The Economics of Ireland's Property Market Bubble

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Abstract

This doctorate explores key aspects of the economics of housing by examining Ireland's housing market bubble of the early 2000s. For earlier chapters, the main source material is a previously unused dataset of almost two million property listings, covering the entire country from 2006 until 2012, maintained by property website daft.ie. An initial chapter outlines stylised facts of Ireland's housing market 2007-2012, including a greater spread of prices over property size in the crash but a narrower spread of rents. In contrast, the geographical spread of prices and rents was largely unchanged. The spread of rents was constrained relative to the spread of prices, suggesting either renter search thresholds or buyer "lock-in" effects. To examine which was at work, the daft.ie dataset is combined with information on a range of amenities, including landscape, transport, education, social capital and market depth. Overall, there is clear evidence that the rent effects of a range of amenities are smaller than the price effects. There is limited evidence of procyclical amenity pricing, which would indicate "lock-in" effects, with the analysis suggesting instead countercyclical pricing, or "property ladder" effects during the bubble. Results from these analyses are based on listed price and rents, rather than transaction prices. The relationship between the two is examined in a separate chapter, using an additional Central Bank of Ireland dataset on mortgages. The spread between list and sale prices gap that exists between the two is decomposed into four parts, a selection spread, a matching spread, a counteroffer spread and a drawdown spread. A selection spread of up to 10% emerged in the Irish housing market after 2009, while the counteroffer spread was positive before 2009 but negative for much of the period 2009-2011. The final chapter uses both inverted-demand and price-rent ratio methods to examine the long-run determinants of house prices in Ireland from 1980 on. In addition to careful treatment of standard fundamentals, it includes a measure of credit conditions as well as the ratio of persons to households, both contributions to the literature. The resulting inverted demand error-correction model shows a clear and stable long-run relationship, which is largely preserved when cointegration between series is explored. Similarly, a model of the price-rent ratio from 2000 shows clear error-correction properties. Together, they suggest that while a range of factors drove Irish prices 1995-2001, credit conditions were largely responsible for the subsequent increase.

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Chapter 1

Introduction

The housing boom that affected much of the OECD during the 1990s and early 2000s has led to renewed focus on the links between housing and the rest of the economy. The pivotal role played by housing markets and housing wealth in the so-called "Great Recession" and in previous cycles has convinced many economists that understanding housing is central to understanding business cycles, one of the primary focuses of macroeconomics (see, for example, Leamer 2007). Indeed, there is evidence of a strong link between housing and business cycles not just throughout the postwar era (e.g. Holly & Jones 1997), but even predating the Industrial Revolution (Eichholtz et al. 2012, O'Rourke & Polak 1991). The strong link between housing and broader economic outcomes should hardly be a surprise, given that even in modern developed economies housing remains both the single most important consumption good and the principal asset in household wealth. In the U.S., for example, shelter comprises roughly one third of the basket underlying the urban CPI, while a 2001 study estimated that over half of household wealth was in housing (Luckett 2001).

Where to live is both a consumption decision and an investment decision. It is a consumption decision as choosing a residence is more than choosing a location for shelter as a service. The choice of accommodation is the choice of a bundle of services, from the amount of space per person to a range of amenities specific to the location or the population that lives there, both clear, such as access to transport services, and nebulous, such as heritage or social capital. The choice of accommodation is also an investment decision. Those who buy are, even if only implicitly, making a statement about the expected capital gain relative to the cost of borrowing, as are those who rent. As an investment decision, the purchase of a dwelling typically involves significant leverage. This means that conditions not only in the housing market but also in the mortgage market – which turns latent demand into effective demand – are also hugely important.

Much of economic research and modelling now is interested in general equilibrium approaches. Unfortunately, it is clear – much to society's cost – that the workhorse DSGE models of macroeconomics so prevalent in the run up to what is now known as the Global Financial Crisis (GFC) were deficient in understanding the key channels through which shocks were propagated through the economic system. There are attempts to adjust these models to incorporate financial frictions and other mechanisms through which standard DSGE models break down. Nonetheless, it is important that economic theory know what the partial equilibrium effects look like, in order to assess the validity of general equilibrium frameworks. Put another way, if macro-prudential policy is to have an impact, it must know what warning signals it is looking out for. Thus, the focus in this thesis is on partial equilibrium analysis, to identify the effects and signals that can inform future models.

It is the objective of this doctorate to explore key aspects of the economics of housing market cycles by examining in detail the extreme bubble and crash in Ireland in the 1990s and 2000s.[1] This is done first through a chapter outlining some stylised facts in relation to Ireland's property market and then three follow-on chapters that explore theoretical and applied issues relating to the economics of housing markets. For much of the work, the principal dataset

[1]The term "bubble" is used here independently of any theoretical connotations, for example regarding rationality, and is motivated simply by the significant run-up in prices in the decade to 2007 and the subsequent fall, by roughly half, in the five years after 2007. Later chapters will address more directly the issue of whether house price reflected fundamentals or not.

used is a heretofore unused dataset of nearly two million property listings in total, both sales and lettings, across the entire country, from 2006 to 2012.

The motivation for looking at Ireland stems from the severity of its housing market bubble. In the decade to 2006, nominal house prices rose more than four-fold. With nominal and real prices in 2013 down over one half from the peak, the crash is one of the most severe of any country not just in the Great Recession but in the entire modern era (The Economist 2011). Thus, findings from Ireland's real estate crash may be relevant to the many other countries that experienced a real estate cycle in the 1990s and 2000s and may also give insights into central questions of bubble-crash cycles and urban economics.

While the temporal trend in Irish house prices is well known, very little is known about the spread of house prices within the market and how that spread changed between bubble and crash. Chapter 2 establishes a number of stylised facts in relation to the distribution of house prices and rents in Ireland, which serve as the backdrop for the analysis of the following chapters. It compares mid-2007, the height of the real estate bubble, and mid-2012, by which time house prices had fallen more than 50%. In particular, it explores and contrasts structural changes in both the sales and lettings markets, geographically and with respect to characteristics of size or type. To do this, in the absence of publicly available transaction-level data, it uses prices and rents from a set of over 1.1 million property listings over the period.

There are four principal findings about the distribution of house prices and rents in Ireland during this period. Firstly, the spread of prices across different property sizes increased significantly in the crash. This is consistent with a "property ladder" effect during the bubble temporarily pushing up the relative price of smaller properties. Secondly and in contrast, the spread of rents from largest to smallest property sizes fell between bubble and crash. Thirdly, once property characteristics are controlled for, there was at most a small fall in the spread of both prices and rents across space. Lastly, in both bubble and crash periods, the spread of rents was constrained relative to the spread of prices, particularly in the upper tail, a finding suggestive of renter search thresholds.

Housing is a composite good, with each dwelling a bundle of property-specific attributes and location-specific amenities, each with its own price. Changing price differentials can reveal demand shifts between these attributes and thereby offer insights in to what happens in a housing bubble. There are competing theoretical suggestions as to what will happen to price changes across different segments during a housing cycle. According to Stein (1995), down-payment constraints make high-value properties more volatile than low-value ones. Costello (2000), however, suggests that if more affordable homes are more liquid and thus more competitive, then these segments may be more volatile over the boom/bust cycle. Empirically, is high-end housing the epicentre of a bubble, as people "lock in" exposure to the asset, and thus more badly affected in the crash? Or are peripheral properties worse hit, a "property ladder" effect where in the frenzy of the bubble, people buy whatever property they can afford in the hope of capital gains?

As housing is an inherently spatial market, an understanding of the economics of location-specific amenities is needed, a topic examined in detail in Chapter 3. It examines the cyclicality of the prices of a range of location-specific amenities, using over 1.2 million sales and rental listings in Ireland, covering both bubble and crash periods, and 25 primary location-specific characteristics, as well as various controls. The first hypothesis tested is whether the valuation of amenities is greater in the sales segment than in the lettings segment, reflecting either tenants' search costs or buyers' desire to lock in supply of the amenity. This was typically found to be the case – there is evidence of an attenuated rental effect for 18 of the 25 amenities. For example, the rental premium for a coastline property was 2.1%, less than half the 4.7% price effect.

To distinguish between tenant search costs and buyer lock-in concerns, the severity of Ireland's housing bubble and crash was exploited. "Lock-in" effects would be expected to be most severe during a bubble, as people pay over the odds to secure access to amenities which are by their very nature fixed in supply. This would suggest relative amenity prices are procyclical, rising in the bubble and falling in the crash. If instead the price of amenities increased in the crash, this would suggest that "property ladder" concerns dominated: in the bubble, the principal concern is not having any property, pushing up the relative price of low-amenity properties. Chapter 3 finds evidence of a lock-in effect, with counter-cyclical amenity pricing for a greater number of amenities, including prominent housing market amenities such as commute time, distance to CBD and proximity to train stations and the coastline. For example, the premium enjoyed by a property 100m from the coast compared to one 1km away increased from 3.4% to 4.4% between bubble and crash. Similarly, moving a property from 5km from the CBD to 1km away was associated with an increase in price of 7.4% in the bubble and 8.2% in the crash.

These findings are based on list prices and rents, rather than sale prices, which are not available in Ireland for this period. While there is a long history of using advertised or assessed values where transactions data are not available, the relationship between the two is not constant. Indeed, in the very first issue of the Journal of Real Estate Research, Miller & Sklarz (1986) highlight the relationship between the two as one of five leading indicators in the housing market. However, their call for future research has largely gone unheeded.

Chapter 4 addresses this issue, by combining the daft.ie dataset used in Chapters 2 and 3 with a dataset maintained by the Central Bank of Ireland (CBI), as part of that country's Prudential Capital Assessment Review (PCAR) "stress tests" of the financial system. It takes as its starting point two pieces of conventional wisdom about the housing market, which would appear to conflict in a market downturn. Firstly, it is expected that in a downturn sale prices will be below list prices, while secondly, it is often asserted that list prices are a lead indicator of sale prices. The analysis shows that both were true for Ireland during the period 2006-2012. The apparent contradiction is thus: if list prices lead sale prices in switching from boom to bust market, how are they above sale prices in the bust? This is resolved by disentangling the ratio of list prices to sale prices into four main components.

The first of the four is the selection spread, a comparison of all list prices to only those that go on to find a buyer. A selection spread exists throughout the period but is particularly pronounced during the market downturn: properties that list for less, *ceteris paribus*, are more likely to find a buyer – a finding that accords with basic economic theory.

The matching spread, secondly, reflects how much house prices change between when a property is listed and it is sale agreed. Given the speed with which prices fell in Ireland during much of the period covered, and the length of the typical time-to-sell, this is quantitatively important in explaining the gap between the two. For most of the period 2008-2011, the list price of properties on which a sale was agreed was 10% or more higher than newly listed properties. While the exact role of nominal price rigidities is a topic for further research, this finding highlights the limitations of comparisons made in the existing literature on valuation accuracy, which use valuations and transactions from different time periods. The drawdown spread, reflecting the time gap between valuations for mortgages and their ultimate draw-down, was similar in nature but much smaller in significance.

The counteroffer spread, finally, is the closest counterpart in the housing market, which lacks liquidity and fungibility, to the bid-ask spread in other financial markets. It reflects how list prices and sale prices compare, when adjusted for time-to-sell and time-to-drawdown, as well as for the fact that some listings will not result in a transaction. Early in the period, the counteroffer spread was large and positive, suggesting that buyers had tough competition in securing a property and thus they offered more than the list price. As boom turned to bust in the Irish housing market, the counteroffer spread turned negative. This idea of the sale price in boom-times "breaking the price ceiling" offered by the list price has also emerged from recent research (Haurin et al. 2013).

The final substantive chapter of this thesis, Chapter 5, examines the determinants of real house prices and the price-rent ratio in the Irish housing market. Credit conditions have been considered in many studies of other housing markets, particularly since the GFC, but the existing literature on Irish housing largely ignores the issue of credit conditions, empirically if not theoretically. In addition, there have been no models of the price-rent ratio in the Irish market. A quarterly dataset from 1980 to 2012 is used to estimate an error-correction model that reveals the long-run relationship between house prices and their long-run determinants. Those determinants include the ratio of income to the stock of housing, the ratio of persons to households, user and transaction costs, and credit conditions, as measured by the ratio of mortgage credit to deposits. This long-run relationship is largely robust to allowing variables such as the income/stock ratio, user cost and the credit/deposit ratio to be endogenous to the system.

The results indicate that while the earlier phase of Ireland's house price boom was a product of many factors, growth between 2001 and 2007 was due almost entirely to an easing of credit conditions. The actual average real house price tracked very closely the price predicted by the long-run relationship. In this sense, it could be argued that there was no bubble in the conventional sense, of prices detaching from fundamentals. This is true to the extent that those fundamentals include supply conditions in the credit market and expectations (reflected in user-cost), both of which changed rapidly during the period 2001-2012.

Using new data on LTVs for first-time buyers, an error correction model of the price-rent ratio in Ireland is presented for the first time, covering the period 2000-2012. In line with the inverted demand model, this indicates that credit conditions were, along with the real rate of interest, key to determining equilibrium in the housing market. This research is rich in policy implications, in particular about the importance of expectations and credit conditions. Assuming that credit conditions fulled readjusted by 2012, normalization of expectations in relation to housing can be expected to generate some upward pressure on prices in coming years.

Chapter 6 draws together the contributions of this thesis and suggests some insights from the Irish housing market bubble for policymakers aiming to both diagnose and prevent future housing bubbles.

Chapter 2

Stylised Facts

As mentioned in Chapter 1, in modern developed economies, housing is both the single most important consumption good and the principal asset in household wealth. Its cycles are closely related to broader macroeconomic fluctuations, with some economists going so far as to argue that housing *is* the business cycle (Leamer 2007). There remains much to learn, however, about the internal mechanics of the housing market, if a proper understanding of what drives housing cycles is to help economists and policymakers understand and ameliorate them in the future. In particular, a growing field is interested in the efficiency of housing markets, as a counterpart to the study of the efficiency of other financial markets. While there is significant research using aggregate data, much less work has been done using more refined housing market segments.

Ultimately, housing is a composite good, with each dwelling made of up property-specific attributes and location-specific amenities, each with its own price. If differentials for particular attributes or locations change, this can reveal demand shifts that offer insights into what happens over the housing market cycle. The Global Financial Crisis (GFC) and the related fall in house prices in a number of countries has generated renewed interest among economists in the structure of house prices. For example, Glaeser et al. (2012) examine the decade-long boom in U.S. house prices, finding evidence that "buyers during the boom overestimated the long-run value of positive local attributes".

There are competing theoretical suggestions as to what will happen price changes across different segments during a housing cycle. According to Stein (1995), down-payment constraints make high-value properties more volatile than low-value ones. Costello (2000), however, suggests that if more affordable homes are more liquid and thus more competitive, then these segments may be more volatile over the boom/bust cycle. This chapter is the first to contrast these two hypotheses with granular housing market data. It examines the property market in Ireland, which has experienced one of the most severe real estate cycles on record, comparing the distribution of both house prices and rents in Ireland in 2007, the height of a real estate boom which saw prices increase four-fold in a decade, and 2012, by which time house prices had fallen by half. In particular, it explores and contrasts structural changes in both the sales and lettings markets, geographically and with respect to characteristics of size or type. To do this, in the absence of publicly available transaction-level data, it uses advertised prices and rents from a dataset of over 1.1 million property listings over the period.

The principal method used is the hedonic regression, drawing on the long literature established by Rosen (1974), with housing understood as a composite good comprising property-specific attributes and location-specific amenities. In addition to a range of type, time and size controls, to understand changes in the geographic spread of prices, an algorithm is used to aggregate 4,500 Census areas into just over 1,100 sales zones of sufficient sample size (312 zones for lettings). These zones are then used in a series of hedonic prices models, which give the estimated average price for a range of standardised properties per zone and per quarter. Figures for the peak and for mid-2012 are then compared.

The chapter is structured as follows. The next section presents a brief overview of related literature on structural changes in the spread of property prices, on Ireland's property market and the hedonic method. Section 3 outlines the data used in this study, the algorithm for compilation of the price zones and the specific hedonic specifications employed. Sections 4 and 5 present the results for the various house price models and for analogous models for the lettings segment. Section 6 presents concluding thoughts.

2.1 Theory & Literature

The theoretical starting point for thinking about the housing market is as an efficient financial market (e.g. Case & Shiller 1989). Such a perspective suggests that house prices can be thought of as forward-looking, depending on fundamentals such as rents or user-costs (Poterba 1992), and that expected capital gains should reflect factors such as demographics (Case & Shiller 1990). However, there is ample evidence that the market is not efficient, as housing prices exhibit boom-bust behaviour and can be predicted to a certain extent by past price changes and the rent-price ratio (see, for example, Gallin 2008). There is particular interest in the extent to which housing markets are informationally efficient, i.e. that prices reflect accurately the forces of supply and demand, although much of the research is at aggregate market level, ignoring differences across segments (Gatzlaff & Tirtiroğlu 1995).

In relation to the structure of house prices, Stein (1995) suggests that one might expect higher price housing to be more volatile over the market cycle. This is due to the presence of down payments and the fact that the typical household holds most of their private net wealth in housing. Consider a negative shock to house prices: this hinders movers from making their next down payment, depressing demand. If high-priced homes are purchased primarily by trade-up buyers, then their prices should have a greater variance over the real estate cycle. The prior expectation, according to this liquidity constraint model, is that houses with higher prices would both rise and fall more dramatically over the cycle than those with lower prices.

There is limited evidence for the thesis, however. Smith & Tesarek (1991) find evidence that this may hold in the property market cycle in the U.S. city of Houston, Texas, over the 1970s and 1980s, where they estimated that during the boom years, the marginal price of quality rose, and when prices started to fall, the structure of prices flattened. However, Case & Shiller (1994) explore two other 1980s boom-bust cycles in U.S. cities, those of Boston and Los Angeles, and largely find the opposite. In Boston, they find evidence of a shift in house price inflation to the lower tier after other tiers had stabilised (1987-9), giving that part of the market the greatest boom in prices. In L.A., there was very similar appreciation across high, medium and low tiers of housing, although higher tier housing did see significantly larger falls. Case & Mayer (1996) focus more closely on the impact of amenities on the distribution of relative house prices, and, contrary to Stein's (1995) hypothesis, controlling for amenities, low-priced towns saw faster house price growth to 1988 and then greater falls after that.

Lower-priced segments experiencing more volatile swings in prices may instead represent another consequence of down-payments for real estate. In equities markets, differing liquidity is believed to explain the so-called "size effect", where returns on the shares of small companies exceed those of larger ones. In housing markets, Costello (2000) suggests, more affordable properties are more liquid and thus these segments will be more competitive, rising more in boom markets and falling more in down markets. Using data for the city of Perth, Western Australia, during the period 1988-1996, Costello finds that repeat sales were biased towards lower price quartiles, suggesting greater liquidity in cheaper segments. He also finds that the top quartile in particular exhibited significantly less real house price inflation than other segments.

Since the start of the Global Financial Crisis (GFC) in 2007, there has been a significant increase in research focus on the housing market. Much of this research examines the relationship between one aggregate measure of house prices and fundamentals such as income, demographics, user cost and housing stock (see, for example, Duca et al. 2011*a*, Fraser et al. 2012, Muellbauer & Williams 2011). The connection between the housing and credit markets and financial stability is also an active area of research (see Muellbauer 2012, and other papers at the same conference).

A smaller literature has examined the internal mechanisms of the housing market during the build-up to the GFC. McMillen (2008) is one of the first works to examine in detail the distribution of house prices across a market. Studying the Chicago market of 1995 and 2005, he finds that the increase in prices in this period was greater for higher value homes. The change in distribution is attributed to changes in the coefficients, rather than changes in the characteristics of the dwellings. Deng et al. (2012) reach a similar conclusion for the housing market in Singapore over the period 1995-2010.

Lastly, Glaeser et al. (2012) analyse the housing price boom in the U.S. in the decade to 2006. They find that price growth was significantly greater in cities that were warmer, less educated, with less initial density and higher initial housing values. They also study within-city changes and conclude that price growth was faster in neighborhoods closer to the city center. The authors conclude that this is largely consistent with a model of buyers during the boom overestimating the long-run value of positive local amenities and the urban amenity in general. Nonetheless, this conclusion is based on a comparison of 2006 with 1996 and any number of factors, including shifts in the distribution of income or in credit conditions, or the impact of technology on work practices and locations, may mean that 1996 is not the appropriate reference point for prices in 2006.

2.1.1 House Prices in Ireland

A number of papers trace the development of Irish house prices from the 1970s; see, for example, Kennedy & McQuinn (2012), Kenny (1999), Murphy (2005), Roche (2001), Stevenson (2003). These papers typically try to model house price using some combination of economic theory (typically a variant of the textbook inverted demand approach, sometimes with a simultaneous supply equation) and statistical methods (for example, regime switching). As noted by Murphy (2005), however, many are ad-hoc specifications and typically suffer from omitted variable bias, as they eschew any treatment of credit conditions (a more recent exception is Addison-Smyth et al. 2009).

A further issue is the quality of data available to the researcher. Until the mid-1990s, hedonic price indices were not available for Ireland and the only published series was a simple mean price, which over time would be subject to a number of limitations, including a quality bias, particularly for regional data. Trends in the mean price differ significantly in the post-2007 period from hedonic trends based on either list or transaction price. This places a limit on the reliability of existing research into house prices in Ireland, in particular research that examines regional trends in house prices, such as Stevenson (2004).

Nonetheless, the broad history of the Irish property market is reasonably well established. Prices were relatively stagnant in real terms from the mid-1970s until the mid-1990s, after which export-led economic growth fuelled economic and demographic expansion, which lifted house prices (Murphy 2005). The policy response stimulated new housing supply. However the expansion in credit meant that prices in the early 2000s increased rapidly, rather than fell due to the increase in supply. By the mid-2000s, with the average house price up almost 300% in just ten years, a growing number of commentators were concerned about likelihood of a domestic real estate bubble. Between 2007 and 2012, prices fell by at least half.[1]

A related strand of reseach examined the relationship between fiscal policy and the housing market (e.g. Berry et al. 2003). Barham (2004), for example, finds that the combination of beneficial fiscal incentives and declining costs, in terms of falling interest rates, drove down the costs associated with owner-occupancy. In particular, the untaxed capital gain afforded to homeowners meant that for the majority of the period he analyses, the user cost of housing

[1] By the end of 2012, the official CSO index of house prices, based on mortgage transactions, was down 49.9% from the peak, while the daft.ie index of list prices was down 55.3%.

in Ireland was negative. In this context, rising house prices were to be expected. An OECD review in 2006 found that the huge increases in house prices in Ireland stemmed from a combination of fundamentals, such as strong economic growth, demographics and low interest rates, but also policy, in particular very generous tax advantages for owner-occupancy and loose banking credit (Rae & van den Noord 2006).

2.1.2 The Hedonic Methodology

The research presented here uses the hedonic price method to estimate the value associated with certain attributes, in particular location, type and size. The hedonic method is well established in the literature and its theoretical foundations are described in Rosen (1974). Its limitations and implicit assumptions are described in Maclennan (1977). Of relevance here is the risk of pooling over submarkets where underlying parameters differ, i.e. aggregation imposing one price structure when in fact price structures may differ across sub-markets. As outlined in Section 2.2.4, the purpose of this analysis is to understand submarkets in the Irish property market and the empirical strategy is designed with this in mind, including specifications that allow type differentials to vary by region. Maclennan (1977) also notes that concerns in relation to implicit assumptions about preferences are less relevant where the aim merely to statistically explain the apparent determinants of relative house values, as is the case here.

More recently, Malpezzi (2003) reviews the hedonic methodology one generation on. Three recurring issues relate to its theoretical footing, the problem of mis-specification (including omitted variables and market definition) and the relationship between design and purpose. He notes that "if samples are large and well-drawn ... more flexible forms and more careful attention to the delineation of submarkets will generally pay off" (Malpezzi 2003, p.24). This is still an active area for discussion. Ellen (2012) notes that while stratification, by type, neighbourhood and even ethnicity, is possible, there exists nonetheless a relationship between the different submarkets, concluding "the debate about segmentation is really about degree – about how large the cross-price elasticity is between different types of housing".

Another segment of the literature examines the accuracy of estimation methods employed in constructing house price indices, including the hedonic method and the repeat-sales method. As is discussed in more detail in Chapter 4, the use of simple averages or indeed repeat sales may lead to biased estimates of house prices changes, as the characteristics of the sample of properties transacted over the cycle changes (Dorsey et al. 2010, Pollakowski 1995). The finding from this literature is that the hedonic methods used here are most appropriate when examining prices across space and time, as well as general price levels and changes.

A paper by Conniffe & Duffy (1999) was one of the first to apply economic and econometric techniques to Irish house prices, using a 1996-1998 dataset from an Irish mortgage provider. They adapted the hedonic method developed for the Halifax House Price Index (Fleming & Nellis 1985), the exponential form of hedonic equation, with log of price regressed on a linear combination of attributes. The authors distinguish between locations in the same region (e.g. within Dublin) and locations in different regions, highlighting that while the price difference between suburbs may capture neighbourhood quality, differences between regions may reflect more fundamental economic differences. They discuss the stability of housing attributes and note the lack of models using interactive terms: most models assume that only one element is time-varying (a dummy capturing that period), while the relative prices of other attributes such as location, house type or size does not change. This lack of interactive terms will be addressed in this study.

2.2 Data & Models

The data used for analysis here was collated by the online accommodation portal, daft.ie. The dataset comprises all properties advertised online between 1 January 2006 and 15 June 2012, both sales and lettings.[2] Its coverage of both segments is unusual in the literature, which typically has focused, for reasons of data availability, on the sales segment. Observations from 2008 are excluded, to create a clear distinction between bubble (2006-2007) and crash (2009-2012) periods, as are those properties whose locations were not known to sufficient accuracy (townland level or better) – Ireland lacks a postcode system.[3] This left a final sales sample of 408,334 ads.[4] As is outlined in Table 2.1, the bulk of properties listed were three-bedroom or four-bedroom properties, while the most common property types were detached and semi-detached. The lettings component of the dataset comprises 704,953 ads. Compared to the sales dataset, there are a greater proportion of smaller properties and Dublin properties: the most common property size is two-bedroom, while Dublin properties comprise almost half of all ads.

2.2.1 Price data

Price information included in the dataset is the listed, or asking, price. An obvious concern is that the list price may not reflect the transaction price, if it exists. List prices in Ireland are not in any way legally privileged. A seller may state that they require offers "in excess of" or "in the region of" the list price, but typically the list prices are for information only and set after agreement

[2]The vast majority of listings in the dataset refer to ads posted on the daft.ie site. The remainder (about 3%) refer to the small fraction of online listings in Ireland that were not advertised on the Daft.ie portal. Most of these date from 2006-2007.

[3]While this is a relatively informal split between bubble and crash periods, it is in line with more statistical tests, with the year-on-year change in prices positive in each quarter 2006-2007 and falling at a rate of more than 10% a year each quarter 2009-2012.

[4]This includes 169,932 ads whose price had changed. These are treated as separate observations; for example, a property listed at €300,000 in January and re-listed at €275,000 in April enters as an observation in Q1 and Q2. This reflects the focus here on relative valuations within a given period of time. The results presented below are robust to the exclusion of these price-change observations.

Table 2.1: *Dataset size, by cohort*

Category	Cohort	Sales	Lettings
Size	One-bedroom	10,885	78,411
	Two-bedroom	61,778	274,810
	Three-bedroom	166,702	216,694
	Four-bedroom	134,096	112,001
	Five-bedroom	34,883	23,037
Region	Dublin	95,429	323,577
	Other cities	41,132	107,034
	Leinster	119,766	164,042
	Munster	81,728	66,604
	Connacht-Ulster	70,289	43,696
Total		408,334	704,953

between the seller and their estate agent. There is considerable precedent for using list prices where no dataset of transaction prices exists, as is the case with Ireland as the bubble ended. Some of the earliest contributions to housing economics use owner estimates of property values, for example in the Annual/American Housing Survey (e.g. Linneman 1980). Estimates of U.S. house prices during the 1890-1934 are based on homeowner recollection and current assessments (Grebler et al. 1956), while estimates for the period 1934-53 are based on newspaper listings (Shiller 2005). It has also been pointed out that listings data may more comprehensively capture relative values than sales data, which will be in some sense truncated samples of the full housing stock (DiPasquale & Somerville 1995, Gatzlaff & Haurin 1998).

Nonetheless, there are differing views as to the accuracy of owner- or agent-assessed values. The general finding appears to be that homeowners tend to overstate the value of their homes (Banzhaf & Farooque 2012, Goodman & Ittner 1992), although this would not present an issue here if this bias did not vary systematically by market segment. Also, prices here are typically based on expert valuations, which are more accurate than owner assessments (Banzhaf & Farooque 2012). Kiel & Zabel (1999) find little difference in appreciation rates between self-reported values and transaction values, while Malpezzi (2003) concludes that hedonic models based on owner assessments would be “reasonably reliable". This issue is addressed in relation to the Irish housing market during this period in detail in Chapter 4.[5]

2.2.2 Location

Based on the earlier discussion of the hedonic method, including points made by Maclennan (1977) and Ellen (2012), the empirical approach allows differentials between property types to vary by region. The model defines five broad regions in the Irish property market, the first of which is Dublin city. The second regional market contains the four other cities in Ireland combined (Cork, Galway, Limerick and Waterford), whose populations vary from 50,000 to 275,000. These are not contiguous but may share marginal price effects due to their status as regional cities. The other three regional markets are based on Ireland's provinces, but excluding the city areas: Leinster, Munster and Connacht-Ulster.

Each of these regions is broken down into zones. There are in total 1,117 sales zones and 312 lettings zones around the country. These zones were developed algorithmically by the National Institute of Regional & Spatial Analysis at NUI Maynooth. The algorithm took as its starting point Ireland's 4,500 Census districts (electoral divisions outside the cities and enumerator areas within the cities). If an individual district k did not have sufficient sample size in both bubble and crash periods (roughly, $n_{tk} \geq 100$ for $t =$ bubble, crash), it was paired with adjoining zones until the threshold was reached.

The principal reason that there are significantly fewer lettings zones is likely to be related to the bubble itself. Those investing in property during the final stages of the bubble appear to have done so principally for capital gains, rather than rental income, and the volume of rental listings in non-urban markets prior to 2008 was small. This motive disappeared as prices fell, leading to a

[5] For example, a possible concern could be that those in larger/higher-value properties may be more averse to realising losses and thus have stickier list prices that are not reflected in outcomes. Evidence from Chapter 4 and from the CBI dataset used in that chapter, however, suggests that this is not the case.

Table 2.2: *Summary of variables used*

Variable	Description (variable names in Regression output tables included where appropriate; controls, where relevant, in italics)
Price	Advertised sale price or monthly rent
Time	Categorical time variables for each quarter from 2006:I to 2012:II; variables with the suffix _cr are the original variable interacted with a categorical variable taking a value of one for the crash period (2009-2012)
Location	Price zone, as described above; 1,117 sales zones, 312 lettings zones
Region	Variables with the suffix _reg$x$ have been interacted with a particular region (1-5, which are respectively Dublin, other cities, Leinster, Munster, Connacht-Ulster)
Type	Property type; five possible values in sales: terraced (ht1), *semi-detached (ht2)*, detached (ht3), apartment (ht4), bungalow(ht6); three in lettings: *apartment (pt1)*, house (pt2), flat (pt4)
Bedrooms	For both sales and lettings segments, number of bedrooms (one, two, *three*, four, five)
Bathrooms	For both sales and lettings segments, number of bathrooms relative to number of bedrooms as follows: one-bed (*1* or more), two-bed (*1*, 2 or more), three-bed (*1*, 2, 3 or more), four-bed (1, *2*, 3, 4 or more), five-bed (1, *2*, 3, 4 or more); variable names take the format bbxy where x refers to bedroom number and y to bathroom number, where $y = m$ refers to any greater number of bathrooms
Bedroom size	For lettings only, stated occupancy of bedrooms (measured by number of single rooms): one-bed (*zero* or one), two-bed (zero, *one* or two), three-bed (zero, *one* or more), four-bed (zero, one, *two* or more), five-bed (zero, one, *two* or more); variable names take the format bx_zs where x refers to the total number of bedrooms and z to number of single rooms (the highest number covers that number and any greater
Facilities	For lettings only, information is available for a range of utilities (including central heating, an alarm system, cable TV and the internet), white goods (washing machine, dryer, dishwasher and microwave) and other features (wheelchair accessible, parking and garden, the one feature also available for sales)
Terms	A range of contract terms are also included in lettings ads (whether pets are allowed, whether rental allowance is considered, a short or long lease, relative to a 12-month control, and whether an agent is used, which is also available for sales)

significant increase in the number of rental listings – for example, the total number of rental properties listed outside the main cities increased from less than 30,000 in 2007 to over 100,000 in 2009. Dublin witnessed a similar increase in listings. While the purpose of the analysis in this chapter is to describe, rather than model, trends in property values, this very significant outward shift in the supply curve is likely to have contributed to the fall in average rents.

2.2.3 Other property attributes

There are five categories of attribute used to explain observed prices and rents, including location (as explained above), the time the ad was listed (grouped by quarter), type, size (measured in bedrooms and bathrooms, and in the case of lettings properties the occupancy of the bedrooms), and other features including facilities and terms of the ad. All variables are categorical variables, as explained in Table 2.2.

2.2.4 Models

Table 2.3 outlines the five models that are applied to both sales and lettings datasets. Model (1), the baseline model, regresses the log of the price (or rent) on five sets of property attributes: time (quarterly dummies); property type; size (bedroom number and bathroom number, relative to bedroom number); and the 1,117 sales zones (312 lettings zones). In effect, it assumes that any changes over time are captured by the time dummies and that no change takes place in the distribution of prices across location or type.[6] As outlined earlier, however, an important finding of the literature is that time, location and other attributes interact. This is explored in the other models.

In equation form, the five empirical models are given below in Equations 2.1-2.5. Each vector of Q, X and Y omits one category as control, and where

[6]This is similar to standard hedonic models used for house price indices, although these typically use no more than four quarters of data.

s refers to the quarter within the year, t to the year (with no $s = 3$ or $s = 4$ for 2012), n to attribute n of $N = 29$ for sales (comprising 5 types, 5 bedroom sizes, and 19 bedroom-bathroom combinations; see Table 2.2) and $N = 50$ for lettings (3 types, 5 bedrooms, 19 bathroom combinations, 16 bedroom sizes and 14 binary features; see Table 2.2), r to regions 1-5 and z to the zones outlined above. C refers to a categorical variable that takes the value of 1 for the crash period only (2009-2012). For the Y-vector of zones, the upper limit, Z, for the sales segment is 1,117; for the rental segment, it is 312.[7]

$$ln(hp)_i = \alpha_0 + \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{ts} Q_i^{ts} + \sum_{n=1}^{N} \beta_{nr} X_i^{nr} + \sum_{z=1}^{Z} \gamma_z Y_i^z + \epsilon_i \tag{2.1}$$

$$ln(hp)_i = \alpha_0 + \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{ts} Q_i^{ts} + \sum_{n=1}^{N} \beta_{nr} X_i^{nr} + \sum_{C=0}^{1} \sum_{z=1}^{Z} \gamma_{Cz} Y_i^{Cz} + \epsilon_i \tag{2.2}$$

$$ln(hp)_i = \alpha_0 + \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{ts} Q_i^{ts} + \sum_{C=0}^{1} \sum_{n=1}^{N} \beta_{Cn} X_i^{Cn} + \sum_{C=0}^{1} \sum_{z=1}^{Z} \gamma_{Cz} Y_i^{Cz} + \epsilon_i \tag{2.3}$$

$$ln(hp)_i = \alpha_0 + \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{ts} Q_i^{ts} + \sum_{C=0}^{1} \sum_{n=1}^{N} \sum_{r=1}^{5} \beta_{Cnr} X_i^{Cnr} + \sum_{C=0}^{1} \sum_{z=1}^{Z} \gamma_{Cz} Y_i^{Cz} + \epsilon_i \tag{2.4}$$

$$ln(hp)_i = \alpha_0 + \sum_{r=1}^{5} \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{rts} Q_i^{rts} + \sum_{C=0}^{1} \sum_{n=1}^{N} \beta_{Cn} X_i^{Cn} + \sum_{C=0}^{1} \sum_{z=1}^{Z} \gamma_{Cz} Y_i^{Cz} + \epsilon_i \tag{2.5}$$

Conceptually, Model (2) includes an additional variable, an interaction with a categorical *crash* variable, for each sales/lettings zone for the crash period (2009 on). This allows the distribution of house prices (rents) across the country, controlling for type and size, to change between bubble (2006-2007) and crash (2009-2012) periods. Model (3) includes similar "crash" interacted variables for each of the type and size variables, as well as zone. This means that the model allows the relative price between, for example, two and three-bedroom properties or between semi-detached properties and apartments to vary between bubble and crash periods.

[7] For ease of identification, regression output in Appendix .1 uses the naming conventions outlined in Table 2.2, rather than the parsimonious forms given in the equations.

Table 2.3: *Outline of models employed and their categorical variables*

Model	Time	Type & size	Sales/lettings zones
Model 1	National	National	Yes
Model 2	National	National	Yes, with crash
Model 3	National	National, with crash	Yes, with crash
Model 4	National	Regional, with crash	Yes, with crash
Model 5	Regional	National, with crash	Yes, with crash

Extending the possibility for interaction between attributes, in Model (4), allowance is made for the price effects of particular property types (and sizes) varying by region, by inclusion of categorical variables where type and size are interacted with the five regions outlined above. Dublin is used as the control region, so statistical significance of region-type-time variable combinations signifies that the price differential (or change in price differential, for crash variables) in a particular region is different to that in Dublin. Lastly, Model (5) captures regional variations in a different way, by interacting quarterly time trends with the regions. In general terms, this should be roughly equivalent to Model (3).

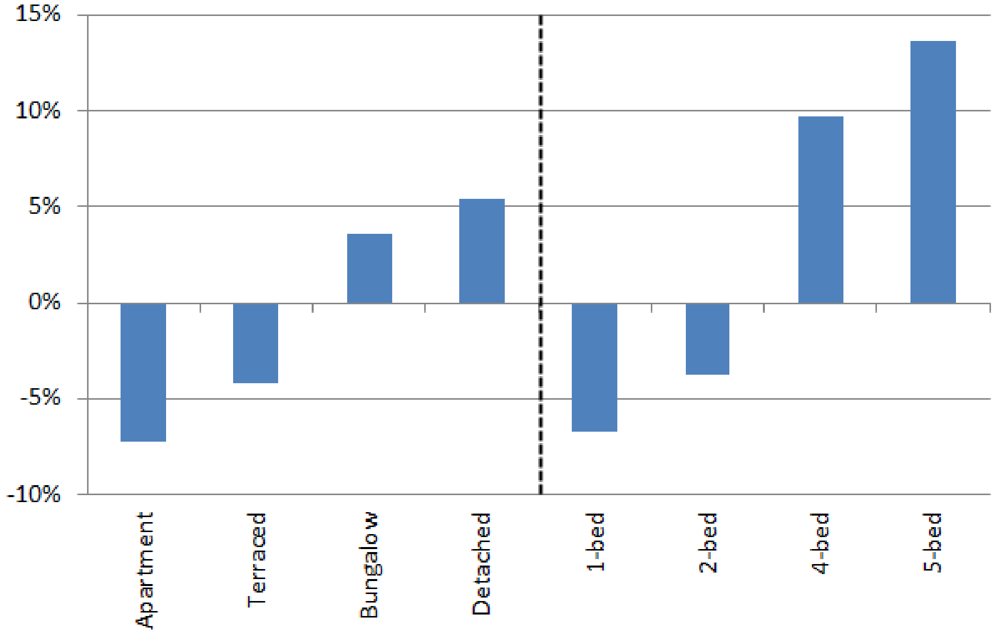
2.3 Distribution of Prices

2.3.1 Price differentials by property size

To what extent did the price differentials associated with particular property types change? Did the gap between, say, a four-bedroom property and a two-bedroom property grow or shrink between bubble and crash periods? As described above, Models (3)-(5) allow the relative prices of particular property attributes (measured by building type or number of bedrooms and bathrooms) to vary between bubble and crash periods. Figure 2.1 shows the effect of the crash on the premium associated with various property types and sizes, as measured by Model (3), i.e. national-level price effects.

The figures shown are the percentage point changes in differential associated with the various major property types, from apartments to detached properties,

Figure 2.1: *Percentage point change in price premium between bubble and crash, by type and size (Model 3)*

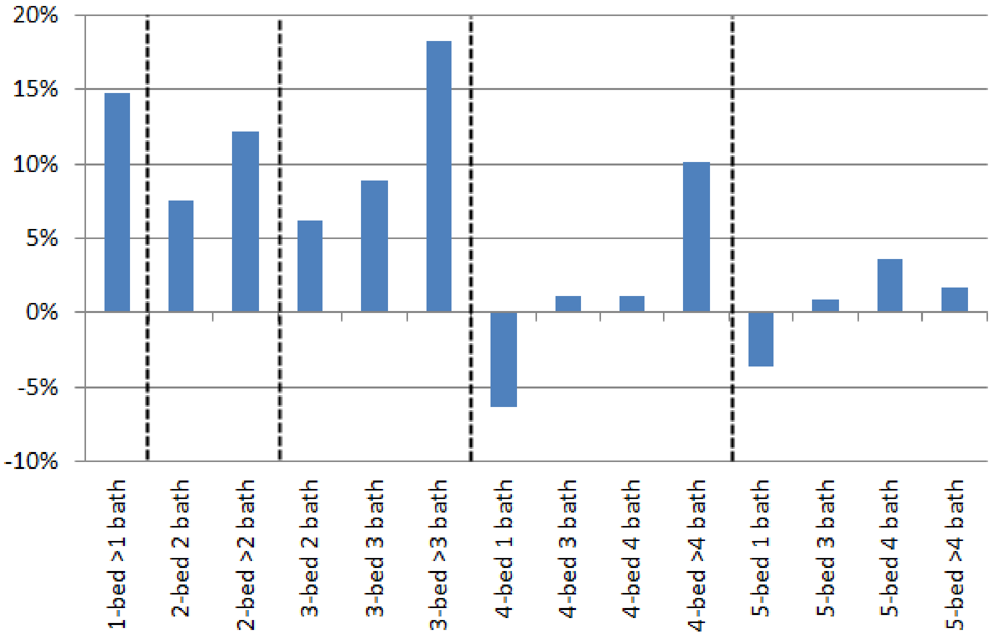


and sizes, as captured by bedroom numbers, relative to the controls (which are semi-detached and three bedroom properties).[8] All results are statistically significant well above the $p = 0.01$ level (as outlined in Table 1 in Appendix .1).

This change in the pattern of differentials in favour of larger properties indicates that the price of larger properties fell by less in the crash. This suggests an increase in the price of space at the margin, in relative terms (i.e. once the overall fall in the price level of real estate is accounted for). It can be explored with a secondary metric of size, number of bathrooms relative to number of bedrooms. This is shown in Figure 2.2; the controls for this dimension are one bathroom for properties with three or fewer bedrooms and two bathrooms otherwise. Again all results are strongly statistically significant,

[8] Differentials are calculated in line with Halvorsen & Palmquist's (1980) recognition of the limitation of the log approximation to percentages and follow the approach of Bourassa et al. (2004); in percentage point terms, they are given by $100[exp(\beta_j) - 1]$, where β_j refers to a variable capturing both type and crash indicators (e.g. $beds1\_cr$). For models with regional interactons, β_j represents the sum of all relevant coefficients, including the base effect, the base crash effect, the regional effect and the regional crash effect.

Figure 2.2: *Percentage point change in price premium between bubble and crash, by bathroom number (Model 3)*

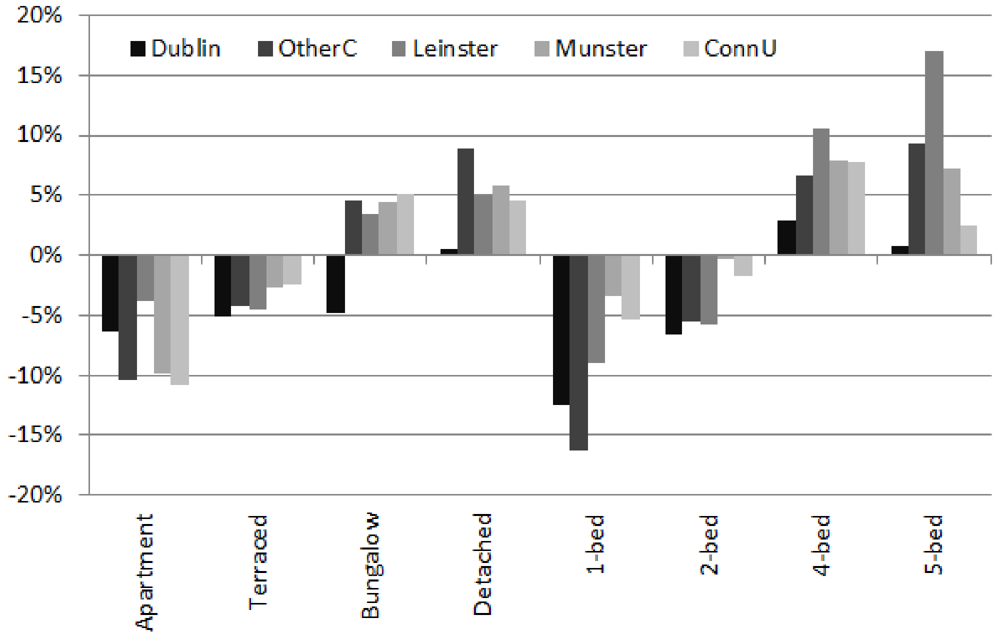


with only three exceptions, where the size of the effect is smaller than 1%: four-bed four-bath, five-bed three-bath and five-bed more than four bathrooms.

As noted earlier, Model (3) assumes that the differentials between property types are national, whereas in fact regional differences may exist. Of the 176 additional type-region coefficients generated by Model (4), 77 are statistically significant at the 1% level, while a further 22 are significant at 5% level. This indicates that not only is there strong evidence from Model (3) that price differentials changed but also that there is evidence that these changes in price differentials varied by region. Figure 2.3 outlines the change in coefficient in the crash period, compared to the bubble, by region and property type. Of the 40 differential changes, just one has a sign counter to expectations, that for Dublin bungalows (which are rare).

What is striking about all three graphs (Figures 2.1-2.3) is the clarity of the result: once the overall fall in property price levels is accounted for, any property associated with more space (across type, bedroom number or bathroom number) saw its relative price increase. For example, using the national average,

Figure 2.3: *Percentage point change in price premium between bubble and crash, by type and size (Model 4)*

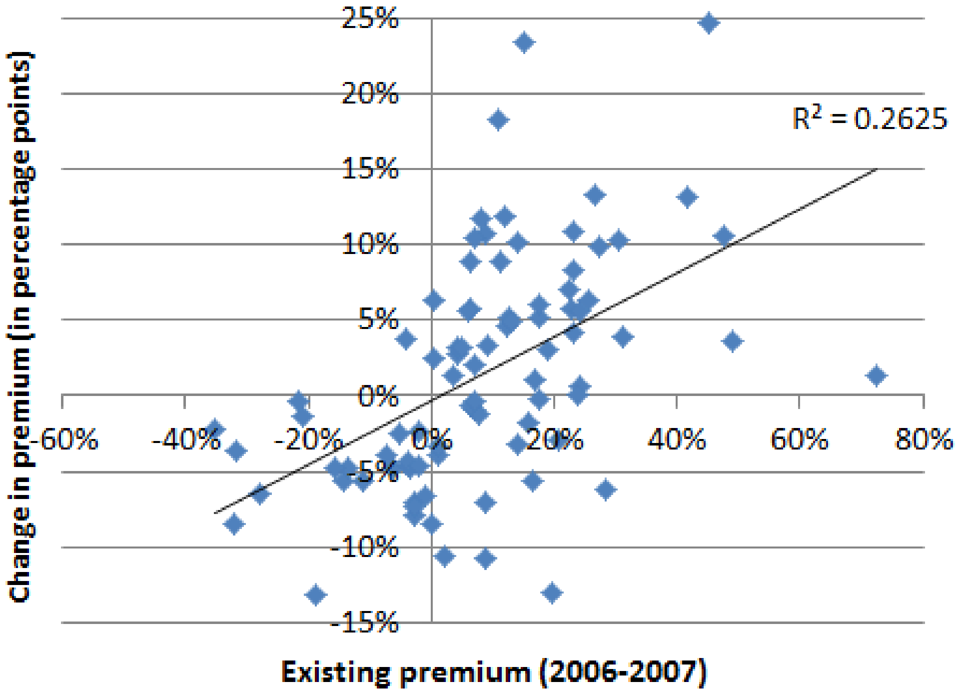


the premium of detached over semi-detached properties (controlling for other attributes) rose from 23.5% in the bubble to 28.9% in the crash. Conversely, the discount associated with one-bedroom properties, relative to three-bedroom properties, rose from 31.9% to 38.6%. To the extent that seller actions reflect changes in buyer behaviour, these changes in differentials between bubble and crash point to a substitution effect, a shift away from smaller properties (and thus, in relative terms, towards larger properties) in the crash.

Section 2.1 outlined two competing predictions, by Costello (2000) and Stein (1995) about the relationship between property values and cyclicality. The results clearly point to a price shift towards larger properties in the crash, evidence in favour of the Costello hypothesis – that more affordable properties would be more volatile over the cycle – and thus against the Stein hypothesis. Figure 2.4 shows this clearly in a different way: a simple linear regression of the percentage point change in premium on the existing premium in 2006-2007.[9]

[9]This scatter-plot does not include "more than" bathroom variables at the regional level as, despite the large sample size overall, Model (4) involves splitting each cohort into ten (each of five regions for both bubble and crash periods), leading to noisy results.

Figure 2.4: *Scatter-plot of existing sales premium and change in premium (Model 4)*



The pattern is clear and positive, with an R-squared of 26%. Controlling for the change in the overall price of housing, the price of quality increased between 2007 and 2011.

2.3.2 Geographic spread of prices

The results presented above indicate that a model which does not allow for changing property-type differentials may draw false conclusions about changes in the geographical spread of house prices. This section compares the conclusions about the spread of house prices from the various models. Eight measures of dispersion are used, based on the average house price (over a basket of five standardised properties) across the 1,117 zones – the coefficient of variation, the Gini coefficient, the 99:1 ratio (and its component 99:50 and 50:1 ratios), the 90:10 ratio, the 80:20 ratio and the 60:40 ratio.[10]

[10]The coefficient of variation expresses variation in percentage terms (the standard deviation divided by the mean). The Gini coefficient is a measure of inequality where a value of

Table 2.4: *Summary measures of spread in house prices, various models*

	Model 2		Model 3		Model 4		Model 5	
Av. change	-53.8%		-53.3%		-54.5%		-53.4%	
	Bubble	Crash	Bubble	Crash	Bubble	Crash	Bubble	Crash
CV	50.6%	46.3%	48.8%	47.8%	49.9%	48.4%	48.4%	47.2%
Gini	25.6%	23.3%	24.6%	24.0%	25.2%	24.3%	24.4%	23.7%
99 to 1	5.96	5.60	5.92	5.72	5.83	5.87	5.88	5.74
99 to 50	3.27	2.94	3.26	3.02	3.26	3.14	3.24	2.97
50 to 1	1.82	1.90	1.82	1.89	1.79	1.87	1.82	1.93
90 to 10	3.01	2.74	2.87	2.76	2.97	2.81	2.84	2.74
80 to 20	2.20	1.95	2.11	2.00	2.14	2.03	2.09	1.99
60 to 40	1.29	1.24	1.28	1.23	1.29	1.24	1.28	1.22

The baseline model indicates that the average price across the basket of properties fell from €373,000 in the second quarter of 2007 to €175,000 five years later, a fall of 53%. The coefficient of variation in the average price across the 1,117 zones is 45.7%. Model (2) allows the distribution of prices to vary between the final stage of the bubble (2006-2007) and the crash (2009-2011). The average fall is similar to that of Model (1), although slightly larger (53.8%). The coefficient of variation in the average price per zone falls relatively noticeably between the bubble and the crash, from 50.6% to 46.3%, suggesting that controlling for property size and type, the geographic spread of house prices narrowed noticeably between 2007 and 2012.

Table 2.4 outlines the summary statistics on changes in the spread of house prices geographically in Ireland, for Models (2) through (5). The noticeable fall in the coefficient of variation in Model (2) largely disappears once the model allows for changes in the relative price of different property types. In Model (3), which includes national type variables for the crash period, the coefficient of variation falls but only slightly (from 48.8% to 47.8%). In Model (4), which allows the price by type to vary across the five regional markets, the coefficient of variation again falls only slightly: from 49.9% to 48.4%. Model (5) shows

0% indicates perfect equality (here: house prices in all zones are the same), and a value of 100% expresses maximal inequality (theoretically, only one zone had non-zero house prices). The various ratios compare different points in the distribution; for example the 90:10 ratio compares house prices at the 90th percentile with those in the 10th percentile. The 50th percentile is the median.

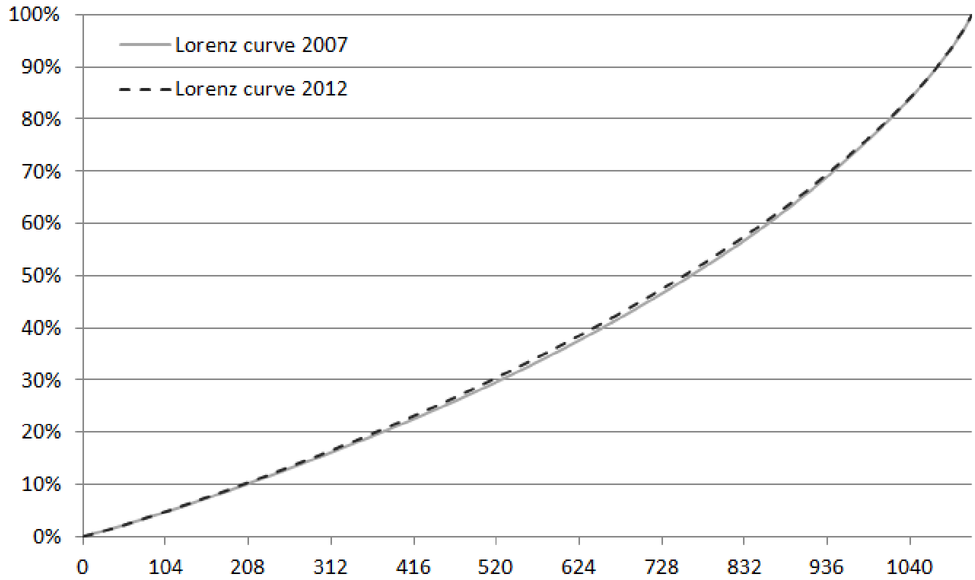
similar results.

These summary statistics suggest then that there is little evidence of a Stein effect, where high value properties are more volatile, proportionately rising more in the bubble and falling more in the crash. Once changes in relative prices of property types are adequately accounted for, the geographic spread of prices did not narrow significantly between the bubble and crash periods. The percentile ratios shown paint a slightly more nuanced picture. Taking Model (4), for example, zones in the 99th percentile were 3.26 times more expensive than the median in the bubble but just 3.14 times in the crash – this suggests that the top half of the geographic spread of price narrowed in the crash. However, the bottom half of the distribution widened in the same period: the median zone was 1.87 times more expensive than the 1st percentile in the crash, compared to just 1.79 in the bubble. While these are not large changes, they indicate that different effects may have been at work at different parts of the distribution of house prices in Ireland in the bubble.

The slightly more nuanced picture suggests that a number of effects may be at work at different parts of the distribution, in a way that the simple dichotomy between the Stein and Costello hypotheses cannot capture. Changes in income and unemployment are likely to have affected different regions and segments differently, with unemployment in particular affecting certain categories of first-time buyer while a switch to more cash-only purchases may have taken place at the top end of the market.

The distribution of prices can be shown in a more comprehensive way using Lorenz curves. The Lorenz curve is a graphical representation of the equality of a distribution, showing in this instance for the bottom x zones, what percentage $y\%$ of housing wealth they have (controlling for differences in property types between areas); perfect equality would be represented by the 45° line. As would be expected from the Gini coefficients, the Lorenz curves shown in Figure 2.5, for Model (4), suggests very little change overall.

Figure 2.5: *Lorzenz curve of average property prices across 1,117 zones (Model 4)*

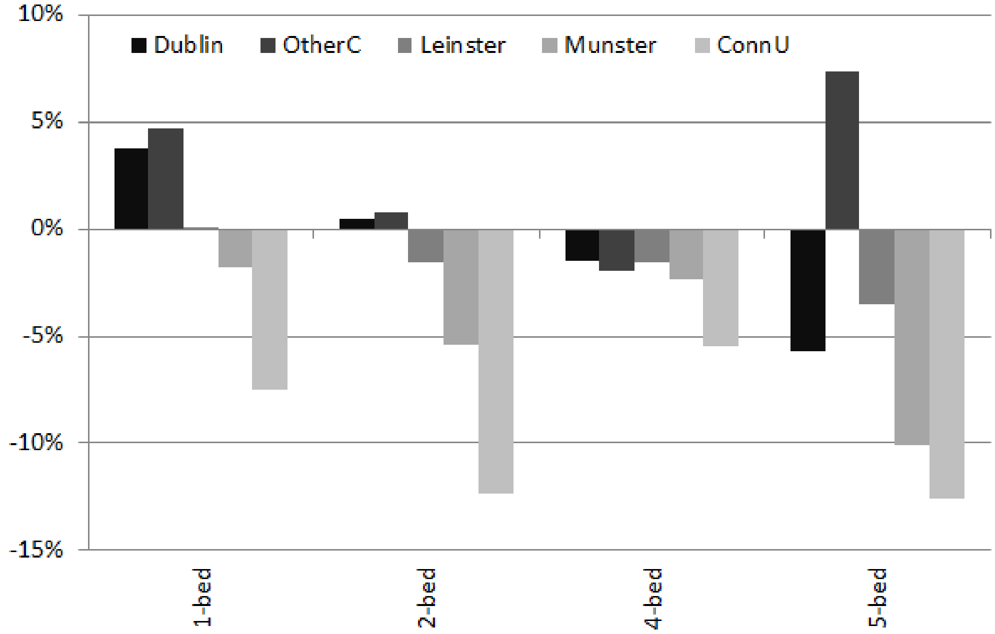


2.4 Distribution of Rents

Given the similarity in the datasets across sales and lettings segments, and given the richness of the lettings dataset (particularly in Dublin), the same set of models can applied to the lettings segment, with one or two modifications. The principal modification is the use of 312 lettings zones, rather than the 1,117 sales zones. Three other modifications relate to property attributes. Firstly, there are fewer type variables, as type is not known beyond whether the property is apartment, house or flat.[11] Secondly, an additional dimension of size is included, namely the size of bedrooms (single or double/twin), relative to the number of bedrooms (e.g. four-bedroom property, of which two are single rooms). Lastly, a range of property facilities and features, including wheelchair accessibility, central heating or a short-term lease, are included as categorical variables (including crash-period and regional variables, where appropriate). These modifications are outlined in Table 2.2.

[11] While there is no rigorous definition of what "flat" denotes in an Irish context, it is typically taken to mean a part of a house not specifically built for multi-household accommodation, in contrast with a purpose built apartment.

Figure 2.6: *Percentage point change in rental premium between bubble and crash, by size (Model 4)*



2.4.1 Rental differentials by property size

Figure 2.6 is the lettings equivalent of Figure 2.3 for the sales segment presented earlier, showing the change in differential by bedroom number, for each of the five regions. Overall, the findings are the opposite of the sales segment, where premiums for larger properties and discount for smaller properties grew. The spread of rents between property types narrowed between bubble and crash periods. For example, in the Dublin lettings market, the discount for a 1-bed (relative to 3-bed) fell from 32% to 29% in the crash, while the premium associated with 5-bed (relative to 3-bed) fell from 47% to 39%. Of 20 size-related differentials, fourteen are associated with a narrowing of the spread of rents across types between bubble and crash.

The extent to which state intervention in the lettings segment through Rent Supplement has an impact on these results, compared to the role of potential first-time buyers excluded from the owner-occupier market, is a topic worthy of future research. In particular, a binding price floor would alter rental differentials by compressing the spread of rents. Rent Supplement is paid by the State to people living in private rented accommodation who cannot afford their accommodation. It is based on a system of maximum thresholds that vary by the applicant household (a couple with three dependent children will be entitled to more than a single person with no children) and by location (the same household may be entitled to twice as much in Dublin as in some local authorities). With the sharp fall in rents in 2008/2009, it is possible that these thresholds have formed a price floor in some segments of the market.

The above evidence is suggestive of extra space in the lettings market being viewed as a luxury: a couple that enjoyed a two-bedroom apartment downsizing to a one-bedroom apartment in the crash, or a family where each child had a double room switching to single rooms. Figure 2.7 plots the change in the premium against the existing 2006-2007 premium, using regional type and size effects (Model 4, 155 differentials in total). While there are exceptions, the overall contrast with the sales segment (cf. the upward-sloping line in Figure 2.4) is clear. Unlike the finding for the sales segment, the larger the rental market premium in the final stages of the bubble, the greater the fall between bubble and crash.

2.4.2 Geographic spread of rents

Table 2.5 outlines measures of the spread of rents, including selected percentile ratios, for the various models presented. As discussed in the previous section, though, there is evidence to suggest that the distribution of rents across size changed, thus the focus should be on models that allow type differentials to vary between bubble and crash [Models (3)-(5)]. These models indicate a more pronounced average fall in rents (nearly 30%) than Model (2), and a slight decline in the spread of rents, the coefficient of variation falling from 33.2% to 31.4% under Model (4). No model suggests a dramatic change in the geographic spread of rents – it is worth noting that Model (5), which allows for different

Figure 2.7: *Scatter-plot of existing lettings premium and change in premium (Model 4)*

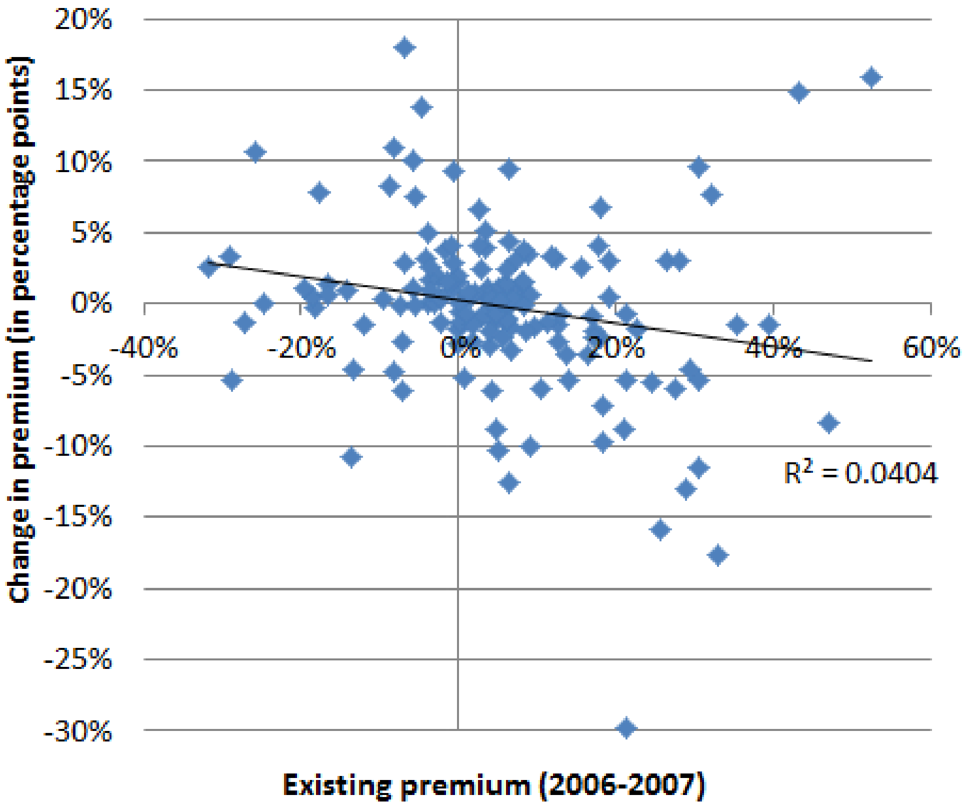


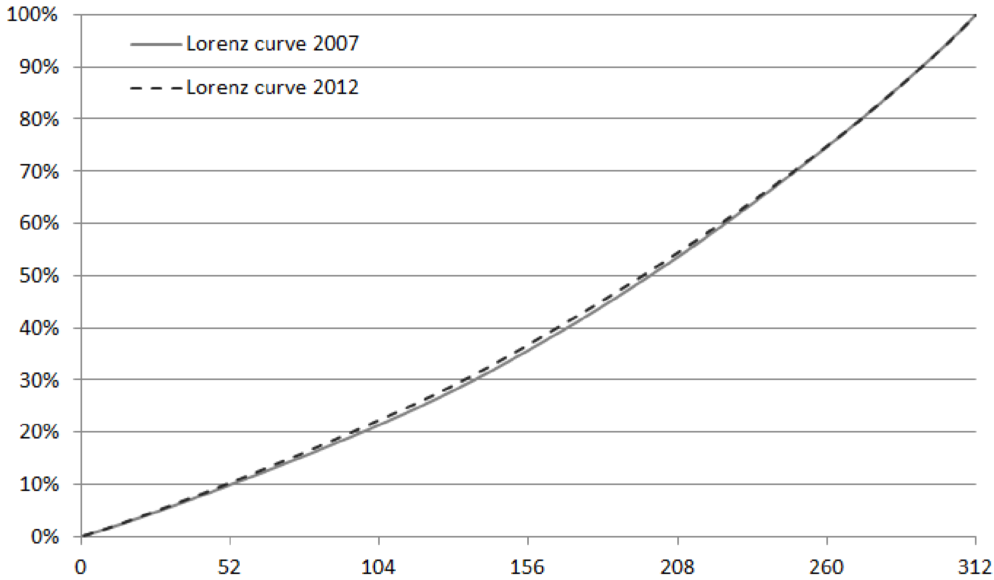
Table 2.5: *Summary measures of spread in rents, various models*

	Model 2		Model 3		Model 4		Model 5	
Av. change	-24.6%		-27.5%		-29.4%		-28.5%	
	Bubble	Crash	Bubble	Crash	Bubble	Crash	Bubble	Crash
CV	34.6%	33.7%	34.6%	33.7%	33.2%	31.4%	34.9%	36.6%
Gini	19.7%	19.0%	19.7%	19.0%	18.9%	17.8%	19.9%	20.8%
99 to 1	3.67	3.59	3.67	3.59	3.45	3.33	3.70	3.91
99 to 50	1.85	1.86	1.85	1.86	1.79	1.76	1.85	1.94
50 to 1	1.99	1.93	1.99	1.93	1.93	1.89	2.01	2.02
90 to 10	2.48	2.45	2.48	2.45	2.41	2.27	2.53	2.65
80 to 20	2.03	1.93	2.03	1.93	1.98	1.85	2.04	2.09
60 to 40	1.33	1.33	1.33	1.33	1.32	1.26	1.34	1.38

regional trends, suggests a modest increase in the spread, unlike the others, which suggest a modest decline.

As with prices, the entire distributions of rents in the bubble and crash can be shown using Lorenz curves. Figure 2.8 shows overall no significant change in the distribution, although – as suggested by the coefficients of variation –

Figure 2.8: *Lorzenz curve of average rents across 312 zones (Model 4)*



some compression in the middle of the distribution. In contrast to the sales market, the fall in 99:1 differential, from 3.45 to 3.33 in Model (4), is due to both a narrowing of the 99:50 and 50:1 differentials.

Appendix .1.2 includes two heatmaps for Ireland's lettings market. Figure 3 outlines a heatmap of the average rent for each of 312 zones for 2012:II rents, across a weighted basket of five stylised properties. Ten bands are shown, the highest being an average rent of more than €1,300 and the lowest band being below €500. Controlling for district-specific differences in housing supply, the most expensive areas to rent in like-for-like terms are largely the same for sales, in the south-eastern part of Dublin. Figure 4 outlines geographically the percentage fall in the average rent by zone. The scale runs from a fall of 15%-20% (lightest purple) to a fall of 35%-45% (darkest purple). Among those areas seeing the largest falls in rents are large parts of Dublin and some of its commuter belt to the south and south-west.

2.5 Conclusion

Housing market cycles are an integral part of modern economies and a key part of broader economic fluctuations. The intention is that this thesis will contribute to a better understanding – and management – of housing market cycles. To do that, an understanding of the internal mechanics of housing markets is necessary and this chapter is one of the first to explore this issue using a granular perspective of housing sub-markets. Contrasting theoretical predictions exist in relation to how values change in different market segments, with high- or low-value segments potentially more volatile over the market cycle. Using a comprehensive listings dataset to provide a unique window into the extreme Irish property market bubble and crash, the aim here was to analyse changes in the structure of prices in Ireland's sales and lettings markets over the five years following the end of the housing bubble in 2007. There are four key findings:

1. In the sales segment, the spread of prices across property types rose substantially in the crash. For example, the fall in price of a five-bedroom property was significantly smaller than that of a one-bedroom property in the same location; the differential between these two properties increased from 118% to 164% nationally.

2. In the lettings segment, the opposite was the case: the spread of rents across different property sizes fell in the crash. The differential between a five-bedroom property and a one-bedroom property in the same location narrowed from 97% to 82%.

3. The geographic spread of both prices and rents was largely preserved across bubble and crash periods, falling only slightly in most models. The Gini coefficient of prices fell slightly (in Model (4), from 25% to 24%), similar to what happened in rents (20% to 19%).

4. As suggested by these Gini coefficients, it is clear that the spread of rents was significantly less than the spread in house prices in both bubble and crash periods. Most of this difference appears to be concentrated in high-amenity areas: while the 50:1 percentile ratios of prices and rents were similar (1.89 compared to 1.93), the 99:50 ratio was substantially greater in prices (3.02 compared to 1.86).

Policy implications from this analysis exist, both for Ireland and further afield. Firstly, if owner-occupier demand in post-GFC Ireland has shifted towards larger property types, this has implications for policy in relation to dealing with legacy vacant properties and "ghost estates". Much of the supply overhang is apartments or smaller homes in developments, which according to the analysis presented here have suffered significantly larger falls in value and face weaker demand. Secondly, there are also implications for policy in relation to future development and planning. The shift in demand away from smaller properties towards larger properties will require a supply-side response, to ensure affordability of family homes. The change in price structure in Ireland since 2007 has implications, thirdly, for financial stability policy in Ireland, in particular in relation to bank recapitalization. If uniform falls from the peak are assumed across different market segments in stress-test calculations, this may lead to an inaccurate assessment of risk for Ireland's financial institutions and the taxpayer.

A related implication, finally, is about warning signals for future bubbles. The Stein and Costello hypotheses have very different implications for policymakers keen to spot potential housing bubbles early on. The experience of Ireland indicates that narrowing differentials between large and small property types when prices are rising might not represent a sustainable shift in consumer demand towards smaller properties, rather an unsustainable trend. This tallies with anecdotal evidence in Ireland that during the bubble, "property ladder" concerns pushed people to buy lower-attribute properties they would otherwise not consider, for capital gains and subsequent trading up. Alternatively, high-LTV lending to borrowers with risky income profiles could explain greater demand for smaller properties.

There are a number of limitations to be noted to this study. Firstly, the dataset does not cover the period prior to 2006, so it is not possible to compare run-up over the decade to 2007 with subsequent falls, as other studies have done, and stops in mid-2012, at which point Dublin prices had largely levelled off but prices elsewhere may not have.[12] Secondly, there are omitted variables, such as age, square meterage and energy efficiency, which may have a role in explaining observed variations. Lastly, the prices presented above are based on advertised prices and rents. Chapter 4 investigates how list and transaction prices are related over the course of the market cycle.

In relation to other avenues for research, the contrast between the findings for sales and lettings segments suggests a model where income and substitution effects apply in different markets. Income effects appear to dominate where there is no outside option (demand for accommodation is income-inelastic if you are a renter): space in the crash is a luxury for tenants. Where there is an outside option – many would-be first-time buyers stayed as renters during this period – substitution effects kicked in: if you are going to buy, you might as well buy big. An implication for future research on tenure choice is that the real estate cycle may not just affect the choice of whether to buy or rent but also what type of property to buy.

While the conclusions about property size are unambiguous, those about location are much less clear. Ultimately, location is a short-hand for bundles of amenities, ranging from labour and consumer markets to social and natural capital amenities. The final finding – that the geographic spread of rents is in some sense constrained at the upper end of the distribution of locations – is consistent with either renters under-valuing certain amenities, for example due

[12] By mid-2013, prices in Dublin had risen 8% year-on-year, while prices elsewhere in the country fell by 1%, according to the official CSO house price index.

to search thresholds, or alternatively buyers over-valuing those amenities, for example due to fear about future access to an amenity that is in fixed supply (e.g. access to schools). Buyer over-valuation due to a desire to lock in access to amenities would reasonably be at its most acute in a bubble and be seen in pro-cyclical pricing of attributes and amenities. The evidence here, however, certainly in relation to attributes, is that pricing was counter-cyclical. Thus, if the "true" valuation is the same in both markets, i.e. assuming buyers and renters are drawn from the same population, this suggests that it is renter under-valuation at work. This issue is explored in more detail looking at a range of location-specific amenities in Chapter 3.

Lastly, the very different trends in prices and rents suggest that the capitalization rate of property narrowed significantly but also that its change was different across market segments. While the first part is consistent with an error-correction set-up for the property market, which reverts back to its equilibrium cap rate, the fact that the equilibrium cap rate could vary significantly by segments is intriguing. A natural avenue for future research is to describe and explain the significant variation over time and space in this fundamental barometer of the property market. Trends and corrections in house prices and the price-rent ratio are explored in more detail in Chapter 5.

Chapter 3

Cyclicality of Amenity Prices

Understanding the link between housing market cycles and the macroeconomy is particularly important given the aftermath of the global economic and financial crisis starting in 2007. A number of OECD economies enjoyed an unprecedented boom in housing prices over the late 1990s and early 2000s. This was followed by a rise in defaults in the U.S. mortgage market, in particular its sub-prime segment, which – due to a range of financial innovations such as securitization – had an impact on the global financial system (Duca et al. 2010). The following years have seen the effects spread to global trade (2008-2009) and sovereign debt (from 2010).

Ireland's economic fortunes have in many respects been a microcosm of those globally. The period from the mid-1990s to 2007 was one of very strong economic growth in Ireland, initially export-led but in later years fuelled by the availability of cheap credit and an unprecedented building boom. From 2007, the economic downturn was severe. National income fell from €163bn in 2007 to €128bn in 2011 (GNP in current prices), while government finances deteriorated sharply, with fiscal deficits of 10% of GDP per year by 2010. Unemployment rose from below 5% in 2007 to almost 15% by 2011, while large inward migration flows changed to emigration. Despite the global nature of the crisis, central to the dramatic change in Ireland's economic fortunes were domestic factors, in particular the end of a domestic real estate bubble.

The case of Ireland highlights the links that exist between housing and other aspects of the economy, including financial stability, the labour market, the government finances, and public service provision. To understand how a housing cycle can affect economic fluctuations, it is important not only to understand the channels through which housing and the wider economy are related (see, for example, Muellbauer (2012), as well as Chapter 5), but also how the housing market itself works. Yet the mechanics of the housing market and its cycles remain poorly understood. The housing market is an inherently spatial one and, property-specific attributes aside, differences in price across the market reflect location-specific amenities. With nominal house prices falls of over 50% between 2006 and 2012, Ireland is a natural case study for studying the ups and downs of housing markets.

This chapter uses a detailed dataset of property listings in Ireland, both sales and lettings, over the period 2006-2012 – and a large dataset of location-specific amenities – to investigate the relationship between amenities and the housing market cycle. Taking the hedonic regression literature started by Rosen (1974), that amenities will be reflected in property prices, it explores two related hypotheses. The first is that price and rent effects of amenities may differ. This may be due to fundamental differences between households that buy and rent specifically about the utility derived from location-specific amenities. If this is not the case, economic theory suggests that a desire on the part of buyers to lock in access to amenities – facilitated by changing credit conditions over time – may push up the price of amenities, relative to their rent effect. Alternatively, renter search thresholds (as outlined in more detail below) may lead to an attenuated rent price of amenities, compared to the sales segment. Secondly, the effect of amenities on the cost of accommodation may vary with the cycle. This may be pro-cyclical, reflecting buyer lock-in concerns, or counter-cyclical, reflecting "property ladder" effects.

The chapter is structured as follows. Sections 3.1 and 3.2 outline briefly the economic theory and existing literature in relation to amenity valuation and the structure of prices in the housing market, while section 3.3 provides details on the data used in this analysis. Section 3.4 outlines the model and empirical strategy and Section 3.5 presents the results. Section 3.6 concludes.

3.1 Theory

3.1.1 Urban economics & bid-rent gradients

Von Thünen's (1863) theory of farmers sorting by opportunity cost of distance to a market extends in a straightforward fashion to models of household location selection. Models along these lines date from Alonso (1964), where, in a monocentric city, one would expect those households with the highest opportunity cost of distance from a given central business district (CBD) to locate closest to it. As outlined by Straszheim (1987), in a standard monocentric model, a household derives utility from its quantity of land consumed (q), its location or distance from the centre (u), and the numeraire composite consumption good (z). Its expenditure includes rent per unit of house size (r) and transport costs (T).

The optimization problem yields an equation of the marginal rate of substitution across housing and non-housing with their price ratio: $V_z/V_q = 1/r(u)$. Choice of location must satisfy a condition equating the change in rent to the trade-off between monetized value of the disutility of a longer commute and the change in transport expenditure: $\partial r/\partial u \cdot q = V_u/V_z - \partial T/\partial u$. The bid-rent gradient from the CBD outwards can be assumed, via partial equilibrium analysis, or derived, via general equilibrium analysis, where assumptions are made about utility levels at different locations. Either way, households will move away from the centre, along the rent gradient, until the marginal disutility of a longer trip just offsets the savings achieved for land consumed.

3.1.2 Hedonic Markets and Implicit Prices

There is an important caveat to the von Thünen set of theories, namely that all models assume that cities are monocentric and indeed that these centres are exogenous. Work such as that by Dubin & Sung (1987) suggests that there are limitations to models that focus on one particular amenity, i.e. proximity to employment, and that impose a particular distribution of that amenity, i.e. entirely within a set central business district. There are a large number of potential considerations beyond employment that may affect a household's choice of residence, from market depth to environmental. Allowing an n-dimensional amenity vector and relaxing the restrictions on the location of amenities across the city space suggests that a more complicated bid function for given levels of utility and income is required.

Rosen's (1974) model contains a market for good z comprising $i = 1, \ldots, n$ attributes (or amenities), where $p(z_1, \ldots, z_n)$ is increasing in all its arguments and has second derivatives. Due to indivisibilities in the good directly traded, its package of amenities cannot be "untied" and therefore there cannot be the arbitrage required to make $p(z)$ linear. The value function $\theta(z_1, \ldots, z_n; u, y)$ represents the expenditure a consumer is willing to pay for different alternative values of z, for a given utility index and income level and is the multi-dimensional counterpart to Alonso's bid-rent function.

The value function θ gives the amount the consumer is willing to pay, while market prices are given by $p(z)$. The optimum will be where these two surfaces are tangent to each other. While utility increases with income, the exact relationship between z_i and income – i.e. whether a particular amenity is a normal good or not – depends on the shape of the price function. Only if $p(z)$ were convex and sufficiently regular everywhere would each z_i be a normal good at all income levels (Rosen 1974).

In practical terms, this means that the value of an amenity should be reflected in the price. A suitable empirical strategy will be able to highlight the marginal willingness to pay for access to that amenity by holding other factors constant and varying access to the amenity. This is the approach used here.

3.1.3 Amenity valuation by tenure

It is possible that, once household characteristics are controlling for, renters and buyers place different relative valuations on the set of amenities. In particular, two mechanisms suggest that buyers will factor in a wider range of amenities than renters; relative to some hypothetical "true value" of an amenity, it is possible that renters underpay or alternatively that buyers overpay.

The first is that there are factors, such as indivisibilities related to search costs, that restrict renters' willingness to pay for amenities. The market for accommodation is one where matching is important, as both occupants and properties have idiosyncratic attributes. Suppose that search costs (s) in the property market, whether renting or buying, involve indivisibilities: finding somewhere to live cannot be done without a given minimum amount of time spent online and visiting properties (κ), in addition to any tenure-specific search costs and/or searcher intensities. Suppose also that prospective buyers and tenants have maximum thresholds (t) to their search costs that are roughly proportional to the value of the transaction (λV, where V denotes the value of the transaction): in practical terms, those buying their home for the next twenty years might be prepared to spend six months searching for the right property, but those renting for the next two years might not.

In such a market, there would be a disproportionality in the $s(\kappa) : t(\lambda)$ ratios for the same household buying or renting: renters are likely to hit their thresholds of search costs sooner. For example, while both buyers and renters may prefer properties closer to the coast or with a southerly orientation, perhaps only buyers may hold out and reward these amenities. Thus, one may expect certain amenities, particularly those that could be regarded as secondary, will not be rewarded to the same extent in the lettings market as in the sales market.

An alternative theory is that there are factors that encourage buyers to "over-capitalize" amenities. One obvious candidate is the frenzy of the bubble, where, due to the fixed supply of amenities, buyers are concerned about securing access to amenities (for example having schools nearby). In particular, buyers may worry about the cost of accessing amenities in the future, leading to a greater valuation by buyers than renters. Alternatively, transaction costs, such as legal fees and transaction-based taxes, may be significant for buyers (but unimportant for renters), restricting buyer mobility and thus encouraging them to lock in supply of particular amenities.[1]

Hypothesis 1 The first hypothesis to be tested empirically is, therefore, that the price effect of amenities is, in relative terms, greater than the rent effect.

3.1.4 Valuation of amenities over the market cycle

One theory suggests that higher price housing should be more volatile over the market cycle, due to the presence of down-payments and the fact that the typical household holds most of their private net wealth in housing (Stein 1995).[2] Consider a negative shock to house prices: this hinders movers from making their next down-payment, depressing demand. If high-priced homes are purchased primarily by buyers trading up (rather than first-time buyers), then their prices should have a greater variance over the real estate cycle. The prior expectation, according to this liquidity constraint model, is that houses with higher prices would both rise and fall more dramatically than those with lower prices. As houses with higher prices are those in locations with greater amenities, this liquidity constraint model suggests procyclical amenity prices: that the price of amenities would rise in the bubble and then fall in the crash.

Alternatively, lower segments of the housing market may experience more volatile swings in prices. Costello (2000) suggests that more affordable prop-

[1] Note also that even if the buyer does not value a particular amenity, if they believe that the amenity will contribute to future capital gains, they will be prepared to pay for it now, unlike a tenant, who has no financial gain for an amenity they do not derive utility from directly. Using U.S. data on expenditure on education, Hilber & Mayer (2009) extend this argument to willingness-to-pay for new amenities by households that will only benefit through the capitalization of the amenity in house prices.

[2] See also Section 2.1.

erties are more liquid and thus these segments will be more competitive, rising more in boom markets and falling more in down markets. This effect may be related to credit conditions. As credit rationing eases, and marginal borrowers become active in the market, there should be greater demand at entry level, a process that goes into reverse when credit rationing tightens again. In lay terms, this can be thought of as a "property ladder" effect. In such a situation, greater importance is attached by buyers to having any property, even one with poor amenities, than at other points in the cycle, as (expected) capital gains will facilitate trading up in the future. Consequently, demand for low-quality (low-amenity) properties shifts up. With relatively less importance attached to amenities in the bubble than at other points in the market cycle, countercyclical amenity prices would be evidence of "property ladder" effects.

Hypothesis 2 The second hypothesis to be tested empirically is, therefore, whether the price effect of amenities is pro-cyclical or counter-cyclical.

3.1.5 Categories of amenities

It is possible to think of a multitude of location-specific characteristics that may impact on a property's desirability. A natural ordering of these amenities is by permanence or mobility. At one end of the spectrum are first-nature endowments of geography and environment. At the other end are population-specific, rather than location-specific amenities, such as market depth or social capital. Such amenities are hypothetically mobile, although taken as given by any individual agent at a point in time.[3]

For the purposes of this analysis, six categories of amenities are considered. Roughly in order from more fixed (first nature) to less (second nature), they are: environmental amenities; transport facilities; educational amenities; the labour market; neighbourhood quality; and agglomeration or market depth:

[3]The categorizaton presented is merely for ease of exposition and does not affect the conclusions reached.

1. Environmental factors, such as proximity to coastline, lakes, rivers, forests or urban green space

2. Transport facilities, such as primary and secondary roads, train stations or light rail services

3. Education facilities, including primary and post-primary schools and higher education institutes; the latter may be particularly important for renters (due to demographic reasons)

4. Labour market amenities, including the unemployment rate, the length of commuting to work and the diversity of general employment opportunities

5. Neighbourhood quality, measured through either incidents (e.g. crime rates) or inhabitants (for example the proportion with a third-level degree)

6. Agglomeration amenities, such as those of von Thünen and Alonso recast, proximity to centres of economic activity, and distance from borders

While the focus here is on the amenities listed above as reflecting the primary location-specific factors, a large number of other amenities may affect house prices, including polluting facilities, national monuments, and facilities such as prisons and stadiums. In addition, location-specific housing supply variables may affect property values, for example proximity to "ghost estates" or zoned land.

3.2 Literature

3.2.1 Hedonic pricing of amenities

Since Rosen's (1974) seminal paper, a large empirical literature has developed, estimating the implicit price of a wide range of amenities.[4] Much of the early

[4] There are over 5,600 papers citing Rosen (1974), according to Google Scholar (Harzing 2007).

literature was focused on environmental public goods, such as air and water quality – reviews are given by Smith & Huang (1995) on air quality, Boyle & Kiel (2001) on water quality and Kuminoff et al. (2010) on environmental amenities. There is also a large literature on the effect of transport facilities on property values, although the hedonic method is just one of a number of methods used here (Debrezion et al. 2007, RICS Policy Unit 2002, Wrigley et al. 2001).

An overview of the importance of amenities and land values in general, when attempting to understanding housing values, is given by Cheshire & Sheppard (1995). The provision of other public services, in particular education, has been the subject of a significant amount of analysis using hedonic pricing methods. Black (1999) exploits differences across boundaries of school districts to estimate household willingness to pay for better school performance in Massachusetts, while similar work exists for England (Gibbons & Machin 2003). The same authors have estimated the impact of the opening of new rail lines in London in 1999 (Gibbons & Machin 2005). In general, well-specified studies find not only statistically significant positive effects of amenities on housing values but also reasonably precise estimates of the average impact of a greater amenity, such as distance to transport facility or better educational outcomes.

A good overview of the hedonic valuation of amenities method and of the findings from recent research on the value of education, transport and safety amenities, is given by Gibbons & Machin (2008). They stress the use of quasi-experimental approaches that exploit variations in the supply of amenities, although recent theoretical research has highlighted the limits to reliance on supply shocks (Coate 2013). Literature on other amenities – in particular social capital but also market-depth – is much less developed at this stage, most likely as the bulk of empirical work is at city- or county-level and thus there is significantly less variation in population-specific characteristics than at country-level.

The literature on the hedonic pricing of amenities in the Irish property market is somewhat more limited. Mayor et al. (2009) and Mayor et al. (2008) examine amenities in the Dublin housing market during the final stages of the bubble (2001-2006). They find evidence that both urban green space and transport access are valued in house prices: increasing by 10% the proportion of urban green space within two kilometres of a house was associated with an increase of at least 7% in the house price. The effect of being less than 2km from a light rail station (Green Luas line) was of a similar magnitude. Another amenity they report is proximity to the coast, associated with a premium of 12%-22% premium for being within a kilometer of the coast (the closer to the coast, the larger the premium). The effect of various amenities is not broken down by phase in the market cycle, however, most likely due to sample size constraints.

Two comments on the general literature are worthwhile. The first is that, by and large, well-specified studies – especially those that both control for omitted variables and exploit supply-side variation – do find that a wide range of amenities is factored into the cost of accommodation with the expected sign, although there is often little agreement across researchers on the magnitude. This is understandable given that the studies vary hugely in terms of regions (and time periods) analyzed, as well as sample sizes and exact specification.

The second is that the established literature has a number of limitations. As is pointed out by Kuminoff et al. (2010), there is no reason to assume that amenities have time-constant prices, yet this is overwhelmingly the strategy adopted in the literature to date, more than likely due to sample size limitations. Likewise, there is very little information on the valuation of amenities in the lettings segment of the residential property market, again more than likely due to limitations of data.

One glimpse into the relationship between amenities and the housing market cycle is given by Case & Mayer (1996). Their study is of 135,000 repeat sales in 168 towns in Eastern Massachusetts over the period 1981-1994, when real house prices rose by 116% (1983-1988) before falling by 27% (1988-1991). Case & Mayer's (1996) model relates relative house prices changes over boom and bust to seven sets of variables, including amenities (employment, proximity to Boston, demographics, crime and schooling), shocks to the supply of land/housing, immigration, and local taxes.

They find that the proportion working in manufacturing and of baby-boomers in 1980 affected changes in properties prices both in the boom and bust (negatively and positively, respectively), while distance from the CBD did not affect price rises but did affect the fall from the peak (those further away fell by more). Crime rates had the opposite effect: the higher the crime rate in 1980, the more prices appreciated in the boom, but there was no equivalent effect in the bust. They also note that the premium attached to homes in high-quality school districts fell during the boom, in line with falling school enrolment in the period. Controlling for amenities, Case & Mayer (1996) find that low-priced towns saw faster house price growth to 1988 and then greater falls after that.

3.2.2 Structure of house prices

Section 2.1 describes much of the existing literature on the structure of house prices and its relationship with the market cycle. In particular, there is a contrast between Stein's (1995) hypothesis of a procyclical spread in house prices and Costello (2000), who concludes greater liquidity in cheaper segments led to a countercyclical spread in prices. Case & Mayer (1996) is evidence against Stein (1995), while Smith & Tesarek (1991) is evidence in favour.

Other research includes Case & Shiller (1994), on Boston on L.A., and Hirayama (2005), who finds that across two cities in Japan (Osaka and Tokyo) during the period 1990-2002, the biggest price falls (60%) were concentrated in bubble-era condominiums, either "super-luxury condominiums" in central districts, whose price had risen most dramatically in the boom years, or "suburban bubble condominiums", which faced competition from steady streams of fresh supply. Chapter 2 found that for property-specific attributes, there are countercyclical relative prices, which suggests that "property ladder" effects may dominate. Is the same true for location-specific amenities?

3.3 Data

The principal dataset used is provided by the online accommodation portal, daft.ie, which provides price (rent) information as well as property attributes, including location. In addition to information on listed purchase or rental price (outlined below), there are seven further dimensions along which the data are segmented: segment; size; type; time; location; property attributes; and location amenities. For time (in particular phase of the market, whether bubble or crash), but also for segment (sales or lettings) and for certain variables type and location, interactions between dimensions are included.

The sales component of the full dataset includes 416,899 properties listed for sale between 2006 and 2012.[5] As is outlined in Table 3.1, almost three-quarters of properties listed were three-bedroom or four-bedroom in size. In terms of regional distribution, two-fifths of the listings were in Ireland's five cities (almost 30% alone in Dublin). Roughly one third of properties were from the Leinster province, large parts of which act as commuter areas for Dublin. The lettings component of the dataset comprises just over 825,000 ads. Compared to the sales dataset, there are a greater proportion of smaller properties and Dublin properties: the most common property size is two-bedroom, while Dublin properties comprise almost half of all ads. Summary stats for both components of the dataset are given in Table 3.1.

There are three distinguishing features about this dataset. The first is its size (well over a million observations), not only relative to the size of Ireland's

[5] The vast majority of listings in the dataset refer to ads posted on the daft.ie site. Roughly 34,000 refer to the small fraction of online listings in Ireland that were not advertised on the daft.ie portal, most of which date from 2006-2007. Where the list price was changed, the revised ad was treated as a new observation, reflecting the fact that the focus here is on price relativities within a given period of time and general market trends are controlled for.

Category	Cohort	Sales		Lettings	
		Count	Percent	Count	Percent
Size	One-bedroom	11,459	2.7%	83,954	10.2%
	Two-bedroom	67,124	16.1%	314,140	38.1%
	Three-bedroom	190,076	45.6%	267,530	32.4%
	Four-bedroom	121,050	29.0%	133,886	16.2%
	Five-bedroom	27,190	6.5%	25,589	3.1%
Region	Dublin	119,898	28.8%	394,376	47.8%
	Other cities	53,069	12.7%	128,806	15.6%
	Leinster	125,467	30.1%	189,041	22.9%
	Munster	69,396	16.6%	69,837	8.5%
	Connacht-Ulster	49,069	11.8%	43,039	5.2%
Total		416,899	100.0%	825,099	100.0%

Table 3.1: *Dataset size, by cohort*

housing market – the country had in Census 2011 just over two million households – but also in absolute terms, compared to studies from other countries. In their review of 69 hedonic studies of willingness to pay for environmental amenities in the two decades to 2006, Kuminoff et al. (2010) find that only about one in five (22%) contains more than 10,000 observations. The second is the fact that the dataset covers an entire country. Only about one in ten hedonic studies (9%) has been at the national level (Kuminoff et al. 2010). The third distinguishing feature is the fact that both sales and lettings markets are included: this is the first study of this type known to the author that has comparable data for both.

3.3.1 Price data

Price information included in the dataset is listed, or asking, price. An obvious concern is that the list price may not reflect any subsequent transaction price. For a discussion of this issue and the findings from the literature, please see Section 2.2.1 and also the analysis in Chapter 4.

3.3.2 Segment

In standard specifications, regressions are pooled across sales and lettings segments, in order to assess whether differences between price and rent effects are statistically signficant. For this, a categorical variable *let* is included, which takes a value of 1 for lettings ads. Interactions are also included between this variable and all other dimensions of the data, i.e. size, type, time, location, attributes and amenities. For example, in relation to size, examples of interacted variables include $beds2\_let$ and $beds2\_let\_cr$, which capture respectively (1) how the differential between 2-bed properties and 3-bed properties (the control) varied across sales and lettings segments, and (2) how the lettings differential changed in the crash period (defined below). Similar variables are included for type, while interactions between *let* and property attributes, quarterly dummies and location dummies (explained below) are also included.

3.3.3 Size

Size in square metres is not a widely used metric by consumers in Ireland and consequently, the majority of sales listings (and all lettings listings) do not include this information. To capture a property's size, indicator variables are included for number of bedrooms (one to five) and then number of bathrooms relative to number of bedrooms.[6] For lettings properties, the occupancy of each bedroom is also known and this is measured by number of single bedrooms out of the total number of bedrooms. Interactions between segment and size are included, as described above.

3.3.4 Type

The most fundamental distinction by type is between apartments and houses. Within apartments, there are additional variables for duplexes (in sales) and "flats" (in lettings; referring to parts of houses that have been subdivided for lettings accommodation). For houses, there is additional information in the sales segment: terraced, semi-detached, detached and bungalow. These are all captured with categorical variables.

[6] For example, $bb41$ refers to properties with four bedrooms and one bathroom.

3.3.5 Time

Categorical variables by quarter are included to reflect the trend in property prices over time. Additional variables (e.g. $2010q1\_let$) allow the trend in rents (which fell 25% between 2007 and 2012) to differ from the trend in list prices (which fell more than 50%). As noted by Conniffe & Duffy (1999), a frequently absent feature of hedonic models was investigating the extent to which time and other attributes interact. Thus, the model includes interactions between different phases of the market and other dimensions of the data. Phases are defined as follows: the bubble (2006-2007, prices rising) and the crash (2010-2012, prices down by at least one third), with the intermediate period 2008-2009 is used as a control where relevant.

3.3.6 Location

Three dimensions of a property's location are used in this research: its regional market, to enable accurate pricing of different property types; its local market, to capture factors not included in the analysis; and its exact physical location, used to calculate distance to amenities.

Regional markets

Five broad regions in the Irish property market are defined. The first is Dublin city, while the second regional market contains the four other cities in Ireland combined (Cork, Galway, Limerick and Waterford), whose populations vary from 50,000 to 275,000. These are not contiguous but may share marginal price effects due to their status as regional cities. The other three regional markets are based on Ireland's provinces, but excluding the city areas: Leinster, Munster and Connacht-Ulster.

Local markets

At a more granular level, areas are grouped into one of about 400 local markets. The model incorporates fixed effects, designed to capture the impact on price of locality-specific factors that are not included in a given specification, including location-specific and population-specific attributes or indeed any pure label effects. Ireland lacks a postcode system, so these markets were manually configured for each part of the country, according to a combination of the volume of listings, geographic coherence and market logic. Each is interacted with the *let* categorical variable, allowing the fixed effect for each local market to vary between sales and lettings segments.

Exact location

The final locational attribute used is the property's physical coordinates. The address of each property advertised is converted at the time of listing into xy coordinates. Also given is a level of accuracy with which these coordinates are known. Both are products of addresses being run through the Geodirectory service, administered jointly by Ireland's official mapping and postal services (OSI and *An Post*). This accuracy can vary from area-level through townland, village and street-level to building-level. Only observations known to building or street level were included, given the focus of the study on amenity valuation using distance based on xy coordinates.[7]

3.3.7 Property attributes

A range of property-specific attributes can be measured from the data. A number, particularly for lettings listings, are included as separate fields in listings; these include white goods (the presence of a washing machine, dryer, dishwasher or microwave), utilities (cable TV, internet, an alarm or central heating), and whether the property has parking, is suitable for pets, wheelchair-accessible, furnished, or available to those on rent allowance. Information is also available on the lease length. For sales properties, there is information on whether the

[7]This restriction involved the exclusion of an additional 264,975 sales listings and 322,809 rental listings over the period 2006-2012.

property is part of a new development, whether it is a re-listing at a different price, and whether the property is being sold by the owner or through an agent. For both sales and lettings listings, there is information on whether the property has a garden.

In addition, it is possible to reflect other potentially important property-specific features, using the text of the ad. This process generates an indicator variable capturing a particular attribute, when one of a number of key phrases that reflect the presence of that attribute occurs in the text of an ad. These variables include a property's aspect (south, west or south-west facing), its age (period, Edwardian, Victorian or Georgian), condition (whether the property has been recently refurbished or renovated), views, whether the property is in a cul-de-sac (no through road), various types of rooms (utility room, conservatory, granny-flat, walk-in wardrobe, wetroom), features related to energy efficiency (underfloor heating, fireplace solar panels, double-glazing) and other features (balcony, bay windows, jacuzzi, fitted wardrobes, ensuite, garage, French doors, high or corniced ceilings, and branded kitchen appliances).

All property attributes are set up as categorical variables, with interactions for segment and for bubble and crash periods. An overview of the property-specific attributes included is given in Table 3.2 in Section 3.4.2.

3.3.8 Location amenities

The focus of this research is on location-specific amenities. A total of 25 location-specific characteritics were included. As explained in more detail in Section 3.4.2, the relationship between many of these characteristics and housing market outcomes is defined by distance, while for others (such as nearby crime or the local unemployment rate) the relationship will be a value, rather than a distance. The data are described below, by broad category of amenity.

While the focus here is the estimation of price and rent effects for a range of amenities individually, alternative approaches are also possible. These include a principal components analysis (PCA) of amenities, where the various different amenities are grouped into a small number of series, or an index of amenity value, as is done in Glaeser et al. (2001). For the purposes of this research, it was felt that analysing a large number of amenities together would offer a better insight into the likely stylised facts of amenity valuation across segments and over the cycle than a smaller number of aggregated amenities (or indeed a single index). It is left to future research to explore which amenities are most important and to see whether PCA would generate substantially different results.

Environmental amenities

Five environmental amenities were included: coastline, rivers, lakes, urban green space and forests. For data on the location of Ireland's coastline, lakes and rivers, the source is Ireland's Environmental Protection Agency (EPA). For both lakes and rivers, controls are included for scale. Data on urban green spaces come from the European Urban Atlas and on Ireland's forests come from the 2006 CORINE Land Cover project (Environmental Protection Agency 2013*a*, European Environment Agency 2013); for both, controls for size are included, as described in Appendix .2.1.

Transport facilities

Six amenities reflecting transport services were included. Four relate to the rail network: stations for commuter/intercity traffic, for DART (suburban) trains, and for Dublin's Luas Red and Luas Green light rail networks. Information on the location of stations is from Railway Procurement Agency (2012). Information is also included on the primary and secondary road network, from a complete dataset of the road network on the island of Ireland, produced by NavTeq (2012) and courtesy of National Institute of Regional & Spatial Analysis (NIRSA) at NUI Maynooth. Controls are included for the speed limit that applies on the nearest stretch of road; see Appendix .2.1.

Educational amenities

Proximity to primary and post-primary schools and higher education institutes is included in this research. The coordinates of all primary and secondary schools were provided directly by the Department of Education and Skills in Ireland, which maintains an annual census of all schools in Ireland (Department of Education 2013). Information on the number and size of classes in each primary school is available from the same source, while information on the proportion of students progressing to higher education from post-primary schools was provided to the author by Grainne Faller, author of the Irish Times ranking of secondary schools. As outlined in Appendix .2.1, controls were included for large and small schools both primary and post-primary, large and small average class sizes (primary) and the rate of progression to university (post-primary).

Labour market

Three labour market amenities are included. Information is available from the April 2011 Census on the neighbourhood ("Small Area") unemployment rate, on the average commute in minutes, and the contemporaneous sectoral allocation of the labour force (Central Statistics Office 2013).[8] The proportion of people employed in agriculture is used as a simple reduced form index of employment opportunity for an area. These three indicators give different measures of the local labour market amenity: unemployment, commuting, and opportunity. These can be best thought of as area-level cardinal rankings, as they are not time-varying and labour market conditions changed substantially over the period under consideration. Information from the 2011 Census, rather than the 2006 Census, is included due to the introduction of "Small Areas" in

[8] The 2011 Census in Ireland was the first to launch administrative units below the level of Electoral Divisions (of which there are 3,409). Almost 18,500 "Small Areas" were used as the basis for enumeration in Census 2011. Each "Small Area" has a population of between 50 and 200 dwellings. They were created by NIRSA to be the lowest level of geography for the compilation of statistics in line with data protection and generally comprise either complete or partial townlands or neighbourhoods.

the later census, allowing a much more granular treatment of neighbourhood-specific labour market conditions.

Neighbourhood

Factors such as class, educational attainment, diversity or sense of community in an area may have an impact on property prices. However, without a more rigorous treatment, many of these factors belong in a second-stage analysis that attempts to describe the underlying demand curve. Much of the literature includes local unemployment rates, to capture some index of neighbourhood quality. Here, unemployment is treated as part of the labour market amenity. Instead, for neighbourhood quality, the focus is on attributes related to social capital that are, in a relative sense, more exogenous or difficult to change.

Five neighbourhood amenities were included that will be relatively fixed, at least in the short run. These include the percentage of residents with a degree and the neighbourhood's population density. As with the labour market amenities, these are the equivalent of cardinal fixed effects, based on a property's "Small Area" district in Central Statistics Office (2013). Three crime-related variables were included, based on station-level statistics for three types of crime over the period 2004-2010: burglary, murders, and drug-related offences. Each property was assigned a unique value for each category of crime, based on an interpolated map of crime incidents. The resulting figure gives an indication of the number of incidents in the nearby area. As with Census-based values, these represent an ordering of areas, rather than reflecting innovations in crime rates over the period under investigation, which is left for future research.

Agglomeration

Lastly, three more general market depth or agglomeration amenities are included. The first two comprise distance from the "national CBD" (central Dublin) and, where relevant, distance from the nearest CBD, which may be across the border in Northern Ireland. The third is distance from the border with Northern Ireland.

Additional controls

To aid exposition, the treatment focuses primarily on these 25 location-specific characteristics. However, other factors may matter in determining the cost of accommodation. In addition to amenity-specific controls (as outlined above) and micro-market fixed effects, a further 45 location features are included as controls. In brief, they include distance from bathing facilities (mostly coast-side beaches), existing and proposed National Heritage Areas, elevation, sports & leisure facilities, rail track, and sea- and airports. They also include 17 different categories of facilities, eleven polluting facilities, so-termed under the system of Integrated Pollution Prevention Control (IPPC) Licensing, and a further six categories of waste facilities, which require a permit to operate and are available from the same source. Also included are the location of mobile phone masts, prisons, stadiums, hospitals, supermarkets, convenience stores and disused mines.

In relation to neighbourhood quality, the following controls were included: an area's maturity and spaciousness, as captured by the proportion of pre-1914 buildings and the average building size (in rooms), the proportion in State-provided housing and whether the property is in (or close to) an Irish-speaking *Gaeltacht* area. Six prominent categories of national monument were also included: castles, church monuments, historic houses, ring-forts, holy wells, and stone monuments (such as standing crosses or Ogham stones). Controls are also included for whether the property lies within the boundaries of a town and, if so, what size of town (by population; seven categories).

Two further controls are included, reflecting housing supply conditions. The first is proximity to officially designated "ghost estates", of which almost 2,900 were recorded by the Department of the Environment in 2011 (Department of the Environment, Community & Local Government 2013*b*). The location of each is known (as a point rather than a polygon), as are a number of other details, including the size of the proposed development and its state of completion. Lastly, information is available on standardized zoning of land around the country, and in particular whether or not the property is on or near land zoned for residential development (Department of the Environment, Community & Local Government 2013*a*).

3.4 Model

3.4.1 General specification

The price of each property in the database can be represented as the sum of the estimated value of its constituent components as well as an error term, ϵ, reflecting the gap between the predicted value and the actual value; in simplified equation form:

$$log(price_i) = \alpha + \beta_0 let_i + X'_{1i}\beta_1 + X'_{2i}\beta_2 + X'_{3i}\beta_3 + X'_{4i}\beta_4 + \epsilon_i \tag{3.1}$$

where: let_i refers to whether the property is for sale or to let, X'_{1i} refers to property-specific characteristics, including size and type and interactions outlined earlier, X'_{2i} refers to the time period (quarterly fixed effects); and X'_{3i} refers to local market fixed effects, and X'_{4i} refers to a vector of location-specific amenities.[9]

3.4.2 Amenity variables

For each amenity, five core sets of variables are included: the base effect (e.g. distance from the coast), the lettings effect (distance from coast interacted with *let*), effects by phase (interactions with indicators variables *bubble* and

[9] The specific functional form applied here – the natural log – is used for reasons of consistency with the vast majority of the literature on amenity pricing (as well as for consistency with other analysis in this thesis). However, it should be noted that a more flexible approach, in particular the Box-Cox functional form, could also be applied. In such an approach, data are transformed using a power parameter of λ, which is estimated; the natural log functional form adopted here is where $\lambda = 0$.

crash, reflecting the 2006-2007 and 2009-2012 periods) and lettings effects by phase (distance interacted with both *let* and one of *bubble* or *crash*). For each amenity, there may also be controls, reflecting amenity type, size and region, as described above. Regional controls may reflect a difference in the nature or supply of the amenity or alternatively income elasticities. Size and type controls are included where possible to ensure that like-for-like comparisons are being made for different instances of what are classed as the same amenity.

How the base effect is captured affects the treatment of the other effects and controls. For most amenities, the treatment of distance is through the use of log-distance with a second-order polynomial, to capture orders of magnitude and diminishing marginal effects. For certain amenities, this will impose an overly restrictive relationship between space and price, particularly where larger distances may matter. Thus, for distance from central Dublin, other CBDs and the border, a combination of log-distance and buffer variables was used, allowing the relationship between distance and price to vary over the following ranges 0-250m, 250m-1600m, 1600m-5000m and beyond.[10]

For the typical distance-based amenity, regression output will be in the form of a number of distance variables: log distance and its square, and similar variables that apply to all lettings, all listings during the bubble, all listings during the crash, lettings listings during the bubble, and lettings listings during the crash. For other amenity-related variables, in particular controls for type, size or region, one additional interacted variable was included.

The final treatment of amenity relates to "score" variables, rather than distance variables (such as the local unemployment rate or the incidence of burglaries nearby). As with distance, it is possible to interact these with indicator variables for *let*, *bubble*, *crash*, *let_bubble* and *let_crash*, as well as regions.

[10] All properties and many amenities are indicated on the map as points, whereas in reality they are polygons. Thus, one other modification, to prevent small distances (and any measurement error at small distances) skewing the results was to set the minimum log-distance from an amenity to 3 (20 metres), or 4 (55 metres) where the property's location is known only to street level.

An overview of the treatment of amenities and location specific controls is given in Table 3.2. Numbers after each refer to the treatment of distance, where 1 refers to log distance with a second-order polynomial, 2 refers to buffer variables (controls only), while 3 refers to a combination log-buffer treatment, as described above, and 4 refers to a "score" variable. Letters refer to the source of the data, where *a* refers to Environmental Protection Agency (2013*a*), *b* Natural Earth Project (2013), *c* European Environment Agency (2013), *d* National Parks & Wildlife Service (2013), *e* Environmental Protection Agency (2013*b*), *f* Commission for Communications Regulation (2013), *g* Railway Procurement Agency (2012), *h* Geofabrik.de (2013), *i* NavTeq (2012), *j* Department of Education (2013), *k* Faller (2011), *m* Central Statistics Office (2013), *n* Office of the Garda Commissioner (2011), *o* National Monuments Service (2013), *p* the Competition Authority, *q* Department of the Environment, Community & Local Government (2013*b*), *r* Department of the Environment, Community & Local Government (2013*a*) and *z* refers to manual calculations by the author.

3.5 Results

Table 3.3 presents regression output, both coefficient size and the associated *p*-values, for each of the 25 location-specific amenities being considered. Values shown for the DART, Luas Green and Luas Red amenities are the net effects, i.e. capturing the difference relative to standard train stations. Amenities marked with a diamond ($^\diamond$) represent those measured with combined log-buffer variables, rather than a second-order polynomial in log distance; the second coefficient shown in each case represents the outermost effect (all those properties less than 5km). Those marked with a dagger (†) are score-based, rather than distance-based amenities.

Category	Amenity (treatment of distance, source)
Environmental	Coastline (1,a); Lakes (1,a); Rivers (1,a); Urban green space (1,c); Forest (1,c)
Transport	Train stations [including Luas and DART] (1,g); Primary roads (1,i); Secondary roads (1,i)
Education	Primary schools (1,j); Post-primary schools (1,jk); Higher education institutes (1,z)
Labour market	Unemployment (4,m); Commute length (4,m); % in agriculture (4,m)
Neighbourhood	Education levels (4,m); Population density (4,m); Burglary (4,n); Murders (4,n); Drugs-related crime (4,n)
Market Depth	Dublin CBD (3,z); nearest CBD (3,z); border (3,b)
Other Controls	IPPC & waste facilities (2/3, e); Prisons (1,z); Mobile phone masts (1,f); Historical Mines (1,a); Stadiums (1,z); Bathing facilities (1,a); Elevation (4,b); Hospitals (1,z); Sports facilities (1,c); National Heritage Areas (2,d); National monuments (2,o); Train track (1,h); Sea port (2,c); Airport (1,c); Area maturity (4,m); Area spaciousness (4,m); Irish-speaking Gaeltacht area (2,m); Local authority housing (4,m); Garda station (1,n); Town size (2,m); Supermarket location (1,p); Convenience store location (1,p); % single (4,m); Ghost estates (1,q); Zoned land (2,r)

Table 3.2: *Summary of location-specific variables used – for legend, see text*

3.5.1 Regression output

On the following pages is an overview of the regression output underlying the results presented above. For each amenity, coefficients and p-values are shown for a range of variables. Four categories of coefficient are reported: the core price effect, the lettings effect, and the price and rent effects in both bubble and crash periods. The figures given are the net effects, so p-values indicate whether that effect is statistically significantly different from the core price effect and any other segment-relevant effects. For further details, see the text discussing the results.

Table 3.3: *Selected regression output: coefficients on amenities (and associated p-values in brackets below)*

Amenity	Core	Square	Let	Let_sq	Bubble	Bu_sq	Crash	Cr_sq	Let_bu	Let_bu_sq	Let_cr	Let_cr_sq
Coastline	−0.1093	0.0069	0.1003	−0.0069	0.0189	−0.0008	0.0182	−0.0013	−0.0201	0.0009	−0.0198	0.0017
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0243)	(0.0002)	(0.0000)	(0.0042)	(0.0627)	(0.0003)	(0.0000)
Lakes	0.0238	−0.0028	−0.0477	0.0035	−0.0078	0.0007	−0.0398	0.003	−0.0057	0.0003	0.034	−0.0026
	(0.0067)	(0.0000)	(0.0000)	(0.0000)	(0.5082)	(0.385)	(0.0001)	(0.0000)	(0.737)	(0.7881)	(0.007)	(0.0038)
Rivers	−0.0133	0.0019	0.0107	−0.0014	−0.0223	0.0022	−0.0231	0.002	0.0359	−0.0032	0.0251	−0.0023
	(0.0139)	(0.0001)	(0.1256)	(0.0262)	(0.0021)	(0.001)	(0.0005)	(0.0008)	(0.0011)	(0.0012)	(0.0022)	(0.002)
Green space	0.0092	−0.0003	−0.0086	0.0003	0.0132	−0.001	−0.0109	0.0009	−0.0053	0.0003	0.0024	−0.0001
	(0.0015)	(0.2827)	(0.016)	(0.3279)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.2231)	(0.3963)	(0.4697)	(0.5873)
Forest	−0.0498	0.0031	0.0326	−0.0019	0.019	−0.0016	−0.0029	0.0007	−0.0411	0.0035	0.0071	−0.0011
	(0.0000)	(0.0000)	(0.0004)	(0.0039)	(0.0296)	(0.0087)	(0.706)	(0.1933)	(0.0024)	(0.0002)	(0.4664)	(0.0955)
Station	−0.0472	0.0027	0.0575	−0.0034	0.0333	−0.0018	0.0075	−0.0007	−0.0601	0.0038	−0.018	0.0012
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0005)	(0.3428)	(0.1242)	(0.0000)	(0.0000)	(0.0419)	(0.0263)
DART	0.0198	−0.0025	−0.0116	0.0014	−0.0026	0.0001	0.0199	−0.0027	−0.0036	0.0009	−0.0176	0.0024
	(0.0003)	(0.0009)	(0.063)	(0.1158)	(0.7197)	(0.9267)	(0.0015)	(0.002)	(0.6926)	(0.4877)	(0.0136)	(0.0153)
Luas G	0.0379	−0.0039	−0.0201	0.0016	0.0127	−0.0019	0.0011	−0.0002	−0.0298	0.0042	−0.0263	0.0036
	(0.0000)	(0.0000)	(0.0017)	(0.0643)	(0.0606)	(0.0423)	(0.8408)	(0.8017)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Luas R	−0.0245	0.0032	0.0295	−0.0043	−0.0052	0.0007	0.0034	−0.0006	0.0065	−0.0007	−0.0088	0.0013
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2796)	(0.3165)	(0.4446)	(0.3618)	(0.2573)	(0.3783)	(0.0738)	(0.0612)
Primary Rd	−0.0045	0.0003	0.0143	−0.0007	−0.0057	0.0003	−0.0127	0.0008	0.0044	−0.0003	0.0076	−0.0006
	(0.2891)	(0.2892)	(0.0061)	(0.052)	(0.2384)	(0.4412)	(0.0038)	(0.0049)	(0.5093)	(0.5366)	(0.1397)	(0.0761)
Second Rd	−0.0088	0.0005	0.0259	−0.0019	−0.0097	0.0007	−0.0025	0.0004	−0.0042	0.0005	−0.0092	0.0003
	(0.0235)	(0.104)	(0.0000)	(0.0000)	(0.033)	(0.0297)	(0.549)	(0.1862)	(0.502)	(0.2472)	(0.0538)	(0.2822)
Prim School	−0.0861	0.0085	0.0412	−0.0045	0.0323	−0.0027	0.0443	−0.0039	−0.0364	0.003	0.0038	−0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0071)	(0.0059)	(0.0000)	(0.0000)	(0.039)	(0.0427)	(0.7678)	(0.9246)
Sec School	−0.0377	0.003	0.0476	−0.0034	−0.0277	0.002	0.0317	−0.0022	0.0041	−0.0002	−0.0284	0.002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0032)	(0.0036)	(0.0003)	(0.0005)	(0.7657)	(0.8583)	(0.0069)	(0.0078)
3rd Level	0.0846	−0.0042	−0.0407	0.0015	0.0132	−0.0002	0.0825	−0.0054	−0.0124	0.0003	−0.1316	0.0081
	(0.0000)	(0.0000)	(0.0034)	(0.0973)	(0.2755)	(0.7794)	(0.0000)	(0.0000)	(0.4396)	(0.7378)	(0.0000)	(0.0000)

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Amenity	Core	Square	Let	Let_sq	Bubble	Bu_sq	Crash	Cr_sq	Let_bu	Let_bu_sq	Let_cr	Let_cr_sq
Unemployment†	−0.2021		0.1901		−0.0398		−0.29		0.1138		0.1842	
	(0.0000)		(0.0000)		(0.0388)		(0.0000)		(0.0000)		(0.0000)	
Commute time†	−0.0016		0.0015		0.0013		−0.0011		0.0007		0	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0425)		(0.9151)	
Agriculture†	0.04		−0.0078		−0.0819		−0.1274		0.3686		0.1445	
	(0.1373)		(0.821)		(0.0182)		(0.0000)		(0.0000)		(0.0002)	
Edu levels†	0.3449		−0.3104		−0.0281		0.0683		0.017		0.0249	
	(0.0000)		(0.0000)		(0.0015)		(0.0000)		(0.1212)		(0.0065)	
Burglary†	0.0853		−0.0115		0.0191		−0.0062		−0.0143		0.0163	
	(0.0000)		(0.0017)		(0.0000)		(0.0235)		(0.0008)		(0.0000)	
Murder†	−0.0616		−0.0005		−0.0057		0.0015		−0.0015		−0.0067	
	(0.0000)		(0.8749)		(0.0513)		(0.5731)		(0.7361)		(0.042)	
Drugs†	−0.0084		0.001		−0.0055		0.0008		0.0069		−0.0024	
	(0.0129)		(0.6763)		(0.0037)		(0.6345)		(0.0155)		(0.2594)	
Density†	−0.0162		0.0071		−0.0039		−0.0015		0.0056		0.0009	
	(0.0000)		(0.0000)		(0.0000)		(0.0721)		(0.0000)		(0.3451)	
Border◇	−0.0082	0.0012	0.007	−0.0056	−0.0266	−0.002	0.0137	−0.0012	0.0138	−0.0017	−0.0109	0.0058
	(0.0331)	(0.1466)	(0.2685)	(0.0000)	(0.0000)	(0.0215)	(0.0000)	(0.1392)	(0.0007)	(0.2237)	(0.0003)	(0.0000)
Central Dub◇	−0.0685	0.002	0.0304	−0.0038	0.0172	−0.0001	0.0157	0.0013	−0.0155	−0.0017	−0.0092	0.0015
	(0.0000)	(0.052)	(0.0000)	(0.0019)	(0.0000)	(0.9242)	(0.0000)	(0.02)	(0.0001)	(0.0227)	(0.0033)	(0.0167)
Other CBD◇	0.0023	0.0028	−0.0008	−0.0014	−0.0005	−0.0023	−0.0009	−0.0038	0.0008	−0.0006	0.0015	0.004
	(0.0000)	(0.0000)	(0.2249)	(0.0888)	(0.2751)	(0.0001)	(0.0365)	(0.0000)	(0.2446)	(0.5345)	(0.0025)	(0.0000)

End of Table

The pattern of p-values indicates that for amenities there is a statistically significant relationship with the cost of accommodation. Of 25 amenities, the core effect was statistically significant at the 5% for 23, the exceptions being proximity to a primary road and the percentage involved in agriculture in an area. The majority of base effects for the lettings segment are also statistically significant (18 of 25 at the 5% level), indicating that different price gradients with respect to distance applied during the period across sales and lettings segments. Similarly, for the bulk of amenities, the bubble and crash base effects are statistically significant (17 of 25 at the 5% level for both).

Model Fit The presence of two distinct segments in pooled regressions prevents the reporting of any meaningful statistics for the full sample. However, running regressions separately on sales and lettings samples can give an indication of model fit. For the sales segment, the R^2 is 80%, compared to 77% for a model without amenity variables. This implies that much of the explanatory power of amenities is at the expense of area-specific fixed effects, although area coefficients in models with and without amenities are highly correlated. Also of note is the signficant improvement in root mean square error when amenities are included; $RMSE$ falls from 0.2583 to 0.2413. The fit of lettings models is similar (R^2 of 79.5% with and 78.7% without amenities; $RMSE$ of 0.1803 and 0.1834 respectively).

Due to the necessarily detailed treatment of distance, the actual effect in a given phase or segment may be different to the simple sign on the coefficient. For that reason, results are presented in Table 3.4 for the following thought experiment: the estimated effect on the price (or rent) of moving a property from 1km to 100m from a particular amenity or facility. The results are displayed graphically in Appendix .2.2, in Figures 5-8.

For those amenities and facilities marked with a diamond ($^\diamond$), the results shows moving a property from 5km to 1km away. Those marked with a dagger (†) are not distance-based amenities and the percentage figures shown represent a one-standard-devation change in the variable; for more details see Table 4 in Appendix .2. Where the effect is not statistically significant at the 5% level, the percentage is shown in italics, signifying for price effects that it is not statistically significantly different from zero and for other effects that one cannot reject the null hypothesis that the particular effect is no different from the base price effect.

The second and third columns show the expected sign and the outcome. The vast majority are in agreement. The positive association between property prices and burglaries appears to be in line with research suggesting that the causality runs in the opposite direction, i.e. burglaries are more likely to occur in valuable areas (Gibbons & Machin 2008). Similarly, the negative relationship between proximity to rivers and property prices may reflect the dominance of flood risk concerns over natural amenity value (Harrison et al. 2001). Costs of congestion may explain the result in relation to primary schools, particularly given that the vast majority of properties in the sample are within 1.6km of a primary school.

More difficult to explain are negative effects associated with green space (particularly given the results in Mayor et al. 2009), higher education institutes and distance from the border. These results are largely robust to specification and are worthy of more detailed future research.

3.5.2 Comparing Price & Rent Effects

The fourth and fifth columns compare the price and rent effects. Evidence in favour of the first core hypothesis, i.e. where the price effect (P) is greater than the rent effect (R) is summarized in the second last column. For all 25 amenities, there is evidence from 18 of an attenuated rent effect, compared to the price effect. In other words, there is overwhelming evidence that a mechanism is at work in the Irish housing market similar in effect to either the search thresholds or buyer lock-in effects described above. It is notable that the principal exceptions relate to distance from the centre (either Dublin or

Amenity	Exp	Out	Price	Rent	Bubble	Crash	Hyp(1)	Hyp(2)
Coastline	+	+	4.7%	2.1%	3.4%	4.4%	P>R	C>B
Lakes	+	+	2.0%	3.1%	*1.8%*	2.8%		C>B
Rivers	+/-	-	-2.0%	*-0.8%*	-2.4%	-1.8%	P>R	
Green space	+	-	-1.5%	-0.2%	-1.9%	-1.3%	P>R	
Forest	+	+	2.7%	0.7%	2.7%	*1.8%*	P>R	
Train station	+	+	3.2%	-0.5%	1.0%	*3.5%*	P>R	C>B
DART station	+	+	5.0%	*0.6%*	*3.3%*	7.7%	P>R	C>B
Luas Green station	+	+	4.9%	1.6%	*4.8%*	*5.4%*	P>R	C>B
Luas Red station	+	+	0.8%	1.2%	*-2.2%*	*1.6%*		C>B
Primary roads	+	+	*0.2%*	-1.2%	*0.8%*	0.8%	P>R	
Secondary roads	+	+	0.7%	-0.1%	1.1%	*0.3%*	P>R	
Primary school	+	-	-2.2%	-0.2%	-2.6%	-2.4%	P>R	
Secondary school	+	+	0.7%	-1.3%	1.6%	-0.7%	P>R	
Higher education◇	+	-	-4.7%	-0.3%	*-7.8%*	-5.9%	P>R	
Unemployment†	-	-	-1.3%	-0.1%	-1.6%	-3.2%	P>R	C>B
Commute time†	-	-	-0.9%	-0.1%	-0.2%	-1.5%	P>R	C>B
Agriculture†	-	+	*0.1%*	0.1%	-0.2%	-0.3%		C>B
Education levels†	+	+	6.0%	0.6%	5.5%	7.2%	P>R	C>B
Crime: Burglary†	+/-	+	9.7%	8.4%	11.9%	9.0%	P>R	
Crime: Murder†	-	-	-6.3%	-6.3%	*-6.9%*	*-6.1%*		
Crime: Drugs†	-	-	-1.2%	-1.0%	-1.9%	*-1.1%*	P>R	
Population density†	-	-	-2.6%	-1.4%	-3.2%	*-2.8%*	P>R	
Border◇	-	+	2.3%	*3.6%*	8.0%	-0.8%		
Central Dublin◇	+	+	7.1%	8.1%	7.4%	8.2%		C>B
Nearest CBD◇	+	+	5.6%	*6.5%*	*7.2%*	7.5%		C>B

Table 3.4: *Effect of moving a property from 1km to 100m away from an amenity; for exceptions (†, ◇), see text*

other CBD). In surveys, those active in the property market emphasise access to employment as among the most important factors when choosing a place to live (Daft.ie 2012). This indicates that renter search thresholds, rather than buyer lock-in effects, are more likely to explain the difference for secondary amenities. Also worth noting is the difference between segments in relation to higher education institutes, with an almost complete absence of the negative price effect possible evidence of countervailing effects valued by renters who are in large part third-level students, and conversely secondary schools, which exhibit a positive price effect but a negative rent effect.

3.5.3 Comparing Bubble & Crash Effects

The sixth and seventh columns of Table 3.4 compare the price effect of proximity to amenities across bubble and crashes phases of the market. The final column summarizes evidence in relation to the second core hypothesis, with

C>B noted for instances where the price effect in the crash period is greater than in the bubble period. For 12 amenities, this is the case, in particular relating to transport amenities (all four categories of train station) and distance from the CBD. The premium associated with moving from 1km to 100m away from the coastline increased from 3.4% to 4.4% in the crash, while the equivalent effect for a suburban DART train station increased from 3.3% to 7.7%.

Particularly noteworthy is the finding that a 30-minute longer commute, *ceteris paribus*, was associated with a 1% lower house price during the bubble but an 8.4% lower price during the crash. This suggests that during the bubble, households were prepared to pay the opportunity and resource costs of longer commutes, possibly as these were offset by capital gains. However, in the crash, the lack of any such capital gains appears to have strengthened the forces of agglomeration in Ireland.

There are a number of amenities where the percentage price effect during the bubble is greater than in the crash, something that would suggest a pro-cyclical "buyer lock-in" effect (similar to the Stein hypothesis), rather than a counter-cyclical "property ladder" effect (similar to the Costello hypothesis). This is clearest for the crime-related amenities, where although not dramatic there was a fall in the discount associated with higher murder and drugs-related crime in the crash.

3.6 Conclusion

Due to the importance of housing as a good and an asset, understanding housing markets cycles and tenure choice will aid policymaker efforts not in relation to housing policy but also in understanding economic fluctuations. This chapter has explored the relationship between the economics of location-specific amenities and both tenure and housing market cycles. Following in the footsteps of a long literature, it traced the impact of amenities on property prices but also on rents, a less common feature of the literature. Of twenty-five location-specific characteristics, almost all were reflected in the housing market with a sign in line with expectations or the existing literature. For example, moving a property from 1km from the coast to 100m away was associated with a 4.7% increase in price.

This chapter exploited the dataset's large size, its coverage of both sales and lettings segments and huge variations in market conditions over the period covered to test whether the valuation of amenities is greater in the sales segment than in the lettings segment, reflecting either tenants' search costs or buyers' desire to lock in supply of an amenity. This was typically found to be the case – there is evidence of an attenuated rental effect for 18 of the 25 amenities. For example, the rental premium for a coastline property was 2.1%, less than half the 4.7% price premium.

To distinguish between tenant search costs and buyer lock-in concerns, Ireland's violent property market cycle was exploited. A sign of "lock-in" effects would be if relative amenity prices were procyclical, rising in the bubble and falling in the crash: during the frenzy of a bubble, people pay over the odds to secure access to amenities which are by their very nature fixed in supply. However, if the relative price of amenities increased in the crash, this would suggest that "property ladder" concerns dominated: normally people prefer to reward access to amenities, but in the bubble, the principal concern is not having any property at all, pushing up the relative price of low-amenity properties. Alternatively, the relaxation of credit constraints boosted demand for lower-amenity housing, an effect that evaporated in the crash.

There was evidence of counter-cyclical amenity pricing, i.e. the relative price rising in the crash, for the majority of amenities for which sensible and statistically significant results emerged, including prominent housing market amenities such as commute time, distance to CBD and proximity to train stations and the coastline. For example, the premium enjoyed by a property 100m from the coast compared to one 1km away increased from 3.4% to 4.4%

between bubble and crash. Similarly, moving a property from 5km from the CBD to 1km away was associated with an increase in price of 7.4% in the bubble and 8.2% in the crash.

It is left to future work to examine income elasticities, using county-level information on incomes, and to exploit supply-side innovations, such as the opening of new motorways, by-passes and train stations, and the opening and closure of schools and hospitals. The publication in late 2012 of the Property Price Register opens the possibility of developng a micro-level datasets of transaction prices, which would enable a comparison of list price and sale price effects that could reveal important differences between the expectations of market participants and final outcomes. The relationship between list prices and sale prices is analysed in Chapter 4.

Chapter 4

Relationship between list and sale prices

Trends in residential house prices matter. They are of interest not only to economists, but also to policymakers and consumers, given the dominant role of housing both as a consumption good and as a vehicle for household investment. The Global Financial Crisis (GFC) starting in 2007 underscores the importance of understanding housing markets, in particular if macro-prudential policy hopes to identify when conditions in the housing market change and bubbles emerge.

Unlike other financial markets, the matching process in housing is one that can take months or indeed fail entirely, particularly during market downturns. The lack of fungibility and liquidity in housing means that statistics relating to the market are patchy and rarely comparable across countries (Malpezzi 2003, Warnock & Warnock 2012).[1] This makes it all the more difficult for economists, policymakers and consumers to identify when the housing market may be overheating.

Despite its potential significance, the relationship between list and sale prices for housing has been the focus of only a handful of studies to date. In the very first issue of the Journal of Real Estate Research, Miller & Sklarz

[1] In the EU, even the introduction of residential house prices – typically the largest single component in a national basket of consumer goods – into the harmonised index of consumer prices (HICP) is a twenty-year project due to come to fruition in 2018 (O'Hanlon 2011).

(1986) highlight the gap between the two as one of five leading indicators in the housing market. However, their analysis – and their call for future research – has largely gone unheeded. A related literature has emerged in commercial real estate, assessing the accuracy of valuations, but the findings are typically not based on like-for-like comparisons, with valuations made at a different time to transactions.

This research uses two population-level datasets of the Irish housing market, over the period 2006-2012, to investigate in detail the relationship between aggregate list and sale prices and establish like-for-like comparisons of buyer and seller valuations. It takes as its starting point two pieces of conventional wisdom about the housing market. Firstly, it is expected that in a downturn sale prices will be below list prices, while secondly, it is often asserted that list prices are a lead indicator of sale prices. At first glance, these would appear to conflict in a market downturn: if list prices lead sale prices in switching from boom to bust market, how are they above sale prices in the bust?

The analysis here shows that both were true for Ireland during the period 2006-2012. This somewhat contradictory finding is explained by disentangling the relationship between the two series into four main components. The first of the four is the selection spread, where properties that ultimately go on to find a seller are listed at lower prices. The matching spread, secondly, reflects how much house prices change between when a property is listed and it is sale agreed. The third component is the counteroffer spread, reflecting whether the sale price achieved is higher or lower than the list price, focusing only on those listings that result in a sale and adjusting for time-to-sell. This is the closest to a bid-ask spread in housing. The final component is the drawdown spread, reflecting how prices change between when a property is sale agreed and when the mortgage is actually drawn down; this largely reflects administrative time costs.

The chapter is structured as follows. The next section presents a more formal discussion of these spreads, while Section 4.2 discusses some of the related literature on this topic. Section 4.3 describes the two datasets used here, Central Bank of Ireland (CBI) and daft.ie, and Section 4.4 describes the empirical specifications employed. Section 4.5 presents the results of the analysis, showing estimates for each of the four spreads for the Irish housing market 2006-2012, while the final section concludes.

4.1 Theory

Housing is in effect a very high-dimension composite good, comprising a bundle of property-specific attributes and location-specific amenities. Not only can each property vary in each composite good, but so too can consumer tastes. The fact that only bundles of these composite goods are available leads to frictions, which mean that it may take a property a significant period of time to sell. This is contrast to most other financial markets and indeed consumer markets.

Suppose there are two datasets: the first contains all properties listed for sale and their list price (p_L), while the second contains all properties sold and their (mortgage-backed) transaction price (p_M). A stylised transaction from the housing market might be as follows. In month 1, a property is listed by its seller. At this point, a list price is revealed. A list price index would use such information, and in that index, this property enters into the list price index in month 1. In month 4, the property has found a buyer whose offer is accepted. The status of the property is changed to "sale agreed". At this time, the bank makes its valuation, upon which the mortgage amount is based. In month 6, the transaction is completed, when the mortgage is drawn down. This property thus enters into any sales price index in month 6.

The issue in assessing valuation accuracy is immediately apparent, as this typically involves comparing the valuation from month 1 with the transaction in month 6. What is needed instead is a comparison of what the seller's valuation would have been in month 4 with the buyer's valuation at the same time. Where the goal is to make like-for-like comparisons of seller and buyer valuations, neither a published list price index, in which the property described above will enter in month 1, nor a sales price index, in which it enters in month 6, is using the correct information at the correct time.

More formally, the ratio of list prices (p_L) to (mortgage-backed) sale prices (p_M) can be decomposed into four distinct market processes:

$$p_L(0)/p_M(\tau) = p_L(0)/p_{\bar{L}}(0) \cdot p_{\bar{L}}(0)/p_{\bar{L}}(\upsilon) \cdot p_{\bar{L}}(\upsilon)/p_M(\upsilon) \cdot p_M(\upsilon)/p_M(\tau) \quad (4.1)$$

where there are three time periods, time of listing ($t = 0$), the time when a sale and price are agreed ($t = \upsilon$), and the time when the mortgage is drawn down ($t = \tau$), and where $\bar{L}$ refers to only those listings that result in a transaction (and hence a mortgage being drawn down).[2] Conceptually, the price spread can be described as follows:

1. the "selection spread", $p_L(0)/p_{\bar{L}}(0)$: what is the point-in-time list-price difference between all properties that are listed and those that subsequently are sale-agreed?

2. the "matching spread", $p_{\bar{L}}(0)/p_{\bar{L}}(\upsilon)$: what is the point-in-time list-price difference between newly listed properties that go on to be sale-agreed and those being sale-agreed now?

3. the "counteroffer spread", $p_{\bar{L}}(\upsilon)/p_M(\upsilon)$: what is the point-in-time difference between the list price of properties that are sale-agreed and the sale price of properties at the time of their valuation?

4. the "drawdown spread", $p_M(\upsilon)/p_M(\tau)$: what is the point-in-time sale-price difference between properties that are being valued and those whose mortgage is being drawn down?

[2]Note that this assumes that all housing transactions are mortgage-backed, which is a simplification.

The counteroffer spread is the closest equivalent to a bid-ask spread in the housing market, due to the frictions involved. It is also the only comparison of the four that uses both datasets.

4.2 Literature

A number of papers examine the accuracy of valuations in the commercial real estate sector; see Crosby (2000) and Dunse et al. (2010) and references therein. However, the literature comparing list and sale prices in residential housing is small. To our knowledge, there is no paper for either sector that decomposes the gap between list and sale prices into various components, as is done here. Nonetheless, a number of papers touch on issues related to the spreads outlined in the introduction (and explained in more detail in Section 4.1); these are described below.

Adjusting valuations to take account of time-to-sell is an issue that has been highlighted by a number of authors on commercial real estate. Matysiak & Wang (1995) suggests some tentative findings in relation to how valuations and sale prices are related across the market cycle, namely that valuers undervalue in rising markets and overvalue in falling markets. Complicating this analysis, however, is the fact that valuations took place between three and six months prior to the sale. As Crosby (2000) notes, this affects the comparability of valuations and sale prices.

The selection spread presented here is related to a point raised by Jud & Seaks (1994) among others, namely that a house price index based on sales will not be representative of housing values more generally, where a sample selection bias exists in properties that are sold. Using a Heckman-style two-stage model, they document such a selection bias, using a decade of sales and property tax returns for Greensboro, North Carolina. The comparison in Jud & Seaks (1994) is between all properties and those that successfully sell, while in this research, the selection spread refers instead to all listings versus those that successfully sell.

The earliest paper that structurally compares both list and sale prices of residential property is Genesove & Mayer (2001), which examines the gap between the two for a sample of just under 6,000 downtown Boston condominiums, during the period 1990-1997. Their focus is not directly on the gap between the two; rather they examine whether loss aversion affects seller behavior (including list price) in the housing market. Their findings suggest that sellers are indeed averse to realizing nominal losses: a 10% increase in a prospective loss leads a seller to set a list price roughly 3% higher, everything else being equal. Related to this, they find evidence that "list prices do not immediately adjust to changes in market prices".

In comparing the Swiss National Bank's median-based house price index using listings (both newspaper and online) with a hedonic index based on sale prices over the period 1985-2006, Bourassa et al. (2008) outline some concerns relating to the use of datasets of list prices. One of these is that the spread between list and sale prices is likely to vary depending on the state of the housing market. This is the issue addressed in this research.

Shimizu et al. (2012) compare the distribution of properties across different datasets for Japan and conclude that – once like-for-like comparisons are being made across the datasets – there are no substantial differences in the distribution of list prices and those on price registers. Like-for-like comparisons are central to this result, suggesting it is related to a stylised fact of the literature on constructing house price indices: hedonic techniques are needed (Knight et al. 1995, Wallace & Meese 1997).[3] The finding from Japan also tallies with published house price indices for Ireland. Two hedonic indices, the mortgage-based CSO index and the listings-based daft.ie index, showed house prices falling at 12-14% year-on-year in early 2011; in contrast, a simple un-

[3] For a fuller treatment of hedonic pricing methods, see Malpezzi (2003).

weighted average (produced by the Dept of the Environment) showed prices 9% *higher*.

More recently, a paper by Haurin et al. (2013) examines the relationship between list and sale prices over the market cycle in Belfast (Northern Ireland), 2002-2009. They find, contrary to standard assumptions made regarding the selling process, that when the housing market is strong, properties sell for more than their list price. (In down or normal markets the list price generally exceeds the sales price.) This is also a feature of the data presented here. The authors conclude that the selling mechanism must switch during boom markets, with the list price acting as a floor, rather than a ceiling. Of relevance for this study is their finding that the list to sale price ratio is "unusually high" during the downturn in Northern Ireland, a finding they attribute to seller loss aversion.

4.3 Data

Two datasets are used in this chapter, one containing list prices and the other mortgage-backed sale prices. For details on the nature of property market transactions in Ireland, see earlier chapters. Worth noting here is that a seller may state that they require offers "in excess of" or "in the region of" the list price, but typically the list price is for information only and set after agreement between the seller and their estate agent. The presence of "in excess of" list prices runs somewhat counter to the assumption made in much of the (typically North American) literature, that the list price represents a ceiling on offers. Since late 2012, prices for individual transactions have been freely available to the public through a Property Price Register.

4.3.1 daft.ie dataset

List price information used for analysis here was collated by online accommodation portal, Daft.ie. The dataset comprises all properties advertised online between 1 January 2006 and 31 December 2012. The dataset contains the following information:

- **Price**: For each property, the list price is known.[4]

- **Location**: Location is known, both generally (all listings are assigned to one of 4,000 areas in the country) and specifically (all listings are assigned latitude and longitude coordinates, and a degree of precision for those coordinates). For comparability with the CBI dataset, the principal information on location used refers to broad region (of which there are four: Dublin, Leinster, Munster and Connacht-Ulster) and county (or postcode within Dublin).

- **Type & Size**: There is information on the property's type (apartment, terraced, semi-detached or detached dwelling). Information is also known about the property's size, measured in terms of bedrooms, and bathrooms relative to bedrooms, while for a subset of properties size in square metres is available.

- **Date**: Information is available for properties within the daft.ie dataset on when they were originally listed, when marked as "sale agreed" (if relevant) and when withdrawn from the market. The time between listing and sale-agreed status is central to estimation of the counteroffer spread in housing outlined in Section 4.1.

Summary statistics on the key variables, for both the full set of listings [daft.ie 1] and the set of listings that subsequently went to be sale-agreed [daft.ie 2] are given in Table 4.1.[5]

[4] Other chapters in this doctorate use a dataset that includes listings where price is changed as separate observations, due to the focus on relative values, with time/market conditions being controlled for. Here the focus is on the set of properties, not the set of seller expectations, and the sale process in its entirety, from first listing to ultimate sale. Therefore, these observations are omitted from the analysis. Future research will examine the role of nominal rigidities within a listing.

[5] It is worth clarifying why the full sample of properties for sale provided by daft.ie is different in Chapters 2, 3 and 4. The sales dataset in Chapter 2 comprised 408,334 listings

4.3.2 CBI dataset

Sale price information comes from the Central Bank of Ireland (CBI) dataset, itself a product of the Prudential Capital Assessment Review (PCAR) process, also known as the "stress tests" of the Irish banking system that followed its collapse in 2009-10. Under PCAR, Irish banks covered by a government guarantee were recapitalized by CBI in return for equity. Such action required loan-level analysis, including of the mortgage portfolio, which involved detailed information for over 600,000 loans on 475,000 properties being made available to CBI.

The analysis here is of loans associated with a housing market transaction (i.e. first-time buyer, mover-purchaser or "buy-to-let" investment) and where certain information criteria are met. The dataset includes all observations from 2006Q1 (when the daft.ie dataset starts) until 2011Q4 (the date of the PCAR process) and contains the following information:

- **Price**: Price information is available in the form of the bank's valuation as part of the mortgage drawdown process, which becomes the official transaction price.

- **Location**: Information on location is known only to county level, of which there are 26 in the Republic of Ireland. However, for two of the four financial institutions covered by PCAR, information is available for Dublin postal districts, of which there are 22 in the most built-up parts of the capital (this dataset is referred to as CBI-2).

- **Type & Size**: Property type relates to whether the property is a semi-detached, detached or terraced house, a bungalow or an apartment. No further information on a property's size is available for all properties.

from 2006 to mid-2012, and excluded all those whose location was not known to sufficient accuracy (street or building level). The analysis in Chapter 3 included additional listings from late 2012, leaving a total sales sample of 416,829. Lastly, the sample here – 420,691 – includes all properties known only to estate or area level (as location in the CBI dataset is imprecisely measured) but excludes all relistings at a different price.

Dataset	daft.ie 1	daft.ie 2	CBI
Total	420,691	76,647	216,685
Av price	€281,478	€269,628	€323,796
Dublin	84,018	23,886	57,074
Leinster	121,052	21,212	59,498
Munster	126,186	19,980	61,542
Conn-Ulster	89,435	11,389	37,571
Terraced	63,916	15,603	36,417
Semi-detached	111,405	24,427	68,424
Detached	199,671	29,038	85,656
Apartments	45,699	7,399	25,188
2006	76,435	3,381	63,016
2007	113,763	17,675	58,763
2008	73,320	12,648	42,460
2009	46,105	8,940	24,704
2010	40,571	10,150	17,603
2011	37,433	9,830	9,139
2012	33,064	13,843	0

Table 4.1: *Summary statistics of the daft.ie and CBI datasets*

- **Date**: For all observations, the dataset contains information on when the mortgage was drawn down. For most observations, there is also information on when the property was valued, information that can be used to estimate the counteroffer spread.[6]

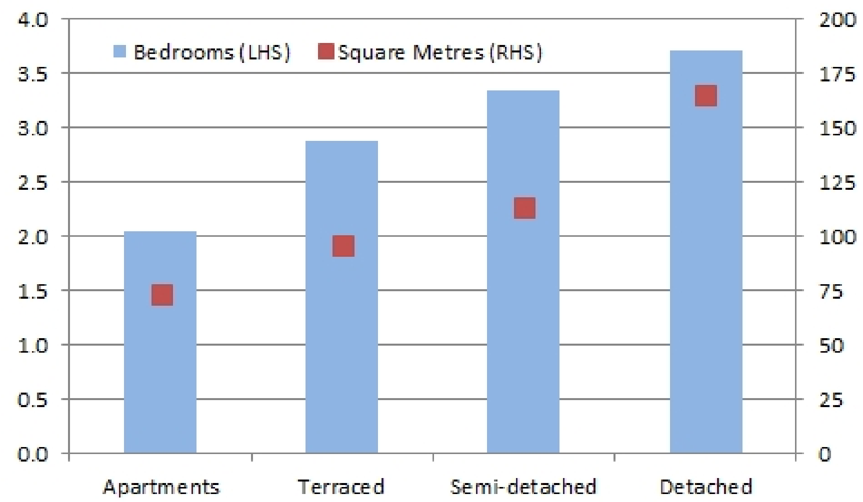
Some summary statistics of the CBI PCAR dataset across all three main dimensions (location, type and date) are given in Table 4.1. For more on the CBI PCAR dataset, the interested reader is directed to Kennedy & McIndoe-Calder (2011).

Omitted variables An obvious omitted variable from the CBI dataset is a detailed measure of size. Standard in the housing economics literature is size in square metres, with number of rooms (or number of bedrooms, available in the case of the daft.ie dataset) also widely used. The lack of information on property size in the CBI dataset raises the question of omitted variables. Using

[6]Only mortgage loans with complete information were included. Roughly 36,000 loans referred to properties where the valuation date was not known and these were thus excluded.

information from the daft.ie dataset, Figure 4.1 shows the average number of bedrooms by property type, together with average square metres for those properties for which it is available. It is apparent that there is a clear correlation between property type and size (measured either way), meaning that type will act as a rough proxy for size in the analysis carried out.

Figure 4.1: *Average number of bedrooms, by property type, daft.ie dataset*



Ideally, other factors, such as year of construction, quality of finish, site size and energy efficiency, would also be included in the analysis. Unfortunately, this quality of information is not available for the Irish housing market during this crucial period in its history. Future analysis should be able to combine information from the Property Price Register, launched in late 2012, with detailed property-level characteristics contained in the Building Energy Rating database. Nonetheless, the necessarily parsimonious models employed here explain large proportions of the variation and can thus be viewed as a solid foundation for analysis.

Cross-dataset comparisons An unresolved issue is the extent to which the two large datasets are substantively similar in unobserved characteristics. The counteroffer spread is a direct comparison of the levels of average price implied by the two datasets and, in level if not in trend, is subject to any structural differences across the two datasets. To some extent, with both datasets covering the vast majority of housing market transactions for the period under analysis, this is less likely to be an issue. Nonetheless, it is not possible rule out all potential effects. For example, if within one county, an estate agent did not advertise online but was facilitating mortgage-backed transactions, the properties sold by that agent would appear in the CBI dataset but not in the daft.ie dataset. Alternatively, if the proportion of transactions that were backed by a mortgage varied with the market cycle, this could introduce some selection effect in the CBI dataset. Ultimately, as these are population-level datasets (all online listings and all mortgage-backed transactions), it is left to the reader to judge the potential relevance of any structural differences across datasets. As noted earlier, this affects only the size of the counteroffer spread, not its trend, nor any of the other spreads calculated.

4.4 Model

The empirical strategy adopted is, per the recommendation of the literature, the hedonic regression, i.e. controlling for the characteristics of the properties traded, to ensure a like-for-like comparison over time. As with O'Hanlon (2011), outliers are excluded from final figures by adopting a two-stage process, and filtering out excessively influential observations by using Cook's Distance (Cook 2000). Similar to the vast bulk of the housing literature, a log-linear model is applied, allowing coefficients to be interpreted, to an approximation, as percentage differentials.

Time The principal options in relation to the treatment of time are monthly or quarterly dummy variables. Due to the long period under investigation, it is not obvious what benefit monthly variables would bring, thus quarterly variables are chosen instead. (An alternative – quite separate from the house price index literature – would be to impose a polynomial on the time-span, although it is not obvious *a priori* what order polynomial would apply. Thus this would become a fitting exercise and effectively tend in the limit to a model with monthly or quarterly dummies.)

Location While specific location is known for the daft.ie dataset, there is limited information on location in the CBI dataset. Thus, county-specific fixed effects are used in all specifications. The treatment of location here is very similar to the official CSO Residential Property Price Index (O'Hanlon 2011).[7]

Type and size As discussed above, very limited information is available on the property's size in the CBI dataset. That information is limited to property type, which is correlated with size. Type-specific fixed effects are included, relative to semi-detached properties as a control. As discussed in Chapter 2, premiums or discounts associated with particular property types may vary by region. Therefore, type interactions with four broad regions are included. Those four regions are: Dublin, the rest of the Leinster province, the Munster province, and Connacht-Ulster.

In equation form, the empirical model is given below, where each vector of Q, X and Y omits one category as control (first quarter of 2007, County Louth and semi-detached properties, respectively), and where s refers to the quarter within the year, t to the year[8], c to county c of $C = 25$, r to regions 1-5 and n to the property type ($N = 4$).

$$ln(hp)_i = \alpha_0 + \sum_{t=2006}^{2012} \sum_{s=1}^{4} \alpha_{ts} Q_i^{ts} + \sum_{c=1}^{C} \beta_c X_i^c + \sum_{n=1}^{N} \sum_{r=1}^{R} \beta_{nr} Y_i^{nr} + \epsilon_i \tag{4.2}$$

[7] For a subset of the CBI dataset (two of the four lenders), as well as for the entire daft.ie dataset, information is available on postal district for Dublin city properties. Robustness checks were carried out using this subsample, i.e. excluding lenders with no information on postal district. The results were substantively similar, with the bulk of the difference stemming from variations between the lenders included and excluded, rather than the impact of additional location controls.

[8] As discussed above, there are no data for 2012 in the CBI dataset, thus the summation for that dataset runs to 2011.

This model is applied to five datasets, in order to calculate the four spreads outlined above:

1. The first dataset is the population of listings, where the date refers to the initial date of listing. This uses the daft.ie dataset in full.

2. The second dataset is the set of listings that subsequently go on to be "sale agreed", where the date used refers to the date of listing. This uses a proportion of the daft.ie dataset.

3. The third dataset is also the set of listings that are "sale agreed" before being withdrawn, but where the date used refers to the date the property was marked sale agreed. This uses the same subset of the daft.ie dataset.

4. The fourth dataset is the population of mortgage-backed transactions, where the date refers to the date at which the property is valued. This uses the CBI dataset in full.

5. The final dataset is the population of mortgage-backed transactions, where this time the date refers to the date of the transaction. This also uses the CBI dataset in full.

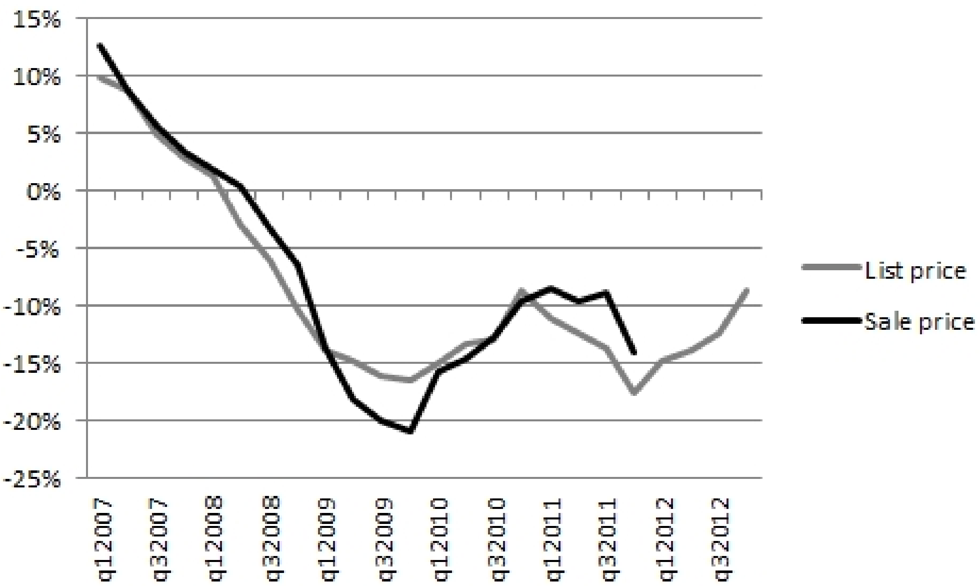
4.4.1 Calculation of averages

As individual properties cannot be matched across datasets, due to the lack of specific information on location in the CBI dataset of transactions, the analysis here uses comparable weighted average hedonic prices. The empirical model given above is used to generate regression output in the form of coefficients, while the CBI dataset of transactions is used to give weights for each of the four property types for each of the counties, as well as for each county within the country.

With four property types and one control, there are three type coefficients for each county. Each county-level type coefficient, which takes into account any region-specific type effects, is then multiplied by the weights within that county for each property type. These three numbers are then added to the generic county coefficient to give a county-specific type-weighted coefficient. Whereas coefficients from regression output give like-for-like differences in prices between areas, these adjusted coefficients reflect the mix of property types and sizes in an area. Thus, counties where apartments and terraced properties are more common will have this reflected in the adjusted coefficients.

These county-specific adjusted coefficients can be used, along with the constant, to calculate a county-specific average price for the control period (2007Q1). The weighted sum of all these county-specific average prices gives a national average price for 2007Q1. Quarter-specific coefficients are then used to generate a series for the period 2006Q1-2012Q4 (2011Q4 for the CBI dataset). The output for each dataset is thus a national average price that reflects the mix of properties within and across counties.

Figure 4.2: *Year-on-year change in sale and list prices, 2007-2012*



Initial overview The introduction made reference to two pieces of conventional wisdom about the housing market. The first is that it is expected that in a downturn, sale prices will be below list prices. Indeed, until recently, it was typically assumed that the list price was an upper bound, but recent research shows that this is not the case (Haurin et al. 2013). Secondly, it is often asserted that list prices are a lead indicator of sale prices. These two appear to be in conflict when the market turns from a rising market to a falling one.

Datasets (1) and (5) above are what would be used to generate indices of list prices and sale prices. Applying the method described above, it is possible to compare trends in both. Figure 4.2 shows the year-on-year change in list and sale prices. What is particularly noteworthy is that list prices appear to lead sale prices throughout: the year-on-year change turns negative earlier, falls in prices abate earlier in 2009 and accelerate earlier in 2010/11.

Thus, in the recent Irish housing market downturn, list prices were above sale prices – but they also led sale prices from boom to bust and throughout the bust. The next section reconciles these two findings, by decomposing the gap between the two series into its constituent components.

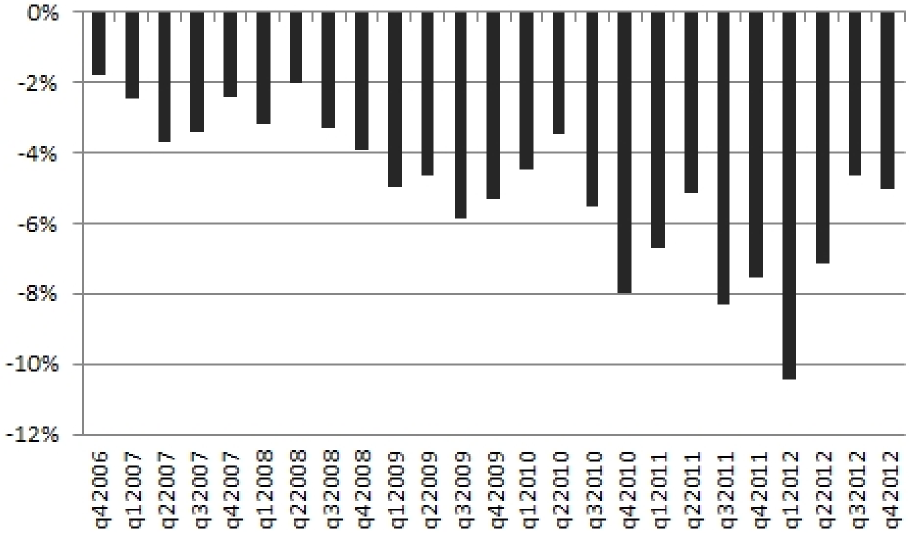
4.5 Results

4.5.1 Selection spread

Figure 4.3 shows the estimated quarterly "selection spread" among listed properties. The gap shown is the percentage gap in list price between those properies that go on to find a buyer (i.e. are marked as sale agreed) and the full complement of properties listed in a given month. As a buyer is not known at time of listing, this is only able to be calculated ex-post by the researcher (not in real time, by the analyst).

A positive number could indicate the importance of unobserved factors (which in this analysis include any factors other than quarter, property type or county). However, the selection spread is negative throughout, indicating that those properties that subsequently find buyers are listed at systematically cheaper prices than those that do not. The fact that the selection spread is

Figure 4.3: *The "selection spread", daft.ie dataset, 2006-2012*



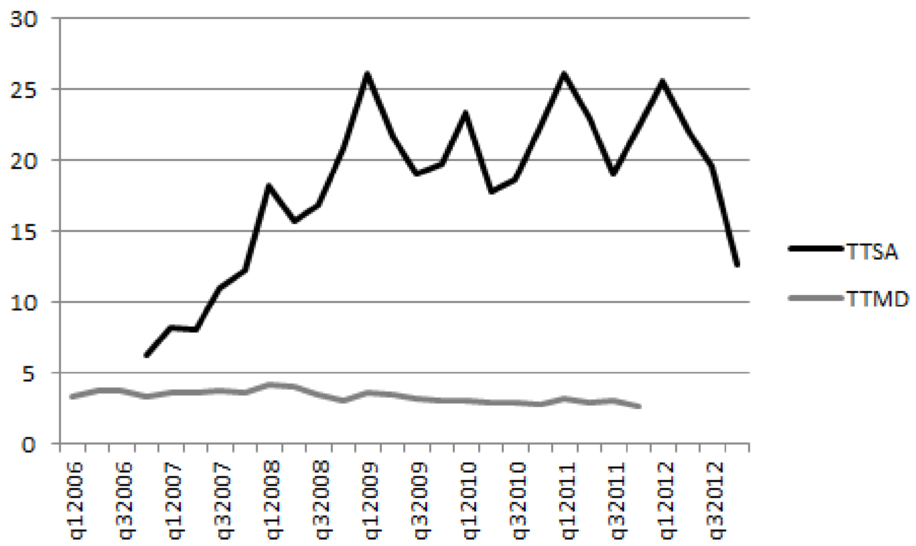
cyclical (a larger negative number when prices are falling faster) indicates that, in a downturn, properties priced more realistically are more likely to sell.

An alternative explanation is that, as quality differences are not included as regressors, lower-quality properties (within property-county cohorts) were more likely to sell as property conditions worsened. However, the evidence from Chapter 2 suggests demand has shifted in the crash period to higher attribute properties, not lower attribute ones, thus this is unlikely to be the case and thus what is captured is indeed the extent to which properties that sell are listed systematically cheaper, *ceteris paribus*, than those that do not.

4.5.2 Matching spread

The second component of the gap between list and sale prices is the matching spread, reflecting time-to-sell: how have prices changed between when the property was initially listed and when a buyer is found? This will reflect information available to the buyer at the time the property is sale agreed but not to the seller when the property was listed. Figure 4.4 shows median time to sell (TTS) nationwide, from initial listing until the property is sale agreed, and indicates a dramatic increase in TTS between late 2006, when it took typically two months to find a buyer, and early 2009, when it took over six months on average. After that, the duration largely remained between five and six months for most of the period 2009-2012.

Figure 4.4: *Median time-to-sell and time-to-drawdown (in weeks), daft.ie and CBI datasets, 2006-2012*

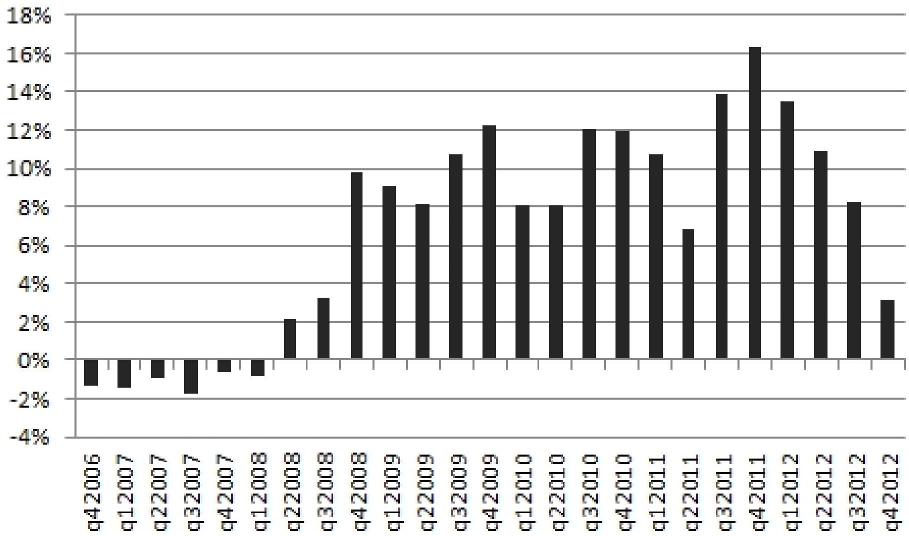


As property prices were falling at more than 10% a year from 2008 until 2011, the fact that it took half a year on average – and significantly longer in many cases – for properties to find a buyer means the time-to-sell spread will be quantitatively significant in explaining the gap between list and sale prices. This gap is shown in Figure 4.5. A positive number – as occurs throughout the period from mid-2008 on – indicates that properties that turned sale-agreed in a given quarter had a higher listed price than properties listed for the first time in that quarter that would ultimately go on to find a buyer.

4.5.3 Counteroffer spread

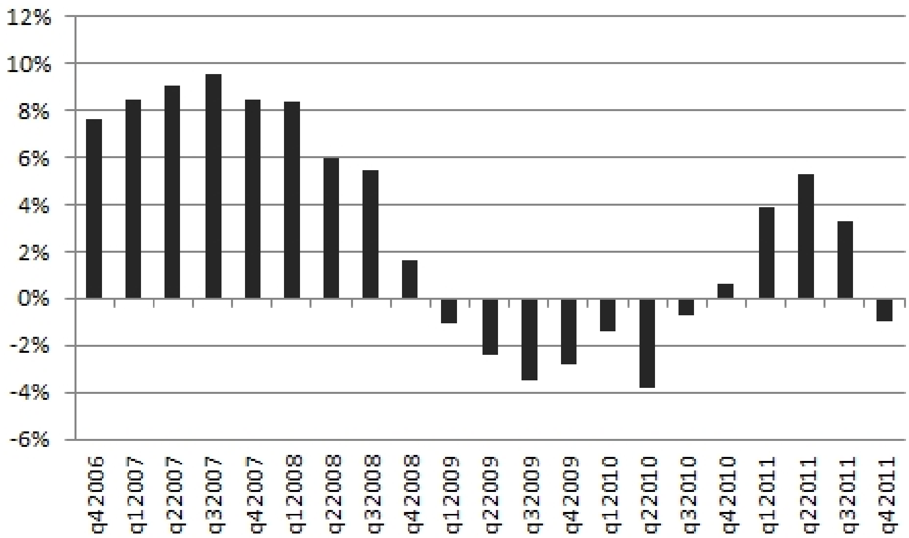
The third stage in the decomposition of the gap between list and sale price is the counteroffer spread, i.e. comparing suitably adjusted list and sale prices, at the time the property was sale-agreed and valued by the mortgage issuer. This is shown in Figure 4.6. It suggests that during 2007, allowing for prices

Figure 4.5: *The "matching spread", daft.ie dataset, 2006-2012*



to have changed between the time of listing and the time the sale was agreed, the offer was typically 8% above the list price. This is supportive of the finding from Haurin et al. (2013) that list prices do not act as a ceiling on offers in booming markets.

Figure 4.6: *The "counteroffer spread", daft.ie and CBI datasets, 2006-2012*



During the market downturn, in particular in 2009 and 2010, buyer offers were typically 2-4% below the list prices of properties that would ultimately find a buyer, even when those list prices were adjusted by how much prices had fallen since their initial listing. However, by 2011, the counteroffer spread was positive again: adjusted list prices were surpassed on average by sale prices. At first, this may seem counterintuitive, particularly given that Ireland became reliant on IMF-EU financing in late 2010. The answer appears to lie in the collective decision of sellers to aggressively cut list prices in 2011: list prices fell 18% that year, compared to 9% in 2010 (see Figure 4.2).

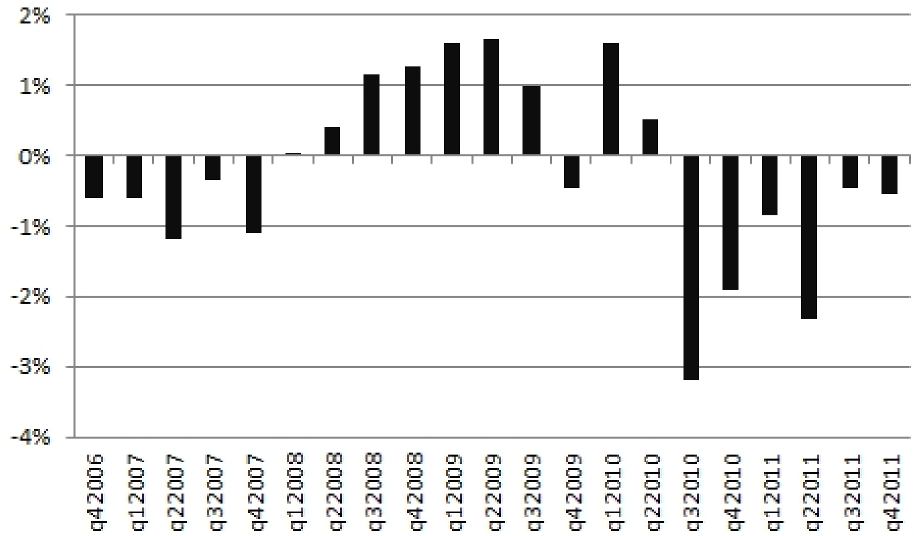
It is worth noting that unlike the other stages, which involve within-dataset comparison, this stage involves comparing price levels across the two datasets. As such, this may be sensitive to the samples underpinning both datasets and any differences in categorization.

4.5.4 Drawdown spread

The final stage in the housing transaction is the drawdown spread, i.e. reflecting changes in prices in the period between when a property is valued (typically when the sale is agreed) and when the mortgage is actually processed (typically when the new owner moves in). Figure 4.4 shows the median time between valuation and mortgage drawdown. While there are fluctuations, the time-to-drawdown is remarkably stable throughout what are very turbulent market conditions. While time-to-sell reflects market conditions and the matching process, time-to-drawdown appears to reflect administrative time-costs.

As a consequence of the relatively stable and short time-to-drawdown, its effect on prices is typically small. When prices are rising early in the period, properties having their mortgage drawn down were worth less than those just being valued (typically by no more than 1%). As prices started to fall in 2008-2009, the opposite was the case – properties having their mortgage drawn down in mid-2009 were valued at roughly 1.5% more than those just being valued. By late 2010, the drawdown spread had turned negative again, although this was close to zero by the end of 2011. Overall, quantitatively, the effect of the drawdown spread on prices is the smallest of all the spreads.

Figure 4.7: *The "drawdown spread", CBI dataset, 2006-2011*

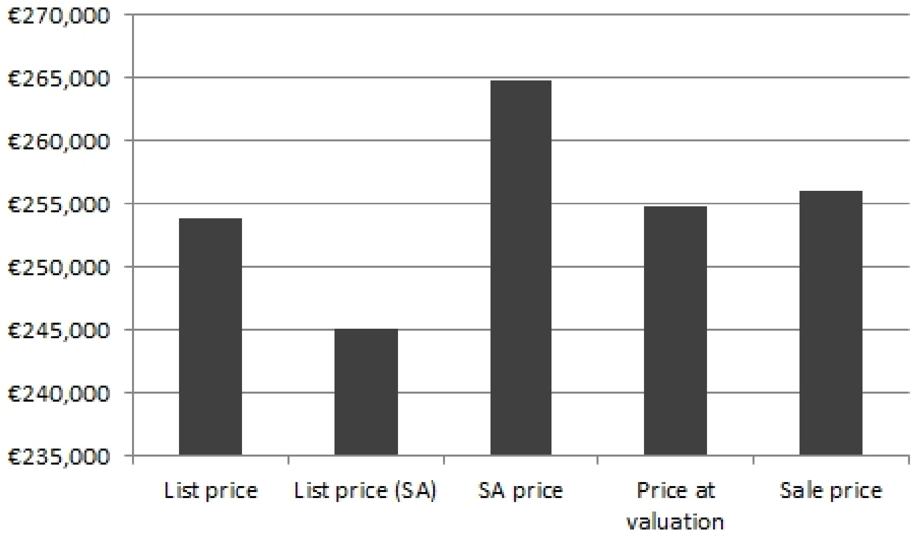


4.5.5 Summary

To summarize, a sample period is shown in Figure 4.8. The gap between the first two columns shows a selection spread of 3.4%: compared to all listings, properties that ultimately sold were listed at systematically lower prices when initially listed (€245,000 compared to €254,000). The gap between the second and third columns shows a matching spread of 8.0%: in 2010Q2, properties that being marked as sale-agreed had an average list price 8% higher (€265,000) than those properties newly listed that quarter which would go on to find a buyer.

The difference between the third and fourth columns is what is termed here the counteroffer spread: comparing list and sale prices on a like-for-like basis, successful bids were on average 3.8% below list prices. The gap between the fourth and final columns is the drawdown spread, reflecting the fact that the average price of properties whose mortgage was drawn down in 2010Q2 was 0.5% than those being valued at that point.

Figure 4.8: *Four spreads for sample period (2010Q2)*



4.6 Conclusion

The aim of this chapter was to decompose the gap between list and sale prices into its constituent processes. The results overcome some of the obstacles to assessing valuation accuracy, reconcile two pieces of conventional wisdom about the housing market and also present a number of metrics that may yield insights into market conditions.

In relation to valuation accuracy, previous studies have shown that listings and assessor valuations at the start of the process can lag the ultimate transaction price over the market cycle – but also that these are not like-for-like comparisons, as valuations are not contemporaneous to transactions. By using hedonic analysis on two population-level datasets, the research undertaken here overcomes these limitations, presenting like-for-like comparisons of list and sale prices.

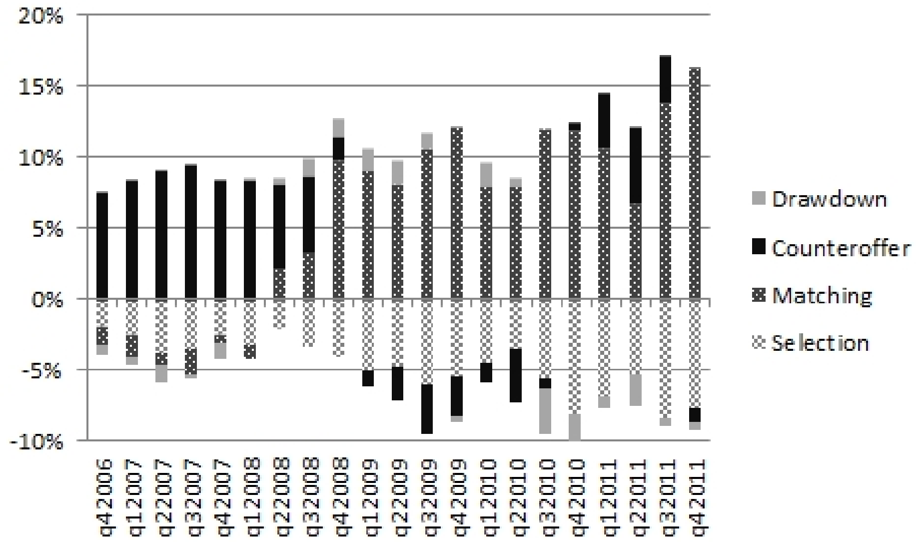
It is often said, firstly, that list prices lead sale prices, as seller expectations can respond instantly, whereas the transaction process means that it can take time for final sale prices to reflect the same news. This was evident for the two datasets presented here, with the year-on-year change in list prices leading that in sale prices throughout the period studied. This suggests that, with appropriate controls for market conditions, list prices can function adequately as a substitute in the absence of sale prices, even in an illiquid market.

It is also said that, in a falling market in particular, the average sale price will be below the average list price, as weak demand means sellers have to accept lower-than-expected outcomes. The research here reconciles those two statements by decomposing the gap between list and sale prices into four spreads: the selection spread, the matching spread, the counteroffer spread, and the drawdown spread. An overview of trends in these over time, and their relative importance, is given in Figure 4.9. The selection spread, capturing the extent to which properties that sell systematically list for less, exists throughout the period but is particularly pronounced during the market downturn: properties that list for less, ceteris paribus, are more likely to find a buyer

While this finding accords with basic economic theory, it does not support findings from some behavioural research that a higher list price can having a priming effect, thereby bringing about better outcomes for the seller (Kahneman 2011). The finding here is based on aggregate data; a study using individual listings and outcomes may shed light on whether this behavioural effect exists and the extent to which it affects quantity outcomes (the probability of a transaction) and price outcomes (the sale price, conditional on a transaction occurring).

The matching spread is a product of both the length of time it takes to find a buyer and the change in prices during that period. Given the speed with which prices fell in Ireland during much of the period covered, and the length of the typical time-to-sell, this is quantitatively important in explaining the gap between the two. For most of the period 2008-2011, the list price of properties being sale agreed was 10% or more higher than newly listed properties. While the exact role of nominal price rigidities is a topic for further research, this highlights the limitations of comparisons using valuations and transactions from different time periods. The drawdown spread, reflecting the time gap between

Figure 4.9: *Overview of four spreads, 2006-2011*



valuations for mortgages and their ultimate draw-down, was similar in nature but much smaller in significance.

The counteroffer spread, finally, is the closest counterpart in the housing market, which lacks liquidity and fungibility, to the bid-ask spread in other financial markets. It reflects how list prices and sale prices compare, when adjusted to time-to-sell and time-to-drawdown, as well as for the fact that some listings will not result in a transaction. Early in the period, the counteroffer spread was large and positive, suggesting that buyers had tough competition in securing a property and thus they offered more than the list price. This idea of the sale price in boom-times "breaking the price ceiling" offered by the list price supports the findings of Haurin et al. (2013).

During the down market, the counteroffer spread was negative for much of 2009 and 2010. However, the entry of Ireland into the IMF-EU program in late 2010 appears to have had an impact on seller expectations, as the fall in list prices in 2011 was twice that of 2010. This greater realism on the part of sellers might explain the return of a positive counteroffer spread in early 2011, although as sale price falls increased in late 2011, the spread turned negative again.

Regarding insights into market conditions, the selection effect is likely to persist, even in a market in equilibrium, as sellers' expectations will not be uniform and those with excessive expectations need to experience market conditions to change. The matching spread is a product of two other process: the matching function itself (time-to-sell) and trends in house prices. Thus, it is likely to be strongly countercyclical as measured here (a large positive number in a falling market).

The counteroffer spread presented here appears broadly procyclical and may offer useful insights into market conditions. While the research presented here relies on aggregate prices from two population-level datasets, future research for Ireland may be able to utilize the Property Price Register, which dates from 2010, to construct a micro-level dataset in real-time of the matching and counteroffer spreads. Similarly, detailed datasets in other countries may allow the calculation of equivalent series to inform policymakers.

Such segment-by-segment analysis should aid policymakers greatly in understanding not only conditions in the housing market generally, which are crucial in determining broader economic conditions, but also conditions in different sub-markets. Future research could explore in more detail what determines time-to-sell and also price rigidities, i.e. looking within the first and second spreads above. Insights from this will be of use not just for macro-prudential policy but also in understanding housing demand and thus shaping policy in relation to development and planning/building permits. Chapter 5 explores the relationship between house prices and other economic factors in more detail.

Chapter 5

Modelling the Irish housing market

As noted in Chapter 3, the case of Ireland exemplifies the links between housing and other aspects of the economy, including financial stability, the labour market, government finances, and public service provision. Research examining its housing crash, however, remains scarce. This chapter uses a quarterly dataset to examine the long-run relationship and short-run dynamics that governed house prices in Ireland from the mid-1970s until 2012. A key focus is on the role of credit conditions, which featured in many earlier models of house prices (see, for example, Jaffee et al. 1979, Meen 1990, Thom 1983) but have been acknowledged as an omitted variable in many housing market analyses in the period preceding the Global Financial Crisis (Duca et al. 2011*a*). Given the huge changes in the financial sector in Ireland between 1980 and 2012, in addition to metrics of income, housing stock, demographics and user cost, the analysis here includes a readily available measure of credit conditions, the ratio of mortgage credit to household deposits.

An error correction model is developed that explains the extraordinary run-up in house prices in Ireland in the decade to 2007, which reveals a clear and stable long-run relationship, to which real house prices respond rapidly. Given how closely actual prices track their fitted values, the Irish housing market "bubble" in some sense disappears – the average Irish house price was well explained in 2007 by its determinants, just as it was in 1987. Those long-run determinants, however, include not only relatively slow-moving fundamentals such as income, demographics and housing stock, but also more rapidly changing factors in relation to extrapolative expectations about future prices and credit conditions. In relation to credit conditions, these fragile fundamentals include a dangerous maturity mismatch embedded in much of the financing of Irish mortgages. The "bubble" remains but at a level further up in the analysis.

It is likely that other factors, in particular the income/stock ratio, user cost and the ratio of credit to deposits, respond in turn to house prices. For this reason, a four-vector system of cointegration is developed, in which the house price relation that emerged from error-correction analysis is largely unchanged. Cointegration results suggest that there exists a latent variable capturing upstream exogenous factors driving both domestic credit conditions and house prices, a topic worthy of future research. Lastly, using new data on the typical loan-to-value for Irish first-time buyers, it also develops the first model of the price-rent ratio in Ireland, covering the period 2000-2012.

The chapter is structured as follows. Sections 5.1 and 5.2 outline briefly the economic theory behind models of house prices and the existing literature on the relationship between credit conditions and housing prices and on the Irish housing market. Section 5.3 provides details on the data used in this analysis. Section 5.4 outlines the empirical results of an error-correction framework applied to an inverted demand model of the Irish housing market, while Section 5.5 explores the cointegration properties between house prices, the income/stock ratio, user-cost and the ratio of credit to deposits. Section 5.6 presents a model of the price-rent ratio in Ireland from 2000 to 2012, while Section 5.7 decomposes Irish house price growth since the 1970s and assesses the policy implications of the analysis presented here. Section 5.8 concludes.

5.1 Theory

There are two main methods with which house prices are modeled over time. The first is the inverted demand approach, which draws on basic consumer theory and the fixed nature of housing supply in the short run. The second, drawing more on financial theory, is the price-rent ratio approach. As both forms of model are employed in this analysis, both are described below.

5.1.1 Inverted Demand

Theoretically, demand for a good depends on its prices, the income of consumers and other demand shifters. Applied to housing, suppose that in any given period t, the quantity of housing demanded, h_t, can be approximated log-linearly by:

$$ln(h_t) = -\alpha ln(rhp_t) + \beta ln(y_t) + z_t \tag{5.1}$$

where rhp_t refers to the real housing price, y_t to (real) household income and z_t to demand shifters, as discussed below. As the supply of housing is fixed in the short run, the demand function can be inverted, giving:

$$ln(rhp_t) = (\beta ln(y_t) - ln(h_t) + z_t)/\alpha \tag{5.2}$$

Where the income elasticity of demand, β, is one, this simplifies further, with house prices being determined by the log income per house ($\frac{y}{h}$) and other demand shifters, z.

Demand shifters can be split into those reflecting fundamentals (and thus would affect the explicit or implicit rent associated with housing), z^F, such as demographics, and those reflecting asset considerations, z^A, in particular user costs and credit conditions. Demographics, for example the proportion of the population of household-forming age (typically 25-34 year-olds), may have an impact on house prices, *ceteris paribus*. Other demographic variables that may capture similar effects include net migration or the ratio of persons to households.

As discussed in more detail below, the user cost, uc_t, reflects the durable asset nature of housing. Measures of the user cost typically include the interest rate, reflecting capital and opportunity costs, any depreciation and maintenance and any transaction or taxation costs. From this is subtracted any expected capital gain: the faster house prices are expected to rise, the less the anticipated cost of owning a house. Theory also suggests that a risk premium term should be included in user cost: everything else being equal, if market participants believe there to be risk associated with current market conditions, this will depress demand and thus prices.

Income, housing stock, user costs and demographics are typically included in inverted demand models. Credit conditions, however, have until recently been omitted, often because such conditions are hard to measure. Theoretically, however, everything else being equal, at a given interest rate, house prices will be higher if banks are more prepared to lend, i.e. if credit conditions are more favourable. This can be thought of as a relaxation of credit rationing, or a fall in shadow price of credit (see Meen 1990). In practical terms, one may think of this as either secular financial liberalization (as occurred in many OECD economies in the generation to 2007) and/or cyclical appetite among financial institutions for mortgage assets. Credit conditions can be captured by proxies, such as the average or maximum loan-to-value offered to first-time buyers (see, for example, Duca et al. 2011*a*) or alternatively can be estimated using latent variables (e.g. Muellbauer & Williams 2011).

5.1.2 Price-to-rent Ratio

An alternative but related approach for establishing the equilibrium level of housing prices is related to the concept of financial arbitrage, where housing prices reflect the discounted future stream of rents: $hp_t = rent_t/\rho_t$, where ρ_t represents a discount rate (Poterba 1984). From a consumer theory perspective, the special treatment of housing reflects its unique position in the household utility function. Unlike general consumption goods, housing is also an asset, while unlike general assets, housing is also a good. This can be thought of as completely equivalent to an inverted demand model, where all the fundamentals (income, supply and z^F) have the same effect on rents as house prices and thus, "dividing through" by rents, the right-hand side consists only of asset considerations (z^A, factors that affect house prices but not rents):

$$hp/p = f(y, h, z^F, z^A) \tag{5.3}$$

$$r/p = f(y, h, z^F) \tag{5.4}$$

$$hp/r = f(z^A) \tag{5.5}$$

This, of course, only applies where markets are fully efficient and thus any factor affecting rents is reflected fully in house prices.

Drawing on earlier work, Meen (1990) develops a model where consumers with non-housing assets maximise utility over housing and consumption goods over multiple periods. First-order conditions give a marginal rate of substitution between housing and consumption that can be interpreted as the user cost (a monetary amount). It reflects borrowing costs (r_t, net of any tax relief) and depreciation (δ_t), less expected capital gains in housing (κ_t). To this one may add costs of transaction and taxation (τ_t).

The monetary user cost can be expressed as a percentage yield (or rental rate) by dividing across by house prices. This means that the ratio of housing prices to rents depends on the yield. Inverting, this gives:

$$hpr = 1/(r + \delta + \tau - \kappa) \tag{5.6}$$

In semi-log formulation, and allowing for flexibility in relation to the relative importance with which the various factors affect the ratio, for period t:

$$ln(hpr_t) = \beta_0 + \beta_1 r_t + \beta_2 \delta_t + \beta_3 \tau_t + \beta_4 \kappa_t + u_t \tag{5.7}$$

where u_t is a residual and where the expectation is that β_1, β_2 and β_3 are negative and β_4 is positive (greater expected capital gains push up house prices). As mentioned above, a risk premium term, π_t, should be included in user cost, while tax relief on mortgage interest will also affect the net cost of capital.

User cost and credit conditions In this canonical model, the differential of the yield with respect to expected inflation is thus dependent on the marginal tax rate and the effect of inflation on nominal interest rates. An increase in inflation should lead to a reduction in the yield. However, Meen (1990) points out two caveats to this result. Firstly, if real interest rates are constant, an increase in expected inflation implies an increase in the nominal interest rate and thus a higher mortgage repayment, leading to potential cashflow problems. This is known as the "tilting" of real mortgage payments. Secondly, capital market constraints may exist such that interest rates for borrowing and lending are different. The budget constraint, therefore, comprises gross assets and gross loans separately, rather than as net financial assets. Where a rationing constraint exists, this increases the user cost of capital by the ratio of lambda (the shadow price of the rationing constraint) and marginal utility of general consumption.

Lastly, as outlined in Kim (2008), if a house provides a different level of rental service to an owner-occupier than to a tenant, and houses are rented out reflecting this "rental efficiency", then the ratio of prices to rents will be positively related to rates of home ownership, θ_t. Put another way, the dividend on housing (the rent-price ratio) will be lower when home ownership is greater, due to the different level of service derived from housing by owner occupiers. Empirically, the log form allows the estimation of the long-run relationship between the various factors:

$$ln(hpr)_t = \beta_0 + \beta_1 r_t + \beta_2 \delta_t + \beta_3 \tau_t + \beta_4 \kappa_t + \beta_5 CCI_t + \beta_6 \theta_t + \beta_7 \pi_t + u_t \quad (5.8)$$

where CCI is specified such that an increase reflects an easing of credit conditions and a reduction in the shadow price of the rationing constraint. Thus the expectation is that β_4, β_5 and β_6 are positive, with all other coefficients (apart from the intercept) negative.

5.2 Literature

5.2.1 Credit Conditions & House Prices

Some of the earliest econometric research on housing market outcomes includes some measure of the non-price conditions in the credit market. For the U.S., Jaffee et al. (1979) stressed the importance of the availability of credit, as well as its cost, and document some research on its importance in determining post-war cycles in housing and construction. They also include in their model fundamentals such as the population aged 25-34 and the "headship rate", or ratio of persons to households. For the availability of credit, their model uses the flow of deposits into thrift institutions and the flow of mortgage credit from federal agencies (both relative to house prices).

The availability of credit – also described in the literature as mortgage rationing – affects prices by acting as a shadow price on the credit constraint. This affects both real house prices and the ratio of prices to rent; for more on the early literature on this, see Meen (1990). Whereas Meen estimated mortgage rationing through the percentage increase in mortgages advanced, Dicks (1990) used loan-to-value (LTV) information for the housing market. More recently, Fernandez-Corugedo & Muellbauer (2006) developed a credit conditions index for the UK over the period 1976-2001. This is done by using quarterly microdata from the Survey of Mortgage Lenders on LTV and loan-to-income (LTI) ratios for first-time buyers, in particular combining data on the proportion of high LTV and LTI loans with aggregate information on debt to give ten quarterly series. A single index is then calculated from the common variation in these ten series that cannot be explained by an extensive set of economic and demographic influences.

Where such rich micro-data is not available, reduced-form proxies have been used as alternatives. Duca et al. (2011*a*,*b*) use American Housing Survey information on the average LTV for first-time buyers in the U.S., for the period 1979-2007, to capture credit conditions. Doing so, they find that the inclusion of credit conditions notably improves models of house price, giving better model fits, reasonable speeds of adjustment, and stable long-run relationships with sensible and more precisely estimated income and user cost coefficients, both for the pre-2002 sample and for the whole period. An alternative approach is taken in Muellbauer & Williams (2011), which models large, unobserved structural changes in the macroeconomy using a latent interactive variable equation system. This involves using smoothed step dummies, informed by knowledge of the specific institutional environment – in this case Australia – to form a spline function.[1]

5.2.2 Ireland's Property Market

Broadly speaking, there have been four phases of applied research on the Irish housing market, with the principal works summarised in Table 5.1. For the table, it is worth noting that the specific data series vary significantly between studies. SOA refers to error-correction speed of adjustment, while regressors are denoted as follows: Y is income (dY change in income), typically in log form so that coefficients reported are the elasticity of price with respect to income; S is housing stock (a count of dwellings); r_r and r_n real and nominal rates of mortgage interest; pop is population, $pop2534$ the population aged 25-34 ($demog$ refers to an alternative measure of demographics); CCI is a credit conditions index; q_mort is quantity of mortgages; rhp_1 is the lagged dependent variable; uc is user cost (as distinct from interest rate); c_build and c_land refer to cost indices for building and land.

The first cohort of studies dates from the late 1970s and early 1980s, in response to the publication of official housing price statistics in the 1970s. Very little research on the market was then undertaken until the late 1990s, when a number of papers attempted to understand the long-run fundamentals determining house prices, in order to assess the probability of a bubble in the

[1]This is similar in spirit to work such as Barrell & Davis (2007), whose research uses indicator variables informed by OECD research to measure the effects of financial liberalization on consumption.

housing market at that time. A similar phenomenon occurred around 2004-2005, as there was growing concern again that house prices were over-valued. Since the crash, a number of papers – led by economists at the Central Bank of Ireland – have undertaken analyses of the housing market, to shed light on where house prices should be and whether they have over-corrected.

Early 1980s Official quarterly bulletins relating to the Irish housing market started around 1970 and by the late 1970s, the first econometric research on the market was emerging (see, for example, Kenneally & McCarthy 1982). While it is not proposed to examine this early literature in detail, the details of one paper are useful motivation for this research. Using a partially mix-adjusted quarterly dataset of new house prices from 1971 to 1980, Thom (1983) outlined a model where the change in house prices is positively related to excess demand. Six demand shifters were included in the analysis: income (proxied by higher-frequency industrial production data); demographic factors (the ratio of marriages to private sector completions); user-cost (net real rate of interest less anticipated change in house prices); credit conditions (described presently); and two other credit market factors, the mortgage repayment in real terms and the elasticity of the present value of the stream of mortgage repayments with respect to the discount rate.

Author	Period	Method	Fundamentals	Finding/Comment
Kenneally & McCarthy (1982)	1969IV-1976III	Quasi-inverted D; 6-eq'n system	Y, S, r_r, demog, q_mort, rhp_1	Levels not logs, lack of statistical significance; unsuccessful inclusion of credit rationing
Thom (1983)	1971I-1980IV	Inverted D; quasi-ECM	Y, S, r_r, demog, CCI, repayment, T	T as described in text; coeff on Y 1.68, coeff on CCI 0.69
Murphy (1998)	1974-1997	Inverted D	Y, S, r_r, pop2534, dY	Coeffs on Y, r 1.4 and -0.35 respectively: both low compared to other countries
Kenny (1999)	1975I-1997I	Inverted D; VECM	Y, S, r_n	Unit elasticities imposed; Y measured by agg GNP (no demographics)
Harmon & Hogan (2000)	1972-1999	Inverted D	Y, S, r_n, pop2534	Only Y significant; prices in 2000 above LR prediction
Murphy & Brereton (2001)	1974-1999	Inverted D	Y, S, r_r, pop2534, dY	LR equation unstable in period 1997-9; demand higher than predicted
IMF (2003)	1976-2002	Inverted D; ECM	Y, r_r, pop2534	1976-97 model suggests 50% overvalued in 2002; no stock measure; SOA=0.31
Stevenson (2003)	1978-2001	Ad hoc, based on inverted D	Y, S, r_r, pop, conf, empl, rhp_1	Interpretation unclear; model without lagged DV performs poorly
Roche (2004)	1979I-2003I	Regime-switching; ad hoc	Y, r_r, av_mort, migr, c_build, c_land	Good fit, but likely due to endogeneity issues (incl of land values)
McQuinn (2004)	1980I-2002IV	Inverted D; ECM in 3-eq system	Y, S, r_r, av_mort, migr, uc	User cost term dropped; LR coefficient on income very low (<0.2), SOA<0.14
Murphy (2005)	1974-2004	Inverted D; two-stage ECM	Y, S, uc, r_r, pop2534	Lower coeff on Y than S; dummies for financial liberalization; SOA=0.44
Rae & van den Noord (2006)	1977I-2004I	Inverted D; two-stage ECM	Y, S, r, pop2544	2nd-hand: coeff on Y and S similar (1.69, -1.68), SOA=0.34; new: only Y, S included
Stevenson (2008)	1978I-2003I	Inverted D; two-stage ECM	Y, S, r_r, pop2534	Large LR coeffs on Y (3.3), S (11); SOA= 0.08 (t-stat of 2); 18% overvaluation by 2003
McQuinn & O'Reilly (2008)	1980I-2005IV	Inverted D; two-stage ECM	Y + r_n (specific functional form), S	LR coeff on Y,r term 0.8; SOA=0.05; report that LTV when included not significant
Addison et al (2009)	1982IV-2009I	Inverted D; 2-eq system ECM	Y + r_n (specific functional form), S	SOA=0.17; coeff on joint Y,r term close to 1
Kennedy & McQuinn (2011)	1982I-2010IV	Inverted D; 2-eq system ECM	Y + r_n (specific functional form), S	Detailed results not reported; DOE price data replaced with hedonic price data post-1996
Kennedy & McQuinn (2012)	1980I-2011III	Inverted D; 4 variants	Y, S, r_r, pop / Y+r_n, S (as above)	Detailed results not reported; prices estimated at 12-26% below fundamental levels
Browne et al (2013)	1980I-2012IV	User cost	N/A	Real user cost of capital negative 1980-4 and 1998-2008

Table 5.1: *Overview of literature on Irish housing market; for notes, see text*

Credit conditions are measured using the growth rate in building society share and deposit liabilities; this measure performed statistically better than alternatives such as average loan-to-value or total mortgage approvals. While not an error correction model, as no lagged level is included, all variables are statistically signifcant at 5% with the expected sign. The implied long-run equation suggested an elasticity of prices with respect to income of 1.68 and to mortgage availability of 0.69.

Late 1990s A number of studies of the Irish housing market appeared between 1998 and 2001, concurrent with a major review of policy in relation to the housing market, known as the Bacon Report. These were typically inverted demand models, using annual data from the 1970s. A summary of four of these, Harmon & Hogan (2000), Kenny (1999), Murphy (1998), Murphy & Brereton (2001), is given in Table 5.1. The most comprehensive, by Murphy & Brereton (2001), concludes that the long-run equation for real house prices was unstable towards the end of the sample (1997-9), suggesting that demand was higher than predicted, a possible indicator of bubble conditions.

Mid-2000s Between 2003 and 2006, a number of studies of Irish housing prices were undertaken, as there were renewed concerns, particularly among international organisations, that the Irish housing market exhibited bubble conditions. In particular, two key metrics – the price-income and price-rent ratios – had risen steadily from 1996 onwards. Table 5.1 lists seven studies: IMF (2003), McQuinn (2004), Murphy (2005), Rae & van den Noord (2006), Roche (2004), Stevenson (2003). This includes papers by the IMF, the OECD and papers commissioned by the Central Bank of Ireland and Ireland's National Competitiveness Council. Two further papers, Stevenson (2008) and McQuinn & O'Reilly (2008), also date from this period, with the later date of publication reflecting the peer-review process.

None of these includes a continuous measure of credit conditions or financial liberalization and some suffer from other issues. For example, analysis by IMF (2003) includes no measure of housing stock, while the preferred specifications in Stevenson (2003) and Roche (2004) are ad-hoc in nature. While McQuinn (2004) uses solid theoretical foundations, the inclusion of the average mortgage term is problematic, and the model has a very low long-run elasticity of price with respect to income (less than 0.2) and slow speed of adjustment (0.14).

Both Murphy (2005) and Rae & van den Noord (2006) use inverted demand error-correction models (ECM), although both impose an error correction term using first-stage OLS results. Murphy (2005) includes dummy variables for financial liberalization and the results indicate rapid adjustment to equilibrium prices, although the coefficient on income is less than on the stock of dwellings, perhaps due to the use of a count of dwellings, rather than their value, which may fail to capture quality increases over time. Rae & van den Noord (2006) use quarterly data in an ECM framework, and the results (for prices of second-hand houses at least) indicate rapid adjustment (speed of adjustment, SOA, of 0.34) and a similar magnitude of coefficients on income and housing stock (roughly 1.7). These strong results come despite the inclusion of no measure of credit conditions; however, the authors do not explain how their results differ so substantially to the existing literature at that time.

Post-crash Since the crash, there has been a growing body of work examining the determinants of Irish house prices. Of interest for this analysis is work by Addison-Smyth et al. (2009), who present a two-equation system of average mortgage levels and house prices that builds on McQuinn & O'Reilly (2008). Analysis by McQuinn & O'Reilly (2008), on the price of new dwellings, uses a specific form of borrowing capacity, that is effectively a restriction on how income and interest rates affect prices. Addison-Smyth et al. (2009) extend this, before undertaking a supplementary specification including the "funding rate", the ratio of the outstanding level of mortgage lending to total domestic deposits. This is found to have considerable power in explaining average mortgage levels in the first stage and thus in explaining average house prices. A plot of fundamental house prices including this factor matches price developments more closely than the more restricted model of mortgage levels.[2]

Two technical papers by economists at the Central Bank of Ireland have recently attempted to understand fundamental house price levels and their likely future path in the post-crash era. Kennedy & McQuinn (2011) uses the model in Addison-Smyth et al. (2009), extending the sample to 2010Q4 and using improved house price information from 1996. They do not report their econometric results in detail, however. Similarly, an overview of house prices in 2011 using four different specifications, all based on the inverted demand approach and including the Addison-Smyth et al. (2009) funding-rate specification, suggests that house prices in mid-2011 were below their fundamentals, by between 12% and 26% (Kennedy & McQuinn 2012).

User cost It is worth noting that there are no known price-rent models of the Irish housing market exist and there has been only a limited interest in the user-cost of Irish housing. Research by Barham (2004) found that user cost associated with owning housing in the Irish market was negative for large parts of the period from 1976 on, principally due to the favourable tax treatment afforded owner-occupancy (including the lack of an annual property tax, any capital gains tax on principal private residences, and generous mortgage interest relief, grants and subsidies). More recently, Browne et al. (2013) have updated this analysis, finding that the user cost is dominated by expected capital gain, where this is measured with the annual gain over the last four years.

Clearly, a negative user cost implies a negative real price of capital, which would be associated with infinite demand. This can be reconciled with basic

[2] McQuinn & O'Reilly (2008) include the average loan-to-value reported by the DOE in robustness checks but this does not improve the fit of their model, which has a very slow speed of adjustment (close to 0.05). For why this might be, see Section 5.3.10.

economic theory in one of two ways. The first is that demand was indeed infinite when the measured user cost was strongly negative, but credit constraints remained – even if in diminishing form during periods of credit liberalization – which limited the quantity of credit and thus the quantity of housing demanded. Alternatively, with credit market liberalization, there were no remaining constraints on demand but instead the measured user cost was not accurate, excluding among other things the risk premium (which is likely to be time-varying), other costs of transactions (such as agent and movers' fees), and psychological costs of moving, which may be significant. In particular, the omitted risk premium is plausibly a function of variables included in the long run solution: for example, it might depend on a measure of overvaluation represented by the deviation of prices from the included long run determinants.

5.3 Data

This section outlines the data used in the analysis of Ireland's housing market. In addition to discussions of the price and rent data, there are sections reflecting each of the fundamentals outlined in Section 5.1: income, housing stock, demographics, interest rates, expected capital gain, transaction costs and credit conditions.

5.3.1 House Prices

The quality of information on trends in Irish housing prices over the period analysed is mixed. Nonetheless, it possible to connect up two sources, the Residential Property Price Index by Ireland's Central Statistics Office (CSO, 2005-2012) and the ESRI index (1996-2010, based on mortgages issued by the PTSB bank) to generate a hedonic index of Irish housing prices from 1996 until the end of the sample.[3]

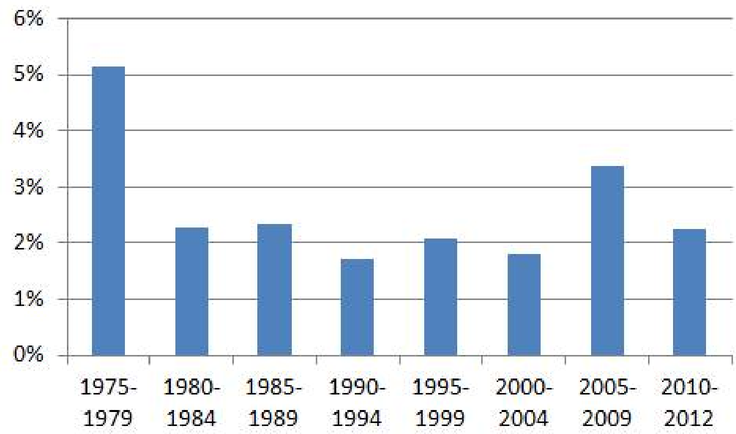
[3] Where a level of house prices is needed, for example comparing actual and fitted values, the Census-weighted average price from the 2012Q4 Daft.ie Report was used.

For the period prior to 1996, however, the only information is a raw average of transaction prices (as reflected by mortgage transactions), provided by the Department of the Environment from the 1970s. Quarterly information for all dwellings (both new and second-hand) is available from 1978Q1, while information on new dwellings is provided quarterly from 1975Q1. There is information on housing prices in Ireland published by the Department of the Environment from 1950 to 1975, but it is affected by changing periodicity (annual from 1965 and 5-yearly prior to this), geographic coverage (Dublin-only, prior to 1968) and scope (alternating between all properties, new dwellings, and new and second-hand separately).

Inflation Conversion from nominal to real house prices is done using the Consumer Price Index (CPI), excluding mortgage interest. This is available from 1975Q4 on. (For any analysis prior to this, the CPI ex-mortgage interest is extended backwards using quarterly changes in the full CPI.) Using the information on house prices and general price levels, this yields two key variables: $lrhp$ and $dlrhp$, the log and change in log of real house prices.

Extending back to 1975 In Section 5.4, the principal analysis is undertaken on the period 1980-2012. As explained above, quarterly data on prices of new dwellings do exist for the period 1975-1978; however, as is shown in Figure 5.1, there is significantly greater volatility in the quarterly change in real house prices in this earlier period. The standard deviation in the quarterly change in real house prices for 1975-9 was over 5%, more than twice the average standard deviation for other intervals shown. This may result from economic factors – the late 1970s saw high inflation which ultimately saw Ireland break its peg with sterling – or due to data issues, as mean prices refer before 1978 solely to new dwellings. Regardless, the greater volatility during the late 1970s affects the precision with which the long-run equation can be estimated, thus a model spanning the entire 1975-2012 period is presented as a supplement to the main analysis.

Figure 5.1: *Standard deviation in quarterly real house price changes, 1975-2012*

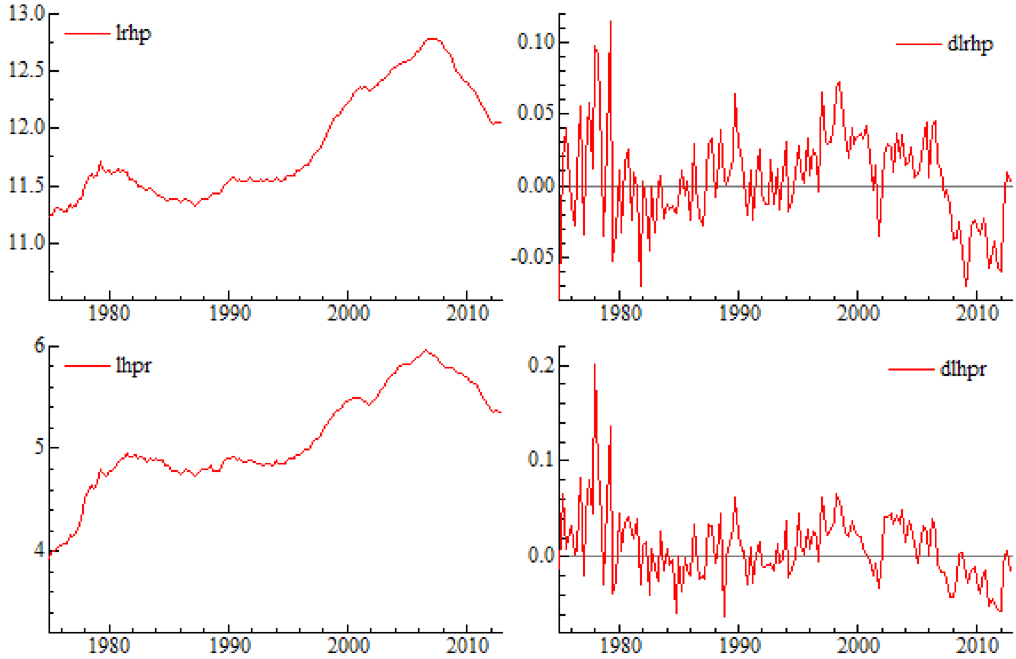


5.3.2 Rents

Information on rents, needed to calculate the price-rent ratio, is from the CSO. While an alternative, mix-adjusted series is available for the period 2002-2012, to investigate the ratio prior to this date, CSO information – typically gathered via a small survey of landlords and lettings agents – is needed. This is available on a quarterly basis, as part of the Consumer Price Index, from 1947 on. As with prices, these indices are converted to levels using the Census-weighted average rent according to daft.ie in 2012Q4 and, where necessary, nominal rents are converted to real rents using the CPI excluding mortgage interest. Using series for house prices and rents gives: *lhpr* and *dlhpr*, the log and change in log of the house price to rent ratio, *hpr*. The various dependent variables are shown in Figure 5.2.

Private renting in Ireland Between 1961 and 1991, the proportion of people renting in Ireland halved to 18%, led initially by falling numbers in private rented dwellings and then by those renting from local government. The fraction of renters rose to 26% between 2002 and 2011, as the proportion privately

Figure 5.2: *Plot of dependent variables, 1975-2012*



renting almost doubled from 11% to 19% in that period. The rapid decline in renting, particularly in the 1970s and 1980s, was associated with a halving in real rents between 1973 and 1983.[4] Coupled with this, there were significant reforms of the private rented sector in Ireland in the late 1990s and early 2000s. This is discussed in more detail in Section 5.6 on the price-rent ratio.

5.3.3 Income

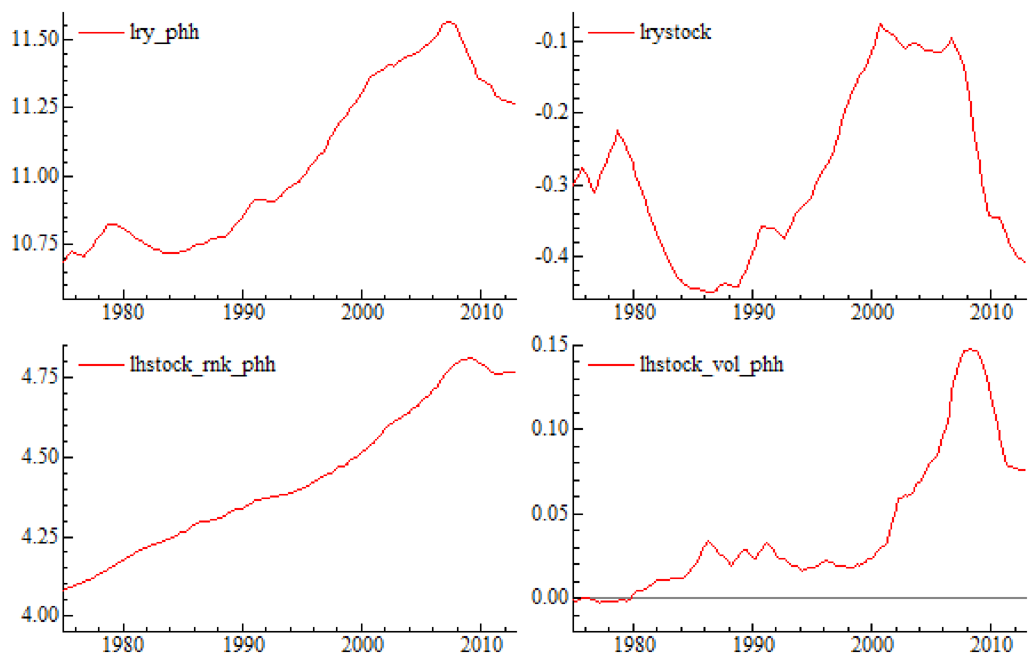
Information is available annually from the AMECO database for the period 1960-2012 on per capita real and nominal gross national disposable income (GNDI)DG ECFIN (2013). As this includes non-labour sources of income, and is after-tax, this is preferred to alternatives such as nominal compensation per employee, which is available on an annual basis, or quarterly earnings data, which are only available (through the CSO) from the 1980s on. Annual infor-

[4]The impact of any rent controls on the level of rents and proportion renting is a topic for future research.

mation on disposable income per capita is converted into quarterly information using interpolation such that the annualized Q4 figure matches the end-of-year statistic in the AMECO database, giving *lry* and *dlry*, log and delta-log of real income per capita or per household (depending on the specification).

As outlined below, the per-household series (*lry_phh*) is preferred to per-capita series, due to its stationarity properties, with the ratio of persons per household captured separately; see Section 5.3.6. Similarly, the ratio of income to housing stock, in log form, is used frequently (*lrystock*). Figure 5.3 plots income per household, the income-housing stock ratio, and the value and volume of housing stock per household, all in logs, for the period 1975-2012.

Figure 5.3: *Plot of regressors: income and housing stock, 1975-2012*



5.3.4 Housing Stock

Ireland's housing stock can be measured in either units (number of dwellings, *hstock_vol*) or value (in constant-price euro, *hstock_rnk*). The latter has the advantage of capturing any changes in the size and mix of housing (e.g. a greater proportion of apartments over time, or counter-cyclical improvements to housing due to negative equity and thus a lack of mobility). For this reason, the real net capital stock in dwellings was used. This is available on an annual basis as part of the CSO National Accounts from 1985 on. For the period preceding this, real gross fixed capital formation in dwellings was used, together with the depreciation rate implied by the National Accounts, to give net fixed capital formation. This rate was estimated from difference between gross and net formation for the period after 1985. For the decade 1986-1995, the rate was a constant 1.66%, so this rate was applied to figures prior to 1985.

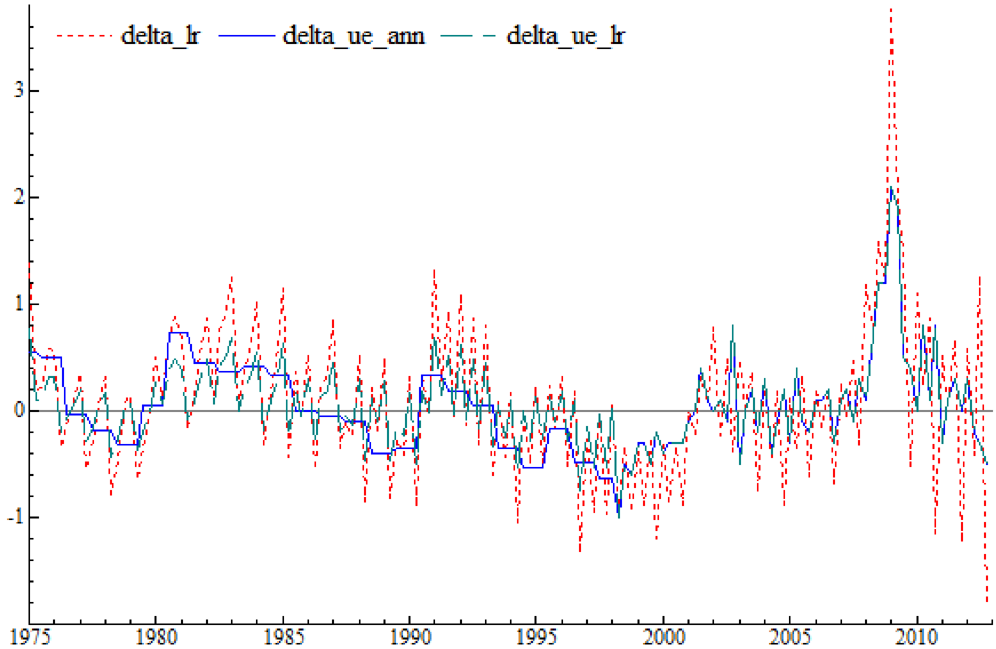
Combining the log of housing stock per household in constant prices (*lhstock_rnk_phh*) with the series on real income gives *lrystock*, the log of the ratio of real income to the stock of housing, measured in 2012€. To give an idea of the scale of this variable, in late 2012, per-household income was measured at €78,000, while per-household housing stock was valued at €117,000, giving a ratio of income to stock of 0.67.

5.3.5 Unemployment

While the bulk of labour market effects will be captured by disposable income, included in certain specifications of the dynamic modelling of changes in real house prices and the price-rent ratio are measures of unemployment. For the period 1998Q1 to 2012Q4, the (seasonally adjusted) unemployment rate is taken from Ireland's Quarterly National Household Survey (QNHS), administered by the CSO, which is Ireland's official unemployment rate. The series is extended to the 1970s using the percentage change in the Live Register, a monthly indicator of those in receipt of unemployment benefits. An alternative is to use a four-quarter moving average of the annual unemployment rate provided by AMECO (ultimately also from the CSO). In all cases, it is the change in percentage points (*delta_ue*) that is included in dynamic specifications.

As illustrated in Figure 5.4, using the AMECO annual data on unemployment (*delta_ue_ann*) results in the same change in unemployment rate in each quarter of a year. Conversely, the Live Register (*delta_lr*) series may be subject to seasonal swings, although this is found to be unimportant empirically. The preferred series is *delta_ue_lr*, which uses the QNHS series after 1997 and changes in the Live Register before this.

Figure 5.4: *Plot of regressors: change in unemployment, 1975-2012*



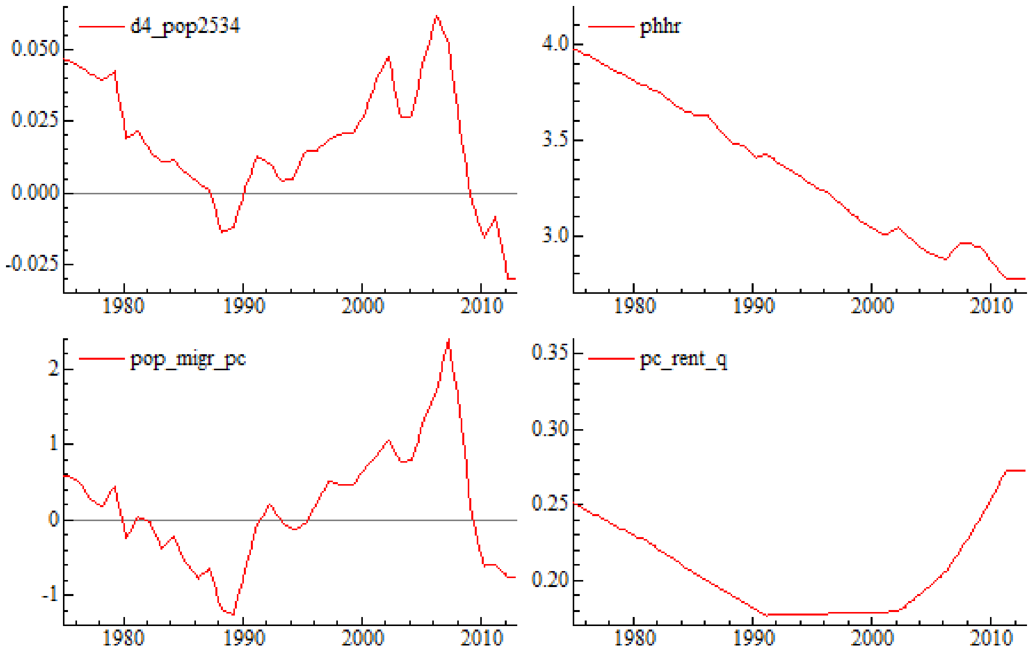
5.3.6 Demographics

Three potential series of demographics are included in the dataset. The first is the proportion of the population aged between 25 and 34, typically regarded as the "home-buying cohort". This is available from annual data published by the CSO and is interpolated into quarterly data. As outlined in Section 5.3.11, $ln(pop_{2534})$ is I(2), so any long-run solution will involve the delta-log form, $dln(pop_{2534})$. The second demographic series is net migration (*pop_migr_pc*), which again is measured annually by the CSO and expressed as a percentage of the total population.

Lastly, and new to studies of the Irish housing market, is the ratio of persons to households, *phhr*. Everything else equal, a smaller number of persons in the average household is associated with a higher level of demand, as the same population is spread across a greater number of dwellings. The number of households is available at typically five-year Censal intervals, while the total population is available on an annual basis. Interpolating the number of households between Census years gives annual and quarterly series for the person to household ratio, *phhr*.

Plots of four demographic variables are given in Figure 5.5: the change in population aged 25-34 (in logs); the person-to-household ratio; the net migration rate (in percent); and the percentage in rented accommodation, *pc_rent_q* (a quarterly interpolation; discussed in more detail in Section 5.6).

Figure 5.5: *Plot of regressors: demographics, 1975-2012*



5.3.7 Interest Rates

Mortgage market interest rates are taken from official sources. For the period from 2003, the quarterly average of the annual percentage rate of charge (APRC) reported by the ECB is used. For the period 1975-2002, the data are from the CSO "representative Building Society mortgage rate". These are variable rates, as these represent the vast majority of mortgages in Ireland; according to Kennedy & McIndoe-Calder (2011), just 15% of the loan-book of the four major Irish lending institutions at the end of 2010 was based on fixed-rate mortgages, most of which revert to variable rates after a certain period.

The series form the gross nominal mortgage rate rm^{GN}, where rm stands for mortgage rate (as opposed to deposit rate or some combination), G for gross and N for nominal. The net nominal mortgage rate, rm^{NN}, is calculated by deducting the marginal rate of mortgage interest relief. For the period 1975-1992, the marginal tax rate for first-time-buyers is lower than the top marginal rate. This is typically lower by one band and is based on average salaries at the time; see Figure 9 in the appendix for more details.

Opportunity cost Technically, if a downpayment of θP is required, where P is the house price, the opportunity cost for a first-time buyer is not given solely by rm. Rather it is given by a weighted average of $\theta rd + (1 - \theta)rm$, where rd represents the (after-tax) rate of return on alternative investments. Using typical deposit rates for rd, a series giving this overall rate of interest is available, using crude information on loan-to-value as discussed below, for θ. In this case, information on rd^{NN}, the net nominal interest rate on deposits, comes from the Central Bank of Ireland (the gross rate) and the Revenue Commissioners (on the rate of tax applied to interest, DIRT).

5.3.8 Expected Capital Gain

Gross interest rates are only part of the cost of home ownership. An offsetting component of user cost is the expected capital gain: if interest costs are 5%

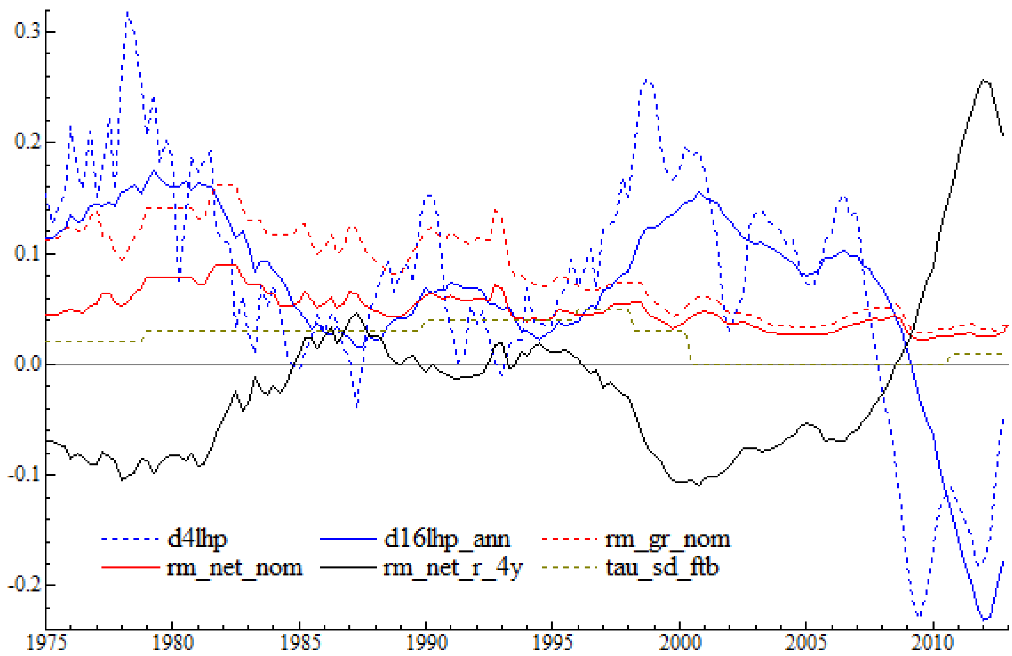
per year but nominal house prices are expected to grow by 10% per year, assuming no other costs to ownership, the real user cost would be perceived as negative. Unfortunately, there are no consistent data on expected capital gains in residential housing for the whole period under analysis. Two separate surveys exist, one by ESRI-IIB for the period 2003-2007 and another by daft.ie from 2012 on.

Based on the top-level findings of both these surveys, one cannot reject a null hypothesis of adaptive expectations, i.e. that housing market participants look at the recent history of the market as their best guide regarding the future direction of prices. For example, in early 2007, a year when nominal house prices were at best stable, participants expected strong price growth, as had been the case in recent years. Similarly, in early 2012, consumers expected prices to fall 10%, the average rate over the previous four years; prices actually fell by 4% in 2012.

The existing literature suggests that for other countries, the four-year average and one-year rates of change in nominal house prices often perform well as measures of expected capital gains based on adaptive or extrapolative expectations (Muellbauer 2012). Depending on the specification, either or both are used here in explaining real house prices and the price-rent ratio, as explained below. This is denoted in the suffix to the net interest rate, where rm^{NR4} indicates an interest rate net of expected capital gains, based on four-year appreciation.

Figure 5.6 plots on one chart annualized changes in nominal house prices over 1- and 4-years ($d4lhp$ and $d16lhp\_ann$; blue lines), the gross and net nominal interest rates (rm_gr_nom and rm_net_nom; red lines), and the principal measure of net user cost, based on deducting four-year house price inflation from the net nominal rate ($rm\_net\_r\_4y$; black line). Also included in this plot is the stamp duty rate that applied to first-time buyers at prevailing house prices (tau_sd_ftb).

Figure 5.6: *Plot of regressors: user-cost, 1975-2012*



5.3.9 Other Costs

Typically, a major cost of owner-occupancy is annual property taxation. However, unusually for developed countries, Ireland had no annual property tax on the typical property for almost all the period under analysis. Recurring property taxes were abolished in 1978 and only reinstituted in 2013. The only exception was a property tax that applied during the period 1983-1996, where certain valuation and income thresholds applied that would not be relevant to the typical first-time buyer (roughly speaking, where both house values and incomes were twice the average). Instead, property taxes took the form of stamp duties, i.e. transaction taxes. The percentage rate that applied was subject to certain bands, but for a first-time buyer of a house of average value, the rate varied during the period from 5% in the late 1990s to 0% throughout most of the 2000s. This is denoted τ^{SD}.[5]

[5] Figures were collected on first-time buyer grants and subsidies available from 1977 to 2002. These were included in additional specifications checking the robustness of results but

Maintenance & transaction costs It is possible to use the CSO Household Budget Survey 2010 to estimate the amount spent on maintenance; based on spending and housing prices in 2010, households spend on average about 0.5% of the value of their dwelling on maintenance. However, setting a fixed proportional cost of maintenance means that this does not vary over the period and thus is irrelevant for a dynamic model of changes in house prices over time. Likewise, based on costs prevailing in early 2013, the (one-off, rather than annualized) financial costs of moving were set at 5%, and as research on the housing market suggests that psychological costs of moving are at least as large as financial costs, these were also set at 5% (Bayer et al. 2011). However, as these do not vary, by construction, they too can play no role in explaining house price changes if the model is linear in user cost. A more detailed understanding of these costs and how they vary over time is a topic worthy of further research.

Risk premium It is very likely that prospective first-time buyers have some assessment of how risky a purchase would be. Nonetheless, research understanding the risk premium associated with owner-occupancy is in its infancy – although Sinai & Souleles (2005) use a model where owner-occupancy is itself a hedge against rent risk. Crucially, the risk premium is likely to be time-varying. Two *ad-hoc* formulations of the risk premium were included in candidate models: the first uses a discounted average of the absolute value of changes in prices over the last four years; the second uses the standard deviation of the last four annual changes in house prices. Neither features as an economically or statistically significant variable.

5.3.10 Credit Conditions

The final fundamental in the housing market – often an omitted variable – is credit conditions. Like the risk premium discussed above, this is often ex-

were found to have no significant effect on real house prices.

cluded as it is viewed as difficult to measure. The Global Financial Crisis and subsequent "Great Recession", however, are a powerful reminder of the importance of including some measure of credit conditions, when trying to understand housing price trends. For Ireland, for the period under consideration, credit conditions are measured using the ratio of mortgage credit to domestic deposits. As mentioned in Section 5.1.1, credit conditions may vary with trends in financial liberalization or due to cyclical appetite among financial institutions for mortgage assets; i.e. they may be due to technology or preferences. Both may be reflected in the ratio of credit to deposits, although it should be noted that this may not capture other forms of liberalization, for example policies that limited credit growth which may also have affected deposits.[6]

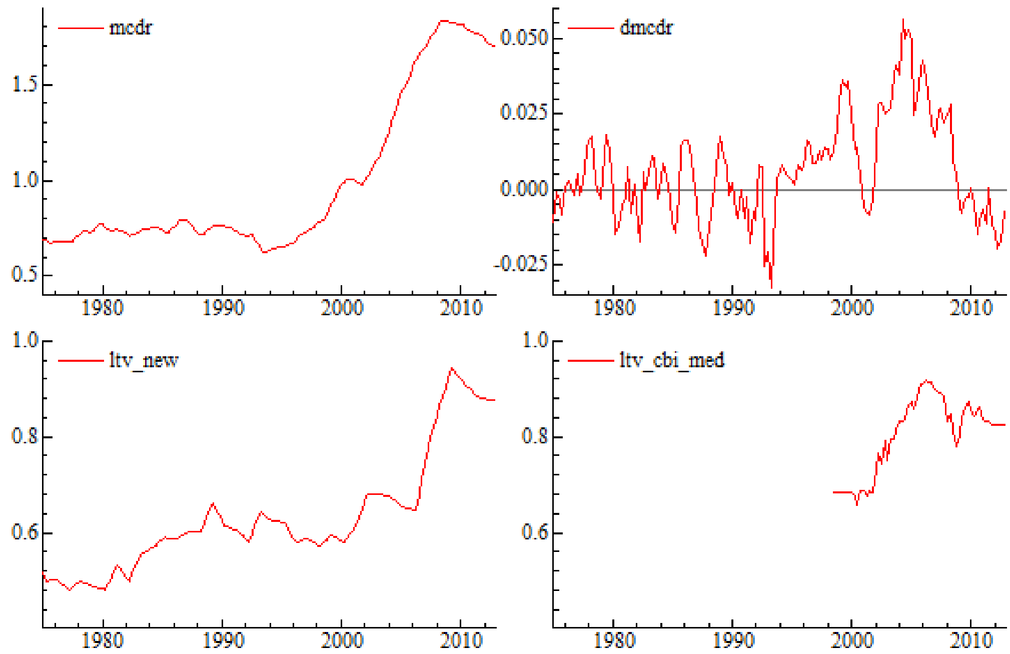
In the case of Irish financial institutions, the most important structural change in the mortgage credit market in the period being analysed was the increasing reliance by Irish banks after entry into the Eurozone on bond financing of mortgages. Thus it is particularly important that the measure of credit conditions used reflects this change. The ratio of credit to deposits was below 80% for the entire pre-Eurozone period but more than doubled to 180% by 2007. The potential endogeneity of this measure is discussed later.

For the period 2003-2012, Central Bank of Ireland data on the outstanding amounts (including securitized loans) of loans for house purchase were used, as were total deposits from Irish private households. This series was extended back to the 1970s using quarterly data from the IMF *International Financial Statistics* on demand and other deposits, and on domestic credit.[7] The series displays some quarter-on-quarter volatility that may not reflect the more slowly-moving nature of credit conditions, so a four-quarter moving average was taken; this series is denoted *mcdr*, i.e. the mortgage credit-deposit ratio.

[6] Work by Meen (1990) investigates a related issue, the pre-1981 rationing of mortgage credit in the UK.

[7] Series breaks in 1976, 1982 and 1995 were, by necessity, ignored; growth in the relevant series for those quarters was set to zero.

Figure 5.7: *Plot of regressors: credit conditions, 1975-2012*



Loan-to-value Some existing studies investigating the role of non-price credit conditions have used the loan-to-value ratio faced by the marginal first-time buyer (Duca et al. 2011*a*). Aggregate statistics on the volume of lending and the average house price, collected by the Department of the Environment (DOE) do yield a figure that can be interpreted as the average loan-to-value for all property purchases in a given year (and thus used to give θ described above). However, this is not the same as the marginal LTV ratio and may be skewed by positive equity during periods of rising prices. A new loan-level Central Bank of Ireland (CBI) dataset, detailed in Kennedy & McIndoe-Calder (2011) and used in Chapter 4, can be used to calculate the mean and median loan-to-value for first-time buyers across four Irish-owned financial institutions (all subsequently recapitalized by the Irish state), for the period 2000-2011. The series is based on over 100,000 loans on the books of the four institutions as at end-2011.

Figure 5.7 plots the estimated ratio of mortgage credit to deposits (*mcdr*),

Indicator	Source	Period	Orig. Frequency
House prices	DoE	1975-1996	Quarterly
	ESRI-PTSB	1996-2005	Monthly
	CSO	2005-2012	Monthly
Rents	CSO	1975-2012	Monthly
Consumer prices	CSO	1975-2012	Monthly
Income	AMECO	1975-2012	Annual
Unemployment rate	QNHS	1998-2012	Quarterly
	AMECO	1975-1998	Annual
Live Register	CSO	1975-2012	Monthly
Stock capital in dwellings	CSO	1975-2012	Annual
Housing stock (volume)	DOE	1975-2012	Annual
Mortgage rates	ECB	2003-2012	Monthly
	CSO	1975-2002	Monthly
Deposit rates	CBI	1975-2012	Monthly
DIRT rates	RevComm	1986-2012	Monthly
Stamp duty rates	RevComm	1975-2012	Monthly
MIR rate	RevComm, Barham	1975-2012	Monthly
Grants & subsidies	Barham	1975-2012	Annual
Mortgage credit	CBI	2003-2012	Monthly
Household deposits	CBI	2003-2012	Monthly
Private sector credit	IFS	1975-2003	Quarterly
Private deposits	IFS	1975-2003	Quarterly
Average LTV	DoE	1975-2012	Annual
Median LTV	CBI	2000-2012	Monthly
Maintenance	CSO HBS	2011	Parameter
Moving costs	Author calculations	2013	Parameter

Table 5.2: *Overview of dataset*

the change in that ratio (*dmcdr*, used in dynamics), the estimated DOE series for loan-to-value on new dwellings[8], *ltv_new*, and the CBI series on median loan-to-value for first-time buyers, from 2000 on (*ltv_cbi_med*). What is striking is how the DOE loan-to-value series peaks after the bubble. The average loan-to-value on new dwellings in mid-2006 was 65%, when both prices and the CBI series on LTV peaked, but nearly 95% at the turn of 2010. Overall, it is clear from the series that the DOE data do not capture accurately the timing of peak in loan-to-value and its subsequent fall. Thus, where the focus of analysis is a period longer than 2000-2012, the ratio of credit to deposits will be used, instead of DOE data on loan-to-value. An overview of all data is presented in Table 5.2.

[8]Note that this includes purchases of new dwellings by investors and other purchasers, as well as by first-time buyers.

5.3.11 Stationarity properties

Table 5.3 outlines the results of augmented Dickey-Fuller tests for a unit root, across all the major variables. Results are shown for the deltas of each variable, thus highlighting whether any series are I(2), thus potentially biasing analysis including such variables in a long-run solution with I(1) series. For all variables in Table 5.3, the sample is 1980I-2012IV, with the 1%, 5% and 10% critical values of -3.48, -2.88 and -2.57 denoted by three, two and one stars respectively.

Using a 10% significance level, it is possible to conclude that in delta form, almost all the variables are stationary, including *dlrhp*, *dlhs_ph*, *dlyhs*, *dmcdr*, *drm_net*, *dphhr* and *due*. Failure to reject the null of a unit root occurs for income per household (*dlry_ph*), although this appears to be marginal, and the proportion of the population aged 25-34, ($d4p2534$). These are explored in more detail in Table 9 in the Appendix. This table presents strong evidence in favour of using the per-household formulation of income and housing stock (suffix *_ph*), instead of the per-capita series (*_ph*), with no rejection of the null hypothesis of a unit root at any conventional significance level for either income per capita or housing stock per capita.

Thus, it is clear that per-capita series for income and housing stock are I(2). Are the per-household series I(2) or I(1)? Results for the 1975-2012 sample for both, denoted by the suffix † in Table 9, suggest that the lack of statistical significance at the 5% or 1% levels for income and stock per household in the 1980-2012 sample may relate more to the power of the test than to the underlying data series. One means of overcoming any uncertainty about the stationarity of changes in income and stock is to use instead changes the ratio of income to stock: at the 10% level for the 1980-2012 series, and at the 1% for the 1975-2012 series, the null of a unit root in *dlrystock* can be rejected.[9]

[9]These results come from use of quarterly data interpolated from annual data. Nonetheless, test results do not change if only annual data are used instead.

Table 5.3: *ADF unit root tests*

Var	D-lag	t-adf		beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
dlrhp	3	-2.908	**	0.775	0.021	1.044	0.298	-7.657	
	2	-2.735	*	0.795	0.021	-3.829	0	-7.664	0.298
	1	-4.063	***	0.698	0.022	-2.893	0.005	-7.57	0.001
	0	-5.691	***	0.607	0.023			-7.523	0
dlry_ph	3	-2.389		0.909	0.005	0.496	0.621	-10.73	
	2	-2.344		0.913	0.005	-0.082	0.935	-10.74	0.621
	1	-2.427		0.912	0.005	0.511	0.611	-10.76	0.881
	0	-2.379		0.916	0.005			-10.77	0.916
dlhs_ph	3	-2.734	*	0.879	0.002	0.353	0.725	-12.54	
	2	-2.739	*	0.883	0.002	0.783	0.435	-12.56	0.725
	1	-2.632	*	0.891	0.002	0.141	0.888	-12.57	0.694
	0	-2.687	*	0.892	0.002			-12.58	0.861
dlyhs	3	-2.619	*	0.887	0.005	0.04	0.968	-10.76	
	2	-2.689	*	0.887	0.004	0.521	0.603	-10.78	0.968
	1	-2.646	*	0.892	0.004	-0.156	0.877	-10.79	0.874
	0	-2.764	*	0.891	0.004			-10.81	0.961
dmcdr	3	-2.975	**	0.857	0.009	-0.347	0.729	-9.466	
	2	-3.225	**	0.852	0.009	1	0.319	-9.48	0.729
	1	-3.067	**	0.865	0.009	1.037	0.302	-9.488	0.575
	0	-2.896	**	0.877	0.009			-9.494	0.538
drm_net	3	-3.156	**	0.689	0.008	1.116	0.267	-9.526	
	2	-2.959	**	0.72	0.008	-3.618	0	-9.532	0.267
	1	-4.751	***	0.574	0.009	-0.871	0.386	-9.449	0.001
	0	-6.088	***	0.534	0.009			-9.459	0.002
dphhr	3	-4.963	***	0.67	0.005	1.92	0.057	-10.57	
	2	-4.529	***	0.719	0.005	1.632	0.105	-10.55	0.057
	1	-4.198	***	0.756	0.005	1.411	0.161	-10.55	0.044
	0	-3.939	***	0.783	0.005			-10.55	0.042
due	3	-3.635	***	0.707	0.044	3.056	0.003	-6.231	
	2	-2.882	*	0.768	0.045	-1.662	0.099	-6.175	0.003
	1	-3.517	***	0.728	0.045	-5.01	0	-6.169	0.003
	0	-6.206	***	0.541	0.049			-6.006	0
d4p2534	3	-1.82		0.985	0.002	-0.921	0.359	-12.76	
	2	-2.091		0.984	0.002	-0.486	0.628	-12.77	0.359
	1	-2.309		0.983	0.002	17.08	0	-12.79	0.583
	0	0.4483		1.006	0.003			-11.62	0

5.4 Inverted Demand Model

In modelling changes in real house prices, there are two sets of factors that may be relevant. The first is long-run fundamentals, including income, housing stock, credit conditions, demographics, and user and transaction costs. The second set of factors is short-run dynamics. While it less clear from theory which dynamics are most likely to matter, six potential factors are suggested from existing research: lagged changes in real house prices (autoregression);

changes in inflation (whether changes in real house prices stem from the numerator or the denominator); changes in the nominal mortgage interest rate (cash-flow concerns); changes in credit conditions; changes in unemployment; and changes in net migration.

It is unclear what particular dynamics might apply to any of these factors – contemporaneous changes might be most important or conversely they may only matter at a lag of up to four quarters. While the following specification is clearly over-parameterized, with almost 40 parameters to be estimated from just over 130 observations in the sample 1980:I-2012:IV, it offers a useful starting point for analysis:

$$\begin{aligned} dlrhp_t = \beta_0 + \sum_{j=1}^{6}\sum_{s=0}^{4}\beta_{js}\delta x_{j,t-s} + \beta_{J+1}(lrhp_{t-1} - \alpha_1 lrystock_{t-1} \\ - \alpha_2 phhr_{t-1} - \alpha_3 dlpop2534_{t-1} - \alpha_4 mcdr_{t-1} - \alpha_5 rm^{NR4}_{t-1} - \alpha_6 \tau^{SD}_{t-1}) \quad (5.9) \end{aligned}$$

where $mcdr$ is the ratio of mortgage credit to household deposits, τ^{SD} the rate of stamp duty applicable to first-time buyers at average prices, and rm^{NR4} refers to the after-tax rate of mortgage interest less the annualized 4-year rate of house price inflation. The j subscript represents the following six potential dynamics: $dlrhp_{t-s}$, dr^{NN}_{t-s}, $dmcdr_{t-s}$, due_{t-s}, $infl_{t-s}$, and $migr_{t-s}$. Full regression output is given in Table 6 in Appendix .4.2. A long-run solution is immediately apparent from this model (one that excludes $dlpop2534$), but it is also clear that most of the dynamics are not statistically significant.

It is possible to iteratively develop increasingly parsimonious models by examining the p-values, and using a rule of thumb p-values of below 0.10 as a guide to potential statistical significance. For example, excluding all dynamic terms in inflation and migration (due to high p-values) still leaves none of the nominal mortgage rate terms significant (at a cut-off of 10%) nor any unemployment lags after the first (the fit of the model, as measured by its standard error, improves substantially, from 0.017 to 0.0165). Excluding these terms – and the fourth lag for $dmcdr$ – suggests that neither second nor third lags of *dlrhp*, nor the contemporaneous value of *dmcdr*, is statistically significant. Parsimony suggests omitting the second and third lags of *dmcdr*. Dropping the population aged 25-34, which is significant in none of the specifications, leaves a model with the following specification[10]:

$$\begin{aligned} dlrhp_t = \beta_0 + \beta_1 dlrhp_{t-1} + \beta_2 dlrhp_{t-4} + \beta_3 dmcdr_{t-1} + \beta_4 due_t + \beta_5 due_{t-1} \\ + \beta_6 (lrhp_{t-1} - \alpha_1 lrystock_{t-1} - \alpha_2 phhr_{t-1} \\ - \alpha_4 mcdr_{t-1} - \alpha_5 rm^{NR4}_{t-1} - \alpha_6 \tau^{SD}_{t-1}) \end{aligned} \quad (5.10)$$

A model with the fourth lag of *dlrhp* is strongly preferred to one without (sigma rises from 0.01673 to 0.01762 without this term), while similarly a model with the one-quarter lag in unemployment included is preferred to one with just contemporaneous changes in unemployment (sigma rises from 0.01673 to 0.01702).

Regression output for this model is shown in Table 5.4, while actual and fitted values are plotted in Figure 10 in Appendix .4.4. As noted above, the sigma for the regression is 0.01673, with the none of the six core tests of model specification indicating a rejection of the null hypothesis. For the period from 1980 to 2012, this model explains over two thirds of the changes in real house prices ($R^2 = 0.696$), with all variables strongly statistically significant (particularly fundamentals) and all with the sign suggested by theory.

5.4.1 Short-run dynamics

The model suggests that for the 33-year period under analysis, there were four elements that mattered for short-run house price dynamics, independent of forces pushing prices back towards their equilibrium level. The first is changes in real house prices in the previous quarter, an element of momentum in house prices. Every one percentage point (pp) increase in prices in the previous

[10] The same equation results from the use of Autometrics software that algorithmically develops a parsimonious model by omitting regressors based on statistical significance, once the long-run variables are forced to be included.

Table 5.4: *Model of dlrhp with parsimonious dynamics, 1980-2012*

	Coeff		S.E.	t-stat	p-value
$dlrhp_{t-1}$	0.1661	**	0.0791	2.10	0.0378
$dlrhp_{t-4}$	-0.256	***	0.0681	-3.76	0.0003
$delta\_ue$	-0.0162	***	0.0044	-3.67	0.0004
$delta\_ue_{t-1}$	-0.0104	**	0.0046	-2.29	0.024
$dmcdr_{t-1}$	0.3097	**	0.1209	2.56	0.0117
Constant	4.0786	***	0.6618	6.16	0.000
log rhp ($lrhp_{t-1}$)	-0.3137	***	0.0522	-6.01	0.000
log y/stock ($lrystock_{t-1}$)	0.3952	***	0.0777	5.08	0.000
person:HH ($phhr_{t-1}$)	-0.1222	***	0.0222	-5.49	0.000
credit:deposit ($mcdr_{t-1}$)	0.1743	***	0.0345	5.05	0.000
user cost (rm^{NR4}_{t-1})	-0.4812	***	0.0915	-5.26	0.000
stamp duty (τ^{SD}_{t-1})	-0.4757	**	0.2118	-2.25	0.0265
AR 1-5			F(5,115)	1.96	0.090
ARCH 1-4			F(4,124)	1.05	0.386
Normality			$\text{Chi}^2(2)$	1.31	0.520
Hetero			F(22,109)	0.57	0.937
Hetero-X			F(77,54)	0.90	0.665
RESET23			F(2,118)	1.12	0.331

quarter was associated with a 0.16pp increase in the current period. The second is the change in real house prices a year ago. Here, the relationship is negative: a percentage point increase in prices in the same quarter a year ago was associated with a 0.26pp decrease in the current period. Everything else being equal, large house price gains in particular quarter in one year were associated with price falls a year later, perhaps a form of supplemental error correction.

The other two factors reflect conditions in the mortgage and labour markets. A percentage point increase in the ratio of mortgage credit to deposits in the previous quarter was associated with a increase in real house prices of 0.31pp in the current period. Lastly, there was a negative relationship between unemployment and changes in house prices in the short-run, an effect that lasted two quarters: a one-percentage point increase in the unemployment rate in a given quarter was associated with a fall in house prices of roughly 1.6% in the same period and 1% in the following period.

5.4.2 Long-run equation

The model presents a clear long-run relationship that determines house prices over this period and indicates that there was fast adjustment to this equilibrium in the Irish housing market. The coefficient on $lrhp_{t-1}$ of -0.314 implies that almost one third of the gap between actual and equilibrium house prices was corrected every quarter. Compared to similar studies for other economies, this represents rapid adjustment, possibly reflecting Ireland's nature as a small, relatively homogeneous economy.

This coefficient can also be used to reveal the underlying long-run relationship between real house prices and their determinants. For the period under analysis, there are five fundamental factors that affected the equilibrium level of house prices. The long-run relationship suggested by the analysis is as follows:

$$lrhp_t = 13.002 + 1.26lrystock_t - 0.39phhr_t + 0.56mcdr_t - 1.53rm_t^{NR4} - 1.52\tau_t^{SD} \tag{5.11}$$

Income-stock ratio The model suggests a strong positive long-run relationship between real house prices and the ratio of household income to the stock of residential housing. The coefficient of just over 1.26 implies that price responds more than proportionately to changes in income and to housing supply. An increase in real income of 10% (relative to the stock of housing) is associated with a 12.6% increase in the real price of housing. The same coefficient can be interpreted as the absolute value of the inverse of the price elasticity with respect to supply; i.e. an increase in the real value of the housing stock of 10% is associated with a fall in real house prices of 8% (-1/1.26).

This coefficient is somewhat smaller than much of the existing literature, both for Ireland and for other countries. One set of existing estimates for Ireland have found the responsiveness of prices with respect to income is between 1.6 and 1.7 (Rae & van den Noord 2006, Thom 1983), while Murphy (1998) presents a lower estimate of 1.4. Similarly, studies of the UK market also suggest higher price elasticities with respect to income. The estimated elasticity presented here is stable, however, with the coefficient on the income/stock ratio stable from 1995 on (see Figure 13 in the Appendix). The data on which this estimate is based are in some sense novel, at least for the Irish case, as they reflect various periods in which incomes were rising rapidly, falling rapidly and also largely stable – most studies do not cover periods when incomes fell rapidly. This may explain the difference not only with respect to the UK case, but also the Irish case. Another window into price elasticities with respect to income could be given by a panel analysis exploiting variation in incomes and housing market outcomes across Irish counties.

Person-household ratio The results indicate a clear relationship between real housing prices in Ireland and the average number of persons per household. The negative coefficient in the long-run relationship of -0.389 can be interpreted as follows: between 1980 and 2012, the average number of people per household fell by one (from 3.79 to 2.78). This increase in effective demand per head of population was associated with a 39% increase in real house prices, controlling for other factors. Breaking the income per house restriction and including per-person or per-household income and stock separately and omitting average household size leads to omitted variable bias, in particular an upward bias on the income coefficient on this interpretation.[11]

[11] It is likely that average household size has some endogenous elements; in the long run, affordability and credit conditions may have an effect on household size. However, there will also be a large demographic component, including longer life spans, more widows, later marriages and more divorces, that will be mostly exogenous and, if excluded, caught up by the income coefficient. Here, omitting *phhr* from the model reduces the speed of adjustment to 10% and doubles the implied long-run coefficient on the ratio of income to housing stock from 1.26 to 2.57. The fit of such a model is substantially worse: the sigma of the regression increases from 0.01673 to 0.01864 and the R^2 reduces from almost 70% to 61.9%. This can be partially remedied by including per-capita income and housing stock separately; see Section 5.4.3 for more details.

Credit-deposit ratio Credit conditions, as measured by the ratio of the stock of mortgages to the stock of deposits, have a long-run impact on house prices, as well as a short-run impact. The coefficient of roughly 0.56 on the credit conditions term in the long-run equation indicates that an increase of ten percentage points in the ratio of mortgage credit to deposits was associated with an increase in real house prices of 5.6%. Ireland's credit-deposit ratio increased by 100 percentage points in the decade to 2007. The model suggests that this was associated with an increase in the equilibrium level of real house prices of 56%.[12]

Real interest rates The user cost for housing – as measured by the difference between nominal rates after tax reliefs and the expected capital gain based on the last four years – represent a drag on housing prices. The coefficient of -1.53 indicates that an increase in user cost of 1 percentage point is associated with a decrease in equilibrium real house prices of 1.53%. The user cost measured in this way increased by 30 percentage points (roughly speaking, from -10% to +20%) between 2006 and 2012. This was associated with a fall in equilibrium prices of 45%.

Stamp duty The final factor suggested by the error correction model as important for the long-run level of house prices is the rate of stamp duty applying to first-time buyer purchases. The coefficient of close to -1.5 on indicates that a decrease in the rate of stamp duty applying to first-time buyers of one percentage point was associated with a 1.5% increase in real housing prices. This more-than-proportionate response indicates that down-payment constraints for first-time buyers were important in the housing market, in the period under analysis. Nonetheless, the small number of changes to the stamp duty rate ap-

[12]Strictly speaking, these are increases in the log of real house prices, rather than in percentage terms. For a more formal discussion of the sources of house price changes over the period, see Section 5.7.

plicable to first-time buyers means that caution should be exercised in relying on this result.

5.4.3 Robustness & Sensitivity

A number of choices were made in the construction of the dataset, each of which may impact the results presented. Two tables in Appendix .4.3 outline a number of robustness and sensitivity checks. Coefficients and p-values are presented for variables, along with two measures of model fit (sigma and R^2) and also whether any of six standard tests failed: AR 1-5, ARCH 1-4, Normality, Hetero, Hetero-X, and RESET23. Also presented, in Figure 13, are recursive estimates of the parameters associated with the long-run variables. It is clear that there are no statistically significant changes in any of the coefficients, although there is small shift in a number of the coefficients between 2002 and 2004.

Table 7 in Appendix .4.3 takes the various fundamentals and explores alternatives for each. An extra fundamental is added, delta log of the proportion aged 25-34, which has almost no impact on the results, as the coefficient on the variable is close to zero. For credit conditions, instead of the ratio of credit to deposits, the estimated average loan-to-value for new dwellings is used. Presumably reflecting the weakness of this data series, the inclusion of this variable effectively destroys the long-run relationship.[13]

Five other specifications are included in Table 7, including splitting out income and stock (which reveals coefficients of similar magnitudes), using per-capita instead of per-household measures of income and stock (replacing the stock of housing measured in constant price values with a series on the number of dwellings, using a weighted rate of interest (across both mortgages and deposits), including a measure of grants for first-time buyers (relative to value), and an alternative measure of quarterly unemployment, based on interpolated

[13] In house price booms, repeat buyers have higher net equity stakes from past appreciation and so can reduce their LTV; hence, average LTV series that include purchasers other than first-time buyers will be a very misleading indicator of credit availability.

official annual unemployment rates instead of changes in unemployment implied by Live Register data. None of these changes has a meaningful effect on the long-run equation, but have worse fit than the specification outlined above.

The second table explores functional form, particularly for the three ratios included in the fundamental long-run equaton. The log of the ratio of income to housing stock was used in the principal specification, while the level of the two other ratios – mortgage credit to deposits, and persons to households – was used. In principle, one might think that as income and housing stock are both euro amounts, relativities matter more than levels, while for the credit-deposit ratio, ten percentage points of deposits lent out at the margin is roughly equivalent at different starting points. Table 8 investigates the importance of this, using different combinations of logs and levels for the three ratios.

While the overall fit of the model does not change greatly across all five specifications, it appears from the fit and test results that the level of the credit to deposit ratio is a better measure of credit conditions than the log, particularly in relation to dynamic effects. A specification where all three ratios (income/stock, credit/deposits, and persons/households) are included in logs suggests the following long-run house price elasticities: 1.15 for the income (relative to stock), 0.64 for the mortgage-deposit ratio, and -1.57 for the ratio of persons to households.

5.4.4 Nominal rigidities

The long-run relationship outlined in the previous section describes the determinants of real house prices in Ireland from 1980 on. However, this period comprises both high and low inflation regimes. The average quarterly change in consumer prices for the period 1975-1984 was 3.4% while for 1985-1994 it was 0.8% (very similar to the average for 1995-2013: 0.6%). Noticeably lower inflation increases the likelihood of some degree of money illusion, where households treat real and nominal prices as equivalent.

Table 5.5: *Model of dlrhp, 1980-2012, allowing nominal inertia after 1985*

	Coeff		S.E.	t-stat	p-value
dlrhp_1	0.157	**	0.076	2.08	0.040
dlrhp_4	-0.218	***	0.066	-3.31	0.001
delta_ue_lr	-0.018	***	0.004	-4.24	0.000
delta_ue_lr_1	-0.012	***	0.004	-2.85	0.005
dmcdr_1	0.239	**	0.118	2.02	0.045
Constant	3.747	***	0.674	5.56	0.000
lrhp_1	-0.294	***	0.052	-5.66	0.000
lrystock_1	0.439	***	0.078	5.60	0.000
phhr_1	-0.082	***	0.031	-2.64	0.009
mcdr_1	0.163	***	0.033	4.94	0.000
rm_net_r_4y_1	-0.397	***	0.100	-3.95	0.000
tau_sd_ftb_1	-0.522	*	0.208	-2.51	0.014
qinfl_ex	-0.975	***	0.272	-3.58	0.001
q_infl85	0.523		0.282	1.85	0.067
AR 1-5			F(5,113)	1.71	0.137
ARCH 1-4			F(4,124)	0.84	0.500
Normality			$\text{Chi}^2(2)$	0.017	0.992
Hetero			F(26,105)	0.956	0.532
Hetero-X			F(102,29)	1.46	0.121
RESET23			F(2,116)	0.447	0.641

This is explored in Table 5.5. As is clear from the table, full nominal inertia was a feature of the Irish housing market after 1985. In addition, the coefficients on both current and lagged changes in unemployment are not statistically significantly different from each other. Lagged values of the dependent variable have been omitted in this case, although this does not affect the overall shape of the implied long-run relationship, nor does their inclusion affect the findings regarding nominal inertia.

5.4.5 Modelling from 1975

As outlined in Section 5.3.1, quarterly data are available from 1975, although house prices changes in the 1975-9 period are substantially more volatile than during the subsequent 33-year period and for most of the period refer only to new dwellings. The core specification for the period 1980-2012 was applied to the dataset running from 1975Q2 on. The results are presented in Table 5.6,

Table 5.6: *Model of dlrhp extended back to 1975*

	Coeff		S.E.	t-stat	p-value
Constant	2.2556	***	0.4695	4.8	0.000
log rhp ($lrhp_{t-1}$)	-0.1646	***	0.0349	-4.72	0.000
log y/stock ($lrystock_{t-1}$)	0.1637	***	0.0515	3.18	0.0018
person:HH ($phhr_{t-1}$)	-0.099	***	0.0249	-3.97	0.0001
credit:deposit ($mcdr_{t-1}$)	0.0751	***	0.0261	2.88	0.0046
user cost (rm_{t-1}^{NR4})	-0.3205	***	0.106	-3.02	0.003
stamp duty (τ_{t-1}^{SD})	-0.1766		0.2495	-0.71	0.4802
$dlrhp_{t-1}$	0.0739		0.0789	0.94	0.3509
$dlrhp_{t-4}$	-0.0378		0.0758	-0.5	0.6185
$delta\_ue$	-0.0175	***	0.0059	-2.97	0.0036
$delta\_ue_{t-1}$	-0.0093		0.006	-1.55	0.1241
$dmcdr_{t-1}$	0.2982	*	0.1662	1.79	0.0749

while the actual and fitted values of *dlrhp* are shown in Figure 11 in Appendix .4.4.

The zig-zag nature of changes in real house prices in the late 1970s affects the autoregressive properties and thus the overall fit of the model (the R^2 is 51% compared to 70% for the model from 1980 on). The estimated income and credit conditions effects are smaller for the model from 1975 than from 1980 (such that the 1980 coefficients are well outside the 95% confidence interval). The effect of real interest rates and the person-household ratio, however, are larger in absolute size, while the stamp duty effect is not significant.

The substantially different results and fit for the 1970s suggests that a structural break in the Irish housing market around 1980. One candidate is the end of the parity peg between the Irish pound and sterling in early 1979, although it is left to future research – with data extending further back and of a higher quality – to examine the nature of the break and the model that preceded it.

5.5 Exogeneity and cointegration

The analysis undertaken in Section 5.4 shows a clear long-run relationship between real house prices and a range of fundamentals, including user cost, the ratio of income to housing stock, the ratio of persons to households and the ratio of mortgage credit to household deposits. However, housing supply, household income and mortgage credit may not be exogenous to the system. When house prices rise, this should increase profitability in the construction sector and may stimulate a supply-side response. Similarly, a rise in house prices may bring about an increase in household income, particularly in sectors related to housing such as construction, banking, real estate, various retail services and even public administration. Lastly, house price increases may make banks more confident and thus cause them to increase loan-to-value ratios (see, for example, Gerlach & Peng 2005), while higher incomes may have a similar effect.

This suggests a rich economic system within which house prices operate. Cointegration between these variables is analysed in this section, with four variables – real house prices, the ratio of real income to the real net housing stock, the user-cost as measured by the real interest rate and the ratio of mortgage credit to deposits – treated as endogenous. There are two issues that arise here.

Firstly, the number of vectors can be tested but a certain degree of caution is needed relying on conventional statistical tests regarding the number of cointegrating vectors. Suppose the model has k endogenous variables and s weakly exogenous variables, i.e. where the reduced rank matrix is of dimension kx$(k+s)$. Because there are more parameters, test statistic tables will be shifted to the right, compared to testing the rank of a standard kxk matrix. Thus, the risk is present, using standard statistical tests, of finding too many cointegrating vectors (Harbo et al. 1998).

$I(1)$ cointegration analysis for the sample from 1980 to 2012 does indicate the presence of 4 cointegrating vectors (CIVs). The trace test associated with a null of 3 vectors is 20.15 and the associated p-value is less than 0.001. Harbo et al. (1998) report that for a system with four exogenous variables (here: *phhr*, *delta_ue*, *q_infl*, and *tau_sd*), and a null hypothesis of one endogenous variable more than the number of cointegrating vectors (4 and 3 in this case), the revised test statistic with a 5% cut-off is 16.7; thus, it seems likely that even correcting for the dimensionality of the full matrix, there are as many vectors as endogenous variables.

Secondly, a finding of four cointegrating vectors where there are only four endogenous variables would be a concern where the system is closed, as it implies the variables would have to be stationary. However, the system here is open, with exogenous, non-stationary variables as outlined above. In a system with four endogenous and two exogenous, non-stationary variables, a system with four cointegrating vectors could be perfectly coherent. Where an unrestricted regression is run on the system from 1985 to 2012 and including all variables as endogenous (with two lags), rank tests reject a null of three vectors, as per above (p-value of 0.006), but not a null of four CIVs (p-value of 0.085).

Allowing for both findings above, identification of the model requires assumptions about the weighting matrix across the four vectors, in particular that the matrix is diagonal. This is tested using two models reported below. The first, described in detail in Table 5.7, is an unrestricted model, i.e. no restrictions on the alpha or beta matrices, meaning that the beta matrix is not identified. Three stars indicates a ratio of the coefficient to its standard error of more than two.

The first vector is clearly recognisable as a house price relationship with rapid error-correction by house prices to that vector. In this unrestricted case, both the user-cost and the credit-deposit ratio respond to this vector, although at significantly slower speeds of adjustment and the smaller ratios of alphas to their standard errors. Given the full rank of the system, reduced rank regression models are not appropriate and a diagonal structure of alphas is legitimate to identify the beta matrix. The output from this model is shown in Table 5.8.

The identification of the beta matrix allows the elimination of variables whose coefficients are very small relative to their standard errors, such as *mcdr* in the second and third vectors and the stamp duty and inflation variables in all vectors apart from the first. This system is shown in Table 5.9. It is possible

Table 5.7: *Unrestricted 4-CIV model, 1980-2012: beta values and alpha values, SEs*

Type	CIV1		CIV2		CIV3		CIV4	
beta								
lrhp	1		0.914		1.558		-0.542	
lrystock	-1.463		1		-2.144		-6.362	
rm_net_r4y	1.231		3.012		1		-13.394	
mcdr	-0.595		-0.341		-1.134		1	
phhr_1	0.236		1.226		0.276		-2.393	
delta_ue2q	0.029		0.015		-0.117		0.019	
tau_sd_ftb_1	2.007		-0.169		1.324		-2.292	
qinfl_ex	3.5		-1.457		-1.787		-7.868	
q_infl85	-2.248		-1.93		-2.024		14.355	
alpha								
lrhp	-0.311	***	0		0.032		-0.003	
lrystock	-0.004		-0.027	***	0.01	***	-0.001	
rm_net_r4y	0.048	***	-0.005		-0.003		0.009	***
mcdr	0.039	***	0.016		0.043	***	0	
SE								
lrhp	0.038		0.02		0.017		0.005	
lrystock	0.009		0.005		0.004		0.001	
rm_net_r4y	0.018		0.009		0.008		0.002	
mcdr	0.017		0.009		0.008		0.002	

to relax the assumption of a diagonal alpha matrix, to test whether any of the other endogenous variables responds to the house price vector. Doing this does not indicate any strong response by other variables to the house price vector, suggesting weak exogeneity of these variables to the house price relationship.

The exogeneity of the credit-deposit ratio is interesting, in light of the findings by (Gerlach & Peng 2005) among others. Relaxing the assumption of a zero coefficient on α_{mcdr} in the first cointegrating vector, the house price relation, there is some evidence of a positive response – error amplification, rather than error correction – of the credit deposit ratio to house prices being above equilibrium: the coefficient on alpha is 0.05 with a standard error of 0.02. This suggests some role for credit demand to show up in the ratio of credit to deposits, although it appears credit supply technology, in particular the ability of Irish banks to borrow from abroad once in the eurozone, is the dominant factor.

Table 5.8: *4-CIV model, 1980-2012, with diagonal alpha matrix*

Type	CIV1			CIV2			CIV3			CIV4		
beta	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t
lrhp	1	0		0.389	0.27	1.441	-0.428	0.228	-1.877	-1.56	0.111	-14.054
lrystock	-1.557	0.206	-7.558	1	0		1.583	0.472	3.354	1.717	0.339	5.065
rm_net_r4y	1.206	0.271	4.45	1.829	0.74	2.472	1	0		-1.804	0.445	-4.054
mcdr	-0.562	0.045	-12.489	0.003	0.173	0.017	0.182	0.146	1.247	1	0	
phhr_1	0.223	0.091	2.451	0.835	0.235	3.553	0.213	0.101	2.109	-0.53	0.166	-3.193
tau_sd_ftb_1	2.215	0.715	3.098	-0.309	1.44	-0.215	-0.905	1.25	-0.724	-1.707	1.208	-1.413
qinfl_ex	4.325	1.091	3.964	-0.421	2.021	-0.208	-1.352	1.708	-0.792	-0.458	1.669	-0.274
delta_ue2q	0.049	0.013	3.769	0.048	0.024	2	-0.023	0.02	-1.15	0.047	0.02	2.35
q_infl85	-2.288	1.14	-2.007	-0.807	2.128	-0.379	-0.472	1.766	-0.267	2.655	1.757	1.511
alpha	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t
lrhp	-0.26	0.028	-9.286	0	0		0	0		0	0	
lrystock	0	0		-0.034	0.006	-5.667	0	0		0	0	
rm_net_r4y	0	0		0	0		-0.08	0.015	-5.333	0	0	
mcdr	0	0		0	0		0	0		-0.077	0.013	-5.923

Table 5.9: *4-CIV model, 1980-2012, diagonal alpha matrix & some beta restrictions*

Type	CIV1			CIV2			CIV3			CIV4		
beta	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t
lrhp	1	0		0.469	0.11	4.264	-0.154	0.075	-2.053	-1.41	0.088	-16.023
lrystock	-1.509	0.207	-7.29	1	0		0.93	0.166	5.602	1.897	0.33	5.748
rm_net_r4y	1.268	0.273	4.645	1.988	0.341	5.83	1	0		-1.374	0.442	-3.109
mcdr	-0.551	0.045	-12.244	0	0		0	0		1	0	
phhr_1	0.258	0.09	2.867	0.891	0.153	5.824	0.132	0.07	1.886	-0.271	0.133	-2.038
tau_sd_ftb_1	2.177	0.674	3.23	0	0		0	0		0	0	
qinfl_ex	4.281	1.025	4.177	0	0		0	0		0	0	
delta_ue2q	0.051	0.014	3.643	0.061	0.027	2.259	-0.018	0.018	-1	0.044	0.022	2
q_infl85	-2.584	1.073	-2.408	0	0		0	0		0	0	
alpha	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t	coeff	s.e.	t
lrhp	-0.243	0.027	-9	0			0			0		
lrystock	0			-0.028	0.005	-5.6	0			0		
rm_net_r4y	0			0			-0.085	0.017	-5	0		
mcdr	0			0			0			-0.071	0.012	-5.917

What do these results suggest about the broader economic system within which house prices existed? Firstly, it is worth stating that the house price relationship revealed through error correction methods above is largely preserved when analysis is extended to allow for potential endogeneity of other variables. In addition, three long-run relationships are implied by the analysis carried about above.

Income/stock relation The ratio of income to housing stock is negatively associated with user cost, the person-household ratio, real house prices and changes in unemployment. This suggests that high user cost and growing unemployment had a stronger effect on income (the numerator) than on supply (the denominator). The negative relationship between the person-household ratio and incomes may reflect growing female participation in the labour force during the period analysed, which would be expected to increase household income, or may reflect an upward trend over time. The negative long-run effect of prices on the income-stock ratio may indicate a greater supply response – where prices represent profitability – than income response. As Figure 5.3 suggests, the rise in income/stock from the late 1980s to 2007 and the subsequent fall is strongly correlated with real house prices. In terms of a housing supply relationship, future research will be required to include currently omitted variables such as costs of inputs (land, labour and materials) and planning/permit conditions.

User-cost relation The user cost (as measured by the real rate of interest) is positively associated with real house prices (and perhaps changes in unemployment) and negatively with income/stock and the person-household ratio. The relationship with house prices may reflect extremely high user cost at a time of high prices late in the sample. Put another way, since user cost is negatively related to 4-year house price appreciation, this seems to suggest greater scope for appreciation when $lrhp$ is low.

Credit/deposit relation The fourth vector says that *mcdr* rises with *lhpr*, user cost and *phhr* and falls with changes in unemployment but also the income/stock ratio. The finding in relation to income/stock seems counter-intuitive but does make sense in terms of a latent variable story. The ratio of credit to deposits was included in error-correction analysis as a proximate indicator of credit conditions. Suppose instead that both it and real house prices depend on something further "upstream", such as international capital market conditions or sentiment, or the degree of European capital market integration.

Suppose that the underlying relationship in vector 1 is as follows:

$$lrhp = \beta_0 + \beta_1 lrystock + \beta_2 rm\_net\_r4y + \beta_3 phhr + \Lambda \qquad (5.12)$$

where Λ is a latent variable capturing exogenous credit conditions (normalized so that its coefficient is 1). Similarly, $mcdr = \gamma_0 + \gamma_1 \Lambda + f(X)$, where X could include variables such as *lrystock*, *rm_net_r4y* and *phhr*. Estimating *lrhp* using the observable *mcdr*, rather than the unobserved Λ, thus has a different interpretation than before. To the extent that *lrystock*, *rm_net_r4y* and *phhr* are not major determinants of *mcdr*, β coefficients may not be that different using *mcdr*, rather than Λ, although this would depend on the exact nature of $f(X)$. The coefficient on *lrhp* suggests that γ_1 may be close to 1.4. Measuring upstream credit conditions, and how they affect both real house prices and the credit-deposit ratio, is left to future research.

Additional variables Other factors that could be included in the cointegration analysis include further measures of demographics (for example, the annual change in the percentage of the population aged 25-34) and the typical nominal (net) mortgage rate of interest. The inclusion of change in the percentage of the population into a model with a diagonal alpha matrix suggests that this is not a statistically significant determinant of any of the four endogenous variables. Similarly, the inclusion of the log nominal interest rate is not significant in any of the first three vectors, although it is strongly significant in the fourth (*mdcr*) vector. The implied sign in the long-run equation is, as expected, negative. The parameter estimates for the long-run solution for real house prices with this augmented system are much the same as those reported in Table 5.8.

In summary, there is clear evidence of a robust house price relationship and also that house prices respond rapidly to this equation – and not to any other equations when other variables, such as income/stock, user-cost and the ratio of credit to deposits are made endogenous. In addition, there is no strong evidence that any of these other variables responds to the house price relationship, meaning that it is reasonable to assume that these variables are indeed (weakly) exogenous for purposes of modelling.

5.6 House Price-to-Rent Model

While there are a variety of factors affect house prices, many will also affect rents, such as incomes, or the ratio of persons to households. The principal difference is the asset nature of housing. "Dividing through" the house price equation, in effect, by rents allows the opportunity to look in more detail as user cost and credit conditions, those aspects unique to the asset nature of house prices.

As outlined in Section 5.3.2, the scale and nature of the private rented sector in Ireland has changed substantially over the period 1975-2012. The first decade or so represents a one-off downward shift in the real cost of renting in Ireland, while the second decade witnessed continued falls in the total proportion renting. This, combined with reforms of the private rented sector in the late 1990s, mean that there is little evidence of any error correction in the price-rent ratio for the period as a whole.[14]

Taking the period 2000-2012, however, during which there was a relatively well-developed private rented sector nationwide, there is strong evidence of an

[14]The extent of any rent controls in the private and State-supported rental sectors is not addressed here – future research may assess the role of such market interventions.

error-correction relationship in the house price-rent ratio. In explaining changes in the ratio of house prices to rents (*dlhpr*), three dynamic terms are included: the lagged value of *dlhpr*, capturing any memory; the contemporaneous change in rents, capturing the extent to which changes in the ratio reflect changes in the denominator; and the contemporaneous change in credit conditions. The long-run equilibrium relationship includes the following fundamentals: the rate of interest (either nominal, and thus expected capital gains terms would also be required, or real) and credit conditions.

Two other terms may matter for the ratio of prices to rents. Firstly, it may be the case that, in comparing mortgage payments with equivalent rents, non-linearities exist. Thus, where a combined real rates of interest term is included, the log of the nominal net interest rate can be included to capture any such effects. Second, as suggested by Kim (2008), the percentage of renters may be inversely related to price-rent ratio in equilibrium, reflecting the differential return from real estate derived by owner-occupiers compared to tenants and landlords.[15]

Two different measures of credit conditions are used. The first is, as with the inverted demand model, the ratio of credit to deposits. Secondly, given the time-frame covered, it is possible to use Central Bank of Ireland (CBI) data on the median loan-to-value for first-time buyers from 2000 on. This may give a more direct measure of changing credit conditions, particularly later in the period when the stock of debt was high and static, due to bubble-era lending. Thus, the sample for the price-rent model is 2000Q1-2012Q4, less any terms lost to dynamics.[16]

[15] A limitation to use of this variable is its interpolated nature and thus the failure to reject the null of the annual change in the percentage renting being I(1).

[16] The CBI dataset only runs to 2011Q4. To utilize 2012 data, the median first-time buyer LTV was set at 82.5%, the level observed in 2011Q4. The median LTV was relatively stable in 2011, averaging 83.2%. As this is an equilibrium term, excluding these points does not have a significant impact on the results, although it does have a meaningful impact on sample size.

Results for three specifications are presented in Table 5.10, for both measures of credit conditions: the exact series used for *cci* is given in the first row. The first specification separately includes the net nominal interest rate, and 1- and 4-year (annualized) house price inflation to reflect extrapolative expectations. For both measures of credit conditions, the results show an order of magnitude difference between the interest rate and expectations terms, suggesting non-linearities are important. Thus, the second specification includes one term for the real net rate of interest, with a weight of 0.6 on 4-year inflation and 0.4 on 1-year (as suggested by their relative coefficients), as well as the log of the net nominal interest rate. In both cases, this improves the fit of the model, although in the *ltv* specification, the coefficient on the log rate is at best marginally significant. The final specification adds the percentage in rented accommodation. For the specification using *mcdr*, this term is significant. However, for the specification using *ltv* to measure credit conditions, this variable is not statistically significant and indeed has the wrong sign.

The models explain between 80% and 85% of the variation observed in changes in the price-rent ratio. The speed of adjustment implied by the coefficient on the lagged level of the price-rent ratio is between 25% and 30% for models using *mcdr* and roughly 18% for models using *ltv*. Across all three specifications, however, the fit of the model using loan-to-value information was substantively better than the fit using the credit-to-deposit ratio (as measured by sigma). Thus, while the ratio of mortgage credit to deposits is a good proxy for credit conditions, it does not perform as well in explaining changes in the price-rent ratio as the loan-to-value for the typical first-time buyer.

The specification using the median loan-to-value for first-time buyers is thus chosen to estimate the long-run relationship; actual and fitted values are plotted in Figure 12. It suggests one important dynamic relationship also: the coefficient on the contemporaneous change in the loan-to-value of 0.26 is statistically significant and implies that as credit conditions are being loosened, the

Table 5.10: *Modelling changes in the price-rent ratio (dlhpr), 2000-2012*

	MCDR		MCDR (non-lin)		MCDR (%rent)		LTV		LTV (non-lin)		LTV (%rent)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	1.296	0.000	1.333	0.000	1.766	0.000	0.732	0.000	0.731	0.000	0.751	0.000
$lhpr_{t-1}$	-0.249	0.001	-0.255	0.000	-0.305	0.000	-0.177	0.000	-0.175	0.000	-0.185	0.000
cci_{t-1}	0.131	0.007	0.134	0.005	0.219	0.000	0.361	0.000	0.36	0.000	0.362	0.000
rm_{t-1}^{NN}	-3.001	0.000					-1.036	0.04				
$d16lhp\_ann_{t-1}$	0.343	0.002					0.211	0.000				
$d4lhp_{t-1}$	0.24	0.001					0.126	0.004				
rrm_{t-1}^{NR41}			-0.581	0.000	-0.409	0.013			-0.34	0.000	-0.402	0.012
$l(rm_{t-1}^{NN})$			-0.078	0.000	-0.081	0.000			-0.024	0.122	-0.026	0.116
pc_rent_{t-1}					-1.244	0.025					0.175	0.667
$dlhpr_{t-1}$	0.21	0.099	0.228	0.058	0.29	0.015	0.192	0.109	0.186	0.105	0.174	0.141
$dlrent$	-0.707	0.000	-0.685	0.000	-0.519	0.001	-0.72	0.000	-0.741	0.000	-0.782	0.000
$dcci$	0.389	0.057	0.466	0.014	0.458	0.012	0.257	0.016	0.261	0.012	0.271	0.012
sigma	0.01377		0.01372		0.01307		0.01287		0.0127		0.01283	
R^2	0.819		0.816		0.837		0.842		0.842		0.843	
p-values for diagnostic tests												
AR 1-4	0.889		0.917		0.763		0.619		0.632		0.620	
ARCH 1-4	0.832		0.906		0.979		0.995		0.993		0.988	
Normality	0.951		0.926		0.947		0.219		0.192		0.197	
Hetero	0.044**		0.320		0.263		0.061		0.610		0.657	
Hetero-X	NA		0.300		NA		NA		0.380		NA	
RESET23	0.175		0.282		0.412		0.152		0.165		0.205	

price-rent ratio rises beyond just what is suggested by the long-run coefficient. The implied long-run relationship from this model is as follows:

$$ln(hpr_t) = 4.18 + 2.05ltv_t - 1.94rm_t^{RN*} - 0.13ln(rm_t^{NN}) \tag{5.13}$$

Credit conditions Credit conditions have a long-run impact on the price-rent ratio, with the coefficient of 2.05 indicating that an increase of ten percentage points in the loan-to-value of the typical first-time buyer was associated with an increase in ratio of prices to rents of 20.5%. Assuming static rents, this translates into a 20.5% increase in house prices. Put another way, suppose average house prices are €170,000 and the average monthly rent is €800; thus the average gross yield (annual rent relative to prices) is 5.6%. An increase in the LTV by 10pp is associated with a fall in the yield from 5.6% to 5.2% in equilibrium. (There would also be a dynamic effect on the price-rent ratio, as outlined above, in this example of 2.6%, pushing the yield down to 5.0%.)[17]

[17] Duca et al. (2011*a*) use the log form of the loan-to-value for first-time buyers and report a long-run elasticity of prices with respect to LTV of 1.4. Here, a model with level of LTV/downpayment ($\sigma = 0.01270$) has better fit than one with log LTV ($\sigma = 0.01282$), and also performs better than one with log down-payment, which will have different non-linearities ($\sigma = 0.01278$). For reference, the implied long-run elasticity of prices with respect to LTV for Ireland 2000-2012 was roughly 1.6, compared to 1.4 in the case of the USA, 1980-2007.)

Real interest rates Real interest rates for housing – as measured by the difference between nominal rates after tax reliefs and the expected capital gain (based on 4-year and 1-year inflation) – are associated with a lower price-rent ratio, as expected. The coefficient of 1.94 indicates that an increase in real interest rates of 1 percentage point is associated with an increase in equilibrium price-rent ratio of 1.94%. This is somewhat larger than the coefficient in the inverted demand model (1.53).

Nominal interest rates In addition to real interest rates for housing, the nominal rate may also matter, although its statistical significance is marginal (potentially a product of the small sample size). A 10% reduction in the nominal after-tax mortgage rate is associated with a 1.3% rise in the price-rent ratio. This may reflect the cash-flow constraints and the direct choice faced by would-be first-time buyers of a particular rent or nominal net mortgage payment.

Robustness & Sensitivity Overall, these results are sensitive to series chosen, due to the small period for which the model is computed. Nonetheless, largely similar results are obtained if an alternate series for rents (from property website daft.ie) is used for the period 2002-2012. Adding other dynamics does not improve model fit, while using loan-to-income information contained in the same CBI data is not preferred. Using the DOE series on LTVs for new dwellings results in a significantly poorer model fit, with neither house price appreciation term statistically significant and the nominal rate only marginally significant.

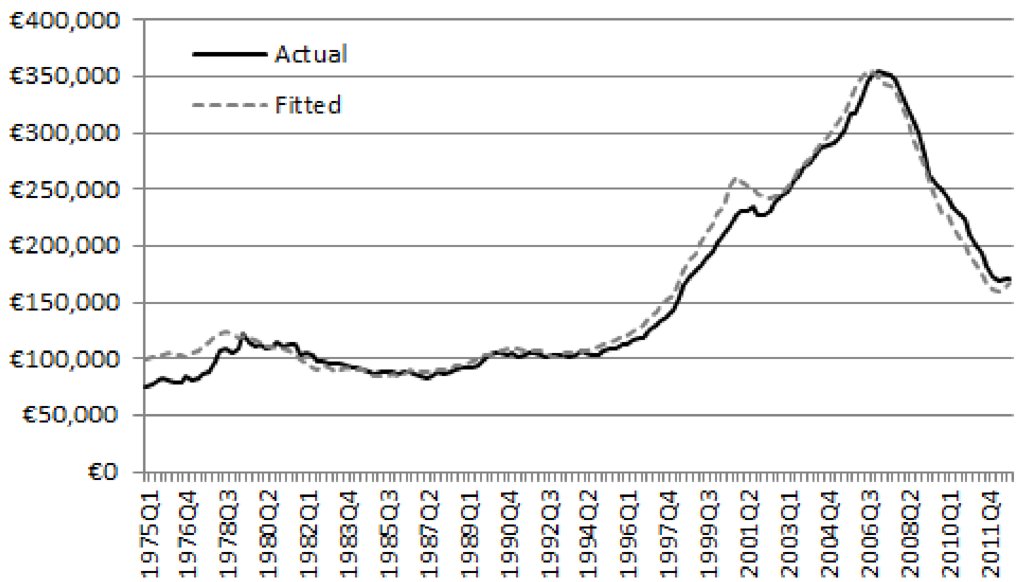
5.7 Decomposition & Analysis

This section decomposes real house price growth in each of six phases from 1975 to 2012 into changes due to the various fundamentals. It also uses the information contained in the inverted demand model to comment on likely future pressures on Irish house prices.

5.7.1 Decomposing Irish house price growth

Figure 5.8 compares actual with fitted values, using the error-correction model outlined above to estimate fitted values of house prices. It shows that there were roughly six phases in the Irish housing market between 1975 and 2012. The first was from 1975 (the start of quarterly information) until 1979:Q2, during which real house prices rose 60%, or almost 12% on an annualized basis. The second finished in 1987:Q2, and between 1979 and 1987, real house prices fell by 32% (or almost 5% on an annualized basis). Between 1987:Q2 and 1995:Q3, real house prices rose by 31%, or 3.3% per year on average.

Figure 5.8: *Actual and fitted real house prices, national average, 1975-2012*



The fourth phase, the period between 1995:Q3 and 2001:Q3, saw the strongest growth, as real house prices rose by 117%, or 13.7% per year on average. Between 2001:Q3 and 2007:Q1, when real house prices peaked, there was further growth of 52%, or just under 8% on an annualized basis. The final phase is from 2007:Q1 to 2012:Q4 (the end of the time series), during which house prices fell by 52%, or an annual average rate of 12%. The overall picture that emerges from Figure 5.8 is one where actual house prices rarely deviated substantially from the level suggested by their long-run determinants, although it should be noted that these "fundamentals" include unrealistic extrapolative expectations and potentially unsustainable levels of mortgage credit relative to household deposits.

Figure 5.9: *Annual house price growth attributed to fundamentals, by market phase, 1975-2012*

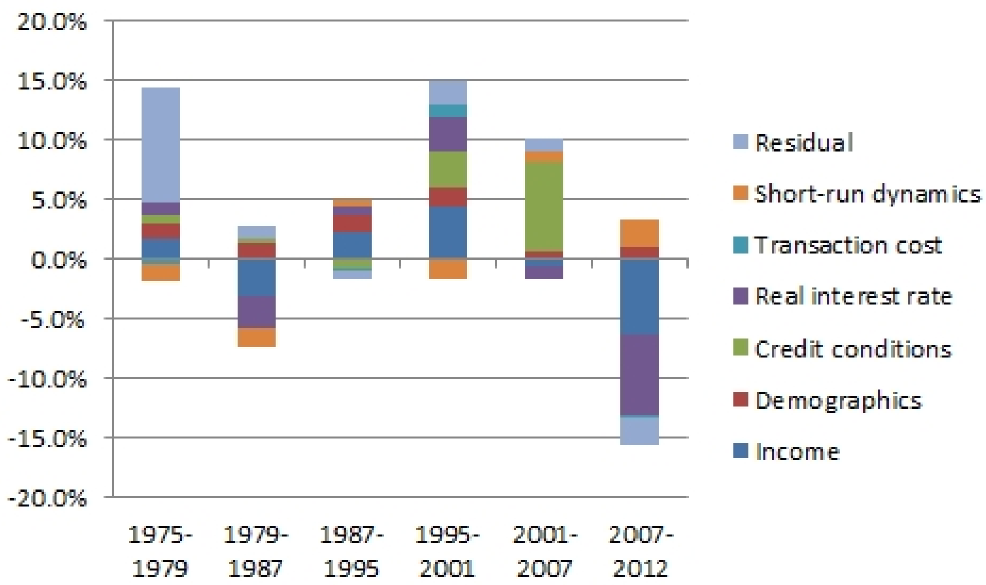


Figure 5.9 uses the long-run equilibrium relationship for the period 1980-2012 to decompose Irish house price growth in each of these six phases into growth driven by each of the five fundamental factors, as well as a proportion not explained by the long-run component of the model, which can be broken into dynamic and residual factors. The percentage rates of change in real house prices are annualized and thus comparable across periods.

Aside from the sheer volatility of house price growth in Ireland during the period as a whole, two things are striking about the figure. The first is the large proportion of house price growth in the 1970s not explained by the long-run component of the model. The second is the nature of house price growth between 2001 and 2007. Unlike the preceding period, where house price growth appears to have been driven by a mix of factors, including income growth (relative to the stock of housing) and demographics, growth in real house prices from 2001 to 2007 was almost entirely driven by credit conditions. Most of the remainder of the growth in house prices during this period is either due to short-run dynamics or else is a residual that may be considered a pure bubble effect. Dynamics and the residual offset a falling ratio of income to housing stock, due to Ireland's extraordinary building boom, and a higher real interest rate (reflecting slower house price growth overall).

5.7.2 Future pressures on Irish house prices

The end of 2012 saw the end of mortgage-interest relief available to first-time buyers. Based on prevailing interest rates at end-2012, this is the equivalent of a 0.07 percentage point increase in the interest rate. According to the long-run coefficient on interest rates, this could be expected to push equilibrium real house prices down by 1.1%, if the model pertaining to the generation to 2012 were to hold in coming years.

Similarly, the local property tax – levied at 0.18% of the value of a property – may be thought of in present value terms as the equivalent of an increase in stamp duty, although this assumes away any deposit constraints associated with stamp duty. Assuming a discount rate of 5% per annum and a seven-year horizon for households, this could be expected to lower equilibrium house prices by 1.7%. It should be noted, however, that it is likely the effect of stamp duty was through down-payment constraints, while it is also worth stating that the long-run effect of stamp duty is not precisely estimated, due to the small number of changes to it during the period analysed.

A final tax issue is one brought up by Browne et al. (2013), namely the preferential tax treatment of capital gains associated with owner-occupancy. Given the significance of expected capital gains in the long-run equation of fundamentals determining Irish house prices, it is clear that were a tax liability to apply for realised capital gains, this would have the ability to dampen somewhat the extrapolative nature of the Irish housing market. If the rate of 33% were to apply to principal private residences, this would clearly have an impact on the user cost calculation of Irish housing market participants.

Related to this, the likely presence of extrapolative expectations suggests that the user cost associated with housing in Ireland in late 2012 was very high: the real rate of interest in housing is estimated at over 20% for late 2012. At some point, this will fall, as the average rate of change in real house prices goes to zero. If house prices were stable between 2012 and 2016, this alone would represent an improvement in the user cost of 18 percentage points. Such an improvement in expectations would – according to the model presented – be associated with an increase in real house prices of more than 25% – which of course would feed in itself into house price expectations.

Lastly, there is the issue of credit conditions. As measured, credit conditions are a linear combination of the level and change in the credit-deposit ratio. While the coefficient on the change term is nearly twice as large as that on the level, the scale of the level of roughly two orders of magnitude larger (for example, between 2000 and 2007, the average value of $mcdr$ was 1.4, while for $dmcdr$ it was 0.026). Thus, as measured, credit conditions remained in late 2012 quite loose by historical standards: the linear combination of $mcdr + 1.78dmcr$ stood at 1.69 in late 2012, down from 1.87 in 2007 but well above the pre-2000 average of 0.74. If a measure that gives greater weight to stocks than flows proves too sticky to capture marginal credit conditions, the typical loan-to-value (as highlighted by the model of the price-rent ratio) may be a better indicator in the future. Nonetheless, the question of how Irish banks will fund their loan books in the future – in particular the balance between internal deposits and external financing – is relevant for the future path of Irish house prices.

5.7.3 Could the bubble have been prevented?

Understanding the determinants of house prices is a key concern for policy-makers, particularly with greater focus now on macro-prudential policy and tracking financial conditions other than the Central Bank interest rate. The analysis undertaken above can be used – however tentatively – to give insights into the potential scale of impact of particular kinds of policy measures. Three alternative scenarios, based on the long-run relation implied by the error-correction model, are presented in Figure 5.10, alongside nominal house prices during the period 1980-2012. These are meant as thought experiments, rather than predicted counterfactuals, as the dynamics between house price and other variables, such as housing stock, are for simplicity not included.

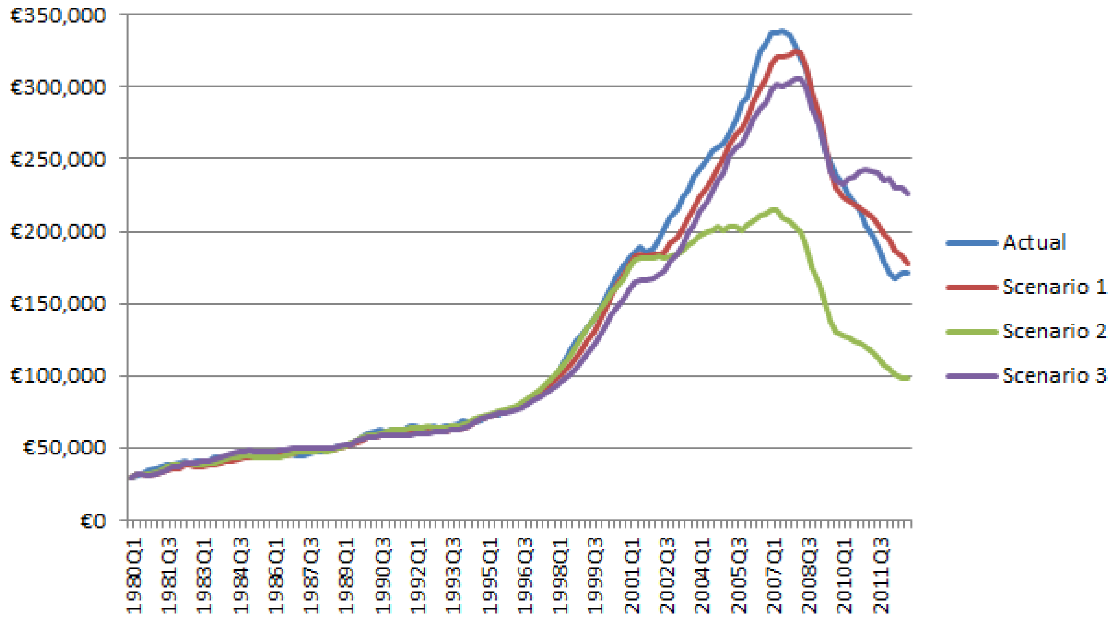
The first, Scenario 1, simulates house prices where the real user cost is adjusted to include a Capital Gains Tax of 33% on principal primary residences.[18] This line closely matches actual house prices, although it is worth noting that both the bubble and the crash are slightly attenuated. At the margins, therefore, this is evidence from static simulations to suggest that a tax on profit from home-ownership may have smoothed the housing market cycle.

However, even with a tax on gains, the bulk of the housing bubble and crash would likely still have occurred. Scenario 2 presents simulated house prices in a situation where macro-prudential policy restricted the ratio of mortgage credit to deposits of 80%. This policy measure would have prevented Irish banks from engaging in any substantial bond-financing of mortgages upon entry into the eurozone. There is a noticeable impact on the run-up of house prices between 1995 and 2007. The increase in prices in Scenario 2 is 180%, just over half the increase actually seen (350%). Clearly, a fuller understanding of the determinants of the credit-deposit ratio within a multi-equation system – including house prices themselves – may change the magnitude of this result, but this offers a useful starting point for the impact of credit on house prices.

[18] For the purposes of simulation, the tax is assumed to have been introduced in 1980:Q1. No further feedback, for example through diminished down-payments, is included.

A more likely policy would be a cap on loans-to-value, as was implemented in Hong Kong. Given the lack of a long-running series on loan-to-value, however, this is not possible here. Nonetheless, the ratio of credit to deposits can be thought of as similar to a system-wide loan-to-value.

Figure 5.10: *Actual and scenario house prices, national average, 1980-2012*



The fall in house prices from the peak in Scenario 2 is still substantial. This indicates that while credit conditions were key to driving up prices, they have not played a significant role in the crash. This, of course, assumes the exogeneity of factors such as housing supply. If the significant easing of credit conditions stimulated a supply response, its absence would alter the ratio of income to stock, thereby affecting the level of real house prices.

The final scenario, Scenario 3, replaces one simplistic calculation of expectations – whatever happened in recent years is the best guide to the near future – with another: the empirical evidence is that in the long run, house price increases match but rarely exceed inflation. That is, user cost is calculated as net interest rates minus average consumer price inflation over the last four years, instead of net interest rates minus average house price inflation. As can be seen in Figure 5.10, this has a far greater impact on prices falls than preceding price rises. Whereas prices are estimated to still have increased by a factor of four, the fall from the peak is 26%, rather than 50%.

Thus, the preliminary evidence from the bubble and crash in Ireland is that both macro-prudential regulation of mortgage products and ensuring consumer expectations are well-educated are important tools in the policymakers fight against destructive housing market cycles.

5.8 Conclusion

This chapter has examined the housing market in Ireland from the mid-1970s until 2012, with a particular focus on the bubble that peaked in 2007 and the crash that followed. Following a growing literature that focuses on the role of credit conditions, a readily available measure of credit conditions was included, the ratio of mortgage credit to deposits, one with both early and more recent antecedents in the Irish housing market literature, which proved highly significant in both inverted demand and price-rent models of the Irish housing market.

The error-correction model developed for the Irish housing market for the period 1980-2012 found that there were four principal fundamentals that determined the long-run equilibrium level of real house prices: the ratio of income to the housing stock, the ratio of persons to households, the ratio of mortgage credit to deposits, and the user cost, as measured by difference between net nominal mortgage interest rates and the annualized 4-year rate of house price inflation. In addition, it seems likely that the rate of stamp duty was important for the level of house prices, while other factors mattered for short-run changes in house prices, in particular conditions in the labour and mortgage markets.

An error-correction approach assumes that variables such as the four fundamentals described above are exogenous when looking at the housing market. This was tested thoroughly, allowing the income/stock ratio, user-cost and also the credit-deposit ratio to be endogenous, and allowing up to four cointegrating vectors across the system. Analysis showed the house price relationship that emerged from single-equation ECM analysis was largely robust as was the speed of adjustment by house prices to this equation. The analysis also found that prices did not respond to any other cointegrating vectors. In addition, there is no strong evidence that any of these other variables responds to the house price relationship, although as house prices enters other cointegrating vectors, there would be important feedbacks.

For much of the early period analysed, the rental market in Ireland was in secular decline. From the mid-1990s, though, the proportion in rented accommodation started to grow, and there is significant evidence of an error-correction relationship in the price-rent ratio for the period 2000-2012. The long-run relationship between prices and rents is more parsimonious than for prices alone, with the user cost and credit conditions the most important factors. Here, user cost is the net interest rate less a combination of 1-year and 4-year inflation, with potential non-linearities applying in relation to the nominal rate of interest. Credit conditions were measured in two ways: firstly, the ratio of credit to deposits, as above, and secondly, using a new dataset of typical loan-to-value rates for first-time buyers from 2000 on. While both measures capture significant variation in the sample, the LTV measure performs better, reflecting the importance of including the change in the credit-deposit ratio, as well as the level.

In both models, credit conditions matter, both for the long-run solution and for short-run dynamics. An increase in the credit-deposit ratio of 10 percentage points was associated with a 5.6% increase in equilibrium house prices but also a 1.7% short-run effect in the following quarter. Similarly, an increase of ten percentage points in the typical first-time buyer LTV was associated with an increase in the long-run price-rent ratio of 20.5%, as well as a short-run effect of 2.6%. This suggests that previous studies of the Irish housing market have suffered from omitted variable bias, attempting to model prices but without accounting for credit conditions.

Indeed, a decomposition of Irish house price growth from 1975 to 2012 into its various phases highlights the importance of credit conditions in the last phase of Ireland's bubble. Whereas house price growth between 1995 and 2001 was due to a combination of factors, including rising income relative to housing stock, lower real interest rates, demographics and credit conditions, during the 2001-2007 period, looser credit conditions were responsible for 7.5 percentage points of growth per annum on average, at a time when annual growth was 7.9%. While incomes were rising during this period, the housing stock rose faster, to the extent that the ratio of income to stock was actually a drag on prices during this time and became a major factor in the post-2007 period.

The demographic variable included in the inverted demand model – the ratio of persons to households – is one rarely commented on in the recent literature, but it is a largely common-sense variable: a population of 4 million with four to a house will demand fewer houses and occupy less land than a population with three to a house. Previous studies, not just for Ireland, that focus solely on income (relative to supply) may be overstating the effect, if part of the effect is actually a greater spread of the population. With an ageing population and smaller family units, it is likely that this variable will continue to put upward pressure on prices over the coming decade, even if income pressures are weak.

Of note in both models, but in particular in the inverted demand approach, is the speed with which real house prices in Ireland during this period adjusted to a new equilibrium. The principal specification suggests that almost one third of the gap between actual and equilibrium prices was closed every quarter. In this sense, Ireland's bubble was not an irrational bubble in the housing market, marked by prices deviating significantly from fundamentals. Rather, the analysis here suggests that Ireland's bubble was one step further up: it was the "fundamentals" themselves – in particular credit conditions and expectations – that had deviated from sustainable levels. However, given the extrapolative nature of expectations of capital gains, one should not regard expectations as a true fundamental: they are ultimately driven by all the shocks that drive house prices. The extrapolative nature of these expectations generates a natural mechanism for house price to overshoot on both upside and downside. How policy can prevent this recurring, for example tracking expectations with regular surveys to warn about future problems, should be an active topic of future research and policy analysis.

Chapter 6

Conclusions

6.1 Contributions to the literature

With the overall objective of a better understanding of the economics of housing market cycles, this thesis has focused in detail on Ireland, the location of the most extreme housing bubble and crash of the Great Moderation and subsequent Global Financial Crisis. Through developing a range of research questions and stylised facts and then exploring those in subsequent chapters, a number of insights have emerged, which make contributions to the literature.

While the economic theory underpinning what happens to the spread of property values in a housing market cycle remains under-developed, two competing predictions emerge from the literature. According to Stein (1995), down-payment constraints make high-value properties more volatile than low-value ones. Costello (2000), however, suggests that if more affordable homes are more liquid and thus more competitive, then these segments may be more volatile over the boom/bust cycle. The research presented here – in particular in Chapters 2 and 3 – is the first to examine which is most likely to have been at work in the Irish market. Chapter 2 did this through a uniquely granular perspective that divided the Irish market into over 1,100 sub-markets. Chapter 3 did this by exploiting a wealth of data on location-specific amenities.

In both chapters, there is little evidence of a Stein effect, where high value properties are more volatile, proportionately rising more in the bubble and falling more in the crash. Looking at particular property types, it is certainly the case that the opposite happened, while there was also evidence of counter-cyclical pricing of core housing market amenities, such as commute time, distance to CBD and proximity to train stations and the coastline. Another contribution of chapter 3 is the presentation of results for the lettings segment of the market, which has mostly been ignored in the literature on amenities. For almost all amenities analysed, compared to the price premium, there was an attenuated rent effect (i.e. a smaller premium or discount in absolute terms). As suggested by the renter search threshold mechanism, the notable exception is distance from the CBD, which actually is valued in percentage terms more by renters than owners.

Another heretofore unaddressed issue in the literature on the accuracy of valuations is that seller and buyer valuations date from different periods. Chapter 4 addressed this by decomposing the gap between list and sale prices into its constituent processes. The results not only overcome some of the obstacles to assessing valuation accuracy but also reconcile two pieces of conventional wisdom about the housing market and also present a number of metrics that may yield insights into market conditions.

The Irish housing market has been the subject of a number of economic studies over the last generation but the vast majority have omitted a treatment of credit conditions while the econometric techniques vary, with the more advanced econmetrically until now imposing a long-run relationship using a two-step Engle-Granger method. Chapter 5 overcame both these issues, including a readily available measure of credit conditions while also allowing the long-run relationship to emerge from house price dynamics. The resulting equation explained the path of Irish house prices from 1980 to 2012, highlighting also a much neglected factor that may be relevant to other economies, namely the ratio of persons to households. Using a new series of loan-to-value for the median first-time-buyer from 2000 on, this chapter also outlined the first error-correction model of the price-rent ratio in the Irish economy.

6.2 Insights for policymakers

There are obvious uses for much of the analysis undertaken in this thesis. The difference in house price falls by size and type will be of use not only for real estate professionals and valuers but also for Irish financial institutions; much of the work on recapitalising the Irish financial system assumed – implicitly – that price falls would be equal across property types and sizes but this is far from the case. The estimation of price and rent effects of a range of location-specific amenities is relevant for local authorities in estimating property tax revenues and burdens, as well as for valuers, homeowners and landlords. The resilience of – and indeed growth in – the value of many non-market amenities will equally be of interest.

However, there are also insights of a broader relevance. As conditions in a housing market heat up, the Irish experience indicates that this may be seen in narrowing differentials between high-quality and low-quality housing, as a "property ladder" concern affects expectations and actions in the housing market (see Chapters 2 and 3). While such effects may not dominate over "lock-in concerns" in all housing markets, the Irish experience does offer another suggestion for the macro-prudential dashboard, as policymakers seek to establish a tool-kit for managing not only the price level of goods but also of assets, in particular housing.

Related to this, Chapter 4 indicates that readily and freely available datasets, such as those made available through the Internet, are appropriate for policy analysis. In general, price trends derived from large datasets of list prices are extremely highly correlated with those from transactions. Where analysis of both is possible, policymakers may derive insights from the cyclical properties of the ratio of average list prices and average sale prices, as shown with the counteroffer spread developed earlier.

One of the main results from chapter 5 was that actual prices tracked their fitted values very closely, even at the height of what would be termed the Irish housing bubble in 2006-07. This is not to suggest that there was no bubble in Irish house prices, but rather that while Ireland's housing market appears to have been very efficient throughout the period 1980-2012, its determinants include not only slow-to-change fundamentals such as hosuehold incomes, demographics and the stock of housing but also factors much more prone to dramatic adjustment, including credit conditions and expectations about the future, a key ingredient of user cost.

Two broad themes have emerged from the thesis. The first is the importance of consumer expectations in the housing market. The increase in user cost alone between 2007 and 2012 is estimated to have lowered real house prices by roughly 40% and this is due not to changing interest rates but to changing expectations about future house prices, although clearly these were driven by negative shocks to other fundamentals such as income. Secondly, as other research has highlighted, non-price conditions in the credit market are pivotal in understanding developments in the housing market. The relevance of these insights is, to borrow medical terminology, in both diagnosis and prevention of housing bubbles.

As macro-prudential policy matures and develops, the findings here suggest that two of the most important things to measure in assessing the risk of a housing price bubble, are consumer expectations, which if unrealistic may drive house prices to unsustainable levels, and the typical loan-to-value for first-time buyers, which is directly related to leverage and risk in housing. These are not yet a priority for policymakers, however, with neither featuring in EU, OECD or national statistics. Ironically, given the resource cost of preparing so many economic indicators, these are remarkably easy to measure – metrics of both have been presented in this research.

In terms of preventing bubbles, there is of course no solution to what is the by-product of intrinsically human behaviour. However, there is significant potential to minimise housing bubbles and their subsequent economic cost. In relation to expectations, the obvious treatment is consumer education. It was a *cliché* in Ireland before-2007 that house prices only went one way, even though long-run counter-evidence existed – for Ireland as well as for other economies. It is possible that assessments of financial literacy will become part of mortgage approval in the future; assessing the realism of expectations should be central to that.

Behavioural economics may be able to contribute on whether methods exist to reveal what those applying for a mortgage expect to happen housing in the future: financial literacy tests may be too easy to game or alternatively attentional bias may mean that making such expectations explicit does in fact alter behaviour. Successfully done, this would not only identify the level of expectations but also their rationale, which could be assessed by those responsible for macro-prudential policy. A range of initiatives by policymakers in developed countries already aim to shape household behaviour in relation to their decisions, for example in relation to exercise, diet, consumption of alcohol and tobacco, and pensions. Efforts to educate consumers about their dominant consumption good and asset would thus not be out of place.

In relation to credit conditions, policy implications are probably more straightforward. A maximum loan-to-value – as was introduced in Hong Kong after a bubble there – would help prevent a repeat of the worst excesses of Irish housing bubble. Just as with measuring loan-to-value, an acyclical downpayment constraint is easy to introduce. As the severe Irish bubble and crash show, preventing the next bubble would be far preferable to cleaning it up.

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Appendices

.1 Appendix material for Chapter 2

.1.1 Regression output for Chapter 2

On the following pages is an overview of the regression output for the five models outlined in Section 2.2, for both sales and lettings segments. For each model, coefficients and p-values are shown for variables. The naming of variables is explained in Table 2.2.

Table 1: *Abbreviated regression output for house price models*

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
ht1	−0.076	0.000	−0.075	0.000	−0.046	0.000	−0.064	0.000	−0.046	0.000
ht3	0.236	0.000	0.237	0.000	0.211	0.000	0.216	0.000	0.211	0.000
ht4	−0.047	0.000	−0.049	0.000	−0.01	0.000	−0.117	0.000	−0.009	0.001
ht6	0.185	0.000	0.187	0.000	0.169	0.000	0.153	0.000	0.17	0.000
beds1	−0.438	0.000	−0.445	0.000	−0.384	0.000	−0.386	0.000	−0.385	0.000
beds2	−0.211	0.000	−0.212	0.000	−0.183	0.000	−0.155	0.000	−0.183	0.000
beds4	0.289	0.000	0.289	0.000	0.246	0.000	0.271	0.000	0.246	0.000
beds5	0.448	0.000	0.449	0.000	0.397	0.000	0.544	0.000	0.398	0.000
bb1m	0.224	0.000	0.229	0.000	0.164	0.000	0.166	0.000	0.163	0.000
bb22	0.124	0.000	0.125	0.000	0.09	0.000	0.062	0.000	0.09	0.000
bb2m	0.197	0.000	0.2	0.000	0.141	0.000	0.082	0.000	0.142	0.000
bb32	0.112	0.000	0.11	0.000	0.077	0.000	0.042	0.000	0.076	0.000
bb33	0.14	0.000	0.139	0.000	0.092	0.000	0.06	0.000	0.092	0.000
bb3m	0.297	0.000	0.289	0.000	0.194	0.000	0.107	0.005	0.194	0.000
bb41	−0.072	0.000	−0.068	0.000	−0.029	0.000	−0.036	0.000	−0.03	0.000
bb43	0.061	0.000	0.058	0.000	0.047	0.000	0.005	0.55	0.046	0.000
bb44	0.208	0.000	0.204	0.000	0.193	0.000	0.148	0.000	0.192	0.000
bb4m	0.412	0.000	0.4	0.000	0.337	0.000	0.603	0.000	0.336	0.000
bb51	−0.057	0.000	−0.05	0.000	−0.022	0.004	−0.038	0.354	−0.023	0.002
bb53	0.061	0.000	0.057	0.000	0.045	0.000	0.083	0.003	0.043	0.000
bb54	0.162	0.000	0.158	0.000	0.127	0.000	0.042	0.241	0.125	0.000
bb5m	0.321	0.000	0.315	0.000	0.294	0.000	0.365	0.000	0.292	0.000
ht1_cr					−0.045	0.000	−0.052	0.000	−0.046	0.000
ht3_cr					0.043	0.000	0.005	0.577	0.043	0.000
ht4_cr					−0.076	0.000	−0.065	0.000	−0.077	0.000
ht6_cr					0.03	0.000	−0.049	0.000	0.029	0.000
beds1_cr					−0.103	0.000	−0.133	0.000	−0.103	0.000
beds2_cr					−0.046	0.000	−0.068	0.000	−0.046	0.000

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	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
beds4_cr					0.073	0.000	0.029	0.001	0.073	0.000
beds5_cr					0.088	0.000	0.008	0.734	0.087	0.000
bb1m_cr					0.118	0.001	0.038	0.571	0.12	0.001
bb22_cr					0.067	0.000	0.052	0.000	0.067	0.000
bb2m_cr					0.1	0.000	0.104	0.000	0.101	0.000
bb32_cr					0.056	0.000	0.026	0.000	0.056	0.000
bb33_cr					0.078	0.000	0.051	0.000	0.079	0.000
bb3m_cr					0.14	0.000	0.128	0.016	0.141	0.000
bb41_cr					−0.067	0.000	−0.05	0.000	−0.067	0.000
bb43_cr					0.011	0.002	0.025	0.016	0.012	0.001
bb44_cr					0.009	0.287	−0.015	0.674	0.009	0.261
bb4m_cr					0.07	0.007	−0.118	0.203	0.071	0.007
bb51_cr					−0.038	0.002	−0.049	0.313	−0.037	0.003
bb53_cr					0.008	0.395	−0.067	0.048	0.009	0.298
bb54_cr					0.031	0.009	0.03	0.485	0.032	0.006
bb5m_cr					0.012	0.559	−0.05	0.568	0.012	0.535
Time FE	YES		YES		YES		YES		YES	
Location FE	YES		YES		YES		YES		YES	
Location-crash FE	NO		YES		YES		YES		YES	
Regional FE	NO		NO		NO		NO		YES	
Regional trends	NO		NO		NO		NO		YES	
Type-region	NO		NO		NO		YES		NO	
Type-region-crash	NO		NO		NO		YES		NO	
R-squared	0.716		0.724		0.727		0.731		0.728	
No. of observations	408,344		408,344		408,344		408,344		408,344	

Table 2: *Abbreviated regression output for rental models*

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
pt2	0.004	0.000	0.005	0.000	−0.009	0.000	−0.001	0.578	−0.009	0.000
pt4	−0.216	0.000	−0.215	0.000	−0.217	0.000	−0.201	0.000	−0.217	0.000
beds1	−0.341	0.000	−0.342	0.000	−0.367	0.000	−0.382	0.000	−0.366	0.000
beds2	−0.182	0.000	−0.182	0.000	−0.18	0.000	−0.203	0.000	−0.18	0.000
beds4	0.154	0.000	0.154	0.000	0.17	0.000	0.204	0.000	0.17	0.000
beds5	0.281	0.000	0.28	0.000	0.311	0.000	0.386	0.000	0.311	0.000
bb1m	0.085	0.000	0.084	0.000	0.027	0.091	0.025	0.149	0.025	0.104
bb22	0.074	0.000	0.074	0.000	0.066	0.000	0.075	0.000	0.066	0.000
bb2m	0.119	0.000	0.119	0.000	0.107	0.000	0.116	0.000	0.106	0.000
bb32	0.059	0.000	0.058	0.000	0.055	0.000	0.059	0.000	0.055	0.000
bb33	0.082	0.000	0.082	0.000	0.074	0.000	0.085	0.000	0.074	0.000
bb3m	0.193	0.000	0.192	0.000	0.213	0.000	0.303	0.000	0.213	0.000
bb41	−0.053	0.000	−0.052	0.000	−0.054	0.000	−0.078	0.000	−0.054	0.000
bb43	0.036	0.000	0.036	0.000	0.03	0.000	0.035	0.000	0.031	0.000
bb44	0.144	0.000	0.143	0.000	0.148	0.000	0.167	0.000	0.149	0.000
bb4m	0.302	0.000	0.302	0.000	0.295	0.000	0.422	0.000	0.295	0.000
bb51	0.009	0.36	0.009	0.365	0.089	0.000	0.193	0.000	0.089	0.000
bb53	0.065	0.000	0.065	0.000	0.082	0.000	0.119	0.000	0.083	0.000
bb54	0.177	0.000	0.175	0.000	0.187	0.000	0.234	0.000	0.189	0.000
bb5m	0.312	0.000	0.311	0.000	0.286	0.000	0.36	0.000	0.286	0.000
b1_s	−0.177	0.000	−0.178	0.000	−0.201	0.000	−0.217	0.000	−0.201	0.000
b2_0s	0.055	0.000	0.054	0.000	0.053	0.000	0.063	0.000	0.053	0.000
b2_2s	−0.096	0.000	−0.096	0.000	−0.066	0.000	−0.085	0.000	−0.066	0.000
b3_0s	0.072	0.000	0.072	0.000	0.079	0.000	0.107	0.000	0.079	0.000
b3_2s	−0.018	0.000	−0.017	0.000	−0.014	0.000	−0.022	0.000	−0.015	0.000
b4_0s	0.112	0.000	0.111	0.000	0.153	0.000	0.266	0.000	0.153	0.000
b4_1s	0.019	0.000	0.018	0.000	0.03	0.000	0.064	0.000	0.03	0.000
b4_3s	0.007	0.107	0.007	0.12	0.017	0.02	0.002	0.836	0.015	0.036

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	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
b5_0s	0.136	0.000	0.137	0.000	0.182	0.000	0.266	0.000	0.183	0.000
b5_1s	0.021	0.000	0.022	0.000	0.035	0.000	0.06	0.000	0.035	0.000
b5_3s	−0.026	0.001	−0.025	0.002	−0.069	0.000	−0.093	0.002	−0.07	0.000
pt2_cr					0.018	0.000	0.015	0.000	0.018	0.000
pt4_cr					0.004	0.279	−0.003	0.453	0.004	0.274
beds1_cr					0.035	0.000	0.037	0.000	0.034	0.000
beds2_cr					−0.003	0.268	0.005	0.105	−0.002	0.32
beds4_cr					−0.022	0.000	−0.015	0.015	−0.023	0.000
beds5_cr					−0.044	0.000	−0.059	0.002	−0.043	0.000
bb1m_cr					0.08	0.000	0.063	0.002	0.082	0.000
bb22_cr					0.009	0.000	0.011	0.000	0.009	0.000
bb2m_cr					0.016	0.009	0.028	0.009	0.017	0.007
bb32_cr					0.004	0.054	0.006	0.041	0.004	0.068
bb33_cr					0.009	0.000	0.032	0.000	0.009	0.000
bb3m_cr					−0.028	0.107	−0.011	0.743	−0.028	0.103
bb41_cr					0.003	0.571	−0.002	0.842	0.002	0.601
bb43_cr					0.007	0.048	0.01	0.197	0.007	0.045
bb44_cr					−0.006	0.535	0.056	0.003	−0.007	0.489
bb4m_cr					0.009	0.753	0.099	0.073	0.01	0.726
bb51_cr					−0.124	0.000	−0.282	0.000	−0.124	0.000
bb53_cr					−0.026	0.017	−0.013	0.514	−0.027	0.013
bb54_cr					−0.015	0.341	0.024	0.373	−0.017	0.281
bb5m_cr					0.032	0.202	0.099	0.017	0.032	0.192
b1_s_cr					0.04	0.000	0.014	0.216	0.039	0.000
b2_0s_cr					0.001	0.476	−0.001	0.679	0.001	0.441
b2_2s_cr					−0.046	0.000	−0.053	0.000	−0.046	0.000
b3_0s_cr					−0.011	0.000	−0.012	0.001	−0.01	0.000
b3_2s_cr					−0.003	0.531	−0.014	0.03	−0.002	0.701
b4_0s_cr					−0.055	0.000	−0.092	0.000	−0.055	0.000

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	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
b4_1s_cr					−0.015	0.000	−0.031	0.000	−0.016	0.000
b4_3s_cr					−0.015	0.101	−0.005	0.776	−0.014	0.141
b5_0s_cr					−0.059	0.000	−0.042	0.076	−0.059	0.000
b5_1s_cr					−0.016	0.157	0.001	0.952	−0.016	0.149
b5_3s_cr					0.063	0.000	0.087	0.011	0.064	0.000
Time FE	YES		YES		YES		YES		YES	
Facilities	YES		YES		YES		YES		YES	
Facilities-crash	NO		NO		YES		YES		YES	
Facilities-regions	NO		NO		NO		YES		NO	
Facilities-regions-crash	NO		NO		NO		YES		NO	
Location FE	YES		YES		YES		YES		YES	
Location-crash FE	NO		YES		YES		YES		YES	
Regional FE	NO		NO		NO		NO		YES	
Regional trends	NO		NO		NO		NO		YES	
Type-region	NO		NO		NO		YES		NO	
Type-region-crash	NO		NO		NO		YES		NO	
R-squared	0.777		0.780		0.782		0.791		0.782	
No. of observations	704953		704953		704953		704953		704953	

.1.2 Heatmaps of list prices and rents in Ireland 2012

The following pages outline "heatmaps" of the variation in like-for-like list prices and rents, across Ireland, for 2012:II, and of the change in prices and rents between 2007:II and 2012:II. An interactive mapping tool, based on this research, is available at Daft.ie/AIRO Property Value Heatmaps.

The maps are based on weighted average prices, where the basket consists of five properties: a one-bedroom apartment, a two-bedroom terraced house, a three-bedroom semi-detached house, a four-bedroom bungalow, and a five-bedroom detached house. (In the lettings segment, the type distinction is between apartments and houses only.) The weights for each of the five property types are an unweighted average of the prevalence of each bedroom size in the sales and lettings segments. Based on this, the weight associated with one- and five-bedroom properties is 6%, while the weights for two-, three- and four-bedroom properties are 27%, 36% and 24% respectively.

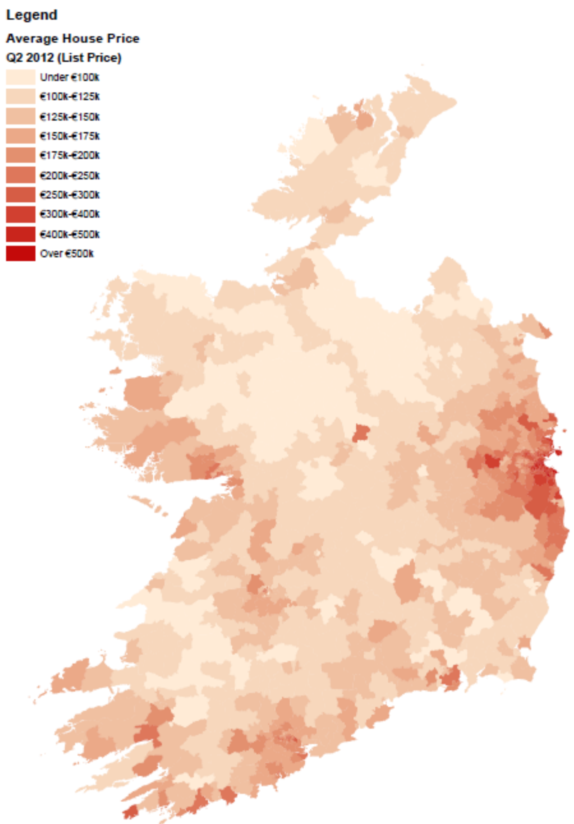


Figure 1: *Average asking prices for property in Ireland by district, 2012:II*

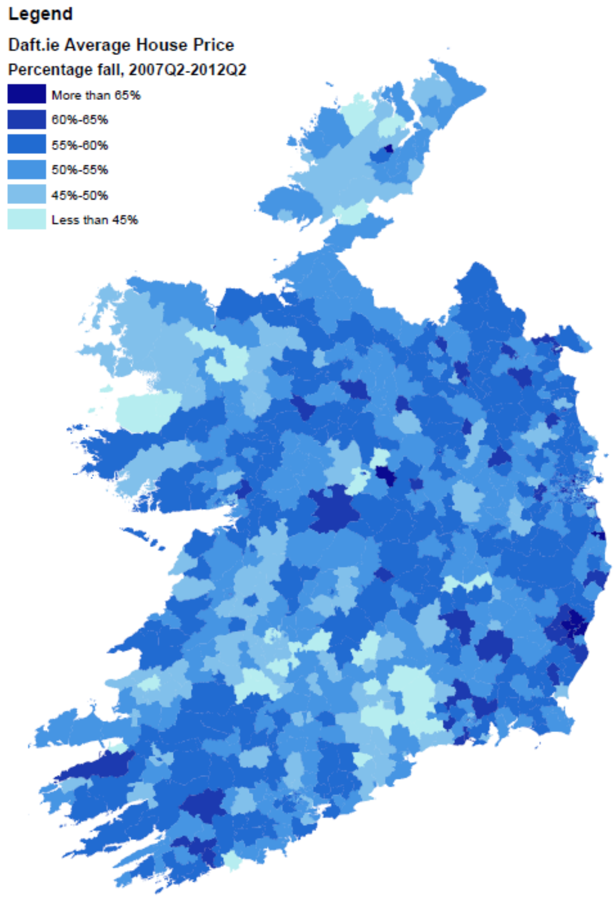


Figure 2: *Fall in average asking prices by district, 2007:II-2012:II*

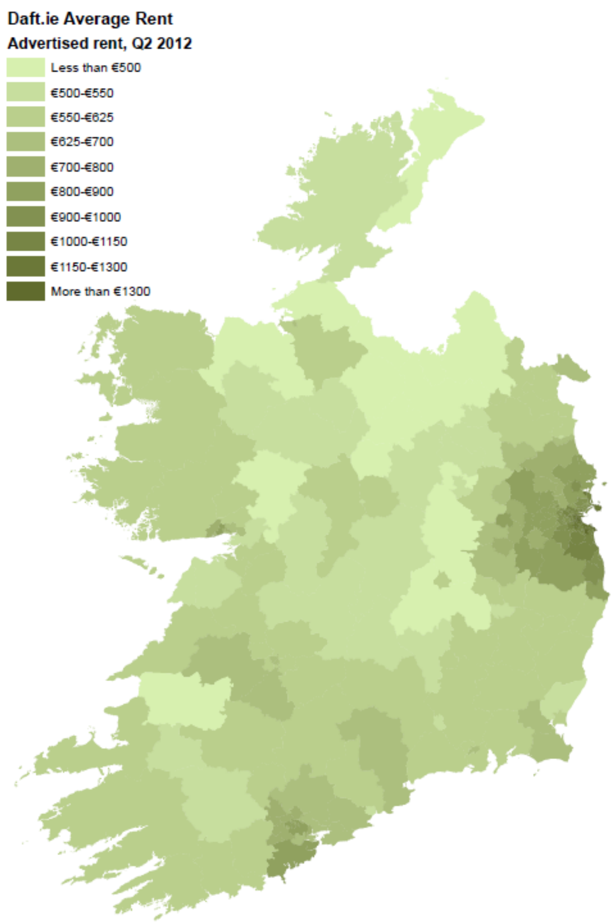


Figure 3: *Average advertised rent in Ireland by district, 2012:II*

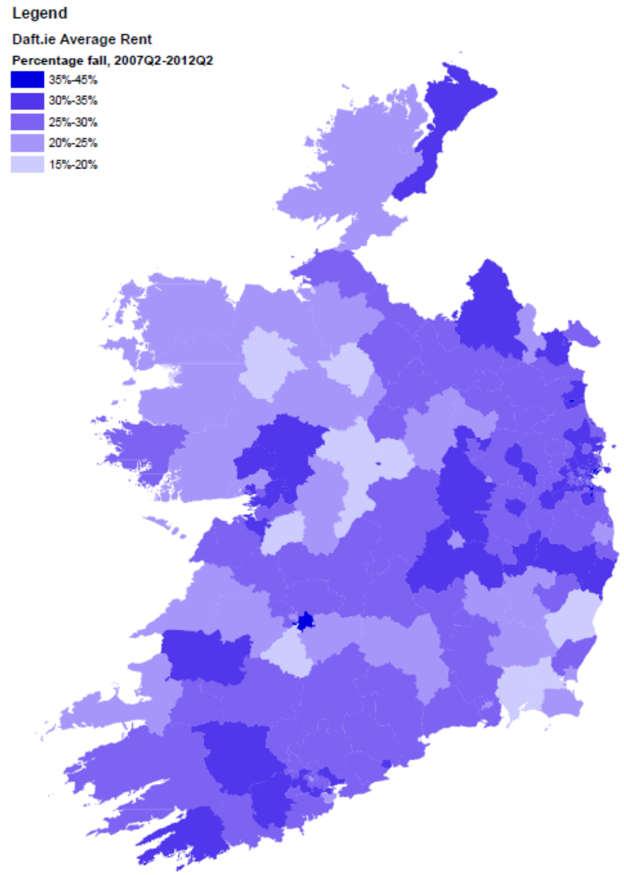


Figure 4: *Fall in average advertised rent by district, 2007:II-2012:II*

.2 Appendix material for Chapter 3

.2.1 Amenity controls

Where possible, controls are included for the class of a particular amenity. For example, the effect on prices of proximity to a lake may be different for small lakes and large lakes, while the effect of proximity to post-primary schools may vary with the proportion of students at those schools that progresses to higher education. Table 3 describes the type controls that apply to various amenities analysed and also describes any region controls. Numbers refer to cut-offs with the control being the middle category; for example, with forests, the control is forests of 50-100 hectares, with variables (indicator variables interacted with any relevant measures of distance) for less than 30, 30-50, 100-200 and more than 200.

The table also outlines regional controls. For most variables to which this apply, they are based on the five broad regions described in Section 3.3.6. For urban green space, they refer to a more refined set of regional markets: six regions within Dublin (central, north city, south city, north county, south county and west); each of the other four cities (Cork, Galway, Limerick and Waterford); Dublin's commuter counties; and all other parts of Ireland.

Table 4 outlines the standard deviation of each of the score-based amenities. These are used to construct price and other effects, as described in the text.

.2.2 Effect of amenities on accommodation costs

Figures 5-8 indicate the estimated effect, in percent, on prices and rents of moving a property from 1km away to 100m away from an amenity (or similar; see text).

Amenity	Type	Regions
Coastline	None	Regions
Lakes	Size (hectares: 0.1, 1, 20, 1000)	Regions
Rivers	Size (order: 1-7)	Regions
Green space	Size (hectares: 3, 10, 50, 100)	-
Forest	Size (hectares: 30, 50, 100, 200)	None
Train station	Type (suburban / N. Ireland rail)	Regions
DART station	None	None
Luas Green station	None	None
Luas Red station	None	None
Primary roads	Speed limit (km/h: 60, 90)	Regions
Secondary roads	Speed limit (km/h: 60, 90)	Regions
Primary school	Number of classes (5, 10); average class size (16, 27)	Regions
Secondary school	School size (1-3); fee-paying (0/1); % progressing to university (15, 25, 35, 50)	Regions
Higher Ed*	Size (number of students: 3,000, 15,000) / university status	Dublin (0/1)
Unemployment†	None	Regions
Commute time†	None	Regions
Agriculture†	None	Regions (rural only)
Education levels†	None	Regions
Burglary†	None	Regions
Murders†	None	Regions
Drugs†	None	Regions
Density†	None	Regions
Border*	None	None
Central Dublin*	None	None
Nearest CBD*	Cross-border	None

Table 3: *Type and region controls for primary amenities*

Amenity	St.Dev.
% with degree	0.1736695
Burglary	1.138635
Murder	1.020988
Drugs	1.407939
Density	1.57652
Unemployment	0.0643738
Commute time	5.386762
% in agriculture	0.035828

Table 4: *Standard deviations for score-type amenities*

Figure 5: *Effect of moving from 1km to 100m away, by segment, natural amenities*

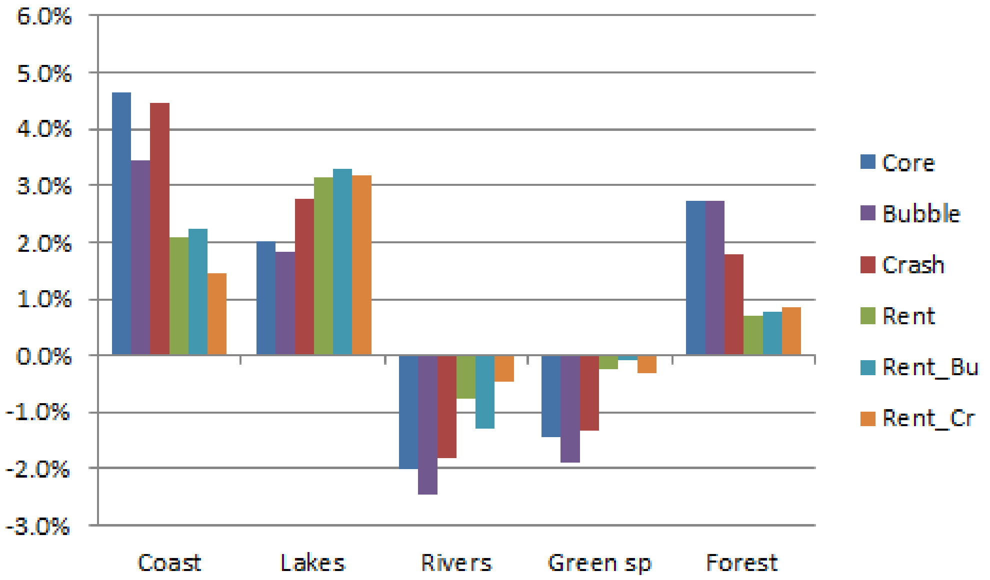


Figure 6: *Effect of moving from 1km to 100m away, by segment, transport amenities*

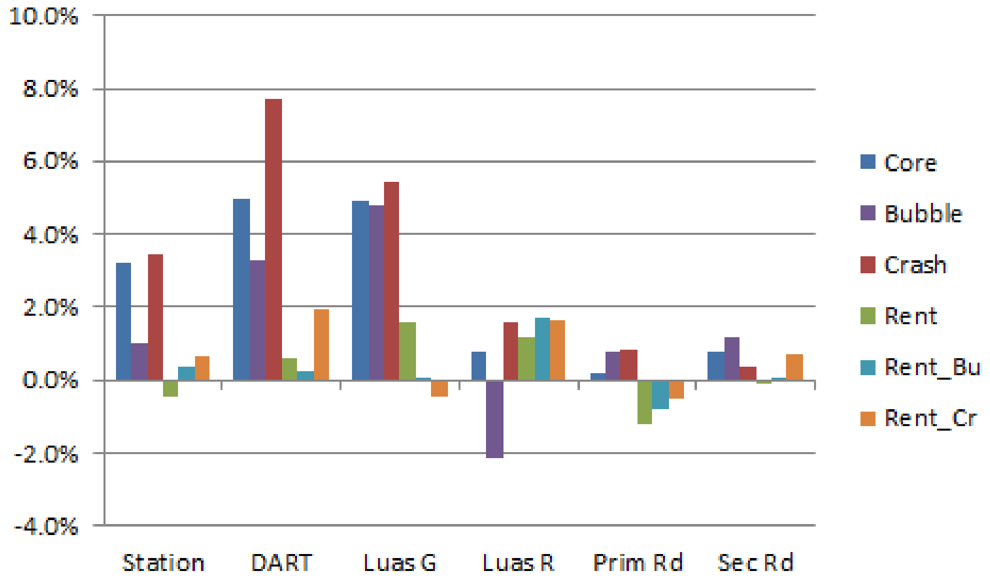


Figure 7: *Effect of moving from 1km to 100m away (†: 5km to 1km), by segment, education & agglomeration amenities*

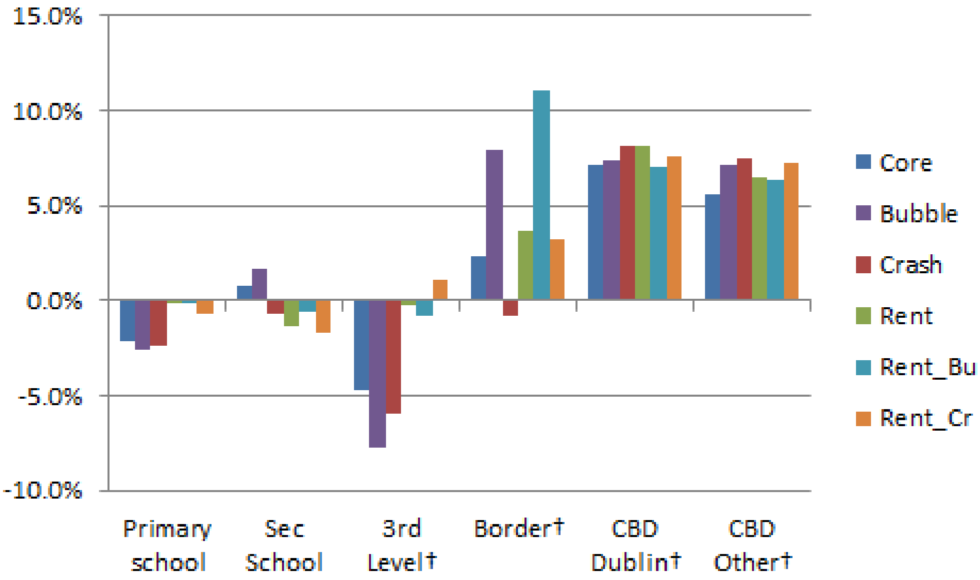
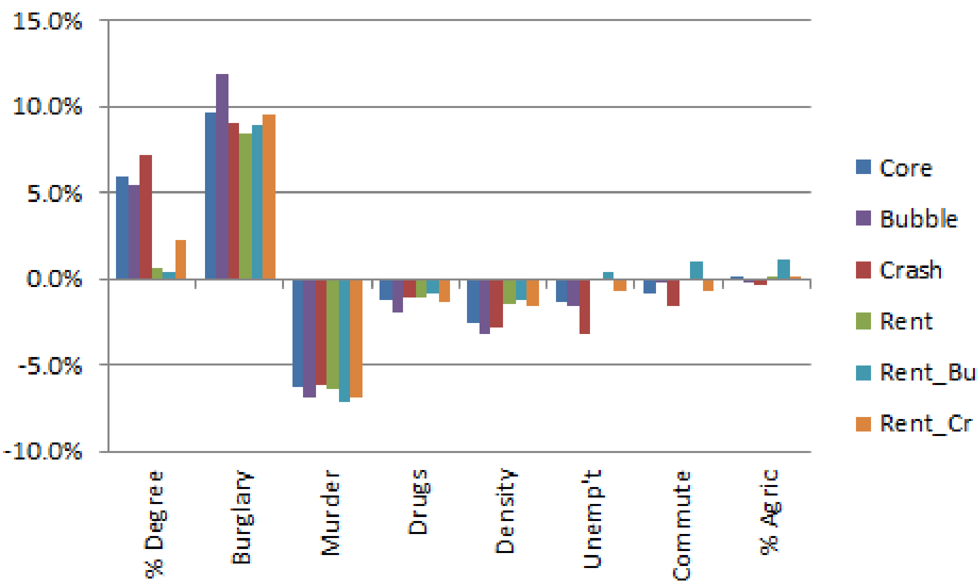


Figure 8: *Effect of one standard deviation change, by segment, neighbourhood & employment amenities*



.3 Appendix material for Chapter 4

Table 5 presents the regression output associated with the models and empirical specification presented in Section 4.4 above. The variables *terr*, *det* and *apart*/*apt* refer to the following house types respectively, where semi-detached is the control: terraced, detached and apartment. Regions 2, 3 and 4 refer to Leinster (ex-Dublin), Munster and Connacht-Ulster repectively.

Table 5: *Regression output: four spreads*

	Listings		Listings (SA)		Sale-ageed		Valuations		Drawdowns	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Dublin	0.465	0	0.462	0	0.441	0	0.463	0	0.462	0
Meath	0.085	0	0.105	0	0.1	0	0.066	0	0.065	0
Kildare	0.121	0	0.157	0	0.145	0	0.121	0	0.121	0
Wicklow	0.289	0	0.293	0	0.293	0	0.259	0	0.259	0
Longford	−0.371	0	−0.412	0	−0.401	0	−0.401	0	−0.399	0
Offaly	−0.161	0	−0.198	0	−0.183	0	−0.209	0	−0.208	0
Westmeath	−0.163	0	−0.187	0	−0.19	0	−0.18	0	−0.175	0
Laois	−0.245	0	−0.26	0	−0.265	0	−0.235	0	−0.236	0
Carlow	−0.187	0	−0.189	0	−0.187	0	−0.219	0	−0.219	0
Kilkenny	−0.118	0	−0.12	0	−0.127	0	−0.15	0	−0.151	0
Waterford	−0.071	0	−0.102	0	−0.114	0	−0.121	0	−0.12	0
Wexford	−0.14	0	−0.191	0	−0.185	0	−0.192	0	−0.194	0
Kerry	−0.14	0	−0.147	0	−0.135	0	−0.166	0	−0.166	0
Cork	0.056	0	0.13	0	0.115	0	0.085	0	0.084	0
Clare	−0.127	0	−0.123	0	−0.129	0	−0.152	0	−0.154	0
Limerick	−0.136	0	−0.091	0	−0.096	0	−0.184	0	−0.184	0
Tipperary	−0.241	0	−0.254	0	−0.248	0	−0.258	0	−0.258	0
Galway	−0.062	0	0.04	0	0.04	0	−0.048	0	−0.05	0
Mayo	−0.321	0	−0.319	0	−0.311	0	−0.309	0	−0.308	0
Roscommon	−0.412	0	−0.433	0	−0.434	0	−0.349	0	−0.348	0
Sligo	−0.25	0	−0.219	0	−0.213	0	−0.235	0	−0.236	0
Leitrim	−0.396	0	−0.425	0	−0.41	0	−0.363	0	−0.365	0
Donegal	−0.324	0	−0.389	0	−0.387	0	−0.379	0	−0.378	0
Cavan	−0.277	0	−0.284	0	−0.273	0	−0.295	0	−0.293	0
Monaghan	−0.183	0	−0.163	0	−0.14	0	−0.187	0	−0.188	0
q12006	−0.094	0					−0.12	0	−0.126	0
q22006	−0.065	0					−0.067	0	−0.074	0
q32006	−0.027	0					−0.038	0	−0.035	0
q42006	−0.014	0	−0.007	0.192	−0.006	0.378	−0.016	0	−0.015	0
q22007	0.019	0	0.006	0.259	0.012	0.069	0.014	0	0.009	0.008
q32007	0.021	0	0.012	0.033	0.009	0.186	0.016	0	0.02	0
q42007	0.014	0	0.015	0.017	0.024	0.001	0.023	0	0.02	0
q12008	0.014	0	0.007	0.275	0.013	0.066	0.014	0	0.019	0
q22008	−0.012	0	−0.007	0.228	0.029	0	0.003	0.309	0.015	0
q32008	−0.041	0	−0.05	0	−0.002	0.783	−0.028	0	−0.007	0.054
q42008	−0.096	0	−0.111	0	−0.002	0.799	−0.062	0	−0.039	0
q12009	−0.136	0	−0.162	0	−0.059	0	−0.144	0	−0.112	0

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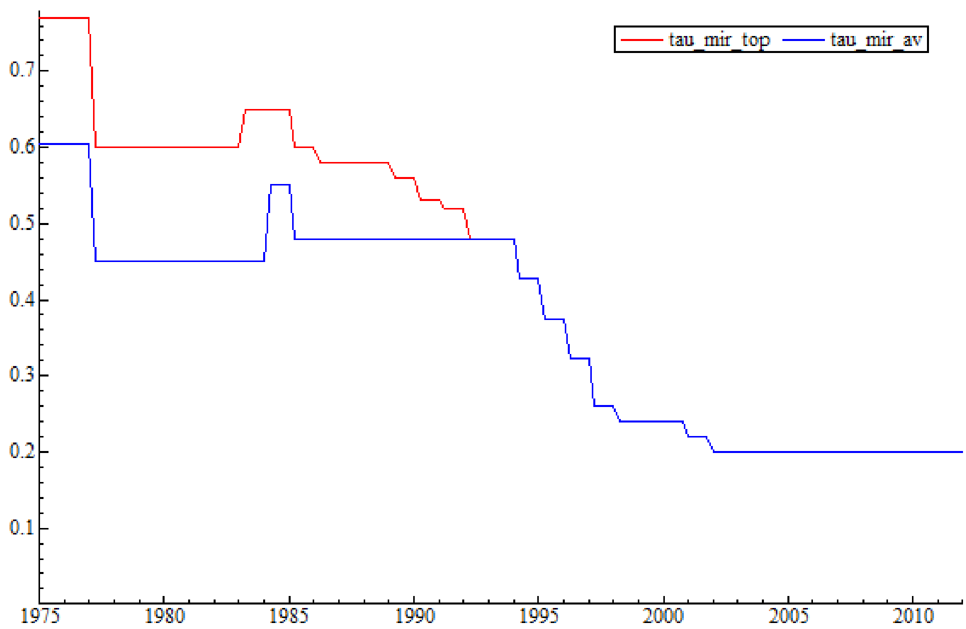
	Listings		Listings (SA)		Sale-ageed		Valuations		Drawdowns	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
q22009	−0.173	0	−0.195	0	−0.101	0	−0.194	0	−0.16	0
q32009	−0.218	0	−0.253	0	−0.137	0	−0.238	0	−0.209	0
q42009	−0.276	0	−0.306	0	−0.175	0	−0.269	0	−0.256	0
q12010	−0.299	0	−0.32	0	−0.228	0	−0.302	0	−0.271	0
q22010	−0.317	0	−0.327	0	−0.235	0	−0.334	0	−0.317	0
q32010	−0.358	0	−0.389	0	−0.261	0	−0.335	0	−0.354	0
q42010	−0.367	0	−0.425	0	−0.298	0	−0.352	0	−0.359	0
q12011	−0.418	0	−0.462	0	−0.345	0	−0.371	0	−0.339	0
q22011	−0.451	0	−0.479	0	−0.398	0	−0.424	0	−0.418	0
q32011	−0.505	0	−0.567	0	−0.422	0	−0.458	0	−0.447	0
q42011	−0.561	0	−0.615	0	−0.449	0	−0.531	0	−0.52	0
q12012	−0.578	0	−0.662	0	−0.521	0				
q22012	−0.6	0	−0.649	0	−0.53	0				
q32012	−0.637	0	−0.659	0	−0.565	0				
q42012	−0.653	0	−0.68	0	−0.634	0				
terr	−0.216	0	−0.216	0	−0.211	0	−0.195	0	−0.196	0
det	0.291	0	0.271	0	0.271	0	0.342	0	0.333	0
apart	−0.313	0	−0.353	0	−0.341	0	−0.251	0	−0.257	0
reg2_ter	0.044	0	0.009	0.29	0.004	0.637	0.061	0	0.062	0
reg2_det	0.027	0	−0.003	0.755	0.001	0.887	0.053	0	0.057	0
reg2_apt	0.113	0	0.098	0	0.093	0	0.093	0	0.097	0
reg3_ter	0.011	0.005	−0.057	0	−0.052	0	0.065	0	0.065	0
reg3_det	−0.034	0	−0.073	0	−0.052	0	0.004	0.377	0.005	0.269
reg3_apt	0.149	0	0.104	0	0.107	0	0.191	0	0.196	0
reg4_ter	0.122	0	0.099	0	0.089	0	0.137	0	0.138	0
reg4_det	−0.007	0.097	−0.066	0	−0.05	0	0.013	0.013	0.013	0.011
reg4_apt	0.268	0	0.23	0	0.215	0	0.258	0	0.262	0
cons	12.611	0	12.604	0	12.592	0	12.632	0	12.626	0
R-squared	0.531		0.561		0.522		0.479		0.473	
No. of observations	395,850		71,657		71,749		246,217		246,427	

.4 Appendix material for Chapter 5

.4.1 Mortgage Interest Relief

In Section 5.3.7, reference was made to mortgage interest relief, through which owner-occupiers received an income tax rebate. This relief was at the marginal rate for earners, and subject to ceilings to time limits at different points. For the purposes of this study, as the relief applied for more than five years throughout the sample, and the ceilings were not binding for those buying at average prices, the key variable in determining the net mortgage rate was the marginal rate of income tax paid. Figure 9 shows the full marginal rate and the marginal rate that would have applied at the average industrial wage, using data from AMECO on nominal average compensation per employee. Mortgage interest relief did not apply in the Irish market from January 2013.

Figure 9: *Rate of mortgage interest relief, marginal and average wage, 1975-2012*



.4.2 Regression Output

Table 6 details the regression output, including coefficients and associated standard errors, t-statistics and p-values, for the model with full dynamics outlined in Section 5.4. As is outlined in the text, the long-run solution is clear, while few of the dynamic terms are statistically significant.

Table 6: *Model 1: dlrhp with full potential dynamics, 1980-2012*

	Coeff		S.E.	t-stat	p-value
Constant	3.9627	***	1.377	2.88	0.0049
lrhp_1	-0.3058	***	0.0811	-3.77	0.0003
lrystock_phh_1	0.3859	***	0.1071	3.6	0.0005
phhr_1	-0.1148	**	0.0562	-2.04	0.0438
mcdr_1	0.1654	***	0.0552	3	0.0035
rm_net_r_4y_1	-0.4387	***	0.1542	-2.85	0.0054
tau_sd_ftb_1	-0.4941		0.3285	-1.5	0.1359
dlrhp_1	0.264	***	0.0993	2.66	0.0092
dlrhp_2	-0.1323		0.1061	-1.25	0.2154
dlrhp_3	0.1427		0.0934	1.53	0.1301
dlrhp_4	-0.2514	***	0.0924	-2.72	0.0078
infl_cpi_ex	-0.2574		0.1984	-1.3	0.1975
infl_cpi_ex_1	0.3451		0.2481	1.39	0.1675
infl_cpi_ex_2	-0.0824		0.2548	-0.32	0.7471
infl_cpi_ex_3	-0.2635		0.2461	-1.07	0.2872
infl_cpi_ex_4	0.2342		0.1794	1.31	0.1949
pop_migr_pc	1.4425		3.006	0.48	0.6325
pop_migr_pc_1	-1.0089		5.848	-0.17	0.8634
pop_migr_pc_2	0.4902		6.09	0.08	0.936
pop_migr_pc_3	-4.0599		5.667	-0.72	0.4755
pop_migr_pc_4	3.5081		2.996	1.17	0.2445
delta_ueq1	-0.0193	***	0.0056	-3.42	0.0009
delta_ueq1_1	-0.0098		0.0059	-1.66	0.1003
delta_ueq1_2	0.0057		0.0059	0.97	0.3363
delta_ueq1_3	-0.0003		0.0059	-0.05	0.9565
delta_ueq1_4	0.0021		0.0052	0.4	0.6883
dmcdr	-0.0223		0.2365	-0.09	0.9251
dmcdr_1	0.4768	*	0.2678	1.78	0.0781
dmcdr_2	-0.415		0.2826	-1.47	0.1452
dmcdr_3	0.4506		0.287	1.57	0.1197
dmcdr_4	-0.2027		0.2336	-0.87	0.3877
lpop_2534_1	0.0007		0.1692	0	0.9965
drm_net_nom	0.2153		0.4498	0.48	0.6333
drm_net_nom_1	-0.2963		0.4466	-0.66	0.5087
drm_net_nom_2	0.8682	*	0.4655	1.87	0.0653
drm_net_nom_3	-0.3328		0.4382	-0.76	0.4495
drm_net_nom_4	0.7072		0.4484	1.58	0.1181

.4.3 Robustness & sensitivity analysis

Tables 7 and 8 show the coefficients and associated p-values for a number of specifications designed to check the robustness of the results outlined in Section 5.4.3. The first table examines alternative data series for a range of fundamentals, while the second table shows results for different functional specifications of the three core fundamental ratios: income to supply, mortgages to deposits, and persons to households. The final rows of each table show measures of model fit and also whether the model failed any of six core tests. Commentary on these results is given in Section 5.4.3.

Table 7: *Robustness analysis of inverted demand model: alternative fundamentals*

	Original		25-34 pop		LTV		Income, stock		Per cap y, stock		Stock (volume)		Weighted r		Grants		Annual unemp	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Constant	4.079	0	3.94	0	0.943	0.001	0.628	0.332	0.431	0.091	-0.477	0.402	3.614	0	3.93	0	3.94	0
lrhp_1	-0.314	0	-0.324	0	-0.06	0.004	-0.339	0	-0.344	0	-0.343	0	-0.284	0	-0.303	0	-0.306	0
lrystock_1	0.395	0	0.405	0	0.073	0.309							0.395	0	0.376	0	0.418	0
phhr_1	-0.122	0	-0.119	0	-0.059	0.022	-0.071	0.099	0	0	0.02	0.539	-0.086	0	-0.113	0	-0.106	0
mcdr_1	0.174	0	0.17	0	-0.023	0.714	0.167	0	0.161	0	0.157	0	0.163	0	0.165	0	0.171	0
rm_nr4_1	-0.481	0	-0.496	0	-0.146	0.037	-0.491	0	-0.495	0	-0.555	0	-0.411	0	-0.465	0	-0.435	0
tau_sd_1	-0.476	0.027	-0.476	0.027	-0.158	0.478	-0.53	0.015	-0.532	0.014	-0.485	0.026	-0.438	0.041	-0.468	0.029	-0.499	0.024
lpop2534_1			0.015	0.94														
lry_1	0	0	0	0	0	0	0.435	0	0.442	0	0.394	0						
lrstock_1	0	0	0	0	0	0	-0.302	0.004	-0.262	0.001	-0.349	0.016						
gtv_1															-0.094	0.266		
dlrhp_1	0.166	0.038	0.17	0.036	0.111	0.211	0.175	0.029	0.18	0.023	0.187	0.022	0.142	0.081	0.159	0.048	0.204	0.013
dlrhp_4	-0.256	0	-0.251	0.001	-0.202	0.007	-0.249	0	-0.243	0	-0.222	0.001	-0.272	0	-0.256	0	-0.256	0
dueq1	-0.016	0	-0.016	0	-0.017	0.001	-0.018	0	-0.018	0	-0.019	0	-0.017	0	-0.016	0	-0.014	0.014
dueq1_1	-0.01	0.024	-0.011	0.022	-0.011	0.03	-0.012	0.012	-0.012	0.007	-0.014	0.004	-0.011	0.023	-0.011	0.021	-0.006	0.295
dmcdr_1	0.31	0.012	0.301	0.016	0.331	0.016	0.298	0.015	0.296	0.015	0.314	0.012	0.302	0.015	0.345	0.007	0.302	0.021
sigma	0.01673		0.01679		0.01841		0.01666		0.0166		0.01686		0.01684		0.01671		0.01725	
R2	0.696		0.696		0.631		0.701		0.7		0.694		0.691		0.699		0.676	
Test failures	None		None		AR1-5		None		None		None		None		None		None	

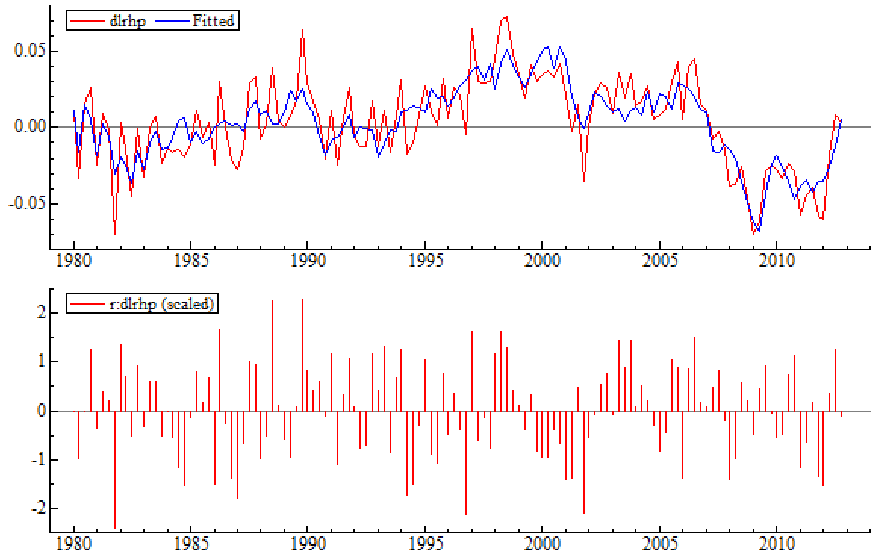
Table 8: *Robustness analysis of inverted demand model: logs vs. levels for ratios*

	No LR		Original		Log MCDR		Log PHHR		All logs		All levels	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Constant	0.003	0.133	4.079	0	2.388	0	4.158	0	2.461	0	3.274	0
lrhp_1			-0.314	0	-0.223	0	-0.312	0	-0.221	0	-0.288	0
lrystock_1			0.395	0	0.264	0	0.38	0	0.253	0	0.487	0
phhr_1			-0.122	0	-0.1	0	-0.426	0	-0.345	0	-0.114	0
mcdr_1			0.174	0	0.148	0	0.168	0	0.142	0	0.163	0
rm_nr4_1			-0.481	0	-0.403	0	-0.495	0	-0.411	0	-0.45	0
tau_sd_1			-0.476	0.027	0.005	0.983	-0.449	0.036	0.015	0.943	-0.247	0.223
dlrhp_1	0.3	0.001	0.166	0.038	0.139	0.088	0.169	0.035	0.144	0.08	0.155	0.053
dlrhp_4	-0.045	0.541	-0.256	0	-0.252	0.001	-0.25	0	-0.246	0.001	-0.258	0
dueq1	-0.02	0	-0.016	0	-0.016	0.001	-0.016	0.001	-0.015	0.001	-0.015	0.001
dueq1_1	-0.015	0.003	-0.01	0.024	-0.011	0.017	-0.01	0.027	-0.011	0.018	-0.01	0.034
dmcdr_1	0.314	0.006	0.31	0.012	0.16	0.161	0.316	0.011	0.162	0.157	0.288	0.02
sigma	0.02045		0.01673		0.01724		0.01681		0.01733		0.01688	
R2	0.522		0.696		0.677		0.693		0.673		0.69	
Test failures	None		None		AR1-5		None		AR1-5		None	

.4.4 Fitted values & Parameter stability

Figures 10 and 11 show the actual and fitted values of the change in real house prices (*dlrhp*) for the model applied to the 1980-2012 period and the same model applied to the 1975-2012 period. Figure 12 shows the actual and fitted values of the change in the house price-to-rent ratio, 2000-2012. Figure 13 shows the recursive estimates of parameters on the long-run variables in the inverted demand specification, starting with a ten-year window (1980-1990). Commentary on all these results is given in the text.

Figure 10: *Actual and fitted values of dlrhp, 1980-2012*



.4.5 Stationarity & Cointegration

Table 9 presents supplementary augmented Dickey-Fuller tests, as described in the text. Figures 14-15 show plots of the following variables in delta form: log real house prices, log real income per household, log real housing stock per household, log of the income-stock ratio, the credit-deposit ratio, user-cost, the person-household ratio and the change in population aged 25-34. Figures 16 and 17 contrast changes in per household income and housing stock (likely to be stationary) with changes in per capita income and stock, which fail unit root tests at all conventional levels of statisticaly significance.

Figure 11: *Actual and fitted values of dlrhp, 1975-2012*

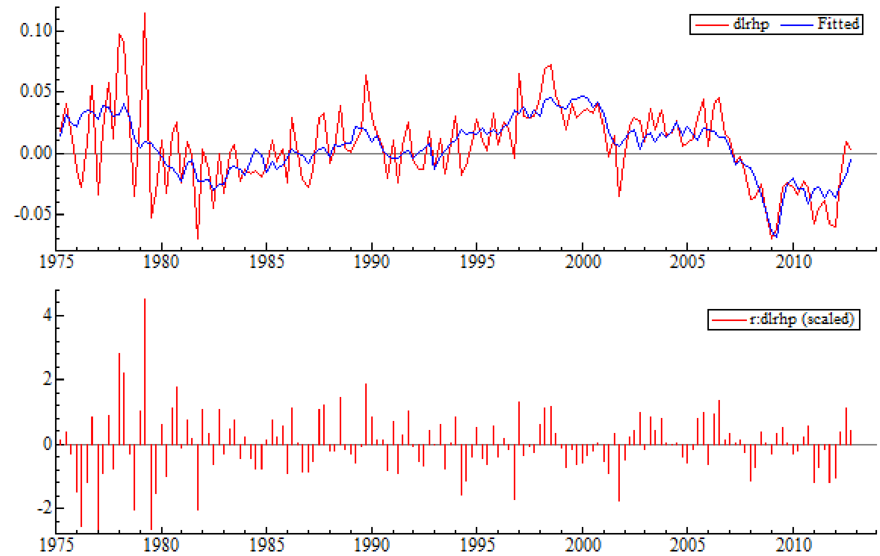


Figure 12: *Actual and fitted values of dlhpr, 2000-2012*

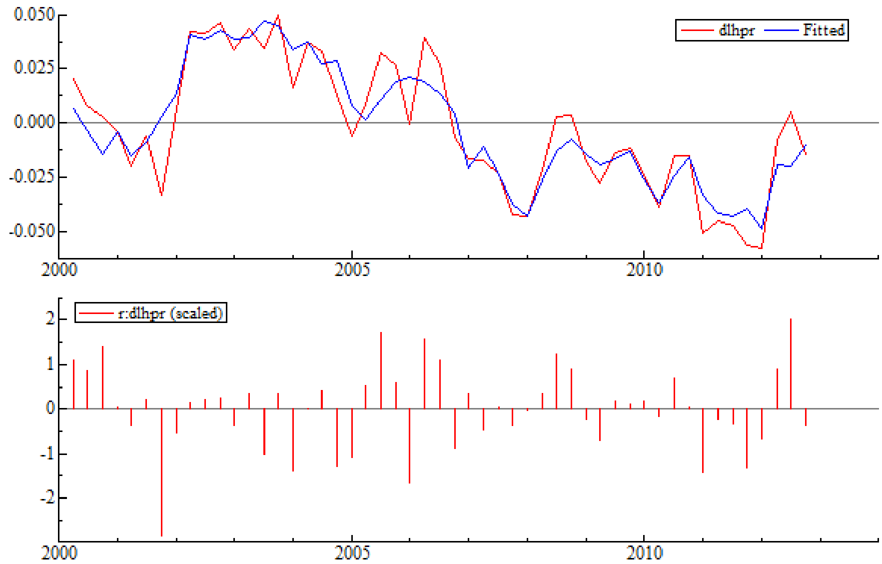


Figure 13: *Recursive estimates of coefficients, inverted demand model, 1990-2012*

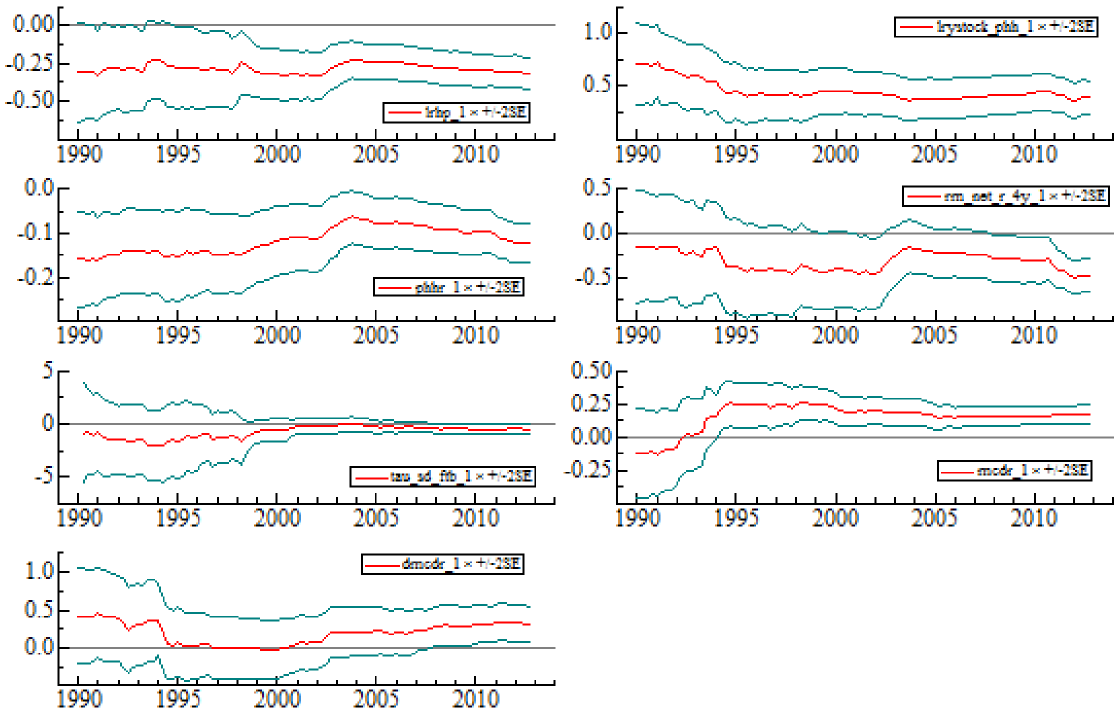


Figure 14: *Plots of changes in house prices, income and housing stock*

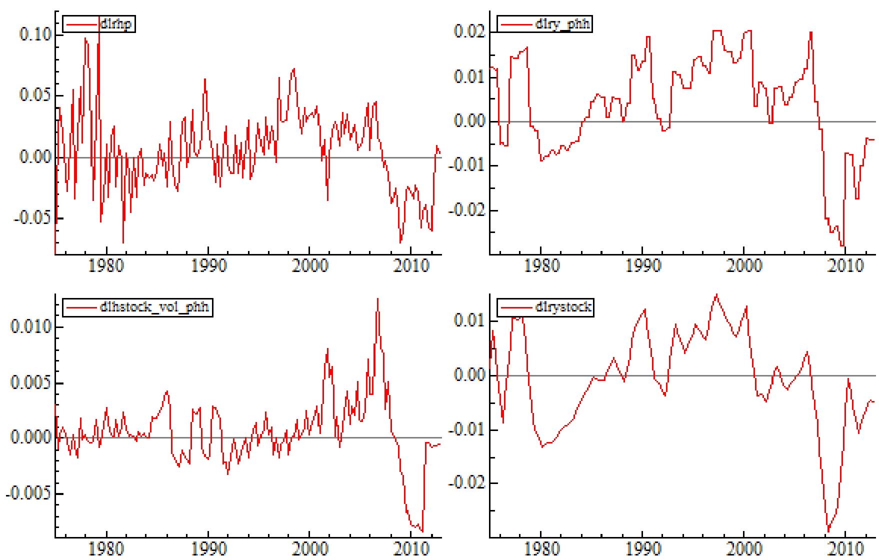


Table 9: *ADF unit root tests: supplementary series*

Var	D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
dlry_pc	3	-2.286	0.919	0.004	0.471	0.639	-10.87	
	2	-2.243	0.922	0.004	0.453	0.652	-10.89	0.639
	1	-2.204	0.925	0.004	0.436	0.664	-10.9	0.809
	0	-2.167	0.928	0.004			-10.91	0.893
dlhs_pc	3	-0.1197	0.996	0.001	-1.658	0.1	-13.62	
	2	-0.437	0.985	0.001	-3.116	0.002	-13.61	0.1
	1	-1.121	0.96	0.001	-3.272	0.001	-13.55	0.003
	0	-1.912	0.932	0.001			-13.49	0
dlry_ph^{dagger}	3	-3.441**	0.854	0.005	0.814	0.417	-10.45	
	2	-3.347**	0.862	0.005	0.379	0.705	-10.46	0.417
	1	-3.363**	0.866	0.005	0.785	0.434	-10.47	0.669
	0	-3.274**	0.873	0.005			-10.48	0.702
dlhs_ph^{dagger}	3	-2.949**	0.878	0.002	0.392	0.696	-12.67	
	2	-2.950**	0.882	0.002	0.854	0.395	-12.68	0.696
	1	-2.831*	0.89	0.002	0.168	0.867	-12.69	0.646
	0	-2.886**	0.892	0.002			-12.7	0.824
dd4pop2534	3	-4.471***	0.746	0.002	1.551	0.124	-12.76	
	2	-4.170***	0.777	0.002	1.366	0.174	-12.75	0.124
	1	-3.927***	0.8	0.002	1.065	0.289	-12.75	0.121
	0	-3.778***	0.815	0.002			-12.76	0.148
dlyhs^{dagger}	3	-3.937***	0.812	0.005	0.664	0.508	-10.46	
	2	-3.905***	0.82	0.005	0.972	0.333	-10.47	0.508
	1	-3.783***	0.832	0.005	0.464	0.644	-10.47	0.503
	0	-3.800***	0.837	0.005			-10.49	0.661

Figure 15: *Plots of changes in other regressors*

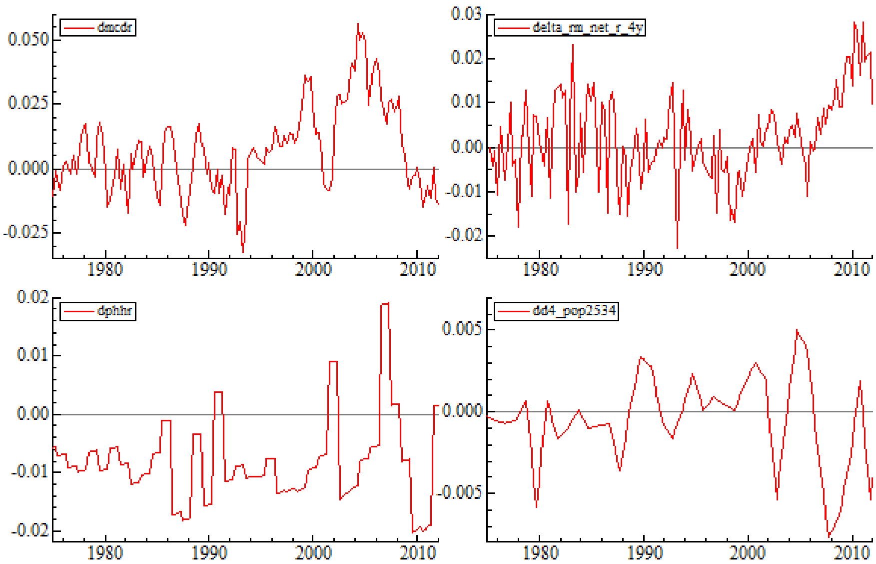


Figure 16: *Plots of changes in per household and per capita income*

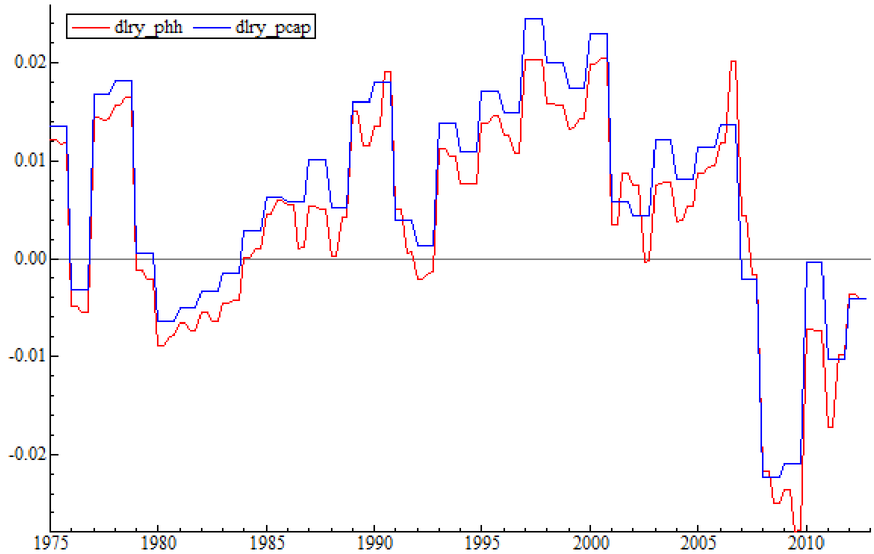


Figure 17: *Plots of changes in per household and per capita housing stock*