

ESSAYS ON SPECULATIVE FINANCIAL BUBBLES

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Abstract

This thesis contributes to the study of long-run relationships between financial assets. We develop a methodology for testing the hypothesis of co-bubbling behaviour in two series, employing a variant of the stationarity test of Kwiatkowski et al. (1992) which uses a conditional 'wild' bootstrap scheme to control size. We subsequently use our method to test for the presence of co-bubbles in a series of different markets. We look at commodities such as gold and silver and the housing market. There is a plethora of research on the efficacy of unit root tests for detecting explosive rational asset price bubbles. However, the migration of these bubbles and the possibility of co-bubbling behaviour of two series have seldom been researched. In the second chapter of this thesis we apply our model to the commodities market and find that the prices of gold and silver co-bubble in the period following the financial crisis. In the third chapter we investigate the migration of speculative housing bubbles between UK geographic regions. In the third chapter we analyse the co-bubbling relationship between rental and housing prices. We find that an explosive bubble behaviour in rental prices will lead to a bubble behaviour in house prices. The two series co-bubble over a period of time of around two years.

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Chapter 1

Introduction

Following the 2007-2009 financial crisis a number of econometrics models have emerged that aim at modelling the behaviour of speculative financial bubbles. Speculative bubbles, especially in financial and housing markets, were blamed for the financial crisis to various degrees. Most prominently Phillips, Wu and Yu (2011) and Homm and Breitung (2012) use recursive right tailed Dickey-Fuller tests to test the null of a series being $I(1)$ against the alternative of an explosive autoregression. More recently, Harvey et al. (2014) [HLS] suggest using Bayesian Information Criterion (BIC) model selection procedure to identify bubble behaviour. The advantage of their method is that it allows for the consistent estimation of the start and end date of a bubble as well as providing for a number of different bubble processes. The HLS model has a significant influence on this entire thesis as we use it across our chapters to identify the start dates of bubbles in individual series.

In the second chapter, building on the HLS model, we explore the possibility of co-bubbling, where the two explosive series differ only by a stationary $I(0)$ component. As the null critical values of our test depend on the form of the bubble process of each series we adopt a conditional 'wild bootstrap' to generate the critical values. Monte Carlo simulations offer promising levels of size control and power. We apply our model to the prices of gold and silver. The long run relationship of the two commodities has been the subject of numerous papers in the financial literature. Historically, they are seen as very close substitutes in terms of risk profile and investment returns. Economic theory suggests that following a financial crisis, due to the uncertainty in financial markets, investors would shift their portfolio towards commodities

such as gold and silver. Our chapter is able to confirm this hypothesis as the prices of the two commodities bubble following the recent financial crisis. Furthermore, typically, the price of gold is found to be leading the price of silver but we do not find evidence to support this. Our results show that the silver prices lead gold prices. We attribute this change to the diversified use of silver for industrial purposes over the past few years thus making it more sensitive to changes in the economic environment.

In the third chapter, we focus our attention on the migration of housing bubbles between UK geographic regions. Theories have been proposed that suggest that there might be a long run relationship between the prices of houses in neighbouring regions. A large amount of empirical research has showed that bubbles occur relatively frequently and with a high intensity on housing markets in large cities (for example, Abraham and Hendershott, 1996, for the US; Ayuso and Restoy, 2003, for the UK and Spain; and Chan et al., 2001, for Hong Kong). However, the migration of these bubbles from one geographic region to the other has been less well documented. Furthermore, the time it takes for a bubble to migrate from one geographic region to another has not been explored yet, as far as we know. It is these two key aspects of the geography of housing bubbles that we aim to better understand in our third chapter.

It has also been proposed that fluctuations in the average income of two geographic regions can also explain fluctuations in house prices. Income is seen as a 'fundamental' variable in determining the prices of housing. Other fundamentals in determining house prices include the interest rates and the rental rate. Case et al., (2005) and Benjamin et al. (2004) find that the effect of wealth is far greater on housing markets than on financial markets. On the other hand, Himmelberg (2005) writes a comprehensive review of the fundamentals that determine house prices and to some extent housing bubbles. He finds that income has a limited explanatory power in explaining the emergence of any housing bubbles.

In our third chapter we look at this hypothesis from a co-bubbling lens. We test to see if changes in income levels between two geographic regions can affect the time it takes for a bubble to migrate. We also test to see the effect of distance on the migration time lag. Using the co-bubbling model developed in the second chapter we find that the distance between two geographic regions can be used to predict whether a housing bubble in one area will migrate

to a neighbouring area. We do not find evidence that the average income in the various UK regions can predict bubble migration.

The fourth chapter examines the migration of bubbles from the prices of rental property to the prices of housing property within UK geographic regions. A number of theories have been proposed within the financial econometrics literature suggesting that the two types of investment are very close substitutes. As a result, researchers have settled on the proposition that there must exist a long run (co-integrating) relationship between the two assets.

In the literature, rents are usually considered an important part of fundamentals for house prices, see Meese and Wallace (1994), Hamilton and Schwab (1985), Himmelberg et al. (2005), Gallin (2008), Ghysels et al. (2013), Brunnermeier and Julliard (2008), Campbell et al. (2009), Plazzi et al. (2010), Cochrane (2011), Engsted and Pedersen (2014, 2015), and Gelain and Lansing (2014). The reason for considering rent as a fundamental factor follows the same logic as dividends being seen as fundamentals for determining the price of a share. Put simply, the owner of a house who also lives in the house, derives a certain utility from the service provided by the house itself. An appropriate proxy for this unobservable housing service are rents. Rents are the equivalent to the dividends that an owner of a share obtains in the equity market.

This relationship has been found and shown using a series of robust statistical methods in recent literature. However, the question of which asset leads the price and the explosive behaviour, if any, of the other asset has yet to be asked. In this chapter we examine the relationship between rental and housing prices using the co-bubbling model developed earlier in the thesis. We are able to confirm both of our hypotheses: a) that there is a strong co-bubbling relationship between rental and housing prices across the UK and b) that a bubble in rental prices will typically precede a bubble in housing prices by about nine quarters.

Chapter 2

Testing for Co-bubble Behaviour in Economic and Financial Time Series

Abstract

The efficacy of unit root tests for detecting explosive rational asset price bubbles is well documented. The possibility of co-bubbling behaviour of two series is, however, less understood. We develop a methodology for testing the hypothesis of co-bubbling behaviour in two series, employing a variant of the stationarity test of Kwiatkowski et al. (1992) which uses a conditional ‘wild’ bootstrap scheme to control size. Monte Carlo simulations offer promising levels size control and power. Combining this test with a recently proposed Bayesian Information Criterion model selection procedure to identify bubble episodes in individual series allows us to determine the presence of any relationship between two explosive series. An empirical application involving world silver and gold prices is discussed.

2.1 Introduction

Methods that aim to model speculative financial bubbles have gained high prominence following the 2008-2009 financial turmoil. This has resulted in a new area of literature that discusses the efficacy of unit root tests for detecting explosive rational asset price bubbles. See, for example, Phillips, Wu and Yu (2011) and Homm and Breitung (2012) who use recursive right

tailed Dickey-Fuller tests to test the null of a series being $I(1)$ against the alternative of an explosive autoregression. More recently, Harvey et al. (2014) [HLS] suggest using Bayesian Information Criterion (BIC) model selection procedure to identify bubble behaviour. This procedure also allows for consistent estimation of the start and end dates of the bubble and can distinguish between different types of bubble processes, for instance, identifying a bubble that does or does not end in a collapse, or a bubble that continues to the end of the sample. For the purposes of this thesis, we define bubbles as substantial deviations of a time series from its fundamental values. By this we mean that if a series begins deviating from its established behaviour (random walk) by an explosive component, then we can conclude that a bubble is present. When this additional term equals zero, then no bubble is present in the observed data. Of course, practically, in order to determine the presence of a bubble, one must first be aware of the fundamentals and be in a position to quantify and define them.

However, the possibility of co-bubbling, whereby two explosive series differ only by an $I(0)$ component has not been explored. It is this concept we introduce and develop a testing methodology for in this paper. Our concept of co-bubbling also naturally leads into the notion of testing for bubble migration, whereby a bubble episode in one series leads (or lags) that in another by a number of time periods. Attempts have been made to empirically document bubble migration (see, for example, Kivedal, 2012) however these approaches lack a robust statistical foundation.

Specifically, we consider testing the null hypothesis of co-bubbling between two series using a variant of the stationarity test of Kwiatkowski et al. (1992) [KPSS]. The null critical value of this test depends on the form of the bubble processes involved, making it difficult to control size. To get round this problem, we adopt a simple conditional ‘wild’ bootstrap. Extensive Monte Carlo simulation exercises show that procedure appears to control size well, even in the presence of heteroscedasticity - a relevant consideration when any application involves financial data. The power of our test to reject a false null of co-bubbling is also investigated via simulation, and shown to be decent, as its ability to identify the timing of bubble migration. Combining this test with the bubble identification and dating procedure of HLS gives a robust empirical methodology for detecting the presence of co-bubbling. We demonstrate this via an application involving world silver and gold prices.

2.2 The Bubble Model

We consider the following model for a generic series x_t , $t = 1, \dots, T$, which is similar to that used in HLS,

$$\begin{aligned} x_t &= \mu_x + u_{x,t} \\ u_{x,t} &= \begin{cases} u_{x,t-1} + \epsilon_{x,t}, & t = 2, \dots, \lfloor \tau_{x,1}T \rfloor, \\ (1 + \delta_{x,1})u_{x,t-1} + \epsilon_{x,t}, & t = \lfloor \tau_{x,1}T \rfloor + 1, \dots, \lfloor \tau_{x,2}T \rfloor, \\ (1 - \delta_{x,2})u_{x,t-1} + \epsilon_{x,t}, & t = \lfloor \tau_{x,2}T \rfloor + 1, \dots, \lfloor \tau_{x,3}T \rfloor, \\ u_{x,t-1} + \epsilon_{x,t}, & t = \lfloor \tau_{x,3}T \rfloor + 1, \dots, T \end{cases} \end{aligned} \quad (2.1)$$

where μ_x is a constant term, $\tau_{x,1}$, $\tau_{x,2}$ and $\tau_{x,3}$ are sample fractions, and $\delta_{x,1} > 0$ and $\delta_{x,2} > 0$. Here $\lfloor \cdot \rfloor$ denotes the integer value. We assume that $\epsilon_{x,t}$ is an innovation process with zero mean and is integrated of order zero, $I(0)$. The model (2.1) imposes a unit root, or $I(1)$ behaviour, on x_t up to time $\lfloor \tau_{x,1}T \rfloor$, after which x_t is explosive until time $\lfloor \tau_{x,2}T \rfloor$. This is followed by a stationary (mean-reverting) regime until time $\lfloor \tau_{x,3}T \rfloor$. The series then returns to unit root behaviour for the final regime.

In terms of modelling bubble behaviour, (2.1) allows for a number of different specifications (models) simply by changing $\tau_{x,1}$, $\tau_{x,2}$ and $\tau_{x,3}$. If $\tau_{x,1} = 1$, then x_t is unit root throughout (which we shall refer to as Model 0). If $0 < \tau_{x,1} < \tau_{x,2} = 1$ the bubble emerges at (sample proportion) $\tau_{x,1}$ and runs up to the sample end (Model 1); while if $0 < \tau_{x,1} < \tau_{x,2} = \tau_{x,3} < 1$ the bubble terminates at $\tau_{x,2}$ and is unit root to the sample end (Model 2). If $0 < \tau_{x,1} < \tau_{x,2} < \tau_{x,3} = 1$ the bubble terminates with an offsetting stationary collapse regime that continues to the sample end (Model 3); while if $0 < \tau_{x,1} < \tau_{x,2} < \tau_{x,3} < 1$, the collapse is followed by a unit root period to the sample end (Model 4). Here $\delta_{x,1}$ and $\tau_{x,2} - \tau_{x,1}$ together control the magnitude and duration of the explosive bubble period, while $\delta_{x,2}$ and $\tau_{x,3} - \tau_{x,2}$ determine the speed and duration of the bubble's collapse (should one occur as in Model 3 and 4).

2.3 A Model of Co-bubbling Behaviour

Suppose a y_t and x_t are two observed series, with x_t a bubble process, i.e. it is generated from one of Model 1-4. then we may consider a relationship of the following form:

$$y_t = \mu_y + \beta_x x_{t-i} + \beta_z z_{t-j} + e_{y,t} \quad (2.2)$$

where z_t is some latent, unobserved bubble process which is generated from one of Model 1-4 (where x is replaced by z in (2.1)), with $I(0)$ mean zero innovation term $\epsilon_{z,t}$ independent of $\epsilon_{x,t}$, and $e_{y,t}$ is a mean zero $I(0)$ innovation term, independent of $\epsilon_{x,t}$ and $\epsilon_{z,t}$. In (2.2), if $\beta_z = 0$, and $\beta_x > 0$, we can then consider that y_t and x_t *co-bubble*, in the sense that they "differ" by an $I(0)$ term. The co-bubbling is contemporaneous if $i = 0$. If $i > 0$, they co-bubble with a delay of i time periods; the bubble in x_t preceding that in y_t . We can therefore think of the bubble in x_t migrating into y_t after i time periods. We do not consider the concept of co-bubbling to be meaningful for $\beta_x < 0$ as this implies that the bubbles in y_t and x_t will be moving in opposite directions. If $\beta_z > 0$, and $\beta_x = 0$, then y_t and z_t are co-bubbling with a delay of j time periods if the latent process z_t is generated from one of Model 1-4, and they are co-integrating if z_t is generated from Model 0. The observed bubble process x_t is then irrelevant as a co-bubble variate for y_t . Our final possibility is the case where $\beta_x > 0$ and $\beta_z > 0$. We exclude this possibility because x_t alone is not sufficient to explain the bubble behaviour observed in y_t since it depends on the additional unobserved component z_t . If $i < 0$, the co-bubble delay turns into a lead.

In terms of testing for co-bubbling behaviour between the observed series, the hypotheses of interest may be stated as

$$H_0 : \beta_x > 0, \beta_z = 0$$

$$H_1 : \beta_x = 0, \beta_z > 0$$

Under H_0 , which forms the null hypothesis, y_t and x_t co-bubble; the alternative hypothesis, H_1 , simply implies they do not co-bubble.

2.4 Testing for Co-bubbling

Our aim is to employ a statistic to test H_0 against H_1 . The statistic we consider to test H_0 against H_1 is motivated by the literature on testing the null of $I(0)$ stationarity against the alternative of $I(1)$ integration. Specifically we consider a variant of the test of KPSS, as extended by Leybourne and McCabe (1994) and Shin (1994) to allow for the presence of an additional exogenous stochastic regressor. In (2.2), supposing that z_t is an $I(1)$ random walk (i.e. it follows Model 0) with an IID Normal innovation process $\epsilon_{z,t}$ and $e_{y,t}$ is itself IID Normal, then, conditioning on x_t , the locally most powerful invariant test of $\beta_z = 0$ against $\beta_z > 0$ is the KPSS-type statistic

$$S = \hat{\sigma}_y^{-2} T^{-2} \sum_{t=i+1}^T \left(\sum_{s=i+1}^t \hat{e}_{y,s} \right)^2$$

where $\hat{\sigma}_y^2 = T^{-1} \sum_{t=i+1}^T \hat{e}_{y,t}^2$ is an estimator of $V(e_{y,t})$, with $\hat{e}_{y,t} = y_t - \hat{\mu}_y - \hat{\beta}_x x_{t-i}$ denoting the OLS residual from a regression of y_t on a constant and x_{t-i} . Here S is invariant to μ_y , β_x and $V(e_{y,t})$. Under the Normality conditions, this form of statistic is essentially a one-sided Lagrange Multiplier test statistic of the null of whether the $V(e_{z,t}) = 0$ against the alternative that $V(e_{z,t}) > 0$. This is observationally equivalent to fixing $V(e_{z,t}) > 0$ and testing $\beta_z = 0$ against $\beta_z > 0$. The IID and Normality assumptions are only used to justify the form of the statistic - they are used in its likelihood-based derivation - but they are not intended to hold in practice.

Although, formally S is designed for testing to distinguish whether $y_t - \mu_y - \beta_x x_{t-i} = z_{t-j} + e_{y,t}$ is an $I(0)$ process or an $I(1)$ process, we would expect it to have reasonable power to distinguish between H_0 and H_1 , where, under H_1 , $z_{t-j} + e_{y,t}$ is a bubble process rather than an $I(1)$ process. The reason for this is that in a Taylor series expansion of a local bubble process, the first term behaves like a random walk.

An obvious question is why not just perform a standard t -test of the null hypothesis $\beta_x = 0$ and infer co-bubbling from a rejection of this null? It is because this test will tend to reject when H_1 is true, along the same lines as the classical spurious regression phenomenon of Granger and Newbold (1974). This results in wrongly concluding co-bubbling between y_t and

observed x_t when it is actually occurring between y_t and the unobserved variable z_t .

A problem with implementing S as a test of H_0 against H_1 is that its distribution under H_0 , and hence the critical values to applied, depend on x_t , even in large samples. This is a familiar problem that arises because x_t is not a stationary stochastic process, indeed it is far from it. The distribution of S will change according which of Model 1-4 is in place for x_t , and even within a given Model, it will further depend on the locations of regime change points, and bubble parameters values. This makes it essentially impossible to calculate the critical values needed to control the size of the test S when it is used in practice. Our solution is to employ a very straightforward conditional wild bootstrap procedure to overcome this serious drawback.

2.5 A Conditional Wild Bootstrap Test for Co-bubbling

A standard unconditional on x_t bootstrap scheme to empirically simulate the unconditional distribution of S under H_0 would involve re-simulating the properties of x_t in each bootstrap replication. This would be very slow to implement, and, quite feasibly, would not be valid as the re-simulated x_t would always be based on estimated, rather than known parameters arising in the model of x_t . At the very least it would be expected to perform poorly in finite samples. A much easier solution is to conduct a bootstrap procedure that conditions on x_t . In other words to use the bootstrap to empirically simulate the conditional on x_t distribution of S under H_0 . Specifically, the bootstrap algorithm we employ, is a conditional 'wild' bootstrap scheme (see, for example, Liu, 1988, and Mammen, 1993) is as follows:

Algorithm 1. Step 1. *Generate T bootstrap samples $y_{tb} = w_t \hat{e}_{y,t}$, $t = 1, \dots, T$, where w_t denotes an independent $N(0, 1)$ sequence.*

Step 2. *Calculate the conditional on x bootstrap KPSS test $S_b \mid x$ using residuals $\hat{e}_{tb} \mid x$ obtained from the regression of y_{tb} on a constant and x_{t-i} .*

Step 3. *Repeat for $b = 1, 2, \dots, B$ and calculate the bootstrap (upper tail) α -level critical value, $c_{\alpha B} \mid x$, of the empirical CDF of $S_b \mid x$.*

Step 4. *Reject H_0 in favour of H_1 if $S > c_{\alpha B} \mid x$.*

By construction, this conditional bootstrap procedure will be correctly sized under H_0 , at least in large samples, irrespective of how x_t is generated. It works essentially because S , being based on $\hat{e}_{y,t}$, is invariant to β_x , so without loss of generality, we can set β_x to zero when generating the bootstrap samples.

The bootstrap could actually be implemented simply using $y_{tb} = w_t$ instead of $y_{tb} = w_t \hat{e}_{y,t}$. The advantage of using the second specification is that it is (asymptotically) robust to any heteroscedasticity in $e_{y,t}$; for example, volatility shifts or trending volatility since multiplication by $\hat{e}_{y,t}$ effectively replicates the pattern of heteroscedasticity present in $e_{y,t}$. Any heteroscedasticity present in $\epsilon_{x,t}$ is implicitly handled in the wild bootstrap via the conditioning on x_t . This robustness property may be pertinent for applications using financial data, where heteroscedastic errors are considered very plausible. In the next section we investigate the size and power performance of our bootstrap procedure via Monte Carlo simulation techniques.

2.6 Monte Carlo Simulations

In this section we examine the finite sample properties of our wild bootstrap procedure based on S for Models 1-4. We implement the the bootstrap at the nominal 0.05-level (i.e. $\alpha = 0.05$) and use $B = 500$ bootstrap replications. We consider a sample size of $T = 200$. In the simulations, we generate $\epsilon_{x,t}$ and $e_{y,t}$ as IIDN (0,1) series. Since the regression for $\hat{e}_{y,t}$ includes a constant as well as x_{t-i} , we can simply set $\mu_x = 0$ and $\mu_y = 0$. We also set the co-bubbling parameter $\beta_x = 1$. At this stage, we assume that the delay parameter i is known. Our results are based on 2000 Monte Carlo replications. All the programs to run the simulation experiments were written in GAUSS 9.0.

2.6.1 Size

Our first set of simulations involving quantifying the size of the bootstrap procedure under H_0 . We begin with the simplest co-bubble model, which uses Model 1 for x_t , where a bubble emerges within the sample and then lasts to the sample end. Here the choice parameters in (2.1) reduce to $\tau_{x,1}$, the timing of the bubble onset as a fraction of T , and $\delta_{x,1}$ the magnitude of the bubble parameter. Since we are operating under H_0 , $\beta_z = 0$ and so there is no need

to simulate a model for z_t at this stage. The simulation results are given in Table 2.1 in the Appendix, and represent the empirical rejection probabilities of the bootstrap procedure at the nominal 0.05 level.

We see that the bootstrap procedure controls empirical size well over all parameter settings for i , $\tau_{x,1}$ and $\delta_{x,1}$; throughout these sizes are close to the nominal 0.05 value. Table 2.2 repeats simulation exercise but under Model 2 for x_t , with bubble termination at $\tau_{x,2} = 0.80$. Again, the sizes are always close to the nominal level. For Model 3, which adds a collapse period with parameter $\delta_{x,2} = 0.20$ at $\tau_{x,2} = 0.80$, Table 2.3 shows that size remains well controlled. The same is also true in Table 2.4, which adds a final random walk regime at $\tau_{x,3} = 0.90$. In general then, we can conclude that the size of the bootstrap procedure is well behaved across the different bubble models we allow for x_t . That is, where a co-bubbling relationship between y_t and x_t exists, the bootstrap test will only reject the presence of such a relationship with probability close to the nominal size.

To also check size robustness to heteroscedasticity, we consider Model 1, just for $i = 0$, $\tau_{x,1} = 0.50$ and $\delta_{x,1} = 0.05$. But we now change the variance of $e_{y,t}$ from 1 to 0.1 at sample fraction τ_h , so that we introduce a downwards shift in variance. The results are shown in Table 2.5. Our test again appears well-sized, irrespective of when the variance break occurs. For comparison, the numbers in brackets are those that we would get if we ran the bootstrap simply using $y_{tb}^* = w_t$ instead of $y_{tb} = w_t \hat{e}_{y,t}$, which would be valid under homoscedasticity but not heteroscedasticity. Here, the sizes are seen to be inflated, particularly for the early variance shift ($\tau_h = 0.25$). This highlights the benefit of using the heteroscedasticity-robust bootstrap samples $y_{tb} = w_t \hat{e}_{y,t}$.

2.6.2 Power

We now examine the power of the bootstrap procedure to differentiate H_0 from H_1 . Here, for a given model for x_t we generate z_t in a similar way, but generate the two series independently and allow $\tau_{z,1}$, the timing of the bubble onset in z_t , to change. The strength of the alternative is controlled by the magnitude of $\beta_z > 0$.

Results for Model 1 are shown in Table 2.6. We see that for a given value of $\tau_{z,1}$, the empirical power of the test increases with β_z , which is as we would expect, since increasing β_z moves

us further away from the null. On the other hand, for a given value of β_z , power decreases with $\tau_{z,1}$. Again we would expect this as increasing $\tau_{z,1}$ reduces the duration of the explosive behaviour in z_t . In Table 2.7, under Model 2. we terminate the bubbles in x_t and z_t at $\tau_{x,2} = \tau_{z,2} = 0.80$. The pattern of results is quite similar to that seen in Table 2.6. The same is true in Table 2.8, where Model 3 adds a collapse regime to x_t and z_t , and also in Table 2.9, where Model 4 follows the collapse regime with a final random walk regime. So, we conclude that the power properties of our bootstrap procedure are very decent across a range of bubble specifications that represent the alternative hypothesis.

2.6.3 Choosing the delay parameter

One important issue is that, in practice, the true value of the delay parameter i in the co-bubbling model (2.2) is unknown. We now investigate the size of the bootstrap procedure under H_0 , but for different choices of the delay parameter, that is, when both correct and incorrect choices are made. Let i^* denote the value of the delay parameter used in the regression to produce the residuals i.e. $\hat{e}_{y,t} = y_t - \hat{\mu}_y - \hat{\beta}_x x_{t-i^*}$. It is only when $i^* = i$ that the appropriate delay is employed, and when $i^* \neq i$ these residuals are no longer invariant to β_x ($= 1$).

We first consider Model 1, with $(\tau_{x,1}$ and $\delta_{x,1}$ taking the same values as in Table 1.1). In Table 2.10 the true delay is $i = 0$, while candidate values from which the $\hat{e}_{y,t}$ are constructed are $i^* = 0, 2, 4, 6$. So for $i^* > 0$ we are imposing too long a delay in the fitted co-bubbling regression. We see that as i^* increases, and the delay becomes more and more inappropriate, the test rapidly starts to reject H_0 . Table 2.11 sets the true delay at $i = 6$, so now for $i^* < 6$ we are imposing too short a delay. Again we see increasing levels of over-rejection as the assumed delay is made shorter and shorter. Tables 2.12 and 2.13 repeat the analysis for Model 2. Here we see the price for incorrect delay choice appears even more dramatic than for Model 1 when $\tau_{x,1} = 0.25$ and $\tau_{x,1} = 0.50$. Similar patterns are found under Model 3, in Tables 2.14 and 2.15, and for Model 4, in Tables 2.16 and 2.17.

In practice then, the test will not be able to distinguish between H_1 being true, and H_0 being true but with incorrect choice of delay parameter, since both will cause a rejection of H_0 . We therefore suggest that different values of the delay parameter be experimented with when

applying our procedure.

2.7 Empirical Implementation

In practice, a necessary initial step is to establish whether a model of the form (2.2) even represents a feasible relationship between the observed series y_t and x_t . For this to be the case, we need to ensure that both y_t and x_t have the same form of model; that is, they are both generated by the same member of Model 1-4. To put it another way, if y_t is generated by Model 1 and x_t is generated by Model 4, then it is not meaningful to consider that H_0 can ever hold (H_1 could still be true, obviously). We also need to exclude the possibility that both series are generated by Model 0, since neither contains a bubble in this situation. It is important to note that in this initial step we do not impose common parameter values in (2.1) applied to both y_t and x_t , just that the same set of model regimes occur (at possibly different locations etc.) for both series.

We conduct this preliminary analysis using the BIC-based model selection approach of HLS. Taking the generic model in (2.1), for Model j , we estimate the regime change point(s) on the basis of minimising the residual sum of squares across all candidate dates, using the fitted OLS regressions corresponding to Model j below:

$$\text{Model 1: } \Delta x_t = \hat{\mu}_1 D_t(\tau_1, 1) + \hat{\delta}_1 D_t(\tau_1, 1) x_{t-1} + \hat{\epsilon}_{1t}$$

$$\text{Model 2: } \Delta x_t = \hat{\mu}_1 D_t(\tau_1, \tau_2) + \hat{\delta}_1 D_t(\tau_1, \tau_2) x_{t-1} + \hat{\epsilon}_{2t}$$

$$\text{Model 3: } \Delta x_t = \hat{\mu}_1 D_t(\tau_1, \tau_2) + \hat{\mu}_2 D_t(\tau_2, 1) + \hat{\delta}_1 D_t(\tau_1, \tau_2) x_{t-1} + \hat{\delta}_2 D_t(\tau_2, 1) x_{t-1} + \hat{\epsilon}_{3t}$$

$$\text{Model 4: } \Delta x_t = \hat{\mu}_1 D_t(\tau_1, \tau_2) + \hat{\mu}_2 D_t(\tau_2, \tau_3) + \hat{\delta}_1 D_t(\tau_1, \tau_2) x_{t-1} + \hat{\delta}_2 D_t(\tau_2, \tau_3) x_{t-1} + \hat{\epsilon}_{4t}.$$

Here, the dummy variables are defined by $D_t(a, b) = 1(\lfloor aT \rfloor < t \leq \lfloor bT \rfloor)$. Break fraction estimators are then calculated according to

$$\text{Model 1: } \hat{\tau}_1 = \arg \min_{0 < \tau_1 < 1} SSR_1(\tau_1)$$

$$\text{Model 2: } (\hat{\tau}_1, \hat{\tau}_2) = \arg \min_{0 < \tau_1 < \tau_2 < 1} SSR_2(\tau_1, \tau_2)$$

$$\text{Model 3: } (\hat{\tau}_1, \hat{\tau}_2) = \arg \min_{0 < \tau_1 < \tau_2 < 1} SSR_3(\tau_1, \tau_2)$$

$$\text{Model 4: } (\hat{\tau}_1, \hat{\tau}_2, \hat{\tau}_3) = \arg \min_{0 < \tau_1 < \tau_2 < \tau_3 < 1} SSR_4(\tau_1, \tau_2, \tau_3)$$

where $SSR_j(.) = \sum_{t=2}^T \hat{\epsilon}_{jt}^2$, $j = 1, \dots, 4$. We then choose Model j_{opt} according to

$$j_{opt} = \arg \min_{j \in \{0,1,2,3,4\}} BIC_j$$

where

$$\begin{aligned} BIC_0 &= T \ln\{T^{-1} SSR_0\} \\ BIC_1 &= T \ln\{T^{-1} SSR_1(\hat{\tau}_1, 1)\} + 3 \ln(T), \\ BIC_2 &= T \ln\{T^{-1} SSR_2(\hat{\tau}_1, \hat{\tau}_2)\} + 4 \ln(T), \\ BIC_3 &= T \ln\{T^{-1} SSR_3(\hat{\tau}_1, \hat{\tau}_2, 1)\} + 6 \ln(T), \\ BIC_4 &= T \ln\{T^{-1} SSR_4(\hat{\tau}_1, \hat{\tau}_2, \hat{\tau}_3)\} + 7 \ln(T). \end{aligned}$$

Here $SSR_0 = \sum_{t=2}^T (\Delta x_t)^2$ corresponds to the no-bubble $I(1)$ model, Model 0. HLS show that this algorithm, referred to as BIC_{opt} , results in correct asymptotic selection between Models 0-4. We therefore require that when applied separately to y_t and x_t , BIC_{opt} selects the same member of Model 1-4 for both series. Assuming this be established, we can, subsequently, validly consider testing H_0 against H_1 in the context of the model (2.2) using our bootstrap procedure.

Finally, to allow for the possibility of weak serial correlation in $e_{y,t}$ we can simply replace the short-run variance estimator $\hat{\sigma}_y^2$ in S with any standard long run-variance estimator. The bootstrap statistics $S_b \mid x$ require no adjustment and can be computed using short-run variance estimator (note that $\epsilon_{x,t}$ can be serially correlated, but no further adjustment to S is required).

2.8 An Empirical Application: Silver and Gold Prices

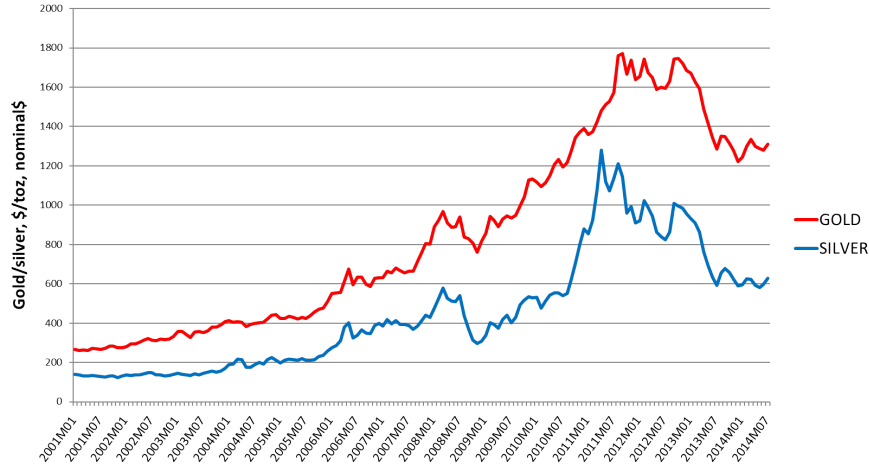
The long run relationship between the price of silver and gold has been a topic of much interest to academics over the past decade. They have historically been seen as close substitutes for one another, both being precious metals that can be used to back currency and both having been used as currency. There is significant evidence from Faff and Hillier (2003) and Adrangi

et al. (2003) that these metals can play a useful role in diversifying risk, as well as being an attractive investment in their own right, thus, one might expect that their prices share similar dynamics.

Common opinion suggests that prices of gold lead the prices of silver. In other words, one would expect that any bubble in silver prices will follow after a bubble in gold prices (see, for example, Ciner, 2010, and Baur and Tran, 2014). Moreover, there is strong evidence that the two series are co-integrated. Baur and Tran (2014), closely following the work of Escribano and Granger (1998) use a 40-year sample period from 1970-2010 and examine the existence and stability of a long-run relationship between silver and gold prices. They focus their attention on the role of bubbles and financial crises for the relationship between silver and gold. The results indicate that extreme price changes in certain periods create long-run (co-integration) relationships since gold and silver are not co-integrated in "normal" periods. Furthermore, Figuerola-Ferretti and Gonzalo (2010) use the period from 1990 to 2009 and find that silver and gold are co-integrated only in an environment of weak US dollar together with increased volatility. Lucey and Tully (2005) use the period from 1978 to 2002 and find that a stable long-run relationship exists. Liu and Chou (2003) use daily data from 1983 to 1995 and Adrangi et al. (2000) use intra-day data between 1993 and 1995 with a focus on price discovery. All these studies use various forms of Vector Error Correction Models for the full sample and derived Granger causality tests to show that gold drives the long-run relationship despite its lower volatility relative to silver. To our knowledge, no study has investigated the possibility of explosive behaviour in these two price indices.

We note that our empirical application does not take into consideration the actual fundamentals of gold and silver. We assume that these fundamentals have already been incorporated into the observed prices of the two precious metals. Moreover, the model of co-bubbling that we have developed does not necessitate the inclusion of fundamental values into its analysis. We also note that in the case of gold, the literature accepts that there are no fundamentals underpinning the evolution of the prices of the series. For silver prices, the demand for the metal for industrial purposes suggests that there are fundamentals that could be explored. For instance, if solar panels (constructed using silver) begin to be seen as a growth industry by investors, that could lead to a significant shift in the expected prices for silver. In turn,

Figure 2.1: Gold and silver co-bubbling application.



this may lead to an explosive bubble behaviour in the price of silver. For the purposes of this chapter, we do not investigate the implications of the prices of the fundamentals of the prices of silver on its actual price, but we do consider that there is scope for further examination in future research.

For our empirical example, we use monthly data of the prices of silver and gold over the period 2000M1-2014M10, which is $T = 185$. The data is taken from the World Bank (GEM Commodities) database. Silver and gold prices are expressed as nominal U.S.\$/troy oz. No standardisation or conversion of the data from nominal to real is required as both series are expressed in the same normalised currency. Figure 2.1 plots the two series and visual evidence of co-movement in prices is clearly evident.

When we apply the HLS procedure to each price series, we find both select Model 4 and, interestingly, with the *same* regime dates: a random walk from the sample start point at 2000M1 until 2009M01, followed by a bubble period to 2012M03, then a collapse period to observation 2013M10, followed by a return to a random walk up to the sample end-point, 2014M10. This reveals that the bubble began some time after the Black Monday event in worldwide stock markets (21st, 2008M1) when FTSE 100 had its biggest ever one-day points fall and European stocks closed with their worst result since 9/11, and Asian stocks dropped as much as 15 basis points. This event could indicate a significant shift in investor's strategy away from financial markets and towards commodity markets. It is generally believed that these events had a significant impact on global commodity markets, and especially the ones

for precious metals. Historically, it is considered that shocks in financial markets lead to speculative bubbles in commodity markets.

Given these results, we can now check whether these price series co-bubble. We set y_t and x_t to be the silver price and gold price, respectively, and apply the KPSS test S , using a range of lead/delay values $i^* = \{-12, -11, \dots, -1, 0, 1, \dots, 11, 12\}$, so permitting an unknown lead or delay of up to one year. To account for serial correlation, for $\hat{\sigma}_y^2$, we use a simple Bartlett long-run variance estimator with 6 lags included. Table 2.18 gives the value of S , together with the 0.05-level bootstrap critical value, based on $B = 500$ bootstrap replications. The italic entries represent those cases where co-bubbling is *not* rejected. So we deduce that silver and gold co-bubble, with the bubble in silver preceding that in gold by 3-5 months.

Our empirical application therefore offers further confirmation that silver and gold prices are indeed strongly linked, even during an explosive period following a financial recession. Interestingly, our analysis does not confirm the previous literature consensus that gold prices lead silver prices. On the contrary, we find that silver prices are the ones leading gold prices during the explosive episode. Since most of the literature on this topic is quite dated we believe that it is not unreasonable to consider that the dynamics between the two commodities have undergone a change, and that silver has now taken the lead position. This would suggest that gold prices have recently become relatively inert to global financial and political events, leaving silver to be the first commodity to react to such events.

Demand for both gold and silver is driven by changes in investors appetite. On the other hand, demand for silver is also very highly affected by retail demand. For the final consumer, silver is a much more accessible precious metal due to its lower price relative to gold. Additionally, silver is increasingly being used for industrial purposes (nearly half of the demand for silver in 2011 was for industrial projects, including the use of silver in new solar panel technology). It is therefore not unreasonable to suggest that silver has recently replaced gold as the "go-to" speculative commodity for investors.

2.9 Summary

In this chapter we have proposed a test procedure for the detection of a co-bubbling relationship between two explosive series. Our statistic is built on a variation of the stationarity test of Kwiatkowski et al. (1992), extended to include explosive exogenous regressors. Because the null distribution of test is dependent on the nature of the explosive regressor, we employ a conditional wild bootstrap procedure to control the size of the test. Monte Carlo simulations provide encouraging results with respect to both the size and power properties of our test. An empirical application was used to understand the value of the test from a practical perspective. We examine silver and gold and prices as the relationship between the two has been widely documented by the literature before now. We find that silver and gold prices exhibited co-bubbling behaviour, following on from the financial recession surrounding the Black Monday event. However, our test does not confirm the literature consensus that gold prices lead silver prices. In contrast, our evidence shows that in the following bubble period, silver prices were the ones leading gold prices, with a time lead of around 4 months.

Appendix

Table 2.1: Finite sample size of bootstrap S , Model 1.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i				i				i			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.049	0.050	0.049	0.046	0.053	0.048	0.048	0.047	0.050	0.045	0.048	0.046
0.50		0.049	0.050	0.047	0.049	0.052	0.048	0.050	0.048	0.050	0.047	0.049	0.048
0.75		0.050	0.051	0.051	0.052	0.050	0.047	0.052	0.050	0.048	0.052	0.048	0.045

Table 2.2: Finite sample size of bootstrap S , Model 2, $\tau_{x,2} = 0.80$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i				i				i			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.050	0.051	0.049	0.053	0.050	0.051	0.051	0.053	0.053	0.052	0.048	0.054
0.50		0.051	0.051	0.047	0.052	0.052	0.049	0.048	0.052	0.052	0.053	0.051	0.052
0.75		0.049	0.052	0.053	0.049	0.053	0.048	0.049	0.053	0.052	0.055	0.055	0.054

Table 2.3: Finite sample size of bootstrap S , Model 3, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i				i				i			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.054	0.053	0.053	0.056	0.054	0.052	0.050	0.047	0.055	0.055	0.053	0.056
0.50		0.048	0.048	0.048	0.051	0.051	0.047	0.047	0.053	0.053	0.052	0.049	0.053
0.75		0.053	0.050	0.052	0.049	0.053	0.046	0.047	0.052	0.054	0.052	0.053	0.056

Table 2.4: Finite sample size of bootstrap S , Model 4, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $\tau_{x,3} = 0.90$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i				i				i			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.053	0.050	0.053	0.056	0.046	0.048	0.053	0.047	0.052	0.048	0.049	0.050
0.50		0.051	0.047	0.046	0.051	0.050	0.051	0.049	0.053	0.055	0.049	0.051	0.048
0.75		0.053	0.050	0.053	0.049	0.050	0.051	0.046	0.052	0.055	0.050	0.052	0.051

Table 2.5: Finite sample size of bootstrap S under heteroscedasticity, Model 1, $i = 0$, $\tau_{x,1} = 0.50$, $\delta_{x,1} = 0.05$.

τ_h	0.25	0.50	0.75
	0.054 (0.133)	0.055 (0.074)	0.053 (0.062)

Table 2.6: Finite sample power of bootstrap S , Model 1, $i = 0$, $\tau_{x,1} = 0.50$, $\delta_{x,1} = 0.05$, $j = 0$, $\delta_{z,1} = 0.05$.

	β_z	0.025	0.05	0.10	0.20
$\tau_{z,1}$					
0.25		0.774	0.873	0.944	0.997
0.50		0.300	0.461	0.653	0.926
0.75		0.153	0.337	0.622	0.885

Table 2.7: Finite sample power of bootstrap S , Model 2, $i = 0$, $\tau_{x,1} = 0.5$, $\delta_{x,1} = 0.05$, $\tau_{x,2} = 0.80$, $j = 0$, $\tau_{z,2} = 0.80$, $\delta_{z,1} = 0.05$.

	β_z	0.025	0.05	0.10	0.20
$\tau_{z,1}$					
0.25		0.764	0.871	0.973	0.995
0.50		0.279	0.424	0.712	0.932
0.75		0.166	0.375	0.689	0.898

Table 2.8: Finite sample power of bootstrap S , Model 3, $i = 0$, $\tau_{x,1} = 0.5$, $\delta_{x,1} = 0.05$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $j = 0$, $\tau_{z,2} = 0.80$, $\delta_{z,1} = 0.05$, $\delta_{z,2} = 0.20$.

	β_z	0.025	0.05	0.10	0.20
$\tau_{z,1}$					
0.25		0.743	0.862	0.975	0.988
0.50		0.226	0.387	0.662	0.900
0.75		0.151	0.374	0.655	0.891

Table 2.9: Finite sample power of bootstrap S , Model 4, $i = 0$, $\tau_{x,1} = 0.5$, $\delta_{x,1} = 0.05$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $\tau_{x,3} = 0.90$, $j = 0$, $\tau_{z,2} = 0.80$, $\delta_{z,1} = 0.05$, $\delta_{z,2} = 0.20$, $\tau_{z,3} = 0.90$.

	β_z	0.025	0.05	0.10	0.20
$\tau_{z,1}$					
0.25		0.760	0.855	0.955	0.990
0.50		0.233	0.405	0.655	0.896
0.75		0.133	0.355	0.701	0.890

Table 2.10: Finite sample size of bootstrap S , Model 1, $i = 0$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.049	0.177	0.555	0.787	0.048	0.220	0.605	0.833	0.050	0.345	0.669	0.853
0.50		0.048	0.350	0.802	0.928	0.050	0.363	0.808	0.933	0.051	0.667	0.900	0.946
0.75		0.050	0.481	0.933	0.951	0.050	0.566	0.902	0.970	0.048	0.772	0.935	0.966

Table 2.11: Finite sample size of bootstrap S , Model 1, $i = 6$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.763	0.505	0.203	0.048	0.805	0.557	0.235	0.049	0.818	0.635	0.301	0.046
0.50		0.888	0.695	0.267	0.048	0.890	0.716	0.288	0.047	0.929	0.845	0.663	0.047
0.75		0.920	0.780	0.372	0.052	0.945	0.800	0.516	0.047	0.982	0.933	0.776	0.050

Table 2.12: Finite sample size of bootstrap S , Model 2, $i = 0$, $\tau_{x,2} = 0.80$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.048	0.953	0.999	1.000	0.047	0.993	1.000	1.000	0.051	1.000	1.000	1.000
0.50		0.047	0.863	0.982	1.000	0.051	0.975	0.997	0.999	0.053	0.998	1.000	1.000
0.75		0.046	0.483	0.903	0.977	0.051	0.525	0.933	0.988	0.049	0.662	0.954	0.986

Table 2.13: Finite sample size of bootstrap S , Model 2, $i = 6$, $\tau_{x,2} = 0.80$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		1.000	0.975	0.862	0.047	1.000	0.995	0.988	0.049	1.000	1.000	0.998	0.047
0.50		0.993	0.965	0.622	0.048	0.996	0.986	0.928	0.050	1.000	1.000	0.993	0.050
0.75		0.980	0.880	0.452	0.051	0.974	0.870	0.418	0.049	0.989	0.903	0.474	0.052

Table 2.14: Finite sample size of bootstrap S , Model 3, $i = 0$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.046	0.906	0.964	1.000	0.047	0.992	0.997	1.000	0.050	0.998	1.000	1.000
0.50		0.049	0.688	0.934	0.997	0.051	0.918	0.975	0.990	0.050	0.987	0.997	1.000
0.75		0.052	0.501	0.863	0.977	0.050	0.533	0.903	0.982	0.049	0.410	0.815	0.991

Table 2.15: Finite sample size of bootstrap S , Model 3, $i = 6$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $\tau_{x,3} = 0.90$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.999	0.990	0.967	0.050	1.000	1.000	0.994	0.051	1.000	1.000	0.995	0.050
0.50		0.990	0.933	0.801	0.053	0.993	0.966	0.953	0.051	1.000	0.996	0.992	0.050
0.75		0.964	0.864	0.527	0.049	0.975	0.878	0.546	0.049	0.962	0.838	0.559	0.049

Table 2.16: Finite sample size of bootstrap S , Model 4, $i = 0$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $\tau_{x,3} = 0.90$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		0.048	0.956	1.000	1.000	0.050	0.994	1.000	1.000	0.048	1.000	1.000	1.000
0.50		0.048	0.783	0.976	1.000	0.049	0.978	0.995	0.997	0.052	0.997	1.000	1.000
0.75		0.051	0.500	0.908	0.987	0.051	0.529	0.940	0.991	0.051	0.674	0.955	0.992

Table 2.17: Finite sample size of bootstrap S , Model 4, $i = 6$, $\tau_{x,2} = 0.80$, $\delta_{x,2} = 0.20$, $\tau_{x,3} = 0.90$.

	$\delta_{x,1}$	0.025				0.05				0.10			
		i^*				i^*				i^*			
$\tau_{x,1}$		0	2	4	6	0	2	4	6	0	2	4	6
0.25		1.000	0.980	0.866	0.052	1.000	0.997	0.992	0.049	1.000	1.000	1.000	0.050
0.50		0.994	0.966	0.633	0.050	0.997	0.986	0.922	0.051	1.000	1.000	0.994	0.050
0.75		0.987	0.878	0.452	0.049	0.975	0.880	0.422	0.051	0.984	0.888	0.445	0.051

Table 2.18: Empirical example using 0.05-level bootstrap.

i^*		S	c_{aB}
-12		0.273	0.139
-11		0.250	0.140
-10		0.226	0.132
-9		0.203	0.137
-8		0.184	0.142
-7		0.168	0.148
-6		0.153	0.147
-5		<i>0.141</i>	<i>0.147</i>
-4		<i>0.132</i>	<i>0.147</i>
-3		<i>0.127</i>	<i>0.145</i>
-2		0.145	0.141
-1		0.167	0.156
0		0.212	0.171
1		0.173	0.149
2		0.160	0.137
3		0.158	0.140
4		0.162	0.141
5		0.168	0.136
6		0.178	0.132
7		0.189	0.140
8		0.201	0.132
9		0.218	0.125
10		0.236	0.127
11		0.253	0.132
12		0.270	0.127

Chapter 3

Examining the determinants of housing bubble migration in the UK

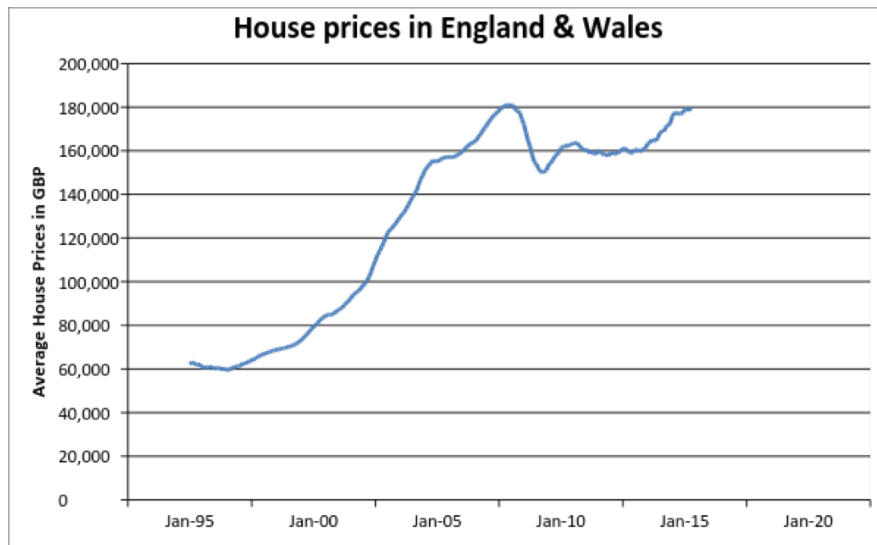
Abstract

This chapter focuses on the migration of housing bubbles between UK geographic regions. Theories have been proposed that suggest that there might be a long run relationship the housing prices of two neighbouring geographic regions and the distance between these regions may affect the time that it takes for a bubble to migrate from one geographic region to another. It has also been proposed that fluctuations in the average income of two geographic regions can also explain fluctuations in house prices. Our attention is restricted on the variables that can cause a housing bubble rather than simply explaining house price fluctuations. Using the co-bubbling model developed in the previous chapter we find that the distance between two geographic regions can be used to predict whether a housing bubble in one area will migrate to a neighbouring area. We do not find evidence that the average income in the various UK regions can predict bubble migration.

3.1 Introduction

The UK housing market has attracted a lot of attention over the past five years, both from academics and policy makers. It is well established that the location of a property significantly

Figure 3.1: Average house prices in England and Wales since 1995



affects its price. However, it is not yet clear whether neighbouring geographic regions can affect each other's housing prices to the extent of causing a 'bubble'. In this chapter we aim to shed some light on this relationship by focusing on 'bubbles' in housing markets across the UK and tracing the key drivers of such explosive behaviours. More specifically, we apply the co-bubbling test developed in a previous chapter to try and identify whether a long-run co-bubbling relationship exists between housing prices across a series of UK regions.

The methodology employed for testing the hypothesis of co-bubbling behaviour in two series is based on a variant of the stationarity test of Kwiatkowski et al. (1992). This uses a conditional 'wild' bootstrap scheme to control size. As we have shown in chapter 2, the Monte Carlo simulations offer convincing levels of size control and power to suggest that this would be an appropriate methodology to be used for the purposes of this chapter as well. Combining this test with a Bayesian Information Criterion model selection procedure to identify bubble episodes in individual series allows us to determine the presence of any relationship between two explosive series robustly - in this case house prices between UK geographical regions.

Figure 3.1 shows the general trend of average house prices in the UK since 1995. As we can see in Figure 3.1, average house prices in England and Wales have varied considerably over the past five years and now exhibit exponential growth with no signs that this trend is about to collapse.

3.2 Background to the housing bubble and geography literature

A large amount of empirical research has showed that bubbles occur quite frequently and with a high intensity on housing markets in large cities (see Abraham and Hendershott, 1996, for the US; Ayuso and Restoy, 2003, for the UK and Spain; and Chan et al., 2001, for Hong Kong). Nonetheless, in some developed countries the evidence shows that housing bubbles can be more modest (see Bourassa and Hendershott, 1995, for Australia; Hort, 1998, for Sweden; and Bourassa et al., 2001, for New Zealand). In countries where country-wide bubbles were not detected, evidence was found of regional speculative behaviour (Levin and Wright, 1997, for London; Roehner, 1999, for Paris; and Roche, 2001, for Dublin).

Based on the discussion presented in Section 3 of this chapter, we take that a housing market bubble occurs when the current house prices deviate significantly from their 'fundamental' price.

There are two categories of papers which considered deviations in the relationship between house price and fundamentals. The first strand of this empirical literature analyses this issue by employing aggregate data. For example, McCarthy and Peach (2004) suggested that in the U.S. housing market, there was no speculative housing bubble according to their evidence and that changes in house prices reflected movements in personal income and nominal mortgage rates. Another example of this approach is Shiller (2005) or Gallin (2006) who used aggregate data on home prices, building costs, personal income, population, and interest rates. They showed that the rapid growth of U.S. house prices after 2000 could not be explained by changes in the fundamentals.

The second stream of this literature relies on regional or micro data in order to gain a more informative insight into the drivers of housing market prices. For example, Himmelberg et al. (2005) focus their attention on 46 Metropolitan Statistical Areas and developed a novel methodology for calculating the cost of owning a house. They used that methodology to prove that the high price-to-rent ratios and value-to-income observed in recent years can be sufficiently explained by changes in long term interest rates. They concluded that there is not sufficient evidence to infer the presence of a speculative bubble in the U.S. housing market. Himmelberg, Mayer and Sinai (2005) focus on the New York and London housing markets.

Using micro data they aim to understand the main drivers of housing bubbles. The conclusion of their paper is that housing markets are not as susceptible as suggested by the literature to an explosive bubble behaviour. They suggest that a rise in house prices is more likely to be due to changes in fundamentals instead of a bubbling behaviour. Their conclusion rests on three lines of reasoning: first, the annual cost of owning a house is not equivalent to the price of the house itself. Consequently, changes in the prices or values of a property do not translate to increased costs of owning the place (which may in turn lead to a bubble burst). Second, exponential growth in the price of a property should not always be taken as evidence that the price of the house has deviated from its fundamentals (i.e. existence of a bubble). The authors argue that it is not uncommon for house prices to rise and exceed the national average rate of appreciation for a few years before they return to their trend. Third, the price-to rent ratio is not solely defined by the price of the house. Changes in taxes or other macroeconomic variables can lead to significant variability in the price-to-rent ratio across markets. Finally, the authors conduct a sensitivity analysis of house prices to shifts in fundamentals. They find that house prices are more susceptible to speculative bubbles when real, long-term interest rates have been kept low for some time while at the same time the expected appreciation of the real estate market is high. However, they note that accelerating house prices should not always be taken as evidence of a bubble.

Smith and Smith (2006) use a sample of matched single-family homes in their research on the impact of fundamentals on house prices. Interestingly, compared to the rest of the literature that found evidence of speculative house bubbles in the US, these authors conclude that house prices were below their fundamental value. To reach this conclusion they use the prices of rents and find that for those given rent values, the price of the property could have been much higher.

Case and Shiller (2003), using regional data and the results of a survey of consumers' attitudes towards housing find some evidence in favour of the emergence of a speculative bubble in some regional U.S. housing markets. Their results, however, are only applicable to the US regions that they analyse and the external validity of their findings is somewhat limited.

Furthermore, Gallin (2006) and Mikhed and ZemcÅŕk (2007) aim at understanding house price dynamics using panel data for the US Metropolitan Statistical Areas. Gallin (2006)

uses income as the fundamental factor in his analysis. Mikhed and Zemc̃ank (2007) use rent as the only fundamental factor in their study. Panel data stationarity tests are used for both studies. Both studies were unable to find evidence that house prices can be explained by shifts in either of the two fundamental variables. They therefore conclude that price changes must be explained by something different to fundamental values. We consider that the lack of explaining power of their tests arises, probably, as a result of failing to take into consideration elements of the demand and supply side in the housing market.

Mikhed and Zemcik (2009) continued on this strand of research and incorporated more variables in their analysis to test again if fundamental values could be used to explain shifts in house prices and speculative housing bubbles. To do so, they employed a panel dataset that included other fundamental variables such as construction costs, income, population, stock index, mortgage rates and rents. All the variables were deflated using a regional Consumer Price Index to get their real value. The authors recognised the possibility of some correlation between the individual time series that they use for their analysis. This is because close regional house markets in terms of geographical proximity tend to be synchronized to a certain degree. This study partially influences our research in this chapter as it is one of the first studies to provide some evidence towards our hypothesis: regional housing markets co-bubble and the shorter the distance between them, the shorter the amount of time it would take for the bubble to migrate from one region to the other.

Cross-sectional dependence is confirmed in Mikhed and Zemcik's (2009) dataset by employing a test from Pesaran (2004). The authors subsequently test for unit roots in all of the involved time series. The authors use an updated version of Im et al.'s (2003) panel unit root test based on an average of t-statistics for autoregressive coefficients in individual Dickey-Fuller regressions. The test they choose to use was developed by Pesaran (2007), and is robust to cross-sectional dependence. The hypothesis that the authors are aiming to test is the following: if house price changes reflect changes in the fundamentals then non-stationary house prices should be co-integrated with other variables. When applying this method to their panel data, they find that their house price series contains a unit root only prior to 2006.

Aggregate data unit root tests cannot reject the unit root in any sub-sample of their dataset. This is in line with the econometric literature that suggests that that panel data unit root

tests have greater power as compared with univariate econometric methodologies. Their study also shows that house prices are not co-integrated with any variables of the same order of integration. To test the robustness of their specification, the authors also split their sample into two periods: before and after 1996. They observe similar statistical characteristics and patterns of behaviour in both sub-samples. Therefore, the authors conclude that is a deviation of house prices from their fundamental value before 2006. Furthermore, the overall outcome of their panel data tests is consistent with the results generated using the aggregate data. Their conclusion is that house prices can move away from their fundamentals for considerable periods of time.

Finally, another way of splitting the housing bubble literature (instead of interregional v aggregate house price shifts, as we have done so far) would be by drawing on lessons from the financial literature. A large amount of academic literature on bubbles is based on financial markets models. The dominant theory of asset pricing is that stock prices are equal to the sum of expected discounted dividends and when market prices deviate from such fundamental value then a 'bubble' may exist. Typically, the financial literature splits the types of speculative bubbles into three key categories according to their characteristics: momentum, explosive and intrinsic. We consider all these types of bubbles in our discussion of the results of this chapter. Momentum investor behaviour that leads to momentum type bubbles, is driven by price alone. Investors buy stock/houses following price increases and sell stock/bubbles after price decreases (DeLong et al., 1990; and Barberis et al., 1998). Such momentum is observed when a price rise (fall) is expected to continue to rise (fall). This is the only type of bubble that the literature typically takes as evidence against investor rationality in the marketplace. By contrast, the two other types of bubbles are usually seen as providing evidence that investors do make rational decisions. In the instance of explosive rational bubbles, prices deviate from their fundamentals as a result of factors extraneous to the value of the asset itself. This means that an exogenous shock can make the price of an asset to deviate from its fundamental value as a result of investors reacting swiftly to the updated expectations. Such bubbles diverge continuously without returning to their fundamental value. These bubbles are also never negative because this would imply a negative asset value (Diba and Grossman, 1988). Intrinsic rational bubbles derive all of their variability from exogenous fundamentals rather

than from extraneous factors (Froot and Obstfeld, 1991). Unlike explosive bubbles, intrinsic bubbles do not continuously diverge but periodically revert back to their fundamental value.

3.3 Definition of a housing bubble

Consensus has not yet been reached on the definition of a housing bubble despite numerous papers that attempted to provide some clarity on the issue. More specifically, researchers are yet to provide a convincing model that distinguishes a significant increase in house prices due to fundamental factors of supply and demand from one caused by speculative behaviour. This section discusses a number of proposed definitions for what would constitute a (housing) bubble and subsequently introduce the definition that we will be using throughout this paper for our analysis.

Kindleberg (1987) was one of the first academic papers that tried to provide a definition of what might constitute a bubble in housing prices. He claimed that a bubble is 'a sharp rise in price of an asset or a range of assets in a continuous process, with the initial rise generating expectations of further rises and attracting new buyers generally speculators interested in profits from trading asset rather than its use or earning capacity. The rise is usually followed a reversal of expectations and a sharp decline in price often resulting financial crisis.' Stiglitz (1990) provided a general definition of asset bubbles as follows: 'if the reason that the price is high today is only because investors believe that the selling price is high tomorrow – when 'fundamental' factors do not seem to justify such a price – then a bubble exists. At least in the short run, the high price of the asset is merited, because it yields a return (capital gain plus dividend) equal to that on alternative assets.' Smith et. Al (1996) define a bubble as a situation in which the market prices assets (such as stocks or real estate) rise far above the present anticipated cash flow from the asset (what Kindleberger use or earning capacity). Since then, research on this topic stagnated and not much effort has been put in understanding explosive bubble behaviour better.

Following the 2008-2009 financial turmoil a number of theoretical methods that aim to model speculative financial bubbles have been developed. This has resulted in a new area of literature that discusses the efficacy of unit root tests for detecting explosive rational asset price

bubbles. See, for example, Phillips, Wu and Yu (2011) and Homm and Breitung (2012) who use recursive right tailed Dickey-Fuller tests to test the null of a series being $I(1)$ against the alternative of an explosive autoregression. More recently, Harvey et al. (2014) [HLS] suggest using Bayesian Information Criterion (BIC) model selection procedure to identify bubble behaviour. This procedure also allows for estimation of the start and end dates of the bubble and can distinguish between various different types of bubble processes, for instance, identifying a bubble that does or does not end in a collapse, or a bubble that continues to the end of the sample. However, the possibility of co-bubbling, where two explosive series differ only by a stationary $I(0)$ component had not been explored yet.

It is this concept we introduced and developed a testing methodology for in the second chapter of this thesis because we believed that it would offer a more insightful view on the long run relationship between two variables. Our concept of co-bubbling also naturally led into the notion of testing for bubble migration, where one bubbling series leads (or lags) another. Attempts have been made to empirically document bubble migration (see, for example, Kivedal, 2012) however these approaches lacked a robust statistical foundation.

Specifically, we considered testing the null hypothesis of co-bubbling between two series using a version of the stationarity test of Kwiatkowski et al. (1992) [KPSS]. Controlling size for our test was a key challenge in chapter 2 as the null critical value of this test depends on the form of the bubble processes involved. To get round this problem, we adopted a simple conditional 'wild' bootstrap. Extensive Monte Carlo simulation exercises showed that the procedure controlled size well, even in the presence of heteroscedasticity. The power of our test to reject a false null of co-bubbling was also investigated via simulation, and shown to be very encouraging. Combining this test with the bubble identification and dating procedure of HLS gave a robust empirical methodology for detecting the presence of co-bubbling. We demonstrated this via an application involving world silver and gold prices.

3.4 The long run relationship between house prices and income

In this chapter we also test the hypothesis that bubbles in incomes may lead to bubbles in house prices (or vice versa).

Income can be used as an indicator for a household's wealth. An increase in wealth increases a household's ability to buy. Cash constrained households tend to be more severely affected by fluctuations in wealth. This is because these fluctuations would affect their ability to borrow as the maximum borrowing amount is usually a multiple of one's total income. In combination with the low interest rates that we have experienced over the past few years, increased incomes are likely to have led to bubbles in housing prices through an increased demand for housing.

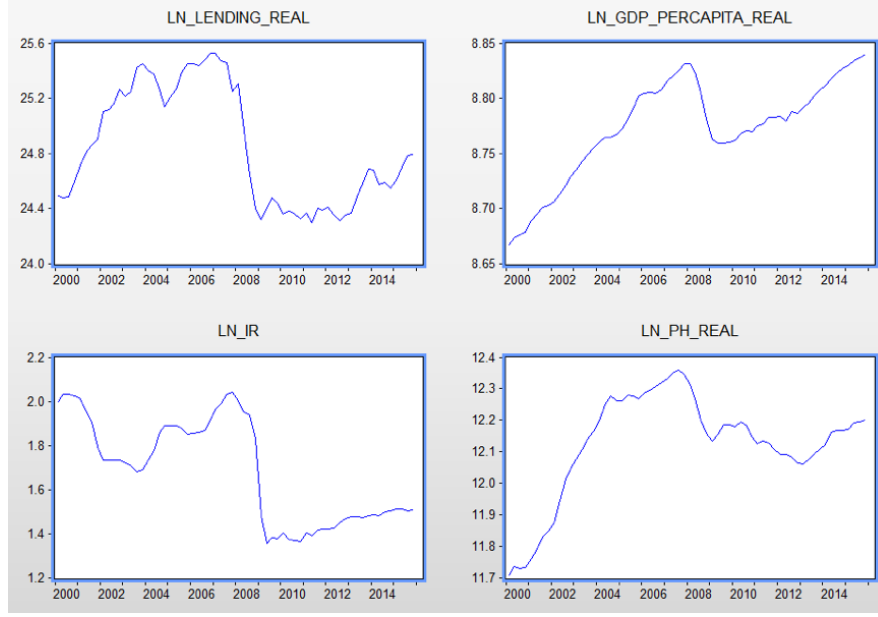
There are many measures of income. Oikarinen (2009) in his study on the housing market uses the total economy's GDP because it captures the general economic environment. Another way of measuring wealth is using the Office for Budget Responsibility's approach that uses GDP per capita in their economic analyses as it reflects the average person's income, and hence ability to pay. Finally the NHPAU (2008) study used the household disposable income because it controls for changes in population. For the purposes of this chapter we choose to follow the Office's for Budget Responsibility and employ Average Gross Domestic Product per head as the explanatory variable.

Figure 3.2 describe both the fundamentals (GDP per capita, interest rate and real lending) as well as housing prices. If we were to superimpose the graph showing the prices of houses in the UK and the graph with the trend in GDP per capita, we may have concluded that there is a long run co-bubbling relationship between house prices and GDP per capita.

The plots in Figure 3.2 describe real lending (LN_LENDING_REAL), real GDP per capita (LN_GDP_CAPITA_REAL), the real interest rate (LN_IR), and the real house prices (LN_PH_REAL). Recent research argues that the exceptionally high house prices relatively to income should be seen as evidence that house prices have significantly deviated from their fundamental and therefore a speculative bubble must be emerging. Some researchers have even gone as far as to say that due to this unsustainable house price increase, there comes a period when the bubble will burst.at house prices must stagnate or fall to allow income to catch up.

The literature would typically examine this concept by assuming a co-integrating relationship between house prices and income, or other fundamentals. Researchers would then esti-

Figure 3.2: The movement of housing prices and fundamentals since 2000



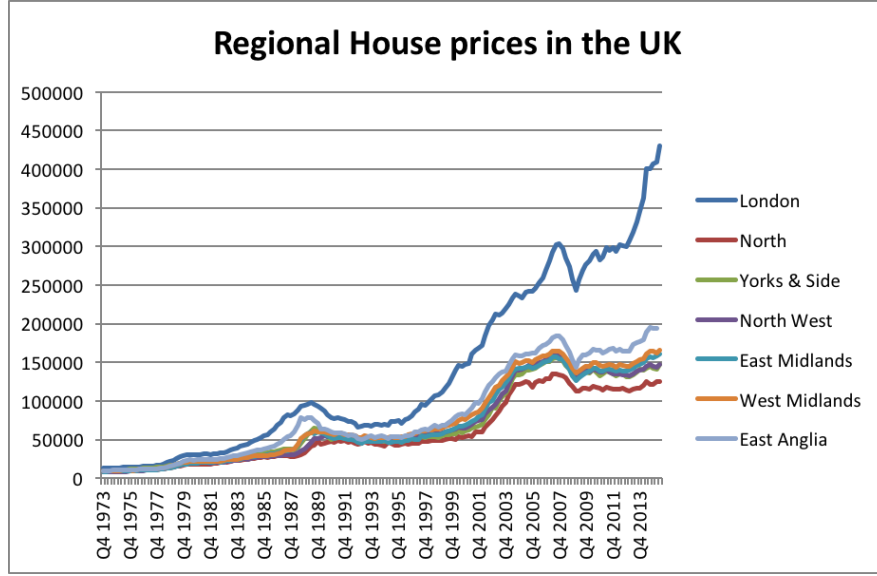
mate an error-correction specification to identify the correct values of the relevant parameters (Malpezzi, 1999; Capozza et al., 2002; Meen, 2002). This means that income and house prices are taken to be interlinked through a stable long-run relationship. However, this relationship is allowed to deviate from time to time as long as it returns to its long run equilibrium.

The justification provided for this theory (i.e. co-integrating relationship between house prices and incomes) is the following: The supply of housing, at least in the short-run, would have a positive slope. This is because it is not easy to build new houses in the short run and there are also zoning restrictions to be taken into account (Glaeser and Gyourko, 2002). Because demand-side shocks such as population and income are not stationary, then it is reasonable to expect house prices to be non-stationary as well. However, if other shocks to the demand curve and all shocks to the supply curve are stationary, then population, income, and price will be related in a way that depends on the elasticities of supply and demand.

3.5 Bubbles between regions

In this chapter we explore how housing bubbles migrate between geographical regions. As we will subsequently demonstrate, changes in wealth do not effect or contribute to housing bubbles. However, distance between regions plays a considerable role in determining the

Figure 3.3: Quarterly Regional House Prices in the UK since 1973



duration of bubble migration. Therefore, for the remaining of this chapter our attention will be focused on the relationship between geography and house prices. A closer look at Figure 3.3 shows that house prices in the UK appear to be strongly correlated and changes in house prices across UK regions appear to happen almost contemporaneously.

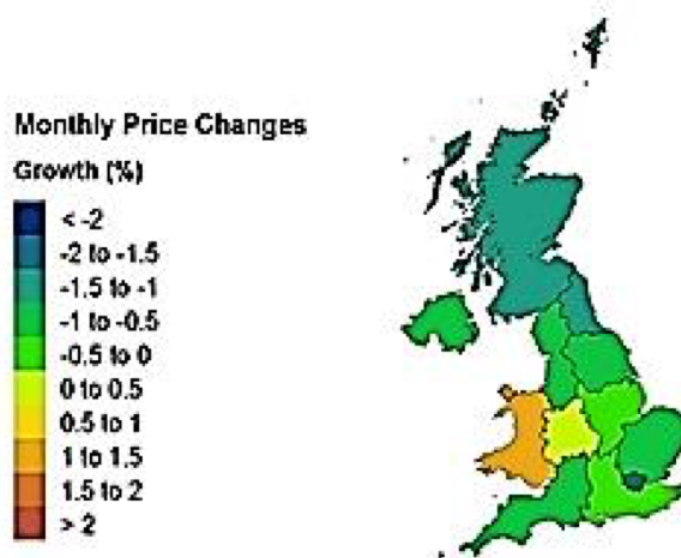
Further, the heatmap of the UK in Figure 3.4, taken from the Office of National Statistics website, provides stronger indication that a co-bubbling relationship or at least a strong correlation in housing prices between regions is plausible. Figure 3.4 shows the monthly price change in housing for 2016. We note that areas with close proximity tend to have similar growth rates in housing prices. Similarly coloured regions are located close to each other, whereas the further a region becomes from another, the higher the likelihood that the housing price changes experienced in those areas will be different.

I

3.6 Inter-regional bubbles empirical application

Housing markets have gained high prominence over the past few years - especially in London where investors speculate that the bubble is about to burst. The financial regulation liberal-

Figure 3.4: Rent price heatmap of the UK



isation and development in complex mortgage products further amplified the importance of the housing market and speculation on this market.

In this chapter we are interested in finding out whether there is some form of bubble migration between UK regions and place special attention on the case of London and its peripheral areas.

We are also interested in finding out how long it takes between the onset of a housing bubble in one geographical area and the onset of another housing bubble in another area - as well as the variables that may determine this time lag.

As a result, we choose to focus on testing the following three hypotheses:

- Within the UK there are strong co-bubbling relationships of house prices between different regions.
- Distance between geographical areas has an effect in determining the intensity of the bubbles that are predicted to occur.
- Wealth differentials within geographical regions have an effect in determining the intensity of the bubbles that are predicted to occur. Our theory is that positive and significant changes in incomes within regions may lead to housing bubbles. There is a series of theoretical and empirical papers that support the view that house prices and

income are co-integrated, thus they could possibly co-bubble.

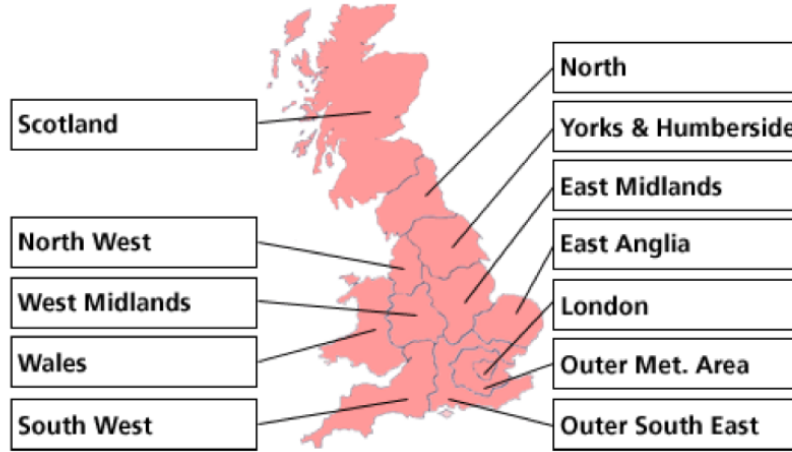
3.7 Data

We choose to use data from well-recognised and trusted sources to estimate the validity of our hypotheses. The Nationwide dataset provides the richest source of data on housing prices across the UK. They provide the longest unbroken run of house price data, stretching back to 1952 on a quarterly basis and 1991 on a monthly basis. House prices are mix adjusted. This means that they are tracked using a representative house price over time rather than the simple average price. The reason for doing so is because the average price can be easily influenced by a change in the mix (such as the proportion of different property types and their locations) of houses. Sample size is based on the number of new loans that Nationwide writes; that is the amount of gross lending for house purchase. Buy-to-let purchases are not included in the data sample. We consider this to be a considerable benefit to our data set because house purchases for the sole purpose of renting the property would skew the results in a way that houses are purely seen as an investment asset. The Nationwide Building Society is currently the second largest mortgage lender in the UK. This allows us to be confident that the series based on Nationwide mortgage data is representative of the whole house market. All the data is in real terms.

We note that the Nationwide definition of regions differs from the ONS definition. The Nationwide definition excludes Cumbria which is added to the North East to comprise the North. The London region comprises the boroughs of London. The Outer Metropolitan region surrounds London and includes among others, South Essex, Reading, St Albans, and Medway. The Outer South East includes North Essex, Oxfordshire, Brighton, Southampton and Sussex. The map of definitions of regions is taken from the Nationwide website and is provided in Figure 3.5.

Data on the wealth/income across UK geographic regions is sourced from the Office of National Statistics. We use quarterly GDP per capita on a constant price basis. The national accounts are drawn together using data from many different sources. This ensures that the national accounts are comprehensive.

Figure 3.5: Geographic regions of the UK



In order to measure the distance between regions we looked at the population in each county that is included in the relevant regions. We use the highest population density city as a proxy for the centre of the region from which we want to measure the distance. We consider that using population to determine the centre of a geographical region is an appropriate approach as higher population would naturally also indicate a higher density of houses. This in turn, makes it more likely that the average house (as we are looking at average house prices) is likely to be found in the city with the highest population. Data on the population of each city was also sourced from the ONS. We used the population declared at the end of 2016. Table 3.6 in the Appendix shows the cities which we have used as proxies for each geographical region and their relevant population.

Once we have determined the city which we would use as a proxy for the geographical region, we map the distance between the regions using google maps. The distance is reported in miles. We use driving distance instead of flying or other methods of commuting. We consider this to be the most accurate way of incorporating the ease of travel in our analysis. Table 3.7 in the Appendix shows the distance between the geographical regions analysed in this chapter.

3.8 Method

To test the hypotheses that we presented in section 5, we employ the co-bubbling test that was developed in the previous chapter. Our hypotheses were (a) that within the UK there are

strong co-bubbling relationships of house prices between different regions, (b) that distance between geographical areas has an effect in determining the intensity of the bubbles that are predicted to occur and (c) that wealth differentials within geographical regions have an effect in determining the intensity of the bubbles that are predicted to occur. Our theory is that positive and significant changes in incomes within regions may lead to housing bubbles. There is a series of theoretical and empirical papers that support the view that house prices and income are co-integrated.

The test developed in Chapter 2 looks for the presence of a co-bubbling relationship between two series. It only finds co-bubbling relationships if the bubbles in the two series are of the same type. The bubble types admitted by the model are the ones developed by HLS. These are: Model one: random walk and then bubble until the end of the sample, Model 2: random walk then bubble and then random walk again to the end of the sample, Model 3: random walk, then bubble, then stationary regime (collapse) until the end of the sample and Model 4: random walk, then bubble, then stationary regime, then random walk until the end of the sample. The advantage of the co-bubbling model that was developed in Chapter 2 is that it allows us to time the duration of the co-bubbling relationship and to some extent infer the migration of a bubble from one series to another.

The first step to understanding the interplay between housing prices and fundamentals is to establish whether a long run co-bubbling relationship exists. The fundamentals of interest for this chapter are income (GDP per capita) and the prices of the houses in the neighbouring regions. Firstly, using the HLS bubble model we check for the existence and types of bubbles in each series. We find a number of bubbles of different types in the housing markets of the different regions. The types of bubbles that we find and their timing is presented in Table 3.1. Conversely, the model does not identify any income bubbles. This is not surprising as incomes have been relatively steady over the past years. Consequently, we do not continue to run our co-bubbling model on the income series. As no significant results were found with regards to income, we do not present those results in this chapter.

However, because we identified explosive bubble behaviour in the house prices of different regions we proceed to use our co-bubbling model on those regions. The HLS model identified

bubble behaviour in all 13 series. We only apply our co-bubbling test on the regions that have presented the same type of bubble. Once we have identified the set of regions whose housing markets co-bubble we measure the distance in miles between the main counties of each region that were identified as having a co-bubbling relationship. As previously discussed, the main counties are chosen according to their population. We use as proxy for each region the county with the highest population.

To understand whether distance plays a role in determining the time it takes between two regions to co-bubble, we run a standard OLS regression. Our initial specification uses the distance between two regions and the wealth differential between the same regions as the independent variables. The outcome variable is the time lag between the two regional bubbles, as identified by our co-bubbling model.

The exact regression specification is below:

$$lag_i = \alpha + \beta dist_i + \gamma wagedif_i + \epsilon$$

Where lag_i is the absolute average value of the lag/lead between the two bubbles.

$dist_i$ is the distance in miles between the two cities.

$wagedif_i$ is the wealth differential between the two regions (as measured as the difference between GDP per capita in the two regions).

ϵ is the error term

The reason that we have re-introduced the wealth variable in our specification is to ensure that we rule out any impact that wealth may be having on housing prices (eventhough as we mentioned before, wealth does not follow any bubble type as described by the HLS model). Including wealth in the OLS regression gives us an indication on whether income might have a short run effect on the co-bubbling relationship between regions. We find 71 co-bubbling pairs of regions. We then only select those pairs of regions leads(lags) where the leads(lags) times for which co-bubbling is found all have the same sign: all positives or all negatives. This reduces the number of pairs to 34. Subsequently, we take the average of those positives

or negatives leads(lags). This is used as the dependent variable in the regression.

3.9 Results

The results generated by the HLS bubble model are presented in Table 3.1. The table shows that the first housing bubble occurred in Northern Ireland. The last region to experience a housing bubble is York and the Humbers. The type of bubble model that formed in each region is also provided in Table 3.1. The most common type that we observe is Model 2, that is Random walk, then bubble and then Random walk again.

Table 3.1: HLS Bubble model selection for rental and housing prices across regions

	Random walk to	Bubble to	Stationary to	Collapse to	HLS bubble type
North	Q3 1995	Q3 2004	N/A	end of sample	2
York and Hside	Q1 2002	end of sample	N/A		1
North West	Q4 1995	Q3 2004	N/A	end of sample	2
East Midlands	Q1 1996	Q3 2004	N/A	end of sample	2
West Midlands	Q4 1995	Q3 2004	N/A	end of sample	2
East Anglia	Q2 1999	Q1 2008	Q4 2009	end of sample	4
Outer S East	Q2 1999	Q4 2007	Q4 2009	end of sample	4
Outer Met	Q2 1996	end of sample	N/A		1
Greater London	Q1 1996	end of sample	N/A		1
South West	Q1 1999	Q4 2007	Q4 2009	end of sample	4
Wales	Q1 1996	Q3 2004	N/A	end of sample	2
Scotland	Q1 1997	Q3 2007	end of sample		3
Northern Ireland	Q4 1991	Q4 2007	end of sample		3

We have found a total of 71 co-bubbles in our data set. Figures 3.6 to 3.8 provide three examples of six UK geographical regions that this chapter has identified as having a co-bubbling behaviour. We first choose the example of North and North West (Figure 3.6) as the distance between the two regions is relatively small and, as we expected, the time lag between the two bubbles is also short (about three quarters). The HLS model that was fitted to these two regions is the second one, i.e. the series is firstly defined by a random walk and subsequently by a bubble behaviour and finally by a random walk behaviour to the end of the sample. The vertical lines show the beginning of each regime (random walk and then bubble and then random walk). This can be seen in Figure 3.6. Table 3.2 provides the timing of the bubble,

i.e when the random walk finished and when the bubble started.

The second graph (Figure 3.7) shows the co-bubbling behaviour between two geographical regions that are further apart - Northern Ireland and Wales (distance between the two regions is 372 miles). Despite the fact that our test shows that the two regions have a strong long-run co-bubbling relationship, the bubble migration takes around four years. The HLS model that was fitted to these two regions is the second one, i.e. the series is firstly defined by a random walk and subsequently by a bubble behaviour and finally by a random walk to the end of the sample. The vertical lines show the beginning of each regime (random walk and then bubble and then random walk). This can be seen in Figure 3.7. Table 3.3 provides the timing of the bubble, i.e when the random walk finished and when the bubble started.

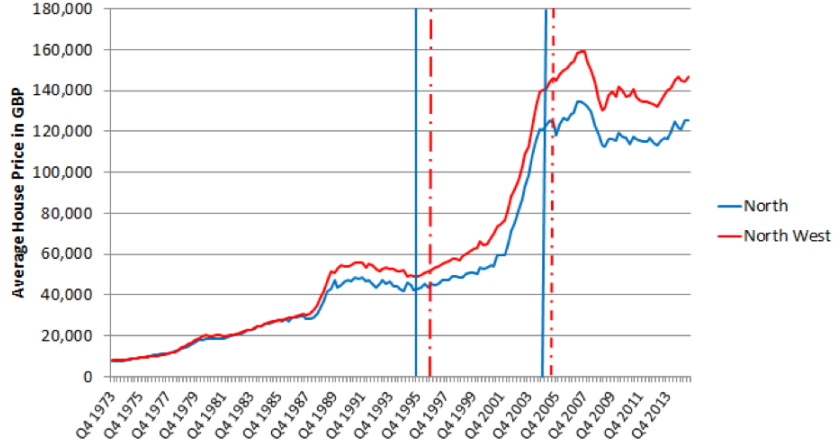
The third graph (Figure 3.8) shows the co-bubbling behaviour between two geographical regions that are 163 miles apart - East Anglia and Outer South East. Despite the fact that the two regions are almost as far away from each other as the North and North West, the bubble behaviours begin almost contemporaneously. The HLS model that was fitted to these two regions is the fourth one, i.e. the series is firstly defined by a random walk and subsequently by a bubble behaviour, then stationary and then collapses to the end of the sample. The vertical lines show the beginning of each regime (random walk, then bubble, then stationary, then random walk). This can be seen in Figure 3.8. Table 3.4 provides the timing of the bubble, i.e when the random walk finished and when the bubble started.

The remaining co-bubbling relationships are provided in the Annex to this paper.

The estimates of our co-bubbling test for the first pair of geographic regions (North and North West) can be found in Appendix 1.

Once we have identified the set of regions that co-bubble, we run the regression specification that we discussed in the Method section. We use average leads(lags) as the dependent variable, and distance and wealth as the independent variables. We find that wealth has no effect in determining a co-bubbling relationship between two regions. Before we drop the variable we run a Redundant Variable Likelihood Ratio test to confirm that the wealth differentials are

Figure 3.6: Example of North and North West (distance 145 miles)

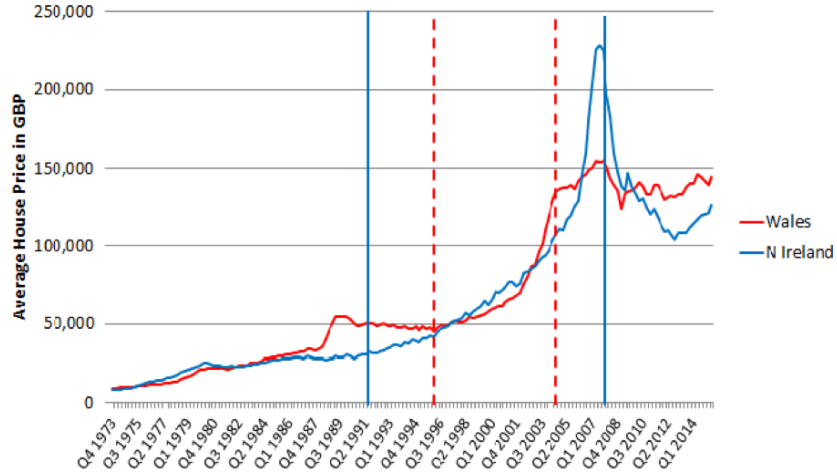


Blue vertical lines indicate bubble start/end in the North; red vertical lines indicate bubble start/end in North West

Table 3.2: Bubble timing North and North West

Region	Random walk to:	Bubble to:
North	Q3 1995	Q4 2004
North West	Q2 1996	Q2 2005

Figure 3.7: Example of Wales and Northern Ireland (distance 372 miles)

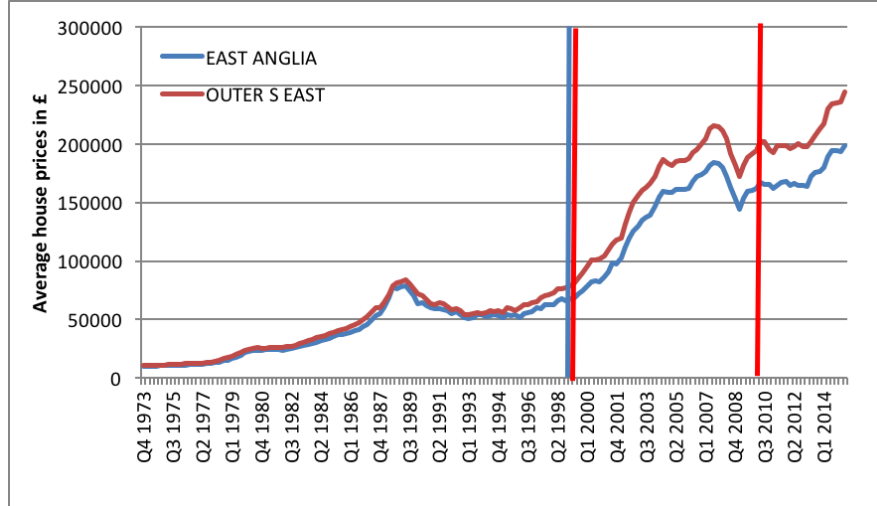


Blue vertical lines indicate bubble start/end in N Ireland; red vertical lines indicate bubble start/end in Wales

Table 3.3: Bubble timing Wales and Northern Ireland

Region	Random walk to:	Bubble to:
N Ireland	Q4 1991	Q4 2007
Wales	Q1 1996	Q3 2004

Figure 3.8: Example of East Anglia and Outer South East (distance 163 miles)



Blue vertical lines indicate bubble start/end in East Anglia; red vertical lines indicate bubble start/end in Outer S East

Table 3.4: Bubble timing East Anglia and Outer South East

Region	Random walk to:	Bubble to:	Stationary to:	Collapse to:
East Anglia	Q2 1991	Q1 2008	Q4 2009	End of sample
Outer South East	Q2 1991	Q4 2007	Q4 2009	End of sample

unable to explain co-bubbling lags/intensity. The test confirms our hypothesis. We proceed with our analysis and drop the wealth variable.

We subsequently run the regression:

$$lag_i = \alpha + \beta dist_i + \epsilon$$

The new regression provides the following results:

$$lag_i = 1.901 dist_i + \hat{\epsilon}$$

- R-squared = 0.260
- st. error: 0.177145
- t-ratio: 10.7323

We note that, for clarity purposes, distance has been divided by 100. Table 3.9 in the Appendix provides the full statistics of our new regression specification.

Our best fitting model allows us to conclude that the distance between two regions can have a significant impact on the average lead(lag) of the two bubbles.

We note that our regression, unsurprisingly, indicated an insignificant constant. This is because if two houses are built on exactly the same space then it would be meaningless to assume that their price trends will differ over time. We also note that the relatively high R-squared value gives us confidence that distance explains relatively well the time length between co-bubbles.

We appreciate that we have made a number of assumptions in developing our methodology. Therefore, to ensure that our specification is correct and robust as much as possible we run a series of robustness checks. We suspect that there might be heteroskedasticity present in the regression residuals. A White heteroskedasticity test confirms our suspicion. To improve our

regression output we need to use heteroskedasticity consistent standard errors.

Our results are not affected significantly; the only effect that we observe is the standard error is changing to 7.85 from 10.73. The results from the regression using heteroskedasticity consistent standard errors are presented in Table 3.11 in the Appendix.

Due to the particularly restricted form of our specification (we only test for one variable), it is reasonable to expect that the explanatory power of the specification is low and that there might be a high probability that we have misspecified our model. The consequences of model misspecification in our regression can be severe in terms of the adverse effects on the sampling properties of both the estimators and tests. To ensure that our results are correct and robust we run a Ramsey Reset test. This test checks whether non-linear combinations of the fitted values help explain the outcome variable. We have also run a goodness-of-fit Jarque-Bera test for normality of errors. The test did not reject the hypothesis of normal errors. The output from the Ramsey Reset test is provided in Table 3.12 of the Appendix.

In light of the results generated from the diagnostics test, we are satisfied that our specification is correct and proceed to analyse the mechanism of effect between the distance between geographic regions and the likelihood of a co-bubbling relationship.

We believe that the most suitable explanation for our results comes from the area of spatial economics. According to this area of research, the closer two geographical regions are to each other, the stronger the trade links between them and the more integrated their labour markets become. Hamilton and Owyang (2012) refer to these effects as clusters of cities that experience simultaneous idiosyncratic housing cycles. Clusters of cities that are highly susceptible to bubble migration have often been identified in the literature (Davis, Morris A et al. (2005), Del Negro (2007), Iacoviello et al. (2010)).

It is not unreasonable to expect that when a geographical region (area A) begins experiencing exceptionally high house prices, the workers living in that area will seek to purchase a property in a nearby area (area B) (assuming that transport links are convenient enough to allow for an easy commute). The surge in demand for real estate in the neighbouring area is likely to lead in turn to another housing bubble in area B.

Workers are less likely to migrate to areas that are much further from the region where they

are employed and if they do so this would only happen once the prices in area B become prohibiting high. We can therefore conclude, that a housing bubble in area A will migrate much faster to area B than to area C.

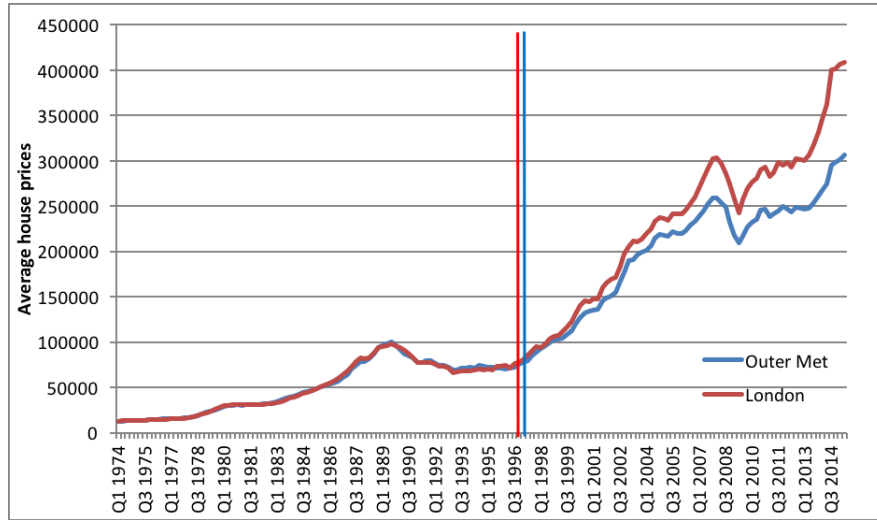
3.10 The London housing market

Since the financial crisis, house prices have grown faster than earnings across the country. London and the South East have been impacted the most by this exponential house price growth. The ratio of house price to earnings rose from 7.8 to 12.9 in London between 2009 and 2016. Figure 3.9 tracks the house prices in London and the outer metropolitan between 1973 and 2015. The model selected by the HLS bubble procedure to fit the London house prices is the first one. That means that house prices in London had a random walk behaviour up until 1996 and since then there has been an explosive bubble behaviour that has not returned to its long run trend. The same bubble model also fits the outer metropolitan area's prices. However, the two series do not co-bubble. Our co-bubbling test indicated that London does not co-bubble with any other UK region, not even with the Outer Metropolitan region which is less than 50 miles away. Table 3.5 presents the time that the random walk pattern ended for London and the Outer Met and when the bubbles began. These are computed using the HLS bubble test procedure.

The lack of a long run co-bubbling relationship between London and any other region is in contrast to a considerable part of the academic literature on this topic. Peasaran et. al (2010) in their paper on spatial and temporal diffusion of house prices in the UK find that shocks in the London housing market will very shortly migrate to the neighbouring areas. However, they do not specifically test for bubble migration in the context of the definition that we have provided for a bubble.

Pesaran develops a novel method for the analysis of the spatial diffusion of shocks in a dynamic system. Our method does not take into account dynamic variations. They use changes in real house prices within the UK economy at a regional level to demonstrate the implications of their paper. They find that exogenous shocks to a dominant region such as London diffuse contemporaneously and spatially to other geographic regions. They in turn impact on other

Figure 3.9: London and Outer Metropolitan housing prices



Blue vertical line indicates bubble start in the outer Met; red vertical lines indicates bubble start in London

Table 3.5: Bubble timing London and Outer Metropolitan.

Region	Random walk to:	Bubble to:
London	Q1 1996	End of sample
Outer Met	Q2 1996	End of sample

and across space include van Dijk et al. (2007) and Holly et al. (2009).

3.11 Limitations

In this section we discuss the limitations of our analysis and ways that can be improved in future research. We also explore avenues for enriching this strand of research to better understand what drives housing bubbles. Our first limitation is the data itself. A richer data set that could link postcodes to the actual price of houses would allow us to estimate the precise relationship between geographic distance and housing bubbles. Furthermore, we wouldn't have to use the average price of a house per region but instead we would be using more precise numbers that would enrich our conclusions.

We believe that there could be other factors that can explain the speed of bubble migration in housing markets such as the ease and cost of transport from one area to another, restrictions to credit on real estate (see Carrasco-Gallego (2013)) and housing planning permissions that can affect the supply of housing (see Rubio (2014)). We propose to explore these avenues in future research.

Furthermore, in a regional context proximity of one region to another can depend on transport infrastructure. The ability to commute easily between two areas is likely to be a much better indication of economic inter-dependence than just physical closeness. To improve the validity of our results we could calibrate the distance between regions by a factor indicating the ease of transportation. We do not expect that our results would vary significantly as transport infrastructure is somewhat homogeneous across the UK. Having said that, we continue to believe that it would be useful to understand the impact that the ease of transport might have on bubble migration.

Moreover, an investigation of the macroeconomic determinants of the observed difference in the length of the house price bubbles for the different regions and their relationship to the overall business cycle is potentially of interest.

Finally, a subject for further study is to see if the co-bubbling patterns that we have identified in this chapter, continue to prevail in other economic applications, not only in the case of house

price diffusion, but also, for example, the diffusion of technological innovations using a suitable economic distance. We are interested in exploring whether the London 'outlier' continues to persist in the analysis of other examples.

3.12 Conclusions

This chapter proposes a novel methodology for modelling the spatial and temporal dispersion of speculative bubbles in the housing markets across the UK. Using UK regional house prices we establish that the closer a geographic region is to another, the shorter the time period that it would take for a speculative bubble to migrate from one area to another. This finding is consistent with previous empirical literature.

London, however, does not co-bubble with any of the other geographical regions. We believe that this is due to London's idiosyncratic features as a large city with a strong financial sector. A number of academic papers confirm London's unique position relatively to other regions. For example, Chudik and Pesaran (2009) establish that London is a dominant region in the sense that shocks to it propagate to other regions simultaneously and over time, whilst shocks to the remaining regions have little immediate impact on London.

We also find that income does not have an effect in determining the time it would take for a housing bubble to migrate from one economic region to another. Furthermore, while theoretically, a bubble in household incomes should lead to a bubble in house prices (and vice versa), we do not find such effects.

Using the approach proposed in this paper we can track the diffusion of housing bubbles between geographical regions. Our approach lends itself to further streams of investigation of bubble migration. These could be in the context of finance or technology.

Appendix

Table 3.6 and Table 3.7 in this Appendix show the population proxies we have used and the distance between geographical regions respectively.

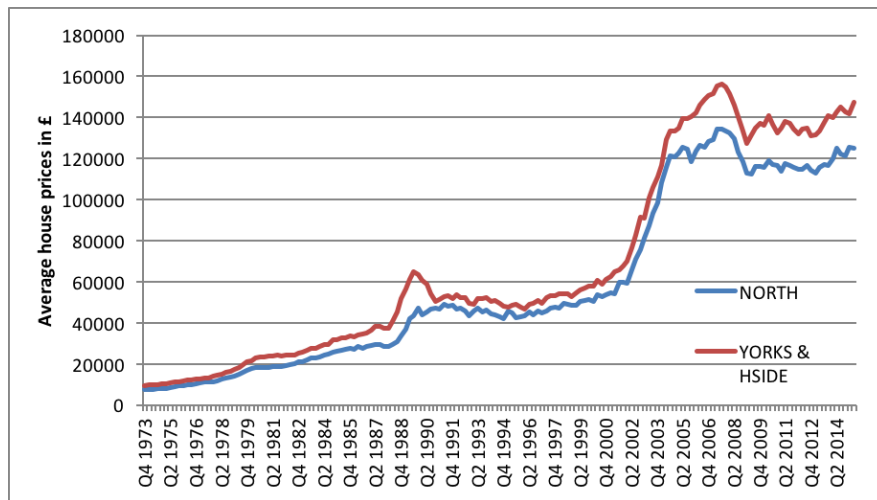
Table 3.6: Proxy counties for geographic regions

Economic planning region	County	Population
North	Northumberland	316,000
	Cumbria	496,200
	Tyne & Wear	1,118,713
	Cleveland	567,600
Yorkshire & The Humber	North Yorkshire	601,200
	Humberside	1,000,000
	West Yorkshire	2,161,000
	South Yorkshire	1,340,000
North West	Lancashire	1,450,000
	Greater Manchester	2,700,000
	Merseyside	138,000
	Cheshire	1,004,000
East Midlands	Derby	248,752
	Nottingham	729,977
	Lincolnshire	731,500
	Leicester	329,839
	Northampton	212,000
West Midlands	Shropshire	306,100
	Stafford	130,800
	West Midlands	5,675,000
	Warwick	23,350
	Hereford & Worcester	500,000
East Anglia	Norfolk	857,900
	Suffolk	730,100
	Cambridge	123,900
South East	Essex	1,396,600
	Hertford	26,000
	Bedford	79,190
	Buckingham	11,572
	Oxford	150,200
	Berkshire	803,657
	Surrey	1,085,000
	Hampshire	1,320,000
	West Sussex	808,900
	East Sussex	527,200
	Kent	1,466,500
South West	Gloucester	858,300
	Avon	1,080,000
	Wiltshire	470,981
	Somerset	531,600
	Dorset	754,460
	Devon	747,900
	Cornwall	532,300
Wales	Cardiff	341,000
N Ireland	Belfast	672,522
Scotland	Edinburgh	495,360

Table 3.7: Distance in miles between geographic regions

Region X	Region Y	Distance in miles	Region X	Region Y	Distance in miles
North	York & HSide	104	York & HSide	North	104
North	North West	149.5	York & HSide	North West	38.5
North	East Midlands	184.6	York & HSide	East Midlands	107.1
North	West Midlands	209.4	York & HSide	West Midlands	126.4
North	East Anglia	241.3	York & HSide	East Anglia	107.1
North	Outer S East	313	York & HSide	Outer S East	267
North	Outer Met	264.3	York & HSide	Outer Met	181.5
North	South West	193	York & HSide	South West	145.4
North	Wales	302	York & HSide	Scotland	257.6
North West	East Midlands	135.7	East Midlands	North West	135.7
North West	West Midlands	98.9	East Midlands	West Midlands	98.7
North West	East Anglia	192.4	East Midlands	East Anglia	57.4
North West	Outer Met	179.8	East Midlands	Outer S East	184.7
North West	South West	129.5	East Midlands	Outer Met	102.7
North West	Scotland	272.4	East Midlands	South West	169.5
West Midlands	Scotland	349.1	Outer S East	East Midlands	184.7
East Anglia	North	241.3	Outer S East	West Midlands	167.5
East Anglia	York & HSide	107.1	Outer S East	Outer Met	88.2
East Anglia	North West	192.4	Outer S East	South West	151.9
East Anglia	East Midlands	57.4	Outer S East	Wales	198.7
East Anglia	West Midlands	147.2	Outer S East	Scotland	463.5
East Anglia	Outer S East	163.4	South West	Outer S East	151.9
East Anglia	Outer Met	96.7	South West	Outer Met	100.6
East Anglia	Scotland	415.1	South West	Scotland	327.7
Outer S East	East Midlands	184.7	Outer Met	South West	100.6
Wales	North	302	Wales	North West	194
Wales	East Midlands	211.2	Wales	West Midlands	112.2
Wales	East Anglia	262.4	Wales	Outer S East	198.7
Wales	Outer Met	157.4	Wales	South West	99.3
Wales	Scotland	395	Scotland	West Midlands	298
Scotland	Outer Met	384.5	Scotland	Greater London	415
Norther Ireland	Wales	372.2	Scotland	Wales	395

Figure 3.10: North and Yorkshire housing market



The list of geographical regions whose housing markets co-bubble including the lead times between the bubbles is provided in Table 3.8.

The estimates of our co-bubbling test for the first pair of geographic regions (North and North West) are provided in Table 3.10.

In this Annex also provide a set of graphs with the regions that our model has identified as having a co-bubbling relationship. The graphs simply plot the house price path of each region between 1973 and 2016. We produce two examples for each region.

Figure 3.11: North and North West housing market

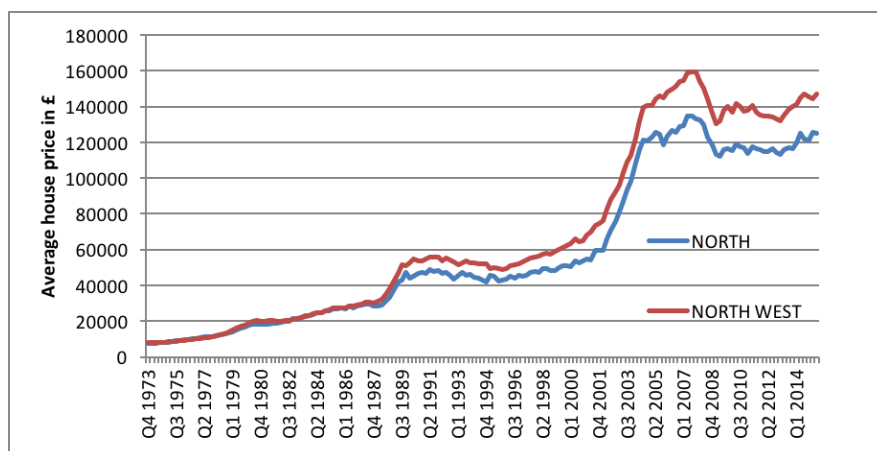


Table 3.8: Identified co-bubbling regions

Region X	Region Y	Lag (from)	Lag (to)	Region X	Region Y	Lag (from)	Lag (to)
North	York & Hside	-4	-2	East Anglia	North West	0	3
North	North West	1	5	East Anglia	East Midlands	0	4
North	East Midlands	-4	2	East Anglia	West Midlands	2	6
North	West Midlands	2	7	East Anglia	Outer S East	-5	-3
North	East Anglia	-5	2	East Anglia	Outer Met	-8	0
North	Outer S East	-5	1	East Anglia	Scotland	-7	1
North	Outer Met	-7	2	Outer S East	East Midlands	1	4
North	South West	-6	0	Outer S East	West Midlands	3	5
North	Wales	-4	-2	Outer S East	Outer Met	-7	6
North	Scotland	-7	-2	Outer S East	South West	-2	4
York & Hside	North	1	6	Outer S East	Wales	-1	0
York & Hside	North West	2	7	Outer S East	Scotland	-7	2
York & Hside	East Midlands	2	6	Outer Met	East Midlands	1	2
York & Hside	West Midlands	4	9	Outer Met	West Midlands	2	3
York & Hside	East Anglia	-4	4	Outer Met	South West	-1	2
York & Hside	Outer S East	-5	4	Outer Met	Scotland	-9	1
York & Hside	Outer Met	-5	6	Greater London	Scotland	2	4
York & Hside	South West	-5	0	South West	East Midlands	2	3
York & Hside	Scotland	-2	4	South West	West Midlands	4	6
North West	East Midlands	-3	0	South West	Outer S East	-5	0
North West	West Midlands	-2	3	South West	Outer Met	-7	3
North West	East Anglia	-4	-1	South West	Scotland	-6	1
North West	Outer Met	-4	-1	Wales	North	2	4
North West	South West	-5	-2	Wales	North West	3	6
North West	Scotland	-8	-4	Wales	East Midlands	2	5
East Midlands	North	-2	1	Wales	West Midlands	5	8
East Midlands	North West	0	3	Wales	East Anglia	-4	2
East Midlands	West Midlands	2	4	Wales	Outer S East	-5	3
East Midlands	East Anglia	-6	0	Wales	Outer Met	-6	5
East Midlands	Outer S East	-6	-1	Wales	South West	-5	1
East Midlands	Outer Met	-7	1	Wales	Scotland	-1	2
East Midlands	South West	-6	-2	Scotland	West Midlands	6	8
East Midlands	Scotland	-8	-1	Scotland	Outer Met	-1	7
West Midlands	Scotland	-10	-5	Northern Ireland	Greater London	-12	-3
East Anglia	North	-2	1	Northern Ireland	Wales	-4	-1
East Anglia	York & Hside	-1	0				

Table 3.9: Regression results of the effect of distance on the likelihood of co-bubbling

Regression details			
Valid cases:	34	Dependent variable:	Y
Missing cases:	0	Deletion method:	None
Total SS:	234	Degrees of freedom:	33
R-squared:	0.26	Rbar-squared:	0.26
Residual SS:	173.259	Std error of est:	2.291
F(1,33):	11.569	Probability of F:	0.002

Table 3.10: Co-bubbling output for North and North West

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-12	0.205	0.113	1
-11	0.198	0.11	1
-10	0.19	0.105	1
-9	0.18	0.105	1
-8	0.172	0.104	1
-7	0.165	0.102	1
-6	0.158	0.104	1
-5	0.154	0.098	1
-4	0.157	0.103	1
-3	0.165	0.106	1
-2	0.185	0.118	1
-1	0.238	0.148	1
0	0.26	0.169	1
1	0.104	0.127	0
2	0.073	0.117	0
3	0.085	0.115	0
4	0.103	0.12	0
5	0.123	0.128	0
6	0.144	0.127	1
7	0.164	0.139	1
8	0.184	0.141	1
9	0.205	0.151	1
10	0.227	0.154	1
11	0.246	0.159	1
12	0.266	0.167	1

Table 3.11: White heteroskedasticity-consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic
X	1.9	0.242	7.85
R-squared	0.26	Mean dependent var	4
Adjusted R-squared	0.26	S.D. dependent var	2.66
S.E. of regression	2.29	Akaike info criterion	4.53
Sum squared resid	173	Schwarz criterion	4.57
Log likelihood	-76	Hannan-Quinn criter.	4.54

Table 3.12: Ramsey RESET Test

Omitted vars: Powers fitted values from 2 to 3							
	Value	df	Pr.		Value	df	Pr.
t- statistic	1.053908	32	0.2998	F- statistic	0.62149	(2,31)	0.5437
F- statistic	1.110723	(1,32)	0.2998	Likelihood ratio	1.33664	2	0.5126
Likelihood ratio	1.160123	1	0.2814				

Figure 3.12: Yorkshire and North West housing market

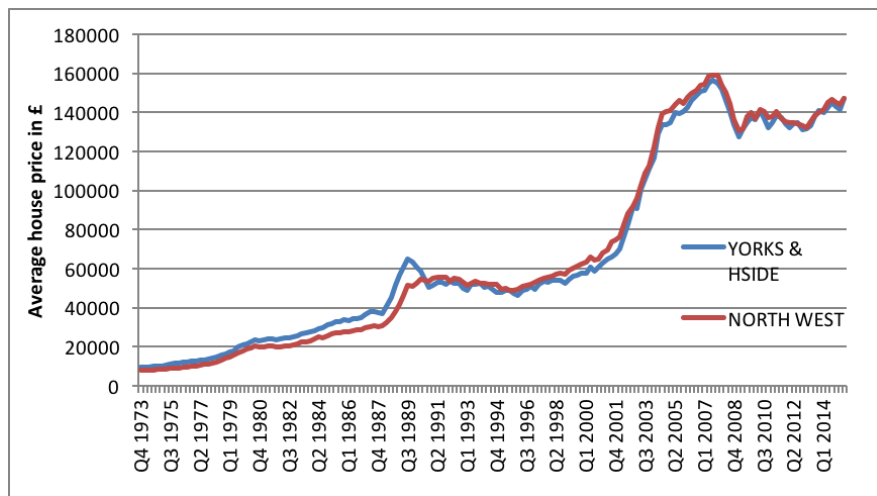


Figure 3.13: Yorkshire and East Midlands housing market

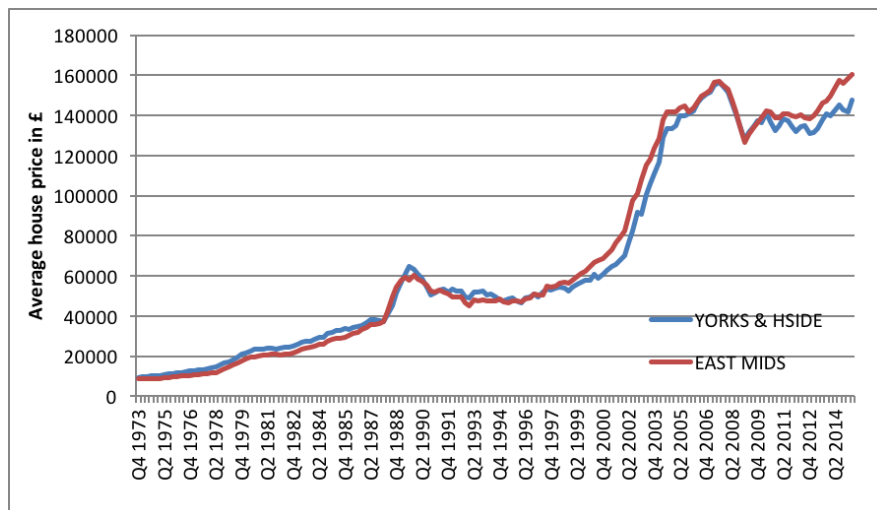


Figure 3.14: North West and West Midlands housing market

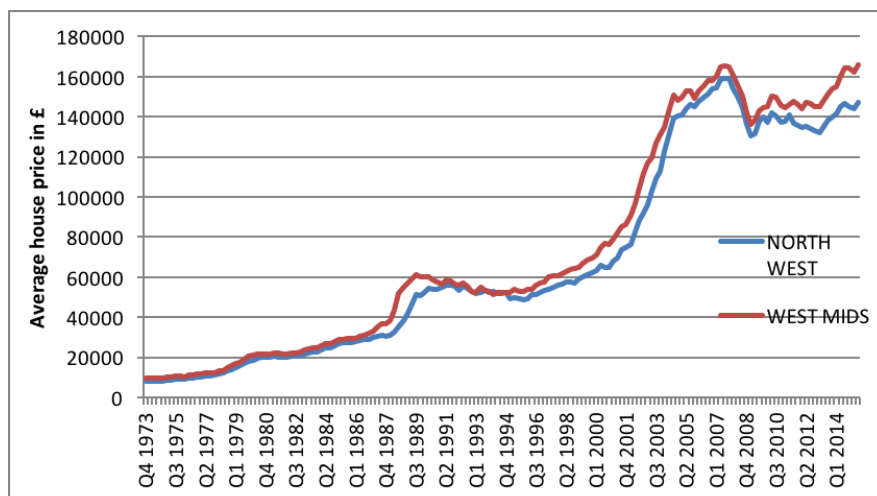


Figure 3.15: North West and East Anglia housing market

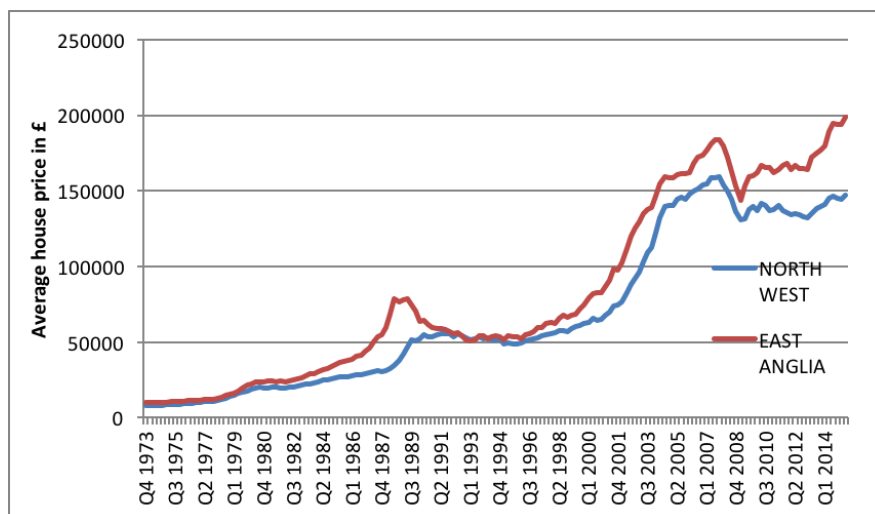


Figure 3.16: East Midlands and North West housing market

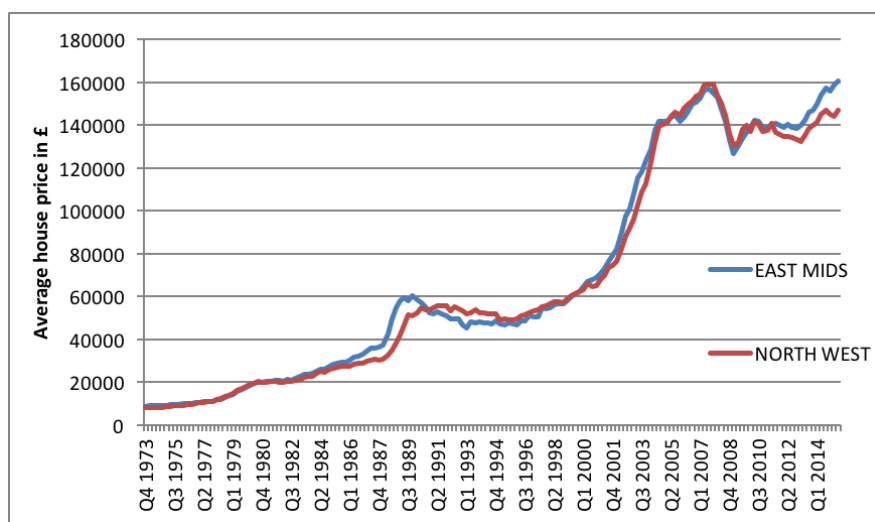


Figure 3.17: East Midlands and East Anglia housing market

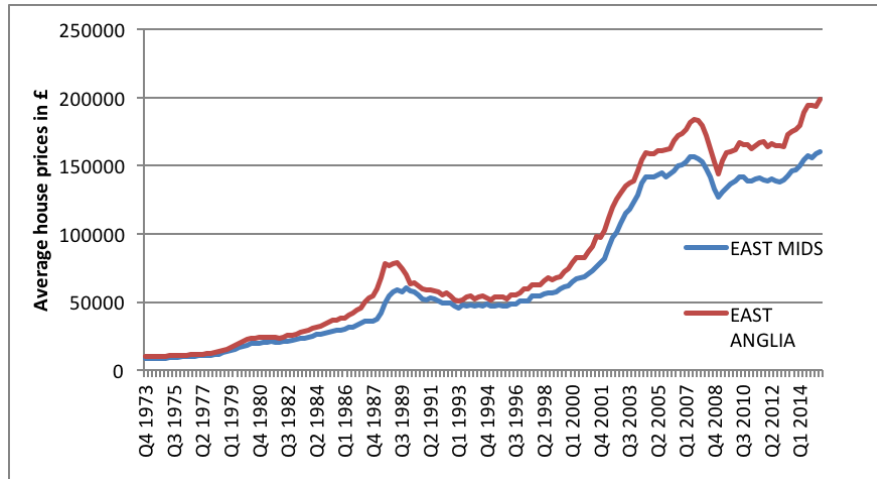


Figure 3.18: North and East Anglia housing market

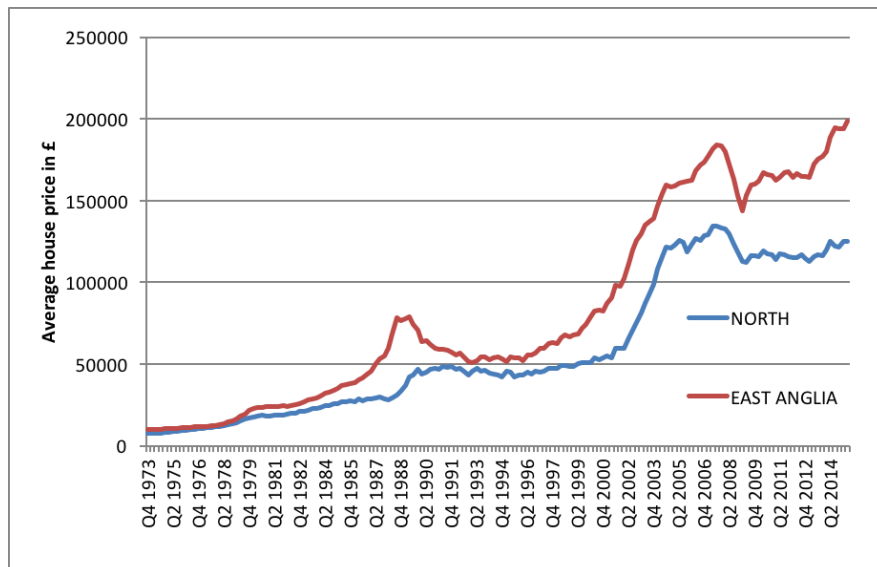


Figure 3.19: East Anglia and Outer S East housing market

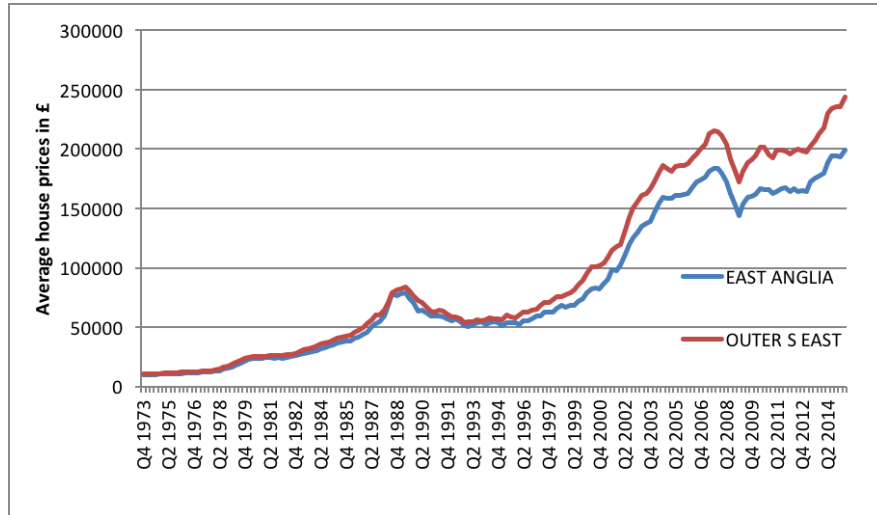


Figure 3.20: Outer S East and Outer Met housing market

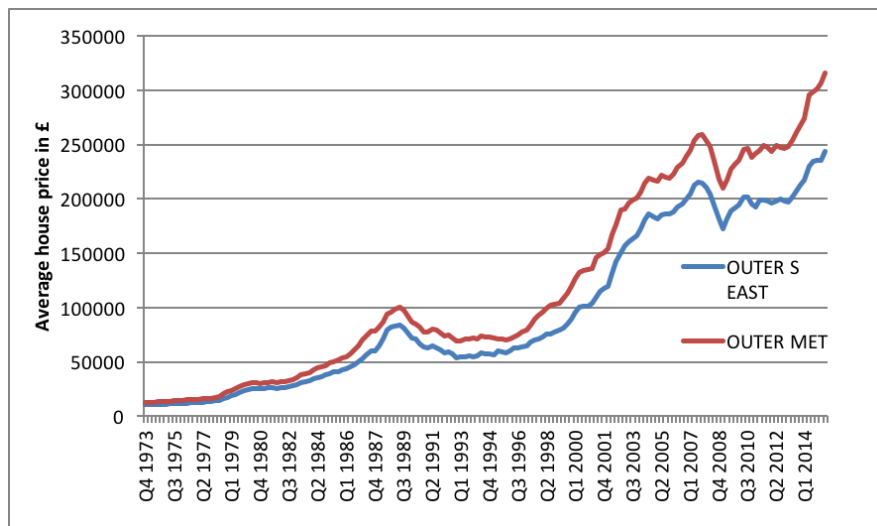


Figure 3.21: Outer S East and East Midlands housing market

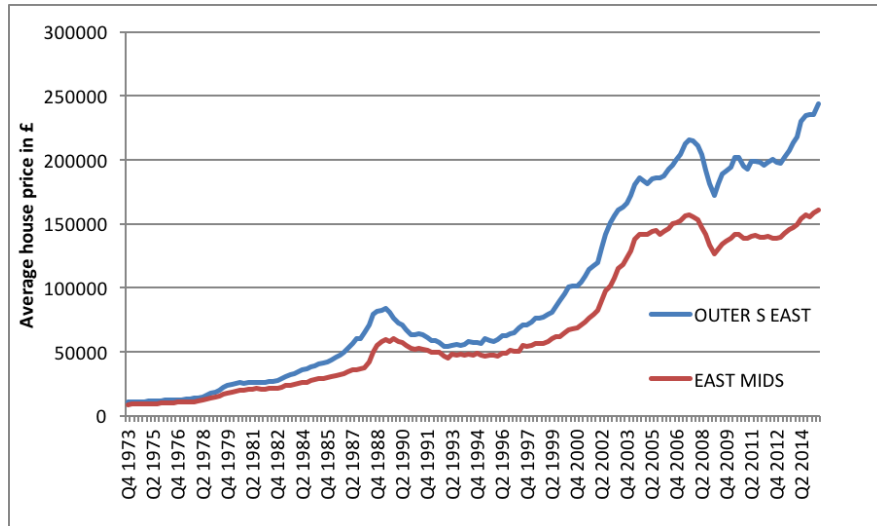


Figure 3.22: Outer Met and East Midlands housing market

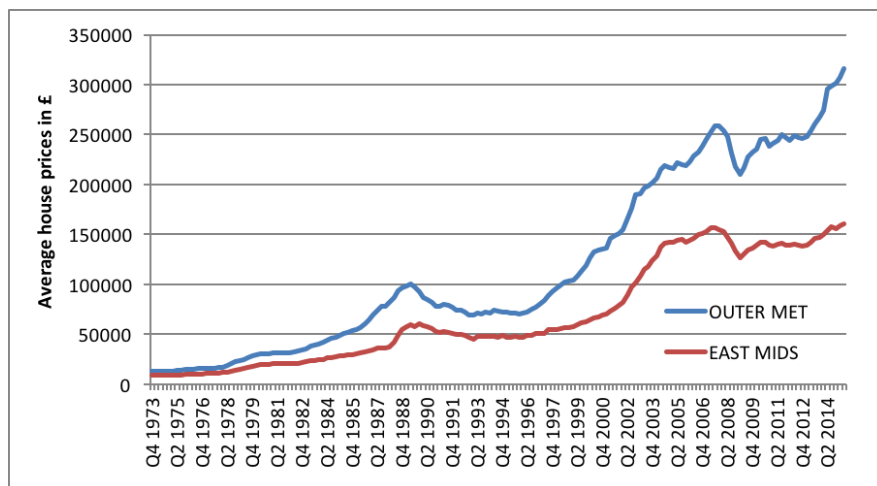


Figure 3.23: Outer Met and West Midlands housing market

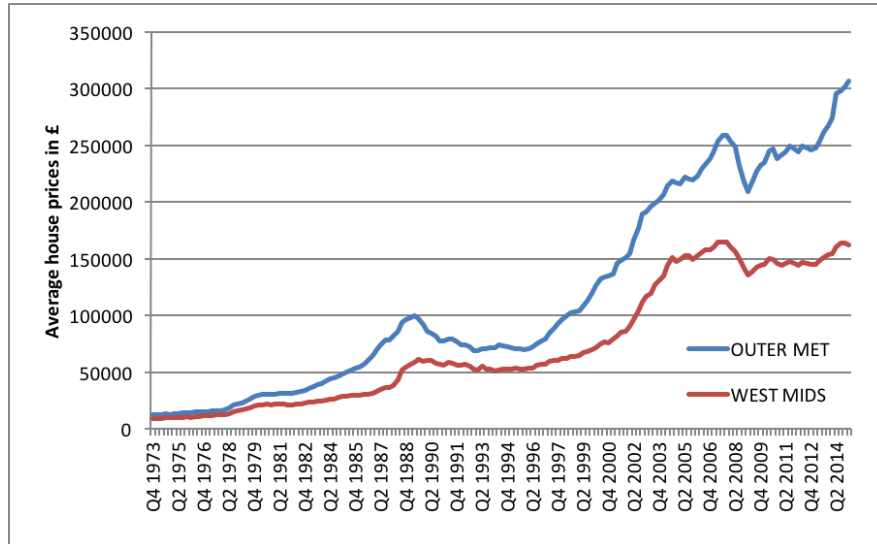


Figure 3.24: South West and East Midlands housing market

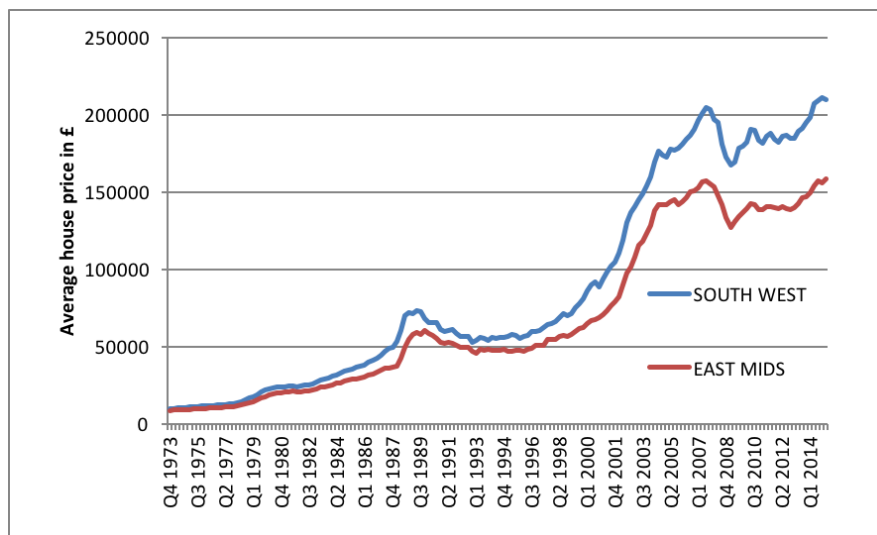


Figure 3.25: South West and Outer S East housing market

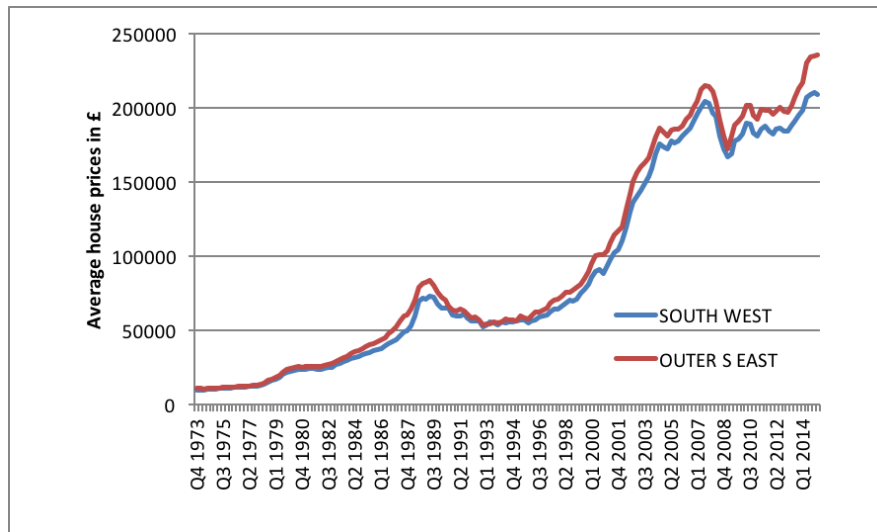


Figure 3.26: Wales and North housing market

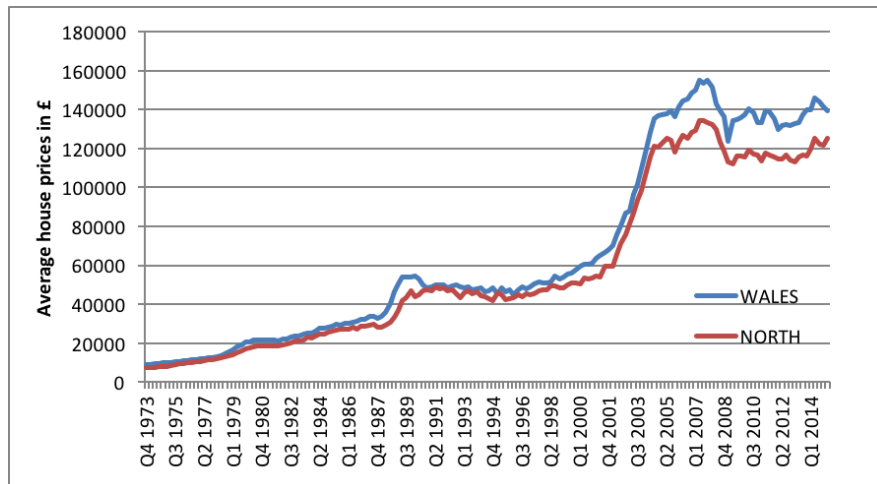


Figure 3.27: Scotland and West Midlands housing market

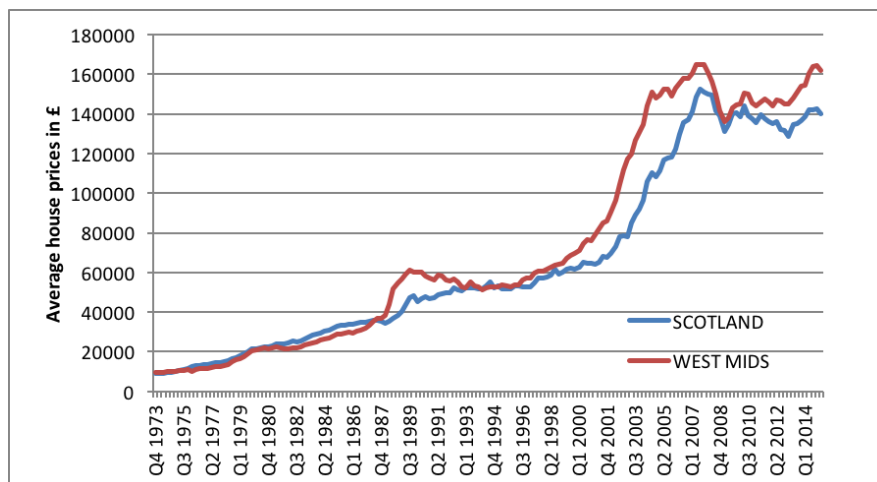
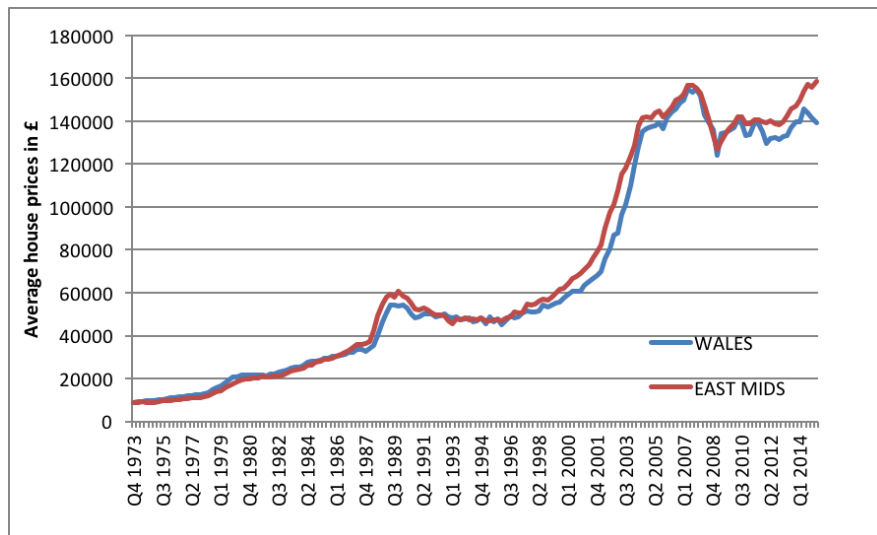


Figure 3.28: Wales and East Midlands housing market



Chapter 4

An examination of the co-bubbling relationship between housing and rental bubbles in the UK

Abstract

This chapter examines the migration of bubbles from the prices of rental property to bubbles to the prices of housing property within UK geographic regions. A number of theories have been proposed within the financial econometrics literature suggesting that the two types of investment are very close substitutes. As a result, researchers have settled on the proposition that there must exist a long run (co-integrating) relationship between the two assets. This relationship has been found and shown using a series of robust statistical methods in recent literature. However, the question of which asset leads the price and the explosive behaviour, if any, of the other asset has yet to be asked. In this chapter we examine the relationship between rental and housing prices using the co-bubbling model developed earlier in the thesis. We are able to confirm both of our hypotheses: a) that there is a strong co-bubbling relationship between rental and housing prices across the UK and b) that a bubble in rental prices will typically precede a bubble in housing prices by about nine quarters.

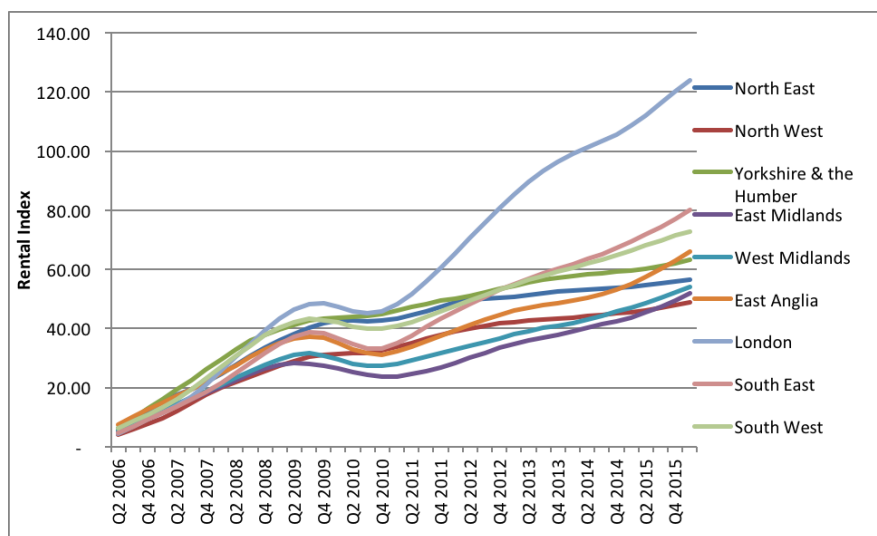
4.1 Introduction

The financial econometrics literature on the relationship between housing and rental prices has focused on establishing a robust relationship between the prices of the two assets and identifying its determinants. In this paper it is proposed that the prices of the two assets not only are strongly correlated but they also co-bubble. More fundamentally, we aim to understand which of the two asset prices will typically bubble first and which one will follow. We consider that better understanding this sequence of events will be of great value to policy makers who may use these findings to anticipate and pre-empt the consequences of another housing bubble crash in the future. In this paper we apply the co-bubbling test developed in the second chapter to try and identify whether a long-run co-bubbling relationship exists between housing prices and rental prices across a series of UK regions.

The methodology employed for testing the hypothesis of co-bubbling behaviour in two series is based on a variant of the stationarity test of Kwiatkowski et al. (1992). This uses a conditional 'wild' bootstrap scheme to control size. As we have shown in the second chapter, the Monte Carlo simulations offer convincing levels of size control and power to suggest that this would be an appropriate methodology to be used for the purposes of this chapter as well. Combining this test with a Bayesian Information Criterion model selection procedure to identify bubble episodes in individual series allows us to determine the presence of any relationship between two explosive series robustly - in this case house prices and rental prices within UK geographical regions.

Figures 4.1 to 4.2 show the general trend of average house prices in the UK since 1995. The graphs are plotted on two different time scales as there are no publicly available data on buy-to-let prices before 2006 whereas time series data on house prices are available via the national statistics website dating back to 1973. We note that due to data availability the series breakdown by region differs in the two figures. To provide a more complete picture of the two markets we plot these series on separate graphs. Subsequently, Figure 4.3 takes the UK average for each market individually and illustrates how rental and housing prices have evolved since the second quarter of 2006. Figure 4.3 shows that the two asset prices co-move in the same direction and they both exhibit a steady but increasing trend. Variations in house

Figure 4.1: Buy-to-let index in UK geographic regions



prices across regions appear to happen almost contemporaneously.

London is perhaps the most interesting case. This is because, in the third chapter, we have found that bubbles in housing prices in London do not (or have not yet) migrate to its neighbouring regions. Figures 4.3 and 4.4 clearly illustrate the difference in the relationship between rental prices and housing prices in London and across the UK. The two asset prices seem to be moving in the same direction, however, the house price bubble in London is more prominent than in the wider UK.

House prices are driven by the choice between renting and buying. This means that a rational buyer would only buy a property if the expected cost of the mortgage interest repayment is lower than the rent for a comparable property. If the expected cost of the mortgage interest repayment is higher than the rent for the property then buying a property is only rational if the investor believes that the capital gain on the property will exceed the difference (i.e. the appreciation in the value of the house will exceed the difference in the rental to ownership cost). Therefore, when house prices are forecasted to increase fast enough, even when rents remain low, investors will choose to invest in the housing market. We consider that this could be a likely explanation for the behaviour that we see in Figure 4.4.

Figure 4.2: Average house prices in UK geographic regions

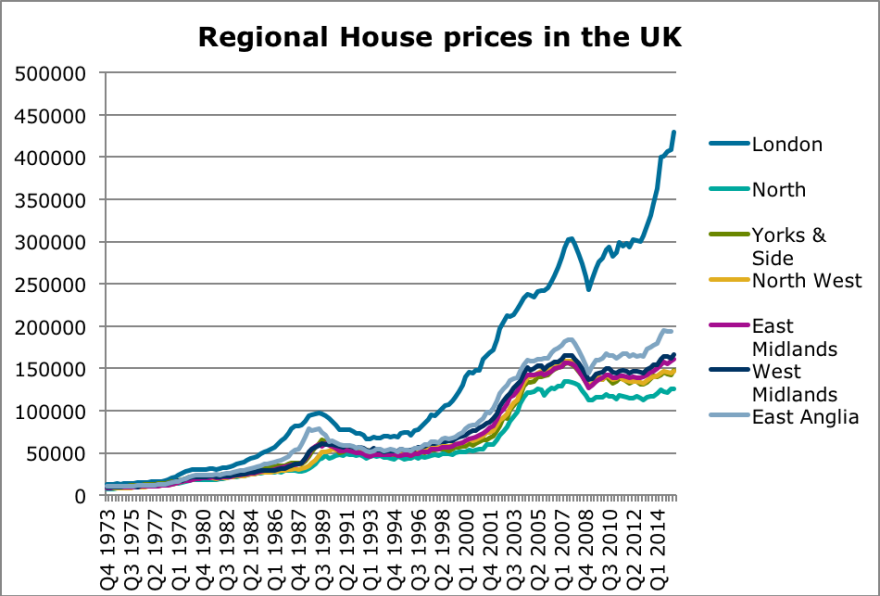


Figure 4.3: UK average house prices compared to buy-to-let index

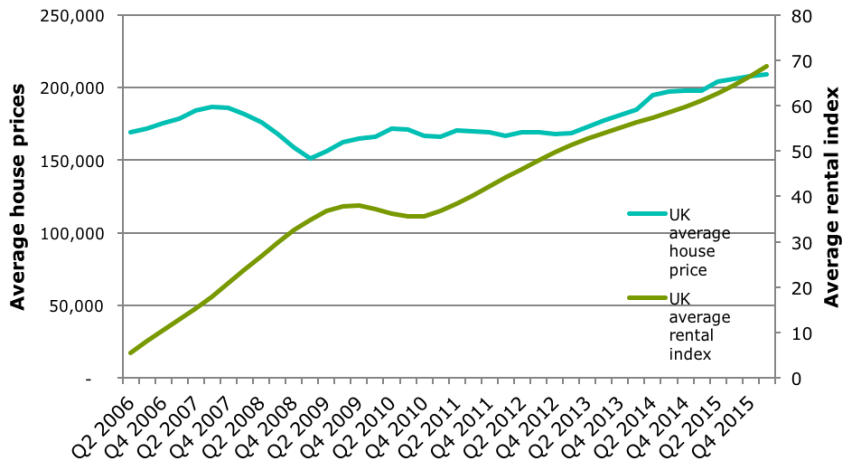
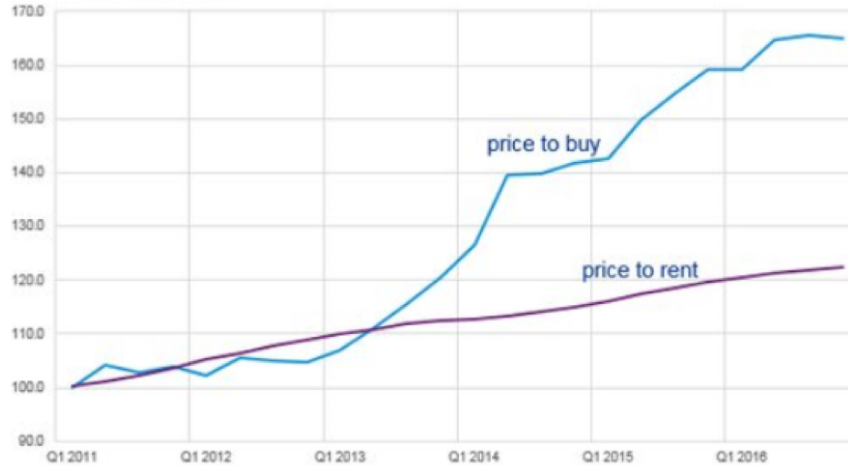


Figure 4.4: London trend of housing prices v rental prices (January 2011 = 100)



4.2 Background to the housing and rental bubble literature

It is well recognised that in the past fifty years there have been observed three bubbles in the UK housing market: one in the early 1970s, one in the late 1980s and there is increasing speculation that we are currently also experiencing a housing bubble. A number of theories have been put forward to explain the causes of these bubbles. These theories are usually focused on the impact of wealth, foreign direct investment, interest rates, the stock market and consumer expenditure in their attempt to explain the determinants of housing bubbles. In this chapter we focus our attention in understanding the impact of rental prices in explaining housing bubbles. We consider that rental prices may have a significant impact in determining the direction of housing prices. Before we begin examining our hypothesis, we first look at the existing literature and results.

Firstly, we begin by taking a closer look at Figure 4.4 that plots the changes in the house price to buy and price to rent a property in London since 2011. 2011 is taken as the base year (i.e. $Q1 = 100$). As we can see the price to rent has increased at a much lower rate than the price to buy. We can deduce from this that buying a property with the sole intention of renting it out becomes a less profitable investment. However, buying a property with the purpose of reselling it in the future would be a rational and profitable decision.

Up until late 2007, the mainstream theory amongst economists and propagated in the UK press was that the house price boom that began in the early 2000's was merely a result of

exceptionally high demand for housing that was outstripping supply. Researchers did not see it as a bubble but rather as a housing boom or a particularly vigorous upturn in the UK's cyclical property market (Barker 2004; Hamnett 1999). The restricted supply side of housing was attributed to slow building rates, scarcity of land and an inflexible planning system. The demand side was explained through factors such as increased immigration, individuals choosing to live alone and low interest rates.

During the financial crisis, academic thinking evolved to attribute housing bubbles to the activities in the banking sector which have created volatility in the housing market. Volatility is considered an attractive attribute by investors because it allows for higher returns. Housing bubbles were seen as just one in a sequence of asset bubbles following the stock market bubble and the technology bubble in the early 2000's (Harvey 2007; Hutton 1995; Stiglitz 2003; Hamnett 2009).

The debate has now been mostly settled by classifying changes in house prices to one of two categories: changing fundamentals that cause significant house price changes or speculative bubbles that are being caused by investors' expectations. A wide range of theories has been put forward to explain the genesis of housing bubbles in the UK and other developed countries, see Himmelberg et al. (2005) and Brunnermeier and Juilliard (2006).

In the literature, rents are usually considered an important part of fundamentals for house prices, see Meese and Wallace (1994), Hamilton and Schwab (1985), Himmelberg et al. (2005), Gallin (2008), Ghysels et al. (2013), Brunnermeier and Juilliard (2008), Campbell et al. (2009), Plazzi et al. (2010), Cochrane (2011), Engsted and Pedersen (2014, 2015), and Gelain and Lansing (2014). The reason for considering rent as a fundamental factor follows the same logic as dividends being seen as fundamentals for determining the price of a share. Put simply, the owner of a house who also lives in the house, derives a certain utility from the service provided by the house itself. An appropriate proxy for this unobservable housing service are rents. Rents are the equivalent to the dividends that an owner of a share obtains in the equity market.

On the 'fundamentals' side of the debate - i.e. the strand of literature that argues that speculative housing bubbles are caused by changes in fundamental values such as rent and interest rates - Himmelberg et al. (2005) argue that conventional metrics, such as house price to rent

ratios, are misleading variables in determining the development of bubble. In their seminal paper, they argue that house prices to rent ratios fail to account for long-run trends in real interest rates. Low real interest rates over the past decade have made housing relatively more affordable in recent years. This increased housing affordability could have led to a housing bubble. Their analysis looks at forty six US Metropolitan Areas between 1980 and 2004. They conclude that in the late 1980s there was a clear housing bubble in the US that was driven by changes in fundamental values such as the interest rate. However, the authors also conclude that the current high level of US house prices cannot be categorised as a bubble once low long-term real interest rates are considered.

Sowell (2009) proposed that the government has a significant role to play in creating housing bubbles. In his research he finds that the housing markets that have experienced explosive growths in their prices were generally markets where the local government imposed land use restrictions that limited the supply of land available for housing.

Furthermore, Krugman (2009) argued that bubbles have mainly been determined by the relaxed mortgage lending standards allowed by the government before the financial crisis. More specifically he argues that the unregulated 'shadow banking system' (hedge funds, investment banks, structured investment vehicles) provided inexpensive finance to households thus leading to a housing bubble.

Another strand of the 'fundamentals' literature argues that real house prices are mainly determined by institutional features and macroeconomic and demographic conditions, most notably inflation, interest rates, bank credit, changes in equity prices, population growth, see Kholodilin et al. (2010) and Muellbauer and Murphy (2008). Lower interest rates decrease the opportunity cost of capital invested in housing, reduce the servicing cost of mortgage credit and raise the present value of future household earnings. The feedback from property prices to credit growth is stronger in countries with more deregulated mortgage markets (Tsatsaronis and Zhu 2004). For example, borrowing costs exert a negative effect on real house changes in US regions (Holly et al. 2010).

On the speculation side of the debate - i.e. the strand of literature that proposes that it is mostly expectations and beliefs that cause bubbles - Brunnermeier and Juilliard (2006) consider that the impact of money illusion on house prices is what generates these specula-

tive bubbles. Their methodology follows Modigliani and Cohn (1979). The results of their paper show that falling inflation in combination with nominal interest rates (i.e. real interest rates are kept fixed) lead to mispricing of housing. According to the authors, people wrongly attribute a decrease in inflation to a decline in the real interest rate and consequently underestimate the real cost of future mortgage payments. Therefore, they demand more housing than they would normally do. Brunnermeier and Juilliard agree that mispricing can explain part of the increasing trend in house prices. They also suggest that the so-called 'tilt' effect cannot explain sufficiently and convincingly the effect of the nominal interest rate on house prices. The 'tilt' effect, describes a situation where changes in inflation shifts the real burden of mortgage repayments towards the earlier years of the financing contract.

Dupor and Conley (2004) support the view that perceived wealth leading to overconsumption patterns coupled with overaccumulation of capital have been the main drivers of the recent housing bubbles. Inaccurate beliefs are taken to be the drivers of the perceived wealth channel. Households expect that their houses will appreciate more than the amount that they actually do. This over-expectation leads them to demand more housing and make considerably more than the market value.

Congdon (2005) arrives at a similar conclusion as Dupor and Conley on the proposition that overaccumulation of capital leads to housing bubbles but using a different perspective. He looks at the marginal utility of money holdings relative to housing and other markets. Overaccumulation of capital arises due to the large liquidity that became available to investors before the financial crisis. This has led to a disequilibrium in their portfolio allocation. To spread their risk investors needed to shift their funds in different markets. This rebalancing exercise has led to higher demand for housing which in turned led to a housing bubble. Adrian and Shin (2008) proposed that the effect of increased liquidity in creating housing bubbles is amplified through the procyclical balance-sheet management of financial intermediaries. During economic upturns (booms) the ratio of total assets to equity is increased, but subsequently reduced during periods of economic downturns. In addition, the relatively low and stable inflation environment reduced risk premia and might have led to higher financial instability, that is, excess credit pressures and additional leverage (Borio and Lowe (2002)). Schiller (2008) emphasized irrational exuberance as the cause of the housing bubbles. In his seminal

paper he proposes that when making decisions, households and investors do not always have a complete set of information on which to base their decision. Therefore, at times they rely on signals from their social circles to help them make a decision. When their circle begins to buy a house, even though it may be overvalued, buyers would still proceed with their purchasing decision as they consider that their peers probably 'knew better' when they made the same decision. In the 1990's this was also known as the herding effect.

The most balanced view found in the literature is given by Gwartney, Macpherson, Sobel, and Stroup (2008). In their view housing bubbles develop as a combination of both fundamental factors and investor speculation. They identified four factors that they consider are the main causes of housing bubbles: (1) low short term interest rates, (2) relaxed lending standards (3) increased debt to-income ratio for households (4) increased leveraging by investment banks (or the impact of shadow banking).

Some researchers have also looked at the impact of international components in determining house bubbles. Holly et al (2010) link the explosive behaviour of house prices in London to the housing bubble experienced in New York and other financial centres. Dreger and Wolters (2009) consider that international spillovers had a greater effect in determining the emergence of house bubbles than the country's own monetary policy (for example strong monetary growth). By spillovers they mean positive shocks to neighbouring countries (within the EU for example) that lead to an increase in the output of the neighbouring country. However, these studies tend to use a general equilibrium analysis and because the conclusions are not tested empirically, we cannot rely on their external validity.

4.3 Signals of bubbles in the real estate market

In this section we explore the area of the literature that tried to identify signals for bubbles in the real estate. Following the burst of a speculative bubble, researchers are quick in identifying the triggers of the explosive behaviour. However, each bubble has different triggers and the literature is scarce in identifying common factors across bubbles within the housing market. For the purposes of this chapter, we consider (and subsequently test) that the rental market is a common factor in determining the emergence of speculative bubbles in the housing market.

However, for completeness we also explore other common factors that have been proposed by the literature as key determinants of bubbles. To do that, we look at papers that have analysed a series of bubbles (at times across countries or across time) to understand these common triggers.

The most common reason cited amongst academic papers for leading to a speculative bubble in houses are low interest rates. Studies conducted by the OECD found that a common denominator to the majority of the housing bubbles that they analysed were the interest rates.

Studies looking at the bubbling features across the different US states found that widely spread perceptions of continuously rising prices were the key denominator for the housing bubbles in those states. Growing overconfidence among buyers has pushed prices beyond their trend levels towards a bubble behaviour. This overconfidence is usually measured in the literature through consumer surveys. Case and Shiller (2003) document this type of common behaviour by surveying 2000 households across the US. The households they analysed had bought homes in May 1988. They compared these households to the ones that bought a house between March and August 2002. The group of 1988 buyers admitted to being influenced by their strong expectations for future price changes and saw their house as an investment. The paper was also able to identify herding behaviour through the survey responses. Overall, the common trigger identified by the authors was expectations. These high expectations are what led to a housing bubble in the early 1990s in the US. Interestingly, the authors, did not find any evidence from their surveys that fundamental values such as the interest rates or the housing stock played a significant role in determining a household's decision to buy a house. The group of people that bought a house in 2003 was chosen because of their similarity to the control group. The responses that they provided to the survey were strikingly similar. Most buyers saw housing as an investment even though less so in 2003 than in 1988. An insignificant amount of buyers considered that the housing market was susceptible to any macroeconomic risks or market fluctuations. For the 1988 households as well as for the 2003 survey the expectation of future price increases were considerably higher than what the available information would allow households to infer. About 90% of all households expected that the price of their house would continue to increase at an exponential rate for the following

seven years. This study that looks at bubbles both across different geographic regions and across time offers a significant contribution to the literature in terms of determining the common denominator in speculative bubbles. A number of subsequent studies provide support to the findings of Case and Schiller (2003). These include Capozza et al. (2004) and Goodman and Thibodeau (2008) that also looked at bubbles across the US and find that speculation was the common denominator in initiating price bubbles.

Studies that looked at triggers of speculative bubbles across other western countries such as England, France and Ireland reach similar conclusions see Roche (2000), Roehner (1999) and Levin and Wright (1997). Overall, the consensus has been that (a) houses are mainly seen as an investment good and (b) through time speculative bubbles have as a common denominator unrealistic expectations by investors.

4.4 Hypotheses

Evidence shows that housing markets are particularly susceptible to bubbles. A continuous succession of housing cycles has been empirically documented in worldwide housing markets; in the UK (Hott and Monnin (2008), Parkinson et al. (2009), Black et al. (2006)) and the rest of the world including Switzerland, Japan and USA (Hott and Monnin (2008)).

In general, housing bubbles have been widely studied. However, the interlinkages between rental markets and housing markets have been less prominent in the housing literature. This chapter aims to shed more light on the long-run relationship between rental prices and house prices. The two hypotheses that we choose to test are:

- Housing prices co-bubble with rental prices within UK geographic region. We could have chosen to look at this relationship at an aggregate level. However, we consider that examining this relationship at a regional level can offer more insight into the interlinkages between housing and rental prices.
- Rental prices lead housing prices. This hypothesis gives an indication on whether house buyers see their houses mostly as an investment good or as a consumption good. Rejecting this hypothesis would indicate that potential house buyers see houses as a consumption good. This is because following a speculative housing bubble, if prices become

unaffordable they would switch to renting a house. As a consequence, rental prices would begin to increase. On the contrary, if our test accepts this hypothesis then we can reasonably conclude that house buyers see houses as an investment good. Investors would wait for rental prices to increase, indicating higher returns to their future investment if they choose to buy a house. Therefore, higher demand for house ownership may eventually lead to a housing bubble.

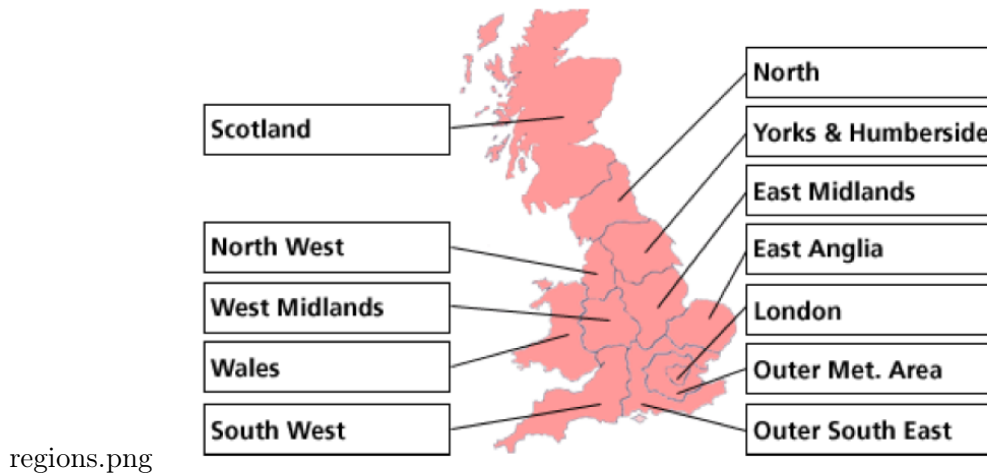
Using the co-bubbling model developed in our previous chapter we test for both our hypotheses. Here, the y series values are the values taken by the buy-to-let index while the x values are the house prices.

4.5 Data

We choose to use data from well-recognised and trusted sources to estimate the validity of our hypotheses. The Nationwide dataset provides the richest source of data on housing prices across the UK. They provide the longest unbroken run of house price data, stretching back to 1952 on a quarterly basis and 1991 on a monthly basis. House prices are mix adjusted. This means that they are tracked using a representative house price over time rather than the simple average price. The reason for doing so is because the average price can be easily influenced by a change in the mix (such as the proportion of different property types and their locations) of houses. Sample size is based on the number of new loans that Nationwide writes; that is the amount of gross lending for house purchase. Buy-to-let purchases are not included in the data sample. We consider this to be a considerable benefit to our data set because house purchases for the sole purpose of renting the property would skew the results in a way that houses are purely seen as an investment asset. The Nationwide Building Society is currently the second largest mortgage lender in the UK. This allows us to be confident that the series based on Nationwide mortgage data is representative of the whole house market. All the data is in real terms.

We note that the Nationwide definition of regions differs from the ONS definition. The Nationwide definition excludes Cumbria which is added to the North East to comprise the North. The London region comprises the boroughs of London. The Outer Metropolitan

Figure 4.5: Map of England regions

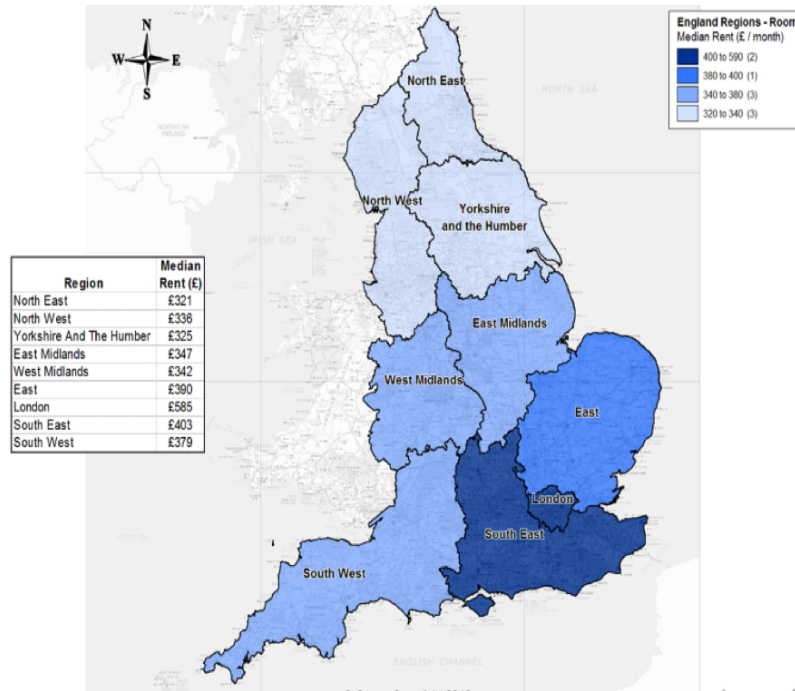


region surrounds London and includes among others, South Essex, Reading, St Albans, and Medway. The Outer South East includes North Essex, Oxfordshire, Brighton, Southampton and Sussex. The map of definitions of regions is taken from the Nationwide website and is provided in Figure 4.5.

Data on the rental prices across the UK have only recently become available through the Office of National Statistics. The data take the form of an experimental index of prices paid for rental properties in Great Britain. The time series data spans from the first quarter of 2006 to the third quarter of 2016. Unfortunately the Office for National Statistics does not publish estimates for the price of privately rented property. The Office of National Statistics does, however, produce and publish inflation estimates (i.e. how much private rental prices increase or decrease) via the Index of Private Housing Rental Prices (IPHRP).

The closest estimate that we are able to get on actual prices for rental properties is provided by the Valuation Agency. However, we are unable to get a sufficiently long time series data set from the valuation agency (earliest estimates provided for 2015). For completeness, we provide Figure 4.6 constructed by the valuation office that gives an indication of actual rental prices across the UK per room in 2016.

Figure 4.6: Room monthly rents recorded between 1 April 2015 and 31st March 2016 for England



4.6 Method

To test the hypotheses that we presented in section 5, we employ the co-bubbling test that was developed in the previous chapter.

We first employ the HLS bubble model to identify the type of bubble that is present in each series. The model also offers us insight into the start date of each individual bubble as well as its duration. The model allows us to identify the type of bubble model that is present in each individual series. Subsequently we employ the co-bubbling model developed in Chapter 2. We only test for co-bubbling relationships within the same region. The results would not be meaningful if we were to test for the existence of a co-bubbling relationship between rental and housing markets of different regions.

For the purposes of this chapter, the y values are the values taken by the buy-to-let index whereas the x values are the house prices. As we will show in the following section, rental values lead house price values.

Table 4.1: Explosive bubble behaviour in the UK property market

	Random (walk to)	Explosive (bubble to)	Stationary ((collapse))
North East (buy-to-let index)	Q4 2007	End of sample	N/A
North East (avg house price)	Q4 2014	End of sample	N/A
North West (buy-to-let index)	Q4 2007	End of sample	N/A
North West (avg house price)	Q2 2009	Q4 2013	N/A
Yorkshire & the Humber (buy-to-let index)	Q4 2007	End of sample	N/A
Yorkshire & the Humber (avg house price)	Q2 2013	End of sample	N/A
East Midlands (buy-to-let index)	Q1 2011	End of sample	N/A
East Midlands (avg house price)	Q1 2013	End of sample	N/A
West Midlands (buy-to-let index)	Q4 2007	End of sample	N/A
West Midlands (avg house price)	Q1 2013	End of sample	N/A
East Anglia (buy-to-let index)	Q4 2007	End of sample	N/A
East Anglia (avg house price)	Q1 2013	End of sample	N/A
London (buy-to-let index)	Q4 2007	End of sample	N/A
London (avg house price)	Q1 2013	End of sample	N/A
South East (buy-to-let index)	Q4 2007	End of sample	N/A
South East (avg house price)	Q1 2013	End of sample	N/A
South West (buy-to-let index)	Q4 2007	End of sample	N/A
South West (avg house price)	Q1 2013	End of sample	N/A

Typically, the standard model used widely in the literature for understanding the determinants of house prices consists of three equations - a demand equation, a supply equation and another one showing how the stock of houses changes over time as new houses are completed.

4.7 Results

Our results presented in Table 4.1 show that over the past decade, in every region of the UK, there has been at least one speculative bubble in either the housing market or the rental market. Most of them have not collapsed yet, with the exception of the North West house prices that have returned to random walk behaviour. Table 4.1 summarises the results of our test.

The results provided in Table 4.1 allow us to confirm our first hypothesis that across the UK the prices of houses and rentals have deviated from their fundamentals and are now presenting an explosive bubble behaviour. Of particular interest we find the fact that in all cases apart from one, the property market is still away from its fundamental value. It is very challenging

to predict when these bubbles might burst or return to their long run equilibrium value. We do not attempt to answer that question as part of this chapter but we consider this finding to be alarming and further research should be undertaken on the topic.

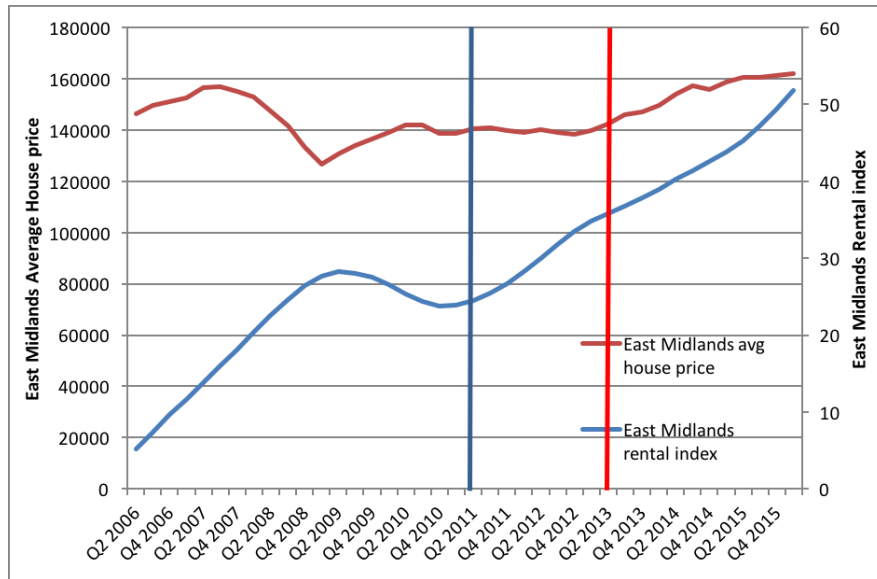
We would like to draw attention to the fact that these results differ from the results of Chapter 3 that looked at the co-bubbling relationship between housing markets within UK geographic regions. The data sample used for that chapter is significantly larger and that's why the bubbles identified as part of that chapter occur at different points in time.

The second hypothesis that we set ourselves to test was whether rental prices lead housing prices. As we explained in the previous section, if rental prices bubble before house prices then buyers see housing as an investment. If, on the other hand, housing prices bubble before rental prices then buyers see housing more as a consumption good and they would swiftly substitute their choice of owning a property to renting a property if house prices become unaffordable.

Figures 4.7 and 4.8 provide two examples of co-bubbling behaviour between rental and housing prices within a region. We choose the two examples based on the time lag between the two bubbles i.e we choose the region in which it took the shortest for the bubble to migrate from one market to the other and the region in which it took the longest for the bubble to migrate from one market to the other. The HLS bubble model that fits all of our examples is Model (1), that means that the series first experience a random walk and subsequently bubble behaviour until the end of the sample. Due to London's unique position, we also include the graph of London here in Figure 4.9. The rest of the graphs showing co-bubbling relationships between UK regions can be found in the Appendix.

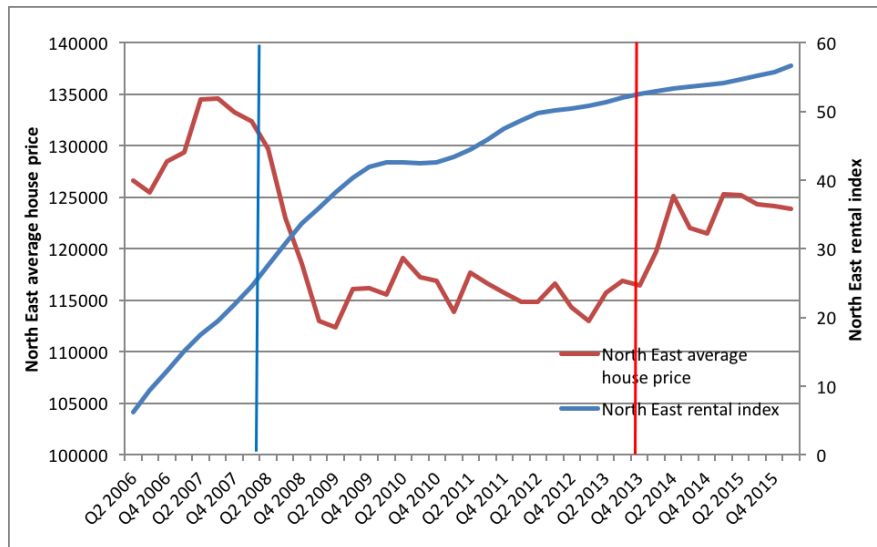
By looking at Figures 4.7 to 4.9, one may infer that it takes some time for a bubble in one market to migrate to the other market. However, the results of our co-bubbling test tell a different story in terms of the average lead/lag. The average regional lag is provided in Table 4.2. This is because for our co-bubbling method to produce accurate results, the two series have to exhibit the same bubble type. Once the regions that exhibit the same bubble type are identified then we can run our co-bubbling model and compute the amount of time that the co-bubbling relationship takes. Tables 4.3 to 4.11 in the Appendix summarise our findings. For all the geographic regions that we have examined, rental prices lead house prices. On

Figure 4.7: East Midlands co-bubbling



Blue vertical line indicates bubble start in buy-to-let; red vertical line indicates bubble start in owner occupied housing

Figure 4.8: North East co-bubbling



Blue vertical line indicates bubble start in buy-to-let; red vertical line indicates bubble start in owner occupied housing

Figure 4.9: London co-bubbling



Blue vertical line indicates bubble start in buy-to-let; red vertical line indicates bubble start in owner occupied housing

average, rental prices lead house prices by about 9.7 quarters.

Table 4.2 shows the average lag between the co-bubbling relationships identified in our series. The results are computed using the results from Tables 4.3 to 4.11 in the Appendix. To compute these averages we looked at the sequences of non-rejections and associated lag and lead times in each individual co-bubbling table. We only look at the tables where the hypothesis of no co-bubbling is rejected. One necessary condition for the existence of a co-bubble (and therefore rejection of the no co-bubbling hypothesis) is that the two series exhibit a bubble of

Table 4.2: Average lag between rental and house price co-bubbling across regions

Region	Lag time (in quarters)
North East	10.5
North West	no co-bubble
Yorkshire and the Humber	10.5
East Midlands	8.5
West Midlands	10.5
East Anglia	8.5
London	12
South East	8.5
South West	8.5

the same type. The types of models that are admitted by our model are presented in Chapter 2 and reiterated in the Method section of this chapter. For each pair of series (rental and housing market) that we investigate, we compute the average lead/lag. For example, Table 4.4 of the Appendix, that specifically examines the co-bubbling relationship between rental and house prices in the North West, shows that the no co-bubbling hypothesis is rejected for the time period of -11 and -10 quarters. This allows us to conclude that on average, the rental price bubble leads the house bubble in the North West by 10.5 quarters or roughly 31 months.

Our results presented in Tables 4.3 to 4.11 in the Appendix confirm our second hypothesis - that is rental prices bubble before house prices. In all the cases that we have looked at this result holds true.

We note that the shortest period between the bubbles of the two markets analysed in this chapter is about 2 years. By this we mean that the shortest time period between the beginning of a bubble in the rental market and the beginning of a bubble in the housing market in the same region is of about two years. This result only arises because the bubbles have been individually estimated using the HLS procedure. Focusing solely on the individual series results can be misleading because we cannot formally attribute bubble migration causality in this set-up as we have not investigated joint behaviour. This is because within these two years a number of other exogenous events might occur that could influence the behaviour of the second time series. Therefore, we suggest some caution when attempting to infer causality from these individual results. Such considerations emphasize the importance of using our co-bubbling test since it combines the information from both series as opposed to looking at them individually. Arguably, the bubble that occurred first chronologically might be causing the emergence of the bubble that came afterwards. In other words, the development of a rental price bubble in North West in 2007 could have caused the development of a house price bubble in North West in 2009. However, there could be other factors that are not taken into account in this chapter that could be causing the emergence of the housing bubble. Such factors may include interest rate shocks, immigration or inflation. For example, it has been widely quoted that the cause of housing bubble in London is the housing bubble in New York. Furthermore, our dataset is

relatively limited. We only make use of forty one observations for each example. In time series literature this can be considered an inadequate number of observations to draw inference from

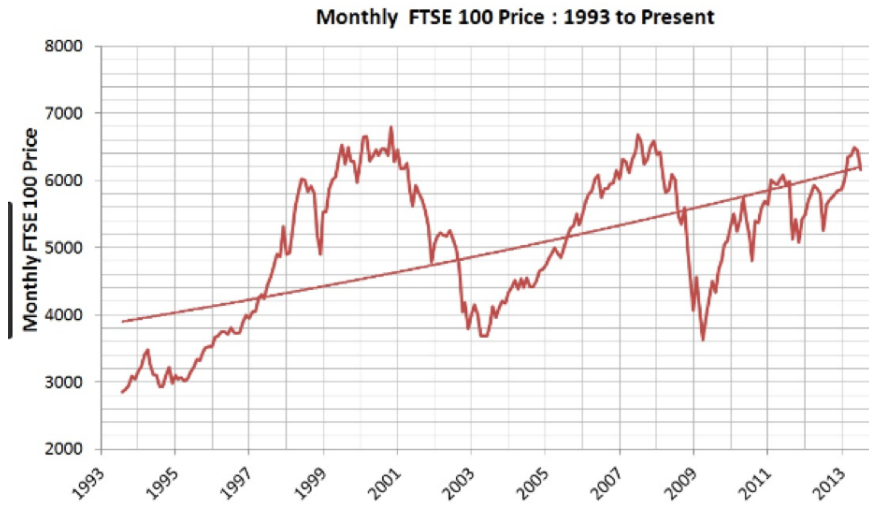
Our results support a number of papers in the recent bubble literature that suggest that housing is mostly seen as an investment opportunity. It is the expectation that house prices will continue to increase exponentially that incentivises investors to continue investing in the housing market even though they may realise that the price they are paying has deviated from its fundamental price.

In financial markets, the fundamental value of a share is derived from its expected stream of future earnings or dividends, usually measured for the next five to ten years. Similarly, the fundamental value of a house is derived from the expected stream of rental income that it might generate. Therefore, it becomes reasonable to expect that when rental prices start increasing, investors become more attracted to the housing market and begin buying more houses. Interestingly, however, investors continue to buy houses even when the cost of repaying a mortgage exceeds the expected returns from rents.

Stock market bubbles are typically characterised by sharp rises in the price to earnings ratios (these measure the value of a company compared to its share earnings), when share prices become very high relative to earnings. In a bubble, investors acquire shares or bonds in expectation that they will be able to sell them at a higher price instead of buying them for the income they provide. The same logic can be applied to housing markets. Investors, in the absence of other lucrative propositions, choose to invest in house prices not because of the expected rental incomes but because of the expected appreciation of the house prices. However, as we show in this chapter, rental prices can be used as indicators that a housing bubble is approaching.

We consider that our conclusions are also consistent from a financial stock market point of view. As we have shown, housing is seen as an investment. An alternative to housing investment is the stock market. When the returns from investing in the stock market are low then investors might look for other channels to invest their money. It has been proposed by recent literature that the relative returns to housing and stock shares may determine the allocation of investment flows in the two markets (Cecchetti et al. 2000). In other words, the

Figure 4.10: FTSE stock index, historical.



two markets can be seen as substitutes. A fall in the stock market may lead to an investor rush towards the housing market in an attempt to spread their risks and gain higher returns. A look at the stock market over the same time period confirms our conjecture. See Figure 4.10.

As shown in Figure 4.10, the stock market has taken a downturn since 2006 and it has struggled to return to its trend level since. Consequently, it is reasonable to expect that investors would be looking for a different investment and the housing market presented a good opportunity.

4.8 Policy implications and discussion

This chapter offers a significant contribution to the housing market literature. We consider that our results can be of great value to policy makers who are looking to maintain the stability of the economy. If housing is seen as an investment, as we have just proven with our model, then regulators and policy makers would need to monitor it closely to avoid any systemic risk building into the economy over time. In what follows we discuss a number of reasons why we consider that our findings can have considerable implications for policy making and present a number of suggestions for future research.

Regulators would justifiably be concerned about housing bubbles as previous experiences have shown that a bubble burst can have real impacts on the economy. House prices influence

the state of the economy through various channels. These channels can be classified in three separate categories: monetary effects, wealth effects and economic development/price stability. The role of the rental market is outlined and discussed for all three channels.

When house prices systematically diverge from their fundamentally justified values, house price bubbles are formed. From a monetary policy perspective, this is an alarming signal as it can distort the link between asset prices and policy actions, especially through inflation. This is what is known as the monetary channel. Recent research around housing bubbles and monetary policy has focused on two key questions: (a) the ability of housing bubbles to indicate future growth in inflation and (b) the way in which inflation is measured and whether the prices of houses should have a higher weighting. Goodhart (1995) suggested that conventional measures of inflation that only look at the prices of goods and services should be updated and proposed that when inflation is measured the price of housing and the stock market are taken into account. His proposition was confronted with some criticism and central banks have not yet updated their inflation measurement tools. Filardo (2000) was the strongest opponent of Goodhart's suggestion, based on empirical observations of previous examples where high asset prices did not lead to high inflationary growth.

We consider that the findings of this paper provide a platform for reconciling these views. We acknowledge that house prices matter for the economy especially when they indicate the emergence of a speculative bubble. However, we propose that instead of using housing as a component in measuring inflation, rental prices could provide a better indicator. This is because, as we have shown rental prices are strongly correlated to house prices and in bubble situations they might be able to predict the emergence of a housing bubble - which might in turn have spillover effects on the rest of the economy and its inflation. Therefore, including rent inflation in aggregate inflation measures could improve the accuracy of the forecasts. Furthermore, with regards to the monetary channel, housing prices have a considerable effect on the transmission of monetary policy (IMF (2008)). Housing bubbles would therefore make it very challenging for policy makers to fine tune the economy. Using rental prices as a signal for upcoming price bubbles may allow regulators to be more prepared or pre-empt such bubbles. Calza et al. (2009) have shown that the response of residential investment and private consumption to monetary shocks is more noticeable in countries with high loan-to-

value ratios (these measure the ratio of the mortgage amount to the value of the property). The UK is amongst the countries with the lowest loan-to-value ratios in the OECD. This means that monetary shocks are more difficult to pass through to the economy due to this feature. Consequently, monetary policy may become even more ineffective in the presence of a speculative housing bubble. Finally, the relationship between the monetary transmission mechanism and house prices is not unidirectional. The developments in the housing market may also affect money demand as proven by Setzer et al. (2010) and Dreger and Wolters (2009). This provides us with all the more reason to monitor the emergence of housing bubbles.

It has also been proven in the literature that a major source of divergence in the development of external imbalances between member states and the euro area arise from idiosyncratic house price developments. This is because accelerating house prices give rise to a boom in private consumption and import demand (Aizenman and Jinjarak (2009)). House price dynamics influence the performance of the financial system through their impact on the profitability and soundness of financial institutions. Understanding and incorporating this behaviour in policy making is of utmost significance for policymakers.

The second channel through which housing bubbles can have an effect on the economy is through the wealth channel. Private consumption is significantly affected by the housing wealth effect as well as the collateral effect. Case et al. (2005) and Dreger and Reimers (2009) found significant evidence on these theories. Their studies found that consumption increases as a result of an increase in housing wealth (or perceived housing wealth). The reason for this is because it has a direct effect on expected lifetime income. House owners begin to consume more if they perceive that their house is worth more. However, house owners are not always aware that they might be part of a housing bubble. Therefore, they might end up buying more goods and services than what they would have done had they understood the actual price of their house in the future. When the bubbles burst, households may be left with a mortgage that they cannot sustain and further credit that they might have received by using their house as a collateral. The second reason is what is known as the collateral effect. The collateral effect has been carefully documented by Aoki et al (2004) and Muellbauer (2008). If policy makers won't to avoid a situation whereby a considerable

number of households got themselves in an unsustainable debt they may want to monitor housing bubble formation more closely.

The final point of concern from a regulators view in the context of housing markets is the interlinkage between asset prices and their impact on the wider stability of the financial system. There is a vast amount of literature that discusses this link and the potential impacts that it may have on systemic stability. Some papers that have looked at the issue include Mishkin (2003) and Zhu (2005). According to this theory, a country's reaction to a crisis will considerably depend on the way that banks value collateral. If banks overestimate the value of a collateral (e.g. due to a housing bubble) then the effects of an economic downturn would be more severe. However, it is difficult for banks to always estimate the correct value of the collateral. We propose that a better way of doing this would be by incorporating the average rental value for similar properties in the collateral estimation. If the value of a property far exceeds the estimated rent return then banks should be concerned that a bubble is possibly developing. Finally, we note that housing markets may have an impact on the overall economic development. Helbling and Terrones (2003) found that bubble busts may lead to total economic output losses that are twice as large as the ones arising from equity bubbles. Furthermore, Zhu (2005) using the same line of reasoning across a number of countries found that increases in house prices were likely to have a positive impact on output although the magnitudes may differ across countries.

Our conclusion is that the close interlinkage between rental and housing markets is very telling about the way house buyers see the market. We find that housing is mainly seen as an investment. We propose and strongly urge policy makers to begin incorporating developments in the rental market in their analyses and decision making processes

Appendix

In the first part of the appendix we provide the graphs of all the UK regions that present a co-bubbling relationship. The type of HLS bubble that was fitted in all the graphs is Model 1, this means that the series first follow a random walk and subsequently enter into a bubble until the end of the sample. The rest of the appendix presents the co-bubbling results generated

by the co-bubbling test we have developed.

Figure 4.11: South East co-bubbling.

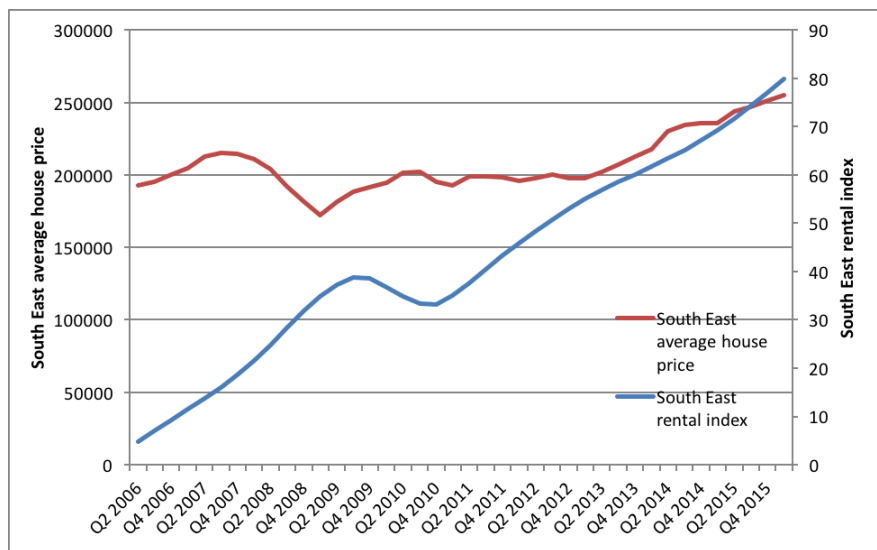


Figure 4.12: South West co-bubbling

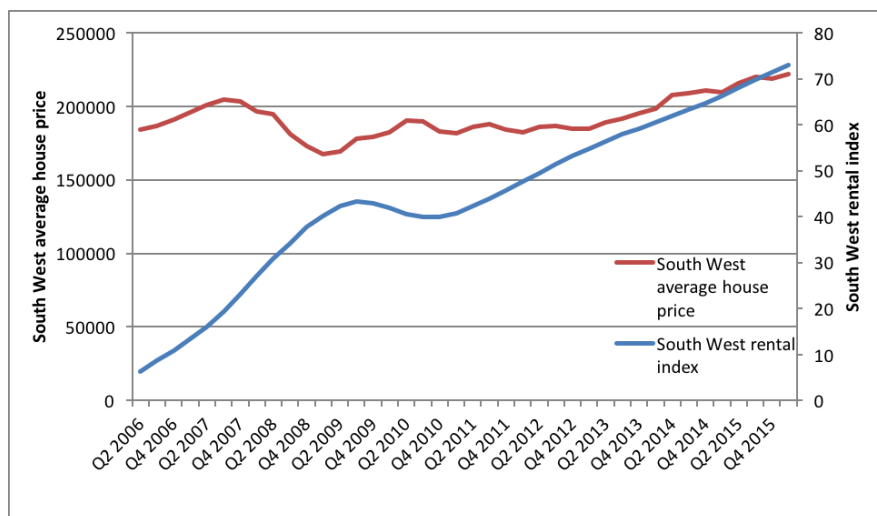


Figure 4.13: Yorkshire co-bubbling

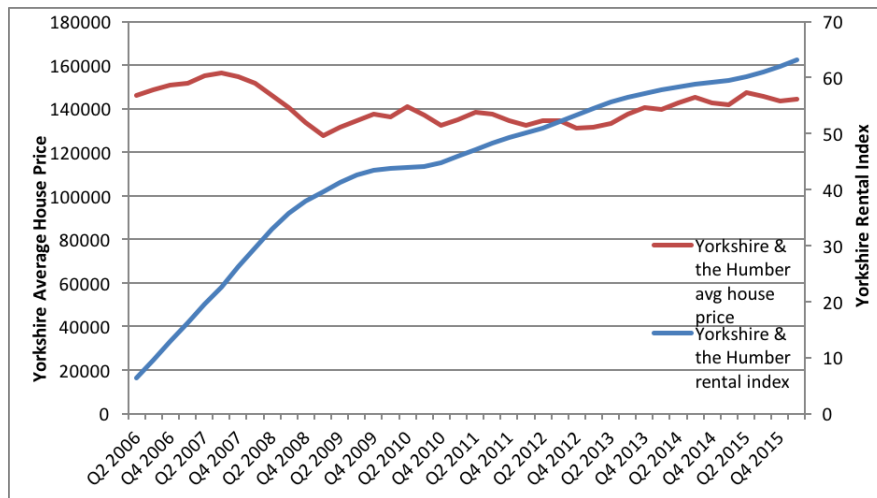


Figure 4.14: West Midlands co-bubbling

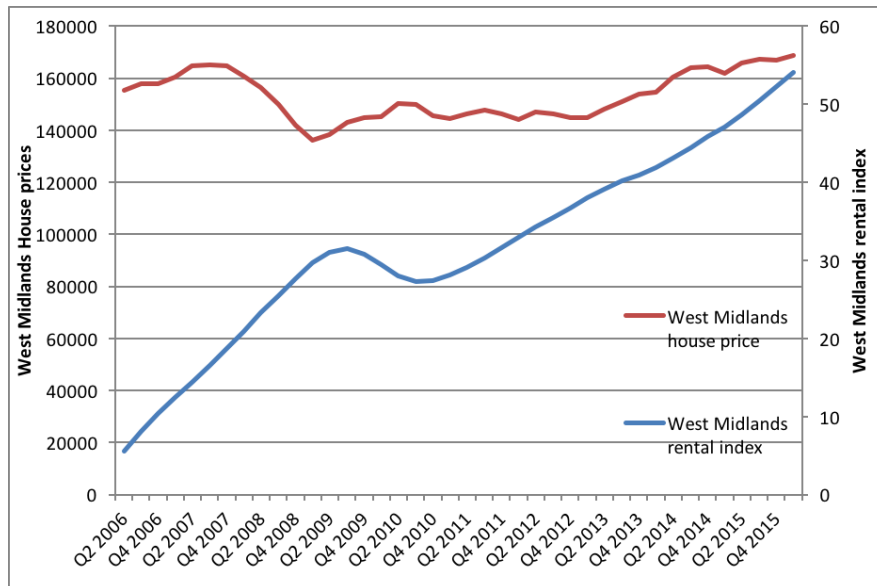


Figure 4.15: East Anglia co-bubbling

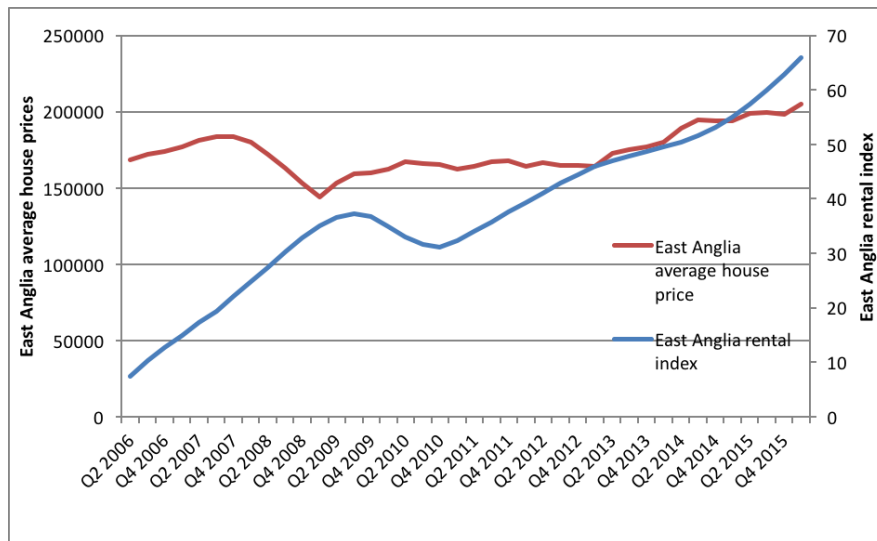


Table 4.3: North East co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.223	0.209	1
-14	0.238	0.224	1
-13	0.235	0.216	1
-12	0.237	0.219	1
-11	0.287	0.292	$\emptyset$
-10	0.371	0.371	$\emptyset$
-9	0.461	0.420	1
-8	0.509	0.421	1
-7	0.541	0.443	1
-6	0.567	0.451	1
-5	0.591	0.473	1
-4	0.627	0.503	1
-3	0.663	0.522	1
-2	0.700	0.520	1
-1	0.721	0.536	1
0	0.740	0.528	1
1	0.694	0.523	1
2	0.644	0.496	1
3	0.592	0.482	1
4	0.536	0.446	1
5	0.478	0.403	1
6	0.448	0.389	1
7	0.418	0.375	1
8	0.356	0.300	1
9	0.326	0.273	1
10	0.311	0.269	1
11	0.290	0.249	1
12	0.273	0.242	1
13	0.267	0.237	1
14	0.253	0.234	1
15	0.226	0.212	1

Table 4.4: North West co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.267	0.254	1
-14	0.284	0.265	1
-13	0.279	0.257	1
-12	0.275	0.252	1
-11	0.298	0.294	1
-10	0.385	0.372	1
-9	0.467	0.410	1
-8	0.514	0.415	1
-7	0.544	0.447	1
-6	0.567	0.442	1
-5	0.589	0.460	1
-4	0.619	0.490	1
-3	0.650	0.506	1
-2	0.682	0.512	1
-1	0.709	0.530	1
0	0.732	0.532	1
1	0.690	0.520	1
2	0.644	0.484	1
3	0.601	0.461	1
4	0.554	0.439	1
5	0.522	0.425	1
6	0.487	0.429	1
7	0.436	0.369	1
8	0.386	0.329	1
9	0.350	0.306	1
10	0.316	0.284	1
11	0.286	0.253	1
12	0.270	0.247	1
13	0.264	0.225	1
14	0.248	0.225	1
15	0.230	0.213	1

Table 4.5: Yorkshire and the Humber co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.252	0.251	1
-14	0.261	0.255	1
-13	0.260	0.244	1
-12	0.250	0.244	1
-11	0.271	0.281	0
-10	0.344	0.368	0
-9	0.431	0.412	1
-8	0.497	0.431	1
-7	0.538	0.451	1
-6	0.570	0.459	1
-5	0.600	0.459	1
-4	0.635	0.499	1
-3	0.669	0.517	1
-2	0.701	0.517	1
-1	0.729	0.547	1
0	0.756	0.548	1
1	0.714	0.540	1
2	0.677	0.518	1
3	0.634	0.488	1
4	0.581	0.459	1
5	0.554	0.433	1
6	0.525	0.453	1
7	0.479	0.398	1
8	0.435	0.365	1
9	0.399	0.353	1
10	0.348	0.312	1
11	0.309	0.277	1
12	0.293	0.273	1
13	0.285	0.258	1
14	0.280	0.261	1
15	0.264	0.238	1

Table 4.6: East Midlands co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.143	0.140	1
-14	0.139	0.135	1
-13	0.131	0.132	0
-12	0.120	0.133	0
-11	0.125	0.152	0
-10	0.158	0.227	0
-9	0.221	0.302	0
-8	0.307	0.376	0
-7	0.380	0.421	0
-6	0.445	0.455	0
-5	0.501	0.480	1
-4	0.543	0.490	1
-3	0.583	0.507	1
-2	0.623	0.520	1
-1	0.657	0.522	1
0	0.689	0.524	1
1	0.677	0.523	1
2	0.664	0.497	1
3	0.650	0.480	1
4	0.634	0.464	1
5	0.614	0.456	1
6	0.586	0.455	1
7	0.547	0.426	1
8	0.495	0.389	1
9	0.440	0.374	1
10	0.389	0.351	1
11	0.340	0.321	1
12	0.306	0.289	1
13	0.288	0.269	1
14	0.280	0.261	1
15	0.274	0.245	1

Table 4.7: West Midlands co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.159	0.158	1
-14	0.162	0.159	1
-13	0.155	0.155	1
-12	0.149	0.154	0
-11	0.159	0.180	0
-10	0.205	0.262	0
-9	0.283	0.335	0
-8	0.366	0.398	0
-7	0.443	0.441	1
-6	0.502	0.472	1
-5	0.553	0.496	1
-4	0.593	0.504	1
-3	0.631	0.518	1
-2	0.671	0.526	1
-1	0.707	0.545	1
0	0.741	0.559	1
1	0.722	0.537	1
2	0.699	0.522	1
3	0.674	0.506	1
4	0.648	0.483	1
5	0.619	0.456	1
6	0.584	0.459	1
7	0.536	0.441	1
8	0.476	0.383	1
9	0.421	0.373	1
10	0.362	0.328	1
11	0.314	0.303	1
12	0.282	0.266	1
13	0.271	0.250	1
14	0.266	0.247	1
15	0.258	0.231	1

Table 4.8: East Anglia co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.134	0.132	1
-14	0.138	0.137	1
-13	0.134	0.135	0
-12	0.126	0.130	0
-11	0.131	0.148	0
-10	0.158	0.192	0
-9	0.211	0.258	0
-8	0.282	0.333	0
-7	0.348	0.373	0
-6	0.402	0.406	0
-5	0.445	0.424	1
-4	0.478	0.433	1
-3	0.509	0.437	1
-2	0.541	0.456	1
-1	0.568	0.467	1
0	0.585	0.462	1
1	0.590	0.470	1
2	0.588	0.472	1
3	0.587	0.457	1
4	0.587	0.442	1
5	0.582	0.441	1
6	0.577	0.450	1
7	0.565	0.435	1
8	0.538	0.420	1
9	0.496	0.394	1
10	0.451	0.378	1
11	0.406	0.353	1
12	0.367	0.325	1
13	0.350	0.310	1
14	0.338	0.295	1
15	0.327	0.287	1

Table 4.9: London co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.119	0.124	0
-14	0.121	0.127	0
-13	0.121	0.126	0
-12	0.120	0.125	0
-11	0.127	0.136	0
-10	0.149	0.161	0
-9	0.183	0.185	0
-8	0.224	0.212	1
-7	0.259	0.233	1
-6	0.285	0.250	1
-5	0.302	0.256	1
-4	0.314	0.260	1
-3	0.324	0.262	1
-2	0.333	0.264	1
-1	0.344	0.267	1
0	0.356	0.276	1
1	0.355	0.275	1
2	0.351	0.271	1
3	0.348	0.269	1
4	0.347	0.263	1
5	0.349	0.269	1
6	0.351	0.275	1
7	0.351	0.275	1
8	0.332	0.263	1
9	0.325	0.277	1
10	0.321	0.280	1
11	0.320	0.273	1
12	0.318	0.278	1
13	0.310	0.266	1
14	0.299	0.262	1
15	0.288	0.251	1

Table 4.10: South East co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.141	0.140	1
-14	0.144	0.144	$\emptyset$
-13	0.142	0.142	1
-12	0.138	0.135	1
-11	0.145	0.147	$\emptyset$
-10	0.172	0.185	$\emptyset$
-9	0.228	0.245	$\emptyset$
-8	0.291	0.292	$\emptyset$
-7	0.343	0.328	1
-6	0.384	0.359	1
-5	0.417	0.375	1
-4	0.437	0.372	1
-3	0.456	0.382	1
-2	0.475	0.390	1
-1	0.495	0.398	1
0	0.513	0.402	1
1	0.518	0.414	1
2	0.523	0.413	1
3	0.526	0.414	1
4	0.529	0.403	1
5	0.527	0.413	1
6	0.526	0.420	1
7	0.523	0.404	1
8	0.515	0.414	1
9	0.493	0.389	1
10	0.465	0.378	1
11	0.436	0.358	1
12	0.409	0.333	1
13	0.386	0.317	1
14	0.367	0.306	1
15	0.347	0.292	1

Table 4.11: South West co-bubbling test results.

lag/lead (i^*)	KPSS (S)	BS CV ($C_{\alpha B}$)	Reject co-bubble
-15	0.148	0.146	1
-14	0.151	0.150	1
-13	0.147	0.146	1
-12	0.144	0.147	0
-11	0.150	0.156	0
-10	0.174	0.196	0
-9	0.241	0.291	0
-8	0.301	0.330	0
-7	0.367	0.382	0
-6	0.424	0.419	1
-5	0.467	0.428	1
-4	0.501	0.443	1
-3	0.528	0.442	1
-2	0.551	0.445	1
-1	0.572	0.458	1
0	0.591	0.465	1
1	0.592	0.474	1
2	0.590	0.464	1
3	0.590	0.454	1
4	0.588	0.446	1
5	0.580	0.445	1
6	0.573	0.458	1
7	0.560	0.428	1
8	0.537	0.417	1
9	0.502	0.396	1
10	0.463	0.386	1
11	0.425	0.356	1
12	0.393	0.332	1
13	0.371	0.314	1
14	0.354	0.301	1
15	0.337	0.289	1

Chapter 5

Conclusion

This thesis contributes to the time series literature on speculative financial bubbles through a novel bubble test procedure and three applications. For this thesis, we have examined the presence of co-bubbling relationships in financial and housing markets. In the second chapter we have developed a test procedure for the detection of a co-bubbling relationship between two explosive series. Monte Carlo simulations offered us promising results on the size and power of the test. Our first empirical application of the test was on the gold and silver markets. We found that the two commodities co-bubble with the bubble in silver preceding the bubble in gold by three to five months. In the third chapter we examined the impact that distance has on the development of housing co-bubbles across the UK. Previous literature suggested that there is an element of housing bubble migration between key geographic regions in the UK. Using the co-bubble test procedure that we developed in the second chapter we test for the existence of co-bubbling relationships between geographic regions and estimate the time that it takes for one housing bubble in one region to migrate to a different geographic region. We subsequently use these findings to estimate whether the driving distance between the two regions has an impact on the duration of the migration i.e. on the amount of time that it would take for the commencing housing bubble to migrate to a separate geographic region. We also tested the hypothesis that differences in local wealth levels can affect the bubble migration time. We find evidence that distance plays a significant role in determining the co-bubble lags. We find no evidence that wealth differential can affect the duration of a housing bubble migration.

In the fourth chapter we investigate the relationship between rental and housing markets in the UK. This chapter sheds light on house buyers' perceptions on a house acquisition (whether buyers see housing as an investment or consumption good). Traditionally, the prices of houses and the rent prices were found to be closely linked. The direction of the relationship however has never been well understood. Literature has not yet determined whether higher house prices would lead to higher rents or whether the causation would run the opposite direction. In the fourth chapter we use the co-bubbling model developed previously in this thesis to test for the presence of long run co-bubbling relationships and perhaps shed some light on the direction of the relationship. We find that rental prices co-bubble with house prices for all the regions with the exception of the North West. We also find that rental prices lead house prices by a lag of around nine quarters. This allows us to conclude that house buyers see housing more as an investment than a consumption good.

We consider that this thesis has shed light to a number of important issues in the housing literature that have not been analysed in depth before. We believe that our co-bubbling model can be employed in a number of different contexts such as the stock market or for foreign exchange. Finally, we also consider that our results can be of great value to policy markets who are looking to maintain the stability of the economy. If housing is seen as an investment, as we have just proven with our model, then regulators and policy makers would need to monitor it closely to avoid any systemic risk building into the economy over time.

References

- Adrangi, B., Chatrath, A. and Raffiee, K. (2003). Economic activity, inflation, and hedging: the case of gold and silver investments. *The Journal of Wealth Management*, 6, 60-77.
- Adrian, Tobias, and Hyun Song Shin. "Financial intermediaries, financial stability, and monetary policy." (2008), Working Paper.
- Aizenman, Joshua, and Yothin Jinjarak. "Current account patterns and national real estate markets." *Journal of Urban Economics* 66.2 (2009): 75-89.
- Alpezzi, Stephen. (1999). "A Simple Error Correction Model of House Prices", *Journal of Housing Economics*, 8, 27-62
- Arora, Navneet, Jeffrey R. Bohn, and Fanlin Zhu. "Reduced form vs. structural models of credit risk: A case study of three models." *Journal of Investment Management* 3.4 (2005): 43.
- Aoki, Kosuke, James Proudman, and Gertjan Vlieghe. "House prices, consumption, and monetary policy: a financial accelerator approach." *Journal of financial intermediation* 13.4 (2004): 414-435.
- Ayuso, Juan, et al. "House prices in Spain." *Economic Bulletin OCT* (2003).
- Banerjee, A. (1999). "Panel Data Unit Roots and Cointegration: An Overview", *Oxford Bulletin of Economics and Statistics*, 61, 607-629
- Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. "A model of investor sentiment." *Journal of financial economics* 49.3 (1998): 307-343.

- Barker, K. 2004 The Barker Review of Housing Supply (17 March) HM Treasury
- Baur, D. G. and Tran, D. T. (2014). The long-run relationship of gold and silver and the influence of bubbles and financial crises. *Empirical Economics* 47, 1525-1541.
- Belke, Ansgar, Walter Orth, and Ralph Setzer. "Liquidity and the dynamic pattern of asset price adjustment: A global view." *Journal of Banking & Finance* 34.8 (2010): 1933-1945.
- Benjamin, J.D., P. Chinloy and G.D. Jud (2004), "Real Estate versus Financial Wealth in Consumption", *Journal of Real Estate Finance and Economics*, Vol. 29, pp. 341-54.
- Bettendorf, T. and Chen, W. (2013). Are there bubbles in the Sterling-dollar exchange rate? New evidence from sequential ADF tests. *Economics Letters*, 120, 350-353.
- Black, A., Fraser, P., and Hoesli, M. (2006) House prices, fundamentals and bubbles, *J. Bus. Finan.* 33, 1535-1555
- Bourassa, Steven C., and Patric H. Hendershott. "Australian capital city real house prices, 1979-1993." *Australian Economic Review* 28.3 (1995): 16-26
- Bourassa, Steven C., Patric H. Hendershott, and James Murphy. "Further evidence on the existence of housing market bubbles." *Journal of Property Research* 18.1 (2001): 1-19.
- Brunnermeier, M. and, Julliard C. (2006), "Money Illusion and House Prices", mimeo, Princeton and LSE. Available online at <http://personal.lse.ac.uk/JULLIARD/research.htm>
- Buckley, R. and Ermisch, J. (1982), "AGovernment Policy and House Prices in the United Kingdom: An Econometric Analysis", *Oxford Bulletin of Economics and Statistics*, 47, 273-304.
- Calza, Alessandro, and Andrea Zaghini. "Nonlinearities in the dynamics of the euro area demand for M1." *Macroeconomic Dynamics* 13.1 (2009): 1-19.
- Campbell, S. D., M. A. Davis, J. Gallin, and R. F. Martin (2009): "What moves housing markets: A variance decomposition of the rent-price ratio," *Journal of Urban Economics*, 66, 90-102.

- Can, A., (1990). The measurement of neighbourhood dynamics in urban house prices. *Economic Geography* 66, 254-272
- Capozza, D. R., Hendershott, P. H., & Mack, C. (2004). An anatomy of price dynamics in illiquid markets: Analysis and evidence from local housing market. *Real Estate Economics*, 32, 1-32
- Capozza, Dennis R., et al. Determinants of real house price dynamics. No. w9262. National Bureau of Economic Research, 2002.
- Case, Karl E., and Robert J. Shiller. "Is there a bubble in the housing market?." *Brookings papers on economic activity* 2003.2 (2003): 299-342.
- Case, Karl E., John M. Quigley, and Robert J. Shiller. "Comparing wealth effects: the stock market versus the housing market." *Advances in macroeconomics* 5.1 (2005).
- Ciner, C. (2010). On the long run relationship between gold and silver prices: a note. *Global Finance Journal*, 12, 299-303.
- Chudik, A. and Pesaran, M. H., (2009b). Econometric analysis of high dimensional VARs featuring a dominant unit, Cambridge University, under preparation.
- Congdon, T. (2005). Money and Asset Prices in Boom and Bust. London: The Institute of Economic Affairs.
- Davidson, R. and MacKinnon, J. G. (1993). *Estimation and Inference in Econometrics*, Oxford University Press.
- DeLong, J.B., A. Schleifer, L.H. Summers and R.J. Waldmann (1990), "The Economic Consequences of Noise Traders", *Journal of Political Economy*, Vol. 98, pp. 703-38.
- Diba, B.T. and Grossman, H.I. (1998). Explosive rational bubbles in stock prices? *American Economic Review*, 78, 520-530.
- Dreger, Christian, and JÃijrgen Wolters. "Money velocity and asset prices in the euro area." *Empirica* 36.1 (2009): 51-63.

- Dupor, Bill, and Timothy Conley. "The fed response to equity prices and inflation." *American Economic Review* 94.2 (2004): 24-28.
- Engle, R. F. and Granger, C. W. J. (1987). "Co-integration and Error Correction: Representation, Estimation, and Testing", *Econometrica*, 55, 251-276.
- Engsted, T., T. Q. Pedersen, and C. Tanggaard (2012): "The Log-Linear Return Approximation, Bubbles, and Predictability," *Journal of Financial and Quantitative Analysis*, 47, 643-665.
- Escribano, A. and Granger, C. W. J. (1998). Investigating the relationship between gold and silver prices. *Journal of Forecasting*, 17, 81-107.
- Faff, R. and Hillier, D. (2003). Gold factor exposures in international asset pricing. *Journal of International Financial Markets, Institutions and Money* 13, 271-289.
- Figuerola-Ferretti, I. and Gonzalo, J. (2010). Price discovery and hedging properties of gold and silver markets. Universidad Carlos III de Madrid Working Paper.
- Filardo, Andrew J. "Monetary policy and asset prices." *Economic Review-Federal Reserve Bank of Kansas City* 85.3 (2000): 11.
- Fingleton B. (2008) Generalized Method of Moments estimator for a spatial model with Moving Average errors, with application to real estate prices, *Empirical Economics*, 34, 35-57.
- Fisher, R.A. (1932). *Statistical Methods for Research Workers*, Oliver & Boyd, Edinburgh, 12th Edition.
- Froot, K.A. and M. Obstfeld (1991), "Intrinsic Bubbles: The Case of Stock Prices", *American Economic Review* Vol. 81, pp. 1189-214.
- Gallin, J. (2008): "The long-run relationship between house prices and rents," *Real Estate Economics* 36, 635-958.
- Ghysels, E., A. Plazzi, W. N. Torous, and R. I. Valkanov (2013): *Handbook of Economic Forecasting*, chap. Forecasting real estate prices, 509-580.

- Glaeser E. L. and Gyourko, J. (2002). "The Impact of Zoning on Housing Affordability", Mimeo.
- Goodhart, Charles AE. *Price stability and financial fragility: Financial stability in a changing environment*, Palgrave Macmillan UK, 1995. 439-509.
- Goodman, A. C., & Thibodeau, T. G. (2008). Where are the speculative bubbles in US housing market. *Journal of Housing Economics* 17, 117-137
- Granger, C.W.J and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics* 2, 111-120.
- Gwartney, J., Stroup, R., Sobel, R., & Macpherson, D. (2008). *Macroeconomics: Public and Private Choice*. Cengage Learning.
- Hamilton, B.W. and R.M. Schwab (1985): "Expected appreciation in urban housing markets," *Journal of Urban Economics* 18, 103 - 118.
- Hamilton, J.D. (1994). *Time Series Analysis*, Princeton University Press, Princeton, NJ.
- Hammoudeh, S. and Yuan, Y. (2008). Metal volatility in presence of oil and interest rate shocks. *Energy Economics* 30, 606-620.
- Hamnett, C. 1999 *Winners and Losers: Home Ownership in Modern Britain*, Abingdon: Routledge.
- Hamnett, C. 2009 The Madness of Mortgage Lenders, Report for IPPR (May) Institute of Public Policy Research.
- Harvey, D. 2007 "Neoliberalism as Creative Destruction", *The Annals of the American Academy of Political and Social Science* 610: 22-44.
- Harvey, D.I., Leybourne, S.J. and Sollis, R. (2014). Testing and dating asset price bubbles. University of Nottingham Working Paper.
- Harvey, David I., et al. "Tests for explosive financial bubbles in the presence of non-stationary volatility." *Journal of Empirical Finance* 38 (2016): 548-574.

- Helbling, Thomas, and Marco Terrones. "When bubbles burst." *World Economic Outlook* 2 (2003): 61-94.
- Hilsenrath, J. E. (2002). "A 91-Year-Old Who Foresaw Selloff is 'Dubious' of Stock-Market Rally", *Wall Street Journal* July 25, 2002.
- Himmelberg, C., Mayer, C. and Sinai, T. (2005), "Assessing High House Prices: Bubbles, Fundamentals and Misperceptions", *Journal of Economic Perspectives*, 19,4, 67-92
- Holly, Sean, M. Hashem Pesaran, and Takashi Yamagata. "A spatio-temporal model of house prices in the USA." *Journal of Econometrics* 158.1 (2010): 160-173.
- Homm, U. and Breitung, J. (2012). Testing for speculative bubbles in stock markets: a comparison of alternative methods. *Journal of Financial Econometrics*, 10, 198-231.
- Hort, Katinka. "The determinants of urban house price fluctuations in Sweden 1968-1994." *Journal of housing Economics* 7.2 (1998): 93-120.
- Hott, C. and Monnin, P. (2008) Fundamental real estate prices: An empirical estimation with international data, *Journal of Real Estate and Financial Economics* 36 427-450
- Hutton, W. 1995 *The State We're In*, New York: Basic Books.
- Im, K., Pesaran, M.H., and Shin, Y. (1997). "Testing for Unit Roots in Heterogeneous Panels", Mimeo, Department of Applied Economics, University of Cambridge.
- Kindleberger, Charles. "Bubbles, The New Palgrave: A Dictionary of Economics, John Eatwell, Murray Milgate, and Peter Newman, eds." (1987).
- Kivedal, B. K. (2012). Testing for rational bubbles in the US housing market. *Journal of Macroeconomics*, 38, 369-381.
- Krugman, P. 2009. The return of Depression Economics and the Crisis of 2008. New York: W. W. Norton & Company.
- Kwiatkowski, D., Phillips, P.C.B., Schmidt P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root ? *Journal of Econometrics*, 54, 159-178.

- Levin, Eric J., and Robert E. Wright. "The impact of speculation on house prices in the United Kingdom." *Economic modelling* 14.4 (1997): 567-585.
- Levin, A., Lin, C. F., and Chu, C. J. (2002). "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties", *Journal of Econometrics*, 108, 1-24.
- Leybourne, S.J. and McCabe, B.P.M. (1994). A simple test for cointegration. *Oxford Bulletin of Economics and Statistics*, 12, 157-166.
- Leyshon, Andrew, and Shaun French. "'We all live in a Robbie Fowler house': The geographies of the buy to let market in the UK." *The British Journal of Politics & International Relations* 11.3 (2009): 438-460.
- Liu, R.Y. (1988). Bootstrap procedures under some non i.i.d. models. *Annals of Statistics* 16, 1696-1708.
- McCabe, B. P. M., and S. J. Leybourne. "Testing for parameter variation in non-linear regression models." *Journal of the Royal Statistical Society. Series B (Methodological)* (1993): 133-144.
- McCoskey, S. and Kao, C. (1998). "A Residual-Based Test of the Null of Cointegration in Panel Data" *Econometric Reviews*, 17, 57-84
- McCarthy, Jonathan, and Richard W. Peach. *Are home prices the next bubble?* (2004).
- Maddala, G. S., and Wu, S. (1999). "A Comparative Study of Unit Root Tests with Panel Data and New Simple Test", *Oxford Bulletin of Economics and Statistics*, 61, 631-652
- Malpezzi, Stephen. (1999). "A Simple Error Correction Model of House Prices", *Journal of Housing Economics*, 8, 27-62
- Mammen, E. (1993). Bootstrap and wild bootstrap for high dimensional linear models. *Annals of Statistics* 21, 255-285.
- Mankiw, G. and Weil, D. (1989), "The Baby Boom, the Baby Bust and the Housing Market", *Regional Science and Urban Economics*, 19, 325-46.

- Martin, Ron. "The local geographies of the financial crisis: from the housing bubble to economic recession and beyond." *Journal of Economic Geography* 11.4 (2011): 587-618.
- Meen, G. (1996), "Ten Propositions in UK Housing Macroeconomics: An Overview of the 1980s and Early 1990s", *Urban Studies*, 33(3), 425-44.
- Meen, G. (2000), "Housing Cycles and Efficiency", *Scottish Journal of Political Economy*, 47, 2, 114-40.
- Meen, G. (2002). "The Time-Series Behavior of House Prices: A Transatlantic Divide?" *Journal of Housing Economics*, 11, 1-23
- Mishkin, Frederic S. "How should we respond to asset price bubbles?." *Banque de France Financial Stability Review - Valuation and Financial Stability* 12 (2008): 65-74.
- Modigliani, Franco, and Richard A. Cohn. "Inflation, rational valuation and the market." *Financial Analysts Journal* 35.2 (1979): 24-44.
- Muellbauer, John, and Anthony Murphy. "Housing markets and the economy: the assessment." *Oxford review of economic policy* (2008): 1-33.
- Muellbauer, J. and Murphy, A. (1997), "Booms and Busts in the UK Housing Market", *Economic Journal*, 107 (November), 1701-27.
- Lucey, B. and Tully, E. (2005). The evolving relationship between gold and silver 1978-2002: evidence from a dynamic cointegration analysis: a note crisis of 1997-1998. The Institute for International Integration Studies Discussion Paper.
- Parkinson, M., Ball, M., Blake, N. Key, T. (2009) The credit crunch and regeneration: Impact and implications. An independent report to the department for communities and local government. [[http://www.ljmu.ac.uk/MKG Global Docs/CLG Credit Crunch Report.pdf](http://www.ljmu.ac.uk/MKG_Global_Docs/CLG_Credit_Crunch_Report.pdf)]
- Pedroni, P. (1997). "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis", Mimeo, Department of Economics, Indiana University.

- Pesaran, M. Hashem, Til Schuermann, and Scott M. Weiner. "Modeling regional interdependencies using a global error-correcting macroeconometric model." *Journal of Business & Economic Statistics* 22.2 (2004): 129-162.
- Phillips, P.C.B., Wu, Y. and Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: when did exuberance escalate stock values? *International Economic Review* 52, 201-226.
- Poterba, J.M. (1991), "A House Price Dynamics: the Role of Tax Policy and Demography", *Brookings Papers on Economic Activity*, 2, 143-203.
- Poterba, J.M. (1984), "A Tax Subsidies to Owner-Occupied Housing: An Asset Market Approach", *Quarterly Journal of Economics*, 99, 729-52.
- Quah, D. (1990). "International Patterns of Growth I: Persistence in Cross-Country Disparities", Working Paper, Massachusetts Institute of Technology.
- Quah, D. (1994). "Exploiting cross section variation in unit root inferences in dynamic data", *Economic Letters*, 44, 9-19.
- Reifschneider, D., Tetlow, R., Williams, J. (1999) "Aggregate disturbances, monetary policy, and the macroeconomy: The FRB/US perspective", *Federal Reserve Bulletin*, 85, Issue 1, 1-19.
- Roche, M. J. (2000). The rise in house prices in Dublin; bubble, fad or just fundamentals. *Economic Modeling*, 18, 281-295
- Roehner. (1999). Spatial analysis of real estate bubbles: Paris 1984-1993. *Regional Science and Urban Economics*, 29, 73-88
- Shiller, R. J. 2008. *The Subprime Solution: How Today's Global Financial Crisis Happened and What to Do about It*. Princeton, New Jersey: Princeton University Press.
- Shiller, R. J. and Perron, P. (1985). "Testing the Random Walk Hypothesis: Power versus Frequency of Observation," *Economic Letters* 18, 381-386.
- Shin, Y. (1994). A residual based test for cointegration. *Econometric Theory*, 10, 91-115.

- Smith, Margaret Hwang, and Gary Smith. "Bubble, bubble, where's the housing bubble?." *Brookings Papers on Economic Activity* 2006.1 (2006): 1-67
- Sowell, T. 2009. *The housing Boom and Bust*. New York: Basic Books .
- Stiglitz, Joseph E. "Symposium on bubbles." *The Journal of Economic Perspectives* 4.2 (1990): 13-18.
- Stiglitz, J. 2003 *The Roaring Nineties: Why We're Paying the Price for the Greediest Decade in History*, Harmondsworth: Penguin.
- Stock, J. H. and Watson, M. W. (1988). "Testing for Common Trends", *Journal of the American Statistical Association*, 83, 1097-1107.
- Tsatsaronis, Kostas, and Haibin Zhu. "What drives housing price dynamics: cross-country evidence." (2004).
- van Dijk, B., Franses, P.H., Paap, R. and van Dijk, D (2007), Modeling Regional House Prices, Tinbergen Institute, Erasmus University, Report EI 2007-55.