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An Econometric Analysis of U.K. Regional Real Estate Markets

Alisa Yusupova

BSc Saint-Petersburg State University of Economics,

MSc Lancaster University

Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy at the Department of Economics, Lancaster University.

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Declaration

I hereby declare that this thesis is my own work and that it has not been submitted for any other degree.

Alisa Yusupova

Signature:

To my mother

Abstract

This thesis presents an analysis of UK national and regional property price dynamics with the focus on changes in the time-series properties of real estate prices and their forecastability. The main research questions addressed are the following. First, have UK regional property prices experienced episodes of explosive dynamics in the past and if so, can these episodes be explained by movements in economic fundamentals. Second, considering the substantial instability of UK real estate markets over the last few decades, which are the best econometric models for predicting future house price dynamics and which economic variables are the most important drivers of property prices movements.

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I would like to express my sincere gratitude to my supervisors, Prof David Peel, Dr Efthymios Pavlidis and Prof Ivan Paya, who put their faith in me, showed me the road and guided me throughout this exciting journey. I thank them for being the source of motivation, for their support and encouragement, and for giving me the opportunity to go farther than I would have ever thought I could go.

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CHAPTER 1

Introduction

Study the past if you would divine the future.
— Confucius, 551-479 BC

Over the last years an interest in the dynamics of UK commercial and residential property prices in the media and among policy makers has been steadily increasing, and for a good reason. The UK property prices have now reached unprecedentedly high levels. In particular, house prices in London rose by nearly 11% in the past year only and currently exceed their pre-crisis peak value of 2007 by more than 50%. Mr. Mark Carney, the Governor of the Bank of England, has expressed his concerns about the risk that the booming housing markets poses to the UK economy:

> *'When we look at domestic risks, the biggest risk to financial stability, and therefore to the durability of the expansion, centres in the housing market.'*
>
> *Mr. Mark Carney (cited in Schomberg and Addison, 2014)*

Following the devastating effects of the latest boom and bust in the housing markets, more and more international organisations, central banks and research institutes become engaged in monitoring the property price developments. IMF economists warn that property prices in the UK, and in London in particular, might be growing too quickly and can soon rise to unsustainable levels:

> *'House price inflation is particularly high in London, and is becoming more widespread. So far, there are few of the typical signs of a credit-led bubble.'*
>
> *IMF (2014)*

In this context, understanding the dynamics of real estate prices, what causes house prices to move and the nature of historical episodes of property price exuberance becomes particularly important. This thesis is built upon two research questions. First, have non-fundamental factors, such as rational speculative bubbles, played a role in the behaviour of the UK housing market in the past? And, second, is there an econometric model that would be able to consistently generate accurate forecasts of future house price movements?

With regards to the first question, a rational speculative bubble was defined by Blanchard and Watson (1982) as the deviation of an asset price from its fundamental value. Hence in order to test for the presence of housing bubbles one requires a model of the fundamental value of housing, which is then assessed against the actual, observed housing value. The finding that property price dynamics can be explained by movements in economic fundamentals serves as an argument in favour of the absence of rational speculative bubbles in the housing market. This approach to testing for rational bubbles has gained a wide popularity in the empirical literature (for UK housing market applications see e.g., IMF (2003, 2005), Barrell et al. (2004), Meen (2002), Cameron et al. (2006)).

At the same time, the presence of a rational speculative bubble, according to Diba and Grossman (1988), introduces explosive dynamics in the asset price series, since a rational bubble occurs when asset prices are driven not only by economic fundamentals but also by the expectation of a gain from future price increases. This explosive nature of non-fundamental asset price components motivates a direct way of testing for rational bubbles. If the series under examination is explosive, while economic fundamentals are at most integrated of order 1, then the evidence of explosive dynamics in the series of asset prices can be interpreted as an indication that speculative bubbles are present. A substantial empirical literature, which deals with detection of asset price bubbles, exploits the explosive nature of non-fundamental asset price components, see Gurkaynak (2008) and Homm and Breitung (2012) for a comprehensive overview of the existing tests.

Chapter 2 approaches the problem of housing bubble detection from two angles: it employs both a structural model of real estate prices and formal econometric tests for explosiveness in the house price series. First, it examines whether the fundamental value model of housing developed by Gavin Cameron, John Muellbauer and Anthony Murphy (2006) is able to explain the UK regional property price movements during the periods of boom and bust in the real estate markets. It pays particular attention to the two episodes in the history of UK housing market dynamics: property price expansion of the late 1980s and the recent housing boom of the early and mid-2000s. The chapter explores the link between the real estate prices and their fundamental determinants. The existence of a stable long-run equilibrium relationship between prices and fundamentals, according to Diba and Grossman (1988), rules out the rational bubble hypothesis. On the contrary, if there exists a rational property price bubble, prices and fundamentals will never converge to an equilibrium.

Next the focus is on the empirical tests for rational asset price bubbles that exploit the explosive nature of non-fundamental asset price components. Specifically, the chapter applies the recently developed recursive unit root tests of Peter C.B. Phillips and his co-authors (2011, 2015) to the series of real estate prices and the price-to-income ratios. The appealing feature of the testing strategy is that it allows not only to detect the presence of explosiveness but also to shed light on the chronology of its origination and collapse. The chapter analyses the timeline of explosive dynamics and examines whether there is a synchronisation of the explosive episodes across regional housing markets and whether it leads to the overall, or nationwide exuberance. Further, the chapter investigates whether the pattern of exuberance propagation is consistent with the notion of the so-called ripple effect, widely documented in the empirical literature on UK housing markets, which implies that house price shocks emanating from Greater London have a tendency to spread out and affect neighbouring regions (see e.g., MacDonald and Taylor (1993), Alexander and Barrow (1994), Drake (1995), Meen (1999), Cook and Thomas (2003), Holly et al. (2010)). Finally, the chapter sets the evidence of the fundamental value model of housing against the evidence of the Phillips et al. (2015) test for explosiveness. If the structural model of Cameron et al. (2006) is not able to explain property price movements during the exuberant phases it will allow us to conclude that the exuberance is driven by non-fundamental factors, such as rational speculative bubbles.

While Chapter 2 can be seen as an in-sample exercise, Chapter 3 presents an extensive investigation of the ability of a battery of econometric models to produce accurate out-of-sample forecasts of property price inflation. The Chapter addresses the second research question by evaluating UK regional and national property price forecastability during the recent upswing and downturn in the real estate market and by identifying the key economic variables that drive property price movements. The choice of the research question is motivated, on the one hand, by the increased concern of the housing market observers about the future behaviour of the real estate prices, and, on the other hand, by the scarcity of the empirical literature on forecasting residential and commercial property price movements outside the US. The topic is addressed by employing a battery of static and dynamic econometric methods to a large macroeconomic data set that spans the out-of-sample period from 1995:Q1 to 2012:Q4, and thus covers the recent boom and bust in the housing markets. The forecasting strategies considered include Dynamic Model Averaging and Dynamic Model Selection, recently developed by Raftery et al. (2010) and used in the housing context by Bork and Møller (2015) for predicting US real estate prices, as well as forecasting techniques that have enjoyed a wide popularity in the academic literature on forecasting real estate prices, such as Time-Varying Parameter models, small-scale and large-scale Bayesian VARs and Autoregressive Distributed Lag models. In addition to comparing accuracy of the out-of-sample forecasts generated by the alternative predictive strategies, the chapter examines the forecasting performance of these models over time. Special attention is paid to the ability of various forecasting models to capture the recent boom and bust in the housing markets.

The dynamic models considered allow different model specifications to hold at each point in time, which is particularly appealing since it enables to trace whether the best predictors during the boom period are different from the variables driving property price inflation during the bust phase. This motivates the choice of the second research topic addressed in the chapter. Specifically, the chapter examines how the predictive ability of 10 regional- and national-level house price predictors varies over time, across regions and forecast horizons. The link between the two main chapters is established by investigating, in addition to the 9 predictors that have been employed by Bork and Møller (2015), the role of credit rationing/liberalisation in determining the dynamics of property price inflation. This is a particularly interesting exercise since, despite the important role of credit markets in the financial crisis, the predictive ability of credit rationing/liberalisation has not been examined in a forecasting context before. Lastly, the chapter discusses how the choice of the house price predictors varies with the volatility of the real estate markets.

An overall summary of the main findings and conclusions of this thesis is provided in the last section of the thesis.

CHAPTER 2

Exuberance in U.K. Housing Markets

2.1. Introduction

House prices in the UK have recently climbed to unprecedentedly high levels, surging ahead of their 2007 peak values. The price growth in London is even more dramatic. According to Nationwide figures, real estate prices in the metropolis have nearly doubled since the trough of 2009, being now 50% above their pre-crisis levels. A concern that property prices in the UK and, in particular, in the metropolitan areas, might be growing too quickly and can soon rise to unsustainable levels has been expressed by international organisations, central banks and the housing market observers in general (see, e.g., the IMF 2014, 2016 Article IV Consultation reports, the 2016 U.K. stress testing exercise of the Bank of England).

In the 2014 annual consultation report, IMF economists have articulated challenges of rapid house price growth for the UK economy, stating that "there are few of the typical signs of a credit-led bubble in the housing market" (IMF, 2014). The report warns that raising residential and commercial property prices in London can potentially spread out to the rest of the country and threaten financial and macroeconomic stability. With the loan-to-income ratios being at historical highs, households become exceedingly exposed to income, interest rates and property price shocks, hence increasing the probability of mortgage and housing collapse (IMF 2014, 2016). At the same time, the Bank of England, in the 2015 Financial Stability Report, documents that commercial property is currently being used as a collateral by 75% of all companies that borrow from commercial banks (Bank of England, 2015). As the recent boom and bust in the housing market has demonstrated, a sharp correction in commercial property prices can undermine financial stability, reduce investment and lead to a slowdown in the economic activity (IMF, 2016).[1]

[1]The Bank of England recognises that the risks associated with rapid growth in residential and commercial property prices "remain elevated" (Bank of England, 2015). It attaches high importance to the role of real estate markets in financial stability and examines resilience of the UK banking system to the house price shocks. The Bank of England is considering a sharp downturn in commercial and residential real estate prices as one of the key elements of its 2016 stress testing scenario (Bank of England, 2016).

The social aspect of increased real estate inflation is another issue of concern. With average price of residential property in

Considering the importance of housing, the devastating effects of the recent house price boom and bust on the real economy, and the increased concern of the UK housing market observers about the future behaviour of real estate prices, understanding the dynamics of property prices and the factors driving the house price movements is particularly important. In this chapter, we look back at the history of the UK regional house price movements and show that non-fundamental factors, such as rational speculative bubbles, have played a role in the dynamics of the real estate markets.

Blanchard and Watson (1982) define a rational asset price bubble as the deviation of asset prices from their fundamental value. What is the fundamental value of housing is not a trivial question. The approach that has enjoyed a wide popularity in the empirical literature on analysing property price movements suggests a direct estimation of the fundamental real estate prices using dynamic equilibrium correction models, which are then assessed against the actual house price series. If the house price movements are fully explained by movements in the economic fundamentals then the conclusion is being made about the absence of asset price bubbles in the housing data.

However, there is no general agreement about the set of house price determinants to be included in the fundamental value model. For instance, IMF (2003, 2005) introduce the simple dynamic equilibrium model with house prices being determined by households' income, interest rates and lagged values of property prices only. In addition to this limited set of fundamentals, Barrell et al. (2004) consider dummy variables corresponding to the years of credit and tax policy changes. The supply side variables are not included in these models, as the authors claim, due to a sluggish supply of housing in the UK, unresponsive to changes in the market conditions (IMF 2003, 2005). On the other hand, the dynamic equilibrium model of Meen (2002) incorporates a wider set of fundamental determinants, including the measure of mortgage rationing/liberalisation, financial wealth and the supply of new constructions. The author finds significant albeit marginal effects of housing supply and demonstrates that an omission of supply-side variables biases the estimates of income elasticity downwards (Meen, 2002). This view is supported by Cameron et al. (2006), who argue that failure to accommodate the supply-side factors, demographic, regulatory and regional aspects leads to an omission of important explanatory variables and hence, results in the model

London being as high as half a million pounds, home-ownership is beyond reach for majority of first-time buyers. Housing affordability has been one of the key topics of the recent London mayoral campaign. Sadiq Khan, the newly elected mayor of London, admitted the existence of housing crisis and called it "the number one issue" for his "generation of London politicians" (cited in Foster, 2016).

misspecification and erroneous inference about the presence or absence of bubbles in the real estate market. The authors propose a model of regional property prices that in addition to the conventional set of demand side variables incorporates an indicator of credit availability, demographics, regional spillover effects as well as the supply side effects. We estimate this model for the sample period that covers the recent boom and bust in the UK housing markets and find that the fundamental model is not able to capture the house price boom of the late 1980s and the upswing of the early and mid-2000s. Furthermore, we find that the house price series under investigation and their fundamental determinants are not cointegrated, which implies that the house prices are not related to the economic fundamentals and tend to diverge rather than converge in the long-run.

At the same time, the evidence that house prices and the fundamentals do not converge to a stable long-run equilibrium is consistent with the rational bubble hypothesis. Rational house price bubbles emerge when property prices are determined not only by the economic fundamentals but are also driven by the expectation of a gain from future price increases, which introduces explosiveness in the house price series. The explosive nature of bubble processes has a major implication for the empirical tests for rational asset price bubbles. A substantial empirical literature that deals with detection of the rational bubbles exploits this feature of non-fundamental asset price components. Diba and Grossman (1988) proposed an application of the right-tailed Augmented Dickey-Fuller (*ADF*) test to the series of asset prices. Given that the economic fundamentals are stationary in the first differences, rejection of the unit root hypothesis in favour of the explosive alternative can be interpreted as the evidence of bubbles in the asset price series.[2] However, the test suffers from low power in detection of the periodically collapsing bubbles (a special class of explosive processes simulated by Evans (1991) that never collapse to zero but restart after a crash). The conventional right-tailed unit root tests fail to detect such periodically collapsing behaviour and hence, may often erroneously indicate the absence of a bubble when the data actually contains one.

To test for exuberance in the UK regional real estate prices we employ the recently-developed tests of Phillips et al. (2011) and Phillips et al. (2015) (the sup *ADF*, *SADF*, and the Generalized sup *ADF*, *GSADF*), which are based on a repeated application of the right-tailed unit root test on a forward-expanding sample

[2]Explosive behaviour of asset prices although consistent with a bubble hypothesis may be equally attributed to other factors, such as explosive nature of the unobserved fundamentals (Diba and Grossman, 1988) or, as shown by Phillips and Yu (2011), time-varying discount rates.

sequence. Two important features of the tests are, first, that the estimation strategy enables us not only to test for exuberance in the underlying series but also allows to shed light on the chronology of its origination and collapse and, second, that the methodology has more power than the conventional unit root tests in distinguishing the periodically collapsing behaviour from stationary, mean-reverting processes. In summary, our results indicate the presence of explosiveness in all regional real estate markets under consideration, while a panel version of the *GSADF* procedure, developed by Pavlidis et al. (2015), uncovers the overall, or nationwide explosiveness. The associated date-stamping strategies generally reveal two explosive episodes in the history of nearly four decades of the UK house price dynamics, namely in the late 1980s and in the early and mid-2000s. These two episodes coincide with the periods of inflated deviations from the long-run equilibrium property prices in the model of Cameron et al. (2006). A conclusion that emerges from our analysis is that the fundamental model of housing does not explain the property price movements during the exuberant phases and hence, suggests that the house price exuberance was driven by non-fundamental factors. The empirical analysis also shows that the equilibrium-correction terms from the estimated fundamental value model of housing are explosive, thereby providing further evidence that the UK regional real estate prices in the past have been driven by non-fundamental, explosive factors, such as rational house price bubbles. This finding improves our understanding of what causes house prices to move and demonstrates the critical importance of monitoring the housing market developments, which can be of particular relevance to policymakers.

The remainder of the chapter is structured as follows. A description of the housing data is presented in Section 2.2. The structural model of regional real estate prices of Cameron et al. (2006) is introduced in Section 2.3. We present the estimation results and discuss the interpretation of no cointegrating relationship between prices and their fundamental determinants. The following section introduces the univariate and the panel recursive right-tailed unit root tests' results for the regional house price series and for the price-to-income ratios. We present and discuss the chronology of exuberance identified with the associated date-stamping mechanisms. The section also describes an application of the recursive unit root tests to the equilibrium-correction terms from the structural model of real estate prices. Finally, Section 2.5 provides concluding remarks. The chapter has three Appendices. A detailed description of the data and the data sources is presented in Appendix A. Appendix B introduces the index of credit availability. Details of the univariate *SADF* and the *GSADF*, the panel *GSADF* and their respective date-stamping strategies are reserved for Appendix C.

2.2. Data

The house price data used in this chapter is from the Nationwide House Price Database.[3] The Nationwide Database, which dates back to the first quarter of 1975, reports quarterly mix-adjusted regional house price indices for thirteen regional real estate markets: the North (NT), Yorkshire and Humberside (YH), North West (NW), East Midlands (EM), West Midlands (WM), East Anglia (EA), Outer South East (OSE), Outer Metropolitan (OM), Greater London (GL), South West (SW), Wales (WW), Scotland (SC) and Northern Ireland (NI). We adopt the suggested regional classification and refer the reader to the Nationwide web page for details on the regional composition. Nominal house price indices are deflated by the Consumer Price Index (all items) obtained from the OECD Database of Main Economic Indicators. In our application we use log transformation of the regional real house price series.

Figure 2.1 illustrates the evolution of regional real house price indices over the whole sample period: from the first quarter of 1975 until the fourth quarter of 2012. To facilitate the analysis, linear time trends are added to each regional diagram. We observe similar patterns of house price behaviour across regions, with a number of boom-bust episodes, in particular: in the late 1980s - early 1990s and in the early and mid-2000s. Let us, first, consider the former.

Credit market of the UK during the late 80s was characterised by low interest rates, removal of credit and exchange controls and easing of prudential regulation, which boosted residential property price growth during that time.[4] The reported diagrams suggest that regional real estate prices in 1989 were on average about 124% higher than the corresponding trend values. Furthermore, examination of Figure 2.2 reveals a dramatic increase in the ratio of real estate prices to personal disposable income of households during the boom years. Following the surge in residential property prices, housing affordability started to deteriorate: the average value of the reported price-to-income statistic across all regional markets of the country rose from about 68% in 1987 to nearly 98% by the middle of 1989, while in some regional markets, in particular in Greater London and East Anglia, the peak value of housing affordability measure stood at nearly 130% in

[3]Details of the methodology used to construct regional house price indices is available from the Nationwide web page: http://www.nationwide.co.uk/ /media/MainSite/documents/about/house-price-index/nationwide-hpi-methodology.pdf

[4]The 1988 Basel I Capital Accord documented a requirement for banks to maintain capital of at least 8% of their risk-weighted assets. The regulatory framework imposed a 100% risk weight on unsecured loans, while mortgage lending received a preferred status with 50% risk weight assigned to loans secured on residential property.

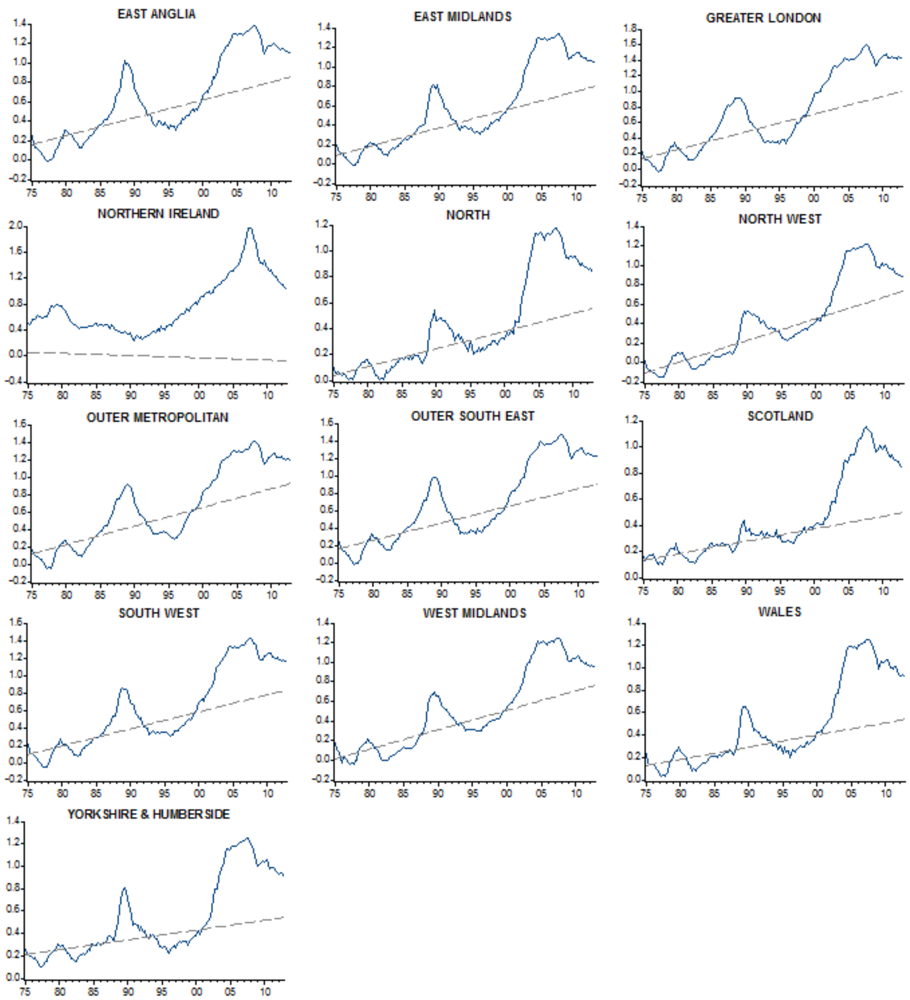

Figure 2.1: Real House Prices: Regional Series. The graph shows the evolution of the log real regional house price indices. The sample period: 1975:Q1-2012:Q4. Following IMF (2003, 2005) the linear time trend, estimated up to 1999:Q4 is added to each regional diagram (dashed line).

1989:Q1.[5] Interestingly, the diagrams of housing prices and the price-to-income ratios indicate that Northern Ireland was the only regional market with no signs of a housing boom during the period under consideration: property prices in the area were, in fact, below the estimated linear trend at the end of 80s.

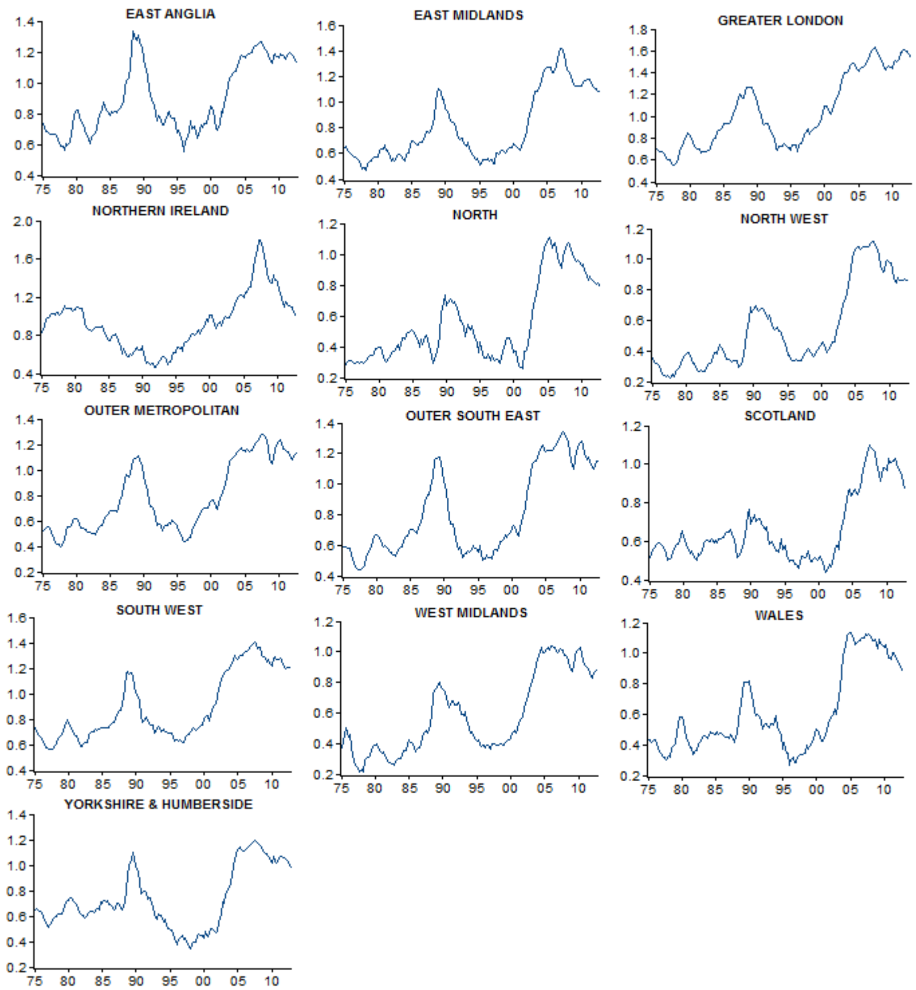

Figure 2.2: Price-to-Income Ratios: Regional Series. Each regional diagram shows the evolution of the log of real house price to real personal disposable income ratio. The sample period: 1975:Q1-2012:Q4.

In an attempt to slow down the expansion and curb the growing inflation, base rates were raised progressively from 7.375% in May of 1988 to almost 13% in the end of the year, finally reaching the unprecedentedly high level of nearly 15% in October 1989. The higher cost of credit made it hard for mortgage borrowers to service the debt, which, eventually, resulted in an increase in the number of property repos-

[5]Regional income data is obtained from the Family Expenditure Survey (FES). Please refer to Table A1 for details.

sessions and a sharp downturn in real estate prices in all property markets of the country. On average, we compute a 60% fall in house prices across the UK regions from the peak of 1989 to the trough of 1993.

Regional real estate markets started to recover from the recession in the mid-1990s. According to Figure 2.1, regional property prices were growing gradually since the first half of 1995, which has marked the beginning of a prolonged period of house price boom that prevailed until 2007:Q3. Population growth, higher income of households, low mortgage rate, financial deregulation and increased credit availability were among the key factors that have fuelled another round of property price expansion, according to Kuenzel and Bjørnbak (2008). During the upswing of the early and mid-2000s, the average real house prices across all regional markets of the country have doubled relative to the previous peak value of the statistic in 1989. Northern Ireland, in particular, has recorded the biggest increase in residential and commercial property prices over the period: housing prices in the area in 2007:Q3 were nearly six times higher than in 1989:Q1. To gain an insight into the scale of the overvaluation Figure 2.1 compares regional property prices and their respective linear time trends. The diagram indicates that housing prices in the UK were, on average, about 109% above the estimated linear trend values in 2007:Q3. At the same time, growth in real personal disposable income of households (38% on average across regions of the UK between the start of the boom phase and 2007:Q3) failed to keep pace with growing residential property prices, which led to rapid deterioration in housing affordability. Turning to Figure 2.2 diagrams, we observe that in all regions of the country, with the exception of East Anglia, the ratio of real house prices to real personal disposable income reached unprecedentedly high levels during the second housing boom. We note that in 2007:Q3, the mean value of the price-to-income statistic across 13 regions of the UK was nearly 70% above the historical average.

Following the start of the sub prime mortgage crisis in the US, all housing markets of the UK have experienced a sharp downturn in residential and commercial property prices. By the first quarter of 2009 all regional real house price indices dropped by nearly 20%, on average, from their 2007:Q3 peak values. Housing market of Northern Ireland once again proved its status of the outlier: the region recorded the biggest fall in real estate prices (around 30%) across all property markets in our sample.

The overall conclusion that emerges from the examination of the regional diagrams is that the property markets of the UK were subject to substantial instability over the last four decades.

2.3. Model of Real Estate Prices: Formulation and Estimation Results

To examine whether non-fundamental factors were driving UK real estate markets we employ the model of Cameron et al. (2006). The model uses regional housing data, incorporates a wide range of national-level and regional-level house price determinants, including the impact of credit liberalisation and regional spillover effects. The model is constructed as the system of inverted housing demand equations, one for each region of the country, where each regional house price equation is modelled as a dynamic equilibrium correction relationship.

We estimate the system of thirteen regional house price equations for the period between 1975:Q1 and 2012:Q4, which, as discussed in the previous section, covers several run-up and collapse episodes. While Cameron et al. (2006) employ annual data and consider the estimation period, which ends in 2003, our data is sampled quarterly and we extend the sample period to incorporate the latest boom and bust in the housing market and the Great Recession. The authors propose a two-stage estimation strategy. In the first step, the system is estimated using Seemingly Unrelated Regressions (SUR) method and the estimated error covariance matrix is stored. The second stage replaces the unknown covariance matrix in Generalised Least Squares (GLS) by the estimate from the first step to get the parameter estimates. Cameron et al. (2006) note that the chosen methodology accounts for heteroskedasticity and contemporaneously correlated disturbances, which is particularly important, since the assumption of uncorrelated shocks in regional real estate markets appears unrealistic.

To assist the reader, the annotated model of regional house prices with detailed description of the fundamental variables and their anticipated effects as well as the data sources are set out in Table A1 of Appendix A.[6] The dependent variable in each regional equation is the growth in log real house price index $\Delta lrhp_{r,t}$.[7] Residential prices adjust to the long-run equilibrium while responding to the effects of income, nominal and real mortgage rates and credit availability. Dynamic effects include last period's house price growth in the

[6] For $r = 1, \ldots, 13$, the basic specification of Cameron et al. (2006) housing regression equation is given by:

$$\begin{aligned}\Delta lrhp_{r,t} = {} & \alpha * (\beta_{0,r} + \beta_1 * lrynhs_{r,t} + \beta_2 * MACCI_t + (1 - \varphi * MACCI_t) * (\beta_3 * \Delta^2 labmr_t + \beta_4 * (labmr_t - mean.labmr)) \\ & + \beta_5 * MACCI_t * (rabmr_t - mean.rabmr) + \beta_6 * rabmr_t - lrhp_{r,t-1}) + \beta_7 * \Delta clrhp_{r,t-1} + \beta_8 * \Delta lrpdin_t \\ & + \beta_9 * \Delta lrpdin_{t-1} + \beta_{10} * MACCI_t * \Delta lrpdin_t + \beta_{11} * \Delta^2 lpc_t + \beta_{12} * \Delta lrftse_t + \beta_{13} * \Delta lrftseneg_t \\ & + \beta_{14} * ror.neg_{r,t} + \beta_{15} * \Delta pop2039_{r,t-1} + \beta_{16} * (\Delta lwpop_{r,t} - lhs_{r,t-1}) + \beta_{17} * D88 + \beta_{18} * D08 + \epsilon_{r,t}.\end{aligned}$$

Please refer to Table A1 for definitions of the house price determinants.

[7] Here and in what follows variables measured at the regional level and region-specific coefficients have the subscript r.

neighbouring regions, income effects, negative returns on housing, the effect of new constructions, inflation acceleration and demographic changes.[8] The cases when the specification of regional equations differs from the one outlined in Table A1, are specifically indicated and will be discussed below. Table 2.1 reports the parameter estimates.

Table 2.1: The Model of Regional House Prices: Parameter Estimates

	Variable	Estimate	t-Statistic
Speed of adjustment	α	0.03	7.78^{***}
Index of credit conditions	$MACCI_t$	1.27	4.57^{***}
Lagged house price growth	$\Delta clrhp.r_{t-1}$	0.24	10.15^{***}
Income effects	$\Delta lrpdin_t$	0.81	3.34^{***}
	$\Delta lrpdin_{t-1}$	0.33	2.26^{**}
	$MACCI_t * \Delta lrpdin_t$	-0.35	-0.83
Interest rate effects	$(1 - \varphi * MACCI_t) * (labmr_t - mean.labmr)$	1.57	3.65^{***}
	$(1 - \varphi * MACCI_t) * \Delta^2 labmr_t$	2.37	2.48^{**}
	φ	2.86	6.03^{***}
	$MACCI * (rabmr_t - mean.rabmr)$	23.29	1.71^{*}
	$rabmr_t$	-8.42	-1.94^{*}
Downside risk	$ror.neg.r_t$	0.09	4.78^{***}
Inflation acceleration	$\Delta^2 lpc_t$	-0.22	-2.51^{**}
Demographic effect	$\Delta pop2039.r_{t-1}$	-1.25	-0.94
Effect of new constructions	$\Delta(lwpop.r_t - lhs.r_{t-1})$	0.001	0.03
Stock market effect	$\Delta lrFTSE_t$	0.06	2.68^{***}
(Outer Met)	$\Delta lrFTSEneg_t$	-0.06	-1.95^{*}
Time	*D88*(ex.SC and NI)	0.06	6.15^{***}
Dummies	*D08*	-0.05	-4.31^{***}

Note: The dependent variable is the log regional real house price growth ($\Delta lrhp_r$). Each regional equation contains a region-specific intercept (estimates are not reported). The average estimated intercept parameter is 0.993. The lagged house price growth effect $\Delta clrhp.r_{t-1}$ is computed as a weighted sum of last period's price growth in the region, regions contiguous to it and in Greater London (see Table A1 in Appendix A). We follow Cameron et al. (2006) in their choice of regional weights:

Weights	Region												
	NT	YH	NW	EM	WM	EA	OSE	OM	GL	SW	WW	SC	NI
Own region	0.505	0	0.505	0.170	0.720	0	0	0	1	0	0	1	1
Greater London	0	0	0	0.112	0.280	1	1	1		1	0	0	0
Contig. regions	0.495	1	0.495	0.718	0	0	0	0	0	0	1	0	0

[8] We examine the unit root properties of the data and conclude that all regional real house price series are non-stationary in levels: we are not able to reject the unit root hypothesis of the *ADF* test at all conventional significance levels. Tax adjusted mortgage rates, indicator of credit availability and all regional income series entering the long-run equilibrium are I(1). Furthermore, all variables of the short-run dynamics: national income, demographics, the number of housing starts etc. proved I(1). These variables enter the house price model in the form of the first differences.

Long-run Equilibrium Determinants According to Cameron et al. (2006), the long-run equilibrium residential prices in region $r = 1, \ldots, 13$ are determined by the economic fundamentals that include household's personal disposable income in this region ($lrynhs_{r,t}$), the indicator of credit availability ($MACCI_t$), nominal ($labmr_t$) and real mortgage rates ($rabmr_t$) and their interactions with the credit conditions index. Each regional equation has a region-specific intercept $\beta_{r,0}$ and the average estimated intercept parameter is 0.993. The authors assign the value of 1.6 to the long-run income elasticity of housing β_1. Cameron et al. (2006) claim that by doing so they economise on the degrees of freedom on the one hand, and retrieve the long-run coefficients on the interaction terms on the other hand. Since higher than unity long-run income elasticity of house prices is a widely estimated value in the housing literature and since our strategy is to examine the validity of the model during the period of the latest boom and bust in the housing market we follow the suggested specification.

One of the key elements of the long-run equilibrium is the index of credit conditions. This indicator, designed as a linear spline function, was proposed by Fernandez-Corrugedo and Muellbauer (2006) to capture the changes in lending policy and prudential regulation. To obtain the index of credit availability for the full period considered in our study, we estimate the index from the system of secured and unsecured debt equations. The reader is referred to Appendix B for a detailed description of the methodology and estimation results, while the sources of the data used in the exercise are described in Table A2 of Appendix A. The estimated effect of credit availability is positive and statistically significant and the magnitude of the coefficient is close to that reported by Cameron et al. (2006). The result supports the hypothesis outlined in Table A1 that easing of prudential regulation and liberalisation of lending policy encourage mortgage borrowing and lead to an increase in real estate prices.

Cameron et al. (2006) argue that it is important to control not only for the direct impact of credit policy changes on residential prices but also for interaction effects of mortgage rates with the index of credit conditions. The authors note that failure to take these facts into account results in model misspecification and incorrect inference about the magnitude and direction of the interest rate effects. The long-run solution includes two mortgage rate measures: nominal and real interest rates of building societies adjusted for the cost of tax relief. Following the argument of Cameron et al. (2006), the interest rates enter the house price model on their own and in interaction with the indicator of credit availability. The estimated positive interaction effect with real interest rate suggests that while an increase in the cost of credit *per se* discourages mortgage borrowing and reduces house prices (one percentage point increase in the real mortgage rate, *ceteris paribus*, leads to 0.08% fall in real estate prices), this negative effect weakens with the removal of lending constraints and easing of prudential regulation. In other words, when credit policy is relaxed it becomes easier for households to find an opportunity to refinance the debt and deal with the burden of interest payments in the near-term.[9]

Fernandez-Corrugedo and Muellbauer (2006) and Cameron et al. (2006) claim that inflation growth, while leaving real interest rates unchanged, raises nominal rates and the burden of mortgage loan in the first few years of the contract. The risk of not being able to service the debt, therefore, deters potential house buyers from mortgage borrowing and results in a fall in real estate prices in the long-run. However, easing of prudential regulation and liberalisation of credit conditions allow households to gain access to numerous refinancing opportunities, thus reducing the negative effect of an increase in nominal interest rates on real estate prices. In the model of Cameron et al. (2006) nominal interest rate effect is conditional on credit availability. According to the results presented in Table 2.1, a one percentage point rise in nominal interest rates reduces commercial and residential property prices more when credit is constrained and $MACCI_t$ is low than when credit conditions are relaxed and the value of the credit availability indicator $MACCI_t$ is high. In other words, negative nominal interest rate effect weakens with credit liberalisation and access to more dynamic and competitive market of mortgage lending.

Dynamic Effects One of the key variables of the short-run dynamics is a composite measure ($\Delta clrhp_{r,t-1}$) that is computed as a weighted sum of last period's price growth in the own region, regions contiguous to it (average house price growth across neighbouring areas) and in Greater London. The weights on lagged growth rates are allowed to take any value on the unit interval and should sum up to 1. To take into account the regional spillover effects, the coefficients vary by area and are assigned based on proximity to London; hence the southern regions (Outer Metropolitan, Outer South East, East Anglia and South West) attach 100% of the importance to the effect of last period's growth in London house prices. This weighting scheme allows to capture the so-called ripple effect, widely documented in the empirical literature on the

[9]This result contradicts the argument of Cameron et al. (2006), who claim that credit liberalisation strengthens the negative effect of real mortgage rate increase. The authors report a negative interaction effect of credit availability indicator with the real mortgage rate.

UK housing markets, which implies that house price shocks emanating from Greater London have a tendency to spread out and affect neighbouring regions with a time lag.[10] As we move farther away from the metropolitan regions the lagged London effect becomes relatively less important since it will take more than a quarter for the house price impulse to reach the distant areas. Hence the northern regions assign higher importance to the own lagged growth rates rather than to the last period's house price growth in London. We follow Cameron et al. (2006) in their choice of regional weights. Please refer to the notes to Table 2.1 for the summary of regional coefficients on the lagged growth rate effects. The estimated dynamic effect of the composite variable is positive, which is consistent with the hypothesis outlined in Table A1, that last period's house price growth in the region (neighbouring areas and Greater London) leads to further price appreciation in this real estate market. Consider, for instance, the southern areas, contiguous to London. A one percentage point rise in the last period's property price growth rate in London, *ceteris paribus*, increases the current housing inflation in the Outer Metropolitan, Outer South East, South West and East Anglia regions by 0.24%. This effect becomes weaker in the midland areas, yet at the same time, the impact of neighbouring regions becomes relatively more important. In East Midlands, for instance, a 1% appreciation in the last quarter's house price growth rates in contiguous regions, *ceteris paribus*, results in a 0.17% increase in the current property price growth rate, while the lagged London effect leads to a marginal 0.03% rise in the current property price inflation. In the northern regions, including the North and North West, we no longer account for the impact of London and consider own lagged house price effects and effects of price growth in contiguous regions. Finally, in Scotland and Northern Ireland the impact of lagged real estate inflation in the own region receives the weight of 1: a one percentage point rise in the own house price growth rates in the previous period leads to a 0.24% appreciation in the current property price inflation in these regions, *ceteris paribus*.

In the dynamics, Cameron et al. (2006) control for both direct effects of current and previous quarter's growth in personal disposable income (measured at the national-level) and for the interaction effect of the former variable with the indicator of credit availability. The interaction term is included to test whether growth in current income of households matters more or less with removal of lending constraints, easing of prudential regulation and access to various financing opportunities. While the size and direction of the

[10]References include MacDonald and Taylor (1993), Alexander and Barrow (1994), Drake (1995), Meen (1999), Cook and Thomas (2003), Holly et al. (2010), *inter alia*.

direct income effects are compatible with those estimated by Cameron et al. (2006), the interaction effect with the index of credit conditions proved insignificant. Our results indicate that credit availability is an important determinant of the long-run equilibrium real estate prices, however it does not provide additional explanatory power to the house price model in the dynamics, when interacted with the growth in personal disposable income.

Each regional equation incorporates a dynamic measure of downside risk ($ror.neg_{r,t}$) defined as a four-quarter moving average of past negative returns on housing in the corresponding real estate market (see Table A1 of Appendix A for details). The effect of past negative returns on the current house price inflation is estimated by using a coefficient common to all regions in our sample. Table 2.1 shows a small but significant positive effect of the dynamic downside risk measure, which is consistent with the conclusion of Cameron et al. (2006) that the four consecutive quarters of negative housing returns depress current real estate prices above and beyond the own lag effect.

The variable that picks up the dynamic effect of an increase in the general price level is a two-period change in the log of consumer expenditure deflator ($\Delta^2 lpc_t$). The inflation acceleration leads to mortgage rate uncertainty, discourages mortgage borrowing and eventually results in lower residential prices. We report a significant negative effect of inflation acceleration, and the estimated coefficient implies that a one percentage point increase in the general price level results in a 0.2% fall in the price of housing.

One of the important elements of the short-run dynamics, considered in the regional model of Cameron et al. (2006), is the change in the supply of new houses relative to the growth in working age population ($\Delta(lwpop_{r,t} - lhs_{r,t-1})$). The literature which deals with modelling real estate prices in the UK often ignores the supply side effects, for instance models of Barrell et al. (2004) and IMF (2003, 2005). At the same time, the work of Hilbert and Vermeulen (2016), who examine the impact of planning policies and local regulatory and geographical constraints on house prices in England, conclude that rigidity of housing supply and the existing physical constraints on new developments are important factors behind the latest boom in the real estate markets. The authors demonstrate that residential prices in England would have been nearly 35% lower in 2008 had the regulatory constraints on local development been removed (Hilbert and Vermeulen, 2016). In addition, international organisations have been citing limits on the supply of houses in the UK among the key aspects of concern, responsible for the recent house price volatility (IMF Article

IV Consultation report, 2014, 2016). Cameron et al. (2006) introduce the effect of changes in the number of new constructions relative to the demographic changes and suggest that when the supply of new homes fails to keep pace with the growth in working age population, this leads to an increase in the price of houses. However, we find no significant effects of this measure in our application.

The variable that captures the impact of the demographic changes on the regional house price inflation is the last period's growth rate in the share of people aged between 20 and 39 in the total working age population in the area ($\Delta pop2039_{r,t-1}$). Cameron et al. (2006) claim that the 20-39 age group represents potential first-time home buyers and hence, growth in the proportion of households in this age segment has a positive effect on the demand for housing and on the real estate prices. Our results do not support this hypothesis, since the estimated demographic effect is not statistically significant.

We also consider whether returns on financial investments are important determinants of the short-run house-price dynamics. The two indicators of the stock market behaviour are considered. The change in the real FTSE index ($\Delta lrFTSE_t$), is included to test the assumption that higher returns on equity raise the wealth of financial investors (potential house-buyers) and eventually lead to higher real estate prices. The second indicator ($\Delta lrFTSEneg_t$, which is equal to $\Delta lrFTSE_t$ only when the latter is negative and is zero otherwise), on the contrary, examines the effect of the stock market downturn. Cameron et al. (2006) suggest that risks of the stock market slowdown can shift the focus of investors from shares to housing, considered by many as a 'safe heaven'. The authors note that the stock market effects are important only in London and in the South - centres of investment, equity ownership and well-paid employees - and have little impact on the rest of the country. Perhaps surprisingly, we find no significant effects of the stock market dynamics in Greater London. At the same time, these effects proved important in Outer Metropolitan, a region contiguous to London.[11] All our data is sampled quarterly, therefore it is not surprising that the returns on financial investments have somewhat smaller effect on the housing market than that reported by Cameron et al. (2006), who are using annual data. Despite the magnitude of the estimated coefficients, the direction of the influence is consistent with the assumption set out in Table A1. Our results suggest an asymmetric response of the real estate prices to positive and negative shocks in the equity market. In particular, a 10% increase in the real FTSE index results in a 0.6% rise in the price of housing in the Outer

[11] In the final model specification, the two effects of the stock market dynamics enter the Outer Metropolitan equation only and are assumed zero in all remaining regions.

Metropolitan area. On the contrary, in the event of a 10% downturn in stock prices there is no effect on commercial and residential property prices in this region: a negative effect of a fall in the wealth of financial investors is offset by a positive effect on house prices from reallocation of investment portfolio and shift from shares to real estate.

Finally, each regional equation includes a number of dummy variables to control for the shocks to demand for and supply of housing. The 1988 year dummy, constructed as a time trend going from 0.25 in the first quarter to 1 in the last quarter of the year, captures the introduction of the Poll Tax system in replacement of the local domestic rates taxation. Since the Poll Tax reform concerned only England and Wales, the 1988 dummy is assumed zero in the equations of Scotland and Northern Ireland. Furthermore, the 1988 time dummy picks up the effect of budget announcement in March of 1988, limiting the number of mortgage interest relief claims to one per property. We report a positive and significant effect of the 1988 variable, which is consistent with the estimate of Cameron et al. (2006). The authors include additional time dummies for 1989 and 2001, however, in our application, the effects proved insignificant when tested. We introduce a dummy variable for 2008 to pick up the effect of the Lehman Brothers collapse in September 2008 followed by a turmoil in the financial markets. According to our estimates, the 2008 dummy has a significant negative effect on the dynamics of the UK regional house prices.

Discussion The summary of singe-equation diagnostics is presented in Table 2.2. We note that the model fits the data poorly. The R^2 measure, reported in the fifth column of Table 2.2, indicates that generally, just about half of the variation in the house price inflation can be explained by the fundamental determinants. The statistic is even lower in Scotland and Northern Ireland, where the model explains only 23% of the price behaviour. The last two columns of Table 2.2 report p-values for the Lagrange Multiplier heteroskedasticity and serial correlation tests. The results are not satisfactory: the null of homoskedasticity is rejected in four regional equations (NT, YH, EA and OM) and we find evidence of serially correlated residuals in each regional model. These findings suggest that the reported parameter estimates and t-statistics are not valid and raise concerns about the structural approach. The Feasible GLS estimator of the SUR method is efficient only if the estimated system consists of stationary time-series and has independent and identically distributed errors (e.g. see Moon (1999)). When regressors are integrated and residuals are serially correlated, the estimator is consistent, but has a skewed, non-standard limit distribution (Moon, 1999). The classical SUR might not be the optimal estimation strategy and methods such as fully-modified estimation of the integrated SUR, which has been proposed by Moon (1999), that correct for the presence of autocorrelated residuals should be used in this case.

Table 2.2: The Model of Regional House Prices: Summary of Single-Equation Diagnostics

Region	Dependent Variable		Equation		Test p-value	
	Mean	Std.Dev	Std.Error	R^2	LM Hetero	LM Auto
North	0.0062	0.038	0.030	0.426	(0.039)	(0.000)
Yorks & Hside	0.0045	0.035	0.027	0.508	(0.001)	(0.000)
North West	0.0061	0.029	0.022	0.523	(0.123)	(0.000)
East Midlands	0.0059	0.033	0.024	0.534	(0.199)	(0.000)
West Midlands	0.0055	0.033	0.026	0.482	(0.588)	(0.000)
East Anglia	0.0062	0.038	0.030	0.426	(0.039)	(0.000)
Outer S East	0.0069	0.034	0.025	0.522	(0.078)	(0.000)
Outer Met	0.0072	0.032	0.024	0.543	(0.039)	(0.000)
Greater London	0.0084	0.035	0.029	0.369	(0.138)	(0.000)
South West	0.0067	0.035	0.026	0.515	(0.094)	(0.000)
Wales	0.0049	0.036	0.026	0.542	(0.588)	(0.000)
Scotland	0.0047	0.028	0.026	0.230	(0.596)	(0.001)
Northern Ireland	0.0036	0.043	0.041	0.232	(0.449)	(0.000)

Note: The last two columns of the table show p-values for the Breusch-Pagan Lagrange Multiplier heteroskedasticity test (the null hypothesis is homoskedasticity) and Breusch-Godfrey Lagrange Multiplier serial correlation test (the null hypothesis is no serial correlation) respectively.

We now shift the focus of our discussion from the estimation strategy to the suggested error-correction specification of the regional house price models. Cameron et al. (2006) model each regional house price equation as an equilibrium-correction relationship, implicit in this formulation is that prices and fundamentals converge to a stable long-run equilibrium relationship, i.e. are cointegrated. In the context of our paper, there exists a stable long-run equilibrium relationship between house prices and economic fundamentals if we confirm that the equilibrium correction terms from the estimated regional house price models are stationary. Otherwise, prices and their fundamental determinants will never converge to a stable long-run equilibrium and hence, according to Granger Representation Theorem, the error-correction models should not be used to model the behaviour of real estate prices.

We test the regional equilibrium correction terms for stationarity and our results indicate, that except for the North and Wales, where the deviations from the long-run equilibrium proved I(0) at 5% level of significance, for all remaining regions the unit root hypothesis cannot be rejected.[12] Therefore, the house prices and the economic fundamentals are not cointegrated and will not converge to a stable equilibrium relationship in the long-run. This finding is in line with the evidence of some empirical studies that explore the relationship between real estate prices and economic fundamentals. The work of Gallin (2006) examines the existence of cointegration between U.S. house prices and various fundamental determinants, in particular, personal disposable income. The author finds no evidence of cointegrating relationship both at the national and city-level and concludes by stating that "it is inappropriate to model house-price dynamics using an error-correction specification" (Gallin, 2006 p. 419). Clark and Coggin (2011), who conduct an extensive investigation of cointegration between U.S. house prices and a wide range of economic determinants, are going a step further in their conclusions. The authors focus on a longer sample period that includes the latest boom in the real estate markets and the results are consistent with Gallin (2006), as the authors report that prices and fundamentals do not converge to a stable equilibrium in the long-run (both at the national and regional level). Clark and Coggin (2011) argue that evidence of no cointegration between real estate prices and their economic determinants not only indicates that the error-correction models are not appropriate but also confirms that U.S. house prices contained a bubble during the period under consideration.

The fact that in the absence of rational speculative bubbles prices and fundamentals should be cointegrated has been first recognised by Diba and Grossman (1988) and can be illustrated using the standard asset-pricing model. In the absence of arbitrage opportunities the price of any asset today is given by the sum of expected future payoffs from this asset and its future re-sale price, discounted at a constant discount rate $r > 0$ (see, e.g., Pavlidis et al. (2015)), as follows

$$P_t = \frac{1}{1+r} E_t \left[(D_{t+1} + U_{t+1}) + P_{t+1} \right]. \tag{2.1}$$

The stream of payoffs in Eq. (2.1) is represented by the sum of observed economic fundamentals, D_{t+1} (rentals in the housing context), and unobserved factors, U_{t+1} that reflect expectations, perceptions of market participants as well as mismeasurement of the housing rents.

[12]For these two regions (North and Wales) the null of a unit root cannot be rejected at 1% significance level.

Solving Eq. (2.1) T periods forward by recursive substitution yields the following expression,

$$P_t = E_t\left[\sum_{i=1}^{T}\left(\frac{1}{1+r}\right)^i (D_{t+i}+U_{t+i})\right] + E_t\left[\left(\frac{1}{1+r}\right)^T P_{t+T}\right], \tag{2.2}$$

where the price of an asset at time t is determined by the discounted stream of the observed and unobserved fundamentals and the present value of the liquidation price of this asset at the terminal time T. By transversality condition, which rules out the bubble behaviour, the last term on the right-hand side of Eq. (2.2) converges to zero as the time horizon T approaches infinity. Therefore, when transversality holds a unique solution to Eq. (2.1) is given by

$$P_t = F_t = E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+r}\right)^i (D_{t+i}+U_{t+i})\right]. \tag{2.3}$$

According to the above expression, when rational bubbles are non-existent, the price of housing is determined only by the economic fundamentals and is referred to as the fundamental price $P_t = F_t$. Under the no bubbles assumption, fundamental house prices and their economic determinants are first difference stationary and cointegrated, i.e. converge to a stable equilibrium relationship in the long-run.

However, when transversality condition is not imposed, Eq. (2.3) is one of an infinite number of forward solutions to Eq. (2.1) and it can be shown that any equation of the form (see, e.g., Diba and Grossman (1988), LeRoy (2004), Pavlidis et.al. (2015))

$$P_t = F_t + B_t, \tag{2.4}$$

where B_t is a bubble process that satisfies

$$E_t(B_{t+1}) = (1+r)B_t, \tag{2.5}$$

also solves Eq. (2.1). Eq. (2.4) posits that the price of an asset can be decomposed into two components: fundamental, defined in Eq. (2.3) and a bubble term that is explosive on expectation, according to Eq. (2.5). Hence if there exists a rational house price bubble, real estate prices are determined not only by the economic fundamentals but are also driven by the expectation of a gain from future price increases (Case and Shiller, 2003). The explosive nature of a bubble process induces exuberance in the house price series, hence prices will not be stationary even after a finite number of differences. Therefore, when the house price series under investigation contains a bubble there no longer exists a stable equilibrium relationship between prices and fundamentals.

Our finding of non-stationary deviations from the long-run equilibrium prices is not consistent with the absence of bubbles and suggests the existence of explosive dynamics in the house price series that is not explained by the economic fundamentals. We proceed by formally testing for explosiveness in the regional house prices and the equilibrium correction terms from the estimated structural model of regional real estate prices. If during the period under examination, housing markets in the UK were indeed driven by non-fundamental factors, such as rational asset price bubbles, regional house price series and the estimated deviations from the long-run equilibrium must be explosive.

2.4. Exuberance in Regional Housing Markets

We apply the test of Phillips et al. (2011, 2015) to the series of regional real house prices and the ratios of real prices to real personal disposable income in order to examine whether the UK regional real estate markets were explosive during the period under consideration. The reader is referred to Appendix C for the details of the *SADF* and the *GSADF* test procedures.

The upper panel of Table 2.3 reports test statistics of the univariate *SADF* and the *GSADF* for both variables under consideration together with finite sample critical values, obtained from Monte Carlo experiments with 2000 replications. Since the total number of observations is relatively small, the size of the smallest moving window (r_0) should be large enough to ensure effective estimation. Following the paper by Phillips et al. (2015), the chosen r_0 comprises 36 observations (24% of the data).

The reported results of the *GSADF* test provide strong evidence of exuberance in regional real house prices: the null of a unit root is confidently rejected at all conventional significance levels in all regions but two - Outer Metropolitan and Greater London, where we can only reject the null at 5% level of significance. When we turn to the ratio of prices to income, the indication of explosiveness remains strong in most of the regional markets excluding East Anglia, for which the unit root hypothesis cannot be rejected. Comparing the results of the *SADF* and the *GSADF* test procedures, we notice that for the former the evidence of exuberance in house prices is weaker and even more so when we look at the statistics of the price-to-income ratio (we fail to reject the null in 7 regions out of 13). This may be due to the higher power of the *GSADF* test documented by Phillips et al. (2015).

In order to identify the origination and termination dates of exuberance we follow the date-stamping strategy suggested by Phillips et al. (2015). Figures 2.3 and 2.4 plot the series of the *BSADF* statistics for the real house prices and the price-to-income ratios respectively together with the sequence of 95% critical values of the *SADF* distribution. For convenience we shade the periods when the estimated *BSADF* lies above the series of critical values. To facilitate visual examination of the date-stamping results Figure 2.5 displays the summary of chronology and duration of the explosive episodes for all regional markets and for both variables under consideration.

Looking at the chronology of exuberance in real house prices we observe a similar pattern across regions. The date-stamping mechanism reveals two explosive episodes during the examined period: in the late 1980s

Table 2.3: The *SADF* and the *GSADF* test results

Panel A: Univariate SADF and GSADF statistics				
	Real House Prices		Price-to-Income Ratio	
Region	*SADF*	*GSADF*	*SADF*	*GSADF*
North	2.38^{***}	4.70^{***}	0.22	1.80^{**}
Yorks & Hside	1.02^{*}	4.21^{***}	-0.16	2.47^{***}
North West	1.33^{**}	4.89^{***}	0.22	3.11^{***}
East Midlands	1.70^{**}	5.10^{***}	1.28^{**}	2.11^{**}
West Midlands	1.46^{**}	4.78^{***}	-0.01	3.94^{***}
East Anglia	2.39^{***}	3.58^{***}	1.24^{*}	1.26
Outer S East	1.56^{**}	3.40^{***}	1.52^{**}	2.53^{***}
Outer Met	1.25^{*}	2.20^{**}	1.16^{*}	2.07^{**}
Greater London	0.86	2.23^{**}	0.55	1.78^{*}
South West	1.92^{***}	4.19^{***}	1.13^{*}	3.08^{***}
Wales	1.48^{**}	6.38^{***}	-0.26	3.26^{***}
Scotland	2.68^{***}	4.59^{***}	0.49	1.90^{**}
Northern Ireland	4.61^{***}	5.72^{***}	1.80^{***}	3.05^{***}
Finite sample critical values				
90%	0.99	1.51	0.99	1.51
95%	1.27	1.78	1.27	1.78
99%	1.75	2.42	1.75	2.42

Panel B: Panel GSADF statistics		
	Real House Prices	Price-to-Income Ratio
	3.62^{***}	1.96^{***}
Finite sample critical values		
90%	1.04	0.56
95%	1.24	0.79
99%	1.79	1.16

Note: Superscripts *, ** and *** denote significance of the reported statistic at 10, 5 and 1 percent level of significance. Finite sample critical values for the sample of 150 observations are obtained from Monte Carlo simulations with 2000 replications. The smallest window r_0 corresponds to 24% of the data and comprises 36 observations. For both variables under consideration, reported univariate *SADF* and *GSADF* statistics as well as panel *GSADF* are computed for autoregressive lag length of one.

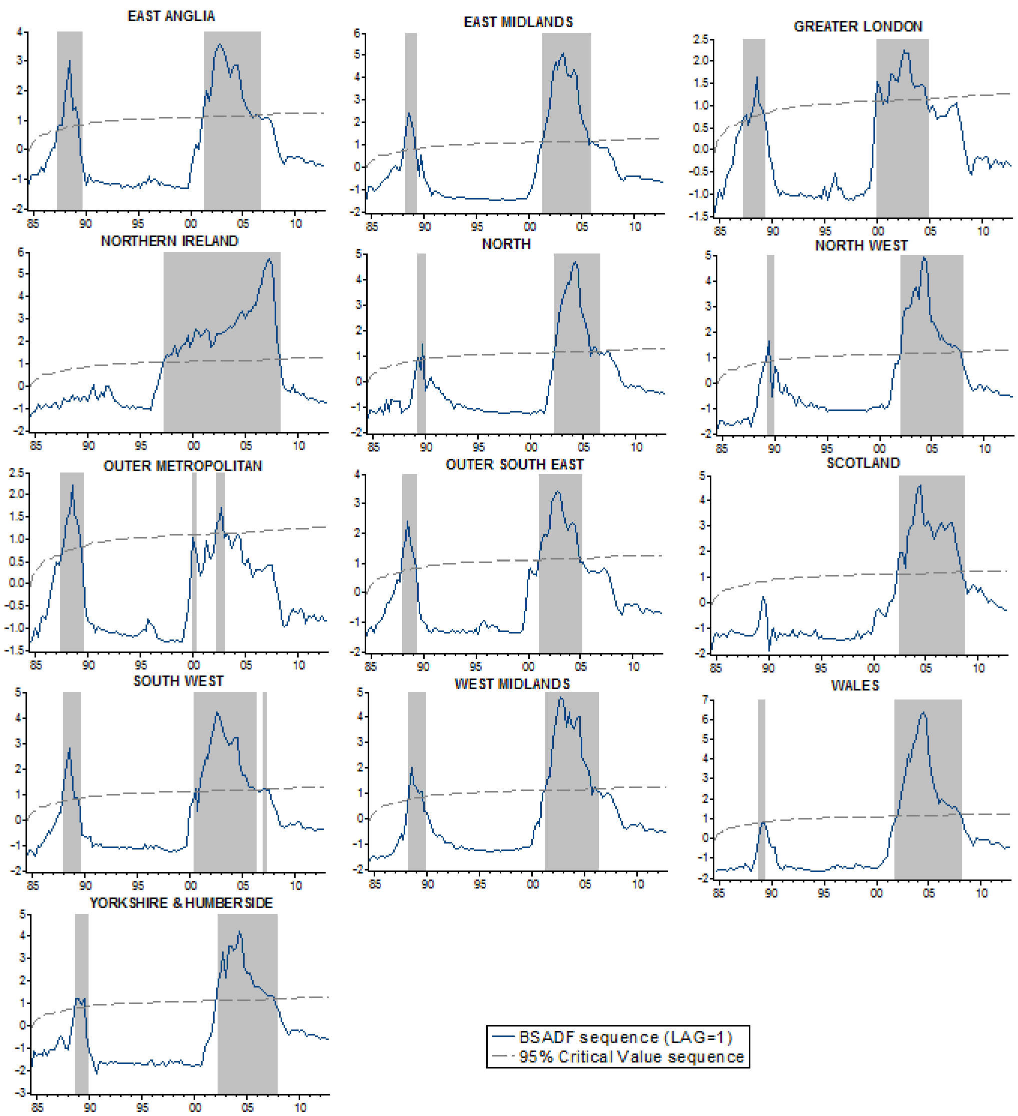

Figure 2.3: Regional Real House Prices: Date-Stamping of Explosive Episodes. Shaded areas indicate identified periods of exuberance (*BSADF* series is above the sequence critical value). The *BSADF* series are computed for the autoregressive lag length 1.

and the first half of 2000s. The former corresponds to the period of soaring real estate prices prior to the UK recession of the early 1990s, while the latter documents the years of the latest boom in the housing market. However, duration of exuberance as well as the dates of its origination and termination vary across regions. Consider the first explosive episode. Greater London and East Anglia were the first regions to enter the exuberant phase in the second quarter of 1987, followed by Outer Metropolitan (1987:Q3) and contiguous areas: Outer South East and South West (1988:Q1). Within a year southern regions were joined by the Midland areas (1988:Q2), Wales and Yorkshire & Humberside (1988:Q4). The exuberance reached the northern area, i.e. North West and the North, by the first and second quarter of 1989 respectively. We note that Scotland and Northern Ireland were the two regional house price series where our date-stamping strategy was not able to detect any explosiveness in the end of 1980s.[13]

The identified timeline of exuberance is consistent with the literature that documents the existence of a strong regional interconnectedness between real estate markets in the UK. MacDonald and Taylor (1993), Alexander and Barrow (1994) *inter alia*, demonstrate the tendency of house price shocks emanating from the southern regions, in particular London and South West to spread out northward and affect the rest of the country, known as ripple-effect.

What is particularly interesting is a striking synchronisation in the termination of the first explosive episode. The signal of price collapse spread out and affected all regional housing markets virtually at the same time, within a few quarters of 1989.

Turning to the second detected episode of exuberance we notice that all regional house prices were explosive in the first half of 2000s. Perhaps surprisingly, Northern Ireland, where the origination date of exuberance is located as the second quarter of 1997, is the first region to enter the exuberant phase. Leaving the housing market of Northern Ireland aside and focusing on the rest of the country, we notice that propagation of exuberance fits into the pattern observed in the late 80s, when explosiveness that took its origin from the southern regions (Greater London and Outer Metropolitan (2000:Q1), South West (2000:Q3) and Outer South East (2001:Q1)) was transmitted through the midland areas (East Anglia, East and West Midlands (2001:Q2), Wales (2001:Q4)) to the northern parts of the country (the North, North West (2002:Q2) and

[13]Comparing the results for different autoregressive lag lengths we note that the GSADF date-stamping estimation with no lags detects a short period of exuberance in real house prices of Scotland and Northern Ireland in the end of 1980s and locates the dates of its origination as 1989:Q3 and 1990:Q1 respectively. In general, the duration of house price explosiveness is longer in the no lag case.

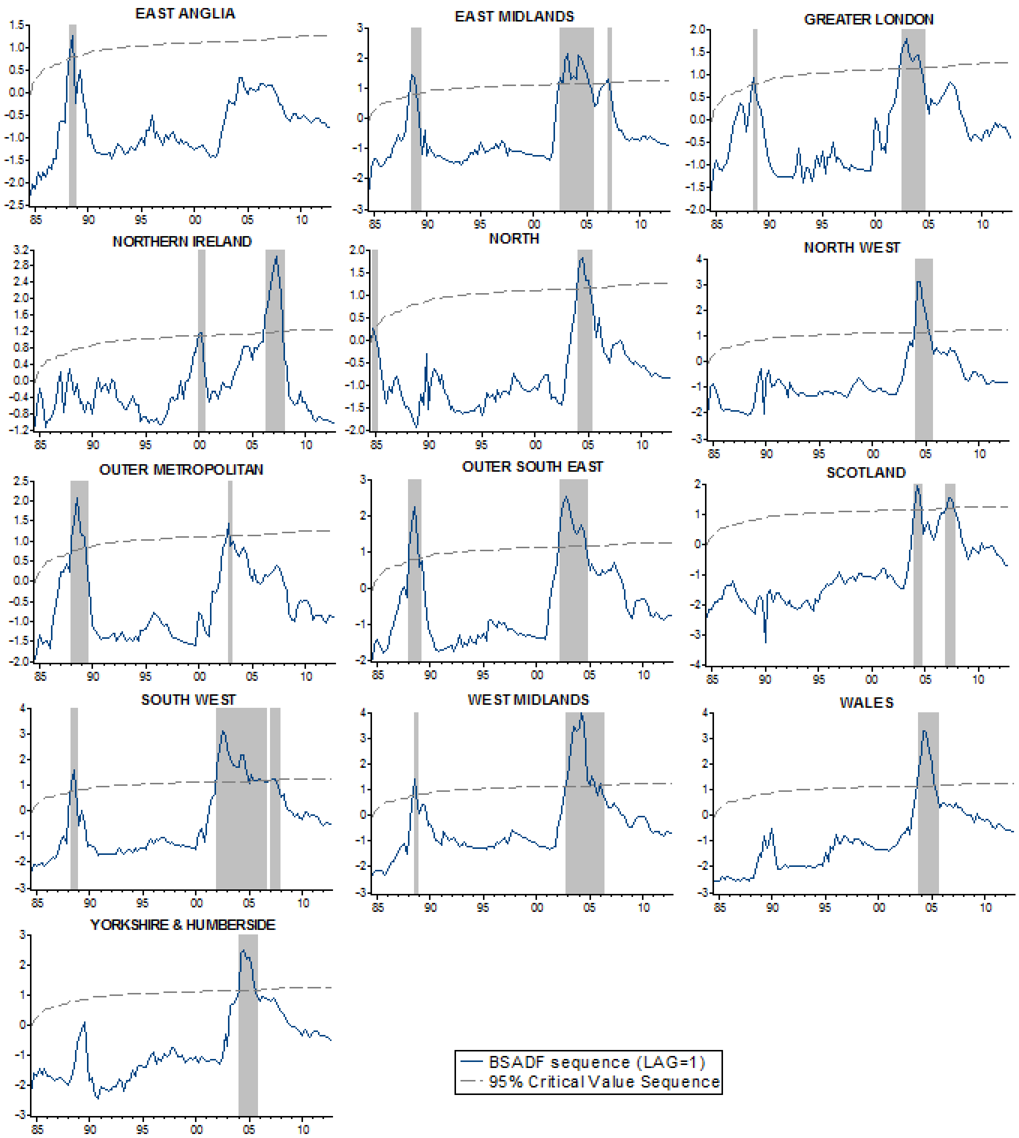

Figure 2.4: Ratio of Real House Prices to Real Personal Disposable Income: Date-Stamping of Explosive Episodes. Shaded areas indicate identified periods of exuberance (*BSADF* series is above the sequence critical value). The *BSADF* series are computed for the autoregressive lag length 1.

Scotland (2002:Q3)).

By contrast with the first period of explosiveness, termination of the second episode was less synchronised as indicated by the end dates of exuberance that vary across regions. The Outer Metropolitan statistic was the first to collapse in the third quarter of 2003, followed by Greater London and Outer South East after more than a year: in 2004:Q4 and 2005:Q1 respectively. Overall, we observe a gradual collapse of the regional statistics during a five-year period: our results indicate that the *BSADF* statistics of Northern Ireland and Scotland, where exuberance prevailed until the third quarter of 2008, were the last to fall below the sequence of critical values.

Turning to the date-stamping results for the price-to-income ratios, we note that the duration of exuberant periods is shorter with fewer regional markets showing explosiveness in the late 80s (8 out of 13). In addition to Scotland and Northern Ireland, North West, Yorkshire & Humberside and Wales, are regions where the date-stamping strategy finds no signs of exuberance in the onset of the UK recession in the early 1990s. The fact that house prices in the last three markets were exuberant during the time, while the ratios of prices to income were not, indicates that it was not the explosive bubble that was driving the real estate prices in these regions but rather growth in the economic fundamentals, in particular households' disposable income.

In the first half of 2000s the *GSADF* methodology detects explosive dynamics in all regional price-to-income ratios but one (East Anglia) with notably shorter phases of exuberance. The Outer Metropolitan area, for instance, was explosive for only two quarters and was the first regional market to collapse in the first quarter of 2003. Overall, synchronisation in the phases of explosive dynamics across regional markets and the pattern of northward propagation of housing shocks that we observed in the real estate prices remain evident when the ratio of price-to-income is the variable under examination.

Finally, we test for the overall, nationwide exuberance in the UK regional housing markets using the panel version of the *GSADF* methodology proposed by Pavlidis et al. (2015). Details of the panel *GSADF* test procedure and the associated date-stamping strategy are reserved for Appendix C. The bottom section of Table 2.3 reports the panel *GSADF* statistics together with the corresponding finite sample critical values computed for both real house prices and the ratio of real prices to real disposable income. The null hypothesis of a unit root is confidently rejected in favour of the explosive alternative for both variables under consideration providing strong evidence of nationwide explosiveness in regional housing markets of the UK.

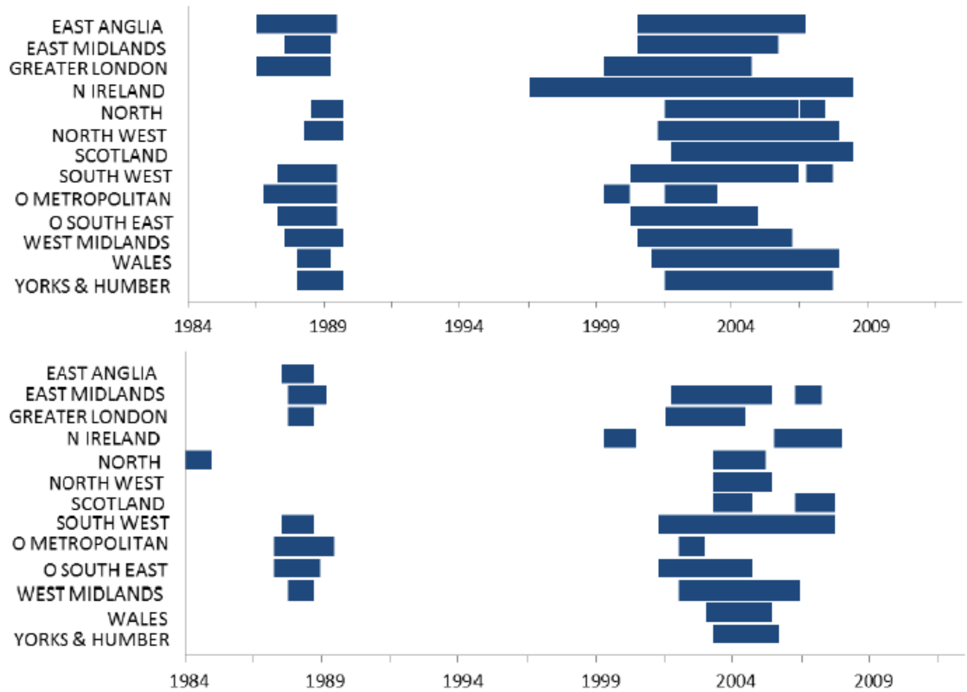

Figure 2.5: Date-Stamping of Explosive Episodes: Real House Prices and Price-to-Income Ratio. Shaded areas indicate periods of exuberance identified by the *GSADF* test.

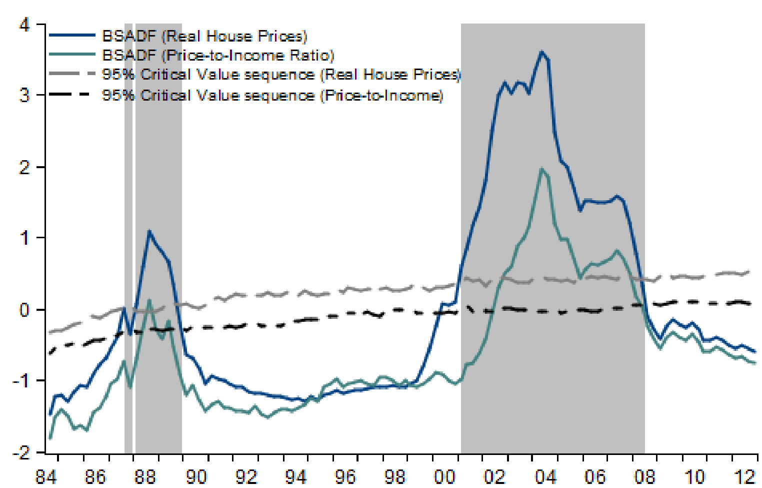

Figure 2.6: Date-Stamping Episodes of Nationwide Exuberance. Shaded areas indicate periods when the series of panel *BSADF* (real house prices) is above the sequence of critical values.

The evolution of the panel *BSADF* statistics, displayed in Figure 2.6, resembles the pattern of the individual regional *BSADF* series discussed above. We observe two episodes of the overall exuberance during the examined sample period regardless of the variable under consideration: in the late 80s and early and mid-00s. The phases of overall exuberance in the panel price-to-income ratios are somewhat shorter than those detected in the panel house price series, which is consistent with the univariate date-stamping results. We note a remarkable synchronisation in the collapse date of the second explosive episode: both price and price-to-income statistics fell below the sequence of their respective critical values in the second quarter of 2008.

Exuberance in Deviations From the Long-Run Equilibrium We now turn back to the house price model estimated in the previous section and examine the implication of house price explosiveness for the fundamental model of regional property prices. We apply the recursive unit root procedure of Phillips et al. (2011, 2015) to the equilibrium correction terms from the structural model of Cameron et al. (2006). The finding of explosive deviations from the stable long-run equilibrium relationship would provide convincing evidence that exuberance in regional property prices was not driven by the economic fundamentals but was induced by non-fundamental explosive element of real estate prices, rational house price bubble.

In our application, when the variable under investigation is not the price level sequence but the series of residuals, finite sample critical values of the *SADF* and the *GSADF* test statistics obtained as described in Appendix C are no longer valid. In order to draw statistical inference, under the null hypothesis of stable long-run equilibrium relationship between price series and economic fundamentals we generate the cointegrated system using Phillips (1991) triangular representation.[14] The recursive unit root tests of Phillips et al. (2011, 2015) are then applied to the simulated series of cointegrating residuals. The procedure is repeated a large number of times to obtain the empirical distributions of the *SADF* and *GSADF* test statistics.

Table 2.4 reports the regional *SADF* and the *GSADF* statistics together with their respective finite sample critical values. The *GSADF* test results indicate that the null of a unit root is confidently rejected in favour of the explosive alternative at all conventional significance levels for all regional equilibrium-correction series. The results of the *SADF* test procedure are somewhat less unanimous. We notice very few rejections of the null, which, as discussed above, is consistent with lower power of the *SADF* test. Figure 2.7 plots the *BSADF*

[14] The details of the procedure are presented in the notes to Table 2.4.

Table 2.4: Equilibrium Correction Terms: The *SADF* and the *GSADF* test results

Region	*SADF*	*GSADF*
North	-1.52*	1.52***
Yorks & Hside	-0.62***	3.24***
North West	-1.35*	3.71***
East Midlands	-1.58	2.23***
West Midlands	-1.87	3.96***
East Anglia	-0.75***	2.55***
Outer S East	-1.86	2.08***
Outer Met	-1.87	2.09***
Greater London	-2.44	0.45***
South West	-1.82	2.88***
Wales	-1.19**	3.07***
Scotland	-0.37***	5.65 ***
Northern Ireland	-1.07**	1.19***
Finite sample critical values		
90%	-1.54	-0.78
95%	-1.32	-0.56
99%	-0.79	-0.23

Note: Superscripts *, ** and *** denote significance of the reported statistic at 10, 5 and 1 percent level of significance. Finite sample critical values for the sample of 150 observations are obtained by Monte Carlo simulations with 2000 replications. For each repetition cointegrated system is simulated using Philips' (1991) triangular representation as follows:
$y_{1t} = \beta_2 y_{2t} + u_t, u_t = 0.75u_{t-1} + \epsilon_t, \epsilon_t \sim iidN(0, 0.5^2)$,
$y_{2t} = y_{2t-1} + v_t, v_t \sim iidN(0, 0.5^2)$.
The *SADF* and *GSADF* tests are then applied to the series of cointegrating residuals, computed as (Cameron et al. (2006)):
$lrhp_{r,t-1} - \beta_{0,r} - \beta_1 * lrynhs_{r,t} - \beta_2 * MACCI_t - (1 - \varphi * MACCI_t) * (\beta_3 * \Delta^2 labmr_t + \beta_4 * (labmr_t - mean.labmr)) - \beta_5 * MACCI_t * (rabmr_t - mean.rabmr) - \beta_6 * rabmr_t$.

series against the sequence of 95% critical values of the *SADF* statistic obtained by repeated application of the test procedure to the series of simulated cointegrating residuals, as discussed above. We note that all regional *BSADF* sequences lie above the series of critical values during the latest boom in the housing market. Generally, the regional *BSADF* series cross the critical value sequence around 2000-2001 and fall below the respective critical value just before the downturn in the housing market, around 2005-2006. We observe that the identified chronology corresponds to the timeline of the second period of explosiveness in the series of property prices and the price-to-income ratios, uncovered by the univariate *GSADF* procedures (see Figures 2.3 and 2.4).

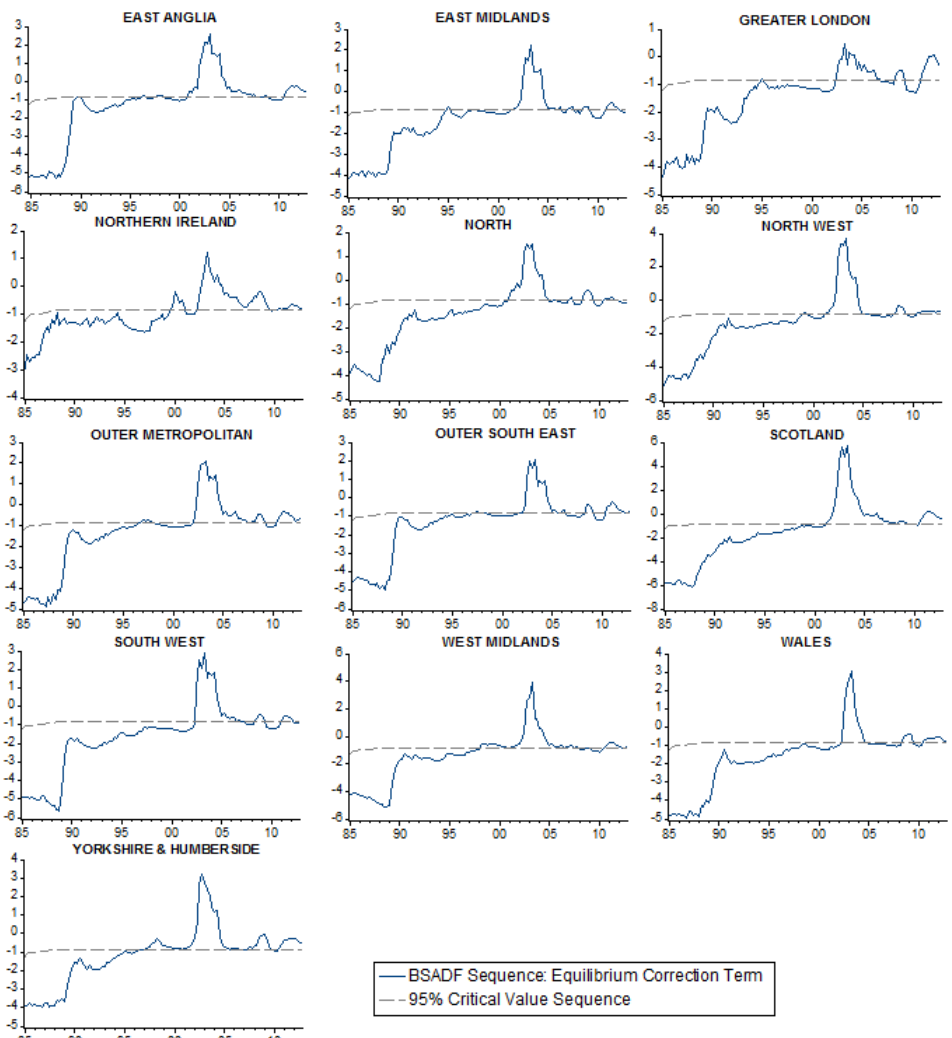

Figure 2.7: Model of Regional House Prices: Equilibrium Correction Terms and Episodes of Exuberance.

Overall, the results confirm that the equilibrium correction terms from the structural model of regional real estate prices, which should be stationary in the absence of house price bubbles, are, in fact, explosive. The evidence of exuberance in the regional real estate prices and the price-to-income ratios, the absence of cointegrating relationship between prices and the economic fundamentals and explosiveness in the deviations from the long-run equilibrium provide strong evidence that the UK real estate markets have experienced episodes of explosive dynamics that cannot be explained by movements in the economic fundamentals.

We complete the analysis by setting the evidence of the structural model against the results of Phillips et al. (2011) and Phillips et al. (2015) test procedures. Figure 2.8 displays the long-run equilibrium correction terms from the estimated regional house price model with shaded areas indicating the chronology of explosive dynamics uncovered by the *GSADF* date-stamping mechanism. To concentrate on explosiveness that is not driven by growth in the fundamentals we chose to report phases of exuberance in the ratios of prices to disposable income. Visual examination of the regional diagrams suggests that the identified episodes of explosive dynamics generally correspond to the periods of inflated deviations from the long-run equilibrium prices. The fact that the economic fundamentals do not explain exuberant behaviour of regional real estate prices in the end of 80s and, in particular, in the first half of 00s, would be consistent with the view that it was driven by the non-fundamental explosive component of house prices, rational bubble in the sense of Diba and Grossman (1988). The conclusion is consistent with the arguments discussed above and provides further support to the hypothesis of rational bubbles in the UK regional real estate markets.

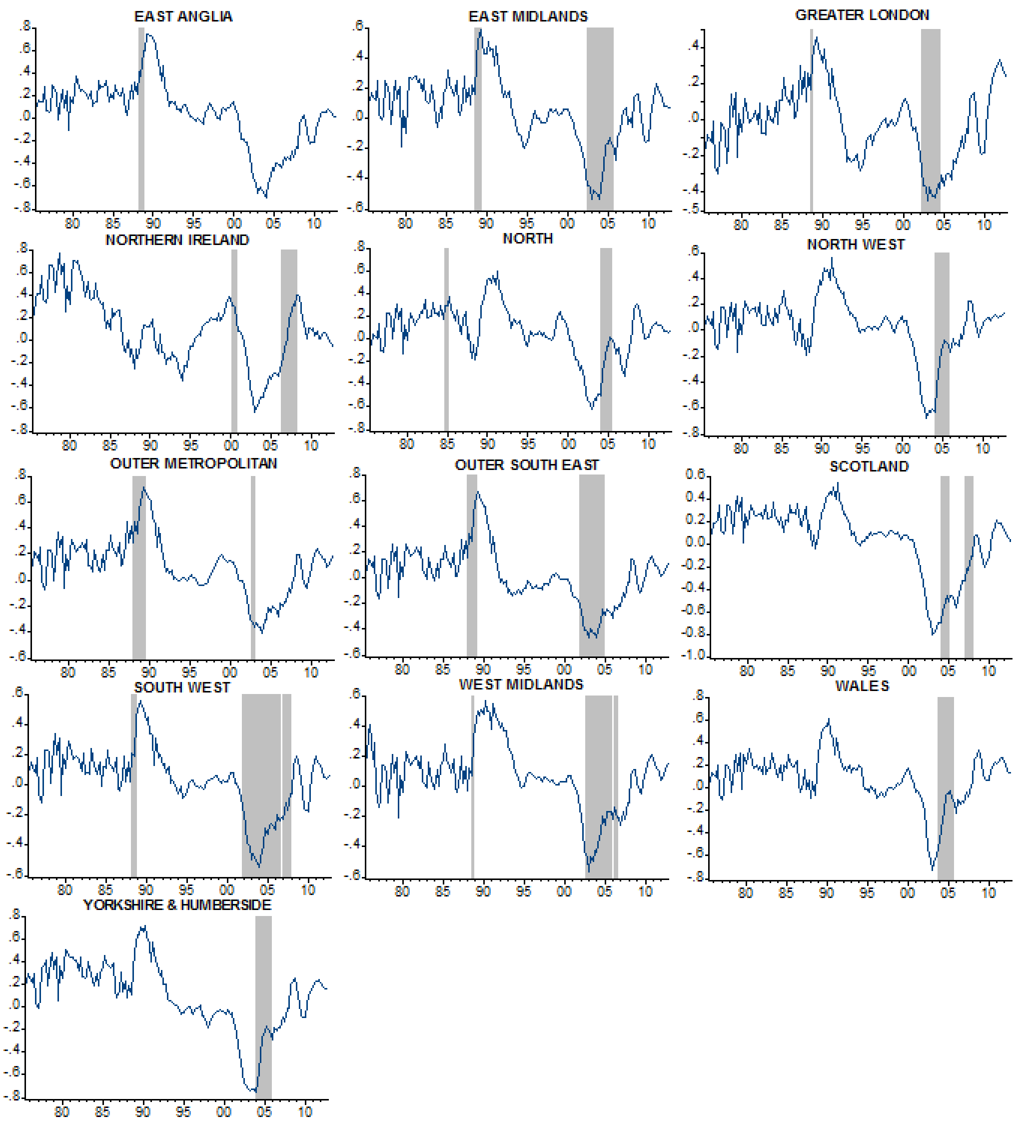

Figure 2.8: Model of Regional House Prices: Equilibrium Correction Terms. Shaded areas indicate episodes of explosive dynamics detected by the *GSADF* test applied to the ratios of prices to disposable income.

2.5. Conclusion

In this chapter, we took a close look at the behaviour of the UK regional housing markets over the last four decades and provided evidence that non-fundamental factors, such as rational asset price bubbles, have played a role in the dynamics of regional property prices in the past. For doing so, we began by estimating the structural model of regional real estate prices suggested by Cameron et al. (2006) that exploits regional housing data, incorporates a wide range of the national-level and the regional-level house price determinants, the impact of credit liberalisation as well as the regional spillover effects. We estimated the model over the period, which incorporates the recent boom and bust in the housing market and found that although the direction and the magnitude of the estimated effects are, generally, compatible with those reported by Cameron et al. (2006), the model does not fit the data. Cameron et al. (2006) model property prices in each region as the equilibrium correction relationship and by looking at the graphs of the deviations of regional property prices from their long-run equilibrium, we came to the conclusion that the model was not able to explain the house price dynamics in the late 1980s and the early and mid-2000s. Furthermore, by testing for cointegration between house prices and fundamentals, we found that there does not exist a stable long-run equilibrium relationship between house prices and their fundamental determinants. The theory of asset price bubbles postulates that any cointegrating relationship between asset prices and fundamentals breaks down when the price series under investigation contains an explosive non-fundamental component, rational asset price bubble. We came to the conclusion that the evidence of non-stationary deviations from the long-run equilibrium is not consistent with the absence of rational bubbles and hence, suggests the presence of explosive dynamics in the house price series that cannot be explained by the economic fundamentals.

As a second contribution of our chapter, we employed the recently developed recursive unit root procedure of Phillips et al. (2011, 2015) to test for explosiveness in the regional house price series. Our results strongly supported the hypothesis of exuberance in all regional real estate prices, while the panel modification of the test procedure suggested by Pavlidis et al. (2015) indicated the presence of nationwide exuberance in the UK housing market. Furthermore, the methodology of Phillips et al. (2011, 2015) enabled us to shed light on the timeline of explosive dynamics. The associated date-stamping procedure uncovered two episodes of explosiveness across regional real estate markets of the country: in the late 1980s and in the early and mid-2000s. At the same time, by applying the recursive unit root procedure to the equilibrium correction terms from the structural model of Cameron et al. (2006), we found explosiveness in all deviations of regional property prices from their respective long-run equilibria. This finding suggested that exuberance in the house price series was driven not by economic fundamentals but was induced by non-fundamental explosive elements of real estate prices. In summary, the evidence of exuberance in regional property prices, exuberance in the deviations from the long-run equilibrium and the fact that the estimated fundamental model was not able to explain the behaviour of regional real estate prices during the exuberant phases provided evidence that the UK housing markets have experienced episodes of explosive dynamics that could not be explained by movements in the economic fundamentals.

Appendix A: Data Description and Sources

Table A1: The Model of Regional House Prices.

Variable	Description	Data Sources
$\Delta lrhp_{r,t} =$	Dependent variable is the log growth in the regional real house price index.	The nominal house price data is from the Nationwide database. To transform the data into real values regional indices are deflated using the CPI (all items) from the OECD Main Economic Indicators.
$+\alpha * \beta_{0r}$	α is the speed of adjustment. β_{0r} is the region-specific intercept term.	
$+\alpha * [\beta_1 * lrynhs_{r,t} - lrhp_{r,t-1}]$	Equilibrium Correction Term. Following Cameron et al. (2006), the long-run income elasticity β_1 is set to 1.6.	Annual regional income data is extracted from the Family Expenditure Survey (FES) (FES runs from 1961 to 2001, from 2001 it was replaced by the Expenditure and Food Survey (EFS), which became the Living Costs and Food Survey (LCF) from 2008). For each year in our sample we split the dataset by region and extract the data on average total household's weekly expenditure (Outer Metropolitan and Outer South East are assumed to correspond to the South East region in the regional classification adopted by the FES). The annual data is then interpolated to obtain quarterly series.
$+\alpha * \beta_2 * MACCI_t$	Effect of credit liberalisation. Appendix B contains detailed description of the (*CCI*) estimation methodology. The moving average of the index is computed as $MACCI_t = \frac{CCI_t + CCI_{t-1}}{2}$.	Table A2 details the sources of data used for the *CCI* estimation.
$+\alpha * (1 - \varphi * MACCI_t) * (\beta_3 * (labmr_t - \overline{labmr}) + \beta_4 * \Delta_2 labmr_t)$	The nominal tax-adjusted mortgage rate is defined as $abmr_t = bmr_t - \frac{CostofMortgageTaxRelief_t}{SD_t}$, where SD_t is the stock of mortgage debt. $labmr_t$ is the natural log of the $abmr_t$ series. The nominal interest rate enters the equation in interaction with the index of credit availability. We expect a positive coefficient in front of the interaction term since liberalisation of credit markets weakens the negative effect of an increase in the nominal mortgage rate.	The data on total amount of lending secured on dwellings is available via ONS.The cost of interest relief can be accessed via HM Revenue & Customs. The data is interpolated to obtain quarterly series. The cost of mortgage relief is zero from 2000Q1 onwards. The source of the building societies' mortgage rate data (bmr_t) is OECD: Main Economic Indicators.
$+\alpha * [\beta_5 * MACCI_t * (rabmr_t - \overline{rabmr})]$	The real tax-adjusted mortgage rate is defined as $rabmr_t = abmr_t - \Delta \log Deflator_t$. We interact the real rate with the index of credit availability. The negative effect of real interest rates weakens with credit liberalisation.	
$+\alpha * \beta_6 * rabmr_t$	We expect a negative effect of real interest rates on house prices.	

Table A1: The Model of Regional House Prices.(Continued)

Variable	Description	Data Sources
$+\beta_7 * \Delta clrhp_{r,t-1}$	Positive effect of lagged house price growth in the neighbouring regions. $\Delta clrhp_{r,t-1} = (1 - w_{1,r} - w_{2,r}) * \Delta lrhp_{r,t-1} + w_{1,r} * \Delta lrhp_{CR,t-1} + w_{2,r} * \Delta lrhp_{GL,t-1}$. Please refer to the notes to Table 2.1 for the $w_{1,r}$, $w_{2,r}$ weights.	The data on regional house prices is available from the Nationwide database. $\Delta lrhp_{CR,t-1}$ is the last period's average growth rate in real house prices in contagious regions and $\Delta lrhp_{GL,t-1}$ is the lagged growth rate in London real estate prices.
$+\beta_8 * \Delta lrpdin_t$ $+\beta_9 * \Delta lrpdin_{t-1}$	We expect a positive effect of current and last period's national income growth on housing inflation.	The Index of Personal Disposable Income adjusted for inflation is from Federal Reserve Bank of Dallas' International House Price Database. We take the log of the reported series.
$+\beta_{10} * MACCI_t * \Delta lrpdin_t$	We expect a negative coefficient in front of the interaction term, since households' non-property income matters less when credit becomes freely available.	
$+\beta_{11} * \Delta^2 lpc_t$	The expenditure deflator is computed as consumption expenditure at current prices divided by consumption expenditure at constant prices. Acceleration in inflation rate discourages mortgage borrowing and hence has a negative effect on house prices.	The data on consumer spending is available via ONS.
$+\beta_{12} * \Delta lrftse_t$ (Outer Met) $+\beta_{13} * \Delta lrftseneg_t$ (Outer Met)	The stock market effect. Enters the OM equation only. $lrftseneg_t = lrftse_t$ if $lrftse_t < 0$ and zero otherwise. Fall in the stock market results in investors reallocating their wealth and choosing real estate as a safe alternative. We expect a negative coefficient in front of the $\Delta lrftseneg_t$ term.	FTSE data is accessed via Datastream. We deflate the nominal index by the CPI (all items) and take the log of the series.
$+\beta_{14} * ror.neg_{r,t}$	Downside risk in the real estate market is defined as a four-quarter moving average of past negative returns on housing in the region. The rate of return on housing is defined as: $ror_{r,t} = \Delta_4 lhp_{r,t-1} + 0.02 - abmr$, where $\Delta_4 lhp_{r,t-1}$ is a four-quarter change in the log regional house price index lagged one period. Negative rate of return $ror.neg_{r,t} = ror_{r,t}$ if $ror_{r,t} < 0$ and zero otherwise.	
$+\beta_{15} * \Delta pop2039_{r,t-1}$	Demographic effect is measured by the last period's change in the share of people aged 20-39 in the total working age population. Population increase has a positive effect on demand for housing and hence on real estate prices.	The data on population estimates by region, age and sex can be accessed via ONS webpage (EA - East, NT - North East, OM and OSE - split the South East values in the ONS classification.). The data is available annually and was interpolated to obtain quarterly series.
$+\beta_{16} * \Delta(lwpop_{r,t} - lhs_{r,t-1})$	The ratio of working age population to housing stock in the previous period. Increase in the population relative to the existing stock of dwellings has a positive effect on real estate prices.	Population estimates by region, age and sex are available from the ONS database. Live tables on housing stock by tenure and region are available from the GOV.UK database.
$+\beta_{17} * D88$ (ex.SC and NI) $+\beta_{18} * D08$	The D88 dummy variable captures the Poll Tax reform and limits on mortgage interest relief claims introduced in 1988. The D08 variable picks up a turmoil in the financial markets following the collapse of Lehman Brothers and seizure of Fannie Mae and Freddie Mac by the US government in September 2008.	Time Dummies are constructed as time trends going from 0 of the corresponding year to 1 in Q4 of that year. The varia otherwise.

Table A2: Description and Sources of the *CCI* Data

Economic Variable	Description and Expected Effect on Secured and Unsecured Lending	Data Sources
Unsecured debt (*UD*)		The data on total consumer credit outstanding is available via Bank of England (BoE) database. The series is nominal and adjusted for seasonal effects
Secured debt (*SD*)		The data on total amount of lending secured on dwellings is available via Office for National Statistics (ONS). The data is nominal and not seasonally adjusted.
Price deflator (*PD*)	The series is defined as consumption expenditure at current prices divided by consumption expenditure at constant prices.	The data on consumer spending is available via ONS.
Real non-property personal disposable income (pdi)	The series is defined as $\frac{posttaxpdi}{pretaxpi} * (wagesandsalaries + mixedincome)$ (Cameron et al., 2006). The resulting series is deflated by consumer expenditure deflator. We expect a positive effect of non-property pdi on UD and SD, since higher income makes servicing of the debt easier.	The data on wages and salaries, mixed income, income pre and post tax is available via ONS.
Income growth	The series is a four-quarter growth rate of non-property pdi. Anticipated growth in income encourages mortgage and consumer borrowing. We expect a positive effect of income growth on the amounts of both unsecured and mortgage debt outstanding.	
Nominal after tax mortgage rate (*labmr*)	Tax adjusted building-societies mortgage rate is defined as $abmr = bmr - \frac{CostofMortgageTaxRelief}{SD}$. $labmr = \log abmr$ and $rabmr = abmr - \Delta \log PD$. We expect negative interest rate effects (nominal and real) on the stock of secured and unsecured credit.	The cost of interest relief can be accessed via HM Revenue & Customs. The data is interpolated to obtain quarterly series. The cost of mortgage relief is zero from 2000Q1 onwards.
Real after tax mortgage rate (*rabmr*)		
Bank of England base rate		The source of the building societies' mortgage rate data is OECD: Main Economic Indicators.
Interest rate expectations	The yield gap between long and short-dated debt instruments is a proxy for future behaviour of short-term interest rates. The higher the expected rates the lower the demand for both mortgage and consumer borrowing.	The yields on gilts of various duration can be accessed via Datastream.
Working age population (*lwpop*)	The series is the UK resident population aged 15-69. We expect a positive effect of increase in population on the stock of secured and unsecured debt.	The data on population estimates by age and sex can be accessed via ONS webpage. The data is available annually and was interpolated to obtain quarterly series.
Proportion of young population (*pop2035*)	The series is defined as the share of persons aged 20-34 in the population aged 20-69. A rise in the proportion of the main credit-demanding age group should lead to growth in both secured and unsecured borrowing.	

Table A2: Description and Sources of the *CCI* Data.(Continued)

Economic Variable	Description and Expected Effect on Secured and Unsecured Lending	Data Sources
Unemployment rate (*UR*)	Growth in the rate of unemployment raises concerns that the borrower will not be able to service the loan. We anticipate a negative effect on both mortgage and consumer borrowing.	The data is obtained from the ONS database.
Consumer confidence	The measure is based on the GfK survey and reflects respondents' confidence in their personal financial situation as well as economic situation in general. We expect a positive effect of growing consumer confidence on the amount of secured and unsecured borrowing.	Consumer Confidence Barometer data is available via GfK Group webpage.
Return on housing (*ror*)	The rate of return on housing is defined as: $ror_t = \Delta_4 lhp_{t-1} + 0.02 - abmr$, where $\Delta_4 lhp_{t-1}$ is a four-quarter change in log house prices. We anticipate a positive effect of real estate price appreciation on the amount of debt, since increase in the value of collateral encourages borrowing.	The UK house price data comes from the Nationwide database.
Risk measure (*RISK*)	Fernandez-Corugedo and Muellbauer (2006) define the risk factor as: $RISK_t = (1/(1+\delta))(\nu_1(aainfma_t + \delta aainfma_{t-4}) + \nu_2(\Delta_4 ur_t + \delta\Delta_4 ur_{t-4}) + \nu_3(nrorma_t + \delta nrorma_{t-4}) + \nu_4(possesma_{t-2} + \delta_1 possesma_{t-6} + \delta_1^2 possesma_{t-10})/(1 + \delta_1 + \delta_1^2))$ where *aainfma* is a four-quarter moving average (MA4)of inflation volatility $aainf_t = abs(\Delta_4 lpd_t - \Delta_4 lpd_{t-4})$; $\Delta_4 ur$ is a four-quarter change in the rate of unemployment; *nrorma* is a MA4 of the negative returns on housing (*nror*=*ror*, when $ror < 0$ and is zero otherwise); *possesma* is a MA4 of the rate of mortgage possessions. We expect that riskiness and perceived uncertainty discourage consumer and mortgage borrowing.	The source of the rate of possessions data is Department for Communities and Local Government, accessed via Datastream.
Cut in income support (ISMI) dummy	The variable takes the value of zero up to 1994:Q4 and one from 1995:Q1 onwards. We expect that considerable reduction in the amount of compensation mortgage payments in the event of unemployment discouraged mortgage borrowing and made unsecured lending relatively more attractive.	
Mortgage indemnity premium (MIP)dummy	The variable is zero up to 1997:Q4 and one in subsequent quarters. On the one hand, MIP abolition for loans with LVR < 0.9 reduced servicing costs for borrowers that are eligible for the exemption and therefore, encouraged mortgage borrowing. On the other hand, it created an incentive for borrowers that do not satisfy the criteria to choose unsecured credit as a funding alternative. We expect a positive effect of the variable on both secured and unsecured credit.	

Appendix B: Index of Credit Conditions

The credit condition index (*CCI*), proposed by Fernandez-Corugedo and Muellbauer (2006), is included in the model of regional house prices in order to examine whether credit market liberalisation is able to explain soaring real estate prices in the late 1980s and early 2000s. The authors estimate the *CCI* for the period 1976-2001 from the system of 10 equations. Dependent variables include two measures of the mortgage default probability, each is examined by age (for young borrowers aged below 27 and for those aged 27+) and region (north and south of the UK) giving the total of eight data series, as well as equations of secured and unsecured lending. Probability of default is given by the proportion of mortgages with the loan-to-value ratio (*LVR*) above 0.9 and the loan-to-income ratio (*LIR*) exceeding 2.5. Fernandez-Corugedo and Muellbauer (2006) formulate each equation as an equilibrium-correction model of the following form:

$$\Delta y_{i,t} = \alpha_i \left(\theta_i CCI_t + \mu_i RISK_t + \Sigma \beta_{i,j} x_{j,t} - y_{i,t-1}\right) + \epsilon_{i,t}, \tag{2.6}$$

where the subscript $i = 1 \ldots 10$ denotes the number of equations in the estimated system, dependent variables ($\Delta y_{i,t}$) are the log changes in consumer and mortgage lending and eight *LVR* and LIR measures by region and age, α_i is the speed of adjustment, $x_{i,t}$ are explanatory variables that include both long-run and dynamic effects and θ_i , μ_i and $\beta_{i,j}$ are the estimated parameters. The index of credit conditions enters all equations and is defined as a function driven by year dummies ($D_{s,t}$), four-quarter changes in credit controls ($\Delta_4 CC_t$) and lagged liquidity ratio of building societies up to the third quarter of 1980 ($liqr_{t-1}$)(Fernandez-Corugedo and Muellbauer, 2006):

$$CCI_t = \Sigma \delta_s D_{s,t} + \lambda_1 \Delta_4 CC_t + \lambda_2 liqr_{t-1}, \tag{2.7}$$

where subscript s denotes the number of time-dummies included in the *CCI* function.

Another factor common to all ten equations in the system is $RISK_t$, defined as a non-linear combination of inflation volatility ($aainf$), negative returns on housing ($nror$), growth in unemployment (ur) and mortgage possessions ($posses$)[15]

$$RISK_t = (1/(1+\delta))(\nu_1(aainfma_t + \delta aainfma_{t-4}) + \nu_2(\Delta_4 ur_t + \delta\Delta_4 ur_{t-4}) + \nu_3(nrorma_t + \\ + \delta nrorma_{t-4}) + \nu_4(possesma_{t-2} + \delta_1 possesma_{t-6} + \delta_1^2 possesma_{t-10})/(1+\delta_1+\delta_1^2)).$$

In an attempt to extend the original measure of credit availability for the post-2001 period we encounter serious limitations. The regional data on *LVR* and *LIR* is not available after 2001, when the Survey of Mortgage Lenders (the source of information on the size of mortgage advances, price of purchased property and income by age and region) ceased to exist. Since the model cannot be estimated in full set-up we focus on the equations of the unsecured and mortgage debt and construct the system of two equilibrium correction equations, where each equation is defined as in Eq.2.6, with $i = 1 \ldots 2$ and the CCI_t and $RISK_t$ entering as the factors common to both equation.

Economic variables that are believed to have an impact on the amount of secured and unsecured lending include: non-property income and expected growth of income; both nominal and real interest rates as well as the yield gap between long-term and short-term gilts as a proxy for the interest rate expectations; a measure of perceived risk and uncertainty; demographic factors and a number of year dummies for the turning points in the history of the UK credit market liberalisation.[16] A detailed description of the economic variables, anticipated direction of the influence and the data sources are presented in Appendix A.

The two-equation system is estimated using Full Information Maximum Likelihood. Details on the formulation of each equation and the interpretation of the estimation results are presented below.

The Equation of Mortgage Debt Mortgage lending is modelled as an equilibrium correction equation of the form (2.6), where our dependent variable is the log change in the amount of secured debt ($\Delta logSD_t$), α_1 is the speed of adjustment and the $x_{j,t}$ represent variables that, as discussed above, are believed to affect the stock of mortgage debt. Following the recommendations of Fernandez-Corugedo and Muellbauer (2006)

[15] See Section 5 of Fernandez-Corugedo and Muellbauer (2006) for details on construction of the four risk indicators.

[16] In addition to the listed factors Fernandez-Corugedo and Muellbauer (2006) include liquid and illiquid financial wealth, housing wealth and the ratio of credit cards outstanding to the working age population in the list of economic variables impinging on the amount of secured and unsecured lending. These economic factors are not among the variables analysed in the present paper as the data is not available for the whole period under consideration. The data on financial wealth from 1987 onwards can be accessed via Office for National Statistics (ONS), while the amount of credit cards in circulation comes from British Bankers Association (BBA) and is only available from 1995.

we chose to set θ_1, the coefficient in front of the CCI_t term in the mortgage debt equation, equal to 2 to ensure identification. Although most of the estimated coefficients are consistent with the sign prior set out in Appendix A, some of the economic factors proved insignificant. The final specification of the secured debt equation is presented in Table B1.

Table B1: Parameter Estimates: Secured Debt Equation

Variable		Estimate	Statistic
Speed of adjustment	α_1	0.03	11.95^{***}
Index of credit conditions	CCI_t	2.00	-
Income effects	$lrpdin.percapita_t$	2.25	6.67^{***}
	$\Delta_4 lrpdin.percapita_t$	1.25	3.06^{**}
Interest rate effects	$labmr_{t-1}$	-0.37	-3.56^{***}
	$spread_t$	-0.19	-4.73^{***}
Risk measures	$RISK_t$	-0.10	-4.14^{***}
	$Downside.risk_t$	-0.16	-3.90^{***}
Abolition of tax relief dummy	$D88$	-0.58	-3.16^{***}
Seasonal effects	*Seasonal.Q1*	-0.09	-2.72^{**}
	Seasonal.Q2	0.05	1.61^{*}
	Seasonal.Q3	0.08	2.37^{**}
Std.error of regression		0.0038	
Adj. R-squared		0.947	
Durbin-Watson		1.562	
Portmanteau Autocorrelation test(1)		(0.075)	
Portmanteau Autocorrelation test(4)		(0.237)	

Note: The Table reports parameter estimates and the corresponding t-statistics of the mortgage debt equation. Superscripts *, ** and *** denote significance of the reported statistic at 10, 5 and 1 percent level of significance. Dependent variable is the log growth in the stock of secured lending in the UK (ΔSD_t) The bottom part of the Table presents the summary of diagnostics checks: regression standard error, goodness of fit, Durbin-Watson statistic and Portmanteau autocorrelation test probabilities at 1 and 4 lags reported in parentheses.

Both the level effect of the non-property income and the dynamic effect of expected growth of income are statistically significant and positive, which is consistent with our predictions. We note however, that the long run income elasticity of 2.25 is somewhat higher than that reported by Fernandez-Corugedo and Muellbauer (2006). As expected, the results indicate that higher income per capita makes servicing of the loan easier and therefore, encourages mortgage borrowing. Positive dynamic effect of income expectations, measured by a four-quarter growth in actual non-property income, implies that optimistic expectations with regard to future disposable income stimulate the current mortgage borrowing. The conclusion is consistent with the notion of consumption smoothing individuals.

The long-run solution includes two interest rate effects and both are significant with the signs consistent with our prior. The first is the lagged log of the tax adjusted building societies mortgage rate ($labmr_{t-1}$) with the estimated coefficient of -0.37, which is only marginally lower than that reported by Fernandez-Corugedo and Muellbauer (2006). An increase in the nominal interest rate by a one percentage point, *ceteris paribus*, leads to a 0.37% fall in the stock of mortgage debt in the long run. The second effect is the yield gap between long- and short-term gilts entering as a proxy for the interest rate expectations. The estimated long-run coefficient has, as expected, a negative sign implying a fall in the stock of mortgage debt as the result of pessimistic interest rates expectations. We have checked for several real interest rate effects using real tax adjusted mortgage rate, real mortgage rate and real base rate (current values and lagged one period) - all were found insignificant.

The complex measure of perceived risk proposed by Fernandez-Corugedo and Muellbauer (2006), defined above, proved insignificant. We construct an alternative risk measure that mirrors variance structure of the four uncertainty indicators using the method of principal components. The created risk measure is significant and has an anticipated negative effect on the individual's readiness to borrow and hence, on the stock of mortgage lending. Another indicator of perceived uncertainty that enters the final specification is a measure of downside risk in the real estate market. The measure is defined as a four-quarter moving average of negative returns on housing. Our results indicate that the greater collateral uncertainty discourages mortgage borrowing, which is consistent with our sign prior. The measure of consumer confidence, on the contrary, proved insignificant in both equations.

The equation includes a set of seasonal dummies since the secured debt data is not seasonally adjusted. The obtained results imply a rise in mortgage borrowing in the second and third quarters of the year. However it should be mentioned that the second quarter dummy is only marginally significant at 10% level of significance. The variable $D88$ that takes a value of 0.25 in the second, 1 in the third quarter of 1988 and zero otherwise is included in the model to capture the effect of the budget announcement in March 1988, limiting number of mortgage interest relief claims to one per property. The changes came into force in August of the same year and the results indicate a considerable increase in mortgage borrowing following the announcement. Changes in the income support for mortgage interest payments (ISMI) scheme that were introduced in the first quarter of 1995 made mortgage borrowing relatively less attractive. As discussed in the Appendix A we would expect a negative coefficient in front of the ISMI term, however, the dummy that measures the effect proved insignificant. Another turning point in the history of the UK credit market liberalisation is the abolition of mortgage indemnity insurance premium (MIP) for secured loans with loan-to-value ratio (LVR) of 0.9 and below, announced in the first quarter of 1998. The dummy that captures this effect was found insignificant. The ISMI and the MIP dummy variables are not included in the final specification, hence the estimated coefficients are not reported.

We estimate a relatively low speed of adjustment of about 0.03, which is almost a half of that reported by Fernandez-Corugedo and Muellbauer (2006). The results suggest that residential mortgage market is slow to respond to income, interest rates, credit liberalisation and other effects in adjustment to its long-run equilibrium. The stock of mortgage debt increased by 2.46 (23%) between 1980:Q3, when credit controls were removed and banks entered the UK credit market (previously dominated by building societies) and 2012:Q4. The index of credit conditions rose by 0.39 over the period and given its long-run coefficient of 2, 0.78 of the rise in mortgage lending is associated with greater credit availability (corresponds to 32% of the increase in lending). With estimated income elasticity of 2.25, the remainder of the rise in the stock of secured debt over the period can be mainly attributed to the growth of non-property income per capita. The other positive effects come from lower nominal interest rates, decline in the RISK factor[17] and the announcement of multiple mortgage relief abolition. Offsetting factors are greater collateral uncertainty, slowing down of income growth and the pessimistic interest rate expectations.

The Unsecured Debt Equation By analogy with mortgage lending, the stock of unsecured debt is modelled as an equilibrium correction equation of the form (2.6) with dependent variable being the log change in consumer credit ($\Delta logUD_t$). The list of economic variables that are expected to affect the amount of unsecured lending was outlined above and the reader is referred to Appendix A for details on the variable

[17] Even though the measure of perceived risk and uncertainty declined over the years 1980:Q3-2012:Q4, there were periods when the climate of high inflation, negative returns on housing and general economic instability played an important role in slowing down the growth of mortgage lending (for instance, between 2008:Q3 and 2010:Q1).

definition, sign priors and the data sources. Table B2 presents the final specification of the unsecured debt equation. We note that some of the economic effects proved insignificant and the fit of the model is poor.

Table B2: Parameter Estimates: Unsecured Debt Equation

Variable		Estimate	Statistic
Speed of adjustment	α_2	0.05	3.71^{***}
Index of credit conditions	CCI_t	2.63	7.04^{***}
Income effect	$lrpdin.percapita_t$	1.68	2.83^{**}
Interest rate effect	$real.baserate_{t-1}$	-2.34	-0.52
Risk measure	$\Delta_4 ur_t$	-0.13	-2.36^{**}
Demographic effect	$pop2035_t$	14.05	1.69^{*}
Income support abolition dummy	$ISMI_{t-1}$	1.09	2.78^{**}
Std.error of regression		0.0274	
Adj. R-squared		0.405	
Durbin-Watson		1.879	
Portmanteau Autocorrelation test(1)		(0.075)	
Portmanteau Autocorrelation test(4)		(0.237)	

Note: The Table reports the parameter estimates and the corresponding t-statistics of the unsecured debt equation. Superscripts *, ** and *** denote significance of the reported statistic at 10, 5 and 1 percent level of significance. Dependent variable is the log growth in the stock of consumer lending in the UK (ΔUD_t). The bottom part of the Table presents the summary of diagnostics checks: regression standard error, goodness of fit, Durbin-Watson statistic and Portmanteau autocorrelation test probabilities at 1 and 4 lags reported in parentheses.

The long-run income elasticity is 1.68, which is about two-thirds of that estimated for mortgage borrowing. The dynamic effect of a four-quarter growth in the non-property income, which enters as a proxy for the income expectations, was found insignificant. The results suggest that mortgage borrowing is more dependent on consumers' current levels of income and their income expectations than the unsecured credit.

According to our estimates, demographic effect, as captured by a proportion of population aged 20-35 in the total working age population, is only marginally significant at 10% level of significance. The long-run demographic coefficient has a predicted positive sign, therefore a rise in the proportion of potential borrowers increases the stock of unsecured borrowing in the long-run.

One possible explanation of the poor fit of the model is that none of the interest rate effects were found significant. We have checked several interest rate effects including a number of nominal and real interest rates as well as the effect of interest rate expectations, approximated by the yield gap between long- and short-term gilts. We failed to find significant effects of any of the measures and report the least insignificant one the effect of lagged real base rate ($real.baserate_{t-1}$) for the record.

As discussed above, the composite risk measure suggested by Fernandez-Corugedo and Muellbauer (2006) was found insignificant and was replaced by the indicator of perceived risk and uncertainty computed using the method of principal components. The created risk factor, however, proved insignificant in the unsecured debt equation. To account for the effects of riskiness of borrowing we considered different specifications of the risk measure, including each of the four risk indicators (inflation volatility, downside risk, etc.) separately. Variable that has a significant effect on the amount of consumer borrowing is a four-quarter change in the rate of unemployment ($\Delta_4 ur_t$). Negative dynamic effect of the latter is consistent with our prior that growing unemployment compromises the ability of borrowers to service the loan and hence, depresses consumer lending.

The set of seasonal dummies is not included in the model since the unsecured debt data is already adjusted for seasonal effects. The effect of changes in the ISMI project has, as expected, significant and positive effect on the amount of unsecured lending. The reform that lowered the maximum amount of mortgage loan qualified for income support and reduced the compensation payments in the event of unemployment deterred potential first-time buyers from mortgage borrowing and made them switch to the unsecured credit instead.

The estimated speed of adjustment is 0.05 which is higher than that of the mortgage debt but the adjustment is very slow compared to the results reported by Fernandez-Corugedo and Muellbauer (2006). Clearly the fact that some economic effects proved insignificant has affected the speed with which unsecured debt restores its long-run equilibrium.

Over the period between 1980:Q3 and 2012:Q4 the stock of unsecured debt has grown by 3.48 , an increase of 40%. We compute the long-run effect of credit liberalisation on the amount of consumer lending as a product of increase in the *CCI* that occurred over the years and its long-run coefficient 2.63. We conclude that 1.03 of the rise in consumer lending can be explained by the favourable credit conditions (30% of the increase in lending). In addition, the positive effects on unsecured borrowing are coming from the higher income per capita (the long-run income elasticity is 1.68), the lower unemployment rate and the changes in the ISMI scheme that resulted in consumers turning to the unsecured borrowing as an alternative to relatively less attractive mortgage credit. The offsetting effect is the result of demographic changes: a decline in the proportion of the main credit demanding age-group is responsible for the fall in the stock of consumer lending by 0.6 in the long-run.

Index of Credit Conditions The index of credit availability is defined as a function of year dummies (see Eq.(2.7)). We follow Fernandez-Corugedo and Muellbauer (2006) in their choice of the *CCI* parameters. The key differences concern some of the year dummies that are found insignificant and, therefore, are removed from the final specification of the *CCI*. Furthermore, to extend the original index for the post-2001 period we add additional dummies for the years after 2001. Parameter estimates of the *CCI* function are presented in Table B3.

Table B3: Parameter Estimates: *CCI* Function

Variable	Estimate	Statistic
D80Q4	0.21	2.83
D81	0.35	4.93
D86	0.19	5.66
D88	-0.23	-5.10
D92	-0.03	-2.47
D95	-0.12	-3.72
D01	0.14	2.02
D02	0.18	3.30
D08	-0.15	-3.07
D10	-0.07	-1.60
$liqr_{t-2}$	-0.04	-4.21

Note:*D80Q4* is a step dummy taking a value of 0 prior to the fourth quarter of 1980 and 1 in all subsequent periods. Other dummy variables (*D81-D10*) are constructed as time trends going from 0.25 in Q1 of the corresponding year to 1 in Q4 and all subsequent quarters. $liqr$ is the liquidity ratio of building societies up to 1980:Q3 minus its 1980:Q4 value. The data is obtained from Building Societies Association.

The variable that marks the turning point in the history of the UK credit liberalisation (*D80Q4*) is defined as a step dummy taking the value of 0 prior to the fourth quarter of 1980 and 1 in all subsequent periods. The rest of the dummy variables (*D81-D10*) are constructed as the time trends going from 0.25 in the first quarter of the corresponding year to 1 in the fourth and all subsequent quarters. The lagged liquidity ratio of building societies ($liqr_{t-2}$) is included as a proxy for credit availability and captures the *CCI* variation prior to 1980:Q4. The reader is referred to the Appendix A for the details on the construction of the *liqr* variable.

Figure B1: Index of Credit Conditions (*CCI*).

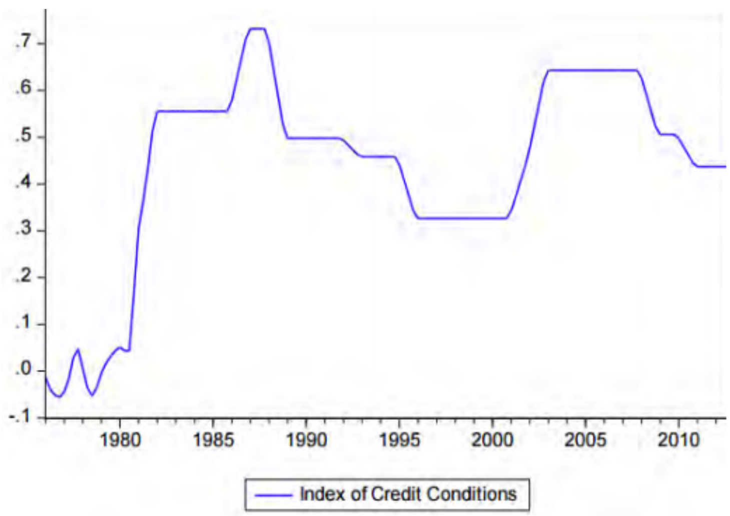

Figure B1 shows the estimated index of credit conditions. We note that the shape of the index up to 2001:Q4 closely resembles that of the *CCI* function reported by Fernandez-Corugedo and Muellbauer (2006). From 1976:Q1 to 1980:Q4 the index was at its lowest level. This time interval corresponds to the period of restrictive credit and exchange controls in the UK, limits on consumer lending and special 'corset' requirements that imposed restrictions on the size of banks' liabilities. Exchange controls were removed in 1979, followed by the abolition of the 'corset' scheme in 1980. The easing of credit requirements is reflected in the sharp increase of the *CCI* in the fourth quarter of 1980. Credit liberalisation continued in the following years as the banks were allowed to enter the market of mortgage lending, previously dominated by building societies. This led to further relaxation of controls and the graph shows the *CCI* reaching its maximum by 1986. Mortgage crisis in the early 1990s resulted in serious strengthening of prudential regulation, toughening of mortgage conditions and reversal of the *CCI*.

The shape of the estimated index in the post-2001 period reflects the situation in the UK credit market at that time. Financial deregulation, innovations in the mortgage instruments, liberalisation of lending conditions in the early 2000s led to another surge in mortgage lending. On the contrary, a collapse of the real estate prices in 2008, mortgage defaults and defaults on the mortgage-backed securities led to the tightening of prudential regulation, higher capital and solvency requirements for banks and reversal of the *CCI*.

To ensure that the estimated relationships are not spurious we check for stationarity of the error-correction terms in both equations. The null of a unit root is confidently rejected in both cases. Portmanteau test for serial dependence applied to the system residuals is satisfactory. We are not able to reject the null of no residual autocorrelation up to the 10th lag order.

Appendix C: The SADF and the GSADF Test Procedures

The Univariate *SADF* and *GSADF*

Consider the time series y_t with $[r_1T]$ and $[r_2T]$ specifying the first and the last observation respectively, where T is the total sample size and r_1, r_2 are the fractions of the total sample. The conventional right-tailed *ADF* test, suggested by Diba and Grossman (1988), estimates the following regression equation:

$$\Delta y_t = \mu_{r_1,r_2} + \phi_{r_1,r_2} y_{t-1} + \gamma^1_{r_1,r_2}\Delta y_{t-1} + \cdots + \gamma^k_{r_1,r_2}\Delta y_{t-k} + \epsilon_t, \tag{2.8}$$

where k denotes the chosen lag length, $\epsilon_t \sim iidN\left(0, \sigma^2_{r_1,r_2}\right)$ and $\mu_{r_1,r_2}, \phi_{r_1,r_2}$ and $\gamma^j_{r_1,r_2}$, where $j = 1...k$ are the regression coefficients. The null hypothesis of the right-tailed *ADF* procedure is that the series y_t contains a unit root, $\underline{H_0} : \phi_{r_1,r_2} = 0$, which is tested against the explosive alternative, $\underline{H_1} : \phi_{r_1,r_2} > 0$.

The conventional test statistic that corresponds to the case when both starting and ending points of the sample are fixed at $r_1 = 0$ and $r_2 = 1$ is labelled as $ADF^{r_2}_{r_1} = ADF^1_0$. The test statistic is compared to the right-tailed critical value from the limit distribution of ADF^1_0 and rejection of the null hypothesis in favour of the alternative signals the presence of explosiveness in the series y_t.

The test has low power in detecting periodically collapsing bubbles - a special class of explosive processes simulated by Evans (1991) that never collapse to zero and restart after the crash. Conventional right-tailed unit root tests fail to distinguish periodically collapsing behaviour from non-explosive processes and hence, may often erroneously indicate absence of a bubble when the data actually contains one.

Phillips et al. (2011) proposed recursive supremum *ADF* (*SADF*) test that proved robust to detection of periodically collapsing behaviour. The new approach suggests repeated estimation of the regression equation (2.8) on a forward expanding sample. The first estimated subsample comprises $[r_0T]$ observations, where r_0 is the predetermined minimum window size as fraction of the total sample. The starting point of the forward expanding sample is fixed at the first observation in our sample $r_1 = 0$, as in the conventional *ADF*, while the ending point is allowed to change $r_2 \in [r_0, 1]$ being incremented by one observation at a pass. Recursive application of the right-tailed *ADF* yields a sequence of test statistics denoted by $ADF^{r_2}_0$.

Statistical inference is based on the value of the largest test statistic in a sequence of $ADF^{r_2}_0$, called supremum *ADF*(*SADF*):

$$SADF(r_0) = \underset{r_2 \in [r_0, 1]}{sup} \{ADF_0^{r_2}\} . \tag{2.9}$$

If the statistic exceeds the right-tailed critical value from the limit distribution of the *SADF*, we reject the null of a unit root in favour of the explosive alternative.

Phillips et al. (2011) demonstrate that the test has more power in distinguishing periodically collapsing behaviour from stationary, mean-reverting processes than the conventional *ADF*. The suggested methodology gives rise to the date-stamping mechanism (discussed below) that allows to identify the origination and termination dates of exuberance and is shown to produce consistent results when applied to the data series with a single explosive episode in the sample (Phillips et al., 2011, 2015).

However Phillips et al. (2015) argue that the *SADF* test is inconsistent and produces conflicting results when applied to long economic series with multiple periods of exuberance within the sample. The authors propose a new test procedure, called Generalised *SADF* (*GSADF*), that covers more subsamples than the earlier approach as both starting and ending points of the forward-expanding sample are allowed to change. The estimation begins with the subsample, the first and the last observation of which are set to $r_1 = 0$ and $r_2 = r_0$ respectively. Holding the beginning point fixed, the subsample is incremented by one observation at a time until $r_2 = 1$. Then we shift the starting point by one observation and repeat the estimation process on the new set of subsamples. The recursive estimation continues until $r_1 = r_2 - r_0$. The largest test statistic over the full range of estimated $ADF_{r_1}^{r_2}$ is labelled as $GSADF(r_0)$:

$$GSADF(r_0) = \underset{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}}{sup} \left\{ADF_{r_1}^{r_2}\right\} . \tag{2.10}$$

As in the test procedures discussed above, we reject the null hypothesis of a unit root if the *GSADF* statistic exceeds the right tailed critical value from its limit distribution.

The Date-Stamping Strategy The univariate *SADF* and *GSADF* procedures discussed above allow not only to test for explosiveness in the underlying series but also to locate the dates of its origination and collapse. The date-stamping strategy associated with the *SADF* methodology defines the starting point of exuberance $[\hat{r}_e T]$ as the first observation whose $ADF_0^{r_2}$ lies above the sequence of corresponding critical values (Phillips et al., 2011, 2015):

$$\hat{r}_e = \underset{r_2 \in [r_0, 1]}{inf} \left\{ r_2 : ADF_{r_2} > cv_{r_2}^{\beta_T} \right\},$$

while the termination date of exuberance $[\hat{r}_f T]$ is defined as the first observation after $\hat{r}_e T + \log(T)$ whose $ADF_0^{r_2}$ falls below the sequence of critical values:

$$\hat{r}_f = \underset{r_2 \in [\hat{r}_e T + \log(T), 1]}{inf} \left\{ r_2 : ADF_{r_2} < cv_{r_2}^{\beta_T} \right\},$$

where $cv_{r_2}^{\beta_T}$ denotes the $100(1 - \beta_T)\%$ critical value of the $ADF_0^{r_2}$ distribution and β_T is the chosen level of significance.

As noted above, Phillips et al. (2015) demonstrate that the *SADF* date-stamping strategy fails to consistently locate origination and collapse dates when the data contains multiple explosive episodes of a different duration. The authors propose date-stamping mechanism associated with the *GSADF* test that overcomes the problem of the earlier technique. The new strategy is based on the value of the largest test statistic from backward expanding sample, labelled *BSADF* and defined as:

$$BSADF_{r_2}(r_0) = \underset{r_1 \in [0, r_2 - r_0]}{sup} \left\{ ADF_{r_1}^{r_2} \right\}, \tag{2.11}$$

To identify the chronology of exuberance the authors propose comparing the series of *BSADF* statistics with the sequence of $100(1 - \beta_T)\%$ critical values of the *SADF* distribution. The origination date of exuberance is defined as the first observation whose *BSADF* exceeds the critical value (Phillips et al. 2015):

$$\hat{r}_e = \underset{r_2 \in [r_0, 1]}{inf} \left\{ r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T} \right\},$$

while the termination of exuberance is the first observation after $\hat{r}_e T + \delta \log(T)$ for which the *BSADF* falls below the sequence of critical values:

$$\hat{r}_f = \underset{r_2 \in [\hat{r}_e T + \delta \log(T), 1]}{inf} \left\{ r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T} \right\},$$

where $scv_{r_2}^{\beta_T}$ denotes the $100(1-\beta_T)\%$ critical value of the *SADF* distribution, β_T is the chosen level of significance and δ is the parameter that depends on the frequency of the data. The assumption that termination date of exuberance is at least $\delta \log(T)$ observations away from its date of origin $[\hat{r}_e T]$ imposes a restriction on the minimum duration of explosive episode.

The Panel *GSADF*

Pavlidis et al. (2015) propose the panel version of the *GSADF* test that provides a way of testing for the degree of global exuberance in the datasets with a large number of cross-sectional units. The new panel *GSADF* test and the associated date-stamping strategy are based on the regression equation (2.8) with notation adjusted for panel structure of the data as:

$$\Delta y_{i,t} = \mu_{i,r_1,r_2} + \phi_{i,r_1,r_2} y_{i,t-1} + \gamma^1_{i,r_1,r_2} \Delta y_{i,t-1} + \cdots + \gamma^k_{i,r_1,r_2} \Delta y_{i,t-k} + \epsilon_{i,t}, \tag{2.12}$$

where $i = 1 \ldots N$ denotes the number of cross-sections in the dataset.

The null hypothesis of the panel *GSADF* procedure is that all cross-sectional units contain a unit root, $\underline{H_0} : \phi_{i,r_1,r_2} = 0$, which is tested against the alternative of an explosive root, $\underline{H_1} : \phi_{i,r_1,r_2} > 0$.

Statistical inference is made on the basis of the panel *GSADF* statistic that is defined as:

$$\text{Panel } GSADF(r_0) = \underset{r_2 \in [r_0,1]}{sup} \left\{ \text{Panel } BSADF_{r_0}(r_0) \right\},$$

where the panel *BSADF* is computed as the average of N individual supremum *ADF* statistics from the backward expanding sample sequence:

$$\text{Panel } BSADF_{r_2}(r_0) = \frac{1}{N} \sum_{i=1}^{N} BSADF_{i,r_2}(r_0),$$

and individual $BSADF_{i,r_2}(r_0)$ is defined as in (2.11) with notation adjusted for the panel application as follows:

$$BSADF_{i,r_2}(r_0) = \underset{r_1 \in [0, r_2 - r_0]}{sup} \left\{ ADF^{r_2}_{i,r_1} \right\}.$$

The suggested date-stamping strategy compares the panel *BSADF* statistic with the sequence of $100(1-$

$\beta_T)\%$ bootstrapped critical values.[18] By analogy with the univariate dating technique, the origination date of the overall exuberance is defined as the first observation that lies above the sequence of bootstrapped critical values, while its end date is located as the first observation that falls below the corresponding bootstrapped *BSADF* critical values.

[18] See Appendix B of Pavlidis et al. (2016) for details of the bootstrap procedure.

CHAPTER 3

Forecasting U.K. House Prices During Turbulent Periods

3.1. Introduction

The latest boom and bust in housing markets and its decisive role in the Great Recession has generated a vast interest in the dynamics of house prices and has emphasised the importance of being able to produce accurate predictions of future property price movements during turbulent times. International organizations, central banks and research institutes have become increasingly concerned about monitoring developments in housing markets across the world.[19] At the same time, a substantial empirical literature has developed that deals with predicting future house price movements (for a comprehensive survey see Ghysels et al., 2012). However, this literature concentrates almost entirely on the US (see, for e.g., Rapach and Strauss, 2009, Bork and Møller, 2015), leaving national and regional markets of other countries, where housing has also played a central role, mostly unexplored.

In this chapter, we contribute to the existing literature by conducting an extensive investigation of the ability of a battery of econometric models to forecast UK national and regional housing prices. Following the study Bork and Møller (2015) for the US, the candidate forecasting strategies that we consider include Autoregressive Distributed Lag (*ARDL*), Bayesian VAR (*BVAR*), Bayesian Factor-Augmented VAR (*BFAVAR*), Time-Varying Parameter model (*TVP*), Bayesian Model Averaging (*BMA*) and Bayesian Model Selection (*BMS*), Dynamic Model Averaging (*DMA*) and Dynamic Model Selection (*DMS*) models. The

[19] For instance, the Global Housing Watch, that has recently been established by the IMF, and the Globalisation and Monetary Policy Institute of the Federal Reserve Bank of Dallas have been keeping an eye on the international property price dynamics, while the UK Housing Observatory of the Lancaster University has been monitoring the UK national and regional house price movements. At the same time, policy makers have attached a larger weight on the importance of housing markets in financial stability and the real economy. Since 2014, the Bank of England has been assessing resilience of the UK banking system to house price shocks and is currently considering a sharp downturn in commercial and residential property prices by more than a third as one of the key elements of its 2016 stress testing scenario (Bank of England, 2016).

out-of-sample forecast evaluation interval covers the latest boom and bust episode, starting in 1995:Q1 and ending in 2012:Q4. In summary, our findings suggest that models that allow both the underlying specification and the parameter estimates to vary over time, i.e. the *DMA* and the *DMS*, produce more (and, in some cases, dramatically more) accurate forecasts than methods where the number of predictors is kept fixed. The *DMS*, in particular, performs remarkably well. First, it uniformly outperforms the benchmark *AR(1)* model for the national and all the regional housing markets and, second, it captures particularly well the housing boom up to 2004 and the price collapse of 2008. The superiority of dynamic over static models is consistent with recent evidence that suggests that the relationship between real estate valuations and conditioning macro and financial variables, such as domestic credit, displayed a complex of time-varying patterns over the last decades (Aizenman and Jinjarak, 2014). Furthermore, the fact that the dynamic models perform better than the static forecasting techniques is consistent with the results presented in Chapter 2. Predictive methods that do not allow for time-variation in both predictors and their marginal effects are not able to capture the explosive nature of the property prices uncovered in the previous chapter.

Our results also demonstrate that, out of the 10 national- and regional-level predictors considered in the chapter, there was no single predictive variable that would have consistently led to significant improvements in predictive accuracy relative to our benchmark *AR(1)* model. We find that the key drivers of house price movements vary considerably across regions, over time and across forecast horizons.

The rest of the chapter is structured as follows. A description of the housing data and the property price predictors is presented in Section 3.2. Section 3.3 introduces the candidate forecasting strategies. The next section compares the predictive accuracy of the alternative forecasting models, evaluates the performance of these models over time, and identifies the optimal dimension of predictive models and the key determinants of future house price movements. Section 3.5 provides concluding remarks.

3.2. Data

We use quarterly mix-adjusted national and regional house price indices for the period 1975:Q1 to 2012:Q4 reported by Nationwide.[20] We follow the classification of UK regions adopted by Nationwide and consider 13 regional housing markets: the North (NT), Yorkshire and Humberside (YH), North West (NW), East Midlands (EM), West Midlands (WM), East Anglia (EA), Outer South East (OSE), Outer Metropolitan (OM), Greater London (GL), South West (SW), Wales (WW), Scotland (SC) and Northern Ireland (NI). To transform the data into real units we divide nominal property price indices by the Consumer Price Index (all items) obtained from the OECD Database of Main Economic Indicators. In our application we use annualised log transformation of real property price inflation calculated as

$$\Delta lrhp_{r,t} = 400 \times \ln\left(\frac{P_{r,t}}{P_{r,t-1}}\right), \quad r = 1, \ldots, 14, \tag{3.1}$$

where $P_{r,t}, P_{r,t-1}$ stand for current and last period's level of national and 13 regional real house price indices.

Table 3.1 presents selected descriptive statistics for the national and for each regional annualised housing price growth rate series over the whole sample period, as well as over the latest boom (1995:Q1-2007:Q3) and bust (2007:Q4-2012:Q4) episodes. Looking at the full-sample statistics, we observe large differences in mean growth rates across regions. The highest mean growth rates have been recorded in the metropolitan and the southern areas, in particular Greater London, where real housing price inflation was about 3% between 1975:Q1 and 2012:Q4. Midland areas showed relatively moderate house price growth: East Midlands, West Midlands, Wales and East Anglia recorded an average real property price inflation of less than 2% over the entire sample period, while the northern regions, including Yorkshire and Humberside and Northern Ireland experienced the lowest real house price growth among regional real estate markets under consideration: 1.58% and 1.25% respectively.

Turning to the subsample statistics (columns 6-13 of Table 3.1), we observe substantial differences in regional house price behaviour during the recent boom and bust periods. During the upturn in residential

[20] Details of the methodology used to construct regional and national property price indices as well as information about the regional composition are available from the web page of Nationwide House Price Database: http://www.nationwide.co.uk/ /media/MainSite/documents/about/house-price-index/nationwide-hpi-methodology.pdf

Table 3.1: Annualised Real Property Price Growth Rates: Summary of Descriptive Statistics

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	1975:Q1-2012:Q4				1995:Q1-2007:Q3				2007:Q4-2012:Q4			
	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max
East Anglia	2.09	15.27	-45.78	52.74	7.99	11.59	-17.36	33.30	-5.41	12.46	-27.21	20.70
East Midlands	2.06	13.21	-28.32	59.23	7.51	10.57	-15.88	32.87	-5.69	9.72	-25.16	7.86
Greater London	3.05	14.11	-30.77	37.70	9.76	10.63	-21.00	29.96	-3.45	13.14	-24.79	17.67
N Ireland	1.25	17.33	-59.86	46.91	12.19	14.63	-17.22	46.91	-18.21	19.68	-59.86	29.67
North	1.85	13.76	-33.36	41.46	7.45	14.99	-24.32	40.99	-6.43	9.06	-26.17	10.56
North West	2.13	12.10	-27.11	37.69	7.05	10.77	-26.66	33.54	-6.69	9.68	-24.51	15.96
Outer Met	2.56	13.12	-32.12	41.72	8.25	8.86	-9.61	27.06	-4.23	12.06	-32.12	15.72
Outer S East	2.43	13.91	-30.25	40.47	8.68	9.71	-10.78	33.24	-4.92	12.30	-30.05	16.31
Scotland	1.69	11.23	-33.11	33.16	6.72	10.76	-19.31	33.16	-6.09	9.75	-26.68	14.45
South West	2.36	14.13	-37.38	57.19	8.46	9.94	-14.29	36.00	-5.26	11.57	-34.07	18.63
West Midlands	1.91	13.51	-47.44	63.29	7.27	9.29	-10.91	31.68	-5.79	9.45	-23.14	11.01
Wales	1.68	14.50	-35.91	52.31	7.39	13.52	-27.70	35.24	-6.26	13.82	-35.91	27.44
Yorks & Hside	1.58	14.19	-37.73	47.26	7.57	12.36	-13.19	39.66	-6.69	10.43	-23.24	8.93
UK	2.12	11.39	-26.98	39.08	8.19	7.99	-11.29	29.28	-5.65	10.29	-26.98	13.11

Note: The Table reports selected descriptive statistics for regional and national annualised log real house price growth rates over the whole sample (1975:Q1-2012:Q4) and out-of-sample boom (1995:Q1-2007:Q3) and bust (2007:Q4-2012:Q4) periods. Annualised housing price inflation is computed as follows: $\Delta lrhp_{r,t} = 400 \times \ln\left(\frac{P_{r,t}}{P_{r,t-1}}\right)$, where $P_{r,t}, P_{r,t-1}$ stand for current and last period's level of Nationwide house price indices deflated by the Consumer Price Index (all items), $r = 1, \ldots, 14$.

and commercial property prices, average house price inflation across all regional markets was 8.2%, which is nearly four times larger than the entire sample figures. Northern Ireland was the region with the highest housing inflation (12.2%) and the highest maximum annualised real property price growth rate (47%) over the period. In the mainland, five southern areas, including Greater London, Outer Metropolitan, Outer South East, South West and East Anglia, experienced house price growth that was on average about 20% higher than in the remaining 7 regions of the country.

During the recent downturn in real estate prices, all regional markets recorded negative mean growth rates that varied from -18.2% in Northern Ireland to -3.45% in Greater London. Furthermore, for the national-level data and for a number of regional markets the full-sample minimum growth rates occurred during the recent bust (e.g., Northern Ireland, Outer Metropolitan, Wales). We note that property markets of metropolitan and southern areas, which rose the most during the boom, experienced higher mean growth rates during the downturn relative to the rest of the country: average housing inflation across the five southern areas was -4.6%, while the corresponding statistic for the remaining areas was -7.7%. Overall, among all regions under consideration, Northern Ireland was the most volatile property market during the out-of-sample period, followed by the North and Wales, while real estate markets of West Midlands, East Midlands and Outer Metropolitan, on the contrary, were relatively stable.

For each region in our sample we consider 10 economic variables as potential predictors of future house price movements: 4 regional-level and 6 national-level predictors.[21] The variables measured at the regional level include the price-to-income ratio, income growth, the unemployment rate, and the growth in the labour force; whilst national-level predictors consist of the real mortgage rate, the spread between yields on long-term and short-term government securities, growth in industrial production, the number of housing starts, growth in real consumption, and the index of credit conditions proposed by Fernandez-Corugelo and Muellbauer (2006). The first 9 variables have been used by Bork and Møller (2015) to forecast house price movements in the US metropolitan states. The last variable, which captures changes in lending policies and easing/tightening of prudential regulation, has not been employed in a forecasting context before and, as we will show in the following sections, is an important determinant of UK regional property price behaviour (see also Chapter 2).[22] We examine the unit root properties of the house predictors, and transform all non-

[21] All 10 predictive variables used to forecast UK house price inflation are measured at the national level.

[22] Fernandez-Corugedo and Muellbauer (2006) design the indicator of credit rationing/liberlisation as a linear spline function,

stationary variables to stationary. For a description of the variables, the data sources and the transformations undertaken to achieve stationarity of the series please refer to the Appendix.

A substantial empirical literature examines the interconnectedness of UK regional real estate markets (see, e.g., Drake, 1995, Meen, 1999, Cook and Thomas, 2003, Holly et al., 2010, *inter alia*). This literature documents the existence of a strong spatial correlation by demonstrating that property prices in a region are being affected by changes in prices in its contiguous regions. On this basis, following Rapach and Strauss (2009), we incorporate lagged property price growth in the contiguous areas as additional predictive variables in the individual *ARDL* models. The number of neighbouring regions for each of 13 real estate markets under consideration lies in the range of 1-5.

Finally, for evaluating the performance of the large-scale Bayesian VAR model, in addition to the 10 predictive variables introduced above, we exploit information from a large dataset of main economic indicators, which contains 97 macroeconomic time-series. The choice of the key macroeconomic indicators is motivated by the works of Stock and Watson (2009), Koop and Korobilis (2009a) and Koop (2013) in forecasting macroeconomic series. The Appendix contains detailed description of the series, information on the sources of the data and the transformation undertaken to achieve stationarity of the information variables.

estimated from the system of 10 equilibrium-correction equations. The reader is referred to Appendix B of Chapter 2 for a detailed description of the methodology, estimation results and sources of the data.

3.3. Forecasting Models

3.3.1. Dynamic Model Averaging and Dynamic Model Selection

We start with the description of the Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) forecasting strategies. These strategies were developed by Raftery et al (2010) and have been used by, among others, Koop and Korobilis (2012) for forecasting US inflation, Koop and Tole (2012) for forecasting European carbon prices, and Bork and Møller (2015) for forecasting property price growth in the US regional real estate markets.

For exposition purposes, we first consider the case of a single model and then generalize the analysis to the case where there are multiple models available for forecasting. Let y_t denote the log real annualised house price growth rate, computed as in Eq. (3.1), $z_t = [1, x_{t-h}]$ denote an $1 \times m$ vector of potential house price predictors that include the intercept term, lags of y_t, and N explanatory variables, and let h be a prediction horizon. When there is no uncertainty regarding the forecasting model, we can display the model in a standard state-space form, where for $t = 1, \ldots, T$ the observation equation is given by

$$y_t = z_t \beta_t + \epsilon_t, \tag{3.2}$$

and the state equation is

$$\beta_t = \beta_{t-1} + \eta_t, \tag{3.3}$$

where β_t is an $m \times 1$ vector of time-varying regression parameters, $\epsilon_t \sim iidN(0, H_t)$ and $\eta_t \sim iidN(0, Q_t)$. Eqs. (3.2) and (3.3) form the basic Time-Varying Parameter (TVP) model, that has been widely used in forecasting literature.[23] The model can be estimated recursively, using standard Kalman filtering methods. Let $y^{t-1} = (y_1, \ldots, y_{t-1})'$ denote all the information available from the start of the sample through time $t-1$, Kalman filter begins with specifying

$$\beta_{t-1} | y^{t-1} \sim N(\hat{\beta}_{t-1|t-1}, \Sigma_{t-1|t-1}), \tag{3.4}$$

[23] References include Cogley and Sargent (2005), Primiceri (2005), Koop and Korobilis (2009b), Koop et al. (2009), Koop and Korobilis (2012). For housing market applications see, for instance, Brown et al. (1997) (UK), Stock and Watson (2004) (7 countries, including the UK), Guirguis et al. (2005) (US).

where $\Sigma_{t-1|t-1}$ is covariance matrix of the state β_{t-1}.[24] Then the prediction is done according to

$$\beta_t|y^{t-1} \sim N(\hat{\beta}_{t|t-1}, \Sigma_{t|t-1}), \tag{3.5}$$

where $\hat{\beta}_{t|t-1} = \hat{\beta}_{t-1|t-1}$ and the standard formula for the state β_t covariance matrix

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t. \tag{3.6}$$

To complete the prediction stage, we are required to specify the state error covariance matrix Q_t, which, as Raftery et al. (2010) point out, can be computationally demanding. The authors suggest replacing the covariance matrix Q_t in the Eq.(3.6) with the following approximation $Q_t = \left(\lambda^{-1} - 1\right)\Sigma_{t-1|t-1}$, where the parameter λ can take any value in the range $\lambda \in (0, 1]$ and is referred to as the forgetting factor. This approximation simplifies computation of the covariance matrix $\Sigma_{t|t-1}$ and implies that

$$\Sigma_{t|t-1} = \lambda^{-1}\Sigma_{t-1|t-1}. \tag{3.7}$$

It follows from the above expression that observations j periods in the past receive the weight of λ^j. Put it differently, the forgetting factor λ controls how many observations are effectively included in the estimation sample and it, specifically, implies that estimation is based on the last $\frac{1}{1-\lambda}$ data points. Koop and Korobilis (2012) advocate that the range of values for the forgetting factor is restricted to $\lambda \in [0.95; 0.99]$. Consider, for instance, the case when the forgetting factor is set equal to 0.99, which is a commonly used value. With quarterly data, it implies that observations 5 years ago receive 82% of the weight assigned to last period's observations. If the value of the forgetting factor is set to its lower limit, $\lambda = 0.95$, then observations 5 years in the past receive 36% as much weight as observations a quarter ago. In our forecasting exercise we consider different values of the forgetting factor, which will be discussed below.

To complete the tth Kalman filter iteration, parameters (states) are updated according to

$$\beta_t|y_t \sim N\left(\hat{\beta}_{t|t}, \Sigma_{t|t}\right), \tag{3.8}$$

[24] Following Koop and Korobilis (2012), in our empirical application, the Kalman filter is initialised with the following values $\hat{\beta}_0 = 0$ and $\Sigma_0 = 10^2$.

where $\hat{\beta}_{t|t}$ and $\Sigma_{t|t}$ are given by:

$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + \Sigma_{t|t-1} z_t' \left(H_t + z_t \Sigma_{t|t-1} z_t'\right)^{-1} \left(y_t - z_t \hat{\beta}_{t|t-1}\right), \tag{3.9}$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} z_t' \left(H_t + z_t \Sigma_{t|t-1} z_t'\right)^{-1} z_t \Sigma_{t|t-1}. \tag{3.10}$$

To avoid specifying the error covariance matrix, H_t, Raftery et al. (2010) suggest replacing it with a consistent estimate $\hat{H}_t$, which approaches H_t as $t \to \infty$. The authors recommend using a recursive method of moments estimator, defined as

$$\hat{H}_t = \begin{cases} H_t^*, & \text{if } H_t^* > 0, \\ \hat{H}_{t-1}, & \text{if } H_t^* \leq 0, \end{cases}$$

where

$$H_t^* = \frac{1}{t} \sum_{r=1}^{t} \left[\left(y_t - z_t \hat{\beta}_{t|t-1}\right)^2 - z_t' \Sigma_{t|t-1} z_t \right].$$

A one-step-ahead forecast of property price inflation is then generated using the predictive density

$$y_t | y^{t-1} \sim N\left(z_t \hat{\beta}_{t|t-1}, H_t + z_t' \Sigma_{t|t-1} z_t\right). \tag{3.11}$$

Estimation is done recursively, running forward through the data and using the prediction (Eq. (3.5)) and updating (Eq. (3.8)) equations.

We now turn to the case of multiple available forecasting models. Unlike the *TVP* method, discussed above, which allows for time-variation in the coefficients but keeps the underlying predictive model unchanged, the *DMA* and the *DMS* let the parameter estimates to vary and also allow different model specifications at each point in time. Let $k = 1, \ldots, K$ denote a specific predictive model, where each k contains a different set of house price predictors in $z_t^{(k)}$. Then Eqs. (3.2) and (3.3) can be generalised to

$$y_t = z_t^{(k)} \beta_t^{(k)} + \epsilon_t^{(k)}, \tag{3.12}$$

$$\beta_t^{(k)} = \beta_{t-1}^{(k)} + \eta_t^{(k)}, \tag{3.13}$$

where $\beta_t^{(k)}$ is the vector of parameters in a particular model k, $\epsilon_t^{(k)} \sim N\left(0, H_t^{(k)}\right)$ and $\eta_t^{(k)} \sim N\left(0, Q_t^{(k)}\right)$. The number of models K is determined by the number of potential predictors. With N information variables on hand, other than a constant and lagged house price growth terms, for the *DMA* and the *DMS* there are $K = 2^N$ different combinations of predictive variables at time t (in our application $K = 1024$). When $K = 1$ the model in (3.12)-(3.13) reduces to the *TVP*, hence the *DMA* or the *DMS* can be seen as a generalisation of the *TVP* method.

In the multiple models case, we require an estimation strategy for the vector of parameters $B_t = \left(\beta_t^{(1)\prime}, \ldots, \beta_t^{(K)\prime}\right)'$. Suppose $L_t = k$ denotes a particular model specification that holds at time t. Unlike in the single model case, Kalman filter estimation of the regression parameters will now be conditional on the given forecasting model $L_t = k$. Equations (3.4), (3.5) and (3.8) then become

$$B_{t-1}|L_{t-1} = k, y^{t-1} \sim N(\hat{\beta}_{t-1|t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}), \tag{3.14}$$

$$B_t|L_t = k, y^{t-1} \sim N(\hat{\beta}_{t|t-1}^{(k)}, \Sigma_{t|t-1}^{(k)}), \tag{3.15}$$

$$B_t|L_t = k, y^t \sim N\left(\hat{\beta}_{t|t}^{(k)}, \Sigma_{t|t}^{(k)}\right), \tag{3.16}$$

where the expressions for $\hat{\beta}_{t|t-1}^{(k)}$, $\hat{\beta}_{t|t}^{(k)}$, $\Sigma_{t|t-1}^{(k)}$ and $\Sigma_{t|t}^{(k)}$ are the same as in the single-model case, with the only difference that superscript (k) is now added as an indicator of a particular forecasting model $k = 1, \ldots, K$. Eqs. (3.15) and (3.16) form the Kalman filter prediction and updating steps.

Because $\beta_t^{(k)}$ is only defined when $L_t = k$, estimation of the full vector of regression parameters, B_t, requires specification of a process that governs the evolution of the predictive model indicator L_t. One solution involves a $K \times K$ transition matrix V, where each element is defined as $v_{k,l} = Pr[L_t = l|L_{t-1} = k]$. However, since the number of forecasting models K can potentially be very large, specification of the full transition matrix V greatly increases the computational burden and can result in inaccurate inference

(Koop and Korobilis, 2012). Instead, Raftery et al. (2010) introduce an approximation, which involves a second forgetting factor $\alpha \in (0, 1]$. To illustrate how the forgetting factor simplifies the estimation process, let $\pi_{t-1|t-1,k} = Pr[L_{t-1} = k|y^{t-1}]$,[25] then probability that the particular model k should be used for predicting property price inflation at time t, given all the information available up to time $t-1$, is

$$\pi_{t|t-1,k} = \frac{\pi^{\alpha}_{t-1|t-1,k}}{\sum_{l=1}^{K} \pi^{\alpha}_{t-1|t-1,l}}. \tag{3.17}$$

Therefore, the probability of using a particular model k for predicting future house price inflation depends on its forecasting performance in the recent past. How recent is this 'recent past' is determined by the forgetting factor α. For instance, when α is fixed at 0.95, specification of the underlying forecasting model changes quite rapidly: performance of the model k 5 years ago receives 36% of the probability weight attached to its last period's performance (when using quarterly data). On the contrary, when $\alpha = 0.99$, the underlying model changes infrequently: forecast performance of the model k 5 years in the past gets 82% as much probability weight as its performance a quarter ago (Koop and Korobilis, 2012). Analogously to the first forgetting factor λ, the range of feasible values of α is limited to the interval $\alpha \in [0.95; 0.99]$.

The model probability is updated as follows

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} p_k(y_t|y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l} p_l(y_t|y^{t-1})}, \tag{3.18}$$

where $p_l(y_t|y^{t-1})$ is the predictive density $N\left(z_t^{(l)}\hat{\beta}^{(l)}_{t|t-1}, H_t^{(l)} + z_t^{(l)\prime}\Sigma^{(l)}_{t|t-1}z_t^{(l)}\right)$ for a given model l evaluated at y_t (Koop and Korobilis, 2012, Bork and Møller, 2015).

Kalman filtering in the multiple models case, therefore, involves two stages. First, the probability that a particular model $L_t = k$ should be used for forecasting at time t is computed (Eq.(3.17)), and then, conditional on $L_t = k$, a prediction of the regression parameters $\beta^{(k)}_{t|t-1}$ is obtained using Eq. (3.15). In the second stage, both parameter estimates and model probabilities are updated according to their respective updating equations (3.16) and (3.18).

The resulting one-step-ahead *DMA* prediction is then computed as the weighted average of K forecasts

[25] For the first state, we assume that all models $k = 1, \ldots, K$ have the same probability of being used for predicting property price inflation. The Kalman filter is initialised with $\pi_{0|0,k} = \frac{1}{K}$.

of future house price growth, where the probabilities $\pi_{t|t-1,k}$ are used as weights:

$$\hat{y}_t^{DMA} = \sum_{k=1}^{K} \pi_{t|t-1,k} z_t^{(k)} \hat{\beta}_{t|t-1}^{(k)}. \tag{3.19}$$

The *DMS*, on the other hand, at each point in time requires selection of the best model k^*, i.e. the model with the highest probability. The resulting *DMS* point prediction is given by:

$$\hat{y}_t^{DMS} = z_t^{(k^*)} \hat{\beta}_{t|t-1}^{(k^*)}. \tag{3.20}$$

In our application, we compare the forecasting performance of the *DMA* and the *DMS* with the following values of the forgetting factors: (a) $\lambda = \alpha = 0.99$, which implies slow changes in both coefficients and model specification, (b) $\lambda = \alpha = 0.95$, which implies relatively rapid variation in parameter estimates and model specification, and (c) a *DMA* model with $\lambda = 1$ and $\alpha = 0.95$, which does not allow for time-variation in parameter estimates.[26]

Finally, we also consider the case that both forgetting factors are set equal to unity, i.e., there is no forgetting and the dynamic forecasting methods the *DMA* and the *DMS* collapse to their static counterparts, namely Bayesian Model Averaging (*BMA*) and Bayesian Model Selection (*BMS*). In our forecasting exercise, we use the *BMA* and the *BMS* to generate h-step-ahead predictions of property price inflation, and examine whether there are any gains in predictive accuracy from allowing for changes in parameter estimates and the underlying model specification.

3.3.2. Alternative Forecasting Strategies

One of the alternative forecasting methods considered in the chapter is the Bayesian VAR (*BVAR*) model with Minnesota prior that has enjoyed a wide popularity in the empirical literature on forecasting real estate prices.[27] A general representation of the *VAR(p)* is given by (see, e.g., Canova (2007), Koop and Korobilis

[26]For DMA/DMS estimation we use the Matlab code provided by Koop and Korobilis (2012), which is available at https://sites.google.com/site/dimitriskorobilis/matlab/dma .

[27]References include Dua and Smyth (1995), Jarocinski and Smets (2008), Das et al. (2009), Das et al. (2011), Gupta et al. (2011), Gupta and Miller (2012), Plakandaras et al. (2015).

(2009a)):

$$y_t = \beta_0 + \sum_{j=0}^{p-1} B_{j+1} y_{t-h-j} + \Gamma_x x_{t-h} + \epsilon_t, \tag{3.21}$$

where y_t is a vector of M variables, $t = 1, \ldots, T$, p is the autoregressive lag length, x_t is a $N \times 1$ vector of exogenous variables, ϵ_t is a $M \times 1$ vector of innovations, which are assumed to be $\epsilon \sim iidN(0, \Sigma)$, β_0 denotes the vector of all the intercepts and B_j, Γ_x are the matrices of regression coefficients.

The *VAR(p)* model in Eq. (3.21) can be rewritten in matrix format. If we let Y to be a $T \times M$ matrix containing all observations on M dependent variables, E denote a $T \times M$ matrix of the innovations and let X to be a $T \times K$ matrix of regressors, such that $X = (1, y'_{t-h}, \ldots, y'_{t-h-(p-1)}, x'_{t-h})$, where $K = 1 + Mp + N$ denotes the number of coefficients in each regression equation i, then the model becomes

$$Y = XB + E, \tag{3.22}$$

where $B = (\beta_0\ B_1..B_p\ \Gamma_x)'$. Alternatively, if we stack all dependent variables in one $y = MT \times 1$ vector of observations and define a $KM \times 1$ vector of the *VAR* regression coefficients as $\beta = vec(B)$, then the model can be expressed in the following form (Koop and Korobilis, 2009a)

$$y = (I_M \otimes X)\, \beta + \epsilon, \tag{3.23}$$

where I_M is the identity matrix of dimension M and $\epsilon \sim N(0, \Sigma \otimes I_T)$.

For the Minnesota prior the error covariance matrix is assumed to be diagonal. To get the diagonal elements of $\hat{\Sigma}$, denoted $\hat{\sigma}_{ii}$, where subscript i is an equation indicator, $i = 1, \ldots, M$, the VAR is estimated equation by equation with OLS. An estimate of the error variance in equation i then becomes the ii^{th} element of $\hat{\Sigma}$.

Given $\hat{\Sigma}$, we are only left with a prior for β, which has the following form

$$\beta \sim N\left(\underline{\beta}, \underline{V}\right).$$

The Minnesota prior typically sets a prior mean for the first own lag of the dependent variable to one and all the remaining elements of $\underline{\beta}$ to zero. In our case, since the dependent variable (property price growth rate) is not expressed in levels, Koop and Korobilis (2009a) recommend setting all elements of the prior mean to zero, $\underline{\beta} = 0$. Regarding the prior covariance matrix $\underline{V}$, this is assumed to be a function of the number of hyperparameters. More specifically, if we assume that $\underline{V}$ is diagonal and define its diagonal elements corresponding to the variable j in the i^{th} equation as $\underline{v}_{i,jj}$, then the Minnesota prior sets (Koop and Korobilis, 2009a)

$$\underline{v}_{i,jj} = \begin{cases} \frac{\underline{\phi}_1}{l^2}, & \text{if}, i = j, l = 1, \ldots, p \\ \frac{\underline{\phi}_2 \sigma_{ii}}{l^2 \sigma_{jj}}, & \text{if }, i \neq j, j \text{ is endogenous}, l = 1, \ldots, p \\ \underline{\phi}_3 \sigma_{ii}, & \text{if}, i \neq j, j \text{ is exogenous}, \end{cases}$$

where ϕ_1, ϕ_2, ϕ_3 are hyperparameters, indicating tightness of the variance of the first own lag (ϕ_1), tightness of the variance of the variable $j \neq i$ relative to the tightness of i (ϕ_2) and relative tightness of the exogenous variables (ϕ_3). In our application, we follow the recommendations of Canova (2007) and Koop and Korobilis (2009c), and set $\phi_1 = \phi_2 = 0.5$ and $\phi_3 = 10^2$. The chosen values of the hyperparameters imply a fairly loose prior on the VAR parameters and an uninformative prior for the 10 potential predictors of housing inflation.

Once the priors for β and Σ have been defined, the analytical posterior solution for β can be obtained by

$$\beta | y \sim N\left(\bar{\beta}, \bar{V}\right), \tag{3.24}$$

where $\bar{\beta}$ and $\bar{V}$ are given by (Koop and Korobilis, 2009a)

$$\bar{V} = \left[\underline{V}^{-1} + \left(\hat{\Sigma}^{-1} \otimes (X'X)\right)\right]^{-1},$$

$$\bar{\beta} = \bar{V}\left[\underline{V}^{-1}\underline{\beta} + \left(\hat{\Sigma}^{-1} \otimes X\right)' y\right].$$

In our forecasting exercise we consider two alternative specifications of the *BVAR* model. The first is the *UBVAR*, which includes only the intercept and p lags of property price inflation, i.e. $X = (1, y'_{t-h}, \ldots, y'_{t-h-(p-1)})$, and the second is the *SBVAR*, which includes the intercept, p lags of property price inflation and the full set of house price predictors, i.e. $X = (1, y'_{t-h}, \ldots, y'_{t-h-(p-1)}, x'_{t-h})$.

Furthermore, we consider a Bayesian Factor-Augmented VAR (*BFAVAR*) model which, in addition to the 10 predictive variables, incorporates information contained in the large macroeconomic dataset. Let Z_t denote a vector of r additional predictors (in our application, $r = 97$, see Section 3.2 and the Appendix) and let F_t be a vector of $f = 2, \ldots, 5$ common static components of Z_t, such that

$$Z_t = \Lambda F_t + \xi_t,$$

where Λ is a $r \times f$ matrix of factor loadings and ξ_t is a vector of idiosyncratic disturbances (Stock and Watson, 2002). The model in Eq.(3.21) can be rewritten to represent a *BFAVAR* model as follows:

$$y_t = \beta_0 + \sum_{j=0}^{p-1} B_{j+1} y_{t-h-j} + \Gamma_x x_{t-h} + \Gamma_f F_{t-h} + \epsilon_t. \tag{3.25}$$

To generate the h-step-ahead predictions of property price inflation, $\hat{y}_{t|t-h}$, the common factors F_t have to be estimated. Following the approach of Stock and Watson (2002) and Gupta et al. (2011), we extract the $f = 2, \ldots, 5$ largest principal components of Z_t, denoted $\hat{F}_t$, and replace F_t in Eq. (3.25) by the resulting factor estimates. We impose the Minnesota prior on the parameters of Eq.(3.25) and proceed with estimation of the *BFAVAR* following the steps described above for the $BVAR$ case.

We evaluate forecasting performance of a *UBFAVAR* specification, which includes a constant, lags of property price growth and f common factors, i.e. $X = (1, y'_{t-h}, \ldots, y'_{t-h-(p-1)}, \hat{F'}_{t-h})$ and the *SBFAVAR* model, which incorporates the intercept, lags of property price growth, f common factors and 10 house price predictors, introduced in Section 3.2, i.e. $X = (1, y'_{t-h}, \ldots, y'_{t-h-(p-1)}, x'_{t-h}, \hat{F'}_{t-h})$.

Finally, in addition to the forecasting methods introduced above, we use a number of individual Autoregressive Distributed Lag (*ARDL*) models to generate one- and four-quarters-ahead out-of-sample forecasts of regional and national property price growth rates. Following Rapach and Strauss (2009), each *ARDL* model contains an intercept, lagged housing inflation terms and one of the potential predictors

$$y_t = \beta_0 + \sum_{j=0}^{p-1} \beta_{j+1} y_{t-h-j} + \sum_{j=0}^{q-1} \gamma_j x_{i,t-h-j} + \epsilon_t, \tag{3.26}$$

where $x_{i,t}$ denotes the $i = 1, \ldots, N$ predictive variable in our dataset, p specifies the autoregressive lag length and q is the number of lags of house price predictors included in the specification. We note that the lag lengths p and q are time-varying, selected at each point in time using Schwarz's information criterion. We consider the values of $p = 0, \ldots, 5$ and $q = 1, \ldots, 5$. For each housing market in our sample, in addition to 10 core predictive variables, introduced in the previous section, we consider lagged property price inflation in the neighbouring regions. In our forecasting exercise, the number of potential predictors, N, lies in the range of 10-15.

Let R and P denote the number of in-sample and out-of-sample observations respectively, so that $R + P = T$. Equation (3.26) is estimated recursively by OLS, starting with a minimum sample size, which comprises the first *R* observations (1975:Q1 - 1994:Q4). For each house price predictor in our dataset, we construct a sequence of $P-(h-1)$ out-of-sample predictions of property price inflation, $\hat{y}_{i,t|t-h}$, using all the data available up to time $t-h$ and the coefficient estimates ($\hat{\beta}_j$ for $j = 0, \ldots, p$ and $\hat{\gamma}_j$ for $j = 0, \ldots, q-1$) obtained from the regression equation (3.26). We generate 10-15 individual *ARDL* out-of-sample forecasts of house price inflation for each property market under consideration. We compare predictive accuracy of the individual *ARDL*s in an attempt to identify variables that stand out as the main drivers of house price growth.

Furthermore, we evaluate the forecasting performance of a number of combinations of the individual *ARDL* forecasts. For each housing market, a weighted average of N individual *ARDL* predictions is computed as

$$\hat{y}_{c,t|t-h} = \sum_{i=1}^{N} \omega_{i,t-h} \hat{y}_{i,t|t-h}, \tag{3.27}$$

where $\omega_{i,t-h}$ denotes the combining weights, determined at time $t-h$. Rapach and Strauss (2009) show that simple averaging methods, which include mean, trimmed mean and median combinations of individual *ARDL*s, offer consistent improvement in forecasting accuracy relative to the benchmark prediction. For a mean combination, the individual forecasts are equally weighted, hence $\omega_{i,t-h} = \frac{1}{N}$. For a trimmed mean combining method, the weights of zero are assigned to the minimum and maximum of the N forecasts, in which case the weights on the remaining $N-2$ predictions are set to $\omega_{i,t-h} = \frac{1}{N-2}$. Finally, the median combination is computed as the median of the N individual *ARDL*s.

Below we present the full list of candidate forecasting strategies considered in our empirical application:

$DMA^{0.99}$	Dynamic Model Averaging with the values of both forgetting factors set to $\lambda = \alpha = 0.99$.
$DMS^{0.99}$	Dynamic Model Selection with the values of both forgetting factors set to $\lambda = \alpha = 0.99$.
$DMA^{0.95}$	Dynamic Model Averaging with the values of both forgetting factors set to $\lambda = \alpha = 0.95$.
$DMA^{0.95}$	Dynamic Model Averaging with the values of both forgetting factors set to $\lambda = \alpha = 0.95$.
$DMA^{\lambda=1}$	Dynamic Model Averaging with no time-variation in parameter estimates $\lambda = 1$, and $\alpha = 0.95$.
BMA	Bayesian Model Averaging, a special case of *DMA* with no forgetting $\lambda = \alpha = 1$.
BMS	Bayesian Model Selection, a special case of *DMS* with no forgetting $\lambda = \alpha = 1$.
TVP-AR	Time-Varying Parameter Model, which includes only the intercept and lags of the dependent variable. Special case of *DMA/DMS* with $\lambda = 0.95$, and $\alpha = 1$.
TVP-AR-X	Time-Varying Parameter Model, which includes the intercept, lags of the dependent variable and all 10 potential predictors. Special case of *DMA/DMS* with $\lambda = 0.95$, and $\alpha = 1$.
UBVAR	Bayesian VAR, which includes only the intercept and lags of the dependent variable.
SBVAR	Bayesian VAR, which includes the intercept, lags of the dependent variable and all 10 potential predictors.
UBFAVAR	Bayesian Factor-Augmented VAR, which includes the intercept, lags of the dependent variable and the $f = 2, \ldots, 5$ principal components extracted from the large macroeconomic dataset (see Appendix).
SBFAVAR	Bayesian Factor-Augmented VAR, which includes the intercept, lags of the dependent variable, 10 potential predictors and the $f = 2, \ldots, 5$ principal components extracted from the large macroeconomic dataset (see Appendix).
$ARDL^1$	Mean combination of N individual *ARDL* predictions.
$ARDL^2$	Median combination of N individual *ARDL* predictions.
$ARDL^3$	Trimmed mean combination of N individual *ARDL* predictions.
ALL	Recursive OLS prediction, implemented using all 10 potential predictors. No time-variation in parameter estimates and model specification.
AR(1)	Recursive OLS prediction, implemented using the intercept and lagged housing inflation rate (lag length of 1). Benchmark model.

3.3.3. Forecast Evaluation

We use the Mean Squared Forecast Error (MSFE) and the ratio of the MSFE from the candidate model to the MSFE from the *AR(1)* benchmark to evaluate the out-of-sample performance of the battery of forecasting models over the period between 1995:Q1 and 2012:Q4 across one- and four-quarters-ahead forecast horizons. A ratio below unity indicates that the given forecasting method succeeded in improving upon predictive accuracy of the benchmark model. To test whether candidate models produce significantly lower forecast errors than the *AR(1)* we follow the approach suggested by Clark and West (2007). The authors recommend using adjusted MSFEs when comparing predictive accuracy of two nested models, since the standard MSFE of a larger model that nests the benchmark is upward biased under the null hypothesis that the benchmark model describes the data (Clark and West, 2005, 2007). The methodology requires computation of the adjusted difference in prediction errors from the two alternative models

$$f_{j,t+h} = (y_{t+h} - \hat{y}_{AR1t,t+h})^2 - \left[(y_{t+h} - \hat{y}_{jt,t+h})^2 - (\hat{y}_{AR1t,t+h} - \hat{y}_{jt,t+h})^2\right], \tag{3.28}$$

where y_{t+h} denotes the realised value of property price inflation at time $t+h$, $\hat{y}_{AR1t,t+h}$ and $\hat{y}_{jt,t+h}$ stand for the forecasts of y_{t+h} made at time *t* using the *AR(1)* benchmark model and the candidate forecasting model j respectively, h is the forecast horizon.

The tested hypothesis is that of an equal forecasting performance of the two models, while the alternative is that candidate method *j* is able to generate more accurate forecasts than the parsimonious, benchmark model. Inference is made based on the value of the t-statistic obtained by regressing the computed $f_{j,t+h}$ on a constant only. Clark and West (2007) show that the distribution of the adjusted statistic is approximately normal in large samples, and, thus, the null hypothesis is rejected in favour of the alternative at the 5% significance level when the resulting test statistic is greater than 1.645.

3.4. Empirical Results

3.4.1. Comparison of Forecast Performance

Table 3.2 presents the ratios of the MSFEs from candidate forecasting methods to the MSFEs from the *AR(1)* benchmark model for the one-quarter-ahead forecast horizon. The table reports the results for each regional real estate market in our sample and for the national-level data together with their respective Clark and West (2007) statistics, shown in parentheses. The cases when the null hypothesis of equal predictive accuracy of the two models is rejected at 5% level of significance are highlighted in bold.

We note that the $DMS^{0.95}$ that allows for relatively rapid variation in both underlying model specification and estimated parameters (column 4 of Table 3.2) is by far the best performing model, being able to significantly outperform the benchmark for the national and all 13 regional property markets. Interestingly, the DMS with $\alpha = \lambda = 0.95$ is the only forecasting method that significantly outperforms the *AR(1)* for the national housing market.[28] The average improvement in predictive accuracy of the $DMS^{0.95}$ model is 15% relative to the MSFE of the *AR(1)* benchmark. Furthermore, the method produces the smallest MSFEs across all forecasting models considered. Scotland and Outer South East, in particular, are the two regional markets with the largest improvement in predictive accuracy (22.5%).

Comparing these results with those for the DMS with $\alpha = \lambda = 0.99$ (column 2 of Table 3.2), we observe that there are fewer rejections of the null hypothesis: the model is able to significantly improve upon the benchmark in 4 regional property markets out of 13. The fact that econometric models that place more weight on the recent past are able to generate more accurate forecasts of future house price movements suggests that UK national and regional housing markets are characterised by substantial instability: both information variables that predict property prices and marginal effects of the predictors vary quite considerably over time.

On the other hand, the $DMA^{0.95}$, which also allows for parameter shifts and changes in the underlying model at each time period, fails to match predictive accuracy of the $DMS^{0.95}$. When we let the model specification and the coefficients change quite rapidly (column 5 of Table 3.2), the $DMA^{0.95}$ offers significant gains in forecast performance in 4 regional property markets out of 13, while its relatively more stable

[28] For the national-level data, forecasts generated using the *BMS* model are also able to produce the ratio of the MSFEs that is below unity, however the reduction in forecast error is not statistically significant at 5% level as indicated by the value of the Clark and West (2007) statistic.

Table 3.2: Forecasting Performance by Region; $h = 1$

(1)	(2) $DMS^{0.99}$	(3) $DMA^{0.99}$	(4) $DMS^{0.95}$	(5) $DMA^{0.95}$	(6) $DMA^{\lambda=1}$	(7) *BMS*	(8) *BMA*	(9) *TVP-AR*	(10) *TVP-AR-X*	(11) *UBVAR*	(12) *SBVAR*	(13) *UBFAVAR*	(14) *SBFAVAR*	(15) $ARDL^1$	(16) $ARDL^2$	(17) $ARDL^3$	(18) *ALL*
EA	1.089	1.214	**0.822**	1.021	1.122	1.180	1.357	0.982	1.158	0.997	1.386	1.119	1.230	**0.921**	**0.945**	**0.915**	1.386
	(1.379)	(0.351)	**(3.586)**	(1.329)	(0.812)	(1.416)	(0.657)	(1.195)	(0.649)	(1.284)	(-0.78)	(-0.19)	(-0.38)	**(2.006)**	**(1.769)**	**(2.061)**	(-0.78)
EM	1.042	1.087	**0.800**	1.014	1.031	1.144	1.169	0.979	1.152	0.999	1.228	1.107	1.194	**0.915**	0.986	**0.923**	1.228
	(1.068)	(0.229)	**(3.308)**	(1.305)	(1.015)	(0.174)	(-0.34)	(1.294)	(0.802)	(0.154)	(0.308)	(-0.16)	(0.086)	**(2.084)**	(0.908)	**(1.998)**	(0.308)
GL	1.049	1.087	**0.916**	1.123	1.034	1.136	1.144	1.033	1.211	0.997	1.319	1.163	1.212	**0.934**	1.014	**0.938**	1.319
	(2.049)	(1.473)	**(3.350)**	(-0.11)	(1.433)	(1.949)	(1.916)	(0.179)	(0.562)	(1.166)	(-0.91)	(0.001)	(0.207)	**(2.207)**	(1.123)	**(2.164)**	(-0.91)
NI	1.135	1.235	**0.853**	**0.969**	**0.989**	1.313	1.318	**0.841**	**0.998**	1.002	1.160	1.008	1.091	**0.977**	1.063	0.996	1.160
	(-0.19)	(-1.09)	**(3.575)**	**(1.797)**	**(1.783)**	(-0.86)	(-1.48)	**(3.284)**	**(1.741)**	(-1.92)	(2.546)	(0.307)	(0.231)	**(1.645)**	(-0.64)	(1.418)	(2.546)
NT	1.112	1.132	**0.867**	1.038	1.102	1.176	1.150	0.973	1.001	1.000	1.485	1.103	1.073	**0.894**	**0.937**	**0.907**	1.485
	(-0.42)	(-1.92)	**(3.311)**	(1.415)	(-0.65)	(-2.03)	(-1.98)	(1.508)	(1.846)	(-0.29)	(0.917)	(0.994)	(0.629)	**(2.900)**	**(2.258)**	**(2.669)**	(0.917)
NW	1.232	1.274	**0.848**	1.162	1.209	1.310	1.337	0.989	1.238	1.001	1.213	1.064	1.302	**0.905**	**0.948**	**0.913**	1.213
	(-0.22)	(-0.79)	**(3.227)**	(-0.17)	(-1.07)	(-0.15)	(-0.49)	(1.193)	(0.006)	(-0.61)	(0.933)	(0.085)	(-1.09)	**(2.347)**	**(1.834)**	**(2.273)**	(0.933)
OM	1.019	1.329	**0.892**	1.221	1.395	1.329	1.571	1.069	1.368	1.001	1.144	1.301	1.362	1.030	1.656	1.021	1.144
	(1.959)	(-1.07)	**(2.525)**	(0.157)	(-0.13)	(0.521)	(-1.07)	(-0.03)	(-1.09)	(-0.56)	(0.384)	(-0.19)	(-0.46)	(0.369)	(-0.54)	(0.509)	(0.384)
OSE	1.032	1.080	**0.775**	**0.953**	0.999	1.024	1.059	**0.961**	1.051	0.998	1.216	1.194	1.379	0.989	0.999	0.992	1.216
	(-0.22)	(-1.71)	**(4.198)**	**(2.220)**	(0.773)	(0.945)	(0.039)	**(1.869)**	(2.086)	(0.788)	(-0.53)	(-0.27)	(-1.47)	(0.970)	(0.735)	(0.912)	(-0.53)
SC	**0.945**	0.989	**0.775**	**0.953**	0.999	1.024	1.059	**0.961**	1.051	1.001	1.544	1.017	**0.964**	**0.942**	1.074	**0.962**	1.544
	(2.402)	(1.294)	**(4.198)**	**(2.220)**	(0.773)	(0.945)	(0.039)	**(1.869)**	(2.086)	(-0.94)	(1.301)	(0.327)	**(1.730)**	**(2.433)**	(-0.64)	**(1.931)**	(1.301)
SW	**0.963**	1.019	**0.865**	1.067	1.119	**0.982**	1.099	1.012	1.119	1.255	1.024	1.146	1.324	0.999	1.074	1.013	1.255
	(1.909)	(1.125)	**(3.185)**	(1.204)	(-0.36)	**(1.699)**	(0.248)	(1.034)	(1.635)	(0.584)	(-1.39)	(0.057)	(-0.95)	(1.247)	(0.115)	(1.125)	(0.584)
WM	**0.949**	0.971	**0.819**	**0.993**	0.971	1.144	1.056	**0.958**	1.182	1.003	1.156	1.069	1.266	**0.822**	**0.887**	**0.835**	1.156
	(1.745)	(1.339)	**(3.098)**	**(1.798)**	(1.371)	(-0.56)	(-0.05)	**(1.809)**	(1.298)	(-1.68)	(1.769)	(0.761)	(0.194)	**(3.063)**	**(2.621)**	**(2.957)**	(1.769)
WW	**0.836**	0.945	**0.804**	0.999	0.957	**0.895**	0.960	0.982	1.133	0.997	1.495	1.047	1.097	**0.869**	**0.880**	**0.855**	1.495
	(2.799)	(1.283)	**(3.118)**	(1.282)	(1.527)	**(2.324)**	(1.112)	(1.003)	(0.814)	(1.343)	(-0.76)	(0.082)	(0.196)	**(3.046)**	**(2.182)**	**(3.279)**	(-0.76)
YH	0.972	1.069	**0.827**	1.039	1.041	1.025	1.047	1.018	1.123	0.999	1.314	1.047	1.054	0.979	1.016	0.979	1.314
	(1.326)	(-0.81)	**(2.375)**	(1.035)	(0.561)	(0.391)	(-0.29)	(0.297)	(1.288)	(0.438)	(-0.13)	(0.197)	(0.881)	(1.290)	(0.538)	(1.373)	(-0.13)
UK	1.012	1.059	**0.832**	1.084	1.094	0.992	1.039	1.031	1.203	1.002	1.116	1.206	1.316	1.018	1.006	1.007	1.115
	(1.252)	(0.179)	**(3.626)**	(0.533)	(-0.62)	(1.359)	(0.608)	(0.494)	(0.163)	(-0.90)	(0.865)	(-0.53)	(-1.66)	(-0.48)	(-0.64)	(-0.19)	(0.865)

Note: The table reports the MSFE ratios of candidate forecasting models relative to the *AR(1)* benchmark together with their respective Clark and West (2007) test statistics shown in parenthesis. Rejection of the null hypothesis, that the ratio of forecast errors is greater than one, at 5% level of significance is shown in bold. The performance of various forecasting methods is evaluated over the out-of-sample period: 1995:Q1-2012:Q4. The UBFAVAR and SBFAVAR results are reported for $f = 2$ number of principal components. With the exception of $ARDL^1$, $ARDL^2$ and $ARDL^3$, where the lag length p and q are determined at each point in time as described in Section 3, all results are reported for the autoregressive lag length 1.

variant (column 3 of Table 3.2) performs abominably, not being able to improve upon the benchmark in any of the housing markets under consideration.

The second and third best performing models in our list of forecasting methods are the mean and the trimmed mean combinations of the individual *ARDL* forecasts (columns 15 and 17 of Table 3.2). These models succeed in generating significantly lower predictive errors than the benchmark model in 9 and 8 regions respectively with an average gain in forecast accuracy of about 6%. The results of the individual *ARDL* models, which are reported in Table 3.3, suggest that this improvement is mostly due to the predictive content of the last period's property price inflation in neighbouring areas. In all regional real estate markets but two (Northern Ireland and Outer Metropolitan) house price growth in contiguous regions is able to significantly reduce the predictive error of the model relative to the *AR(1)* benchmark. On the other hand, the performance of core house price predictors is somewhat mixed. We observe that, with the exception of the price-to-income ratio, all of the property price predictors offer significant gains in forecast accuracy for some regional markets, but lead to significant losses for others. For instance, the inclusion of consumption growth, which is the best performing variable among all the predictors examined, improves forecast accuracy by 12% for Wales but worsens forecast accuracy by the same percentage for South West.[29] Similarly, the inclusion of the labour force, the best regional-level predictor, results in lower MSFEs in 4 regions, but higher MSFEs in the remaining 9.

Overall, the individual *ARDL* results suggest that there is no single predictive variable that consistently outperforms the *AR(1)* across the housing markets under consideration. Furthermore, our results indicate that combinations of the *ARDL* forecasts are able to produce more accurate predictions of future house price inflation than individual *ARDL* models. This conclusion is in line with the substantial empirical literature on forecast combination that has emerged over the years.[30]

In general, forecasting methods that do not allow for time-variation in parameter estimates and/or keep the set of house price predictors fixed at each point in time perform poorly. *BMA*, *BVAR*, *UBFAVAR* and the 'kitchen-sink' forecasts are not able to generate lower predictive errors than the benchmark model in any

[29]Interestingly, according to the results of the individual *ARDL* models, Wales is the housing market with the strongest forecastability: with the exception of the price-to-income ratio, all of the house price predictors succeed in significantly reducing the forecast error of the benchmark model in this region.

[30]References include Becker and Clements (2008), Clemen (1989), Diebold and Lopez (1996), Fang (2003), Hendry and Clements (2002), Hibon and Evgenoiu (2005), Makridakis and Winkler (1983), Rapach and Strauss (2009), Timmermann (2008), *inter alia*.

Table 3.3: Forecasting Performance: ARDL Models; $h = 1$

(1) Predictor	(2) EA	(3) EM	(4) GL	(5) NI	(6) NT	(7) NW	(8) OM	(9) OSE	(10) SC	(11) SW	(12) WM	(13) WW	(14) YH	(15) UK
Regional Variables:														
Income Growth	0.997	1.094	1.017	1.046	**0.934**	**0.971**	1.058	1.039	1.062	1.218	1.051	**0.931**	1.005	0.967
	(1.128)	(-0.723)	(1.467)	(0.986)	**(2.266)**	**(1.727)**	(1.063)	(-0.526)	(-0.962)	(0.247)	(1.625)	**(2.217)**	(1.195)	(1.473)
Labour Force	0.974	1.017	**0.983**	1.056	**0.954**	0.994	1.094	1.017	1.081	1.043	**0.926**	**0.904**	1.021	1.105
	(1.291)	(-0.821)	**(1.853)**	(0.893)	**(1.982)**	(1.285)	(-0.900)	(0.436)	(-1.688)	(-0.237)	**(2.025)**	**(2.857)**	(0.291)	(-0.024)
Unemployment Rate	1.104	1.177	1.012	1.036	1.069	0.990	1.091	1.205	0.980	1.047	**0.926**	**0.898**	1.088	1.111
	(0.242)	(-0.754)	(1.904)	(1.361)	(1.127)	(1.203)	(0.151)	(-1.089)	(1.049)	(-0.230)	**(2.041)**	**(2.935)**	(-0.477)	(-1.204)
Price-to-Income	2.160	1.625	1.664	1.672	2.032	1.595	1.678	1.038	1.809	1.687	1.654	2.315	1.990	1.481
	(-1.554)	(0.277)	(-1.371)	(1.609)	(0.212)	(0.265)	(-0.247)	(-1.365)	(1.104)	(-0.725)	(1.077)	(-1.903)	(-1.497)	(-1.770)
National Variables:														
CCI	0.991	1.027	**0.978**	1.065	**0.966**	1.008	1.086	1.047	1.031	1.028	1.046	**0.921**	1.031	1.006
	(1.013)	(-1.076)	**(1.857)**	(0.823)	**(1.789)**	(1.020)	(-1.014)	(-0.738)	(-0.700)	(0.355)	(0.789)	**(2.637)**	(0.036)	(-0.922)
Consumption	1.087	0.981	**0.954**	**0.983**	**0.924**	**0.979**	1.045	1.020	1.006	1.128	**0.947**	**0.880**	1.008	1.054
	(0.377)	(1.524)	**(2.271)**	**(1.813)**	**(2.520)**	**(1.839)**	(0.757)	(0.985)	(0.516)	(0.837)	**(2.272)**	**(3.063)**	(0.915)	(0.701)
Housing Stock	1.190	1.088	1.012	1.022	**0.984**	1.104	1.338	1.304	**0.955**	1.257	1.311	**0.899**	1.169	1.244
	(0.708)	(0.078)	(1.797)	(1.311)	**(2.162)**	(1.076)	(-0.446)	(-0.083)	**(1.817)**	(0.412)	(0.687)	**(2.547)**	(-0.635)	(-0.594)
Industrial Production	1.049	1.037	1.001	1.022	**0.951**	0.976	1.095	1.035	1.039	1.031	**0.967**	**0.921**	1.034	1.022
	(0.174)	(-0.899)	(1.522)	(1.119)	**(2.079)**	(1.397)	(-0.699)	(0.132)	(-0.803)	(0.573)	**(1.974)**	**(2.494)**	(-0.087)	(-0.706)
Mortgage Rate	0.996	1.016	0.977	1.005	**0.967**	0.996	1.066	1.005	1.039	1.068	**0.944**	**0.898**	1.035	0.999
	(0.849)	(-0.856)	(0.993)	(1.348)	**(1.948)**	(1.122)	(-0.676)	(0.646)	(-1.014)	(0.072)	**(1.922)**	**(2.917)**	(-0.157)	(0.579)
Spread	**0.969**	1.024	**0.984**	1.056	1.001	1.013	1.120	1.053	1.048	1.048	1.065	**0.934**	1.053	1.021
	(1.793)	(-0.309)	**(1.998)**	(1.018)	(1.470)	(1.252)	(-0.479)	(0.543)	(-1.383)	(1.402)	(1.491)	**(2.513)**	(-0.336)	(0.173)
Contiguous Regions:	**0.881(EM)**	**0.873(YH)**	1.055(EA)	1.004(SC)	**0.768(YH)**	**0.981(NT)**	1.196(OSE)	**0.929(OM)**	1.033(NT)	1.032(OSE)	**0.909(NW)**	**0.771(NW)**	1.029(NT)	
	(3.221)	**(2.345)**	(1.451)	(2.039)	**(3.648)**	**(2.302)**	(1.719)	**(2.118)**	(1.481)	(2.466)	**(2.014)**	**(3.438)**	(1.539)	
	0.881(OSE)	**0.936(NW)**	**0.771(OM)**		**0.723(NW)**	**0.908(YH)**	1.865(GL)	1.011(SW)	**0.835(NI)**	**0.987(WW)**	1.085(WW)	**0.771(WM)**	**0.849(NW)**	
	(2.903)	**(2.486)**	**(3.417)**		**(3.605)**	**(2.832)**	(-0.573)	(1.687)	**(2.889)**	**(2.331)**	(2.439)	**(3.085)**	**(2.550)**	
	0.724(OM)	**0.809(WM)**				1.048(WW)	1.202(EA)	1.223(WM)		1.097(WM)	**0.900(SW)**	**0.820(SW)**	**0.807(EM)**	
	(4.014)	**(2.698)**				(2.076)	(1.318)	(0.292)		(1.223)	**(3.071)**	**(3.830)**	**(2.364)**	
	1.045(GL)	**0.903(OSE)**				**0.967(WM)**		1.202(EA)			**0.848(OSE)**			
	(1.498)	**(2.238)**				**(2.613)**		(0.429)			**(3.205)**			
		0.971(EA)				**0.888(EM)**		1.086(EM)			**0.796(EM)**			
		(1.926)				**(3.213)**		(0.837)			**(3.691)**			

Note: The table reports the MSFE ratios of individual *ARDL* models relative to the *AR(1)* benchmark together with their respective Clark and West (2007) test statistics shown in parenthesis. Rejection of the null hypothesis, that the ratio of forecast errors is greater than one, at 5% level of significance is shown in bold. Each *ARDL* model includes a constant, lags of dependent variable and one of the predictors listed in the first column. The number of lagged dependent variable terms is selected at each time period using the SIC. The performance is evaluated over the out-of-sample period: 1995:Q1-2012:Q4.

of the property markets in our sample, while the *DMA* with no variation in the coefficients (column 6 of Table 3.2), the *SBFAVAR* and the *TVP-AR-X* succeed in improving forecast accuracy in only one regional market. This outcome is consistent with Koop and Korobilis (2012) and Bork and Møller (2015), who argue that the use of a large number of explanatory variables can cause model over-fitting and, as a result, lead to inaccurate predictions.

Results for the longer horizon ($h = 4$) are presented in Table 3.4. We can see that the *DMS* with $\alpha = \lambda = 0.95$ remains the best performing model, as it offers significant gains in predictive accuracy for the national and all regional real estate markets of the UK (column 4 of Table 3.4). The average reduction in the MSFE relative to the benchmark is even higher than for the one-quarter-ahead forecasts: 22% across property markets under consideration.[31] Interestingly, the improvement in predictive accuracy at longer horizons is even larger for the *DMA* when the forgetting factors are set to 0.95, with the model now outperforming the benchmark for the national and all regional property markets but two, Northern Ireland and Wales (column 5 of Table 3.4). Analogous to the one-quarter-ahead results, dynamic models that allow for relatively more rapid changes in the underlying model and parameter estimates demonstrate superior predictive ability when compared to the dynamic methods with slower forgetting. Finally, we also observe a considerable improvement in the forecast accuracy of the *TVP* model, which includes only a constant and lags of the dependent variable (column 9 of Table 3.4), as the forecast horizon increases. Specifically, the number of rejections of the null hypothesis increases from 4 for the one-quarter-ahead predictions to 11 for the four-quarters-ahead forecasts.

Conversely, our results suggest that the predictive ability of the *ARDL* model deteriorates at longer horizons. For each of the combinational *ARDL* four-quarter-ahead predictions, we observe much fewer rejections of the null hypothesis of an equal predictive accuracy, compared to the shorter horizon forecasts. Consider, for instance, the trimmed mean combination of the *ARDL* predictions (column 17 of Table 3.4). The model fails to generate significantly lower MSFEs in any of the property markets under consideration, producing an average increase in the predictive error of about 2% relative to the benchmark model.

We now turn to the individual *ARDL* results, presented in Table 3.5, and note the poor predictive ability of each of the house price predictors at longer forecast horizons. Even the last period's house price growth in

[31]The *DMS* has recorded the largest gains in forecast accuracy relative to the *AR(1)* in real estate markets of Yorkshire & Humberside and East Midlands: 37% and 30% respectively.

Table 3.4: Forecasting Performance by Region; $h = 4$

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	$DMS^{0.99}$	$DMA^{0.99}$	$DMS^{0.95}$	$DMA^{0.95}$	$DMA^{\lambda=1}$	*BMS*	*BMA*	*TVP-AR*	*TVP-AR-X*	*UBVAR*	*SBVAR*	*UBFAVAR*	*SBFAVAR*	$ARDL^1$	$ARDL^2$	$ARDL^3$	*ALL*
EA	**0.918**	1.092	**0.822**	**0.977**	1.203	1.583	1.595	0.976	1.230	0.999	1.170	1.399	1.528	1.010	1.020	1.014	1.265
	(3.073)	(1.275)	**(3.821)**	**(2.629)**	(0.806)	(0.401)	(0.201)	(1.225)	(0.713)	(0.451)	(-1.69)	(-0.96)	(-0.91)	(-0.39)	(-2.52)	(-0.82)	(-2.14)
EM	**0.989**	1.056	**0.696**	**0.903**	**0.877**	1.409	1.296	**0.909**	**0.925**	1.003	1.397	1.466	1.673	1.036	1.057	1.043	1.460
	(3.168)	(2.936)	**(4.559)**	**(2.880)**	**(3.127)**	(0.889)	(1.431)	**(2.364)**	**(2.913)**	(-1.27)	(-1.63)	(-1.76)	(1.711)	(-0.98)	(-1.98)	(-1.39)	(-2.21)
GL	1.072	1.080	**0.836**	**0.969**	1.034	1.301	1.273	**0.954**	1.068	0.997	1.356	1.308	1.498	1.016	1.009	1.010	1.482
	(-1.19)	(-1.18)	**(3.129)**	**(2.078)**	(1.433)	(-0.64)	(-0.93)	**(1.954)**	(2.150)	(1.461)	(-2.33)	(-0.86)	(-2.08)	(-0.99)	(-1.35)	(-0.81)	(-2.44)
NI	1.059	1.105	**0.908**	1.099	1.096	1.049	1.113	1.028	1.184	1.000	1.185	0.990	1.181	1.068	1.067	1.061	1.224
	(1.088)	(0.292)	**(2.653)**	(-0.01)	(0.214)	(1.591)	(0.138)	(0.656)	(0.102)	(-0.16)	(-2.35)	(0.870)	(-2.36)	(-2.06)	(-1.87)	(-1.76)	(-2.43)
NT	1.043	1.085	**0.799**	**0.921**	1.045	1.144	1.189	**0.902**	**0.922**	1.002	1.102	1.085	1.224	**0.957**	**0.963**	0.954	1.131
	(-0.35)	(-1.22)	**(2.673)**	**(2.114)**	(0.885)	(-0.85)	(-1.73)	**(1.988)**	**(2.451)**	(-1.29)	(-0.91)	(-0.89)	(-1.67)	**(1.810)**	**(1.810)**	(1.371)	(-0.88)
NW	**0.974**	1.049	**0.787**	**0.910**	**0.901**	**0.979**	1.108	**0.929**	**0.926**	1.004	1.143	1.259	1.412	1.012	1.028	1.015	1.208
	(3.273)	(2.732)	**(3.519)**	**(2.742)**	**(3.082)**	**(3.681)**	(2.966)	**(1.905)**	**(3.261)**	(-1.23)	(-0.98)	(-0.76)	(-1.72)	(-0.24)	(-0.79)	(-0.37)	(-1.43)
OM	0.981	0.994	**0.781**	**0.963**	1.052	0.989	1.002	**0.934**	1.117	0.999	1.193	1.325	1.537	0.999	0.997	0.993	1.440
	(0.942)	(0.446)	**(2.833)**	**(2.048)**	(0.861)	(0.678)	(0.287)	**(2.614)**	(1.436)	(0.677)	(-0.29)	(-1.19)	(-0.83)	(0.310)	(0.579)	(0.844)	(-0.71)
OSE	0.975	1.026	**0.746**	**0.942**	**0.960**	1.038	1.045	**0.941**	1.024	0.997	1.237	1.402	1.459	1.020	1.007	1.018	1.569
	(1.561)	(0.829)	**(3.429)**	**(2.444)**	**(1.955)**	(2.653)	(1.326)	**(2.206)**	(2.169)	(1.313)	(-0.97)	(-1.07)	(-0.89)	(-0.96)	(-2.50)	(-1.54)	(-1.49)
SC	1.095	1.139	**0.718**	**0.984**	1.127	1.208	1.234	**0.903**	1.838	1.001	1.030	1.066	1.111	**0.953**	1.047	0.998	1.037
	(0.735)	(0.138)	**(3.789)**	**(2.048)**	(-0.94)	(-0.27)	(-0.58)	**(2.119)**	(-0.36)	(-1.05)	(0.566)	(-1.51)	(0.287)	**(1.781)**	(-2.24)	(0.444)	(0.685)
SW	1.006	1.133	**0.860**	**0.976**	1.124	1.101	1.109	**0.967**	1.040	0.999	1.254	1.405	1.483	1.015	1.013	1.019	1.419
	(1.223)	(-0.27)	**(3.907)**	**(2.499)**	(0.843)	(0.055)	(0.059)	**(1.767)**	(2.374)	(0.214)	(-2.68)	(-1.25)	(-0.89)	(-1.19)	(-2.70)	(-2.36)	(-2.59)
WM	1.019	1.040	**0.758**	**0.945**	**0.934**	1.012	1.032	**0.942**	1.051	0.993	1.442	1.439	1.709	1.023	1.019	1.022	1.158
	(1.609)	(1.291)	**(3.429)**	**(2.805)**	**(2.525)**	(1.345)	(1.239)	**(2.091)**	(2.138)	(0.822)	((-4.48)	(-0.84)	(-1.78)	(-0.78)	(-0.62)	(-0.73)	(-3.95)
WW	1.104	1.292	**0.858**	1.039	1.213	1.223	1.362	0.972	1.199	1.003	1.186	1.222	1.357	1.011	1.030	1.012	1.272
	(-0.55)	(-1.81)	**(2.394)**	(1.472)	(0.093)	(-1.44)	(-1.91)	(1.434)	(1.001)	(-1.40)	(-0.91)	(-1.41)	(-1.62)	(-0.16)	(-0.79)	(-0.19)	(-0.87)
YH	**0.932**	**0.969**	**0.629**	**0.854**	**0.857**	1.057	1.078	**0.877**	**0.897**	1.004	1.217	1.241	1.428	1.065	1.065	1.061	1.315
	(2.031)	**(1.728)**	**(3.590)**	**(2.838)**	**(2.747)**	(1.213)	(1.007)	**(2.455)**	**(2.892)**	(-1.77)	(-2.08)	(-2.09)	(-2.57)	(-2.49)	(-2.32)	(-2.29)	(-1.97)
UK	0.969	**0.966**	**0.783**	**0.941**	**0.984**	**0.968**	**0.958**	**0.958**	**0.993**	1.001	1.236	1.417	1.457	1.018	1.009	1.010	1.368
	(1.573)	**(1.809)**	**(4.044)**	**(3.595)**	**(2.162)**	**(1.649)**	**(2.140)**	**(1.998)**	**(4.212)**	(-0.52)	(-2.23)	(-1.63)	(-1.94)	(-2.08)	(-1.61)	(-1.30)	(-1.83)

Note: The table reports the MSFE ratios of candidate forecasting models relative to the *AR(1)* benchmark together with their respective Clark and West (2007) test statistics shown in parenthesis. Rejection of the null hypothesis, that the ratio of forecast errors is greater than one, at 5% level of significance is shown in bold. The performance of various forecasting methods is evaluated over the out-of-sample period: 1995:Q4-2012:Q4. The UBFAVAR and SBFAVAR results are reported for $f = 2$ number of principal components. With the exception of $ARDL^1$, $ARDL^2$ and $ARDL^3$, where the lag length p and q are determined at each point in time as described in Section 3, all results are reported for the autoregressive lag length 1.

neighbouring areas, which proved to be an important predictor of property price inflation for the one-quarter-ahead forecasts, no longer improves upon predictive accuracy of the benchmark model in the majority of regional markets.[32] Similarly, models with no shifts in parameter estimates and no variation in the set of property price predictors (*ALL*, *UBVAR*, *SBVAR*, *UBFAVAR*, *SBFAVAR*) perform remarkably poor at longer forecast horizons. Like for the one-quarter-ahead forecasts, these models display the worst predictive ability.

In summary, the above results indicate the superior forecasting performance of dynamic over static models in forecasting house price inflation. Next, we examine the performance of the various econometric models over time.

3.4.2. Evolution of the Out-of-Sample Performance

To gain further insight into the evolution of the out-of-sample performance of alternative forecasting methods we follow Bork and Møller (2015) and compute the cumulative difference between the predictive errors generated by the benchmark model and those from the candidate models under consideration. For each of the regional property markets, the sequence of the cumulative statistic is calculated as follows:

$$CDSFE_{j,t} = \sum_{t=1994:Q4+h}^{2012:Q4} \left(e^2_{AR1,t} - e^2_{j,t}\right), \tag{3.29}$$

where $e^2_{AR1,t}$ and $e^2_{j,t}$ stand for squared forecast errors of the benchmark model and the alternative model *j* respectively, and *h* is the prediction horizon. A positive value of the statistic implies that a particular model *j* produces more accurate predictions of future house price inflation than the *AR(1)* benchmark.

To assess the relative performance of a particular model *j* across all property markets in our sample, we compute the summary measure $\sum_{r=1}^{13} CDSFE_{j,r,t}$, where $r = 1, \ldots, 13$ denotes one of the regional housing markets of the country. Figure 3.1 illustrates the evolution of the overall cumulative statistics during the out-of-sample period for both one- and four-quarters-ahead forecast horizons. A positive slope indicates periods, in which the predictive ability of the given model *j* is superior to that of the *AR(1)* benchmark, while negative slope of the line, on the contrary, unveils periods, in which the forecast accuracy of the

[32] On the other hand, forecastability of the national-level house price growth improves at longer horizons, as indicated by the individual *ARDL* results. According to Table 3.5, the income growth and the price-to-income ratio are the two house price predictors that offer statistically significant, albeit marginal improvement in predictive accuracy relative to the *AR(1)* benchmark.

Table 3.5: Forecasting Performance: ARDL Models; $h = 4$

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Predictor	EA	EM	GL	NI	NT	NW	OM	OSE	SC	SW	WM	WW	YH	UK
Regional Variables:														
Income Growth	1.018	1.101	1.062	1.069	0.968	1.052	1.002	0.999	1.006	1.001	1.046	1.047	1.067	**0.985**
	(-0.451)	(-2.507)	(-0.731)	(-1.787)	(1.578)	(-0.109)	(0.417)	(0.414)	(0.914)	(0.057)	(-0.693)	(-0.109)	(-1.386)	**(1.706)**
Labour Force	1.028	1.101	1.046	1.101	**0.958**	1.014	1.019	1.026	1.056	1.016	0.999	1.054	1.074	1.002
	(-0.237)	(-2.659)	(-0.662)	(-1.835)	**(1.889)**	(0.489)	(-0.096)	(-0.262)	(-0.739)	(-0.299)	(0.469)	(-0.891)	(-2.134)	(0.017)
Unemployment	1.136	1.353	1.009	1.163	0.989	1.218	1.014	1.306	1.069	1.019	(1.048)	(1.048)	1.071	1.039
Rate	(0.689)	(-1.349)	(-0.073)	(-1.587)	(0.914)	(-0.964)	(0.220)	(-0.192)	(-1.131)	(-1.647)	(-2.091)	(-0.137)	(-1.757)	(-0.683)
Price-to-Income	1.092	0.996	1.065	0.995	1.042	0.994	1.002	0.999	1.162	1.008	1.028	1.092	1.043	**0.985**
	(-1.103)	(0.679)	(-0.567)	(0.528)	(-2.041)	(0.922)	(0.417)	(0.414)	(-2.532)	(0.627)	(-0.218)	(-1.991)	(-1.602)	**(1.705)**
National Variables:														
CCI	1.052	1.096	1.012	1.126	0.993	1.119	1.097	1.114	1.052	1.029	1.056	1.067	1.104	1.035
	(-1.816)	(1.681)	(-3.727)	(-1.917)	(0.662)	(-2.781)	(-3.013)	(-2.829)	(-0.684)	(-1.983)	(-0.376)	(-0.888)	(-2.257)	(-2.130)
Consumption	0.994	1.066	1.002	1.075	**0.908**	1.054	1.003	1.009	1.024	0.999	1.051	**0.979**	1.102	1.006
	(0.912)	(0.212)	(-0.199)	(-1.924)	**(3.135)**	(0.537)	(-1.135)	(-1.899)	(-0.228)	(0.130)	(0.478)	**(1.921)**	(-0.991)	(0.332)
Housing Stock	1.031	1.162	1.032	1.032	0.978	1.188	1.016	1.029	1.008	1.049	1.167	1.051	1.121	1.072
	(-3.063)	(-3.686)	(-2.452)	(-0.753)	(1.329)	(-2.449)	(-0.077)	(-1.906)	(0.519)	(-3.455)	(-2.306)	(-0.760)	(-1.844)	(-4.560)
Industrial	1.032	1.167	1.019	1.063	1.002	1.154	0.991	1.011	1.032	1.013	1.090	1.079	1.121	1.031
Production	(-2.019)	(-3.302)	(-1.851)	(-1.459)	(0.255)	(-2.749)	(1.182)	(-2.685)	(-0.543)	(-3.204)	(-2.074)	(-1.526)	(-2.719)	(-3.539)
Mortgage Rate	0.986	1.067	0.983	1.061	0.964	1.063	0.997	0.993	1.046	1.006	0.981	1.014	1.050	0.996
	(0.981)	(-1.409)	(1.054)	(-1.440)	(1.619)	(-1.539)	(0.438)	(0.641)	(-1.753)	(-0.101)	(1.105)	(0.149)	(-1.364)	(0.465)
Spread	1.113	1.191	1.154	1.118	0.991	1.060	1.129	1.156	1.076	1.145	1.049	1.137	1.159	1.155
	(-1.139)	(-2.288)	(-1.119)	(-2.091)	(0.967)	(-0.532)	(-0.608)	(-0.815)	(-2.001)	(-1.655)	(0.326)	(-1.818)	(-2.379)	(-1.232)
Contiguous Regions:	1.108(EM)	1.046(YH)	1.006(EA)	1.066(SC)	**0.907(YH)**	1.060(NT)	0.975(OSE)	1.062(OM)	1.089(NT)	1.135(OSE)	1.134(NW)	1.010(NW)	1.148(NT)	
	(-1.726)	(-1.157)	(-1.394)	(-2.175)	**(2.672)**	(-1.859)	(1.525)	(-0.034)	(-2.008)	(0.112)	(-1.872)	(-0.239)	(-0.892)	
	0.982(OSE)	1.073(NW)	1.031(OM)		**0.916(NW)**	0.994(YH)	0.986(GL)	1.190(SW)	1.018(NI)	1.196(WW)	1.068(WW)	**0.913(WM)**	1.162(NW)	
	(1.147)	(-2.625)	(0.455)		**(2.485)**	(0.777)	(1.313)	(-0.476)	(0.009)	(0.191)	(-0.008)	**(3.115)**	(-1.266)	
	1.064(OM)	**0.955(WM)**				0.992(WW)	1.021(EA)	1.084(WM)		1.023(WM)	0.998(SW)	**0.936(SW)**	0.986(EM)	
	(0.313)	**(1.987)**				(1.138)	(-0.904)	(-0.121)		(-0.101)	(0.874)	**(2.058)**	(1.294)	
	1.144(GL)	1.155(OSE)				**0.885(WM)**		1.022(EA)			1.108(OSE)			
	(0.057)	(0.760)				**(2.972)**		(-1.115)			(-0.058)			
		1.103(EA)				**0.900(EM)**		1.114(EM)			1.028(EM)			
		(0.834)				**(2.645)**		(0.622)			(-0.769)			

Note: The table reports the MSFE ratios of individual *ARDL* models relative to the *AR(1)* benchmark together with their respective Clark and West (2007) test statistics shown in parenthesis. Rejection of the null hypothesis, that the ratio of forecast errors is greater than one, at 5% level of significance is shown in bold. Each *ARDL* model includes a constant, lags of dependent variable and one of the predictors listed in the first column. The number of lagged dependent variable terms is selected at each time period using the SIC. The performance is evaluated over the out-of-sample period: 1995:Q4-2012:Q4.

model deteriorates.

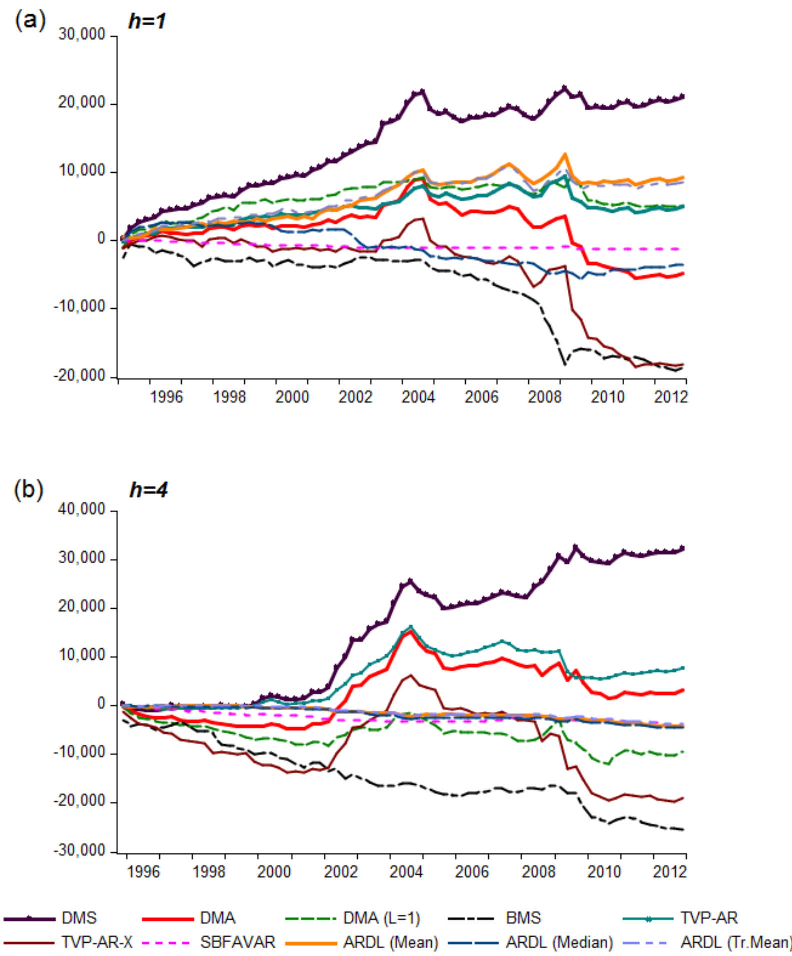

Figure 3.1: Relative Out-of-Sample Performance of Candidate Forecasting Models: (a) $h = 1$ and (b) $h = 4$. Only models that, according to the results presented in Table 3.2 and Table 3.4, succeeded in beating the benchmark prediction in at least one regional real estate market are included in the analysis. We consider the *DMA* and the *DMS* models with values of the forgetting factors set to 0.95.

Examination of the upper diagram (Figure 3.1(a)) reveals that the *DMS* with $\alpha = \lambda = 0.95$ produces consistently more accurate forecasts than the other predictive techniques during the first decade of the recent house price boom: from the start of the evaluation period until around 2004. Furthermore, the $DMS^{0.95}$ is doing remarkably well in capturing the property price downturn of 2008. On the contrary, the predictive power of all forecasting models, including the $DMS^{0.95}$, starts to deteriorate in 2004:Q3, when all regional property markets experienced a sharp reversal in house price growth rates.[33] We also note the poor forecast performance of our models at the start of the bust phase and in the end of 2008 - beginning of 2009, when all regional housing markets experienced a few consecutive quarters of negative property price inflation.

Moving on to the diagram for the longer forecast horizon (Figure 3.1(b)), we notice remarkably weak predictive ability of our models at the start of the evaluation period: none of the candidate forecasting methods is able to beat the benchmark prediction during the first years of the recent house price boom from 1995 to the early 2000s. The diagram suggests, that a number of forecasting models, including the $DMS^{0.95}$, the *TVP-AR*, and the $DMA^{0.95}$, start to gain predictive power only from around 2001. The $DMS^{0.95}$, in particular, produces the lowest predictive errors and remains the best performing model until the end of 2004. Similarly, the four-quarter-ahead results demonstrate that the $DMS^{0.95}$ performs better than any other alternative forecasting method during the property price downturn from the end of 2007 until around 2009. Similarly to the one-quarter-ahead results, periods during which the $DMS^{0.95}$ fails to outperform the benchmark model generally coincide with sharp corrections in real estate prices, in particular, in the end of 2004 and in 2009-2010.

3.4.3. Best House Price Predictors: Over Time and Across Regions

A conclusion that emerges from our empirical analysis so far is that models that include the entire set of predictive variables and do not allow for time variation in the number of predictors tend to perform poorly, regardless of the prediction horizon. Dynamic models, on the other hand, demonstrate superior predictive ability, particularly at longer horizons. But what is the optimal number of information variables to be included in the forecasting exercise? Koop and Korobilis (2012) suggest using the *DMA* probabilities to determine the optimal dimensionality of the forecasting models as well as to gain more insight into which economic variables are important for predicting future property price inflation.

Consider a model *k*, which includes $Size_{k,t}$ predictive variables at time *t*, other than the intercept and the lags of the dependent variable. If the probability that this model *k* should be used for forecasting at time *t* is given by $\pi_{t|t-1,k}$, then for each property market in our sample, the expected number of predictors used

[33] Annualised property price inflation figures dropped by more than 31% on average across regional markets of the UK in 2004:Q3. Regions, which showed the largest collapse in house price growth rates were Yorkshire & Humberside (-63%), East Midlands(-54%) and Scotland(-53%).

in the *DMA* forecast at each point in time can be calculated as follows:

$$E(Size_t) = \sum_{k=1}^{K} \pi_{t|t-1,k} Size_{k,t}. \tag{3.30}$$

Figure 3.2 plots the median (across the 13 regional property markets) expected number of predictors for the *DMA* with $\alpha = \lambda = 0.95$ and for both one- and four-quarters-ahead horizons. To get an understanding of the degree of variation in the dimensionality of the forecasting models across regional markets, in addition to the median expected size of the *DMA* model, we show the 16th and 84th percentiles. Examination of the diagram for the shorter horizon (Figure 3.2(a)) reveals, first, preference for the parsimonious models and second, stability of the average model size throughout the evaluation period: the median value of the reported statistic hovers around 4 predictive variables throughout the out-of-sample period, while the value of the upper percentile is never above 5. Moving on to the results for the longer forecast horizon (Figure 3.2(b)), we observe that the gap between upper and lower percentile is somewhat wider, indicating greater variation in the average number of predictors used to generate the *DMA* forecasts in different regional property markets under consideration. Furthermore, we note an increase in the median model size from 4 to 5 predictive variables during the boom phase from mid-90s untill around 2005, which is more pronounced, compared to the shorter forecast horizon.

The *DMA* probability weights can be used not only to determine the optimal dimension of the forecasting model but also to cast light on which economic variables are important for predicting future property price movements and examine how the best house price predictors vary over time, across regional markets and across forecast horizons. Following the methodology of Koop and Korobilis (2012), for each information variable in our dataset, we scan through the $k = 1, \ldots, 1024$ models of the *DMA* and select those, which contain that specific predictor.[34] Following Koop and Korobilis (2012) and Bork and Møller (2015), we refer to the probability that the *DMA* assigns to models with this predictor as posterior inclusion probability.

Figures 3.3 and 3.4 plot the median inclusion probabilities across all regional property markets of the country at one- and four-quarters-ahead horizons respectively. To assist the reader in understanding the degree of variation in the choice of house price predictors across different housing markets, each diagram, along with the median probability weights, shows the 16th and 84th percentiles of the posterior inclusion

[34] In what follows we consider the *DMA* with the values of both forgetting factors set equal to 0.95.

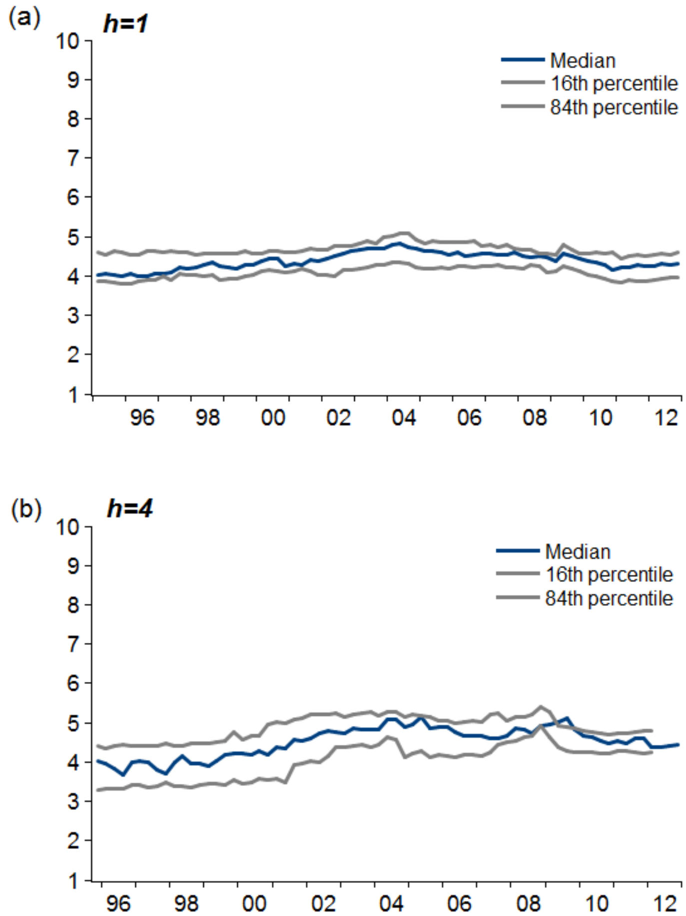

Figure 3.2: Expected Dimension of *DMA*: (a) $h = 1$ and (b) $h = 4$. Both diagrams illustrate the median *DMA* dimension across 13 regional property markets, shown with 16th and 84th percentiles. We use model probabilities $\pi_{t|t-1,k}$ determined by the *DMA* with values of the forgetting factors set to 0.95.

probabilities. The figures illustrate in a clear manner why predictive methods that allow changes in the underlying model specification tend to produce more accurate forecasts than methods that keep the set of predictors fixed. We observe that with the exception of the price-to-income ratio, the mortgage rate and the spread, for which inclusion probabilities were virtually constant over time, across regions and forecast horizons, it is not the same set of property price predictors that is driving house prices during the periods of upswing and downturn in real estate prices. Moreover, the wide gaps between upper and lower percentile probabilities of all remaining information variables suggest that these predictors are not equally important across regional property markets under consideration. A prime example is the indicator of credit availability in the *DMA* forecasting exercise at $h = 1$ (Figure 3.3). According to our results, the liberalisation of credit conditions and the ease of access to various financing opportunities are the main drivers of property price inflation during most of the boom phase, from the beginning of 2002 unit the first quarter of 2005. The 2004:Q3 peak value of the median inclusion probability of the credit availability index is nearly 0.75, while in some property markets, probability of including this variable in the *DMA* forecast is close to one at that time.[35] In contrast, in the onset of the recent house price collapse, the posterior inclusion probability of credit conditions drops to just 0.4.

The patterns of posterior inclusion probabilities at the longer forecast horizon (Figure 3.4) become somewhat more complicated. This implies that it is more important to allow for changes in the underlying model specification when making four-quarters-ahead predictions. Furthermore, we see a wider gap between upper and lower probability percentiles, which implies that the probabilities of including different house price predictors in the forecasting model vary more at the four- than at the one-quarter-ahead horizon. Contrary to the one-quarter-ahead results, we observe that the index of credit availability is no longer the single major determinant of property price inflation during the boom phase. Growth in industrial production is particularly important at the start of the recent upswing, with the median inclusion probability being above 0.8. This predictor remains the key driver of future house price movements almost throughout the rest of the out-of-sample period.

Finally, Figures 3.5 and 3.6 illustrate the probabilities of including various house price predictors in the *DMA* forecasting exercise for each of the three most volatile and three most stable property markets in our sample at one- and four-quarters-ahead horizons respectively. In each figure, the diagrams on the left display the posterior inclusion probabilities for Northern Ireland, the North and Wales, while diagrams on the right show which predictors are important in relatively stable property markets of West Midlands, Outer Metropolitan and East Midlands. To keep the diagrams readable, we chose to report the three most important information variables for each regional real estate market under consideration. A predictor is classified as important and is included in the diagrams only if its posterior inclusion probability is above 0.5 for most of the out-of-sample period.

[35] In 2004:Q3, the credit availability indicator receives the highest probability weight in the following regional markets: the North (0.97), North West (0.93) and Wales (0.92). On the contrary, credit conditions play the least important role in property markets of Northern Ireland, Outer Metropolitan and Outer South East, where posterior inclusion probabilities of this variable are 0.37, 0.42 and 0.44 respectively.

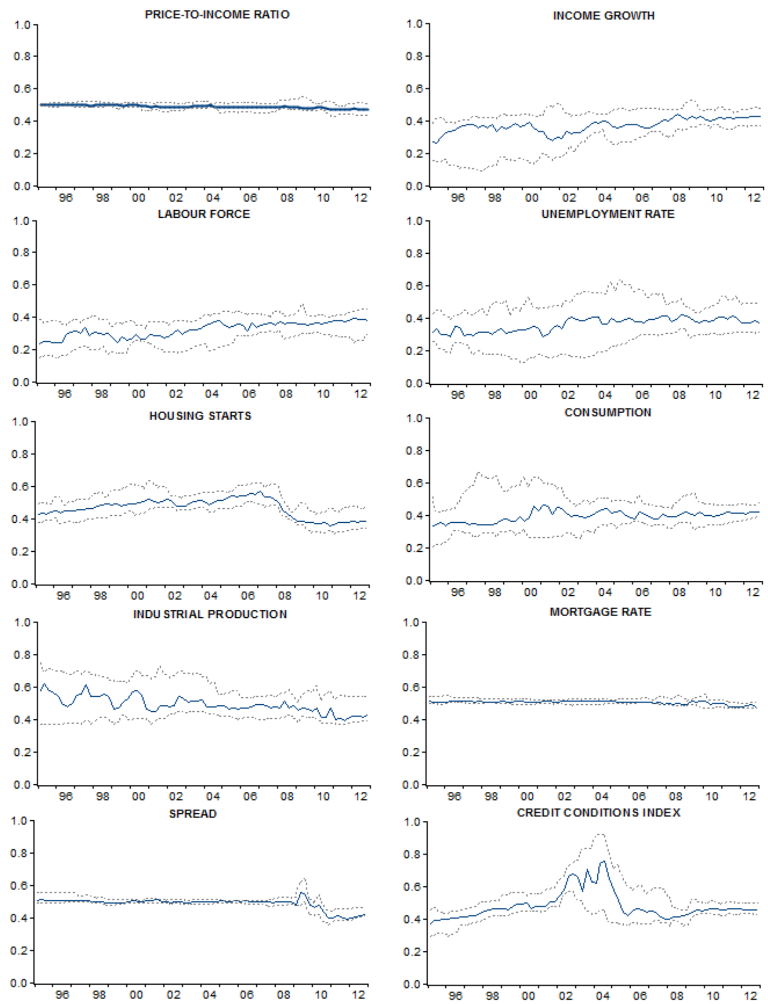

Figure 3.3: Ten House Price Predictors: Posterior Probabilities of Inclusion (*h=1*). Each diagram presents median inclusion probability of the property price predictor across 13 regional housing markets (blue solid line), shown with 16th and 84th percentiles (grey dashed lines). We use model probabilities determined by *DMA* with values of the forgetting factors set to 0.95.

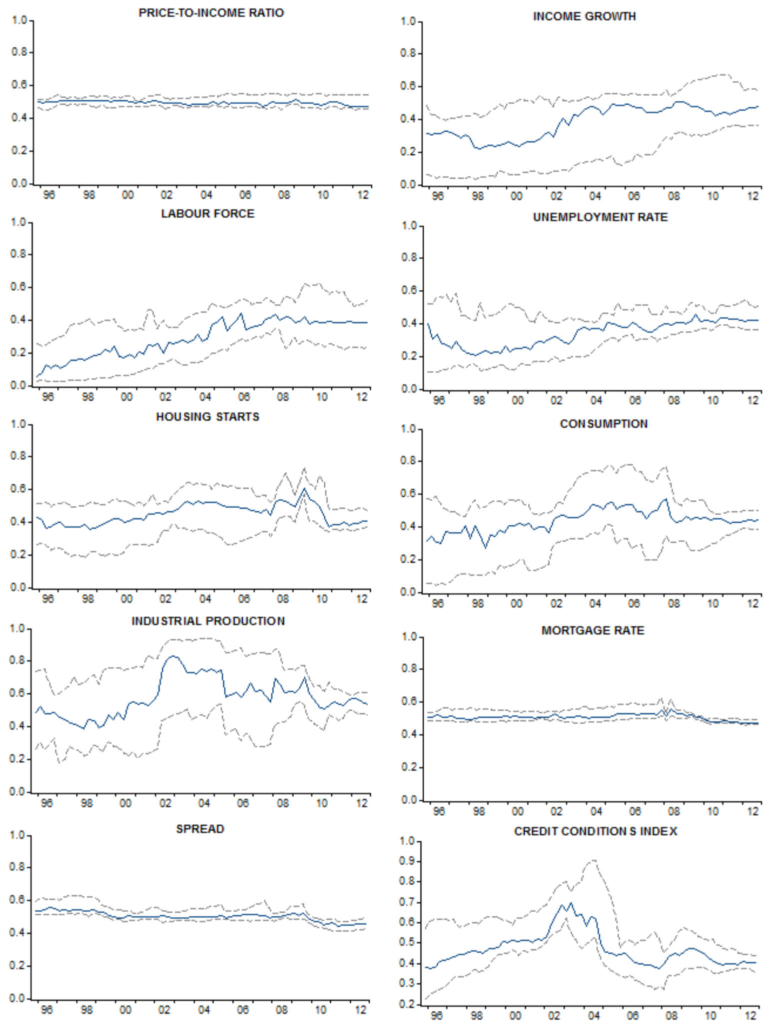

Figure 3.4: Ten House Price Predictors: Posterior Probabilities of Inclusion (*h=4*). Each diagram presents median inclusion probability of the property price predictor across 13 regional housing markets (blue solid line), shown with 16th and 84th percentiles (grey dashed lines). We use model probabilities determined by *DMA* with values of the forgetting factors set to 0.95.

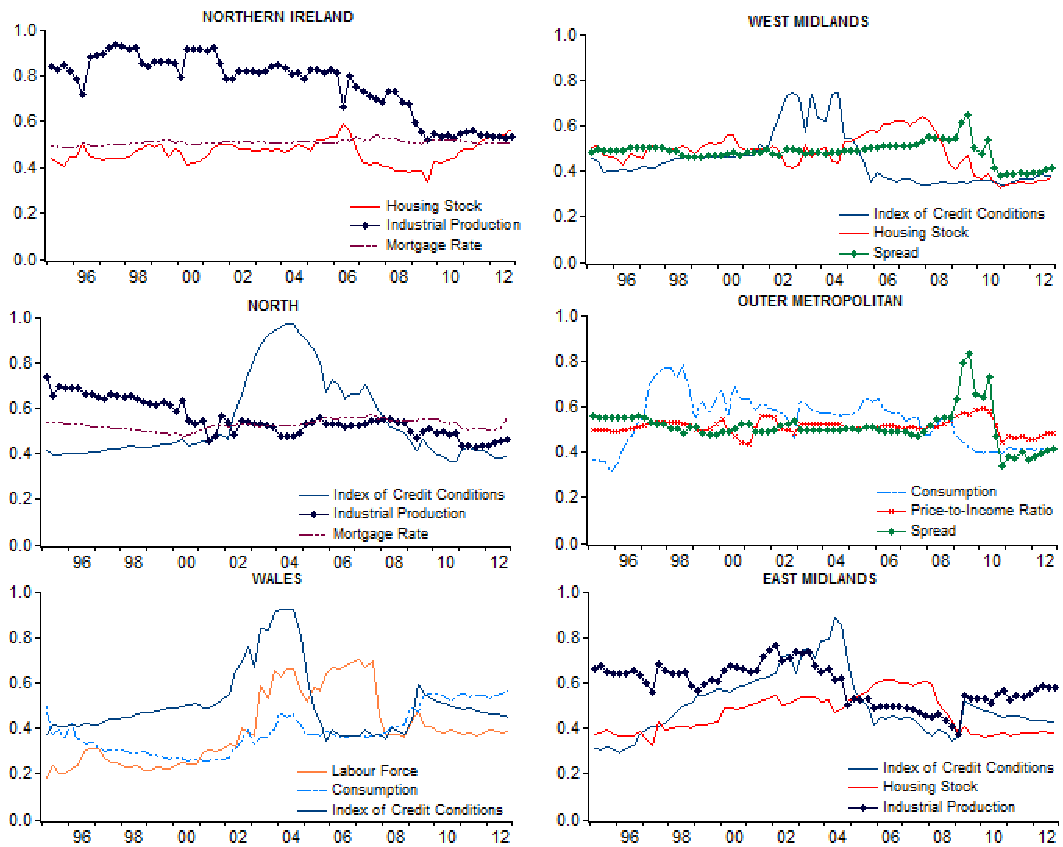

Figure 3.5: Best House Price Predictors in Volatile and Stable Property Markets: Posterior Probabilities of Inclusion (*h=1*). We use model probabilities determined by the *DMA* with values of the forgetting factors set to 0.95.

Looking at the shorter-horizon results, displayed in Figure 3.5, we cannot identify a single predictive variable that is consistently the most important. In two volatile regions out of three, credit availability is the key house price predictor during the recent boom in the real estate markets. In Wales and in the North, the probability of including the index of credit conditions stays at 0.4 during the first few years of the evaluation period, however, from around 2001, liberalisation of lending conditions makes the credit availability indicator play the key role in determining future house price movements in these regions. The 2004 peak value of the probability of including this variable in the *DMA* is close to unity, but it drops back to 0.4 just before the downturn in commercial and residential property prices. According to the graphs of the posterior inclusion probabilities, growth in industrial production is another variable that plays an important role in predicting future house price movements in 2 volatile property markets (Northern Ireland and the North) out of the 3 considered. Interestingly, the probability of including this variable in the forecasting model of Northern Ireland, which is the most volatile region in our sample, is around 0.8 almost throughout the evaluation period: from the mid-90s until the end of 2006. The predictive ability of industrial production starts to decline in the first quarters of 2007, when house price inflation in the region started to slow down, and falls to 0.5 by 2009, following the sharp downturn in property prices in the area. Lastly, we observe that the mortgage rate is an important predictor of house price inflation in Northern Ireland and the North, however the probability of including this variable in the forecasting exercise is only marginally above 0.5 for the entire duration of the evaluation period.

When it comes to the other predictive variables, we note that most of them are important in some volatile regions, but not in the others. Perhaps the most striking example is the labour force, which is one of the key determinants of future property price movements in Wales during the recent boom in the real estate market. The posterior inclusion probability of this variable is nearly 0.7 from 2003:Q2 until the end of the boom phase (2007:Q3), while the probability of including the labour force in the predictive models of Northern Ireland and the North is never above 0.5.

Moving on to the graphs of the stable housing markets of West Midlands, Outer Metropolitan and East Midlands (Figure 3.5(right)), we note that there is no single information variable that turns out to be equally important in all three markets. The gap between yields on long-term and short term gilts, the housing stock and the credit availability indicator each stands out as the main determinant of future house prices in 2 stable regional markets out of 3. In West Midlands and Outer Metropolitan the yield gap becomes an important predictor during the bust phase (probability of including this variable in the *DMA* forecast for Outer Metropolitan region stands at 0.83 in 2009:Q3), until then, this variable has about 50% likelihood of being included. The two other predictors (the housing stock and the credit availability indicator), on the contrary, are important in the time of the recent upswing in real estate prices. The index of credit availability is the key determinant of property price inflation in the midland areas at the start of the boom phase: from the first quarters of 2001 until the end of 2004 (in East Midlands, for instance, the *DMA* attaches nearly a 90% inclusion probability to the credit indicator in 2004:Q2). The stock of dwellings, on the other hand, has the greatest predictive power in the second half of the upturn period: from the last quarters of 2004 until the collapse of property prices, after which the probability of including this variable falls to 0.4. Similarly to the volatile property markets, the remaining predictors show mixed predictive ability: they are important in some housing markets, but fail to overcome the 0.5 inclusion probability threshold in the others.

In order to compare the choice of the key house price predictors across different forecast horizons we turn to the patterns of posterior inclusion probabilities for the longer horizon, $h = 4$, displayed in Figure 3.6. By analogy with the one-quarter-ahead graphs, we show predictive variables with the inclusion probabilities above 0.5 in the three most volatile and the three most stable property markets. One striking feature of our findings is that the choice of the house price predictors and the patterns of their inclusion probabilities vary considerably with the length of the forecast horizon. East Midlands stands out as the only regional real estate market, where the same trio of predictive variables is important both at one- and four-quarters-ahead horizons. This is not the case in the remaining markets. Consider, for instance, the real estate market of Northern Ireland. Out of the three predictive variables that are important for the one-quarter-ahead prediction, the industrial production remains the only predictor with the posterior inclusion probability of not less than 0.5 during some episodes of the out-of-sample period at $h = 4$. At the same time, the probability of including the industrial production in the forecasting model of Northern Ireland is no longer high throughout the most part of the evaluation interval. The pattern of inclusion probability indicates that for $h = 4$, this variable is important only at the start of the out-of-sample period and during the boom phase: from the first quarters of 2002 until the beginning of 2005. The predictive ability of the industrial production starts to deteriorate at the end of 2005, when the posterior inclusion probability of the variable drops to 0.3. On the

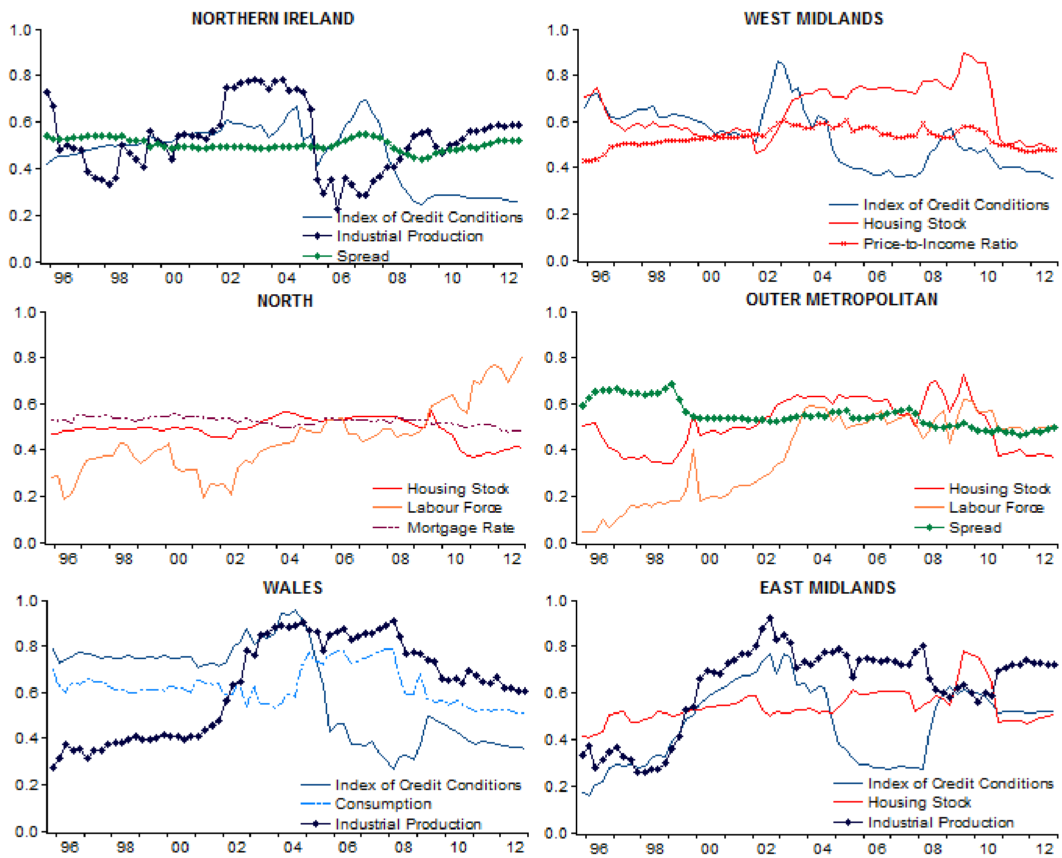

Figure 3.6: Best House Price Predictors in Volatile and Stable Property Markets: Posterior Probabilities of Inclusion (*h=4*). We use model probabilities determined by the *DMA* with values of the forgetting factors set to 0.95.

contrary, the $h = 1$ results suggest that probability of including the industrial production in the forecasting exercise remains at 0.8 until the end of the boom phase (2007:Q3).

Finally, for the $h = 4$ forecasts, the stock of dwellings stands out as the most important house price predictor in relatively stable property markets, particularly during the initial collapse in housing prices. We note the striking synchronisation in the patterns of the posterior inclusion probabilities at the end of 2008-beginning of 2009 in all three stable markets under consideration. In East Midlands, West Midlands and Outer Metropolitan, the probability of including the housing stock variable reaches the value of about 0.8 in 2009:Q3 and then starts to decrease gradually following the sharp reversal in the rates of house price growth in 2009:Q4, and, finally, falls below 0.5 at the end of the evaluation interval.[36]

The overall conclusion that emerges from examining the estimated posterior inclusion probabilities is that there is a considerable variation in the choice of house price predictors over time, across regions and across forecast horizons. It provides an illustration of why forecasting strategies that allow changes in the underlying model specification (*DMA* and *DMS*) tend to produce more accurate forecasts of future house price movements.

[36]The rates of property price inflation in 2009:Q4 decreased by an average of 63% across three stable real estate markets: East Midlands (-43%), Outer Metropolitan (-64%) and West Midlands (-82%).

3.5. Conclusion

In this chapter, we provided an extensive evaluation of the forecastability of property price inflation in the national and the 13 regional real estate markets of the UK. For doing so, we applied a battery of static and dynamic econometric methods to a large macroeconomic data set that spans the out-of-sample period from 1995:Q1 to 2012:Q4, and thus covers the recent boom and bust in the housing markets. The econometric models considered include the *ARDL*, *BVAR*, *FABVAR*, *TVP*, *BMA*, *BMS*, *DMA* and *DMS*.

In summary, our results indicate that dynamic models that allow for changes in both the parameter estimates and the underlying model specification deliver more accurate forecasts than models in which the number of house predictors is kept fixed. Among the various models, the *DMS* with low values of the forgetting factors performs best in terms of forecast accuracy, outperforming the benchmark *AR(1)* for all real estate markets. By examining the performance of the methods over time, we found that dynamic models are doing remarkably well in capturing the upswing in real estate markets (1995:Q1) as well as part of the latest price collapse (2008:Q1-2008:Q3 and 2009:Q1-2009:Q3), especially at the shorter forecast horizon. The *DMS* method, in particular, produces consistently more accurate forecasts than any other alternative throughout the evaluation period. Its performance, however, similarly to that of other forecasting methods, deteriorates during the episodes of sharp reversals in the rates of house price inflation (2004:Q3; 2007:Q3; 2008:Q4; end of 2010 - beginning of 2011).

The estimation results of the *DMA* enabled us to shed light on the optimal number of predictors included in the forecasting model and on which are the best economic variables for predicting future house price movements. Two important conclusions with regard to model dimensionality are, first, that parsimonious models are preferred to models with a large number of predictive variables and, second, that the number of property price predictors is, generally, stable over time, across regions and different forecast horizons. When it comes to the best predictors, the probabilities of including different economic variables in the forecasting exercise reveal that there does not exist a single predictor that is consistently chosen by the dynamic models as the key determinant of future property price movements. In the majority of regional markets, the credit availability indicator was the main determinant of property price inflation during the recent boom phase but not throughout the out-of-sample period and not for all regional markets.

As a final contribution of our chapter, we examined how the set of house price predictors varies with the volatility of regional real estate markets. By looking at the three most volatile and three most stable property markets in our sample, we found that the main predictors in volatile regions generally differ from those in stable housing markets. Our findings suggest that the index of credit availability and the growth in industrial production were the key drivers of house price inflation in volatile regions, particularly during the boom phase; while in relatively stable property markets, the stock of dwellings was the main determinant of housing dynamics on the eve of house price collapse.

During turbulent periods, when the choice of a proper forecasting model is of a critical importance, these conclusions become particularly relevant.

Appendix: Data Description and Sources

Price-to-Income Ratio: National-level: ratio of real house price index (all houses, seasonally adjusted, deflated by the CPI, in logs, source: Nationwide) to personal disposable income per capita computed as in Cameron et al. (2006) (non-property personal disposable income $pdin = \frac{posttaxpdi}{pretaxpi} * (wagesandsalaries + mixedincome)$, deflated by the CPI, in logs ($lrpdin$), source: Office for National Statistics (ONS). Per household measure is computed as $lrynhs = lrpdin - log(hs_{-1}) - 0.7 * log(poo_{-1})$, where hs_{-1} is the number of housing starts in the previous period (source: Department for Communities and Local Government) and poo_{-1} is proportion of owner occupied houses in the previous period (source: Department for Communities and Local Government). In first differences.

Regional-level: ratio of real regional house price index (all houses, seasonally adjusted, deflated by the CPI, in logs, source: Nationwide) to average total household's weekly expenditure, deflated by the CPI (Source: Family Expenditure Survey (FES) (FES runs from 1961 to 2001, from 2001 it was replaced by the Expenditure and Food Survey, which became the Living Costs and Food Survey from 2008, annual data is interpolated to obtain quarterly values). OM and OSE are assumed to correspond to the South East region in the regional classification of the FES. In first differences.

Income growth: National and regional level: quarterly changes in real per capita disposable income (see above). In logs and annualised.

Labour Force Growth: National-level: number of unemployed (sum of unemployed male aged 16+ and unemployed female aged 16+; thousands of persons, seasonally adjusted, source: ONS) plus the number of employed (sum of employed male (aged 16-64) and employed female (aged 16-64); thousands of persons, seasonally adjusted, source: ONS). Quarterly changes, in logs and annualised.

Regional-level: number of unemployed people plus the number of employed people. Quarterly changes, in logs and annualised. Source: Labour Force Survey (LFS). The 1975-1992 data is available annually, from 1992 onwards the data is published quarterly. We interpolate the pre-1992 values to obtain quarterly series. The OSE and OM values are obtained by splitting the South East region (LFS regional classification) into two equal parts. In 1983 the GL region is absent from the LFS classification: the South East region for this year only is split into three equal parts.

Unemployment Rate: National-level: unemployment rate, all persons aged 16+, seasonally adjusted.

In first differences. Source: ONS. Regional-level: ratio of unemployed people to labour force, times 100. In first differences. Source: LFS.

Real Mortgage Rate: mortgage rate of building societies (source: OECD: Main Economic Indicators), adjusted for the cost of mortgage tax relief as in Cameron et al. (2006) (the cost of mortgage relief is zero from Q1:2000, source: HM Revenue & Customs, interpolated to obtain quarterly values). Deflated by the CPI. In first differences.

Spread: difference between 10-year Government Bond yield (quarterly, source: Saint Louis FRED Economic Data, series ID: IRLTLT01GBQ156N) and rate of discount on 3-month Treasury Bills (quarterly average, source: Bank of England, series ID: IUQAAJNB).

Industrial Production Growth: total industrial production of all industries, constant prices, seasonally adjusted. Quarterly changes, in logs and annualised. Source: ONS.

Real Consumption Growth: final consumption expenditure of households and non-profit institutions serving households (millions of UK sterling pounds), constant prices, seasonally adjusted. Quarterly changes, in logs and annualised. Source: ONS.

Housing Starts: number of permanent dwellings started, all dwellings, UK. In logs. Source: Department for Communities and Local Government. Quarterly data is available from Q1:1978 onwards (Table 211), while annual data is available from 1969 (Table 208). For years 1975-1977 we assume that every quarter an equal number of dwellings is starter and divide annual figures by 4 to obtain quarterly series.

Index of Credit Conditions: see Appendix B of Chapter 2 for a detailed description of the methodology, estimation results and sources of the credit availability data.

Data used for Factor Augmented BVAR

We adopt the list of macroeconomic variables employed by Stock and Watson (2009), Koop (2013) and use similar economic indicators of the UK economy in our BFAVAR application. Some variables are available at an annual frequency and have been interpolated to obtain quarterly series. The following employment indicators are available only up to Q1:2011 and have been extrapolated using linear trends: EMPLTCIV(55), EMPLSER(56), AAHMAN(57), EMPLMAN(58), EMPLAGR (59), EMPLPOP(61), LFPR(62), ULCTOT(65), ULCBS(66), ULCIND(67), ULCMAN(68). All data series have been transformed to achieve stationarity. The table below lists all macroeconomic variables with details of the data sources and undertaken transformation. Following Koop (2013), the transformation codes are as follows: 1 - level of the series (no transformation); 2 - first difference; 3 - second difference; 4 - logarithm transformation; 5 - first difference of log transformed variables; 6 - second difference of log transformed variables.

No.	Mnemonic	Description	Tr.Code	Source
Money and Credit Aggregates				
1	M0	Notes and Coins in circulation outside Bank of England (Mln.£)	5	BoE
2	M2	Money Supply M2, Money and Quasi Money (Mln.£)	5	WDI
3	M4	Broad Money (Mln.£)	6	OECD
4	HMR	Ratio of Monetary Base to Broad money	6	WDI
5	M2DEP	Ratio of M2 to Total Reserves	5	WDI
6	UD	Total Consumer Credit Outstanding (Mln.£)	5	BoE
7	SD	Total Amount of Lending Secured on Dwellings (Mln.£)	6	ONS
8	RBMTR	Ratio of Broad Money to Total Reserves	5	WDI
9	DMPS	Deposit Money Banks, Claims On Private Sector (Bln.£)	5	IMF
10	DMCOE	Deposit Money Banks, Claims On Official Entities (Bln.£)	5	IMF
11	DMDTS	Deposit Money Banks, Demand, Time, Savings and Foreign Currency Deposits (Bln.£)	5	IMF

No.	Mnemonic	Description	Tr.Code	Source
12	DMRES	Deposit Money Banks, Reserves (Bln.£)	5	IMF
13	RESASS	Reserve Assets, Special Drawing Rights(£)	5	OECD
14	TOTDEP	Total Deposits by All Sectors (Mln.£)	6	OECD
15	IIPTLM	Investment by Insurance Companies, Pension Funds and Trusts, Loans and Mortgages (Mln.£)	5	ONS
16	IIPTGS	Investment by Insurance Companies, Pension Funds and Trusts, British Government Securities (Mln.£)	5	ONS
Stock Prices				
17	FTSE	FTSE All Share Price Index	5	Datastream
18	FTSEDY	FTSE All Share Dividend Yield (%)	5	Datastream
19	SMALL	Datastream Small Companies Price Index	5	Datastream
20	INDUS	Datastream Industrials Index	5	Datastream
21	FINDAT	Datastream Financials Index	5	Datastream
22	OILDAT	Datastream Oil and Gas Price Index	5	Datastream
23	TMRKPE	Datastream Total Market Index, Price-Earnings Ratio	5	Datastream
Exchange Rates				
24	EXREU	Foreign exchange rate: EU (Euro per Pound)	5	Datastream
25	EXRUS	Foreign exchange rate: US (US $per Pound)	5	Datastream
26	EXRJAN	Foreign exchange rate: Japan (Yen per Pound)	5	Datastream
27	EXRCAN	Foreign exchange rate: Canada (Canadian $per Pound)	5	Datastream
Interest Rates				
28	IRM1	Thomson Reuters UK T-Bills Bid Yield 1 Month (%)	5	Thomson Reuters
29	IRM3	Discount Rate 3-Month Treasury Bills (%)	5	OECD
30	IRGB10	Long-Term Government Bond Yields: 10-year (% per annum)	5	FRED
31	IRGB20	Gross Redemption Yield On 20 Year Gilts (%)	5	Thomson Reuters
32	OBANKR	End Quarter Official Bank Rate (%)	5	BoE

No.	Mnemonic	Description	Tr.Code	Source
33	SFYGM1	Spread between 1 months Treasury Bills Rate and Bank Rate (%)	1	
34	SFYGM3	Spread between 3 months Treasury Bills Rate and Bank Rate (%)	1	
35	SFYGT10	Spread between 10 year Bills Rate and Bank Rate (%)	1	
36	SFYGT20	Spread between 20 year Bills Rate and Bank Rate (%)	1	
Real Output and Income				
37	PYQ	Disposable Income of Households and NPISH (£)	5	ONS
38	GDPPC	Gross Domestic Product by Capita (£)	5	WDI
39	GSAVE	Gross Saving (Mln. £)	5	ONS
40	HSSR	Saving Ratio of Households and NPISH (%)	2	ONS
41	RGDP	Real Gross Domestic Product (Mln.£)	5	ONS
42	GVA	Gross Value Added (Mln.£)	5	ONS
43	CGOS	Gross Operating Surplus, Corporations (Mln.£)	5	ONS
44	NOSPC	Net Operating Surplus Private Non-Financial Corporations (Mln.£)	5	ONS
45	GFCF	Gross Fixed Capital Formation (Mln.£)	5	ONS
46	PSNCR	Public Sector Net Cash Requirement (Mln.£)	2	ONS
47	HSDEBT	Total Credit to Households and NPISH (Bln.£)	6	FRED
Production				
48	IPTOT	Production of Total Industry (Index 2010=100)	5	FRED
49	CBI	Changes in Inventories, Private Non-Financial Corp. (Mln.£)	1	ONS
50	IOPMIN	Index of Production, Mining and Quarrying (Index, 2011=100)	5	FRED
51	PIGMAN	Total Production of Investment Goods for Manufacturing (Index 2010=1.00)	5	OECD
52	PINTMAN	Total Production of Intermediate Goods for Manufacturing (Index 2010=1.00)	5	OECD
53	INVGN	Holding Gains On Inventories: Private Non-Financial Corp. (Mln.£)	2	OECD

No.	Mnemonic	Description	Tr.Code	Source
Employment and Hours				
54	LHUR	Unemployment Rate: All workers, 16 years & over (%)	5	ONS
55	EMPCIV	Civilian Employment of All Persons (Thousands of persons)	5	OECD
56	EMPSER	Adjusted Employment in Services (Thousands of persons)	5	OECD
57	AAHMAN	Average Annual Hours in Manufacturing (Index, 2002=100)	2	OECD
58	EMPMAN	Manufacturing Employment (Index, 2002=100)	5	OECD
59	EMPAGR	Agriculture Employment (Thousands of Persons)	5	OECD
60	SEMP	Self-Employment Jobs (Thousands of Persons)	5	OECD
61	EMPOP	Employment - Population Ratio (%)	1	ONS
62	LFPR	Labour Force Participation Rate (%)	2	ONS
63	LPROD	Labour Productivity, Output Per Filled Job (Index, 2011=100)	2	ONS
64	OUTHR	Labour Productivity, Output Per Hour Worked (Index, 2011 = 100)	2	ONS
65	ULCTOT	Total Benchmarked Unit Labour Costs (Index,2010=1.00)	5	FRED
66	ULCBS	Benchmarked Unit Labour Costs, Business Sector (Index,2010=1.00)	5	FRED
67	ULCIND	Benchmarked Unit Labour Costs, Industry (Index,2010=1.00)	5	FRED
68	ULCMAN	Total Unit Labour Cost, Manufacturing (Index, 2010=1.00)	5	FRED
69	HUMCAP	Index of Human Capital per Person	2	FRED
70	JOBWRK	Ratio of Whole Economy Jobs to Workers (Index,2006=100)	5	ONS
Price Indexes				
71	PPCOM	Producer Prices Commodities (Index,2010=100)	4	ONS
72	PPIMAN	Output Prices, All Manufactured Products (Index,2010=100)	4	ONS
73	PUNEW	CPI:All items (Index,2010=100)	4	OECD
74	PUF	Consumer Price Index Food (Index, 2010=100)	5	OECD
75	PUE	Consumer Price Index Energy (Index, 2010=100)	5	OECD

No.	Mnemonic	Description	Tr.Code	Source
76	TRETTR	Total Retail Trade (Index 2010=200)	5	OECD
77	PUXFE	CPI All items non-food non-energy (Index, 2010=100)	4	OECD
78	PUXMI	CPI: All Items Less Mortgage Interest Rate (Index, 2010=1.00)	5	OECD
Housing Starts and Sales				
79	PRCOMP	Permanent Dwellings Completed : Private enterprise (Number of Dwellings)	5	DCLG
80	HSPRNI	Permanent Dwellings Started: Private enterprise, NI (Number of Dwellings)	5	DCLG
81	HSPRSC	Permanent Dwellings Started: Private enterprise, SC (Number of Dwellings)	5	DCLG
82	HSWW	Permanent Dwellings Started: All, WW (Number of Dwellings)	5	DCLG
83	PERMIT	Permits Issued for Dwelling in UK (Index, 2010=100)	5	OECD
Earnings				
84	HEMAN	Hourly Earnings: Manufacturing (Index, 2010=1.00)	2	OECD
85	WEALL	Weekly Earnings: All Activities (Index, 2010=1.00)	2	OECD
86	AWEMAN	Average Weekly Earnings, Manufacturing (Index, 2010=100)	2	OECD
Consumption				
87	HCED	Household Consumption Expenditure: Durable Goods (Mln.£)	5	ONS
88	HCESD	Household Consumption Expenditure: Semi-Durable Goods (Mln.£)	5	ONS
89	HCEND	Household Consumption Expenditure: Non-Durable Goods (Mln.£)	5	ONS
90	HCESER	Household Consumption Expenditure: Services (Mln.£)	5	ONS
91	HCEHWE	Household Consumption Expenditure: Housing, Water, Electricity, Gas and Other Fuels (Mln.£)	5	ONS
92	GFCE	Government Final Consumption Expenditure (Bln.£)	5	ONS

No.	Mnemonic	Description	Tr.Code	Source
Balance of Payments				
93	BOPCUR	Balance of Payments : Current Account Balance (Mln.£)	2	ONS
94	BOPCAP	Balance of Payments : Financial and Capital Account Balance (Mln.£)	2	ONS
Miscellaneous				
95	CCI	Consumer Confidence Indicator	1	OECD
96	CBIBO	Business Optimism	1	CBI
97	NOCNST	New Orders, Construction	5	ONS

Note: We use the following abbreviations: *BoE*, Bank of England ; *WDI*, World Development Indicators; *IMF*, International Monetary Fund; *OECD*, Organisation for Economic Cooperation and Development; *FRED*, Federal Reserve Economic Data; *ONS*, Office for National Stati - stics; *DCLG*, Department for Communities and Local Government; *CBI*, Confederation of Business Industry.

CHAPTER 4

Concluding Remarks

This thesis analyses changes in the time-series properties of UK regional real estate prices and examines forecastability of the national and regional property price inflation. The following research topics are considered: (i) specification and estimation of the fundamental value model of regional real estate prices, (ii) testing for the presence of explosiveness in the property price series and dating the timeline of explosive dynamics, (iii) forecasting of house price inflation using static and dynamic econometric methods, and (iv) identification of the key economic variables driving property price movements during the periods of upswing and downturn in the real estate prices.

The first two topics are addressed in Chapter 2. In particular, this chapter analyses the behaviour of UK regional housing prices over the past four decades by employing the structural model of Gavin Cameron, John Muellbauer and Anthony Murphy (2006) and the recently developed recursive unit root tests of Peter C.B. Phillips and his co-authors (2011, 2015). We show that the estimated structural model of regional property prices is not able to capture the house price dynamics in the late 1980s and in the early and mid-2000s. Further, we demonstrate that these periods coincide with the episodes of explosive dynamics in the regional property price series identified using the recursive unit root procedure. The main conclusion that emerges from our analysis is that the regional real estate prices have experienced episodes of explosiveness that cannot be explained by movements in economic fundamentals. This finding suggests that non-fundamental factors, such as rational speculative bubbles, have played a crucial role in the dynamics of UK housing market over the last decades. In addition, it implies that the estimation results of conventional structural models of real estate prices should be interpreted with caution since they are based on the assumption, which is not supported by the data, that the series under investigation are non-explosive.

Chapter 3 investigates the ability of a battery of static and dynamic econometric models to forecast UK national and regional house price inflation over the last two decades. The contribution to the literature is fourfold. First, we show that models that allow for changes in both parameter estimates and the underlying model specification tend to produce much more accurate out-of-sample forecasts than models, where the number of house price predictors and marginal effects of those predictors are not time-varying. We demonstrate that the more rapid are the shifts in the coefficients and the set of house price predictors the better is the forecasting performance of the dynamic models. Second, we examine the performance of various forecasting methods over time and conclude that dynamic models, in particular the Dynamic Model Selection, are doing remarkably well in capturing the recent upswing in the real estate prices as well as some part of the recent house price collapse. On the other hand, we show that the forecasting strategies under consideration experience deterioration in predictive ability during the episodes of sharp reversals in the rates of property price inflation. Third, although we find that the number of property price predictors included in the dynamic model is stable over time, across regions and different forecast horizons, we are not able to identify a single predictor that consistently stands out as the key determinant of future property price movements. We demonstrate that the probabilities of including different predictive variables in the forecasting models vary considerably across regions, over time and across forecast horizons. Finally, we find that the main drivers of house price movements in volatile regions differ from those in stable housing markets. In particular, the indicator of credit availability and growth in industrial production are the main determinants of house price inflation in volatile real estate markets, while the stock of dwellings stands out as the most important predictor of the recent property price collapse in relatively stable housing markets.

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