeconomic variables. In essence, they found that the quality of lending for households varies inversely with the growth rates of real GDP and house prices, and positively with the unemployment rate and the short-term nominal interest rate.[35] Therefore, we control for the impact of domestic economic conditions by including macroeconomic fundamental variables that are identified in the literature as drivers of NPLs.

[35] Other studies that explored the effect of the macroeconomic environment on NPLs include Vogiazas and Nikolaidu, (2011), Espinoza and Prasad (2010), Bercoff *et al.* (2002), Warue (2013) and Dash and Kabra (2010).

The study follows the methodology adopted by Beck, Jakubik and Piloiu (2013), who empirically explored the determinants of bad loans across 75 countries using yearly panel data from 2000-2010. Their variables of interest are exchange rates, lending interest rates, share prices, international claims and stock market capitalisation, which prevents comparability between their findings and ours. They used both fixed effects and GMM models to estimate baseline models, accounting for the impact of macroeconomic variables, and then investigated the impact of the additional variables in turn to achieve parsimonious estimations. In their study, to avoid the consequences of a small sample size, constraints were imposed on the number of instruments, as well as on exogenous variables. As their analyses were conducted over an annual panel data set, with considerable similarities between the purpose of their analyses and ours, this legitimates following a similar methodology, despite the fact that our sample size is smaller due to the lack of availability of the data. Following the estimation of a baseline model that includes macroeconomic condition proxies, the indicators of house price growth, financial development, housing affordability and household vulnerability were added sequentially to the baseline model, in order to examine their additive explanatory power.

3.4. THE ECONOMETRIC MODEL

In this section, we briefly review the econometric methodology used to investigate the issues mentioned above. Starting with a static model, it is of interest to start our analyses with fixed effects models for many reasons: (i) Since our analysis is restricted to a specific set of individuals, and all variables of interest are time-variant, it is reasonable to use the fixed effects technique to accommodate the time-constant unobserved heterogeneity between countries; (ii) This technique addresses the omitted-variables bias problem by controlling for country-specific effects and allows the unobserved individual-specific variables to be arbitrarily correlated with the determinants of NPLs (Wooldridge, 2002);[36] (iii) Using fixed effects helps to evaluate the necessity for a dynamic model that is able to accommodate the persistence in the dependent variable, in order to avoid any misspecification and misleading inferences.

However, limiting the analysis to fixed effects models ignores the fundamental heterogeneity between the countries in terms of financial systems developments, housing market characteristics, household indebtedness levels and house price dynamics, which differ substantially both over time and in a geographical dimension across countries. Hence, limiting the analysis to fixed effects models ignores the heterogeneity between countries. Furthermore, as will be seen in section 3.6, NPLs reveal high persistence, suggesting the need for further dynamic models that are able to deal with the autocorrelation problems that might arise from including lags of the dependent variable. The required dynamic models should also be able to avoid the bias and inconsistency that might result from depending on least square estimators obtained from fixed effects models. More importantly, some of the independent variables that are included in the estimation, such as interest rates, might have bidirectional effects that can be identified using pairwise regressions. Such variables have to be included in the model as endogenous, as they might have a correlation with the error term. Finally, the model must have the ability to capture the heterogeneity between the economies under scrutiny.

Among other dynamic models that might satisfy the aforementioned requirements and account for the heterogeneity among the various selected markets, the Arellano and Bond (1991) two-step difference GMM is widely considered in the literature to be the most efficient (see Roodman, 2009). It is designed for short, wide panels, and to accommodate linear models with one dependent variable, additional controls and fixed effects. The main feature

[36] According to Wooldridge (2002), a fixed effects model can control the individual-specific differences, and also allow for correlations between unobserved country-specific variables and the other explanatory variables. See Wooldridge, J. (2002). “Econometric Analysis of Cross Sectional and Panel Data”. MIT Press.

of a dynamic panel data specification is the inclusion of a lagged dependent variable in the set of regressors. It takes the general form shown in Eq. (3.1):

$$y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t}^{'} + \varepsilon_{i,t} \quad |\alpha| < 1 \quad \varepsilon_{i,t} = \mu_i + v_{i,t} \;\; E[\mu_i] = E[v_{i,t}] = E[\mu_i v_{i,t}] = 0, \quad (3.1)$$

where $i = 1, \dots \dots, N$ indexes cross-sectional observational units and $t = 1, \dots \dots . T$ indexes time. $y_{i,t-1}$ is the lag of dependent variable. α is a scalar and $x_{i,t}^{'}$ is a $1 \times k$ vector of the remaining explanatory variables (controls) and might include lagged values of the dependent variable y. β is the $k \times 1$ vector of coefficients to be estimated. $\varepsilon_{i,t}$ is the disturbance term, which has two orthogonal components: the time-invariant unobservable individual-specific fixed effects μ_i, and idiosyncratic shocks $v_{i,t}$.

A crucial assumption for an unbiased estimation of the OLS is the exogeneity of explanatory variables, that is, explanatory variables are uncorrelated with the error term $E(\varepsilon_{i,t} | x_{i,t}) = 0$. However, the inclusion of the lags of the dependent variable in the set of the explanatory variables violates this assumption, as it is inherently correlated with individual-specific μ_i, which makes the OLS estimation method produce biased and inconsistent estimates (see, for instance, Blundell and Bond (1998)).

To account for this problem, Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) suggest the generalised method of moments GMM estimation method. Arellano and Bond (1991) proposed the subsequent elimination of the individual effects μ_i through the first difference transformation; by subtracting $y_{i,t-1}$ from both sides of Eq. (3.1), we get an equivalent equation for growth, as shown below:

$$\Delta y_{i,t} = (\alpha - 1) y_{i,t-1} + \beta x_{i,t}^{'} + \varepsilon_{i,t}, \quad (3.2)$$

The panel has dimensions $N \times T$ where Δ is the first difference operator.

In Eq. (3.2), the lagged dependent variable $y_{i,t-1}$ is, by construction, correlated with the error term, which imposes a bias in the estimation of the model. Nonetheless, $y_{i,t-2}$ (which might be correlated with $\Delta y_{i,t-1}$ and has zero correlation with the error term for $t = 3 \dots \dots T$)

can be used as an instrument when estimating Eq. (3.2), assuming that $\varepsilon_{i,t}$ are not serially correlated. This proposes that for lags two and more of the dependent variable to satisfy the following moment conditions:

$$E(y_{i,t-l}\Delta\varepsilon_{i,t}) = 0 \quad \forall\, t \geq 3, l \geq 2. \tag{3.3}$$

A second source of bias in this estimation could come from the probable endogeneity of some variables, which leads to a correlation with the error term. In the strictly exogenous variables, all their past and future values are uncorrelated with the error term, which proposes the following moment conditions:

$$E(x_{i,t-l}\Delta\varepsilon_{i,t}) = 0 \qquad \forall\, t \geq 3 \quad \text{and for all } l \tag{3.4}$$

However, the invalidity of strict exogeneity doesn't hold in the presence of reverse causality. On the other hand, for weakly exogenous or predetermined variables, only current and lagged values of $x'_{i,t}$ are valid instruments with the following moment conditions:

$$E(x_{i,t-l}\Delta\varepsilon_{i,t}) = 0 \qquad \forall\, t \geq 3, l \geq 2. \tag{3.5}$$

The orthogonality restrictions stated in Eq. (3.3) and Eq. (3.5) are considered as the keystones of the one-step GMM, which produces consistent parameter estimates given the independent and homoscedastic residuals.

The standard instrument set for difference GMM avoids the trade-off between instrument lag numbers and sample size by zeroing out missing observations of lags (Holtz-Eakin, Newey and Rosen (HENR; 1988) cited in Roodman (2009)). Furthermore, it contains instruments for each time period. For example, as an instrument for $\Delta y_{i,3}$, a variable that is two lags away from y is used, taking the value of $y_{i,1}$ for period 3 and zero for all other periods. In a nutshell, the resulting instruments matrix Z_i is composed of stacked blocks that belong to $(T-2)(T-1)/2$ moment conditions and takes the following form:

$$Z_i = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ y_{i,1} & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & y_{i,2} & y_{i,1} & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & y_{i,3} & y_{i,2} & y_{i,1} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}, \tag{3.6}$$

where the first row of the instruments matrix Z_i is booked for period 2 and occupied by zeros for all cells, due to the differencing in period 1 for all the variables. In the same vein, analogous instrument groups again will be generated for items of x that are assumed to be endogenous or predetermined – due to correlations with past errors – and might be endogenous after first-differencing. To sum up, the process that drives the increase in instrument numbers in the difference GMM is a quadratic growth of (4), taking into consideration the time periods number T.

The two-step GMM estimator relaxes the assumption of homoscedasticity in the error terms, which makes it more efficient (see, for example, Blundell and Bond (1998) and Arellano and Bond (1991)). Due to the dependence on the estimated residuals, the two-step GMM may cause downward bias in the estimated asymptotic standard errors. More precisely, small sample sizes and a large number of instruments make the two-step GMM useless (Arellano and Bond, 1991). To overcome this shortcoming of different two-step GMM regressions, we employ Windmeijer's (2005) finite sample correction with the two-step GMM to correct the bias in the computed standard errors (*i.e.* corrected variance) and to get more accurate standard errors, which result in more reliable asymptotic statistical inference.[37] Finally, to avoid correlation between errors, and to achieve more efficient estimations, a robust two-step differenced GMM specification is adopted for this purpose.

The asymptotic efficiency gains brought about by differenced GMM estimator are not attained without a cost. From an econometric point of view, the estimators are seriously impacted by the proliferation bias generated by the number of instruments, which tends to increase rapidly with the increase in time units compared to the number of cross-sectional units (Roodman, 2009). Instrument proliferation has many consequences on the estimated coefficients, such as the overfitting of endogenous variables, leading to a finite sample bias, which weakens the Sargan/Hansen test by increasing the likelihood of wrong positive results

[37] Windmeijer (2005) found that a two-step GMM produces better estimations than a one-step GMM, with standard errors that are less biased, more accurate and superior to cluster-robust one-step estimation. See Windmeijer, F. (2005). "A finite sample correction for the variance of linear efficient two-step GMM estimators". Journal of Econometrics 126: 25-51.

and deteriorating the specification tests, such as the Hansen J-test (1982) (Roodman, 2009). More precisely, including a number of instruments greater than or equal to the number of groups (cross-sectional units), violates both the standard errors and the Sargan test, leading to downwards-biased and consequently misleading asymptotic inference. Due to the small number of countries (cross-section) in our sample, additional constraints are imposed on the number of instruments and the number of exogenous variables. In essence, we add just one variable (or sometimes two variables) at a time, to avoid the need for extra instruments and to keep their total number less than or equal to the number of cross-sectional units in the sample, until we accomplish the best parsimonious model. Hence, the number of instruments has to be always kept lower than the number of groups in the GMM models.

Since the validity of the instruments can be indicated by the structure of the error, Arellano and Bond (1991) also reported test statistics that provide $AR(1)$ and $AR(2)$ statistics associated with their significance probabilities for first and the second order disturbance autocorrelation. For the best specifications, the null hypothesis of no first order serial correlation in the residuals has to be rejected; simultaneously, the second null hypothesis of no second order serial correlation of the residuals has to be accepted.

The consistency of the estimator using a GMM relies on the rational selection of the instruments to be used in the estimation, as well as the assumption that the error term should not show evidence of serial correlation. To address the validity of the selected instruments, Arellano and Bond (1991) proposed a Hansen test and a Sargan test for the joint validity of the instrument sets and over-identification restrictions. The null hypotheses of these tests suggest that the instruments are valid and the higher the probabilities of their statistics, the better, since high p-values indicate that the instruments are exogenous and not correlated with the error term. These tests can also confirm the robustness of regressions and improve the validity of the instruments.

3.5. DATA

This section provides some stylised facts about the variables that are considered in the empirical analyses. We used a balanced panel dataset comprising 23 countries over the time period 2000-2012. The country sample included Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherland, New Zealand, Norway, Poland, Portugal, Spain, Switzerland, United States and United Kingdom. Our balanced panel data are compiled from three main sources: the UKDS, the IMF and the World Bank. The World Development Indicators from the UKDS, the Financial Soundness Indicators from the IMF and the World Bank compiled data on the ratio of NPLs, with an annual frequency, but for different time periods. The data are retrieved primarily from the UKDS and extended from the other two sources. The probable differences in methodology between the three sources are accounted for by matching values of NPLs over the overlapping periods. Table 3.5.1 lists all explanatory variables used in this study, together with their acronyms, expected signs and data sources. However, these data are discussed in more detail below.

Table 3.5.1 Summary of Variables, Acronyms, Expected Signs and Data Source

VARIABLES	Acronym	Sign	Data Source
Non-performing loan to gross loans	$NPL_{i,t}$		UKDS and other source
Unemployment rate	$UR_{i,t}$	+	World Bank
Real GDP per capita growth rate	$GDP_{i.t}$	-	World Bank
Interest rates	$IR_{i,t}$	+	OECD
Real residential property price growth	$HP_{i.t}$	-/+	National Statistical Office
Household debt to disposable income	$HD_{i,t}$	+	OECD
Consumption to disposable income	$HC_{i,t}$	+	OECD
Financial development and lending	$FD_{i,t}$	+	OECD, Bank of England, World Bank
Housing affordability	$HA_{i,t}$	+	OECD

A. Dependent Variable, Non-performing Loans ($NPL_{i,t}$)

The dependent variable of the models is the ratio of NPLs relative to gross loans. The data for NPLs ratio are only available at annual basis with a short time period. The natural logarithmic ratio of NPLs to gross loans (NPL) has been used as the dependent variable to account for any plausible measurement error.

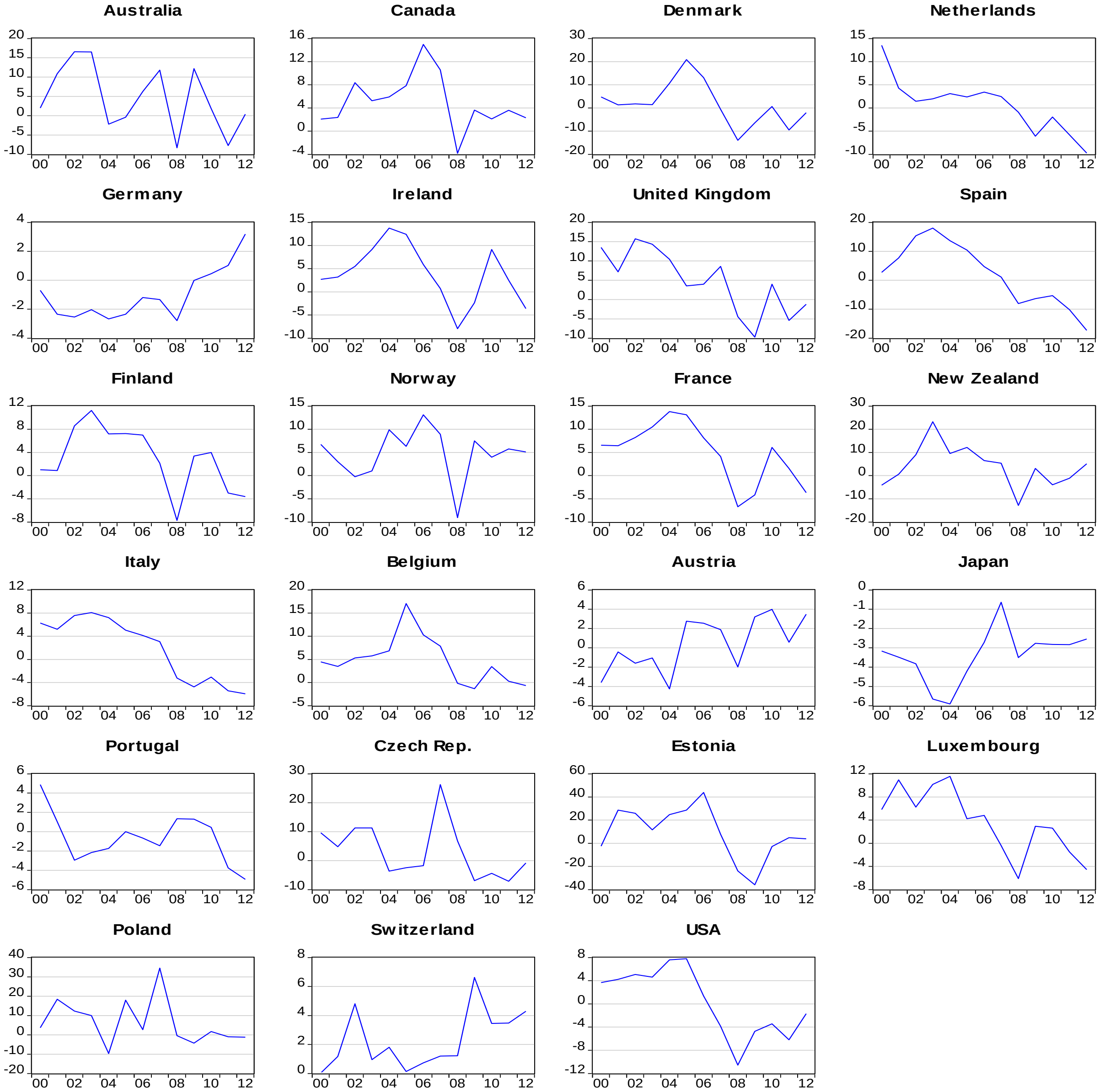
B. Real Residential Property Price Growth ($HP_{i.t}$)

Financial stability is systematically related to the real estate market, due to the high dependence of the real estate market on banking products, in addition to using properties as collateral for loans. Therefore, depreciation in property prices can severely reduce the quality of banks assets and negatively impact their profitability, and consequently reduce their lending capacity (see, for example, Bernstein (1996) and Ahuja *et al*. (2010)). As a proxy for house prices, real residential property price growth has been used in the estimation.

Figure 3.5.1 plots the growth in real residential property prices. It shows that house prices had been growing positively at an accelerating pace until the second half of 2008, when the financial crisis took place, from which point a plunge in house prices has been witnessed in the majority of the countries in our sample. This behaviour of real residential property price growth seems to be clear in Belgium, Canada, Czech Republic, Denmark, Estonia, Japan, Poland, Norway and the USA. A comparison across countries before this troubled period demonstrates that house prices underwent a dramatic upswing in the majority of countries. By contrast, house prices in some countries, such as Germany, Netherlands and Spain, had a downward trend during the period under consideration.

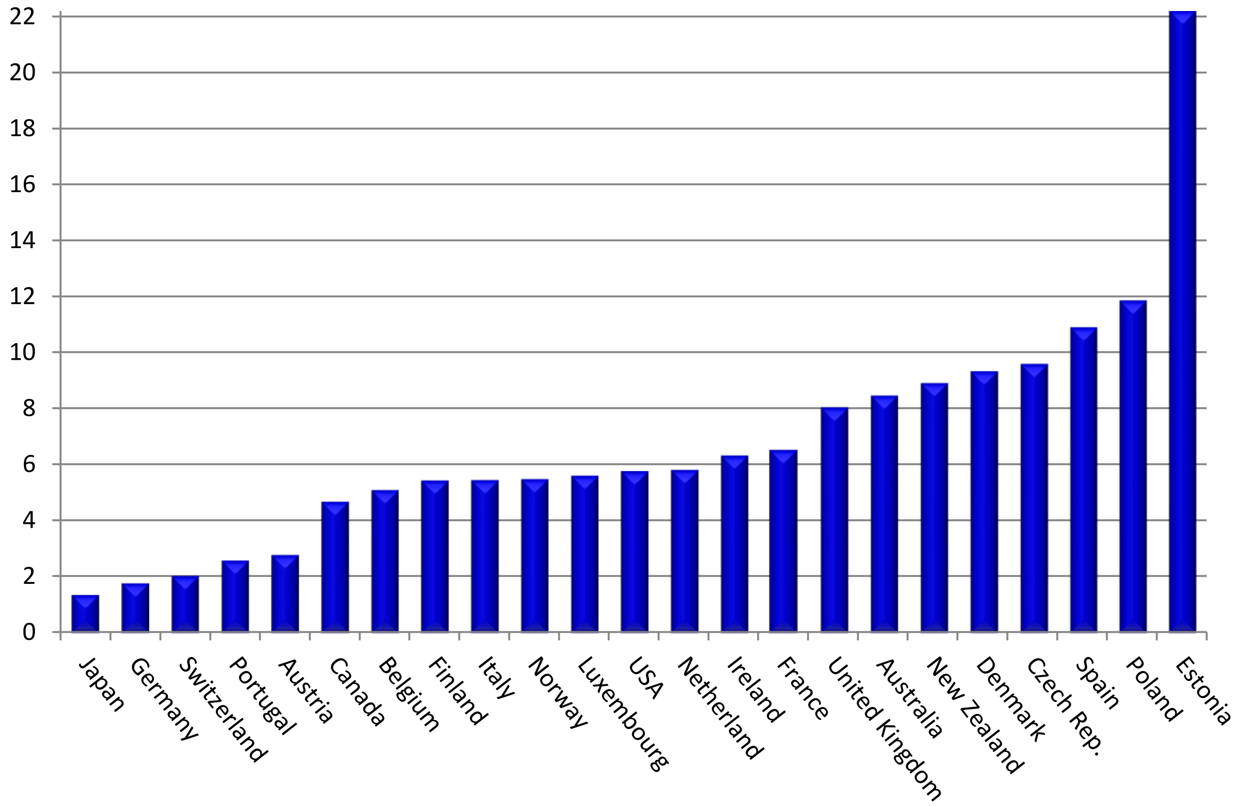
Furthermore, with a more insightful look at Figure 3.5.1, we can see that the trend of property prices to increase had different starting points in different countries, before they all reached their peaks in 2008. Of the selected countries, Ireland seems to have had the most severe experience during the financial crisis, with large declines in house prices. According to Morgan Kelly (2010), the real estate sector contributed around 20% of Ireland’s GDP during this turbulent period.

Figure 3.5.1 Real Residential Property Price Growth in Selected Countries



It is noteworthy that fluctuations in residential property prices in the selected countries have been accompanied by manifest differences in their volatilities (Figure 3.5.2). The standard deviations reveal high property price volatility in countries where a trend of rapid price increases was observed, suggesting a cyclical effect of house price variations that helps to create a trend that takes a long time to recover from. This high volatility is more pronounced in Estonia, Poland, Spain, Czech Republic, Denmark, New Zealand, Australia, United Kingdom, France and Ireland. By contrast, countries with low variations in their residential property prices, such as Germany, reflect more than a decade of stagnant house prices.

Figure 3.5.2 Standard Deviation of Real Residential Property Price Growth between 2000 and 2012



C. Financial Development ($FD_{i,t}$)

A common problem with measuring financial development is the difficulty in constructing a measure that reflects the financial development in a country precisely, due to the wide range of financial intermediaries that provide financial services. Domestic credit provided by the banking sector, relative to GDP, is regarded as the best measure of banking industry depth and of the financial sector's development in a country. Additionally, this indicator is consistent with the aim of this study in investigating the impact of bank-based financial proxy represents the segment of the financial development that have direct influence on NPLs. On the other hand, the composition of banks' loan portfolios clearly shows a rapid increase in mortgage lending, rather than other types of loan, suggesting a higher probability of default among mortgagors and urging the need for a proxy to reflect banks' mortgage lending behaviour.[38] Based on these considerations, a unique composite indicator that is able to reflect both financial development and banks' mortgage lending behaviour is needed. Hence, we use principal component analysis (PCA) to construct a summary measure of financial development, proxied by domestic credit provided by the banking sector relative to GDP, and mortgage lending behaviour, proxied by the mortgage to GDP ratio, given the high correlation (72%) between the two variables. The results of the principal component analysis test are reported in Table 3.5.2.

The outcomes of the PCA test indicate that the eigenvalue associated with the first component is significantly higher than one and can explain more than 86% of the standardised variance in the two variables, while the second component represents only around 13% of these variations. Therefore, the first principle component, denoted below as (FD), has been constructed and used as a summary indicator of the financial development and mortgage lending behaviour.

Table 3.5.2 Principal Components Analysis for Financial Development

Component	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
Comp 1	1.724323	1.448647	0.8622	1.724323	0.8622
Comp 2	0.275677	---	0.1378	2.000000	1.0000
No. of observations included: 299; No. of components: 2					

It is worth mentioning that the financial crisis in 2008 was preceded by increases in both the provision of domestic credit to the private sector and mortgage lending in the majority of the countries under consideration. The exceptions to this behaviour include Canada, Germany and Japan, where steady or downward trends were observed. Interestingly, Ireland, which had the worst experience in terms of house price depreciation during the financial crisis, experienced a sizeable expansion in credit over that period. Looking deeply at the data, mortgage to GDP ratios show a substantial dissimilarity between

[38] See, for example, Geanakoplos, J. (2010). "Solving the Present Crisis and Managing the Leverage Cycle". Federal Reserve Bank of New York Economic Policy Review. See also, Favara, G. and Imbs. J (2009). "Credit Supply and the Price of Housing". HEC Lausanne Swiss Finance Institute.

the countries in terms of their mortgage lending expansion, ranging on average from 9.741 per cent in Poland to 107.6669 per cent in Denmark. The small value of the ratio in Germany again indicates a long-term profile of sound lending policies, which is translated into relatively steady house prices, while in countries such as the Netherlands, the United Kingdom, New Zealand, Australia, Ireland, Spain, Canada and the USA, a rapid growth in mortgage lending was observed during the same time period.

D. Household Vulnerability ($HD_{i,t}$ and $HC_{i,t}$)

Widely used as measures of household vulnerability, the ratio of household debt as a percentage of net disposable income, and household housing consumption as a percentage of housing disposable income, are used.[39] These variables are widely regarded in empirical studies as adequate indicators of household indebtedness and fragility in terms of housing costs (see, for example, Gadanecz and Jayaram (2008)). Relative household debt to net disposable income had a general trend of increasing in all countries, with the exception of Germany, which witnessed a decrease of around 23% from 2000 to 2012. By contrast, the growth was moderate, ranging between 12%-65%, in countries such as Australia, Canada, the United Kingdom, Spain, Finland, Italy and the USA, while other countries, such as Denmark, the Netherlands and Ireland, recorded the highest growth of around 121%, 137% and 143%, respectively.

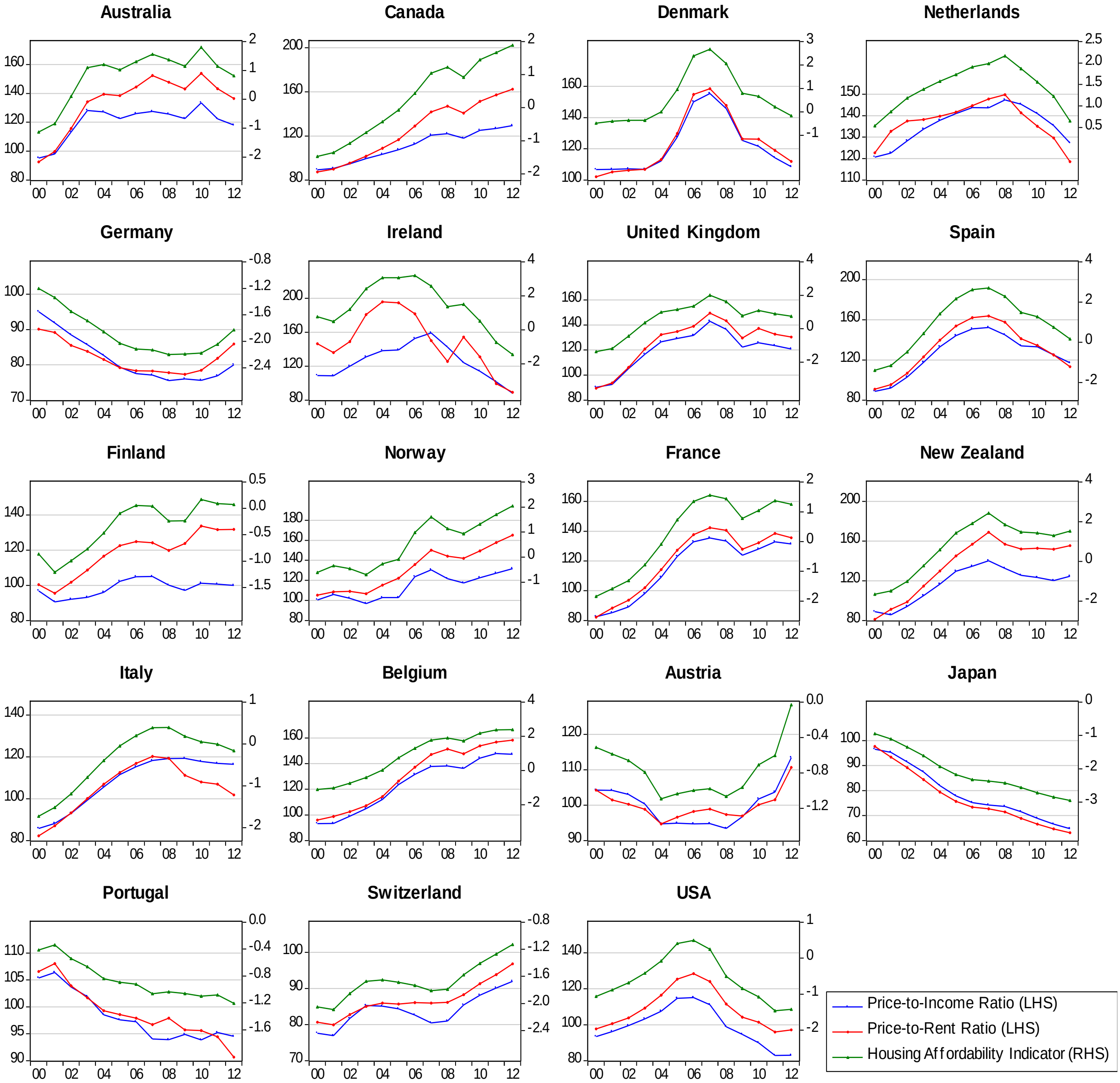
E. Housing Affordability ($HA_{i,t}$)

Commonly used measures to assess the affordability of housing are the price-to-income ratio and the price-to-rent ratio, which reflect the average household’s ability to afford housing, and provides information on the performance of housing markets. Thus, high values for these ratios could be a signal of overvalued houses prices and rents, cases in which households would find it difficult to own or rent a house.

[39] In order to construct a summary measure of the two household fragility indicators, the principle component test was carried out first, but the results showed that two principles should be used to explain the standardised variance in the variables under consideration. Therefore, we prefer to use the actual data instead of using the principles.

Figure 3.5.3 plots price-to-income and price-to-rent ratios (scaled on the left-hand axis) and the constructed housing affordability indicator (scaled on the right-hand axis). The chart conveys that, for almost all the countries, the two ratios increased substantially until the onset of the financial crisis, when a declining trend emerged, but this was still above the long-term average of the series.

Figure 3.5.3 Price-to-Income, Price-to-Rent and Housing Affordability Indicator



Note: price-to-income and price-to-rent ratios are scaled on the left-hand side axis and the housing affordability indicator is scaled on the right-hand side axis.

Importantly, in countries where a remarkable increase in house prices was detected (France, Norway, Ireland, New Zealand, Spain, Canada, Denmark, United Kingdom and

USA), these ratios exceeded their long-term averages by 20 per cent or more. In countries such as Australia, Germany, Italy, and the Netherlands, the increase was more moderate, but still represented historical peaks.

Due to the high correlation between these two variables (91%) and with the aim of reducing the number of regressors in the estimation, we used principal component analysis (PCA) over these two indicators to construct a summary composite measure of housing affordability. It is noteworthy that, owing to data availability issues, the impact of this variable is limited to a subsample of our total sample, consisting of only 19 countries.[40] A principal component analysis was conducted and the outcomes are reported in Table 3.5.3.

Table 3.5.3 Principal Component Analysis of Housing Affordability

Component	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
Comp 1	1.916255	1.832511	0.9581	1.916255	0.9581
Comp 2	0.083745	---	0.0419	2.000000	1.0000
No. of observations included: 247; No. of components: 2					

The eigenvalue accompanying the first component is significantly higher than one and can explain around 96% of the standardised variance in the variables under consideration. The explanation of the second component does not exceed 5% of these variations. Thus, the first principle component, denoted below as (HA), was used as a summary indicator of housing affordability.

F. Domestic Economic Conditions ($GDP_{i.t}$, $UR_{i,t}$, $IR_{i,t}$)

An economy enjoying a stable rate of growth provides an attractive environment in which to make profit, and also dampens the effect of shocks in the real estate market on the financial sector (see, for example, Collins and Wanjau (2011) and Nkusu (2011)). Among empirical studies, there is a general consensus that a contractionary phase of an economy is

[40] The subsample for testing the impact of housing affordability consisted of: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Switzerland, United Kingdom and USA.

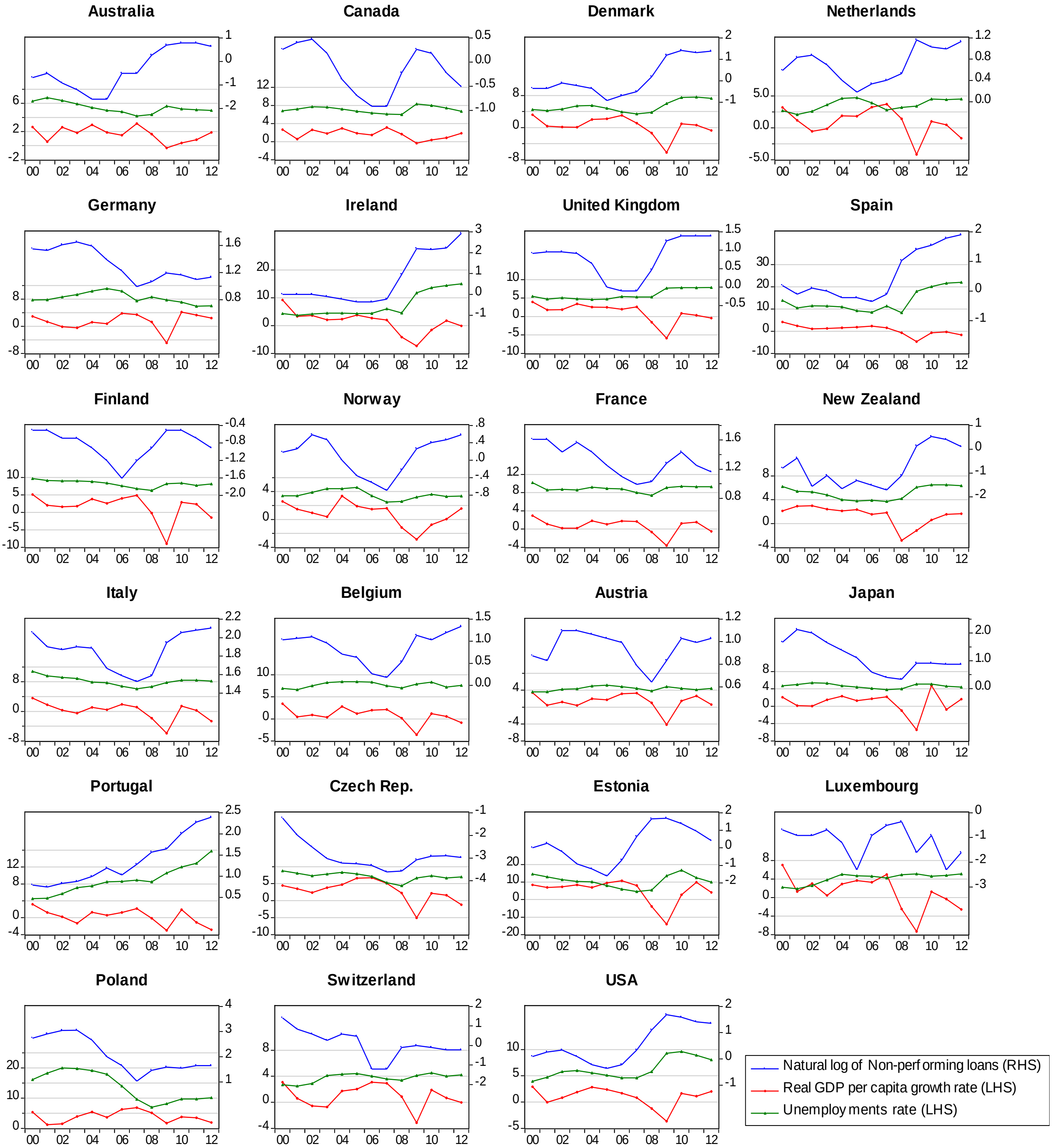
always accompanied by a high level of NPLs (see, for example, Louzis *et al*. (2010), Salas and Saurina (2002) and Bofondi and Ropele (2011)). Real domestic product, as an indicator of economic growth and business cycles, is supposed to play a key role in the quality of bank loan portfolios, because sluggish economic growth seemingly undermines the ability of households and companies to fulfil their obligations, and is therefore expected to exhibit a countercyclical pattern with NPLs.

Similarly, the unemployment rate is also recognised as one of the fundamental determinants of NPLs in the literature (see, for instance, Rinaldi and Arellano (2006) and Bofondi and Ropele (2011)). Increasing unemployment rates weaken borrowers' financial capacity to pay back their contracted debts, and might motivate them to default, or at least terminate their payments. Thus, higher rates of unemployment are expected to be translated into higher NPL ratios. Interest rate rises, on the other hand, affect loan performance for banks as they imply a higher cost of loans for borrowers (see, for example, Nkusu (2011), Louzis *et al.* (2010), Bofondi and Ropele (2011) and Collins and Wanjau (2011)). Due to the lack of mortgage interest rate data, and the fact that most mortgage loans are agreed for a long time, long-term 10-year government bond interest rates have been used as an indicator for this purpose, and are expected to negatively impact the ratio of NPLs.

Against this background, real domestic product per capita growth $GDP_{i.t}$, unemployment rate ($UR_{i,t}$) and real interest rate ($IR_{i,t}$) are included in the estimation to control for the impact of local economic circumstances.

Depictions of the evolution of NPL ratios (scaled on the right-hand axis), and unemployment rates and real GDP per capita growth (scaled on the left-hand axis), in Figure 3.5.4 show that an increase in GDP and a decrease in the unemployment rate is clearly associated with a decline in NPL ratios. Furthermore, most of the selected countries show a huge decline in GDP per capita at the beginning of 2008, at the onset of the financial crisis, which is reported to be associated with a general trend of an increase in NPL ratios, as well as in unemployment rates (Figure 3.5.4).

Figure 3.5.4 NPLs Ratios, Unemployment Rates and Real GDP Growth



Note: The natural logs of non-performing loans are scaled on the right-hand axis, whereas unemployment rates and GDP per capita growth rates are both scaled on the left-hand axis.

The descriptive statistics in Table 3.5.4 show that, on average, 2.658% of the gross loans in the sample countries were nonperforming, with relatively small variations between the sample individuals, as indicated by the standard deviation of about 3.127.

Table 3.5.4 Descriptive Statistics of the Seleceted Variables

Variables	(1) N	(2) Mean	(3) Median	(4) Standard deviation
$NPL_{i,t}$	299	2.64	1.80	3.07
$UR_{i,t}$	299	7.03	6.30	3.53
$GDP_{i.t}$	299	1.38	1.60	2.86
$HP_{i.t}$	299	2.88	2.37	8.19
$IR_{i,t}$	299	4.40	4.29	1.55
$HD_{i,t}$	299	132.81	127.27	64.82
$HC_{i,t}$	299	17.58	17.29	2.31
$FD_{i,t}$	299	0.00	-0.18	1.32
$HA_{i,t}$	247	0.00	-0.10	1.39

To examine the stationarity of the variables used in the models, Levin-Lin-Chu (LLC, 2002) is regarded as an appropriate test for this purpose. The LLC test estimates the following equation:

$$\Delta y_{i,t} = \alpha_i + \delta_i t + \theta_t + \rho_i y_{i,t-1} + \varsigma_{i,t} \text{ where } \quad i = 1,2,\dots N, \;\; t = 1,2,\dots T. \qquad (3.7)$$

The coefficients (α and θ) in the estimation mean that the test allows for two dimensions of fixed effects, in addition to unit-specific time trends. The fact that the coefficient of the lagged dependent variable is constrained to be homogeneous across the units of the panel makes the unit-specific fixed effects a significant source of heterogeneity. Considering the LLC test's assumption, which states that the individual processes are independent in cross-section, correction factors are assumed to be normally distributed under the null hypothesis. The LLC method produces a bias-adjusted t statistic, which is denoted as t star, that has an asymptotic normal distribution. The Levin-Lin-Chu test is called a pooled Dickey-Fuller test. The test has been conducted for all the variables included in the models (see Table 3.8.1 in APPENDIX 3.8) and the null hypothesis of non-stationarity has been rejected for all examined variables, *i.e.* all variables are stationary $I(0)$.

3.6. EMPIRICAL RESULTS AND FINDINGS

In this section, the macroeconomic variables affecting the growth of NPL ratios are tested first, to check the consistency of our findings with those found in the literature. Then, proxies for real residential property prices, household indebtedness, financial developments and housing affordability are included in turn, respectively. Thus, we start by estimating the baseline model shown in Eq. (3.8) for the fixed effects models:

$$NPL_{i,t} = \sum_{j=1}^{2} \beta_{1j} GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} UR_{t-j} + \sum_{j=1}^{2} \beta_{3j} IR_{t-j} + \sum_{j=1}^{2} \beta_{4j} X_{t-j} + \varepsilon_{i,t}, \qquad (3.8)$$

where $\varepsilon_{i,t},$ is the error term, and $i = 1,\ldots,23,$ $t = 1,\ldots,13$, and X_{t-j} refer to a variable or vector of variables to be included sequentially in the baseline model shown in Eq. (3.8). In particular, X_{t-j} represents the proxies for real residential property prices, household indebtedness, financial developments and housing affordability, respectively.

Furthermore, we estimate the baseline model shown in Eq. (3.9) for the GMM models:

$$NPL_{i,t} = \alpha NPL_{i,t-1} + \sum_{j=1}^{2} \beta_{1j} GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} UR_{t-j} + \sum_{j=1}^{2} \beta_{3j} IR_{t-j} + \sum_{j=1}^{2} \beta_{4j} X_{t-j} + \varepsilon_{i,t}, \qquad (3.9)$$

where $\varepsilon_{i,t} = \mu_i + v_{i,t}$, $|\alpha| < 1,$ $i = 1,\ldots,23,$ $t = 1,\ldots,13,$ and X_{t-j} is as defined as above.

3.6.1. STATIC MODELS (FIXED EFFECT ESTIMATIONS)

Starting with the static model, we estimate the fixed effect models with robust standard errors to control for heteroskedasticity, in an attempt to capture short-term movements in the NPL ratio over five models. Table 3.6.1 reports the estimated coefficients of robust fixed effects, along with their T-values and asterisks indicating the p-value of the statistical significance of coefficients.

Table 3.6.1 Determinants of Non-performing Loans (Fixed Effects Estimation)

Dependent: $NPL_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$IR_{i,t-1}$	1.155***	1.152**	1.224***	1.257***	1.058***
	(0.0542)	(0.0581)	(0.0451)	(0.0580)	(0.0382)
$UR_{i,t-1}$	1.091**	1.085**	1.085***	1.066**	1.073***
	(0.0354)	(0.0340)	(0.0278)	(0.0313)	(0.0132)
$GDP_{i,t-1}$	-0.920***	-0.954***	-0.975*	-0.982**	-0.954***
	(0.0134)	(0.0157)	(0.0164)	(0.0161)	(0.00922)
$HP_{i,t-1}$		-0.974***	-0.979***	-0.982**	
		(0.00681)	(0.00727)	(0.00654)	
$HD_{i,t-1}$			1.009***		
			(0.00233)		
$HC_{i,t-1}$			0.926**		
			(0.0111)		
$FD_{i,t-1}$				1.609***	
				(0.220)	
$HA_{i,t-1}$					1.028**
					(0.0328)
$Constant$	-0.470**	-0.507*	-0.444	-0.369***	0.671***
	(0.145)	(0.171)	(0.365)	(0.0941)	(0.0778)
No of Observations	276	276	276	276	228
R-Squared	0.301	0.378	0.464	0.482	0.348
No of Countries	23	23	23	23	19

*Notes: Coefficients and T-values in parentheses from fixed effects estimation with robust standard errors. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

Overall, the estimated models are able to explain the variations in non-performing loan ratios in the selected economies reasonably well. As mentioned before, economic growth, unemployment rates and interest rates have been added as control variables for two purposes: first, to capture the effect of macroeconomic fundamentals and financial aspects on the scale of NPLs, and second, to test the consistency of our findings regarding the impact of these factors with those found in the literature. As can be seen in the first column of Table 3.6.1, the estimations of the fixed effects are highly consistent with the findings found in the literature regarding the macroeconomic variables. Specifically, the results clearly confirm that real GDP per capita growth has a negative association with the evolution of NPLs at the 1 per cent significance level, while unemployment rates and interest rates have positive relationships with the dependent variable at the 1 per cent significance level, with interest rates and GDP showing the highest significance of the three control variables.

The estimated coefficients of the lagged real residential property price variations are, as they look in the second, third and fourth columns of Table 3.6.1, negative and statistically significant in the second, third and fourth fixed effect estimated models. These results indicate that the performance of a loan is highly sensitive to the fluctuations in real residential house prices, and the negative sign is consistent with the findings in the literature that attribute this impact to the increased ability of borrowers to meet their commitments, which is associated with increases in their property values, particularly in the case of collateralised loans. However, more mixed impacts of real residential property prices on NPLs have been found in the dynamic estimated models, which will be addressed later.

As a proxy for household vulnerability, the ratio of household debt to disposable income (column 3 of Table 3.6.1) shows a positive and statistically significant association with the scale of NPLs. That is to say, the greater the household indebtedness burden, the higher the default probability due to potential difficulty in fulfilling their scheduled obligations. Large household debts undermine borrowers’ ability to pay obligated debts and make them more likely to stop payments in response to a negative income shock. Consequently, banks’ loan portfolios are more likely to witness a higher volume of NPLs, which in turn explains the sensitivity of banks’ loan portfolios to variations in household vulnerability. Furthermore, banks may hesitate to lend, and become more disposed to tighten their terms on loans to households, when they find that the default probability is increasing. This behaviour by banks leads to a reduced supply of credit, and consequent depreciation in house prices, which in turn undermines the capital position of banks through the collateral revaluation channel. The ratio of household housing consumption to household housing disposable income, as an additional indicator of household vulnerability, shows evidence of significance on the level of NPLs in the fixed effects estimations, with the positive sign indicating that an increase in household housing consumption is expected to result in a higher level of household vulnerability.

As far as the financial development indicator is concerned, the fourth column of Table 3.6.1 demonstrates that the overall effect of financial development is highly significant at the 1 per cent significance level. The associated positive sign is indicative and implies that easier access to credit, and a relaxation in lending standards, would result in an increase in the volume of NPLs. There is a general consensus in the literature that a relaxation in lending by banks in the presence of an under-regulated financial market can increase NPL ratios and jeopardise macroeconomic stability (see, for example, US Census Bureau, 2007). Theoretically, Fofack (2005) argued that credit supply to the private sector is expected to grow rapidly in periods preceding a crisis, and then fall dramatically when the financial crisis occurs (see also Gavin and Hausmann, 1998). However, he found an ambiguous magnitude of the impact of credit provided to the private sector on the evolution of NPLs. In particular, he found that the magnitude of this effect depends on the ownership of the active banks in the nation, whether they are state-owned banks or privately-owned banks; the positive association between these two variables was witnessed in state-owned banks. Our findings are highly consistent with Fofack's (2005) results, given that the majority of the active banks in the countries included in the sample are state-owned. It is worth mentioning that the indicator used in this study is a composite measure that includes, in addition to the ratio of credit provided to the private sector to GDP, the ratio of mortgages to GDP, in order to give greater weight to variables that really reflect housing finance.[41]

Finally, housing affordability, proxied by a composite measure of price-to-income and price-to-rent, has a positive and statistically significant association with the level of NPLs (column 5 of Table 3.6.1). That is, when the affordability of housing in a country decreases, so does the level of NPLs. A depreciation in housing affordability takes place when either

[41] The effect of mortgages to GDP was tested alone for a robustness check of the magnitude of banks' lending behaviour, and the results confirmed no material difference from the overall impact of our constructed financial development measure. However, these results are not reported in favour of brevity.

house prices (or rents) increase or incomes decrease; both cases undermine households' debt servicing ability, contribute to the reduced affordability of buying (or renting) a house and consequently result in a higher probability of defaults.

To conclude, the five fixed effects estimations help to explain the variations in loan performance well; however, the models for household fragility and financial development seem to be the best specifications (see columns 3 and 4 of Table 3.6.1). All the variables included in these estimations reveal high statistical significance. Moreover, more than 46% of the variations in the rate of NPLs can be explained when household indebtedness is taken into consideration (column 3 of Table 3.6.1) and around 48% of the fluctuations in bad loans can be explained by the model that accounts for the impact of financial development (column 4 of Table 3.6.1). Models 3 and 4 would thus be our preferred fixed effects models.

3.6.2. ARELLANO-BOND ESTIMATION

Due to the high persistence seen in NPLs, we account for the persistence and any plausible measurement error by using the difference of the natural logarithm of NPLs as the main dependent variable, denoted below as $DNPL$.

In this section, we employ a dynamic specification, allowing the inclusion of the lagged dependent variable in the empirical model, which accommodates any autocorrelation issues that might arise. Furthermore, we treat some variables as endogenous, since causality may run both ways, and some variables might have significant correlation with the error term. Finally, in an attempt to avoid problems of correlation in the errors, and to achieve efficient estimators, a generalised method of moments (GMM) estimator with instrumental variables is used. In all estimated models, the instruments are selected from the explanatory variables and their total number has been kept lower than the number of cross-sectional units. An Arellano-Bond two-step difference GMM estimation with robust standard errors is the most adequate for these purposes, in order to investigate the effect of the macroeconomic factors, as well as other variables of interest, on the evolution of NPLs.[42]

Congruent with the analyses conducted using the fixed effect models, five models have been estimated and the coefficients of the variables, along with their T-values and asterisks that indicate the p-value of the statistical significance of coefficients, are reported in Table 3.6.2.

Starting with the main feature of GMM estimation, which is the inclusion of lags of the dependent variable, the coefficients of the lagged dependent variable are statistically significant in all of the estimated models, with a prevailing negative sign (row 1 of Table 3.6.2). The dominant negative signs in all of the estimated models suggest that the current NPL ratio is negatively driven by its previous values. The implication of the negative sign is that the NPL ratio is supposed to decrease when high numbers of NPLs are observed in the previous year, due to write-offs.[43] Louzis *et al*. (2010) found a negative impact of the lagged NPLs; however, the coefficients of the lagged NPLs were not statistically significant. The findings of our model are consistent with their results, despite the fact that our dependent variable comprises aggregate NPLs in countries, while their dependent variables were classified for special types of loan.

Overall, macroeconomic fundamentals are compatible with economic intuition, as well as the theoretical arguments that have been highlighted in the literature review and in the fixed effects arguments. Despite their significance in three models and insignificance in two models, all interest rate lags carry the positive sign, indicating a positive association between NPLs and real interest rates (row 2 of Table 3.6.2). This finding is consistent with all the studies surveyed in the literature review concerning the effect of interest rates on the

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[42] See Roodman (2009) “How to do xtabond 2: an introduction to “Difference” and “System” GMM in Stata.” The Stata Journal (2009) 9, Number 1, pp. 86-136

[43] Sorge and Virolainen (2006) found that the coefficient of the lagged loan loss provisions for the Finnish banking system, as the dependent variable in their model, to be negative. The economic interpretation for the negative coefficient in our case is similar.

evolution of NPLs. Higher interest rates increase the lending cost for borrowers, and might encourage them to default as debt burdens become unaffordable.

Table 3.6.2 Determinants of Non-performing Loans (Arellano-Bond Estimation)

Dependent: $DNPL_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$NPL_{i,t-1}$	-0.388	-0.164***	-0.516***	-0.0181	-0.527***
	(0.343)	(0.0522)	(0.0871)	(0.0296)	(0.0595)
$IR_{i,t-1}$	0.220*	0.369***	0.00107	0.206**	0.0742
	(0.130)	(0.0682)	(0.0552)	(0.0974)	(0.0475)
$UR_{i,t}$	0.350***				
	(0.106)				
$UR_{i,t-1}$	0.383***	0.273***	0.0543	0.0517	0.140***
	(0.143)	(0.0726)	(0.0451)	(0.0431)	(0.0328)
$GDP_{i,t}$	-0.203***	-0.108***	-0.0817***	-0.112***	-0.0472***
	(0.0438)	(0.00891)	(0.00582)	(0.00693)	(0.00796)
$GDP_{i,t-1}$	-0.0958***	-0.0352***	-0.0555***	-0.0295***	-0.0216***
	(0.0230)	(0.00958)	(0.00442)	(0.00335)	(0.00458)
$HP_{i,t}$		-0.0139**		-0.00817	-0.0197***
		(0.00553)		(0.00517)	(0.00416)
$HP_{i,t-1}$		0.0696***		0.0488***	0.00540
		(0.00994)		(0.0167)	(0.00540)
$HD_{i,t}$			0.0245***		
			(0.00917)		
$HD_{i,t-1}$			-0.0116		
			(0.00715)		
$HC_{i,t}$			0.987***		
			(0.0416)		
$HC_{i,t-1}$			-0.455***		
			(0.0786)		
$FD_{i,t}$				-0.559***	
				(0.200)	
$FD_{i,t-1}$				0.941***	
				(0.0486)	
$HA_{i,t}$					-0.231**
					(0.0984)
$HA_{i,t-1}$					0.372***
					(0.132)

*Notes: Coefficients and T-values in parentheses from Arellano-Bond two-step difference GMM estimation with robust standard errors and finite sample correction (xtabond2 in Stata). * Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

Similarly, the unemployment rate is found to be positively associated with the volume of NPLs in all estimated models, although it shows significance only in three models (row 4 of Table 3.6.2). The positive sign suggests that a growing unemployment rate undermines the ability of borrowers to service their debts, and may incentivise them to default, or at least terminate their interest rate payments, with a decrease in their incomes. The unemployment rate coefficient in row 4 of Table 3.6.2 is not significant in models 3 and 4, however, removing it from the estimation would destabilise the model and result in misspecification issues, because it might influence the changes in the NPLs indirectly, through their effect on the other right-hand-side variables.

An equally important determinant of NPLs is real GDP per capita growth. The contemporaneous and lagged values of GDP show high significance for all the included regressors, and also conserve the negative sign in all the estimated models (rows 5 and 6 in Table 3.6.2). This strongly supports our findings from the fixed effects estimation, and is highly consistent with numerous previous studies. More importantly, GDP growth seems to govern the relationship between NPLs and the macroeconomic factors, with its relatively high coefficients in all estimated models.

Even considering their insignificance in some models, the coefficients and lags' coefficients of real residential property price fluctuations reveal indicative information with the prevailing negative contemporaneous sign and the positive sign of the lags (see rows 7 and 8 of Table 3.6.2). Building and investing in the real estate market are mainly funded by loans and mortgages from banks and other financial institutions, for which properties are pledged in return, as collateral to guarantee the borrowers' debts. This generates a strong correlation between credit supply and house prices, which evolves with the availability and diversity of housing finance sources. This link, consequently, fosters the financial accelerator mechanism and puts property prices in an implosive position to trigger a bubble in the real estate market. Growth in collateral values provides privilege to investors to secure more house purchase loans under more flexible terms, and they might engage in speculative actions in the real estate market as their financial health is scaled by their collateral values to secure mortgages. The cumulative effects of all the aforementioned causes might accelerate the growth in house prices and aggravate the situation, which ends up with a housing boom.

Household vulnerability, proxied by the ratio of household debt to disposable income, shows positive contemporaneous and negative lagged impacts on the evolution of NPLs, where both coefficients are statistically significant, reflecting a positive association with NPL ratios in the short-term and a negative association in the long-term (see column 3 of Table 3.6.2). These findings support our previous results in the fixed effects estimations, with more detailed aspects of this effect. In other words, high household indebtedness burdens the borrowers and undermines their ability to settle their scheduled obligations in the short term. However, with a one-year lag, this variable might warn the lender of the higher level of fragility in their borrowers' financial health, which stimulates the need for more cautious lending standards to mitigate risky loans by adopting tighter lending terms on loans to households with high indebtedness. Consequently, more constrained access to loans would help to reduce the amount of NPLs, with a one-year lag. These finding reveal that banks take time to recognise and react to borrowers' negative financial shocks. Notably, the overall impact of household indebtedness (*i.e.* the sum of the contemporaneous and lagged coefficients) on the evolution of impaired loans is positive and in line with theoretical arguments.

The ratio of household housing consumption to household housing disposable income, as an additional indicator of household fragility, demonstrated high significance in the dynamic estimation. The coefficient of this variable revealed a positive impact on the scale of NPLs in the fixed effects model; however, the results seem to be more complicated in the dynamic estimation (column 3 of Table 3.6.2). The contemporaneous effect remains positive, consistent with our finding in the fixed effects estimation; however, the lagged effect turns negative, implying that with a one-year lag, households either find a new source of income to finance their housing expenses or adjust their housing consumption to avoid the consequences of a default by fulfilling their obligated debts. On the whole, the overall impact of relative household housing consumption to household housing disposable income (*i.e.* the sum of the contemporaneous and lagged coefficients) on the evolution of impaired loans is still positive, which is consistent with theoretical notions found in the literature, as well as the expectation.

The coefficients of financial development are highly statistically significant. However, the variable in the estimated equations has a negative sign in the contemporaneous effect and a positive sign in the lagged effect (column 4 of Table 3.6.2). The implication of the negative sign in the short term is that in periods of credit booms, more borrowers will be encouraged to seek mortgages for house purchases, which results in high demand for loans, burdening borrowers with higher interest rate costs. In one lagged year, the increase in the interest rate incurs borrowers higher cost of debts undermining the borrowers' ability to satisfy their debts and resulting in higher amounts of NPLs when these burdens become unaffordable in the long term. In this interpretation, the positive impact of financial development on the evolution of NPLs in the long-term is reasonably justified. Given the fact that mortgage contracts are usually issued over a long term, the negative consequences of excessive mortgage lending are supposed to appear later, in a year or more. Again, the overall impact of financial development (*i.e.* the sum of the contemporaneous and lagged coefficients) on the scale of impaired loans is positive and in agreement with the fixed effects findings.

Finally, the impact of housing affordability is found to be consistent with the outcomes found in the fixed effects estimation, with slightly complicated implications (column 5 of Table 3.6.2). The contemporaneous and lagged coefficients of the variable reveal higher statistical significance than their peers in the fixed effects; however, the contemporaneous coefficient carries the negative sign, while the lagged is positive. The negative contemporaneous effect of housing affordability, as mentioned before, comes as a result of house price increases, which enhance households' ability to get loans, reaping the benefits of increases in their collateral values and the credit supplied by banks. However, with a one year lag, house prices start to depreciate when the market turns and the bust period begins, which undermines the ability of households to afford housing. As a result of the deterioration in affordability for households, banks impose tighter conditions on loans for households, who then suffer from low creditworthiness, pushing house prices down and leading to a high volume of negative equity held by banks, and a high number of NPLs in the banks' loan portfolios. This means that lenders take time to recognise the decline in housing affordability through a slight increase in NPLs in their loan portfolios and adjust their lending behaviour accordingly by tightening lending terms to households with fragile financial health. To sum up, the overall impact of housing affordability (*i.e.* the sum of the contemporaneous and lagged coefficients) is, as expected, that it is positively associated with the level of NPLs, which is fairly consistent with the theoretical opinions highlighted in the literature.

Table 3.6.3 presents important model specifications, robustness checks and diagnostic tests discussed in section 3.4.

Table 3.6.3 Model Specifications and Diagnostic Tests

Dependent: $DNPL_{i,t}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Number of observations	253	253	253	253	209
Number of countries	23	23	23	23	19
Number of instruments	13	12	12	14	14
Arellano-Bond test for $AR(1)$ p-value	0.0214	0.0943	0.0741	0.0605	0.0973
Arellano-Bond test for $AR(2)$ p-value	0.829	0.598	0.461	0.303	0.388
Hansen test of overid. restrictions p-value	0.970	0.730	0.715	0.349	0.619
Sargan test of overid. restrictions p-value	0.994	0.945	0.941	0.896	0.772
Wald test p-value	0.000	0.000	0.000	0.000	0.000

*Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

The results in Table 3.6.3 clearly show that all the estimated GMM models are globally robust and pass the misspecification tests. In essence, models used in these analyses provide evidence for high first-order autocorrelation (low p-value of the $AR(1)$ statistics) and a lack of significant second-order autocorrelation (high p-value of the $AR(2)$ statistics) confirming that the results are robust across all regressions and the instruments used are valid. However, the tests become weaker when a higher number of instruments is included. Furthermore, the null hypotheses of the Hansen test and the Sargan test for the joint validity of the instrument sets and over-identification restrictions are accepted, confirming that the instruments are exogenous and not correlated with the error term. The tests also lend support to the validity of the instruments with the corresponding high p-values.

3.7. CONCLUSION

This chapter investigated the impact of household indebtedness, housing affordability and financial development on the evolution of impaired loans, controlling for the effect of macroeconomic fundamentals and house prices. For this purpose, we empirically employed both static models and dynamic models, using a balanced panel dataset for a group of countries that show fundamental heterogeneity in the amplitudes of these factors.

Real residential property price fluctuations are found to be negatively correlated with the scale of NPLs, revealing the high sensitivity of loan performance to fluctuations in real residential house prices in the majority of the estimated models. These findings are consistent with the view that most financial crises have been triggered by imperfections in the real estate market.

Household indebtedness, proxied by household debts to disposable income, was found to evolve in the same manner as the level of NPLs in the fixed effects models, implying that the higher the household indebtedness is, the higher the default probability is. However, it shows statistically significant positive contemporaneous impacts when a GMM is employed, reflecting a positive association with the NPL ratio in the short term, while a negative association was detected in the long term, revealing additional aspects of this effect. This means that an increase in household indebtedness is found to burden borrowers in the short term, undermining their ability to settle their scheduled obligations, and working as an indicator to foreshadow the lender of the fragility of their borrower's financial ability. These events motivate the former to adopt tighter lending terms, by imposing stricter constraints on access to loans for those in vulnerable financial positions, lending support to the idea that banks take time to respond to a negative shock to their borrowers' financial statuses.

Housing expense seems to be highly significant both in the fixed effects estimations and dynamic models. The contemporaneous effect of housing expense is found to have a positive relationship with the scale of NPLs; however, the lagged effect converts to being negative, indicating that in one year, lag households either establish new sources of income to finance their housing expenses, or manage their housing consumption to avoid the negative consequences of defaulting. To sum up, the overall positive impact of housing consumption is consistent with theoretical arguments found in the literature, as well as the expectation.

Financial development, on the other hand, is found to be highly significant, implying that a relaxation in lending standards would expose banks' loan profiles to higher amounts of NPLs. According to the GMM estimations, financial development is found to be highly statistically significant; however, the variable carries a negative sign in the contemporaneous effect and a positive sign in the lagged effect. This finding supports the notion that a bank's loan performance depreciates with a lag owing to the lax credit standards adopted during the boom period.

While seeming to show a positive association with the volume of NPLs in the fixed models, housing affordability is found to have a negative contemporaneous effect on the escalation of bad loans, reflecting the impact of increasing house prices on the strengthening borrowing capacity of the household through the increase in collateral values. However, with a one-year lag, the high quantity of negative equity held by banks is translated into higher numbers of NPLs in the banks' loan portfolios. In the end, the overall impact of housing affordability (*i.e.* contemporaneous and lagged) reveals a positive association with the level of NPLs, which is fairly consistent with theoretical notions and our expectations.

The empirical econometric analyses support a lot of the evidence in the established literature suggesting that real GDP, unemployment rates and interest rates are among the main drivers of NPL ratios over the last decade. More importantly, GDP growth seems to govern the relationship between NPLs and macroeconomic factors. Consequently, a fall in economic activity and/or an increase in the unemployment rate and interest rate still remain the most fundamental controls on bank loan performance.

3.8. APPENDIX

Table 3.8.1 reports the Levin-Lin-Chu (LLC, 2002) test for the unit roots of the variables under consideration:

Table 3.8.1 Levin-Lin-Chu Stationarity Test

Series	Coefficient	T-value	T-star	$P > t$	Level
$NPL_{i,t}$	-0.29179	-9.4430	-2.9026	0.0019	$I(0)$
$UR_{i,t}$	-0.35196	-9.4080	-4.17544	0.0000	$I(0)$
$GDP_{i,t}$	-0.83910	-11.571	-6.85113	0.0000	$I(0)$
$HP_{i,t}$	-0.40800	-6.805	-1.11978	0.0705	$I(0)$
$IR_{i,t}$	-0.34767	-8.023	-2.67386	0.0037	$I(0)$
$HD_{i,t}$	-0.10778	-8.738	-6.88246	0.0000	$I(0)$
$HC_{i,t}$	-0.13266	-8.940	-2.78767	0.0318	$I(0)$
$FD_{i,t}$	-0.09458	-8.045	-6.26470	0.0000	$I(0)$
$HA_{i,t}$	-0.15847	-9.761	-6.8919	0.0000	$I(0)$

4. CHAPTER FOUR

MORTGAGE DEFAULTS, PROPERTY PRICES AND BANKS' LENDING BEHAVIOUR IN HONG KONG SAR

4.1. 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 developments 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 minimise 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 behaviour studies are also appreciated by policy makers 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)).

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 chapter 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 most 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.[44] 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

[44] 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.

to counteract banks' exposure to swings in real estate prices, many macroprudential 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 macroprudential tools over the past two decades in an attempt to safeguard the stability of its banking system. Among other macroprudential 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.[45] 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 characterised by significant downturns in the property market of around 30-40%.

Despite the growing consensus on the importance of using macroprudential 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.

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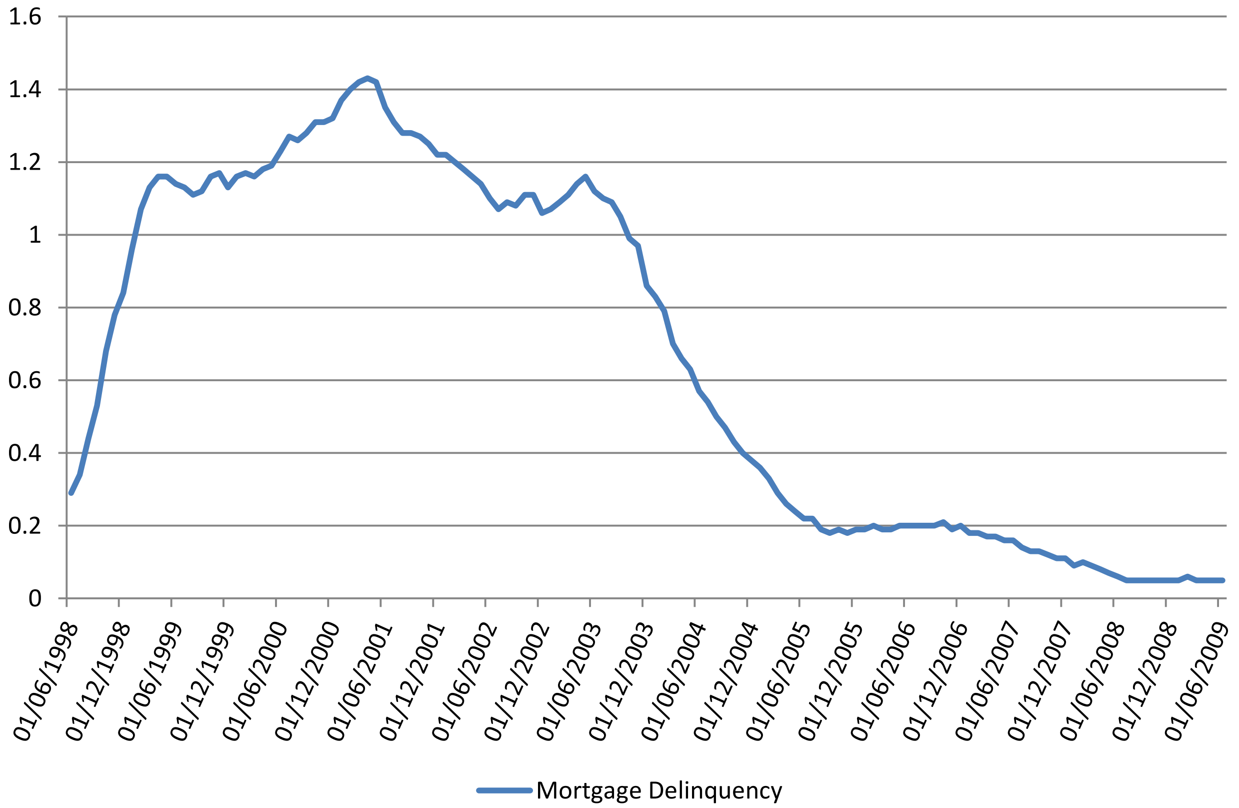
[45] The HKMC is a Hong Kong government corporation established in 1997 to support bank stability through: (i) functioning as a source of liquidity for borrowers, contributing to a reduction in mortgage risk accumulation, (ii) propagating home ownership and (iii) facilitating the growth and development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

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 4.1.1 Mortgage Delinquency Ratio in Hong Kong



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 4.1.1).

In the present chapter, 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 behaviour 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 chapter is organised as follows. The following section provides a brief overview of the literature on mortgage delinquency, property prices and bank lending, and their implications. Section 4.3 clarifies the methodology and the econometric model that is used to address the research questions. In Section 4.4 data sources and the characteristics and construction of some variables that are used in the empirical analysis are presented. Section 4.5 presents the empirical results of the analyses and their inferences. Finally, Section 4.6 provides some concluding remarks along with their implications with regards to policy.

4.2. 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 fulfil 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 collateralised 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)).[46]

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 authorised 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.[47] 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

[46] For more information, see Michael *et al.,* (2006) and Karim *et al.* (2010).

[47] For a detailed discussion of determinants of delinquency and foreclosure, see Demyanyk and Van Hemert (2011).

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.[48] 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.[49]

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

[48] Mortgagors are supposed to continue their payments for the collateralised 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.

[49] For a wider literature review of the empirical mortgage default see Quercia and Stegman (1992) and Tam, M. W.-Y., Hui, e., & Zheng, X. (2010).

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. 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 collateralised loans, where borrowers use the value of their property against their debts.[50] 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.

4.3. 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).

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

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 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 levelled 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. (4.1) 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:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_t, \tag{4.1}$$

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. (4.1) as a general vector autoregressive model of order p, in $\mathcal{Z}_t$:

$$\mathcal{Z}_t = c_0 + \beta t + \sum_{i=1}^{p} \emptyset_i \mathcal{Z}_{t-i} + \varepsilon_t \,, t = 1,2,3,\cdots\cdots,T \tag{4.2}$$

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. (4.3) can be derived to correspond to the representation in Eq. (4.2):

$$\Delta\mathcal{Z}_t = c_0 + \beta t + \prod \mathcal{Z}_{t-1} + \sum_{i=1}^{p} \Gamma_{\mathrm{i}}\, \Delta\mathcal{Z}_{t-i} + \varepsilon_t \,, t = 1,2,3,\cdots\cdots,T \tag{4.3}$$

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 $(k+1)$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. (4.3) can be converted to the following representation:

$$Y_t = c_{y0} + \beta t + \delta_{yy} Y_{t-1} + \delta_{xx} X_{t-1} + \sum_{i=1}^{p-1} \lambda_i\, \Delta Y_{t-i} + \sum_{i=0}^{p-1} \xi_i\, \Delta X_{t-i} + \varepsilon_{yt} \,,$$
$$t = 1,2,3,\cdots,T \tag{4.4}$$

Following Liang and Cao (2007), Whyte (2010) and Adebola *et al.* (2011), and based on the foundation of Eq. (4.4), 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. (4.5):

$$\Delta\, Y_t = \alpha_1 + \beta_1 Y_{t-1} + \beta_2\, X_{1t-1} + \beta_3 X_{2t-1} + \beta_4\, X_{3t-1} + \sum_i^{p} \gamma_i \Delta\, Y_{t-i} + \sum_j^{q1} \delta_j \Delta X_{1t-j} +$$
$$\sum_l^{q2} \varphi_l \Delta X_{2t-l} + \sum_m^{q3} \eta_m\, \Delta X_{3t-m} + \varepsilon_t, \tag{4.5}$$

where α_1 , $\beta_1, \cdots\cdots, \beta_4, \gamma_i$, δ_j , φ_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. (4.5) 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. (4.5), 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. (4.5) 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. (4.6):

$$Y_t = \alpha_1 + \sum_{i=1}^{p} \gamma_i\, Y_{t-i} + \sum_{j=0}^{q1} \delta_J\, X_{1t-j} + \sum_{l=0}^{q2} \varphi_l X_{2t-l} + \sum_{m=0}^{q3} \eta_m\, \Delta X_{3t-m} + v_{yt}. \qquad (4.6)$$

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 outperformed AIC. 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. (4.7):

$$\Delta\, Y_t = \alpha_1 + \sum_{i}^{p} \gamma_i \Delta\, Y_{t-i} + \sum_{j}^{q1} \delta_j \Delta\, X_{1t-j} + \sum_{l}^{q2} \varphi_l \Delta X_{2t-l} + \sum_{m}^{q3} \eta_m \Delta X_{3t-m} + \vartheta\, ecm_{t-1} + v_{\Delta yt}, \qquad (4.7)$$

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 4.8.

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.

4.4. 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 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:

$\boldsymbol{D}$: *Residential Mortgage Loans Delinquency Ratio.* The series is supplied by the Hong Kong Monetary Authority (HKMA) in the Monthly Residential Mortgage Survey (RMS).[51]

$\boldsymbol{HP}$: *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 4.9.1 in APPENDIX 4.9). 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.[52] 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.

[51] 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 authorised institutions included in this survey account for over 95% of the total residential mortgage lending business.

[52] 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)).

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.[53] Table 4.7.1 in APPENDIX 4.7 shows the outcomes of the principal component analysis. From Table 4.7.1, it appears that the eigenvalue associated with the first component is significantly higher than one and represents more than 96% of the standardised 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.[54] Figure 4.9.1 in APPENDIX 4.9 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 ($\boldsymbol{HP}$).

$\boldsymbol{L}$: *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 whom 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.

$\boldsymbol{LTV}$: *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

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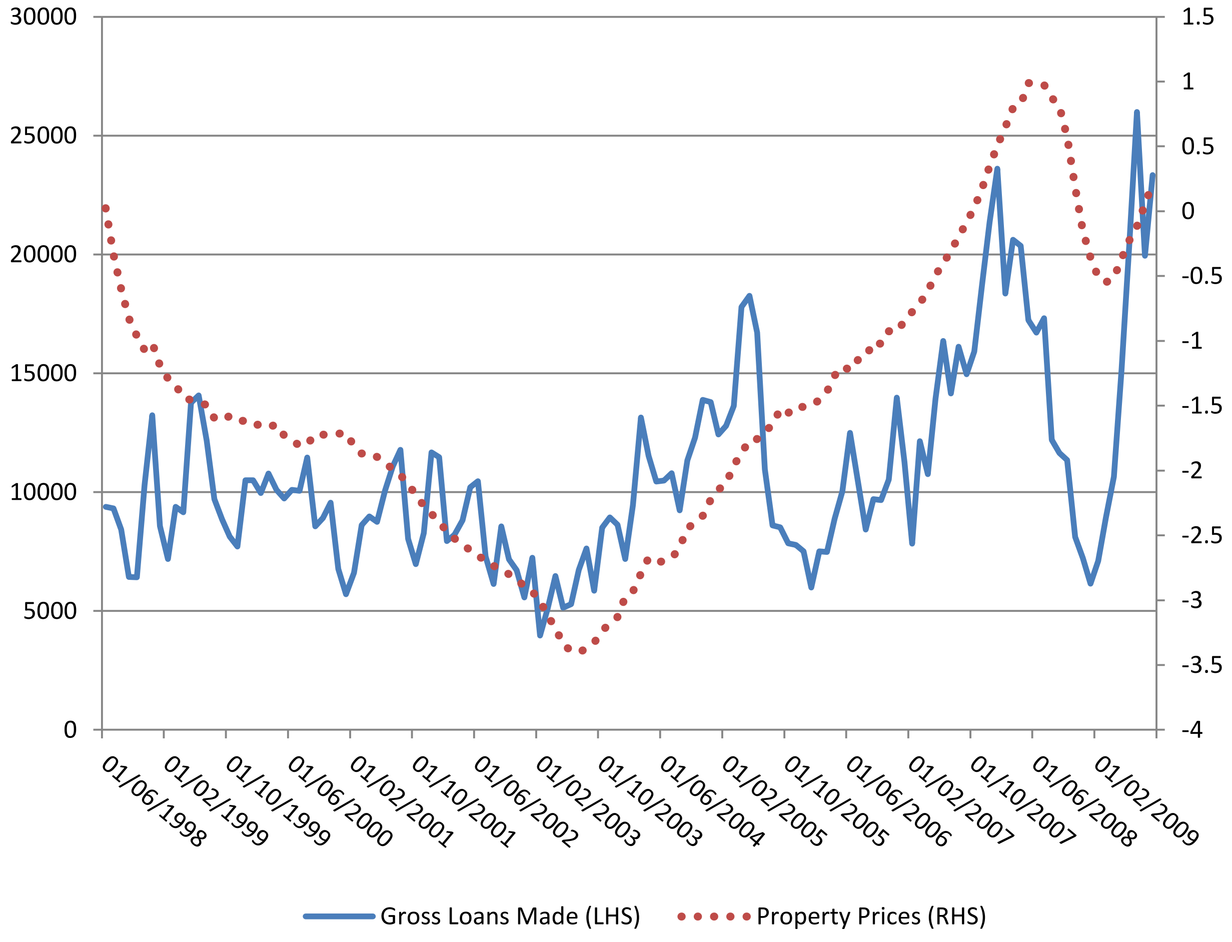
[53] These indexes are compiled by the Rating and Valuation Department of the Hong Kong government, based on market transaction data and reflect changes in prices and rents per square foot of the properties with comparable building and location qualities.

[54] 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.

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).[55]

Figure 4.1.1 plots banks' lending (scaled on the left-hand side axis) and property prices (scaled on the right-hand side axis).

Figure 4.4.1 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.

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[55] 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.

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 characterised by the high frequency of occurrence of episodes of increases or decreases in prices. More importantly, Figure 4.1.1 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 scrutinised using an error correction model specification.

Table 4.4.1 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 4.1.1.

Table 4.4.1 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 4.3 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 4.1.1).[56] 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 APPENDIX4.8, to examine the existence of up to a maximum of five breakpoints, and the outcome of the test is provided in Table 4.4.2.[57]

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 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.

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[56] 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%.

[57] Eq. $(1.B)$ in APPENDIX4.8 corresponds to Eq. (4.5) presented in Section 4.3.

Table 4.4.2 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 4.4.3.

The results in Table 4.4.3 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 $TB2$ in Table 4.4.3 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 4.4.3 Clemente-Montañés-Reyes (1998) Unit Root Tests [58]

Variable	Level			First difference			Decision
	$\boldsymbol{T}$-Statistic	$\boldsymbol{TB1}$	$\boldsymbol{TB2}$	$\boldsymbol{T}$-Statistic	$\boldsymbol{TB1}$	$\boldsymbol{TB2}$	
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.*

4.5. 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 scrutinise the effect of macroprudential policy on mortgage defaults, loan-to-value is also considered. Estimations of Eq. (4.5) 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 4.5.1 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.

Looking at Table 4.5.1, the normalised 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

[58] To 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.

estimations. This means for the mortgage delinquency model, at the 5% significance level, there is cointegration between the variables. The normalised 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.

Table 4.5.1 Results of the Bound Tests at 5% and 10% Significance Levels [59]

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).

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 normalised on the related variables. Therefore, the findings confirm a unidirectional effect between mortgage default and banks' lending behaviour.

[59] 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.

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 chapter is to investigate causality between mortgage delinquency, property prices and bank lending, the cointegration relationship is assessed by normalising on mortgage delinquency.

4.5.1. THE LONG-TERM RELATIONSHIP

Estimation of Eq. (4.6) is conducted to find the long-term parameters and the results reported in Table 4.5.2 are obtained by normalising on mortgage delinquency $\boldsymbol{D}$. Overall, the results presented in Table 4.5.2 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 4.5.2 Estimated Long-term Coefficients Using the ARDL Approach

$ARDL\ (4, 0, 0, 0)$ Selected Based on Schwarz Bayesian Criterion				
Dependent variable is D_t				
Regressors	**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 $\boldsymbol{HP}$ is statistically significant with a negative sign (see Table 4.5.2). 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 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 collateralised 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 4.5.2 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.[60]

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,

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[60] For further reading, see Demyanyk and Van Hemert (2011).

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.

4.5.2. SHORT-TERM ESTIMATION AND ADJUSTMENT

Estimation of Eq. (4.7) has been conducted to investigate the short-term dynamic and the speed of adjustment to equilibrium. The estimation results are reported in Table 4.5.3. 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 4.5.3 Error Correction Representation for the Selected ARDL Model

$\boldsymbol{ARDL}\ (\mathbf{4, 0, 0, 0})$ Selected Based on Schwarz Bayesian Criterion

Dependent variable is $\Delta \boldsymbol{D_t}$

Regressors	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%.*

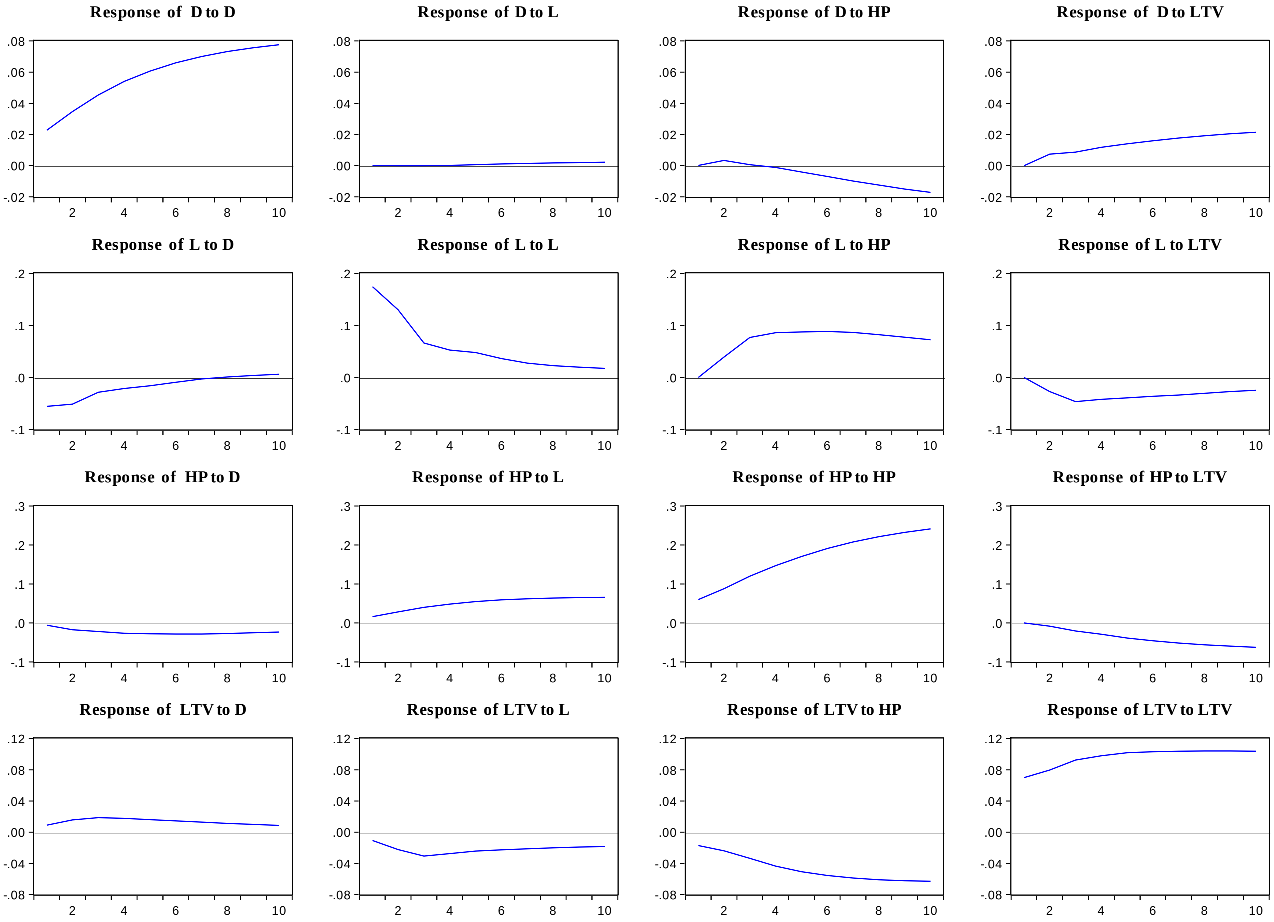
The coefficient of the lagged error correction term ($\boldsymbol{ecm_{t-1}}$) for the mortgage delinquency $ARDL$ model is highly significant and occurs in the negative direction. This finding confirms the long-term relationship between mortgage delinquency and the other variables included in the estimation, 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 adjusts 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. (4.8):

$$ecm = D - 0.35 * L + 0.28 * HP - 0.47 * LTV + 0.01 * TREND - 4.33 * C - 0.13 * DV. \quad (4.8)$$

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 4.5.1.

Figure 4.5.1 Impulse Response Functions to Cholesky One S.D. Innovations



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

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 4.5.1 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 4.5.1 also confirms the persistence of mortgage delinquency.

4.5.3. 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 4.5.4. The misspecification tests show that the residuals have no serial correlation, the correct functional form and normally distributed residuals. Unfortunately, the null hypothesis of homoscedastic error cannot be accepted, indicating heteroscedastic 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.

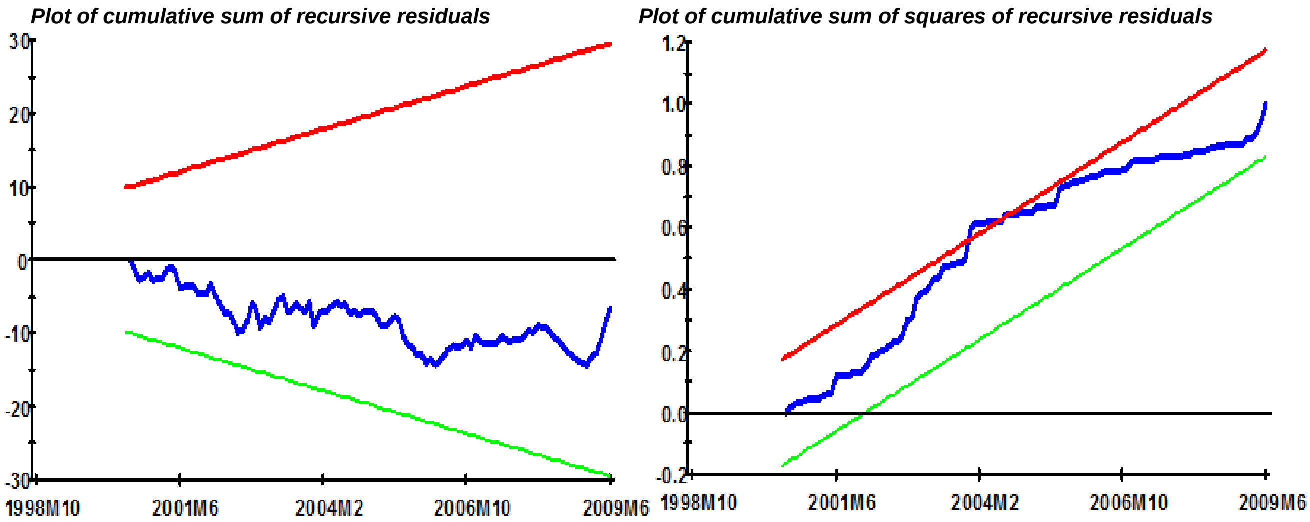
Table 4.5.4 Diagnostic Tests of ARDL VECM Model of Mortgage Delinquency

$R^2 = 0.9986$		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. (4.5). 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.

Figure 4.5.2 plots the CUSUM and the CUSUMSQ stability test of the estimated coefficients of the residuals of Eq. (4.6). 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.

Figure 4.5.2 CUSUM and CUSUMQ Coefficient Stability in the ECM



The straight lines represent the critical bounds at 5% significance level *The straight lines represent the critical bounds at 5% significance level*

4.6. CONCLUSION

This chapter 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.

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 multifunctional toolkit that consists of financial, monetary and macroprudential methods that are able to manage this interdependence and preserve a balanced relationship between these factors 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.

4.7. 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 4.9.1 in APPENDIX 4.9, and the results of the analysis are shown in Table 4.7.1.

Table 4.7.1 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 standardised 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.

4.8. 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):

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

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

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

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

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):

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

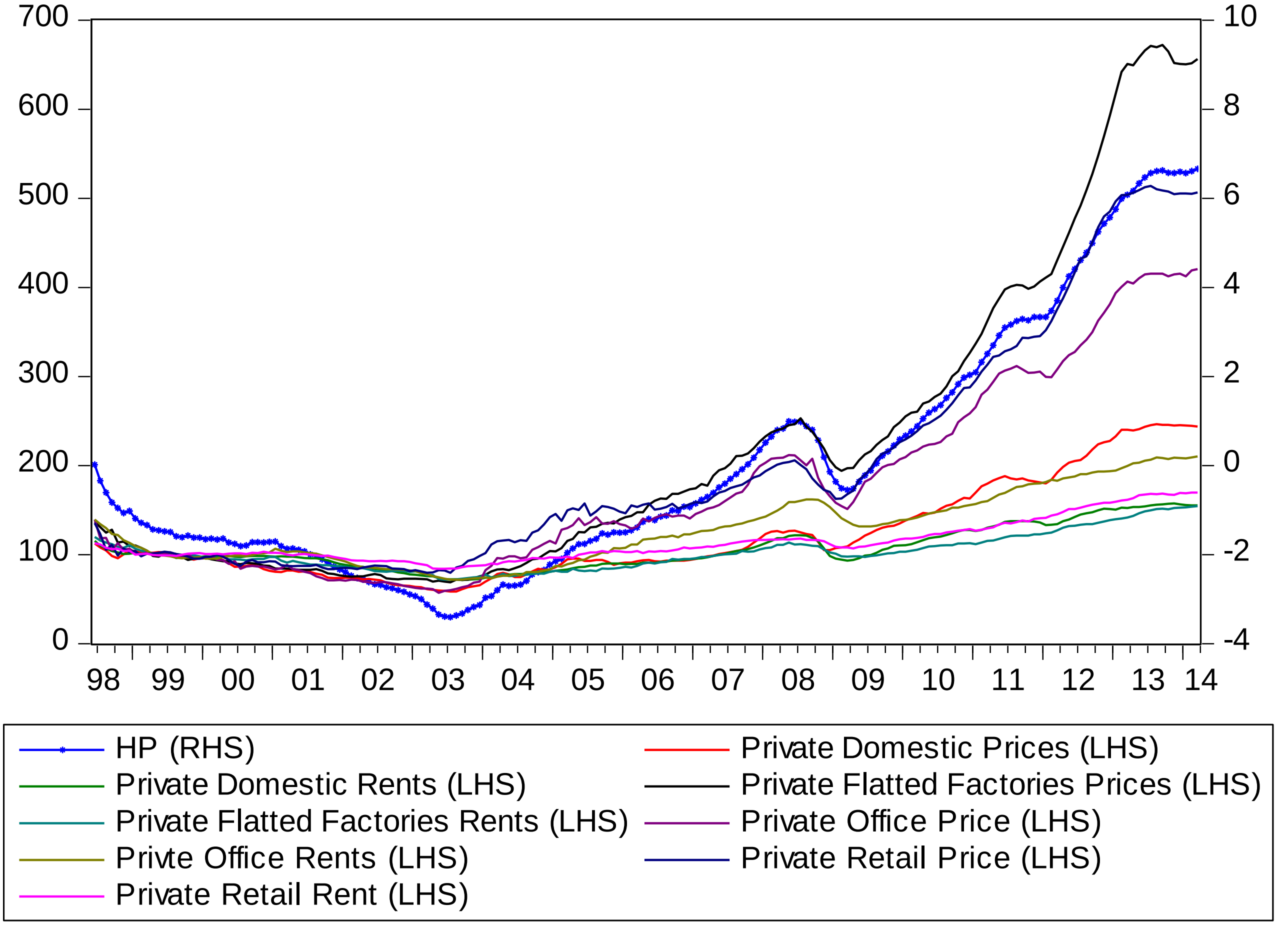
As the final step, the error correction models along with the short-term dynamic coefficients are estimated as shown in Eq. (6.B):

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

4.9. APPENDIX

Figure 4.9.1 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 ($\boldsymbol{HP}$). 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 4.9.1 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.

5. CHAPTER FIVE

CONCLUDING REMARKS

Similar to the Great Depression, the causes of which are debated to the present day, the financial meltdown that occurred in 2008-2009 is not fully understood, despite intense focus on it by the media and academic research. Since the onset of the 2008-2009 crisis, worldwide banking systems have been exposed to a wide-ranging spectrum of challenges which have confirmed that the lessons from the crisis are not comprehensively understood. Because the financial crisis of 2008-2009 resulted in negative economic growth throughout the world's economies, it has resulted in increasing efforts explore what exacerbated the crisis and its repercussions on the global financial system.

In a search for scapegoats, the earliest efforts were directed at identifying the guilty, and paid little attention to understanding the multifaceted nature of the calamity. Financial institutions were blamed for being greedy, corrupt and engaged in speculative and deceptive actions, while other observers went even further and allude to the failure of decision-makers to take contingent decisions, such as the refusal to bail out Lehman Brothers in September 2008, the event after which an avalanche of financial institutions collapsed. On one hand, empirical studies adopted a variety of explanations to what led to the crisis, concentrating on the financial segment and deregulation by regulatory authorities, while others blame the policy of excessive lending embraced by the Federal Reserve over the period between 2002 and 2005. On the other hand, some researchers, such as Reinhart and Rogoff (2009), argue convincingly that, historically, financial crises occur due to banks' lending behaviour that results in a credit boom and creates house price bubbles in the real estate market. In another subset of studies, credit booms and price bubbles have been attributed to the absence of macroprudential monitoring by financial institutions, which resulted in bubbles in the real estate markets.

Generally speaking, the world observed a systemic financial meltdown in which various causal elements interacted, leading to a decline in global GDP of around 10 per cent between 2008 and 2010. Therefore, many of these causes can be judged as neither true nor incorrect since they are not able to fully explain how a crisis in a small sector of the financial industry (subprime mortgages) was exacerbated and went on to create a global crisis. Furthermore, the rapid transmission of the crisis between nations reveals that the risk of contagion is considerably higher than many economists formerly predicted. One undeniable fact is that the arsenal of powerful modern tools devised by banks still falls short of producing an efficient set of instruments that is able to fight housing bubbles and maintain banking stability during house price booms.

The interaction mechanism between the real estate market and the financial system in the US has been blamed for being the root cause of the crisis, through the accumulation of housing market bubbles, which resulted in the ultimate collapse of the market. Tremendous efforts have been made to determine the main drivers of the banking crisis at the institution level (see, for example, Reinhart and Rogoff (2009) and Louzis *et al*. (2010)), as well as at the country level (see, for example, Beck, Jakubik and Piloiu (2013) and Kaminsky and Reinhart (1999)). Simultaneously, other efforts were dedicated to devising and exploring the efficiency of policy tools that are able to detect early warning signs of banking instability (see, for example, Kaminsky and Reinhart (1999)). The growing banking literature was also largely responsible for major developments in the regulatory framework that observes and manages all sources and types of risk that might threaten the stability of financial institutions, in order to maintain sustainable, robust and resilient banking systems. Most observers include the role of real estate market factors as a major cause of the crisis, and emphasise that the roots of the financial meltdown lie in the pattern of the housing market. Yet, how to protect the banking industry against deficiencies in the housing sector, in light of the interdependence and integration of the two, is central to the on-going debates.

Despite all the effort put into banking research, the globe witnessed a catastrophic financial meltdown, which began in the early 2000s in the United States and rapidly spread like wildfire throughout the world, due to the close links between the world economy and the US financial sector. Indeed, by the second half of 2008, most developed economies were going through a deep recession, and in the last quarter of 2008, the world economy nearly ground to a halt, economic growth plummeted, institutions' losses soared and lending interest rates declined considerably. The onset of the financial crisis exposed the insufficiency of the regulatory and supervisory frameworks adopted by financial institutions prior to the onset of the crisis.

Meltdown of the financial sector made it clear that greater effort is required in at least four areas to mitigate the hazards associated with financial crises and tackle them when they happen. These are: *(i)* Searching for more efficient tools that are able to evaluate systemic risk and prevent its build-up during periods of economic stability; *(ii)* Enhancing transparency and the disclosure of the underlying risks that are taken by different market actors; *(iii)* Intensifying the scope of regulation, both at the domestic and international levels, without violating constructive diversity; *(iv)* Devising and employing advanced operative mechanisms for more efficient and consistent activities. Among other areas, these steps legitimate the tremendous efforts dedicated to research the multiple reasons, repercussions, consequences and effects of the financial meltdown in the aftermath of the crisis, and urges the need for additional effort since the full cause is still unknown.

The present thesis contributes to the existing literature through three empirical investigations into the nexus between the real estate market and financial institutions' exposure to credit risk. In essence, these are: an exploration of the link between fluctuations in house prices and the growth of NPLs in the banking sector in the US before, during and after the financial crisis; an evaluation of the impact of housing affordability, household vulnerability and financial developments on the evolution of NPLs using a balanced panel dataset of 23 countries; and an exploration of the long-term equilibrium relationships and short-term dynamics between mortgage defaults, property prices and banks' lending behaviour in Hong Kong. Therefore, the thesis contains several econometric methods, including non-parametric analysis, univariate and multivariate regressions, and dynamic models for both time series and panel data. The following paragraphs offer a synopsis of the thesis.

CHAPTER TWO scrutinised the relationship between house prices and NPLs in US metropolitan areas, using unbalanced panel data from 1999 to 2009. The subprime mortgage crisis of 2007-2008 in the US was instigated by bubbles in the real estate market and led to a dramatic collapse in the financial and banking system, prompted by falling property prices. Financial institutions were blamed for being among the main creators of the housing bubble through the adoption of expansive lending policies with lax borrowing conditions prior to the crisis, which resulted in a credit boom. This suggests a robust link between house price fluctuations and banking system stability. However, the dynamics of house prices differ markedly with geographical and time dimensions, as asserted by Holly *et al.* (2010). The increase in real estate prices prior to 2006 was not uniform across US metropolitan areas (Sinai, 2012). These variations in the behaviour of house price swings over different episodes of real estate booms and busts presumably trigger regional heterogeneous impacts on loan performance and banking stability in a broader context. This chapter was therefore an endeavour to fill an important gap in the existing literature on credit defaults by investigating the extent to which geographical differences in the origin of credit defaults are consistent with regional variations in house prices across US metropolitan areas.

In this chapter, it was conjectured that NPLs across the states of the US follow similar patterns to house prices and submits this conjecture to statistical scrutiny by testing whether or not the magnitudes of NPLs in states are as regionally clustered as house prices across US metropolitan areas. To this end, US states are grouped into four geographical categories, based on the corresponding records of house appreciations observed between 1998 and 2006. Each state is placed into one of four groups, $Code\,1$, $Code\,2$, $Code\,3$ and $Code\,4$, corresponding to regions that witnessed house price increases of greater than 80%, between 40% and 80%, between 20% and 40% and less than 20%, respectively. Moreover, the onset of the financial crisis was supposed to have exaggerated the impact of house prices on the evolution of NPLs. States are therefore clustered according to the scale of changes in the observed house prices, and investigated over rationally selected years to reflect the pre-crisis period of the housing boom, during the crisis when the house price bubble build-up took place and post-crisis bust period. This methodology enabled us to capture the impact of house prices on NPLs during all phases of the financial crisis.

To test the above assumption, a stochastic dominance analysis was used to examine whether NPLs in states with large house price appreciation stochastically dominate their analogues in states that had lower house price increases. Furthermore, our analyses go beyond stochastic analyses and estimate the GMM models, aiming at determining the magnitude and direction of the effect of house prices on the evolution of bad loans, controlling for the impact of essential macroeconomic fundamental variables, such as the unemployment rate, GDP and interest rates. As a final investigation, a generalised panel threshold model allowing for regime intercepts, proposed by Bick (2010), is used to test for the existence of a threshold point at which different impacts of house prices on the evolution of credit defaults can be estimated, using house price index returns as the threshold parameter and macroeconomic fundamentals as control variables.

The results of the stochastic dominance analysis, with few exceptions, indicated that the growth of NPLs was lowest in states grouped in $code\ 4$ where house prices witnessed an increase of less than 20% and went up steadily in states where house prices underwent a more pronounced increase, to reach its peak in states grouped in $code\ 1$, where observed house price increases were found to be greater than 80%. Consistent with the aforementioned sampling procedure, these findings suggest a similar ranking pattern of NPL distributions. The outcomes of the stochastic dominance are visualised by plotting the empirical cumulative distribution functions ($ECDFs$) of the NPLs of the regions under inspection. Notably, the magnitude of the difference between the groups of states is detected to be more pronounced in 2006 and 2008, *i.e.* during and after the crisis. Although house prices on the East and West coast recorded high upsurge associating with high volumes of NPLs during the bubble period, these States recovered faster than states in other regions when the house price bubble burst. Important policy implications can be identified from these results, suggesting that future plans that address the exposure of the banking sector to house price fluctuations should account for fundamental state-specific factors, and hence need to be planned on the state level, rather than the national level, and taking into account the current phase of the economy.

Since the stochastic dominance analyses indicated differentials between the NPL $CDFs$ without providing interpretations for these differences, we employed the Arellano-Bond (1991) generalised method of moments (GMM) estimation in an attempt to quantify the magnitude of house price changes, as well as the impacts of gross domestic product, unemployment rates and lending interest rates on the evolution of NPLs. The outcomes of the GMM estimation reveal a negative relationship between banks' loan performance and house prices swings, indicating that an increase in house prices would improve borrower's abilities to service their debts, by providing additional privilege to get loans in light of the increasing value of their collaterals (see, for example, Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)). As far as macroeconomic factors are concerned, NPLs were found to be positively influenced by unemployment rate and lending interest rate, as a result of increasing debt costs and decreasing expected income flows. On the other hand, an increase in GDP is found to contribute to a decrease in NPL growth, implying that an economy enjoying a stable rate of growth presumably subsidise a borrower's ability to service their debts and, hence, reduces the probability of defaulting.

As a final investigation, a generalised panel threshold model, allowing for regime intercepts, was used to investigate the nexus between NPLs and house price index, controlling for the macroeconomic variables examined in the empirical analyses of the GMM.

The purpose of this model was to determine the presence of a threshold point in the house price return index, at which two different impacts of house prices on NPLs were estimated.

The model delivered a highly significant threshold point, at which two different impacts of house price index returns on the growth of NPLs can be estimated. In essence, the threshold point indicates the greater and more harmful impact of house prices on the growth of NPLs when house prices fluctuate above the threshold point. The policy implications of this threshold point are that the threshold value, as well as the lower bound of the confidence interval, refer to the point at which the detrimental impact of house prices on bank loan performance starts, and more importantly, this impact becomes considerably greater with each subsequent move of house prices further from this point. Therefore, an important aim of policymakers to safeguard banks against exposure to house price fluctuations should be to keep house prices as much as possible around the threshold point, in order to achieve low NPL ratios in banks' loan portfolios. Furthermore, these findings suggest the need for innovative policy instruments that are able to fully control house price fluctuations. Finally, procedures for banking stability need to be designed at the regional level, taking into account idiosyncratic local factors and the economic situation of the area.

CHAPTER THREE established an empirical link between NPLs, housing affordability, household indebtedness and domestic financial development, controlling for macroeconomic fundamentals by employing static and dynamic models. The spectacular escalation and following collapse of US property prices during the early years of the new millennium are seminal moments in the history of real estate markets in the world economy. They were associated with dramatic events that started with banking and financial instability and ended up with the catastrophic collapse of the banking and financial systems, within a short space of time. Despite the abundance of literature on the nexus between the real estate market and financial stability (see, for example, Ferguson and Navarrete (2003)), not much has been said on the impact of financial development, the level of house affordability and household indebtedness on the growth of NPLs. In an endeavour to fill this gap, this chapter analysed the impact of these factors on NPL growth. It provides a contribution to the credit default literature by producing empirical evidence on the role of the joint effect of real estate, borrower and financial development factors on the evolution of impaired loans in the banking sector.

A balanced panel data sample that comprised 23 countries was selected in order to reflect fundamental heterogeneities in terms of financial systems, housing characteristics, household indebtedness and house price developments over a time period of a decade. As prefatory analyses, fixed effects models were employed in an attempt to capture the presence of persistence in the dependent variable. However, since fixed effects models neglect fundamental disparities in house price dynamics with both time and regional dimensions, the analysis has been extended by estimating robust two-step differenced GMM models for two reasons: (i) To account for the persistence in the dependent variable; (ii) To account for the heterogeneity between the selected countries.

Consistent with the findings provided by Louzis *et al*. (2010), the estimations of the GMM models revealed that NPLs are highly persistent and the growth of NPLs is largely driven by their previous values. Furthermore, property price fluctuations, proxied by real residential property price growth, are found to be negatively correlated with the volume of NPLs, revealing the high sensitivity of loan performance to depreciations in real residential house prices. This relationship can be attributed to the fact that depreciation in property prices can severely undermine borrowers' ability to pay back their debts through the wealth channel, scaled by collateral revaluations.

Household fragility, proxied by household debts to disposable income, was found to evolve in the same manner as the level of NPLs, indicating that a high household debt burden are translated into a higher probability of credit defaulting. The impact becomes more severe when households experience negative income shocks. Consequently, a higher level of NPLs is supposed to be witnessed in the banks' loan portfolio at this stage. On the other hand, an increase in household indebtedness might encourage banks to tighten their lending terms as the probability of borrower defaults increases, resulting in limited credit availability and consequent depreciation in property prices, undermining the capital position of banks.

The ratio of household consumption to disposable income, as an additional indicator of household vulnerability, showed a positive contemporaneous effect on the growth of NPLs, thus we may infer that an increase in housing consumption would additionally burden the household and result in an increasing risk of defaulting on a loan. However, households seem to have managed to find new sources finding new sources of income to finance their housing expenses, or adjust their housing consumption to prevent the negative consequences of defaulting.

Financial development, proxied by a composite measure reflecting financial development and banks' mortgage lending behaviour, showed a negative contemporaneous effect and a positive lagged impact on NPLs. This mixed relationship might be related to borrowers' behaviour; due to lax lending terms in episodes of credit booms, they presumably become motivated to get loans to finance house purchases. However, the interest rate might consume a substantial portion of borrowers' income and lead to defaulting when the burden of these debts becomes unaffordable. Furthermore, relaxing lending standards in an under-regulated environment, as found in several empirical studies, exposes a higher volume of credit to the risk of default (see, for example, Gavin and Hausmann (1998)).

Finally, housing affordability was proxied by a summary measure of two commonly used indicators for affordability, namely price-to-income and price-to-rent. These indicators suggest that a reduction in affordability happens when either house prices (or rents) increase, or incomes decline, since each of these cases contributes to weakening households' ability to buy or rent housing, thus they are supposed to undermine households' ability to fulfil their obligated debts and subsequently result in a higher probability of default. Therefore, a positive association between housing affordability and loan performance is supposed. The results of the fixed effects estimations are consistent with this interpretation, demonstrating a positive relationship between the two variables. However, mixed results were detected in the dynamic estimations of the GMM models; specifically, the contemporaneous impact was found to be negative, while the lagged impact became positive. The explanation for the negative contemporaneous effect relies on the notion that an increase in house prices enhances borrowers' creditworthiness, gaining for them the benefits of growth in collateral values (see, for example, Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)). However, when house prices start to depreciate along with collateral values, at the beginning of the bust period, the resulting high volume of negative equity is rapidly translated into an increase in NPLs in financial institutions' portfolios. These findings indicate that banks take time to feel the decrease in housing affordability and adjust their lending behaviour to households with fragile financial health, which stresses the essential importance of the continuous review and reassessment of borrowers' creditworthiness, and taking action accordingly.

Compatible with economic intuition, and in agreement with our findings from Chapter Two, economic growth, unemployment rates and interest rates have been included as control variables to capture the effect of macroeconomic fundamentals and financial aspects on the progress of NPLs (see, for example, Louzis *et al.* (2010), Rinaldi and Arellano (2006) and Bofondi and Ropele (2011)). The results of the estimations show high consistency with our previous findings, and confirm that real GDP per capita growth has a negative association with the evolution of NPLs, while unemployment rates and interest rates have positive relationships, with GDP being the main governor of these relationships.

CHAPTER FOUR investigates the long-term equilibrium relationships and short-term dynamics between mortgage defaults, property prices and banks' lending behaviour in Hong Kong, controlling for the impact of loan-to-value (LTV), using monthly time series ranging from June 1998 to June 2009. The choice of Hong Kong was based on its fundamental features, which make it an interesting case study. Among other distinctive characteristics, Hong Kong is an externally-oriented country, has one of the most developed mortgage markets where the government plays a key role in the real estate market, residential mortgage lending comprised a substantial proportion of the banks' lending, it has a history of volatile house prices with repeated episodes of boom and bust, bank lending is also highly volatile, it is engaged in the Currency Board regime, linking the Hong Kong dollar to the US dollar, and it was one of the pioneers in devising and implementing LTV.

Swings in house prices, as well as in banks' lending behaviour, have long been considered to be reliable indicators of future financial instability in the established literature. According to Gadanecz and Jayaram (2008), the importance of the link between financial stability and house prices can be attributed to the remarkable interdependence and the multifaceted nonlinear interactions between various elements of the financial system and components of real estate markets. While Gerlach and Peng detected the influence of house prices on bank lending in Hong Kong, in their investigation of the feedback effect, using a set of Asian countries during the Asian financial crisis, Collyns and Senhadji (2002) confirmed the influence of banks' lending behaviour on changes in property prices.

A general criticism that can be levelled at the majority of empirical works on the association between banks' lending behaviour, property prices and changes in banks' credit risk is that they suffer from "*simultaneity problems*". That is, most of these works concentrate on a single-equation setup to examine the nexus between one of these cycles on the other ignoring the interaction and the magnitude of causality. Therefore, Chapter Four contributes to the existing literature by testing the long-term relationships and short-term dynamics between bank lending, residential property prices and mortgage defaults, by employing a multivariate cointegration framework on aggregated data at the country level.

The residential mortgage loan delinquency ratio has been used to proxy credit default. The property price index has been extracted from different types of properties (residential, private offices, private retail, and flatted factories) due to the remarkable similarity in evolution these property prices and to avoid multicollinearity problems while accounting for all types of properties that involves a demand for credit. Bank lending behaviour is proxied by data of gross loans made in Hong Kong to take into account loans to corporations operating in the construction and property development field and to be consistent with the above mentioned property price indicator. Finally, current loan-to-value is derived by dividing loan-to-value at mortgage origination by suitable property price index (see *i.e.* Clapp *et al*. (2001)) and used to capture the actual impact of macroprudential tools in protecting bank's loan performance. It is worth mentioning that, due to the inclusion of the Asian financial crisis in the sample under consideration, a suitable dummy variable has been constructed and included in the estimation to account for the structural breaks on the evolution of mortgage delinquency caused by the crisis in the Hong Kong (see Figure 4.1.1).[61]

Among the most common methods to test cointegration and estimate long-term and short-term relationships Engle and Granger approach (1987) and the Johansen approach (1988, 1991) have been criticised with considerable limitations concerning stationary of the included variables (see *i.e.* Banerjee *et al*. (1986) and Asteriou and Hall (2011)). Therefore, Autoregressive Distributed Lags model ($ARDL$) or Bounds testing proposed by Pesaran *et al.* (2001) is used to capture the data generating process (DGP). Bounds testing can deal with small sample size and allows for the inclusion of a sufficient number of lags to overcome problems concerning omitted variables and autocorrelations (Pesaran *et al.*, 2001). Bearing the above advantages in mind, the Bounds test for $ARDL\ (p, q1, q2, q3)$ model is used to explore the long-term relationships and dynamic interactions between mortgage delinquency, property prices, and banks' lending behaviour accounting for the impact of loan-to- value.

The calculated F-statistics resulted from normalizing on the variables of interest in the $ARDL - OLS$ estimations reveal the existence of a long-term cointegration within the indicators implying a two way causality between mortgage default and banks' lending behaviour. Based on the existence of a unidirectional effect between the mortgage default and banks' lending behaviour, $ARDL\ (4,0,0,0)$ specification is estimated and the long-term as well as short-term coefficients are evaluated by normalizing on mortgage delinquency.

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[61] Mortgage delinquency in Hong Kong witnessed a substantial upsurge from 0.3% in the fourth quarter of 1998 to 1.4% in 2001 in the wake of the Asian financial crisis before dropping to less than 1% at the end of 2003.

The results ascertain that mortgage delinquency is greatly affected by loan-to value caps, banks' lending behaviour and property price swings. Property prices show high significance on the ratios of mortgage default in the long-term. This relation can be attributed to the supplemental privilege that borrowers get from the appreciation in collateral values which contributes to the reduction of credit default probability (see for example Bernanke *et al.* (1999), Kiyotaki and Moore (1997) and Collyns and Senhadji (2002)). On the other hand, an increase in property prices helps improving banks' capital positions through revaluation of assets owned by the banks.

As far as banks' lending behaviour is concerned, a high positive significance of banks' lending on the growth of credit default has been found. Our findings are in line with various empirical studies suggest high exposure to credit default can be triggered by expansionary bank lending behaviour. However, this impact varies positively with the extent to which a bank is engaged in mortgage lending, which in the case of Hong Kong is markedly huge (see *i.e.* Gerlach and Peng, 2005).

Loan-to-value, on the other hand, prove to be the most important tool in reducing the exposure to credit default in the Hong Kong as the forerunner in using LTV to mitigate credit default. Furthermore, the variable presents positive impact on mortgage delinquency suggesting that higher caps on LTV ratio would expose higher fraction of a loan to the default risk (see e.g. Earley and Herzog, 1970).

Finally, the Asian Financial crisis is identified as an essential contributor to credit default growth with the included dummy variable show high positive significance signifying the role of financial turbulence in jeopardizing banking loan performance.

The lagged error correction term of the $ARDL$ model confirms the long-term relationship between the credit default and the other variables included in the estimation and establish that any disequilibrium triggered by previous shocks is corrected and converges back to the long-term equilibrium with relatively slow adjustment speed.

From a policy point of view, the existence of cointegration between mortgage default, property prices and bank' lending behaviour suggests devising new instruments contain financial, monetary and macroprudential ingredients to control the interdependence between these indicators to the best of banking stability. Moreover, policies that manage these indicators need to be continuously mapped and reviewed in wider policy contexts through cooperation among representatives of the real estate market and bank policymakers.

The history of the recent financial crises suggests a regular global recession occurrence every eight years, it is, therefore, a matter of time before the world's economy rock new financial meltdown. Indeed, the headlines of the international news keep talking about new upcoming financial collapse providing convincing signs and indicators for their predictions. The repeated occurrence of banking turmoil and financial distress, undoubtedly call for further efforts to be made in this segment of literature. First, it is crucial to consider reviewing the regulatory framework in a wider policy context through engaging representatives from the financial sector and the real estate sector in a cooperative environment to maintain a balanced relationship between financial stability and real estate market as the major source of financial distress. Second, design these policies at local level rather than at a nationwide level in a way that helps curbing local crises before they spread to other local and international economies exacerbating the situation to be global crisis which is a more challenging task to control. This urges the need for more empirical studies concerning crisis transmission across local and international economies and determine the drivers behind transmission mechanism. Third, facilitating financial and monetary instruments that are able to help implementing the government plans and facilitate timely intervention through the government bailout programs targeting individual financial institution stability.

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