AN EMPIRICAL ANALYSIS OF THE SCOTTISH HOUSING MARKET BY PROPERTY TYPE

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ABSTRACT

This paper studies house price dynamics of the different property types in Scotland. We find evidence of i) breakpoints around the recent financial crisis in three property types (flats, terraced, semi-detached) and in the average house prices, ii) volatility clustering in the detached house prices, with the CGARCH being the optimal volatility model, iii) negative impact of the unemployment and interest rates on house prices irrespective of the property type and positive effect of the CPI in the prices of the detached, terraced and average houses. Our results have significant implications for appropriate economic policy selection and investment management.

Keywords House prices, Scotland, Structural break, Volatility, CGARCH

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1 INTRODUCTION

The analysis of real estate markets has long been the subject of interest in different economies. Housing markets have important effects in an economy through many channels. For instance, they affect selling/buying prices directly and financial institutions indirectly through mortgage defaults. Moreover, housing is an important asset constituting a substantial input to the total asset of several households (Lee, 2009), while holding a twofold role through consumption and investment as opposed to several other assets and commodities (Lee, 2017). However, housing investment cannot be considered safe because of the numerous housing bubbles all over the world, while recent crises suggest a failure of the banking and financial sectors to appropriately price housing risk (Morley and Thomas, 2016).

The most recent financial crisis, in particular, has drawn the attention of policymakers and investors alike towards the importance of house price volatility (Lee, 2009) and proved the importance of housing markets to the economy, as housing systems are related to the distribution of welfare and wealth, and housing finance is linked to the most recent international financial crisis (Schwartz and Seabrooke, 2009). As a result, studying house price dynamics is of high importance in different markets, such as financial, mortgage and housing. Moreover, analysing housing market volatility in particular is important for policy decision making and homeownership. Policy makers seek a less volatile housing market to increase homeownership. Lee and Reed (2014) found that first-time buyer schemes support housing affordability and housing price stabilisation. In addition, Stephens and Williams (2012) highlight the importance of stability to a socially sustainable housing market.

It has been previously shown that house prices share some properties with financial time series (see, e.g., Campbell *et al*., 2009; Dolde and Tirtiroglu, 1997; Karoglou *et al*., 2013; Lin and Fuerst, 2014; Miles, 2011a). Following the vast literature on modelling the volatility of financial assets using the class of Generalised Autoregressive Conditional Heteroscedasticity

(GARCH) models, recently there has been heightened interest in modelling house price volatility employing similar methods. However, there is rather limited literature on house price volatility that focuses on specific regions, instead of aggregate effects, or on different property types, even though there has been evidence of discrepancies in house price dynamics and volatility clustering as well as in risk-return relationships found not only across countries but also across regions and property types.

Analysing real estate markets effectively is crucial for appropriate economic policy selection and portfolio management at both national and regional level. Real estate has become an important part for portfolio diversification. Although unsafe, direct and indirect investment (through funds) in real estate could still be considered as a relatively safer investment than other assets. Investors who want to eliminate risk want to include assets with different correlations. Diversification can be achieved not only among different assets (e.g., stocks, bonds, real estate) but also within the same asset class. For example, Eichholtz *et al*. (1995) examined real estate portfolio diversification across the US and UK and found diversification potential (by both property type and region) but did not find a common conclusion across different regions and property types.

Real estate is a major part of the Scottish economy and supports the economic activity across Scotland (e.g., investment, jobs). According to the Fraser of Allender Institute (2018), the economic contribution of commercial property activity is 4% of Scotland's economic output and is a valuable investment for trusts and pension funds. The property market plays a key role in capital circulation and as any market needs a social order to work properly. Apart from an important source of tax revenue, there are also significant spill-over effects in the whole economy. Housing is a central part of the national and local political-economic policies in general (Aalbers and Christophers, 2014).

Nevertheless, previous studies of UK housing markets have focused mainly on England and Wales, often excluding Scotland, though. Exceptions include the studies of Maclennan and Tu (1998), Miles (2011b; 2015) and Begiazi and Katsiampa (2018). Interestingly, while Maclennan and Tu (1998), in their study of UK cities, included Glasgow, as its house prices continued to rise, similar to the rest of Scotland, and moved in the opposite direction of Bristol and Luton during 1989-1993, Miles (2015) found that Scotland exhibited the least variable returns in his sample. However, Bell and Blanchflower (2007), while considering various conditions, including housing, among others, found that Scotland's well-being suffers more than any other UK region. Moreover, of these studies, only Miles (2011b) and Begiazi and Katsiampa (2018) examined the volatility of the Scottish housing market, both of which considered Scottish house prices in aggregate effects and not by property type, though. Furthermore, even though it is important to test for potential structural breaks if the period under examination includes an unstable time, such as a financial crisis, as ignoring structural breaks may result in an erroneous inference (Chien, 2010), there exists very limited literature on testing for structural breaks prior to modelling conditional volatility, especially for the Scottish housing market. What is more, to the best of the authors' knowledge, no previous study has examined the determinants of the Scottish housing market.

Consequently, we aim to contribute to the literature not only by investigating whether the Scottish house prices exhibit constant or time-varying conditional variance and if the results are consistent with earlier studies, but also by testing for structural breaks and identifying potential breakpoints, which could help us correlate them with specific events (e.g., financial crises, etc.). Moreover, as different forms of housing are used for various purposes and attract different types of buyers (Morley and Thomas, 2016), not only do we study the average Scottish house prices, but we also examine whether house price dynamics vary across different property types in Scotland. These include flats, terraced, semi-detached and detached houses. Finally, we consider exogenous macroeconomic variables in order to study the determinants of the Scottish housing market. This is, therefore, the first study that comprehensively explores the price dynamics of the Scottish housing market.

The paper is organised as follows: The next section reviews the relevant literature, followed by a description of the data and methodology used in the third and fourth sections, respectively. The fifth section details our empirical results, while the conclusions drawn and the implications for policy making are presented in the last section.

2 LITERATURE REVIEW

Over the last two decades, there has been an increased research interest in the analysis of house prices. House price volatility has been studied in different countries and economies. For instance, Lee (2009, 2017) and Lee and Reed (2013) examined house price volatility in Australia, Hossain and Latif (2009) and Lin and Fuerst (2014) studied Canadian house price volatility, while Coskun and Ertugrul (2016) modelled house price volatility in Turkey. However, the two countries that have drawn the most attention in terms of studying real estate, as well as other asset, prices and volatility are the US and the UK. Examples of authors who have studied US house prices include Dolde and Tirtiroglu (1997), Crawford and Fratantoni (2003), Miller and Peng (2006), Campbell *et al*. (2009), Miles (2008, 2011a), Miao *et al*. (2011), Karoglou *et al*. (2013), Zhu *et al*. (2013) and Webb *et al*. (2016). On the other hand, studies of regional house price volatility in the UK include those of Tsai *et al*. (2010), Willcocks (2010), Miles (2011b, 2015), Tsai (2015) and Morley and Thomas (2011, 2016).

Nevertheless, despite the fact that the importance of modelling individual areas separately when studying house price volatility has been highlighted in various studies (see, e.g., Miller and Peng, 2006; Lee, 2009; Miles, 2008, 2011b; Morley and Thomas 2016), examining Scottish house price dynamics has been rather limited, even though previous studies have examined volatility of other areas of the UK, namely England and Wales. To the best of the authors' knowledge, only Willcocks (2010), Miles (2011b) and Katsiampa and Begiazi (2018) considered Scotland, among other regions, in their studies of conditional variances of quarterly UK regional house prices, all of whom found evidence of a lack of volatility clustering, though. Moreover, even though it could be expected that house price dynamics differ not only at regional but also at property type level, the literature on house prices by property type is extremely limited. Again to the best of the authors' knowledge, only Valadkhani *et al*. (2016), Morley and Thomas (2016) and Begiazi and Katsiampa (2018) have studied house price dynamics by property type. However, Valadkhani *et al*. (2016) examined regional seasonality in Australian house and apartment price returns, Morley and Thomas (2016) studied regional house prices by property type only for England and Wales, excluding Scotland, while Begiazi and Katsiampa (2018) considered only aggregate, and not regional, house prices by property type in the UK.

Earlier studies of house price volatility have employed different GARCH-type models. For example, the simple ARMA-GARCH model has been used by, e.g., Hossain and Latif (2009), among others, in an attempt to identify the determinants of house price volatility, while the Exponential GARCH (EGARCH) model has been preferred when studying asymmetries in house price volatility (see, e.g., Lee, 2009). Nevertheless, the GARCH-in-Mean (GARCH-M) and Exponential GARCH-in-Mean (EGARCH-M) models seem to have been the most popular ones. For instance, Dolde and Tirtiroglu (1997) used an ARMA-GARCH-M model in order to examine patterns of temporal and spatial diffusion of real estate price changes, while Stevenson *et al*. (2007) used a GARCH-M model to study the sensitivity of real estate securities to changes in interest rates. On the other hand, examples of studies that employed the EGARCH-M model include those of Willcocks (2010), Lin and Fuerst (2014) and Morley and Thomas (2011, 2016) who found evidence suggesting that house prices in some regions exhibit characteristics similar to stock indices. Other GARCH-type models used in studies of house price volatility include the Regime Switching ARCH (SWARCH) model (Tsai *et al*., 2010), the Threshold GARCH (TGARCH) model (Miles, 2008, 2011b), the Component GARCH (CGARCH) model (Lee and Reed, 2013; Miles, 2011a) and the Asymmetric Component GARCH-in-Mean (ACGARCH-M) model (Karoglou *et al*., 2013; Lee, 2017). However, even though previous studies have attempted to model house price volatility using the family of GARCH-type-models, most of them have not considered comparing different GARCH-type models.

In addition, examining the model stability prior to testing for volatility clustering is of paramount importance. Although, previous studies have shown that some regions exhibit conditional volatilities (see, e.g., Miles, 2011a, 2011b; Morley and Thomas, 2016; Willcocks, 2010), housing markets often face large shocks which may cause structural breaks, while breaks in the variance might appear as volatility clustering (Diebold, 1986). Furthermore, despite the fact that accurate forecasting could be affected by structural breaks (Lee *et al*., 2006; Rapach and Straus, 2008), there is rather limited literature on structural break analysis of house price dynamics, especially prior to modelling conditional volatilities. Among few authors who have investigated potential breakpoints of house prices are Chien (2010), who examined breakpoints in the Taiwan housing market, and Karoglou *et al*. (2013) and Canarella *et al*. (2012), who studied breakpoints in the US housing market, while authors who have investigated potential breakpoints in the UK house prices include Miles (2015), Zhang *et al*. (2017) and Begiazi and Katsiampa (2018).

Finally, understanding the risk-return relationship in housing markets as well as the determinants of housing markets is of utmost importance to both investors and policymakers. Previous studies of risk-return relationships in real estate markets include those of Karoglou *et al*. (2013), Morley and Thomas (2016) and Lee (2017). On the other hand, earlier studies of the determinants of housing prices include those of Case and Shiller (1990), Abelson *et al*. (2005), Lee (2009, 2017) and Lee and Reed (2013). However, no earlier study has considered investigating the risk-return relationship or the determinants of the Scottish housing market. Moreover, earlier studies on the determinants of housing markets mostly consider first moments, with limited existing literature on the determinants of house price volatility (Lee, 2009).

Therefore, this paper extends the literature by studying house price dynamics in Scotland not only in average prices but also by UK property type, namely flats, terraced, semi-detached and detached houses. More specifically, we conduct structural break analysis aiming to identify any potential breakpoint dates and correlate them with specific events, prior to testing for ARCH effects. In addition, for the property types exhibiting volatility clustering, we consider various GARCH-type models in order to identify the optimal volatility model and then study the risk-return relationship. Finally, we study the determinants of the Scottish housing market, not only in the first moments but also in volatility.

3 DATA

In order to investigate whether the Scottish housing market exhibits structural breaks and/or volatility, this paper uses monthly house price data by property type for Scotland from January 2004 (as the earliest date available) to May 2017, giving a total of 161 observations for each property type. The dataset is derived from the UK House Price Index which is based on house price data collected by the UK Land Registry and covers the four property types of detached, semi-detached and terraced houses and flats/maisonettes as well as the average house price of the different property types in Scotland. The data are publicly available online at https://www.gov.uk/government/statistical-data-sets/.

The data are converted to natural logarithms, and then we define the housing returns for each property type as

$$R_{it} = lnP_{it} - lnP_{it-1}, \tag{1}$$

where R_{it} is the logarithmic house price change in month t for house property type i, and P_{it} is the average monthly house price in month t for house property type i. It should be noted, though, that following Willcocks (2010), the returns are not smoothed or adjusted for inflation, as this could hide the impact of volatility changes over adjacent time periods.[4]

In addition, in order to study the determinants of the Scottish housing market, we also include the Scottish unemployment rate, UK interest rate and UK CPI index in our dataset. All of these variables are key macroeconomic policy instruments. Monthly data for the Scottish unemployment rate and UK CPI index were extracted from the Office for National Statistics (https://www.ons.gov.uk/), while the monthly data for the monthly UK interest rate are available online at the Bank of England's website (http://www.bankofengland.co.uk).

4 METHODOLOGY

In this section, the methodology employed in this study is discussed. More specifically, the unit-root and breakpoint tests conducted are first presented, followed by a discussion on the ARMA and volatility modelling procedures. Finally, we present the model where the three exogenous variables are incorporated as determinants of the Scottish housing market.

[4] Moreover, following Miles (2011a), Karoglou et al. (2013) and Lee (2017), among others, in our study we employ non-seasonally adjusted data, as seasonal adjustment could hide useful information about the data. It is also worth mentioning that the linear X-11 filter, which is one of the most common methods for seasonal adjustment, and the actual seasonal adjustment procedure produce serious downward biases in ARCH effects as well as in their persistence (Ghysels et al., 1997).

Unit-root testing

We start the empirical analysis by performing unit root tests, the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) tests in particular, in order to examine the stationarity of the house price returns, by allowing for changes in either the intercept only or in both the intercept and linear trend under each technique. However, in the presence of a breakpoint, structural changes need to be taken into consideration when testing for unit roots (Perron, 1989), as the conventional unit root tests may lead to a wrong decision when the null hypothesis is not rejected (Thornton, 2007; Chien, 2010), while inconsistent results from unit root tests suggest the eventuality of a structural break in the series (Göktaş and Dişbudak, 2014). Hence, as the period under examination covers the recent financial crisis of 2007 which affected the house prices overall as well as other events (e.g., UK referendum) that could possibly cause instability, it is important to also test for structural breaks.

Consequently, modified Dickey-Fuller tests are also performed allowing for either an innovational outlier break, assuming that the break occurs gradually and follows the same dynamic path as the innovations, or an additive outlier break, assuming that the break occurs immediately. In each case, we allow for non-trending data with an intercept break, or trending data with both intercept and trend breaks. The framework follows the work of Perron (1989), Perron and Vogelsang (1992), Banerjee *et al*. (1992) and Vogelsang and Perron (1998).

Identification of structural breaks

Once stationarity is ensured, following the methodology of Göktaş and Dişbudak (2014), we test for multiple unknown structural breakpoints using Sequential Bai-Perron (Bai, 1997; Bai and Perron, 1998) tests allowing for up to five breakpoints, after fitting an Autoregressive (AR) model with a constant to our house price return series, selecting the lag order according to the statistical significance of the estimated parameters. Any date identified as a potential breakpoint according to the Sequential Bai-Perron tests is further tested using Chow's breakpoint test (Chow, 1960) as well as the Quandt-Andrews test (Andrews, 1993; Andrews and Ploberger, 1994) in order to verify the results.

We also test for potential breakpoints in the variance. Consequently, following Göktaş and Dişbudak (2014) and Begiazi and Katsiampa (2018), the squared residuals of the AR models are regressed on a constant, and Sequential Bai-Perron tests are then re-performed. Once again any date identified as a potential breakpoint in the variance according to the Bai-Perron tests is also tested using Chow's test and the Quandt-Andrews test in order to confirm the results.

ARMA modelling

Next, following Willcocks (2010), we model each return series by an ARMA (*p*,*q*) process. It should be noted that for the property types exhibiting structural breaks, different ARMA models are fitted before and after the breakpoint as long as there is a sufficient number of observations in each interval. The ARMA (*p*,*q*) model has the following form

$$R_{t,i} = \mu + \varphi_1 R_{t-1,i} + \cdots + \varphi_p R_{t-p,i} + \varepsilon_{t,i} + \theta_1 \varepsilon_{t-1,i} + \cdots \theta_q \varepsilon_{t-q,i}. \tag{2}$$

Similar to Willcocks (2010), the appropriate lag structure for each property type is selected according to information criteria, Akaike (AIC) and Bayesian (BIC) information criteria, in particular. We also use the LM test for autocorrelation in order to check whether there is any remaining autocorrelation in the residuals prior to testing for ARCH effects, as it is assumed in ARCH modelling that the residuals are uncorrelated, even though autocorrelation exists among the squared residuals (Miles, 2008, 2011b). Allowing for different lag orders across different property types is on the basis of assuming that expectations for each property type are heterogeneous, similar to the assumption of Miller and Peng (2006) and Willcocks (2010) that expectations in different areas are heterogeneous.

Volatility modelling

We then use Engle's (Engle, 1982) ARCH-LM test applied to the residuals from the ARMA models in order to test for potential ARCH effects and see whether volatility modelling is required. If volatility clustering is found in a series, we proceed by fitting six GARCH-type models, namely ARCH, GARCH, Exponential GARCH (EGARCH), GJR-GARCH, Component GARCH (CGARCH) and Asymmetric CGARCH (ACGARCH), to the given series. The conditional volatility model takes the following form

$$\varepsilon_t = h_t z_t,\ \ z_t \sim \mathrm{i.i.d.}\,(0,1), \tag{3}$$

where ε_t is the error term, z_t is a white noise process, h_t is the conditional standard deviation, and hence h_t^2 is the conditional variance.

In the simple ARCH model (Engle, 1982), the conditional variance depends on previous squared errors, and the first order model takes the following form

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2, \tag{4}$$

while in the GARCH model (Bollerslev, 1986), the conditional variance depends on both previous squared errors and past volatility, as follows

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2, \tag{5}$$

with $\omega > 0, \alpha \geq 0$ and $\beta \geq 0$. However, although the GARCH model is a popular model for time-varying conditional variances, it cannot model the leverage effect which often appears in the behaviour of heteroskedastic time series. As opposed to the ARCH and GARCH models, the EGARCH, GJR-GARCH and ACGARCH models take asymmetric effects of positive and negative shocks in the conditional variance into consideration. More specifically, in the EGARCH model (Nelson, 1991), the conditional variance is written as

$$\log(h_t^2) = \omega + \alpha\left(\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| - \sqrt{2/\pi}\right) + \beta \log(h_{t-1}^2) + \delta \frac{\varepsilon_{t-1}}{h_{t-1}}, \tag{6}$$

allowing for asymmetric volatility responses to negative news, i.e. $\varepsilon_{t-1} < 0$, and positive news, i.e. $\varepsilon_{t-1} > 0$, as indicated by the sign of δ. Similarly, in the GJR-GARCH model (Glosten *et al.*, 1993), the conditional variance is defined as

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}, \tag{7}$$

where I_t is an indicator function, with $I_t = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise, indicating that positive and negative shocks have again different impact on volatility. A negative leverage EGARCH (δ) parameter estimate and a positive asymmetry GJR-GARCH (γ) parameter estimate suggest that negative return shocks have a greater impact on the conditional volatility than positive shocks of equal magnitude.

Moreover, while the conditional variance of the GARCH model shows mean reversion to ω, which is a constant for all time, the CGARCH model (Engle and Lee, 1999) decomposes the aggregate volatility into a short-term (transitory) component, $h_t^2 - q_t$, and a long-run (permanent) component, q_t, (Lee, 2017) which is time-varying and slowly mean-reverting. The CGARCH model can thus be expressed as

$$h_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1}^2 - q_{t-1}), \tag{8}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \theta(\varepsilon_{t-1}^2 - h_{t-1}^2), \tag{9}$$

The transitory volatility component, $h_t^2 - q_t$, converges to 0 with powers of $\alpha + \beta$ (Lee, 2017), while ϱ measures the speed of convergence to the long-run level of volatility (Karoglou *et al*., 2013). Christoffersen *et al*. (2008) showed that including both volatility components allows the CGARCH model to outperform the GARCH model. It is worth noticing that the CGARCH model has found several applications in the literature on housing market volatility dynamics. Finally, the ACGARCH model combines the CGARCH and GJR-GARCH models and can be written as

$$h_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta(h_{t-1}^2 - q_{t-1}) \tag{10}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \theta(\varepsilon_{t-1}^2 - h_{t-1}^2), \tag{11}$$

where *D* is a dummy variable which indicates negative shocks, while positive values of γ suggest the presence of transitory leverage effects in the conditional variance.[5]

The optimal GARCH-type model is chosen according to AIC, BIC, and Hannan-Quinn (HQ) information criteria, all of which consider how satisfactory the fitting of the model is as well as the number of model parameters. The selected model is the one with the minimum information criteria values. For the selected model, we also estimate its GARCH-in-mean counterpart, which includes the conditional standard deviation as a regressor in the mean equation as follows

[5] It is worth mentioning that some of these models can be viewed as a special case of other GARCH-type models under specific conditions or restrictions. More specifically, if the asymmetry ACGARCH (γ) parameter equals zero, we obtain the CGARCH model, while if $\rho = \theta = 0$ in the CGARCH model, we obtain the GARCH model. Similarly, the GARCH model is nested in the GJR-GARCH model for a zero asymmetry GJR-GARCH (γ) parameter. Finally, if the GARCH (β) parameter equals zero, we obtain the simple ARCH model.

$$R_{t,i} = \mu + \varphi_1 R_{t-1,i} + \cdots + \varphi_p R_{t-p,i} + \varepsilon_{t,i} + \theta_1 \varepsilon_{t-1,i} + \cdots \theta_q \varepsilon_{t-q,i} + \lambda h_t. \tag{12}$$

The incorporation of the conditional standard deviation, which measures the risk, in the mean equation of the model is required for the identification and measurement of any risk-return relationship (Karoglou *et al*., 2013; Morley and Thomas, 2011). Positive values of λ suggest that investors, especially risk-averse ones, would demand a higher risk premium in return of increased risk, while negative values of λ indicate that investors would require lower risk premium during periods of high risk (Karoglou *et al*., 2013; Lee, 2017).

Determinants of Scottish housing market

Finally, we study the determinants of the Scottish housing market. Similar to Abelson *et al*. (2005), Lee (2009) and Lee and Reed (2013), we examine whether the unemployment rate and CPI affect house prices. Moreover, following Lee (2009, 2017), we also include interest rate as an exogenous variable in the mean equation. Consequently, the regression model in the mean equation takes the following form

$$\begin{aligned} R_{t,i} = \mu + \varphi_1 R_{t-1,i} + \cdots + \varphi_p R_{t-p,i} + \varepsilon_{t,i} + \theta_1 \varepsilon_{t-1,i} + \cdots \theta_q \varepsilon_{t-q,i} \\ + \beta_1 Unemployment\ rate_{t-1} + \beta_2 Interest\ rate_{t-1} + \beta_3 CPI_{t-1}. \end{aligned} \tag{13}$$

For the property types exhibiting ARCH effects, we also study whether their current volatility is affected by past Scottish unemployment rate, UK interest rate, and UK inflation, by incorporating the aforementioned variables as exogenous variables in the conditional variance equation of the preferred model, accordingly.

5 RESULTS

Overview

Figure 1 illustrates the price movements of the various property types in Scotland over time. As might be expected, detached houses are the most expensive, followed by semi-detached and terraced houses, with flats being the most affordable property type. It is worth mentioning, though, that since the recent financial crisis the price of semi-detached houses has exceeded the average Scottish house price. Another interesting fact is that detached house prices rose by 10% in March 2015. However, this was a one-off spike and could be connected to the new Land and Buildings Transaction Tax (LBTT) that was introduced in Scotland on 1st April 2015, replacing the Stamp Duty Land Tax, indicating that high-end real estate buyers purchased expensive properties before the introduction of higher rates of stamp duty, as this tax would negatively affect only highly priced properties, a fact which led to a significant rise in the number of such transactions compared to the usual average. Moreover, the price return movements of each property type can be found in Figure A1 (Appendix). We notice that the spike in the detached house prices around March 2015, which affected the average house prices as well, is also evident in Figure A1. We also notice that the housing returns fluctuate in both the positive and negative regions. They also seem to follow a similar pattern and could, therefore, be correlated. Table 1 presents the Pearson correlation coefficient values for the different pairs of property type price returns. The Pearson correlation coefficient is a measure of the linear correlation between two variables. It can be noticed that all the correlations are positive, as could have been expected. Interestingly, the highest correlation is observed between semi-detached and terraced houses (0.948), while flats have the highest correlation with terraced houses (0.807). On the other hand, detached houses display the lowest correlation with any other property type.

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Table 1 here: see appendix

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Unit-root testing

As mentioned in the previous section, the first step of our empirical analysis consists of testing for the presence of unit roots. As our sample includes the recent financial crisis of 2007 which affected the house prices overall and could have caused breakpoints, we also need to use amended unit root tests allowing for structural breaks, as discussed earlier. Table 2 presents the results of the conventional unit root tests, along with the results of the breakpoint unit root tests. When testing for stationarity allowing for breakpoints, we always fail to accept the null hypothesis of a unit root for the returns of any property type, and, hence, stationarity is ensured across all the property types in Scotland. However, when testing for stationarity without taking any breakpoint into consideration, the results of the conventional ADF and PP unit root tests are overall contradictory. More specifically, although the results of the PP test agree with the results of the breakpoint unit root tests, i.e., resulting in failing to accept the null hypothesis of a unit root for any property type price returns, based on the results of the ADF test without allowing for a breakpoint, we fail to accept the null hypothesis of a unit root only for the returns of the detached houses. This could be an indication of structural breaks in the returns of the flats, terraced and semi-detached houses as well as in the average house price returns distracting the ADF test results.

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Table 2 here: see appendix

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Identification of structural breaks

The next step of our empirical analysis is to fit an AR model with a constant to the house price returns of each property type, selecting the lag order according to the statistical significance of the estimated parameters, and then conduct Sequential Bai-Perron breakpoint tests for multiple unknown structural breakpoints. The results obtained by fitting AR processes on the housing returns before conducting the multiple-breakpoint tests are reported in Table 3, while the results of the breakpoint tests are given in Table 4. As shown in Table 3, the best AR model for the price returns of the terraced houses is the AR(1) model, while for all the other property types the best model was the one including only an intercept.

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Table 3 here: see appendix

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According to the results shown in Table 4 for the mean equations, there is one single structural break in the average Scottish house price returns taking place in July 2007, as identified by the Bai-Perron test at a 0.10 significance level and further confirmed by both Chow's and Quandt-Andrews breakpoint tests at a 0.01 significance level. This result is somewhat consistent with Begiazi and Katsiampa (2018) who using quarterly data found that there is a structural break in the fourth quarter of 2007 for the average Scottish house price index returns. Moreover, when examining each property type separately, it is clear that there is also a structural break taking place in July 2007 in the price returns of flats, while semi-detached and terraced houses exhibit a structural break in September 2007. On the other hand, according to the Bai-Perron test, the detached houses do not have any structural break. It should also be noted that for the flats, terraced, semi-detached and average house price returns we also tested the alternative hypothesis of two breakpoints versus the null hypothesis of one break, but we always accepted the null hypothesis of one breakpoint.

We have also tested for potential breakpoints in the variance. Similar to Göktaş and Dişbudak (2014) and Begiazi and Katsiampa (2018), and while taking the identified breakpoints in the mean equation into account as appropriate, the squared residuals of the estimated AR models were regressed on a constant, and Bai-Perron tests were then reperformed. Once again any date identified as a potential breakpoint in the variance according to the Bai-Perron tests was also tested using Chow's and Quandt-Andrews tests in order to confirm the results. These results can also be found in Table 4. We notice that semi-detached as well as average house price returns also have structural breaks in the variance. More specifically, semi-detached house price returns exhibit a structural break in the variance in May 2015, which could be related to the Land and Buildings Transaction Tax that was introduced in Scotland in April 2015. Moreover, both semi-detached as well as average house price returns were found to exhibit a structural break in the variance in April 2009. It is worth mentioning that Begiazi and Katsiampa (2018) also found a structural break in the second quarter of 2009 for three UK regions as well as for the UK as a whole, but in the mean equation, relating it to the house price recovery of the 2007-2008 financial crisis.

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Table 4 here: see appendix

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Summary statistics

Table 5 summarises the descriptive statistics of the average house price returns as well as of the price returns of each property type in Scotland. For the property types that have a structural break (average, flats, terraced and semi-detached houses), the descriptive statistics of the two sub-periods - before and after the breakpoint - are also presented. As can be easily seen, all property types provide positive average total monthly returns. Mean total returns range from 0.36 (flats) to 0.43 (terraced). A comparison between the periods prior and post the breakpoint indicates the series have much lower mean returns after the structural break, with flats, in particular, being the only property type that reports slightly negative mean return after the July 2007 breakpoint. Interestingly, detached houses exhibit the highest kurtosis and constitute the only property type in Scotland with negative skewness. The latter fact indicates that the left tail is longer than the right in the case of the monthly detached house price returns, while the opposite result holds for the remaining property types.

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Table 5 here: see appendix

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ARMA modelling

We then proceeded by fitting ARMA models to the return series. For the property types that have a structural break (average, flats, terraced and semi-detached houses), an ARMA model is fitted only to the data after the breakpoint, as effective ARMA modelling requires an adequate number of observations (at least 50, according to Chatfield, 2003, p.70). The lag order of the estimated ARMA model for each property type is reported in Table 6. We have found that different ARMA model lag orders are present across the different property types, a finding which is in accordance with Miller and Peng (2006) and Willcocks (2010), who highlight that housing markets are heterogeneous.

Residual diagnostic tests, including LM tests for autocorrelation and ARCH-LM tests for volatility clustering or ARCH effects, have been performed and the results are also presented in Table 6. While we have found evidence of homoscedasticity for the returns of the flats, terraced and semi-detached houses as well as for the average house price returns, the results of the ARCH-LM tests clearly suggest that we fail to accept the null hypothesis of homoscedasticity for the returns of the detached houses, as ARCH effects are present. Consequently, in the case of the detached houses, the ARMA model for the conditional mean needs to be expanded to include an Autoregressive Conditional Heteroscedasticity process to model the conditional variance as well. This finding is to some extent in contrast to the results of Willcocks (2010) and Miles (2011b), who found evidence of a lack of volatility clustering in quarterly aggregate Scottish house price returns. Our results are also somewhat in contrast to the results of Begiazi and Katsiampa (2018), who did not find volatility clustering in average UK detached house price returns, and to the findings of Morley and Thomas (2016), who found that the property types less likely to exhibit volatility clustering effects are the detached houses and flats/maisonettes. However, our results support Morley and Thomas's (2016) finding that the results differ across property types, similar to obtaining different results across regions. The ARCH effect observed in the price returns of the detached houses suggests that the Scottish housing market is consistent with other markets where volatility is time-varying. Moreover, our finding rejects the conventional views that the volatility of housing series is constant over time (Lee, 2009).

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Table 6 here: see appendix

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Volatility modelling

Next, we proceeded by estimating six GARCH-type models for the detached house price returns. Table 7 reports the estimation results for each model. Interestingly, all the three information criteria agree and select the CGARCH model. According to the estimation results for the CGARCH model, the transitory component, $h_t - q_t$, converges to zero with powers of 0.64 $\left(= \hat{\alpha} + \hat{\beta}\right)$, meeting the stationarity condition of $\hat{\alpha} + \hat{\beta} < 1$, while the long-run component, q_t, converges to ω with powers of 0.99 $(= \hat{\varrho})$. Moreover, the very high value of the parameter estimate of ϱ suggests that the permanent volatility component is very persistent and converges gradually to a steady state (Lee, 2017). Furthermore, all the parameter estimates are statistically significant at a 10% significance level, while the results of the ARCH and $Q^2(10)$ tests, which have been used as diagnostic tests, applied to the squared residuals and squared standardised residuals, respectively, of the ARMA(10,4)-CGARCH model, suggest that the selected model is appropriate for the detached house price returns, as we cannot reject the hypotheses of no remaining ARCH effects and no autocorrelation. In addition, the value of the Jarque-Bera test ensures the normality of the residuals. Consequently, these results highlight the importance of allowing for both a short-run, h_t, and a long-run, q_t, component of conditional variance when studying house price volatility and support the findings of Miles (2011a), Karoglou *et al*. (2013) and Lee and Reed (2013), who concluded that the CGARCH model is a good modelling technique for US and Australian house price volatility.

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Table 7 here: see appendix

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For the selected volatility model, we also estimated its GARCH-in-mean counterpart, i.e. CGARCH-M model, which includes the conditional standard deviation as a regressor in the mean equation, in order to measure the risk-return relationship. The estimation results are reported in Table 8. We found a negative and significant at the 5% level estimate of λ, indicating that investors would require a lower return to compensate for higher risk (Miles, 2011b; Karoglou *et al.*, 2013; Lee, 2017). However, the values of all the three information criteria were higher and the log-likelihood value was lower for the CGARCH-M model compared to the values given for the CGARCH model, suggesting that the CGARCH model is preferred to the CGARCH-M model.

Overall, we have observed several differences between detached houses and any other property type. Not only are detached houses the only property type exhibiting volatility clustering and no breakpoint, but they also exhibit the highest unconditional variance/standard deviation in the full sample and display low correlations with any other property type, as seen earlier. A possible explanation of the behaviour that detached houses exhibit, including the volatility clustering, could be the high property value. Houses are assets that can be used by either owner-occupiers or investors. However, detached houses are the most private and expensive property type, mainly used by home owner-occupiers. Furthermore, Lee (2017) suggests that, in housing markets that are dominated by owner-occupiers who are less sensitive to investment factors, it could be anticipated that it is less likely to have a negative risk-return relationship. However, this is not true in our case, as we have found a negative risk-return relationship for the detached houses of the Scottish housing market.

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Table 8 here: see appendix

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Determinants of Scottish housing market

Finally, we examined the impact of the Scottish unemployment rate, UK interest rate, and UK inflation, as measured by the UK CPI, on the different property types' price returns. For the flats, semi-detached and terraced as well as average house prices we ran regression models of the return series on the ARMA terms and on the lagged exogenous variables in the second sub-sample, i.e. in the sub-period from the breakpoint identified in the mean equation until May 2017. On the other hand, in the case of the detached house price returns, we ran the regression model in the full sample, since no structural break was identified. Furthermore, since the detached house price returns exhibit ARCH effects, we included these three exogenous variables in both the conditional mean and variance equations. Moreover, since the preferred GARCH-type model for the conditional volatility of the detached house prices is the CGARCH model, which consists of two components as discussed earlier, and following Lee and Reed (2013), we included the three exogenous variables in both the transitory and permanent components of the conditional variance.

According to the results (see Table 9), the coefficient of unemployment rate in the conditional mean equation is negative and statistically significant at the 1% or 5% level in all cases, suggesting that past unemployment rates determine current housing price returns, irrespective of the property type. The coefficient of interest rate in the conditional mean equation is also negative in all cases, and statistically significant at the 1% level for the average house price returns and the price returns of all the property types except for the detached houses. Consequently, an increase in the unemployment rate or interest rate should lead to a decrease in house prices and vice versa. On the other hand, the coefficient of CPI has been found negative for the price returns of flats and semi-detached houses but positive for detached, terraced and average house price returns, indicating that an increase in CPI will result in a decrease in the prices of flats and semi-detached houses but in an increase in the detached, terraced and average house prices. However, the estimated coefficient is significant only for detached, terraced and average house prices.

When examining the impact of the three exogenous variables on both the transitory and permanent components of the conditional variance of the detached house price returns, we find that no coefficient is statistically significant, implying that the Scottish unemployment rate, UK interest rate, and UK inflation do not have a significant effect in the volatility of the detached house price returns.

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Table 9 here: see appendix

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6 CONCLUSIONS

Housing markets have drawn a lot of attention in recent years. On the one hand, they have important effects in the economy through their impact on financial markets, while, on the other hand, shocks in the economy could affect housing markets. Real estate markets have their own characteristics and market dynamics, and both region and property type play an important role in that.

Our study contributed to the existing literature in several ways. Firstly, previous studies of the UK housing market have focused mainly on aggregate house prices in England and Wales, without always taking Scotland into consideration. In this study, not only did we consider average Scottish house prices, but we also examined house prices by property type (i.e., detached, semi-detached, terraced houses and flats) separately. Secondly, the inclusion of structural break tests supports our analysis and enhances the results of the proposed volatility modelling. Thirdly, in order to study the house price volatility effectively, we employed different GARCH-type specifications in our analysis. Fourthly, we studied the determinants of the Scottish housing market, not only in the first moments but also in volatility.

Our study revealed several important findings. According to the results, house price dynamics differ across property types in Scotland, highlighting the importance of studying each property type separately. Moreover, it was shown that the recent financial crisis gave rise to breakpoints in the mean equation around July and September 2007 indicating parameter change in three out of four property types (flats, terraced and semi-detached houses) as well as in the average Scottish house price returns. We also identified breakpoints in the variance equation of the semi-detached and average house prices. Furthermore, in contrast to previous studies which found evidence of a lack of volatility clustering in Scottish data, this paper found evidence that detached house price returns in Scotland display time-varying conditional variances. Yet, it was found that the best model for the detached house price volatility in the Scottish housing market is the CGARCH. This result highlights the importance of including both a short-run and a long-run component of conditional variance in housing markets and is consistent with earlier studies on other countries' data. Finally, it was shown that the unemployment rate and interest rate have a negative impact on house prices irrespective of the property type, while the CPI has a negative effect in the prices of flats and semi-detached houses but a positive effect in the detached, terraced and average house prices. However, none of the three exogenous variables has a significant impact on the volatility of the detached house price returns.

All in all, studying housing markets by property type is of great importance, as different types of housing attract different types of investors. Due to the growing interest in property investment, analysing the stability of returns in real estate markets effectively is crucial for decision-making based on house price movements, while examination of house price volatility is of paramount importance for improving risk management. What is more, portfolio and risk management tools need to consider both a short-run and a long-run component of conditional variance that specific property types display, a fact which could support more informed investment and have important implications for investors and policymakers. Our structural break and volatility approach is, thus, useful for understanding house price movements over time and informing policymakers and stakeholders in general, who deal with supply and demand movements in housing markets, as well as investors in real estate markets, who need to be aware of specific characteristics and differences across property types. Hence, our results have significant implications for appropriate economic policy selection and investment management.

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Table 1

Correlation matrix

	Detached	Semi-detached	Terraced	Flats
Detached	1.000			
Semi-detached	0.689	1.000		
Terraced	0.544	0.948	1.000	
Flats	0.363	0.718	0.807	1.000

Table 2

Unit-root tests in the log-returns by property type

	Without break point				With 1 break point			
	ADF		P-P		ADF *t*-statistic - Innovation outlier		ADF *t*-statistic - Additive outlier	
Property type	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept
Average	-2.000	-1.712	-10.786***	-10.980***	-8.355***	-8.690***	-10.721***	-11.212***
Detached	-2.656*	-16.371***	-15.880***	-16.336***	-8.679***	-9.020***	-9.020***	-17.306***
Semi-detached	-1.980	-1.670	-51.024***	-51.935***	-8.199***	-8.376***	-11.961***	-12.363***
Terraced	-2.055	-1.885	-10.919***	-11.206***	-7.769***	-8.364***	-10.927***	-11.430***
Flats	-1.740	-1.322	-11.373***	-11.546***	-5.850***	-8.564***	-11.291***	-11.291***

*** and * indicate significance at 1 and 10 % levels, respectively.

Table 3

Estimation results of the AR model for house price returns

Property type	Average	Detached	Semi-detached	Terraced	Flats
c	0.386 (0.038)	0.371 (0.029)	0.398 (0.026)	0.373 (0.023)	0.358 (0.070)
AR(1)	-	-	-	0.146 (0.034)	-

Table 4

Breakpoint tests

	Mean equation				Variance equation			
Property type	Bai-Perron test Scaled F-statistic	Breakpoint Date	Chow test F-statistic	Quandt-Andrews test	Bai-Perron test Scaled F-statistic	Breakpoint Date	Chow test F-statistic	Quandt-Andrews test
Average	8.451*	2007M07	17.540***	17.540***	9.825**	2009M04	15.415***	15.415***
Detached	6.114				0.815			
Semi-detached	8.140*	2007M09	12.842***	12.842***	10.974**	2009M04 2015M05	23.223*** 5.825**	23.223***
Terraced	10.877*	2007M09	6.953***	6.953**	7.025			
Flats	10.320**	2007M07	15.758***	15.758***	3.423			

*, ** and *** represent the significance at the 10%, 5% and 1% levels, respectively. The breakpoint date refers to the estimated breakpoint date of the Sequential Bai-Perron test. For the Quandt-Andrews test, the probabilities are calculated using Hansen's (1997) method.

Table 5

Descriptive statistics of Scottish returns by property type

	Mean	Median	Std. Dev.	Skewness	Kurtosis	JB test	Obs.
Average							
Total	0.386	0.141	1.972	0.505	3.504	8.487	160
Before break (until 2007M06)	1.444	1.579	2.350	0.185	2.478	0.699	41
After break (from 2007M07)	0.039	-0.009	1.732	0.232	3.514	2.180	109
Detached							
Total	0.371	0.649	2.726	-0.521	6.726	99.796***	160
Semi-detached							
Total	0.398	0.463	2.098	0.527	3.922	13.085***	160
Before break (until 2007M08)	1.343	1.448	2.771	0.133	2.886	0.149	43
After break (from 2007M09)	0.050	0.010	1.673	0.087	2.937	0.166	117
Terraced							
Total	0.426	0.172	2.186	0.667	4.207	21.591***	160
Before break (until 2007M08)	1.517	1.187	2.805	0.342	3.205	0.915	43
After break (from 2007M09)	0.025	-0.076	1.760	0.149	2.762	0.709	117
Flats							
Total	0.358	0.140	2.241	0.410	3.031	4.493	160
Before break (until 207M06)	1.505	1.496	2.497	0.116	2.935	0.099	41
After break (from 2007M07)	-0.037	-0.153	2.010	0.328	2.778	2.778	119

*** represents the significance at the 1% level.

Table 6

Estimation results of ARMA models

	Average After break	Detached Whole period	Semi-detached After break	Terraced After break	Flats After break
ARMA(p,q)	(7,6)	(10,4)	(9,8)	(8,8)	(7,10)
Adj. (R^2)	0.439	0.421	0.461	0.506	0.458
LM(8)	5.964	12.277	5.610	6.043	8.489
	(0.651)	(0.139)	(0.691)	(0.642)	(0.387)
LM(16)	12.534	19.542	16.294	12.937	20.489
	(0.707)	(0.242)	(0.433)	(0.677)	(0.199)
ARCH(1)	1.884	28.537***	0.599	1.218	0.134
	(0.170)	(0.000)	(0.439)	(0.270)	(0.715)
ARCH(5)	5.252	32.559***	5.910	4.772	1.600
	(0.386)	(0.000)	(0.315)	(0.444)	(0.901)
ARCH(10)	7.101	32.501***	13.829	8.927	9.214
	(0.716)	(0.000)	(0.181)	(0.539)	(0.512)

*** represents the significance at the 1% level. The p-values associated with the statistical tests are presented in brackets.

Table 7

Estimation results of GARCH-type models for detached house price returns

	ARCH	**GARCH**	**EGARCH**	**GJR-GARCH**	**CGARCH**	**ACGARCH**
Const (ω)	2.868*** (0.000)	1.746 (0.168)	1.364*** (0.000)	1.670 (0.293)	5.578*** (0.001)	3.780*** (0.000)
ARCH (α)	0.157* (0.075)	0.154* (0.068)	0.310 (0.102)	0.247 (0.135)	0.160* (0.061)	0.002 (0.992)
GARCH (β)	-	0.333 (0.461)	-0.334 (0.212)	0.382 (0.493)	0.479* (0.051)	-0.124 (0.843)
EGARCH (δ)	-	-	0.208 (0.142)	-	-	-
GJR-GARCH (γ)	-	-	-	-0.227 (0.361)	-	-
CGARCH/ ACGARCH (ϱ)	-	-	-	-	0.988*** (0.000)	0.588** (0.047)
CGARCH/ ACGARCH (θ)	-	-	-	-	-0.083*** (0.005)	0.347** (0.019)
ACGARCH (γ)	-	-	-	-	-	-0.499** (0.024)
LL	-302.587	-301.704	-302.491	-300.772	**-291.067**	-297.288
AIC	4.261	4.263	4.287	4.264	**4.148**	4.244
BIC	4.602	4.624	4.668	4.645	**4.549**	4.665
HQ	4.400	4.409	4.441	4.419	**4.311**	4.415
ARCH(1)	1.622 (0.203)	1.693 (0.193)	0.393 (0.531)	0.726 (0.394)	0.057 (0.812)	0.193 (0.660)
ARCH(5)	2.332 (0.802)	2.208 (0.820)	2.383 (0.794)	1.380 (0.926)	1.272 (0.938)	0.610 (0.988)
ARCH(10)	2.709 (0.988)	2.537 (0.990)	2.799 (0.986)	1.771 (0.998)	6.861 (0.739)	1.312 (0.999)
$Q^2(10)$	2.923 (0.983)	2.673 (0.988)	2.874 (0.984)	1.937 (0.997)	6.549 (0.767)	1.453 (0.999)
JB	127.609 (0.000)	182.264 (0.000)	70.230 (0.000)	139.662 (0.000)	1.680 (0.432)	102.506 (0.000)

* and *** represent the significance at the 10% and 1% levels, respectively. The p-values associated with the statistical tests are presented in brackets.

Table 8

Estimation results of CGARCH-M model for detached house price returns

	CGARCH-M
λ	-0.439 (0.038)
Const (ω)	3.3370 (0.000)
ARCH (α)	0.088 (0.997)
GARCH (β)	0.375 (0.986)
CGARCH/ ACGARCH (ϱ)	0.463 (0.151)
CGARCH/ ACGARCH (θ)	0.075 (0.997)
ACGARCH (γ)	-
LL	-299.897
AIC	4.279
BIC	4.700
HQ	4.450
ARCH(1)	0.292 (0.589)
ARCH(5)	0.470 (0.993)
ARCH(10)	0.666 (1.000)
$Q^2(10)$	0.661 (1.000)
JB	168.751 (0.000)

*, ** and *** represent the significance at the 10%, 5% and 1% levels, respectively. The p-values are presented in brackets.

Table 9

Estimation results of models including the exogenous variables.

	Average After break	Detached Whole period	Semi-detached After break	Terraced After break	Flats After break
Mean equation					
Unemployment rate	-0.170**	-0.163***	-0.098**	-0.175**	-0.169***
	(0.013)	(0.000)	(0.035)	(0.021)	(0.001)
Interest rate	-0.403***	-0.021	-0.383***	-0.284***	-0.272***
	(0.000)	(0.789)	(0.000)	(0.000)	(0.000)
CPI	1.003***	0.259	-0.103	1.134***	-0.221
	(0.009)	(0.636)	(0.726)	(0.000)	(0.589)
Variance equation - Transitory component					
Unemployment rate		-0.205			
		(0.910)			
Interest rate		0.312			
		(0.940)			
CPI		1.506			
		(0.339)			
Variance equation - Permanent component					
Unemployment rate		-0.101			
		(0.866)			
Interest rate		0.340			
		(0.768)			
CPI		-1.935			
		(0.301)			

*, ** and *** represent the significance at the 10%, 5% and 1% levels, respectively. The p-values are presented in brackets.