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# Contagion, Interdependence and Diversification across Regional UK Housing Markets

**William Miles**
Dept. of Economics, Wichita State University, 1845 Fairmount, Wichita, KS 67260-0078. Phone: 316-978-7085. Fax: 316-978-3308. E-mail: william.miles@wichita.edu.

UK home prices often exhibit only moderate (and sometimes barely positive) correlation across different regions. This reflects segmentation in the national housing market and also provides an apparent opportunity for lenders and investors to diversify their exposure to regional downturns, for instance, by creating residential mortgage backed securities out of geographically dispersed home loans. Unfortunately, in a crisis, correlations may rise, and the benefits from geographical diversification may disappear just when investors desire them the most. By using a flexible generalized autoregressive conditional heteroskedasticity technique, we find that regional correlations indeed rose dramatically during the latest downturn, in some cases, to unprecedented levels. Moreover, this increase in co-movement was clearly financial contagion, and not merely interdependence. Lenders, as well as investors in mortgage-backed and other housing securities should thus not rely on house price correlations calculated during "normal" times.

**Keywords**

Contagion, Interdependence, Housing, UK

# 1. Introduction

The global housing crisis caused big losses for financial institutions and investors, and in addition, played a key role in sparking sharp recessions across the United Kingdom (UK) and many other countries. Investors and financial institutions suffered losses on defaulted mortgages, which constrained further lending to housing and the rest of the economy. If housing values across the UK did not exhibit excessive co-movement, investors and institutions could in principle avoid such large losses by diversifying lending and housing investment across the UK. Thus a housing crash in one part of the country need not be excessively damaging to a portfolio of housing-related securities if those securities were backed by mortgages from across different areas in the UK, rather than being geographically concentrated. Indeed, some previous research has suggested that diversifying real estate holdings across the UK does indeed bring benefits to investor portfolios (see, for example, Worthington and Higgs, 2003). Furthermore, this issue does have importance for the UK, as it has the largest residential mortgage-backed security (RMBS) market in Europe, with 252.1 billion euros outstanding (compared to the Netherland's market, with 249.7 billion euro outstanding) (Bloomberg, 2014).

However, in a crisis, such as the housing bust which began around 2007, home values across the country may co-move much more than in "normal" periods. A downturn which begins in say, the south east part of the UK, may lead house prices in this region to appear to "contaminate" home values in other regions, thus making the co-movement of returns across different housing markets much greater than usual. This process of increasing correlation across markets in bad times is known as contagion. If such contagion in a crisis exists, it means that the benefits of diversification decrease or disappear precisely when investors most want them.

Not all observers agree that the apparent increase in co-movement of asset prices -whether for equities, currencies or housing- over a crisis constitutes contagion. Forbes and Rigobon (2002) define contagion between national equity markets as "a significant increase in cross-market linkages after a shock to one country or group of countries" (p. 2223). They note that different assets often exhibit co-movement in stable periods. If this co-movement continues during a market crash, this does not, according to Forbes and Rigobon (2002), constitute contagion, but rather, the authors term such co-movement as *interdependence*. The authors do hold, again, that if there is an increase in cross-market linkages-in their case (and ours) measured by correlation-this does constitute contagion. However, they note that correlation is conditional on volatility. If volatility in one market increases, it will increase the uncorrected correlation coefficient between itself and related markets and appear to indicate contagion. Forbes and Rigobon (2002) show that correlation coefficients are thus subject to heteroskedasticity, and when estimated correlation is not corrected for this heteroskedasticity, researchers will erroneously conclude that contagion has occurred. The authors show that the Asian crisis of 1997-98, widely believed to be an episode of contagion across different financial markets, was, according to their corrected correlation estimates, only an episode of continued interdependence.

Other authors, such as Corsetti et al. (2005), find that the restrictions Forbes and Rigobon (2002) impose onto their "corrected" correlation coefficient are overly restrictive and implausible. When a more plausible estimation method is employed, Corsetti et al. (2005) find contagion across some markets for which Forbes and Rigobon (2002) find only interdependence.

Chiang et al. (2007) note that a particular multivariate-generalized autoregressive conditional heteroskedasticity (GARCH) model, the dynamic conditional correlation (DCC) technique developed by Engle (2002), allows the estimation of time-varying correlation *and* at the same time, controls directly for the heteroskedasticity that concerns Forbes and Rigobon. The authors, who use the DCC-GARCH model, find, contrary to Forbes and Rigobon (2002),that contagion did indeed occur across a number of markets during the Asian crisis.

The topic of contagion in housing markets has received attention in the wake of the recent crisis. DeFusco et al. (2013) find, by using a proprietary data set and a particular method, contagion across a number of municipal housing markets in the United States, although they find contagion over booms rather than busts. Zimmer (2014) does apply the DCC-GARCH model across four US cities by using the Case-Shiller price index and finds that correlations have risen in the recent boom and bust years. Somewhat similar to DeFusco et al. (2013), his results show peaks in co-movement at least as often in the pre-2007 years as in the subsequent crash.

The DeFusco et al. (2013) and Zimmer (2014) studies are important contributions. In this paper, we will apply the DCC-GARCH model to different UK regions to obtain an estimate of co-movement across an entire nation, rather than just a handful of particular cities. We will also differ from Zimmer (2014) in controlling for overall, national UK house prices in our estimation (the relevance of this will be explained below), and we will use a longer span of data than DeFusco et al. (2013) or Zimmer (2014). We find that dynamic correlations did indeed change in the UK. The correlations between regions were often low in the late 1980s, and they have risen sharply over the crisis and peaked for most regions in 2009 or 2010, which indicate very high contagion. The peak co-movement of our results is mostly in the crash, not boom years, which is different from the findings of DeFusco et al. (2013) and Zimmer (2014) for the United States. Investors who believe that they are well-diversified based on house price co-movements during non-crisis periods will thus be disappointed as correlations do increase to near unity during crises.

This paper proceeds as follows. The next section describes the previous literature. The following section details the data and methodology. The fourth section describes the results, and the fifth section concludes.

## 2. Previous Literature

Asset returns often exhibit apparently higher than usual co-movement in “bad” times. These ostensibly higher co-movements have often been labeled contagion (King and Wadhwani (1990) would be an early example). This is, of course, problematic; investors often hold assets which appear to have low or negative co-movement based on the available data in order to minimize portfolio losses (see, for example, Gallo et al. (2013), and Cheok et al. (2011) for discussions of portfolio diversification in real estate). Real estate investment trusts (REITs) will often geographically diversify holdings, and Zimmer (2014) points out that investment companies have created mortgage-backed securities based on geographically diversified housing markets.

There is at least some mixed support for the idea that UK housing markets exhibit some segmentation (see, for example, Cook (2005) and Holmes (2007)). Thus it appears that holding a spatially diverse group of housing assets should yield diversification benefits-when one region is experiencing a housing downturn, other regions will often be doing better. However, if there is contagion, the co-movement of house prices, fairly low most of the time, increases during a housing market crash, and the benefits of diversification may disappear just when they are most desired.

Forbes and Rigobon (2002), however, state that an increase in observed co-movement in asset returns (in their case, they were focusing on equity markets) may not be contagion. These authors define contagion as “a significant increase in cross-market linkages”. Forbes and Rigobon (2002) state that correlation coefficients between assets are subject to heteroskedasticity, which, when not corrected for, leads to the false conclusion of contagion. The authors state that asset returns are linked and exhibit correlation in “normal” times - this they label interdependence. During crisis periods, volatility may increase in one or more markets, and given interdependence between markets, will increase estimated correlations.

The authors point to the example of the Asian crisis of 1997-98, often viewed as an example of contagion as currency and equity market crashes seemed to spread from country to country. The authors show that standard, uncorrected correlation coefficients between equity markets in Asian countries did seem to increase over the crisis period. However, when a correction to the correlation coefficient is applied, the authors find that there was no actual increase in cross-market movements, and find that the crisis was a case of interdependence, rather than contagion.

Corsetti et al. (2005) show that the correction to correlation developed by Forbes and Rigobon (2002) entails restrictions to be placed on the variance of country-specific shocks which are both unrealistic and theoretically inconsistent (see pp. 1185-86). Upon implementing an alternative specification in which returns for each market depend on a common “global” factor, as well as asset-specific shocks, Corsetti et al. (2005) find that a number of cross-country linkages between equity markets over the Asian crisis indeed exhibited contagion-i.e. an increase in correlation “too large to be accounted for” by the standard data-generating mechanism that the authors specify, which does allow for linkages between markets in both tranquil and crisis periods.

Chiang et al. (2007) apply a different technique to the question of contagion across Asian equity markets in the late 1990s. The authors employ a DCC GARCH model to obtain time-varying conditional correlations, based on the results of a multivariate GARCH estimation of nine national equity markets. The DCC GARCH model, developed by Engle (2002), is an important innovation in determining interdependence versus contagion. The estimator yields conditional correlation results that, by coming from a GARCH model, directly control for heteroskedasticity. Thus if one runs a DCC GARCH model for a group of different asset returns, and observes an increase of correlation over a crisis period, such an increase is not simply interdependence. Chiang et al. (2007) go on to point out that the conditional correlations obtained through the DCC-GARCH model can be estimated and observed in crisis and tranquil periods “without arbitrarily dividing the sub-sample into two sub-periods” (p. 1208). The DCC-GARCH model also allows, in keeping with Corsetti et al. (2005), for the inclusion of a global factor that affects all returns. Chiang et al. (2007) note that failure to include a global factor could result in misleading estimates. Chiang et al. (2007) accordingly employ the S&P 500 stock market returns from the United States in their DCC-GARCH model along with the nine Asian nations in question. Upon estimating the DCC-GARCH model, the authors find that the dynamic correlations among the nine countries indeed increase over the crisis period. They then take the pairwise conditional correlations, and by using the Schwarz's Bayesian criterion (SBC), estimate autoregressive (AR) models for the correlations between Thailand and five other Asian crisis countries. The authors then add dummy variables for the crisis period to the AR models of the dynamic correlations. The authors find that these crisis dummies are significant, thus indicating contagion.

Investigations into financial contagion have been mostly focused on equity, bond and currency markets. However, given that housing, like these other asset markets, is subject to boom-bust cycles (see Chan et al. (2011) and Nneji et al. (2013) for a discussion) there have recently been a couple of studies which have touched on the issue of contagion versus interdependence for housing, and examined the United States. DeFusco et al. (2013) investigate contagion in the US housing market. The authors exploit a proprietary data set on ninety-nine metro areas, and cover the period 1993-2009. The authors address the criticism of Forbes and Rigobon (2002) as they "adjust for the volatility in prices being higher than normal when the boom starts by directly controlling for the time line of the focal market's boom" (p. 4). They define contagion as being an increase in the correlation between two markets following a shock to one of the markets "that is above and beyond that which can be justified by common aggregate trends" (p. 1). By using their methodology, the authors find substantial contagion between markets. They find that geographical proximity seems to make contagion more likely, and that contagion is likely to happen when shocks go from large to smaller cities. Interestingly, the authors find "strong evidence of contagion during the housing boom but not during the bust" (p. 1).

Zimmer (2014) uses an alternative approach and employs the DCC-GARCH method for four US metropolitan housing markets - Los Angeles, Miami, New York City and Phoenix, although he does not use the factor-based method of Chiang et al. (2007). The author uses data from the Case-Shiller price index for these four metro areas running from 1989 to 2013. The author only estimates DCC GARCH models between pairs of the four cities, rather than estimating the model for all markets in question simultaneously, as did Chiang et al. (2007). This yields six city pairs - Miami/LA, Miami/NY, Miami/Phoenix, LA/Phoenix, LA/NY and Phoenix/NY. While the author uses the term "contagion", he does not address the distinction between contagion and interdependence. The author does find that correlations between these four markets obtained from the DCC GARCH estimation do indeed vary substantially over the sample period, going in many cases from lows in the 1990s or earlier 2000s and reaching peaks over the middle of the last decade. Somewhat similar to DeFusco et al. (2013), Zimmer (2014) finds that the peak of contagion appears over the pre-2007 boom years in at least half of the country pair cases. In addition, Leung et al. (2013) study the issue of changing co-movement in a housing market after a crisis, and examine the housing sector of Hong Kong.

There is literature on the interaction of regional house prices for the UK. One strand of the literature focuses on the "ripple effect"; that is, do shocks to house prices in one region "ripple out" to the rest of the UK? The maintained method of transmission is typically that house price changes begin in the southeast and then affect the rest of the UK. Alexander and Barrow (1994) find that modified ripple effect-price changes tend to originate in the South East (instead of London) and flow to other southern regions, and most price flows tend to be northward. Ashworth and Parker (1997), on the other hand, present results that cast the existence of the ripple effect in doubt.

Another strand of the literature investigates the question of convergence of house prices across regions. Cook (2003) and Holmes and Grimes (2008) both find that, in the long run, prices tend to converge across the UK, although there is evidence that the manner of convergence differs across regions. The results on convergence and segmentation across UK housing markets, overall, are not entirely clear. Moreover, none of these papers on UK regional home price interactions address contagion; indeed the word contagion is never mentioned in any of the four above-cited papers. Given the importance of contagion to housing markets, we will examine the regions investigated in these papers as to whether there has been contagion in the UK. We will not follow the method of DeFusco et al. (2013), as these authors had access to micro data for the USA, and used fundamentals such as average income of borrowers, migration flows, metropolitan statistical area (MSA) unemployment, percentage of speculators, most of which are not available for the British Nationwide Building Society data, which has been employed in all studies of UK regional home values of which we are aware. Instead, we will follow Chiang et al. (2007) by employing a common factor and estimating a DCC GARCH model to obtain time-varying correlations across the UK.

## 3. Data and Methodology

The data on regional UK house prices are obtained from the Nationwide Building Society, quarterly, and run from 1973:4 through 2014:1. The data have been employed in other studies of UK regional house price movements. Given the quarterly nature of the data, and the well-known seasonality that can affect housing prices, we compute returns as the log difference between home values in a given quarter and the value four quarters earlier. This will give us a sample for the DCC estimates of 1975:1-2014:1. This span of data is longer than either the DeFusco et al. (2013) or Zimmer (2014) study, which begin in 1993 and 1989, respectively.

The twelve regions which have been analyzed in the past are Northern, Yorkshire and Humberside, East Midlands, West Midlands, North West, East Anglia, Greater London, South East, South West, Wales, Scotland and Northern Ireland. As the model to be employed is a GARCH model, the returns for the regions to be analyzed should have GARCH effects. Miles (2011) investigates the different regions of the UK for GARCH; seven of the twelve exhibit GARCH effects. In this study, we have nearly five more years of data than those employed in Miles (2011). A larger sample size may increase the power of the Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) (this test posits as the null hypothesis that there are no ARCH effects) and make it more likely that ARCH effects will be found. We thus tested the remaining five regions in which Miles (2011) does not find ARCH effects with the new data. In four of the regions, there are clearly no ARCH effects; however, in the West Midlands, we could reject the null of no ARCH effects. Accordingly, we will model the following eight regions: East Anglia, East Midlands, Northern Ireland, Outer South East, South West, Wales, West Midlands, and Yorkshire and Humberside.

Figures 1 through 8 display the returns through time. Table 1 displays the summary statistics for the returns for the eight regions. South West and Outer South East have the highest mean returns over four decades, while Northern Ireland has the lowest return. In contrast, Northern Ireland has the highest unconditional volatility, with the largest standard deviation of all the regions, followed by East Anglia and Outer South East. Six of the eight regions saw their highest returns in the late 1980s, thus highlighting the 1980s boom-bust episode. All but one region - Yorkshire and Humberside - had their lowest returns during the crisis quarters of 2008 or 2009. The Jarque-Bera test (column "JB" in the table) indicates that returns are non-normal in the majority of the regions. This non-normality is suggestive of large shocks and has been found in other asset returns, such as those for equities. We will accordingly employ Bollerslev-Wooldridge standard errors, which are robust to non-normality in our GARCH estimation.

**Figure 1 East Anglia Annual Returns**

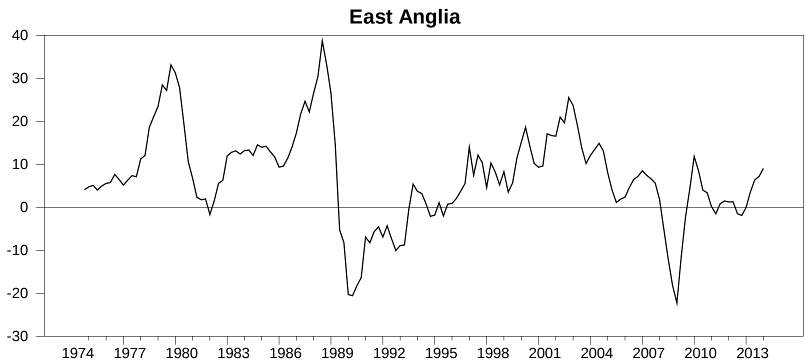
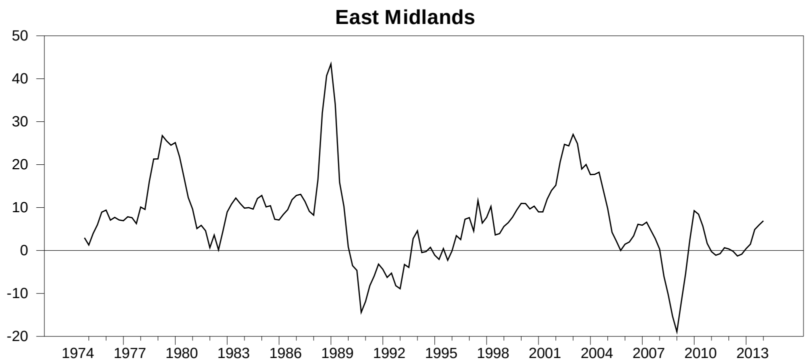
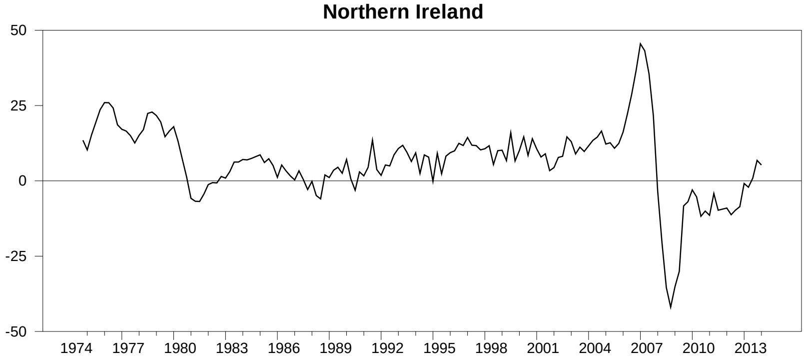


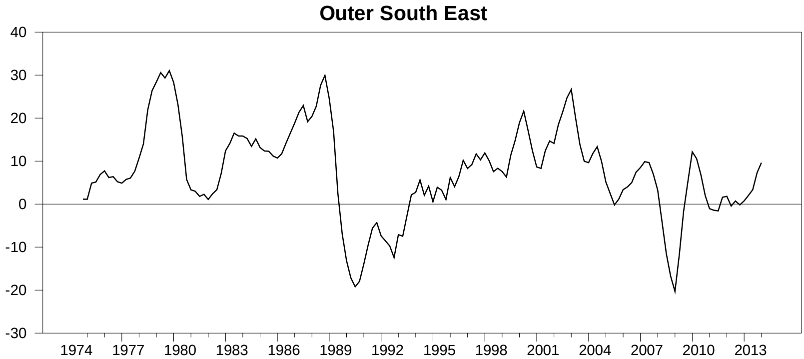

**Figure 2 East Midlands Annual Returns**



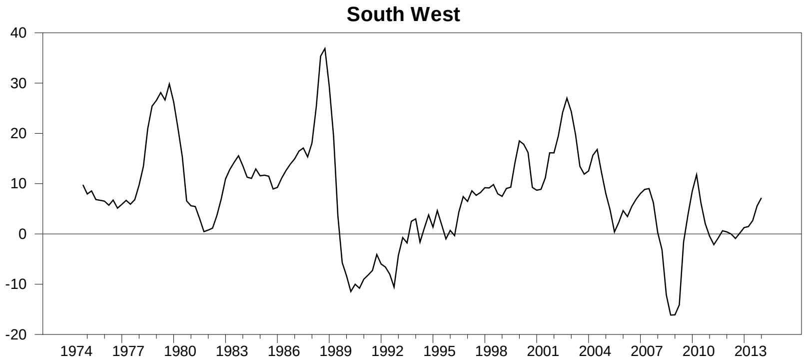
## Figure 3 Northern Ireland Annual Returns



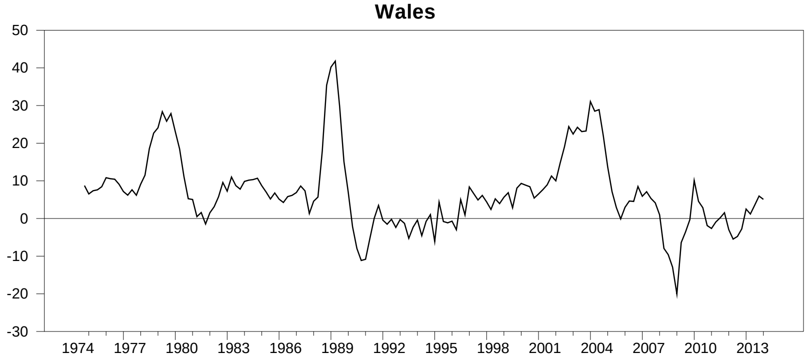

## Figure 4 Outer South East Annual Returns



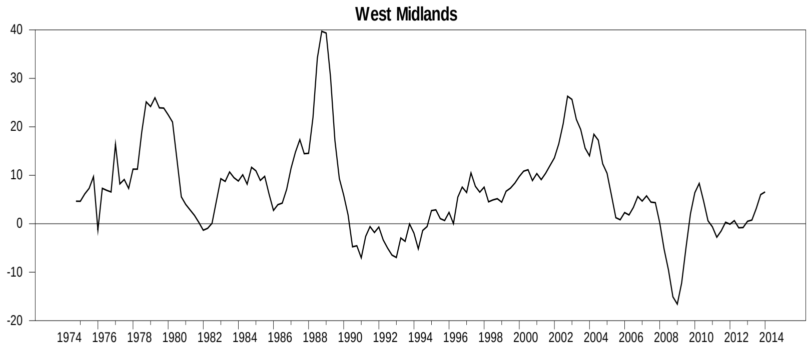

## Figure 5 South West Annual Returns



## Figure 6 Wales Annual Returns




## Figure 7 West Midlands Annual Returns




## Figure 8 Yorkshire and Humberside Annual Returns

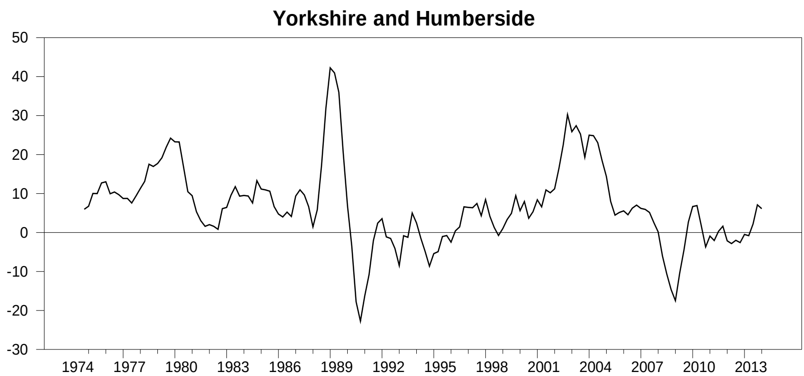


**Table 1 Summary Statistics for Regional Annual Returns**

| | Mean | SD | Max | Date | Min | Date | Skewness | P-value | Kurt. | P-Value | JB | P-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **E. Ang** | 7.24 | 10.9 | 38.6 | 1988:3 | -22 | 2009:1 | 0.019 | 0.921 | 0.637 | 0.109 | 2.68 | 0.261 |
| **E. Mids** | 7.1 | 9.92 | 43.4 | 1989:1 | -18 | 2009:1 | 0.63 | 0.001 | 1.633 | 0.000 | 28.2 | 0.000 |
| **N. Ire** | 6.53 | 12.2 | 45.4 | 2007:1 | -41 | 2008:4 | -0.55 | 0.00 | 3.29 | 0.000 | 79.8 | 0.000 |
| **OSE** | 7.47 | 10.5 | 31 | 1979:4 | -20 | 2009:1 | -0.16 | 0.415 | 0.26 | 0.513 | 1.12 | 0.57 |
| **SW** | 7.5 | 9.89 | 36.8 | 1988:4 | -16 | 2008:4 | 0.25 | 0.2 | 0.47 | 0.23 | 3.1 | 0.211 |
| **Wal.** | 6.82 | 9.97 | 41.79 | 1989:2 | -20 | 2009:1 | 0.953 | 0.000 | 1.7 | 0.000 | 42.9 | 0.000 |
| **W. Mids** | 6.97 | 9.38 | 39.7 | 1988:4 | -16 | 2009:1 | 0.795 | 0.000 | 1.4 | 0.000 | 31.3 | 0.000 |
| **YH** | 6.7 | 10.4 | 42.2 | 1989:1 | -22 | 1990:4 | 0.538 | 0.006 | 1.6 | 0.000 | 24.6 | 0.000 |

***Note:*** E. Ang stands for East Anglia, E. Mids stands for East Midlands, N. Ire stands for Northern Ireland, OSE stands for Outer South East, SW stands for South West, Wal. Stands for Wales, and YH stands for Yorkshire and Humberside. Mean and SD refer to the average and standard deviation of each region's annual return over the sample. Max refers to the maximum return for each respective region over the whole sample; the date to the right of Max is the date on which this maximum occurred. Similarly, Min and the date to the right of Min refer to the minimum return and the date on which this minimum return occurred. Skewness, Kurt. and JB refer to tests for skewness, excess kurtosis and normality (JB is an abbreviation for the Jarque-Bera test) and the P-value columns are the probability values for these respective tests.

We then turn to implementing the DCC GARCH model for the eight regions. Engle (2002) motivates the development of this model by discussing the importance of estimating the correlation of asset returns for financial management. Before the development of multivariate GARCH techniques, univariate GARCH models were specified with a conditional mean and a conditional variance for the asset return in question, for example:

$$r_{it} = \alpha_0 + \alpha_1 r_{it-1} + \varepsilon_{it} \tag{1}$$
$$\varepsilon_{it} = v_{it} h_{it}^{0.5} \tag{2}$$
$$h_{it} = a_0 + a_1 \varepsilon^2_{it-1} + \beta h_{it-1} \tag{3}$$

where (1) is an AR(1) model of returns for asset i at time t, and (3) captures the time-varying volatility present in many financial markets. The multivariate GARCH model was an extension of the standard, univariate model. The multivariate specification allowed the conditional variance of one asset return to affect the conditional variance of a different asset. Of course, the capturing of such interactions in volatility requires the specifying of a highly parameterized model; as a result, the obtaining of convergent and significant coefficient estimates is often difficult. This is especially the case as the number of dependent variables, in this case asset returns like $r_t$ in Equation (1), grows. There are some models, such as the constant conditional correlation (CCC) multivariate GARCH model which imposes restrictions onto parameter values to make convergence easier to obtain. However, these restrictions may not be plausible-in the CCC case, the imposing of the restriction that the correlation between markets is time-constant would completely defeat the purpose of examining time-varying relationships. Engle (2002) goes on to note that a number of previous papers which have proposed different variants of multivariate GARCH models and demonstrated their use in estimating the interactions of different assets rarely use more than five different assets, which limits the usefulness of the technique for portfolio management. Engle, however, develops a two-step technique to gauge asset correlations. In the first step, a univariate GARCH model is separately estimated for each asset return, as in Equations 1-3. The separate estimation for each series gives this method a flexibility that other multivariate GARCH techniques lack, as estimating all series simultaneously would quickly exhaust degrees of freedom. In the second step, the residuals $\varepsilon_{it}$ are standardized by their estimated, conditional (GARCH) standard deviations. This yields the following standardized residual:

$$u_{it} = \varepsilon_{it}/(h_{it})^{0.5} \tag{4}$$

Then a correlation matrix is estimated for all of the $u_{it}$. It is important to note that since $\varepsilon_{it}$ is divided by the time-varying $h_{it}^{0.5}$, this method controls for the heteroskedasticity that concerned Forbes and Rigobon (2002). The first step, in which each asset is allowed its own different GARCH specification, greatly saves on degrees of freedom compared with standard multivariate

GARCH models and allows for many more assets to be analyzed. The second step then allows for the estimation of time-varying correlation among the returns. Engle (2002) then runs a simulation and shows that the DCC GARCH model usually out-performs other multivariate GARCH models in terms of generating accurate conditional correlations.

There are other types of DCC GARCH models, such as the asymmetric, generalized DCC GARCH, which has been employed in real estate applications (see Yang et al. (2012)). However, this involves the estimating of more parameters than the standard DCC GARCH, and would lead to convergence problems (Yang et al. (2012) use daily data and around 2,300 observations, while the data available for this investigation are quarterly. In addition, the generalized DCC GARCH has not been employed to investigate interdependence versus contagion, while the standard DCC GARCH model has been employed in such a fashion, so we will use it for comparison purposes). We will follow Chiang et al. (2007) in specifying the conditional mean of our returns - Equation (1) in our example above, as a function of lagged own returns plus the lagged returns of a common factor. Chiang et al. (2007) correctly observe that national equity markets in a given Asian country interact with other national equity markets in Asia, but are also affected by a common factor (see Corsetti et al. (2005)) Failure to control for this common factor will result in misleading findings. Chiang et al. (2007) use the US S&P 500 stock index as a common factor for smaller Asian equity markets. In this paper, we will employ the national UK home price index from the Nationwide Building Society as a common factor. Our conditional mean equation for the DCC GARCH model of each region will thus be:

$$r_{it} = \alpha_0 + \alpha_1 r_{it-1} + \alpha_2 r^{UK}_{t-1} + \varepsilon_{it} \qquad (1')$$

which is identical to Equation (1) in Chiang et al. (2007), except of course, that $r_{it}$ here refers to regional housing returns and $r^{UK}_{t-1}$ refers to national UK housing returns. The conditional variance will be modeled, as in Chiang et al. (2007), as a standard GARCH(1,1) specification. In estimating the dynamic correlations, in order to keep the number of correlations from becoming unwieldly, one of the dependent variables is chosen as a "base", and the correlations are estimated with correlations between the remaining variables and the base. Chiang et al. (2007) choose Thailand as their base country, and DCCs are estimated relative to Thailand for the other Asian countries in the sample. A number of papers (see for instance, Alexander and Barrow (1994), Drake (1995), Cook and Thomas (2003)) have pointed out that the South East tends to drive prices elsewhere. We will accordingly use the Outer South East as our base region.

As noted, once Chiang et al. (2007) estimate their DCC GARCH model and obtain their time-varying correlations, they specify AR models of the correlations, and then add dummies to these AR models for the period of the crisis as well as the post-crisis period. They examine the significance of these dummies to see the impact of different periods, such as the Asian crisis, on equity co-movement. In this way, the authors test for "breaks" in the DCCs. We agree that it is important to see if there are breaks in the dynamic correlations; among other reasons, to see if these correlations are indeed dynamic and time-varying. However, the addition of dummies to the model based on knowledge of economic and financial events is problematic - a form of data mining. Hansen (1992) demonstrates that testing for breaks in this way makes the dummies appear "significant" when standard critical values are used; unfortunately, the test statistic used to test the significance of the dummy does not have a standard distribution.

Intuitively, to avoid the problem of data mining and the choosing of break points based on prior knowledge, one could test all points (one might first trim the data set by dropping the first and last few observations) for a break, and choose that date which yields the largest test statistic. This is the approach of Quandt (1960). However, this test statistic will not have a standard distribution, and if one is using a nominal size of five percent, one is almost certain to reject the null of no break even when the null of no break is true, for any reasonably large data set. Andrews (1993) and Hansen (1997) develop test statistics and critical values which overcome the problems of Quandt (1960). However, the Andrews procedure tests for only one break in the data set. In addition, Eksi (2009) states that the Andrews procedure is only valid if the residuals are independent and identically distributed (i.i.d.). Fortunately, Bai and Perron (2003) have developed a better procedure, which allows for multiple breaks, and also yields interval estimates around the date of the most likely breaks. Thus obtaining a break that occurred with a 95 percent confidence interval within a narrow range, such as two or four periods around the estimated break, gives credibility to the notion that a break did indeed occur, and did so near the estimated date. We will thus employ the Bai-Perron procedure to the estimated DCCs.

## 4. Results

Table 2 displays the estimated coefficients for the DCC-GARCH model. For the conditional mean, all AR(1) terms are positive and significant. This is consistent with the results on housing going back to Case and Shiller (1989), who find that, unlike well-developed equity markets, house prices in their US sample show persistence, with positive AR terms. This is also similar to the findings of Chiang et al. (2007) for emerging equity markets in Asia, in which seven markets have significant AR terms, and five of these are positive.

The lagged overall UK house price index term in the conditional mean is positive and significant at the five percent level in six of the eight markets, with Northern Ireland and West Midlands being the two regions in which national home returns do not appear to have an impact on the conditional mean. The "$a_1$" estimates for the conditional variance are positive and significant in all eight cases, while the "$\beta$" estimates significant in six of the eight cases.

**Table 2 DCC GARCH Estimation Results**

| | Return Eqn. | | | Variance Eqn. | | |
|---|---|---|---|---|---|---|
| | **Constant** | **AR(1)** | **UK(1)** | **Constant** | **α** | **β** |
| **E. Ang** | 0.489<br>(0.45) | 0.522<br>(0.00) | 0.415<br>(0.00) | 10.31<br>(0.00) | 0.512<br>(0.00) | 0.472<br>(0.00) |
| **E. Mid** | 0.12<br>(0.79) | 0.532<br>(0.00) | 0.398<br>(0.00) | 6.7<br>(0.00) | 0.468<br>(0.00) | 0.549<br>(0.00) |
| **N. Ire** | 1.57<br>(0.00) | 0.856<br>(0.00) | -0.04<br>(0.29) | 13.3<br>(0.00) | 0.621<br>(0.00) | -0.07<br>(0.09) |
| **OSE** | 0.77<br>(0.24) | 0.68<br>(0.00) | 0.22<br>(0.00) | 18.6<br>(0.00) | 0.713<br>(0.00) | 0.04<br>(0.81) |
| **SW** | 0.53<br>(0.33) | 0.507<br>(0.00) | 0.391<br>(0.00) | 16.7<br>(0.00) | 0.536<br>(0.00) | 0.231<br>(0.00) |
| **Wal.** | 0.241<br>(0.636) | 0.6<br>(0.00) | 0.269<br>(0.00) | 7.8<br>(0.00) | 0.588<br>(0.00) | 0.533<br>(0.00) |
| **WM** | 0.145<br>(0.791) | 0.722<br>(0.00) | 0.177<br>(0.11) | 32.52<br>(0.00) | 0.531<br>(0.01) | -0.33<br>(0.02) |
| **YH** | 0.134<br>(0.74) | 0.622<br>(0.00) | 0.283<br>(0.00) | 3.8<br>(0.03) | 0.491<br>(0.00) | 0.679<br>0.00) |

***Note:*** The return equation refers to Equation 1, and the variance equation refers to Equation 3. Numbers in parentheses are p-values. E. Ang stands for East Anglia, E. Mid stands for East Midlands, N. Ire stands for Northern Ireland, OSE stands for Outer South East, SW stands for South West, Wal. stands for Wales, WM stands for West Midlands, and YH stands for Yorkshire and Humberside.

It is important that GARCH models capture all of the time-varying volatility in a series. Accordingly, we run LM ARCH tests on each of the GARCH(1,1) models for the eight regions. The results are displayed in Table 3. As noted, for none of the eight regions could we reject the null, in that there are no remaining ARCH effects in returns once the GARCH(1,1) models were fitted. Thus, this specification appears to be the appropriate one for capturing the time-varying volatility in returns.

Figures 9 through 15 display the dynamic conditional correlations that ran from 1975:1 through 2014:1 for the seven regional pairings. All of the dynamic correlations exhibit a marked increase in the mid-to-late 2000s; indeed, in five of the seven cases, the DCC reaches a peak in the 2009 or 2010 crisis years, a point to which we shall return. For now, we want to emphasize that the majority of DCCs that reach their peak in the crisis, rather than boom years, are different from the results found for the US by DeFusco et al. (2013) and Zimmer (2014).

**Table 3 Post-GARCH Model Tests for Remaining ARCH Effects**

| Region | P-value |
|---|---|
| **E.Anglia** | 0.8904 |
| **E. Mids** | 0.5694 |
| **N. Ire.** | 0.9642 |
| **OSE** | 0.8446 |
| **SW** | 0.8059 |
| **Wales** | 0.9333 |
| **WM** | 0.2238 |
| **YH** | 0.85 |

***Note:*** OSE stands for Outer South East, SW stands for South West, WM stands for West Midlands, and YH stands for Yorkshire and Humberside. The p-value refers to the p-value from the LaGrange-multiplier test for remaining ARCH effects applied to each GARCH(1,1) model for each region after GARCH estimation.

**Figure 9 DCC between Outer South East and East Anglia**

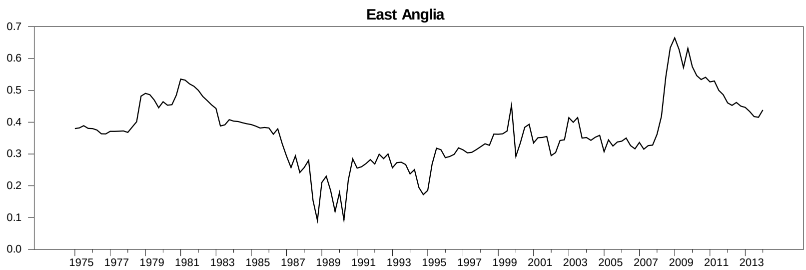
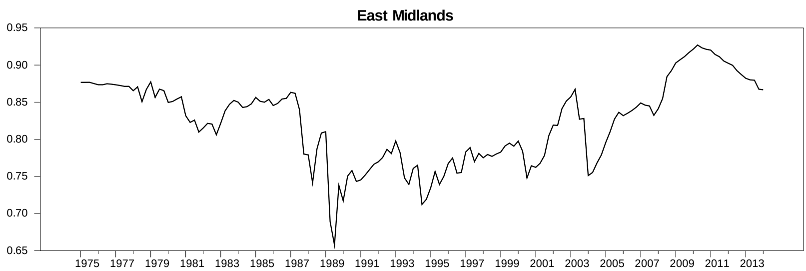
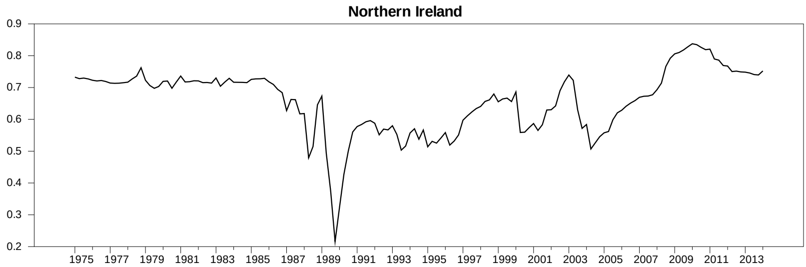


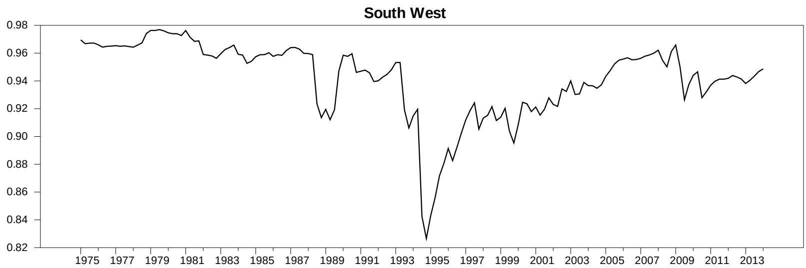

**Figure 10 DCC between Outer South East and East Midlands**



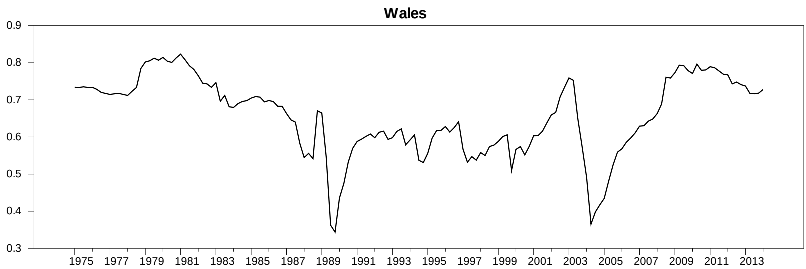
## Figure 11 DCC between Outer South East and Northern Ireland




## Figure 12 DCC between Outer South East and South West




## Figure 13 DCC between Outer South East and Wales




## Figure 14 DCC between Outer South East and West Midlands

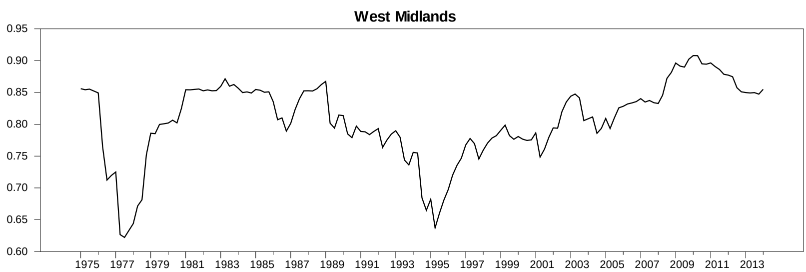
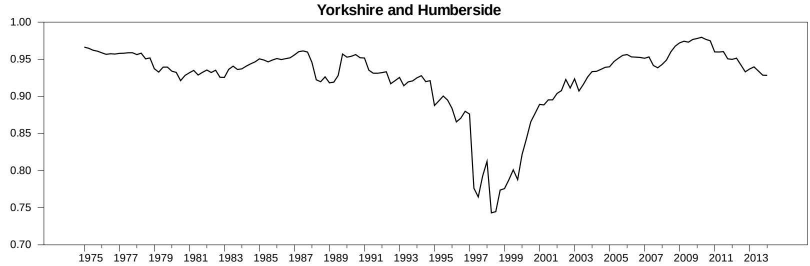


**Figure 15 DCC between Outer South East and Yorkshire and Humberside**




All of the DCCs exhibit either a minimum point (in three cases) or a "local" minimum, or notable dip, in the late 1980s. This was just around the late 1980s/early 1990s housing boom and bust in the UK. This episode was quite dramatic for the UK, and fueled by a number of country-specific factors. Baddeley (2005) notes that the 1980s witnessed much deregulation of the British housing market. Before the 1980s, the author points to credit rationing for potential mortgage borrowers, as mortgages were usually provided by building societies. However, in the 1980s, "a large range of other financial institutions were allowed into the mortgage market" (p. 5). Mortgage terms "became more flexible and generous (including 100% mortgages)" (p. 5). These changes were followed by a noted increase in homeownership-as well as a sharp rise in mortgage debt. Baddeley (2005) goes on to point out that many borrowers had adjustable-rate mortgages, and thus difficulties in repaying once interest rates rose. Another important change in the housing market occurred in 1988, when it was announced that double mortgage tax relief would be ended. According to Cameron et al. (2006), this set off a spike in purchases before double tax relief was ended. The subsequent recession and housing bust is associated with an increase in the DCCs from the global and "local" troughs that they exhibited in the late 1980s.

For the individual dynamic correlations, Table 6 shows the DCC between the Outer South East and South West has the highest mean of all six DCCs, second highest maximum, and highest minimum. This DCC is high through most of the sample, and has a small drop in the mid-to-late 1980s, with a "mini-trough" at 1989:2, after which it rises, and then later falls, hitting a trough at 1994:4. It then rises and stays fairly high for the rest of the sample.

The dynamic link between the Outer Southeast and East Midlands has the third highest mean, third highest maximum, and third highest minimum. There is a "local" trough at 1988:2, and a global minimum at 1989:3. The peak is at 2010:2. Likely reflecting its overall high level of segmentation from the overall UK housing market, Northern Ireland has the fifth lowest mean as well as maximum and sixth lowest minimum DCCs of any of the seven. The minimum was at 1989:4, and the maximum was at 2010:1

As noted, South West has the highest mean DCC, highest minimum and second highest maximum. There is a local trough at 1989:2, and the minimum is at 1994:4. The overall peak is at 1979:3. However, the DCC rises fairly steadily from the mid-1990s, and stays high for the rest of the sample, including the crisis years.

Wales has the sixth highest average DCC, sixth lowest maximum and fifth lowest minimum. This suggests that, like Northern Ireland, Wales is a somewhat segmented region of the UK housing market. The DCC has a minimum at 1989:4, then rises, before falling and hitting a local minimum again at 2004:3, after which it rises and hits near peak values during the crash period.

West Midlands initially falls, and has its minimum value in 1977. It then rises, before starting to fall in the late 1980s and 1990s, hitting a near minimum value in 1995. The DCC for this region then rises and hits a peak in the crisis period in 2010.

Finally, Yorkshire and Humberside has the second highest mean and minimum as well as the highest maximum. There is an overall minimum at 1998:2, and a global maximum in the crisis quarter of 2010:2.

The figures demonstrate that the correlations between the regions do indeed change, and reach "global" or at least "local" peaks during the post-2007 crisis years. Chiang et al. (2007) investigate the changing nature of the conditional correlations by estimating the correlations as time series, AR models, and then using dummies to test for structural change. It is useful to examine variation in the DCCs (as evidence, for example, that the correlations do indeed vary through time). However, the use of dummies for particular time periods, as discussed in the previous section, could lead to erroneous results. We will, as a result, employ the Bai-Perron procedure to allow for several endogenous breaks. As explained in Eksi (2009), the Bai-Perron procedure allows for multiple breaks. It begins by choosing a break date that minimizes the sum of squared residuals. Then further dates are examined for whether they further reduce the sum of squared residuals. As in the case of Chiang et al. (2007), we will use the SBC criteria to choose the optimal number of AR lags for each of our eight conditional correlations. In five of the cases, the optimal number of lags for the DCC model is two, while in three, one lag is chosen by using the SBC. We then allow for three breaks by using the Bai-Perron procedure. The results for the break dates, along with the 95 percent confidence interval around the break date, are shown in Table 4.

**Table 4 Bai-Perron Results**

| E.A. | BP1 | Lower 95% | Upper 95% | E.M. | BP1 | Lower 95% | Upper 95% | N.I. | BP1 | Lower 95% | Upper 95% | S.W. | BP1 | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **(1)** | 1988:2 | 1987:3 | 1988:3 | **(1)** | 1987:3 | 1986:2 | 1987:4 | **(2)** | 1988:1 | 1987:4 | 1988:2 | **(3)** | 1993:2 | 1993:2 | 1993:3 |
| | BP2 | | | | BP2 | | | | BP2 | | | | BP2 | | |
| | 1990:3 | 1990:2 | 1991:3 | | 1989:1 | 1988:4 | 1989:2 | | 1989:3 | 1989:3 | 1989:4 | | 1994:2 | 1994:2 | 1994:2 |
| | BP3 | | | | BP3 | | | | BP3 | | | | BP3 | | |
| | 2007:4 | 2004:4 | 2009:1 | | 1990:1 | 1989:4 | 1990:2 | | 1990:2 | 1990:2 | 1990:2 | | 1995:2 | 1995:2 | 1995:2 |

| Wal. | BP1 | Lower 95% | Upper 95% | WM | BP1 | Lower 95% | Upper 95% | YH | BP1 | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **(2)** | 1988:3 | 1988:3 | 1988:4 | **(4)** | 1977:2 | 1977:1 | 1977:3 | **(1)** | 1988:2 | 1987:3 | 1988:3 |
| | BP2 | | | | BP2 | | | | BP2 | | |
| | 1989:2 | 1989:2 | 1989:2 | | 1993:2 | 1993:1 | 1993:3 | | 1990:3 | 1990:2 | 1991:3 |
| | BP3 | | | | BP3 | | | | BP3 | | |
| | 1990:2 | 1990:1 | 1990:2 | | 1995:2 | 1995:1 | 1995:3 | | 2007:4 | 2004:3 | 2009:1 |

***Note:*** E.A. stands for East Anglia, E. M. stands for East Midlands, N.I. stands for Northern Ireland, and S. W. stands for South West. BP1, BP2 and BP3 denote the first second and third break dates found by the Bai-Perron procedure. Lower 95% and Upper 95% are the lower and upper bounds of the 95 percent confidence interval for the break date found by this procedure. Wal. stands for Wales, WM stands for West Midlands, and YH stands for Yorkshire and Humberside. BP1, BP2 and BP3 denote the first second and third break dates found by the Bai-Perron procedure. Lower 95% and Upper 95% are the lower and upper bounds of the 95 percent confidence interval for the break date found by this procedure.

As displayed, there are indeed palpable breaks in the AR models of the conditional correlation series. There are ten breaks in the 1990s, and eight in the 1980s, with two over the 2000s decade. Overall, the majority of breaks are in the late 1980s/early 1990s. This again likely reflects the major changes in the British housing policy and the boom and bust episodes of the period. The intervals estimated for most of the breaks are very "tight"- most estimated break quarters are within two or four quarters for their ninety-five percent confidence intervals.

**Table 5 Skewness, Excess Kurtosis and Normality Tests for Dynamic Correlations**

| | Test | Test Statistic | P-value |
|---|---|---|---|
| **OSE/EA** | Skewness | 0.188 | 0.34 |
| | Kurtosis | 0.466 | 0.24 |
| | Jarque-Bera | 2.35 | 0.308 |
| **OSE/EM** | Skewness | -0.259 | 0.189 |
| | Kurtosis | -0.581 | 0.146 |
| | Jarque-Bera | 3.96 | 0.137 |
| **OSE/NI** | Skewness | -0.96 | 0.000 |
| | Kurtosis | 1.93 | 0.000 |
| | Jarque-Bera | 48.73 | 0.000 |
| **OSE/SW** | Skewness | -1.5 | 0.000 |
| | Kurtosis | 3.13 | 0.000 |
| | Jarque-Bera | 126.05 | 0.000 |
| **OSE/W** | Skewness | -0.58 | 0.003 |
| | Kurtosis | 0.067 | 0.864 |
| | Jarque-Bera | 8.9 | 0.011 |
| **OSE/WM** | Skewness | -0.93 | 0.000 |
| | Kurtosis | 0.747 | 0.061 |
| | Jarque-Bera | 26.52 | 0.000 |
| **OSE/YH** | Skewness | -2.10 | 0.000 |
| | Kurtosis | 4.2 | 0.000 |
| | Jarque-Bera | 235.35 | 0.000 |

***Note:*** OSE refers to the Outer South East region. EA, EM, NI, SW, W and YH refer to East Anglia, East Midlands, Northern Ireland, South West, Wales, West Midlands and Yorkshire and Humberside, respectively. Skewness, Kurtosis and Jarque-Bera refer to tests for skewness, excess kurtosis and normality and the P-value columns are the probability values for these respective tests.

While it seems obvious from the graphs of the DCCs, the fact that all conditional correlations exhibit such clear breaks is strong evidence that the dynamic correlations are indeed dynamic, and have changed throughout the nearly four decades of the sample. Tables 5 and 6 and Figures 9 through 15 give us details on the dynamics of the regional house price co-movements. The Outer South East/South West DCC has, as noted, the highest mean in the sample, while the Outer South East/East Anglia has the lowest. Table 5 shows that five of the seven DCCs are negatively skewed (those for East Anglia and East Midlands do not appear to be negatively skewed). Four of the seven dynamic correlations exhibit excess kurtosis, and five of the seven are non-normal, by the Jarque-Bera test.

**Table 6 DCC Summary Statistics**

| | Mean | SD | Max | Date | Min | Date |
|---|---|---|---|---|---|---|
| **EA** | 0.367 | 0.104 | 0.664 | 2009:1 | 0.091 | 1988:4 |
| **EM** | 0.823 | 0.055 | 0.926 | 2010:2 | 0.657 | 1989:3 |
| **NI** | 0.657 | 0.100 | 0.837 | 2010:1 | 0.216 | 1989:4 |
| **SW** | 0.941 | 0.027 | 0.976 | 1979:3 | 0.826 | 1994:4 |
| **W** | 0.656 | 0.103 | 0.823 | 1981:1 | 0.343 | 1989:4 |
| **WM** | 0.806 | 0.06 | 0.907 | 2010:1 | 0.622 | 1977:3 |
| **YH** | 0.924 | 0.048 | 0.979 | 2010:2 | 0.743 | 1998:2 |

***Note:*** EA, EM, NI, SW, W, WM and YH refer to East Anglia, East Midlands, Northern Ireland, South West, Wales, West Midlands and Yorkshire and Humberside, respectively. Mean and SD refer to the average and standard deviation of the dynamic correlation of each region. Max refers to the maximum value of the DCC for each respective region over the whole sample; the date to the right of Max is the date on which this maximum occurred. Similarly, Min and the date to the right of Min refer to the minimum value of the DCC and the date on which this minimum return occurred.

To repeat, the Bai-Perron test results clearly demonstrate that the conditional correlations are not constant and have changed over the last thirty-seven years. Were the values of the DCCs sufficiently different from their “normal” values over the housing bust that the bust episode can be reasonably considered as a case of contagion? As Table 6 displays, in five of the seven DCCs, the peak, highest value for the entire sample occurred in 2009 or 2010. The remaining two DCCs (those between Outer South East and South West and Outer South East and Wales) have very high values in 2009 and 2010. These DCC measures are corrected for heteroskedasticity, and given their extremely tight co-movement over the crisis years, contagion is an apt description.

## 5. Conclusion

The housing bust of the late 2000s produced tremendous turmoil among "systemically important" financial institutions, both in the UK and the United States. The safety of MBSs, despite being created from loans made across different regional markets, was grossly over-estimated. During "normal" times, home prices across different parts of the UK indeed exhibit moderate (and sometimes even negative) co-movement, but during the recent crisis, dynamic correlations rose in most cases to all-time highs.

The method employed in this study controlled for time-varying volatility across markets. This fact, when combined with the finding that the overall dynamic correlations for most of the sample were at their peak over 2009-2010 indicate that, as in the case of Chiang et al. (2007) and equities over the Asian crisis, the late 2000s period in UK housing was one of contagion, and not merely interdependence. Portfolio management techniques which fail to account for potentially very large changes in house price co-movement thus leave financial institutions at great risk.

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