



**Financial Stability Models of the Irish
Banking Sector: Deposit Flows and
Property Price Dynamics**

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to my husband

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Summary

Since the global financial crisis, there has been renewed focus on the analysis of systemic risk. Systemic risk refers to possibility that vulnerabilities across the financial system and between the financial system and the real economy will be triggered. As a result, intermediation activities may be curtailed and a financial crisis may occur. There are a number of aspects to systemic risk and related financial stability analysis. First, imbalances and risk can accumulate in both the financial system and in the composition of economic activity during an economic upswing, due to either adverse incentives or myopia by economic agents. Second, macro-financial linkages and contagion channels between financial intermediaries not only amplify potential risk during the boom period, but also exacerbate the economic impact when the cycle turns, or if there is an adverse shock. This thesis focuses on two current issues in financial stability research for the banking sector, namely the analysis of bank funding risk during a financial crisis and the detection of unsustainable property price movements. Funding risk and asset price bubbles, particularly in the commercial real estate market played a significant role in the origins of both the Irish and the global financial crisis. Across three chapters, this thesis presents original research on these topics using Irish data as a statistical example.

Chapter one examines the determinants of weekly corporate deposit levels in Irish banks over the period March 2009 to August 2010. This sample includes the early stages of the Irish banking crisis, which began in 2008. The global financial crisis resulted in Irish banks experiencing more acute funding difficulties than institutions elsewhere. Using a unique high-frequency database and drawing on both the financial crisis and market discipline literature, the sensitivity of corporate depositors to movements in both idiosyncratic and systemic risk factors is tested. There is statistical evidence that measures of risk for the Irish banking sector such as implied ratings and credit default swap spreads can explain corporate deposit levels over the sample, validating the market discipline hypothesis. These results further provide an empirical

link between counter-party credit risk and bank funding risks. Additionally, tensions in European inter-bank markets are found to negatively impact corporate deposits indicating contagion channels between funding markets during periods of systemic stress. The empirical relationship between daily corporate and retail deposits is also examined. Although retail deposit flows move in the same direction as corporate deposits, retail deposits appear to exhibit relatively higher inertia up to August 2010. Chapter one has been re-drafted from a co-authored policy-orientated research paper with Kieran McQuinn which is available as a Central Bank of Ireland Research Technical Paper (No.2/12) entitled “Modelling the corporate deposits of Irish financial institutions: 2009-2010”.

Expanding the dataset to early-2014, chapter two models the dynamic behaviour of weekly customer deposits (i.e., both retail and corporate) held with Irish banks over the period March 2009 to end-December 2013 using an ARDL(1,1) - GARCH(1,1) framework. Over the sample, which covers the Irish systemic banking crisis, weekly customer deposit flows are found to respond to measures of banking sector and sovereign risk which is consistent with the theory of market discipline among depositors. Although the data cover resident and non-resident depositors, idiosyncratic and Irish-specific risk factors seem to have more explanatory power for deposit growth. Indicators of general stress in international financial markets are found to be statistically insignificant. Once market-based risk factors are included in the model, no direct macro-economic influence is found. Over the sample, statistical evidence of a regime shift is found, with deposits switching from a high variance regime to a low variance regime with the onset of an EU/ECB/IMF Programme of assistance for Ireland in early-December 2010. Interestingly, evidence of a GARCH-in-Mean effect indicates that the conditional variance of customer deposits negatively affects deposit growth rates over the sample. An adverse reaction to risk as proxied by the conditional volatility would be consistent with flight-to-quality theories of deposit behaviour.

Chapter three analyses price developments in the Irish commercial property market over the period 1985Q1 to 2012Q4 using time-series techniques. First, three different statistical approaches are used to test if prices can be explained by fundamental determinants such as income, interest rates and credit. Evidence of some deviations between actual and fundamental prices over the sample period is found. Second, two popular models of price misalignment from the stock price literature are used to test whether these estimated misalignments between actual prices and fundamentals (i.e.,

non-fundamental prices) suggest that there is an irrational fad or a rational bubble in Irish commercial property prices over the period under study. To distinguish between these two models, regime switching methodology is used. The study finds evidence of a number of periods where commercial property prices deviate from fundamentally determined values for a sustained period. The periods of estimated misalignment are found to be broadly consistent across the various approaches. In testing between a rational bubble and the irrational fad hypothesis, evidence of regime shifts over the sample provide some support for the presence of a bubble. However, the point estimates of expected returns in each regime are not fully in-line with the theoretical predictions of the rational bubble theory. Therefore, the results are not conclusive in favour of the rational bubble hypothesis.

List of Conferences and Presentations

Drafts of the research in this thesis were presented at the following seminars and conferences,

Chapter one

- June 2011: Internal seminar with Governor and senior management within Central Bank of Ireland.
- June 2011: End-year PhD seminar with Economics, Finance & Accounting Faculty in Maynooth University, Ireland.
- October 2011: European Central Bank Workshop on “Analytical Tools to support Systemic Risk Assessments: Stress Testing and Network Analysis” in Frankfurt, Germany.
- May 2012: Irish Economic Association Annual Conference in Dublin, Ireland.

Chapter two

- March 2015: Chief Economist’s seminar in the Central Bank of Ireland.
- May 2015: End-year PhD seminar with Economics, Finance & Accounting Faculty in Maynooth University.

Chapter three

- February 2014: End-year PhD seminar with Economics, Finance & Accounting Faculty in Maynooth University.
- May 2015: Irish Economic Association 2015 Annual Conference in Dublin.
- August 2015: European Economic Association 2015 Annual Conference in Mannheim, Germany.

Chapter 1

A High-Frequency Model of Corporate Deposits: March 2009 to August 2010

1.1 Introduction

This chapter revisits the disciplining role of the standard deposit contract in the context of the recent financial crisis. In particular, the focus is on corporate deposits and their behaviour during the initial stages of the Irish systemic banking crisis (i.e., March 2009 to December 2010). The Irish banking crisis occurred during the global financial crisis which began in 2007. Both crises were extremely costly for the affected economies. Macro-financial linkages combined with highly interconnected and complex banking systems meant that the unwinding of excesses built up prior to 2006 in a number of these economies was sharp and disorderly. Consequently, significant economic output losses were recorded and many banks required financial support and liability guarantees from national authorities. These events have reinvigorated economic research on banks and in particular, the risks inherent in their structure and their role as risk transmitters to the real economy and other parts of the financial system. This chapter focuses on bank funding risk and specifically, on deposits.

The original micro-economic models of banking show that the standard deposit contract poses a significant risk for banks (Diamond and Dybvig, 1983). In these models, banks provide an important intermediation role between savers and those who offer productive investment opportunities. Savers, however, may face uncertain

liquidity preferences in the future due to possible income shocks. The deposit contract offered by banks provides insurance against such liquidity shocks. This liquidity creation role comes at a cost, as banks cannot tie the deposit contract to savers' individual liquidity preferences so deposits are generally offered on demand or for short maturities. A bank's assets, by contrast, are generally less liquid. The ensuing mismatch between the maturity of a bank's assets and liabilities increases a bank's vulnerability to runs by depositors or other funding providers. In the Diamond-Dybvig (1983) model, bank runs by depositors are driven by self-fulfilling expectations. If depositors believe that others will run on a bank, it is optimal for all to withdraw funds due to the assumption of a sequential service constraint and an illiquid investment asset in the model. Such runs lead to costly bank liquidations. In the financial crisis literature, triggers for bank runs can be due to panic/mob psychology (Kindleberger, 1978), fears about the negative impact of an impending recession on future bank returns (Gorton, 1988 and Allen and Gale, 1998) or as a result of a deterioration in bank fundamentals (See Allen and Gale, 2007 for a full treatment of this topic).

In addition to consumption flexibility, Calomiris and Kahn (1991) show that the deposit contract provides another benefit. The first-come, first-served assumption creates an incentive for depositors to monitor the bank and if deemed risky, run on the bank. The risk of bank runs, in turn, creates an incentive for banks to maintain sound business models in normal times. Calomiris and Kahn, therefore, modify the Diamond and Dybvig (1983) representative bank framework to show that demandable bank debt can solve agency problems in banking. First, it is assumed that banks are monopolistic and the possibility of bank fraud is introduced. In certain states of the world, bank managers face the incentive to abscond with depositor funds if the realised value of their investments is less than aggregate deposit payments. Second, some depositors actively monitor the bank by investing in receiving a signal about future profitability. Depositors are more likely to run when they receive bad signals because there is a higher probability that bankers will abscond when realised returns are low. Also in the event of a run, depositors will receive payment with certainty. In good times, depositors will choose not to liquidate the bank which leads to a higher pay-off but comes with the risk that the banker will abscond. Passive depositors also gain indirectly from the disciplining effects of the active monitors. In equilibrium, profit-maximising bankers will choose contracts that maximise social gains and lead to the most efficient intermediation outcome. Demand deposits contracts are optimal in this context.

There is a significant empirical literature testing the validity of this market discipline hypothesis. Many of these studies examine the sensitivity of deposit flows or deposit rates to changes in measures of bank financial soundness. If the market discipline theory holds, there should be a negative relationship between deposit flows and bank risk. Deposit rates may increase in line with risk as banks may have to offer a premium to compensate depositors for higher levels of uncertainty about future profitability. Flannery (1998) and Berger and Turk-Ariss (2010) provide a good review of the empirical literature in this area.

This chapter investigates the key determinants of corporate deposits in Irish banks using a unique high-frequency database of deposits over the period March 2009 through December 2010. Specifically, in line with the market discipline literature, the sensitivity of depositors to movements in both idiosyncratic and systemic risk factors is tested. The focus is on corporate depositors given their potentially higher resources and incentives to invest in monitoring banks and to actively manage their investments. The role of macro-financial linkages and contagion across funding markets is also examined.

While the recent financial crisis revealed the precariously short-term sources of wholesale funding for many international financial institutions, the relatively fragile nature of Irish banks' funding structure pre-2007 was particularly evident. The Irish banking sector, which had witnessed significantly concentrated lending in the property market throughout the past decade, was funded throughout this period by increasingly short-term non-retail liabilities. Funding difficulties in late-2008, led to the introduction of a broad guarantee on certain liabilities for Irish banks by the national authorities.

Funding risks remained to the fore throughout 2009 and 2010. Investors became increasingly worried about the potential fragility of Irish banks' balance sheets as the values of Irish property continued to contract and the economy shrank. As the global crisis unfolded, risk aversion pervaded international capital markets. The emergence of the sovereign debt crisis in Europe from mid-2010 further exacerbated funding difficulties and created a self-reinforcing negative dynamic between the Irish sovereign and the domestic banking system. Consequently, over the period 2009 to mid-2010 the funding durations of Irish institutions moved to ever shorter maturities, wholesale funding costs increased and the ability of these institutions to access certain categories of funding became limited. Compounding the difficulties was the deterioration in

the state of the Irish public finances. The situation confronting the Irish system exacerbated considerably in the final quarter of 2010 as the sovereign crisis escalated. The net consequence was that the Irish financial system became substantially reliant on liquidity support from the European Central Bank (ECB) and the Irish Central Bank. Inevitably, Ireland, in November 2010, negotiated a fiscal support programme from the International Monetary Fund (IMF), the European Commission (EC) and the European Central Bank (ECB). The scale of the Irish banking crisis and the central role of funding issues, therefore, provides a useful case study to study deposit dynamics.

The model focuses on a period of relative stability identified within the time period under question. While the period in general occurs after the initiation of the Irish financial crisis in 2008, a period of relative stability is observed in the aggregate customer deposit levels in Irish banks up to August 2010. A key turning point for both the retail and corporate deposit series is found to be 20 August 2010. The levels of both series are found to exhibit a marked downward trend from this date until the end of the sample (i.e., end 2010). Therefore a model of corporate deposits is specified with the estimation sample running from March 2009 to August 2010.

The specification for corporate deposits controls for bank-specific indicators of financial soundness such as the implied credit rating for Irish banks as estimated by Kamakura, 5-year senior Credit Default Swap (CDS) spreads and aggregate funding market conditions as proxied by the 3-month Euribor/ Overnight Index Swap (OIS) spread. The results show that measures of risk for the Irish banking sector have some explanatory power for corporate deposits over our sample. Specifically, a deterioration in these risk factors has a negative influence on corporate deposits, validating the market discipline hypothesis and providing an empirical link between counter-party credit risk and bank funding risks. The CDS spread may also be controlling for changes in sovereign risk given the banking stabilisation measures undertaken by the Irish authorities during the crisis. Over the estimation period, there is a notable positive correlation between the sovereign and bank CDS spreads. Sovereign measures of risk become insignificant or have the incorrect sign, once the specification controls for banking sector risk.

Tensions in European interbank markets are also found to negatively impact corporate deposits indicating contagion channels between funding markets during periods of systemic stress. During the global financial crisis, concerns about counter-party

credit risk and higher preferences for liquidity led to a period of significant dislocation in international funding markets (Some empirical investigations of the determinants of interbank spreads are Heider, Hoerova and Holthausen (2009) and Fukuda (2012)). Corporate depositors in Irish banks appear to be influenced by such developments. This result may be due to their own liquidity needs, general risk aversion towards banks or towards Irish banks in particular.

The chapter also investigates the relative “stickiness” of retail deposits compared with corporate deposits. Our model shows that corporate deposits react to negative signals about the financial health of Irish banks and general stress in other funding markets. Of interest are possible intra-deposit dynamics and likelihood that outflows in corporate deposits are associated with retail deposit withdrawals up to August 2010. The presence of a long-run relationship between the stock of retail and corporate deposits within an error-correction framework is examined, thereby allowing the perceived “stickiness” of retail versus corporate deposits to be estimated. Although retail deposit flows are found to move in the same direction as corporate deposits using causality tests, retail deposits do not quickly adjust to deviations in the long-run relationship between the two categories. Less resources to monitor banks, switching costs and high levels of inertia may explain the relative stickiness of retail deposits over the sample.

The rest of the chapter is structured as follows. Section 1.2 introduces the deposit data while the relevant literature is discussed in Section 1.3. In Section 1.4 a model of corporate deposits is specified. A subsequent section addresses inter-deposit dynamics. A final section concludes and provides a discussion of further work.

1.2 Irish customer deposit data (February 2009 - December 2010)

This chapter draws on a Central Bank of Ireland internal dataset containing the net movement across a number of key funding sources for Irish financial institutions. Funding liabilities can be broadly decomposed into three categories namely, deposits both customer and interbank, debt securities and other secured funding such as repurchase agreements. The daily net flow is defined as the difference between the value of total funding inflows and outflows for each funding category. The full dataset covers

customer deposits¹ and debt capital markets and begins on 23 February 2009. The analysis here focuses primarily on the aggregate retail and corporate deposit books of the Irish banks. Deposit figures for Non-Bank Financial Intermediaries (NBFI) are included in the corporate category. The data are consolidated on a group basis and are available at a daily frequency. The banks covered by this dataset are those retail banks that are currently headquartered in Ireland, namely, Bank of Ireland, Allied Irish Banks plc (including Educational Building Society) and permanent tsb. The dataset also contains banks that are no longer in existence such as Anglo Irish Bank Corporation plc and Irish Nationwide Building Society. During the Irish crisis, the Irish banking sector underwent significant consolidation which reduced the number of retail banks from six to three.

To facilitate empirical analysis, the daily net flows were transformed into stocks using internal supervisory funding profile data. In particular, using the historical net flow data, the value of outstanding corporate and retail deposits as at February 2011, were adjusted to back out a time-series of outstanding amounts for both categories. These data may not, however, correspond exactly to funding profile data at various points in time given potential timing issues with underlying transactions for the net flows data (e.g., trade date versus value date etc). However, this series should capture broad trends in the underlying net flows data. The focus is on the period 23 February 2009 to 2 December 2010, as this interval covers a phase of considerable financial stress in Ireland.

Figure 1.1 plots the aggregate series of our transformed data as an index. The base for the index is end-August 2010. What is immediately observable is the sharp decline in the series from late-August 2010 to the end of the sample. As a result, for much of the analysis, the sample is separated into pre and post end-August 2010. Table 1.1 presents summary statistics for the aggregate deposit data over the total period and for the two sub-samples. The summary statistics for the corporate deposit flows show that the mean daily percentage outflow for this category exceeds that of retail deposits over all sample periods. The relatively higher standard error and min/max range also confirm the volatility of corporate deposits during the crisis. The average daily percentage outflow across both categories increased after end-August 2010. The largest daily outflow for both categories also occurs in the latter period.

There may be a number of factors explaining the decline in deposits from late-

¹Interbank deposits are not included in the dataset.

August 2010. First, the expiration of the original guarantee scheme, the Credit Institutions Financial Support (CIFS) scheme in end-September 2010 resulted in a significant proportion of the Irish banks' term debt falling due during this month². There were concerns about the scale of the Irish banks' refinancing commitments during this time. It was not clear if there was sufficient market appetite to roll this debt and re-issue under the revised guarantee scheme, the Credit Institutions Eligible Liabilities Guarantee (ELG). Furthermore, from late-Summer 2010, there was an intensification of the self-reinforcing negative dynamic between the Irish sovereign and the banking sector in the context of the initial phase of the European sovereign debt crisis. Investors were concerned about the capacity of the Irish sovereign to meet the costs of restructuring and recapitalising the banking sector. Moody's downgraded the Irish sovereign on 19 July 2010 while Standard and Poor's (S&P) cut the long-term rating on 24 August 2010. The Irish 10-year sovereign bond yields reached 6 per cent per annum for the first time on 16 August 2010 before following a general upward trend until the end of our sample. An application for external assistance by the Irish Government from the EU/IMF and the ECB followed in late-November 2010 amidst a continuing outflow of deposit levels from the Irish system. The deterioration in the measures of sovereign risk from end-August 2010 may have had implications for the perceived protection of State support by depositors in Irish banks.

1.3 Literature on deposits and bank funding risk

In specifying a model of corporate deposits, particularly over a period of some distress in market funding conditions, the market discipline literature and recent papers on bank funding risks during the global financial crisis provide a useful guide.

Given the link between solvency and liquidity, a number of studies have investigated the disciplining forces of banks' creditors. The disciplining effects of short-term or subordinated debt and deposits are the focus of such papers. As noted in the introduction, the origins of the market discipline literature can be traced to the theoretical models of Diamond and Dybvig (1983) and Calomiris and Kahn (1991). The latter paper shows that demandable debt can provide incentives for banks to reduce risk-taking behaviour due to possibility of a bank run. As banks engage in maturity transformation, the sector is particularly vulnerable to liquidity risks and bank runs. Sironi (2003) notes that there are two aspects to the bank discipline literature. The

²This guarantee was introduced by the Irish authorities in September 2008.

first relates to the ability of investors to appreciate the scale of risk taking by banks and influence this behaviour by increasing the cost (and/or reducing the availability) of funding. The second aspect investigates whether market prices contain useful information on the financial position of banks for bank supervisors. This chapter focuses on the former approach. Flannery (1998) and Berger and Turk-Ariss (2010) provide a good review of the empirical literature on this area. As we shall see in the following examples, the empirical results appear to differ by market and by bank characteristic.

Hori, Ito and Murata (2009) make use of a large panel of deposit-taking institutions in Japan over the period 1992 to 2002 to examine if depositors are able to distinguish between healthy and risky institutions. They find evidence in favour of this hypothesis during the Japanese crisis. The authors also contend that the scale of the risk sensitivities are high enough to influence bank managers. Size is found to be an important factor as the paper finds that depositors at large institutions are more sensitive to changes in bank risk than those at smaller institutions. In terms of methodology, Hori, Ito and Murata (2009) look at the impact of bank-level indicators of risk on both deposit growth and deposit interest rates while also controlling for type of financial institution (i.e., banks versus credit cooperatives) and for structural changes in the Japanese market. To overcome simultaneity problems of supply/demand equations, reduced form specifications for both deposit growth and interest rates are estimated. Fundamental variables include the capital-asset ratio and bank profitability (i.e., the ratio of operational profits to total assets).

Berger and Turk-Ariss (2010) also test for the presence of market discipline by depositors across European banks and banks in the United States (US) over the period 1997 to 2007. The paper is motivated by the discussion during the crisis on the potential adverse impact of policy measures on depositor discipline such as increasing coverage under deposit protection schemes and protecting systemically important banks. To this end, Berger and Turk-Ariss (2010) examine how deposit growth and deposit risk premia (i.e., deposit rates) respond to changes in measures of bank risk through a number of empirical applications in the period prior to the crisis. First, tests are run separately on both US and European samples as the authors contend that the perceived probability of bank bail-outs is higher in Europe. The empirical results reveal that depositor discipline is relatively higher in US, consistent with a priori expectations. The second application controls for size with a threshold of \$50 billion in total assets. The results show that depositor discipline is lower for

larger institutions, which contrasts with Hori et al., 2009. The authors also examine the impact of being listed on the stock market. Depositor discipline is found to be higher at smaller listed institutions relative to smaller unlisted banks reflecting the availability of financial information. For larger banking institutions, the authors find relatively higher discipline at unlisted institutions. Finally, the paper attempts to identify ratios to which depositors respond more rapidly. Equity ratios are found to be more important than measures of loan performance or asset quality. In terms of methodology, the paper employs three different empirical models, namely, reduced form models of both deposit growth and rates, joint determination models to capture interrelated supply and demand dynamics and finally, dynamic models which capture gradual adjustment in the context of switching costs or inertia. Bank risk-taking behaviour is proxied by the ratio of equity to assets and a measure of asset quality such as the ratio of net charge-offs, loan loss reserves or non-performing loans to total loans.

A number of papers contend that a certain definition of deposits, namely, “core” deposits are more sticky than other forms of deposits and may be rate inelastic. The definition of core deposits varies across the literature. Feldman and Schmidt (2001) define core deposits as checking/savings accounts, money market deposits and time deposits, while Berlin and Mester (1999) measure core deposits as those with a value less than \$100,000.³ Song and Thakor (2007) use the provision of liquidity and advisory services as the defining factor for core deposits. They exclude brokered certificates of deposit, large time deposits and any other deposits where no services are provided from the definition and instead label this category as “purchased money”. The presence of deposit insurance and potential switching costs are posited as reasons for higher levels of inertia on these types of deposit. This literature provides some rationale for the belief that certain categories of customer deposits should be relatively stable in normal times. The presence of deposit insurance, however, may also reduce the incentives for depositors to monitor banks. In the market discipline literature some authors distinguish between insured and uninsured deposits to test this hypothesis.

Looking specifically at the United States, Goldberg and Hudgins (1996) investigate the existence of depositor discipline during the Savings and Loan (S&L) crisis. These authors find evidence that there was a decrease in the share of uninsured deposits in total deposits in those Savings and Loan Associations with a higher likelihood

³In an alternative specification, small value time deposits are also excluded from the definition.

of failure over the period 1984 to 1989. In terms of methodology, the paper first estimates a logistic model for the probability of default which is, in turn, nested in a model of uninsured deposits.

Another US study by Hannen and Hanweck (1988) tests for the presence of market discipline in the market for large (i.e., over \$100,000) uninsured certificates of deposits (CD). This paper focuses on interest rate spreads (over the risk free rates) on various CD maturities in 1985 and estimates the sensitivity of these spreads to insolvency risk. The authors find that indicators of bank risk such as the standard deviation of return on assets, measures of the probability of insolvency and the capital/asset ratio all impact rates on jumbo CDs consistent with the market discipline hypothesis.

Prior to the crisis, increasing reliance on short-terms sources of wholesale funding became a feature of the commercial banking industry in certain markets. The recent crisis showed that certain categories of banks' funding did not yield the associated diversification benefits during market dislocation. This feature was particularly evident in global money and credit markets. Therefore many papers have emerged since the crisis began on the risks associated with wholesale funding. It is likely that some large corporate depositors may act like wholesale funding providers for a number of reasons.

First, they are more likely to have higher resources than retail depositors and so be in a better position to actively manage their investments. They may, therefore, react to similar signals monitored by debt holders and other financial intermediaries about the financial health of individual banks or about the sector as a whole. Observed tensions in international funding markets may signal to corporates that certain banks are a risky investment, especially if these banks are reliant on these funding markets. Such reactions can create indirect contagion channels across funding markets. The deposit run on the mortgage lender Northern Rock in the United Kingdom (UK) in September 2007 shows the sequencing of modern bank runs and is discussed in Shin (2009). Shin highlights that withdrawals by wholesale and large informed depositors preceded the eventual run by retail depositors. Second, institutional investors may have investment thresholds such as the level of CDS spreads or a certain credit rating that cannot be surpassed for regulatory or internal risk management reasons. Consequently as soon as these limits are breached, such investors will withdraw their funds. Given the potential similarities between corporate deposits and short-term wholesale

funding, it is useful to review the literature on the latter to help specify a model of corporate deposits.

A recent paper by Huang and Ratnovski (2010) provides theoretical proof that under certain circumstances wholesale funding can be destabilising to financial stability. To extend the Calomiris and Kahn (1991) model (CK), Huang and Ratnovski (2010) introduce a costless but noisy public signal into the CK theoretical framework. This extension shows the potentially negative effects of wholesale funding on financial stability in addition to the positive first order effects of market discipline in the CK model. The actions of wholesale financiers are shown to be socially optimal only when fully informed. Specifically, the presence of this signal serves to reduce the incentives of wholesale investors to monitor the bank. Further, when wholesale investors have a senior claim to the liquidated assets, it is shown that these financiers have higher incentives to liquidate the bank (i.e., refuse to roll over funding) based on noisy public information. As a result, such investors pose a refinancing risk and contribute to inefficient bank runs if the information is not accurate. It is assumed that retail investors are passive and risk insensitive in the model possibly due to deposit insurance and are not aware of the noisy signal. The authors draw the conclusion that these negative externalities are more applicable to banks that have a large exposure to tradable assets with freely available public information such as credit ratings and prices. The results therefore apply to highly correlated financial systems with readily available but noisy market-based indicators of risk. Huang and Ratnovski (2010) contend that this analysis is more applicable to the current business models of banks than the CK framework as the crisis revealed the volatility of short-term wholesale funding.

Using a theoretical framework, Acharya, Gale and Yorulmazer (2010) describe how financial institutions can experience an inability to roll short-term funding in the presence of only a small change in the value of collateral underpinning this debt and without other distortions such as asymmetric information. Such events can occur if the roll-over frequency of debt is higher than the arrival of news and when all potential buyers of this debt have a short-term investment strategy. In this instance, the recoverable value of debt may fall below its fundamental value and even high-quality collateral will not be traded. Such market freezes were observed in the asset-backed securities market and in money markets during the recent global financial crisis. Given the significant dislocation in the latter market during the crisis, a number of papers have investigated empirically the roles of credit risk and liquidity risk on interbank

spreads during this time. Some examples are Heider, Hoerova and Holthausen (2009) and Fukuda (2012).

There has also been a growth in the literature addressing the different types of liquidity risk during a crisis. Liquidity risk can broadly be divided into two categories, namely, market liquidity risk and funding liquidity risk. There are a few definitions of both categories in the literature. Some examples are Brunnermeier and Pederson (2009), Tirole (2011) and Borio (2010). As noted in Tirole (2011), market liquidity can broadly be considered as pertaining to the asset side of a bank's balance sheet while funding liquidity relates to the liability side although both categories may be correlated, particularly in a crisis. Brunnermeier and Pedersen (2009) provide a theoretical link between the market liquidity of an asset and the liquidity funding risk faced by traders in this asset during a period of financial turmoil. Drehman and Nikolaou (2013) use a proxy for funding liquidity risks faced by banks (i.e., based on bidding behaviour at ECB open market operations) and empirically test the theoretical relationship between market and funding liquidity over the period 2005 to 2007. The authors find that a significant and negative relationship emerges between the two categories from 2007. This finding is in accordance with the theory as the relationship is only significant when banks experience constrained funding patterns in the context of declining asset prices and low levels of market liquidity. Borio (2010) contends that underpinning the development of most liquidity crises is a self-reinforcing dynamic between market liquidity risk, funding liquidity risk and counter-party credit risk. In an expansionary period, this dynamic can lead to highly-leveraged balance sheets and in this context can lead to a sudden evaporation in liquidity during a period of aggregate financial stress.

The link between liquidity issues and the real economy is explored in Shin (2010). This book entitled "Risk and Liquidity" deals with the endogeneity of financial risk and how the under-pricing of this risk played a key role in the global financial crisis. Specifically, the author looks at the emergence of systemic risk and the role played by leverage and liquidity risk in the propagation of the global crisis. Prior to the crisis, Shin contends the financial system became increasingly interconnected with the emergence of long intermediation chains between end-borrowers and original lenders. Shin then characterises a crisis as a situation where highly leveraged and constrained participants significantly reduce their exposures in response to a decline in prices, increase in measured risk or a decline in correlations, thereby leading to fur-

ther decreases in prices (i.e., so called “liquidity black holes”)⁴. Consequently there is widespread deleveraging across the system and credit supply to the real economy is curtailed.

The above papers on funding risks during the global financial crisis highlight the inherent fragility of bank funding during periods of severe financial stress. The flows of bank funding can be sensitive to general investor sentiment and the financial position of funding providers in addition to the credit-worthiness of the deposit-taking bank. Therefore any model of deposits needs to consider the impact of both macro-financial conditions and bank financial soundness indicators.

1.4 Specification of corporate deposit model

In specifying a model for Irish corporate deposits a number of possible explanatory variables are identified. Borrowing from the market discipline literature and conjunctural analysis of events in 2009/2010, these variables should reflect idiosyncratic/bank risk or aggregate risk developments. Given the high frequency nature of the deposit data, the focus is mainly on market-based indicators. Therefore, the sample is restricted to Irish banks listed over the full period under study (i.e., late-February 2009 to early-December 2010), namely, Allied Irish Banks, Bank of Ireland and Irish Life & Permanent plc.⁵ To minimise the presence of noise in daily observations, weekly data are used for the estimation of the model.⁶ The estimation sample is shortened to the period prior to 20 August 2010, as a clear turning point emerges subsequent to this date in terms of the movements of corporate deposits in the Irish financial system (see Section 1.2). Consequently, there are 74 observations in the sample covering the period from the week beginning 2 March 2009 through to 20 August 2010. The following possible explanatory variables are identified,

- 3-month Euribor/OIS spread,
- Implied credit rating,
- Credit default swap (CDS) spreads.

⁴Additionally, it is contended that marketable assets (i.e., through mark-to-market accounting and securitisation) played a key role in the financial crisis by amplifying the feedback mechanism between agents and their environment.

⁵Anglo Irish Bank was delisted in January 2009 following nationalisation and so is excluded from the sample.

⁶Daily data were converted to weekly averages using the RATS software programme.

The 3-month Euribor/OIS spread is commonly used as a measure of tension in the euro money markets. As is common practice the spread is measured in basis points. This variable is included as a measure of general funding risk to which investors or corporate deposit holders may react. A negative relationship is expected.

The implied credit rating variable is estimated by Kamakura Risk Information Services (KRIS) and provides a quantitative measure of financial soundness. The implied credit rating model by Kamakura is based on firm-specific attributes, the term structure of default probabilities for the firm as estimated by Kamakura, industry classifications, macroeconomic factors and the historical behaviour of ratings agencies (KRIS, 2011). Based on all of these factors a measure of a likely credit rating, conditional on having a rating, is estimated for the public firm. Credit ratings data from Standard and Poor's are used by Kamakura. The credit rating variable is added to the model using a linear scale where 1 corresponds to the highest rating, AAA and 21 to the lowest, D. Therefore, an increase in this variable is expected to lead to a decrease in corporate deposits. Implied ratings were available for all three listed banks over the estimation period. However, it was decided to go with AIB given the results of Granger causality tests,⁷ which suggested its leading role within the industry.

The median 5-year senior CDS spread in basis points for the three listed Irish banks in the sample is used as a measure of perceived credit worthiness. CDS spreads are not used by Kamakura in the implied rating model. A negative relationship is also expected with corporate deposits if the market discipline hypothesis holds.

1.4.1 Estimation and results

The model is estimated in an error correction framework using the Engle-Granger (1987) two-step methodology. This model allows us to control for both long- and short-run dynamics. All four series in log format are first tested for the presence of a unit root. In log levels all series are found to be non-stationary.⁸ The series were subsequently transformed into first differences and the unit root tests were performed on the growth rates of the variables.

The three unit root tests carried out are the ADF-GLS test by Elliot *et al.* (1996), with the lag length chosen on the basis of the modified AIC suggested by Ng and

⁷To perform Granger causality tests, a VAR is estimated using only the daily deposit flows of the covered institutions. Following standard lag length tests, the final application has a lag of 5 days and the estimation is conducted over the period February 2009 to August 2010.

⁸Results are not presented in the interests of brevity but are available upon request.

Perron (2001), the classical Dickey-Fuller (1981) and the Philips-Perron (1988) tests. To ensure robustness, a range of lag lengths were chosen for the latter two tests. The results are presented in Table 1.2. Although the ADF-GLS test only rejects the null hypothesis of a unit root for the differenced CDS spreads, both the Dickey-Fuller and the Philips-Peron tests suggest that all differenced variables are stationary at 4 lags⁹. Therefore, it is assumed that all transformed variables are integrated of order zero.

A number of tests for the presence of a cointegrating vector were conducted on the residuals of the long-run equation. In addition to the ADF-GLS test, the Engle-Granger (1987) test and the cointegrating regression Durbin-Watson (CRDW) test by Sargan and Bhargava (1983) are applied. Critical values for both tests are from MacKinnon (1991) and Banerjee *et al.* (1993). The lag length for the Augmented Engle-Granger test was chosen on the basis of standard selection criteria (e.g., AIC, SBC). The tests were minimised at lag length of one. Both of these tests reject the null of a unit root. The ADF-GLS test, however, suggests that the residuals are not stationary. Drawing on the evidence for cointegration, the following long-run model is estimated

$$c_t = \beta_0 + \beta_1 spread_t + \beta_2 aibirat_t + \beta_3 medcds_t + \epsilon_t \quad (1.1)$$

where $spread_t$ refers to the spread between 3-month Euribor and the euro 3-month overnight indexed swap (OIS) rate, $aibirat$ refers to the implied credit rating of Allied Irish Banks plc (AIB) as estimated by Kamakura and $medcds$ represents the median CDS spread.

Table 1.3 presents the results while Figure 1.2 compares the actual and fitted log corporate deposits along with the residuals. All explanatory variables are found to have the expected negative relationship with our dependent variable. As the variables are in log format, the long-run elasticities show that the the implied credit rating exerts the highest influence among the explanatory variables. As mentioned previously, this variable is itself estimated from a reduced form model which controls for other indicators of financial fragility such as default probabilities as well as the historical behaviour of the credit rating agency S&P and, therefore, may provide an early indication of future ratings actions. An increase in this rating implies that the fundamentals of the bank have deteriorated and may be downgraded (if the rating differs

⁹In the case of the Augmented Dickey-Fuller test, the number of lags refers to the number of additional lags in the autoregression (Estima, 2012).

from the actual) if S&P assigned a rating based on default probabilities and applied a similar rating approach as it had used over the period 1990 to 2008 (KRIS, 2011). The negative relationship clearly shows that corporate deposit holders can exert market discipline by withdrawing funds when the financial condition of deposit-taking banks weakens. Also corporates appear to be sensitive to our indicator of credit risk, namely the median CDS premia across our listed banks. The model, therefore, shows that there is a link between counter-party credit risk and liquidity funding risk. Additionally, the importance of conditions in the inter-bank market (Euribor/OIS spread) in the model indicate that funding markets are not segmented and that tensions in one market can spill-over into other funding categories.

Diagnostic tests of the long-run residuals reveal some evidence of serial correlation. To control for this, fully-modified ordinary least squares (FM-OLS)¹⁰ is used. All variables remain significant and have the hypothesised sign (Table 1.3).

Corporate deposits were covered by an Irish Government guarantee during the period under study and therefore could be considered as “core” deposits based on the literature. During a financial crisis, however, the solvency of the insurer is also likely to play a role. The European sovereign crisis emerged in May 2010 with concerns about the fiscal sustainability of Greece. By late-Summer market concerns spread to other peripheral countries such as Ireland. International investors were worried about the capacity of peripheral European states to meet fiscal obligations. Attention in international markets began to focus on Ireland given the scale of the banking stabilisation measures being undertaken by the Government at that time and the strains emerging in the Irish public finances. The policy response to the crisis created a link between the sovereign and the Irish banks. Such measures began in September 2008 with the introduction of the Government guarantee on banks’ liabilities and also included recapitalisations, nationalisations and the establishment of a “bad bank” (National Asset Management Agency-NAMA) over the course of 2009 and 2010. See the Office of the Comptroller and Auditor General (2011) for more details on the banking stabilisation measures. Some details on the various international guarantee schemes introduced in 2008 and deposit insurance schemes are discussed in Schich (2008).

¹⁰According to Enders (2010, pg. 426-427), inference may be inappropriate if there is evidence of serial correlation in the errors of the cointegrating vector. Endogeneity may also be an issue. In this instance, the procedure of Phillips and Hansen (1990) may be used instead. This procedure adds leads and lags of changes in the explanatory variables to the regression and adjusts the t statistics from the original equation using a modified version of the variance of the error term from the expanded equation.

Sovereign variables (e.g., bond spreads, CDS spreads) were found to be insignificant or had the wrong sign over the sample period once bank specific risk had been controlled for (Table 1.4). The variable on Irish banks' CDS spreads for the banks may be picking up some of the sovereign issues given the aforementioned links between the sovereign and the banks. Figure 1.3 shows the high levels of positive correlation between the sovereign CDS spreads and median CDS spreads for the Irish banks between end-February 2009 and-August 2010. Therefore although we cannot disentangle the impact of sovereign and bank-specific risk in this specification, it is likely that both factors may be influencing deposits over our sample.

The results of the static OLS are included in the short-run model. Specifically, the lagged residuals from the long run model are incorporated into the following short-run model.

$$\begin{aligned} \Delta c_t = & \lambda (c_{t-1} - \beta_0 - \beta_1 spread_{t-1} - \beta_2 aibirat_{t-1} - \beta_3 medcds_{t-1}) \\ & + \sum_{i=0}^p \delta_i \Delta spread_{t-i} + \sum_{i=0}^p \phi_i \Delta aibirat_{t-i} + \sum_{i=0}^p \eta_i \Delta medcds_{t-i} + u_t \end{aligned} \quad (1.2)$$

Both the current value and the first lag of each of the differenced log implied rating, the differenced log median CDS spread and the differenced log Euribor/OIS spread are included as possible explanatory variables. Therefore p equals 1.

The results are contained in Table 1.5. Only the error correction term was found to have explanatory power for deposit changes so the insignificant variables are excluded from the final short-run specification (Table 1.6). The error correction term is found to be highly significant and negative. The equation is balanced due to the presence of cointegration between the variables in levels and the fact that the short-run variables are integrated of order zero. The estimated coefficients suggest that if there is a deviation between the actual and the long-run level of corporate deposits, 36 per cent of this gap will be closed in a week. This results suggests quite a fast adjustment by corporate deposits to any deviations from long-run levels over our sample period. The other short-run explanatory variables turn out to be statistically insignificant. Figure 1.4 shows the actual and fitted values of the short-run model and the corresponding residuals.

A number of standard diagnostic tests on the model are also conducted and the results are contained in Table 1.7. The correlogram of the short-run residuals indi-

cate stationarity; a finding further confirmed by the Ljung-Box (1978) Q test. The Breusch-Godfrey (1978) Lagrange Multiplier Test confirms the absence of serial correlation. White's (1980) test also does not reject the null of homoskedasticity and we find no evidence of ARCH effects in the residuals. The Jarque-Bera (1987) test also does not reject that the residuals are normally distributed.

It is possible that there may be some structural change within the estimation period. To ensure the robustness of our error correction term, the stability of the coefficient using recursive estimation of the short-run model is examined. The initial estimation period for the exercise is limited to between 23 February 2009 to 28 February 2010 being mindful of sample length (i.e., 52 observations). The end-date is extended sequentially up to the end of the full estimation sample. Figure 1.5 plots the value of each estimated coefficient and the corresponding estimated ± 2 standard deviation band or confidence interval. The coefficient appears relatively stable and statistically significant.

1.4.2 Out-of-sample performance

In the above estimation, the model is run on weekly data over the period early-March 2009 to mid-August 2010. The short-run model is also simulated beyond the end-date to see if it could have predicted the declining trend after late-August. Actual values for the explanatory variables are used in the exercise. The simulation period is up to late-October 2010. Figure 1.6 compares the estimation results of the short-run model and the actual weekly percentage changes of corporate deposits. The model clearly fails to predict the dislocated period in Q4. The significant difference between the two series indicates that other factors are driving the corporate deposits during this time. The intensification of sovereign risk concerns may be one such factor. Although the various measures of sovereign risk were not found to be significant in the initial estimation process, it may be possible that the relationship intensifies post-August 2010.

1.5 Examining inter-deposit dynamics

During the financial crisis, it has been observed how corporate deposit figures have been much more volatile than those of retail deposits. This is driven, in part, by the profile of the investor base as large corporate depositors may be more sensitive

to negative news or developments in financial markets. The model shows that corporate deposits react to negative signals about the financial health of Irish banks and general stress in other funding markets. Moreover, institutional investors may have investment thresholds such as the level of CDS spreads or a certain credit rating that cannot be surpassed for regulatory reasons. Internal risk management thresholds such as limits to sovereigns or certain sectors may also dictate the investment practices of corporates or non-bank financial intermediaries. Some papers have, however, contended that retail depositors will also run on banks during financial crises and can distinguish between healthy and weak banks (see Section 1.3). Further, we saw in Section 1.2 that retail deposit outflows from Irish banks were also recorded after August 2010. Focusing on the period of relative stability up to August 2010, possible intra-deposit dynamics are examined and the likelihood that outflows in corporate deposits are associated with retail deposit withdrawals is tested.

While corporate flows tend to be more volatile in nature for a variety of institutional reasons, there is also likely to be a long-term relationship between the stock of corporate and retail deposits held by financial institutions. The possibility of such a relationship is explored within a Vector autoregression (VAR) framework by initially running standard Granger-Causality tests for both the growth rate and levels of corporate and retail deposits. The results from the VAR are in Table 1.8.¹¹ For both the levels and growth rates of the flows, there would appear to be strong evidence of corporate flows Granger causing retail movements.

Accordingly, a two-equation system for corporate and retail flows is specified. Based on the VAR results, the error correction term for corporate flows regressed on retail flows is included in both equations. In each case, a general-to-specific approach is used, removing any variables in the dynamic specification which are not significant. This results in the following system being estimated.

$$\Delta r_t = \lambda_r (r_{t-1} - \alpha_0 - \alpha_1 c_{t-1}) + \gamma_1 \Delta r_{t-3} + \gamma_2 \Delta r_{t-5} + \gamma_3 \Delta c_{t-2} + \gamma_4 \Delta c_{t-8} + u_t$$

$$\Delta c_t = \lambda_c (r_{t-1} - \alpha_0 - \alpha_1 c_{t-1}) + \gamma_5 \Delta c_{t-1} + \zeta_t. \quad (1.3)$$

Coefficient estimates are presented in Table 1.9. Note that with this empirical approach both long-run and short-run coefficients are estimated simultaneously. Of

¹¹The lag length of the VAR are determined using standard AIC and SBC criteria.

particular interest is the coefficient on the error correction term in the retail flows regression - λ_r as this captures the speed of adjustment between the actual and the long-run level of retail deposits and, therefore, can be interpreted as an estimate of the stickiness of retail deposit flows. From the estimates, it is clear that λ_r is quite small. It suggests that if there is a deviation between the actual and the long run level of retail deposits, only 5 per cent of this deviation would be closed on a daily basis.

1.6 Conclusions

Availing of a relatively unique high-frequency database on customer deposit flows within the Central Bank of Ireland, this chapter specifies a model of weekly corporate deposit flows. This model is estimated over a period between March 2009 and August 2010 when funding conditions were relatively stable. Drawing on the market discipline literature, deposits are related to measures of bank risk, thereby linking credit risk and liquidity funding risk. The empirical results show that corporate depositors are sensitive to measures of banking sector risk, validating the market discipline hypothesis for the Irish market during the initial phases of the Irish banking crisis. Contagion across different categories of funding markets is also found, as tensions in the interbank market have explanatory power for corporate deposits during our sample period.

The empirical relationship between daily corporate and retail flows over the same period is also examined to investigate if corporate outflows are associated with retail outflows. Although retail deposit flows are found to move in the same direction as corporate deposits, retail deposits appear to exhibit relatively higher inertia up to August 2010.

While the analysis is confined to the Irish market, it is clear that the results will be of interest to financial institutions in an international context. While the recent financial crisis may have had particularly severe implications for the Irish banking sector, it is clear that common trends are now apparent in the underlying vulnerabilities, particularly, across European financial institutions. Further, the analysis shows that any deterioration in the financial soundness of a deposit-taking entity will have implications for its deposit-gathering capacity and ability to retain existing funds, especially in the corporate market. This will be an important consideration for many European banks seeking to re-orientate their funding structures towards a

higher reliance on customer deposits and other stable sources of funding in line with new liquidity requirements under Basel III.

Given that the international banking system continues to face a period of uncertainty in the post-crisis period, it is evident that much more analysis and understanding is required of these sources of institutional funding. While the results presented here are of general interest, clearly there are a number of fruitful avenues for future research. These include extending the analysis to incorporate the period after August 2010 and examining the underlying volatility of these deposits.

1.7 Figures and tables

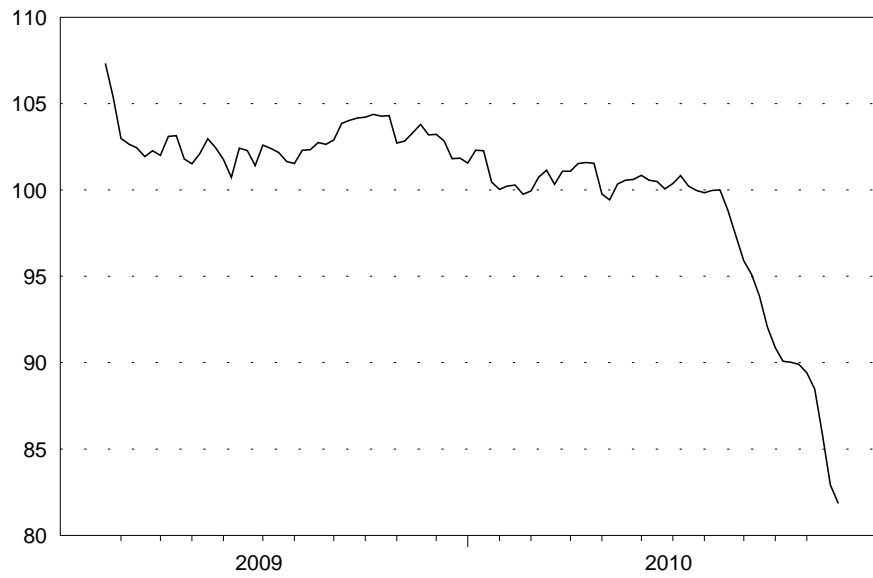


Figure 1.1: Index of weekly customer deposits: 23 February 2009 to 6 December 2010. Index = 100 in August 2010

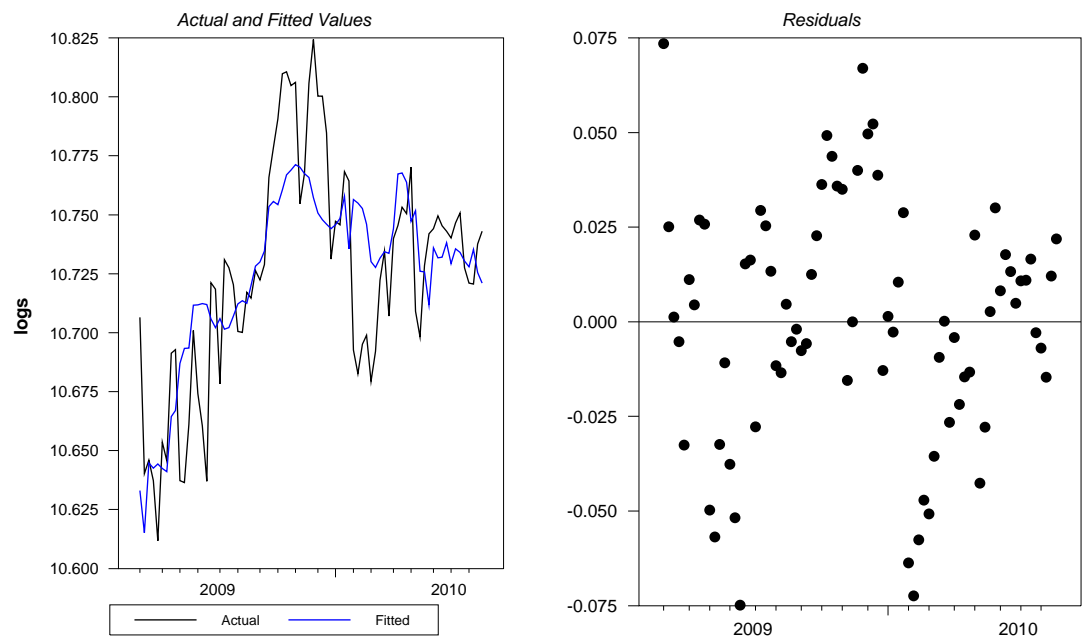
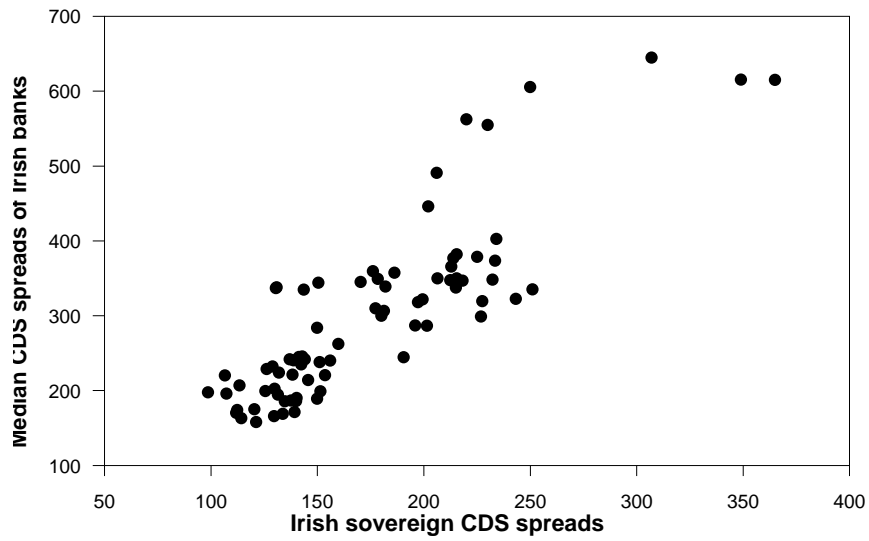


Figure 1.2: Long-run corporate deposit model: March 2009 to August 2010



Note: Data are weekly and expressed in basis points.

Figure 1.3: Irish bank CDS spreads versus Irish sovereign CDS spreads: February 2009 to August 2010

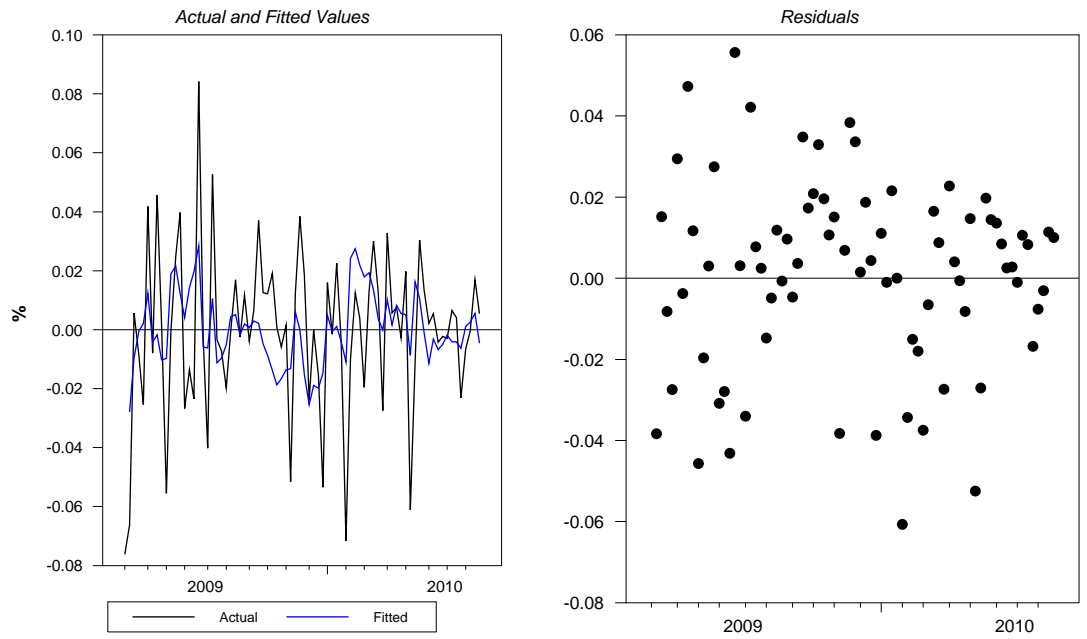


Figure 1.4: Short-run corporate deposit model: March 2009 to August 2010

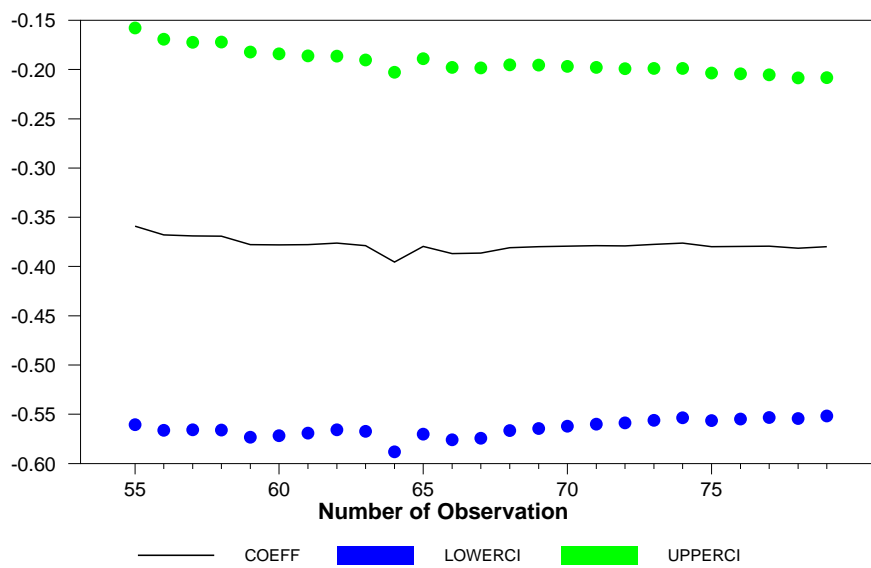


Figure 1.5: Recursive estimation of ECM coefficient λ

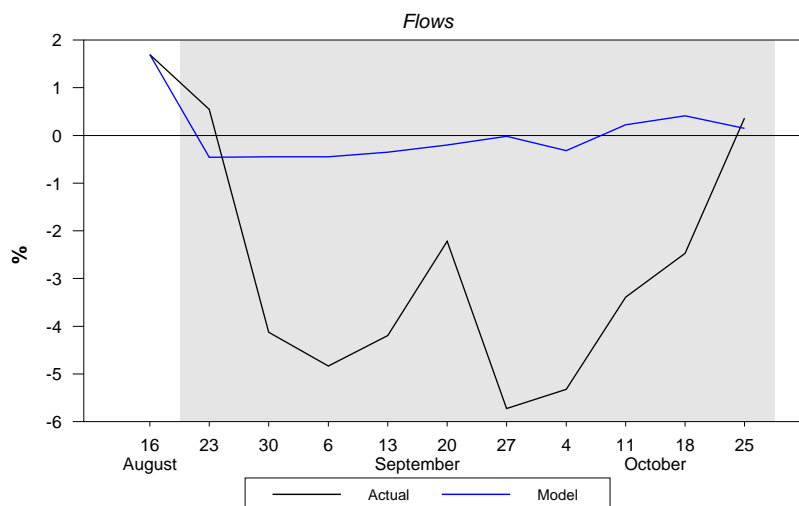


Figure 1.6: Performance of corporate deposit model: 16 August 2010 to 20 October 2010

Table 1.1: Summary statistics of daily percentage changes in customer deposits in Irish banks: 23 February 2009 to 2 December 2010:

Flows Category	Obs	Mean	Std Error	Minimum	Maximum
Sample: 23/02/2009 - 02/12/2010					
Total	452	-0.06	0.48	-1.85	1.90
Corporate	452	-0.16	1.56	-6.84	6.05
Retail	452	-0.02	0.15	-0.64	0.45
Sample: 23/02/2009 - 20/08/2010					
Total	378	-0.02	0.49	-1.85	1.90
Corporate	378	-0.04	1.55	-5.84	6.05
Retail	378	0.00	0.14	-0.48	0.32
Sample: 20/08/2010 - 02/12/2010					
Total	75	-0.27	0.40	-1.82	0.61
Corporate	75	-0.78	1.45	-6.84	2.38
Retail	75	-0.10	0.18	-0.64	0.45

Note: Sample covers Irish headquartered banks that were active over the period.

Table 1.2: Tests for unit roots and cointegrating relationships

Variable	Dickey-Fuller			Philips-Perron		ADF-GLS
	0 lag	4 lag	8 lag	0 lag	4 lag	Ng-Perron lag length
Δc_t	-9.06 ++	-5.31 ++	-2.32	-9.06 ++	-9.76 ++	-1.67
$\Delta spread_t$	-7.06 ++	-3.08 ++	-2.51	-7.06 ++	-7.15 ++	-1.76
Δcds_t	-5.67 ++	-2.71 +	-3.14 +	-5.67 ++	-5.66 ++	-3.74 ++
$\Delta aibirat_t$	-12.08 ++	-4.94 ++	-4.10 ++	-12.08 ++	-13.18 ++	-1.73
Test	Cointegration tests on long-run residuals					
Engle-Granger	-4.64 ++					
CRDW	0.69 ++					
ADF-GLS	-2.51					

Note: ++ denotes rejection at 5% and + at 10%. The first part of the table tests for the presence of a unit root. In the case of the Dickey-Fuller test, the number of lags refers to the number of additional lags in the autoregression for the Augmented Dickey-Fuller test (Estima, 2012). c refers to corporate deposits, $spread$ refers to the 3-month Euribor/OIS spread, $aibirat$ refers to the implied rating for AIB as estimated by Kamakura, $medcds$ refers to the median 5-year senior CDS spreads for Irish listed banks. The variables are first differenced logs. The second part of the table tests for cointegration among the four variables, all in log levels using residuals from the following equation

$$c_t = \beta_0 + \beta_1 spread_t + \beta_2 aibirat_t + \beta_3 medcds_t + \epsilon_t$$

Table 1.3: Long-run model of corporate deposits: 2 March 2009 to 23 August 2010

<i>Dependent variable: c_t</i>		
	OLS	FM-OLS
<i>Constant</i>	11.61 (64.92)	11.84 (55.52)
<i>spread_t</i>	-0.06 (-3.48)	-0.06 (-3.20)
<i>aibirat_t</i>	-0.18 (-2.55)	-0.26 (-3.14)
<i>medcds_t</i>	-0.04 (-2.46)	-0.04 (-2.07)

Note: T-statistics are in parentheses. FM-OLS refers to Fully Modified OLS and is due to Philips and Hansen (1990). All variables are in log format and data are weekly frequency. c is corporate deposits, $spread$ refers to the 3-month Euribor/OIS spread, $aibirat$ refers to the implied rating for AIB as estimated by Kamakura, $medcds$ refers to the median 5-year senior CDS spreads for Irish listed banks.

Table 1.4: Controlling for sovereign variables in long-run model of corporate deposits: 2 March 2009 to 23 August 2010

<i>Dependent variable: c_t</i>			
	1	2	3
<i>Constant</i>	11.517 (61.95)	11.097 (153.77)	11.087 (128.56)
<i>spread_t</i>	-0.051 (-3.10)	-0.086 (-6.34)	-0.090 (-7.78)
<i>aibirat_t</i>	-0.157 (-2.27)		
<i>medcds_t</i>	-0.076 (-2.84)		
<i>iecds_t</i>	0.042 (1.65)	-0.011 (-0.65)	
<i>iebundspread_t</i>			-0.007 (-0.38)

Note: T-statistics are in parentheses. All variables are in log format and data are weekly frequency. c is corporate deposits, $spread$ refers to the 3-month Euribor/OIS spread, $aibirat$ refers to the implied rating for AIB as estimated by Kamakura, $medcds$ refers to the median 5-year senior CDS spreads for Irish listed banks. $iecds$ refers to the Irish sovereign 5-year CDS spreads while $iebundspread$ refers to the difference between yield on Irish 10-year sovereign bonds and German 10-year sovereign bonds.

Table 1.5: Long- and short-run model of corporate deposits: 2 March 2009 to 23 August 2010

<i>Dependent variable: c_t</i>	
<i>Constant</i>	11.61 (64.92)
<i>spread_t</i>	-0.06 (-3.48)
<i>aibirat_t</i>	-0.18 (-2.55)
<i>medcds_t</i>	-0.04 (-2.46)
<i>Dependent variable: Δc_t</i>	
<i>ecm_{t-1}</i>	-0.34 (-3.99)
Δ <i>aibirat_t</i>	0.02 (0.29)
Δ <i>aibirat_{t-1}</i>	-0.02 (-0.37)
Δ <i>spread_t</i>	-0.05 (-0.98)
Δ <i>spread_{t-1}</i>	-0.00 (-0.00)
Δ <i>medcds_t</i>	-0.02 (-0.51)
Δ <i>medcds_{t-1}</i>	-0.03 (-0.76)
R²	0.17

Note: T-stats are in parentheses. Data are weekly frequency and the Engle-Granger (1987) two-step approach to error correction modelling is used. c is corporate deposits, $spread$ refers to the 3-month Euribor/OIS spread, $aibirat$ refers to the implied rating for AIB as estimated by Kamakura, $medcds$ refers to the median 5-year senior CDS spreads for Irish listed banks. All variables in the long-run model are in log format, while the short-run model is in first differences. ecm is the error correction term, λ . The table shows the estimation results from the following equation,

$$\Delta c_t = \lambda (c_{t-1} - \beta_0 - \beta_1 spread_{t-1} - \beta_2 aibirat_{t-1} - \beta_3 medcds_{t-1}) + \sum_{i=0}^p \delta_i \Delta spread_{t-i} + \sum_{i=0}^p \phi_i \Delta aibirat_{t-i} + \sum_{i=0}^p \eta_i \Delta medcds_{t-i} + u_t$$

Table 1.6: Long- and short-run model of corporate deposits: 2 March 2009 to 23 August 2010

<i>Dependent variable: c_t</i>	
<i>Constant</i>	11.61 (64.92)
<i>spread_t</i>	-0.06 (-3.48)
<i>aibirat_t</i>	-0.18 (-2.55)
<i>medcds_t</i>	-0.04 (-2.46)
<i>Dependent variable: Δc_t</i>	
<i>ecm_{t-1}</i>	-0.36 (-4.27)
R ²	0.19

Note: T-stats are in parentheses. Data are weekly frequency and the Engle-Granger(1987) two-step approach to error correction modelling is used. c is corporate deposits, $spread$ refers to the 3-month Euribor/OIS spread, $aibirat$ refers to the implied rating for AIB as estimated by Kamakura, $medcds$ refers to the median 5-year senior CDS spreads for Irish listed banks. All variables in the long-run model are in log format, while the short-run model is in first differences. ecm is the error correction term, λ . Statistically insignificant terms have been dropped from the short-run specification.

Table 1.7: Diagnostic tests on the residuals of short-run model of corporate deposits

	Statistic	Sig. Level
Ljung-Box Q (1978) Ho: No Autocorrelation		
Q(2)	1.93	0.38
Q(4)	2.76	0.60
Q(6)	4.54	0.60
Q(8)	5.29	0.73
Q(10)	7.13	0.71
Q(20)	25.01	0.20
White (1980) Ho: Homoscedasticity		
	4.12	0.99
Engle (1982) Ho: No ARCH effects		
ARCH(4)	0.31	0.99
Jarque-Berra (1987) test for normality		
	3.21	0.20

Table 1.8: F-tests from VAR model of retail and corporate flows

F Stat Significance				
	Δc_t	Δr_t	c_t	r_t
Δc_t	3.414 (0.00)	3.059 (0.00)		
Δr_t	1.023 (0.41)	6.018 (0.00)		
c_t			214.66 (0.00)	3.92 (0.00)
r_t			0.626 (0.71)	457.29 (0.00)

Note: P-values are in parentheses. Results of multivariate Granger-Causality Tests on a VAR(2) with weekly data are shown.

Table 1.9: Long- and short-run retail and corporate deposit model results: 23 February 2009 to 20 August 2010

Coefficient	Estimate	T-Stat
α_0	10.33	29.83
α_1	0.142	4.55
λ_r	-0.048	-3.08
λ_c	0.539	2.92
γ_1	-0.186	-3.86
γ_2	0.168	3.58
γ_3	0.010	2.36
γ_4	0.010	2.41
γ_5	-0.147	-2.87

Note: T-stats are in parentheses. Both retail and corporate equations estimated simultaneously using a VECM and non-linear OLS with the following equations;

$$\Delta r_t = \lambda_r (r_{t-1} - \alpha_0 - \alpha_1 c_{t-1}) + \gamma_1 \Delta r_{t-3} + \gamma_2 \Delta r_{t-5} + \gamma_3 \Delta c_{t-2} + \gamma_4 \Delta c_{t-8} + u_t$$

$$\Delta c_t = \lambda_c (r_{t-1} - \alpha_0 - \alpha_1 c_{t-1}) + \gamma_5 \Delta c_{t-1} + \zeta_t$$

Chapter 2

Investigating the Time-Varying Volatility of Irish Banks'

Customer Deposits: March 2009 to December 2013

2.1 Introduction

Since the global financial crisis, there is widespread recognition that reliance on wholesale funding and excessive maturity mismatch are not optimal. Liquidity regulation under Basel III focuses on need for “stable” and long-term sources of funding to match banks’ long-term assets. Customer deposits are generally considered less risky than wholesale funding. Therefore, banks have competed aggressively for deposits to meet future regulatory standards and to try to replace market funding. For banks that ran into difficulty during the crisis and required lender-of-last-resort facilities, deposits have become their main source of funding. The return of the traditional deposit to the top of the funding pecking-order increases the need for further research on the empirical properties of this funding source. Furthermore, the scale of the global financial crisis and the central role of liquidity/funding risk provides the perfect sample period from which to draw stylised facts about deposit trends. Such information can help policy-makers with liquidity stress-testing design and more broadly, increase market participants understanding of this key funding category.

This chapter aims to look at the dynamic behaviour of customer deposits in an advanced economy during a period of systemic financial stress. In particular, it uses time-series statistical methods applied to a novel high-frequency database of customer deposits in Irish owned-banks. The chapter is informed by theoretical models of bank deposit and funding behaviour during crisis conditions. The data refer to the period March 2009 to early-2014 and therefore covers most of the recent Irish banking crisis. The Irish story is of interest given the country's experience with a systemic banking crisis and associated economic recession during the global financial crisis, which resulted in a need for external financial assistance. By 2012, there were some emerging macroeconomic signs that the Irish economy was in recovery although at present, the domestic banking sector is still dealing with legacy issues such as mortgage arrears. In tandem with solvency issues, the Irish banks also experienced a period of systemic funding stress. During the crisis, Irish banks lost access to a range of funding markets, recorded deposit outflows and required official funding support from the European Central Bank/Central Bank of Ireland. Therefore, the experience of Irish banks with customer deposits during the crisis provides a useful statistical sample for many research questions, especially given the high-frequency nature of the data.

The chapter focuses on deposit volatility, as wide swings in deposit holdings increase refinancing risk for banks and introduces uncertainty. Banks may have to hold more liquid assets to hedge this risk and this higher requirement, in turn, can impact aggregate lending in the economy if such banks are systemically important. Using a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) approach due to Bollerslev (1986), weekly deposit flows are examined to see if they remain stable over the sample or become more volatile during certain periods. Given that the sample covers an intense period of financial stress for the Irish banks there is the possibility of statistical breaks in the series. Therefore regime switching methods are used to test if there is change in the time-series behaviour of the data. Using a reduced form approach, this chapter also investigates the determinants of customer deposits and tests if customer depositors respond to banking sector risk, sovereign risk or cyclical factors during a crisis as contended by the deposit/funding literature. Stress in other funding markets and general risk aversion in financial markets may also impact customer deposits, especially in an interconnected financial system and where access to financial information may be easy. Therefore measures of stress in these markets are included in the specification to test their statistical significance.

Over the sample, weekly customer deposit flows are found to respond to measures of banking sector and sovereign risk, validating the market discipline hypothesis. Although the data cover resident and non-resident depositors, idiosyncratic and Irish-specific risk factors seem to have more explanatory power for deposit growth, as indicators of general stress in international financial markets are found to be statistically insignificant. Once market-based risk factors are included in the model, no direct macro-economic influence is found. Customer deposit growth rates exhibit autocorrelation at the weekly frequency. Statistical evidence of a discrete variance regime shift is found, with deposits switching from a high volatility regime to a low volatility regime on 8 December 2010 coinciding with the beginning of an European Commission/European Central Bank (ECB)/International Monetary Fund (IMF) Programme of assistance for Ireland. Uncertainty about Irish banks' financial health prior to this date may have contributed to the volatility.

Additionally, the baseline ARDL (1,1) - GARCH (1,1) framework is extended to test if the volatility of customer deposit flows reacts more to good or bad news. Using a range of tests, there is no statistical support for an asymmetric response to the sign of a shock.

The specification is also extended to test if the conditional volatility has explanatory power for weekly deposit flows over the week. Interestingly, the volatility of customer deposits seems to have a negative influence on deposit flows over the sample with evidence of a GARCH-in-Mean effect suggesting risk aversion and potential flight-to-quality concerns. This is a novel empirical application of the GARCH-in-Mean approach. In standard finance theory, a GARCH-in-Mean approach is justified by the assumption that investors will demand higher returns for an asset when its volatility is elevated to compensate for additional risk. The empirical results here suggest that investors reduce their demand for deposits in the presence of higher volatility.

Customer deposits comprise both retail and corporate deposits. The latter deposit type are considered relatively more risky and may exhibit higher volatility. In essence such deposits may be more like wholesale funding during periods of financial stress. The time-varying volatility of both deposit types is examined over the sample using multivariate GARCH models. Statistical interdependence and causality-in-variance are also tested. Corporate deposits are found to be more volatile than retail deposits over the sample. There is, however, evidence of statistical dependence, as the con-

ditional covariance increases during a period of extreme financial stress. The weekly changes in both categories are positively correlated over the sample and there is evidence that there are volatility spill-overs from corporate to retail deposits. These findings indicate that although retail deposits are generally more stable than corporate, both deposit types will become more volatile and unreliable during a period of financial stress. Therefore there are no diversification benefits during financial crises.

This chapter draws on and contributes to the literature on deposit or funding dynamics during a financial crisis. Although the global financial crisis renewed interest in economic research on funding matters, there is of course, a long tradition of studies on banking crises and in particular, on bank runs and possible contagion. Some key papers are Diamond and Dybvig (1983) and Allen and Gale (1998) which focuses on the risk of bank runs in a representative bank setting, while others such as Diamond and Rajan (2005) and Allen and Gale (2004) consider the possibility of contagion among banks arising from liquidity shortages. Other papers test the ability of depositors to distinguish between healthy and weak banks during a crisis, drawing on the theoretical links between demandable debt (e.g., deposits) and market discipline in Calomiris and Kahn (1991). Some examples are Goldberg and Hudgins (1996) who examine the experience of Savings and Loan Associations with uninsured deposits during the late-1980s in the United States (US), Hori, Ito and Murata, (2009) who find evidence of market discipline among depositors during the Japanese crisis and Berger and Turk-Ariss (2010) who examine the sensitivity of depositors at both European and US banks to bank-specific risk prior to 2007.

Bank runs during the global financial crisis did not just depend on the bank/depositor relationship as wholesale funding played a significant role. Shin (2009) draws on 2007 Northern Rock episode and highlights that the initial phases of recent bank runs are driven by non-retail and market sources of funding due to aggregate risk aversion and binding external constraints on these funding providers' own financial positions. Retail depositors then run, once funding pressures become acute and visible at the bank. Research on funding issues have also expanded since the crisis with papers exploring the links between the market liquidity and funding (e.g., Drehman and Nikolaou, 2013). Recent papers also focus on the close correlation between funding risk and credit risk/solvency risk (Borio, 2010) and sovereign risk (CGFS, 2011).

In the Irish market, there have been a number of papers looking at deposit or funding dynamics in recent times. Chapter one focuses on modelling weekly corporate

deposits in Irish banks over the period March 2009 to August 2010 using the same database as the current chapter. Kelly *et al.*, (2014) looks at household deposits and test if Irish households respond to changes in deposit rates across the Irish banks over the period 2003Q1 to 2013Q2 using panel data techniques while Lane (2015) discusses changes in funding categories of the Irish banking system over the period 2003 through 2008 highlighting the importance of non-euro funding and foreign offices of Irish banks.

To the author's knowledge, however, this is the first study to investigate the time-series behaviour of customer deposits through the Irish crisis and up to end-2013 on a high-frequency basis. This chapter also explicitly models the time-varying volatility over the sample. A deeper understanding of the time-varying volatility of this key funding category is important from a financial stability risk perspective and allows for more efficient estimation and forecasting.

The chapter is structured as follows. Section 2.2 introduces the dataset and presents some preliminary data analysis while Section 2.3 specifies and estimates an Autoregressive Distributed Lag (1,1) - GARCH (1,1) model of weekly customer deposit flows. Section 2.4 test some additional enhancements to the basic model such as investigating possible regime shifts, testing the significance of asymmetric terms in the GARCH specification and including GARCH-in-Mean effects. Section 2.5 investigates the statistical dependence between retail and corporate deposits over the sample while Section 2.6 concludes.

2.2 Customer deposit data

The research benefits from access to a unique, internal database of daily net funding flows created in the Central Bank of Ireland to monitor funding developments in the Irish banks during the crisis. A net flow is the difference between the inflows and outflows across funding categories as at close of business each day. The liabilities data are consolidated. This research focuses on the customer deposit component on this database. The term customer deposits covers both retail or household deposits and corporate or firm deposits. Recall that chapter one also draws on this dataset but focuses on the period March 2009 to late-2010. The data used in this chapter refer to the period March 2009 through February 2014. In terms of estimation, the 2014 data are excluded so that out-of-sample performance can be evaluated.

Customer deposit data aggregated at a system level are used. The Irish bank sample covers the banks headquartered in Ireland and active over this period such as Allied Irish Banks plc, The Governor and the Bank of Ireland, Educational Building Society, Irish Life and Permanent plc/permanent tsb, Anglo Irish Bank Corporation and Irish Nationwide Building Society. Over the sample period, the Irish banking sector underwent significant restructuring in response to the domestic crisis. Delevering, mergers and a liquidation meant that the above sample of six was reduced to three during the sample.

Prior to estimation, a deposit levels series is created from the net flows using outstanding deposits as at December 2013. In particular, by adjusting the outstanding amounts with the daily net customer deposit flows over the sample a daily deposit series is created. To minimise potential noise from daily transactions, weekly data are used. Wednesday data are used in this analysis to remove any potential days-of-the-week effects and to reduce loss of observations due to bank holidays.¹ Figure 2.1 shows the weekly percentage change in customer deposits over the period March 2009 through December 2013. Weekly percentage changes are calculated as follows,

$$\Delta d_t = 100 * [ln(d_t) - ln(d_{t-1})] \quad (2.1)$$

where ln is the natural logarithm and d are weekly customer deposits. The large swings in the weekly percentage changes in deposits up to late-2010 compared with the rest of the sample are clearly evident. The largest weekly decline was in late-November 2010 at 4.1 per cent just prior to the EU/ECB/IMF program of external assistance for Ireland (See Table 2.1). The figures appear to remain negative until Summer 2011 which would have coincided with the renegotiation of debt terms between Ireland and its external creditors under the Programme and the receipt of private investment for one the main Irish banks (e.g., Bank of Ireland). Such developments may have had a positive impact on deposit flows.

Looking a little closer at the data, the average growth rate over the sample was -0.12 per cent per week. Table 2.1 shows evidence of non-normality. Relative to the normal distribution, the data are suggestive of a more fat-tailed distribution, with the negative skewness result indicating that the distribution is skewed to the left. As we can see from the associated density function in Figure 2.2 there are a number of large negative outliers. Given that the sample period includes the recent systemic banking

¹ Any remaining missing values are interpolated.

crisis in Ireland, this result is not surprising.

As noted, this chapter is interested in the volatility of customer deposits. As a preliminary examination of this issue, standard statistical measures of time-varying volatility are shown in Figure 2.3. In addition to a rolling average estimate of volatility, an exponentially weighted average is used which places less weight on the distant past. A one-year window is used so 2009 is excluded from the figure. As can be seen, the volatility spikes around late-2010 and then reduces. This initial examination suggests that volatility may not be constant over the period. There appears to be two distinct phases which is confirmed by the regime switching analysis in Section 2.4.1. The period before 2011 appears to be one of heightened volatility while the period thereafter was relatively tranquil.

2.3 Modelling customer deposits

This analysis uses a Generalised Autoregressive Conditional Heteroscedastic (GARCH) framework to capture the time-varying volatility of the customer deposit series. Both Autoregressive Conditional Heteroscedastic (Engle, 1982) and GARCH (Bollerslev, 1986) models can capture periods of turbulence and relative calm within a data series. With this approach both the conditional mean and the conditional variance of weekly deposit changes will be estimated simultaneously using Maximum Likelihood and the following system of equations,

$$\Delta d_t = \phi \Delta x_t + \epsilon_t, \quad (2.2)$$

$$\epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1) \quad (2.3)$$

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad (2.4)$$

Here Δd_t is the weekly percentage change in customer deposits and Δx_t is our vector of possible explanatory variables, which are discussed in subsection 2.3.2. GARCH-in-Mean effects are also tested in subsection 2.4.4. ϵ_t is the random error term while h_t is the conditional variance of ϵ_t and v_t is standardised white noise with a mean of 0 and a variance of 1. ϕ , α and β are parameters to be estimated².

²These models estimate the variance recursively so pre-sample GARCH parameters need to be specified. The econometric software package RATS uses the unconditional estimates of both the lagged squared residuals and the lagged variance from the mean model estimates for these pre-

The variables p and q determine the order of the GARCH specification. For example, if p is equal to 0 and q equal to 1, a GARCH (0,1) model is used. The values of p and q are determined by information criteria or by comparing the fit of the model. To ensure stability of the GARCH process, the sum of α_1 and β_1 in equation 2.4 must be less than one. Also all of the parameters in the GARCH specification must be positive to ensure a positive conditional variance.

2.3.1 Literature on deposit dynamics during a financial crisis

The first step in GARCH modeling is to determine an appropriate model of deposit flows (i.e., specify the conditional mean). As a guide to potential determinants of customer deposits over this period, the literature on deposits dynamics during a crisis is useful, in addition to Irish market developments.

In normal or non-crisis periods, deposits changes may be driven by cyclical factors and a range of microeconomic or deposit characteristics such as term, origin, price, insured versus uninsured. During crises however, there are range of competing theories for deposit movements. Most of these papers are concerned with explaining withdrawal risk. The seminal theoretical bank run paper is Diamond and Dybvig (1983) which shows that in a representative bank setting, bank runs can be self-fulfilling events in the context of a “first come, first served” assumption and an illiquid investment asset. Bank runs are one possible outcome in this multiple equilibria setting. The literature then divides on what factors can trigger this outcome.

Earlier papers say that depositor panic and related withdrawals can be due to mass hysteria and random events (Kindleberger, 1978) while other papers link deposit outflows to changes in the business cycle and depositors’ change in perceptions about future bank fundamentals (Gorton, 1988 and Allen and Gale, 1998). In the latter literature, depositors lack bank-specific information and so derive a risk assessment from aggregate information about economic activity. Emerging signs of a recession increases the likelihood that future bank returns will drop. To protect their future consumption, depositors will remove their savings in advance. As depositors cannot distinguish between banks, a number of banks in an economy will be affected. Gorton contends that depositor behaviour is the same in both crisis and normal times. It is sample values (See Estima, 2012 and Doan, 2013). These assumptions are, therefore, used in this chapter.

the cumulative impact of many indicators about an impending recession which leads to depositor panic.

Assuming a sequential service constraint as in Diamond and Dyvbig (1983), Calomiris and Kahn (1991) show that costly deposit contracts can also discipline banks. In this context, depositors or other types of demandable debt have an incentive to monitor banks and will run on the bank if its fundamentals deteriorate. There is a large body of research that contend that depositors or other holders of demandable bank debt could distinguish between healthy and weak banks. Therefore deposits or other sources of funding would respond negatively to increased risk on banks' balance sheets and/or such banks would need to offer higher rates of return to retain the funding. In essence such short-term funding categories could help to discipline bank's risk-taking behaviour. This market discipline hypothesis and related empirical literature are introduced in chapter one, (section 1.3). An example of an early market discipline paper is Hannen and Hanweck (1988) who examine the US market for large uninsured certificates of deposit (CD) and found evidence that interest rate spreads on certain CD maturities were sensitive to various measure of insolvency risk in 1985. The authors find that indicators of bank risk such as the standard deviation of return on assets, measures of the probability of insolvency and the capital-asset ratio all impact rates on jumbo CDs consistent with the market discipline hypothesis.

As noted in chapter one, Hori, Ito and Murata (2009) use a large panel of deposit-taking institutions in Japan over the period 1992 to 2002 to examine if depositors are able to distinguish between healthy and risky institutions during the Japanese crisis. In terms of methodology, this paper looks at the impact of bank-level indicators of risk on both deposit growth and deposit interest rates. To overcome simultaneity problems of supply /demand equations, reduced form specifications for both deposit growth and interest rates are estimated. Fundamental variables include the capital-asset ratio and bank profitability (i.e., the ratio of operational profits to total assets). They find evidence in favour of the market discipline hypothesis.

Many of the aforementioned factors relate to supply-side shocks for the banks. During a period of financial stress, a reduction in deposits could be also be due to demand-side shocks, in that depositors may need to draw down savings to smooth consumption or pay down debts. There is clearly evidence of such effects in the Irish crisis with declines in the personal saving rate being partly explained by household debt consolidation. (Cussen *et al.*, 2012). Chari and Jagannathan (1988) show that

bank runs can also occur even in the absence of specific bad news about a bank's financial position. Certain uninformed depositors will base their actions on the actions of other depositors. If a run is observed outside a bank or if many depositors withdraw funds to meet their own liquidity requirements, both cases may lead the uninformed depositors to run on the bank.

Based on the literature, specific triggers for such bank runs are asymmetric information on the probability of bank default risk, coordination failure among depositors or information cascades among different classes of depositors. Liquidity risk can also be contagious. Papers that deal with systemic liquidity risk are Allen and Gale (2004), Cifuentes, Ferrucci and Shin (2005) and Diamond and Rajan (2005).

As a result of the global financial crisis (GFC), research on bank funding risk has grown and in particular, on the possible correlation between funding risk and other risks faced by credit institutions during a period of financial stress. Specifically, papers have addressed the negative relationship between funding and market liquidity (e.g., Brunnermeier and Pedersen, 2009, Drehman and Nikolaou, 2013), the close correlation between funding and solvency risk or credit risk (Borio, 2010) and of course, the GFC showed that the negative bank/sovereign nexus affected the banks mainly through the funding channel (CGFS, 2011).

In the Irish market, there have been a number of papers looking at deposit or funding dynamics in recent times. Chapter one uses the same database and focuses on modelling weekly corporate deposits in Irish banks over the period March 2009 to August 2010. The relationship between retail and corporate deposit levels over this period is also examined in the previous chapter. Specifically, the chapter tests the responsiveness of weekly corporate deposits to changes in measures of bank soundness such as CDS spreads and implied ratings and to changes in funding market conditions. The study finds evidence of market discipline among corporate depositors as deposits responds negatively to a deterioration in banks' perceived creditworthiness. Adverse developments in international funding markets are also shown to have a negative impact on Irish banks' corporate deposits. In terms of retail versus corporate, the chapter finds that retail deposits were relatively more sticky than corporate deposits over the period using an error correction framework.

2.3.2 Specifying a model of Irish customer deposit growth

Drawing on the deposit literature weekly changes in Irish customer deposits are hypothesised to be influenced by movements in measures of bank risk, sovereign risk, domestic cyclical factors and general stress in financial markets. The presence of substitution effects with other financial assets is also tested. A simple Autoregressive Distributed Lag (ARDL) time-series model is used which includes lagged values of the explanatory variables and lagged values of the dependent variable to capture persistence. In this reduced form model, each of the estimated coefficients represent the marginal effect of the respective variable on the dependent variable, holding the other variables constant. Unit root testing finds evidence that the variables of interest in first differences are difference stationary and integrated of order 0 (See Appendix 1 for further details). Equation 2.5 is our baseline specification.

$$\Delta d_t = \phi_0 + \sum_{i=1}^m \phi_i \Delta d_{t-i} + \sum_{i=1}^n \delta_i \Delta x_{t-i} + \epsilon_t \quad (2.5)$$

where Δd_t is the weekly percentage change in deposits and x_t is a vector of the following possible explanatory variables;

- Weekly percentage change in the Irish banking sector's share price ($\Delta Bksp$),
- Weekly percentage change in the Irish sovereign's senior Credit Default Swap spread (CDS), ($\Delta IEcds$),
- Weekly percentage change in the value of Irish equity prices ($\Delta ISEQgen$),
- Weekly percentage change in a measure of general market stress across European financial markets ($\Delta CISS$),
- Weekly percentage change in a measure of stress in European money markets, ($\Delta MMspread$),
- Weekly percentage change in Irish consumer sentiment index ($\Delta CONsent$) .

A bank's share price is considered a good measure of the market's perception of its financial soundness and so proxies for bank-specific risk in our specification. A simple average of the share prices of the Irish banks that were listed over the sample period is used. If the market discipline hypothesis holds, a positive relationship between $\Delta Bksp$ and our dependent variable is expected.

During a crisis, if a systemic bank runs into difficulty, investors may link the credit risk of the sovereign to that of the troubled bank if there is an explicit or indeed implicit state guarantee in place. In September 2008, the Irish Government introduced a wide guarantee on the domestic banks' liabilities in an attempt to alleviate funding pressures. Such a guarantee created a contingent liability for the Irish State. As the Irish crisis unfolded, national authorities maintained a State guarantee on bank liabilities, albeit with different scope and coverage and also provided capital to the domestic banks. Such actual and contingent liabilities for the State link bank funding risk and sovereign creditworthiness. Sovereign CDS spreads provide a possible measure of the market's perception of the degree of counter-party credit risk posed by the respective state. In this chapter, Euro senior 5-year CDS spreads for the Irish Government are used to control for Irish sovereign risk. As with bank share prices, it is expected that customer deposits will vary inversely with changes in sovereign risk.

3

A measure of the value of alternative Irish financial assets is also included to capture possible substitution effects by household and firms. In particular, the value of the ISEQ General Index which covers all non-financial firms listed on the Irish stock exchange is used. Depositors may decide to move their savings into such investments to gain a relatively higher return or in a flight-to-safer assets, particularly during a banking crisis.

A measure of stress in international financial markets is included. Drawing on chapter one which finds that corporate deposits in Irish banks are negatively related to increased tensions in European money markets, the spread between the 3-month Euribor rate and the Overnight Indexed Swap rate is used, $\Delta MMspread$. A general financial stress index for European financial markets developed by economists at the European Central Bank called the "Composite Indicator of Systemic Stress" or CISS for short (see Holló *et al.*, 2012 for further details) is also tested to see if it has explanatory power for customer deposits in Irish banks. The CISS indicator is generally considered useful as a coincident measure of systemic financial stress facilitating real-time monitoring of systemic risk. This indicator tracks stress across the financial system while also controlling for each market's time-varying cross-correlations.

³In some of the market discipline literature it is contended that the presence of deposit insurance reduces the incentives for depositors to monitor the financial soundness of banks. Therefore, market disciplining effects may not hold. This effect cannot be tested here due to both the comprehensive nature of the Irish guarantees during the crisis on customer deposits and insufficient granularity to distinguish between insured and non-insured deposits over the sample.

All of the market-based data are sourced from Thomsen Reuters/Datastream with daily observations compacted to weekly frequency. As with the deposit data, where possible, Wednesday on Wednesday data are used.

To control for cyclical factors and aggregate risk, high-frequency leading indicators of Irish economic activity are required. The monthly Irish consumer sentiment index sourced from the European Commission/Eurostat is interpolated before being included in the general specification. The nature of the relationship between economic growth and deposits can be complex. In an economic upswing, depositors may decide to increase precautionary savings so that consumption can be smoothed over the cycle. Additionally bank profitability may be positively related to favorable macroeconomic conditions, particularly in countries where banks derive most of their income. Consequently, banks can choose to increase their deposit interest rates to attract and retain customer deposits. As such banks are more financial sound, depositors may also be more confident about holding their savings there. Such dynamics may operate in reverse in a recession. In this case a positive relationship is expected between deposit growth and economic activity.

However, it may be possible that deposits holdings could decrease during a period of economic growth, especially when banks can easily substitute deposits for cheaper sources of market-based funding. Deposit rates may, therefore, be relatively lower than the returns that could be achieved on other types of financial and non-financial assets by households and firms. A further issue is that rates offered by banks on both loans and deposits generally track the policy rate if the monetary transmission mechanism is fully operational in a currency area. So if the prevailing monetary policy stance is accommodative, deposit rates may not be high enough to attract new deposits. Prior to the global financial crisis, interest rates were historically low and certain banks relied on non-deposit sources of funding to increase their assets. Such effects may have a dampening effect on deposits and may in turn, offset the positive effects of higher economic growth.

2.3.3 ARDL (1,1) results

In this chapter, both m and n in (2.5) are one so we have an ARDL (1,1) specification. A general-to-specific approach is used to determine the most parsimonious specification of weekly percentage change in deposits. The results are shown in Table

2.2. This is the initial model as the final model will be obtained when both the conditional mean and the conditional variance are estimated together. In column (1), all explanatory variables are included with the exception of $\Delta CISS$ and $\Delta MMspread$, which are included separately in (1) and (2) respectively, as both variables control for similar effects.

Neither of the market measures of risk are significant. In columns (3) and (4) the least significant variable are dropped sequentially. So in this case, the coefficients on the weekly percentage changes in the Irish consumer sentiment index and on the money market spread are insignificant. The regression results in (4) show that our variables have the expected signs and are significant at conventional level. Customer deposit flows in Irish banks over the period 2009 through 2013 appear to react to changes in both measures of bank-specific and sovereign risk. There is also some evidence of persistence in the deposit data and substitution effects appear to be in operation. The coefficient on the lagged dependent variable is less than one so the process is convergent. But surprisingly the results show no significant macro-economic effects. It may be possible that the effects of the high-frequency market data reduces the effects of the interpolated economic indicator.

Standard misspecification testing on the residuals shows no evidence of serial correlation using the Ljung-Box (1978) Q (4) statistic. Engle's (1982) Lagrange multiplier test points to ARCH effects in the squared residuals indicating serial dependence and some clustering of large residuals. The $\overline{R^2}$ is low at 10 per cent, although not uncommon with modelling weekly percentage changes. As can be seen in Figure 2.4 the presence of some larger residuals, particularly before 2011 suggests that other factors outside of our specification such as aggregate uncertainty or negative sentiment may also be playing a role in explaining customer deposits over the period.

To check stability of the initial coefficient estimates over the sample, recursive least squares estimation is used. Figure 2.5 shows that after the initial burn-in period, the estimates are relatively stable although the lagged dependent variable does appear to change sign early in the regressions. Although the time-varying volatility will be explicitly modelled in Section 2.3.4, Eicker-White Standard Errors are used to ensure consistent parameter estimates for the ARDL(1,1) specification. The results are shown in column (5) in Table 2.2. All of coefficients remain significant although the lagged dependent variable is just significant at the 10 per cent level.

Although the weekly deposit data are not public until the banks publish consolidated financial information, which is usually at a lower frequency, reverse causality could be an issue. Potential endogeneity between deposit growth and the explanatory variables is tested using a multivariate version of Granger (1969) causality tests. First, a Vector Autoregressive (VAR) equation with the lag length determined by the Akaike Information Criterion is estimated. Two lags are deemed optimal. The p-values from the associated F tests are shown in Table 2.3. The null hypothesis is that lagged values of the explanatory variables do not have predictive power for the respective dependent variable in each equation of the VAR. Based on the first row of the table, there is no statistical evidence that lags of d_t Granger causes the other variables. This result justifies our single equation approach. Interestingly, lagged values of the weekly changes in the ISEQ general index do not appear to provide a good forecast for customer deposit growth. Indeed, this variable becomes statistically insignificant when the conditional mean and the conditional variance are estimated together in the GARCH framework in Section 2.3.4.

2.3.4 Controlling for GARCH (1,1) effects

Table 2.4 shows the results of our GARCH model which is estimated over the period 11 March 2009 to 1 January 2014 (i.e., 252 observations). Assuming normal errors, Maximum Likelihood estimation is used. Having also tried a number of low order ARCH and GARCH models ⁴, a GARCH(1,1) was a good fit for the conditional variance of the residuals of the ARDL (1,1) model based on a comparison of log likelihood functions and information criteria (See Appendix 2 for details). Turning to the conditional variance equation for h_t , we can see that the GARCH coefficients are all positive, statistically significant and the sum of α_1 and β_1 is less than one implying a mean-reverting/stationary process. As the sum of the coefficients on α_1 and β_1 coefficients is close to unity, this implies that any shocks to the conditional variance will be persistent for a time.

The ARCH parameter, α_1 (i.e., coefficient on the lagged squared residuals) is much less than the GARCH parameter (β_1) indicating that the volatility of weekly deposits respond more to its own lagged values than to news. On the mean model, only the coefficients on our lagged dependent variable, Δd_{t-1} and bank share price ($\Delta BKsp_{t-1}$) are significant at the 5 per cent level. The point estimate of our coefficient on Irish

⁴Generally, low order GARCH models are found to work well in empirical studies.

sovereign CDS spread is statistical significant at the 10 per cent level.

Figure 2.6 shows the standardised residuals. These are the residuals divided by their conditional standard deviation. If the mean model is correctly specified, the standardised residuals should approximate white noise and have no remaining serial correlation as they are an estimate of v_t in Equation (2.3). The Ljung-Box (1978) Q statistic shows that under the 5 per cent significance level, the standardised residuals are not serially correlated up to order 4. There is some evidence of higher-order serial correlation in the residuals. The Jarque-Berra (1987) test indicates non-normality in the standardised residuals in Table 2.4.

In order to determine if our GARCH process is sufficient to capture all of the dynamics of the conditional variance, the autocorrelations of the squared standardised residuals are examined. The autocorrelation function and the McLeod-Li (1983) test (i.e., a modified version of the Ljung-Box (Q) statistic) shows no evidence of remaining GARCH effects in the squared standardised residuals (see Figure 2.6 and Table 2.4).

2.4 Enhancements to baseline ARDL (1,1) - GARCH (1,1) model

2.4.1 Stability of the conditional variance and testing for possible regime shifts

The fitted values for the conditional variance in Figure 2.7 raise concerns about the stability of the series over the sample period. The conditional variance appears to have relatively large values prior to 2011. The simple statistical measures of volatility in Section 2.2 also suggested the possibility of a change in the dynamic behaviour of deposit volatility over our sample. Further, as we saw in Table 2.4 the sum of α_1 and β_1 is close to one signaling persistence in the conditional volatility of customer deposit flows. Hillebrand (2005) shows that an unmodelled statistical break can cause highly persistent conditional volatility.

Rather than arbitrarily choosing a break date, regime switching methods are used to detect possible break points in the variance of the error term. Specifically, the variance of the error term, ϵ_t in Equation 2.6 is tested to see if it switches over the sample

using a first-order Markov process and assuming constant transition probabilities (See Appendix 3 for further details).

$$\Delta d_t = \phi_0 + \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \gamma \Delta ISEQgen_{t-1} + \epsilon_{i,t} \quad (2.6)$$

where

$$\epsilon_{i,t} \sim N(0, \sigma_i^2), i = 1, 2$$

As can be seen from the estimated smoothed probabilities in Figure 2.8, two distinct regimes emerge. A high volatility period up to end-November 2010 with a low volatility period beginning in early-December 2010 and prevailing until the end of the sample.

A variance shift dummy, D_t is therefore included in the conditional variance specification before re-estimating the GARCH (1,1) - ARDL model. In particular, the binary variable takes a value of 1 from 11 March 2009 up to 8 December 2010 and 0 thereafter. To correct the standard errors for any effects of the non-normal standardised residuals on the likelihood function, quasi-maximum likelihood (QMLE) is implemented. Furthermore, any insignificant variables are subsequently omitted to obtain a parsimonious specification for Δd_t . The revised specification for customer deposits is given by the following ARDL (1,1) - GARCH (1,1) system of equations,

$$\Delta d_t = \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \epsilon_t \quad (2.7)$$

$$\epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1) \quad (2.8)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \eta D_t \quad (2.9)$$

Table 2.5 shows the results. The intercept in the variance equation now captures the mean variance after the break-date while the coefficient on our dummy variable shows the increase in the average variance before 8 December 2010. The volatility prior to 8 December 2010 is higher by a factor of about 8. This result indicates that customer deposits in Irish banks became less variable after Ireland entered a Programme of external assistance on 28 November 2010. Greater movement in deposit flows prior to the Programme may reflect investor uncertainty about the default risk posed by Irish banks up to that date. The GARCH parameters remain statistically significant and as expected, the persistence reduces significantly once we control for

the statistical break. The estimated conditional variance controlling for the break point is compared to the estimated variance from the Markov switching regression in Figure 2.9.

2.4.2 Out-of-sample evaluation of ARDL (1,1) - GARCH (1,1) model

In the previous subsection, we saw that an ARDL (1,1) with GARCH (1,1) errors had a satisfactory in-sample fit. The model's out-of-sample performance is also tested using actual data for early-2014. Specifically, an 8-step dynamic forecast is conducted using the mean model specification. The conditional standard deviation is used to construct a two standard error confidence interval. Figure 2.10 compares the actual weekly percentage change in customer deposits with the forecasts over the forecast horizon, namely 8 January 2014 to 26 February 2014. The model seems to capture the general trend although it does not fully reflect the scale of the decline on the fifth week.

2.4.3 Other GARCH specifications - asymmetries

In Section 2.3.4 a simple GARCH (1,1) explains the conditional volatility of customer deposits relatively well. This subsection investigates if other variants of the GARCH model are useful in describing the data. Specifically, the statistical significance of asymmetric terms is examined.

In equity markets, negative shocks or bad news appear to exert a greater effect on the volatility of price returns than positive shocks. It is contended that leverage effects may be at play in this instance. The standard GARCH specification makes no allowance for this possibility as the squared residuals are used. To initially investigate if customer deposits respond asymmetrically to different types of news, a simple test based on Enders (2010) is employed. The squared standardised residuals from our Equations 2.7 and 2.9 are regressed on a constant and lags of the standardised residuals. If there are leverage effects, the squared standardised residuals will be correlated with the levels of the standardised residuals. The results from this regression and the associated F test are shown in Appendix 4. As can be seen, the null that coefficients are equal to zero cannot be rejected. This specific test provides no evidence of leverage effects in the weekly customer deposit data.

An additional method of testing for asymmetric effects involves the inclusion of an asymmetric term in the conditional variance equation and evaluating its statistical significance. This asymmetric response can be modelled with an exponential GARCH (E-GARCH) specification due to Nelson (1991) or with a Threshold GARCH (TARCH) specification due to Glosten, Jagannathan and Runkle (1993). Both approaches are applied to the data. The results are contained in Appendix 4. As can be seen, the asymmetric terms are not found to be statistically significant in either case. Therefore we can conclude that the sign of innovations does not matter to the volatility of customer deposits.

2.4.4 GARCH-in-Mean effects

It may also be possible that the conditional variance has some explanatory power for the weekly change in customer deposits. The inclusion of the conditional variance h_t in the mean model is called a GARCH-in-Mean specification (GARCH-M). This approach is often applied to asset markets, where it is assumed that risk averse buyers demand a risk premium to compensate for the risk of holding the asset, as proxied by the conditional variance. Excess returns may therefore be positively related to the conditional volatility of the returns (See Engle, Lilien and Robins (1987) for an example of an ARCH-M model).

Although the GARCH-M approach may be more applicable in markets where prices are freely observable, a relationship between weekly customer deposit growth and the riskiness of these savings as proxied by the conditional variance may exist. Large swings in customer deposits increase refinancing risk for banks. During a period of systemic financial stress, funding may be tight and any significant shortfall between inflows and outflows may create challenges for banks in meeting their funding commitments as they fall due. In subsection 2.3.3, no evidence of reverse causality between deposit growth and the various measures of counterparty credit risk. Certain large depositors or institutional depositors who actively manage their investments may be able to infer the inherent riskiness of Irish banks over the sample using a range of other publicly available financial data outside of our current explanatory variables such as rating agency reports.

Therefore, our conditional mean equation is respecified to include h_t which is estimated as in Equation 2.9. The new specification for d_t is given by Equation 2.10. If the conditional variance proxies for the riskiness associated with deposits in Irish

banks over the sample, there should be a negative relationship between h_t and d_t . The GARCH-M(1,1) - ARDL(1,1) model is estimated using QMLE. Table 2.6 displays the results. The contemporaneous conditional variance is found to have explanatory power for weekly percentage changes in customer deposits. The estimated coefficient is negative, implying that an increase in volatility of customer deposits leads to a decrease in customer deposits within the week. Specifically a 1 per cent increase in the conditional volatility of customer deposit flows is found to decrease deposit growth by 0.3 per cent on a weekly basis. There is some improvement in model fit as the log likelihood increases. The GARCH term β_1 drops slightly in significance but remains well within the 10 per cent significance level.

$$\Delta d_t = \phi_0 + \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \tau h_t + \epsilon_t \quad (2.10)$$

2.5 Corporate versus retail deposits and multivariate GARCH models

Customer deposits refer to both retail and corporate deposits. In this section, the data are disaggregated by deposit type and the time-varying volatility of each series is modelled. Multivariate GARCH techniques are used as it is likely that both types of deposits are subject to certain common shocks, which may affect the volatility of the weekly flows in each category. Also, by estimating the conditional variance of retail and corporate deposits and their conditional covariance simultaneously, statistical interdependence over the sample can be tested in addition to deposit-specific volatility. The issue of correlation is also addressed.

2.5.1 Preliminary statistical analysis

Figure 2.11 shows the contribution of retail and corporate deposits to the weekly growth rates of aggregate customer deposits over the sample March 2009 to end-2013. The wide swings in weekly growth rates prior to the regime shift in early-December 2010 appears to be driven by corporate deposits with retail deposits contributing more to the weekly changes after the break point. This pre-2010 trend is confirmed when we look at the individual weekly growth rates in Figure 2.12. Over the sample retail deposits account for the majority of customer deposits at 78 per cent. Up to end-November 2010, the retail deposit share averaged 70 per cent before increasing to an

average share of 83 per cent for the remainder of the sample due to relatively higher falls in corporate deposits. Even with the higher weighting for retail, the significant swings in corporate deposits up to late-2010 appear to drive the aggregate series.

Table 2.7 looks at the summary statistics for each deposit type over the sample. On average, retail records a weekly decline of just 0.04 per cent compared to 0.3 per cent for corporate deposits. The greatest decline for both deposit categories is in November 2010. Corporate deposits fall by 12 per cent per week while retail deposits fall by 2 per cent. In terms of inflows the maximum increase is significantly higher for corporate deposits. The sample standard deviation is also 6.6 times higher for corporate deposits. For both categories, the skewness coefficient suggests that weekly flow distribution is negatively skewed and the Kurtosis coefficient suggests that the tails of the distribution are thicker than those of a standard normal. Such evidence of non-normality is confirmed by significance of the Jarque-Berra (1987) test statistic, leading to a rejection of the null hypothesis of normally distributed deposit changes.

2.5.2 BEKK model and testing for volatility spill-overs

To test for volatility spill-overs between retail and corporate deposits, a bivariate BEKK model is used. This approach was made popular by Engle and Kroner (1995). To ensure a positive definite variance-covariance matrix, certain restrictions are imposed. Specifically all parameters enter the model in quadratic form. The interest in this section is on the conditional variance of each series rather than explaining the deposit flows. Therefore, a constant conditional mean for both retail (Δr_t) and corporate (Δc_t) deposit flows is assumed. To estimate the BEKK model, the following system of equations is used,

$$\Delta c_t = \mu + \epsilon_{1t} \tag{2.11}$$

$$\Delta r_t = \delta + \epsilon_{2t} \tag{2.12}$$

$$\epsilon_{1t} = v_{1t} \sqrt{h_{11t}} \tag{2.13}$$

$$\epsilon_{2t} = v_{2t} \sqrt{h_{22t}} \tag{2.14}$$

$$\epsilon_{it} | \Omega_{t-1} \sim (0, H_t), i = 1, 2 \tag{2.15}$$

$$H_t = CC' + A' \epsilon_{t-1} \epsilon_{t-1}' A + B' H_{t-1} B \tag{2.16}$$

where in our two variable case,

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{pmatrix}, C = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}, A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

h_{11} and h_{22} are the conditional variance of the weekly percentage changes in corporate (Δc_t) and retail (Δr_t) deposits respectively. h_{12} or h_{21} is the conditional covariance between two shocks. H_t , the variance-covariance matrix of the residuals, depends on the squared residuals, cross-products of the residuals and the conditional variances and covariances of the two variables in the system. The 2 by 2 matrix A shows the ARCH effects while the 2 by 2 matrix B covers the GARCH effects and the variance intercept matrix C is lower triangular. The diagonal elements in B show the effects of lagged volatility, with the cross-deposit effects contained in the off-diagonals. Similarly, the off-diagonals in the A matrix shows the bilateral impact of news or shocks to one deposit type on the variance of the other deposit type. Therefore, drawing on a Wald test proposed by Hafner and Herwartz (2004), it is possible to test the direction of variance causality between retail and corporate deposits. Specifically the following hypotheses are tested:

- if there is variance causality from corporate to retail a_{12t} & b_{12t} should be jointly statistically significant,
- if there is variance causality from retail to corporate, a_{21t} & b_{21t} should be jointly statistically significant.

In both cases a Wald Test with a χ^2 test statistic and 2 degrees of freedom may be used. The estimation results are contained in Table 2.8. The simple test for causality suggest that the direction of variance causality may run from corporate to retail but not in reverse. For both categories of deposits the own-effects are significant. The multivariate Q statistic⁵ on the standardised squared residuals shows no residual ARCH effects. Figure 2.13 presents the fitted values for the conditional variances and the conditional covariance. Based on the conditional variances, it is clear that corporate deposits are much more volatile than retail deposits. The variance of both series spikes in late-2010 and there is an increase in the conditional covariance at this time.

⁵See pp. 83-85 in Doan (2013) for further details.

2.5.3 Correlation and CCC model

To further investigate statistical comovement between the two series, the analysis in this subsection focuses on correlation. Based on a 24-week rolling average correlation coefficient in Figure 2.14, weekly retail and corporate appear to be positively correlated for a period between mid-2010 to early-2011. To formally test if both series were correlated over the sample, a Constant Conditional Correlation (CCC) multivariate GARCH model due to (Bollerslev, 1990) is used ⁶. The conditional mean equations are as in Equations 2.11 and 2.12 and it is assumed that the residual series (ϵ) for both retail and corporate deposits can be estimated as a GARCH(1,1) process. Therefore with the subscript 1 referring to corporate and the 2 retail, the following equations are used,

$$h_{11t} = c_{10} + a_1\epsilon_{1t-1}^2 + b_1h_{11t-1} \quad (2.17)$$

$$h_{22t} = c_{20} + a_2\epsilon_{2t-1}^2 + b_2h_{22t-1} \quad (2.18)$$

$$h_{12} = \rho_{12}\sqrt{h_{11t}h_{22t}} \quad (2.19)$$

In the CCC model, the conditional covariance (h_{12}) between two series is proportional to the square root of the product of the conditional variance for each series. Therefore the conditional correlation (ρ_{12}) between the two series is assumed constant but unknown over the sample, so it must be estimated. The results are shown in Table 2.9. The conditional correlation coefficient is significant and positive. Based on this model, both categories of deposits are correlated to the order of 15 per cent over the sample.

The Irish banking sector experienced systemic stress in the period leading up the application for external assistance. In addition to solvency issues, funding stress was quite acute and customer deposits were quite volatile. The results in this section shows evidence of inter-linkages across both categories of customer deposits during this time. Future work might need to address the conditional mean model in more detail.

2.6 Conclusions

In this chapter the dynamic behaviour of customer deposits, a key funding category for banks since the global financial crisis is examined. Specifically weekly customer

⁶The Dynamic Conditional Correlation (DCC) Model was also estimated. However, the resultant time-varying correlation did not display meaningful trends.

deposit growth in Irish banks between March 2009 and December 2013 is modelled using an ARDL (1,1) model with GARCH (1,1) errors. The sample includes a period of systemic financial stress. In line with the market discipline hypothesis, bank-specific and country-specific risk factors are found to influence weekly percentage changes in customer deposits but there is also evidence of persistence in growth rates. Domestic factors seem to matter to depositors as indicators of stress in international financial markets are not significant. Surprisingly, no significant macro-economic influence is found.

Between 11 March 2009 and 8 December 2010, customer deposit flows exhibit large swings on a weekly basis. There is evidence of a regime shift in the conditional variance in early-December 2010, coinciding with the onset of Ireland's Programme for External Support. Prior to the regime shift, customer deposits are relatively more volatile. The inclusion of a discrete variance shift lowers the persistence of the estimated GARCH parameters. The sign of the shocks to deposit growth is not found to have any explanatory power for its conditional variance. There is, however, a strong GARCH-in-mean result. The conditional volatility of customer deposit flows is found to negatively influence deposit growth rates. Higher volatility appears to be associated with higher levels of risk which in turn, influences depositor behaviour.

This chapter also disaggregates customer deposits by type and investigates the volatility of retail versus corporate deposits and also tests for inter-linkages. Corporate deposits are found to be relatively more volatile over the sample but there is evidence of volatility transmission to retail deposits over the sample. The conditional covariance between the series increases in late-2010, indicating higher interdependence during periods of acute systemic funding risk. Further, although retail and corporate depositors may be quite different, there is evidence that both series are positively correlated to the order of 15 per cent during this time.

Further work in the area could involve developing the mean models for retail and corporate deposits or disaggregating the data further and conducting a bank-level analysis of deposit volatility spill-overs.

2.7 Figures and tables

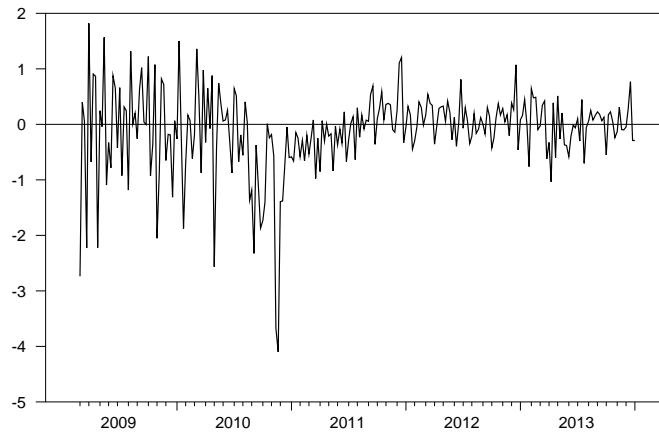


Figure 2.1: Weekly percentage change in customer deposits in Irish banks: March 2009 to December 2013

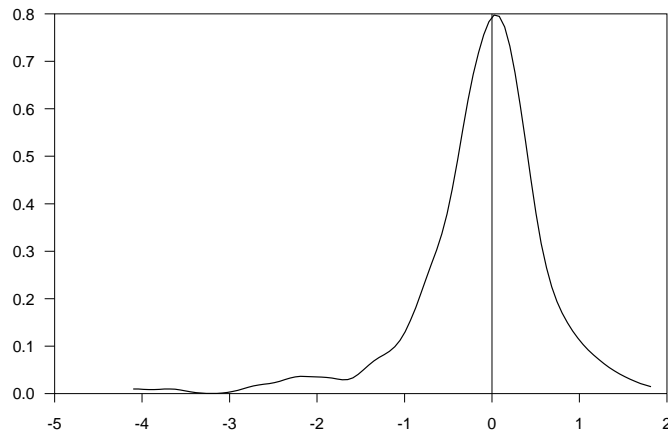


Figure 2.2: Kernel density of weekly customer deposit growth: March 2009 to December 2013

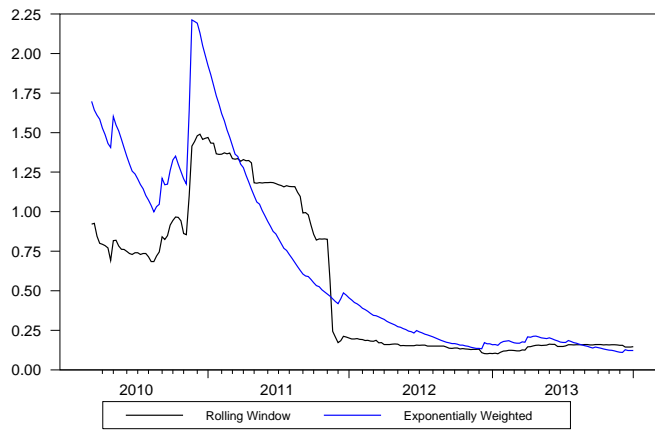


Figure 2.3: Time-varying estimates of historical volatility with a one-year window: March 2010 to December 2013

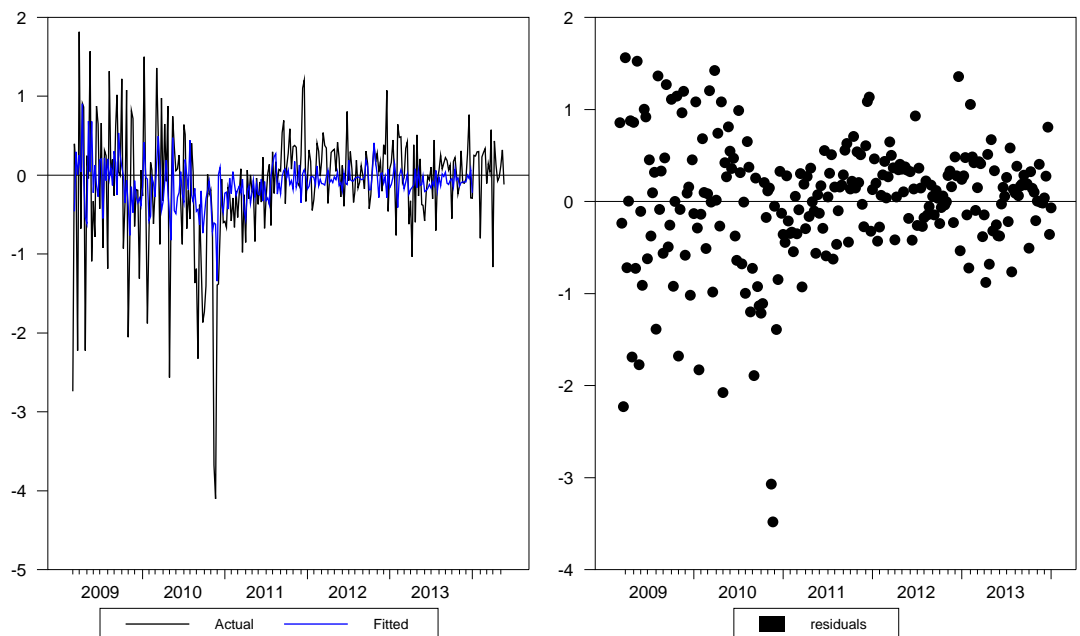


Figure 2.4: ARDL(1,1) model of weekly customer deposit growth: March 2009 to December 2014

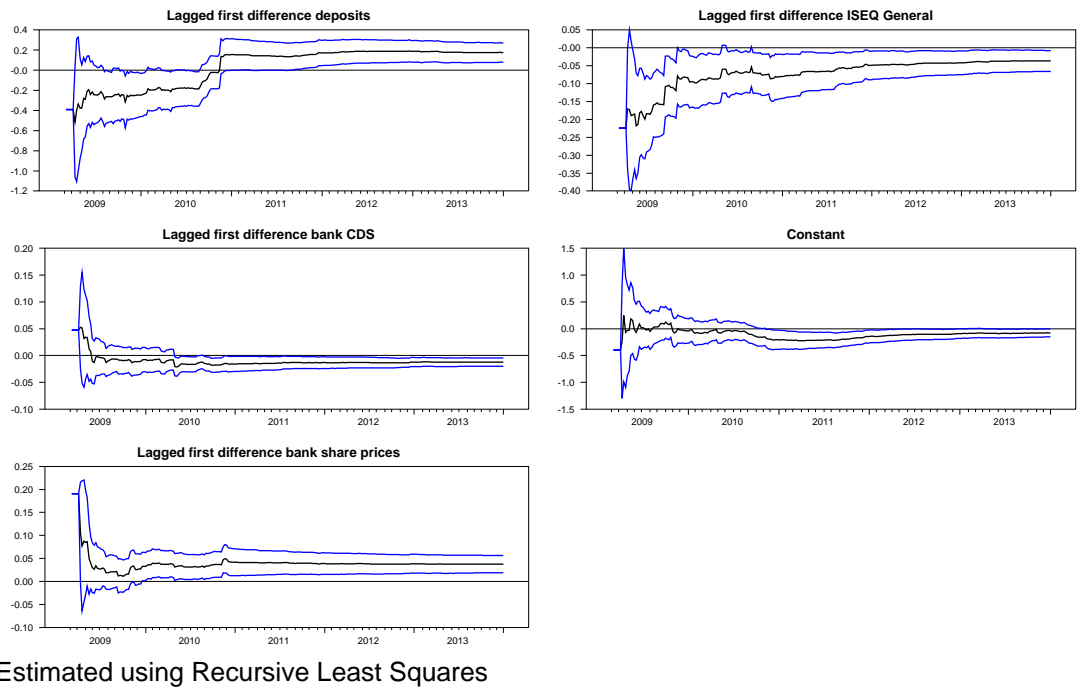


Figure 2.5: Coefficient estimates from ARDL(1,1) model with 95% confidence interval

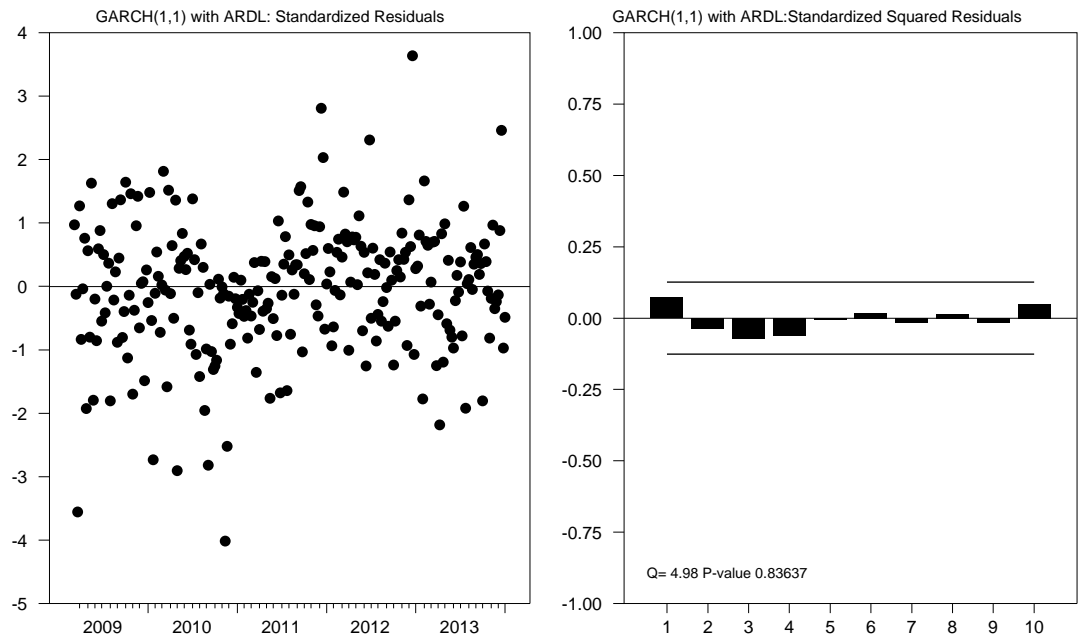


Figure 2.6: Diagnostics on ARDL(1,1) - GARCH (1,1) model of customer deposits: 11 March 2009 to 1 January 2014

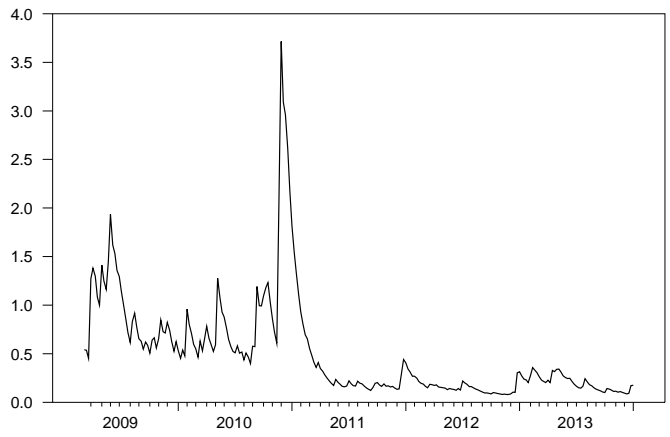


Figure 2.7: Fitted values for conditional variance from ARDL (1,1) - GARCH (1,1) model: 11 March 2009 to 1 January 2014

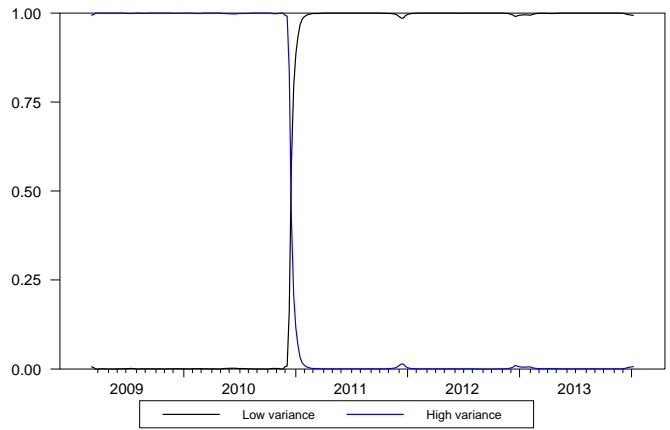


Figure 2.8: Smoothed probabilities of high and low variance regimes

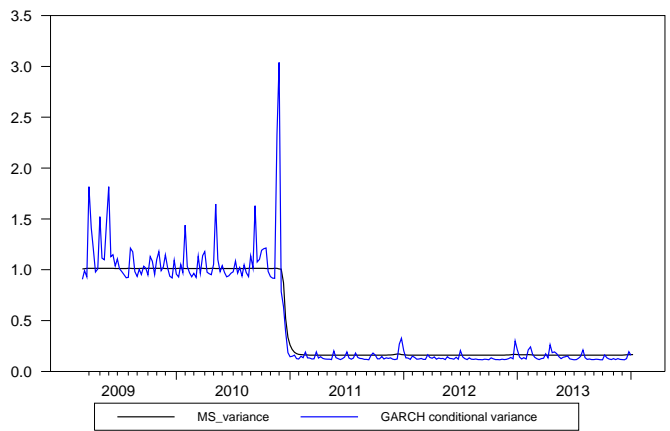


Figure 2.9: Comparison of Markov Switching variance with ARDL (1,1) - GARCH (1,1) model and variance shift

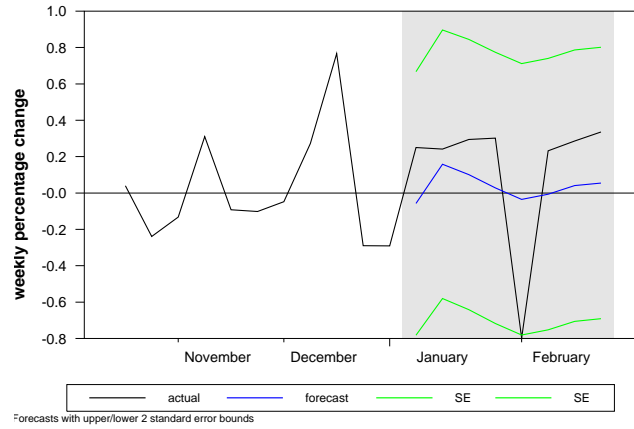


Figure 2.10: Out-of-sample performance of ARDL (1,1) - GARCH (1,1) model: 8 January to 26 February 2014

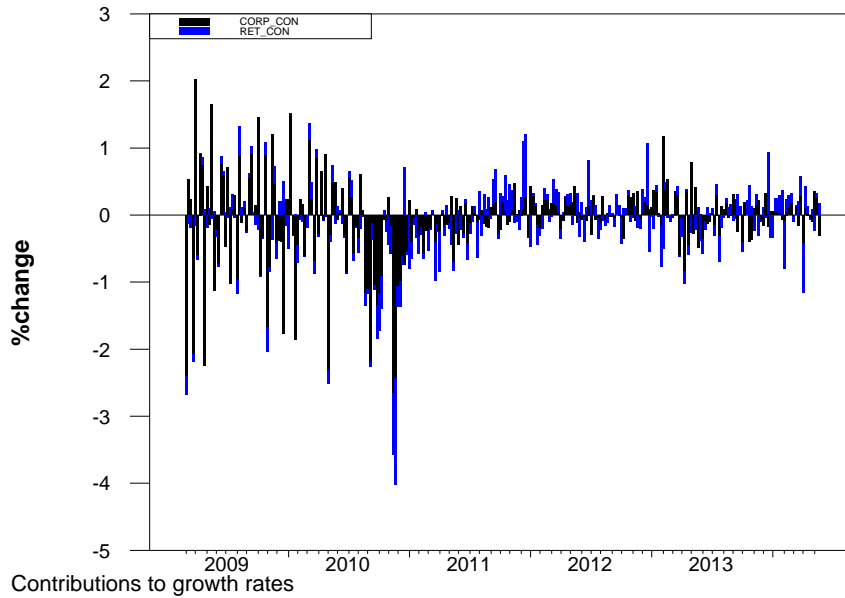


Figure 2.11: Contribution by deposit type to weekly growth rates

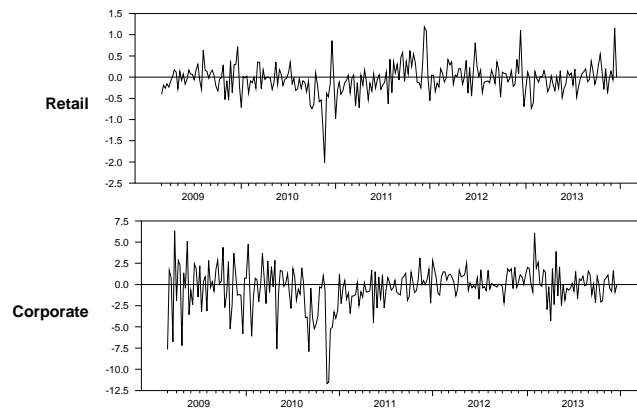


Figure 2.12: Weekly growth rate of retail and corporate deposits: March 2009 to December 2013

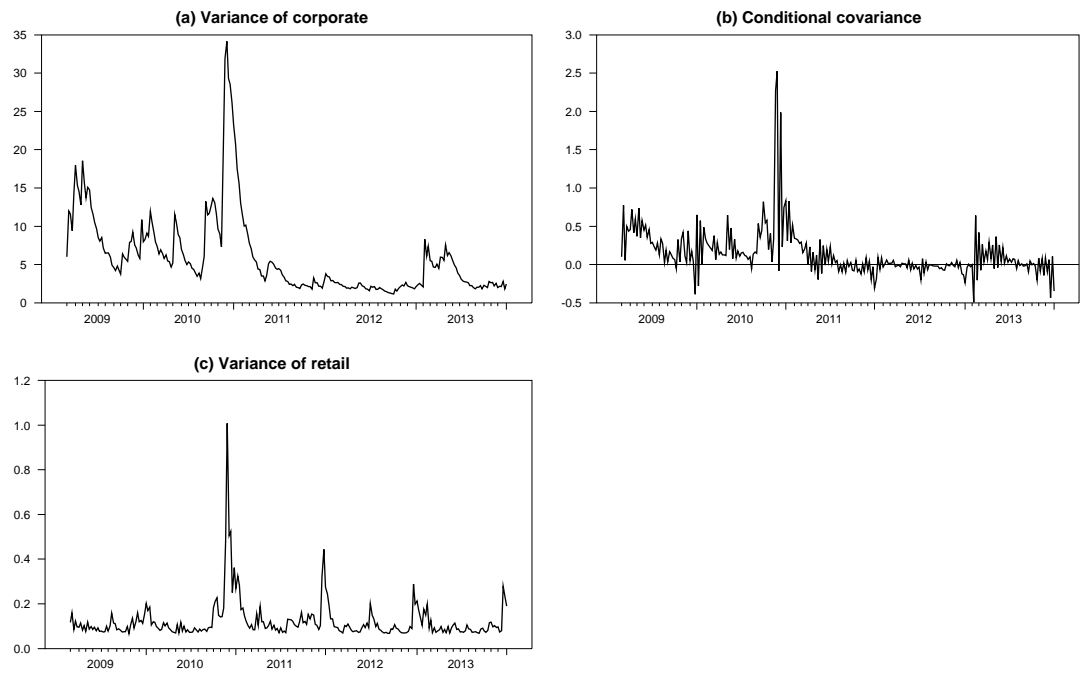


Figure 2.13: Bivariate BEKK model on retail and corporate deposits

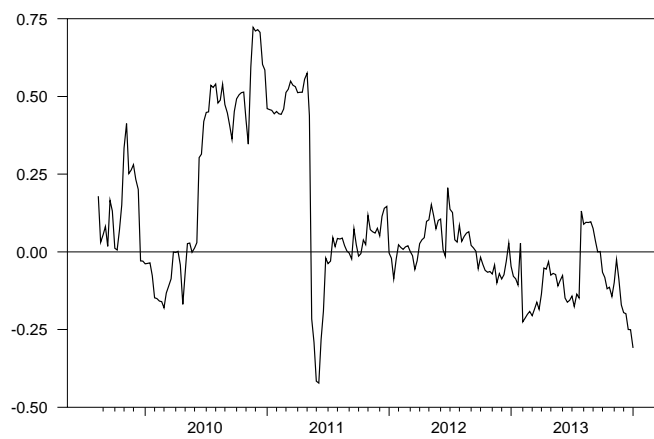


Figure 2.14: 24-week rolling sample correlation between retail and corporate deposit changes: August 2009 to December 2013

Table 2.1: Summary statistics of weekly percentage change in customer deposits

Mean	-0.12	sig.level(mean=0) 0.053
Standard Deviation	0.76	
Skewness	-1.53	sig.level(sk=0) 0.000
Excess Kurtosis	5.61	sig.level(ku=0) 0.000
Jarque Berra	428.48	sig.level(jb=0) 0.000
Minimum Value	-4.10	22 November 2010
Maximum Value	1.82	30 March 2009

Note: Data cover March 2009 through December 2013.

Table 2.2: ARDL (1,1) model of customer deposit growth: 11 March 2009 to 1 January 2014

	(1)	(2)	(3)	(4)	(5)
Δd_{t-1}	0.262 (4.30)	0.258 (4.24)	0.173 (2.94)	0.175 (2.98)	0.175 (1.64)
$\Delta IEcds_{t-1}$	-0.011 (-2.35)	-0.011 (-2.39)	-0.012 (-2.63)	-0.012 (-2.63)	-0.012 (-2.06)
$\Delta BKsp_{t-1}$	0.032 (2.65)	0.031 (2.56)	0.037 (3.26)	0.038 (3.34)	0.038 (2.08)
$\Delta ISEQgen_{t-1}$	-0.02 (-0.93)	-0.018 (-0.98)	-0.037 (-2.11)	-0.037 (-2.08)	-0.037 (-1.73)
ΔMMs_{t-1}		-0.003 (-0.59)	-0.002 (-0.47)		
$\Delta CISS_{t-1}$	0.008 (0.69)				
$\Delta CONsent_{t-1}$	-0.007 (-0.22)	-0.007 (-0.22)			
<i>Constant</i>	-0.066 (-1.47)	-0.069 (-1.55)	-0.079 (-1.76)	-0.078 (-1.73)	-0.077 (-1.86)
$\overline{R^2}$	0.11	0.11	0.10	0.10	0.10
Ljung Box Q(4) sig. level				0.16	
ARCH(4) LM Test sig. level				0.00	

Note: t-statistics in brackets. This table shows the results of running an ARDL (1,1) of the weekly percentage change in deposits, Δd_t . *IEcds* is the Irish sovereign senior CDS spread, *BKsp* is the average of Irish listed banks' share price, *ISEQgen* refers to the value of the ISEQ general (i.e., Irish stock index that excludes financials), *MMspread* is the 3-month Euribor/OIS spread, *CISS* is the ECB's composite indicator of systemic stress, *CONsent* is the Irish consumer sentiment index. All variables are expressed as weekly percentage changes. Column (5) uses Eicker-White standard errors.

Table 2.3: P-values from multivariate Granger Causality F tests (4 March 2009 to 1 January 2014)

	Δd	$\Delta BKsp$	$\Delta IEcds$	$\Delta ISEQgen$
Δd	0.019	0.994	0.373	0.547
$\Delta BKsp$	0.001	0.063	0.268	0.545
$\Delta IEcds$	0.008	0.690	0.024	0.945
$\Delta ISEQgen$	0.146	0.171	0.432	0.016

Note: This table shows the p-values from running multivariate Granger Causality F tests. Specifically a VAR(2) is used with the lag length based on Akaike Information Criteria. d_t refers to customer deposits, $IEcds$ is the Irish sovereign senior CDS spread, $BKsp$ is the average of Irish listed banks' share price and $ISEQgen$ refers to the value of the ISEQ general (i.e., Irish stock index that excludes financials). Data are weekly percentage changes.

Table 2.4: ARDL (1,1) - GARCH (1,1) model of weekly percentage change in deposits:
11 March 2009 to 1 January 2014

Model of h_t	
α_0	0.009 (2.02)
α_1	0.155 (3.56)
β_1	0.826 (20.76)
Model of Δd_t	
<i>Constant</i>	-0.007 (-0.22)
Δd_{t-1}	0.141 (1.95)
$\Delta IEcds_{t-1}$	-0.006 (-1.74)
$\Delta BKsp_{t-1}$	0.044 (3.28)
$\Delta ISEQgen_{t-1}$	-0.013 (-1.04)
Log Likelihood = -222.43	
No. of Observations = 252	
McLeod-Li(1983) p-value for residual ARCH = 0.83	
Jarque Berra normality test of standardised residuals, p-value=0.00	

Note: t-statistics in brackets.

Table 2.5: ARDL (1,1) - GARCH (1,1) model of weekly percentage change in deposits:
11 March 2009 to 1 January 2014

Model of h_t	
α_0	0.088 (5.01)
α_1	0.144 (2.25)
β_1	0.227 (2.16)
D_t	0.62 (3.99)
Model of Δd_t	
Δd_{t-1}	0.157 (2.42)
$\Delta IEcds_{t-1}$	-0.005 (-1.89)
$\Delta BKsp_{t-1}$	0.046 (3.32)
Log Likelihood = -203.16	
No. of Observations = 252	
McLeod-Li (1983) p-value for residual ARCH = 0.96	

Note: t-statistics in brackets. Robust standard errors from Quasi Maximum Likelihood Estimation. The table shows the estimation results from the following system of equations,

$$\Delta d_t = \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \epsilon_t$$

$$\epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \eta D_t$$

Table 2.6: ARDL(1,1) - GARCH-M (1,1) model of weekly percentage change in customer deposits: 11 March 2009 to 1 January 2014

Model of h_t	
α_0	0.085 (4.72)
α_1	0.145 (2.03)
β_1	0.251 (1.84)
D_t	0.553 (3.83)
Model of Δd_t	
<i>Constant</i>	0.033 (0.91)
Δd_{t-1}	0.134 (2.06)
$\Delta IEcds_{t-1}$	-0.006 (-1.67)
$\Delta BKsp_{t-1}$	0.047 (3.26)
h_t	-0.268 (-2.36)
Log Likelihood = -200.6	
No. of Observations = 252	
McLeod-Li (1983) p-value for residual GARCH = 0.51	

Note: t-statistics in brackets. Robust standard errors from Quasi Maximum Likelihood Estimation used. The table shows the estimation results from the following system of equations,

$$\Delta d_t = \phi_0 + \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \tau h_t + \epsilon_t$$

$$\epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \eta D_t$$

Table 2.7: Summary statistics of weekly percentage change in retail and corporate deposits: 2 March 2009 to 6 January 2014

	Δr_t	Δc_t
Mean	-0.042	-0.327
Standard Deviation	0.356	2.436
Skewness	-0.300	-1.212
Excess Kurtosis	4.922	3.925
Jarque-Berra	260.208	225.288
p-value for JB=0	(0.00)	(0.00)
Maximum value	1.19 (12:12:2011)	6.33 (30:03:2009)
Minimum value	-2.01 (22:11:2010)	-11.68 (15:11:2010)

Table 2.8: MV-GARCH-BEKK model of customer deposits: 11 March 2009 to 06 January 2014

	Coefficient	S.E
<i>Mean</i> (1)	-0.041	0.11
<i>Mean</i> (2)	-0.026	0.02
<i>c</i> (1, 1)	0.445***	0.11
<i>c</i> (2, 1)	-0.136***	0.03
<i>c</i> (2, 2)	0.000	0.34
<i>a</i> (1, 1)	0.366***	0.05
<i>a</i> (1, 2)	0.012	0.01
<i>a</i> (2, 1)	-0.464	0.46
<i>a</i> (2, 2)	0.397 ***	0.08
<i>b</i> (1, 1)	0.871 ***	0.05
<i>b</i> (1, 2)	0.070 ***	0.02
<i>b</i> (2, 1)	1.200	0.87
<i>b</i> (2, 2)	-0.739***	0.06

No. of Obs: 254
 Log Likelihood: -622.7
 Test for multivariate ARCH: 22.25 (0.22)

Variance causality, c_t to r_t : $H_0: a(1, 2) \ \& \ b(1, 2) = 0$ (Sig.level = 0.001)
 Variance causality, r_t to c_t : $H_0: a(2, 1) \ \& \ b(2, 1) = 0$ (Sig.level = 0.376)

Note: *** refers to significance at the 1 % level, ** refers to significance at the 5 % level and * denotes significance at the 10 % level. The table shows the estimation results from the following system of equations,

$$\begin{aligned} \Delta c_t &= \mu + \epsilon_{1t} \\ \Delta r_t &= \delta + \epsilon_{2t} \\ \epsilon_{1t} &= v_{1t} \sqrt{h_{11t}} \\ \epsilon_{2t} &= v_{2t} \sqrt{h_{22t}} \\ \epsilon_{it} | \Omega_{t-1} &\sim (0, H_t), i = 1, 2 \\ H_t &= C' C + A' \epsilon_{t-1} \epsilon_{t-1}' A + B' H_{t-1} B \end{aligned}$$

Table 2.9: CCC model of corporate and retail deposit growth: 2 March 2009 to 6 January 2014

	Coefficient
μ	-0.046 (-0.36)
δ	-0.31 (-1.43)
c_1	0.158 (1.21)
c_2	0.028 (3.014)
a_1	0.155 (2.42)
a_2	0.232 (2.38)
b_1	0.820 (11.81)
b_2	0.550 (5.084)
ρ_{12}	0.150 (2.049)
Log Likelihood = -629.34	
No. of Obs. = 254	

Note: t statistics in parenthesis. The table shows the estimation results from the following system of equations,

$$\begin{aligned} \Delta c_t &= \mu + \epsilon_{1t} \\ \Delta r_t &= \delta + \epsilon_{2t} \\ h_{11t} &= c_{10} + a_1 \epsilon_{1t-1}^2 + b_1 h_{11t-1} \\ h_{22t} &= c_{20} + a_2 \epsilon_{2t-1}^2 + b_2 h_{22t-1} \\ h_{12} &= \rho_{12} \sqrt{h_{11t} h_{22t}} \end{aligned}$$

2.8 Appendices

Appendix 1: Preliminary statistical tests of customer deposits and explanatory variables

Prior to estimation our variables of interest are transformed into logs and tested for evidence of stationarity. As the average of the domestic banks' share price falls below €1 over the sample, we add 1 to the entire series over the sample to ensure that the log share price does not go negative.

Figure 2.15 shows the Autocorrelation and Partial autocorrelation functions for the variables of interest in log levels over 50 lags. The slow, almost linear decay of the ACFs is indicative of a unit root process for all variables. The Ljung-Box (Q) statistic for all variables exceeds the chi-squared critical value of 34.8 with 50 degrees of freedom and at 95 per cent significance level. Therefore, the null hypothesis that all of the autocorrelations up to 50 lags are zero cannot be rejected.

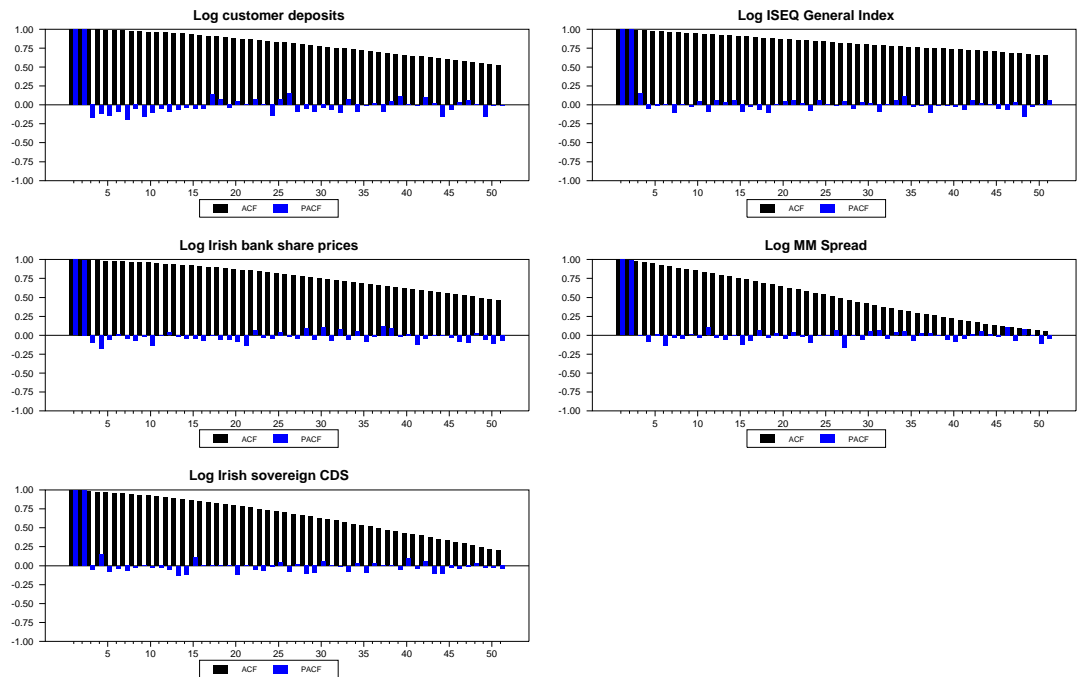


Figure 2.15: Autocorrelation and Partial Autocorrelation Functions

Each variable is then transformed into 100 times its first difference, prior to estimation. The results are shown in Figure 2.16. The transformed variables are formally tested for unit roots using Augmented Dickey Fuller Tests (ADF). Lag length for lagged dependent variable is chosen using the Schwartz Bayesian Information Criterion with the maximum number of additional lags set at 8 in all ADF regressions. No trend or constant is initially included as the data are in first differences. The ADF

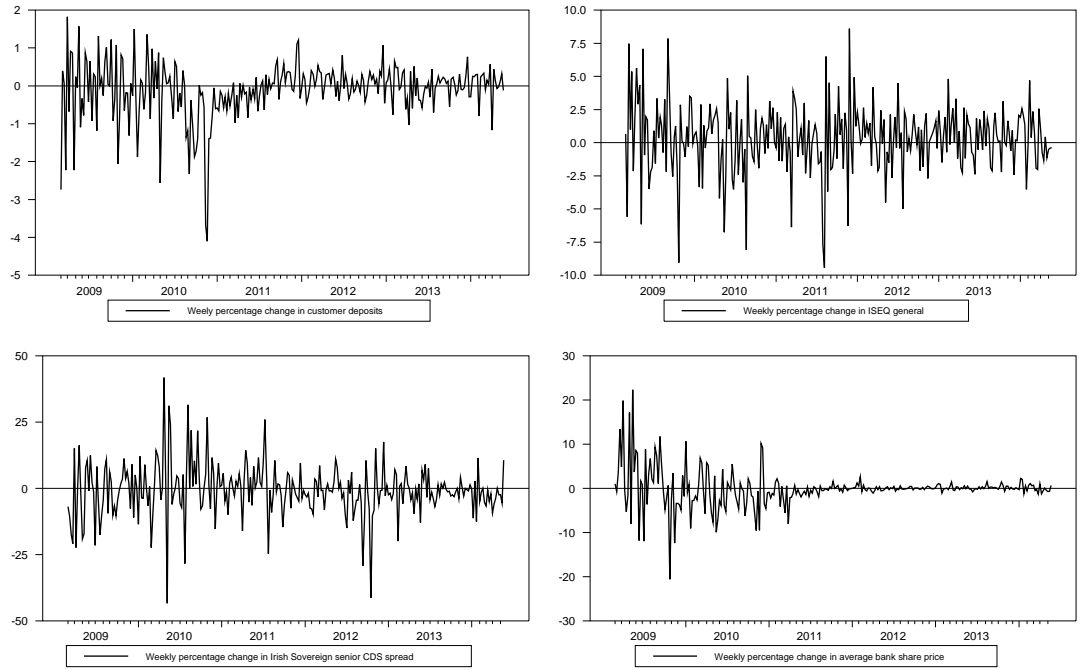


Figure 2.16: Customer deposit growth rates and explanatory variables

tests incorporate a null hypothesis of a unit root. The critical values are those that are linearly interpolated from the Fuller (1976) results (Estima, 2012). Table 2.10 shows the results. In all cases, the null of a unit root can be rejected at the 1% significance level. This results holds even if an intercept is included in the ADF specification. Each variable in logs is, therefore, difference stationary and integrated of order one.

Table 2.10: Testing for unit roots using Augmented Dickey Fuller Tests.

Variable	Test Statistic
Δd_t	-13.58 ***
$\Delta BKsp_t$	-6.66 ***
$\Delta IEcds_t$	-12.97 ***
$\Delta ISEQgen_t$	-18.81 ***
$\Delta MMspread_t$	-15.45 ***

Notes:*** represents 1% significance level.

Lags chosen by SBC information criterion.

Appendix 2: Initially testing the order of p and q in GARCH model

In order to determine the order of p and q for the GARCH (p,q) model, information criteria such as Akaike and Schwarz-Bayesian and the estimated log likelihood functions are used to compare models. Specifically an ARCH(1), ARCH(2) and a GARCH(1,1) are compared for the initial goodness of fit to our customer deposit flows. The best-fitting model will have the lowest information criteria and highest log likelihood. The results are shown in Table 2.11. As can be seen a GARCH(1,1) is preferred.

Table 2.11: Comparing various GARCH (p,q) models

Order(p,q)	AIC	BIC	Log likelihood
$p=0,q=1$	511.39	536.09	-248.69
$p=0,q=2$	492.28	520.53	-238.15
$p=1,q=1$	460.86	489.10	-222.43

Appendix 3: Testing for variance regime shifts in customer deposits using Markov Switching models

To formally test the stability of the conditional variance estimated using our GARCH (1,1) - ARDL (1,1) model, Markov Switching techniques are used. Such techniques allow us to test if the statistical distribution of a series remains constant over the sample period or switches between different regimes. Although the random variable governing the switch between regimes is often unobserved, the use of a probabilistic model based on a Markov chain imposes some structure on data generating process for this random variable (Hamilton, 2008). A first order Markov chain implies that the probability that the data process is in a particular regime S at time t is dependent on the regime in the previous period. Ω_{t-1} is our information set up to time $t - 1$.

$$Prob[S_t = i \parallel \Omega_{t-1}] = Prob[S_t = i \parallel S_{t-1} = j] \quad (2.20)$$

The chapter tests if the variance of the error term, ϵ_t in Equation 2.21 switches over the sample using a first-order Markov process and assuming constant transition probabilities. Maximum Likelihood is used to estimate the switching regression. Two regimes are found to be a good fit.

$$\Delta d_t = \phi_0 + \phi_1 \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \gamma \Delta ISEQgen_{t-1} + \epsilon_{i,t} \quad (2.21)$$

where

$$\epsilon_{i,t} \sim N(0, \sigma_i^2), i = 1, 2$$

The results indicates that there is a high and low variance regime. The smoothed probabilities in Figure 2.8 show that the switch occurs around 8 December 2010, which is just after the formal application by Ireland for the external assistance on 28 November 2010. Prior to 8 December 2010, there is a high volatility regime. From 8 December 2010 to the end of our estimation sample, a regime of relatively lower volatility prevails. Based on these results, 8 December 2010 is therefore used as the date for the inclusion of our variance shift in our GARCH model. Figure 2.9 compares the variance over the sample estimated using our Markov Switching specification with the variance estimated from our ARDL(1,1) - GARCH (1,1) model with a variance shift on 8 December 2010.

Table 2.12: Markov Switching results: 11 March 2009 to 1 January 2014

σ_1^2	0.160 (9.34)
σ_2^2	1.013 (7.76)
$p(1, 1)$	0.996 (210.59)
$p(1, 2)$	0.005 (0.78)
Log Likelihood = -218.65	
No. of Observations = 252	

Appendix 4: Testing for leverage effects

In this section, a number of tests are applied to the customer deposit model to investigate if leverage effects are present over the sample. First, drawing on Enders(2010), we regress the squared standardised residuals from the joint estimation of (2.7) and (2.9) on a constant and lags of the standardised residuals (Equation 2.22).

$$\Delta s_t^2 = \text{constant} + s_{t-1} + s_{t-2} + s_{t-3} + \mu_t \quad (2.22)$$

where s_t^2 is standardised squared residuals and s_{t-i} is the lagged squared residuals. If there are leverage effects, the squared standardised residuals will be correlated with the level of the standardised residuals. This can be formally tested with an F test on the joint significance of the coefficients on the lagged standardised residuals. The results are shown in Table 2.13. As can be seen, the null that coefficients are equal to zero cannot be rejected. There appears to be no statistical evidence of leverage effects in the weekly customer deposit data based on this test.

Table 2.13: Testing for leverage effects

Variable	Coefficient estimate
s_{t-1}	0.12 (1.03)
s_{t-2}	-0.02 (-0.19)
s_{t-3}	-0.04 (-0.31)
<i>constant</i>	0.99 (8.26)
F(3, 245): 0.40 with sig. level 0.76	

Note: t-statistics in brackets

An additional method to test the presence of the an asymmetric response to the

size of shocks is to include a leverage term in the model of the conditional variance and test its statistical significance. Such a term can be modelled with an exponential GARCH (E-GARCH) specification due to Nelson (1991) or with a Threshold GARCH (TARCH) specification due to Glosten, Jaganathan and Runkle (1993) (GJR).

An E-GARCH with asymmetries can be estimated using the following equation;

$$\Delta d_t = \phi \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \epsilon_t, \epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1) \quad (2.23)$$

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + l_t \left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \beta_1 \ln(h_{t-1}) + \eta D_t \quad (2.24)$$

where l_1 is our leverage term. Table 2.14 shows the estimation results. As can be seen, l_1 is not statistically significant at conventional levels.

Table 2.14: Asymmetry with E-GARCH(1,1) - ARDL (1,1) model of weekly percentage change in deposits: 11 March 2009 to 01 January 2014

Model of h_t	
α_0	-1.16 (-2.65)
α_1	0.33 (2.28)
l_1	(0.07) (0.92)
β_1	0.54 (2.80)
D_t	0.99 (2.47)
Model of Δd_t	
Δd_{t-1}	0.18 (2.91)
$\Delta IEcds_{t-1}$	-0.01 (-2.11)
$\Delta BKsp_{t-1}$	0.04 (2.78)
Log Likelihood = -205.87	
No. of Observations = 252	
Note:t-statistics in brackets	

The GJR Threshold GARCH model is also applied using the following equation;

$$\Delta d_t = \phi \Delta d_{t-1} + \chi \Delta BKsp_{t-1} + \delta \Delta IEcds_{t-1} + \epsilon_t, \epsilon_t = \sqrt{h_t} v_t, v_t \sim N(0, 1) \quad (2.25)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \lambda_1 l_{t-1} \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \eta D_t \quad (2.26)$$

where l_{t-1} is our leverage effect coefficient on a dummy variable which is equal to one when $\epsilon_{t-1} < 0$. This approach allows us to test the effects of both positive and

negative shocks. If λ_1 is statistically significant, there is a threshold effect in the data. If λ_1 is statistically significant and > 0 , negative shocks will have a relatively larger effect on the volatility of customer deposits than positive ones. As per Enders (2010, pg. 156), the impact on conditional volatility from negative shocks will be given by $(\alpha_1 + \lambda_1)\epsilon_{t-1}^2$. The results from the application of the GJR equations 2.25 and 2.26 to the customer deposit table is shown in Table 2.15. λ_1 is not found to be statistically significant.

Table 2.15: GJR Threshold GARCH (1,1) - ARDL (1,1) model of weekly percentage change in deposits: 11 March 2009 to 1 January 2014

Model of h_t	
α_0	0.08 (4.25)
α_1	0.25 (1.67)
λ_1	-0.13 (-0.89)
β_1	0.25 (1.72)
D_t	0.59 3.77
Model of Δd_t	
Δd_{t-1}	0.157 (2.42)
$\Delta IEcds_{t-1}$	-0.005 (-1.89)
$\Delta BKsp_{t-1}$	0.046 (3.32)
Log Likelihood = -202.81	
No. of Observations = 252	

Note:t-statistics in brackets.

Chapter 3

Testing for Fundamentals, Fads and Rational Bubbles in Irish Commercial Property Prices: 1985Q1 to 2012Q4

3.1 Introduction

Property price dynamics have intrigued economists for years. Boom and bust conditions feature regularly in this market often with significant real effects. Researchers continue to search for theoretical and empirical explanations for such developments. While house prices garner relatively more attention due to the potential wealth effects for households, commercial property prices also merit attention given the market's key role in many financial crises. Historical examples regularly cited are the Savings and Loan crisis in the United States in the late-1980s, the Nordic crisis in the 1990s, the East Asian and the Japanese crisis of the 2000s (Herring and Wachter, 1999 and ECB, 2008). Commercial property-related lending tends to be relatively riskier than residential mortgages during periods of financial stress given that such lending is primarily for investment purposes and as the exposures are larger and more heterogeneous. Also some borrowers in this market tend to be covered by limited liability.

The Irish financial crisis is a recent example of the adverse impact of commercial

property prices on financial stability. Real Irish commercial property prices increased by circa 200 per cent between 1995 and mid-2007 with bank credit the funding of choice for many investors. This was a period of rapid economic growth for the Ireland with GDP per capita converging on our European counterparts¹ and borrowing costs declining in line with policy rates, a reduction in perceived risk and increased access to cheaper European funding markets. The combination of favourable demand conditions and an increased willingness to supply credit boosted the commercial property market in Ireland. The Irish housing market also followed a similar pattern.

By end-2012, however, commercial property prices had fallen by almost 70 per cent from their peak in 2007 with many Irish banks facing expected losses on their property exposures. Market liquidity evaporated and investor sentiment became increasingly negative towards anything property related. While the global financial crisis provided the external shock, vulnerabilities within the domestic banking system such as imprudent lending standards and skewed balance sheets led to a costly systemic crisis.² The misallocation of real resources up to 2007, with aggregate investment heavily dependent on property also rendered domestic demand vulnerable to such shocks. While adjustments in both residential and commercial property markets caused problems for the banks, the initial phases of the crisis (i.e., 2008-2010) saw relatively higher declines in the quality of the commercial portfolios and sharper price deflation.³ The Irish case and other historical examples highlight the importance of detecting unsustainable commercial price developments, particularly if investors are highly leveraged.

Even if a property boom is not accompanied by rapid credit growth, its reversal can have real effects. Investment may flow into this market to gain a high return, creating a potential misallocation of economic resources and affecting the relative price of other assets (Blanchard and Watson, 1982). Periods of rapid price growth are generally not sustainable and their reversal may be abrupt. Persistent deviations of prices from fundamentally justified values may signal future adjustment and so provide a useful guide among other indicators. There is renewed interest in the identification of property price misalignment following the recent global financial crisis and policy makers' focus on actively mitigating systemic risk using macro-prudential policy (Hartmann, 2015). Macro-prudential researchers are focused on developing

¹See Honohan and Walsh, 2002.

²See Honohan (2010) and Regling and Watson (2010) for details on the origins of the Irish crisis.

³The Irish Government established the National Asset Management Agency (NAMA) in 2010 to remove problem commercial property loans from domestic banks' balance sheets.

indicators to aid the systemic risk assessment of property markets (ECB, 2011 and ESRB, 2014). This chapter aims to contribute to this research drawing on the Irish experience.

The estimation of Irish commercial property prices has received relatively less attention in the literature compared with house prices. There are a number of published papers on supply and rent dynamics in the Dublin office market (McCartney, 2008, 2011) and on land prices (Browne and Fagan, 1992, Roche and McQuinn, 2000). International commercial property markets have been the subject of a number of papers such as Hendershott (2000) on the Sydney office market, Chervachidze and Wheaton (2013) on capitalisation rates⁴ in the United States and Ball and Grilli (1997) on commercial property investment in the United Kingdom. Commercial property prices have also featured in cross-country studies such as Davis and Zhu (2011) who examine the link between bank lending and price determination and in Hendershott *et al.*, (2005) who review tests for market rationality in a number of countries.

To address the gap in the Irish literature, this chapter examines the dynamic behaviour of Irish commercial property prices. First, we investigate if quarterly price movements can be explained by economic fundamentals such as income and interest rates using reduced form econometrics between 1985Q1 and 2012Q4. A further specification controls for the influence of credit on price movements. Given the difficulty in correctly approximating a fundamental price, some simple statistical analysis based on the price-to-rent ratio is used to complement the econometrics. The results show periods over the sample where commercial property prices persistently deviate from fundamentally-determined prices, revealing a non-fundamental price component in the data. Positive misalignment or overvaluation is found in the late-1980s/early-1990s and consistently through the 2000s up to 2007, while there is evidence of undervaluation in the mid-1990s and during the crisis period.

To gain a better understanding of the nature of the misalignment, the chapter further tests if there is evidence of an irrational fad or a rational stochastic bubble in Irish commercial property prices over the period under study. Such models have been used in the stock market literature to explain why equity prices vary relative to their intrinsic value based on theoretically justified determinants (e.g., Schiller, 1984, Cutler, Poterba and Summers, 1991 and Blanchard and Watson, 1982). The underlying theory and methodology from this literature are applicable to commercial

⁴The ratio of net operating income to price or capital values.

property given its role as an important investment asset. A deeper understanding of commercial property price dynamics can help to model and forecast prices more efficiently. The fads theory assumes temporary deviations of prices from equilibrium values due to some form of market irrationality. Therefore, if Irish prices are subject to faddish behaviour, the deviation between actual and fundamental prices should have explanatory power for future price returns. The rational bubble hypothesis assumes that prices returns differ depending on whether prices are in an expansionary or contractionary phase. So non-linear estimation is required. Investors are aware that the market is subject to bubble-like behaviour so their existence is factored into price expectations. As the boom period develops, investors demand higher and higher prices to compensate for losses when prices eventually crash. With both fads and bubbles, the collective action of investors lead to price spirals and periods where prices move out-of-line with fundamentals.

The chapter draws on an empirical approach by Van Norden (1996) and Schaller and Van Norden (2002) which allows us to test between a fad and a bubble using regime-switching techniques. The framework nests the fad specification within a general rational bubble equation so that by testing the validity of the restrictions associated with the presence of a fad, we can infer which model best fits the data. There are some differences in the empirical approach. Schaller and Van Norden use simple switching techniques, while this chapter uses Markov switching methodology to capture persistence. Time-invariant transition probabilities are assumed rather than imposing the assumption that the size of the misalignment governs the switch between regimes. Based on the Irish experience, the possibility that other exogenous factors such as an expectations shock or news may also generate the switch between regimes is preferred. The restrictions imposed by the fads model cannot be accepted and there is some evidence in favour of a bubble. The theoretical features of the bubble hypothesis, however, are not fully supported across our three estimates of misalignment or non-fundamental price series.

The chapter is structured into a number of sections. Section 3.2 discusses the theory of asset prices in the context of fads and stochastic bubbles. Section 3.3 focuses on the Irish commercial property market and specifies a model for real prices, which allows the identification of periods where prices deviates from their fundamental value. A statistical indicator of misalignment is also used to complement the econometrics. The estimated misalignment is used in section 3.4 to test for the presence of a fad or

a bubble in Irish commercial property prices. A summary and the main conclusions are contained in the final section.

3.2 Asset pricing theories: irrational fads versus rational bubbles

This chapter applies the analytical framework of Schaller and Van Norden (2002, hereafter SVN), to Irish real commercial property prices. The SVN approach is based on two particular strands of the equity price literature that seek to explain why prices vary so much relative to the intrinsic value of the asset. The two strands are fads and rational bubbles. Although potentially similar in general terms, the explanation for fads and rational collapsing bubbles differ in the dynamic description of price behaviour and in their assumptions regarding the rationality of market participants.

Fads are associated with some form of irrationality among investors that cause prices to temporarily deviate away from equilibrium values (Schiller, 1984). As prices are assumed to eventually return to an equilibrium value, proponents of the fad theory believe that price changes may, therefore, be predictable at certain horizons which conflicts with the efficient market hypothesis (EMH). The fads model in Cutler, Poterba and Summers (1991) is used in the SVN framework.

It is assumed that asset prices have both a fundamental p_t^f and non-fundamental component p_t^{nf} with lower case denoting logs in all equations.

$$p_t = p_t^f + p_t^{nf} \quad (3.1)$$

The fundamental price is assumed to be non-stationary and v_t is a white noise error term.

$$p_t^f = p_{t-1}^f + v_t \quad (3.2)$$

$$v_t \sim iid(0, \sigma_v^2)$$

The non-fundamental price is assumed to follow a stationary autoregressive process of order (1) with the coefficient ρ bounded between zero and one (3.3). The assumption of this stationary component implies that returns may be predictable.

$$p_t^{nf} = \rho p_{t-1}^{nf} + e_t, \quad (3.3)$$

$$1 > \rho > 0, e_t \sim iid(0, \sigma_e^2)$$

By re-arranging equations (3.1) through (3.3), we can express log price changes between period t and $t+1$ relative to deviations between actual prices and fundamental prices.

$$p_{t+1} - p_t = \beta_0 + \beta_b(p_t - p_t^f) + e_{t+1}$$

Fundamental prices are difficult to observe in practice so p_t^f must be estimated using a proxy p_t^p which introduces some measurement error, w_t .

$$p_t^p = p_t^f + \omega_t, \tag{3.4}$$

$$w_t \sim iid(0, \sigma_\omega^2)$$

Assuming $\omega_t \approx 0$ in (3.4), we can replace p_t^f with p_t^p to yield (3.5)

$$p_{t+1} - p_t = \beta_0 + \beta_b(p_t - p_t^p) + e_{t+1} \tag{3.5}$$

The difference between the actual price and the fundamental price at time t is assumed to have explanatory power for price changes at time $t + 1$ if the market is subject to a “fad”. In Cutler *et al.*, (1991) the fads model is estimated as a simple linear regression. If the asset price series follows a fad, the coefficient β_b should be negative so that any misalignment or gap will fall over time. An increase in the gap today leads to a decrease in rate of price growth tomorrow. As these misalignments are not sustainable, prices do not exhibit explosive behaviour.

The term “bubble” is often more popular than “fads” to discuss periods of boom and bust in asset prices among the general public. The existence and exact definition of a “bubble”, however, is the subject of much debate among economists.⁵ The SVN framework focuses on stochastic bubbles as defined by Blanchard and Watson (1982). Collapsing bubbles are assumed to be jointly consistent with the *no arbitrage* assumption of the EMH in the presence of rational expectations (Blanchard and Watson, 1982, hereafter BW). In equilibrium, an asset price P_t is assumed to equal the discounted present value of future income or dividends D_t , with the latter assumed to represent the fundamental price. The discount rate r is assumed constant.

⁵See Taipalus (2013) and Brunnermeier in the 2008 New Palgrave Dictionary of Economics for good reviews of the various types of economic bubbles.

$$P_t = \frac{E_t(P_{t+1} + D_t)}{1 + r} \quad (3.6)$$

According to BW, there are other price solutions, which satisfy the equilibrium condition. The market price can, therefore, deviate from fundamental values without violating the no arbitrage condition. Prices are assumed to contain both a fundamental and bubble component, with the size of the bubble B_t given by the following equation,

$$B_t \equiv P_t - P_t^f \quad (3.7)$$

The bubble must grow in expectations each period at a rate r to entice investors to participate in the market.

$$E_t(B_{t+1}) = (1 + r) * B_t \quad (3.8)$$

BW consider one possible example of a rational bubble where the bubble will survive in state (S) or burst in state (C) with probability, (q) and $(1 - q)$ respectively. If the bubble survives, returns must be higher than r so as to compensate for the crash.

$$E_t(B_{t+1}|S) = \left(\frac{1 + r}{q}\right) * B_t \quad (3.9)$$

The expected value of the bubble in a collapse is zero. In other words if the bubble is positive and it collapses, the actual price falls by the value of the bubble.

$$E_t(B_{t+1}|C) = 0 \quad (3.10)$$

In summary, stochastic bubbles are assumed to be consistent with rational expectations, even though prices can move out-of-line with fundamentals, as the expected discounted value of future bubbles is reflected in current prices. Although these bubbles are assumed to grow over time, they will eventually burst with some probability. As actual prices increase above fundamental prices, the probability of crash increases, justifying further increases in prices or higher returns to compensate investors for the corresponding increase in risk. Investors know that there may be a bubble and that prices will eventually decline. They will participate in the market as they believe they can exit before the price collapses (Taipalus, 2013). Stochastic collapsing bubbles can occur in certain markets where fundamentals are difficult to assess; there are no con-

straints on short-selling and there are new market participants over time (Blanchard and Watson, 1982).

SVN extend the BW model in two ways. First it assumed that the probability of the bubble surviving, q is negatively related to the proportional size of the bubble,

$$b_t \equiv \frac{B_t}{P_t} \quad (3.11)$$

SVN also allow for the possibility that bubbles may partially collapse in a particular period as they contend some market crashes may be gradual rather than instantaneous. They relate the expected size of the bubble in state C to the size of the bubble in the previous period. Applying a first-order Taylor expansion to the conditional expected returns in each state, SVN derive the following linear expressions for the expected price returns (omitting the expectations operator).

$$R_{i,t+1} = \beta_{i0} + \beta_{ib}b_t + e_{i,t+1}, \quad (3.12)$$

$$e_{i,t+1} \sim N(0, \sigma_i^2), i = S, C$$

Equation (3.12) is the general regime switching model of SVN. $R_{i,t+1}$ refers to price returns between time t and $t + 1$, and b_t is the estimated bubble term. The bubbles model implies that expected returns vary depending on the prevailing regime. Expected returns should be higher in the survival state relative to collapse state. Consequently, $\beta_{s,0}$ need not equal $\beta_{c,0}$ and $\beta_{b,s}$ must be greater than $\beta_{b,c}$.

In contrast to the fads literature, the theoretical underpinnings of the rational bubbles models are considered well developed but the empirical results are relatively less conclusive (Camerer, 1989). Many empirical papers test for the presence of fads and collapsing bubbles separately but the approach of SVN facilitate the joint testing of both. The novel feature of SVN is the assumption that the error term in (3.5) is heteroscedastic due to presence of two states. It is assumed that the variance of σ_e^2 in the survival period is less than the variance in the crash period. Many of the empirical tests for the presence of fads find that the residuals are heteroscedastic. SVN assume heteroscedastic returns for two further reasons. First, to ensure that when testing for fads, the presence of heteroscedastic residuals do not affect the results. Second, this assumption is invoked to ensure possible identification of the fads model with hypothesis testing. With this innovation, the fads model is nested within the general

regime switching specification for a rational bubble.

The fads model implies that expected returns (conditioned on B_t) will be the same in each regime. The equality of the point estimates for the intercept and slope coefficients can be tested using Wald Tests. Both restrictions can be jointly tested using Likelihood Ratio tests. If $\beta_{s,0} \neq \beta_{c,0}$ and $\beta_{b,s} \neq \beta_{b,c}$ we cannot accept the series under study conforms to the fads model and must consider the alternative hypothesis of a rational bubble. Conversely, if the restrictions are found to be valid, we must reject the hypothesis of a bubble in favour of the fads model.

SVN apply this approach in a number of papers covering exchange rates and equity prices. One such example is Schaller and Van Nordon (2002). The authors examine monthly US stock price data over the period 1926 to 1989 for evidence of fads or rational bubbles using regime switching techniques. They find some evidence that the estimated deviations from the fundamental price have predictive power for stock market returns, thereby supporting the fads model thesis. However, when the restrictions imposed by the fads model are tested relative to a general regime switching specification, these restrictions are generally rejected. In the bubble scenario, the coefficients in the collapsing regime are found to be negative and smaller than the slope coefficient in the survival regime which is in line with *ex ante* expectations. Expected returns should be positively related to the size of the bubble in the survival period to compensate investors. The paper, however, finds a consistently negative sign. In summary, the paper finds that the data do not fully conform to the fads hypothesis but there is not overwhelmingly consistent evidence in favour of rational bubbles.

In an Irish context, Roche (1999) looks at Dublin and UK house prices from late-1970s up to 1999 and applies the SNV regime switching framework. Roche (1999) tests between three hypotheses, namely that prices can be explained by either fundamentals, fads or stochastic bubbles. Both endogenous and exogenous switches are assumed. Roche (1999) finds evidence of a stochastic bubble but estimates that the probability of a crash in Dublin house prices in 1999 was less than the probability estimated for Britain in late-1980s. The UK housing market suffered a significant adjustment in late-1980s/early-1990s.

To apply this approach to the Irish market, it is first necessary to estimate a fundamental commercial property price series or approximate a non-fundamental component in the price data to obtain our explanatory variable. The need to proxy

both components introduces measurement error. Therefore, any estimate of a non-fundamental price may be biased. However according to Roche (1999, 2000), even if we mis-specify the magnitude or the relative size of the bubble term, it should not affect our tests for regime-switching models. Wald tests for coefficient restrictions and the associated Likelihood Ratio tests are not sensitive to linear transformations of non-fundamental prices/bubble component. Therefore, while noting its existence we assume that the measurement error is negligible.

3.3 Irish commercial property prices and fundamental values

3.3.1 Modelling commercial property prices

In this subsection a model of Irish commercial property prices is specified. Given the shortage of Irish literature specifically on price determination⁶, we must look to international studies for guidance. The international research on commercial property prices focuses either on testing the market for efficiency using an empirical finance-based approach or on estimating a reduced form econometric model where the underlying economic determinants of prices are suggested by economic theory in a demand/supply framework. As noted by Hordahl and Packer (2007), there are many challenges associated with the finance-based approach given that both the property-risk premium and expected future cash flows are unobservable and therefore must be estimated. To approximate a fundamental price, this chapter, therefore, focuses on investigating the economic determinants using reduced form econometrics rather than the finance approach.

The analytical framework of Davis and Zhu (2004 & 2011, hereafter DZ) is closely followed. Using a reduced form model⁷, commercial property cycles are shown to be influenced by two channels, namely exogenous shocks to the economic cycle and by market-specific features over the cycle which can amplify the effects of the macro-economic shocks leading to oversupply. In the DZ paper, commercial property prices are determined by a four equation system.

$$D_t \equiv \frac{N[1 - F(P_t)]L(Y_t, i_t, P_t, \omega_t)}{P_t}, L_y > 0, L_i < 0, L_p > 0 \quad (3.13)$$

⁶The lack of published academic research on modelling Irish capital values may reflect the fact that Irish commercial property data are not publicly available.

⁷The reduced form model draws on earlier work by Carey (1990) and Wheaton (1999).

$$K_t = (1 - \delta)K_{t-1} + I_{t-1} \quad (3.14)$$

$$I_{t-1} = \alpha B_{t-1}(Y_{t-1}, i_{t-1}, P_{t-1}, \omega_{t-1}), \text{ where } B_y > 0, B_i < 0, B_p > 0 \quad (3.15)$$

$$D_t = K_t \quad (3.16)$$

Equation (3.13) describes the market demand D_t for commercial property at current prices P_t which is a function of the number of potential investors N and their access to bank credit for commercial property L . It is assumed that these investors differ only in terms of their reservation price due to either private information or different valuation approaches. The sum of these reservation prices follow a cumulative distribution function, $F(P_t)$. If an investor's reservation price exceeds the current market value, they will pursue the property and seek external funding.

Investment in commercial property is usually highly leveraged and bank credit is a key source of funding. To overcome asymmetric information on the degree of counterparty credit risk on the loan contract, banks demand collateral so commercial property prices are closely linked to credit growth (Kiyotaki and Moore, 1997 and Bernanke *et al.*, 1994). A positive relationship is assumed between credit and current prices. Credit market imperfections and possible departures from rational expectations are cited as reasons for the assumed reliance on current prices by banks. DZ also assume that credit availability is positively related to the investor's endowment which can be proxied by personal disposable income or real Gross Domestic Product (GDP). Investors can borrow more if interest rates, i_t are low and banks' lending standards are accommodative, ω_t .

Equations (3.14) and (3.15) focus on construction and supply-side dynamics. If prices exceed replacement cost, developers will initiate new projects using bank financing. Construction supply is assumed fixed in the short run due to development lags (assumed one period here). Therefore the stock of new supply K_t will evolve according to (3.14) where δ is the depreciation rate and I_{t-1} is the stock of completed development projects last period, which like investment also depends upon bank credit for financing B_{t-1} . The same factors which determine credit supply to investors are also assumed to apply to construction financing. The market clears when

demand equals supply (3.16) so market prices P and level of commercial property K are assumed to be constant over time in equilibrium.

The model predicts that prices and bank credit are positively related but bank credit may have a negative impact on prices in the long run if there is oversupply. While it is assumed that income and interest rates impact commercial property prices, the macro effects may vary across markets depending on the relative elasticity of supply and demand. DZ contend that if the supply response is relatively elastic, overbuilding in response to a positive income shock will dampen price growth leading to a price cycle. Conversely if the supply response is quite slow, market prices may increase even faster than fundamental prices resulting in misalignment.

DZ use this framework to examine the macro-economic determinants of commercial property prices using an unbalanced panel of 17 countries generally over the period 1970 to 2003. Irish data are included.⁸ The paper uses both panel and vector error correction models for individual countries. The empirical work relies on the following five variables; real commercial property prices, real GDP, real interest rates, real credit and real private investment. In general, the results accord with the model in that a positive relationship is found between GDP and prices in both the short and long run while credit is found to be positively related to prices in the short run but negatively related in the long run. Property prices are also found to positively affect bank credit. A negative relationship is generally found between investment and prices. Contrary to a priori expectations, Davis and Zhu (2011) find a positive long-run relationship between short-run interest rates and prices in some markets. Some of the results vary by type of property market and according to where a country is in its property cycle.

Following DZ we hypothesise that current Irish commercial property prices are determined by macro-economic determinants such as real GDP and real long-term interest rates, among other factors. Even in the absence of a credit channel, an increase in economic growth should lead to an increase in investor demand for commercial property, all other things being equal. This is a derived demand equation as investors anticipate an increase in demand for rental space for offices, retail and industrial units. This in turn, leads to an increase in expected income/rental return on commercial property, which may increase investors' reservation prices. Ireland experienced rapid economic expansion from the late-1990s with a marginal slowdown in 2000/01. The

⁸The Irish data are annual and cover the period 1982 to 2002.

Celtic Tiger years was a time of economic convergence on our European counterparts. Unsustainable economic imbalances, however, arose towards the end of this time with domestic demand heavily reliant on property. Figure 3.1 shows that the annual change in real commercial prices and in real GDP in Ireland appears to move broadly in tandem between 1985 and 2012. Although clearly highly cyclical, property price growth appears to have a relatively greater amplitude than GDP growth. Figure 3.1 also compares the series in logs which shows the relatively higher adjustment in commercial property prices after 2007.

Davis and Zhu (2011) use real short-term interest rates in their model. Long-term rates are preferred here to proxy for both the cost of external finance and the discount factor or required rate of return⁹. In line with theory we expect a negative relationship between long-term real interest rates and commercial property prices. An increase in funding costs faced by investors or in the discount rate can lead to a decline in demand for commercial property. Interest rates and prices are compared in Figure 3.2. The period between the advent of European Monetary Union (1999) and the beginning of the global financial crisis (2007) saw historically lower real interest rates and this coincided with high commercial property prices in Ireland.

The role of credit in driving property prices is also examined. According to Woods (2007), commercial property-related credit increased significantly up to 2007, accounting for a quarter of total private sector credit to Irish residents. Financial liberalisation and deregulation during the 1980s and 1990s followed by closer integration of European capital markets in 2000s allowed banks to increase their credit supply to meet rising demand. The close links between corporate credit and commercial property prices are shown in Figure 3.3.

Table 3.1 displays some descriptive statistics for real prices, income, credit and interest rates over the period 1985 to 2012. Although GDP records a higher level of maximum quarterly growth (i.e., circa 11 per cent) over the period, the price and credit series have relatively higher maximum quarterly declines. Prices fell by almost 19 per cent, credit by 16 per cent while GDP declined by 6.3 per cent in one quarter. Real rental figures and unemployment are also included for comparison as both series are included in alternative estimates of misalignment. Over the sample, the rental series did not increase to the same extent as prices, credit or GDP with a maximum

⁹For completeness in the Appendix, real short-term rates are included in a variation on the specification.

growth rate of 5 per cent. During the crisis, the Irish unemployment rate increased by a maximum of 23 per cent.

All of the aforementioned factors focus on demand-side influences. Unfortunately a long-run consistent series on commercial property supply in the Irish market is not available. There have been some papers on supply-side dynamics but these are based on low frequency data. Some examples are McCartney (2008 and 2011) which refers to the Dublin office market and look at vacancy rates. DZ use private investment as a proxy but in the Irish case, this variable is highly correlated with GDP, given the role of domestic demand in driving economic activity prior to the crisis. The Appendix discusses this issue further.

Lagged commercial property prices are considered as a possible explanatory variable in one of the specifications in line with DZ. There is a high degree of persistence in the Irish commercial property price data, which is common in valuation-based indices. In addition to valuation practices, low levels of liquidity/market transactions and the general heterogeneity of assets in this market complicate the price discovery process. Other issues potentially leading to price errors by investors or valuers are the dependence on local knowledge (Zhu, 2003), high transaction costs, lack of a common market place and the inability to engage in short-selling practices (Hendershott *et al.*, 2005). Therefore, as noted by DZ, prices may deviate from fundamental values because of market-specific characteristics creating endogenous cycles which amplify the effects of economic factors. Although it is not possible to fully control for these idiosyncratic market features, the inclusion of a lagged dependent variable in one of the specifications may go some way in capturing institutional features that can cause persistence in the data.

3.3.2 Data and preliminary statistical tests

Data on Irish commercial property prices are obtained from the Society of Chartered Surveyors & the Investment Property Databank (SCS/IPD) Irish index. The Irish commercial property price data cover the sectors office, retail and industrial as well as providing a total series. The aggregate data are of interest to this chapter. According to IPD the Irish index should be broadly representative of market activity in our sample covering 80 per cent of outstanding commercial property holdings in Ireland as at December 2011 (IPD, 2012). The properties included the index are mainly in the Dublin area.

In common with other international commercial property data, the SCS/IPD Irish Index is based on valuations of standing investments by participating investors rather than actual transactions in the market. Ball, Lizieri and MacGregor, (2006) highlight that these valuation indices suffer from smoothing which can lead to low volatility and complicate comparisons with other asset classes where price data are freely available. These authors contend that the index value at each point in time is a weighted-average of the true market value and past values. Possible reasons offered are; valuers seem to react slowly to news with conventional valuation techniques based on extrapolation of past values and the fact that valuation may not be collected at exactly the same date. With regard to the latter point, Ball *et al.*, 2006 notes that published indices may be a weighted average of valuations taken over a two-month period especially if the index has a large coverage. Additionally, Whitley and Windram, (2003) highlight that low market liquidity makes it difficult to assess if these valuation-based indices are representative of movements in actual market capital values.

The commercial price data used in this study cover the period 1984 through 2012. As quarterly data are only available from the first quarter of 1995 from SCS/IPD, annual index data from 1984 are interpolated to form a historical quarterly series (See the Appendix 1 for further details). To convert the SCS/IPD index to a price series in levels, an average commercial property price per square metre is estimated from sectoral (i.e., office, retail and industrial) rent and yield data from CBRE EMEA Q1 2013. These data are aggregated using a weighted-average with each sector's share of IPD portfolio in Q1 2013 used as weights. Data are in Euro per square meter. Commercial property price data are deflated using the Consumer Price Index (CPI), which is from the Central Statistics Office (CSO).

In terms of other explanatory variables, GDP is sourced from the CSO and the Central Bank of Ireland. These data are available quarterly from 1997Q1 from the CSO. Prior to 1997, the annual data are interpolated and are from the Central Bank's macro-modeling dataset (See McQuinn, O'Donnell and Ryan, 2005 for further details). Corporate credit data are also sourced from the Central Bank of Ireland and is defined as total private-sector credit less household credit and less credit for financial intermediation. Both series are also deflated using the CPI. The long-term real interest rate is proxied by ten-year Irish Government bond yield less the CPI inflation rate. These data are sourced from the Central Bank of Ireland and Thomson/Reuters Datastream. Residential mortgage rate data from the Central Bank are also used as

an alternative to the bond yields.

Prior to estimation, real GDP, real corporate credit, real commercial property prices are transformed into logs. These transformed variables and the real interest rate are tested to see if they are stationary using an Autocorrelation Function (ACF) or correlogram with up to 50 lags (Figure 3.4). All variables are found to non-stationary in logs/levels. The slow almost linear decline of the autocorrelations suggests the presence of a unit root. Formal unit root testing using the Augmented Dickey-Fuller and Phillips-Perron (1988) tests confirm the finding¹⁰. First differences are subsequently taken to remove the unit root.

Table 3.2 presents the results of unit root testing on the transformed variables. Unit root tests are considered to have low power in distinguishing between a unit root and near unit root process. Therefore for robustness, two formal tests are used, namely Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF). For the PP test four lags and a constant are chosen while both two and four lags and a constant are in the ADF test. No trend is included as the data are in first differences. Both of these tests incorporate a null hypothesis of a unit root. MacKinnon approximate p values based on MacKinnon (1994) are used to determine the significance of the test statistics. The PP test indicates that all differenced variables are integrated of order (0). This result is confirmed for interest rates, prices and GDP using the ADF test with either four or two lags. However, using one lag, the ADF test confirms that a unit root is not present in the credit growth variable. Changes in the unemployment rate are included in the test as this variable is used instead of GDP in the short-run model in subsection 3.3.3.

The preceding paragraph shows that our variables of interest are integrated of the same order. We now turn to testing for possible cointegrating relationship given the theoretical justification for long-run relationship between the variables. Given that we could have potentially more than one cointegrating vector, we rely on the Johansen (1988) methodology to test for the number of cointegrating equations. No evidence of cointegration using all four variables over the full sample period is found. However, omitting credit, we find some evidence of one cointegrating vector between prices, GDP and interest rates using the trace statistic (Table 3.3). The maximum eigenvalue statistic, however, suggests two cointegrating relationships. If two lags are

¹⁰Results are not included for brevity but are available upon request.

used in the deterministic regression instead of four, both the maximum eigenvalue and the trace statistic agree on one cointegrating relationship.

A long-run relationship between prices, GDP and interest rates is, therefore, assumed based on economic theory. This specification is used in the next section to approximate a fundamental commercial property price. It is also likely that credit is an important part of the Irish commercial property story and there is a strong empirical literature linking property and credit cycles. Therefore a simple time-series model is also specified, to estimate the relationship between prices and credit, while also controlling for income and interest rates.

3.3.3 Empirical results and misalignment

In this subsection, two different estimates of misalignment between the fundamental price and actual commercial property prices are discussed.

Cointegration - income and interest rates

A long-run relationship is assumed to exist between commercial property prices, GDP and interest rates, all in real terms, given the results of the cointegration testing and based on theory. The Engle-Granger (1987) two-step approach is used with the long-run specification approximating our fundamental price. The following linear specification is used,

$$c_t = \alpha_0 + \alpha_1 gdp_t + \alpha_2 i_t + \mu_t \quad (3.17)$$

where c_t is the log of real commercial property prices, gdp_t is the log of real gross domestic product and i_t is real long-term interest rates¹¹. In addition to simple Ordinary Least Squares (OLS), Fully Modified OLS (FM-OLS)¹² is used to estimate the regression as the latter controls for potential endogeneity and serial correlation¹³.

¹¹ Appendix 3 also presents the results of some alternative explanatory variables drawing on Davis and Zhu (2011) and economic theory. The results are not fully in line with theory. Therefore this specification is preferred.

¹² According to Enders (2010, pg. 426-427), inference may be inappropriate if there is evidence of serial correlation in the errors of the cointegrating vector. Endogeneity may also be an issue. In this instance, the procedure of Phillips and Hansen (1990) may be used instead. This procedure adds leads and lags of changes in the explanatory variables to the regression and adjusts the t statistics from the original equation using a modified version of the variance of the error term from the expanded equation.

¹³ Tests for higher-order serial correlation using the Ljung-Box test on the simple OLS residuals suggest the presence of autocorrelation (Ljung-Box Q statistic for 8 lags is 311.8 with a significance level of 0.000).

Table 3.4 shows the results, which are similar across both methods. The explanatory variables have the expected sign and are statistically significant. A one per cent increase in real GDP will lead to a 0.3 per cent increase in real capital values, all other things being equal. As interest rates are not in logs, the point estimate for its coefficient shows the semi-elasticity of prices with respect to rates.

Figure 3.5 plots the actual prices against the fitted values from the OLS regression and also displays the residuals over the sample period. Although the fitted values track the actual values, there are periods of deviation between the two series. Actual prices are above the fitted value or fundamentally justified prices in the late-1980s/early-1990s, briefly in late-1990s and from 2004 to late-2007. There is a spike in the residuals in 2009/2010 suggesting overvaluation which would be contrary to intuition given that this was a period of falling prices and financial stress. This misalignment seems to be driven by the relatively higher fall in the fundamental price or fitted values. Real rates increased in 2009 and the Irish economy began to contract significantly. Both of these factors would have reduced fundamental prices in the model. Actual prices do not seem to have fallen as sharply over this time.

After 2011, there is marked divergence between actual and the fitted values until the end of our sample. Given the emergence of the European sovereign debt crisis in mid-2010, long-term nominal interest rates as proxied by the Irish Government bond yield increased. This would have had an initial dampening effect on fundamental prices until the positive effects of the emerging macroeconomic recovery took effect toward the end of the sample (See Figure 3.1). Therefore after a rebound in 2009, fundamental prices decline briefly in 2010 before increasing in 2011 and 2012. By contrast, actual prices continue to fall until end-2012 suggesting that other factors not captured in our model are at play. Negative investor sentiment may be one such factor. The period from late-2007 to 2012 was one of risk aversion and very low levels of activity in the Irish commercial property market. As noted in the Central Bank of Ireland's 2015 Macro-Financial Reviews, 2013 was a turning point for Irish commercial property. Investor appetite returned and the market began to recover. The low interest rate environment and the possibility of purchasing large distressed commercial property loan portfolios attracted many institutional investors and other funds to the Irish market.

As noted, the European sovereign debt crisis caused bond yields to spike in 2010 due to concerns about the credit worthiness of the Irish Government. These devel-

opments raise concerns that that this variable may not be a good proxy for either the real cost of funding faced by firms investing in commercial real estate or the discount rate over this time. Also the model is estimated over a period that covers the Irish financial crisis which was accompanied by a severe contraction in the domestic economy. Therefore it is important to check the stability of the estimated long-run relationship. Stability of the estimated parameters is formally tested using a Bai-Perron test¹⁴ and recursive least squares (RLS) on the long-run equation (3.17). The RLS results indicate that although the coefficient on real GDP is broadly stable, the coefficient on the interest rate variable appears to trend downwards (Figure 3.6). The Bai-Perron Break Point test indicates that there may have been a slight shift in the estimated relationship between the explanatory variables and prices in late-2009.

Given the potential concerns about the stability of the interest rate coefficient, the bond yield series is replaced by the real residential mortgage interest rate. This rate should be a good proxy for funding costs in the commercial property investment market as residential mortgages are also typically extended for long maturities. Also this variable should better reflect the price of bank credit during the sovereign bond crisis. As can be seen in Figure 3.7, both rates in real terms follow similar trends over time. Therefore, (3.17) is re-estimated using the mortgage rate. Table 3.5 shows the results. Both variables have the expected signs and are statistically significant. The point estimate for the interest rate variable is marginally lower than in Table 3.4. In Figure 3.8, we can see the actual and fitted values for this regression along with the new results of the recursive least squares estimation. This model shows a period of undervaluation in the early-1990s with overvaluation emerging in the late-1980s and a sustained period of overvaluation from late-1990s to 2007. The coefficient on interest rates is also relatively more stable than previously.

Given that the price and macro data are interpolated prior to the mid-1990s, the long-run equation is re-estimated excluding the earlier period as a further robustness check. As can be seen from Appendix 2, the long-run relationship remains significant with a relatively higher cyclical influence on prices. The results also remain the same if the crisis period is excluded. The residual from (3.17) is therefore used as the non-fundamental price.

The second stage of the Engle-Granger approach incorporates the residuals of the

¹⁴The Bai-Perron (2003) algorithm tests for unknown breaks that minimise the sum of squared residuals in a linear regression. The critical values for the number of breaks only applies to stationary data (Estima, 2012).

long-run cointegrating relationship into a short-run dynamic model of price changes. Therefore prices respond to both deviations from long-run levels and other short-run influences. Table 3.5 shows the results of the error correction model. The LM test for ARCH (2) and ARCH (4) reveals some evidence of heteroscedasticity in the residuals. Therefore, Eicker-White heteroscedasticity robust standard errors are used. The Breusch-Godfrey test for autocorrelation in the residuals showed no evidence of autocorrelation using AR (1) and AR (4). The Error Correction Term, ecm_{t-1} is found to be significant (albeit at the 8 per cent level) and negative. If there is a deviation between actual and fitted values last period, this deviation will be reduced at a rate of 2 per cent per quarter. The second lag of economic growth and the lagged dependent variable also exert an influence on commercial property prices in the short run.

To test the performance of the model, actual values of the explanatory variables are used to simulate prices and price changes between 2012Q4 and 2013Q4. Figure 3.9 compares the predicted values with the actual out-turn for prices. The model captures the rebound in prices but predicts a slightly faster recovery. This is our first model (i.e., *Model A*) for approximating b_t .

ARDL model with credit

The cointegration approach showed periods of misalignment between actual and fundamental prices, indicating a possible role of non-fundamental influences. However it may be that some of the misalignment may be due to the omission of credit. This section attempts to address this issue. Our second approach uses an Autoregressive Distributed Lag (ARDL) specification. This model incorporates short-run influences from changes in income, real interest rates, corporate credit in addition to controlling for lagged commercial property price growth. The change in the log unemployment rate is used instead of GDP to proxy for occupier demand and is expected to have negative influence on future price changes. Bearing in mind the discussions in the previous section, the residential mortgage rate is used as the interest rate variable. The following specification is used to estimate an $ARDL(p, q)$ model in first differences:

$$\Delta cp_t = \delta_0 + \sum_{i=1}^p \delta_i \Delta cp_{t-i} + \sum_{i=1}^q \omega_i \Delta ue_{t-i} + \sum_{i=1}^q \vartheta_i \Delta i_{t-i} + \sum_{i=1}^q \tau_i \Delta cred_{t-i} + \epsilon_t \quad (3.18)$$

where Δcp_t is differenced log real commercial property prices, Δue_t is differenced

log unemployment rate, Δi_t is differenced long-term real interest rates and $\Delta cred_t$ is differenced log corporate credit.

The initial lag length for the explanatory variables q and for the lagged dependent variable p was set at two. To reduce potential endogeneity, contemporaneous values of unemployment, interest rates and corporate credit are not included in the specification. Davis and Zhu (2011) find that current commercial property prices also exert an influence on bank credit which is in line with their analytical framework. Given the role of commercial property as collateral for most commercial-property related exposures, price developments may influence bank credit decisions in addition to causality running from credit to prices. Therefore to reduce any simultaneity bias, lagged credit growth is preferred here. A general-to-specific approach is used to obtain a parsimonious specification. All insignificant coefficients are dropped sequentially until just the statistically insignificant constant remains. The results are contained in Table 3.6.

The overall fit of the model as estimated by the $\overline{R^2}$ is relatively high at 77 per cent. As suspected, lagged values of the dependent variable exert a significant influence of up to two quarters on commercial property price changes showing that Irish commercial property price changes are quite persistent. Changes in the unemployment rate are found to be significant and negatively related to prices. The credit variable is also found to have a positive lagged effect on capital values. Misspecification testing on the residuals from the *ARDL* model indicates evidence of autoregressive conditional heteroscedasticity (ARCH) effects. Therefore we use heteroscedasticity robust standard errors. Figure 3.10 shows the actual and fitted values of the regression along with the residuals.

The fitted values from the *ARDL* regression yield estimates of quarterly changes in fundamental capital values. These quarterly changes are used to compute a fundamental price series using the price in 1984Q4 as the initial starting value. The deviation between the actual prices and the fundamental price series is calculated to approximate an alternative measure of $p_t^{n.f}$. Figure 3.12 shows that misalignment is 10 per cent or more in late-1980s, late-1990s/early-2000s and between 2004 and 2007. These periods are in line with the results of the long-run model. The estimate of misalignment is used as our second model (i.e., *Model B*) of b_t .

3.3.4 Statistical indicator of misalignment

To complement the formal econometric approaches, a measure of misalignment in commercial property prices using the price-to-rent ratio is used. There should be a long-run relationship between prices and rents as the latter proxies for the income stream accruing to commercial property investors. Figure 3.11 shows prices and rents for Irish commercial property over the sample (i.e., 1985Q1-2012Q4) along with the price-to-rent ratio. The deviation from the ratio's long-run average is used as to measure misalignment. Using this approach, there is a sustained period of misalignment prior to the Irish crisis which emerged in the mid-1990s.

This is the broadest measure of misalignment as no other determinants of prices are taken into account. Also ECB (2011) notes that prices may be more responsive than rental changes as the latter may be subject to fixed contracts which could influence the degree of misalignment. This could be especially relevant in Ireland where certain leases may be subject to upward-only rent reviews.

3.4 Testing between a fad and a rational bubble using switching models

In the previous section, we showed that there were a number of periods where actual real commercial property prices deviated from our estimates of a fundamental price series or approximations of misalignment. The SVN approach outlined in Section 3.2 is applied, to determine if these periods of misalignment suggest that Irish commercial property prices were subject to a fad or a bubble over the sample period. There are, however, two differences between this empirical approach and that of SVN. First, Markov switching rather than simple switching techniques are used. Second, SVN assume that the probability of being in a survival state depends upon the size of the bubble or misalignment. Here it is assumed that the transition probabilities are time invariant.

Simple switching methods based on Goldfeld and Quandt (1976) are used by SVN to estimate (3.12). This approach assumes a particular stochastic process for the transition probabilities which is based on mixture normal distributions. The probability of the occurrence of a particular state in period t is independent of the prevailing state in period $t - 1$. In the case of fads model (3.5), SVN assume that

the volatility of the residuals moves randomly with the state and do not allow for any persistence in stock market volatility. The authors concede that this assumption may conflict with some empirical evidence of equity price behaviour. With regard to the bubble model (3.12), it is assumed that the probability of the bubble regime surviving, (q) is a function of the relative size of the bubble (b_t).

The institutional features of commercial property markets and preliminary examination of the Irish price data in subsection 3.3.2 suggest that an assumption of some persistence may be important. Although the random variable governing the switch between regimes is often unobserved, the use of a probabilistic model based on a Markov chain imposes some structure on the data generating process for this random variable (Hamilton, 2008). A first order Markov chain implies that the probability that the data process is in a particular regime or state at time t is dependent on the regime in the previous period.

$$Prob[S_t = i | \Omega_{t-1}] = Prob[S_t = i | S_{t-1} = j] = p_{ij} \quad (3.19)$$

where p_{ij} is the probability of moving from regime j to regime i and is subject to $0 \leq p_{ij} \leq 1$ and $\sum_{j=1}^2 p_{ij} = 1$.

Constant rather than time-varying transition probabilities (TVTP) are assumed for a number of reasons. First, it can be challenging to estimate the parameters of the transition probability matrix accurately using TVTP, especially if there are only a small number of switches between regimes (Hamilton, 2008). Second, the choice of indicator series may be difficult. It is not clear if the proportionate size of the bubble or misalignment, although plausible, would be the main factor determining regime shifts in the commercial property market over the full sample.

As we have two states, one where the bubble survives (S) and one where the bubble crashes (C), time invariant transition probabilities for a first order Markov chain are as follows,

$$Prob[S_t = s | S_{t-1} = s] = p_{ss} = q,$$

$$Prob[S_t = c | S_{t-1} = s] = p_{cs} = 1 - q,$$

$$Prob[S_t = c | S_{t-1} = c] = p_{cc} = p,$$

$$Prob[S_t = s | S_{t-1} = c] = p_{sc} = 1 - p.$$

Although the levels equation is the same as SVN (3.12), the transition probabilities differ. According to Van Norden (1996), if their model is estimated using Markov rather than simple switching, similar dynamics may be captured, if there is a bubble. The transitional probabilities in SVN are driven by proportionate size of the bubble which can be serially correlated so results may be similar.

The equation for the general regime switching specification is once more;

$$R_{i,t+1} = \beta_{i,0} + \beta_{i,b}b_t + e_{i,t+1}, \quad (3.21)$$

$$e_{i,t+1} \sim N(0, \sigma_i^2), i = S, C$$

where $R_{i,t+1}$ is the quarterly log commercial property price return between time t and $t + 1$, and b_t is our estimated bubble term or non-fundamental price using our three estimates of misalignment in section 3.3. To estimate this model, we need to evaluate the conditional log likelihood function over our sample and maximise this function with respect to the parameter set (i.e., $\beta_{i,0}$, $\beta_{i,b}$, σ_i^2 , p , q). The data are forward filtered using an iterative algorithm based on Hamilton (1989) and estimated using Maximum Likelihood. The log likelihood function (dropping terms which do not affect the maximisation) is:

$$L = \sum_{t=1}^T \ln f(R_{t+1}|\Omega_t) \quad (3.22)$$

where

$$f(R_{t+1}|\Omega_t) = f(R_{t+1}|S_{t+1} = i, \Omega_t) * P(S_{t+1} = i|\Omega_t) \quad (3.23)$$

and where

$$f(R_{t+1}|S_{t+1} = i, \Omega_t) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{(R_{i,t+1} - \beta_{i,0} - \beta_{i,b}b_t)^2}{2\sigma_i^2}\right) \quad (3.24)$$

To test the validity of restrictions imposed by the fads model (3.5) Wald and Likelihood Ratio tests are used. The empirical results are discussed in the next section.

3.4.1 Results

Tables 3.7 and 3.8 shows the results of the estimation of the general regime switching (bubble) specification of quarterly log commercial property growth. The various measures of non-fundamental price or deviation between actual and fundamental prices from Section 3.3 are included in the three columns.

The label *Model A* refers to the non-fundamental price recovered from the long-run cointegrating relationship in the error correction model using GDP and interest rates. The label *Model B* refers to the non-fundamental price based on the estimated quarterly growth rates from the autoregressive distributed lag model using changes in unemployment, credit and lagged commercial property price returns. The *statistical* term represents our simple statistical measure of misalignment (i.e., deviation of the price-to-rent ratio from its long-run average). Figure 3.12 compares the three approaches. As can be seen all three estimates are generally correlated over the sample although there is a range of over/undervaluation across the models.

There is some evidence that the rational bubble hypothesis may be a good explanation for Irish real commercial property prices over our sample. The Likelihood Ratio test results in Table 3.8 show that we cannot accept the joint significance that the restrictions imposed by the Fads model are valid across the three approaches¹⁵. Also the Wald Tests show that the equality of either the slope or the intercept coefficients across both regimes cannot be accepted at conventional statistical levels using Model B and the statistical approach. Model A, however, suggests that the two estimated slope coefficients may not be statistically different.

Turning to the switching regressions in Table 3.7 the results are mixed. None of the approaches have all statistically significant point estimates for both the slope and the intercept coefficients in the two regimes. For Model A and the statistical approach, $\beta_{c,b}$ is statistically significant and negative which is in line with the rational bubble theory. However, the coefficient $\beta_{s,b}$ is not significant in these two models. For Model B, the coefficient $\beta_{s,b}$ has a negative sign. Expected returns should be higher in the survival period so this result conflicts with theory.

The last two rows in Table 3.7 show estimates for the transition probabilities. It appears that the both regimes are quite persistent. The probability of staying in the

¹⁵The Wald test is asymptotically distributed with one degree of freedom, when the null is correct, while the Likelihood Ratio test is asymptotically chi squared distributed with two degrees of freedom.

survival regime ranges from 0.95 to 0.99 while the probability of staying the crash regime is 0.89 to 0.95. The probability of moving to a crash regime from a survival period is between 5 and 11 per cent based on the sample data. The estimates of this probability is not statistically significant for Model B. Based on Model A and the statistical approach, the expected duration of the survival period is between 4 and 6 years while the expected duration of the crash period is between 2.25 to 5 years. Over our sample, therefore there may be a number of regime switches.

Figures 3.13, 3.14 and 3.15 compare the smoothed probabilities of each regime across all approaches. Smoothed probabilities allow us to infer which regime Irish commercial property prices are in, on a given date, using information over the full sample. Both Model A and the statistical approach display a number of switches over the sample, suggesting that there might be a non-linear relationship between price returns and speculative behaviour in the commercial property market. High probabilities of the crash/high volatility regime are generally consistent across the models although the timing varies. While Model A suggests that the data remain in a crash regime from 2005 through 2012, the statistical approach suggests that the probability of a the crash regime began to ease from 2011.

By contrast, Model B only displays one regime switch in 2007, suggesting that Markov Switching techniques may not be an appropriate estimation technique for the relationship between price returns and estimated fundamental prices from this model. Also recall from Figure 3.12 that this approach did not yield clearly defined periods of over and undervaluation unlike the other two approaches. Further, an ARDL approach may be more applicable to estimating and forecasting prices rather than determining deviations from equilibrium values.

3.5 Conclusions

This chapter examines real price movements in the Irish commercial property market over the period 1985Q1 to 2012Q4. Two reduced form models are specified and estimated which incorporate theoretically motivated explanatory variables for commercial property prices such as income, interest rates and credit. The models do not have a supply side indicator given the lack of long-run Irish data on this side of the market. Although these models are found to provide a good description of prices, there are a number of periods where actual prices are found to persistently deviate from the

estimated fundamental prices. As a fundamental commercial property price series is unobservable, a suite of indicators is preferable for robustness. The chapter approximates a simple estimate of misalignment between actual and fundamental prices using the price-to-rent ratio and its deviation from its historical average. Averaging across the three approaches, Irish commercial property prices appear to be overvalued relative to fundamentally justified values in the early-1990s and between 2000 and 2008. The results suggest undervaluation in the mid-1990s and from 2009/2010 to the end of the sample, 2012Q4.

Informed by the stock price literature, this chapter also investigates the nature of the estimated misalignment and tests whether Irish real commercial property prices conform to the irrational fads hypothesis or the rational collapsing bubble theory over the sample period. If Irish commercial property prices are subject to faddish behaviour the deviation between actual and fundamental prices will have some explanatory power for future prices changes. As the deviation is assumed to be temporary, an increasing gap or positive price misalignment should lead to a decrease in price returns. Herding behaviour among investors may be one possible explanation for the existence of fads in the data. The stochastic bubble theory assumes that if a bubble exists, investors incorporate this into their valuations for current prices. As the probability of a bubble surviving increases, investors demand higher returns to compensate for the potential losses when a crash occurs. Bubbles are thus the outcome of self-fulfilling expectations about future prices. In both cases, the collective action of investors lead to price spirals and periods where market prices rise above fundamentals. Commercial property is also an investment asset so these stock price theories are deemed applicable.

Using regime switching techniques, the fads hypothesis cannot be accepted. Therefore, the alternative hypothesis of a rational bubble must be considered. Although there is evidence of non-linearity, the empirical results for expected returns in each regime do not fully conform to the stochastic bubble theory.

Further research could address a number of different avenues. As per Gurkaynak (2008), one limitation of the approach in this chapter is that it assumes that there is no regime switching in the fundamental determinants. Further work could address this issue. Also there are a number of other possible tests for bubbles that rely on univariate analysis of prices, using unit root tests (e.g., Taipalus, 2013) or regime

switching analysis (e.g., Hall, Psaradakis and Sola, 1999). Both approaches could be applied to the Irish property market to complement the analysis in this chapter.

3.6 Figures and tables

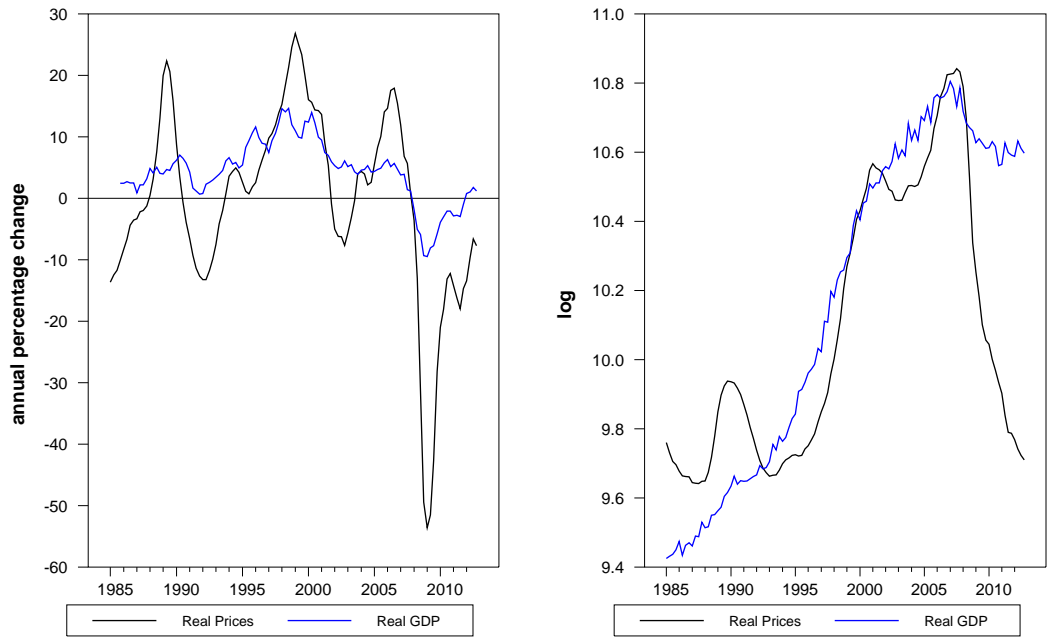
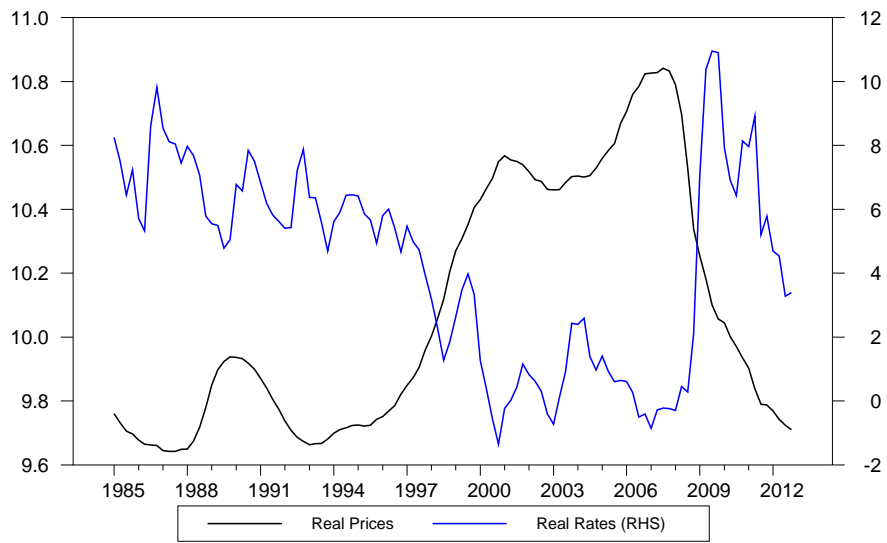


Figure 3.1: Irish real commercial property prices and real GDP: 1985Q1 to 2012Q4



Note: Prices are in logs while rates are in per cent per annum

Figure 3.2: Irish real commercial property prices and real long-term interest rates: 1985Q1 to 2012Q4

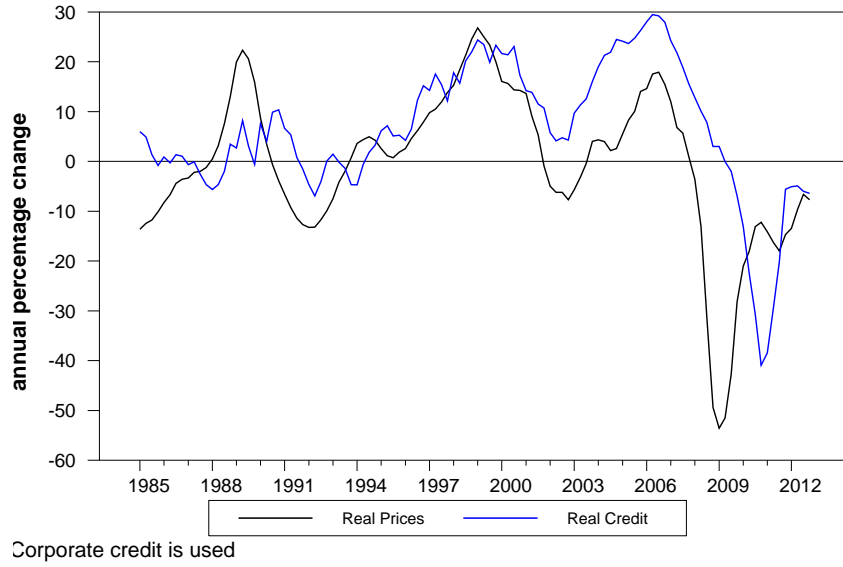


Figure 3.3: Annual change in Irish real commercial property prices and in corporate credit:1985Q1 to 2012Q4

ACF and PACF

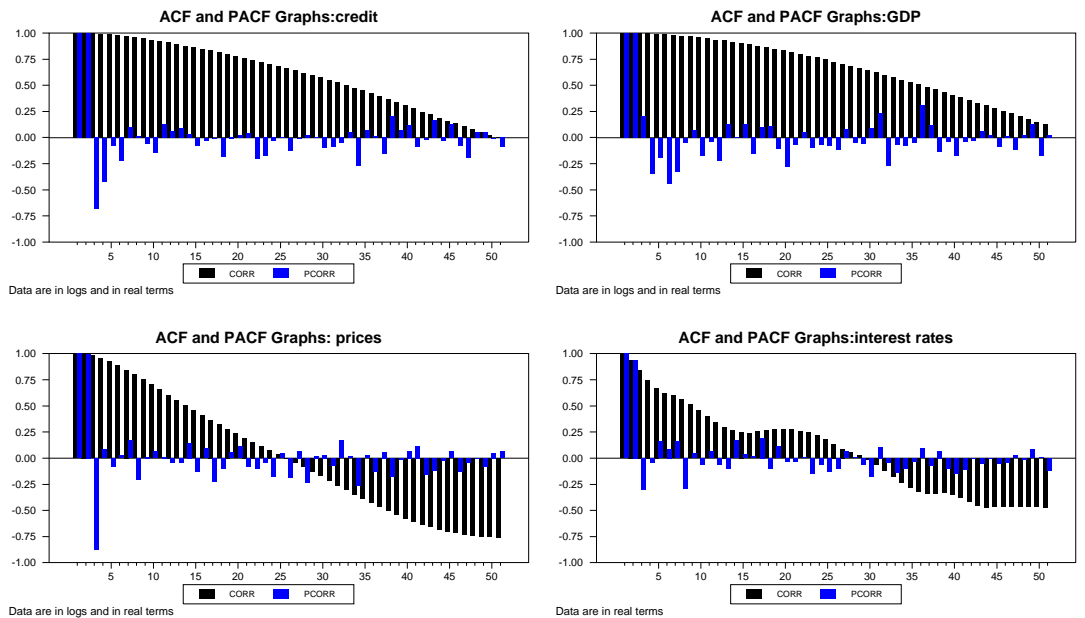


Figure 3.4: Autocorrelation and Partial Autocorrelation Functions: 1985Q1 to 2012Q4

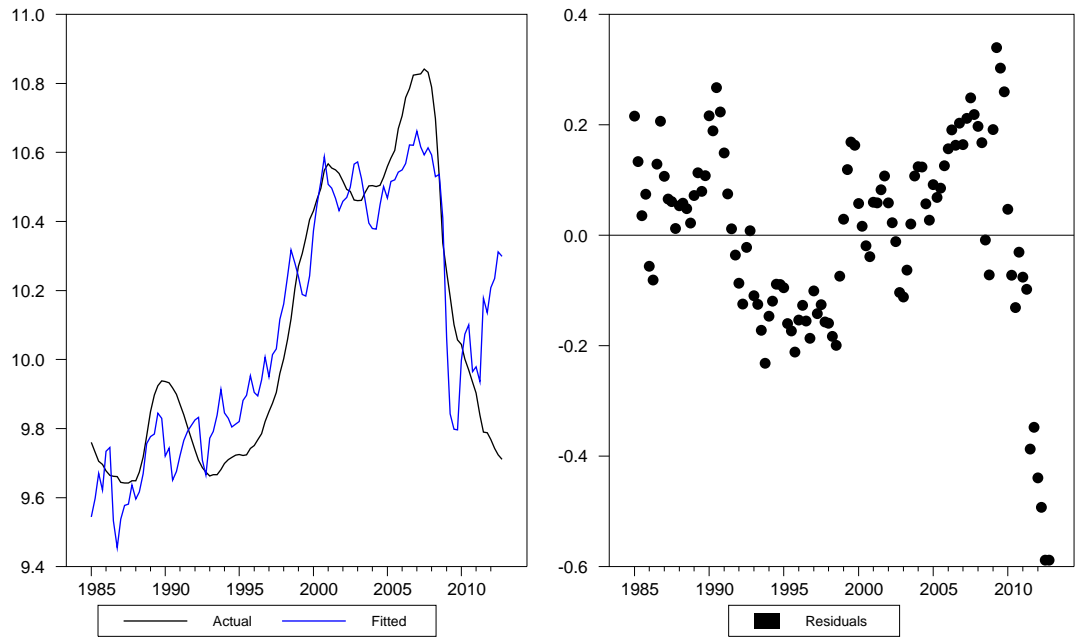
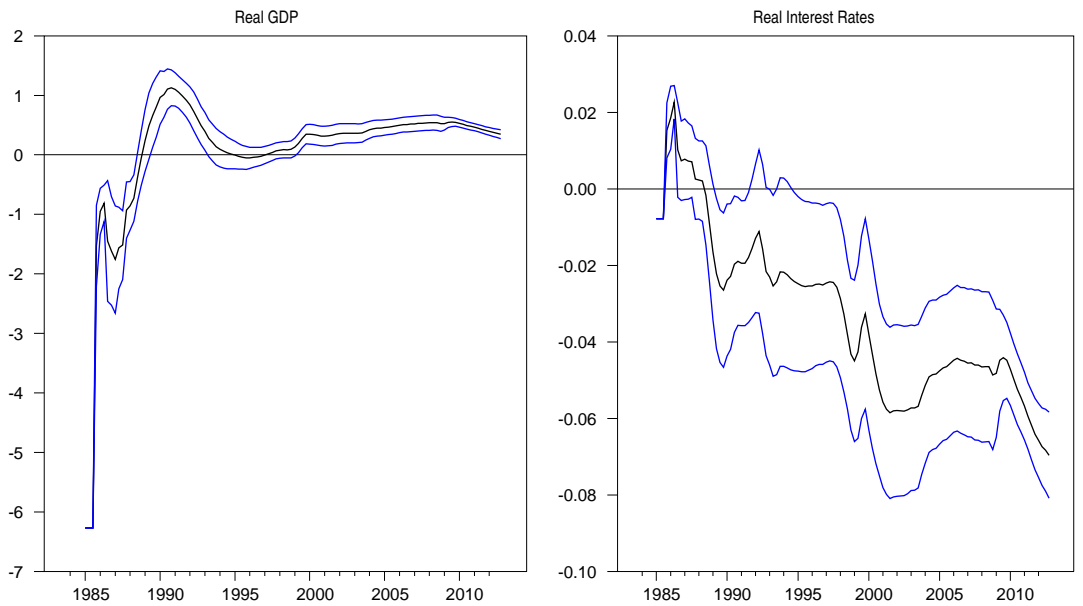


Figure 3.5: Long-run model of real Irish commercial property prices: 1985Q1 to 2012Q4



Estimated using Recursive Least Squares

Figure 3.6: Recursive estimation of GDP and interest-rate coefficient with 95% confidence intervals

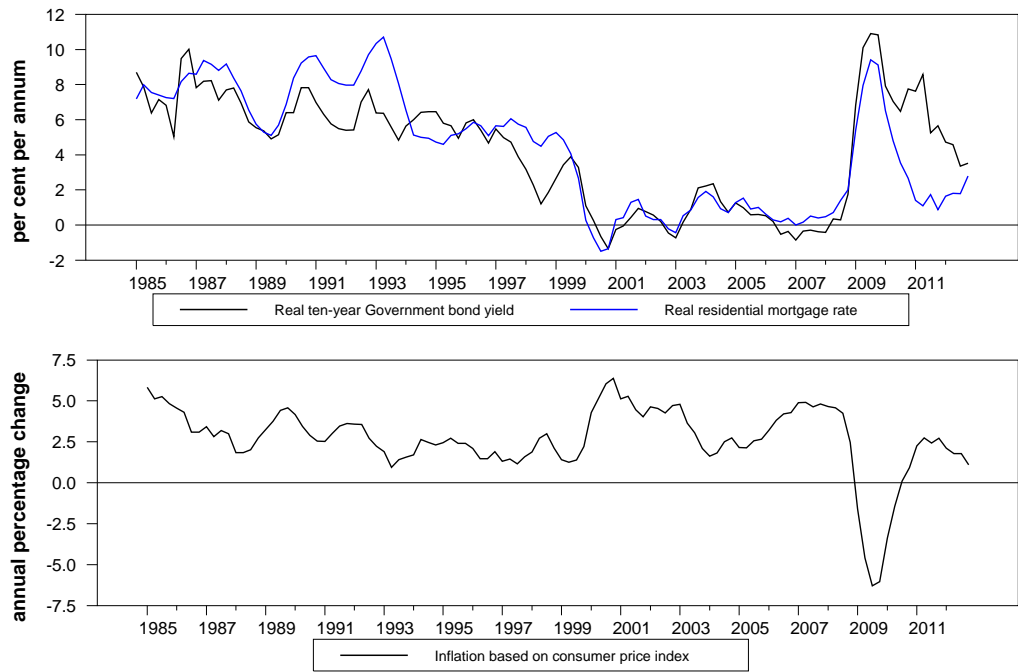


Figure 3.7: Irish real interest rates and inflation: 1985Q1 to 2012Q4

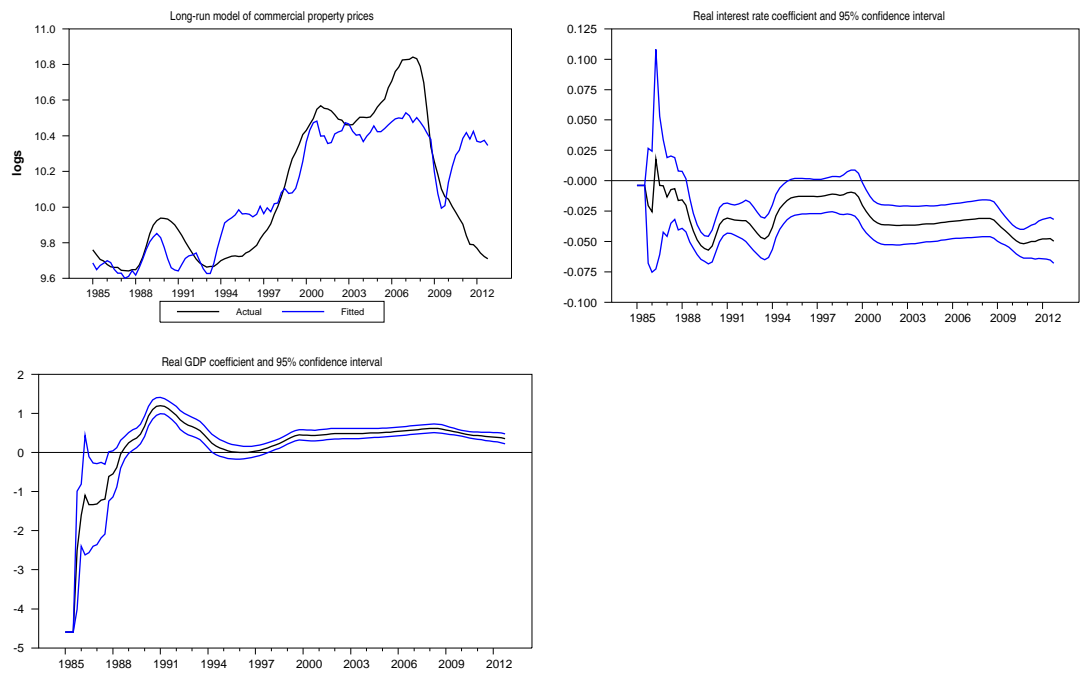


Figure 3.8: Long-run model of Irish commercial property prices controlling for GDP and mortgage rates: 1985Q1 to 2012Q4

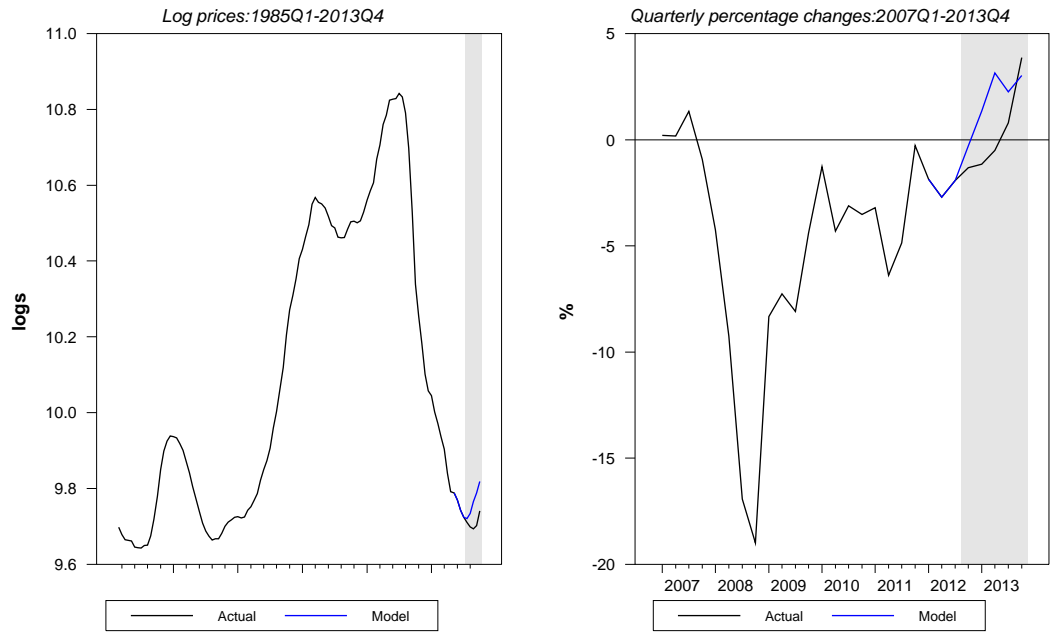


Figure 3.9: Out-of-sample performance of ECM model: 2012Q4 to 2013:Q4

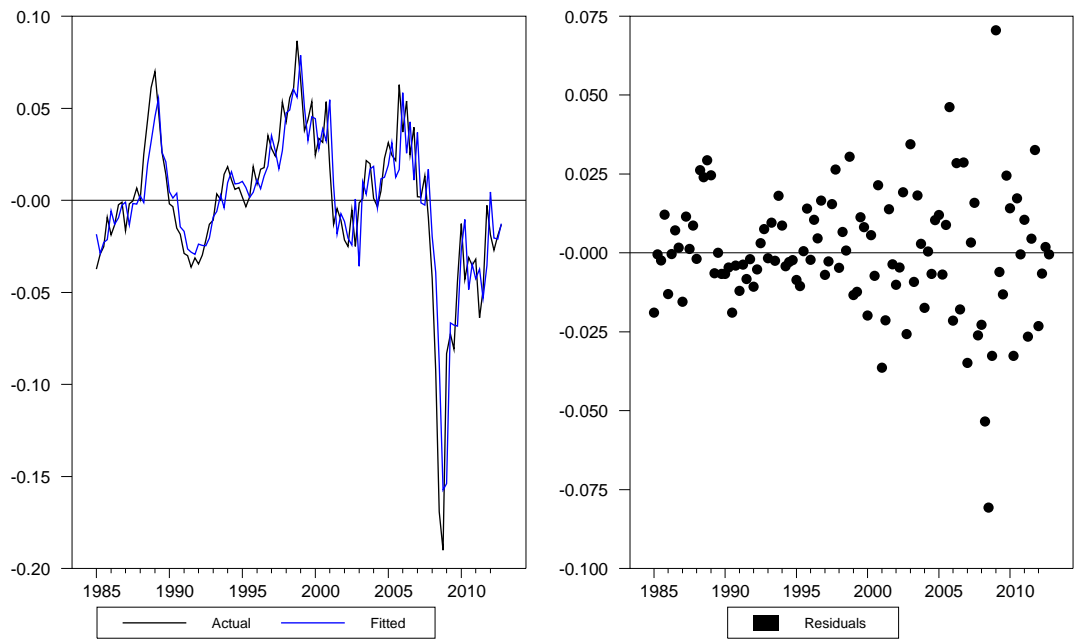


Figure 3.10: Short-run model of Irish commercial property prices: 1985Q1 to 2012Q4

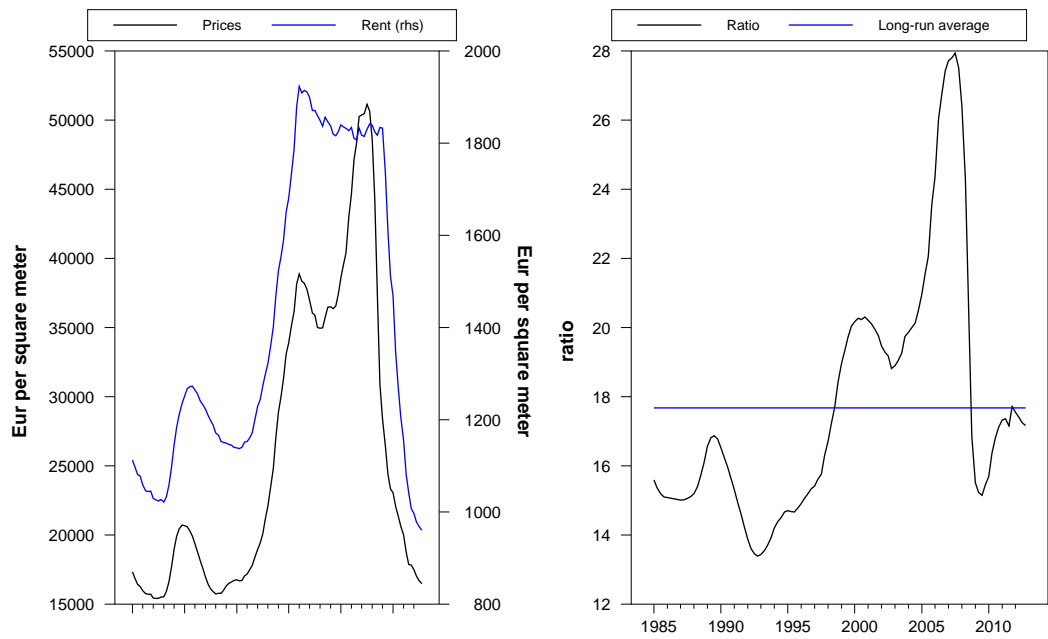


Figure 3.11: Commercial property prices and rents: 1985Q1 to 2012Q4

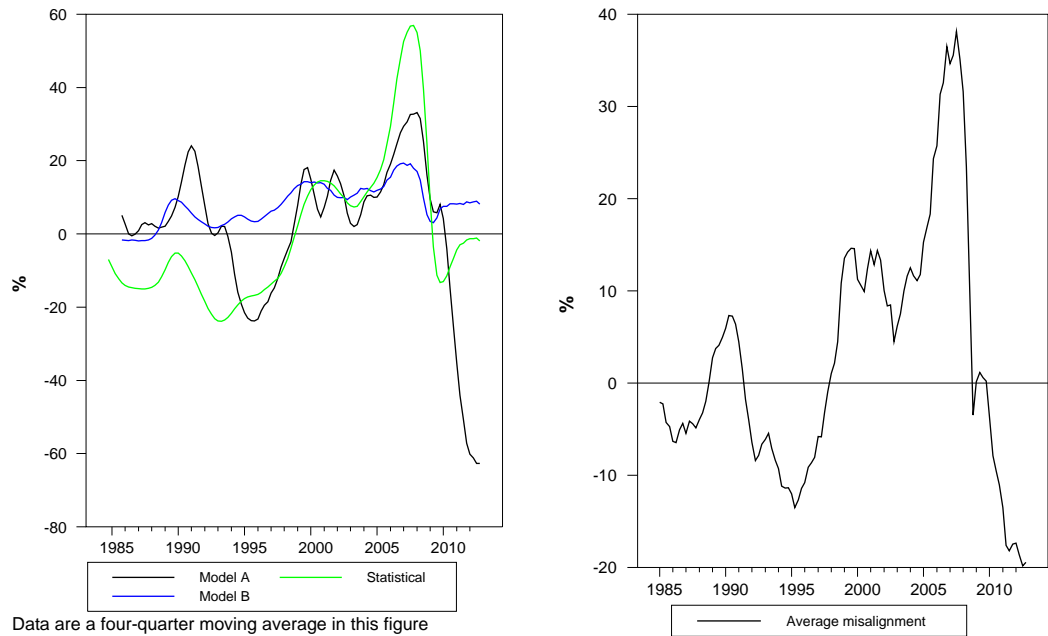


Figure 3.12: Estimates of deviation between actual and fundamental commercial property prices: 1985Q1 to 2012Q4

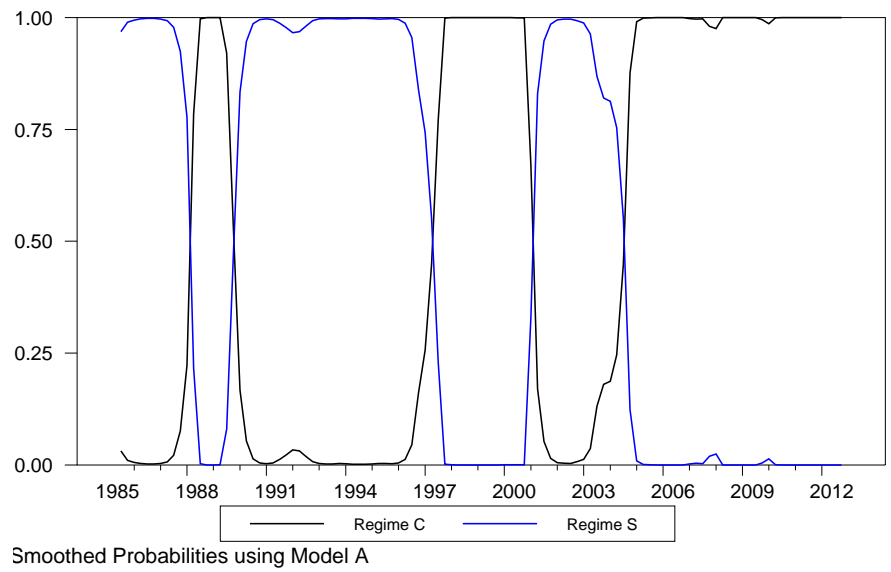


Figure 3.13: Smoothed probabilities using Model A: 1985Q1 to 2012Q4

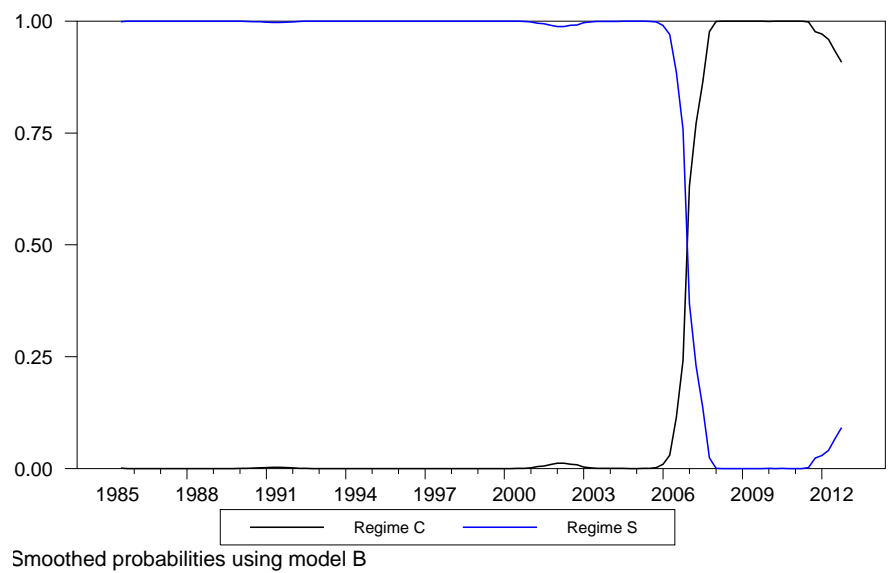


Figure 3.14: Smoothed probabilities using Model B: 1985Q1 to 2012Q4

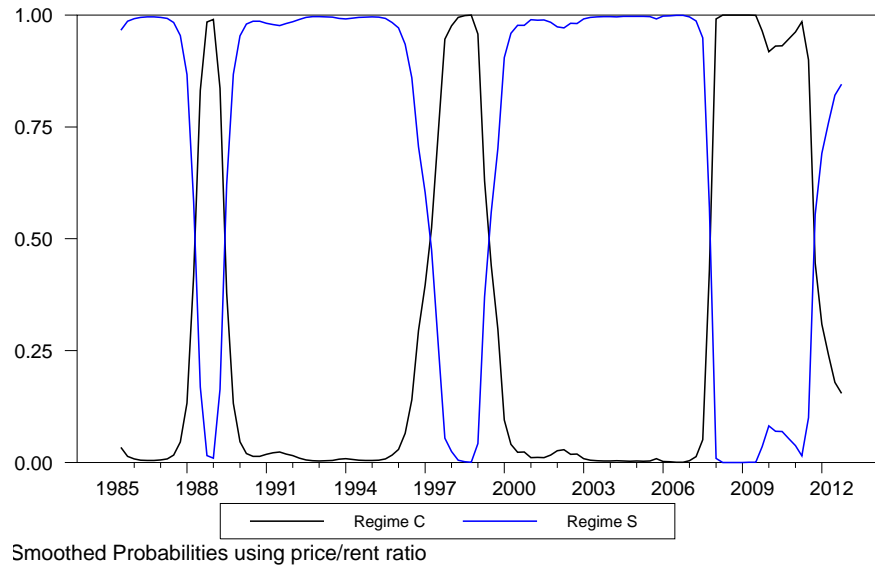


Figure 3.15: Smoothed probabilities using price-to-rent ratio: 1985Q1 to 2012Q4

Table 3.1: Summary statistics: 1985Q2 to 2012Q4

Variable	No. of Observations	Mean	Standard Error	Minimum	Maximum
Δcp	111	-0.05	4.16	-19.00	8.66
$\Delta cred$	111	1.54	4.02	-15.98	8.68
Δgdp	111	1.13	3.24	-6.31	10.88
Δi	111	-0.05	1.12	-3.33	5.07
$\Delta rent$	111	-0.13	2.37	-8.51	5.01
Δue	111	-0.14	5.39	-15.25	23.05

Note: All variables are in real terms and data are quarterly. Δcp_t refers to first differenced log commercial property prices. Δgdp_t is first differenced log GDP. $\Delta cred_t$ is first differenced log corporate credit while Δi_t is first differenced interest rates. Δue is first differenced log unemployment and $\Delta rent$ is first differenced log rent. Commercial property prices, rent, GDP, corporate credit, rent and unemployment are expressed in 100 times first differenced logs (i.e., approximately quarterly percentage change) while interest rates are levels differenced (i.e., in percentage points).

Table 3.2: Tests for unit roots

Variable	Dickey-Fuller		Philips-Perron	
	4 Lags	2 Lags	Test Statistic	MacKinnon p-value
Δcp_t	-3.25 ⁺⁺	-2.76 ⁺⁺	-2.99	0.04
Δgdp_t	-2.51	-5.42 ⁺⁺⁺	-14.13	0.00
$\Delta cred_t$	-2.18	2.54	-5.06	0.00
Δi_t	-6.67 ⁺⁺⁺	-5.80 ⁺⁺⁺	-8.49	0.00
Δue_t	-2.40	-2.95 ⁺⁺	-3.94	0.00

Note: +++ refers to rejection at 1% level, ++ denotes rejection at 5% and + at 10% level. Δcp_t refers to first differenced log commercial property prices. Δgdp_t is first differenced log GDP. $\Delta cred_t$ is first differenced log corporate credit while Δi_t is first differenced interest rates. Δue_t is the first differenced log unemployment. All variables are in real terms. Data are quarterly and cover the period 1985Q1 through 2012Q4. Four lags and a constant are included the Philips-Perron Tests.

Table 3.3: Tests for Cointegration

Johansen Trace Statistic		
Maximum Rank	Trace Statistic	5% Critical Value
0	42.81	29.68
1	14.68	15.41
2	0.059	3.76
Johansen Maximum Eigenvalue Statistic		
Maximum Rank	Max Statistic	5% Critical Value
0	28.13	20.97
1	14.62	14.07
2	0.059	3.76

Note: This table shows the results of running Johansen tests for cointegration on log commercial property prices, log GDP and interest rates, all in real terms over the period 1985Q1 to 2012Q4. Four lags are used based on the Akaike Information Criterion. A constant is included.

Table 3.4: Long-run model of Irish real commercial property prices: 1985Q1 to 2012Q4

<i>Dependent variable: cp_t</i>		
	OLS	FM-OLS
<i>constant</i>	6.85 (14.18)	7.43 (12.33)
<i>gdp_t</i>	0.35 (7.61)	0.29 (5.17)
<i>i_t</i>	-0.07 (-10.16)	-0.08 (-9.45)
<i>Bai-Perron Break Point</i>	2009:04	

Note: Absolute t-statistics in brackets. *gdp_t* refers to log real GDP while *i_t* is long-term real interest rates. FM-OLS refers to Fully Modified OLS and is due to Philips and Hansen (1990).

Table 3.5: Long- and short-run model of Irish real commercial property prices: 1985Q1 to 2012Q4

<i>Dependent variable: cp_t</i>	
<i>constant</i>	6.71 (8.04)
<i>gdp_t</i>	0.35 (4.52)
<i>i_t</i>	-0.05 (-4.53)
<i>Dependent variable: Δcp_t</i>	
<i>ecm_{t-1}</i>	-0.02 (-1.78)
Δcp_{t-1}	0.85 (8.63)
Δgdp_{t-2}	0.16 (2.39)
$\overline{R^2}$	0.78

Note: Absolute t-statistics in brackets. The Engle-Granger (1987) two-step approach to error correction modelling is used. Heteroscedasticity-Consistent (Eicker-White) Standard Errors used in short-run model. *gdp_t* refers to log real GDP and *i_t* is long-term real interest rates as proxied by the mortgage rate. *ecm_{t-1}* is the error correction term, Δcp_{t-1} refers to quarterly lagged changes in commercial property prices and Δgdp_{t-2} is the second lag of GDP growth.

Table 3.6: Autoregressive Distributed Lag Model of commercial property prices: 1985Q1 to 2012Q4

<i>Dependent variable: Δlcp_t</i>	
<i>variable</i>	<i>Coefficient (t statistics)</i>
<i>constant</i>	-0.002 (-1.091)
Δcp_{t-1}	0.886 (6.021)
Δcp_{t-2}	-0.234 (-1.868)
$\Delta rcred_{t-2}$	0.108 (1.736)
Δue_{t-1}	-0.148 (-2.450)
R^2	0.77

Note: Data are quarterly and in real terms. Heteroscedasticity consistent standard errors used. Δcp_{t-i} refers to lagged commercial property price changes, $\Delta rcred_{t-2}$ is the second lag of credit growth and Δue_{t-1} is lagged unemployment growth.

Table 3.7: General Regime Switching model of Irish commercial property prices: 1985Q3 to 2012Q4

<i>Various estimates of b_t</i>			
	<i>Model A</i>	<i>Model B</i>	<i>Statistical</i>
$\beta_{s,0}$	-0.007 (-2.20)	-0.005 (-1.16)	0.004 (1.22)
$\beta_{c,0}$	-0.011 (-0.86)	0.23 (4.91)	0.043 (3.33)
$\beta_{s,b}$	0.010 (1.22)	-0.094 (-5.31)	-0.010 (-0.86)
$\beta_{c,b}$	-0.10 (-1.65)	0.49 (2.98)	-0.14 (-2.01)
$P(S, S)$	0.95 (30.38)	0.99 (111.56)	0.96 (41.04)
$P(S, C)$	0.05 (1.85)	0.02 (0.69)	0.11 (2.05)

Note: Dependent variable is change in quarterly log commercial property prices while b_t is the estimated non-fundamental component of prices. Absolute t-statistics are in brackets. Model A controls for income and interest rates. Model B focuses on short-run determinants and controls for changes in lagged unemployment, changes in lagged corporate credit and changes in lagged price effects. Statistical uses the deviation between the price/rent ratio and its long-run average. Survival regime S is the low volatility period. P(S, C) is the prob. of moving from regime C to regime S.

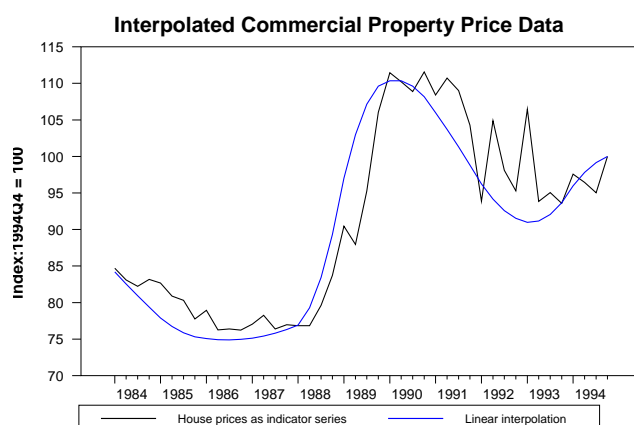
Table 3.8: Testing the restrictions imposed by the fads models

	<i>Model A</i>	<i>Model B</i>	<i>Statistical</i>
	<i>p-values for Wald Test</i>		
$HO : \beta_{s,0} = \beta_{c,0}$	0.00	0.00	0.00
$HO : \beta_{s,b} = \beta_{c,b}$	0.37	0.00	0.06
	<i>p-values for Likelihood Ratio Test</i>		
$HO: Restrictions are valid$	0.00	0.00	0.00

3.7 Appendices

Appendix 1: Data issues

The commercial price data used in this study cover the period 1984 through 2012. As quarterly data are only available from the first quarter of 1995 from SCS/IPD, annual index data from 1984 are interpolated to form a historical quarterly series. Two methods of linear interpolation were considered. First, we use a simple linear interpolation method. This method constrains the average of the values in each quarter to be the last value in the annual data. This process yields a very smooth series and tracks the annual data quite well. We also interpolated the price data using an indicator series. The difficulty with this method lies in the subjective choice of the indicator series and data availability. The growth in new house prices provided a benchmark. The house price data are from the Department of the Environment. The below Figure shows the two series. The interpolated series using house prices is quite volatile and so the series using the linear interpolation is chosen.



Appendix 2: Robustness checks

Given that both the commercial property data and GDP data were interpolated before the mid-1990s, the long-run OLS specification controlling for income and interest

rates are re-run, excluding data before 1995 as a robustness check. The results in Table 3.9 show that the point estimates for log real GDP and real interest rates remain significant and correctly signed. What is noticeable is that the elasticity with respect to GDP is relatively higher at 0.6 compared with 0.3 over the full sample (i.e., 1985Q1 to 2012Q4). The point estimate for real interest rate coefficient remains unchanged.

Recall from this chapter's introduction that the Irish systemic banking crisis had significant real effects and the commercial property market adjusted quite rapidly from the peak in 2007Q3/Q4. In addition to the parameter stability tests, the long-run specification is also estimated excluding the crisis period as a further check. Therefore the estimation is conducted over the period 1985Q1 to 2006Q4. Table 3.9 shows that the results remain unchanged. The sensitivity of Irish real commercial property prices to the business cycle is clear across all samples. The relatively higher elasticity with respect to GDP since the mid-1990s and in the pre-crisis period may be reflective of the strong performance of the Irish economy during this time.

Table 3.9: Long-run model of Irish real commercial property prices

<i>Dependent variable: cp_t</i>			
	1985Q1 to 2012Q4	1995Q1 to 2012Q4	1985Q1 to 2006Q4
<i>constant</i>	6.71 (8.04)	4.56 (3.04)	4.47 (6.25)
<i>gdp_t</i>	0.35 (4.52)	0.56 (3.96)	0.57 (8.52)
<i>i_t</i>	-0.05 (-4.53)	-0.06 (-4.03)	-0.03 (-3.63)

Note: T-statistics are in parentheses. Dependent variable is log real commercial property price. gdp_t refers to log real GDP and i_t is long-term real interest rates.

Appendix 3: Testing for alternative long-run determinants

Supply elasticity or tax issues may have a significant impact on price. To control for possible supply side effects in the long run, an alternative specification using real investment is also estimated. As real investment and real GDP are likely highly correlated or co-linear in the Irish case, the log of the unemployment rate is used instead to control for potential income returns. An increase in unemployment may reduce the potential demand for office, retail or industrial space. A reduction in occupier demand may reduce future rental growth and constrain the investment return. In Davis and Zhu (2011), an increase in investment generally leads to an increase in

prices although in the long-run, the relationship may also be negative depending on supply. The elasticity of the supply responses can determine the duration of property cycles. Short-run real interest rates are also included to capture the opportunity cost of finance.

A simple variant of the user cost of capital is also included instead of short rates in an alternative specification drawing on the housing literature (Browne, Conefrey and Kennedy, 2013). The user cost of capital comprises a number of components such as expected capital gains/losses, depreciation, cost of finance and tax treatment. The latter component is considered an important driver of demand for commercial property and favourable tax treatment played a key role in Irish commercial property in the pre-crisis period. Unfortunately a full treatment of the tax for commercial property investment over the period 1985 to 2012 is beyond the scope of this thesis. It is also assumed that depreciation is constant over the sample. Therefore the real lending rate minus the expected future capital gains/losses is used to proxy the user cost of capital (Kennedy and McQuinn, 2012). Given the potential for myopia in property investment, a weighted average of the previous four quarters of prices is assumed for expected future capital gains/losses. In empirical studies on the housing market a strong negative relationship is found between house prices and the user cost of capital. Given that commercial property is primarily an investment asset, we also expect a negative relationship.

Table 3.10 shows the results. Across all specifications a negative relationship is found between unemployment rate and prices, while investment appears to have a positive impact on prices. The coefficient on both the short-term interest rate and the user cost of capital is found to be positive which conflicts with theory. Davis and Zhu (2011) find a positive long-run relationship between short-run interest rates and prices in some markets.

Table 3.10: Alternative long-run models of Irish real commercial property prices:1985Q1 to 2012Q4

<i>Dependent variable: cp_t</i>		
	1	2
<i>constant</i>	8.14 (19.61)	8.12 (19.51)
<i>ue_t</i>	-0.45 (-12.40)	-0.45 (-12.39)
<i>invest_t</i>	0.34 (8.31)	0.34 (8.32)
<i>rsr_t</i>	0.02 (3.80)	
<i>user_t</i>		0.017 (3.81)

Note: T-statistics are in parentheses. Dependent variable is log real commercial property price. *ue_t* refers to log unemployment rate, *invest_t* is log real investment, *rsr_t* is real short-run interest rate, *user_t* is a simple proxy for the user cost of capital.

Concluding Remarks

In light of the recent global financial crisis, empirical research on banks and asset price bubbles is a priority for academics and policy-makers in the financial stability field. Drawing on standard banking and financial asset pricing theory, this thesis tests a number of hypotheses using novel Irish data over the period 1985 to 2013.

Although the empirical work relates to Ireland, the results will be of general interest. Economists and policy-makers are focused on developing their analytical framework to support macro-prudential policy discussions. Macro-prudential policy aims to prevent and mitigate systemic risk and is top of the international financial stability agenda after the global financial crisis. The original research on funding risk and property price bubbles in this thesis contributes to this field. The unwinding of a leveraged commercial property boom and bank funding difficulties played important roles, among other factors, in the Irish crisis. Such factors are also common to other episodes of systemic stress in advanced economies. Therefore analysis of both commercial property price developments over the cycle and the dynamic behaviour of deposits during a period of systemic stress expands our understanding of the origins and propagation of systemic financial crises.

In chapters one and two, the thesis draws on a unique high-frequency database of customer deposits in Irish banks over the period 2009 through 2013. Customer deposits are an important funding category for retail or commercial banks. Although volatility is observed in the weekly growth rates, deposit levels appear relatively stable during the early stages of the Irish banking crisis (i.e., March 2009 to August 2010). By specifying a model of corporate deposits over this period of relative stability, a number of research questions are addressed. In line with market discipline theory are corporate depositors sensitive to measures of banking sector risk? Do sovereign risk factors play a role up to August 2010? Will stress in other funding markets such as the interbank market impact corporate deposits, thereby reducing diversification

possibilities? Using time-series methods, chapter one shows that corporate depositors can impose market discipline by reacting to measures of bank financial soundness and that there are contagion channels across funding markets.

Extending the sample out to early-2014, chapter two investigates the issue of deposit volatility and the determinants of weekly customer deposit flows. Two distinct volatility regimes are found, namely a high volatility regime up to early December 2010 and low volatility regime from December 2010 to end-2013. The timing of this regime shift coincides with Ireland's application for external financial assistance in late-November 2010. A possible conclusion is that depositors were uncertain about the default risk posed by the Irish banks up to Ireland's entry into an external programme and this uncertainty manifested itself in inflows/outflows into Irish bank deposits. Evidence of a GARCH-in-Mean effect and a negative relationship between the deposit flows and their conditional variance suggest an empirical link between higher volatility and risk aversion. Beyond August 2010, the Irish banking crisis intensifies with the emergence of the European sovereign debt crisis. In line with this development, the empirical analysis in this chapter show that measures of both banking sector risk and sovereign risk have individual explanatory power for weekly deposit changes.

During the early stages of the Irish banking crisis, there was anecdotal evidence that corporate deposits were less stable than retail deposits and therefore posed a higher refinancing risk. However, the financial crisis literature is replete with theory and evidence of retail deposit runs during periods of systemic stress. Further the sequencing of modern bank runs is such that more-informed funding providers run first, followed by retail depositors as the crisis deepens. This thesis tests these hypotheses and provides evidence that retail depositors display more inertia up to a certain point. In the Irish case, the turning point was August 2010 as both the creditworthiness of both the Irish sovereign and the Irish banks deteriorated. After this date, outflows were recorded for both retail and corporate deposits. This research also provides empirical support for the relatively higher volatility of corporate deposit flows and evidence of volatility spill-overs from corporate to retail deposit flows during a crisis.

In chapter three, the dynamic behaviour of real commercial property prices is investigated over the period 1985Q1 to 2012Q4. Sharp corrections in commercial property prices have preceded many episodes of financial crisis, particularly if the preceding price appreciation was funded by credit and private-sector leverage. Unlike

housing markets, data on commercial property market developments are relatively scarce and often not freely available due to its commercial value. Research on commercial property prices is therefore confined to relatively transparent markets such as the United States, Australia and the United Kingdom, although there have been a few cross-country studies using subscription data from private-sector sources. Bridging these data and analytical gaps is a priority among national systemic risk analysts. In Ireland, to the author's knowledge, there has been limited published empirical research on commercial property price movements. Therefore, chapter three investigates the role of possible fundamental determinants such as income, interest rates and credit in explaining Irish real commercial property prices over the sample period. Given potential model uncertainty, a number of approaches are used.

Broadly similar periods of misalignment from fundamentally determined prices are found across these approaches. In all cases, commercial property prices are found to be persistently overvalued prior to the market peak and subsequent price collapse from late-2007. Drawing on asset pricing literature, these periods of misalignment are used to test between the rational bubble theory and the irrational fad hypothesis, using regime switching techniques. Although the results are not fully conclusive, evidence of non-linearity in expected price returns suggest that Irish commercial property prices may be subject to bubble-like behaviour. This result suggests that self-fulfilling expectations may have a role in explaining price growth in this market. Investors may be aware of the unsustainable nature of commercial property price booms but high capital gains are attractive and they may assume they will exit before the crash.

There are a number of possible avenues for further work across both aspects of this research. With regard to funding stress, contagion within the banking sector could be investigated both in terms of deposit flows and their volatility. Certain fundamental determinants of commercial property prices such as GDP or credit may be subject to structural change or regime switches over the sample. Finally, regime switching methods are just one possible option for testing for asset price bubbles. Further extensions could involve univariate analysis of commercial property prices using unit root tests.

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