UK Housing Bubbles and Contagion: Identification under Cross-Sectional Dependence and Spatial Heterogeneity

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Abstract

Recent trends in econometrics have led to a proliferation of statistical tools that lend themselves to data-driven evaluations of the housing market (Phillips et al., 2011, 2015; Bailey et al., 2016). This thesis evaluates the suitability of existing statistical procedures in the identification of explosive unit root processes, alongside the analysis of price diffusion in a time and cross-sectionally dependent system. Having date-stamped three regional housing bubbles consistent with the historical narrative, the predictive ability of macroeconomic and financial variables in bubble formation is estimated.

Implementing the multi-step procedure proposed by Bailey et al. (2016), we estimate a heterogeneous dynamic spatial autoregressive model of the English housing market. The spatial parameters yield unexpected results in contradiction to prevailing economic theories of spatial dependence that remain unaddressed in the literature. To this end, we derive a unifying framework that captures the endemically heterogeneous characteristics of house price spillovers with joint treatment of common factors without loss of generality. The STARF model presents a parsimonious representation of house price diffusion with directional analysis of spillovers and identification of dominant units in the network. The derived spatial and system-wide diffusion multipliers provide meaningful insights into how a perturbation in neighbourhood house price inflation impacts a given district over a specified time horizon. The results reflect the London-centric ripple effect as a dominant factor while core-periphery spillovers dominate in urbanised areas. This thesis contributes a salient evaluation of housing dynamics and network effects consistent with theories of rational bubbles, new economic geography and spatial dependence.

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Chapter 1

Introduction

Residential property possesses a variety of disparate, near incompatible characteristics that culminate in a complex effect on the wider economy. It is both a durable consumption good, distributing a service stream, and an asset effectuating capital accruals or losses (Beatty et al., 2010; Muellbauer and Murphy, 2008). At the individual level, housing fulfils the basic necessity of shelter (Abraham and Hendershott, 1996; Capozza et al., 2002; Meen, 2002; Otto, 2007; Abelson et al., 2005), while concurrently functioning as a store of purchasing power (Zhu, 2005; Barker, 2005). The housing market itself is mired by high transaction costs, low turnover volumes and complications arising from pricing a highly heterogenous good under a distinctly asymmetric information setting. In the wake of the Global Financial Crisis (GFC), the deep and complex interlinkages between housing market have become painfully apparent, as financial innovations have fuelled contagion effects across geographical segments and asset classes (Bernanke et al., 1996).

While global real estate markets have had a shared experience of increased volatility, the UK presents a unique system of housing conditions. London house prices are consistently ranked amongst the highest in the world, and remain sustained across the country[1] (**?**). Real house prices have increased at a rate unsurpassed by any other OECD country. In comparison to our OECD counterparts, the UK economy is particularly affected by changes within the housing market due to a steady increase over time in the value added of the real estate sector. This has almost doubled since 1990 where the property sector contributed 6 percent of output[2], compared

[1]Compared to more densely populated countries, a new house is 38% or 40% smaller in London than in Germany or Netherlands respectively

[2]measured in terms of gross value added (GVA)

to 12 percent in 2013.[3] In light of this, the UK is considerably higher than the OECD and G7 average, accentuating the expanding role of housing in the UK economy[4].

The recessionary wielding powers of the property market has firmly placed housing market dynamics at the heart of the macroeconomic stability agenda in the the 21st century (Forni et al., 2003). Recent trends in econometrics have led to a proliferation of statistical tools that lend themselves to data driven evaluations of the housing market (Phillips et al., 2011, 2015; Bailey et al., 2016). We are able to analyse the suitability of existing statistical procedures in gleaning meaningful insights in practical applications. In doing this, we fill this lacuna for a unifying framework able to capture the endemically heterogenous characteristics of house prices alongside global impacts of macroeconomic factors without loss of generality. This thesis contributes a salient evaluation of house price dynamics and network effects consistent with theories of rational bubbles, the new economic geography and spatial dependence in the housing context.

1.1 Overview

1.1.1 Housing Bubbles

Historically, the housing market has played a primary role in financial crises, with housing booms preceding sluggish economic growth. Chapter 2 contributes to understanding this mechanism by evaluating the formation of bubbles in regional segments of the housing market between 1983(1) to 2014(4). By contrasting the experience of prices with their fundamentals, we ascertain whether explosive episodes are driven by fundamentals or speculative behaviour reconcilable with the notion of an asset price bubble. We contribute to the existing literature by identifying periods of exuberance in the regional housing market using a data driven approach. Common criticisms of data driven methods pertain to failure to taking into consideration qualitative factors and the economic context. We account for this by providing a in-depth historical analysis of the identified periods. Furthermore, we contribute the first study to provide a robust analysis of the role of financial and macroeconomic variables in predicting explosive trends in the UK housing market, accounting for regional differences. To this end, the correlated random effects model is

[3]This value balloons further from 12 percent to 25 percent when sectors relating to the property market are included; these are as finance, real estate and construction.

[4]See International Monetary Fund (2014) for a detailed account

estimated using the Mundlak-Chamberlain correction to control for region specific heterogeneity. While studies have considered changes in stock prices, interest rates and income (Muellbauer and Cameron, 2006), the results highlight the predictive content of the unemployment rate across regions that has not been evaluated in the existing literature.

The testing outcomes reveal two prominent bubbles materialise, firstly in the late eighties to early nineties, followed by a greater peak in the noughties. In the first episode during the early nineties, our findings indicate southern regions are typically the first to experience the advent of explosive growth, before nearby regions successively sharing the same experience from the mid nineties. The length of bubbles also tend to decrease as distance from the southern areas increases, leading to Northern regions experiencing a shorter exuberant period. These episodes are unmatched by explosive growth in fundamentals, indicating bubbles persisted across regions during the late nineties to early noughties.

There is a decoupling of this spatial relationship during the GFC, where we find bubbles materialise across regions contemporaneously, lasting for two years on average. The results present evidence of the ripple effect initially, however in recent periods there is a decoupling of this pattern when considering how the first bubble transpires across regions compare to the second bubble in the early 2000s episode. Unexpectedly, real house prices in Yorkshire first experiences bubble behaviour in mid 2007, before being detected further north and further south over the successive year. We note less evidence of the ripple effect perhaps due to more interconnectedness between regional housing markets and credit conditions. The duration of exuberance is lower than the preceding boom, with most regions failing to exceed two years in price and affordability measures. Cross referencing these periods with historical events, we find the episodes are explained by the macroeconomic context (Muellbauer and Murphy, 2008).

The unemployment rate is found to be a good predictor of regional bubbles across England, particularly in Northern areas. We find the marginal effect in predicting exuberant episodes is particularly weak in London. The findings indicate underlying structural differences across regions with housing bubbles in the south driven less by economic factors (such as unemployment) than in northern regions. In contrast to this, changes in disposable income have no power in predicting exuberance in the price to earnings ratio, and an extremely low marginal impact in predicting explosivity in prices. Our findings are consistent with Muellbauer and Cameron (2006) who also find that region specific income growth rates hold surprisingly little explanatory power with respect to house prices. As expected, interest rates are found to be predictive of exuberant episodes. We note that as the Bank of England official bank rate decreases, the probability of exuberance in the housing market increases, both in reference to price and affordability measures. These findings support concerns pertaining to monetary policy creating a chronically low interest rate environment since the GFC, potentially instigating exuberance in the property market. These concerns may be materialising given the detected bubble in the South West commencing in 2014.

1.1.2 Spatio-Temporal Models of the Housing Market

Recent developments in panel data methods have precipitated substantial progress in characterising and modelling cross-sectional dependence (CSD). It has become increasingly apparent that panel data models ignoring CSD may suffer from biased and inconsistent estimates (Chudik et al., 2011; Pace et al., 2000). Nonetheless, the majority of studies fail to account for local and global forms of CSD (Rapach and Strauss, 2009; Gupta and Das, 2010; Kuethe and Pede, 2011). Previous studies have often focused on the spatial effects (Whittle, 1954; Anselin, 1988; Kelejian and Prucha, 1999; Lee, 2004) or common effects[5].

The interdependence between cross sectional units in the housing literature is a widely recognised (Can, 1990; Gillen et al., 2001; Basu and Thibodeau, 1998). Houses are often constructed at the same time in a given area leading to commonalities in dwelling age, building materials, and architectural features. Secondly, houses within the same area may capitalise on shared amenities that are reflected in the property price. For example, proximity to public services and accessibility benefits are common across the neighbourhood (Can, 1990). House prices are a function of these characteristics and shared amenities, leading to house prices clustering across geographical areas (Gillen et al., 2001). These relationships between cross-sectional units may be characterised by spatial econometric models.

From a computational perspective, subregional house price data provides a rich environment to evaluate the dynamics of the property market in detail (Brakman et al., 2009). Decisions affecting residential property prices have the scope to be implemented at the district level, and

[5]See Hotelling (1933); Stone (1947); Bai (2003); Stock and Watson (2003)

as such, a greater understanding of the effect an area has on nearby districts may precipitate a more cohesive housing policy on aggregate. While some studies utilise regional data, few favour the district level disaggregation applied in Chapters 3 and 4. The analysis put forward in this thesis captures the heterogeneity within regions that is shown to be a prevalent feature across both models. Local government plays a vital role in housing, local planning and building strategy at the local authority district level. Delineating the housing market into districts, we are able to capture whether the differences arising from administrative structures affect the transmission of house price inflation between neighbourhoods. Some districts may be highly affected by neighbourhood house price inflation, while others behave less interdependently. We summarise the key findings from both estimation methods.

Estimation under Bailey et al. (2016) Model

Chapter 3 continues in the tradition of panel estimation under network dependence (Anselin, 1988; Elhorst, 2003; Baltagi, 2005; Anselin et al., 2008; Kapoor et al., 2007; Fingleton, 2008, 2010) with a focus on revealing the spatial structure of house prices diffusion in England. The results confirm a factor structure exists. Estimation methods that do not explicitly account for the factor structure may overstate spillover effects[6]. After accounting for common factor regional and national effects, evidence of spatial dependence is found in two thirds of regions indicating interdependencies between neighbourhoods. The results highlight both positive and an unexpectedly high incidence of negative spillover effects.

We extend our analysis by deriving spill-in and spill-out effects following a partial derivative decomposition of the impacts of persistence in house prices. This approach extends the analytical framework put forward in BHP to allow for directional analysis of district level impacts on their respective neighbours and vice versa. However, these measures also suffer from a high level of negative values that are incompatible with theories of spatial spillover effects in the literature pertaining to neighbourhood effects, migration and capital transfer and follower behaviour (Gill, 2012). In reference to the ripple effect hypothesis, our results indicate a more nuanced spatial impact than the theory implies, where areas with higher levels of economic activity find stronger spillover effects that are not unique to London areas but also districts surrounding cities such as

[6] Assuming factors are positively related to house price inflation.

Nottingham and Sheffield.

The results indicate region or nation wide policies may serve to increase divergence in house price inflation across districts, as clusters of areas are not only more susceptible to impacts of house price growth in neighbouring areas, but also vary in terms of the impact having either negative or positive long run impacts. As local government is able to control housing policy at the district level, the findings suggest cities and transport networks play a key role in the propagation of multiplier effects.

Estimation under STARF Model

Motivated by the unexpectedly negative spatial estimates derived from the procedure put forward in Bailey et al. (2016), we derive a heterogeneous model of house prices in England using a novel dynamic spatial panel model put forward by Shin (forthcoming). The STARF model presents a parsimonious representation of house price diffusion with joint treatment of common factors and spatial dependence.

The derived spatial and system wide diffusion multipliers provide meaningful insights into how a perturbation in neighbourhood house price inflation impacts a given district over a given time horizon. Our findings indicate rural areas experience stronger spatial dependence that may be attributed to increased reliance on nearby urban areas for services and commodities. Cumulative dynamic multipliers with respect to neighbourhood house price changes, we find that more urban areas are characterised by faster rates of adjustment. This may be explained by more individuals in densely populated areas serving to pass on information signals pertaining to changes in neighbourhood house prices and developments in amenities between districts at a more efficient rate compared to their rural counterparts. This may be explained by higher levels of commuters travelling to urban areas and higher provision of services and commodities in urban settlements. Lending from the network literature, we estimate in-degree and out-degree measures for a directional analysis of house price spillovers. Ranking these out-degree effects we identify periphery areas to economic centres have the most influence on neighbourhood house price changes. The findings underscore preferences for convenience and low commuting times may often be at odds to good quality air and landscapes.

In contrast to the ripple effect, we hypothesise periphery areas surrounding cities play a primary role in propagating spillover effects to the neighbouring regions, accordant with the core-periphery and new economic geography framework (Berry, 1969; Krugman, 1997). The importance of the physical characteristics of the periphery areas is integral in the formation of our hypothesis, while the ripple effect is underpinned by urbanisation effects. The importance of these geographic characteristics are consistent with **?**Saiz (2010) who find areas facing geographical or regulatory constraints[7] experience low elasticities of supply which are in turn endogenous to price growth. The areas that are able to provide both sets of attributes are found to be dominant units in influencing house prices in a given area. The findings in this chapter confirm the importance of proximity to economic centres in influencing house price inflation in nearby areas, aligning with the findings of Fik et al. (2003). These findings may reflect the London-centric ripple effect as a dominant factor while the core-periphery spillover effect would be dominant at higher levels of urbanisation. Our findings may also reflect the time-varying nature of the house price inflation spillover as we note the variation in the speed of adjustment between urban and rural areas.

1.2 Outline

The rest of the thesis is structured as follows. Chapter 2 identifies and dates-stamps exuberance in regional housing markets during 1983(1) to 2014(4) using the econometric procedures devised by Phillips et al. (2011, 2015). We identify two bubbles common across regions during the mid nineties and noughties which are compatible with the historical narrative. Additionally, we extend our analysis by considering the predictive ability of financial and macroeconomic variables in anticipating explosive growth in the housing market. Estimating a correlated random effects probit model, we identify a set of significant variables including unemployment as potential predictors of exuberance in the housing market, that has previously been overlooked in the literature. Chapter 3 constructs a spatio-temporal model of house price changes in England following the BHP methodology. We derive spill-in and spill-out measures to provide a directional analysis of spill over effects. While the results highlight the heterogenous nature of spatial dependence across districts, the prevalence of negative spillover effects is unexpected. Given theories of spatial dependence in the housing market predominantly endorse positive spillover

[7]The green belt is a prominent example of regulatory constraints.

effects, the outcomes from this method are problematic. In response to this, Chapter 4 proposes a spatio-temporal model with factors devised by Shin (forthcoming) which generates results in line with the economic theories pertaining to spillover effects in the housing market. Furthermore, we derive dynamic multipliers with respect to neighbourhood price changes and system wide diffusion multipliers. The results highlight core-periphery relationships that are analysed in the urban/rural context. Finally, Chapter 5 outlines the limitations of the research, alongside policy recommendations and potential venues for future research work.

Chapter 2

Testing for Multiple Episodes of Exuberance in the UK Regional Housing Market

2.1 Introduction

The Global Financial Crisis (GFC) triggered by the US sub-prime mortgage market has served to attracted a renewed interest in housing market dynamics. The depth of the subsequent recession marked the longest downturn on record[1] in the UK (Hincks et al., 2014). Asset bubbles are a long-standing subject of interest for both theoretical and empirical research. This chapter employs the novel method of Phillips et al. (2011) and Phillips et al. (2015) for testing and date stamping exuberant episodes in asset prices to detect bubble behaviour across UK regions throughout the past thirty years. Through the analysis of time series properties of regional house prices, our research contribution is twofold; firstly we are able to identify the date stamp when house price appreciation mutates into exuberance for each area. Secondly, our findings illustrate the synchronisation of regional segments of the housing market which ultimately improve our understanding of how national UK house price bubbles materialise through inspection of the disaggregate components. In the context of the extensive literature surrounding the transmission of house price shocks to surrounding areas, this chapter finds mixed evidence supporting the established 'ripple effect' hypothesis.

By addressing these research aims, we further the framework for both monitoring and under-

[1]Since quarterly data began publication in 1955. Measured in terms of gross domestic product

standing the UK housing market. The policy implications are both retrospective in the analysis of past bubble formation, but also proactive in furthering the existing framework of anticipating episodes of exuberance. This ultimately leads to the design of effective policy. Additionally, these methods serve as an early warning diagnostic of bubble activity for UK regions. Our research provides the starting point for further analysis into what are the fundamental antecedent factors in the evolution of house price exuberance.

The results indicate two bubbles transpire across the tested period, firstly in the late eighties to early nineties, followed by a greater peak in the noughties. GSADF and SADF testing substantiates house prices were explosive for all regions during both peaks, however the severity of house price appreciation and ensuing decline vary across regions. While the duration and scale may vary, the severity of house price appreciation and ensuing decline vary from region to region similarities in the hypothesis testing results affirm fundamental house price drivers are common among regions. The first bubble detected is more distinctive than the noughties episode. The latter manifests a largely undisrupted protracted period of exuberance for some regions such as Scotland and the South West, while other regions have more fractious experiences of explosive prices that could be disaggregated to two smaller peaks; the first in and around 2005, preceding the larger peak in 2008. While some general trends are shared between price and affordability anchors in terms of testing for exuberance, the results demonstrate a far higher incidence of rejections of the null hypothesis for testing prices compared to both tested ratios, indicating several exuberant episodes are not driven by fundamentals but may be attributed to speculative forces (Shiller, 2014).

The rest of the chapter is organised as follows. Section 2.2 outlines the relevant literature in terms of bubbles in the UK housing market and detecting periods of explosive growth in a given asset class. Section 2.3 summarises the data selection. Section 2.4 specifies the model and describes the process of testing and date-stamping periods of explosive growth in the housing market. Section 2.5 proposes the correlated random effects model to analyse the ability of macroeconomic and financial variables to predict periods of exuberance in the housing market. Section 2.6 presents an analysis of the estimated results, and Section 2.7 concludes.

2.2 Related Literature

2.2.1 UK Housing Market Bubbles

Regional house prices in the UK have been intensively researched using a range of techniques. These studies range from aggregate and regional studies of house price fundamentals and the presence and of bubbles. Please refer to Muellbauer and Cameron (2006) for an exposition of the UK regional house price literature. The range of fundamentals vary from paper to paper, but typically include income, stock of housing, interest rates, credit conditions and demographic factors. Notable studies of this class are (Muellbauer and Murphy, 1997) and (Muellbauer and Cameron, 2006).

The most prevailing theory of regional house price trasmission is the 'ripple effect' hypothesis developed in the seminal work of Meen (1999). The term refers to "a distinct spatial pattern over time, rising first in a cyclical upswing in the south-east and, then, spreading out over the rest of the country." Meen (1999). This shock may ripple out across the economy through migration, equity transfers, spatial arbitrage and other variables that play a determinant role. Meen (1999) puts forward a convincing case outlining the theoretical underpinning of the hypothesised effect. Numerous studies have explored this hypothesis including Macdonald and Taylor (1993); Alexander and Barrow (1994); Drake (1995); Ashworth and Parker (1997); Meen (1999); Peterson et al. (2002); Cook and Thomas (2003); Cook (2005); Holmes and Grimes (2008); Holmes et al. (2011).

Empirical investigations have often revised the boundaries of what constitutes the ripple effect. Drake (1995) finds house price changes occur more substantially and imminently in South-east England compared to other regions as evidence of this. Studies conducted by Macdonald and Taylor (1993); Cook (2005) find evidence of an asymmetric 'ripple effect'. The term refers to a "consistent pattern of reversion to equilibrium occurring more rapidly when housing prices in the south of England decrease relative to those of other regions and occurring in a slower place when the prices increase relative to that of other regions" (Tsai, 2014).

Empirical estimation techniques have also varied in their detection methods. While some research has opted for Granger causality testing, others have employed a Vector Autoregressive (VAR) model in order to capture a leader follower pattern of behaviour between regions Kuethe and Pede (2011); Gupta and Miller (2012). Cointegration tests have also been used by authors including Macdonald and Taylor (1993); Alexander and Barrow (1994); Ashworth and Parker (1997), utilising the work of Engle and Granger (1987) and Johansen (1988). Given the date stamping attributes of the bubble detection method this chapter uses, we are able to analyse whether our finds are congruous with the 'ripple effect' hypothesis. Following the framework of Drake (1995), bubbles are hypothesised to begin first in the South East region before detection in other areas in subsequent periods.

Regional and national house price ratios are often applied Meen (1999); Peterson et al. (2002) for stationarity testing where the objective is to find whether affordability and relative price ratios show constancy.If the house price to earnings ratio is nonstationary, a shock would have a permanent effect thus decreasing the probability for the series to revert to initial pre-shock levels (Gregoriou et al., 2014). Accordingly, stationarity properties can indicate the long run outlook for the housing market alongside providing evidence in relation to the ripple effect (Cook, 2005).

A range of empirical papers consider housing affordability. Girouard et al. (2006) test for unit roots in house price to income ratios across 18 OECD countries spanning 35 years; the findings indicate the presence of unit roots cannot be rejected. Similarly, Malpezzi (1999) also find nonstationarity across a panel of 133 maj metropolitan areas in American from 1979-96. More recently, Gregoriou et al. (2014) test the UK and desegregate regions and are unable to reject the the trends contain a unit root between 1983 and 2009. These findings are relatively robust given the allowance for structural breaks and use of both linear and non linear unit root tests.

The relationship between income and house prices are considered in Muellbauer and Murphy (2008) in which the findings indicate long-run elasticity of house prices with respect to non-property income relative to the housing stock are both positive and surpass unity at 1.6, while also asserting most instances of house price increases since 1997 are attributable to corresponding rises in average real income per household. These findings are in accordance with Muellbauer and Cameron (2006) in which income dynamics are found to be significant determinants of house prices when tested on a regional panel of UK house prices. The linkage is most prominent in London and the Southeast. In terms of bubble detection, the results conclude a bubble cannot be precluded during the late eighties.

2.2.2 Identifying Asset Price Bubbles

The existence of bubbles in asset markets remains one of the fundamental debates in economics and finance, yet challenges to crafting suitable tests for bubbles have prevented an empirically-driven resolution to the discourse (Giglio et al., 2014). In the literature there is debate even with regard to the definition of bubbles. The asset pricing approach defines a bubble as the proportion of the market price overshoots or undershoots the fundamental value of the asset (West, 1987; Diba and Grossman, 1988; van Norden, 1996). Muellbauer and Murphy (2008) state 'the deviation of prices from their long run fundamentals is then the 'bubble- burster' in reference to house prices may appreciate by the agency of a series of positive shocks to fundamentals. The expectation of future price increases precipitates over-valuation of the asset. Eventually the realisation that appreciation in fundamentals has been outstripped by house price growth instigates a deceleration of price increases. Based on this, the detection of a bubble involves estimating the fundamental drivers of asset prices, such as income. The fundamental price refers to the discounted present value of payoff streams based on all information presently available (Taipalus, 2012). As surmised by Brunnermeier and Oehmke (2013) "identifying bubbles in the data is a challenging task. The reason is that in order to identify a bubble, one needs to know an assets fundamental value, which is usually difficult to measure."

The literature also encompasses alternative methods where the fundamental asset value does not require modelling. These span from the Markov-Switching process method (Hall et al., 1999) to the logistic curve approach (Foster and Wild, 1999). The former method devised by Hall et al. (1999) discerns between explosive and non explosive periods, captured using Markov chains. The explosive periods are characterised by an explosive autoregressive unit root. The Markov switching Augmented Dickey Fuller (MSADF) test detects the explosive AR process where bubble and non bubble regimes are defined.

The test suffers from low power in the presence of high volatility as the distinction between high volatility and explosive autoregressive unit root is not always distinguishable in GSADF testing. This issue is especially notable in light of asset price volatility often being pervasive. While the Markov switching process is prone to misspecification owed to MSADF testing sensitivity (as discussed further in Shi (2013)), this method has the added benefit of multiple bubble detection capabilities.

Similar to the present chapter, Black et al. (2006) investigates the connection between house prices and earnings also utilising the present-value approach adapted from the stock market research undertaken by Campbell and Shiller (1998). Under this framework, the paper estimates the fundamental housing value in relation to real disposable income. Akin to the method employed in Case and Shiller (2003), they employ cointegration and unit root testing to find evidence of a cointegrated relationship between variables in contrast to stationarity in the UK house price to income ratio. While the unit root test findings are not robust given the standard linear unit root testing employed and the effect of extended upswing periods, the overall findings indicate UK housing market is unaffected by explosive bouts of exuberance. These findings may be debated given the weak evidence from unit root testing and the possibility of intrinsic mispricing typical within the property market (Muellbauer and Murphy, 2008). The effects may be sustained such that upswings are smoothed and gradual (André, 2011), thus accounting for the empirical results obtained by (Black et al., 2006).

2.3 Data

Regional house price and housing affordability data is used to identify explosive growth periods. The results derived from GSADF and SADF tests are then regressed against macroeconomic and financial variables to ascertain the predictive power of exuberant episodes.

We use quarterly data recorded by the UK mortgage lender Halifaxover the period 1983(1) to 2014(4). Data is collected across these regions aggregating to form the UK; namely: North (N), Yorkshire & The Humber (YH), North West (NW), East Midlands (EM), West Midlands (WM), East Anglia (EA), Wales (W), South West (SW), South East (SE), Greater London (GL), Northern Ireland (NI) and Scotland (S). Three datasets are considered; these include the House Price Index (HPI henceforth), House Price to Earnings Ratio (HPER) and Mortgage to Earnings Ratio (MER). The Halifax House Price Index have been described as a "good compromise between accuracy and timeliness" (Wood, 2005, p. 218). Similar to the Nationwide housing indices, the data uses hedonic regression methods for quality adjusting the data allowing for like for like comparisons between houses in different regions. The indices provided by both building societies are more encompassing than their mixed adjusted counterparts.

The hedonic regression method specifies a set a characteristics which contribute in different ways to the price of the house. The weighting and treatment of each characteristic actualise the majority of differences between the Halifax and Nationwide statistics. while this approach enables comparisons to be drawn between regions, the framework comes with drawbacks. A well documented failing pertains to the sample selection bias from the collection of only a single mortgage lender, unlike for example the Land Registry House Price Index that is not consigned to a single bank or building society. However, among the two hedonic regression based house price indices, Nationwide has a smaller dataset thus exacerbating the bias compared to the Halifax HPI. The index is adjusted for inflation using the private consumption deflator for the UK accessed through the OECD statistical database.

Ratios of housing prices to income and rents are often used as indicators of over valuation of housing prices . House price to income ratios are a measure of the affordability of property as they gauge whether housing is within the reach of a typical buyer. Deviations between house prices and income growth are in theory unable to diverge indefinitely (André et al., 2014) as households will eventually be unable to afford property thus reducing demand resulting in downward pressure on house prices, lowering to the new market clearing rate. If this ratio exceeds its long term average trend, it can be take as evidence that prices are overvalued (Girouard et al., 2006).

The house price to earnings ratio variable produced by Halifax is estimated as the ratio of Halifax standardised average house prices for all houses and all buyers, to the average earnings for full-time male employees. The standardisation accounts for variations through the use of hedonic regression method outlined above. By only incorporating male only earnings, results for HPER may result as biased from overestimation of the severity of non-affordability (Gregoriou et al., 2014). Incorporating male only earnings may have been suitable in the context of 1983 when data was first collected, however the bias caused can be attributed to the rise of both individuals in a housing unit often earning, so they are able to share the burden of mortgage repayment costs. Data from the 1991 census reveals 23.81 per cent of owner occupied households are headed by women with these households generally comprising of single women (Gilroy and Woods, 1994). By only including male only earnings, this considerable demographic , which has increased since 1991, is excluded from the housing affordability measure. Furthermore, the

General Household Survey 1991 identifies married couples comprise a far higher percentage (77%) than any other group. This trend has only continued based on The English Housing Survey 2014-15 identifying more first time buyer households were couples than single people, compared with 20 years ago (DCLG (Department for Communities and Local Government), 2015). The study notes 80% of all first time buyers were couple households, a significant increase since 1994-95 (63%) and 2004-05 (62%). The report ascribes this trend to the growing need for two incomes for households to afford purchasing property. Based on these identified trends, the bias increases over the timespan, as households increasingly rely on both male and female earnings to shoulder mortgage costs.

The use of male only full time earnings also induces bias from the exclusion of part time income and individuals participating in the 'gig' economy. The rising number of workers participating in these more flexible forms of employment result in full-time earnings painting a less representative measure of household earnings. Congruent to the bias from exclusion of female earnings, the use of full-time income in the affordability measure also leads to an underestimation of bubbles in housing markets, with this bias increasing over the time-span. Despite these drawbacks, the dataset benefits from a large time frame, comprehensive coverage and regional comparisons can be easily drawn. In light of these advantages, we opt to retain use of the Halifax dataset with the drawbacks in mind.

The price to income ratio is often used as a bubble indicator. A popular justification is given by (Case and Shiller, 2003, p.308) where the relationship between these two components in the US case are shown to be very stable across time. The paper finds in most instances that when this ratio increases, it later regresses back to an historical average (Case and Shiller, 2003, p. 311). These findings are compatible with the characteristics of bubble behaviour and the desirable traits of a "bubble indicator" set out by (Lind, 2009, p. 84), where "the purpose of the indicators is to identify cases where a strong increase in the price is (more) likely to be followed by a decrease".

For a given substantial house price increase, the price to income ratio will most likely also demonstrate an increase given changes in income tend to be incremental and less prone to sudden changes proportional to house prices. Ideally an indicator should draw a distinction between the situation where an appreciation in the price to income ratio is likely to be followed by a notable decline, from the situation where this is not probable. Case and Shiller (2003) propose a simple workaround whereby a significant increase in the price to income ratio will always be followed by a fall, such that no specific indicator is necessary (Lind, 2009). McCarthy and Peach (2004); Himmelberg et al. (2005) warn against this mechanistic use of the price to income ratio as a bubble indicator. Accordingly, agents may be more sensitive to the relationship between housing expenditure and earnings as opposed to price and earnings, hence we employ the use of the mortgage to earning ratio.

Smith and Smith (2006) also prefer mortgage to income compared to to the price to income variable given that mortgages are more accurate indications of payments made by households McCarthy and Peach (2004). This is partly attributable to mortgages often reflecting changes in interest rates, but measurement difficulties exist from variations such as interest rates are typically lower when the payment period is longer.

2.3.1 Data Trends

Figure 2.1 demonstrates the regional variation in both real house prices and affordability over time. Normalised to the start date, we are able to map how house prices and affordability across regions has diverged over the past thirty years. These trends underscore our motivation to cultivate a deeper understanding of how these variations have evolved over time and why regional dynamics have continued to branch further apart from the late nineties onwards. As noted by Chamberlin (2009), regional house prices show a uniformity in their experience of appreciation and decline over time, albeit at varying rates of adjustment.[2]

Up until the late eighties, we note a marked divergence across regions, with Greater London and the South East appreciating faster than other regions throughout the mid to late eighties. While the effect looks modest in figure 2.1, this increase was accompanied with a period of high inflation, masking the steep price increase across a short time scale. In contrast, Scotland, North West and North depict the lowest speeds of increase. This North-South regional disparity continues across the following decades, further exacerbated during boom periods, with Southern regions showing a greater proclivity to increment over boom periods, while bust periods tend to

[2]Contrastively, the US experience bears a differentiated narrative, where regional trends were much more divergent. In this respect, several areas experienced sharp declines in house prices while the national house prices were at an all time high.

narrow the disparity between regions, notably in the late nineties. However, this contractionary effect between regional prices decreases over time, leading to a sustained and widened gap between London and the southern regions compared to the northern areas of the UK. Affordability demonstrates a relatively similar reflection of trends in real house prices until more recent periods. We note similar levels of appreciation from 1983 to 1989 where both real house prices and mortgage to earnings both just over doubled. However, as one would expect from an affordability measure, the dynamics are less pronounced compared to real house prices, reflected in the range of values across both series.

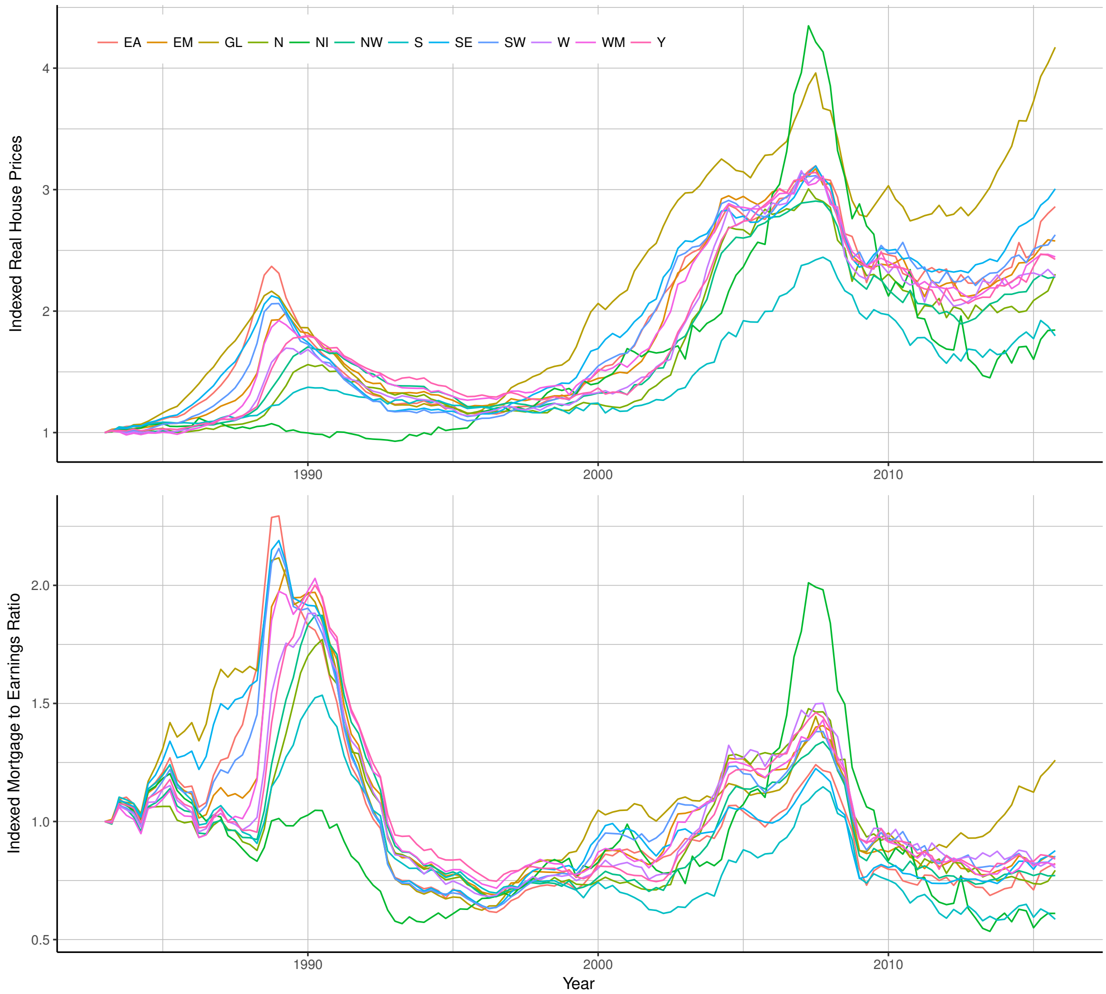


Figure 2.1: Normalised Real House Prices and Mortgage to Earnings by Region over Time (Index:1983Q1=1)

These divaricating trends are representative of a decoupling of regional housing markets, engendering labour inflexibility, income inequality among a host of other derivative impacts across the wider economy. While housing affordability explains parts of this puzzle, it is unable to capture how regions may have different sensitivities to changes in the macroeconomic and financial environment. Under the assumption that an equilibrium relationship exists between between house prices and income, the two variables can themselves evolve over time linked with other fundamentals. This relationship has changed due to structural shifts in financial markets and institutional changes that have exerted varying levels of pressures across regions (Campbell and Cocco, 2007). The proposed model is able to capture potential regional heterogeneity from the impact of these macroeconomic variables.

Two notable examples are credit availability and the interest rate regime. In the mid-1980s financial deregulation led to a rapid easing of credit constraints, making it easier to borrow larger sums for housing purchases (Chamberlin, 2009). As discussed in Evans and McCormick (1994), the effect of financial liberalisation was greatest in the South due to a larger oner occupied sector and buoyant expected growth rates in an already high price environment. Hence, McCormick (1997) reason the easing of credit conditions contribute to the increased relative sensitivity to interest rate fluctuations in the South. The authors posit the increased cyclicality in the more prosperous southern regions and rationing of incremental loans in this period has promoted increase differentials in regional unemployment. Ashworth and Parker (1997) finds low income elasticity in the South East that may be a possible impact of unemployment. As such, we find it pertinent to estimate the impact of unemployment on bubble formation.

Short term interest rates and long term bond yields are included in our model to account for the impact of shifts in the credit environment on the formation of bubbles across regions and to measure how this impact has affected regions differently. The shift towards inflation targeting from 1993 has coincided with a protracted low interest rate environment, depressing the cost of borrowing and incentivising households to purchase mortgages. We account for these changes by incorporating the official bank rate in our estimated model. The final model also includes alternative asset classes to capture the financial characteristics of housing when purposed in the context of a commodity. The commodification of housing is likely to be most strongly experienced in London and southern regions given higher levels of foreign investment and 'Buy to Let' purchases (Wallace et al., 2017). While there is an distinct lack of statistics pertaining to the scale of investment outside of London, it is widely accepted that the prevalence of foreign investment in residential property is higher in London compared to other regions (Savills, 2014). As such, we expect growth in alternative asset classes such as gold and shares to be related to booms in the London and southern housing submarkets. In more recent periods, we expect this relationship to be heightened given how property has increasingly become a mainstay of investor portfolios (Chan et al., 2011).

Summary statistics are provided for nominal house prices, real house prices, house price to earnings and mortgage to earnings ratio in Table 2.2. In both nominal and real terms, house prices are highest in greater London on average across the sample. However, while affordability ratios identify Greater London as relatively unaffordable, it is superseded by South East England as the most unaffordable region on average. The level of variation is much higher in Greater London in both real and nominal terms than all other regions. The difference is less pronounced in the mortgage to earnings ratio, with the South East and South West both demonstrating higher levels of dispersion to Greater London. The South East in particular shows a larger range in values, with the mortgage to earnings ratio reaching as high as 99.8. The lowest variation in affordability ratios is experienced in the Northern regions, particularly in Scotland, North West and North.

Table 2.1: Summary Statistics of Financial and Macroeconomic Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Unemployment	6.947	1.653	4.7	10.6	111
10 year Government Bond Yield	5.777	2.693	1.681	12.172	111
Official Bank Rate	5.268	3.884	0.5	14.875	111
Real Disposable Income Per Capita	3837.928	609.139	2649	4535	111
FTSE100 index	85.568	27.858	33.018	126.578	111
Δ FTSE100	0.741	4.954	-20.132	11.031	111
Gold Price	391.204	278.172	161.819	1076.126	111
Δ Gold Price	1.157	6.471	-12.41	25.063	111
Oil Price	44.979	30.793	12.93	123.78	111
Δ Oil Price	1.916	14.411	-50.393	47.552	111
Current Account	-7417.306	6786.693	-32662	1018	111
Δ Current Account	48.747	355.327	-462.868	3043.456	111

Table 2.2: Summary Statistics for House Prices and Affordability Ratios

	Nominal House Prices				**Real House Prices**			
Area	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
EA	390.853	170.469	190.1	712.033	196.943	61.604	112.461	311.761
EM	387.438	166.126	178.4	648.6	195.313	59.807	118.634	310.993
GL	474.64	238.562	190.4	1045.172	235.33	85.396	113.86	409.459
N	350.581	156.891	133.2	619.1	176.025	57.154	108.958	296.849
NI	342.476	191.076	126.4	892.800	170.713	79.601	91.409	428.083
NW	358.647	149.982	144.8	604	180.896	52.445	118.446	287.834
S	296.494	112.901	136.1	502.1	150.076	35.670	111.33	238.322
SE	402.186	177.863	181.2	753.135	201.733	24.800	111.208	313.439
SW	393.641	175.027	183	665.172	197.696	63.588	108.733	311.179
W	371.58	167.225	154.6	648.5	186.493	60.374	113.271	313.889
WM	394.612	162.117	179.7	655.300	199.3	56.973	126.766	311.287
YH	378.561	161.614	146.9	648.4	190.754	56.965	120.164	310.898
UK	378.476	175.461	126.4	1045.172	190.106	64.977	91.409	428.083

	Mortgage to Earnings				**House Price to Earnings**			
Area	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
EA	34.071	13.062	21.818	81.332	4.247	0.825	3.141	6.871
EM	32.675	10.867	21.701	65.327	4.102	0.852	2.942	5.537
GL	41.77	13.28	24.112	81.711	4.926	1.404	2.928	9.629
N	29.186	8.662	20.341	53.016	3.786	0.939	2.555	5.918
NI	28.151	10.143	17.035	64.064	-	-	-	-
NW	29.253	9.140	20.661	57.033	3.693	0.764	2.595	5.062
S	27.542	7.724	19.216	50.888	3.596	0.562	2.604	4.83
SE	44.903	16.32	28.771	99.805	5.349	1.093	3.727	8.032
SW	41.213	13.974	25.286	86.149	5.13	1.197	3.315	7.009
W	31.847	9.803	21.264	58.574	4.126	0.983	2.836	6.105
WM	36.301	11.786	24.794	70.132	4.539	0.918	3.18	6.15
YH	28.379	8.782	20.456	54.922	3.635	0.754	2.448	5.127
UK	33.774	12.724	17.035	99.805	4.284	1.127	2.448	9.629

2.4 Testing and Date-stamping Bubbles under the Present Value Approach

Based on the time series properties of a series, periods of mild explosive should be amenable to such statistical testing given these stochastic characteristics. Based on the outcome of the testing procedure, explosive behaviour is recognised regardless of cause.[3] Rooted in the standard asset pricing model, we assume risk neutral agents and rational behaviour. The model adopts

[3]The cause may span from pricing errors to biases.

the prevailing framework for explosive asset price behaviour analysis discussed further in Clayton (1996); Hiebert and Sydow (2011).

To ensure the robustness of the findings, we employ both the log linear and levels specification for asset pricing with rational bubbles. While log-linear appropriations of this type are often used interchangeably with its levels counterpart for both theoretical and empirical work, Phillips et al. (2011) remark the log-linear approximation "may be less satisfactory in non stationary contexts where the sample means do not converge to the population constants." As such, we also test the series both in log levels and in levels in our empirical work. Based on the findings of Phillips et al. (2011), we expect very similar results across both cases.

Appendix A.2 outlines the standard asset pricing model employed and how exuberant house price behaviour s characterised by explosive behaviour within this framework. Consequently, we relate asset pricing theory with the chosen testing procedures to generate findings parsimonious with the prevailing rational theory literature.[4] A bubble subsequently manifests in the dynamic and stochastic properties of the observed asset price. Hence, we are able to detect bubble behaviour through statistical methods consistent with this specification.

In our adoption of Mortgage to Earnings and House Price to Earnings ratios, we rely on incomes to account for all fundamental drives of house prices. Given this is not a conclusive way to account for the complete set of fundamental components, (such as property taxation and other factors examined in Himmelberg et al. (2005)), episodes of exuberance in both affordability ratios may still yet be derived from unobserved fundamentals (U_t) unaccounted for by income level. While we cannot be certain that detected periods of explosive growth in affordability ratios are due to bubbles, this method is more rigorous that sole reliance on house price estimation.

While the log linear approximation is employed in other papers such as Caspi (2013), we follow the advice of Phillips et al. (2011) and use the levels approach given the data for prices and affordability ratios is non stationery. As a robustness check results using the logarithm of prices is included in Appendix A.4. As expected, the results are both very similar.

[4]The classic rational bubble is the workhorse model of bubbles in macroeconomics. It is based on a failure of the transversality condition that necessitates the present value of a payment occurring infinitely far in the future to be zero (Giglio et al., 2014). See A.2 for a detailed account.

2.4.1 Monitoring the Housing Market for Rational Bubbles

According to Case and Shiller (2003), a rational bubble occurs when expectations of future price increases drives current house prices up, as opposed to price increases in fundamentals. Hence testing for periods of bubbles can be specified as a statistical test for explosive tendencies in the log price to dividend ratio.Based on the stochastic properties, we know that if economic fundamentals follow either an I(0) or I(1) process as described above, asset prices show explosive tendencies compatible with the rational bubble literature. We may then detect for mildly explosive behaviour in the time series properties of the data itself. While the results may indicate rational bubble behaviour, the results are not conclusive and must be treated as such. Indeed, explosive dynamics may materialise in house prices that are not associated with bubbles. House prices may present explosive tendencies due to fundamentals showing exuberance. As such despite no bubble necessarily prevailing, a fundamentals caused period of explosive prices may without direct observability.

These findings provide evidence supporting the use of housing affordability data. When testing the time series properties on housing ratios, we account for movements in fundamentals through the use of earnings data. While other factors feed into the determination of the fundamental house price, given the key role of income, we find this to be a particularly informative tool.[5]

2.4.2 Econometric Methodology for Detecting Bubbles

We utilise a right tailed recursive process adaptation of the augmented Dickey Fuller (ADF) test developed by (Phillips et al., 2015, 2011). These tests allow for *ex post* identification of mildly explosive periods and corresponding date stamps for each series. We apply these tests on real house prices for each region and national series to detect explosive behaviour in both real house prices and the potential decoupling between house prices and the fundamental price.

Housing affordability is considered through testing the house price to earnings ratio so we can draw conclusions as to whether housing is over or undervalued in rental terms. As this ratio

[5]See Pavlidis et al. (2014) for an account of fundamental driven exuberance and the role of time varying discount rates as instances in which explosive behaviour may manifest itself in the testing procedure in spite of no rational bubble arising.

diverges from fundamental values, we can infer market prices are maligned with fundamentals. While this model is intended to review rental data, we adapt the model in line with Pavlidis et al. (2014) through extension of the present value model in equation A.5 with "other economic relationships that relate housing rents to a set of macroeconomic variables (fundamentals)". Our methods are consistent with the literature in using the house price to earnings ratio as an assessment of how aligned prices are to the fundamentals providing an insight into whether prices are (un)sustainable.

Fundamentals are considered through the participation of income in the house price to earnings ratio. This strategy allows an exposition of the dynamics of these fundamentals. Explosive behaviour ascribed from fundamental movements can thus be considered, allowing one to determine whether observed fundamentals instigate bubble behaviour.

In line with the conventions of Phillips et al. (2015), the following random walk process with asymptotically negligible drift is assumed:

$$y_t = dT^{-\eta} + \theta y_{t-1} + e_t, \quad e_t \overset{iid}{\sim} N(0, \sigma^2), \quad \theta = 1 \tag{2.1}$$

where d denotes a constant, η is a localising coefficient for controlling the magnitude of the drift as sample size, denoted by T approaches infinity and e_t represents the error term. Following Phillips et al. (2011), the model is set to random walk without drift such that $n \to \infty$. The generalised form developed in Phillips et al. (2015) differ as d, η and θ are set to unity.

The Rolling Augmented Dickey Fuller (RADF) test, Suprenum Augmented Dickey Fuller (SADF) test and Generalised Suprenum Augmented Dickey Fuller (GSADF) test are based on variations of the reduced form equation given below.

$$y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \epsilon_t \tag{2.2}$$

where y_t is the asset price, μ denotes the constant, p is the maximum lag length, ϕ_i for $i = 1, \ldots, p$ refers to the differenced lag coefficients and ϵ_t is the error term. We test for episodes of exuberance using a variation on a right tailed Augmented Dickey Fuller test in which the null refers to a unit root, against the alternative hypothesis of a mildly explosive process. That is,

$$H_0: \quad \delta = 1$$
$$H_1: \quad \delta > 1$$

As a benchmark for the work of Phillips et al. (2011, 2015), we additionally implement the Rolling Augmented Dickey Fuller (RADF) test. The RADF test is the basis which Phillips et al. (2011, 2015) build upon and as such have many common characteristics. The RADF is a rolling version of the ADF test where the ADF test statistic is calculated over a rolling window with a fixed size such that $r_w = r_0$ across all computations. r_w refers to the fractional window size of the regression across the normalised sample $[r_1, r_2]$ with r_0 denoting the initial window size. The dataset covers a normalised sample interval of $[0, 1]$ and δ_{r_1,r_2} relate to the coefficients given above.

The RADF test rolls forward in increments of one observation, at each point the estimated ADF test statistic is calculated and referred to in the form ADF_{r_1,r_2}. This overlapping process involves $r_2 - r_w$ statistic calculations. We define the RADF statistic as the supremum ADF_{r_1,r_2} statistic across all estimated windows. The SADF test also relies on iterative calculations of the ADF statistic with a fixed point of departure. However, the SADF has a user specified increasing window size. While the first observation begins at $r_1 = 0$, r_2 is determined through a minimal window size, so r_0 is determined according to $r_w = r_2$. The ADF procedure is then estimated across the incrementing window size, with the subsample increasing each time by a singe observation, each producing an ADF_{r2}. Eventually the final computation includes the complete sample thus equating to ADF_1. Henceforth we refer to the SADF statistic as the supremum of ADF_{r_2}.

The GSADF test pioneered by Phillips et al. (2015), outlines a general form of the SADF test through increased flexibility with window estimation. This is achieved through the starting point also being able to vary between $[0, r_2 - r_0]$. It is denoted as follows:

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1}^{r_2} \tag{2.3}$$

this specification is inherently suitable for testing bubbles because the drift term is asymptotically negligible such that the drift term does not dominate the outcome.

2.4.3 Date Stamping Explosive Episodes

A key benefit of the procedures developed by Phillips et al. (2011, 2015) is the property to consistently estimate start and end dates for explosive periods. If the null hypothesis is rejected, we are able to determine commencement and termination dates. We consider the date stamping methodology in brief.

The SADF test functions through the comparison of each subset rolling window sequence to the relevant critical values of the original ADF statistic. The start date of a bubble is defined as the first observation for which the relevant test statistic is greater than the corresponding critical value. These critical values are constructed through Monte Carlo simulations of 1000 replications. In a similar vein, the end date of an exuberant episode is noted as the first observation occurring after the episode commencement date where the test statistic is less than the relevant critical value. The episodes are then manually checked to ensure the identified periods are greater than $\log(T)$ units, in our case 5 quarters. This selection process is demonstrated in 2.6, 2.7, 2.8 and 2.9 where dark grey periods signify a length of 5 or more consecutive periods of exuberance. Periods under 5 quarters are shown in light grey for full disclosure of test results.[6]

2.5 The Predictive Ability of Macroeconomic and Financial Variables

2.5.1 Probit Model with Correlated Random Effects

We estimate a correlated random effects probit model to determine the in-sample predictive capability of a range of financial and macroeconomic variables. The panel probit likelihood function is calculated by Gauss–Hermite quadrature. We included an established set of financial and macroeconomic predictors based on theoretical underpinnings discussed in Pavlidis et al. (2014). The model is described as:

[6] In addition to the aforementioned results given in the proceeding section, Appendix A summarises the outcomes for a smaller window size of 13 observations on the logarithm of prices. Both set of results are extremely similar, serving well as a robustness check. This appendix is able to capture periods of exuberance otherwise missed in the late eighties given the larger window size eschews these periods predating $r_1 = 0$.

$$B_{it} = \beta x_t + \gamma z_{it} + v_i + \epsilon_{it} \text{ where } \epsilon_{it} \sim N(0,1) \tag{2.4}$$

Where x_t, the vector of countrywide predictive variables, z_{it}, the vector of region specific predictive variables and $B_{i,t}$ is the dependent binary variable for $i = 1, ..., N$. $B_{i,t}$ takes on a value of one when a period of exuberance is detected at a given time t in region i, and zero otherwise. Formally,

$$B_{i,t} = \begin{cases} 1, & \text{if } GSADF_{i,t}(r_0) < scu_t^{\alpha}, \\ 0, & \text{if } GSADF_{i,t}(r_0) > scu_t^{\alpha}, \end{cases} \tag{2.5}$$

The respective probabilities that a region is in a state of exuberance given the covariates x_t and z_{it} are fitted by the probit model under maximum likelihood estimation with random effects as follows:

$$P(B_{it} = 1|x_t, z_{it}) = \Phi(\beta x_t + \gamma z_{it} + v_i) \text{ for } i = 1, \ldots, N \quad t = 1, \ldots, T \tag{2.6}$$

where Φ denotes the standard normal cumulative distribution function. Nationwide indicators in the model include unemployment, growth in GDP, inflation and changes in oil prices. These variables capture macroeconomic developments and have some predictive content with respect to consumption and investment in property. We account for global economic conditions using gold crude oil prices from the West Texas Intermediate Growth in real disposable income per capita encompasses fundamental housing demand drivers expected to maintain long term prices. Given the majority of individuals fund house purchases through mortgage products, we examine growth in the current account.

With respect to the behaviour of housing as an investment tool, we consider long and short interest rate spreads.The former is proxied with ten year government issued bond yields and serves to capture changes in future expectations of interest rates and market conditions. In addition to bond yields, we also include changes in the share price index which serves to incorporate future profitability of alternative asset classes alongside reflecting fluctuations in household wealth.

Variable z_{it} denotes regional growth in real disposable household income. As households have experience a growth in disposable income , this may lead to increased demand for housing, thus increasing the likelihood of explosive growth in house prices. However, typical estimates of the income elasticity of demand for housing lie in the between 0.5 to 0.8[7] indicating demand for housing may be less sensitive to changes in income levels. Hence we hypothesise income growth is likely to have a low impact on the probability of exuberance in a given period.

We estimate a correlated random effects model using the Mundlak-Chamberlain correction following Wooldridge (1995); Mundlak (1978); Chamberlain (1980, 1982) in order to control for the unobserved heterogeneity between regions by including the the region specific average of time varying covariates. In our case, this only applies to the growth in real disposable household income.

2.5.2 Comparing Predictive Power Across Regions: Regional Probit Model

By estimating a probit model for each region on a set of covariates such that differences in predictive ability of macroeconomic factors can be assessed across regions. Given the same vector of predictive variables are used as in the panel probit estimation, the model follows equation (2.5). Some areas may be more sensitive to changes in the economy than others. By estimating these variations, policy makers are able to better target regional housing market and anticipate explosive growth in the housing sector based on the macroeconomic environment.

We estimate the following model for each region:

$$B_t = \beta x_t + \gamma z_t + \epsilon_{it} \text{ where } \epsilon_{it} \sim N(0,1) \tag{2.7}$$

where

$$P(B_t = 1|x_t, z_t) = \Phi(\beta x_t + \gamma z_t) \text{ for } t = 1, \ldots, T \tag{2.8}$$

where Φ denotes the standard normal cumulative distribution function, x_t is a vector of countrywide predictive variables (as given above), z_t denotes growth in disposable income for the respective region, and B_t is the dependent binary variable. B_t takes on a value of 1 when a period of exuberance is detected at a given time t, and zero otherwise. This follows extremely closely to the panel probit model but is estimated separately for each region such that the

[7] See Malpezzi and Wachter (2012) for a recent survey

marginal effects may then be compared.

2.6 Empirical Results

The SADF and GSADF test is first employed to identify explosive properties for both house price series and affordability ratios. In light of the findings of exuberance for a given series, we are then able to further inspect the duration and episodes in time when the trend is explosive, thus indicating bubble behaviour. We consider how synchronised periods of exuberance are across the sample period and compare whether housing affordability ratios experience exuberance concurrently with house price movements. Results are provided for GSADF, SADF and RADF testing of regional and national areas.

2.6.1 SADF and GSADF Hypothesis Testing Results

The Augmented Dickey Fuller test statistics for nominal and real house prices alongside the respective critical values are given in Table 2.2 . The overall results indicate all regions follow a unit root process when considering the three methods of testing in tandem. GSADF testing yields the strongest evidence of nonstationarity across both national and regional house prices with all t statistics significant to the 99 percent level, with the exception of real house prices in Greater London slightly less significant at the 95% level. This outcome is bolstered by the SADF results with again exception to Great London real house prices, while all other regions are significant at the 99 percent significance level in both nominal and real terms. RADF testing echoes similar findings, with marginally lower levels of significance in the case of Greater London, Northern Ireland and Scotland house prices. We find the more robust testing methods used in the GSADF procedure provide convincing evidence of non stationary house prices significant at the 99 percent level. The results outlined in Table 2.3 summarise the non stationary nature of both regional and national housing affordability ratios. With the exception of SADF results for Scotland, Mortgage to Earnings is found significant across RADF, SADF and GSADF testing for all series with GSADF results presenting the most convincing case for unit root processes across all regions significant at the 95 percent level at least. House Price to Earnings data present mixed evidence for the case of nonstationarity across certain regions. With respect to GSADF results, East Midlands, Greater London and the South East do not provide enough evidence to conclude nonstationarity at the 90% level. However, SADF testing finds the aforementioned areas are nonstationary at the 90% level. The least evidence for a unit root process is attributed to the South East, however even in this case stationarity is rejected under SADF testing at the 90% significance level. In conclusion, all regions are found to show some evidence of a unit root process.

As expected, fewer instances of rejecting the null of a unit root process occur across RADF and SADF results compared to GSADF results. This can be attributed to lower power of SADF testing under multiple instances of bubbles that are likely to be prevalent over three decades of house price data. Given the GSADF test performs better in cases of multiple periods of exuberance, the GSADF findings that most series are significant across regions and nationwide hold superior credence. In summary, the ADF test results for house prices and affordability anchors provide overwhelming evidence rejecting a unit root process in favour of explosive trend properties, thus indicating the potential for one or multiple housing bubbles transpiring across the sample time frame.

2.6.2 Periods of Exuberance in House Prices and Affordability Ratios

GSADF results are presented by region in Figures 2.6, 2.7, 2.8 and 2.9 for real house prices, nominal house prices, house price to earnings and mortgage to earnings. Figures 2.6.3 to 2.6.3 plot each series coupled with the SADF results[8]. Across both house price indices, RADF results demonstrate a higher incidence of exuberance detection compared to GSADF and SADF testing. The latter two exhibit more distinct episodes of explosive house prices. With the exception of Northern Ireland, all regions tend to have some commonality with respect to when periods of exuberance take place.

The upper graph in each figure summarising house price movements has a prevailing theme of a peak in the late eighties to early nineties, followed by a greater peak in the noughties. While the severity of house price appreciation and ensuing decline vary from region to region, GSADF and SADF testing substantiates house prices were explosive for all regions during both

[8]SADF House price to Earnings results are relegated to Appendix A.3. Results using nominal house prices are available on request.

peaks. While the duration and scale may vary, similarities in the hypothesis testing results affirm fundamental house price drivers are common among regions. This serves as an impetus for estimating how sensitive regional segments of the housing market may be to macroeconomic and financial variables.

The first bubble detected is more distinctive than in the two thousands period. The latter manifests a largely undisrupted protracted period of exuberance for some regions such as Scotland and the South West, while other regions have more fractious experiences of explosive prices that could be disaggregated to two smaller peaks; the first in and around 2005, preceding the larger peak in 2008. For certain regions such as the North and East Midlands, this manifests as a sustained increase in house prices coinciding with a protracted period of rejections of the null hypothesis interspersed.

Table 2.3: Regional ADF Test Results for Nominal and Real House Prices

Test Statistics

	Nominal House Prices			Real House Prices		
Region	*RADF*	*SADF*	*GSADF*	*RADF*	*SADF*	*GSADF*
EM	5.324***	5.669***	5.669***	4.678***	4.996***	4.996***
EA	3.695***	3.695***	4.814***	10.114***	10.114***	10.114***
GL	1.895***	1.895***	2.225***	1.129**	0.165	1.129**
NI	0.989**	8.060***	8.060***	0.579*	6.791***	6.791***
N	3.134***	2.991***	9.045***	2.917***	2.20***	7.676***
NW	2.250***	2.752***	6.928***	1.984***	2.098***	6.281***
S	1.174**	1.191***	3.732***	1.451***	1.241***	3.297***
SE	3.200***	3.200***	3.200***	4.987***	4.987***	4.987***
SW	2.071***	2.134***	3.188***	3.048***	3.048***	3.048***
WM	2.554***	2.554***	3.656***	3.497***	3.826***	3.826***
W	2.268***	2.150***	7.771***	5.200***	5.576***	5.823***
YH	5.825***	6.132***	6.135***	4.584***	4.852***	5.321***
UK	0.692*	0.679**	1.661***	1.788***	1.788***	3.405***
Critical Values						
99%	-0.151	0.980	1.672	-0.151	0.980	1.672
95%	-0.786	0.485	1.118	-0.786	0.485	1.118
90%	-1.122	0.207	0.868	-1.122	0.207	0.868

*, ** and *** denote statistical significance to the 10, 5 and 1 percent level respectively.

Table 2.4: Regional ADF Test Results for House Price to Earnings and Mortgage to Earnings

Test Statistics

	House Price to Earnings			Mortgage to Earnings		
Region	*RADF*	*SADF*	*GSADF*	*RADF*	*SADF*	*GSADF*
EM	0.561*	0.596**	0.61	4.219***	4.219***	4.219***
EA	2.442***	2.542***	2.542***	6.652***	6.652***	6.652***
GL	0.792**	0.367*	0.792	1.854***	1.391***	1.856***
NI	0.372	1.191***	2.037***			
N	1.067**	0.253*	3.194***	1.617***	1.896***	3.307***
NW	1.204***	0.525**	1.558**	0.918**	1.197***	2.332***
S	0.879**	-0.121	1.274**	0.827**	0.057	1.465**
SE	0.445	0.464*	0.695	1.586***	1.586***	1.604**
SW	1.117**	1.117***	1.117**	2.589***	2.589***	2.589***
WM	1.329***	1.500***	1.500**	3.359***	3.359***	3.359***
W	1.557***	1.130***	2.588***	1.886***	1.885***	4.021***
YH	0.886**	0.547**	2.153***	4.742***	4.742***	4.742***
UK	0.692*	0.679**	1.661***	1.788***	1.788***	3.405***
Critical Values						
99%	-0.151	0.98	1.672	-0.14	1.03	1.648
95%	-0.786	0.485	1.118	-0.782	0.497	1.12
90%	-1.22	0.207	0.868	-1.123	0.238	0.891

*, ** and *** denote statistical significance to the 10, 5 and 1 percent level respectively.

Table 2.5: Regional Incidence of Detected periods of Exuberance in Price and Affordability Measures under GSADF Testing

Area	No. of periods $B_{it} = 1$				% Periods $B_{it} = 1$ as proportion of T			
	RHP	NHP	ME	HPE	RHP	NHP	ME	HPE
Northern Ireland	42	34	17	-	37.84	30.63	15.32	-
South	46	45	18	22	41.44	40.54	16.22	20.00
North	35	33	20	31	31.53	29.73	18.02	28.18
North West	40	34	11	31	36.04	30.63	9.91	28.18
Yorkshire & Humber	36	36	17	25	32.43	32.43	15.32	22.73
Wales	37	41	12	23	33.33	36.94	10.81	20.91
West Midlands	51	41	11	31	45.95	36.94	9.91	28.18
East Midlands	32	39	13	27	28.83	35.14	11.71	24.55
East Anglia	40	42	18	22	36.04	37.84	16.22	20.00
Greater London	30	47	14	20	27.03	42.34	12.61	18.18
South East	29	39	10	14	26.13	35.14	9.01	12.73
South West	29	37	8	17	26.13	33.33	7.21	15.45
United Kingdom	47	52	10	29	42.34	46.85	9.01	26.36

While general trends are shared between price and affordability anchors in terms of testing for exuberance, the results demonstrate a far higher incidence of rejections of the null hypothesis for testing prices compared to both tested ratios, indicating several exuberant episodes are not driven by fundamentals. Indeed, detected 'bubble' periods are less enduring such that the majority do not surpass the specified minimum length; The North West experiences the longest bubble in housing affordability (measured by house price to earnings ratio) of thirteen quarters - this is far less than those detected in prices which on occasion exceed twenty quarters. Housing affordability ratios both share a bout of exuberance in the late eighties or early nineties, corroborating the same findings in house prices. Affordability ratios have a lower incidence of exuberance detection, implying that the periods of explosive growth in prices unmatched by the ratios may be inherited from escalating growth in housing fundamental drivers. Variation between the frequency of periods sustaining explosive properties is also greater in the later period of exuberance encountered in the two thousands. While the estimation results indicate common factors have affected housing affordability across the UK, the variation in periods of exuberance underscore regional disparities in sensitivities to housing determinants which potentially worsen over time. As the decoupling in patterns of exuberance become more disparate between affordability and price movements variables.

2.6.3 Chronology of Exuberance

Tables 2.6 and 2.7 display date-stamped periods of exuberance in real and nominal house prices respectively using the GSADF testing procedure across 12 UK regions and nationwide. The results for the same testing procedure on the affordability ratios are also provided in Table 2.9 and 2.8.

Unlike its English and Scottish counterparts, Northern Ireland remains markedly different in its explosive growth properties with little to no synchronisation across the tested period. This result is accordant with the institutional and geographical distinctions that affect housing policy in Northern Ireland. Alongside Scotland and Wales, Northern Ireland enjoys devolved status such that housing policy is decided by the NI assembly. As the smallest and historically most deprived region as discussed in McCord et al. (2011), this area is more susceptible to volatility with higher levels of unemployment, lower productivity and greater reliance on public sector subvention. House Prices in Northern Ireland start at a much lower price base in our tested period and Scotland has its own housing market system based on sealed bids that differentiates its regional housing market to the rest of the UK. The differences between this area and the remaining UK regions is further compounded through geographical separation, curbing labour market mobility and population migration. Wales and Scotland are expected to demonstrate less interdependent behaviour with English regions due to devolved parliamentary powers and geographical separation to a lesser extent; the results confirm this behaviour but remain related to English house price movements unlike the tested Northern Ireland series.

The nationwide results for nominal and real house price GSADF testing indicate bubble behaviour from 1988Q2 to 1989Q2 and to 1989Q1 respectively. This duration is the first phase of exuberance in real and nominal house price appreciation detected at the advent of the testing period. Referred to by Congdon (2005) as the ‘Lawson boom’, this explosion in property wealth heralded a bust of a (then) unprecedented scale during the 1990s. Figure 2.2i demonstrates this upswing in real house prices throughout the late eighties, finally peaking in 1989Q2 before falling by a third (or 58 index points) over the subsequent seven years. While the dataset range precludes date stamping the advent of explosive growth in real and nominal house prices, closer inspection of regional components demonstrate the termination of exuberance follows a geographical progression across England.

Table 2.6: Episodes of exuberance detected in real house prices using GSADF testing

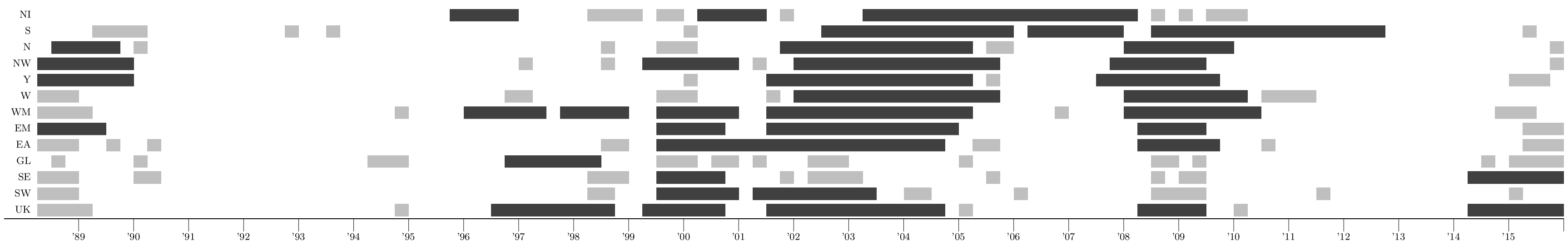


Table 2.7: Episodes of exuberance detected in nominal house prices using GSADF testing

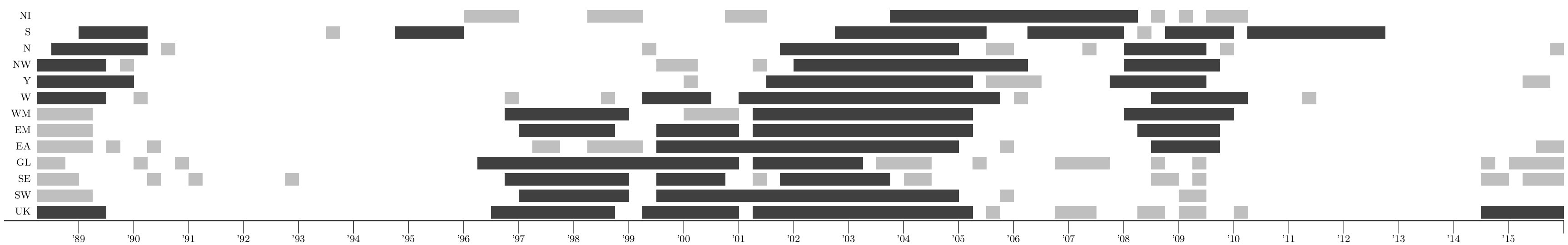


Table 2.8: Episodes of exuberance detected in the Mortgage to Earnings Ratio using GSADF testing

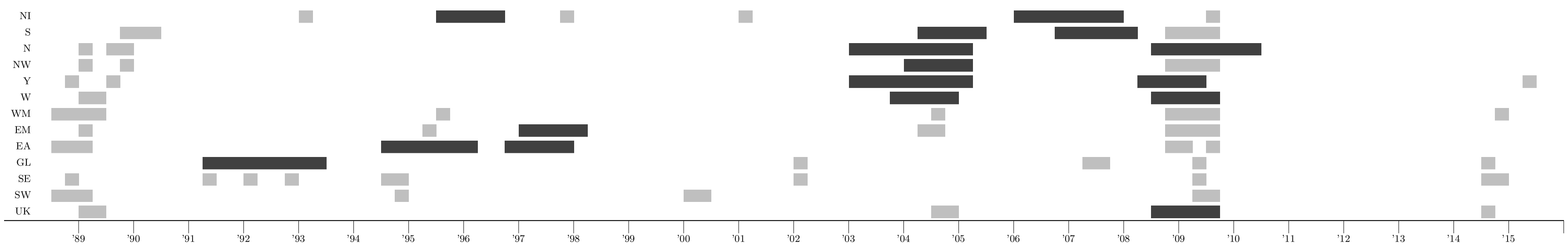
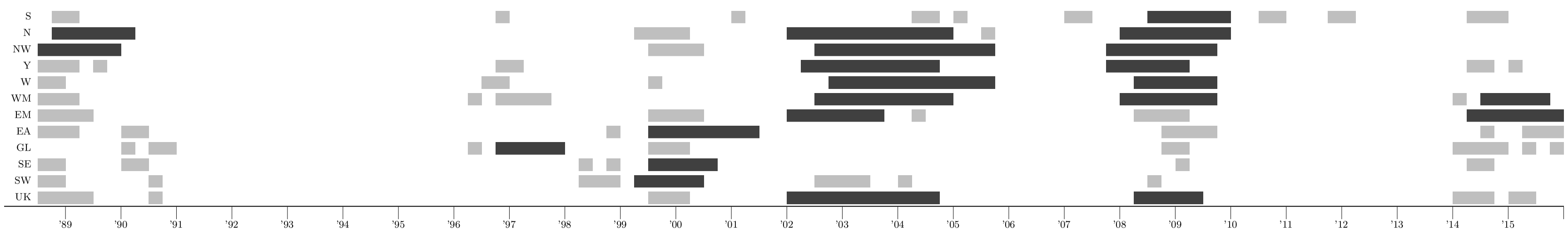
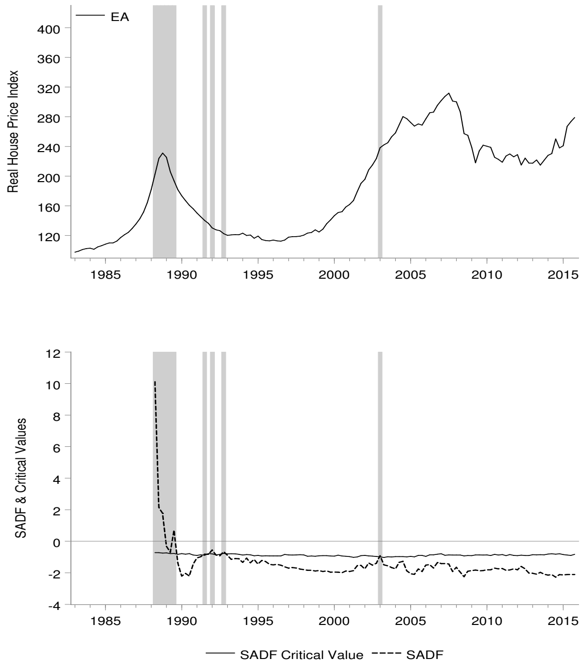
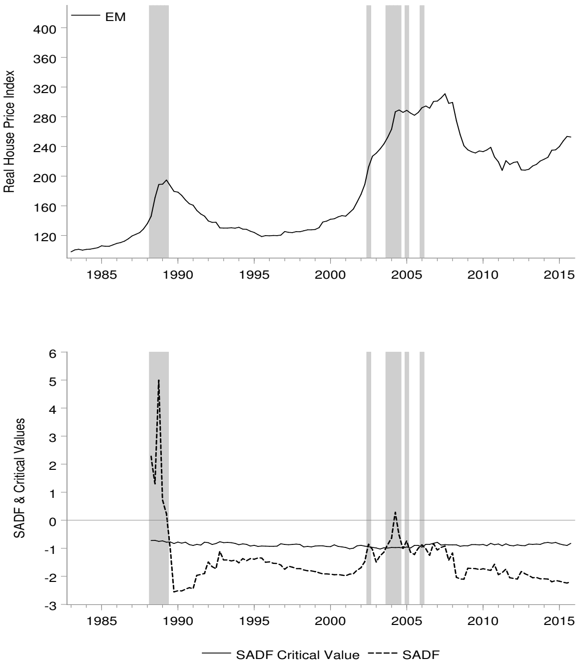


Table 2.9: Episodes of exuberance detected in the House Price to Earnings Ratio using GSADF testing

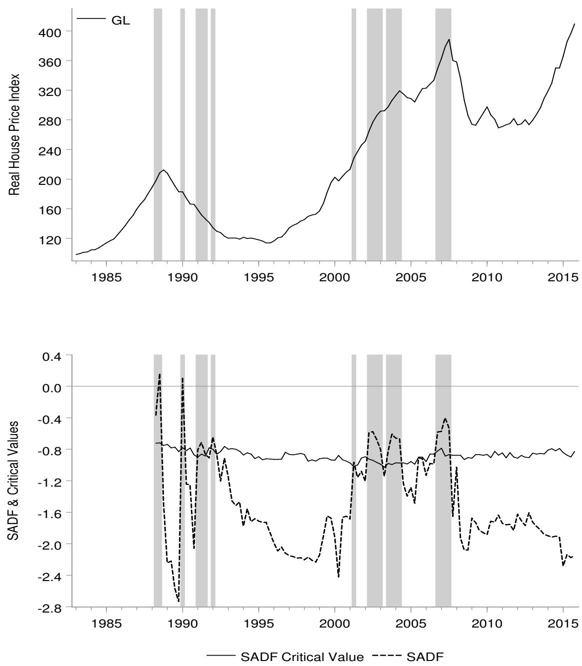




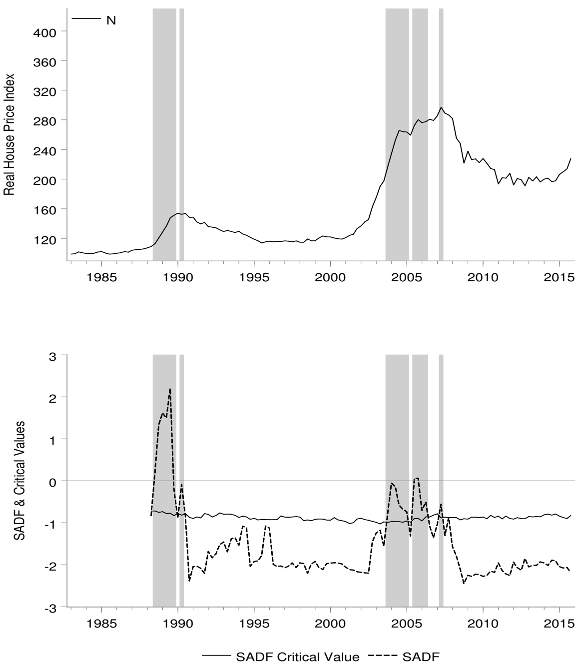
(a) East Anglia



(b) East Midlands

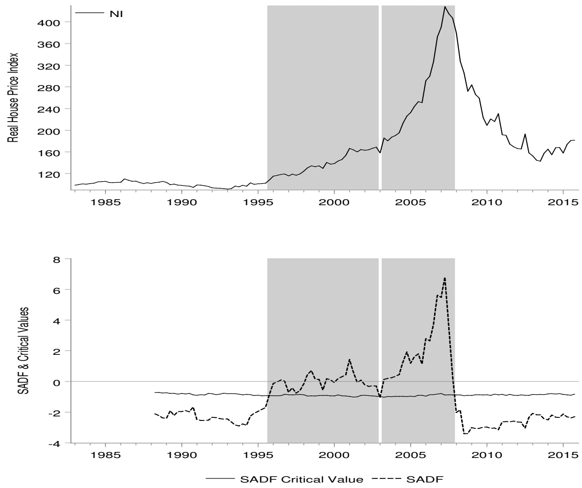


(c) Greater London

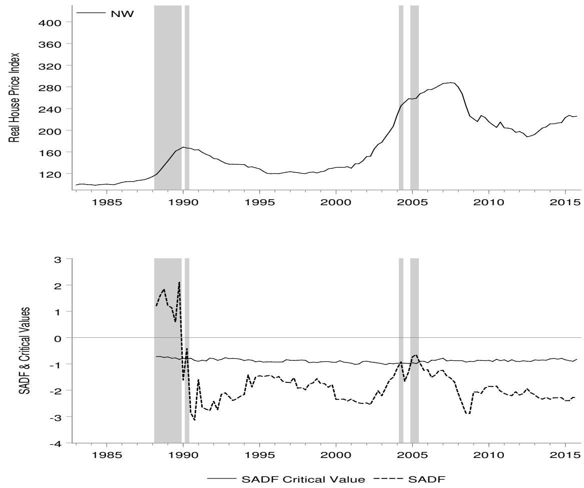


(d) North

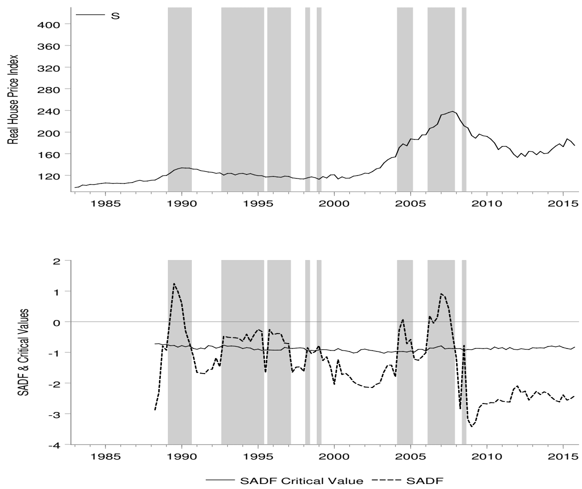
Figure 2.2: Date-stamping periods of exuberance in real house prices using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



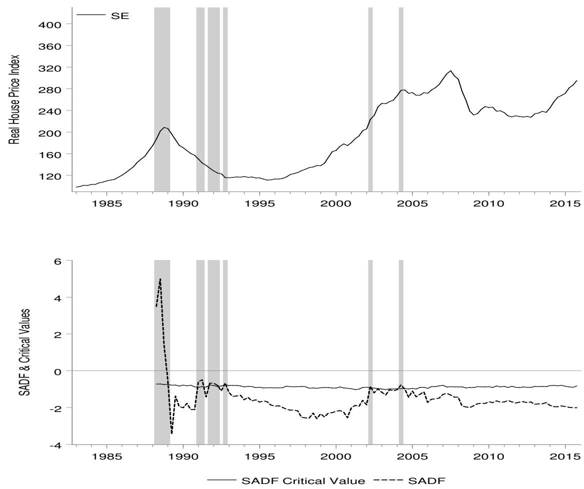
(a) Northern Ireland



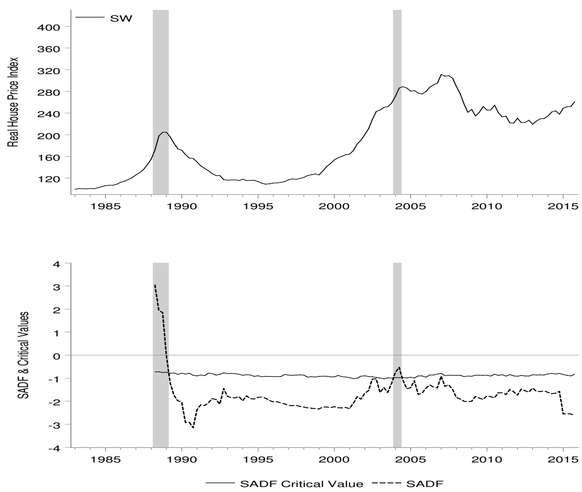
(b) North West



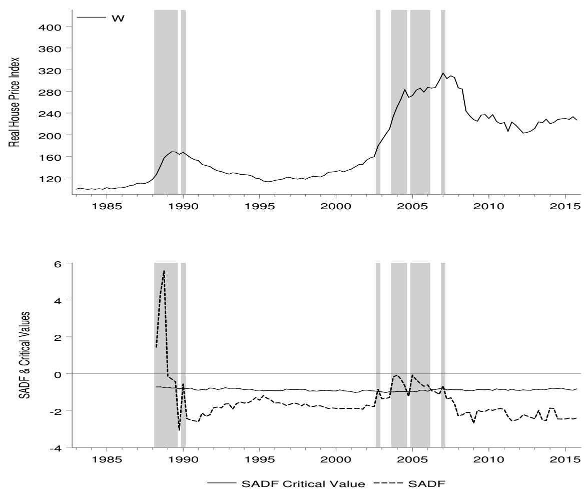
(c) Scotland



(d) South East

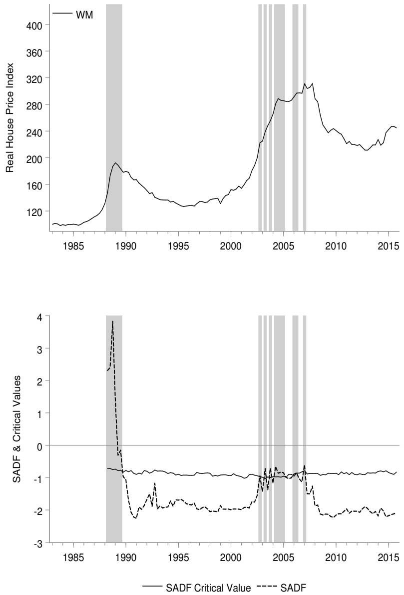


(e) South West

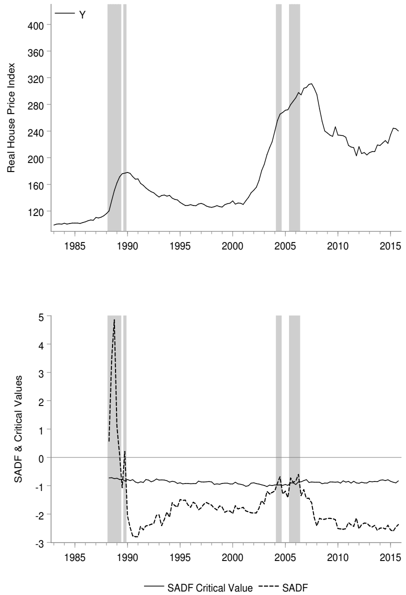


(f) Wales

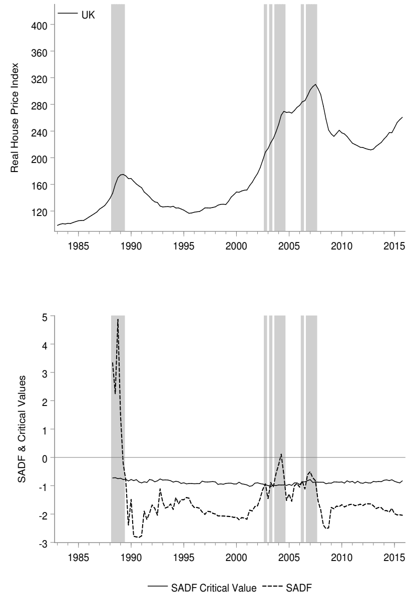
Figure 2.2: Date-stamping periods of exuberance in real house prices using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the SADF testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



(g) West Midlands

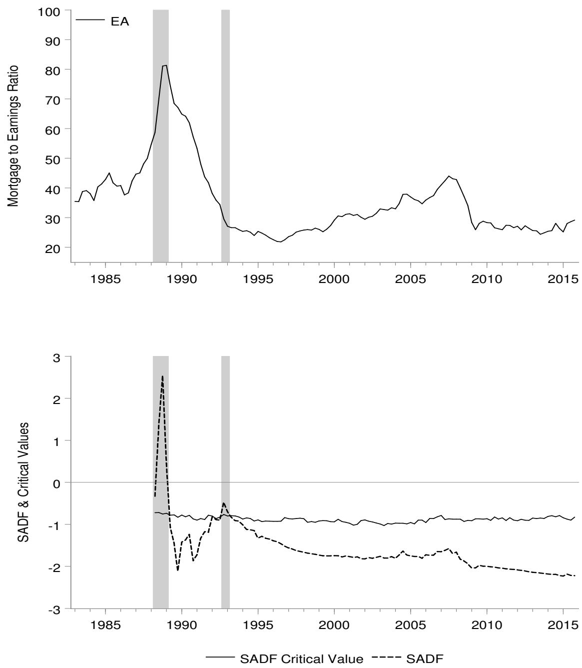


(h) Yorkshire & the Humber

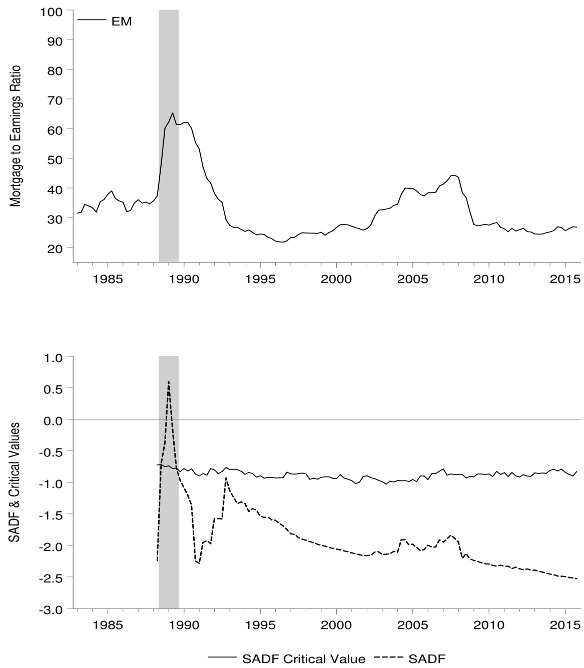


(i) United Kingdom

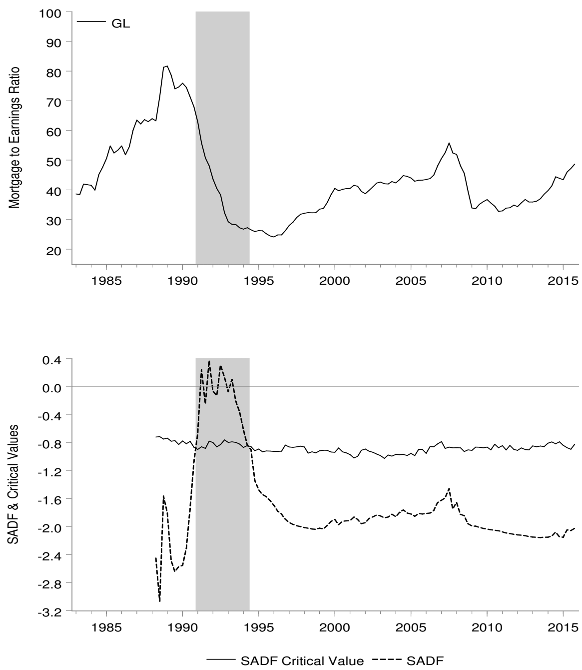
Figure 2.2: Date-stamping periods of exuberance in real house prices using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the SADF testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



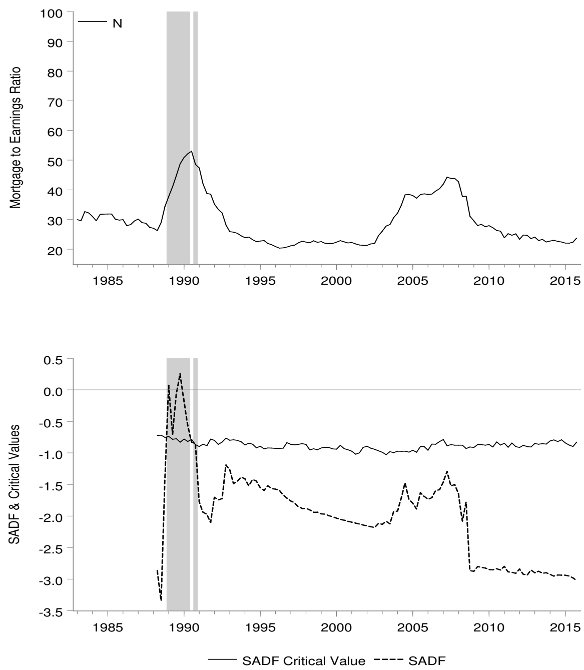
(a) East Anglia



(b) East Midlands

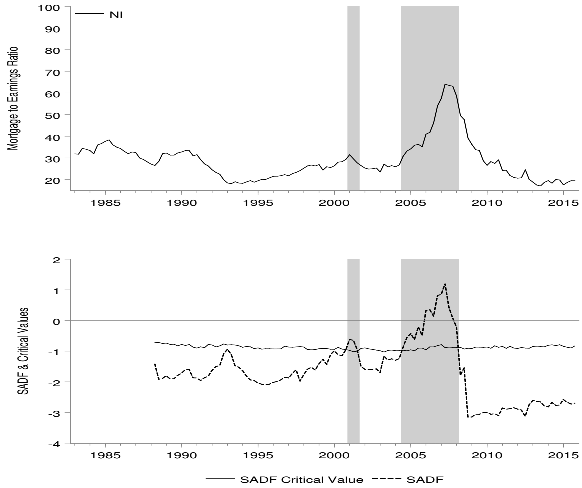


(c) Greater London

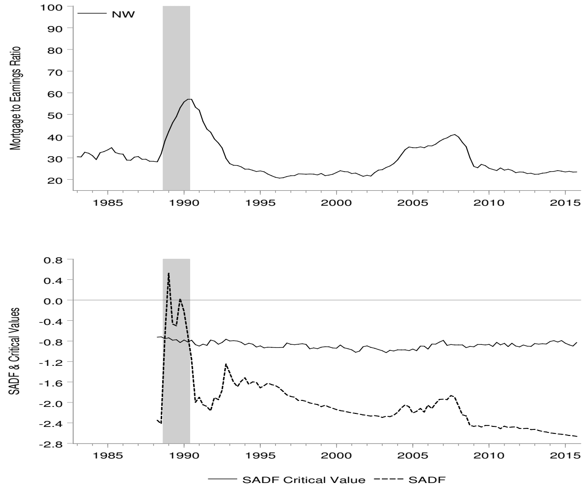


(d) North

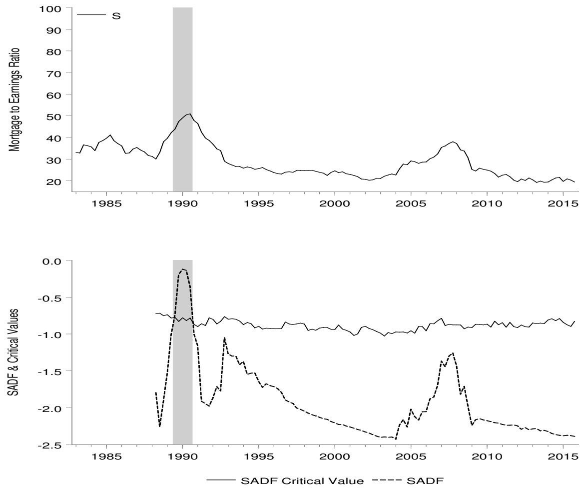
Figure 2.3: Date-stamping periods of exuberance in mortgage to earnings using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



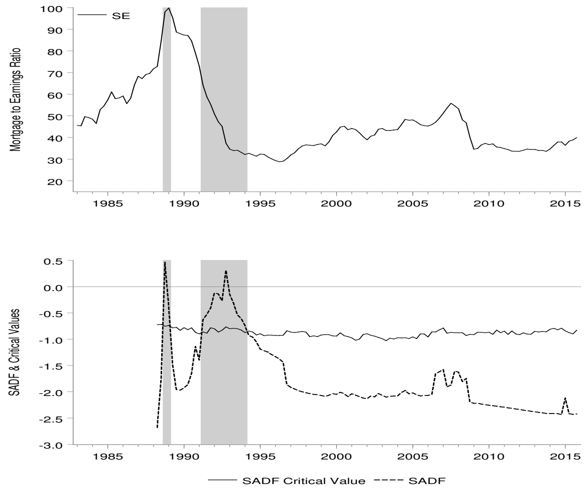
(e) Northern Ireland



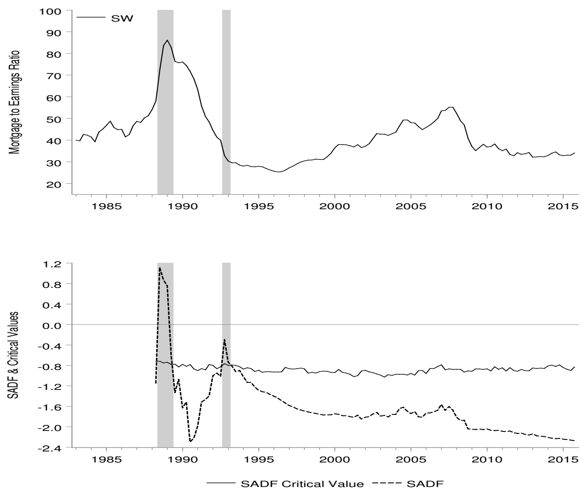
(f) North West



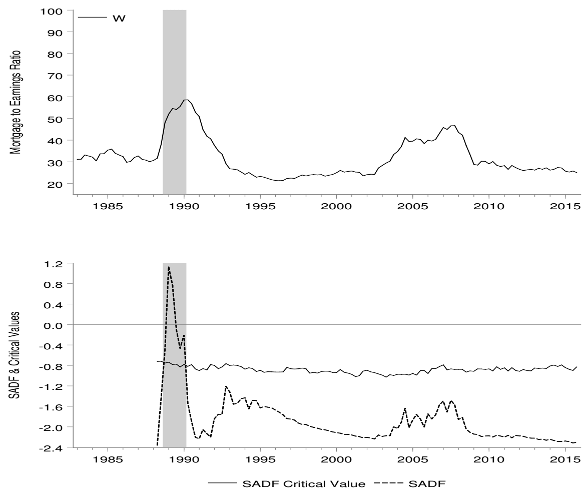
(g) Scotland



(h) South East

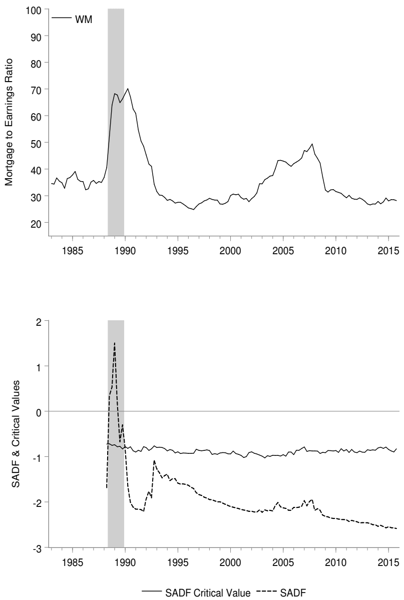


(i) South West

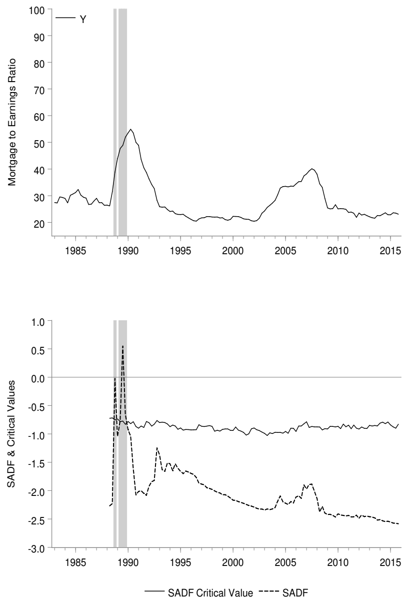


(j) Wales

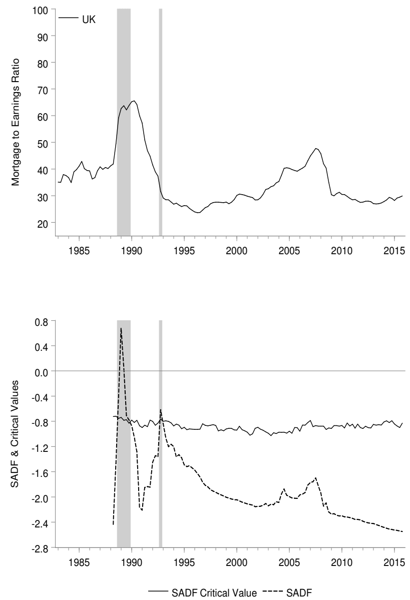
Figure 2.3: Date-stamping periods of exuberance in mortgage to earnings using SADF testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the SADF testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



(k) West Midlands



(l) Yorkshire & the Humber



(m) United Kingdom

Figure 2.3: Date-stamping periods of exuberance in mortgage to earnings using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.

Appendix A.4 provides results using a smaller window size thus allowing inspection of exuberance in the mid to late eighties that are sacrificed in the principal model in favour of more robust outcomes. In regional terms, the period of explosive growth is first experienced in the South East of England, closely proceeded by the South West and East Anglia. An increasingly lagged effect is evident across West Midlands, East Midlands, Yorkshire and Humber, North West and Northern England respectively. The first phase of exuberance initiates in the North 9 quarters after the South East. This spatial pattern of exuberance experienced further forward over time gives credence to the 'ripple effect' hypothesis put forward by Meen (1999) as it demonstrates "a cyclical upswing in the south-east and, then, spreading out over the rest of the country".

Rejections of the null hypothesis also occur during the late eighties in both affordability measures. While most of these episodes are too short lived to constitute a 'bubble', there is evidence that all regions experienced explosive growth during this period at various intervals, indicating the escalation in prices are driven beyond the changes in housing fundamentals. As discussed in Muellbauer and Murphy (1997), financial deregulation in the eighties made mortgage credit easily available such that households were able to leverage their house more than before. The result of this is evident in the widening between mortgage debt to earnings, resulting in a sharp upswing in the upper graphs in Figure 2.3. Indeed, income to earnings shows more sustained periods of exuberance as a result of the shortfall between house prices and earnings being met by credit. GSADF results in Table 2.9 depict a secondary short lived bout of exuberance for the following southern regions: South West, South East,Greater London and East Anglia. While results for Mortgage to Earnings ratio identifies the advent of exuberance in each region, house price to earnings data for seven regions are in a phase of exuberance from the first tested window. Appendix A.4 signals the rejection of the null for house price to earnings ratio has a longer duration than the scope of the primary results set. Tables 2.8 and 2.9 also display a geographical spreading of exuberance from the South to the Northern regions by both measures. The mismatch in magnitude between the duration of exuberance in prices and affordability underscore a decoupling of movements in property value and earnings across all regions.

Greater London behaves anomalously as it bucks the trend of exuberance during this period in real prices and affordability ratios. This result may be a consequence of market distortions due to the political ramifications of abolishing domestic rates of local property tax in 1988 for the subsequent introduction of the Poll tax alongside mortgage interest restrictions to a single property per household. As noted by Muellbauer and Cameron (2006), the political upheaval sustained through to the early nineties with sizeable collection costs and ensuing demise of the Poll tax, decoupling the impact of this from a house price bubble is not readily distinguishable. The rapid rise and ensuing fall in both real and more unusually in nominal house prices, during the late eighties to early nineties is evident across all other English regions and Scotland. Weeken (2004) attribute this to housing asset over-valuation caused by mistaken perceptions of key fundamental price drivers. An alternative explanation is suggested by Baddeley (2005) as house price appreciation was a result of fiscal policy changes. Notably, the broadcasting of upcoming restrictions to Mortgage Interest Relief at Source is considered to have fuelled a house price upswing in mid 1988.

In the wake of the sharp and prolonged house price deflation lasting until the mid nineties, interest rates were increased to fifteen percent for a year to combat stagflation. As unemployment reached three million, record levels of households could not meet their mortgage repayments taken out during credit expansion that fuelled the bubble. These conditions ensured the housing market did not recover until the mid nineties. Nationwide house prices show evidence of only mildly explosive behaviour across all regions from the early nineties until mid 1996.

First detected in Greater London, nominal property prices exhibit bubble tendencies in the South East, South West and Midlands in the run up to 1997 with some regions lasting until 1999. Certain areas experience more protracted periods of explosive growth; most notably the West Midlands exhibits exuberance from 1996Q1 to 2005Q1 in all but 5 quarters. Table 2.6 and 2.7 depict a spatial progression of exuberant episodes across England in a more convincing geographical pattern compared to the 'Lawson boom'. Results summarised in Table 2.7 show the sequence is more gradual in its advent compared to the contagion of the termination date of exuberance. Evidence is further strengthened from real house price testing, suggesting evidence of more immediate synchronisation of a reversion from explosive to mildly explosive house price movements than vice versa. This pattern is most evident in nominal house prices but is also strongly apparent in real house prices in Table 2.6. As a prospect of this mismatch in diffusion of onset and expiry, regions further northward experience shorter periods of detected explosive house price behaviour.

GSADF testing reveals house prices have behaved explosively since 1996, corroborating the findings of UK property overvaluation in Girouard et al. (2006). In contrast Meen (2008) argues the strength of house prices can be explained in terms of fundamentals. This preposition is strengthened by the results of Muellbauer and Cameron (2006) where no strong evidence of a bubble exists. This is chalked up to chronically low levels of interest rates with future expectations of low inflation, coupled with notably strong income growth and weak housing supply. During the early nineties, Meen and Andrew (1998) consider the reform of the labour markets a key structural change in the housing market composition. The effect on income distribution adversely affected younger households; a change that has yet to be reversed (Andrew, 2012). While income growth may explain some of the boom in house prices, the increase in prices far outstrips earnings growth per household. The population increase between 1996 and 2006 of 1.8 million net additional households increased housing demand; coupled with income growth, Muellbauer and Cameron (2006) found both factors almost completely account for appreciation in prices.

With the exception of Scotland and Northern Ireland, expiry of explosive growth in both prices and affordability terminate for all regions by (or during) 2006. Both of these regions are alone in their experience of exuberance in mortgage to earnings ratio during 2006-7. All remaining regions test negatively for explosive growth until mid 2007 in prices and 2008 onwards in affordability.

The third episode of explosive growth shows more immediate signs of synchronisation with all regions rejecting the null within the space of a year. Unexpectedly, real house prices in Yorkshire first experiences bubble behaviour in mid 2007, before being detected further north and further south over the successive year. We note less evidence of the ripple effect perhaps due to more interconnectedness between regional housing markets and credit conditions. The duration of exuberance is lower than the preceding boom, with most regions failing to exceed two years in price and affordability measures. The southern regions of South East, South West and Greater London encounter some quarters of null hypothesis rejection, but not for a sufficiently prolonged time frame to constitute a bubble. Upper graphs in real and distinctly in nominal price movements (shown in Figure 2.6.3) demonstrate that price appreciation was greatest through this period despite the short duration. Termination of explosive growth is more contemporaneous across areas than historic periods; this is particularly apparent in affordability measures. The boom in this period was fuelled by a combination of chronically low housebuilding interplayed with demand side factors, including fifteen years of steady growth, cheap credit and a rising population.

From mid 2010, houses prices and affordability do not exhibit explosive growth for four successive years. This can be attributed to after effects of the global financial crisis originating from the US sub prime lending contagion. In the wake of the crisis in 2008, credit conditions became more restricted. Mortgage interest rate premiums over the central bank base rate increased as fewer products were made available on the market. Lenders required increased downpayment, leading to a decrease in modal Loan to Value from 95% to 75% from before and after the crisis (White, 2015). This effect is reflected across all regions in both affordability measures as most households rely on mortgages to afford property purchases.

In a bid to combat low LTVs the government introduced the Help to Buy mortgage guarantee scheme with the expectation of increasing market transactions and supporting demand in the housing market. As discussed in White (2015), evidence suggests significant increases in mortgage lending since the policy's inception. This factor may have fed into detected periods of exuberance from 2014 onwards. First detected in southern regions, prices have begun to behave explosively, most noticeably in the South West of England. House price to earnings also shows evidence of exuberance most substantially in the southern regions. However, Mortgage to Earnings shows a lower incidence of null hypothesis rejections. This may be due to sustained downward pressure lending since the financial crisis. The identification of these final periods of exuberance potentially continue beyond our timeframe such that we are unable to datestamp the termination date.

2.6.4 Correlated Random Effects Probit Estimation Results

Table 2.10: Correlated Random Effects Probit Estimation with Mundlak-Chamberlain Correction using GSADF Outcomes

Variable	(1) Real House Price	(2) House Price to Earnings
Region Specific:		
Real Disposable Income	-0.0000125***	-0.00000220
	(0.00000315)	(0.00000329)
Nationwide:		
Unemployment	-0.516***	-0.341***
	(0.0426)	(0.0452)
Δ FTSE100	-0.0400***	-0.0329***
	(0.00832)	(0.00888)
Δ Oil Price	0.00351	0.00281
	(0.00280)	(0.00300)
Δ Current Account	-0.0000680	-0.000385
	(0.000125)	(0.000238)
Δ Gold Price	0.0156**	0.00149
	(0.00634)	(0.00686)
[1em] Official Bank Rate	-0.206***	-0.0994**
	(0.0372)	(0.0412)
10 year Government Bond Yield	0.271***	0.180**
	(0.0647)	(0.0721)
Constant	2.793***	1.227***
	(0.269)	(0.260)
$ln(\sigma_u^2)$	-3.847***	-11.93
	(0.758)	(19.33)
Observations	1296	1177

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 2.11: Marginal effects from correlated random effects estimates on GSADF outcomes

Variable	Real House Price		House Price to Earnings	
	dy/dx	Standard Error	dy/dx	Standard Error
Region Specific:				
Real Disposable Income	-3.62e-06 ***	9.00e-07	-5.72e-07	8.56e-07
Nationwide:				
Unemployment	-.1493868 ***	.010475	-.0886922 ***	.0112705
Δ FTSE100	-.0115842 ***	.002353	-.0085527 ***	.0022785
Δ Oil Price	.0010157	.0008087	.0007315	.0007792
Δ Current Account	-.0000197	.0000363	-.0001	.0000618
Δ Gold Price	.0045132 **	.0018257	.0003875	.0017841
Official Bank Rate	-.0597499 ***	.0104754	-.0258411 **	.0106797
10 year Government Bond Yield	.0783101 ***	.0184447	.0469024 **	.0186606
Observations	1,296		1,177	

* p<0.10, ** p<0.05, *** p<0.01

The results in Table 2.10 denote multiple significant outcomes within groups. In general terms, the evidence suggests macro and financial variables have some predictive power for exuberance. With the exception of changes in the current account and oil prices, all macroeconomic and financial variables are found to have some predictive content with respect to exuberance in real house prices. While other studies have considered changes in stock prices, interest rates and income (Muellbauer and Cameron, 2006), no studies formally assess the role of unemployment which we find to be a strong predictor of bubbles across most regions.

The strongest predictor of exuberance in both housing affordability and house prices is the unemployment rate, demonstrating how a fall in the unemployment rate is closely associated with the increased likelihood of exuberance in the housing market. In contrast to this, we find that changes in disposable income have no power in predicting exuberance in the price to earnings ratio, and an extremely low marginal impact in predicting explosively in prices. While the effect is found to be significant, the value is negative and very close to zero. Inspection of the results at the regional level may yield more information as to how the relationship between changes in disposable income impact bubble behaviour in the housing market. Our findings are consistent with Muellbauer and Cameron (2006) who also find that region specific income growth rates hold surprisingly little explanatory power with respect to house prices. As expected, interest rates are found to be predictive of exuberant episodes. As interest rates increase, the cost of mortgages rises, reducing demand for housing as prospective home-buyers are deterred by higher costs and may choose to substitute towards the rental sector. We note that as the Bank of England interest rate decreases, the probability of exuberance in the Housing market increases, both in reference to price and accounting for fundamentals. These findings are reconcilable with the concerns of protracted periods of low interest rates since the Global Financial Crisis (GFC) that have led critics to be wary of how this form of monetary policy may encourage the formation of asset bubbles. These findings indicate this may indeed be a valid concern, with the Official Bank Rate is found to be significant at the 1% for exuberance in real house prices and mortgage to earnings ratio respectively. As the official bank rate increases, the probability of an episode of exuberance is less likely; this is consistent with the findings of Pavlidis et al. (2014).

With respect to changes in the stock market, we find that increased growth in the FTSE100 decreases the likelihood of exuberance in both price and affordability measures. This may be evidence of speculators substituting between both asset classes, such that as expected rates of return in shares decreases, individuals may look for to housing as an alternative asset class, fuelling the likelihood of a housing bubble. Our findings contrast with Muellbauer and Cameron (2006) who find changes in stock prices have significant positive effects in London and the South. Changes in the gold price however are positively associated with the increased probability of exuberance in house prices. In the wake of the GFC, consumer confidence and investor fears may have supported a shift towards investors seeking less risky investments such as gold and housing. Exuberance in the housing market is also found to be robust to changes in worldwide macroeconomic conditions, proxied by changes in the oil price and current account. These variables are found to have no predictive power in anticipating periods of explosive growth in house prices or their fundamental drivers. The findings reveal exuberance in the UK housing market is robust to global macroeconomic conditions given the low predictive ability of changes in the oil prices and the current account.

The results in Table A.6 to A.9 summarise the GSADF probit results by region[9] for real house prices and house price to earnings, along with their respective marginal effects. The results demonstrate the strong impact of unemployment in predicting regional explosivity in house prices, with all English regions except Greater London showing unemployment rates have

[9] Tables are reported in Appendix A.5

predictive power over periods of exuberance at the 1% level. The marginal effect is highest in the North and Midlands, while the South East and West show a lower impact compared to the other regions. Greater London finds unemployment to be a predictor of exuberance in housing affordability at the 1% and the short term rate at the 5%; all other variables are shown to have no predictive power over exuberance in the region. These outcomes indicate that the drivers of bubbles in these given areas are not adequately explained by the covariates enlisted.

2.7 Concluding Remarks

In this chapter we employ the novel method of Phillips et al. (2011) and Phillips et al. (2014) for testing and date stamping exuberant episodes in asset prices to detect bubble behaviour across UK regions from 1983(1) to 2014(4). Through the analysis of time series properties of regional house prices, our research contribution is twofold; firstly we are able to identify the date stamp at which house price appreciation mutates into exuberance for each area. By contrasting the experience of prices with their fundamentals, we are able to ascertain whether explosive episodes are driven by fundamentals or speculative behaviour consistent with the notion of a bubble. Secondly, our findings illustrate the synchronisation of regional segments of the housing market which ultimately improve our understanding of how national UK house price bubbles materialise through inspection of the disaggregate components. In the context of the vast literature surrounding the transmission of house price shocks to surrounding areas, this paper finds mixed evidence supporting the established 'ripple effect' hypothesis.

By addressing these research aims, we further the framework for both monitoring and understanding the UK housing market. The policy implications are both retrospective in the analysis of past bubble formation, but also proactive in furthering the existing framework of anticipating episodes of exuberance. This ultimately leads to the design of effective policy. Additionally, these methods serve as an early warning diagnostic of bubble activity for UK regions. Our research provides the starting point for further analysis into what were the fundamental antecedent factors in the evolution of house price exuberance.

The results indicate a high prevalence of bubble episodes experienced in prices with only a fraction also exhibited in the affordability ratios. Based on these outcomes, we find house price fundamentals do not explain the explosive tendencies in house prices, most prominently experienced in the late 90's and early 00's, during which both affordability measures demonstrate a decoupling effect from their exuberant price counterparts. These decoupled episodes of exuberance can be thought of as bubbles given their departure from their fundamentals and explosive characteristics. The relatively short periods of exuberance in both ratios have a lagged onset compared to prices. Interestingly, we find a higher number of exuberant episodes in southern areas that are unmatched by respective exuberance in housing affordability measures. Furthermore, our results indicate unemployment and short term interest rates hold significant power in predicting regional episodes of exuberance. Regional results also demonstrate a significant level of heterogeneity across regions, with London demonstrating the least episodes of exuberance in real house prices combined with the lowest predictive content from the covariates in the correlated random effects probit model.

The use of median salaries of full-time male earners severely limits the suitability of the affordability measure. The exclusion of female and part time participation underestimates the detection of bubbles over the tested period. Over the given timeframe, the number of females and part time workers have steadily increased with joint household income playing a dominant role in housing affordability. Indeed, as house prices have outstripped earnings in appreciation, households have increasingly relied on both incomes to afford housing, in addition to part-time and flexible working earners also contributing to housing costs. In light of this, the likelihood of bubbles that are not detected using affordability measures comprising of full-time male median salaries increases over the tested period. The bias arising from the use of full-time male only earnings data incurs severe errors-in-variables that must be taken into consideration when interpreting the estimation output.

A key limitation of the GSADF procedure is that it lacks the flexibility to allow for both an explosive root and a unit root (Engsted et al., 2015). The null hypothesis underlying the test assumes the time series follows an I(1) process, against the alternative that the series is characterised by an explosive process. Applying the test on the price to income ratio and rejecting the null hypothesis is implicitly assuming that prices and income are cointegrated; this may not be the case in practice. It is also important to note that both affordability measures are unable to capture all fundamentals in house prices, and as such a major limitation of our work pertains to these unaccounted for fundamentals.

Future research would thus benefit from evaluating the cointegrating relationship between prices and fundamentals in tandem with exuberance. We may pursue this using Engsted and Nielsen (2012) co-explosive VAR framework to test for bubbles while concurrently allowing cointegrating relationship between prices and their fundamentals and estimating the strength of this cointegrating relationship. By using the SADF and GSADF procedure, we are able to date-stamp the commencement and termination of bubbles for use in co-explosive VAR; this information must be provided a priori so our existing GSADF estimation is a parsimonious extension in this context. Alternatively we may also contrast our findings against a fractional integration approach. We also consider extending the variable set to ascertain whether other measures may be good predictors of bubbles. For example, behavioural measures of investor optimism and market stress indicators may provide meaningful insights into the formation of bubbles.

Chapter 3

Estimating Spillover Effects in the English Housing Market: A Heterogeneous Spatial Autoregressive Panel Approach

3.1 Introduction

Recent advances in the analysis of cross-sectional dependence has led to a range of novel techniques in efficiently modelling cross-sectionally dependent systems. Spatial dependence has been the recipient of exhaustive analysis in a wide range of disciplines ranging from geographical areas to more abstract network systems. This chapter utilises the recent contribution of Aquaro et al. (2015); Bailey et al. (2016) in estimating a sub-regional spatio-temporal model of the English housing market, accounting for both strong and weak forms of cross-sectional dependence.

While the UK housing market has long sustained the scrutiny of empirical research, the contributions from this chapter are novel in the use of nascent techniques that account for cross-sectional dependence (CSD hereafter) to allow for accurate estimates of spatial dependence. This chapter continues in the tradition of panel estimation under network dependence (Anselin, 1988; Elhorst, 2003; Baltagi, 2005; Anselin et al., 2008; Kapoor et al., 2007; Fingleton, 2008, 2010) with a focus on revealing the spatial structure of house prices diffusion in England. Further contributions arise from the use of sub-regional data, capturing a rich set of dynamics that elucidate how shocks to the system propagate across both dimensions. The estimated model exploits a large timeframe through the use of monthly data, capable of capturing short term adjustments that are missed in lower frequency studies. The heterogenous spatial autoregressive (HSAR) model allows for variation in the degree of spatial dependence in house price growth between neighbouring districts, in addition to differences in the persistence of these changes over time. The proposed model also allows for the effects of neighbourhood changes in house price inflation to affect each corresponding area in the following period, alongside variation on intercept and noise variance across districts. This level of flexibility is particularly suitable given the complexity of the housing market and how housing by its very own nature is heterogenous.

In addition to the exogenous weights matrices, we also consider more recent developments by Bailey et al. (2016) (hereafter BHP) using a data driven weighting matrix. Existing empirical analysis allowing for weak cross sectional dependence often accounts for spatial relationships using *a priori* information that may be inadequate in capturing all interrelations between cross-sectional units. These imprecisions may lead to inaccurate calculations of spatial lags or incorrect spillover mechanisms (Pesaran et al., 2004). To combat this, we utilise the proposed method by Bailey et al. (2016) where the spatial matrix is constructed using a data driven method. We adapt this method by removing the multiple testing correction due to the sizeable reduction in significant pairwise relationships. In the absence of this modification, the resulting weights matrix is too sparse to characterise a reasonable number of neighbours, rendering the spatial estimation procedure redundant.

The results indicate a common factor structure exists in the tested panel of English house price growth alongside spatial effects. The estimated model show temporal dependence in house price inflation is highly significant across all regions, indicating substantial persistence in house price growth over time. After accounting for common factor impacts at the regional and national level, evidence of spatial dependence is found in two thirds of regions (under the 5 nearest neighbour weights specification) indicating interdependencies between neighbourhoods.The results highlight both positive and negative spillover effects that can be attributed to equilibrating and substitution effects between districts. Furthermore, neighbourhood price changes are found to affect house price inflation to a greater extent in the next month than contemporaneously, with indications of mean reversion between current and lagged effects. Interestingly, the mean group estimate results of regional impact mask the rich dynamics of spatial dependence across the country. The results indicate region or nation wide policies may serve to increase divergence in house price inflation across districts, as clusters of areas not only more susceptible to impacts of house price growth in neighbouring areas, but also vary in terms of the impact having either negative or positive long run impacts. At the subregional level, the results indicate delineating housing markets by regions fails to capture significant inter-regional effects that are masked in single parameter estimates for a region. As local governments are able to control housing policy at the district level, the findings suggest cities and transport networks play a key role in the propagation of multiplier effects.

The rest of the chapter is organised as follows. Section 3.2 outlines the relevant literature in characterising spatial dependence within the housing context. Section 3.3 summarises the data selection. Section 3.4 specifies the model and derives the marginal effects of persistence in house prices on neighbourhood house price inflation. Section 3.5 presents an analysis of the estimated results, and finally, Section 3.6 concludes.

3.2 Related Literature

Housing markets have often been considered better characterised as a series of interconnected regional and local markets (Meen, 1996). Indeed, whilst house prices change over time and space, these variations are not independent of one and other (Gong et al., 2016). These arise from differentials in house price and construction costs across space such as income levels. Furthermore, even assuming spatial homogeneity in this respect, structural differences between local areas engender heterogenous adjustment mechanisms primarily with respect to migration flows and wages (Meen, 1996). The reverse is also true as migration and wages are also affected by housing market characteristics.

In theory, house prices at equilibrium are set by the balance between demand and supply. However, in situations where supply is insensitive to increased prices, or where factors other than fundamentals motivate price movements, housing may be persistently overvalued or deemed unaffordable. This can place upward pressure on wages and the labour costs at the individual and firm level, in addition to increased risks for macroeconomic stability. In this sense, residential property prices play a key function in urban economic models, equilibrating house prices such that individuals and firms are indifferent between houses situated across all spatial units. The impact of this calibration can only be fully realised in the long run due to the difficulties associated with household relocation and the time-scale for housing construction.

If a district is overpriced, the divergence from the long run house price should diminish over time as consumers' search activity substitutes away from the overpriced home, redirecting search behaviour towards other homes within the local housing market area. The upward pressure on property prices in neighbouring districts combined with the downward pressure of prices in the initial district may lead to an equilibrating impact over time (Jones et al., 2004). In this sense, a housing market may be considered as a group of dwellings with shared dwelling characteristics such that individuals are largely substitutable between properties. This theory is compatible with Pollakowski and Ray (1997) who find spillovers are not restricted to neighbours but posit only an economic relationship is required.

The interregional relationships of house prices are often typified by theories of convergence (Holmes and Grimes, 2008; Cook, 2005; Cotter et al., 2011) or diffusion mechanisms. The latter is examined across regions in Britain in Alexander and Barrow (1994); Ashworth and Parker (1997); Meen (1996, 1999). A popular hypothesis of diffusion is put forward by Meen (1999) as the 'ripple effect', where the diffusion of house price increases first occur in the South East and London, before spreading across the rest of the country (Giussani and Hadjimatheou, 1991; Meen, 1996, 1999). Balcilar et al. (2013); Canarella et al. (2012); Pollakowski and Ray (1997) consider a transitory or pervasive spillover effect in this context. Canarella et al. (2012) finds that migration flows may precipitate the ripple effect as households relocate in response. As noted in Meen (1999), spatial dependence is not required for rationalising the ripple effect. Meen and Andrew (1998) identify five potential causes of spillovers arising from the ripple effect, namely: migration, transaction and search costs, equity transfer, spatial arbitrage and leads and lags in house prices. Some district level studies have considered house price spillovers in the Scotland, England and Wales (Jones and Leishman, 2006; Gray, 2012). Gray (2012) finds some evidence supporting the ripple effect, in addition to significant spatial and temporal lags of London areas on low priced homes in the North.

Understanding the propagation of house price movements across both dimensions is also important in the context of the economic signals these movements send. High growth in property prices in a district implies that future residents have to pay escalating costs to reside in a given area. The effect is exacerbated in areas with greater population growth. While fundamentals of price theory denote that persistently raised house prices precipitate a corresponding increase in the supply side, in the case of housing, the limitations to changes in supply persist. In the case of no supply constraints, where land is available in abundance and construction could supply new units in response to prices increasing sufficiently above production costs to provide them a profitable return, prices would never surpass the construction costs in the long run. Other researchers have studied supply side constraints, demonstrating compelling evidence of hurdles that raise the cost of developing new housing imposed by local and national governing bodies (Glaeser and Gyourko, 2003; Glaeser et al., 2005b,a; Gyourko et al., 2008; Saks, 2008).

While this chapter focuses on the estimation of interdependencies in house price growth, there exists a considerable literature dedicated to understanding what motivates these changes in the price level. Gyourko et al. (2010) considers four drivers for growth in house prices stemming from urban research of the housing market. Firstly, agglomeration effects have an increasing value in areas characterised by inelastic housing supply. House price growth may also be a result of increased productivity unrelated to the impact of agglomeration. Alternatively, the increases may be driven by increased levels of amenities in cities or the dispersion may stem from an increasing number of high income households at the national level in tandem families ’sorting’ across districts. In the latter case, high income households are able to outbid other families for the scarce properties in a supply constrained district.

3.3 Data

We use house price data collected by the Land Registry made available through the Office of National Statistics (ONS). The subregional dataset includes 33 London boroughs, 201 non-metropolitan districts, 36 metropolitan districts and 55 unitary authorities. Henceforth, these areas are collectively referred to as districts.[1]

From 1974, a two tier administrative structure was instigated across England and Wales, impacting the division of functions between councils and districts. This process created a struc-

[1] The history and structure of the UK administrative geography is reviewed in Wilson and Game (2011).

ture of shire counties and non-metropolitan districts, with the exception of the Isles of Scilly, Greater London and the metropolitan counties. While counties assumed responsibilities such as transport, education, strategic planning, local authority districts appropriated functions including local planning, housing and building. Further restructuring in the 1990s introduced unitary authorities as single tier structures with full responsibility across all local government operations. The subdivision of district level disaggregation is primarily used by local government.

The districts may be further aggregated into nine regions: South East, London, North West, East, West Midlands, South West, Yorkshire and the Humber, East Midlands and North East. Monthly data spanning from January 1995 to August 2016 is used to capture a rich set of dynamics often masked in quarterly or annual data studies. House prices are adjusted for inflation as follows.

$$p_{irt} = \ln\left(\frac{P_{irt}}{CPI_t}\right), i = 1, ..., N_r; r = 1, ..., R; t = 1, ..., T \tag{3.1}$$

where average house price of district i situated in region r in month t is given by P_{irt}, for i= $1, ..., N_r$, $r = 1, ..., R$ and t= $1, ..., T$, where $\sum_{r=1}^{R} = N_r = N = 325, R = 9$ and T= 260. CPI_t denotes the national consumer price index at month t. Seasonally adjusted growth in house prices, π_{irt} are derived using the X-12-ARIMA process.

3.4 Econometric Methodology

3.4.1 Testing for Cross Sectional Dependence

In spite of the considerable spatial literature concerning house prices, past studies often fail to assess the level of cross sectional dependency (Rapach and Strauss, 2009; Gupta and Das, 2010; Kuethe and Pede, 2011). Models incorrectly specified for spatial connections where factor dependence persists puts the validity and accuracy of the results obtained into question. [2]

The degree of cross sectional correlation is assessed using the CD test and exponent of CSD.

$$CD = \left[\frac{TN(N-1)}{2}\right]^{\frac{1}{2}} \hat{\bar{\rho}}_N \tag{3.2}$$

[2]See Chudik et al. (2011) for a detail account of weak and strong CSD.

where:

$$\hat{\bar{\rho}}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{3.3}$$

The CD statistic conforms to the standard normal distribution as shown in Pesaran (2015), where the null hypothesis denotes weak CSD. Strong cross-sectional dependence is accounted for using cross sectional national and regional averages. After testing for weak cross sectional dependence against the alternative of strong CSD, if evidence of the latter is found, residuals are taken from the estimated factor model. This process accounts for the strong cross-sectional dependence in the model. Alternative methods exist including principal components analysis (Bai, 2003) and maximum likelihood estimation of observed factors (Robertson and Symons, 2007). Accounting for all observable factors affecting house price changes requires more data than available at the district level on a monthly basis. We opt to use cross sectional averages due to the clear economic interpretation of both factors. Additionally, Bailey et al. (2016) compute both principal components analysis and cross sectional averaging methods - while both methods demonstrate effective in accounting for common effects, the use of cross sectional averages is less computationally demanding.

Following the Office of National Statistics classification of regional boundaries, we use this hierarchical model to assign each district to its respective region. Changes in real house prices are regressed on a constant, national average and relevant regional average. The defactored house price changes are given by the residuals in the regression below. In the instance of strong CSD, seasonally adjusted changes in real house prices are de-factored using national and regional cross-sectional averages:

$$\pi_{irt} = \varrho_{ir} + \beta_{ir}\bar{\pi}_{rt} + \gamma_{ir}\bar{\pi}_t + \xi_{irt} \quad i = 1, ..., N_r; r = 1, ..., R; t = 1, ..., T \tag{3.4}$$

where $\bar{\pi}_t = N^{-1} \sum_{i=1}^{N} \pi_{it}$, $\bar{\pi}_{rt} = N_r^{-1} \sum_{i=1}^{N_r} \pi_{irt}$, with N_r denoting the number of districts within each region r for $r = 1, \ldots, R$, $\sum_{r=1}^{R} N_r = N$. The residuals from the above equation denote the de-factored real house price changes, $\hat{\xi}_t$. The CD test and the strength of CSD are both measured again for comparison with the results obtained from the original real house price changes to ensure the process has been successful in extracting the strong component of CSD.

Table 3.1: Summary Statistics of House Price Indices Adjusted for Inflation

	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	No. Districts
NE	6.94	0.370	7.61	6.27	-0.229	1.63	12
NW	6.99	0.438	7.92	5.92	-0.250	2.15	39
YH	7.08	0.440	8.01	6.11	-0.173	2.06	21
EM	7.14	0.419	8.02	6.16	-0.395	2.20	40
WM	7.22	0.416	8.04	6.10	-0.405	2.32	30
E	7.45	0.452	8.57	6.29	-0.462	2.50	47
L	7.88	0.521	9.52	6.60	-0.0462	3.00	33
SE	7.62	0.445	8.79	6.24	-0.577	2.75	67
SW	7.44	0.413	8.19	6.39	-0.660	2.27	36
England	7.37	0.523	9.52	5.92	-0.0738	2.75	325

3.4.2 *A priori* Weights Specifications

The selection of a suitable spatial weight matrix is a key element of the spatial model; it assumes a predetermined structure of spatial dependence, which attempts to summarise the spatial dependencies derived from the true DGP. Hence, we may consider the weighting matrix as a method to parameterise Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things." (Tobler, 1970). Spatial weights are interpreted as functions of proximity, often using geographic or economic measures (Anselin, 1988). Ord (1975) built on the work of Whittle (1954) to propose a salient parameterisation of the dependence between units by imposing a structure on the dependencies between units, giving rise to a spatial autoregressive data generating process. Following in the tradition of the spatial literature, three types of exogenous weights matrices are considered; queen, nearest neighbour and inverse distance measures are implemented as a robustness check. In order to account for different levels of connections, we connect districts based on a proximity of 7.5, 10 and 15 miles. These measures yield a population of 0.56%, 1.04% and 2.47% respectively.

Using GIS software, each 'polygon' or district is converted to a centroid value. The process summarises an area space into the most central point from its bounding perimeter. The latitude and longitude coordinates for each centroid is then used to determine distances between districts. We opt for orthodromic (or 'great-circle') distance in place of Euclidian measures.[3] The Haversine

[3]While both measures calculate the shortest distance between two points, the former accounts for the spherical surface of the Earth to provide more accurate values of distance compared to the non-projected straight-line measure between coordinate sets in Euclidean space.

formula below calculates great-circle distances between each district centroid.

$$d_{st} = r \times c$$

where,

$$c = 2a\tan 2(\sqrt{a}, \sqrt{1-a})$$

$$a = \sin^2 \Delta\left(\frac{\text{lat}}{2}\right) + \cos(\text{lat}_1)\cos(\text{lat}_2)\sin^2\left(\frac{\Delta\text{long}}{2}\right)$$

where r denotes the radius of the Earth measured in miles, d is the distance, and coordinates are given at two points 1 and 2 in terms of latitude and longitude coordinates.

3.4.3 Pairwise Correlation Determined Spatial Weights Matrix

We also employ Bailey et al. (2016)'s pairwise correlation based method of establishing the spatial weights matrix using de-factored house price changes. The sample correlation matrix from equation (3.4), gives:

$$\hat{\rho}_{\hat{\xi},ij} = \hat{\rho}_{\hat{\xi},ji} = \frac{\sum_{t=1}^{T}(\xi_{it} - \bar{\xi}_i)(\xi_{jt} - \bar{\xi}_j)}{\left[\sum_{t=1}^{T}(\xi_{it} - \bar{\xi}_i)^2\right]^{1/2}\left[\sum_{t=1}^{T}(\xi_{jt} - \bar{\xi}_j)^2\right]^{1/2}} = \frac{\hat{\sigma}_{\hat{\xi},ij}}{[\hat{\sigma}_{\hat{\xi},ii}\hat{\sigma}_{\hat{\xi},jj}]^{\frac{1}{2}}} \tag{3.5}$$

where $\bar{\xi}_i = T^{-1}\sum_{t=1}^{T}\xi_{it}$. The purpose of the adjacency matrix is to summarise the relationships between cross-sectional units. In the case where the weights matrix has near zero connections, this purpose is unfulfilled. The BHP method recommends implementing Holm (1979)'s multiple testing correction at a specified significance level (set at 5% in their application), where N(N-1)/2 pairwise connections take a value of 1 or 0 based on the statistical significance of the respective correlation. In our application, the multiple testing correction dramatically reduces the incidence of connections in the adjacency matrix to near zero connections (0.03%). Given this violates the purpose of the weights matrix, we trial the use of the less conservative Bonferroni correction but find this has the same overly penalising effect. In light of this, no multiple correction is applied. Based on whether statistically significant correlations are negative or positive, values are distinguished into $\hat{W}^-$ and $\hat{W}^+$ matrices respectively such that $\hat{W} = \hat{W}^- + \hat{W}^+$.

In order to ascertain how closely related the correlation based weights matrices are to the distance based measures $\mathbf{W_d}$[4], the statistical association between the weights is measured using Pearson's chi-squared statistic. Given the weights matrices are by their nature sparse, the probability that both weights will share a zero realisation lies near unity. Following the BHP method, we create a contingency table from the upper triangular portion of the adjacency matrices given their symmetric nature as follows:

$$\begin{pmatrix} n_{11} & n_{10} \\ n_{01} & n_{00} \end{pmatrix}$$

The 4 categories are: 1) n_{11} denotes the incidence that elements from $\hat{\mathbf{W}}^{+}$ displays an entry of 1 when $\mathbf{W_d}$ also displays 1 2) n_{00} denotes the incidence that elements from $\hat{\mathbf{W}}^{+}$ displays an entry of 0 when $\mathbf{W_d}$ also displays 0 3) n_{01} denotes the incidence that elements from $\hat{\mathbf{W}}^{+}$ displays an entry of 0 when $\mathbf{W_d}$ displays 1 4) n_{10} denotes the incidence that elements from $\hat{\mathbf{W}}^{+}$ displays an entry of 1 when $\mathbf{W_d}$ displays 0 Consequently, $n_{11} + n_{00} + n_{01} + n_{10} = N(N-1)/2$ and the Pearson chi-squared statistic is:

$$\chi^2 = \frac{N(N-1)}{2}\left[\sum_{i,j=0}^{1} \frac{n_{ij}^2}{(n_{i.} + n_{.j})} - 1\right] \tag{3.6}$$

where $n_{i.} = n_{i0} + n_{i1}$, $n_{.j} = n_{0j} + n_{1j}$.

3.4.4 The Heterogenous Spatial Autoregressive Model

The spatial autoregressive panel (SAR hereafter) model with homogeneous spatial autoregressive coefficient, ψ is given as

$$\xi_t = \psi \sum_{j=1}^{N} w_{ij}\xi_{jt} + \varepsilon_{it}, \quad i = 1, 2, ..., N; \quad t = 1, 2, ..., T, \tag{3.7}$$

where $\boldsymbol{w_i'\xi_t} = \sum_{j=1}^{N} w_{ij}\xi_{jt}$ with $\boldsymbol{w_i} = (w_{i1}, w_{i2}, ..., w_{iN})'$ denoting an N x 1 vector of fixed weights associating the i^{th} district to it's respective neighbours where $w_{ii} = 0$. Furthermore, $\boldsymbol{\xi_i} = (\xi_{i1}, \xi_{i2}, ..., \xi_{iN})'$ and ε_{it} represents the district specific error component, assumed to be both serially and cross-sectionally independently distributed. Equation 3.7 can be stacked across N

[4] For this purpose, we use $\mathbf{W_{d=15m}}$

units to give $\boldsymbol{\xi_t} = \psi \boldsymbol{W y_t} + \varepsilon_t, \quad t = 1, 2, ..., T$, where $\boldsymbol{W} = (w_{ij}), i, j = 1, 2, ..., N$ denoting an $N \times N$ row normalised spatial weight matrix summarising all the connections between cross sectional units. Given the restrictive nature of enforcing a constant spatial autoregressive parameter across all districts, we utilise the contribution of Aquaro et al. (2015) (hereafter ABP). Adapted from the first order SAR given in equation 3.7, the HSAR model can be written as:

$$\xi_{it} = \psi_i \sum_{j=1}^{N} w_{ij} \xi_{jt} + \varepsilon_{it}, \quad i = 1, 2, ..., N; \quad t = 1, 2, ..., T, \tag{3.8}$$

where ψ_i is the spatial autoregressive parameter. In matrix form this gives:

$$\boldsymbol{\xi_t} = \boldsymbol{\Psi W \xi_t} + \boldsymbol{\varepsilon_t} \quad t = 1, 2, ..., T \tag{3.9}$$

where $\boldsymbol{\Psi} = diag(\boldsymbol{\psi}), \boldsymbol{\psi} = (\psi_1, \psi_2, ..., \psi_N)'$, and $\sigma^2_{\varepsilon_i} = var(u_{it}), i = 1, 2, ..., N$. BHP adapt the ABP model to incorporate temporal and spatial effects:

$$\boldsymbol{\xi}_t = \sum_{j=1}^{h_\lambda} \boldsymbol{\Lambda}_j \boldsymbol{\xi}_{t-j} + \sum_{j=0}^{h_\psi} \boldsymbol{\Psi}_j \boldsymbol{W} \boldsymbol{\xi_{t-j}} + \boldsymbol{\zeta}_t \tag{3.10}$$

where $h_\lambda = \max(h_{\lambda 1}, h_{\lambda 2}, ..., h_{\psi N}), h_\psi = \max(h_{\psi 1}, h_{\psi 2}, ..., h_{\psi N})$. $\boldsymbol{\Lambda}_j, \boldsymbol{\Psi}_j$ are $N \times N$ matrices with diagonal elements of λ_{ij} and ψ_{ij} respectively. Note the variance of the disturbance term, $\sigma^2_{u_i} = \text{var}(u_{it})$, alongside λ_{ij} and ψ_{ij} are able to vary across each district i. We model defactored house price changes $\hat{\xi}_{it}$ using the following spatio-temporal model under QML estimation in ABP:

$$\hat{\boldsymbol{\xi}}_t = \boldsymbol{a}_\xi + \boldsymbol{\Lambda}_1 \hat{\boldsymbol{\xi}}_{t-1} + \boldsymbol{\Psi}_0 \widetilde{\boldsymbol{W}} \hat{\boldsymbol{\xi}}_t + \boldsymbol{\Psi}_1 \widetilde{\boldsymbol{W}} \hat{\boldsymbol{\xi}}_{t-1} + \boldsymbol{\zeta}_t \tag{3.11}$$

The model is estimated using the concentrated log likelihood function:

$$\ell\left(\psi_0^+, \psi_0^-\right) \propto T \ln\left|I_N - \mathbf{\Psi}_0^+ \mathbf{W}^+ - \mathbf{\Psi}_0^- \mathbf{W}^-\right| - \frac{T}{2} \sum_{i=1}^{N} \left(\frac{1}{T} \tilde{\xi}_i' \mathbf{M}_i \tilde{\xi}_i\right) \tag{3.12}$$

where $\psi_0^+ = \left(\psi_{10}^+, ..., \psi_{N0}^+\right)', \psi_0^- = \left(\psi_{10}^-, ..., \psi_{N0}^-\right)', \tilde{\xi}_i = \xi_i - \psi_{i0}^+ \xi_i^+ - \psi_{i0}^- \xi_i^-, \mathbf{M}_i = \mathbf{I}_T - \mathbf{Z}_i \left(\mathbf{Z}_i' \mathbf{Z}_i\right)^{-1} \mathbf{Z}_i, \mathbf{Z}_i = \left(\xi_{i,-1}, \xi_{i,-1}^+, \xi_{i,-1}^-\right)$

The lagged coefficients λ_1, ψ_1^+ and ψ_1^- are estimated by least squares for each individual district conditional on ψ_{i0}^{+} and ψ_{i0}^{-}. Inferential analysis is based on the unconcentrated log-likelihood, $\theta = (\theta_1', ..., \theta_N')'$, where $\theta_i = \left(\psi_{i0}^{+}, \psi_{i0}^{-}, \psi_{i1}^{+}, \psi_{i1}^{-}, \lambda_{i1}, \sigma_{ui}^2\right)'$. The variance–covariance matrix of $\hat{\theta}_{ML}$ is computed as

$$\hat{\Sigma}_{\hat{\theta}_{ML}} = \left[-\frac{1}{T}\frac{\partial^2 \ell\left(\hat{\theta}_{ML}\right)}{\partial\hat{\theta}_{ML}\partial\hat{\theta}_{ML}'}\right]^{-1}$$

In the case where *a priori* weights are used, separate parameters for positive and negative spillovers are not implemented. In this case, the log-likelihood function takes the form:

$$\ell\left(\psi_0\right) \propto T\ln\left|I_N - \mathbf{\Psi}_0\mathbf{W}\right| - \frac{T}{2}\sum_{i=1}^{N}\left(\frac{1}{T}\tilde{\xi}_i'\mathbf{M}_i\tilde{\xi}_i\right) \tag{3.13}$$

where $\psi_0 = (\psi_{10}, ..., \psi_{N0})'$, $\tilde{\xi}_i = \xi_i - \psi_{i0}$, $\mathbf{M}_i = \mathbf{I}_T - \xi_{i,-1}\left(\xi_{i,-1}'\xi_{i,-1}\right)^{-1}\xi_{i,-1}$. Lagged estimates are calculated using least squares estimates for each individual district conditional on ψ. However, interpretation at the district level requires analysis using the unconcentrated log likelihood function as discussed in BHP. We also consider the model proposed by BHP in the context of the data driven weights matrix:

$$\hat{\boldsymbol{\xi}}_t = \boldsymbol{a}_\xi + \mathbf{\Lambda}_1\hat{\boldsymbol{\xi}}_{t-1} + \mathbf{\Psi}_0^{+}\widetilde{\boldsymbol{W}}^{+}\hat{\boldsymbol{\xi}}_t + \mathbf{\Psi}_0^{-}\widetilde{\boldsymbol{W}}^{-}\hat{\boldsymbol{\xi}}_t + \mathbf{\Psi}_1^{+}\widetilde{\boldsymbol{W}}^{+}\hat{\boldsymbol{\xi}}_{t-1} + \mathbf{\Psi}_1^{-}\widetilde{\boldsymbol{W}}^{-}\hat{\boldsymbol{\xi}}_{t-1} + \boldsymbol{\zeta}_t \tag{3.14}$$

where $\boldsymbol{W}^{-}$ and $\boldsymbol{W}^{+}$ are row standardised versions of $\hat{\boldsymbol{W}}^{-}$ and $\hat{\boldsymbol{W}}^{+}$ respectively; $\boldsymbol{a}_\xi = (\alpha_{\xi1}, \alpha_{\xi2}, ..., \alpha_{\xi N})'$; is an $N \times 1$ vector of intercepts. $\mathbf{\Lambda} = diag(\lambda)$, $\mathbf{\Psi}_0^{+} = diag(\psi_0^{+})$, $\mathbf{\Psi}_0^{-} = diag(\psi_0^{-})$, $\mathbf{\Psi}_1^{+} = diag(\psi_1^{+})$, $\mathbf{\Psi}_1^{-} = diag(\psi_1^{-})$, where $\boldsymbol{\lambda_1} = (\lambda_{11}, \lambda_{12}, ..., \lambda_{1N})'$,$\boldsymbol{\psi}_r^{+} = (\psi_{r1}^{+}, \psi_{r2}^{+}, ...\psi_{rN}^{+})'$, $\boldsymbol{\psi}_r^{-} = (\psi_{r1}^{-}, \psi_{r2}^{-}, ...\psi_{rN}^{-})'$, for r=0 and 1, and $\boldsymbol{\zeta_t} = (\zeta_{1t}, \zeta_{2t,...,}\zeta_{Nt})'$ gives the error terms. We assume under QML estimation $\zeta_{it} \sim IIDN(0, \sigma_{\zeta_i}^2)$ for $i = 1, ..., N$. This model allows for heterogeneity across spatial dependencies and dynamics for all districts alongside no minimum restrictions on the number of neighbours.

3.4.5 Interpreting the HSAR model estimates

We base our discussion on LeSage and Chih (2016)'s derivation of the marginal effects for the HSAR model. The reduced form HSAR model can be decomposed into an N × N matrix of partial derivatives in the form:

$$\frac{\partial \boldsymbol{y}_t}{\partial \boldsymbol{y}'_{t-1}} = \begin{bmatrix} \frac{\partial y_1}{\partial y_{1,t-1}} & \frac{\partial y_1}{\partial y_{2t-1}} & \cdots & \frac{\partial y_1}{\partial y_{N,t-1}} \\ \frac{\partial y_2}{\partial y_{1,t-1}} & \frac{\partial y_2}{\partial y_{2,t-1}} & \cdots & \frac{\partial y_2}{\partial y_{N,t-1}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial y_{1,t-1}} & \frac{\partial y_N}{\partial y_{2,t-1}} & \cdots & \frac{\partial y_N}{\partial y_{N,t-1}} \end{bmatrix} = (I_N - \Psi_0 W)^{-1}(\Lambda + \Psi_1 W) \tag{3.15}$$

The above expression summarises how the persistence in house prices in a given district could impact own-district house price inflation in addition to house price inflation in all other districts.[5] The diagonal elements of the matrix in expression (3.15) denote own-partial derivatives, expressing how the persistence of house prices in the given district directly impacts own-district house price inflation in the current period. The cross-partial derivatives which populate the off-diagonal elements show how persistence in house prices in a district spillover to affect house price inflation in other districts. To capture the heterogeneity between districts, we follow the conventions put forward in LeSage and Chih (2016) where each diagonal element estimates the direct effects of persistence in house prices for each district, and the row sum of the off-diagonal elements produce a vector of district specific indirect effects. The cumulative sum of off diagonal elements of each row give a vector of district-specific cumulative spill-in effects(i.e. $\partial y_i/\partial y_{j,t-1}, j \neq i$). These effects show how changes in neighbouring districts' persistence in house price inflation create a spill-in impact on each district i's house price growth. The cumulative sum of the off-diagonal columns produces the cumulative spill-out effects, measuring how changes in house price growth in district i impact neighbouring districts $j \neq i$ (i.e. $\partial y_j/\partial y_{i,t-1}, j \neq i$).

[5]This discussion is analogous to Korniotis (2010) where internal and external habit formation is analysed. See Section 4.6.1 for further discussion.

3.5 Empirical Results

3.5.1 Weights Specification

Figure 3.1 summarises the weights matrices in this chapter. All connections are identified in black, with the white areas signifying no connections. Observations are organised in order of distance from a ‘corner’ of England. To serve this purpose, Cornwall is selected for its far South West placement. We restrict all areas to not be neighbours with itself, keeping the diagonal of each matrix clear. The contiguity and nearest neighbour based measures are very similar, both in terms of distribution and sparsity at 1.65% and 1.54%. We consider three distance based measures to yield similar levels of sparsity to the tested values in BHP. Districts within 7.5, 10 and 15 miles correspond to sparsity levels of 0.56%, 1.04% and 2.47% respectively. Results from 7.5 and 10 mile inverse distance adjacency matrices are relegated to the appendices. The difference in the data driven spatial weights compared to all exogenous measures is most apparent. The matrix is extremely sparse with only 17 connections out of a possible 52650 connections; this low value corresponds to 0.03%. Noticeably, all boroughs in London are connected. This is most marked using the distance based measures, showing the close proximity shared by the districts in the city.

Table 3.2: Contigency table for $\mathbf{W}^{+}_{\mathbf{CS}}$ and $\mathbf{W}^{-}_{\mathbf{CS}}$ vs $\mathbf{W_{15m}}$

		$\mathbf{W_{15m}}$					$\mathbf{W_{15m}}$		
		1	0	$\sum_{rows}$			1	0	$\sum_{rows}$
$\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$	1	52	1261	1313	$\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$	1	52	1462	1514
	0	1248	50089	51337		0	1248	49888	51136
	$\sum_{cols}$	1300	51350	52650		$\sum_{cols}$	1300	51350	52650

Table 3.3: Contigency table for $\mathbf{W_{cs+}}$ and $\mathbf{W_{cs-}}$ vs $\mathbf{W_{pc+}}$ and $\mathbf{W_{pc-}}$

		$\hat{\mathbf{W}}^{+}_{\mathbf{PC}}$					$\hat{\mathbf{W}}^{-}_{\mathbf{PC}}$		
		1	0	$\sum_{rows}$			1	0	$\sum_{rows}$
$\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$	1	906	314	1220	$\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$	1	1039	385	1424
	0	407	51023	51430		0	475	50751	51226
	$\sum_{cols}$	1313	51337	52650		$\sum_{cols}$	1514	51136	52650

Table 3.4: Pearson's χ^2 statistics against $\hat{\mathbf{W}}_{\mathbf{CS}}$

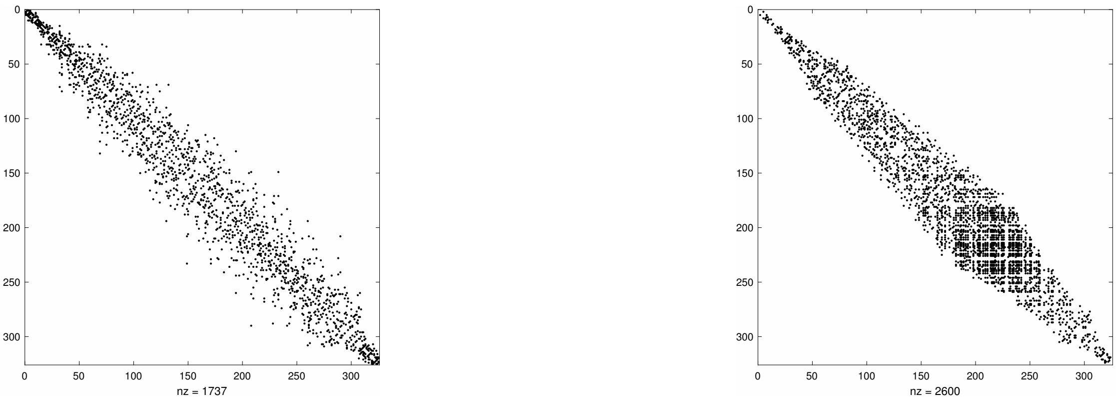
	$\mathbf{W}_{\mathbf{7.5m}}$	$\mathbf{W}_{\mathbf{10m}}$	$\mathbf{W}_{\mathbf{15m}}$	$\mathbf{W}_{\mathbf{QC}}$	$\mathbf{W}_{\mathbf{5NN}}$
$\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$	8.19	5.31	12.4	5.13	4.16
$\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$	0.773	3.50	6.03	5.08	0.160

Table 3.5: Pearson's χ^2 statistics against $\hat{\mathbf{W}}_{\mathbf{PC}}$

	$\mathbf{W}_{\mathbf{7.5m}}$	$\mathbf{W}_{\mathbf{10m}}$	$\mathbf{W}_{\mathbf{15m}}$	$\mathbf{W}_{\mathbf{QC}}$	$\mathbf{W}_{\mathbf{5NN}}$
$\hat{\mathbf{W}}^{+}_{\mathbf{PC}}$	10.0	12.4	15.2	5.03	6.00
$\hat{\mathbf{W}}^{-}_{\mathbf{PC}}$	4.70	10.5	36.4	26.7	16.0

Table 3.2 presents the contingency table for $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$ and $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$ against $\mathbf{W}_{\mathbf{15m}}$. It is apparent that $\mathbf{W}_{\mathbf{15m}}$ shares equal similarities with $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$ and $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$. Both contingency results demonstrate 52 connections are shared with both $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$ and $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$. However, this is the minority of detected connections (total of 1300) demonstrating a low level of similarity as expected from the demonstrably different patterns in the figures. These results contrast to the US house price case in BHP, where the similarities between both $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$ and $\mathbf{W}_{\mathbf{15m}}$ are stronger than with $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$. The Pearson's $\chi^2_{5\%}$ statistics given in Table 3.4 and Table 3.5 compare *a priori* adjacency matrices against the cross-sectional and principal component data driven matrices respectively using a critical value of 3.84. The cross-sectional weights matrices have statistically significant χ^2 statistics particularly with respect to $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$, demonstrating a close association with the pre-specified weight specifications. $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$ shows a statistically significant similarity with $\mathbf{W}_{\mathbf{15m}}$ and $\mathbf{W}_{\mathbf{QM}}$, but low association with $\mathbf{W}_{\mathbf{7.5m}}$, $\mathbf{W}_{\mathbf{10m}}$ and $\mathbf{W}_{\mathbf{5NN}}$.

The contingency results in Table (3.3) show the de-factored house price changes using both methods obtain similar results across positive and negative counterparts. The shared outcomes have a far higher incidence than the $\hat{\mathbf{W}}^{+}_{\mathbf{CS}}$ and $\hat{\mathbf{W}}^{-}_{\mathbf{CS}}$ versus $\mathbf{W}_{\mathbf{15m}}$ results in Table (3.2). The Pearson $\chi^2_{5\%}$ statistics given in Table (3.5) show statistically significant results across all *a priori* weights matrices against the $\hat{\mathbf{W}}^{+}_{\mathbf{PC}}$. The results are convincingly similar to the $\hat{\mathbf{W}}^{+}_{\mathbf{PC}}$ case, with only $\mathbf{W}_{\mathbf{7.5m}}$ showing a statistically insignificant association. The results underscore a significant difference between the data driven weights in comparison to the distance based measure. At this stage, the findings indicate that nearby areas may not be a reasonable indicator of association, or that these data driven methods do not adequately characterise the local relationships between units. In the former case, it provides evidence against the 'ripple effect' hypothesis, which dictates areas near London or the South East have an impact on nearby areas, which then move further onwards to other neighbouring districts.[6]



(a) Queen contiguity (b) Districts within 15 miles

Figure 3.1: Sparsity of *A Priori* Weights Matrices $\mathbf{W_{QC}}$ and $\mathbf{W_{15m}}$

3.5.2 Cross-Sectional Dependence in House Price Changes

In order to assess the level of cross sectional dependence in real house price growth, we utilise the CD statistic developed by Pesaran (2004, 2015). Results are summarised in Table (3.6). Before defactoring, real house price changes compute an average pairwise correlation $\rho_\pi = 0.241$ and $CD_\pi = 888.24$, greatly surpassing a critical value of 1.96 at the 5% significance level. This statistically significant result infers a sizeable degree of cross sectional dependence in real house price movements. The outcome rejects the null hypothesis of weak dependence, in turn signifying strong cross sectional dependence persists. This may be attributed to common country and region wide effects. As the null hypothesis of weak cross sectional dependence is rejected, the exponent of cross sectional dependence may then be estimated using the procedure outlined in Bailey et al. (2016). The obtained measure $\alpha_\pi = 0.9998$ with standard error 0.03, is very close to one, suggesting a high degree of correlation across areas. Both results indicate strong cross sectional dependence, hence rendering typical spatial methods on real house price changes as inappropriate and severely biased.

After defactoring, The CD test on the residuals greatly decreases from 888.24 to -8.82. Additionally, pairwise correlation has substantially decreased from 0.241 to -0.002. The exponent

[6]Due to the similarity in sparsity between 15km inverse distance and the correlation based adjacency matrices, we only report the the results using both of these weights.

of cross sectional dependence has also fallen from near unity ($\alpha_\pi = 0.9998(0.03)$) to near the lower bound value of 0.5 ($\alpha_\tau = 0.515$ with an associated standard error of 0.01). These results demonstrate a sufficient level of cross sectional dependence allowing the use of spatial techniques to account for the remaining weak CSD.

Table 3.6: CD Test and Cross sectional Exponent Measures before and after De-factoring Changes in Real House Prices given in Equation 3.4

Variable	$\bar{\hat{\rho}}_{ij}$	CD	α	95% CI_α
π_{it}	0.241	888.24 (0.027)	0.9998	[0.947,1.053]
$\hat{\xi}_{it}$	-0.002	-8.82 (0.013)	0.515	[0.490,0.541]

π_{it} denotes house price inflation in district i at time t and $\hat{\xi}_{it}$ refers to de-factored house price inflation using Equation (3.4). $\bar{\hat{\rho}}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$ measures average pairwise correlation. $CD = \left[\frac{TN(N-1)}{2}\right]^{\frac{1}{2}} \bar{\hat{\rho}}_N$. α denotes the exponent of CSD and CI_α refers to the 95% confidence interval for α. See Bailey et al. (2016) for details on exponent calculations.

Table 3.7: Region Specific CD Test and Cross sectional Exponent Measures before and after De-factoring Changes in Real House Prices given in Equation 3.4

	Seasonally adjusted HPI			Defactored HPI Using CSA Approach		
	$\hat{\rho}_{ij}$	CD statistic	α of CSD	$\hat{\rho}_{ij}$	CD statistic	α of CSD
North East	0.278	36.8	1.00 (0.0922)	−0.0855	−11.2	0.484 (0.145)
North West	0.267	118	1.00 (0.0527)	−0.0198	−8.66	0.704 (0.0271)
Yorkshire & Humber	0.312	73.6	1.000 (0.0643)	−0.0398	−9.28	0.669 (0.0558)
East Midlands	0.226	103	1.00 (0.0484)	−0.0238	−10.7	0.349 (0.0678)
West Midlands	0.276	93.6	1.00 (0.0448)	−0.0319	−10.7	0.448 (0.0641)
East	0.296	159	1.00 (0.0424)	−0.0201	−10.6	0.463 (0.0468)
London	0.337	126	1.00 (0.0435)	−0.00475	−1.76	0.854 (0.0244)
South East	0.305	233	1.00 (0.0397)	−0.0145	−11.0	0.350 (0.0451)
South West	0.274	112	1.00 (0.0407)	−0.0246	−9.95	0.469 (0.0421)

Table 3.8: Quasi Maximum Likelihood estimates of the spatio-temporal model 3.11 applied to de-factored changes in house prices derived from equation 3.4 using predetermined adjacency matrices.

$\mathbf{W_{QC}}$	λ_1	ψ_0	ψ_1	σ_ζ
Median	0.0448	0.0033	0.0618	1.2703
Mean Group Estimates	0.0470***	-0.0088	0.0433***	1.3390
	(0.0049)	(0.0126)	(0.0108)	(0.0271)
% significant (at 5% level)	21.8%	15.1%	14.2%	-
Number of non-zero coef.	325	325	325	325
Maximum	0.3263	0.5879	0.6384	5.8213
Minimum	-0.2203	-0.9950	-0.9458	0.6026
$\mathbf{W_{15m}}$	λ_1	ψ_0	ψ_1	σ_ζ
Median	0.0467	-0.0097	0.0487	1.2639
Mean Group Estimates	0.0470***	-0.0518***	0.0528***	1.3407
	(0.0049)	(0.0178)	(0.0152)	(0.0272)
% significant (at 5% level)	22.5%	18.3%	11.3%	-
Number of non-zero coef.	325	301	301	325
Maximum	0.3371	0.7571	1.2926	5.8261
Minimum	-0.2048	-0.9950	-1.8759	0.5983

Table 3.9: Quasi Maximum Likelihood estimates of spatio-temporal model 3.14 applied to de-factored changes in house prices derived from equation 3.4 using data driven weights matrices. Pairwise correlations are detected after de-factoring through CSA or PCA.

$\mathbf{W_{CS}}$	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
Median	0.0302	0.4744	-0.5531	0.0029	0.0054	1.0147
Mean Group Estimates	0.0302***	0.5023***	-0.5776***	-0.0011	-0.0067	1.0866
	(0.0046)	(0.0127)	(0.0138)	(0.0107)	(0.0130)	(0.0263)
% significant (at 5% level)	17.5%	90.5%	95.7%	13.5%	11.7%	-
Number of non-zero coef.	325	325	325	325	325	325
Maximum	0.2572	0.9950	0.9948	0.7036	0.6903	6.1894
Minimum	-0.1848	-0.5817	-0.9950	-1.1109	-2.2507	0.4204
$\mathbf{W_{PC}}$	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
Median	0.0338	0.4273	-0.5256	0.0031	0.0204	1.0376
Mean Group Estimates	0.0370***	0.4259***	-0.5235***	0.0079	0.0290	1.1183
	(0.0047)	(0.0176)	(0.0160)	(0.0115)	(0.0116)	(0.0267)
% significant (at 5% level)	19.1%	83.4%	89.2%	10.8%	12.0%	-
Number of non-zero coef.	325	325	324	325	324	325
Maximum	0.2848	0.9950	0.9950	1.4266	0.8641	5.7168
Minimum	-0.1947	-0.9950	-0.9950	-0.5549	-0.7016	0.4137

Mean group estimates are calculated as unweighted averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1}\sum_{i=1}^{N_r}\hat{\psi}_{i0}$ for $i = 1,\dots,N$, $r = 1,\dots,R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)}\sum_{i=1}^{N_r}(\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. Parameter coefficients are restricted to zero if district i has no connections: $\hat{\psi}_{i0} = 0, \hat{\psi}_{i1} = 0$ for $i = 1,\dots,N$.

Table 3.10: Quasi Maximum Likelihood estimation of spatio-temporal model from equation 3.11 using W_{15m} weights matrix. Results are given for de-factored house price changes from equation 3.4 are provided for each region

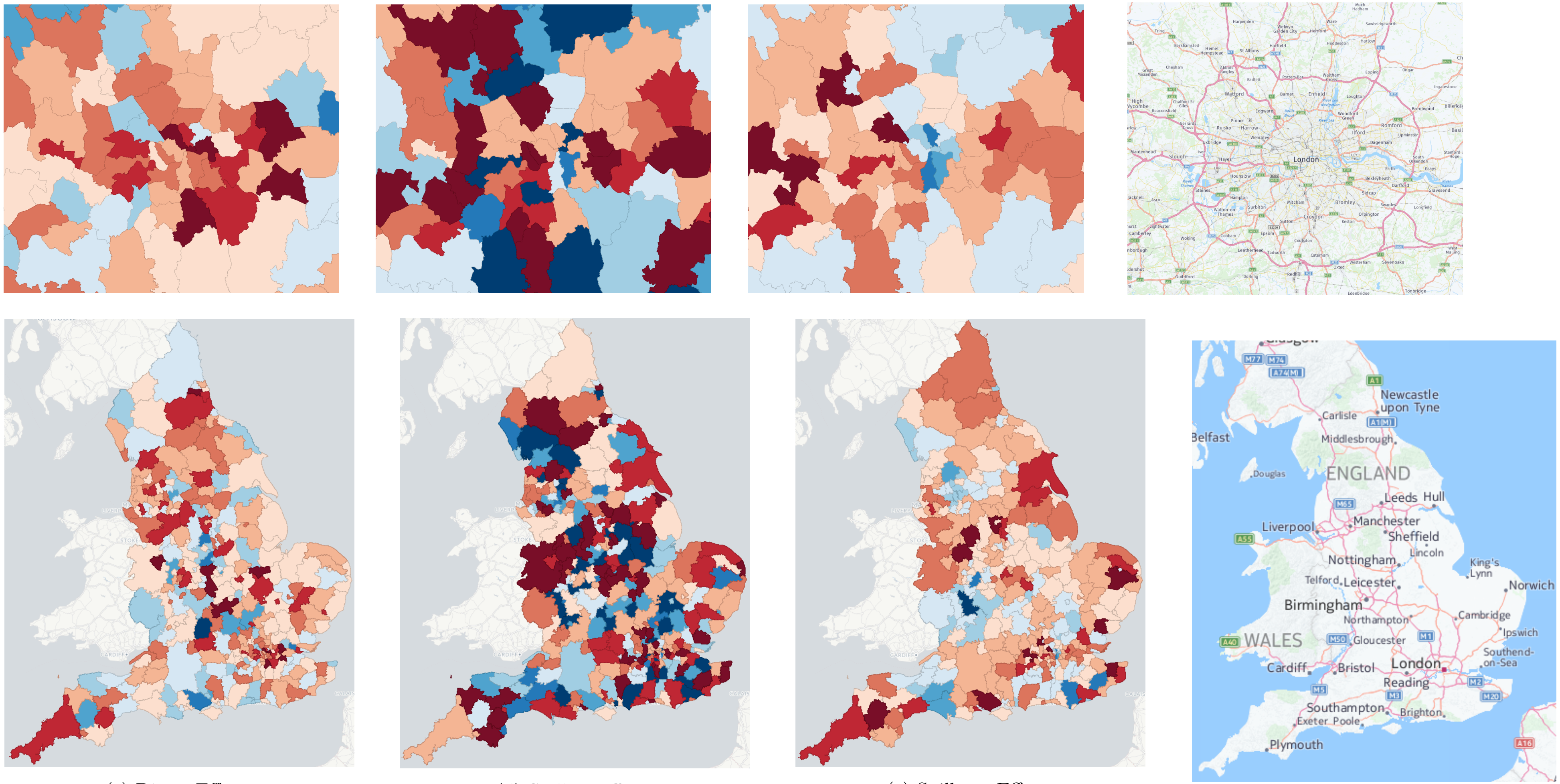
	λ_1	ψ_0	ψ_1	σ_ζ
North East				
Median	0.0614	-0.2358	0.0029	1.3000
Mean Group Estimates	0.0808***	-0.1632**	0.0718	1.3717
	(0.0271)	(0.0750)	(0.0690)	(0.0858)
% significant (at 5% level)	41.7%	30.0%	30.0%	-
Number of non-zero coef.	12	10	10	12
Maximum	0.2258	0.2958	0.5713	2.0418
Minimum	-0.0408	-0.4335	-0.2104	0.8773
London				
Median	0.1140	-0.4771	0.2020	1.0576
Mean Group Estimates	0.1192***	-0.4381***	0.1270	1.2798
	(0.0165)	(0.0815)	(0.1047)	(0.1605)
% significant (at 5% level)	45.5%	33.3%	9.1%	-
Number of non-zero coef.	33	33	33	33
Maximum	0.3371	0.5375	1.2926	5.8261
Minimum	-0.0749	-0.9950	-1.8759	0.6101
South West				
Median	0.0294	-0.0316	0.0441	1.2818
Mean Group Estimates	0.0309**	-0.0280	0.0400**	1.4102
	(0.0122)	(0.0306)	(0.0194)	(0.0830)
% significant (at 5% level)	16.7%	6.9%	6.9%	-
Number of non-zero coef.	36	29	29	36
Maximum	0.1736	0.3735	0.3046	2.8779
Minimum	-0.1396	-0.4559	-0.1349	0.7068
East Midlands				
Median	0.0395	0.0358	0.0425	1.5270
Mean Group Estimates	0.0286*	-0.0010	0.0591**	1.5201
	(0.0161)	(0.0319)	(0.0269)	(0.0603)
% significant (at 5% level)	27.5%	7.7%	7.7%	-
Number of non-zero coef.	40	39	39	40
Maximum	0.2349	0.3457	0.5158	2.5958
Minimum	-0.1619	-0.6323	-0.3514	0.7089
North West				
Median	0.0752	0.0063	0.0257	1.2653
Mean Group Estimates	0.0584***	0.0053	0.0120	1.4861
	(0.0128)	(0.0529)	(0.0370)	(0.0995)
% significant (at 5% level)	20.5%	24.2%	9.1%	-
Number of non-zero coef.	39	33	33	39
Maximum	0.1912	0.7571	0.4201	3.1764
Minimum	-0.1064	-0.6299	-0.5243	0.7090
West Midlands				
Median	0.0371	-0.0653	0.0395	1.2339
Mean Group Estimates	0.0453***	-0.0573	-0.0032	1.2262
	(0.0154)	(0.0426)	(0.0351)	(0.0595)
% significant (at 5% level)	23.3%	6.9%	20.7%	-
Number of non-zero coef.	30	29	29	30
Maximum	0.2074	0.3308	0.4572	1.9704
Minimum	-0.1154	-0.5634	-0.4013	0.5983
South East				
Median	0.0139	0.0510	0.1122	1.2575
Mean Group Estimates	0.0180*	0.0185	0.0681***	1.2573
	(0.0101)	(0.0320)	(0.0247)	(0.0295)
% significant (at 5% level)	14.9%	20.9%	7.5%	-
Number of non-zero coef.	67	67	67	67
Maximum	0.2062	0.5410	0.9308	1.7213
Minimum	-0.2048	-0.6343	-0.3266	0.7682
East				
Median	0.0434	0.0174	-0.0030	1.2460
Mean Group Estimates	0.0481***	0.0362	0.0379	1.2697
	(0.0113)	(0.0410)	(0.0299)	(0.0447)
% significant (at 5% level)	17.0%	18.2%	13.6%	-
Number of non-zero coef.	47	44	44	47
Maximum	0.2355	0.6701	0.5855	2.0676
Minimum	-0.1742	-0.8729	-0.4060	0.7703
Yorkshire and The Humber				
Median	0.0614	0.0182	0.0610	1.0536
Mean Group Estimates	0.0483***	0.0005	0.0587*	1.2762
	(0.0171)	(0.0511)	(0.0332)	(0.1196)
% significant (at 5% level)	14.3%	23.5%	17.6%	-
Number of non-zero coef.	21	17	17	21
Maximum	0.1636	0.2922	0.4393	2.6325
Minimum	-0.0961	-0.6989	-0.2019	0.6861

Mean group estimates are calculated as unweighted averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1}\sum_{i=1}^{N_r}\hat{\psi}_{i0}$ for $i = 1,\ldots,N$, $r = 1,\ldots,R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)}\sum_{i=1}^{N_r}(\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. Parameter coefficients are restricted to zero if district i has no connections: $\hat{\psi}_{i0} = 0, \hat{\psi}_{i1} = 0$ for $i = 1,\ldots,N$.

Table 3.11: Regional Results from HSAR model with CSA de-factored pair-wise correlation based weights matrix

	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
North East						
Median	0.0674	0.3910	-0.5717	0.0529	-0.0391	1.0297
Mean Group Estimates	0.0485*	0.5041***	-0.6565***	0.0668	-0.0079	1.1030
	(0.0248)	(0.0803)	(0.0620)	(0.0483)	(0.0539)	(0.0735)
% significant (at 5% level)	25.0%	100.0%	100.0%	8.3%	8.3%	-
Maximum	0.1594	0.9947	-0.4015	0.4689	0.4915	1.6390
Minimum	-0.0798	0.1371	-0.9950	-0.1148	-0.2641	0.7114
London						
Median	0.0736	0.4648	-0.3409	-0.0318	-0.0119	0.8242
Mean Group Estimates	0.0778***	0.5053***	-0.3546***	-0.0130	-0.0330	1.0982
	(0.0160)	(0.0483)	(0.0566)	(0.0299)	(0.0323)	(0.1736)
% significant (at 5% level)	33.3%	87.9%	93.9%	15.2%	3.0%	-
Maximum	0.2572	0.9950	0.9948	0.4006	0.2207	6.1894
Minimum	-0.1279	-0.4201	-0.9949	-0.2841	-0.9499	0.4857
South West						
Median	0.0058	0.4292	-0.5428	-0.0196	0.0154	1.0370
Mean Group Estimates	0.0218	0.4648***	-0.5851***	-0.0006	0.0045	1.1503
	(0.0135)	(0.0312)	(0.0372)	(0.0293)	(0.0247)	(0.0748)
% significant (at 5% level)	16.7%	86.1%	88.9%	16.7%	8.3%	-
Maximum	0.1953	0.9475	-0.2081	0.3610	0.3438	2.5832
Minimum	-0.1486	0.1506	-0.9949	-0.3558	-0.4385	0.5647
East Midlands						
Median	0.0074	0.5159	-0.6408	0.0383	0.0187	1.2272
Mean Group Estimates	0.0008	0.5366***	-0.6159***	0.0337	0.0007	1.2289
	(0.0138)	(0.0342)	(0.0347)	(0.0324)	(0.0277)	(0.0537)
% significant (at 5% level)	17.5%	80.0%	95.0%	10.0%	15.0%	-
Maximum	0.1434	0.9948	-0.2267	0.4445	0.3485	2.2710
Minimum	-0.1744	0.1197	-0.9950	-0.5682	-0.3154	0.6106
North West						
Median	0.0356	0.4278	-0.4630	0.0146	0.0041	1.0147
Mean Group Estimates	0.0328**	0.4375***	-0.4946***	-0.0065	-0.0662	1.2458
	(0.0131)	(0.0458)	(0.0456)	(0.0380)	(0.0702)	(0.0959)
% significant (at 5% level)	15.4%	84.6%	89.7%	15.4%	15.4%	-
Maximum	0.2176	0.9950	0.4807	0.5227	0.4899	3.1907
Minimum	-0.1848	-0.5817	-0.9950	-1.1109	-2.2507	0.5554
West Midlands						
Median	0.0012	0.4761	-0.5313	0.0384	-0.0635	1.0192
Mean Group Estimates	0.0162	0.5237***	-0.5725***	0.0243	-0.0388	0.9856
	(0.0149)	(0.0389)	(0.0344)	(0.0303)	(0.0404)	(0.0492)
% significant (at 5% level)	13.3%	96.7%	100.0%	10.0%	23.3%	-
Maximum	0.1588	0.9948	-0.1730	0.2749	0.4269	1.5503
Minimum	-0.1136	0.1808	-0.9950	-0.4386	-0.6302	0.4204
South East						
Median	0.0196	0.4314	-0.6285	-0.0155	0.0158	1.0043
Mean Group Estimates	0.0169*	0.5060***	-0.6477***	-0.0209	0.0078	0.9904
	(0.0099)	(0.0260)	(0.0243)	(0.0197)	(0.0219)	(0.0251)
% significant (at 5% level)	16.4%	95.5%	100.0%	13.4%	11.9%	-
Maximum	0.1778	0.9949	-0.1899	0.3918	0.4617	1.4113
Minimum	-0.1713	0.1566	-0.9950	-0.4679	-0.4741	0.5854
East						
Median	0.0266	0.5143	-0.6434	-0.0229	0.0382	0.9724
Mean Group Estimates	0.0441***	0.5505***	-0.6320***	-0.0185	0.0474*	1.0027
	(0.0105)	(0.0266)	(0.0345)	(0.0345)	(0.0287)	(0.0344)
% significant (at 5% level)	14.9%	97.9%	97.9%	17.0%	10.6%	-
Maximum	0.2275	0.9764	-0.0854	0.7036	0.6903	1.6492
Minimum	-0.1285	0.1481	-0.9950	-0.5189	-0.4076	0.5812
Yorkshire and The Humber						
Median	0.0584	0.4874	-0.5770	0.0247	0.0254	0.8339
Mean Group Estimates	0.0417**	0.4655***	-0.6127***	-0.0129	-0.0087	1.0219
	(0.0163)	(0.0563)	(0.0401)	(0.0427)	(0.0555)	(0.1056)
% significant (at 5% level)	9.5%	85.7%	95.2%	9.5%	4.8%	-
Maximum	0.1702	0.9950	-0.2717	0.3743	0.3435	2.4767
Minimum	-0.1300	-0.2218	-0.9949	-0.6172	-0.9139	0.5708

Mean group estimates are calculated as unweighted averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N$, $r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)} \sum_{i=1}^{N_r} (\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. All districts have one or more neighbours so no parameters coefficients are restricted to zero in the model.



(c) Direct Effects

(d) Spill-in Effects

(e) Spill-out Effects

Figure 3.2: Choropleth map of direct and indirect effects of persistence in house price inflation based on the HSAR model using $\mathbf{W_{QC}}$, with red and blue areas signifying positive and negative values respectively. Indirect effects are given as spill-in and spill-out effects. The darkest red (blue) areas signify values over 0.2 (less than -0.2) with shades increasing at 0.05 increments across 5 red and 5 blue shade categories.

3.5.3 A Heterogenous Spatio-Temporal Model of English House Price Changes

We generate model estimates using contiguity, nearest neighbour and distance measures. Table 3.10 presents mean group estimates by region using the 15 mile inverse distance matrix.[7] Median and mean group estimated coefficients for $\hat{\lambda_1}, \hat{\psi_0}, \hat{\psi_1}$ and $\hat{\sigma_\zeta}$ are reported, with standard errors for mean group estimates provided in parentheses. Mean group estimates are calculated as unweighted averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N$, $r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)} \sum_{i=1}^{N_r} (\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate.

Contemporaneous spatial dependence is measured by the parameter $\hat{\psi_{i0}}$, while $\hat{\psi_{i1}}$ represents space-time lagged values of changes in house prices. The inclusion of $\hat{\psi_{i1}}$ allows for a time lag of the average neighbouring values of the dependent variable observed during the previous period, $W\xi_{i,t-1}$. House price growth in an area may serve as complementary or substitutes between a different district, leading to negative or positive relationships between neighbourhood price changes and own district property price growth. This may be due to individuals substituting property in one area for nearby lower priced district. This behaviour increases demand for housing in the neighbourhood, driving house price growth up; that is, causing positive spillover effects in the housing market. Alternatively, as amenities improve in an area, house prices in the neighbourhood may adjust to a new price level, representing the difference in amenities between both districts. The change in relative prices leads to neighbourhood house prices to fall as the value of amenities pushes prices in the given area higher. In this case, the neighbourhood responds to the growth in house prices in a district with a fall in house price growth in the connected area, known as a negative spillover effect.

It is immediately apparent there is strong evidence of both temporal and spatial effects across the country given on all temporal effects are significant at the 1% level, and most spatial effects are significant at the 10% level. This outcome suggests changes in house prices are affected

[7] Queen contiguity and 5 nearest neighbour specifications are relegated to Appendix B.3.

by past property price growth in the same district, alongside changes in house prices in the neighbourhood in the contemporaneous and past month. Very similar results between mean and median values demonstrate evidence of temporal estimates having close to symmetrical distributions across districts. Estimates for ψ_0 show higher median estimates compared to the mean, indicative of slight leftward distributional skew across cross-sections. With respect to ψ_1, results are fairly similar across spatial weight specification, serving as a robustness check for the validity of the estimated results. Our findings show less precise estimates of contemporaneous spatial effects, compared to the temporal and space time lagged values. This may be attributed to the variation in adjustment time required for house prices to incorporate neighbourhood changes in house prices into setting their own values.

Mean group estimates for the temporal effect are considerable in size, with the contiguity based model estimating the average effect as high as 0.0571 (0.0052), very similar in value to the distance based coefficient estimates. The effect is large considering common factors that drive house prices across the nation and each region have been accounted for. With respect to contemporaneous spatial effects, the magnitude is smaller than the respective lagged spatial effect. This means that the impact of neighbourhood house price changes on a given district is lower in the same month compared to the effect of price inflation movements from the last month. As such, spillover effects from the last month is stronger and more significant than spillovers in the current period. Furthermore, the effect goes from negative to positive, indicating a level of reversal, with the spatial lagged change dominating. The spatial lag ψ_0 is not statistically significant using contiguity weights in our estimation, and is only significant at the 10% level using the 10 mile distance based connected model, indicating a lack of robustness in the estimates. Comparing the spatial lag and temporal effect, we see evidence of a comparable effect of spatial spillovers to the temporal impact, with the spatial lag surpassing the temporal effect in the distance based case. This highlights the significance of spatial effects in the housing market, showing how pervasive these interrelationships are at the aggregate level.

Table 3.10 and Tables in Appendix B.3 summarise regional estimates of spatial and temporal effects with a range of exogenous weights matrices. The temporal effect is most convincing, with all regional mean group estimates found to be significant at the 10% with the exception of the two lower distance weights measures. In particular, the temporal effect is as great as 0.1391 for

London, which is found to have the strongest level of serial correlation over time by a significant magnitude. All coefficient values are positively autocorrelated, with the effect next strongest in the North, with Southern and Midlands areas showing far lower levels of persistence.

London also demonstrates a strong spatial effect, negative in the current period but turning positive when lagged. This effect is particularly striking in Table 3.10, where London parameters, denoting a large negative value (-0.438) for the contemporaneous spatial lag that drastically changes in value in the diffusion term at 0.127. The results show the lagged spillover effect is positive and among the strongest across the country. This mean reverting behaviour is representative of the the growing difference between prices paid on average for properties in different London boroughs across 1995 to 2014. Over a short period of time prices had increased rapidly in an already high value market, with large fluctuations in price changes demonstrating significant negative spillovers, with the City of London far surpassing the mean group average, with a contemporaneous neighbourhood effects in Tower Hamlets (-0.31406**) and Kensington and Chelsea (-0.29718**). These findings are in accordance with Holly et al. (2011) who also find house prices in London have an impact on the neighbouring region. We also find both negative and positive relationships between districts and the impact of neighbour price growth on own house price inflation. Holly et al. (2010) find this is the case in the American housing market, indicative of districts behaving as both substitute and complimentary areas. We attribute this to structural changes in areas and relative changes in district level attributes that may lead to changes in house prices between areas (Berger et al., 2008; Chen and Rosenthal, 2008; Mcduff, 2011).

The spatial effect is weaker than the analogous temporal impact showing stronger serial dependence compared to spatial dependence. This is consistent with US house price dynamics studied by BHP. In contrast, Holly et al. (2011) find evidence that the effects of a shock decay more slowly along the geographical dimension in comparison to over time with respect to London price shocks. Focussing on the results in Table 3.10, The Midlands, North West and East mean group estimates are not statistically significant with respect to the contemporaneous and lagged spatial effect. However, district level results shows Burnley, South Holland and Liverpool (in North West, East Midlands and East) have strong same period positive spatial effects ranging from 0.563 to 0.450, significant at the 5% level. While the impact in London is fairly uniform across the region, this does not hold true across the rest of the country. Figure 3.2 demonstrates how districts often do not share the same spillover effects as the rest of the region. Taking Burnley as an example, this finding is unsurprising looking at neighbouring districts such as Calderdale which has a significant at the 5% and a comparably high spatial lag value of 0.267. Despite these districts sharing a boundary, both are classified in different regions, highlighting how aggregate measures using regional data often masks the level of variation that persists in the transmission of spillover effects. Inspection of Figure 3.2 confirms this, as we find clusters do not remain delineated by regions. Instead, small clusters of districts share similarities in the magnitude of the detected spillover effects, even after stripping common factor effects away. Comparing both quantile choropleth maps, there is evidence that the effect of neighbourhood price changes from the last period are more tightly distributed around cities such as Leicester, Sheffield, Nottingham and Birmingham. The effect is equally significant for estimates of the spatial lag in different areas with this effect even greater in magnitude in Eden, North West at 0.687. While some areas have significant contemporaneous and lagged spatial effects, a significant proportion find only one spatial parameter to be significant, indicating heterogeneity in not only the size but also the responsiveness of neighbourhood effects across different areas.

The spillover effects of house prices are not easily delineated by region, showing large variations within regions, often with certain districts being far more affected than other close by neighbours. Once the common factors are accounted for, we find the spatial effects are still significant scattered across England in a less uniform method than the ripple effect hypothesis would lead us to believe. However, the diffusion of house prices may require a longer timeframe to manifest this effect, and as such, our model is not well placed to consider this hypothesis. There is however, evidence of spillover effects of a greater magnitude in London and surrounding areas.

3.5.4 Estimation of Spatial Connections

Following the method of BHP, pair-wise correlations of de-factored price changes are used to estimate a matrix of connections. The sample correlation matrix is estimated then Holm's multiple testing procedure is applied to the N(N-1)/2 pairwise correlation coefficients at a significance level set to 10%. Based on the signage of the correlation coefficient for each pairwise correlation, each significant pair at the 10% is separated into a positive and negative weight matrix. Unlike the results obtained on US house prices by BHP, the resulting matrix of spatial connections is extremely sparse with some regions results in no spatial connections. Only 17 statistically significant connections are found - this prevents some regions from having any spatial parameters to estimate in Table 3.14. As such, we opt to focus our discussion on the results derived from the exogenously determined weights matrices which provide more information on the heterogeneity of spatial and temporal effects across regions.

Table 3.11 displays computed parameters in the QML estimates of the spatio-temporal model with standard errors included in parenthesis. Most striking is the low incidence of connections. As such, all inferences drawn from these results are not robust with respect to the spatial parameters. Results across districts are reasonably symmetrically distributed based on the relative similarity between median and mean group estimates. In particular, the size of the temporal effect $\hat{\lambda}_1$ is modest (0.0456) - this may be due to de-factoring accounting for the majority of common dynamics across across changes in house prices.

In reference to spatial spillover effects, both positive and negative contemporaneous spillovers (0.157 and -0.140) are far greater than their lagged counterpart values of -0.045 and 0.023 respectively. Interestingly, positive contemporaneous spillover effects have a greater magnitude than negative spatial effect, compatible with tradition theories of spatial dependence in property markets (Can and Megbolugbe, 1997). The reverse holds true for the lagged equivalent estimates. The mean group estimate of the lagged spatial effect $\psi_1^+ = -0.027$ and $\psi_1^- = 0.038$ show a reversal of the immediate spatial effect based on the change in sign. This may be due to some level of correction or dampening of the spatial effect. Our findings confirm similar behaviour to US MSA house prices in BHP where the magnitude of positive spillovers surpassed the negative effects. This is expected in the UK given the asymmetric nature in the persistence of house price appreciation compared to insensitivity to declining prices.

The results summarised in Table 3.11 show London has the highest percentage of significant estimates at 45.5%. In addition to this, London has the strongest temporal effect with $\hat{\lambda}_1 = 0.12(0.017)$, this is far greater than any other region with all other regions taking values spanning 0.0231 (South East) to 0.077 (North East). This may be partly attributable to the close proximity of London boroughs compared to the distance between districts in the rest of England.

Compared to the temporal effect, the contemporaneous spatial impact is weaker with the lagged effect weaker still. Conclusions based on the data driven weights matrix about house price spillovers are limited due to the low incidence of statistically significant connections between districts; this is most marked in Yorkshire and the Humber where no spillovers are found in either the immediate or lagged spatial effects. This is due to no detected connections in this region, so no parameter estimates could be calculated. Looking at Figure 3.2, notable exceptions in the North East include large market towns, Stockton on Tees and Darlington. Both theses areas have benefitted large employers (for example EE in Darlington) and service industries. Interestingly, both Darlington and Stockton on Tees amongst other areas demonstrate a negative spillover effect in the first period that is overshadowed by a positive spillover in the space time lagged coefficient. This may be evidence of mean reversion or simply indicative of higher volatility in price changes as prices overshoot and correct in the next period. There is a pattern of more economically active areas experiencing stronger spillover effects, revealing how economic activity and agglomeration effects may have a crucial role to play in the transmission of house price inflation between districts. Further analysis using economic data is required to analyse whether this is indeed the case.

Parameter heterogeneity allows us to compare the impact of changes in house prices across all regions but we choose to focus on earlier results using traditional weights matrices given the incidence of connected areas. The results indicate some level of variation given median and mean group values are fairly similar for all regions, but this is mainly due to the low number of connections that prevent us from being able to draw conclusions about the distribution across multiple districts.

3.5.5 Marginal effects

Direct effects estimates are taken from the diagonal elements of the matrix in expression (16) denoting own-partial derivatives with the values summarised in 3.2. This expresses how the persistence of house prices in the given district directly impacts own-district house price inflation in the current period. Rural areas situated further away from cities are found to have the lowest persistence in house prices, most apparent across the East coast. Unsurprisingly, we find strong levels of persistence in house prices in several London boroughs, specifically Tower Hamlets, Camden, Croydon and Bromley. However, several pockets of highly persistent house prices exists across the country. Notable small districts such as Cambridge show high levels of persistence that are distinctive to their neighbouring districts. These small areas are often characterised by strong transport links and favourable amenities. Other highly persistent areas include Cornwall, Bury St Edmunds and Lancaster which represent more affluent areas of the country with access to favourable landscapes and less pollution.

The spill-in effects show how changes in neighbouring districts' persistence in house price inflation create a impact on each district i's house price growth. Areas around the Northern cities demonstrate strong positive spill-in effects, denoting how these nearby cities create an impact on these districts' own house price growth. Surprisingly, there is a larger prevalence of negative spill-in effects compared to its spill-out counterparts. This indicates an inverse relationship between house price inflation in neighbouring regions and the effect this has on a given district.

The cumulative sum of the off-diagonal columns produce the cumulative spill-out effects, measuring how changes in house price growth in district i impact neighbouring districts $j \neq i$ (i.e. $\partial y_j / \partial y_{i,t-1}, j \neq i$). The results indicate house prices spill out most strongly from districts situated near scenic areas with good transport links or highly built up towns such as Canterbury and Colchester. These districts have strong local economies and have enjoyed improved transport links to London that attract commuters. This commuting proximity combined with accessibility to the countryside is common across Three Rivers, Surrey Heath, Hart, Windsor and Maidenhead districts; all districts with strong influences on house price inflation to their neighbouring districts based on spill out estimates.

With reference to the ripple effect, our results do not show a strong inclination towards the South East and London as primary centres where persistence in house prices have a strong positive impact on their respective neighbours. There is some scattered evidence of areas in the South East and London exerting spillover effects, however, it is not unique to these areas. Indeed, the transmissions for spillover effects does not show a clear trend towards the North. Instead we find that areas near economic centres have strong spillover effects. These findings underscore the importance of a strong local economy and evidence against reliance of areas such as London to influence areas further afield.

3.6 Concluding Remarks

In the context of understanding the transmission of house price spillovers, the previous literature has often failed to account for strong cross sectional dependence, inflating the level of spatial relationships between areas. This chapter estimates a spatio-temporal model of house price inflation across England from 1995 to 2016 using monthly data to reveal the short term dynamics between districts. Having accounted for common factors we are able to reveal what spatial relationships exist at the district level. The results indicate a high level of heterogeneity at both the regional and subregional level. Stripping away the impact of national and regional factors, we find London has a high level of both temporal and spatial dependence, with some reversal of this effect in the lagged period.

The variation on spatial dependence across districts demonstrate how delineating the housing market by regions may mask strong spatial effects in local areas (Bhattacharjee et al., 2016). Our findings indicate a rich set of spatial and temporal dynamics across the country with neighbourhood spillover effects stronger in the following period compared to the impact in the current period. Given the impact nearby districts have on house price growth, our findings suggest local government housing policy would benefit from incorporating changes in housing markets and policies implemented in nearby districts into the decision making process. We find evidence of both positive and negative spillover effects between districts, demonstrating districts serving as substitutes and complements for other areas. Using the method of BHP, we find evidence to show asymmetry in positive and negative spillovers with mean reversion in the next period. However, the findings using this method lack precision due to the low level of detected connections. Hence, future work considers different approaches to the multiple testing problem to ensure sufficient connections may be detected for spatial modelling. In reference to the ripple effect hypothesis, our results indicate a more nuanced spatial impact than the theory implies, where areas with higher levels of economic activity find stronger spillover effects that are not unique to London areas but also districts surrounding cities such as Manchester and Nottingham. However, the spill-out effects show a cluster of strong positive impacts in London and the South East that provide some indication of spillover effects originating to surrounding areas. However, given this effect is prevalent across a number of economic centres, we find the theory too simplistic to be used to characterise house price diffusion across the UK.

The BHP method possesses a number of limitations. The proposed data driven weights specification in BHP was unable to characterise the spatial dependence in the dataset. While a high incidence of connections was initially found, the Holm-Bonferroni multiple testing procedure stripped away nearly all connections. While alternative lower power methods were trialled including the Bonferroni correction, these led to the same outcome. As a result we use the pairwise approach without the multiple testing correction, however the results did not provide any material benefit over the predetermined weights matrices. This may be due to the unreliable coefficient estimates based on the high incidence of negative values across a range of weights specifications. Future research may benefit from a combination of both methods, such that the data driven method is used with the added restriction of a minimum distance restriction. In any case, we note the arbitrary nature of the *a priori* weights matrix. Recent developments in GLASSO methods may provide a better alternative to the adjacency matrices used in this study.

A key limitation of the BHP method pertains to the high prevalence of negative spatial estimates. Simulation studies to better understand this outcome would be beneficial. These results may be contrasted against alternative models to ascertain under what conditions the BHP method performs best. Interpretation of the results are also limited given the two stage method returns spillover effects measured in terms of 'de-factored' price changes. This measure does not readily lend itself to providing useful values to practitioners.Additionally, the impact of common factors are not estimated, instead they are accounted for. Ascertaining the impact of common factors in the housing market is an interesting avenue for future research that this model is unable to accommodate.

Chapter 4

Spatial Dependence and Common Factors in the English Housing Market: A STARF Model

4.1 Introduction

The recent emergence of heterogenous spatio-temporal models are a welcome contribution to the growing cross-sectional dependence literature. However, existing methods have in practice failed to provide reasonable estimates, with a high prevalence of negative spatial parameters that are unintuitive and unexpected from a theoretical perspective, (Bailey et al., 2016). To fill this lacuna, we derive a heterogeneous model of house prices in England using a novel dynamic spatial panel model put forward by Shin (forthcoming). The proposed method provides a unified characterisation of local and global cross-sectional dependence, improving on the multi-step procedure proposed in Bailey et al. (2016) and Halleck Vega and Elhorst (2016) one-step variant. The STARF model presents a parsimonious representation of house price diffusion with joint treatment of common factors and spatial dependence. Several benefits arise from this model specification; our application accounts for the endogeneity in the spatial lag term, leading to consistent estimates of structural parameters that may later allow comparisons with competing models. Notably, we derive spatial and system-wide diffusion multipliers, providing insights into how a perturbation in neighbourhood house price inflation impacts a given district over a given time horizon. Borrowing from the network literature, we estimate in-degree and out-degree measures for a directional analysis of house price spillovers (Wasserman and Faust, 1994; Atalay et al., 2011; Sun et al., 2015) . Ranking these out-degree effects identifies units which exert the most influence on neighbourhood house price changes.

Heterogenous models of house price diffusion have been a recent application emerging from the growing cross-sectional dependence literature. BHP apply their proposed two stage model to US real house price changes at the Metropolitan Statistical Areas level, yielding a high incidence of negative spatial connections. While the application highlights the procedure's ability to capture both negative and positive spatial connections, no discussion of the economic interpretation of this outcome is provided. In the context of the housing market, this outcome is puzzling given the lack of convincing explanations for outcome. Traditional theories of spatial dependence in the property sector ascribe to notions of spatial arbitrage of capital, following behaviour and migration and equity transfer (Can, 1990; Gillen et al., 2001). In Chapter 3 we apply the BHP method to English house price inflation, yielding an unexpectedly high proportion of negative spatial parameters, in accordance with the findings in BHP. While some areas may be inversely related to neighbourhood house price changes, for example, due to affluent districts being surrounded by deprived areas (for example Solihull district), we hypothesise these cases would be in the minority. Motivated by this outcome, this chapter proposes the use of the STARF model for providing more reasonable outcomes compatible with the prevailing theories of positive spatial dependence in the housing market.

In addition to analysis of the housing market delineated by regions, we also classify areas based on the level or urban/rural settlements. In reference to the cumulative dynamic multipliers with respect to neighbouring house price inflation, we hypothesise more urban areas express faster rates of convergence to their long run level of spatial dependence due to increased footfall from commuters and higher relative populations. These attributes serve to increase the efficacy of information signals pertaining to house price changes in neighbouring areas. The findings indicate the urban/rural classification method demonstrates a better characterisation compared to aggregating by region. Furthermore, we derive spill-in and spill-out impacts across all districts. The findings show limited support for the ripple effect hypothesis, with the impact of house prices near London affecting areas within an approximate 50 mile radius. Our findings show house prices in London do spread out to the periphery areas, but are not responsible for house price appreciation in areas beyond the 50 mile radius. Instead, local economies play a key role in propagating spillover effects. Interestingly, we identify key dominant districts that influence house price changes within their respective neighbourhoods. These areas are found to be periphery to cities and active economic areas typically situated on the green belt. The importance of these geographic characteristics are congruous with Hilber and Vermeulen (2016); Saiz (2010) who find areas facing geographical or regulatory constraints experience low elasticities of supply which are in turn endogenous to price growth. The areas that are able to provide both sets of attributes are found to be dominant units in influencing house prices in a given area. The findings in this chapter confirm the importance of proximity to economic centres in influencing house price inflation in nearby areas, reconcilable with the findings of Fik et al. (2003). These findings may reflect the London-centric ripple effect as a dominant factor while the core-periphery spillover effect would be dominant at higher levels of urbanisation. Our findings may also reflect the time-varying nature of the house price inflation spillover as we note the variation in the speed of adjustment between urban and rural areas.

The rest of the chapter is organised as follows. Section 4.2 outlines the relevant literature in characterising spatial dependence within the housing context. Section 4.3 reviews the existing heterogenous spatial models and how the proposed procedure provides a timely contribution to the growing literature. Section 4.4 specifies the STARF model and derives the spatiotemporal and system-wide diffusion dynamic multipliers and Section 4.5 summarises the data selection. Section 4.6 presents an analysis of the estimated results, and finally, Section 4.7 concludes.

4.2 Spatial Dependence in House Prices

Spillover effects in the housing market are a key channel for the transmission of information across geographical distance. The property market is plagued with the obscurity of pricing a highly heterogenous good in a profoundly information asymmetric setting. Combined with the variation in nature and prevalence of public amenities and the chronically low elasticity of housing supply, the perceived behaviour of house price inflation in nearby areas may be a primary source of information for potential buyers and sellers engaging in the property market. Housing markets are best characterised as a series of interconnected submarkets, often interacting on the basis of migration and labour flows, capital transfers and market conditions.

House price growth may spillover into nearby districts for a variety of reasons. For instance, as house price growth in a district increases, the differential in property prices between housing nearby may lead to equity transfers towards the lower priced location, causing the house price increase in the initial areas to 'ripple out' across regions. A great deal of research has investigated how changes in house prices are first observed in London before propagating to the rest of the country (Macdonald and Taylor, 1993; Alexander and Barrow, 1994; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Holmes and Grimes, 2008). Holly et al. (2011) analyse the diffusion of house prices in UK regions, finding evidence of shocks to London propagate to nearby areas. Many studies have imposed London as a dominant region. In the US case, Chiang and Tsai (2016) find evidence supporting this among metropolitan areas where cities such as Los Angeles, New York and Miami are found to propagate shocks to their respective regions. A more recent study by Cohen et al. (2016) demonstrates past growth in house prices in contiguous Metropolitan Statistical Areas (MSAs) help explain price inflation in the contemporaneous period.

House price growth is affected by long and short-term influences. Over the long term horizon, factors that influence house price growth include changing demographics, growth in household income and features of the taxation system to (dis)incentivise home ownership. On the supply side, the cost and scarcity of land, construction costs and quality of dwelling stock have long term impacts. Supply-side changes are typically inelastic, with the bureaucratic process of UK land planning schemes ensuring particularly sluggish responses to increased demand for housing. The housing market is intrinsically characterised by local attributes with lengthy timeframes to approve and construct new housing stock, exacerbating the differences between districts. This inertia combined with differences in response to national and regional factors can give rise to significant variation in house price growth dynamics across districts. The cost and provision of financing is a key factor in determining housing purchases. The availability and cost of financing plays a significant role in the growth of house prices as this in turn drives the return on housing as an asset class in the short term. As interest rates decrease, the cost of servicing mortgages decreases, boosting demand for housing. The UK mortgage market is characterised by a prevalence of floating rate contracts, thus increasing the sensitivity of mortgage payments in response to short-term dynamics of interest rates.

While the UK geographic landscape remains predominantly rural, under one third of the land area classified as urban, the remaining small urban areas account for 60 percent of the population. It is well documented in the literature that there are substantial differences between rural and urban areas; including crime, unemployment, demographics and other factors that impact the demand for housing. Analysis by Pateman (2011) indicates that house prices are less affordable to local workers in rural areas than urban areas in addition to increased costs, travel time and carbon emissions resulting from transport. With respect to the supply side, the effect of constraints due to local scarcity of developable land is largely confined to highly urbanised areas Hilber and Vermeulen (2016). In light of these differences, we hypothesise rural districts to display lower levels of diffusion in house price inflation.

The economic geography literature stresses the role of mobility, transport costs and travel time for the growth of local districts (Fujita et al., 1999).The economic performance of a district affects the equilibrium price on housing markets. Socio-economic factors have a direct influence on house prices. For example, opportunities for employment serve as an attractive driver of local house prices. Higher levels of unemployment are expected to drive property prices down (Berger et al., 2008). To this end,De Bruyne and van Hove (2013) associates more agricultural areas with lower opportunities for jobs, thus depressing house prices in these rural areas. Highly urbanised areas are also likely to benefit from advanced transport infrastructure which have proven to have a strong positive impact on property prices (Alonso, 1964; Muth and Wetzler, 1976; Evans, 1973; Haig, 1974). Empirical studies by Coulson and Engle (1987); Damm et al. (1980); Dewees (1976); Laakso (1992); Chau and Ng (1998) show transport network improvements have increased house prices. More recently, empirical studies have confirmed the importance of proximity to economic centres in the determination of house prices. Fik et al. (2003) provide empirical evidence that accessibility and distance to economic centres is related to the the value of a location[1]. These findings are echoed by Brounen and Huij (2004) in their empirical application to the Dutch housing market.

We hypothesise that key cities, such as London, Manchester and Birmingham influence surrounding districts' house price inflation through information signals. Housing market activity in these areas impact demand for housing in the neighbourhood through driving economic activ-

[1]The authors make the case that location value cannot be disentangled from the constituent determinants of housing value

ity in nearby areas and the benefits of increased infrastructure for transmitting these benefits to surrounding districts. Correspondingly, areas with high urban populations are expected to display more persistence in house price changes. Ioannides and Thanapisitikul (2008) considers how informational inefficiency in housing markets exhibits itself as persistence in prices. The considerable frictions within the market often prevent prices readjusting in response to economic shocks.

We estimate a heterogeneous spatio-temporal autoregressive model with factors (STARF) to capture the diffusion of house price growth across districts in Englands from January 1995 to August 2016. Each estimated spatial lag coefficient reflects the influence of neighbourhood house price changes on district i. House price changes in district i are related to past values, π_{t-1}, neighbouring districts house price growth, $W\pi_t$ and previous changes in the neighbourhood, $W\pi_{t-1}$ and common factors f_t. Point estimations from spatial regression models to identify spillover effects may lead to incorrect identifications of spatial dependence. Instead, we follow the recommendations of LeSage and Pace (2009, p.74) who conclude a partial derivative interpretation is a preferable method for testing for spatial dependence. Our analysis contrasts to BHP who rely on mean group coefficient estimates alone. The proposed dynamic multipliers provide a parsimonious representation of the marginal impacts of neighbourhood house price changes over different time horizons.

4.3 Review of Heterogenous Spatial Models

Almost all spatial models impose parameter homogeneity with a few notable exceptions that have arisen in recent years. Given the increasing availability of large datasets, heterogenous models which capitalise on the large time dimension can be exploited to produce heterogenous parameter estimates. Aquaro et al. (2015) present the first contribution to the literature, outlined in the preceding chapter. The proposed heterogenous spatial autoregressive model uses a QML procedure[2] While the former method does not account for common factors, BHP consider a two step extension of this method to first control for global impacts that we apply to the English housing market in Chapter 3. The method comes with a number of drawbacks highlighted in

[2]See Section 3.5.3 and Aquaro et al. (2015) for a detailed exposition.

the previous chapter. Most notably, the interpretation of the final parameter estimates are not straightforward based on the 'de-factored' values in the second stage. While we may infer the relative strength of spatial dependence across districts, it is unclear how to interpret the parameter estimates in practice. The multi-stage method also fails to provide any formal distribution theory that accounts for sampling errors arising in the first step. Secondly, the heterogenous impact of aggregate factors is not captured in the final model. Rather, common factor impact is 'accounted for' (in the first step) as opposed to being a feature of interest to be estimated. While this may be appropriate in some settings, there are numerous examples where global effects are of interest, including our application to the housing market. The impact of nationwide macroeconomic policies (for example the introduction of Help to Buy or Buy to Let policies in UK), or global financial market conditions on subsets of the housing market are are of intrinsic interest to economists and policy makers.

Halleck Vega and Elhorst (2016) (VE) propose a one-step variant of the BHP method with an application to regional unemployment in the Netherlands. Based on the Brechling-Thirlwall cyclical sensitivity model:

$$u_{rt} = \gamma_{0r} + \gamma_{1r}\left(N^{-1}\sum_{j=1}^{N} u_{jt}\right) + e_{rt} \simeq \gamma_{0r} + \gamma_{1r}u_{Nt} + e_{rt} \tag{4.1}$$

where u_{rt} denotes the unemployment rate for region $r = 1, \ldots, N$ at time $t = 1, \ldots, T$, and e_{rt} is an iid error term with zero mean and constant variance σ_e^2. VE achieve this by substituting the de-factored regional unemployment rate, $\hat{e}_{rt} = u_{rt} - \hat{\gamma}_{0r} - \hat{\gamma}_{1r}u_{Nt}$ into the second stage of the BHP method, modelling the de-factored regional unemployment rates using the dynamic spatial panel model:

$$\hat{e}_{rt} = \alpha_0 + \alpha_1\hat{e}_{rt-1} + \alpha_2\sum_{j=1}^{N} w_{rj}\hat{e}_{jt} + \alpha_3\sum_{j=1}^{N} w_{rj}\hat{e}_{j,t-1} + \mu_r + \lambda_t + \varepsilon_{rt}$$

VE simultaneously accounts for spatial dependence and common factors by substituting $\hat{e}_{rt}$ with e_{rt}:

$$\begin{aligned}(u_{rt}-\gamma_{0r}-\gamma_{1r}u_{Nt}) &= \alpha_0+\alpha_1(u_{rt-1}-\gamma_{0r}-\gamma_{1r}u_{Nt-1}) \\ &\quad +\alpha_2\sum_{j=1}^{N}w_{rj}(u_{jt}-\gamma_{0j}-\gamma_{1j}u_{Nt}) \\ &\quad +\alpha_3\sum_{j=1}^{N}w_{rj}(u_{jt-1}-\gamma_{0j}-\gamma_{1j}u_{Nt-1})+\varepsilon_{rt}\end{aligned} \tag{4.2}$$

Rearranging terms, the regional unemployment rate can be expressed as:

$$\begin{aligned}u_{rt} &= \{\alpha_0+(1-\alpha_1)\gamma_{0r}\}-(\alpha_2+\alpha_3)\bar{\gamma}_0^w \\ &\quad +\alpha_1u_{rt-1}+\alpha_2u^*_{rt}+\alpha_3u^*_{r,t-1}+(\gamma_{1r}-\alpha_2\bar{\gamma}_1^w)u_{Nt}-(\alpha_1\gamma_{1r}+\alpha_3\bar{\gamma}_1^w)u_{Nt-1}+\varepsilon_{rt}\end{aligned} \tag{4.3}$$

Parameters are estimated by:

$$u_{rt}=\beta_1u_{rt-1}+\beta_2u^*_{rt}+\beta_3u^*_{r,t-1}+\beta_{4r}u_{Nt}+\beta_{5r}u_{Nt-1}+\mu'_r+\varepsilon_{rt} \tag{4.4}$$

where $\beta_1=\alpha_1$, $\beta_2=\alpha_2$, $\beta_3=\alpha_3$, $\beta_{4r}=\gamma_{1r}(1-\alpha_2)$, $\beta_{5r}=\gamma_{1r}(-\alpha_1-\alpha_3)$ and $\mu'_r=\{\alpha_0+(1-\alpha_1)\gamma_{0r}\}-(\alpha_2+\alpha_3)\sum_{j=1}^{N}w_{rj}\gamma_{0j}$. VE use a bias corrected QML estimator with regional fixed effects and additionally with time fixed effects developed by Yu et al. (2008) and Lee and Yu (2010) respectively. The first three coefficients are the same for all regions, while the next two coefficients are heterogenous. The imposition of homogeneity for these parameters is unduly restrictive given $\alpha_1,\alpha_2,\alpha_3$ are heterogenous in (4.2).

VE note that by not imposing the restriction

$$\gamma_{1r}=\frac{\beta_{4r}}{(1-\alpha_2)}=\frac{\beta_{5r}}{(-\alpha_1-\alpha_3)} \tag{4.5}$$

the simultaneous approach becomes more general than the two-stage variant[3]. However, based

[3]BHP can be obtained from imposing the restriction $\frac{\beta_{4r}}{(1-\alpha_2)}=\frac{\beta_{5r}}{(-\alpha_1-\alpha_3)}$ for $r=1,\ldots,N$.

on (4.3) , this restriction in (4.5) is incorrectly specified[4]. Hence,

$$\beta_{4r} = \gamma_{1r} - \left(\alpha_2 \sum_{j=1}^{N} w_{rj}\gamma_{1j} \right) = \gamma_{1r} - \alpha_2 \bar{\gamma}_1^w \neq \gamma_{1r} \left(1 - \alpha_2\right) \tag{4.6}$$

$$\beta_{5r} = -\alpha_1\gamma_{1r} - \left(\alpha_3 \sum_{j=1}^{N} w_{rj}\gamma_{1j} \right) = -\left(\alpha_1\gamma_{1r} - \alpha_3 \bar{\gamma}_1^w\right) \neq \gamma_{1r} \left(-\alpha_1 - \alpha_3\right) \tag{4.7}$$

In view of the misspecified exposition and unnecessary homogeneity across regions in parameters $\alpha_1, \alpha_2, \alpha_3$, the STARF model improves on the VE method. Both ABP and VE methods deal with the endogeneity of the spatial lag term using QML estimation. By implementing the control function approach, we obtain consistent estimates of the structural parameters that may be directly comparable to the BHP and VE method. Finally, the discussed models do not provide any discussion of spatial or system-wide diffusion multipliers. The STARF model is able to capture the total diffusion multiplier effects across time and space with respect to changes in neighbourhood price changes, or financial market conditions. This provides a substantial improvement to alternative methods given the tractability of implementation and straight-forward interpretation.

With reference to application of the BHP method in Chapter 3, we find the HSAR model produces a high proportion of negative spatial parameters. These findings are consistent with the outcomes from BHP in US housing market application. While a key feature of the proposed BHP model involves the detection of positive and negative relationships between cross-sectional units, we note the authors do not provide a convincing economic interpretation or why this transpires, or take note of the prevalence of negative spatial parameters as a cause for concern. This may be caused by a lack of stability in the spatial parameter. According to Anselin (1988), positive spatial autocorrelation occurs when high (or low) values for a random variable tend to cluster in space. Clustering in the context of housing may arise from the fact that properties in similar areas tend to have been built near the same time, with similar structural features, materials and design characteristics leading similar house prices. Secondly, nearby properties share amenities with the rest of the neighbourhood, including schools, job opportunities and public service provision. In contrast, negative autocorrelation occurs when districts tend to be surrounded by neighbours

[4] Consequently, the results presented by VE in comparison to BHP using this restriction are not comparable.

with dissimilar values. In application to house price growth, the former holds more intuitive appeal. While there may be specific areas that are inversely related to their neighbours, such as affluent areas in pockets of relative deprivation (for example Solihull), these areas are unlikely to constitute a significant proportion of all districts. Given the high incidence of negative spatial parameter estimates, we are motivated to use an alternative model to test the robustness of this unexpected outcome.

4.4 Econometric Method:[5] The Spatio-Temporal Autoregressive Model with Factors

Consider the following STARF(1) model with heterogenous parameters:

$$\pi_{it} = \phi_i \pi_{i,t-1} + \gamma_{0i}\pi^*_{it} + \gamma_{1i}\pi^*_{it-1} + \boldsymbol{\lambda}'_{0i}\boldsymbol{f}_t + \boldsymbol{\lambda}'_{1i}\boldsymbol{f}_{t-1} + \alpha_i + e_{it} \tag{4.8}$$

where π_{it} is the house price inflation of district i at time t and π^*_{it} is its spatial lagged variable. We define π^*_{it} is defined by $\pi^*_{it} = \sum_{j=1}^{N} w_{ij}\pi_{jt} = \boldsymbol{w}_i\boldsymbol{\pi}_t$ with the $N \times 1$ vector $\boldsymbol{\pi}_t = (\pi_{1t}, ..., \pi_{Nt})'$where $\boldsymbol{w}_i = (w_{i1}, ..., w_{iN})$ denotes a $1 \times N$ vector of spatial weights determined *a priori* with $w_{ii} = 0$. We opt to use an inverse distance weights specification with a 50 mile cutoff where districts within the specified radius are assigned a value of one. As discussed in Chapter 3, the choice of weights specification remains somewhat arbitrary. Districts are typically small spatial units that often benefit from amenities in other nearby areas due to proximity that may exceed immediate bordering districts. In light of this, contiguity measures seem restrictive and less preferable to distance based measures which allow for a more permissible characterisation of neighbours within the 50 mile radius. Alternative weight specifications also include nearest neighbour and various distance based measures with various cut off values[6]. The author notes future research would benefit from a more economically grounded weights specification in the model; the use of commuting or migration data would be a useful future contribution. The matrix is then row normalised. Correspondingly, $\pi^*_{i,t-1} = \sum_{j=1}^{N} w_{ij}\pi_{j,t-1} = \boldsymbol{w}_i\boldsymbol{\pi}_{t-1}$ Factors are represented by $\boldsymbol{f}_t$ which denote national house price inflation, or observed data at the national level. The

[5]This section is derived following Shin (forthcoming)

[6]Results using the alternative weights specifications outlined in Section are available on request.

former procedure uses the cross sectional averaging approach put forward by BHP as a method to account for unobserved common factors. Adopting this method, we consider:

$$\pi_{it} = \phi_i \pi_{it-1} + \phi_{0i}^* \pi_{it}^* + \phi_{1i}^* \pi_{it-1}^* + \lambda_{0i} \bar{\pi}_t^N + \lambda_{1i} \bar{\pi}_{t-1}^N + \alpha_i + \varepsilon_{it} \tag{4.9}$$

where $\bar{\pi}_t^N = N^{-1} \sum_{i=1}^N \pi_{it}$ is the unweighted national average of house price inflation. This model includes BHP and VE as a special case. Here, π_{it}^* and $\bar{\pi}_t^N$ may be endogenous. To deal with the endogeneity of π_{it}^* in (4.9), we apply the control function approach, and consider the following control function DGP for π_{it}^* by:

$$\pi_{it}^* = \boldsymbol{\varphi}_i' \boldsymbol{z}_{it} + v_{it} \text{ with } E\left(\boldsymbol{z}_{it}' v_{it}\right) = \mathbf{0}$$

where $\boldsymbol{z}_{it}$ is the $\ell \times 1$ vector of exogenous variables. For now we may assume that $\pi_t^n \left(= N^{-1} \sum_{j=1}^N \pi_{jt}\right)$ is exogenous. With reference to the selection of $\boldsymbol{z}_{it}$, we simply suggest to use $\bar{\pi}_t^r = N_r^{-1} \sum_{i=1}^{N_r} \pi_{it}$, $r = 1, ..., R$ with $N = \sum_{i=1}^R N_r$, as IV for π_{it}^* in which case we have:[7]

$$\pi_{it}^* = \boldsymbol{\varphi}_i' \bar{\pi}_t^r + v_{it} \tag{4.10}$$

In the second stage, we augment (4.9) with the control variable, v_{it} as:

$$\pi_{it} = \phi_i \pi_{i,t-1} + \phi_{0i}^* \pi_{it}^* + \phi_{1i}^* \pi_{it-1}^* + \lambda_{0i} \pi_t^n + \lambda_{1i} \pi_{t-1}^n + \alpha_i + \boldsymbol{\varphi}_i v_{it} + \varepsilon_{it}^* \tag{4.11}$$

where π_{it}^* is now uncorrelated with ε_{it} and $\varepsilon_{it}^* = \varepsilon_{it} + \boldsymbol{\varphi}_i \left(\hat{\boldsymbol{\varphi}}_i - \boldsymbol{\varphi}_i\right)' \boldsymbol{z}_{it}$ depends on the sampling error in $\hat{\boldsymbol{\varphi}}_i$ unless φ_i is exogeneous. Then, the OLS estimator from (4.20) is consistent.

Stacking the district-specific equations, STARF$(1,1)$ from (4.8):

$$\boldsymbol{\pi}_t = \boldsymbol{\Phi}_1 \boldsymbol{\pi}_{t-1} + \boldsymbol{\Phi}_0^* \boldsymbol{W} \boldsymbol{\pi}_t + \boldsymbol{\Phi}_1^* \boldsymbol{W} \boldsymbol{\pi}_{t-1} + \boldsymbol{\Lambda}_0 \boldsymbol{f}_t + \boldsymbol{\Lambda}_1 \boldsymbol{f}_{t-1} + \boldsymbol{v}_t + \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_t^* \tag{4.12}$$

[7] While BHP and VE use QML estimation to deal with the endogeneity of the spatial variable, the control function method is required for us to draw the necessary comparison with the BHP and VE method.

where

$$\underset{N\times N}{\boldsymbol{W}} = \begin{bmatrix} w_{11} & \cdots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NN} \end{bmatrix},\ w_{ii}=0,\ \underset{N\times G}{\boldsymbol{\Lambda}_h} = \begin{bmatrix} \boldsymbol{\lambda}'_{1h} \\ \vdots \\ \boldsymbol{\lambda}'_{Nh} \end{bmatrix},\ h=0,1$$

$$\underset{N\times N}{\boldsymbol{\Phi}_1} = \begin{bmatrix} \phi_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \phi_{1N} \end{bmatrix},\ \underset{N\times N}{\boldsymbol{\Phi}^*_h} = \begin{bmatrix} \phi^*_{1h} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \phi^*_{Nh} \end{bmatrix}, h=0,1$$

The following stability conditions are considered: **Spatial stability**: The eigenvalues of $\boldsymbol{\Phi}^*_0\boldsymbol{W}$ lie inside the unit circle. **Time stability**: We rewrite equation (4.12) as

$$\boldsymbol{\pi}_t = \boldsymbol{F}_1\boldsymbol{\pi}_{t-1} + \tilde{\boldsymbol{\varepsilon}}_t, \tag{4.13}$$

where $\boldsymbol{F}_1 = \left(\boldsymbol{I}_N - \boldsymbol{\Phi}^*_0\boldsymbol{W}\right)^{-1}\left(\boldsymbol{\Phi}_1 + \boldsymbol{\Phi}^*_1\boldsymbol{W}\right)$, and $\tilde{\boldsymbol{\varepsilon}}_t = \left(\boldsymbol{I}_N - \boldsymbol{\Phi}^*_0\boldsymbol{W}\right)^{-1}\boldsymbol{\varepsilon}_t$. The roots of the $N\times N$ matrix polynomial $\boldsymbol{F}(z) = \boldsymbol{I}_N - \boldsymbol{F}_1 z$ lie outside the unit circle.

4.4.1 The Spatio-temporal Dynamic Multipliers

It is straightforward to derive the dynamic multipliers associated with unit changes in π^*_t on π_t, denoted $\frac{\partial\pi_{i,t+h}}{\partial\pi^*_{it}}$. To this end rewrite the STARF(1) model, (4.8) as

$$\phi_i(L)\,\pi_{it} = \phi^*_i(L)\,\pi^*_{it} + u_{it} \tag{4.14}$$

where

$$\phi_i(L) = 1-\phi_i L;\ \phi^*_i(L) = \phi^*_{0i} + \phi^*_{1i}L;\ u_{it} = \boldsymbol{\lambda}'_{0i}\boldsymbol{f}_t + \boldsymbol{\lambda}'_{1i}\boldsymbol{f}_{t-1} + \alpha_i + e_{it}$$

Premultiplying (4.14) by the inverse of $\phi_i(L)$, we obtain:

$$\pi_{it} = \tilde{\phi}^*_i(L)\,\pi^*_{it} + \tilde{u}_{it} \tag{4.15}$$

where $\tilde{\phi}_i^*(L)\left(=\sum_{j=0}^{\infty}\tilde{\phi}_{ij}^* L^j\right)=[\phi_i(L)]^{-1}\phi_i^*(L)$, and $\tilde{u}_{it}=[\phi_i(L)]^{-1}u_{it}$. The dynamic multipliers, $\tilde{\phi}_{ij}^*$ can be evaluated using the recursive relationship:

$$\tilde{\phi}_{ij}^*=\phi_{i1}\tilde{\phi}_{i,j-1}^*+\phi_{i2}\tilde{\phi}_{i,j-2}^*+\cdots+\phi_{i,j-1}\tilde{\phi}_{i1}^*+\phi_{ij}\tilde{\phi}_{i0}^*+\phi_{ij}^*,\ j=1,2,... \tag{4.16}$$

where $\phi_{ij}=0$ for $j<1$ and $\tilde{\phi}_{i0}^*=\phi_{i0}^*$, $\tilde{\phi}_{ij}^*=0$ for $j<0$. Then, the cumulative dynamic multiplier effects of π_{it}^* on $\pi_{i,t+h}$ can be evaluated as

$$m_{\pi_i}(\pi_i^*,H)=\sum_{h=0}^{H}\tilde{\phi}_{ih}^*,\quad H=0,1,...$$

By construction, as $H\to\infty$,

$$m_{\pi_i}(\pi_i^*,H)\to\beta_{yi}^*$$

where $\beta_{yi}^*=\sum_{h=0}^{1}\phi_{ih}^*/(1-\phi_i)$ is the long-run coefficient.

4.4.2 The Diffusion Multipliers

We now derive the diffusion (spatial-dynamic) multipliers in terms of the spatial system representation (4.12):

$$\boldsymbol{\Phi}(L)\boldsymbol{\pi}_t=\boldsymbol{\Phi}^*(L)\boldsymbol{W}\boldsymbol{\pi}_t+\boldsymbol{u}_t \tag{4.17}$$

where

$$\boldsymbol{\Phi}(L)=\boldsymbol{I}_N-\boldsymbol{\Phi}_1L;\boldsymbol{\Phi}^*(L)=\boldsymbol{\Phi}_0^*+\boldsymbol{\Phi}_1^*L;\boldsymbol{u}_t=\boldsymbol{\Lambda}_0\boldsymbol{f}_t+\boldsymbol{\Lambda}_1\boldsymbol{f}_{t-1}+\boldsymbol{\alpha}+\boldsymbol{e}_t$$

Premultiplying (4.17) by the inverse of $\boldsymbol{\Phi}(L)$, we obtain:

$$\boldsymbol{\pi}_t=\tilde{\boldsymbol{\Phi}}^*(L)\boldsymbol{W}\boldsymbol{\pi}_t+\tilde{\boldsymbol{u}}_t \tag{4.18}$$

where $\tilde{\boldsymbol{\Phi}}^*(L)\left(=\sum_{h=0}^{\infty}\tilde{\boldsymbol{\Phi}}_h^*L^h\right)=[\boldsymbol{\Phi}(L)]^{-1}\boldsymbol{\Phi}^*(L)$, and $\tilde{\boldsymbol{u}}_t=[\boldsymbol{\Phi}(L)]^{-1}\boldsymbol{u}_t$. The dynamic multipliers, $\tilde{\boldsymbol{\Phi}}_j^*$ for $j=0,1,...$, can be evaluated using the following recursive relationships:

$$\tilde{\boldsymbol{\Phi}}_j^*=\boldsymbol{\Phi}_1\tilde{\boldsymbol{\Phi}}_{j-1}^*+\boldsymbol{\Phi}_2\tilde{\boldsymbol{\Phi}}_{j-2}^*+\cdots+\boldsymbol{\Phi}_{j-1}\tilde{\boldsymbol{\Phi}}_1^*+\boldsymbol{\Phi}_j\tilde{\boldsymbol{\Phi}}_0^*+\boldsymbol{\Phi}_j^*,\ j=1,2,... \tag{4.19}$$

where $\mathbf{\Phi}_j = 0$ for $j < 1$ and $\tilde{\mathbf{\Phi}}_0^* = \mathbf{\Phi}_0^*$, $\tilde{\mathbf{\Phi}}_j^* = 0$ for $j < 0$ by construction. The matrix of the cumulative dynamic multiplier effects can be evaluated as

$$\boldsymbol{m}_{\pi^*}(H) = \sum_{h=0}^{H} \frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{*\prime}} = \sum_{h=0}^{H} \tilde{\mathbf{\Phi}}_h^*,$$

But, $\boldsymbol{m}_{y^*}(H)$ are block-diagonal because $\tilde{\mathbf{\Phi}}_h^*$ is block-diagonal.

Suppose that we are interested in the dynamic multipliers in terms of $\frac{\partial \pi_{i,t+h}}{\partial \pi_{jt}}$ for $ij, = 1, ..., N$. Then, it is straightforward to show that

$$\frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{\prime}} = \frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{*\prime}} \times \boldsymbol{W}$$

where

$$\frac{\partial \pi_{i,t+h}}{\partial \pi_{jt}} = \frac{\partial \pi_{i,t+h}}{\partial \pi_{it}^*} \times w_{ij} \text{ for } i \neq j$$

Therefore, we have:

$$\frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{\prime}} = \begin{bmatrix} \frac{\partial \pi_{1,t+h}}{\partial \pi_{1t}} & \frac{\partial \pi_{1,t+h}}{\partial \pi_{2t}} & \cdots & \frac{\partial \pi_{1,t+h}}{\partial \pi_{Nt}} \\ \frac{\partial \pi_{2,t+h}}{\partial \pi_{1t}} & \frac{\partial \pi_{2,t+h}}{\partial \pi_{2t}} & \cdots & \frac{\partial \pi_{2,t+h}}{\partial \pi_{Nt}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \pi_{N,t+h}}{\partial \pi_{1t}} & \frac{\partial \pi_{N,t+h}}{\partial \pi_{2t}} & \cdots & \frac{\partial \pi_{N,t+h}}{\partial \pi_{Nt}} \end{bmatrix} = \begin{bmatrix} 0 & \frac{\partial \pi_{1,t+h}}{\partial \pi_{1t}^*} \times w_{12} & \cdots & \frac{\partial \pi_{1,t+h}}{\partial \pi_{1t}^*} \times w_{1N} \\ \frac{\partial \pi_{2,t+h}}{\partial \pi_{2t}^*} \times w_{21} & 0 & \cdots & \frac{\partial \pi_{2,t+h}}{\partial \pi_{2t}^*} \times w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \pi_{N,t+h}}{\partial \pi_{Nt}^*} \times w_{N1} & \frac{\partial \pi_{N,t+h}}{\partial \pi_{Nt}^*} \times w_{N2} & \cdots & 0 \end{bmatrix}$$

where $\frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{\prime}}$ can be use used to identify the network effects from house price diffusion across districts. Borrowing from the network analysis literature, we use the in-degree and out-degree measure to construct a ranking of to and from spillover effects, demonstrating the direction and level of influence across heterogenous districts (Wasserman and Faust, 1994; Atalay et al., 2011; Sun et al., 2015).

We construct the row sum that measures the spillovers of neighbours' house price inflation on the region i's inflation. Now, we construct the row sum that measures the spillovers of neighbours' house price inflation on the region i's inflation (similar to from-spillover or in-degree effect) by

$$r_i^{sum} = \frac{\partial \pi_{i,t+h}}{\partial \pi_{it}^*} \sum_{j=1}^{N} w_{ij} = \frac{\partial \pi_{i,t+h}}{\partial \pi_{it}^*}$$

which is equal to the dynamic multiplier of π^*_{it} on $\pi_{i,t+h}$. The column sum is given by

$$c_i^{sum} = \sum_{j=1}^{N} \frac{\partial \pi_{j,t+h}}{\partial \pi^*_{jt}} w_{ji}$$

and this measures the spillover of the region i's house price inflation on neighbours. The outdegrees may then be used to estimate and rank the districts by the spillover effect of house price inflation in district i has on neighbouring districts.

4.5 Data

The Index of Production is a key short-term measure of economic activity in the United Kingdom. The dataset is used in the construction of Gross Domestic Product (GDP), with production industries' comprising a 14.6% weighting of GDP under the output approach. The Index measures the production volume from manufacturing, mining and quarrying, energy supply, and water and waste management industries at specified base year prices. UK producer price inflation data is used to deflate the index and underlying components are seasonally adjusted before the Index is compiled. The dataset is transformed into growth in the Production Index as $\eta_t = \ln\left(\frac{IP_t}{IP_{t-1}}\right)$ where IP denotes the Index of Production at time t.

Monthly interest rates of standard variable rate mortgage rates from UK monetary financial institutions to households is obtained from the Bank of England statistical database. The series is seasonally adjusted using the X-12-ARIMA procedure also applied to the house price inflation variable.

We adopt the ONS classification based on their rurality where local authorities are categorised as rural or urban based on the proportion of their resident population in rural areas or rural-related hub towns (DEFRA, 2004). Districts are categorised into 6 urban/rural classifications, defined by the ONS as follows:

1. MU: Urban with major conurbation: districts with either 100,000 people or 50% of their population residing in urban areas with a population over 750,000.

2. LU: Urban with minor conurbation: districts with either 50,000 people or 50% of their

population in urban areas with a population ranging from 250,000 to 750,000.

3. OU: Urban with city and town: districts with fewer than 37,000 people or less than 26% of their population in rural settlements and larger market towns.

4. SR: Urban with significant rural: districts with more than 37,000 people or more than 26% of their population in rural settlements and larger market towns.

5. R50: Largely rural: districts with at least 50% but less than 80% of their population in rural settlements and larger market towns.

6. R80: Mainly rural: districts with at least 80% of their population in rural settlements and larger market towns.

The first three categories are predominantly urban with over 74% of the resident population living in urban areas, whilst largely and mainly rural areas have over 50% of the resident population and are thus referred to as predominantly rural.

4.6 Empirical Results

We estimate two variations of the heterogenous STARF(1) model based on the different type of factors: cross sectional averages and nationwide economic data. Districts are often influenced by the same aggregate housing demand and supply shocks. However, variation in economic conditions across cross-sectional units can and do significantly influence district specific responses. While monetary policy changes or financial shocks may be nationwide, the influence of these common factors are often heterogenous. While BHP and VE allow for unobserved factors following the cross-sectional averaging approach, both methods do not consider observed aggregate effects. While the analysis of systemwide unobserved effects may be of interest in general terms, analysis using observed variables can be prescriptive in setting local governmental policies or anticipating the influence of macroeconomic conditions. For example, while monetary policy sets interest rates as a nationwide policy, district-level variations in home ownership levels and wealth distribution leads to amplifying the transmission channel of monetary policy on segments of the housing market. Several studies have highlighted the special transmission mechanism house prices plays through the influence of mortgage interest rates and bank lending channels (Maclennan et al., 1998; Boivin et al., 2010). Fratantoni and Schuh (2003) confirm regional housing markets have heterogenous influences on the efficacy of monetary policy in the US. Variation in the responses of districts or regions to interest rate changes may reflect differences in the intensity of competition of the banking sector, legal practices, regulations in the rental sector and housing transaction costs between districts. The STARF model begets a parsimonious dynamic multiplier framework to analyse how nationwide factors (such as interest rates or changes in economic activity) affect the system of districts over time. While observed factors are compatible with the VE method, the BHP method is able to account for these observed effects in the first step only. Consequently, the latter method is not well placed to evaluate the observed factors interest. In contrast to the BHP and VE applications, the use of observed factors in this chapter allow for readily interpretable impacts of nationwide factors of economic importance.

Using the two-step procedure, we obtain the reduced form residuals, $\hat{v}_{it} = \pi^*_{it} - \hat{\boldsymbol{\varphi}}'_i \boldsymbol{z}_{it}$ and run the following regression:

$$\pi_{it} = \phi_i \pi_{i,t-1} + \phi^*_{0i}\pi^*_{it} + \phi^*_{1i}\pi^*_{it-1} + \lambda_{0i}\boldsymbol{f}_t + \lambda_{1i}\boldsymbol{f}_{t-1} + \alpha_i + \boldsymbol{\varphi}_i \hat{v}_{it} + \varepsilon^*_{it} \tag{4.20}$$

We evaluate the dynamic multipliers of π_{it} with respect to unit changes in π^*_{it} for $h = 0, ..., H$ and for $i = 1, ..., N$. Using choropleth maps in Figure 4.4, we are able to view the heterogeneity in short and long-run impacts from neighbourhood price changes. Dynamic multipliers are evaluated in terms of the impact of neighbourhood house price changes with respect to a percentage change in neighbourhood house price inflation.

We report the system-wide diffusion multipliers at a horizon of 1 to compute the in-degree effects and use the out-degree measure to identify and rank districts based on the magnitude of spillover of district i onto its neighbours.

Dynamic multipliers are evaluated in terms of the impact of neighbourhood house price changes with respect to a percentage change in neighbourhood house price inflation. Across both short and long term horizons, there are apparent clubs of districts with shared responses to property price inflation in nearby areas. These findings are compatible with the new economic geography theories of core-periphery models (Krugman, 1997). Conversely to the London-centric models of house prices, the results show largely urban local economies have strong linkages with the surrounding rural area consistent with the findings of (Fik et al., 2003). In comparison of long and short run dynamic impacts, there is more concentrated clusters of spillover effects over the long term, confirming the same findings using the BHP method in Chapter 3. While there may be a heterogeneity in the pervasiveness of neighbourhood house prices in the short run, the results indicate that areas experiencing similar effects from neighbouring areas cluster together more convincingly over time. The long run dynamic multiplier results demonstrate strong contemporaneous spillover effects clustered on and around green belt areas. These areas represent government policy to ring-fence surrounding areas of the countryside to prevent urban sprawl. While reducing the availability of land for the construction of new dwellings, the value of houses in such areas benefit from proximity to attractive landscapes, preserved characteristics of historic towns without the threat of urbanisation encroachment over time. The effect is notably apparent in the North and North West of outer London in the counties of Buckinghamshire, Cambridgeshire and Hertfordshire. The results indicate these clubs of districts are impacted by house price inflation in the neighbouring areas in the same period. Strong positive impact multipliers are expected in these areas given how the value embedded in properties on the green belt are likely driven by geographical characteristics which are captured by the spatial parameter.

Table 4.1: Mean Group Estimates by Urban/Rural Classification from STARF(1) with $W_{d=50m}$ with Unobserved Common Factors (Cross-Sectional Averaging Approach)

	α	ϕ_1	ϕ_0^*	ϕ_1^*	λ_0	λ_1	$\hat{v}$
MU	-0.0214	0.0880 ***	0.465 ***	0.449 ***	0.641 ***	-0.527 ***	-1.35 ***
	(0.0131)	(0.0104)	(0.0738)	(0.0615)	(0.0881)	(0.0692)	(0.254)
LU	-0.0388 ***	0.0317 **	0.633 ***	0.335 ***	0.357 ***	-0.281 ***	-1.14 ***
	(0.00839)	(0.0127)	(0.0844)	(0.0750)	(0.0951)	(0.0871)	(0.0956)
OU	-0.0507 ***	0.0499 ***	0.823 ***	0.117	0.289 ***	-0.163 **	-1.55 ***
	(0.00970)	(0.0112)	(0.0760)	(0.0725)	(0.0716)	(0.0730)	(0.210)
SR	-0.0471 ***	0.0296 **	0.881 ***	0.146 **	0.165 *	-0.172 **	-1.43 ***
	(0.00684)	(0.0125)	(0.0680)	(0.0565)	(0.0907)	(0.0766)	(0.122)
R50	-0.0396 ***	0.0232 *	0.753 ***	0.218 ***	0.264 ***	-0.210 ***	-1.67 ***
	(0.00697)	(0.0128)	(0.0765)	(0.0715)	(0.0850)	(0.0808)	(0.151)
R80	-0.00712	0.0327 ***	0.976 ***	0.0498	0.0940	-0.140	-2.03 ***
	(0.00798)	(0.0108)	(0.109)	(0.0811)	(0.122)	(0.0967)	(0.211)

Rural/Urban classification follows categories: major urban (MU), minor urban (LU), urban with city/town (UO), largely rural (R50) and mainly rural (R80). See Section (4.5) for details.
Mean group estimates are calculated as simple averages from district level parameter estimates as follows: $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_u} \hat{\psi}_{i0}$ for $i = 1, \ldots, N, u = 1, \ldots, U$ where N_u is the total number of districts with connections in rural/urban classification u and $\hat{\psi}_{i0}$.

Table 4.2: Mean Group Estimates by Urban/Rural Classification from STARF(1) with $W_{d=50m}$ with Observed Common Factors[a]

	α	ϕ_1	ϕ_0^*	ϕ_1^*	λ_0^{IR}	λ_1^{IR}	λ_0^{IP}	λ_1^{IP}	$\hat{v}$
MU	0.0161	0.0801 ***	0.895 ***	0.121 ***	−0.0651	0.0596	0.140	0.191	−1.30 ***
	(0.0247)	(0.0104)	(0.0372)	(0.0444)	(0.0956)	(0.0953)	(0.168)	(0.189)	(0.240)
LU	0.0223	0.0287 **	0.843 ***	0.200 ***	−0.0879	0.0776	−0.0689	0.0969	−1.19 ***
	(0.0215)	(0.0117)	(0.0430)	(0.0409)	(0.0790)	(0.0784)	(0.151)	(0.165)	(0.0857)
UO	−0.00285	0.0496 ***	1.01 ***	0.0450	0.0388	−0.0464	0.0866	0.0508	−1.57 ***
	(0.0174)	(0.0111)	(0.0458)	(0.0446)	(0.0915)	(0.0902)	(0.167)	(0.173)	(0.198)
SR	−0.0380 *	0.0273 **	0.944 ***	0.0723 **	−0.0367	0.0373	−0.0540	0.166	−1.38 ***
	(0.0207)	(0.0123)	(0.0290)	(0.0311)	(0.101)	(0.100)	(0.189)	(0.152)	(0.124)
R50	−0.0394 *	0.0205	0.903 ***	0.122 ***	−0.0681	0.0683	0.0567	−0.159	−1.70 ***
	(0.0216)	(0.0128)	(0.0497)	(0.0455)	(0.0879)	(0.0877)	(0.232)	(0.188)	(0.144)
R80	−0.0730 ***	0.0302 ***	1.03 ***	−0.0270	0.0108	−0.0000158	−0.383 **	−0.373 *	−1.95 ***
	(0.0210)	(0.0110)	(0.0569)	(0.0554)	(0.117)	(0.115)	(0.185)	(0.191)	(0.192)

[a] Mean group estimates are calculated as simple averages from district level parameter estimates as follows: $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_u} \hat{\psi}_{i0}$ for $i = 1, \ldots, N, u = 1, \ldots, U$ where N_u is the total number of districts with connections in rural/urban classification u and $\hat{\psi}_{i0}$

Table 4.3: Mean Group Estimates by Region from STARF(1) with $W_{d=50m}$ with Unobserved Common Factors [a]

Region	α	ϕ_1	ϕ_0^*	ϕ_1^*	λ_0	λ_1	$\hat{v}$
North East	−0.0992 ***	0.0652 **	0.879 ***	0.0166	0.364 ***	−0.134	−2.23 ***
	(0.0242)	(0.0259)	(0.0774)	(0.0591)	(0.0838)	(0.100)	(0.315)
North West	−0.0273 *	0.0582 ***	0.849 ***	0.0697	0.151 *	−0.0620	−2.05 ***
	(0.0139)	(0.0128)	(0.0966)	(0.0762)	(0.0794)	(0.0805)	(0.308)
Yorks. & Humber	−0.0182 **	0.0548 ***	0.879 ***	0.159	0.223 *	−0.242 ***	−1.49 ***
	(0.00815)	(0.0156)	(0.127)	(0.0982)	(0.118)	(0.0873)	(0.273)
East Midlands	−0.0327 ***	0.0225	0.636 ***	0.379 ***	0.424 ***	−0.366 ***	−1.75 ***
	(0.00836)	(0.0151)	(0.107)	(0.109)	(0.111)	(0.105)	(0.219)
West Midlands	−0.0324 ***	0.0465 ***	0.548 ***	0.216 **	0.494 ***	−0.255 ***	−1.51 ***
	(0.00813)	(0.0158)	(0.0765)	(0.0859)	(0.119)	(0.0828)	(0.154)
East	−0.0459 ***	0.0453 ***	0.833 ***	0.200 ***	0.215 **	−0.241 ***	−1.21 ***
	(0.00701)	(0.0107)	(0.0890)	(0.0693)	(0.0908)	(0.0906)	(0.116)
London	−0.00551	0.113 ***	0.258 **	0.558 ***	0.940 ***	−0.687 ***	−1.46 ***
	(0.0261)	(0.0161)	(0.105)	(0.0950)	(0.136)	(0.0973)	(0.523)
South East	−0.0495 ***	0.0231 **	0.806 ***	0.242 ***	0.240 ***	−0.275 ***	−1.28 ***
	(0.00574)	(0.0104)	(0.0643)	(0.0579)	(0.0773)	(0.0774)	(0.0898)
South West	−0.00744	0.0267 *	1.03 ***	0.0266	−0.0266	−0.0310	−1.51 ***
	(0.00949)	(0.0154)	(0.133)	(0.0912)	(0.159)	(0.115)	(0.226)

[a] Regional group estimates are calculated as simple averages from district level parameter estimates as follows: $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N, r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$

Table 4.4: Mean Group Estimates by Region from STARF(1) with $W_{d=50m}$ with Observed Common Factors[a]

Region	α	ϕ_1	ϕ_0^*	ϕ_1^*	λ_0^{IR}	λ_1^{IR}	λ_0^{IP}	λ_1^{IP}	$\hat{v}$
North East	−0.0534	0.0682 ***	1.02 ***	0.0316	0.125	−0.124	−0.136	−0.518	−2.26 ***
	(0.0441)	(0.0256)	(0.0848)	(0.0485)	(0.216)	(0.214)	(0.410)	(0.425)	(0.320)
North West	−0.00133	0.0625 ***	0.925 ***	0.0686	−0.0481	0.0456	−0.169	0.0496	−2.02 ***
	(0.0229)	(0.0133)	(0.0661)	(0.0567)	(0.117)	(0.117)	(0.179)	(0.225)	(0.296)
Yorks. & Humber	−0.0285	0.0603 ***	0.972 ***	0.0490	−0.00743	0.00849	0.0497	0.108	−1.54 ***
	(0.0319)	(0.0170)	(0.0891)	(0.0840)	(0.158)	(0.156)	(0.327)	(0.218)	(0.258)
East Midlands	−0.0253	0.0167	0.890 ***	0.185 ***	−0.00197	0.000758	−0.00885	0.0355	−1.71 ***
	(0.0269)	(0.0148)	(0.0616)	(0.0617)	(0.0989)	(0.0968)	(0.210)	(0.211)	(0.223)
West Midlands	0.0123	0.0432 ***	0.870 ***	0.134 **	−0.110	0.103	−0.0550	−0.0157	−1.48 ***
	(0.0320)	(0.0152)	(0.0481)	(0.0538)	(0.117)	(0.116)	(0.235)	(0.234)	(0.160)
East	−0.0271 *	0.0392 ***	0.943 ***	0.0754 *	−0.0518	0.0497	−0.0152	−0.0224	−1.21 ***
	(0.0151)	(0.0108)	(0.0386)	(0.0406)	(0.0872)	(0.0867)	(0.177)	(0.182)	(0.104)
London	0.0114	0.0973 ***	0.937 ***	0.107	−0.0825	0.0788	0.0400	0.200	−1.37 ***
	(0.0479)	(0.0165)	(0.0603)	(0.0808)	(0.177)	(0.177)	(0.300)	(0.326)	(0.494)
South East	−0.0392 **	0.0212 **	0.955 ***	0.0633 *	0.00658	−0.00777	0.0200	−0.0197	−1.29 ***
	(0.0180)	(0.0102)	(0.0312)	(0.0343)	(0.0790)	(0.0782)	(0.173)	(0.149)	(0.0833)
South West	−0.0170	0.0233	1.00 ***	0.0158	−0.0519	0.0523	−0.0397	−0.0427	−1.47 ***
	(0.0238)	(0.0141)	(0.0604)	(0.0542)	(0.149)	(0.147)	(0.244)	(0.220)	(0.169)

[a] Regional group estimates are calculated as simple averages from district level parameter estimates as follows: $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N, r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$

4.6.1 Urban and Rural Districts

Mean group parameter estimates based on urban and rural classifications are given in Table 4.1. Mean group estimates are calculated as simple averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_u^{-1} \sum_{i=1}^{N_u} \hat{\psi}_{i0}$ for $i = 1, \ldots, N$, $u = 1, \ldots, U$ where N_u is the total number of districts with connections in a specific urban classification u and $\hat{\psi}_{i0}$. The results indicate spatial and temporal dependence across all all levels of urbanisation even after stripping away the impact of common factors. As discussed in Chapter 3 in the absence of factors, we may obtain inflated spatial and diffusion measures, assuming common factors have a positive impact on house prices. Having accounted for this global form of CSD, we are able to derive the pure spatial effects.

There is a well-documented debate pertaining to the role of urban centres in rural development (Boarnet, 1994; Krugman, 1997; Saraceno, 1994; Hughes and Holland, 1994). Where linkages are strong between rural and urban areas, a regional approach to development may be optimal. In instances where these connections are weak, targeted policies in rural areas may be more appropriate. The strength of relationships between rural and urban areas may be ascertained by measuring the effects of a change in economic activity in one district on the level of economic activity in the other district (Roberts, 2000). The application in this chapter is thus able to ascertain the influence of major urban areas on their peripheral counterparts in the housing market. We hypothesise rural areas are more dependent on nearby urban settlements due to employment, amenities and services that are more readily available in large economic centres.

The estimates in Table 4.1 display a clear pattern of stronger levels of persistence in more urbanised areas, with major urban areas over twice as more affected by neighbourhood house price inflation than in mainly rural areas. Major cities and large settlements have increased footfall as commuters travel for work in and through other developed areas. These migration population flows ensure information pertaining to house prices and neighbourhood characteristics are made more apparent. These interactions may serve to ensure contemporaneous spillover effects as other nearby areas adjust their expected house value based on their experience in the neighbourhood.

In contrast to the ripple effect hypothesis, we conjecture house prices are not only driven by London and the South East, rather local economies play an integral role in generating spillover impacts. In this respect, we depart from a London centric approach to anticipating house price dependence, that has often been a central feature in regional models of housing dynamics in the UK (Holly et al., 2011).

We base the following discussion on the interpretation of the time-space recursive model in Korniotis (2010). Using U.S. consumption data, the author investigates internal versus external habit formation.[8] In the housing context, we may consider the dynamic lag term ϕ_1 measures the internal persistence of house prices, contrasted against the contemporaneous neighbour effect ϕ_0^*. In this respect, we may ascertain whether house price inflation in a given district is determined by internal persistence in one's own district or inflation is externally formed from neighbourhood house price changes. We hypothesise the external contemporaneous neighbourhood effect will outweigh the internal persistence in house prices in most instances. Given the small size of districts, we expect the conditions in surrounding districts are likely to have a greater impact on house price inflation in a given district in contrast to internal persistence.[9] Furthermore, given the minor size of a district relative to all neighbours, we anticipate the persistence in house price inflation is only likely to be comparable to the spatial impact in highly urbanised areas given the chronically high levels of demand in an typically highly densely populated area. For example, in London we may anticipate high levels of persistence in house prices, however, good transport linkages and urban sprawl around these areas may displace the demand to nearby areas, alleviating the persistence in house prices. The extent of this can be evaluated by the strength of the external neighbourhood effect term, ϕ_0^* against ϕ_1.

Most strikingly, the short term spatial impact drastically outweighs the own lagged impact of house price inflation. As expected, we find contemporaneous neighbourhood house price inflation

[8]Korniotis (2010)investigates the issue of internal versus external habit formation using the annual consumption data for the U.S. states, employing the time-space recursive model which imposes the zero restriction on the contemporaneous spatial effect. In the more general case where the contemporaneous spatial lag term is significant, Korniotis's main empirical finding that the US state consumption growth is not significantly affected by its own (lagged) consumption growth but it is affected by lagged consumption growth of nearby states, are rather misleading. Thus, our current approach will provide a more general insight.

[9]The logic here is somewhat analogous to the notion small economies are often more vulnerable to global macroeconomic developments. This may be due to reliance on imports for production processes, exports accounting for a large proportion of demand, or the lack of a large population to prop up domestic demand that may otherwise mitigate changes in the external environment.

outweighs internal persistence in house price inflation across all urban classifications, presented in table 4.1. The difference of influence between past values of house price inflation compared to the spillover effects from the neighbourhood is often over double, with mainly rural areas nearly three times more affected by changes in the neighbourhood price inflation compared to own district persistence in price movements. This evidence suggests persistence in house price inflation is indeed greater in major urban areas relative to the contemporaneous neighbourhood impact in comparison to rural settlements. Even in the major urban category, the internal persistence is superseded by the external impact. While the diffusion parameter for major and largely urban areas is significant, we find the cumulative impact of the contemporaneous and space time lag show that major rural areas show greater spatial dependence. These findings reinforce a preference for dynamic multipliers as an intuitive framework to evaluate spatial dependence (for example see Figure 4.6.1).

Table 4.1 shows the impact of unobserved common factors (measured by cross sectional averages) increases as areas are more urbanised. Given the concentration of the population in these highly urban areas, it is unsurprising to find no statistically significant impact of common factors in very rural districts. This is partly attributed to the demographic of individuals living in rural areas of older individuals a disproportionate number of retired individuals relative to urban areas (Pateman, 2011). This may reduce the sensitivity of households in rural areas to changes in wages, unemployment levels and financial shocks. While rural areas make up over 85% of land, 82.4% of the population live in urban areas (DEFRA, 2004). In light of the low proportion of individuals living in rural areas, the average house price inflation across all districts is likely not be proportionally reflective of changes in the rural environment. That is, rural areas comprise a relatively small proportion of districts and hence is likely not to be as closely correlated with rural house price inflation movements, particularly in the major rural case. For all other levels of rural population, there is some influence of national factors on district level house price growth. The impact in the lagged period is negative, however the net effect for all categories demonstrates a positive association between national house price changes and house price appreciation over time. The fluctuations near zero across both estimates may be indicative of the volatility of house price changes that are well documented in England (Hilber and Vermeulen, 2016). For example, given house prices are characteristically volatile in the UK, small areas are likely to display more volatility than the aggregate trend. Common factors are by their very nature aggregated to the regional or national level in our model, and hence likely to display lower levels of variation. While there may be a positive relationship between house price inflation in a given district with national house prices, month to month, this may deviate from the long run relationship between the two variables.

The estimation results from Table (4.2) summarise the STARF(1) model with observed common factors. Surprisingly, both factors are found to have little to no influence on house price inflation. However, at the district level, we find 51 areas show interest rates have an influence on house price inflation at the 10% significance level; 49 of these districts also find lagged interest rates influence house price inflation at the 10% significance level. These results may indicate delineating the housing market by urban classification (or region) does not capture the subset of districts that show sensitivity to interest rate changes. Alternatively, by controlling for both regional and global factors, this may have precluded estimating the impact of the selected factors due to potential collinearity. The dynamic and spatial effects are well established, with the short run impact of neighbourhood house price changes significant at the one percent level across all urban/rural classifications. The estimates closely mirror the earlier findings of strong spillover effects in more rural areas. The spatial impact is relatively strong across all areas, with the lowest value of 0.843 still demonstrating strong spillover effects in minor urban areas. While the immediate spatial effect has increased in power, the estimated diffusion parameters have fallen compared to the estimated coefficients from the cross sectional averaging approach. Major urban, minor urban, urban with city/town and largely rural areas shows statistically significant diffusion effects but at the fraction of the impact from dynamic and spatial effects separately. The cumulative dynamic multipliers with respect to neighbourhood house price inflation by mean group estimates for rural/urban classifications are given in 4.6.1. In line with the core-periphery models of the new economic geography, we hypothesise urban areas experience faster rates of adjustment due to the increased flow of commodities and services from urban (core) districts to nearby rural (periphery) areas (Krugman, 1997; Roberts, 2000). This directional dependence should manifest itself in the spill-in impacts, denoting a district affinity to be affected by neighbourhood (in this case core area) house price changes. This conjecture is in accordance with the notion of economic growth 'trickling down' to the periphery area, serving to increase demand for the goods and services within the vicinity, eventuating overall regional growth (Berry, 1969). Urban areas however, benefit from agglomeration effects related to the degree of urban classification[10] includes transport, access to material and labor inputs by firms, in addition to employment, cultural, leisure, and consumer services by households. These agglomeration benefits lead to increased population density that serve as information signals pertaining to changes in amenities or services in a given area, allowing households to respond to changes in neighbouring areas at a faster rate of adjustment than in rural market segments.

We find more rural areas show a slower change in impact as over time from their neighbours, but the overall impact is elevated above 1%. Both these findings are consistent with our predictions. Major urban areas show the fastest rate of convergence to their long run level. This may be attributable to increased information signals from more densely populated areas to higher footfall from commuters. De Bruyne and van Hove (2013) theorise agricultural areas have fewer job opportunities; we may argue this leads individuals living in rural areas to rely on neighbouring districts for employment, strengthening the spatial dependence between districts compatible with the core-periphery framework. Largely rural areas with significant rural settlements show the highest levels of contemporaneous spatial dependence which then converge to a long-run level just above unity. This contrasts with major urban areas at horizon zero, where the marginal impact of neighbours is half that of its rural counterpart. While figure 4.6.1 shows a difference in long run cumulative dynamic multipliers for different levels of urban/rural measures, these differences are small in magnitude, with long run values ranging across classifications from 0.991 to 1.055. The author acknowledges the model may benefit from the inclusion of more lagged terms which may improve the ability of the cumulative dynamic multipliers to capture the impacts over time.

[10]The impact of urban scale is studied in Partridge et al. (2009)

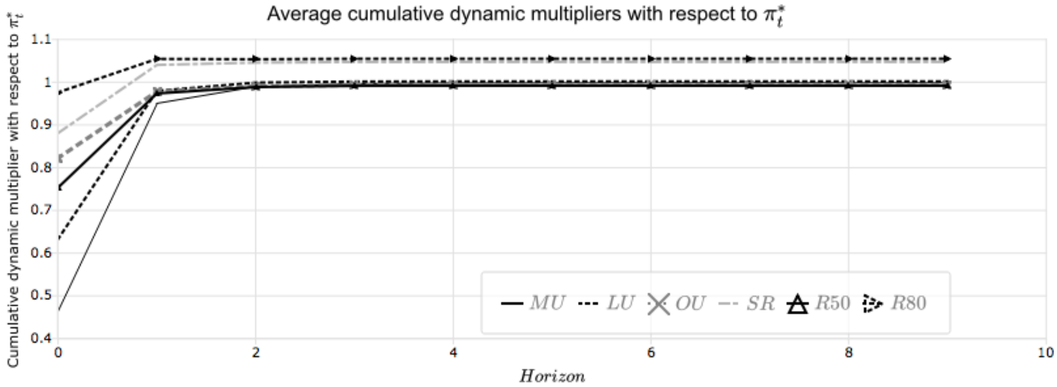


Figure 4.1: Average cumulative dynamic multipliers by classification of rurality. The district level cumulative dynamic multiplier effects of π_{it}^* on $\pi_{i,t+h}$ are evaluated as $m_{\pi_i}(\pi_i^*, H) = \sum_{h=0}^{H} \tilde{\phi}_{ih}^*$, $H = 0, 1, ..9$. Average cumulative dynamic multiplier estimates are calculated as simple averages from district level parameter estimates for a given subgroup. $E(\phi_{i0}) = \phi_0$ where$m_{\pi_i}(\hat{\pi}_i^*, H)_{U_r,MG} = N_u^{-1} \sum_{i=1}^{N_u} \sum_{h=0}^{H} \hat{\tilde{\phi}}_{ih}^*, H = 0, 1, ..9$ for $i = 1, \ldots, N, u = 1, \ldots, U$ where N_u is the total number of districts with connections in a specific urban classification u.

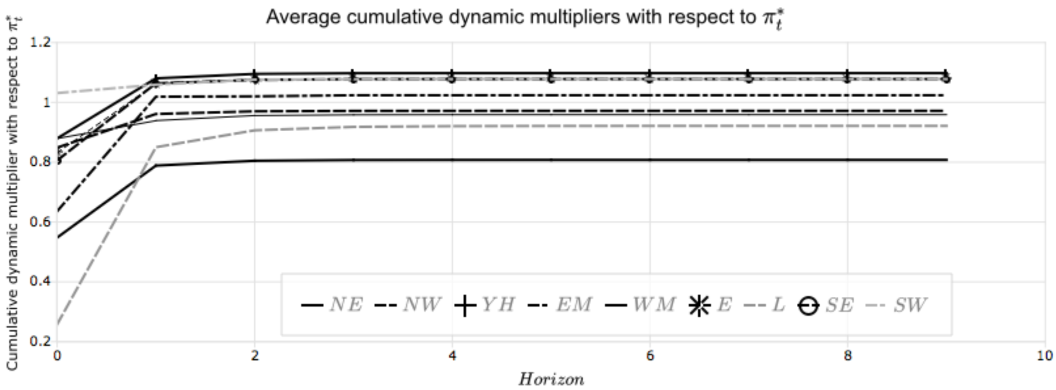


Figure 4.2: Average cumulative dynamic multipliers by region. The district level cumulative dynamic multiplier effects of π_{it}^* on $\pi_{i,t+h}$ are evaluated as $m_{\pi_i}(\pi_i^*, H) = \sum_{h=0}^{H} \tilde{\phi}_{ih}^*$, $H = 0, 1, ..9$. Average cumulative dynamic multiplier estimates are calculated as simple averages from district level parameter estimates for a given subgroup. $E(\phi_{i0}) = \phi_0$ where $m_{\pi_i}(\hat{\pi}_i^*, H)_{N_r,MG} = N_r^{-1} \sum_{i=1}^{N_r} \sum_{h=0}^{H} \hat{\tilde{\phi}}_{ih}^*$, $H = 0, 1, \ldots 9$ for $h = 1, \ldots, H, i = 1, \ldots, N_r, r = 1, \ldots, N_R$ where N_r is the total number of districts with connections in a specific region r.

4.6.2 Regional Estimates

Regional estimates are calculated as simple averages of district parameter estimates as outlined in Pesaran and Smith (1995). Regional group estimates are calculated as simple averages from district level parameter estimates as follows: $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N, r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$. The results indicate common factors and spatial dependence both play a dominant role in determining house price inflation in a given area. Inflation in house prices also show signs of persistence as all regions except the East Midlands having a statistically significant effect at the 10% level. House prices in London are found to be far more persistent than in other regions at 0.113, almost double the estimated effect compared to other regions. These findings are in accordance with government reports outlining how London house prices display more volatility and increase growth compared to other regions (Barker, 2008). Interestingly, surrounding areas such as South East and South West demonstrate far lower levels of persistence in house prices, contradicting some of the literature relating London house prices closely to changes in the South East (Alexander and Barrow, 1994; Macdonald and Taylor, 1993).

The spatial effect is far more pronounced compared to the lagged dynamic parameter across all regions with impacts ranging from 1.03 in the South West, to 0.258 in London. The evidence indicated high levels of persistence in London house prices while the impact of neighbourhood prices places a less, albeit statistically significant role, while the opposite holds true for all other regions. The Southern areas show high levels of interdependence in house price inflation from neighbourhood inflation changes. This also holds true for Northern regions, with North East, North West, Yorkshire and Humber providing similar estimates across dynamic and spatial parameters. These areas in addition to South West do not show statistically significant evidence of price diffusion. However, it is worth noting that given the significant spatial and dynamic parameters in the model, the impact of past spatial and dynamic effects may still be felt recursively at a decaying rate. The results taken from the dynamic multipliers provide a more reliable source of information for inference.

In spite of the insignificance of the observed factors in the second STARF(1) model presented in Table 4.4, we find estimated spatio-temporal coefficients do not materially change in value across both factor specifications, demonstrating robust estimates of spatial dependence. The findings contrast with Meen (1999) who finds interest rates have a significant impact on house prices, with an increasingly positive effect moving northwards. Regional mean group cumulative dynamic multipliers are reported in Figure 4.6.1 for $H = 1$. We note all regions display a relatively fast convergence to the long run multiplier with all regions close to convergence with their long-run multiplier after two months with the exception of London where this occurs after the three month horizon. London also demonstrates the largest adjustment value, with the initial spatial impact of 0.258% that approaches a long run value approximately at 0.921%. In contrast, the least adjustment occurs in the South West, where the long run dynamic multiplier is only superseded by Yorkshire and Humber. We also find the South East shows a high level of spatial dependence compared to West Midlands, approaches a value of 0.808% over a longer horizon.

In comparison to the results in the BHP method, no areas display negative spatial autocorrelation. The incidence of significant regions is also higher, with all regions demonstrating contemporaneous neighbourhood effects and persistence in house prices, with the exception of the East Midlands. These findings contrast with the BHP method where the North East and London alone experience contemporaneous neighbourhood effects, both of which are negative. While both measures cannot be compared directly, London is found to display the highest level of persistence by a considerable margin following both methods.

4.6.3 System-wide Diffusion of House Prices

In practice, we may represent (4.12) as follows:

$$\pi_t = \left(\mathbf{I}_N - \mathbf{\Phi}_\mathbf{0}^* \mathbf{W}\right)^{-1} \left(\mathbf{\Phi}_\mathbf{1} + \mathbf{\Phi}_\mathbf{1}^* \mathbf{W}\right) \pi_{t-1} + \left(\mathbf{I}_N - \mathbf{\Phi}_\mathbf{0}^* \mathbf{W}\right)^{-1} \left(\mathbf{\Psi}_\mathbf{0} \hat{\boldsymbol{v}}_t + \boldsymbol{\epsilon}_t\right), \tag{4.21}$$

$$\begin{aligned} \frac{\partial \pi_t}{\partial \pi_{t-1}} &= \left(\mathbf{I}_N - \mathbf{\Phi}_\mathbf{0}^* \mathbf{W}\right)^{-1} \left(\mathbf{\Phi}_\mathbf{1} + \mathbf{\Phi}_\mathbf{1}^* \mathbf{W}\right) \\ &= \left(\mathbf{I}_N + \mathbf{\Phi}_\mathbf{0}^* \mathbf{W} + \left(\mathbf{\Phi}_\mathbf{0}^* \mathbf{W}\right)^2 + \cdots\right)^{-1} \left(\mathbf{\Phi}_\mathbf{1} + \mathbf{\Phi}_\mathbf{1}^* \mathbf{W}\right) \end{aligned}$$

Given the equivalence of $\frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t'} = \frac{\partial \boldsymbol{\pi}_{t+h}}{\partial \boldsymbol{\pi}_t^{*\prime}} \times \boldsymbol{W}$ in Shin (2018) where $\frac{\partial \pi_{i,t+h}}{\partial \pi_{jt}} = \frac{\partial \pi_{i,t+h}}{\partial \pi_{it}^*} \times w_{ij}$ for $i \neq j$, we are able to report the diffusion multipliers at $h = 1$ for $\frac{\partial \pi_{i,t+1}}{\partial \pi_{jt}}$, using the row and column sum of $\left(\mathbf{I}_N - \mathbf{\Phi}_\mathbf{1}^* \mathbf{W}\right)^{-1} \left(\mathbf{\Phi}_\mathbf{1} + \mathbf{\Phi}_\mathbf{1}^* \mathbf{W}\right)$ to calculate the spill-in and spill-out effects respectively.

Figure 4.7 summarises the to and from spillover effects of neighbourhood house price inflation across districts over the one month horizon. The from-spillover effects measure the spillovers of neighbours' house price inflation on the district i's inflation. From Figure 4.5a, there is markedly notable spatial distribution of strong in-degree effects greater surrounding London and certain Northern cities. Areas surround these major cities display strong levels of dependence on neighbouring house price inflation. These areas experience similar levels of long run impacts as they tend to cluster around cities and key transport networks. The effect is not limited to London, but also remains distinctive around Nottingham and the motorways associating major Northern cities to one another, such as Birmingham and Sheffield. These findings indicate these areas have a unifying similarity in terms of how neighbourhood house prices changes play a relatively sizeable role in house price growth in a given districts. The relationship for these shared characteristics may be a result of similar levels of amenities and shared proximity to rural areas whilst remaining accessible to the agglomeration benefits from being situated by large economic centres. These findings are affirmative of our initial hypothesis predicting periphery areas to large economic centres are likely to experience large spill-in effects due to their sought after placement balancing convenience and quality of life (relating to proximity to nature, quality of air etc.) for large commuting populations. While individuals may reside in these periphery districts, the working population are likely to commute into cities where the availability of employment is higher. Individuals are thus likely to benefit (or suffer) from changes in the city environment. For example, policies to improve congestion are likely to have a beneficial effect on commuters travelling within the city. Given the policy impacts the commuters living in the periphery areas, house prices may appreciate in these areas due to the spillover effect of improved conditions in the city. The spill-in effects show clustering around London and the South East, providing some evidence of the ripple effect. The hypothesis refers to the propensity for house prices to rise first in the South East of the country during an upswing and to gradually spread out to the rest of the country over time. However, we find this effect does not spread to the North as the areas surrounding the strong positive spill-in band of areas around London are they themselves surrounded by districts that display little to no spill-in effects. In this respect, we find that the spill-in effects in the North are instigated by Northern districts, as opposed to the aftereffects that have rippled out from London. These findings are compatible with the conclusions drawn from Chapter 3 where economic centres were also seen to be the source of spatial dependence. In this application however, we find there is some evidence that house price inflation does ripple out, but within an approximate fifty mile radius only. In light of this, we find limited evidence of the ripple effect. Importantly, we note these regions are situated on the green belt. Inconsistent with the ripple effect hypothesis, we find London does not share the same spill-in effects. We consider the results in this chapter more robust than the estimates derived in the previous chapter due to the lower incidence of negative spatial parameters that are unexpectedly prevalent in the the preceding chapter and BHP application.

Table 4.5: District ranking by strength of spillover effect of district i's house price inflation onto neighbouring districts. Outdegrees are calculated from the STARF(1) model with national house price inflation as factors.

District	Rank	Outdegrees	Region
Cheltenham*	1	2.711	South West
Shropshire*	2	2.678	West Midlands
Cannock Chase	3	2.466	West Midlands
Wiltshire	4	2.346	South West
Thanet*	5	2.280	South East
Rushcliffe*	6	2.270	East Midlands
Lincoln	7	2.258	East Midlands
West Dorset	8	2.250	South West
Charnwood	9	2.227	East Midlands
Newark and Sherwood	10	2.136	East Midlands
New Forest	11	2.082	South East
City of Bristol	12	2.078	South West
North Warwickshire	13	2.072	West Midlands
Lambeth*	14	2.032	London
Hartlepool*	15	2.012	North East
Kettering	16	2.009	East Midlands
South Lakeland*	17	1.990	North West
Nuneaton and Bedworth	18	1.944	West Midlands
Calderdale*	19	1.914	Yorkshire and The Humber
Gravesham	20	1.912	South East
Barking and Dagenham	21	1.907	London
Brighton and Hove	22	1.879	South East
City of Westminster	23	1.876	London
Weymouth and Portland	24	1.869	South West
Shepway	25	1.868	South East
Craven	26	1.867	Yorkshire and The Humber
Dacorum*	27	1.867	East

$*$ denotes 1st rank by strength of spillover effect of district i's house price inflation onto neighbouring districts in each respective region. The column sum of $(\mathbf{I}_N - \mathbf{\Phi}_\mathbf{1}^*\mathbf{W})^{-1}(\mathbf{\Phi}_\mathbf{1} + \mathbf{\Phi}_\mathbf{1}^*\mathbf{W})$ to calculate the spill-out effects respectively.

The spillover of region i's house price inflation on neighbours' inflation is estimated from the out-degree effect. Areas are then ordered by the level of influence exerted on neighbourhood price inflation. The ranking based on influence on neighbouring district inflation is given in Table with asterisks denoting the largest to-spillover effects for a given region. Cheltenham district in Gloucestershire has the strongest spillover effects to its neighbours. The district is located on the edge of the Cotswolds, with sceneries protected by the green belt in addition a high number of internationally renowned schools and low crime rates; these positive attributes affecting house prices are unlikely to fluctuate greatly over time. The areas that are able to provide both sets of attributes are found to be dominant units in influencing house prices in a given area. The findings in this chapter confirm the importance of proximity to economic centres in influencing house price inflation in nearby areas, consistent with the findings of Fik et al. (2003).

These findings may reflect the London-centric ripple effect as a dominant factor while the core-periphery spillover effect would be dominant at higher levels of urbanisation. Our findings may also reflect the time-varying nature of the house price inflation spillover as we note the variation in the speed of adjustment between urban and rural areas. All highly ranked districts enjoy the benefits of protection under the green belt policy in addition to high performing schools and other sought after characteristics associated with increased demand for housing. While the increased demand for housing in such areas cannot be met by increased supply given restrictive planning permissions, individuals may substitute to nearby areas to enjoy the shared amenities through proximity, hence these areas may propagate strong spillover effects to neighbouring districts. The majority of districts reside in the South West, South East and the Midlands, in contracts to the East which first appears in the ranking in 27th place, demonstrating low levels of spillover effects from districts in the region to its respective neighbours.

Studies by Hilber and Vermeulen (2016) and Saiz (2010) demonstrate areas facing geographical or regulatory constraints[11] experience low elasticities of supply which are in turn endogenous to price growth. Our findings provide evidence supporting the role of inelastic supply in sustaining house price inflation in these areas.

[11] The green belt is a prominent example of regulatory constraints.

4.7 Concluding Remarks

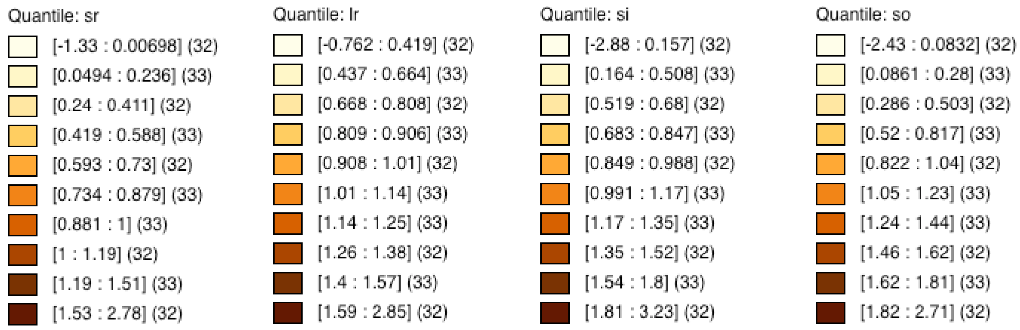
The results in this chapter demonstrate a highly heterogeneous housing market, characterised by strong spatial dependence in strategic subsets of the housing segments. Notably, periphery areas to economic centres are shown to have the most influence on neighbourhood house price changes. The findings underscore the complexity of the housing market where preferences for convenience and low commuting times may often be at odds to good quality air and landscapes. In contrast to the ripple effect, we hypothesise periphery areas surrounding cities play a primary role in propagating spillover effects to the neighbouring regions, consistent with the new economic geography framework. Our conjecture contrasts with the ripple hypothesis in two key respects: firstly, we put forward that economic centres are key in the transmission of house price spillovers as opposed to the London-centric view where house price appreciation begins in the South East and London before spreading to the rest of the country. This implicitly confers London as the single dominant unit. Secondly, the ripple effect attributes spillover effects first from an urban area (London) which then fans out to the rest of the country over time. While cities are economic centres, we put forward that they do not directly propagate the spillover effects in the first instance. Instead, these periphery areas characterised by their placement near the countryside while retaining access to the city are salient features of spatial dependence in the housing market. The importance of the physical characteristics of the periphery areas is integral in the formation of our hypothesis, while the ripple effect is underpinned by urbanisation effects. The importance of these geographic characteristics are consistent with Saiz (2010) who find MSAs who face geographical or regulatory constraints[12] experience low elasticies of supply which are in turn endogenous to price growth. The areas that are able to provide both sets of attributes are found to be dominant units in influencing house prices in a given area. Areas surrounding London are found to be most susceptible to the impact of neighbourhood house price changes, providing limited evidence of house prices rippling out from areas surrounding London. However, this impact decays beyond the approximate 50 mile radius, indicating that the comparable strong spill-in effects in the North (surrounding key cities such as Manchester and Sheffield) are the source of the spill-in effects experienced in these areas surrounding the strong local economies.

[12]The green belt is a prominent example of regulatory constraints.

This is inconsistent with the theory that house prices ripple from the south-east and London to reach the North over time. Furthermore, inconsistent with the ripple effect, London itself does not play a dominant role in the propagation of spillover effects.

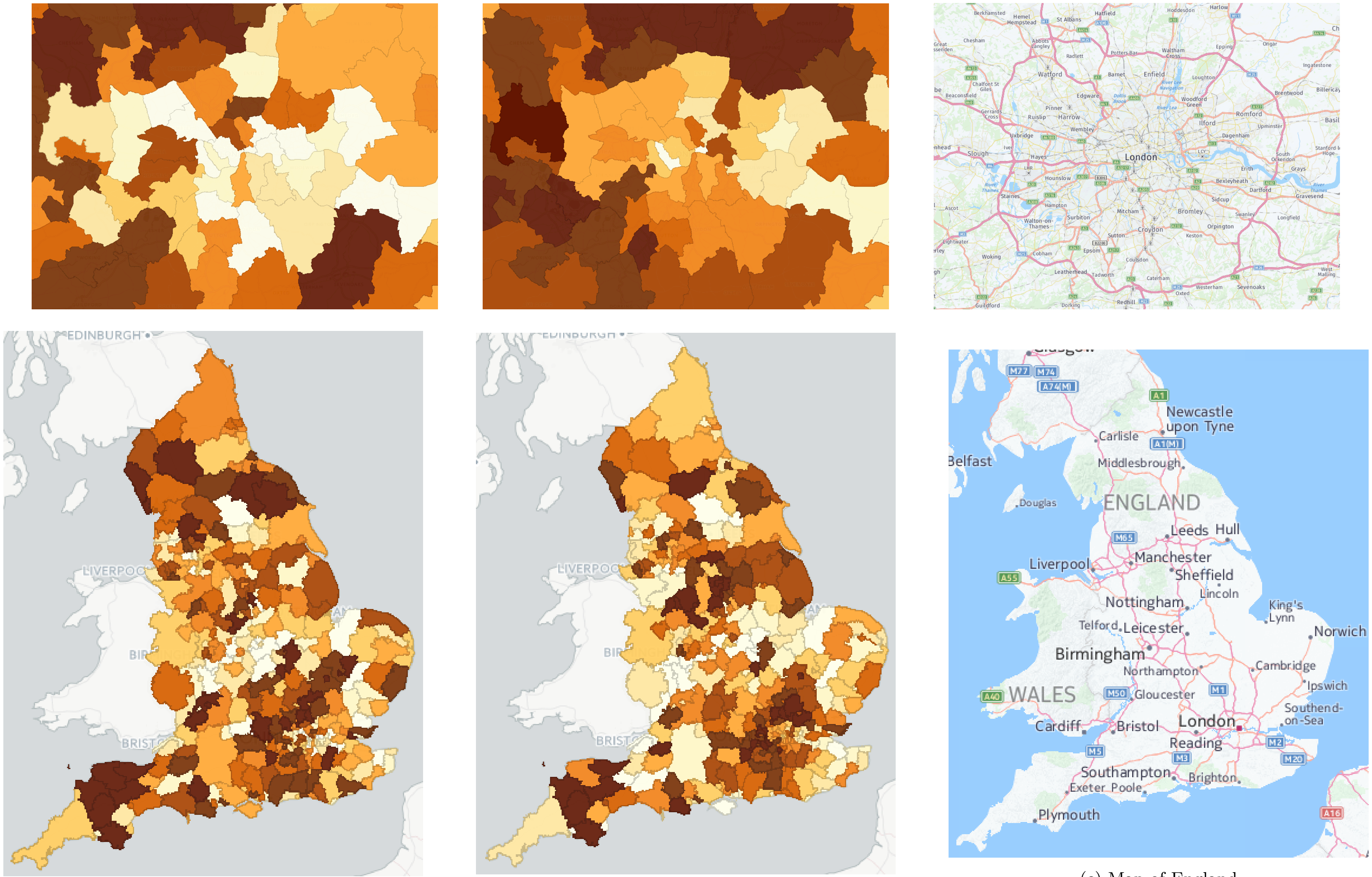
The results presented provide a parsimonious representation of spatial diffusion of house prices in England that present results more in line with the economic theories of spatial dependence in house prices. While we contribute a substantial improvement over existing methods for analysing the housing market, the estimated model can be readily improved in a number of ways. Through the use of an information criterion, the number of lags to include in our estimation may be selected. This would prevent spatial and serial correlation in the error terms that may in turn have biased our estimates. Furthermore, the use of factors should be changed given the low association of house price inflation with the use measures of economic activity and interest rates. Furthermore, we have made an arbitrary choice to use a weights matrix with a 50 mile distance cut off. In place of this, we may extend our model with the use of an adjacency matrix based on economic data with time variation to account for changing spatial dependence over time. While we have made some general comparisons to the BHP method, we would benefit from some Monte Carlo simulation results to formally compare how the three heterogenous models compare in performance.

In future research, we may try alternative variables as factors in our model in light of the low association of house price inflation with measures of economic activity and interest rates. Furthermore, we have made an arbitrary choice to use a weights matrix with a 50 mile distance cut off. In place of this, we may extend our model with the use of an adjacency matrix based on economic data with time variation to account for changing spatial dependence over time. The development of dynamic multipliers with respect to factors would be a natural and straightforward extension. The analysis of its application may lead to better understanding of how house prices in a given area respond to a financial or productivity shock. We may ascertain differences in the speed of adjustment between districts, providing policy makers with tools to better anticipate how macroeconomic shocks may unfold over time and space.



(a) Short Run DM (b) Long Run DM (c) Spill-in (d) Spill-out

Figure 4.3: Key for quantile value ranges in chloropleth maps for short run dynamic multipliers (4.4a), long run dynamic multipliers (4.4b), spill-in (4.5a) and spill-out (4.5b) effects in figures (4.4) and (4.7).

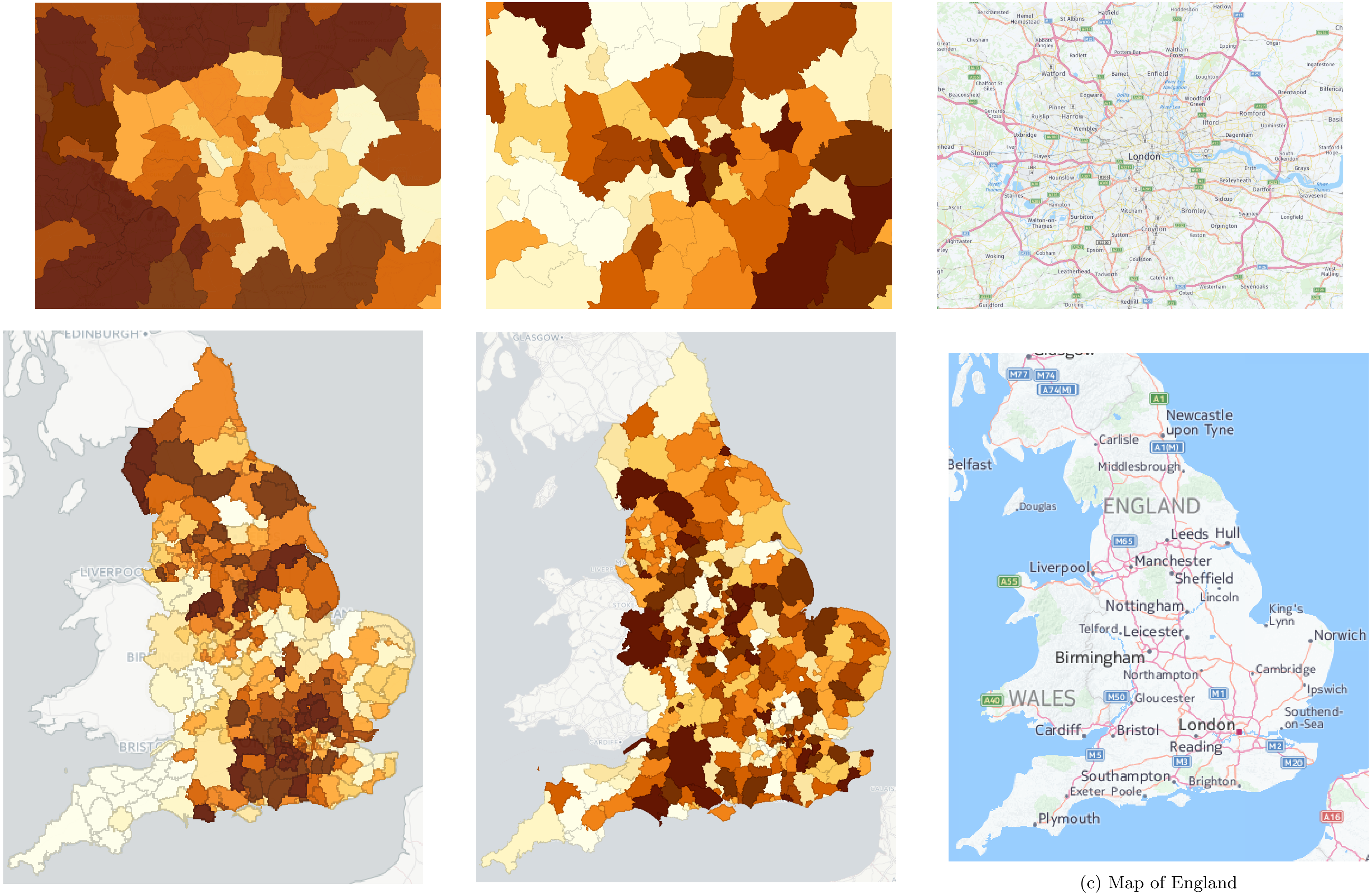


(a) Short Run Dynamic Multipliers

(b) Long Run Dynamic Multipliers

(c) Map of England

Figure 4.4: Ten quantile choropleth map of long and short-run impacts of neighbouring house price inflation with darker areas signifying higher dynamic multiplier values.Figure 4.7 provides value ranges for each quantile.



(a) Spill-in

(b) Spill-out

(c) Map of England

Figure 4.5: Ten quantile choropleth map of spill-in and spill-out effects of neighbouring house price inflation with darker areas signifying higher dynamic multiplier values. The row and column sum of $\left(\mathbf{I}_N - \mathbf{\Phi}_1^* \mathbf{W}\right)^{-1} \left(\mathbf{\Phi}_1 + \mathbf{\Phi}_1^* \mathbf{W}\right)$ to calculate the spill-in and spill-out effects respectively. Figure 4.7 provides value ranges for each quantile.

Chapter 5

Concluding Remarks

This thesis evaluates house price dynamics in the UK using a range of data driven techniques. We now provide a succinct summary of the three chapters together with the limitations of the research, policy recommendations and potential venues for future research work.

Chapter 2 identifies and dates-stamps exuberance in regional housing markets during 1983(1) to 2014(4) using the econometric procedures devised by Phillips et al. (2011, 2015). A consistent timeline of historic events in the UK housing market emerges from the empirical findings supporting the use of the testing procedure in identifying bubbles within a regional context. Using affordability ratios, we are able to differentiate between exuberance driven by fundamentals which prove to be less common. We find unemployment and short term interest rates are able to predict bubbles in the housing market, while disposable income does not. Our findings highlight the heterogeneity between regional segments of the housing market and identify factors that may predict these episodes for policy makers.

The use of median salaries of full-time male earners severely limits the suitability of the affordability measure used in detecting bubbles in housing affordability. The exclusion of female and part time participation underestimates the detection of bubbles over the tested period. As house prices have outstripped earnings, households have increasingly relied on both incomes to afford housing, in addition to part-time and flexible working earners also contributing to housing costs. The bias arising from the use of full-time male only earnings data incurs severe errors-in-variables that must be taken into consideration when interpreting the estimation output.

The key limitation of the GSADF procedure is that it lacks the flexibility to allow for both an explosive root and a unit root (Engsted et al., 2015). The null hypothesis underlying the test assumes the time series follows an I(1) process, against the alternative that the series is characterised by an explosive process. Applying the test on the price to income ratio and rejecting the null hypothesis is implicitly assuming that prices and income are cointegrated; this may not be the case in practice.

Future research would thus benefit from evaluating the cointegrating relationship between prices and fundamentals in tandem with exuberance. We may pursue this using Engsted and Nielsen (2012) co-explosive VAR framework to test for bubbles while concurrently allowing cointegrating relationship between prices and their fundamentals and estimating the strength of this cointegrating relationship. By using the SADF and GSADF procedure, we are able to date-stamp the commencement and termination of bubbles for use in co-explosive VAR; this information must be provided *a priori* so our existing GSADF estimation is a parsimonious extension in this context. Alternatively we may also contrast our findings against a fractional integration approach. Given the interdependencies between regions, our study would benefit from explicitly estimating the spillover impact using a spatial term. We may then be able to test whether the ripple effect changes over time. We also consider extending the variable set to ascertain whether other measures may be good predictors of bubbles. For example, behavioural measures of investor optimism and market stress indicators may provide meaningful insights into the formation of bubbles.

Chapter 3 implements the 2 stage procedure devised by Bailey et al. (2016) to estimate a heterogenous model of house price diffusion. The results indicate region or nation wide policies may serve to increase divergence in house price inflation across districts, as clusters of areas more susceptible to impacts of house price growth in neighbouring areas. As local government is able to control housing policy at the district level, the findings suggest cities and transport networks play a key role in the propagation of spatial effects that may alleviate persistence in house prices in a given district.

The BHP method possesses a number of limitations. Final parameter estimates are measured in terms of 'de-factored' price changes. This measure does not readily lend itself to providing estimated spillover effects to practitioners. The two stage method also lacks any formal distributional theory accounting for sampling errors derived from the first stage. Additionally, the impact of common factors are not estimated, instead they are accounted for. Ascertaining the impact of common factors in the housing market is an interesting avenue for future research that this model is unable to accommodate. Most prominently, the high incidence of negative spatial parameter estimates is a cause of concern. These findings are inconsistent with theories of spatial spillover effects in the housing market (Gillen et al., 2001) which anticipate positive spatial dependence in most cases.[1] While we have made some general comparisons to the BHP method, we would benefit from some Monte Carlo simulation results to formally compare how the Bailey et al. (2016); Halleck Vega and Elhorst (2016) and STARF models compare in performance under different conditions.

Future work is required to implement the proposed data driven method in BHP. We propose a mixed approach, where a minimum distance cut-off measure is used in tandem with the pairwise base spatial weights. At this stage, the poor HSAR estimates from the data driven weights may be attributed to the either the adjacency matrix or the HSAR estimates which show a high prevalence of negative values.

Chapter 4 provides a parsimonious representation of spatial diffusion of house prices in England that present results more in line with prevailing economic theories of spatial dependence in house prices. While we contribute a substantial improvement over existing methods for analysing the housing market, the estimated model can be readily improved in a number of ways. The use of an information criterion to select the number of lags in the model would be a straightforward and material improvement. This would prevent spatial and serial correlation in the error terms that may in turn have biased our estimates. Furthermore, we may try alternative variables as factors in our model in light of the low association of house price inflation with measures of economic activity and interest rates. Furthermore, we have made an arbitrary choice to use a weights matrix with a 50 mile distance cut off. In place of this, we may extend our model with the use of an adjacency matrix based on economic data with time variation to account for potentially time-varying and endogenous spatial dependence.

The STARF model provides an exciting workhorse for the development of future analytical tools. While we have only considered multipliers with respect to neighbourhood house price

[1] The STARF model succeeds in providing a material improvement with respect to the aforementioned drawbacks.

changes, it is straightforward to extend this framework to evaluate the dynamic multiplier effects of factors. Furthermore, we may also recast the STARF model under a VAR framework and compute impulse responses and forecast error variance decomposition analyses. In the housing context, impulse response analysis is ideally placed to test the ripple effect hypotheses. These results may then be contrasted against impulse responses from core-periphery groups.

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Appendices

Appendix A

A.1 Data Characteristics

Real households' disposable income is combined with historic data accessed via the ONS from the Regional Accounts dataset, 1971-1999[1] which is interpolated using the cubic spline method for quarterly results. Disposable income data is manually adjusted to convert GOR regions to their predecessor, SSR to follow the format of the Halifax house price regional dataset. Prices are expressed in real terms using chained volume measures. The process involves expressing prices in terms of the preceding year, then chain linking the figures such that the effect of changes in price are eliminated. The unemployment rate is given as the percentage of the working population aged 16 and over as a proportion of the working population. CPI data is not seasonally adjusted and observations predating 1988 are estimated values and the GDP growth rate is measured according to the expenditure approach compared to the previous quarter with seasonal adjustments. Crude oil prices and gold price data serve as an gauge of international economic conditions. The share price index reveals information on the profitability of an alternative asset class as the price embodies future valuation by investors. The IMF provides UK share price index data before April 1984. Since April 1984, FTSE100 index values are collected by the Bank of England. Other financial predictors include long and short term interest rates. The former is estimated using ten year government bond yield data whilst short term is accounted for using the official bank rate set by the Bank of England.

[1] Office for National Statistics, Regional Accounts Data, 1971-1999 [computer file]. 8th Edition. Colchester, Essex: UK Data Archive [distributor], December 2002. SN: 4010

Table A.1: Data Sources and Characteristics

Variable	**Units**	**Source**	**Notes**
Unemployment Rate	Percent	ONS	SA (Seasonally Adjusted)
10 year government bond yield	Percent	Bank of England	Nominal Par Yield
Official Bank Rate	Percent	Bank of England	NSA (Not Seasonally Adjusted)
Real Disposable Income per Capita	GBP per head	ONS/Nomis	SA, interpolated & adjusted for SSR
FTSE 100 Index	Index	IMF/Bank of England	IMF pre April 1984
Gold Price	GBP	Bank of England	Governed by ICE Benchmark Administration
Oil	USD per barrel	Western Texas Intermediate	NSA
Current Account	GBPm	ONS	SA
Consumer Price Index	Index	OECD	NSA, Expenditure approach

A.2 Asset Pricing with Rational Bubbles

This approach to the property market is based on the instrumental research of Blanchard (1979); Blanchard and Watson (1982) and ensuing rational bubble literature in line with rational expectations theory. The following exposition of asset pricing theory follows the notation of (Pavlidis et al., 2014) closely. [2]

The house price is derived under the following no arbitrage and risk neutrality conditions,

$$\varrho_t = \mathbb{E}_t(R_{t+1}) \tag{A.1}$$

expressly, the discount rate $\varrho > 0$ is initially assumed time invariant, such that $\mathbb{E}_t(R_t) = \varrho$ for all values of t. The no arbitrage condition expresses the return on an asset is equivalent to the risk free expected net return denoted as $\varrho > 0$, on an alternative investment opportunity. Here the expectations operator $\mathbb{E}_t$ accounts for all available information up until time period t and R_{t+1} is the rate of return on the asset at time period $t+1$ connotes the return on the asset as,

$$R_{t+1} \equiv \frac{P_{t+1} + F_{t+1}}{P_t} - 1 \tag{A.2}$$

where P_t denotes asset price and F_t is the stream of payoffs arising from the asset. This future stream may be monetary or otherwise. The latter can be generally specified as below, where F_t denotes the economic fundamentals of (the asset which in our case is) the housing market. This is comprised of payoff stream, X_t and the unobserved factors driving price U_t:

$$F_t = X_t + U_t \tag{A.3}$$

where $\{U_t\}_{t=1}^{\infty}$ denotes the stream of unobserved price driving factors. These unobserved fundamentals, which may for example include the impact of bias, pricing errors, and mismeasurment issues, are captured by U_t term.

[2] While we adopt the levels approach, the exposition following the log-linear approximation is available on request.

In the housing case, $\{X_t\}_{t=1}^{\infty}$ refers to the payoff stream of housing rents including housing services. Blanchard and Watson (1982); Campbell et al. (1997) detail the payoff stream process in general terms while Gordon and Shapiro (1956) provide as an account on the dividend discount model adapted for constant growth rate for the payoff stream $\{X_t\}_{t=1}^{\infty}$. The payoff stream can be alternatively specified whereby macroeconomic fundamentals are linearly related through a housing demand equation A.4. Imposing further constraints on preferences , the following linear expenditure function is constructed

$$F_t = \theta + \delta Y_t + U_t \tag{A.4}$$

Note this specification also retains the unobserved term U_t while demand for rental housing describes the relationship between housing rents X_t and macroeconomic fundamentals, here given as disposable income, Y_t.Rearranging and solving the equation A.2 for P_t under the no arbitrage condition in A.1 yields the log-linear approximation:

$$P_t = \frac{1}{1+\varrho}\mathbb{E}_t[P_{t+1} + F_{t+1}] \tag{A.5}$$

where the asset prices (ex dividended) in the current period t equates to the expected fundamental price combined with the expected price from the sale of the asset in the future period $t+1$, both discounted to reflect present value. Solving forward by iterative substitution, the standard asset pricing function is derived:

$$P_t = \mathbb{E}_t\left[\sum_{j=1}^{T}\left(\frac{1}{1+\varrho}\right)^j F_{t+j}\right] + \mathbb{E}_t\left[\left(\frac{1}{1+\varrho}\right)^T P_{t+T}\right] \tag{A.6}$$

where asset price at time period t comprises of the expected future dividend (or payoffs) up until the final time period T, and expected discounted price of asset resale in time T. Prescribing the following transversality condition:

$$\lim_{t\to\infty} \mathbb{E}\left[\left(\frac{1}{1+\varrho}\right)^T P_{t+T}\right] = 0 \tag{A.7}$$

and setting T to tend towards infinity, equation A.6 can be rewritten as equation A.8:

$$P_t^* = \mathbb{E}_t \left[\sum_{j=1}^{\infty} \left(\frac{1}{1+\varrho} \right)^j F_{t+j} \right] \tag{A.8}$$

where $\left(\frac{1}{1+\varrho}\right)^T$ is a valid stochastic discount factor for this asset. Note how this function is determined entirely by the discount rate ϱ and the economic fundamentals F_t, such that P_t^* denotes the fundamental-based asset price at time t. This is consistent with dividend based models in valuing equity. Examples include Gordon and Shapiro (1956) where the dividend stream growth rate remains constant while Blanchard and Watson (1982); Campbell et al. (1997) relax this for a general treatment of $X_{t t=1}^{\infty}$. In this instance, the asset price refers to the fundamental based price, $P_t = P_t^*$.

Asset asset prices are determined by fundamental drivers alone, predicated that the transversality condition must always hold. Often the very existence of housing bubbles associated with a failure of the transversality condition that requires the present value of payments occurring infinitely far in the future to be zero. [3] The transversality condition ensures there is one solution to the difference equation for asset pricing, as opposed to infinite forward solutions that would otherwise exist. Asset Price can thus be decomposed into following form, made possible by solving for into the unique form:

$$c + B_t \tag{A.9}$$

where B_t is the non fundamental bubble components, fulfilling the submartingale property:

$$\mathbb{E}(B_{t+1}) = (1+\varrho)B_t \tag{A.10}$$

Given we assume ($\varrho > 0$), the expectation for the bubble term must accordingly be explosive. Whether the stochastic discount factor $\varrho_t > 0$ is $I(0)$ or autoregressive, there is no impact to alter the submartingale shown above in equation A.10. Periods in which prices depart from the economic fundamentals fuel expectations exhibiting exuberant behaviour as agents expect to be compensated for overpriced (based on fundamental price) assets in the future, based on

[3] See Giglio et al. (2014) for the treatment of bubbles associated with the failures of the transversality condition.

expectations of future price appreciation with remunerations expected at the discount rate ϱ.By combining equations A.8 and A.9 as ascribed by Campbell and Shiller (1988), it follows:

$$P_t = \frac{1}{\varrho}F_t + \left(\frac{1+\varrho}{\varrho}\right)\mathbb{E}_t\left[\sum_{j=1}^{\infty}\left(\frac{1}{1+\varrho}\right)^j \Delta F_{t+j}\right] + B_t \tag{A.11}$$

where F_t denotes the fundamental component known as the economic rent of housing. Assuming the economic rent of housing follows an AR(1) process,

$$F_t = \phi F_{t-1} + \epsilon_t, \epsilon_t \sim WN(0, \sigma_\epsilon^2) \tag{A.12}$$

where ϵ_t is a stationary process and F_t follows an I(1) process when $\phi = 1$, and explosive when $\phi > 1$. In the instance of no bubbles such that $B_t = 0 \forall t$, equation A.9 denotes price equates to the fundamental component such that equations A.11 and A.12 give:

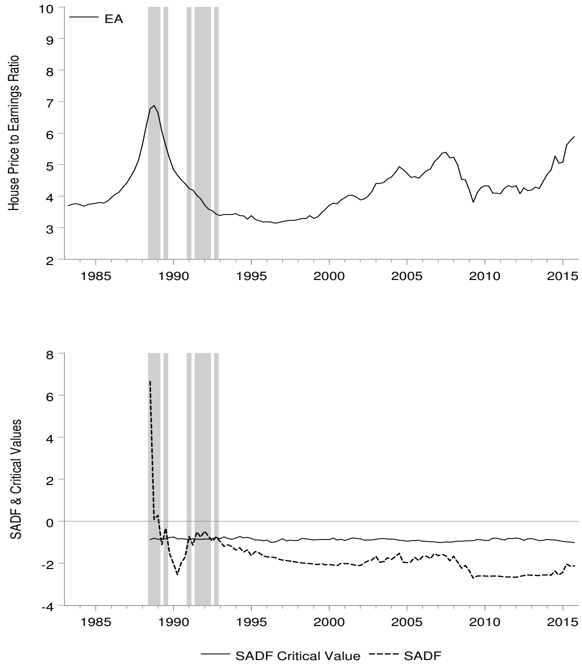
$$P_t = P_t^* = \left[1 + (1-\phi)\left(\frac{1+\varrho}{1+\varrho-\phi}\right)\right]\frac{1}{\varrho}F_t \tag{A.13}$$

While property prices may exhibit explosive trends due to the underlying explosive dynamics in fundamentals (that is, $\phi > 1$ in A.2), this does not preclude the absence of a bubble. As noted by Pavlidis et al. (2014, p.6), in this instance, "exuberance in the housing market is inherited from fundamental factors which might not be directly observable." While this may be the case with house prices, the ratio of prices to fundamentals is not explosive in the case of no bubbles regardless of the value of ϕ. This ratio is given as:

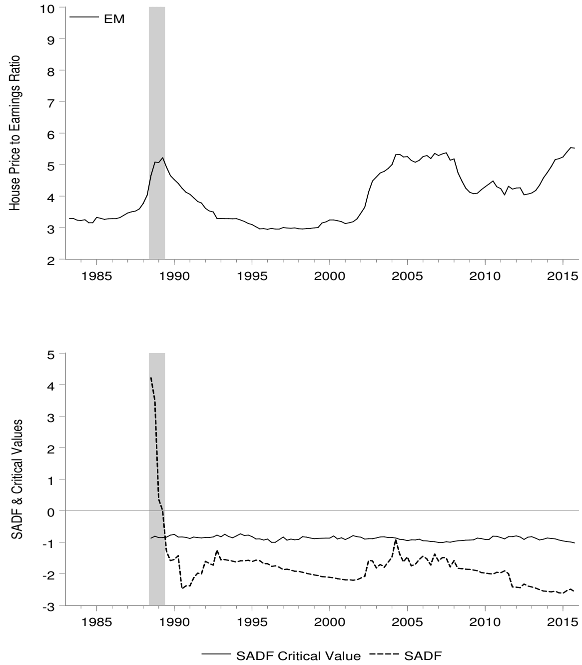
$$\frac{P_t}{F_t} = \left[1 + (1-\phi)\left(\frac{1+\varrho}{1+\varrho-\phi}\right)\right]\frac{1}{\varrho} \tag{A.14}$$

In light of this benefit, we include estimation on affordability ratios in our results.

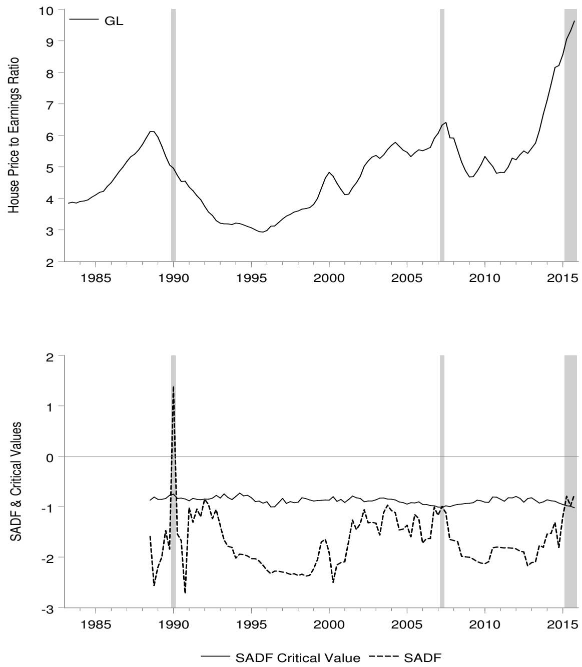
A.3 Exuberance in House Price to Earnings Ratio



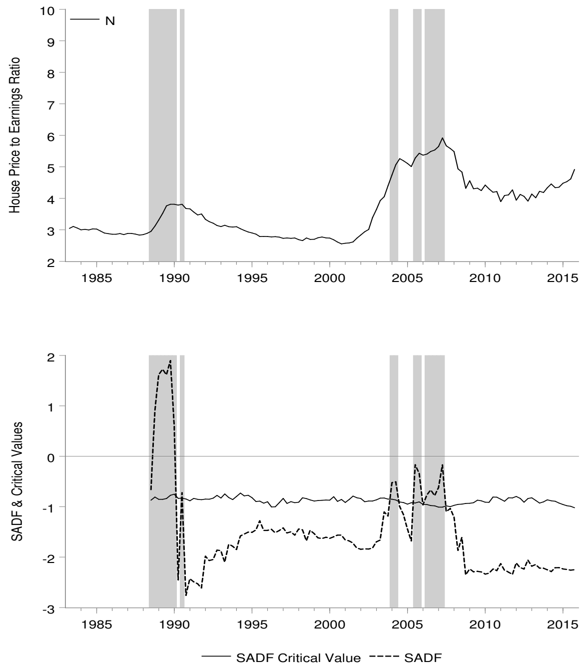
(a) East Anglia



(b) East Midlands

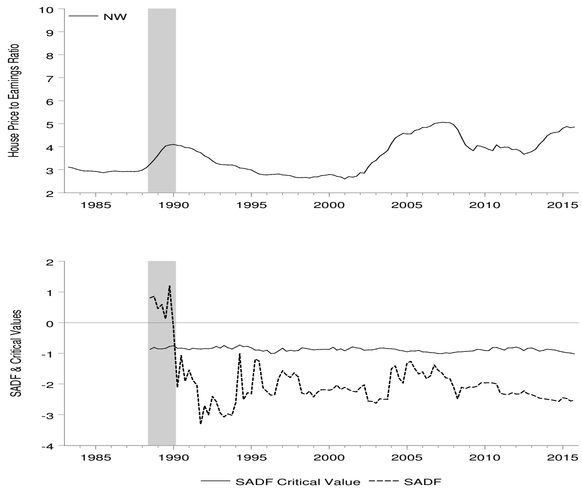


(c) Greater London

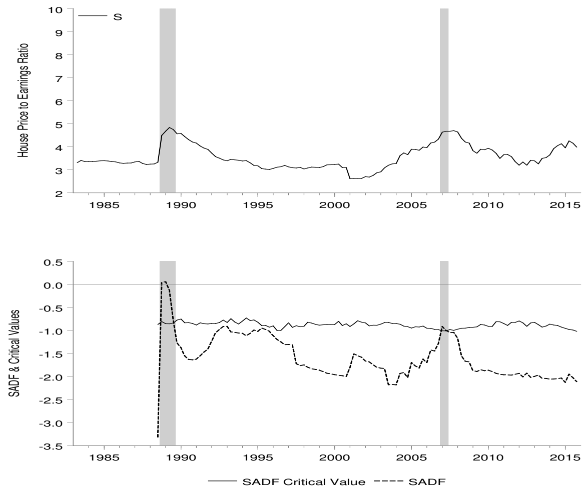


(d) North

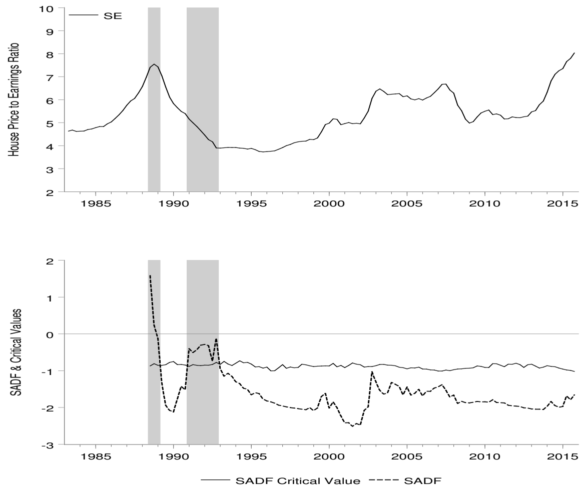
Figure A.1: Date-stamping periods of exuberance in house price to earnings using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



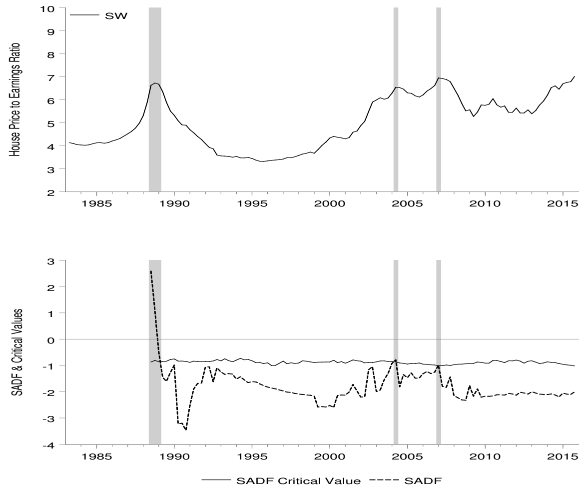
(a) North West



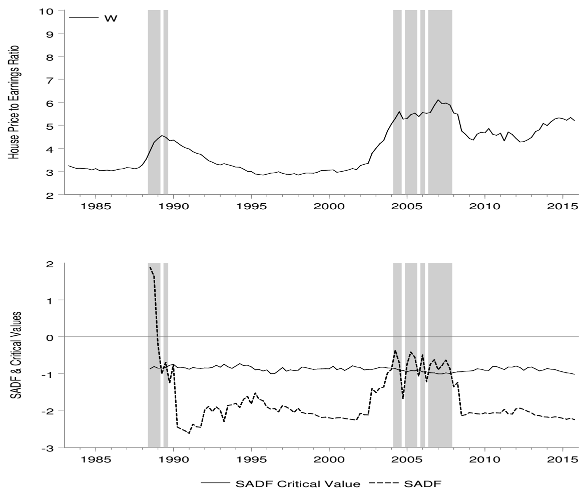
(b) Scotland



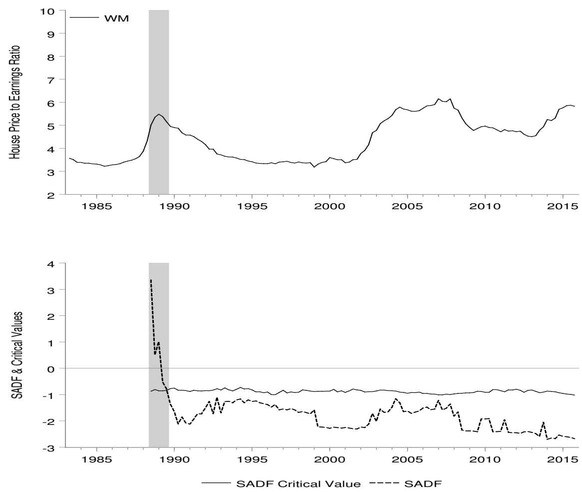
(c) South East



(d) South West

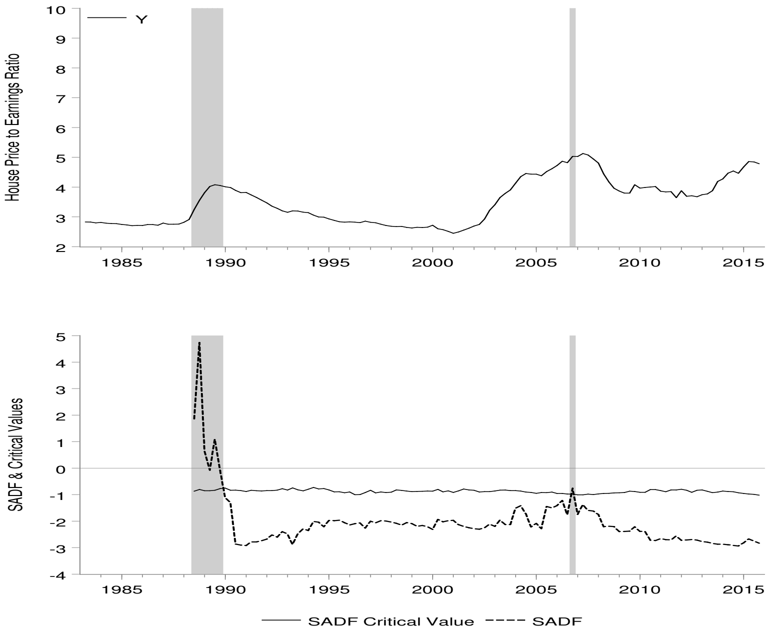


(e) Wales

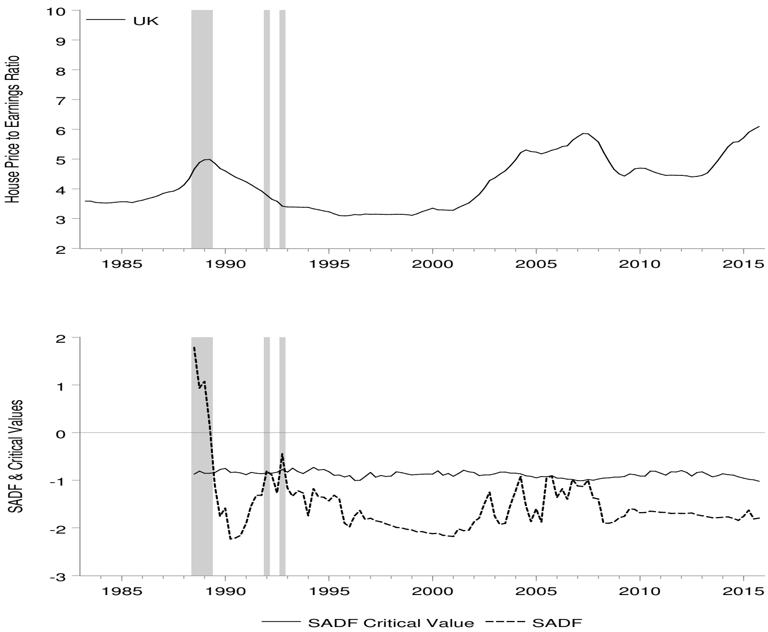


(f) West Midlands

Figure A.1: Date-stamping periods of exuberance in house price to earnings using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.



(g) Yorkshire & the Humber



(h) United Kingdom

Figure A.1: Date-stamping periods of exuberance in house price to earnings using sadf testing across 12 UK regions and nationwide. The upper graph in each subfigure displays the behaviour of real house prices. The lower graph demonstrates the sadf testing results, with shaded areas corresponding to detected periods of exuberance demonstrated across both graphs.

A.4 GSADF Testing with Smaller Window

Table A.2: Episodes of exuberance detected in the logarithm of nominal house prices using GSADF testing

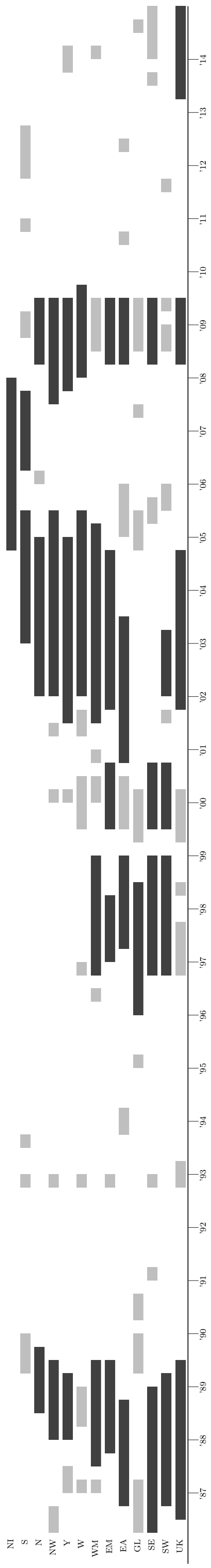


Table A.3: Episodes of exuberance detected in the logarithm of real house prices using GSADF testing

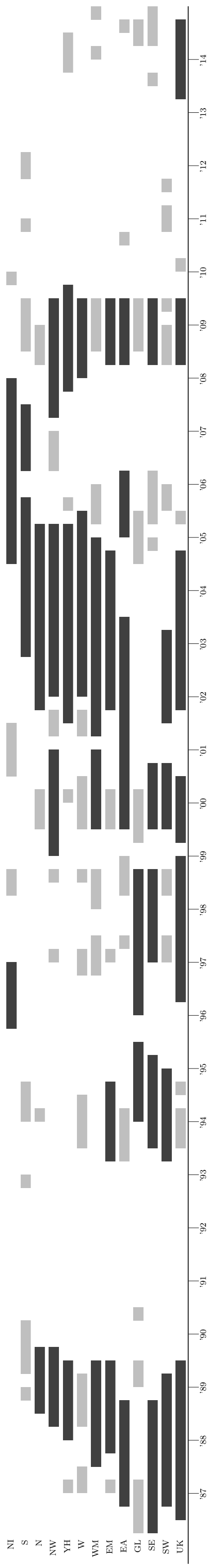


Table A.4: Episodes of exuberance detected in the House Price to Earnings Ratio using GSADF testing

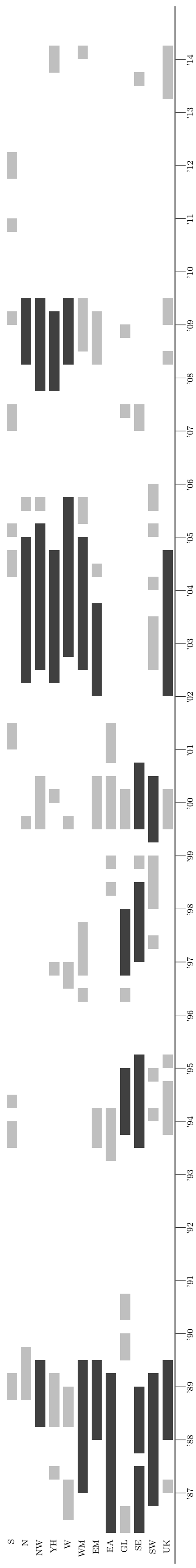
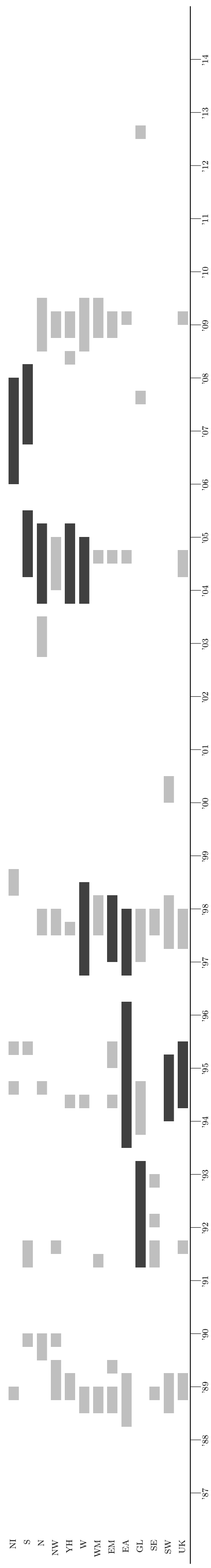


Table A.5: Episodes of exuberance detected in the Mortgage to Earnings Ratio using GSADF testing



A.5 Probit Estimation Results by Region

Table A.6: Regional Probit Estimation on GSADF outcomes with Respect to Real House Prices

	(1) EA	(2) EM	(3) GL	(4) N	(5) NI	(6) NW
Unemployment	-1.058*** (0.337)	-1.549*** (0.431)	-0.387* (0.226)	-0.927*** (0.312)	0.113 (0.279)	-1.244*** (0.367)
10YBY	0.0226 (0.286)	0.422 (0.323)	0.399 (0.269)	0.271 (0.281)	0.148 (0.293)	-0.105 (0.299)
Official Bank Rate	-0.373** (0.175)	-0.615*** (0.203)	-0.316** (0.139)	-0.284* (0.164)	-0.0346 (0.160)	-0.276 (0.180)
Disposable Income	-0.000237*** (0.0000878)	-0.000178*** (0.0000594)	-0.00000722 (0.0000147)	-0.000117 (0.0000742)	0.000386*** (0.000147)	-0.000116*** (0.0000383)
Δ FTSE100	-0.111*** (0.0361)	-0.112*** (0.0399)	-0.0299 (0.0286)	-0.0390 (0.0297)	0.0492 (0.0310)	-0.0849** (0.0349)
Gold Price	0.00267 (0.00208)	0.00542** (0.00252)	-0.000604 (0.00193)	0.00229 (0.00181)	-0.00908*** (0.00291)	0.00345* (0.00203)
Δ Oil Price	0.00399 (0.0109)	0.0176 (0.0115)	-0.0116 (0.00992)	0.0128 (0.00994)	-0.00607 (0.0113)	0.0261** (0.0109)
Δ Current Account	-0.000419 (0.000607)	-0.000755 (0.00110)	-0.0000254 (0.000507)	-0.000196 (0.000544)	0.000402 (0.000688)	-0.000480 (0.000677)
Constant	14.48*** (4.302)	17.63*** (5.161)	2.438 (2.972)	8.880** (4.197)	-5.892 (3.864)	17.51*** (4.874)
Observations	108	108	108	108	108	108

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

	(7) S	(8) SE	(9) SW	(10) W	(11) WM	(12) YH
Unemployment	-0.0795	-0.627**	-0.908***	-1.137***	-0.937***	-1.212***
	(0.202)	(0.257)	(0.315)	(0.383)	(0.283)	(0.341)
10YBY	0.158	-0.0504	-0.321	1.004***	0.365	0.480
	(0.240)	(0.256)	(0.289)	(0.348)	(0.255)	(0.299)
Official Bank Rate	0.0435	-0.131	-0.301*	-0.770***	-0.572***	-0.364**
	(0.139)	(0.155)	(0.161)	(0.201)	(0.159)	(0.173)
Disposable Income	0.0000534*	-0.0000434**	-0.000123***	-0.0000753	-0.0000854**	-0.0000757*
	(0.0000292)	(0.0000186)	(0.0000405)	(0.0000721)	(0.0000411)	(0.0000424)
Δ FTSE100	-0.00295	-0.0586**	-0.119***	-0.0539*	-0.0293	-0.0564*
	(0.0271)	(0.0297)	(0.0360)	(0.0325)	(0.0312)	(0.0316)
Gold Price	-0.000389	0.00325*	0.00275	0.00249	0.000801	0.00376**
	(0.00137)	(0.00171)	(0.00194)	(0.00197)	(0.00162)	(0.00183)
Δ Oil Price	0.00773	-0.00400	-0.00615	0.0196*	-0.0117	0.00909
	(0.00949)	(0.00978)	(0.0117)	(0.0109)	(0.0104)	(0.00991)
Δ Current Account	0.000114	-0.000363	0.0000831	-0.000164	-0.000530	-0.000103
	(0.000384)	(0.000558)	(0.000397)	(0.000680)	(0.000581)	(0.000570)
Constant	-4.124	8.931**	16.00***	7.063*	12.47***	9.861**
	(2.860)	(3.502)	(4.628)	(4.245)	(4.395)	(4.215)
Observations	108	108	108	108	108	108

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table A.7: Marginal Effects from Correlated Random Effects Probit Estimation with Mundlak-Chamberlain Correction using GSADF Outcomes

	EA	EM	GL	N	NI	NW
Variables	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Unemployment	-0.236***	-0.306***	-0.106*	-0.245***	0.0238	-0.260***
	(0.0679)	(0.0696)	(0.0592)	(0.0739)	(0.0587)	(0.0662)
10YBY	0.00505	0.0834	0.110	0.0717	0.0310	-0.0219
	(0.0638)	(0.0626)	(0.0718)	(0.0735)	(0.0611)	(0.0624)
Official Bank Rate	-0.0833**	-0.121***	-0.0866**	-0.0751*	-0.00726	-0.0577
	(0.0370)	(0.0348)	(0.0353)	(0.0416)	(0.0335)	(0.0366)
Disposable Income	-5.29e-05***	-3.51e-05***	-1.98e-06	-3.09e-05	8.10e-05***	-2.43e-05***
	(1.83e-05)	(1.02e-05)	(4.03e-06)	(1.92e-05)	(2.82e-05)	(7.18e-06)
Δ FTSE100	-0.0248***	-0.0220***	-0.00821	-0.0103	0.0103*	-0.0177***
	(0.00720)	(0.00691)	(0.00775)	(0.00770)	(0.00625)	(0.00683)
Gold Price	0.000596	0.00107**	-0.000166	0.000605	-0.00191***	0.000721*
	(0.000463)	(0.000469)	(0.000530)	(0.000474)	(0.000532)	(0.000413)
Δ Oil Price	0.000891	0.00347	-0.00317	0.00338	-0.00128	0.00546***
	(0.00242)	(0.00216)	(0.00268)	(0.00255)	(0.00238)	(0.00209)
Δ Current Account	-9.34e-05	-0.000149	-6.98e-06	-5.19e-05	8.44e-05	-0.000100
	(0.000134)	(0.000217)	(0.000139)	(0.000144)	(0.000144)	(0.000141)
Observations	108	108	108	108	108	108

	S	SE	SW	W	WM	YH
Variables	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Unemployment	-0.0261	-0.160***	-0.188***	-0.287***	-0.252***	-0.306***
	(0.0663)	(0.0615)	(0.0595)	(0.0826)	(0.0640)	(0.0712)
10YBY	0.0518	-0.0129	-0.0665	0.254***	0.0981	0.121*
	(0.0786)	(0.0654)	(0.0587)	(0.0775)	(0.0665)	(0.0727)
Official Bank Rate	0.0143	-0.0335	-0.0624*	-0.195***	-0.154***	-0.0920**
	(0.0454)	(0.0393)	(0.0321)	(0.0388)	(0.0344)	(0.0410)
Disposable Income	1.75e-05*	-1.11e-05**	-2.55e-05***	-1.90e-05	-2.30e-05**	-1.91e-05*
	(9.14e-06)	(4.46e-06)	(7.55e-06)	(1.78e-05)	(1.04e-05)	(1.04e-05)
Δ FTSE100	-0.000969	-0.0150**	-0.0246***	-0.0136*	-0.00787	-0.0143*
	(0.00892)	(0.00718)	(0.00639)	(0.00783)	(0.00830)	(0.00766)
Gold Price	-0.000128	0.000830**	0.000570	0.000628	0.000215	0.000950**
	(0.000451)	(0.000422)	(0.000396)	(0.000482)	(0.000435)	(0.000441)
Δ Oil Price	0.00254	-0.00102	-0.00127	0.00495*	-0.00314	0.00230
	(0.00309)	(0.00250)	(0.00244)	(0.00263)	(0.00276)	(0.00246)
Δ Current Account	3.75e-05	-9.27e-05	1.72e-05	-4.14e-05	-0.000142	-2.60e-05
	(0.000126)	(0.000142)	(8.23e-05)	(0.000172)	(0.000154)	(0.000144)
Observations	108	108	108	108	108	108

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Regional Probit Estimation on GSADF outcomes with Respect to House Price to Earnings

	(1) EA	(2) EM	(3) GL	(4) N	(5) NW	(6) S
Unemployment	-0.113	-0.437***	-0.388**	-0.534***	-0.492***	0.0159
	(0.149)	(0.163)	(0.187)	(0.175)	(0.166)	(0.140)
10YBY	-0.209	0.146	0.914***	0.192	0.0937	0.329
	(0.267)	(0.288)	(0.346)	(0.308)	(0.282)	(0.276)
Official Bank Rate	0.124	-0.126	-0.328**	-0.147	-0.0295	0.00250
	(0.143)	(0.144)	(0.164)	(0.150)	(0.148)	(0.142)
Disposable Income	-0.0000288	- -0.0000149	0.0000184**	-0.0000438	-0.0000343	0.0000591**
	(0.0000441)	(0.0000271)	(0.00000869)	(0.0000476)	(0.0000651)	(0.0000235)
Δ FTSE100	-0.0438	-0.0713**	-0.0229	-0.0432	-0.0433	-0.0110
	(0.0309)	(0.0325)	(0.0326)	(0.0305)	(0.0302)	(0.0315)
Δ Gold Price	-0.00382	0.00635	-0.0176	0.0511**	0.0399	-0.0146
	(0.0234)	(0.0238)	(0.0241)	(0.0245)	(0.0246)	(0.0223)
Δ Oil Price	-0.00118	-0.00533	-0.00651	0.0293***	0.0193*	-0.000222
	(0.0101)	(0.0106)	(0.0106)	(0.0109)	(0.0103)	(0.0107)
Δ Current Account	-0.000769	-0.000480	0.000165	-0.000125	-0.000241	-0.000639
	(0.00128)	(0.000906)	(0.000699)	(0.000538)	(0.000585)	(0.000952)
Constant	1.216	2.770	-4.248**	4.042	2.886	-7.370**
	(2.236)	(2.446)	(2.062)	(2.731)	(2.105)	(3.062)
Observations	107	107	107	107	107	107

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

	(7) SE	(8) SW	(9) W	(10) WM	(11) YH
Unemployment	-0.172	-0.196	-0.705***	-0.543***	-0.578***
	(0.172)	(0.221)	(0.195)	(0.161)	(0.182)
10YBY	-0.213	-0.994**	0.714**	0.742***	0.573*
	(0.286)	(0.396)	(0.356)	(0.286)	(0.316)
Official Bank Rate	0.130	0.199	-0.476***	-0.378***	-0.238
	(0.162)	(0.205)	(0.168)	(0.141)	(0.148)
Disposable Income	-0.0000193	-0.0000683***	-0.00000450	0.0000452	0.0000154
	(0.0000213)	(0.0000200)	(0.0000224)	(0.0000446)	(0.0000267)
Δ FTSE100	-0.00517	-0.0992**	-0.0175	-0.0285	-0.0520
	(0.0350)	(0.0453)	(0.0299)	(0.0306)	(0.0321)
Δ Gold Price	0.00801	-0.0508	-0.0121	-0.0196	0.0148
	(0.0253)	(0.0424)	(0.0246)	(0.0229)	(0.0243)
Δ Oil Price	-0.0103	0.0277*	0.00176	-0.0104	-0.00787
	(0.0116)	(0.0151)	(0.0105)	(0.00987)	(0.0104)
Δ Current Account	-0.000633	-0.00187	0.000181	-0.00171	-0.000663
	(0.00113)	(0.00217)	(0.000525)	(0.00162)	(0.00119)
Constant	1.756	13.36***	2.576	-0.722	0.103
	(2.311)	(3.741)	(2.627)	(2.656)	(2.876)
Observations	107	107	107	107	107

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table A.9: Marginal Effects from Regional Probit Estimation on GSADF outcomes with to House Price to Earnings

	(1) EA	(2) EM	(3) GL	(4) N	(5) NW	(6) S
Variables	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Unemployment	-0.0268	-0.104***	-0.0851**	-0.130***	-0.123***	0.00384
	(0.0353)	(0.0356)	(0.0393)	(0.0374)	(0.0369)	(0.0338)
10YBY	-0.0495	0.0348	0.201***	0.0467	0.0234	0.0797
	(0.0630)	(0.0684)	(0.0713)	(0.0747)	(0.0704)	(0.0663)
Official Bank Rate	0.0293	-0.0300	-0.0719**	-0.0358	-0.00736	0.000606
	(0.0338)	(0.0342)	(0.0346)	(0.0362)	(0.0369)	(0.0345)
Disposable Income	-6.83e-06	-3.53e-06	4.03e-06**	-1.07e-05	-8.55e-06	1.43e-05**
	(1.04e-05)	(6.41e-06)	(1.85e-06)	(1.15e-05)	(1.62e-05)	(5.28e-06)
ΔFTSE100	-0.0104	-0.0169**	-0.00502	-0.0105	-0.0108	-0.00265
	(0.00716)	(0.00719)	(0.00711)	(0.00721)	(0.00734)	(0.00762)
ΔGold Price	-0.000906	0.00151	-0.00387	0.0124**	0.00995*	-0.00355
	(0.00556)	(0.00565)	(0.00527)	(0.00564)	(0.00593)	(0.00535)
ΔOil Price	-0.000279	-0.00127	-0.00143	0.00713***	0.00481**	-5.38e-05
	(0.00241)	(0.00252)	(0.00231)	(0.00238)	(0.00241)	(0.00259)
ΔCurrent Account	-0.000182	-0.000114	3.62e-05	-3.05e-05	-6.02e-05	-0.000155
	(0.000301)	(0.000215)	(0.000153)	(0.000131)	(0.000145)	(0.000229)
Observations	107	107	107	107	107	107

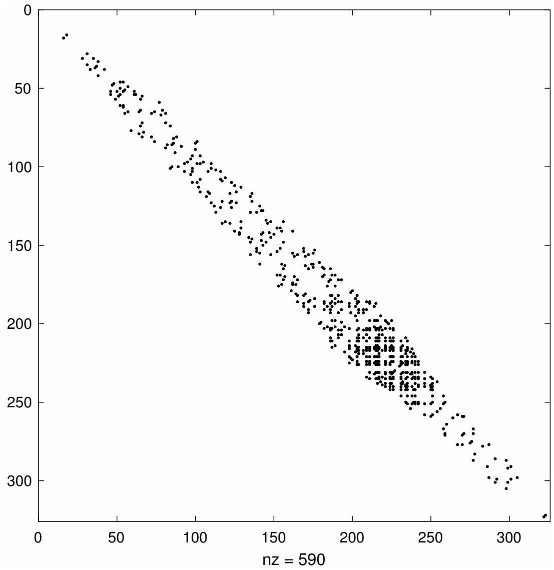
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(7) SE	(8) SW	(9) W	(10) WM	(11) YH
Variables	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Unemployment	-0.0331	-0.0260	-0.164***	-0.146***	-0.141***
	(0.0329)	(0.0293)	(0.0382)	(0.0367)	(0.0389)
10YBY	-0.0408	-0.132***	0.166**	0.200***	0.140*
	(0.0547)	(0.0466)	(0.0795)	(0.0708)	(0.0749)
Official Bank Rate	0.0250	0.0265	-0.111***	-0.102***	-0.0581*
	(0.0310)	(0.0267)	(0.0356)	(0.0346)	(0.0353)
Disposable Income	-3.70e-06	-9.08e-06***	-1.05e-06	1.22e-05	3.76e-06
	(4.09e-06)	(2.22e-06)	(5.20e-06)	(1.19e-05)	(6.50e-06)
ΔFTSE100	-0.000991	-0.0132**	-0.00406	-0.00766	-0.0127*
	(0.00670)	(0.00538)	(0.00691)	(0.00814)	(0.00751)
ΔGold Price	0.00154	-0.00676	-0.00280	-0.00527	0.00361
	(0.00485)	(0.00553)	(0.00570)	(0.00610)	(0.00590)
ΔOil Price	-0.00198	0.00368*	0.000411	-0.00279	-0.00192
	(0.00221)	(0.00192)	(0.00245)	(0.00262)	(0.00253)
ΔCurrent Account	-0.000121	-0.000248	4.21e-05	-0.000462	-0.000162
	(0.000216)	(0.000285)	(0.000122)	(0.000429)	(0.000290)
Observations	107	107	107	107	107

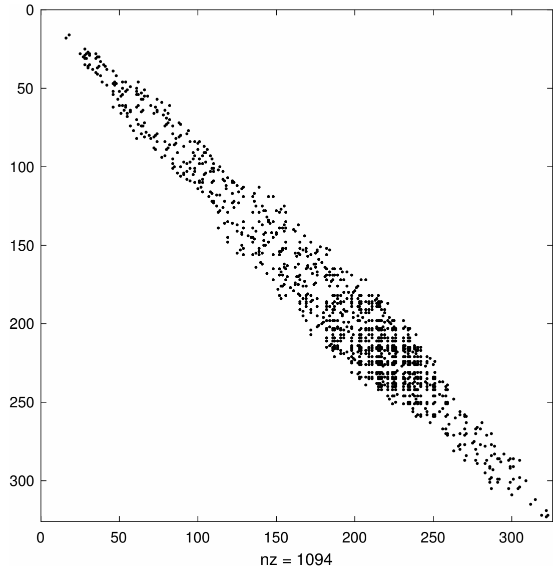
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B

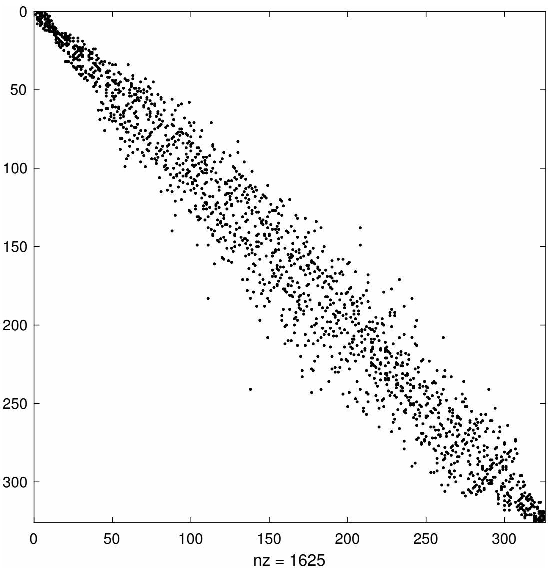
B.1 Sparsity of Alternative Adjacency Matrices



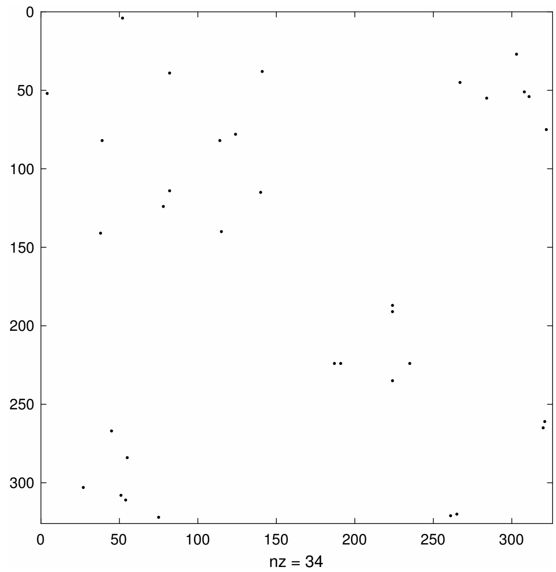
(a) Districts within 7.5 miles



(b) Districts within 10 miles

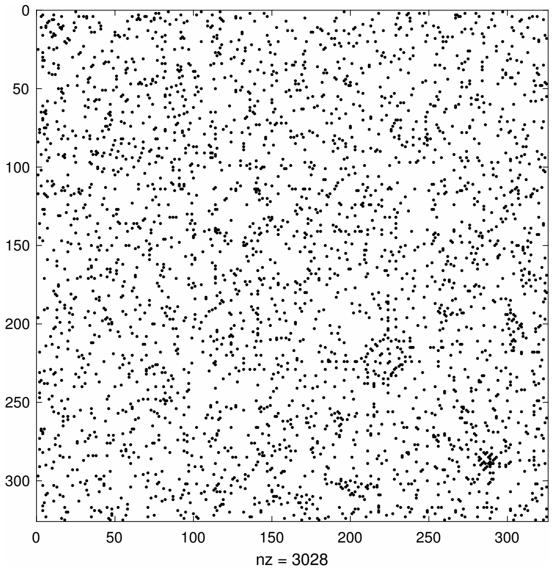


(c) 5 Nearest neighbours

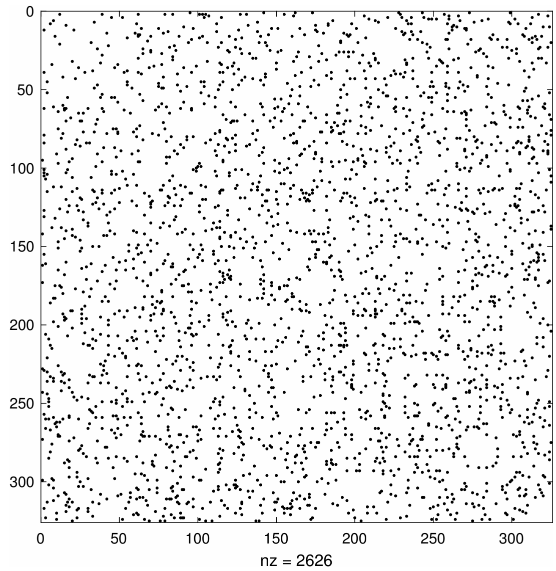


Data driven matrix of using CSA pairwise correlations with MT

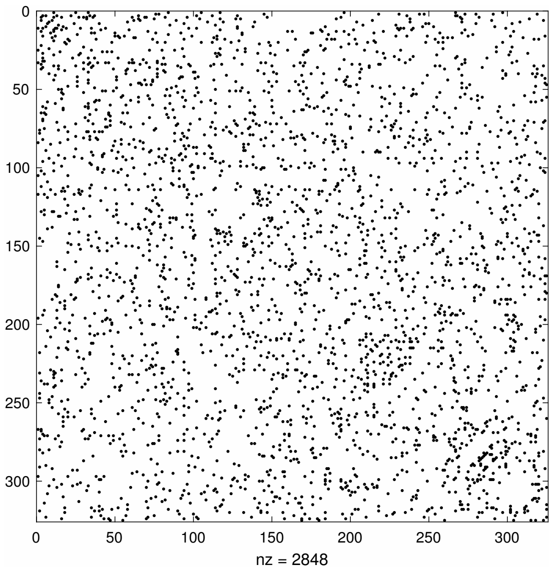
Figure B.1: Sparsity of Alternative *A Priori* Weights Matrices



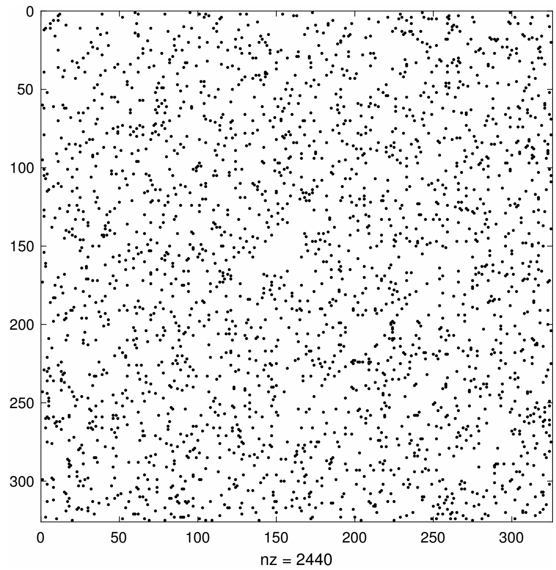
(a) Negative connections under CSA approach with no MT at 1% significance level



Positive connections under CSA approach with no MT at 1% significance level



(b) Negative connections under PCA approach with no MT at 1% significance level



Positive connections under PCA approach with no MT at 1% significance level

Figure B.2: Sparsity of Correlation Based Weights Matrices

B.2 Alternative Specifications of Adjacency Matrices

Table B.1: Quasi Maximum Likelihood estimates of spatio-temporal model 3.11 applied to de-factored changes in house prices derived from equation 3.4.

$W_{7.5m}$	λ_1	ψ_0	ψ_1	σ_ζ
Median	0.0439	0.0171	0.0267	1.2687
Mean Group Estimates	0.0471***	-0.0292	0.0420***	1.3471
	(0.0049)	(0.0216)	(0.0134)	(0.0272)
% significant (at 5% level)	21.8%	19.3%	11.4%	-
Number of non-zero coef.	325	166	166	325
W_{10m}	λ_1	ψ_0	ψ_1	σ_ζ
Median	0.0456	0.0073	0.0203	1.2697
Mean Group Estimates	0.0462***	-0.0432*	0.0530***	1.3454
	(0.0049)	(0.0231)	(0.0190)	(0.0272)
% significant (at 5% level)	21.5%	23.9%	12.4%	-
Number of non-zero coef.	325	218	218	325
$\mathbf{W_{5NN}}$	λ_1	ψ_0	ψ_1	σ_ζ
Median	0.0456	0.0063	0.0650	1.2658
Mean Group Estimates	0.0472***	-0.0165	0.0478***	1.3409
	(0.0049)	(0.0134)	(0.0096)	(0.0272)
% significant (at 5% level)	22.5%	14.5%	12.3%	-
Number of non-zero coef.	325	325	325	325
Maximum	0.3319	0.9708	0.7352	5.8542
Minimum	-0.2112	-0.9950	-0.3854	0.6010

B.3 Regional Mean Group Estimates from Alternative Weights Specifications

Table B.2: Quasi Maximum Likelihood estimation of spatio-temporal model using Queen contiguity weights matrix. Results are given for de-factored house price changes from equation 3.4 are provided for each region

	λ_1	ψ_0	ψ_1	σ_ζ
North East				
Median	0.0720	-0.1656	0.0558	1.2981
Mean Group Estimates	0.0834***	-0.1549***	0.0706	1.3728
	(0.0262)	(0.0553)	(0.0605)	(0.0863)
% significant (at 5% level)	41.7%	8.3%	25.0%	-
Maximum	0.2241	0.2428	0.5346	2.0504
Minimum	-0.0432	-0.4117	-0.2268	0.8753
London				
Median	0.1086	0.0726	0.0716	1.0434
Mean Group Estimates	0.1102***	0.0348	0.0353	1.2874
	(0.0165)	(0.0442)	(0.0428)	(0.1607)
% significant (at 5% level)	42.4%	12.1%	21.2%	-
Maximum	0.3263	0.4959	0.5410	5.8213
Minimum	-0.0829	-0.9950	-0.9458	0.6289
South West				
Median	0.0218	-0.0176	0.0706	1.2812
Mean Group Estimates	0.0316***	-0.0059	0.0444	1.3997
	(0.0122)	(0.0331)	(0.0318)	(0.0815)
% significant (at 5% level)	13.9%	11.1%	22.2%	-
Maximum	0.1720	0.5879	0.4364	2.8370
Minimum	-0.1081	-0.3443	-0.4487	0.6992
East Midlands				
Median	0.0397	-0.0219	0.0845	1.5180
Mean Group Estimates	0.0300*	-0.0166	0.0573*	1.5174
	(0.0159)	(0.0347)	(0.0323)	(0.0605)
% significant (at 5% level)	25.0%	7.5%	15.0%	-
Maximum	0.2379	0.3395	0.5263	2.6096
Minimum	-0.1756	-0.4358	-0.3402	0.7115
North West				
Median	0.0700	0.0176	0.0134	1.2703
Mean Group Estimates	0.0586***	0.0203	0.0231	1.4846
	(0.0126)	(0.0380)	(0.0318)	(0.0988)
% significant (at 5% level)	20.5%	20.5%	7.7%	-
Maximum	0.1974	0.4953	0.6384	3.1397
Minimum	-0.1092	-0.4860	-0.4235	0.7045
West Midlands				
Median	0.0368	-0.0497	0.0412	1.2341
Mean Group Estimates	0.0463***	-0.0496	0.0312	1.2243
	(0.0157)	(0.0356)	(0.0410)	(0.0592)
% significant (at 5% level)	23.3%	13.3%	23.3%	-
Maximum	0.2122	0.4179	0.5625	1.9303
Minimum	-0.0997	-0.4022	-0.5089	0.6026
South East				
Median	0.0229	0.0520	0.0682	1.2642
Mean Group Estimates	0.0179*	-0.0004	0.0417*	1.2546
	(0.0101)	(0.0277)	(0.0226)	(0.0295)
% significant (at 5% level)	13.4%	19.4%	11.9%	-
Maximum	0.2092	0.4486	0.4523	1.7045
Minimum	-0.2203	-0.7430	-0.3542	0.7630
East				
Median	0.0442	-0.0077	0.0443	1.2454
Mean Group Estimates	0.0493***	0.0092	0.0427*	1.2713
	(0.0117)	(0.0365)	(0.0235)	(0.0451)
% significant (at 5% level)	17.0%	17.0%	6.4%	-
Maximum	0.2326	0.5486	0.4869	2.0809
Minimum	-0.1861	-0.5807	-0.2394	0.7773
Yorkshire and The Humber				
Median	0.0812	-0.0092	0.0709	1.0392
Mean Group Estimates	0.0535***	-0.0473	0.0735**	1.2701
	(0.0179)	(0.0493)	(0.0317)	(0.1184)
% significant (at 5% level)	23.8%	19.0%	4.8%	-
Maximum	0.1556	0.2612	0.4138	2.6088
Minimum	-0.0942	-0.6761	-0.2784	0.6858

Mean group estimates are calculated as simple averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N$, $r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)} \sum_{i=1}^{N_r} (\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. All districts have one or more neighbours so no parameters coefficients are restricted to zero in the model.

Table B.3: Quasi Maximum Likelihood estimation of spatio-temporal model from equation 3.11 using 5 nearest neighbours weights matrix. Results are given for de-factored house price changes from equation 3.4 are provided for each region

	λ_1	ψ_0	ψ_1	σ_ζ
North East				
Median	0.0575	-0.1920	-0.0048	1.3069
Mean Group Estimates	0.0795***	-0.2146**	0.0713	1.3676
	(0.0251)	(0.0887)	(0.0713)	(0.0841)
% significant (at 5% level)	41.7%	33.3%	16.7%	-
Maximum	0.2252	0.4123	0.6718	2.0071
Minimum	-0.0377	-0.7023	-0.3352	0.8674
London				
Median	0.1151	0.0418	0.0693	1.0459
Mean Group Estimates	0.1123***	0.0038	0.0470*	1.2904
	(0.0165)	(0.0422)	(0.0248)	(0.1616)
% significant (at 5% level)	45.5%	15.2%	15.2%	-
Maximum	0.3319	0.4999	0.2803	5.8542
Minimum	-0.0861	-0.9950	-0.2695	0.6289
South West				
Median	0.0245	-0.0230	0.0744	1.2841
Mean Group Estimates	0.0298**	-0.0438	0.0590*	1.4025
	(0.0120)	(0.0345)	(0.0305)	(0.0817)
% significant (at 5% level)	13.9%	8.3%	11.1%	-
Maximum	0.1732	0.3710	0.6497	2.8747
Minimum	-0.1108	-0.4353	-0.2448	0.6995
East Midlands				
Median	0.0381	0.0207	0.1022	1.5293
Mean Group Estimates	0.0286*	0.0099	0.0617**	1.5179
	(0.0162)	(0.0355)	(0.0248)	(0.0606)
% significant (at 5% level)	27.5%	12.5%	10.0%	-
Maximum	0.2444	0.5659	0.3413	2.6047
Minimum	-0.1711	-0.3996	-0.2937	0.7092
North West				
Median	0.0737	0.0044	0.0454	1.2634
Mean Group Estimates	0.0603***	0.0079	0.0114	1.4831
	(0.0125)	(0.0408)	(0.0336)	(0.0985)
% significant (at 5% level)	20.5%	17.9%	12.8%	-
Maximum	0.1831	0.5869	0.7352	3.1106
Minimum	-0.1043	-0.7719	-0.3854	0.7072
West Midlands				
Median	0.0405	-0.0555	0.0742	1.2397
Mean Group Estimates	0.0476***	-0.0415	0.0433	1.2279
	(0.0154)	(0.0377)	(0.0294)	(0.0596)
% significant (at 5% level)	23.3%	13.3%	13.3%	-
Maximum	0.2114	0.3340	0.4484	1.9614
Minimum	-0.1133	-0.5033	-0.2987	0.6010
South East				
Median	0.0133	0.0592	0.0819	1.2628
Mean Group Estimates	0.0192*	0.0037	0.0538***	1.2552
	(0.0101)	(0.0266)	(0.0190)	(0.0293)
% significant (at 5% level)	13.4%	13.4%	9.0%	-
Maximum	0.2014	0.5374	0.3504	1.6898
Minimum	-0.2112	-0.5831	-0.3166	0.7650
East				
Median	0.0449	0.0063	0.0035	1.2441
Mean Group Estimates	0.0497***	-0.0044	0.0324	1.2791
	(0.0115)	(0.0438)	(0.0268)	(0.0459)
% significant (at 5% level)	17.0%	14.9%	14.9%	-
Maximum	0.2384	0.9708	0.5879	2.0659
Minimum	-0.1935	-0.8233	-0.2770	0.7702
Yorkshire and The Humber				
Median	0.0708	-0.0200	0.1078	1.0532
Mean Group Estimates	0.0514***	-0.0402	0.0795**	1.2710
	(0.0178)	(0.0454)	(0.0370)	(0.1184)
% significant (at 5% level)	23.8%	14.3%	14.3%	-
Maximum	0.1557	0.2859	0.3238	2.6286
Minimum	-0.1086	-0.5466	-0.3484	0.6859

Mean group estimates are calculated as simple averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1} \sum_{i=1}^{N_r} \hat{\psi}_{i0}$ for $i = 1, \ldots, N$, $r = 1, \ldots, R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)} \sum_{i=1}^{N_r} (\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. All districts have one or more neighbours so no parameters coefficients are restricted to zero in the model.

Table B.4: Regional Results from HSAR model with PCA de-factored pair-wise correlation based weights matrix

	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
North East						
Median	0.0718	0.2617	-0.5772	0.0022	0.0631	1.0453
Mean Group Estimates	0.0664***	0.2374	-0.5537***	-0.0076	0.0625	1.1536
	(0.0209)	(0.1613)	(0.0708)	(0.0399)	(0.0602)	(0.0876)
% significant (at 5% level)	25.0%	91.7%	91.7%	8.3%	0.0%	-
Maximum	0.1637	0.9950	-0.1808	0.2256	0.3592	1.9118
Minimum	-0.0752	-0.9950	-0.9950	-0.2707	-0.3611	0.7364
London						
Median	0.0939	0.3620	-0.4039	-0.0136	0.0593	0.8469
Mean Group Estimates	0.0918***	0.3412***	-0.4174***	0.0335	0.0358	1.1148
	(0.0151)	(0.0676)	(0.0625)	(0.0537)	(0.0358)	(0.1599)
% significant (at 5% level)	33.3%	78.8%	90.9%	9.1%	3.0%	-
Maximum	0.2848	0.9948	0.9950	1.4266	0.7743	5.7168
Minimum	-0.0766	-0.9950	-0.9950	-0.3184	-0.3763	0.4786
South West						
Median	0.0105	0.3476	-0.5266	0.0256	0.0137	1.0608
Mean Group Estimates	0.0192	0.3687***	-0.5162***	0.0440	0.0029	1.1847
	(0.0166)	(0.0542)	(0.0586)	(0.0352)	(0.0336)	(0.0803)
% significant (at 5% level)	27.8%	75.0%	83.3%	11.1%	11.1%	-
Maximum	0.1936	0.9928	0.9950	0.7383	0.4737	2.8245
Minimum	-0.1680	-0.9950	-0.9950	-0.5549	-0.4811	0.5726
East Midlands						
Median	0.0092	0.5003	-0.5998	0.0115	0.0118	1.2644
Mean Group Estimates	0.0100	0.4840***	-0.5541***	0.0225	0.0137	1.2633
	(0.0152)	(0.0559)	(0.0473)	(0.0345)	(0.0260)	(0.0606)
% significant (at 5% level)	25.0%	75.0%	80.0%	15.0%	10.0%	-
Maximum	0.1804	0.9950	0.4347	0.7434	0.5402	2.6216
Minimum	-0.1947	-0.9946	-0.9950	-0.4620	-0.2100	0.6128
North West						
Median	0.0436	0.4604	-0.3684	-0.0065	0.0296	1.0428
Mean Group Estimates	0.0454***	0.4426***	-0.4585***	0.0113	0.0310	1.2699
	(0.0125)	(0.0508)	(0.0432)	(0.0324)	(0.0370)	(0.0993)
% significant (at 5% level)	15.4%	82.1%	84.6%	7.7%	10.3%	-
Maximum	0.2125	0.9712	0.2789	0.7991	0.6036	3.2128
Minimum	-0.1658	-0.5237	-0.9950	-0.4706	-0.7016	0.5471
West Midlands						
Median	0.0111	0.4672	-0.5045	0.0237	0.0290	1.0256
Mean Group Estimates	0.0290*	0.4327***	-0.5279***	0.0070	-0.0257	1.0175
	(0.0153)	(0.0545)	(0.0329)	(0.0315)	(0.0444)	(0.0567)
% significant (at 5% level)	13.3%	86.7%	90.0%	10.0%	16.7%	-
Maximum	0.1988	0.9223	-0.2284	0.3116	0.4555	1.7993
Minimum	-0.0977	-0.3180	-0.9950	-0.3449	-0.5242	0.4137
South East						
Median	0.0173	0.4116	-0.5757	-0.0127	0.0054	1.0584
Mean Group Estimates	0.0204**	0.4447***	-0.5792***	-0.0168	0.0360	1.0209
	(0.0094)	(0.0262)	(0.0250)	(0.0201)	(0.0235)	(0.0266)
% significant (at 5% level)	13.4%	88.1%	97.0%	13.4%	13.4%	-
Maximum	0.1933	0.9036	-0.0443	0.4368	0.5997	1.4611
Minimum	-0.1903	-0.0557	-0.9950	-0.4327	-0.2863	0.6267
East						
Median	0.0467	0.4549	-0.5517	-0.0299	0.0302	0.9921
Mean Group Estimates	0.0413***	0.4889***	-0.5689***	-0.0086	0.0390	1.0388
	(0.0103)	(0.0366)	(0.0414)	(0.0341)	(0.0317)	(0.0415)
% significant (at 5% level)	12.8%	89.4%	91.3%	10.6%	19.6%	-
Maximum	0.1772	0.9949	0.1362	0.7369	0.4916	1.9892
Minimum	-0.1228	-0.1969	-0.9950	-0.5110	-0.3671	0.6075
Yorkshire and The Humber						
Median	0.0732	0.4158	-0.4980	0.0130	0.0333	0.8413
Mean Group Estimates	0.0554***	0.4120***	-0.4644***	-0.0022	0.1037*	1.0647
	(0.0161)	(0.0736)	(0.0864)	(0.0292)	(0.0531)	(0.1169)
% significant (at 5% level)	14.3%	85.7%	90.5%	4.8%	14.3%	-
Maximum	0.1487	0.8420	0.9950	0.2869	0.8641	2.7384
Minimum	-0.1139	-0.7791	-0.9950	-0.2999	-0.1816	0.5708

Mean group estimates are calculated as simple averages from district level parameter estimates. $E(\psi_{i0}) = \psi_0$ where $\hat{\psi}_{0,MG} = N_r^{-1}\sum_{i=1}^{N_r}\hat{\psi}_{i0}$ for $i = 1,\ldots,N$, $r = 1,\ldots,R$ where N_r is the total number of districts with connections in region r and $\hat{\psi}_{i0}$ denotes QML estimation of ψ_{i0}. As detailed in Pesaran and Smith (1995), $\widehat{\text{var}}(\hat{\psi}_{0,MG}) = \frac{1}{N_r(N_r-1)}\sum_{i=1}^{N_r}(\hat{\psi}_{i0} - \hat{\psi}_{0,MG})^2$ denotes the non-parametric estimator of the variance. Standard errors of MGE are reported below each regional estimate. All districts have one or more neighbours so no parameters coefficients are restricted to zero in the model.