Real Estate Cycles and Bank Systemic Risks

Georgina Ge

Department of Applied Finance and Actuarial Studies,

Faculty of Business and Economics,

Macquarie University

December 2, 2015

Contents

List of Tables

Acknowledgments

I would like to express my very great appreciation to my principal supervisor, Egon Kalotay, as well as my associate supervisor, Stefan Trueck, for their valuable and constructive suggestions during the planning and development of this research work. Their willingness to give their time so generously has been very much appreciated.

My special thanks are extended to the staff of Macquarie University for their support and consideration during this period. Thanks must go to associate professor Geoff Loudon and Dr. Thomas Longden for their ongoing advice and support.

Abstract

This thesis presents an empirical study of the linkages between boom-bust cycles in the real estate market and systemic banking crises. The work contributes to the literature by estimating the conditional probability of systemic banking crises as a function of time varying market and macroeconomic conditions, as well as characteristic information on real estate markets. The model is expected to offer regulators a quantitative basis for assessing the vulnerability of the financial system to real estate cycles. The findings suggest that a disconnection between credit aggregation to economic output, as well as that between property values and income levels tend to precede banking crises. In addition, growth rates of housing prices in the short-term are found to have a strong predictive power in providing early warning signals for banking crises.

1 Introduction

Is there a link between real estate cycles and systemic banking crises? Although one can occur without the appearance of the other, they are observed to be highly correlated "in a remarkable number of instances ranging over a wide variety of institutional arrangements, both in advanced industrial nations and emerging economies" (Herring and Wachter, 1999). More recently, according to Crowe et al. (2013), about two-thirds of the 46 systemic banking crises in the past 30 years were preceded by boom-bust patterns in property prices. This thesis presents an empirical study of the linkages between boom-bust cycles in the real estate market and systemic banking crises and proposes a quantitative model to help financial regulators, such as the Australian Prudential Regulatory Authority (APRA), assess the vulnerability of banks and other lending institutions to real estate cycles.

A systemic banking crisis is typically a disastrous event which can cause huge economic output losses and lead to a deep recession and a slow recovery. In the existing literature, a variety of approaches have been used to capture the occurrences of systemic banking crises with statistical variables, either dichotomous or continuous. Following Laeven and Valencia (2008, 2012), a systemic banking crisis is defined in this study as an event that causes notable financial distress in the banking system (such as significant bank runs, losses in the banking system, and/or bank liquidations) and significant government intervention in response to the huge losses. The significance of the intervention can be determined using six measures. The level of government intervention is considered high if three of the six criteria are met, that are liquidity support that surpasses 5% of the sum of deposits and liabilities to non-residents, banking restructuring gross costs greater than 3% of GDP, significant bank nationalisations, the implementation of significant guarantees, asset purchases greater than 5% of GDP and the imposition of deposit freezes and/or bank holidays (Laeven and Valencia, 2013). Additionally, borderline cases of crisis events, where only two of the six measures are met, are also considered in this study.

There are increasing studies focusing on identifications of potential causes of this devastating event by examining historical experience on a case-by-case basis. The occurrence of a systemic banking crisis can be linked to various potential factors, but the rapid growth in credit together with leverage in the financial system, especially in the housing sector, are suggested to be closely associated with a crisis event (Jordà et al., 2014). This thesis provides evidence to show that the housing sector can be a source of shocks to financial systems. A collapse in property values, preceded by price booms, is highly likely to trigger a crisis in the financial system. Crowe et al. (2013) observe that 21 out of the 23 countries in their sample with "twin booms" in real estate and credit markets ended up suffering from a financial crisis and/or a severe decline in economic output. It is shown in this study that both credit and asset price booms can increase the banking sector's exposure to systemic crisis.

Real estate markets can be highly attractive to both investors and lenders due to a period of strong performance followed by an initial boom in price. Herring and Wachter (1999) argue that market-clearing prices have a great propensity to reflect the expectations of investors whose estimates of property values are mainly based on their extrapolations of past price increases, and thus deviate above their fundamental values. On the other hand, banks and other financial intermediaries, as investors' credit suppliers, tend to make implicit assumptions by basing their assessments on market transaction prices and thus concentrate their lending in the housing sector (Case et al., 2005). The main business of banks has changed from deposit-taking institutions to high-leveraged lending intermediaries in the last ten decades, with a lack of awareness of the potential risks (Jordà et al., 2015). With the existence of over-optimistic investors and credit suppliers and their diminished awareness of low frequency shocks, property prices can sustainedly deviate above their fundamental values and thus give rise to a bubble. Consequently, the financial vulnerability to real estate sourced shocks can be heightened with an increasing exposure of the system to the housing sector.

In Australia, there has not been yet a substantial systemic banking crisis, although its economic exposure to the real estate sector is large. According to the latest Credit Suisse Global Wealth Report (2014), Australia is the wealthiest country in the world in terms of median wealth per adult and the second wealthiest in terms of average wealth (Shorrocks et al., 2014). However, it is observed that the composition of wealth is heavily skewed towards real assets forming around 60% of gross household assets, which reflects a high real estate prices. With properties being the main storage of wealth for

Australian households, the economy has a large exposure to the real estate sector. In the meanwhile, there is an ongoing debate around whether a bubble exists in Australian property prices. What can be observed in the market is the sustainedly increasing house prices, which can hardly be justified using fundamental econometric techniques.

Disconnections can be observed both between property prices and the Australian income level, as well as between the credit stock and economic output. The Australian Financial Review reported that in one of the largest cities, Sydney, the annual growth rate of housing prices (14.5%) was observed to be four times faster than the wage increase (2.4%) in 2014 (Bloomberg, 2015). Moreover, the household debt-to-income ratio had increased from 34% in 1977 to 154% in 2014. Besides, Australia also has the highest growth rate of 77% bank lending-to-GDP ratio among most of the developed countries over the past 50 years (Jordà et al., 2014). The increasing credit level in Australia is disconnected to economic output and income level. Australia survived the 2008 global financial crisis (GFC), but so did its housing boom. While other countries are deleveraging after the GFC, Australia still has growing property prices and household debt, and thus a large exposure to the real estate sector.

Although there are excellent studies investigating the causes and consequences of historical systemic banking crises, few have attempted to quantify the increased risk exposure of financial intermediaries through formal econometric modelling. According to Jordà et al. (2013), the costs of banking crises preceded by credit expansion are observed to be more severe, which highlights the potential importance of quantifying the circumstances under which such crises are likely to arise. This study models financial intermediaries' exposure to the risk of a banking crisis with a major focus on real estate cycles. Although various stylised factors have been investigated, there is not yet, a hazard model that is applicable in the Australia context and thus can be used to quantify the probability of a banking crisis sourced by the real estate sector. Due to the dearth of Australian experience and thus historical crisis data on which to assess vulnerability, this study aims to propose a hazard model that can be used to measure Australia's exposure to risk sourced by real estate shocks in light of the international experience.

Using this hazard model, quantitative estimates of the probability of a crisis are presented based on asset prices and bank sector data from 18 developed countries. The disconnection between property price and income level is shown to offer strong predictive power for the occurrence of a crisis event. Additionally, the amount of credit deflated by GDP in the economy and the reliance on overseas financing are also shown to have predictive importance in signalling early warnings of a crisis event.

Interestingly, the long-term percentage change in the ratio of property price-to-income is positively related to the probability of a banking crisis, while a negative relationship is found between the short-term growth of the housing price-to-income ratio and the probability of the crisis event. The contrasting pattern of association between the probability of a crisis and long versus short-term growth in the ratio of house prices to income is consistent with boom-bust patterns of adjustment in the property market whereby long-term growth in the ratio of house prices to income suggest a steadily increasing exposure to a banking crisis a risk that escalates dramatically in the wake of rapid (short-term) declines in the ratio of prices to income. Moreover, the sensitivity to short-term declines in the price to income ratio is consistent with sensitivity to property market busts, hence, the sign and relative magnitudes of the coefficients provide indirect evidence of bubble-like patterns of adjustment in the property market. The signs and relative magnitudes of the coefficients also suggest the need for caution interpretation of the outputs of the model. While short term increases in the price in income ratio suggest a diminishing exposure to crisis risk, the risk response to short term declines in the ratio is asymmetric and rapid.

By modelling international experience on the Australian perspective, the proposed hazard model provides Australian regulators with an analytical tool to assess the vulnerability of the banking system to real estate cycles and thus assists the regulators' argument on pre-emptive actions, such as tightening banks' lending standards and capital requirements. With the seemingly strong performance of banks' lending books, supervisory authorities have a lowering power of setting limits on their lending activities. Banks' displaced confidence can be implied from their overly optimistic assessments on serviceability of home loans, in terms of both borrower's income and debts, and it seems only the regulators are concerned about the bubble in real estate prices (SMH, 2015). The proposed model can offer a quantitative basis to

Australian regulators for making assessments on their financial vulnerability to real estate sourced risks.

The thesis sections are arranged as follows. Section 2 introduces the economic background of real estate cycles and systemic banking crises. Section 3 discusses prior empirical modelling issues related to potential predictors of banking crises, followed by Section 4, which focuses on the research design of the hazard model in terms of data specification and modelling method. Section 5 provides detailed modelling results and discussions. Lastly, Section 6 concludes the major findings of the study.

2 Economic Background

The role of the financial system in economic activities is now central due to expansions of the financial sector in both advanced economies and emerging markets. The growth of economic leverage, together with the aggressive financial intermediation in the real estate sector contribute to the increasing exposure of the financial system to the risk of banking crisis sourced by real estate cycles. The sharp increase in credit-to-GDP ratios contributes greatly to the rising scale of the financial sector, which reflects increasing lending activity in the global economy (Joyce, 2011). Financial intermediation, as the vital credit supplier, leverages itself highly as a response to the booming need of credit. It is a sharp credit increase, together with a high level of leverage, that leads to a deeper recession and a slower recovery from financial crises in recent times (Jordà et al., 2014).

2.1 The Growth of Leverage

Schularick and Taylor (2012) argue that credit booms can threaten financial stability and note that the role of the credit system has changed from an amplifier of shocks to an independent source of shocks in the post World War II (WWII) era. Shocks in the real estate sector, the main destination of credit flows, can be important in the lead up to a crisis event. As shown by Jordà et al. (2014), the real estate sector has accounted for a much larger proportion of mortgage loans in banks' lending experience in the course of the 20th century (Jordà et al., 2014).

There is increasing literature aimed at providing explanations for the phenomenon of financialisation and thus determining the driving forces of financial crises. Although there might be a variety of sources that contributes to financial fragility, which can not be completely listed, there is one key covariate, namely credit aggregation, that can be determined (Crowe et al., 2013). According to Schularick and Taylor (2012), the credit-to-GDP ratio has almost doubled in the past century, and they argue that the credit system, instead of being a disaster amplifier, now has significant influence on financial stability and thus should be treated as a potential source of a financial crisis. Jordà et al. (2013) provide evidence that the larger the preceding credit booms, the worse the recessions, all else equal, which implies that the buildup of credit bites back during a financial crisis.

The potential long-lasting impact of credit aggregation, especially in the housing sector, reveals the importance of assessing the vulnerability of the banking system to real estate cycles. Credit growth in real estate markets can be a powerful predictor of financial crises (Leamer, 2007). Although both mortgage loans (lending to residential and commercial real estate) and non-mortgage loans (business and unsecured lending) play important and independent roles in the financial system, their marginal effects are not the same. With the increasing share of mortgage loans in banks' lending books since WWII, debt overhang from real estate booms has been more severe and long-lasting (Claessens et al., 2009), while non-mortgage loans have had little effect on the path of a recession (Jordà et al., 2014).

The expanding credit aggregation and its concentration in the real estate sector can lead to an increasing exposure of the banking system to real estate shocks. From a recent study by Crowe et al. (2013), investment in real estate markets is a more common way of wealth storage in the economy, and thus, according to Bordo (2008), the wealth effect of house price changes can be much more significant than those of other price changes in credit and business cycles. While the purpose of this credit aggregation matters with reference to the soundness of the financial system, increasing credit aggregation can directly influence financial stability.

2.2 The Growth of Intermediation

The banking sector, as the major credit supplier, plays a vital role in real estate cycles as investors cannot conduct their trading activity without the supply of financial resources. Credit availability has been shown to be an important factor to the increased size and duration of the boom (Herring and Wachter, 1999). Real estate markets seem highly attractive to banks during boom mainly because the repayment record of mortgage loans outperforms other types of loans. Additionally, banks' value of capital rises together with an increase in asset prices, in terms of the rising value of both the assets they own and the collaterals of loans, as the event of default is considered less likely.

Moreover, a higher proportion of banks' capital can be invested in real estate markets compared to investments in businesses and corporations. Mortgage loans are expected to provide higher levels of safety since they are collateralised by the underlying assets. Under Basel I's capital requirements, the risk weight of mortgage loans is only half that of non-mortgage loans, and thus banks can hold less capital reserve if they increase their proportion of investment in real estate markets. Although risk sensitivity of different capitals has been employed under Basel II and later increased for residential mortgages under Basel III, the real estate sector is still highly attractive to banks and other financial intermediaries. Due to the apparent safety provided by a sustained increase in asset prices, banks tend to relax their lending standards, even leveraging themselves by borrowing from the public, for example, through issues of mortgage-backed securities, or even across countries to obtain extra funding during a boom.

Banks have heavily concentrated their loans in the real estate market without detecting the underlying risks of their credit aggregation. Jordà et al. (2014), with their disaggregated data set composed of 17 advanced economies, observe that the ratio of bank's mortgage loans to total loans has almost doubled in the past century, from around 30% in 1900 to 60% in 2014. The seemingly strong performance of real estate loans as well as the rising economic value of bank capital reduces the perceived risk of real estate lending and encourages banks to offer further credit to attractive real estate markets. It is the risk of heavy concentration that is underestimated by banks. Banks are often subject to "disaster myopia" by underestimating the low frequency shocks sourced by real estate markets due to the sustained increase in asset prices with no declines (Herring and Wachter, 1999).

Moral hazard also contributes to the concentration of mortgage loans. The performing repayment record of real estate lending and the apparent safety of this investment can incentivise bank managers to increase mortgage lending in order to improve their salaries and bonuses, which are based on banks' reported short-term profits (Case et al., 2005). Additionally, bank managers may be pushed to underprice the risk of mortgage loans by relaxing their financing constraints due to the high level of competitions in the banking industry. With one competitor pricing mortgage lending with zero probability of default, others have to follow to maintain their competitive power in the housing market. This herding behaviour of banks is observed in the buildup periods of historical banking crises, where banks tend to take on largely similar exposures, so if a crisis occurs, there is no one in particular to blame. The moral hazard problem can also occur due to the deposit insurance generally provided by the government. Large banks, that are "too-big-to-fail", believe they will be protected by the government through deposit insurance even if a crisis occurs, such that they can keep increasing their exposure to the real estate market with fewer considerations of the potential consequences.

2.3 Real Estate Price Booms

With the increasing exposure of banks' activity to the housing sector, real estate cycles, treated as intrinsic to property markets, are of greater influence on the stability of the banking sector. The distinct features of real estate markets can be the initial trigger of a price boom, which includes construction lags, impossibility of short-selling, infrequent trades and illiquidity (Schularick and Taylor, 2012). With a low vacancy rate, a positive demand shock cannot be satisfied in the short term due to construction lags of the new supply. The fixed supply in the short-term can lead to a further increase of demand and thus a boom in property prices. The boom in prices can keep expanding during the construction period and this continuous increase in real estate prices can attract both speculative investors and property buyers by sending a positive signal of ongoing future price growth. Additionally, short sales are almost impossible in the illiquid real estate market. When the market price deviates above its equilibrium, it can hardly be restored in the short-term. Theoretically, a decline in real estate prices should occur after the new supply is available. However, the existence of optimists in the market can further slow the pace of price recovery due to their non-ignorable influence on market-clearing prices. Investors hold high expectations about future price growth by extrapolating the limited record of past trades. These features of the real estate market can lead to a sustained positive deviation of property price from its fundamental values.

The true asset value should reflect the expectation of future cash flows that can be generated by the underlying asset. To price a property, the present values of future housing services as well as the expectation of the trading price must be considered. The value of services provided by the property in terms of rent income might change gradually over time, but the expectation of future sale prices can fluctuate sharply. The transaction price of a property reflects the highest bidding price offered by purchasers. This market-clearing price can change rapidly over time due to changes in the vacancy rate of properties of similar types, changes in the cost of financing the purchase of the property and changes in other market participants' expectations of future price growth. Case et al. (2005) argue that when market-clearing price increases can only be justified by beliefs of indefinite continuous future price growth, this boom in real estate prices should be treated as a market bubble.

Speculative bubbles in property prices can inevitably increase the probability of a financial crisis in the case of real estate prices collapsing (Allen and Gale, 2000). However, identifying a bubble in asset prices is extremely challenging since the real estate boom-bust cycle is inherent to real estate markets once a bubble arises. Instead of distinguishing a bubble from a boom directly, the alternative focus can be chosen by observing the common features of past boom-bust episodes, which is a sharp increase in both credit and leverage (Crowe et al., 2013). There is expected to be an equilibrium point for property values relative to income levels. In the case of a bubble, a disconnection between property values and the country's income level will appear. An initial boom in property prices can be caused by the distinct features of real estate markets, while it is the rapid increase in credit and leverage that can potentially turn a coincident boom into an unsustainable bubble. Such a situation will then also increase the risk exposure of both households and financial intermediaries to the real estate sector and thus the financial fragility of the banking system.

Poor data quality and weak analysis can contribute to the rapid growth of banks' leverage in real estate markets. With market clearing prices being the only source of data available, banks make an implicit assumption that the market price is a correct estimation of property price, which lead to their exposure to appraisal bias and thus errors in underwriting. Market clearing prices tend to reflect investors' future expectation of the markets, whose estimate is based on their extrapolation of past prices. Market prices can sustainedly deviate from fundamentals during a boom, and with sufficient credit supply to the market from financial intermediaries, this boom can turn into a bubble. However, real estate transaction records are the only available data source for banks. Under the appraisal process, current market values are estimated based on observations of recent transaction prices of properties with similar characteristics. While the present market value should reflect the long-term expectation of future returns from the loan, the transaction prices can be subject to a market bubble and deviate significantly from fundamentals, and thus banks can be exposed to appraisal biases due to the distortions of market values. When a bank's loan-to-value ratio on its lending book is fixed, the overestimation of asset value can lead to an over-estimated true leverage ratio and thus increase its sensitivity to fluctuations in real estate markets. With the increasing availability of banks' supply of financial resources, the bubble in property prices can be accelerated, resulting in a positive feedback loop and thus a further distortion of asset prices from fundamentals.

2.4 Booms Gone Bust

As boom-bust cycles can be treated as intrinsic to real estate markets, it is the build-up of credit and leverage that has the potential to make the bust outcome more disastrous to households, banks and thus the financial stability. Debt overhang and deleveraging are the two common phenomena observed in the bust phase of real estate cycles (Jordà et al., 2014). When property prices fall below the nominal value of loans in the banks' lending book, both the speculative investors and owner-occupiers are likely to default, either because they are unwilling to repay their over-priced loans or they fail to roll over their loans and are unable to sell the properties in the declining market. When the real estate price collapses, the proportion of non-performing loans in the banks' lending book can increase sharply and incur great losses to banks in the short-term. The value of banks' capital decreases when real estate prices drop, due to the decline in the value of both banks' own assets and collaterals of mortgage loans. The declining capital value increases banks' perceived risks and thus reduces their supply of credit to real estate markets. On the other hand, an increasing number of mortgage-backed securities buyers, who are the creditors of banks, will leave the market when the bust occurs. With the falling value of properties, the uncertainty of the quality of underlying loans increases sharply, which can lead to a decline in the value of mortgage-backed securities. Both security issuers and holders, who are themselves highly leveraged will be forced to leave the market due to lack of extra funding to fill their losses (Bordo, 2008). Consequently, property prices will further decline due to the decrease in the supply of credit to the market, and thus lead to the start of a downward spiral (Crowe et al., 2013). The bust in real estate markets can result in huge losses for both investors and financial intermediaries, and it is the features of the bust, including debt overhang and deleveraging, that potentially cause slow recovery of the economy.

3 Prior Empirical Modelling

The aftermath of a banking crisis can be disastrous not only to countries experiencing the crisis but also to the global economy due to its contagion effect, which reveals the importance of early regulatory intervention in the boom period. Although distortions will come together with the implementation of a certain preventive strategy to the financial system, the premise of "benign neglect" no longer exists since the aftermath of a bust can be far more costly than the possible distortions (Crowe et al., 2013). Since the late 1990s, there has been an increasing number of studies on causes and consequences of systemic banking crises, including both descriptive case-by-case studies on country's historical experiences and empirical analysis based on a panel dataset (Kauko, 2014).

Descriptive literature normally aims to identify historical regularities before a banking crisis occurs and evaluates the effectiveness and efficiency of management policies applied after the collapse of the banking system, while panel studies mainly focus on identifying stylised factors that can indicate the event of banking crises as well as influence the severity and the recovery pace of crises.

Empirical analysis contributes more to the identification of indicators of financial fragility, and the quality of panel data used can directly affect the consistency of the model outcomes. Caprio and Klingebiel (1996) made great efforts to collect data of crisis countries, dates, basic macroeconomic indicators and related policy measures through investigation of various studies and interviews of experts and completed the probably the first international panel database of banking crises. This dataset has been used as one of the data sources in some studies in the late 1990s, which includes those of Kaminsky and Reinhart (1999) and Demirgüç-Kunt and Detragiache (1998) on possible causes of banking crises. Schularick and Taylor (2012), Jordà et al. (2011, 2013), and Boissay et al. (2013) have used a dataset that includes 14 advanced economies ranging from 1870 to 2008 to investigate the effect of credit booms on banking crises. More recently, a disaggregated dataset has been collected by Jordà et al. (2014) which has enabled them to dissect credit aggregation and analyze the impact of different types of lending booms on financial fragility as well as the recovery pace after crises. All of these studies consistently confirm credit boom being a determinant of banking crises although they have different focuses on the causes of the credit boom.

3.1 Predictive Variables of Banking Crises

Identifying possible causes of banking crises in terms of leading indicators is the primary objective of most empirical studies on banking crises. Although the level of credit stock has been confirmed to be a powerful predictor of banking crisis, other variables are also widely considered in a range of empirical analysis, which include asset prices, external imbalances, economic growth and output, exchange rate and price stability, monetary aggregates, short-term and long-term interest rates, fiscal deficits and banking sector

Table 1: Leading Indicators of Banking Crises by Author/s

Source	Credit Stock	Asset Prices	Current Account	GDP	Exchange Rate	Inflation	Monetary Aggregation	Interest Rate	Fiscal Deficits
Demirgüç-Kunt and Detragiache (1998)**	x		x	x	-	x	x	x	-
Kaminsky and Reinhart (1999)	x	x	x	x	x		x	x	x
Borio and Lowe (2002)	x	x			x				
Domaç and Peria (2003)	x		-	x	x	x	x	-	
Demirgüç-Kunt and Detragiache (2005)	x		x	x	-	x	x	x	x
Beck et al. (2006)	x		x	x	x	x	x	x	
Davis and Karim (2008a)	x		x	x	-	x	x	x	-
Borio and Drehmann (2009)	x	x							
Schularick and Taylor (2012)*	x	x		x			x	x	
Barrell et al. (2010)	-	x		-		-	-	-	x
Büyükkarabacak and Valev (2010)	x		-	-		-	x	x	
Angkinand and Willett (2011)	x		-	x	x	-		x	
Joyce (2011)	x		-	x	x	x	-		
Bordo and Meissner (2012)*	x			x			-	x	
Kauko (2012)	x		x	x		-	-		-
Karim et al. (2013)	-	x	x	-		-	-	x	
Sarlin and Peltonen (2013)*	x	x	x	x		-			-
Jordà et al. (2014)	x								
Jordà et al. (2015)	x	x						x	
Lainà et al. (2015)	x	x	-	x		-		-	

x = significant.
- = not significant.
* = financial crisis.
** = both banking and financial crisis.

factors (Kauko, 2014).

Different combinations of predictors are used in the analysis of banking crises and the significance of the explanatory power of a certain variable varies across studies. Firstly, countries of interest may be different. Evrensel (2008) argues that being a developed country can decrease the hazard of banking failure by comparing G-10 countries to non-G-10 countries. While some studies focus on crisis events in developing or developed countries, others may focus on the combination of both. Secondly, different selections of sample period and length can also lead to inconsistent results. Since banking crises are low-frequency events, a long time span is ideal for cross-country studies to ensure a sufficient number of observations. However, the explanatory power of a certain factor may vary through time, for example, the role

Table 2: Data Span and Panel Countries

Source	Sample Period	Number of Countries
Advanced Countries		
Borio and Drehmann (2009)	1980 - 2008	18
Schularick and Taylor (2012)	1870 - 2008	14
Barrell et al. (2010)	1970- 2007	14
Bordo and Meissner (2012)	1920 - 2002	14
Karim et al. (2013)	1980 - 2008	14
Jordà et al. (2014)	1870 - 2011	17
Jordà et al. (2015)	1870 - 2012	17
Lainà et al. (2015)	1980 - 2013	11
Developing and Emerging Countries		
Joyce (2011)	1976 - 2002	20
Heterogenous Samples		
Demirgüç-Kunt and Detragiache (1998)	1980 - 1994	65
Kaminsky and Reinhart (1999)	1970 - 1995	20
Borio and Lowe (2002)	1960 - 1999	34
Domaç and Peria (2003)	1980 - 1997	88
Demirgüç-Kunt and Detragiache (2005)	1980 - 2002	94
Beck et al. (2006)	1980 - 1997	69
Davis and Karim (2008a)	1979 - 2003	105
Büyükkarabacak and Valev (2010)	1990 - 2007	37
Angkinand and Willett (2011)	1990 - 2003	114
Kauko (2012)	2000 - 2006	34
Sarlin and Peltonen (2013)	1990 - 2010	28

of monetary aggregates in the pre-WWII period is observed but not after WWII (Schularick and Taylor, 2012). Moreover, the selection of variables may be subject to data availability. A narrow panel is often compromised by a long time span and a set of ideal variables. Table 1 lists the inclusion and effect of widely-used indicators in related studies and Table 2 documents the data span and total number of countries included for each study.

3.1.1 The Credit Stock

The most extensively used crisis predictors in the existing literature are those of the excessive credit stock. As discussed previously, credit aggregation can potentially heighten the instability of the financial system. The growth rate of the credit stock and the ratio of credit-to-GDP are the two forms of lending variables that are commonly used by researchers.

The growth rates of different focuses of credit have been investigated in prior studies. Domaç and Peria (2003) and Schularick and Taylor (2012) show that there is a positive relationship between the lagged credit growth and the risk of a banking crisis. Additionally, some studies focus on the credit stock of the private sector. The private credit-to-GDP ratio is shown to perform well in the prediction of banking crises (Borio and Drehmann, 2009; Demirgüç-Kunt and Detragiache, 2005), while the business or corporate credit expansion offers a weaker result (Büyükkarabacak and Valev, 2010). More recently, mortgage lending has been included in empirical testing after collection of large amounts of data and has been shown to have a stronger explanatory power than that of non-mortgage lending (Jordà et al., 2014; Lainà et al., 2015).

Compared to the percentage change of credit, the credit deflated by GDP can be used to investigate whether the level of disconnection of credit from economic output is related to a crisis event. Additionally, it can provide some intuition about the level of financialisation in a particular country. Inconsistent conclusions have been drawn in research papers when the credit-to-GDP ratio has been used as one of the predictive variables. Some studies have confirmed that the credit-to-GDP ratio is a powerful predictor of banking crises (Kaminsky and Reinhart, 1999; Borio and Lowe, 2002). However, for those studies focusing on crisis events in emerging markets it has been found to be insignificant (Joyce, 2011; Hahm et al., 2013).

3.1.2 Asset Prices

Asset prices are also the potential drivers for financial instability. Allen and Gale (2000) argue that historically a banking crisis is often preceded by some sort of asset bubbles, for example, the South Sea bubble in England, the Mississippi bubble in France. Although real estate prices are a more ideal proxy for asset prices, stock market indices are sometimes selected due to data limitations of property prices. Schularick and Taylor (2012) find the interaction between equity prices and credit-to-GDP ratio can highly effect banks' exposure to a crisis event. Borio and Lowe (2002) show that equity price performs better for advanced economies, while it has little explanatory power for developing countries.

Although equity prices can be a potential predictor of banking crises, the growth rate of real house prices is shown to be a better crisis predictor in recent studies (Borio and Drehmann, 2009; Jordà et al., 2015), even a more powerful predictor than credit growth (Barrell et al., 2010). However, while changes in real property prices have been considered in the existing literature, no researchers have investigated the effect of disconnection between property values and income level on the financial fragility.

3.1.3 External Imbalances

External imbalances are also proposed to affect the soundness and stability of the financial system. Various indicators are used as proxies of external imbalances, which include current account deficit, trade balance and net foreign debt. In the previous discussion of real estate markets, financial intermediaries are likely to borrow from overseas to assist their lending to the markets. External imbalances can have a potential role in heightening the vulnerability of a country's financial system. Some studies find the absolute current account deficit to be a significant predictor (Kauko, 2012; Sarlin and Peltonen, 2013; Karim et al., 2013), while others argue that it can offer some explanations of crisis events only in the presence of some other variables (Jordà et al., 2011; Roy and Kemme, 2012).

While little evidence is shown in the predictive power of trade balance with a proxy of changes in the terms of trade (Demirgüç-Kunt and Detragiache, 2005; Büyükkarabacak and Valev, 2010), net foreign debt reflects a country's cross-border exposure and has a promising role in signalling banking crisis, since obtaining funding from overseas can put the borrower in a more dangerous position than accessing credit domestically. Angkinand and Willett (2011) and Hahm et al. (2013) confirm the predictive power of net foreign balance to banking crises in both developed and developing countries.

3.1.4 Macroeconomic Variables

Macroeconomic variables, such as the level and growth of GDP, inflation rate and interest rates, are often included in the analysis of the causes of banking crises. While the GDP growth rate implies changes in economic output, real GDP per capita is often used as a proxy for the income level of a country. Both indicators are not found to be robust. A negative relationship between GDP growth rate in pre-crisis years and the crisis risk is found in some studies (Angkinand and Willett, 2011; Davis and Karim, 2008a), but Domaç and Peria (2003) and Schularick and Taylor (2012) fail to find a connection.

Contradictory conclusions have been drawn for the inflation rate variable. While Büyükkarabacak and Valev (2010) and Kauko (2012) find that it has little effect on explaining the occurrence of banking crises, Demirgüç-Kunt and Detragiache (1998) and Joyce (2011) find a positive relationship between the level of inflation and crisis risk.

Interest rate variables, as another macroeconomic variable, have also been closely investigated in prior studies. Short-term interest rates can directly affect banks' cost of funds, and some studies have shown that a low short-term interest rate can promote the credit boom and thus increase the exposure of risk to a banking crisis (Bordo and Meissner, 2012; Jordà et al., 2015). Büyükkarabacak and Valev (2010) find contradictory results and argue that real interest rate is positively related to the probability of a banking crisis.

3.1.5 Financial Sector Variables

Other variables of the financial sector, which include foreign exchange rate, monetary aggregates and fiscal deficits, also have the potential to influence the stability of the financial system. Exchange rates are more relevant in the cases of "twin crises", which include both currency and banking crisis with the former worsening the latter (Kaminsky and Reinhart, 1999). Demirgüç-Kunt and Detragiache (2005) and Beck et al. (2006) find no connection between currency depreciation and banking crisis, which is contradictory to Domaç and Peria (2003) and Angkinand and Willett's (2011) findings.

Regarding monetary aggregates, there are several types of proxies that are commonly used, which include the broad money to foreign exchange reserves, the ratio of money-to-GDP and the growth rate of broad money. Most significant evidence is found by investigating the relationship between money-to-reserves ratio and the probability of a banking crisis (Domaç and Peria, 2003; Demirgüç-Kunt and Detragiache, 2005; Büyükkarabacak and

Valev, 2010). Schularick and Taylor (2012) argue that broad money can be a good proxy for credit before WWII, but not after.

Lastly, fiscal deficits have not been widely investigated in the existing literature, and the evidence is not robust even within the limited related studies. Demirgüç-Kunt and Detragiache (1998) find there is no connection between fiscal surplus and crisis events, while Kaminsky and Reinhart (1999) find that larger fiscal deficits can heighten the probability of a banking crisis.

3.1.6 Banking Sector Factors

Some studies also focus on the impact of the banking sector in terms of its institutional environment and banks' balance sheet information, but the evidence is inconsistent. Beck et al. (2006) use a set of structural factors to investigate the contribution of different banking environments to the financial fragility with a dataset composed of both developing and developed countries. Their study shows that a more concentrated banking system, in terms of the ratio of assets of the three largest banks to the total in the system, is less likely to incur a crisis, and the higher the level of entry restrictions or the lower the banking freedom, the higher the system's vulnerabilities. Additionally, they also find that explicit deposit insurance can increase the probability of a banking crisis which confirms Demirgüç-Kunt and Detragiache's (2002) finding.

However, Barrell et al.'s (2010) studies on advanced economies claim that the indicator of deposit insurance or the level of financial liberalisation offer little insight into the system's fragility. They find little evidence of the predictive powers of bank concentration and supervision variables to crisis events. Instead, they focus on banks' balance sheet variables and show that both banks' capital adequacy and level of liquidity are negatively related to the probability of a crisis. Büyükkarabacak and Valev (2010), on the other hand, fail to find the connection between banks' liquidity ratio and crisis events, but they show that a higher growth rate of banks' debt can heighten the vulnerability of the banking system. Over the last century, the primary business of banking has switched from business financing to mortgage intermediation (Jordà et al., 2015). These changes in the composition of banks' balance sheets increase banks' exposure to the property markets and thus have the potential to increase the financial fragility in the case of asset bubbles.

Prior studies on potential predictors of systemic banking crises vary from both selections of predictive variables and choices of analytical tools. As discussed above, inconsistent conclusions have been drawn on the significance of explanatory variables among different variable classes. In this study, selections of variables are studied in the international setting with a focus on the real estate market, which will be further discussed in Section 4. Both property prices and the credit stock variables are included in the baseline specification to examine the "two disconnections" in the lead up to crisis events, including the disconnection of property values to income levels and that of the credit aggregation to economic output. Other potential predictive variables include share prices, net foreign liabilities, interest rate variables and banking sector variables.

3.2 Comparison of Methods

Several analytical techniques have been employed in previous studies on early warning systems of systemic banking crises. Signal extraction and binary regressions are the two dominant methods.

Kaminsky and Reinhart (1999) first introduced the signals method, and it has also been used by Borio and Lowe (2002) and Borio and Drehmann (2009). The crisis event is likely to occur if the predictive variable fluctuates beyond a threshold value. The threshold value is determined to minimise the noise-to-signal ratio, which is defined as the ratio of the proportion of false alarms in all possible false signals to the proportion of correct alarms in all possible correct signals. While strong non-linearities are allowed between the explanatory variable and the crisis occurrence under the signals method (Alessi and Detken, 2011), it is an univariate model such that the joint significance of multiple variables cannot be tested.

Binary regression is the most widely used method in previous literature. Demirgüç-Kunt and Detragiache (2005), Beck et al. (2006) and Davis and Karim (2008a) used the panel logit model to assess the predictive power of potential predictors, while Wong et al. (2010) applied the probit regression model. Lainà et al. (2015) used both signal extraction and logistic regression methods in their study and found that although the signals method is univariate, its results are supported by the multivariate logistic model.

The binary recursive trees method has also been used by several researchers in the studies of early warning systems. Cashin and Duttagupta (2008), Karim (2008) and Davis and Karim (2008b) applied binary recursive trees to their analysis of systemic banking crises. This model can be used to distinguish the best predictor and then test interaction effects between predictive variables. Other methods have been used in the literature, but the numbers are limited, which makes the comparisons among studies difficult. Sarlin and Peltonen (2013) used the self-organising maps method and Kauko (2012) employed standard linear Ordinary Least Squares (OLS) regression.

The logit method is ideal for this study. As a multivariate model, it enables the assessment of the predictive power of variables from different classes in forecasting systemic banking crisis. From Barrell et al.'s (2010) study, multivariate methods, including logistic regressions and binary recursive trees, are shown to outperform the univariate signal extraction in terms of type I and type II errors. Additionally, the logit model is shown to outperform the other methods (Karim, 2008), especially in the international context.

4 Data and Method

The economic framework developed in the previous section shows that the feedback effect among the growth of leverage and intermediation, and the behaviour of participants in real estate markets contributes to the sustained positive deviation of market expectations from fundamentals. There are a number of variable classes suggested in the existing literature which potentially have a certain level of predictive power for empirical systemic banking crises. This section describes the implementation of hazard models to quantify the probability of a banking crisis, with a focus on the real estate sector. A data set consisting of country-level information of potential crisis predictors is developed so as to produce a hazard model and then to examine its predictive power.

4.1 International Context

To produce a hazard model from the Australian perspective in light of the international experience, the data sample is a collection of historical systemic banking crises suffered by Organization for Economic Cooperation and Development (OECD) countries in the last four decades. It is the 18 advanced economies that are of main focus, which include Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, South Korea, Spain, Sweden, the United Kingdom and the United States, which is a combination of crisis and non-crisis countries. As systemic banking crises are rare events and in order to obtain a long time series, both the latest wave of banking crises, the GFC, as well as those around the 1980s are considered. In total, the data set contains 18 systemic banking crises during the period from 1975 to 2014. The whole data sample consists of two parts of information, including the systemic banking crisis data and that of the potential explanatory variables.

4.1.1 Systemic Banking Crisis Data

In this study, the focus is on banking crises which have caused country-level distress, namely systemic banking crises. As mentioned in Section 1, this study, following Laeven and Valencia (2013), defines a systemic banking crisis to be a event resulting in a large number of defaults and causing a wide range of financial distress in the banking system, as well as involving policy intervention from the country's government. Table 3 lists the 18 countries in the data sample and the included crisis periods based on quarterly intervals [1]. The durations of the crises are sourced from the World Bank (WB) database, in which the starting years of the crisis events are consistent with those recorded in Laeven and Valencia's (2008; 2013) systemic banking crisis database. Both databases identify the banking crises in the years of occurrence. To better picture the lead up to those crises, it is useful to code the exact quarter of the year in which a banking crisis occurred since most of the explanatory variables obtained in the data sample have a quarterly frequency. As listed in Table 3, the starting quarters of the crisis events are

[1] Scenarios both with and without the inclusion of borderline cases are considered and show consistent results. Model estimates are reported based on the scenario with the inclusion of borderline cases.

determined by searching through relevant newspaper articles and academic evidence. There are three countries in the data sample that have no historical systemic banking crisis, namely, Australia, Canada and New Zealand.

Table 3: Systemic Banking Crises Periods between 1975 and 2014

Country	**Pre-2000s**	**2000s**
Australia	-	-
Belgium		2008:Q3 - 2011:Q4
Canada	-	-
Denmark		2008:Q3 - 2011:Q4
Finland	1991:Q3 - 1995:Q4	
France*		2008:Q3 - 2011:Q4
Germany		2008:Q4 - 2011:Q4
Ireland		2008:Q3 - 2011:Q4
Italy*		2008:Q2 - 2011:Q4
Japan	1997:Q4 - 2001:Q4	
Netherlands		2008:Q3 - 2011:Q4
New Zealand	-	-
Norway	1991:Q4 - 1993:Q4	
South Korea	1997:Q3 - 1998:Q4	
Spain	1977:Q4 - 1979:Q4	2008:Q3 - 2011:Q4
Sweden*	1991:Q3 - 1995:Q4	2008:Q4 - 2011:Q4
UK		2007:Q2 - 2011:Q4
US	1988:Q4 - 1988:Q4	2007:Q3 - 2011:Q4

Notes: Crisis periods are sourced from the World Bank database. The starting quarters of the crises are determined by investigating newspaper articles and relevant academic papers.
- = no crisis event.
* = a borderline case of crises

4.1.2 Explanatory Variables by Class

As mentioned in the previous section, there is a burgeoning literature suggesting the variables and characteristics that may be of predictive importance. The data sample includes both macroeconomic and market data as well as those from the financial sector, which have been obtained from various sources, including the bank of international settlements (BIS), Federal Reserve Bank of Dallas (FRBD), Datastream, and OECD and WB databases. Table 4 presents the original data obtained from various sources by classes, which will later be used in the transformation of potential explanatory variables for hazard models. Most of the variable classes are consistent with those emphasised in Kauko's (2014) review paper, with additional variables are also considered in this thesis. The variable classes include credit stock, asset prices, the current account, monetary aggregations, interest rates, fiscal deficits, macroeconomic conditions and banking sector specific factors. As can be seen from Table 4, most of the variables have quarterly frequencies, while others are on an annual basis.

4.2 The Hazard Model

In this thesis, hazard models are proposed to estimate the conditional probability of a systemic banking crisis through multivariate logistic regressions. According to Shumway's (2001) study, hazard models offer a well-developed framework and such models have been very successfully employed in related applications, including models of firm-level financial distress.

In contrast to static models, such as a logit model, hazard models have several advantages. Hazard models address the censoring problems inherent

Table 4: Variables and Data Sources by Class

Variable	**Data Frequency**	**Sources**
Credit Stock		
Domestic credit (% of GDP)	Annual	WB
Private credit loaned by financial institutions	Annual	WB
Asset Price		
BIS residential property price index	Quarterly	BIS
Real house price index	Quarterly	FRBD
Share price index	Quarterly	Datastream
Current Account		
International debt securities issued by banks	Quarterly	BIS
Monetary Factor		
Liquid liabilities (% of GDP)	Annual	WB
Interest rate		
Long-term interest rates	Quarterly	OECD
Real interest rates	Annual	WB
Bank lending rates	Annual	WB
Fiscal deficit		
Government debt (% of GDP)	Annual	OECD
Macroeconomy		
Gross domestic product (USD)	Quarterly	BIS
Real personal disposable income	Quarterly	FRBD
Banking Sector		
Bank capital (% of Total Assets)	Annual	WB
Bank credit (% of Bank Deposits)	Annual	WB

Notes: This table lists the original data from various sources, including the bank of international settlements (BIS), Federal Reserve Bank of Dallas (FRBD), and OECD and World Bank (WB) databases.

in modelling time to event data by controlling for time at risk. The problem of time at risk is not adjusted by static models, but hazard models adjust for period at risk automatically. Additionally, hazard models incorporate time-varying covariates, what is not possible when using static models.

With the application of hazard models, the conditions in the lead up to crisis events can be measured in terms of changes in the explanatory variables such that early warning signals for a banking crisis can be effectively captured by the applied models. The panel logistic regressions method is used in the construction of the hazard model. As discussed in Section 3.2, the logit analysis outperforms alternative methods in the global context, which implies that it is the most appropriate choice for predicting banking crisis using international experience (Davis and Karim, 2008a).

To construct a hazard model, a dependent dummy variable, $Y_{i,t}$, is used to indicate whether or not a crisis event occurs for country i at time t. With the specific crisis dates, the dummy variable is coded 1 at the specific quarter of the crisis starting year as shown in Table 3, as well as for the three quarters before the starting time for country i. During a crisis period, the country is in a state without predictive importance for a banking crisis. To address this censoring problem without losing observations, the crisis dummy is treated as missing values instead of zeros during the country's crisis period except for the starting quarter of the crisis year. At all other times, the crisis dummy is coded zero. For countries with no recorded crisis (i.e., Australia, Canada and New Zealand), the crisis dummy is coded zero for all quarters during the whole sample period. For the other 15 countries which have at least one historical crisis, the crisis dummy is coded as follows,

$$Y_{i,t} = \begin{cases} 1 & \text{if } t = T_i,\ T_i - 1,\ T_i - 2 \text{ or } T_i - 3 \\ missing & \text{if } t \in \Omega_i \text{ and } t \neq T_i \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where Ω_i denotes the crisis period, and T_i denotes the starting time of the crisis year for country i. This study aims to model the conditional probability $P(Y_{i,t} = 1|X_{i,t})$, where $X_{i,t}$ denotes a vector of selected explanatory variables. By coding the crisis dummy variable as above, the conditional probability is defined as the probability of a banking crisis in the next year. Let $P_{i,t}$ denotes the probability of a banking crisis at time t for country i, so that,

$$P_{i,t} = P(Y_{i,t} = 1|X_{i,t}) \tag{2}$$

According to the logit model, the logistic function of $P_{i,t}$ is as follows,

$$P_{i,t} = \frac{e^{\beta X_{i,t}}}{1 + e^{\beta X_{i,t}}} \tag{3}$$

where β denotes the coefficients for $X_{i,t}$, including an intercept component. To estimate the conditional probability of a crisis, the logistic function is transformed into an equation of the log of odds ratio, where the odds ratio is defined as the ratio of the conditional probability of a crisis to that of a safe state without crisis events. Let $I_{i,t}$ denotes the log of odds ratio, such that,

$$I_{i,t} = ln\frac{P_{i,t}}{1-P_{i,t}} \tag{4}$$

Now the original logit model can be transformed into a linear regression equation and the model estimates can be obtained using the following regression function,

$$\hat{I}_{i,t} = \hat{\beta}X_{i,t} \tag{5}$$

where $\hat{\beta}$ is a vector containing the estimated coefficients, which are calculated using a maximum-likelihood method under random effect model [2]. In the estimation of the variance of the maximum likelihood estimators, Huber sandwich estimators of variance or robust standard errors are used to ensure the model's robustness against heteroskedasticity (Hoechle, 2007). $\hat{I}_{i,t}$ denotes the estimated log of odds ratio at time t for country i, and the estimated conditional probability, $\hat{P}_{i,t}$, can then be computed using the following equation,

$$\hat{P}_{i,t} = \frac{e^{\hat{I}_{i,t}}}{1+e^{\hat{I}_{i,t}}} \tag{6}$$

As shown in Table 4, the dataset contains both annual and quarterly variables as some variables are only available annually. The quarterly frequency enables the transformation of per quarter growth rates for some variables. The logistic regression is run on an annual basis with a particular quarter of interest. For quarterly variables the observations for the chosen quarter are used to obtain model estimates for each year.

[2]Hausman test has been conducted and shown evidence of random effects at a significance level of 10 %. Hence random effect model is applied instead of fixed effect model.

Model estimates are obtained by running regressions on an annual basis using quarter three observations for each year. The hazard model is a forward looking model, which predicts the probability of a banking crisis in the next year. The crisis indicator switches to 1 as soon as a particular quarter is within a year of the crisis. All predictors are lagged either by a quarter or a year to ensure that they are observable for a given quarter. For example, for the Italian 2008 crisis which starts at 2008:Q2, the dependent variable is coded 1 at 2007:Q3, 2007:Q2, 2008:Q1 and 2008:Q2. Since quarter three observations are used, only the dependent variable on 2007:Q3 and the corresponding observations of the explanatory variables are used in the regression and this crisis happens in within the year subsequent to 2007:Q3.

4.3 Selection of Variables

In the previous sections, it has been documented that there are variables and characteristics suggested by prior studies that may have predictive importance for a systemic banking crisis. The predictive variables for the hazard model are selected based on suggestions from both descriptive and empirical literature. Different combinations of explanatory variables have been considered with regards to various variable classes as discussed in Section 3; other economic intuitive variables have also been assessed in the model selection process.

Table 5: Baseline Model Summary Statistics

Panel A: Australia				
Variable	Mean	Std. Dev.	Min	Max
P/I 1y growth rate (%)	1.33	6.30	-8.18	17.21
P/I 15y growth rate (%)	34.38	11.31	8.00	53.97
Share price growth rate (%)	7.00	12.43	-25.26	24.21
Domestic credit (% GDP)	106.73	32.49	70.36	159.27
International debt growth rate (%)	28.56	25.61	-6.36	71.63
Bank credit/deposit	128.11	7.60	118.38	143.73
Δ (Long-term interest rate) (%)	-0.39	1.04	-2.60	1.41
Panel B: Full Sample				
Variable	Mean	Std. Dev.	Min	Max
P/I 1y growth rate (%)	1.22	5.96	-15.73	19.91
P/I 15y growth rate (%)	11.30	36.29	-64.72	124.53
Share price growth rate (%)	8.08	21.22	-45.86	100.82
Domestic credit (% GDP)	126.92	58.11	47.37	338.09
International debt growth rate (%)	58.40	98.20	-70.33	914.91
Bank credit/deposit	127.82	43.82	47.13	306.89
Δ (Long-term interest rate) (%)	-0.26	1.00	-4.27	5.92

Notes: This table reports the summary statistics of variables included in the baseline model. Panel A contains the summary statistics for Australia, while Panel B lists those for the full data sample and for each year, only quarter three data is used. Domestic credit (% GDP) denotes domestic credit as a percentage of GDP. P/I 1y growth rate and P/I 15y growth rate denote the 1-year and 15-year growth rates of the ratio of property price-to-income, respectively. Share price growth rate denotes the 1-year growth rate in share price index. International Debt growth rate denotes the 2-year growth rate of international debt issued by banks. Bank credit/deposit denotes the ratio of bank credit to bank deposit. Δ (Long-term interest rates) denotes the annual change in the long-term interest rate expressed as a percentage.

Table 5 lists the explanatory variables [3] selected for the baseline model with the summary statistics. Panel A contains the descriptive statistics for Australia, and Panel B includes those for the full sample. The variable classes considered in the baseline model include asset prices (in terms of property and share prices), credit stock, external imbalances, and macroeconomic and banking sector variables.

To investigate both the short-term and long-term effects of property prices on the stability of the banking system, both the 1-year and 15-year growth rates [4] are included in the baseline model. Instead of computing the percentage changes of the property price index, the growth rates of the ratio of property price to personal disposable income are derived for the model. This ratio can potentially address the effects of the disconnection of property price and income.

The deviation of property values from long-term growth trend may be cyclical. It may also imply that property values are rising at a higher than sustainable rate, which can in turn lead to a greater risk exposure of the overall financial system. It can be expected that an increase in the long-term percentage changes in the ratio heighten the probability of a banking crisis. The short-term growth rate, on the other hand, is used to capture the recent shift in the price-to-income ratio. The relationship of short-term

[3] All the variables except for Domestic credit (%GDP) and Bank credit/deposit are stationary. Domestic credit (%GDP) and Bank credit/deposit variables are trend stationary.

[4] For the long-term growth rates in the ratio of house price to income, 10-year, 15-year and 20-year growth rates are considered. Model results are insensitive to choices of different long-term growth rates.

changes in the price-to-income ratio to a crisis event cannot be projected on a strong ex ante basis. As short-term growth rates are derived from the price-to-income ratio, it is possible that the property values are growing at a faster pace than wages income. To this extent, the short-term growth rate has a similar role as the long-term variable in which to indicate a larger exposure of the banking system to the housing sector. On the other hand, a negative relationship between short-horizon shifts and the crisis probability can also be expected if the possibility of a boom-bust cycle is admitted. At this stage, clear expectations cannot be given on the relationship between short-term price-to-income ratio changes and the probability of a crisis event.

As shown in Table 5, both the short-term and long-term averages in the growth rate of price-to-income ratios for Australia are higher than the sample average in the period from 1990 to 2015. For the 15-year growth rate of the standardised property prices in Australia, the minimum is 8.00%, which implies that there is a sustained positive deviation of house prices from disposable income. While for some other countries, there are both rises and falls in the price-to-income ratio in the long-term: for the full sample this variable varies from -64.72% to 124.53%.

The share price growth rate in the equity market is also included in the baseline model. For each quarter, the share price index uses the closing price of the last trading day of the quarter. For each year, the closing share prices on 31st March, 30th June, 30th September and 31st December are coded for quarter one, two, three and four, respectively. Additionally, the share price index for the overall equity market is used instead of that of the banking sector. The annual growth rates are then derived using this end-of-quarter price index. It is generally expected that a decrease in the short-term growth of the equity market can potentially cause distress of the overall financial system. Australia's average growth rate is quite close to the sample average. As expected, the short-term stock price growth is more volatile than that of the property prices in terms of standard deviation.

The credit stock variable has been applied in many prior studies and shown by most to be of predictive importance for a systemic crisis. The domestic credit deflated by GDP is included to examine the effect of the disconnection between a country's credit aggregation and its domestic productivity. With the inclusion of asset price and credit growth variables, it can be examined whether a "twin-boom" is likely to exist in the lead-up to a banking crisis. A higher level and concentration of credit aggregation can hasten the negative feedback loop in which investors start deleveraging when asset prices start to fall. A sharp increase in the country-level leverage is expected to increase the vulnerability of the financial system and thus the country's risk exposure to a banking crisis. For Australia, the average credit aggregation level is slightly lower than the sample average.

Other explanatory variables used in the baseline model include the 2-year growth rate of international debt securities issued by banks, the ratio of bank credit to bank deposit and the change in long-term interest rates. The growth rate of reliance on offshore funding (denoted as International debt growth rate) is a potential measure of external imbalances of a country's banking sector. With a higher level of exposure to foreign liabilities, the probability of a banking crisis may be higher. The ratio of bank credit to deposit offers some insight on the leverage of the banking system. As mentioned in the previous sections, as the main intermediaries of mortgage loans, an increasing leverage of the banking system can potentially affect the stability of the financial sector. Lastly, the long-term interest rate offers some insight into policy changes, which can also be treated as a proxy for banks' lending rate for mortgage loans. A loose monetary situation, implied by decreasing long-term interest rates, can be a potential trigger for booms in real estate markets (Jordà et al., 2015) and thus increase the risk exposure of the banking sector to a banking crisis sourced by real estate markets.

Table 6: Correlations between Predictive Variables for Baseline Model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) P/I 1y growth rate (%)	1.000						
(2) P/I 15y growth rate (%)	0.247	1.000					
(3) Share price growth rate (%)	0.130	-0.108	1.000				
(4) Domestic credit (% GDP)	-0.073	0.119	-0.126	1.000			
(5) International debt growth rate (%)	0.248	0.083	-0.039	-0.115	1.000		
(6) Bank credit/deposit	-0.001	0.272	-0.110	0.052	0.129	1.000	
(7) Delta (Long-term interest rate) (%)	0.063	0.145	0.159	-0.029	0.096	-0.036	1.000

Notes: Data relates to quarter 3. Variables are defined in Table 5.

Table 6 provides the correlations between the predictive variables in the baseline model so as to address the problem of potential multicollinearity for the regression model. The result of most interest is the correlation between the 1-year and 15-year growth rates of the property price-to-income ratio. The correlation coefficient is about 0.247 which is relatively low compared to a perfect correlation coefficient of 1. The correlation between the ratio of bank credit to deposit and long-term growth rate of standardised property prices is the highest of all, with a coefficient of 0.272. Once again, it is the level of correlation can be treated as sufficiently low compared to a perfect correlation. It can be expected that the potential problem of multicollinearity is has limited impact on the baseline model.

5 Results

This section includes discussions of the modelling results of the baseline hazard model and an in-sample analysis of model performance. To check the robustness of the baseline specification, alternative models with different forms of the property price variables and those with additional predictive variables are also considered and compared to the baseline model in terms of goodness of fit, predictive power and out-of-sample performance.

5.1 Model Estimates

Table 7 presents the specification and the estimates for the baseline hazard model using quarter 3 observations, as most of the historical crises occurred in the third quarter of the crisis year, as shown in Table 3. Variable classes considered in the baseline model include asset prices, the credit stock, external imbalances, and macroeconomic and banking sector variables. For a predictive model to forecast a country's level of risk exposure in the next year, all explanatory variables are lagged by one quarter or one year in length. LagQ denotes a lag length of one quarter which is applied to the quarterly variables, while Lag denotes a lag length of one year, which is used for variables with annual frequencies. The estimates of coefficients are reported for the regression function of the log of odds ratio as in Equation 5.

The ratio of real house price to real personal disposable income is used to measure the disconnection between property prices and income level instead

Table 7: Baseline Hazard Model Specification and Estimates

Explanatory Variables	**Model (1)** Baseline
LagQ P/I 1y growth rate (%)	-0.163***
	(0.0486)
LagQ P/I 15y growth rate (%)	0.0234***
	(0.00615)
LagQ Share price growth rate (%)	-0.0349**
	(0.0159)
Lag Domestic credit (% GDP)	0.00579*
	(0.00341)
LagQ International debt growth rate (%)	0.00442***
	(0.00151)
Lag Bank credit/deposit	0.00356
	(0.00412)
LagQ Δ (Long-term interest rate) (%)	-0.0185
	(0.0939)
Intercept	
Constant	-5.457***
	(0.984)
Test Statistics	
LR Chi^2	32.02***
AIC	102.37
AUC	0.845
	(0.0227)
Number of Observations	
Total Observations	336
Number of Countries	18

Notes: The definitions of the explanatory variables are consistent with those in Table 5. Lag denotes one year lag of the annual variable and LagQ represents one quarter lag of the quarterly varible. LR Chi^2 denotes the chi squared statistics for the likelihood ratio test. AIC denotes the Akaike Information Criterion statistics. AUC represents the area under the receiver operating characteristic curve. The estimated coefficients are obtained using the regression function for the log of the odds ratio in Equation 5, Section 4. The figures within the brackets represent the standard deviations of the estimated coefficients.
*** = Significant at the 1% level.
** = Significant at the 5% level.
* = Significant at the 10% level.

of including the growth rate of house prices. As discussed in the previous section, both the short-term and the long-term growth rates of price-to-income ratio are included in the baseline model. As shown in Table 7, the price-to-income ratio is of predictive importance for a banking crisis in terms of both short-term and long-term effects at a significance level of 1%. Interestingly, the signs of the estimates are the opposite, with positive for the 15-year growth rate and negative for the 1-year growth rate. In the longer-term, deviation of property values from the long-term growth trend implies a greater exposure of the financial system to the risk of a banking crisis. In the short-term, a collapse in property prices gives a potential shock to the real estate market and thus increases the probability of a banking crisis.

The opposite relationships of the short-term and long-term changes in the price-to-income ratio, or in other words, the boom-bust patterns, can be evidenced, to some extent, by observing the historical trends of the variables for the crisis countries. Figures 1 and 2 show the movements of the 1-year and 15-year growth rates for six countries in the data sample, namely, Australia, Denmark, Ireland, Italy, Norway and the US.

As expected, the short-term variations in price-to-income ratio are relatively higher than the long-term fluctuations. The red vertical lines represent the coded historical banking crises in Figures 1 and 2. As shown in Figure 1, a sharp decrease in the 1 year growth rate tends to occur in the lead up to a crisis, which is obvious for countries like Denmark, Ireland and Norway, while for Italy and the US, the negative change in the growth rate is rela-

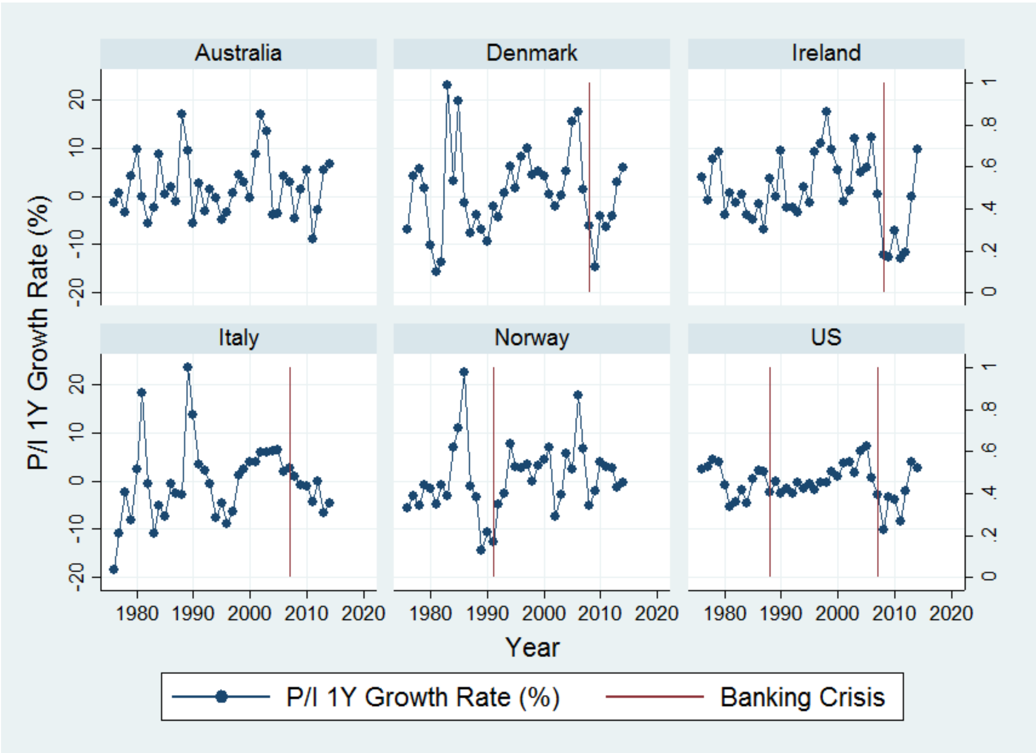


Figure 1: One Year Growth Rate of Price-to-Income Ratio

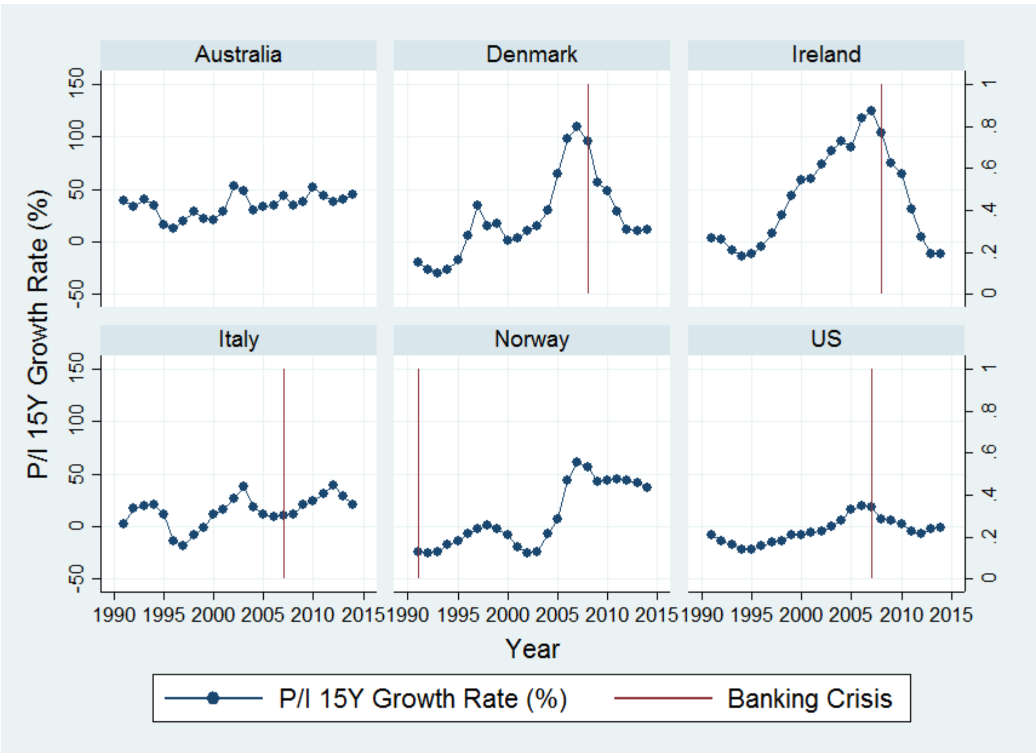


Figure 2: Fifteen Year Growth Rate of Price-to-Income Ratio

tively difficult to detect.

The long-term dynamic of the price-to-income ratio tends to be captured for the 15-year growth rate. A further deviation of the property values tends to capture the unsustainable growth rate and thus a larger exposure to the risk of a banking crisis. As shown in Figure 2, a sharp increase can be expected before the occurrence of a crisis. The growth rate peaked at or just before the crisis year for Denmark, Ireland and the US. However, around the crisis years for Italy and Norway, the long-term growth rates remained stable. Laeven and Valencia (2013) treat the Italy 2008 crisis as one of the borderline cases for systemic banking crises, the causes of which may be subject to the contagion effects of the 2008 GFC.

The contrasting pattern of association between the probability of a crisis and long versus short-term growth in the ratio of house prices to income is consistent with boom-bust patterns in the real estate market. The long-term growth trend in the ratio indicates a steadily increasing exposure to a banking crisis, and the risk escalates dramatically in the wake of rapid short-term declines. Moreover, the sensitivity to short-term declines in the ratio is consistent with sensitivity to property market busts, hence, the sign and relative magnitudes of the coefficients provide indirect evidence of bubble-like patterns of the adjustment in the property market, which also suggest the need for caution interpretation of the outputs of the model. It is difficult to reconcile the sign and magnitudes of the coefficients relating to short and long term adjustments in the ratio to the risk of a systemic crisis if one excludes the possibility of boom-bust cycles in real estate markets, and as discussed in Section 2, there are strong ex-ante reasons to believe that such patterns of adjustment are a feature of these markets.

With the complexity of the financial system, there can hardly be a predictive variable that satisfies the conditions for all countries in the international context. However, as implied by the baseline model and shown by historical evidence, both the short-term and long-term growth rates can be regarded as potential predictors of banking crises.

The annual growth rate of share price indices is also included in the baseline model so as to assess the impact of the overall equity market in the lead up phrase to a banking crisis. Similar to the short-term property price, the estimated coefficient has a negative sign, which indicates that a decrease in the share price growth rate can potentially increase the probability of a banking crisis, which is consistent with the expectation of this thesis.

Domestic credit as a percentage of GDP is a credit stock variable which is used as a proxy for the country-level credit aggregation after GDP deflation. It is statistically different from zero with a 5% significance level. The coefficient estimate is positive, implying that when a country's credit aggregation increases relative to its GDP, so does its probability of a systemic banking crisis. As expected, a further disconnection of the credit aggregation from its gross production can contribute to a banking crisis.

International debt securities issued by banks variable is employed to measure the level of a country's external imbalances. The positive coefficient estimate implies that the probability of a banking crisis increases with a boost in the cross-border exposures of the banking system. When banks rely too much on the international financing and incur losses on foreign portfolios, the vulnerability of the financial system increases. The coefficient of estimate is significantly different from zero at a 1% level. For the recent GFC, advanced economies had the strongest exposure to contagion shocks which arose from failures of their related foreign portfolios (OECD, 2012).

Table 8: Ranges of Decile Groups for Estimated Probabilities (Baseline)

Decile	Mean (%)	Min Pr. (%)	Max Pr. (%)	No. of Crises	Crisis Frequency (%)	Cum. % of Crises
1	0.11	0.01	0.22	0	0.00	100.00
2	0.36	0.22	0.48	0	0.00	100.00
3	0.59	0.49	0.68	0	0.00	100.00
4	0.79	0.68	0.93	0	0.00	100.00
5	1.13	0.94	1.31	0	0.00	100.00
6	1.68	1.36	2.02	2	5.88	100.00
7	2.35	2.03	2.75	2	5.88	85.71
8	3.50	2.77	4.48	2	6.06	71.43
9	7.10	4.49	10.50	1	2.94	57.14
10	24.44	10.76	92.02	7	21.21	50.00

Notes: Min Pr. and Max Pr. denote the minimum and maximum of estimated probabilities in each group as a percentage. The fifth column contains the number of estimated probabilities of historical crises included in each group. Crisis Frequency reports the number of crises as a percentage of the total observations in each decile group. The last column lists the cumulative proportion of crises captured by the model from the highest decile group to the lowest.

As the coefficients in Table 7 represent the estimated results for linear regression of the log of odds ratio function, it is difficult to interpret the numerical figures directly. As mentioned in Section 4.2, the estimated probabilities can be computed using Equation 6. Table 8 reports the range of each

Table 9: Marginal Effects for Australia (Baseline)

			Panel A				
Std.Dev	0	0.5	1	1.5	2	2.5	3
All Variables							
Δ Pr.	0.00	2.39	8.55	22.33	45.31	69.79	86.06
Decile	6	8	9	10	10	10	10
			Panel B				
Std.Dev	0	0.5	1	1.5	2	2.5	3
P/I 1y growth rate							
Δ Pr.	0.00	0.86	2.30	4.61	8.23	13.70	21.49
Decile	6	7	8	9	9	10	10
P/I 15y growth rate							
Δ Pr.	0.00	0.16	0.38	0.62	0.89	1.21	1.56
Decile	6	6	6	6	7	7	8
Share price growth rate							
Δ Pr.	0.00	0.30	0.69	1.18	1.77	2.50	3.40
Decile	6	6	7	7	8	8	9
Domestic credit (% GDP)							
Δ Pr.	0.00	0.11	0.25	0.41	0.58	0.77	0.97
Decile	6	6	6	6	6	7	7
International debt growth rate							
Δ Pr.	0.00	0.05	0.13	0.22	0.31	0.41	0.51
Decile	6	6	6	6	6	6	6
Bank credit/deposit							
Δ Pr.	0.00	0.01	0.01	0.03	0.05	0.07	0.09
Decile	6	6	6	6	6	6	6
Δ (Long-term interest rate)							
Δ Pr.	0.00	0.01	0.03	0.04	0.05	0.07	0.08
Decile	6	6	6	6	6	6	6

Notes: This table reports the marginal effects of changes in explanatory variables on the estimated probabilities of a banking crisis for Australia. The first row represents the number of standard deviation changes in the unfavourable direction for the variable(s). Δ Pr. denotes the change in percentage in the estimated probability resulting from the changes in the variable(s). Decile denotes the decile group within which the new probability falls, according to the decile ranges in Table 8.

decile group for the estimated probabilities of the whole sample set and the number of crises for each group. There are around 34 observations in each decile group. Seven out of fourteen historical crises are within the highest decile group, which captures 50% of the historical crises. All the crisis events are captured by the baseline model from the highest decile up to the sixth decile group. The expected crisis frequency for the highest decile is 21.21% (7 out of 33), although the range of the group is quite wide, from 10.76% to 92.02%.

The latest estimated probability of a crisis for Australia as of quarter 2, 2015 in the following year is relatively low at around 1.37%, which falls in the sixth decile group. In the data sample, there is an expected 5.88% probability of crisis in this decile group as shown in Table 8. To assess the marginal effects of changes in the explanatory variables on the estimated probabilities from Australia's perspective, the changes of the variables in terms of standard deviations are considered. The results are reported in Table 9. Different scenarios of changes in terms of standard deviations are considered to compute the changes in the estimated crisis probability for Australia in 1-year's time, as well as the decile group of the new probability under each scenario. Six scenarios are included: ±0.5, ±1.0, ±1.5, ±2.0, ±2.5 and ±3.0 standard deviation changes in the unfavourable direction of the variables. The standard deviations are calculated subject to Australia and are consistent with the summary statistics listed in Table 5, Panel A.

Panel A in Table 9 represents changes in all explanatory variables included in the baseline model, while Panel B denotes changes are only applied to the lagged one-year growth rate of the property price-to-income ratio. The decile groups are determined with reference to the decile ranges listed in Table 8, or stated differently, the other estimated probabilities in the sample are held as unchanged for the different scenarios.

Due to the non-linearity of the logistic model, cautions need to be taken in interpreting of the table results. Comparing the results in Panels A and B, with one standard deviation changes in all of the variables in the unfavourable direction, the estimated probability of an Australian crisis increases by 8.55%, which results in an increase from the sixth to the ninth decile group. On the other hand, if changes are only applied to the short-term growth rate of the standardised property prices, one standard deviation decrease in the short-term growth rate can result in an increase of 2.30% in probability for an Australian crisis. When the short-term growth rate reduces by 2.5 standard deviations, Australia's probability of a banking crisis in the next year shifts to the highest decile group.

If a three-standard deviation change is applied to the variables independently, the resulting increase in the risk level is 21.49% (1-year growth rate of standardised property prices), 1.56% (long-term growth rate of price ratio), 3.40% (share price growth rate), 0.97% (credit-to-GDP), 0.51% (international debt by banks growth rate), 0.09% (ratio of bank credit-to-deposit), and 0.08% (change in the long-term interest rate). Therefore, changes in property prices standardised by the income level have a relatively strong impact on Australia's risk exposure to a systemic banking crisis, compared to other predictors. Referring back to Figures 1 and 2, in Australia, there has been a steady increase of the long-term growth rate over the past two decades together with moderate fluctuations in the short-term growth rate. However, Australia has not suffered a systemic crisis yet, despite the various evidence showing an increasing exposure of Australia to the real estate sector as discussed earlier in Section 1. By taking into account the possibility of the existence of a market bubble, it is a sharp short-term price correction that will trigger a crisis event. Australia has not been hit by a short-term house price shock, which may be due to various potential reasons, such as the increasing positive expectations of both domestic and foreign investors. However, the sensitivity of the Australian banking system to real estate price fluctuations as shown by the hazard model, to some extent, supports regulators' argument on pre-emptive actions, such as tightening banks' lending standards and capital requirements.

Three test statistics are computed to measure and compare the goodness-of-fit and predictive power between models, which include the chi-squared statistic for likelihood ratio test (LR Chi^2), the Akaike information criterion (AIC) and the area under receiver operating characteristic curve (AUC). The likelihood ratio test is applied to examine the goodness-of-fit of the hazard model, compared to a null model. With a LR Chi^2 of 32.02, the baseline model outperforms a null model at a significance level of 1%.

The AIC statistic, on the other hand, is used to address the potential problem of over-fitting. It measures the information lost when the model is used to fit a given dataset. It deals with the trade-off between the goodness-of-fit of the model and the complexity of the model in terms of the number of explanatory variables included. When conducting model selections, the model offering the lowest AIC statistic is preferred.

Lastly, the AUC statistics are expected to offer some insight into the predictive power of the models, which is of vital importance for this study. Figure 3 shows the Receiver Operating Characteristic (ROC) curve for the baseline model. The ROC curve is used to measure the discriminatory power of the model in classifying the crisis event. The curve plots the true positive rate against the false positive rate, for all thresholds. Let λ denotes the value of the threshold. The binary classifier gives value of 0 if the estimated probability, $\hat{P}$, is less than or equal to λ, while it has a value of 1 if $\hat{P}$ is greater than λ. When λ is very large and negative, the classifier is highly likely to make crisis calls and thus both the true positive and false positive rates converge to 1; conversely, if λ is large and positive, the classifier is very conservative and both true positive and false positive rates converge to 0. A good classifier is expected to have a higher true positive rate compared to a false positive rate. The reference line is where the true positive rate equals the false positive rate, and where the model is a uninformative classifier such that each crisis call signalled by the model has a 50% probability to be true and also a 50% to be false (a 'coin toss' scenario).

To assess the predictive prower of the model, the AUC is computed to

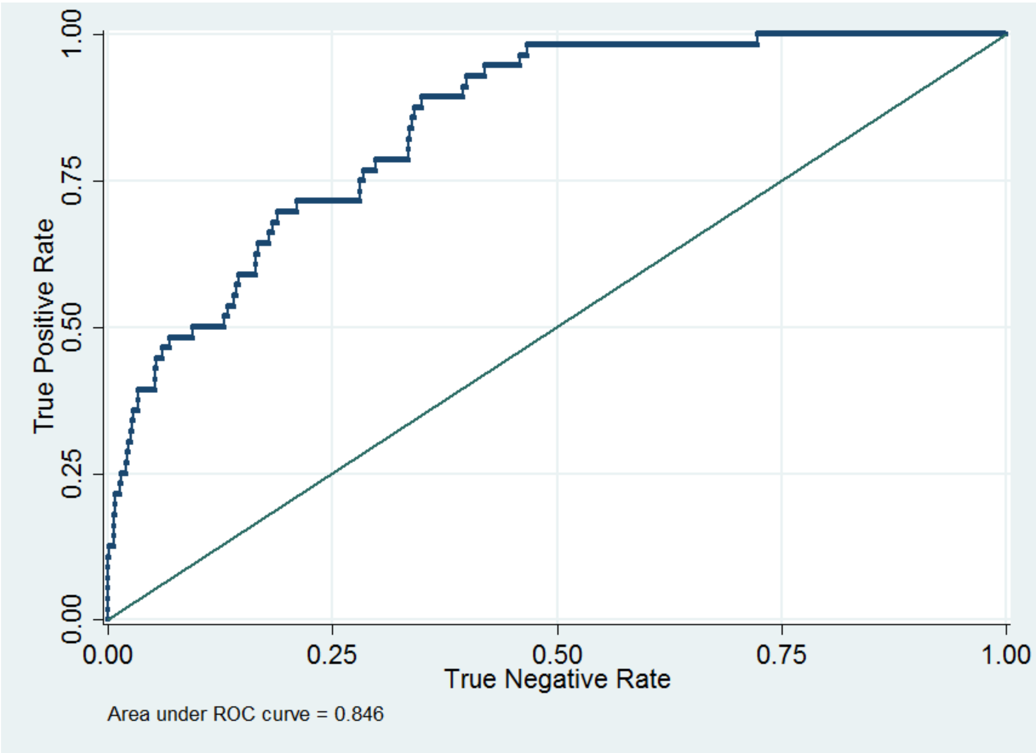


Figure 3: In Sample Receiver Operating Characteristic Curve (Baseline)

test whether the model's signals are informative such that the distribution is statistically different under crisis and non crisis states. If the AUC statistic is less than or equal to 0.5, the model is regarded as a uninformative classifier of crises, while an AUC of 1 indicates the model is a perfect classifier. For the baseline model, the AUC statistic is 0.846 with a standard error of just 0.0227, which implies that the baseline model has a relatively high level of predictive power although not perfect.

5.2 Alternative Measures of Real Estate Prices

The baseline model examines both the short-term and long-term variations of property price-to-income ratios on the financial system's risk exposure to a banking crisis. The impacts of these variations have been confirmed and analyzed. This section takes into consideration the alternative measures of property prices, including the use of the short-term or the long-term growth rates only for the standardised property prices, and that of the growth rates for the house price indices instead of those of the price-to-income ratio. The performance of the alternative models will be compared with that of the baseline model in terms of goodness-of-fit and predictive power.

Table 10 lists the regression results for the baseline model, as well as the three alternative models with different property price variables. Model (2) employs the short-term effect of changes in price-to-income ratio, while Model (3) only considers the long-term effect. As shown in the table, both the 1-year and 15-year growth rates remain significant at a 1% level, which confirms the role of the property price-to-income ratio in the predictive model of banking crises. For Model (2), the estimate of the ratio of bank credit-to-deposit ratio becomes significant with a positive sign, which is consistent with the original expectation that with more aggressive banking activities, the risk level the banking system increases. For the three alternative models, the property price variable(s) and the credit stock variable remain significant. By modelling the international experience of banking crises, both the disconnection between property price and income level, and the level of credit aggregation are the potential driving forces for systemic banking crises.

The baseline model outperforms Models (2) and (3) in terms of model fitting and predictive power. It has a higher LR Chi^2 statistic and a lower

Table 10: Baseline Model and Alternative Measures of Property Prices

Explanatory Variables	**Model (1)** Baseline	**Model (2)** (1) without long-term growth	**Model (3)** (1) without short-term growth	**Model (4)** Replace P/I with property price
LagQ P/I 1y growth rate (%)	-0.163***	-0.124**		
	(0.0486)	(0.0499)		
LagQ P/I 15y growth rate (%)	0.0234***		0.0163***	
	(0.00615)		(0.00627)	
LagQ Property price 1y growth rate (%)				-0.107**
				(0.0424)
LagQ Property price 15y growth rate (%)				0.00188
				(0.00137)
LagQ Share price growth rate (%)	-0.0349**	-0.0432**	-0.0475***	-0.0388**
	(0.0159)	(0.0180)	(0.0171)	(0.0184)
Lag Domestic credit (% GDP)	0.00579*	0.00649**	0.00762**	0.00623*
	(0.00341)	(0.00308)	(0.00327)	(0.00346)
LagQ International debt growth rate (%)	0.00442***	0.00411**	0.00205	0.00383**
	(0.00151)	(0.00166)	(0.00150)	(0.00156)
Lag Bank credit/deposit	0.00356	0.0103***	0.00566*	0.00967***
	(0.00412)	(0.00308)	(0.00338)	(0.00321)
LagQ (long-term interest rate) (%)	-0.0185	0.0679	-0.00150	0.0325
	(0.0939)	(0.0943)	(0.161)	(0.116)
Intercept				
Constant	-5.457***	-5.912***	-5.584***	-5.654***
	(0.984)	(0.765)	(0.915)	(0.997)
Test Statistics				
LR Chi^2	32.02***	26.06***	24.36***	25.42***
Adjusted AIC	98.05	101.65	103.42	102.19
Adjusted AUC	0.845	0.794	0.801	0.808
	(0.0227)	(0.0269)	(0.0286)	(0.0256)
Number of Observations				
Total Observations	336	350	336	336
Number of Countries	18	18	18	18

Notes: This table reports the regression results for models with alternative forms of property price variable with the baseline model included. Property price 1y growth rate denotes the one year percentage growth rate of the BIS house price index. Property price 15y growth rate denotes the fifteen year growth rate of the BIS house price index. Other variable definitions are consistent with those in Table 7. Adjusted AIC and adjusted AUC denote the adjusted statistics when regressions are applied to a subsample with common observations among the five models. The subsample contains 336 observations across 18 countries.
*** = Significant at the 1% level.
** = Significant at the 5% level.
* = Significant at the 10% level.

adjusted AIC, implying a better model fit. For different model specifications, the total number of observations may be different, and thus to make it more comparable, both the adjusted AIC and AUC statistics are calculated based on a common set of observations. The highest AUC statistic with the lowest standard deviation also shows the stronger forecasting ability of the baseline model compared to the other two. There is evidence that both short-term and long-term growth rates of the standardised property price have a certain level of impact in the lead up to crises.

In Model (4), the price-to-income ratio is replaced with the property price index, sourced from BIS to see whether a time-series definition of the property price will outperform the ratio definition. Similar to the baseline, both the short-term and long-term growth rates of the price index are included, yet only the coefficient estimate of the short-term growth is significant. The signs of the two growth rates are consistent with those in the baseline model. A decrease in the short-term property price growth tends to trigger a crisis event, while a stronger positive deviation over the long-term can increase the vulnerability of the financial system. Even with different forms, the property price variable seems to have both short-term and long-term effects on the risk exposure to a systemic banking crisis. The test statistics imply that the baseline model still ranks above Model (4) in terms of goodness-of-fit and predictive power. It is worth noticing that the AUC statistics as well as the standard deviations of both models, are quite close.

5.3 Out-of-Sample Testing

In the previous section, the baseline model has been shown to outperform the others in terms of in-sample performance by comparing LR Chi^2, AIC and AUC statistics. To further investigate the predictive power of the models, an out-of-sample testing, known as the cross validation method, was applied in this section. Random subgroups were drawn to obtain new estimates of the hazard model and then to produce AUC statistics. The predictive power of the hazard models can be assessed by observing and comparing the distributions of the AUC statistics.

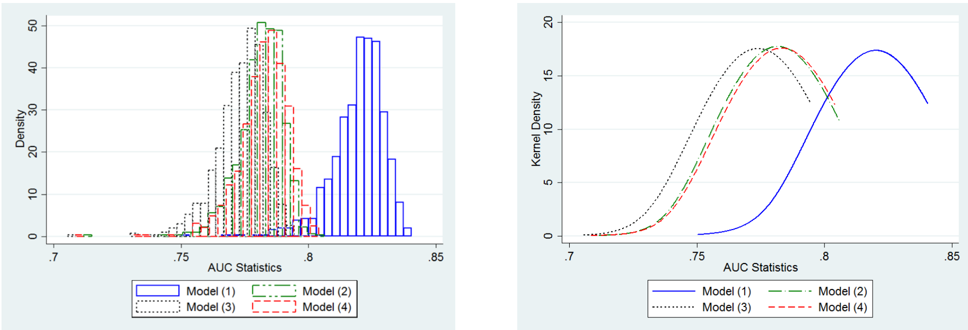
5.3.1 Cross Validation

The cross validation method can be used to analyse how well a model predicts a new outcome for new observations that are not used in fitting the model. For each subgrouping time, the data sample is randomly divided into 10 disjoint subsets. Then for each subset, the remaining nine subsets are used as the estimating sample, while the selected subset is left for testing. Predictions of that subgroup are computed using the new model estimates obtained from the combined subsample of the remaining nine subsets. Then the AUC statistic is calculated after all the subsets have obtained out-of-sample predictions. This process is repeated 1,000 times so as to obtain a distribution of AUC statistics for that model.

For the four model specifications listed in Table 10, the same subgrouping

Table 11: Cross Validation: AUC Statistics Summary

AUC	Mean	Std. Dev.	Min	Max
Model (1)	0.820	0.0103	0.750	0.841
Model (2)	0.781	0.0086	0.712	0.806
Model (3)	0.774	0.0094	0.706	0.794
Model (4)	0.783	0.0094	0.708	0.804



(a) Histograms (b) Kernel Density Plots

Figure 4: Cross Validation: AUC Distributions

is used for each time in the 10-fold cross validation. Table 11 provides summary statistics for the AUC of the models. Comparing the mean values of AUCs to those listed in Table 10, it can be observed that the former is lower than the later. The cross-validated AUC is expected to be lower than the in-sample AUC since they are computed using the subsamples that are not included in the model fitting. The ranking of the AUC average is consistent with the that shown in Table 10. The baseline model is once again shown to have the strongest predictive power in terms of average AUC, although the standard deviations of the AUC statistics are quite similar among the four models. Figure 4 shows both the histograms and kernel density plots of the resampled AUC statistics for the four models listed in Table 10. By observing the graphs, the outperformance of the baseline model can be clearly observed. In summary, from the evidence shown through both in-sample and out-of-sample testing, the baseline model has a higher ranking over the alternative models in terms of both model fitting and predictive power.

5.3.2 Tests for Equality in Distribution

To further examine the distributions of AUC statistics obtained using cross validation for the four models, two non-parametric tests for equality distribution are applied, that is the Kruskall-Wallis (KW) and the Wilcoxon signed-rank sum tests. The KW test is used to assess the hypothesis that the location of Model (1) AUCs is equal to those of the AUCs of the other three models, while the matched Wilcoxon test further examines whether the location of Model (1) is to the right of the others, indicating higher out-of-sample AUCs.

Table 12 reports the three KW test results for the location difference among Model (1) and the other three models. The test hypothesis for each KW test is as follows.

$H_0:$ Locations of populations are the same

$H_A:$ At least two population locations differ

Let n denotes the overall sample size and n_j denotes the sample size for the jth sample, where $j = 1, 2, 3, 4$. Let $R_j = \sum_{i=1}^{nj} R(X_{ji})$ denote the sum of the ranks for the jth sample. The KW one-way analysis-of-variance test statistic, denoted H, is calculated using the following equation:

$$H = \frac{12}{n(n+1)} \sum_{j=1}^{4} \frac{{R_j}^2}{n_j} - 3(n+1) \tag{7}$$

where the sampling distribution of H is approximately χ^2 with 3 degrees of freedom. From Table 12, the p-value of the test is less than 0.001, and thus H_0 is rejected at 1% significance level. It can be concluded that at least two AUC distributions are significantly different from each other.

Table 12: Kruskall-Wallis Test

Test Results Population	Observation	Rank Sum ($\times 10^6$)
Model (1)	1,000	3.48
Model (2)	1,000	1.70
Model (3)	1,000	0.98
Model (4)	1,000	1.84
Test Statistics		
H Statistic	2499.53	
p-Value	0.0001	

Now the direction of the location differences can be further tested using the pairwise Wilcoxon test. It is worth noticing that the KW test is built on the assumption of independence distributions. As mentioned in the Section 5.3.1, for each time of the random grouping, the same subgroups are used for the computation of AUCs for the four models. Therefore, the matched-pairs Wilcoxon Signed-Rank Sum test is applied here instead of the Wilcoxon Rank Sum test, which assumes independent distributions.

Let d_i denote the difference for any matched pair of observations, where $d_i = x_{1i} - x_{2i}$, for $i = 1, 2, ..., n$. To further examine whether Model (1) produces a higher out-of-sample AUC, the following test hypothesis for the pairwise Wilcoxon Rank Sum test is applied.

$H_0 : \ d_i = 0$

$H_A : \ d_i > 0$

By considering the signs of d_j, the signed rank for observation i is denoted as r_i, where $r_i = \text{sign}(d_i)\text{rank}(|d_i|)$. Let T denotes the test statistic, which is the sum of all r_is and T_+ denotes the sum of the positive signed-ranks, with $E(T_+) = \frac{n(n+1)}{4}$ and $Var(T_+) = \frac{1}{4}\sum_{i=1}^{n} {r_j}^2$. Since the sample size is 1,000, a normal approximation is used to calculate the z statistics, where

$$z = \frac{T_+ - E(T_+)}{\sqrt{Var(T_+)}} \tag{8}$$

Table 13 reports the test results when differences of AUC are considered between Model (1) and Model (2), Model (3) or Model (4), respectively. For all three tests, d_i is found to be positive for all observations, which implies that Model (1) produces the highest AUC among the models for each random subsample. The null hypothesis is rejected for all three tests at a 1% significance level and thus it can be concluded that the AUC distribution for Model (1) is to the right of those of the other three models, which confirms the outperformance of the baseline specification in terms of out-of-sample predictive power.

Table 13: Wilcoxon Signed-Rank Sum Test

Population A	Population B	$d_i > 0$	$d_i < 0$	$d_i = 0$	z Statistics	p-Value
Model (1)	Model (2)	1,000	0	0	27.39	0.00
Model (1)	Model (3)	1,000	0	0	27.39	0.00
Model (1)	Model (4)	1,000	0	0	27.39	0.00

Notes: $d_i > 0$ denotes the total number of positive d_is; $d_i < 0$ denotes the total number of negative d_is; $d_i = 0$ denotes the total number of d_is equalling zero.

5.4 Additional Predictive Variables

Previously in Section 3, it has been documented in the literature that there are various variables classes, which are argued to be of predictive importance for systemic banking crises. The two key variable classes considered in the baseline model include the credit stock and asset prices, which are shown to have a vital role in crisis prediction. Additionally, the effect of the level of net foreign liabilities of the banking system has also been confirmed. However, there are several variable classes that are not covered by the baseline case. To underscore the value of the baseline model based on the combination of short-term and long-term effects of property prices, several additional variables are added to the baseline specification to assess their explanatory power in the lead up to a banking crisis.

Model (5) includes a country's government debt deflated by its GDP as a proxy for the level of fiscal deficits, which have been proved to be positively related to the probability of a banking crisis (Kaminsky and Reinhart, 1999; Barrell et al., 2010). However, the role of government debt in the crisis lead up time is not confirmed in this study. The coefficient estimate is found to

Table 14: Baseline Model with Additional Variables

Explanatory Variables	Model (1) Baseline	Model (5) (1) plus fiscal deficits	Model (6) (1) plus GDP growth	Model (7) (1) plus monetary aggregation	Model (8) (1) plus bank capital/assets
LagQ P/I 1y growth rate (%)	-0.163***	-0.202***	-0.160***	-0.166***	-0.134***
	(0.0486)	(0.0465)	(0.0523)	(0.0520)	(0.0336)
LagQ P/I 15y growth rate (%)	0.0234***	0.0245***	0.0234***	0.0244***	0.0292**
	(0.00615)	(0.00647)	(0.00620)	(0.00808)	(0.0121)
LagQ Share price growth rate (%)	-0.0349**	-0.0325**	-0.0339*	-0.0364**	-0.0300
	(0.0159)	(0.0160)	(0.0174)	(0.0156)	(0.0203)
Lag Domestic credit (% GDP)	0.00579*	0.00601	0.00576*	0.0109	0.00430
	(0.00341)	(0.00380)	(0.00339)	(0.0119)	(0.00758)
LagQ International debt growth rate (%)	0.00442***	0.00470***	0.00441***	0.00452***	0.00489**
	(0.00151)	(0.00150)	(0.00150)	(0.00163)	(0.00199)
Lag Bank credit/deposit	0.00356	0.00457	0.00344	0.000861	0.00219
	(0.00412)	(0.00511)	(0.00407)	(0.00695)	(0.00414)
LagQ Δ (long-term interest rate) (%)	-0.0185	-0.127	0.000163	-0.0161	0.0755
	(0.0939)	(0.164)	(0.102)	(0.100)	(0.122)
Lag Government debt (% GDP)		0.00223			
		(0.00897)			
LagQ GDP growth rate (%)			-0.0676		
			(0.267)		
Lag Liquid liabilities (% GDP)				-0.00914	
				(0.0180)	
Lag Bank Capital/Assets					0.167
					(0.232)
Intercept					
Constant	-5.457***	-5.657***	-5.355***	-5.008***	-6.053**
	(0.984)	(1.289)	(1.027)	(1.065)	(2.813)
Test Statistics					
LR Chi^2	32.02***	34.86***	32.07***	32.13***	22.30***
Adjusted AIC	76.47	78.31	78.43	77.76	77.66
Adjusted AUC	0.824	0.821	0.826	0.829	0.844
	(0.0294)	(0.0291)	(0.0291)	(0.0303)	(0.0309)
Number of Observations					
Total Observations	336	308	336	332	182
Number of Countries	18	18	18	18	17

Notes: This table reports the estimating results of models when additional explanatory variables are considered. The government debt (% GDP) denotes the government debt as a percentage of GDP. GDP growth rate denotes a 1-quarter growth rate of GDP. Liquid liabilities (% GDP) denotes the liquid liabilities as a percentage of GDP. Adjusted AIC and adjusted AUC denote the statistics when regressions are applied to a subsample with common observations among the five models. The subsample contains 170 observations across 17 countries.

*** = Significant at the 1% level.

** = Significant at the 5% level.

* = Significant at the 10% level.

be insignificant, which indicates a lack of explanatory power for the crisis events. A higher level of government debt, instead of being a causal effect for a banking crisis, is more likely to be a measure of the ability of a country's government to offer policy interventions such as deposit guarantees or liquidity support to the banking system when the crisis hits.

Model (6) adds the quarterly growth rate of GDP as another macroeconomic variable to the baseline specification to assess whether changes in the country's productivity are relevant to the vulnerability of the economy. It can be expected that a weaker macroeconomic environment tends to increase the country's risk exposure to a systemic banking crisis. In contrast to some studies stating the relevance of the domestic production to the crisis events (Demirgüç-Kunt and Detragiache, 1998; Domaç and Peria, 2003), the insignificant coefficient estimate shown in Model (6) is consistent with Büyükkarabacak and Valev (2010) and Karim et al.'s (2013) findings. There is little evidence showing that GDP growth rate is closely related to the probability of a banking crisis

Liquid liabilities deflated by GDP is employed by Model (7), which can be treated as a proxy for the level of monetary aggregation. With an insignificant coefficient of the variable, this study confirms with Schularick and Taylor's (2012) finding that in the post WWII era, monetary aggregation is lacking explanatory power for the occurrence of a banking crisis. Finally, Model (8) takes into consideration another banking sector variable of interest, which is the ratio of bank capital to total assets, to assess whether the level of bank's capital adequacy can affect the stability of the banking system. The insignificant estimate can be interpreted as not contributing to the lead up phase of a crisis; the capital adequacy in the banking system may offer more insight into the ability to absorb losses when the crisis occurs.

The inclusion of additional variables in model specification squeezes the number of observations in the estimating sample, due to data availability. In terms of in-sample performance, none of the models can outperform the baseline with either a better fitting or a stronger classifying ability. It is found that AIC statistics tend to decrease with a reduced sample size. To further address this issue, an adjusted set of AIC statistics are reported for the five models' regression results based on a same subsample with common observations. By observing the adjusted AICs, the baseline model still provides the lowest figure indicating an outperforming model specification. Similarly, the adjusted AUC statistics are computed with the same number of estimated probabilities, and hence the adjusted AUC for the baseline has dropped slighted from 0.846, as shown in Table 7, to 0.824. The overall AUC statistics and the corresponding standard deviations are quite close, which implies that the extended model specifications can only improve the classification ability slight.

Summing up the results from Table 14, it can be inferred that although some of the additional variables may matter in some contexts, for example, in other samples that include emerging markets, these factors are not the main predictors for financial instability in advanced economies. The role of property prices in terms of both short-term and long-term growth is once again confirmed and remains a vital predictor across all model specifications.

5.5 Model Limitations

Due to the complexity of the financial system, the baseline specification is not expected to explain all variations in the lead up to a crisis and is subject to several limitations.

Firstly, systemic banking crises are low-frequency events, which make model construction challenging. King and Zeng (2001) show that rare events are difficult to explain and predict and they suggest that data quality is inevitably subject to the number of observations of the rare events. Additionally, although different definitions of systemic banking crises have been considered by including the borderline cases as identified by Laeven and Valencia (2013), only binary crisis variables are tested in this study. As an extension, it may be interesting to use alternative continuous crisis variables in the hazard model.

Secondly, this study is subject to data availability due to the requirement for country level data in an international context. Due to the unavailability of quarterly frequencies in the credit data, the analysis can only be run on an annual basis. Additionally, as an international model, it can only explain the variations in the lead up to crisis events from a macro level, and hence there can hardly be a predictive variable that satisfies the conditions for all countries in the international context.

Moreover, other variables that are specific to the changing loan exposure profile of financial institutions portfolios and capital positions, and other controls for fundamental determinants of property prices for example demographic shifts, are not considered in this study.

6 Conclusions

Within this study, a hazard model has been developed in light of the international experience to quantify the banking system's exposure to the risk of a systemic crisis sourced by the real estate sector. The model provides early warning signals for the occurrence of a banking crisis, and offers regulators information that may be helpful with designing pre-emptive actions in policy formulation.

With reference to the potential crisis drivers identified by prior studies, this study selects predictive variables offering economic intuition in the international context. In particular three classes of variables are found to have strong predictive power in forecasting banking crises, which are asset prices (in both property and equity markets), credit aggregation and external imbalances.

The property price-to-income variable measures the level of disconnection between housing prices and personal income, which is found to offer more insights into systemic fragility than absolute price levels. The findings of the contrasting pattern of relationship between long versus short-term changes in the price-to-income ratio and the probability of a crisis is consistent with boom-bust patterns of adjustment in the property market. While a long-term increase in the ratio indicates the growing vulnerability of the financial system to real estate markets, the short-term growth rate captures the recent shift in the price-to-income ratio, and a crisis risk escalates dramatically in the wake of rapid short-term declines in the ratio. Moreover, the sensitivity to short-term declines in the price to income ratio is consistent with sensitivity to property market busts. Therefore, the sign and relative magnitudes of the coefficients provide indirect evidence of boom-bust patterns of adjustment in the property market. On the other hand, it is difficult to reconcile the sign and magnitudes of the coefficients relating to short and long term adjustments in the price-to-income ratio to the risk of a systemic crisis if one excludes the possibility of boom bust cycles in real estate markets.

The positive relationship between credit aggregation and systemic risks implies that aggressive lending activities can foster the negative feedback loop and thus a crisis event. Consistent with Crowe et al.'s (2013) finding, a "twin boom" in asset and credit markets can exaggerate the fragility in the financial system. Moreover, the significance of international debt levels in the banking sector further indicates that a greater dependence on offshore funding and, thus, a country's increasing imbalance between domestic borrowings and savings, may be connected to the occurrence of banking crises.

As discussed in Section 3, similar to prior studies, contradictory results in the significance of other variables were also found in this study. One of the explanations might be the different variables in contexts. Variables found of little importance in this study may matter in other contexts. Additionally, due to the complexity of the financial system, the proposed baseline specification is not expected to explain all variations in the lead up to a crisis. It aims to measure the banking system's exposure to a crisis event quantitatively and thus provides evidence to regulators and offers insights for their pre-emptive policy formulation.

References

Alessi, L. and C. Detken (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy 27*(3), 520–533.

Allen, F. and D. Gale (2000). Bubbles and crises. *The Economic Journal 110*(460), 236–255.

Angkinand, A. P. and T. D. Willett (2011). Exchange rate regimes and banking crises: The channels of influence investigated. *International Journal of Finance & Economics 16*(3), 256–274.

Barrell, R., E. P. Davis, D. Karim, and I. Liadze (2010). Bank regulation, property prices and early warning systems for banking crises in oecd countries. *Journal of Banking & Finance 34*(9), 2255–2264.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance 30*(5), 1581–1603.

Bloomberg (2015, April). Sydney home prices are growing five-times faster than wages. http://www.afr.com/real-estate/residential/sydney-home-prices-are-growing-fivetimes-faster-than-wages. [Online; posted 28-April-2015].

Boissay, F., F. Collard, and F. Smets (2013). Booms and systemic banking crises. *European Central Bank working paper*.

Bordo, M. D. (2008). An historical perspective on the crisis of 2007-2008. Technical report, National Bureau of Economic Research.

Bordo, M. D. and C. M. Meissner (2012). Does inequality lead to a financial crisis? *Journal of International Money and Finance 31*(8), 2147–2161.

Borio, C. E. and M. Drehmann (2009). Assessing the risk of banking crises–revisited. *BIS Quarterly Review, March*.

Borio, C. E. and P. Lowe (2002). Assessing the risk of banking crises. *BIS Quarterly Review, December*.

Büyükkarabacak, B. and N. T. Valev (2010). The role of household and business credit in banking crises. *Journal of Banking & Finance 34*(6), 1247–1256.

Caprio, G. and D. Klingebiel (1996). Bank insolvencies: cross-country experience. *World Bank policy research working paper* (1620).

Case, B., S. Wachter, et al. (2005). Residential real estate price indices as financial soundness indicators: methodological issues. *BIS working paper 21*, 197–211.

Cashin, P. A. and R. Duttagupta (2008). The anatomy of banking crises. *IMF working paper*, 1–37.

Claessens, S., M. A. Kose, and M. E. Terrones (2009). What happens during recessions, crunches and busts? *Economic Policy 24*(60), 653–700.

Crowe, C., G. DellAriccia, D. Igan, and P. Rabanal (2013). How to deal with real estate booms: lessons from country experiences. *Journal of Financial Stability 9*(3), 300–319.

Davis, E. P. and D. Karim (2008a). Comparing early warning systems for banking crises. *Journal of Financial Stability 4*(2), 89–120.

Davis, E. P. and D. Karim (2008b). Could early warning systems have helped to predict the sub-prime crisis? *National Institute Economic Review 206*(1), 35–47.

Demirgüç-Kunt, A. and E. Detragiache (1998). The determinants of banking crises in developing and developed countries. *Staff Papers-International Monetary Fund*, 81–109.

Demirgüç-Kunt, A. and E. Detragiache (2002). Does deposit insurance increase banking system stability? an empirical investigation. *Journal of Monetary Economics 49*(7), 1373–1406.

Demirgüç-Kunt, A. and E. Detragiache (2005). Cross-country empirical studies of systemic bank distress: a survey. *National Institute Economic Review 192*(1), 68–83.

Domaç, I. and M. S. M. Peria (2003). Banking crises and exchange rate regimes: is there a link? *Journal of International Economics 61*(1), 41–72.

Evrensel, A. Y. (2008). Banking crisis and financial structure: A survivaltime analysis. *International Review of Economics & Finance 17*(4), 589–602.

Hahm, J.-h., H. S. Shin, and K. Shin (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit and Banking 45*(s1), 3–36.

Herring, R. J. and S. M. Wachter (1999). Real estate booms and banking busts: An international perspective. *The Wharton School Research Paper* (99-27).

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal 7*(3), 281.

Jordà, Ò., M. Schularick, and A. M. Taylor (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review 59*(2), 340–378.

Jordà, Ò., M. Schularick, and A. M. Taylor (2013). When credit bites back. *Journal of Money, Credit and Banking 45*(s2), 3–28.

Jordà, Ò., M. Schularick, and A. M. Taylor (2014). The great mortgaging: housing finance, crises, and business cycles. Technical report, National Bureau of Economic Research.

Jordà, Ò., M. Schularick, and A. M. Taylor (2015). Betting the house. *Journal of International Economics 96*, S2–S18.

Joyce, J. P. (2011). Financial globalization and banking crises in emerging markets. *Open Economies Review 22*(5), 875–895.

Kaminsky, G. L. and C. M. Reinhart (1999). The twin crises: the causes of banking and balance-of-payments problems. *American Economic Review*, 473–500.

Karim, D. (2008). The use of binary recursive trees for banking crisis prediction. *Brunel University Department of Economics and Finance Working Paper, Brunel University.-2008*.

Karim, D., I. Liadze, R. Barrell, and E. P. Davis (2013). Off-balance sheet exposures and banking crises in oecd countries. *Journal of Financial Stability 9*(4), 673–681.

Kauko, K. (2012). External deficits and non-performing loans in the recent financial crisis. *Economics Letters 115*(2), 196–199.

Kauko, K. (2014). How to foresee banking crises? A survey of the empirical literature. *Economic Systems 38*(3), 289–308.

King, G. and L. Zeng (2001). Explaining rare events in international relations. *International Organization 55*(03), 693–715.

Laeven, L. and F. Valencia (2008). Systemic banking crises: a new database. *IMF working paper*, 1–78.

Laeven, L. and F. Valencia (2012). Systemic banking crises database: An update. *IMF working paper 12/163*.

Laeven, L. and F. Valencia (2013). Systemic banking crises database. *IMF Economic Review 61*(2), 225–270.

Lainà, P., J. Nyholm, and P. Sarlin (2015). Leading indicators of systemic banking crises: Finland in a panel of EU countries. *Review of Financial Economics 24*, 18–35.

Leamer, E. E. (2007). Housing is the business cycle. Technical report, National Bureau of Economic Research.

OECD (2012). Financial contagion in the era of globalised banking? *OECD Economics Department Policy Notes*, No. 14, June.

Roy, S. and D. M. Kemme (2012). Causes of banking crises: Deregulation, credit booms and asset bubbles, then and now. *International Review of Economics & Finance 24*, 270–294.

Sarlin, P. and T. A. Peltonen (2013). Mapping the state of financial stability. *Journal of International Financial Markets, Institutions and Money 26*, 46–76.

Schularick, M. and A. M. Taylor (2012). Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870–2008. *The American Economic Review 102*(2), 1029.

Shorrocks, A., J. Davies, and R. Lluberasis (2014, October). Global wealth report 2014. Technical report, Credit Suisse AG.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model*. *The Journal of Business 74*(1), 101–124.

SMH, Pascoe, M. (2015, May). The Sydney housing bubble to pop but how? http://www.smh.com.au/business/the-economy/the-sydney-housing-bubble-to-pop–but-how-20150519-gh3vau. [Online; posted 19-May-2015].

Wong, J., T.-C. Wong, and P. Leung (2010). Predicting banking distress in the EMEAP economies. *Journal of Financial Stability 6*(3), 169–179.

Appendix

A Robustness Check for Choices of Quarter

As mentioned earlier, my dataset contains combined variables with quarterly and annual frequencies, while the regression is conducted on an annual basis. Model estimates listed in Table 7, 10 and 14 are obtained using observations from quarter 3, as historically, most of crises occurred in the third quarter of the crisis year. This section aims to carry out a robustness check for the sensitivity of the modelling results from the baseline model specification to choices of different quarters.

Table 15 lists the model estimates for the baseline specification when observations from different quarters are used as the testing sample. In the previous analyses, quarter 3 observations are applied in the regression as most of the historical crises occurred in quarter 3 of the crisis year, referring to Table 3. Comparing the model estimate with different quarters selected, the overall results are quite close in terms of test statistics and significance of the variables. The three main variables, including 1-year and 15-year growth rates of standardised property prices as well as the credit-to-GDP variable, are not subject to the choice of quarter, indicated by the consistency in sign, significance and magnitude of the coefficient estimates. Interestingly, the annual change in long term interest rate becomes significant when quarter 1 and quarter 2 observations are used, although the positive sign is not expected.

Table 15: Baseline Specification with Observations of Different Quarters

Explanatory Variables	**Quarter 1**	**Quarter 2**	**Quarter 3**	**Quarter 4**
LagQ P/I 1y growth rate (%)	-0.118**	-0.129**	-0.163***	-0.126**
	(0.0517)	(0.0655)	(0.0486)	(0.0512)
LagQ P/I 15y growth rate (%)	0.0247***	0.0262***	0.0234***	0.0279***
	(0.00593)	(0.00686)	(0.00615)	(0.00628)
LagQ Share price growth rate (%)	-0.0115	-0.0483***	-0.0349**	-0.0173
	(0.0109)	(0.0124)	(0.0159)	(0.0109)
Lag Domestic credit (% GDP)	0.00930**	0.00862**	0.00579*	0.00631*
	(0.00408)	(0.00393)	(0.00341)	(0.00382)
LagQ International debt growth rate (%)	0.00337**	0.00384**	0.00442***	0.00462***
	(0.00141)	(0.00180)	(0.00151)	(0.00153)
Lag Bank credit/deposit	0.00481	0.00453	0.00356	0.00367
	(0.00431)	(0.00448)	(0.00412)	(0.00390)
LagQ Δ (long-term interest rate) (%)	0.618***	0.425***	-0.0185	0.324
	(0.154)	(0.145)	(0.0939)	(0.245)
Intercept				
Constant	-5.906***	-6.032***	-5.457***	-5.466***
	(1.091)	(1.131)	(0.984)	(0.980)
Test Statistics				
LR Chi^2	28.65***	35.29***	32.02***	26.87***
AIC	103.90	98.85	102.37	107.27
AUC	0.840	0.848	0.846	0.845
	(0.0242)	(0.0221)	(0.0227)	(0.0234)
Number of Observations				
Total Observations	315	333	336	333
Number of Countries	18	18	18	18

Notes: This table reports the regression results of the baseline model specification with alternative quarters of observations. Model estimates listed in previous tables used observations in quarter 3.

*** = Significant at the 1% level.

** = Significant at the 5% level.

* = Significant at the 10% level.

For test statistics, there is no large difference among the four scenarios of the baseline specification. The results from quarter 2 data show a slightly better performance than those from quarter 3 in terms of goodness-of-fit, but with fewer observations. Overall, there is little evidence that the choices of quarter has a strong impact on the results of baseline model specification. The indications show consistency with those discussed in Section 5.