

Modelling house price volatility states in Cyprus with switching ARCH models

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Abstract

A switching ARCH model is used to estimate the dynamics of the housing market price change volatility in Cyprus during the period 2001q1-2016q2. The results indicate that two states exist: one with high and one with low volatility. Both volatility states exhibit a high degree of persistence. The probability of being in the high volatility state is close to one in the early stages of the sample, and started its decrease when the Cypriot housing boom was peaking around 2008-2010. The findings suggest that booms could be re-enforcing, given the degree of persistence. In addition, higher volatility can be associated with higher credit growth during the period, suggesting that credit expansion can bring more investors to the housing market and increase speculation therein. As overall higher housing volatility increases systemic risk in the economy, the results point out that more regulation would perhaps be advisable.

Keywords: Housing prices; volatility; SWARCH

1. Introduction

The housing market in most countries constitutes a popular topic of study. From the public-sector perspective, it comprises a big part of government revenue (through taxes on house ownership and stamp duties imposed on transactions in real estate market), while from the household's perspective, it usually comprises the biggest part of their wealth and the most common type of collateral for mortgage. Hence, housing markets have important effects on the macro economy, largely through the wealth channel and through their influence on financial markets.

Regarding the latter (i.e. financial markets) housing investment has historically been viewed as a reasonably safe asset. Nevertheless, recent

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crises suggest a failure to appropriately price housing risk by the banking/financial sectors (Case et al., 2001). Therefore, the issue of house price volatility has become more important, as the housing market and its associated risks were central to the financial crisis (see for instance, Miles and Pillonca, 2008; Campbell et al., 2009; Lin Lee, 2009; Miles, 2009a,b; Willcocks, 2010; Tsai et al., 2010; Morley and Thomas, 2011; Miles, 2012; Karoglou et al., 2013).

A few older studies thought, have also tried to capture the volatility of property prices using different methods to model housing risk. For instance, Giussani and Hadjimatheou (1991) and Hendry (1984) have modelled the volatility by using univariate nonlinear specifications to capture extreme movements in house prices. Other studies (such as Miles, 2009a,b; Dolde and Tirtiroglu, 2002; Miller and Peng, 2006) were based on various forms of the GARCH models. Generally, the main findings of the above studies (which are based mostly on US or UK data) suggest that housing volatility is clustered and displays substantial persistence or long-memory.

Although the above studies provide evidence for housing volatility in developed economies with a large and dynamic housing market, there is a lack of evidence for the case of smaller countries/economies. Hence, the main purpose of this article is to study volatility properties in a smaller housing market but equally important for its economy, the housing market of Cyprus. At this point it should be mentioned that housing investment is of a significant importance in small economies such as Cyprus and it is the key to the economic growth of the island.

To measure the volatility of price changes in housing prices, autoregressive (AR), ARCH-type models are used, which allow to examine whether housing volatility changes over time (specifically, for the period from 2001q1 to 2016q2). However, since studies (e.g. Lamoureux and Lastrapes, 1990) have shown that these models may not be suitable in the case of structural changes in the data, we also employ the AR-SWARCH model, which has been shown to account for this issue (see Tsai et al., 2010 for an application for the case of the UK).

The AR-SWARCH model allows for the testing of whether different states of volatility exist in the housing market and estimates the probabilities of changes in these states. In addition, it allows to study the time series properties of the changes in housing prices, such as conditional variance dynamics and persistence. These are useful for forecasting the volatility of changes in housing prices and for policy purposes to evaluate periods of high/low volatility and their effects on the economy.

The rest of the article is structured as follows. The next section describes the methodology and reviews the data and tests the time series properties. Estimation results are reported and discussed in Section 3, and the last section provides a summary of the main findings and draws some conclusions.

2. The GARCH family and SWARCH models for house prices

2.1 Methodology

To capture the volatility of house prices, we employ an ARCH-type model to account for the changing volatility of house prices. To examine whether this estimated volatility process is regime-changing, the SWARCH model is then used.

Economists have long known that volatility and mean of many time series are not constant. However, they have been unable to model them until Engle (1982) showed that is possible to simultaneously model the time-dependent mean and variance, introducing the ARCH model. In particular, assuming that y_t is a stationary time series then the error process obtained from a first-order autoregression for y_t can be specified as:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varepsilon_t \quad (1)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \quad (2)$$

$$h_t = \omega_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 \quad (3)$$

The above specification is known as the ARCH(q) model, where q is the number of ARCH terms and h_t is the heteroskedastic conditional variable, which is correlated with the lagged error terms. The ARCH(q) model was generalised by Bollerslev (1986), who developed the GARCH(p, q) model that allows for both autoregressive and moving average components in the heteroskedastic variance. The specification, in which p is the number of GARCH terms and q is again the number of ARCH terms, retains equations (1) and (2) and replaces equation (3) with

$$h_t = \omega_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i} \quad (4)$$

Though ARCH and GARCH models have been widely used in many areas of economic studies, Lamoureux and Lastrapes (1990) have shown that these models may not be suitable in the case of structural changes in the

data. To account for this, Hamilton and Susmel (1994) proposed a regime-switching ARCH (SWARCH) model, allowing the conditional variance to stochastically switch among a finite number of regimes. In particular, the SWARCH(K, q) model is specified as:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varepsilon_t \quad (5)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \quad (6)$$

$$\varepsilon_t = \sqrt{g_{s_t}} u_t \quad (7)$$

$$u_t = \sqrt{h_t} v_t \quad (8)$$

$$h_t = \omega_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 \quad (9)$$

where K is the number of regime states and q is the number of ARCH terms. v_t follows a Gaussian distribution, s_t denotes an unobserved random variable and g_{s_t} are scale parameters which capture the magnitude of volatility in different regimes. In line with other studies in the literature the number of regimes is set to 2. The scale parameter for the first state g_1 is set to unity, with $g_{s_t} \geq 1$ for $s_t = 2$ such that state 1 is the lowest volatility regime, and state 2 is the high volatility regime. The regime-switching is assumed to follow a Markov process.

The switching probabilities between the three states follow the transition probabilities in matrix P , such that the row i , column j element of P is the transition probability p_{ij} , denoting the probability of state i switching to state j . Note that $p_{ij} < 1$ for all i and j and every row of P sums to unity. Therefore, only six out of the nine transition probability elements of matrix P need to be estimated. Specifically, Matrix P is specified as:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

For the estimation of probabilities, let ϑ denote the lagged term of y_t and $P\{s_t = j; \vartheta\}$ denote the long-term probability of $s_t = j$.

Hence, $p(y_t, s_t = j; \vartheta) = f(y_t | s_t = j; \vartheta) \cdot P\{s_t = j; \vartheta\}$ and the probability distribution of y_t is as follows:

$$f(y_t; \vartheta) = \sum_{j=1}^2 p(y_t, s_t = j; \vartheta)$$

and the log-likelihood function is $L(\vartheta) = \sum_{t=1}^T \log f(y_t; \vartheta)$. The maximum likelihood function (MLE) is then employed to estimate the model

coefficients, while the estimation of the model also offers the ‘smoothed probability’ $P_t\{s_t = j; \vartheta\}$ which provides information about the likelihood that house prices are in a particular volatility state at time t , based on full sample observations.

2.2 Data

Based on the related literature and the work of Pashardes and Savva (2009) we use quarterly data for house market price index.²⁶ More specifically, we use the index constructed by Economics Research Centre (University of Cyprus). The data spans from 2001q1-2016q2 and is the longest quarterly data available. However, it should be noted that even though this is the longest time series available, given the small number of observations the results should be interpreted with caution.

In Table 1, we present the descriptive statistics for the percentage change of this variable while its time-varying behaviour is depicted in Figure 1 (at levels and percentage change in panels a and b, respectively).²

TABLE 1

<i>Descriptive Statistics</i>	
Variable	% Δ HP
No. of observations	62
Mean	1.465
SD	4.067
Skewness	0.747
Kurtosis	2.533
ADF test	-2.007 (0.044)
ARCH test	11.164 (0.000)

Table 1 shows that the average growth in house prices is quite high, at 1.47% per quarter or 5.86% per annum. The distribution of the percentage change in the housing price index suggests a positive skewness (i.e. it has a longer right tail) while there is negative excess kurtosis (i.e. below 3) implying that house price growth is platykurtic. Unit root test suggests that the series in percentage change is stationary with the ARCH test

¹See also Sivitanides (2015) for a more recent perspective.

²Unit root test on the levels revealed non-stationarity, therefore we use percentage change data to estimate the empirical models.

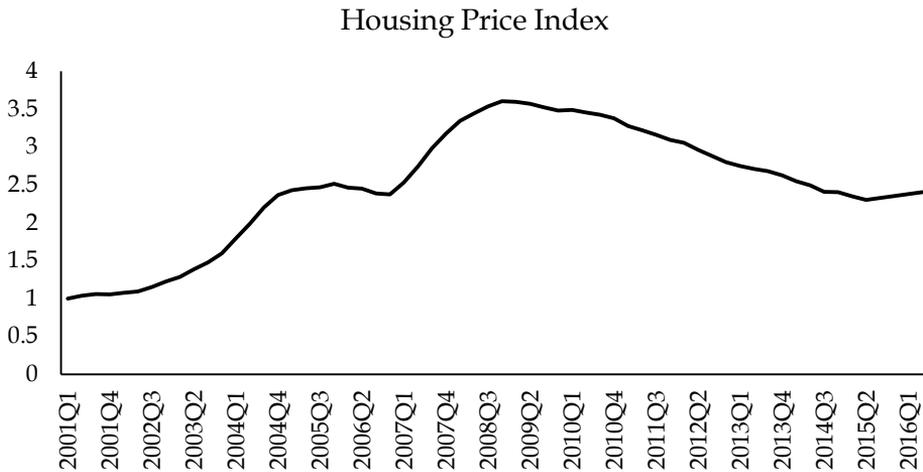
suggesting that second moments are likely to experience time-varying dependencies and therefore the use of ARCH family models is necessary.

Figure 1 plots the quarterly time series of the levels of housing prices and percentage changes. Housing prices are booming during 2002 to 2006 and 2007 to 2009, decline for the rest of the period with an increase observed in 2016. Nevertheless, these values and patterns may conceal substantial differences over time, which cannot be captured only at the descriptive level and therefore a more advanced specification is needed to uncover possible differences over time.

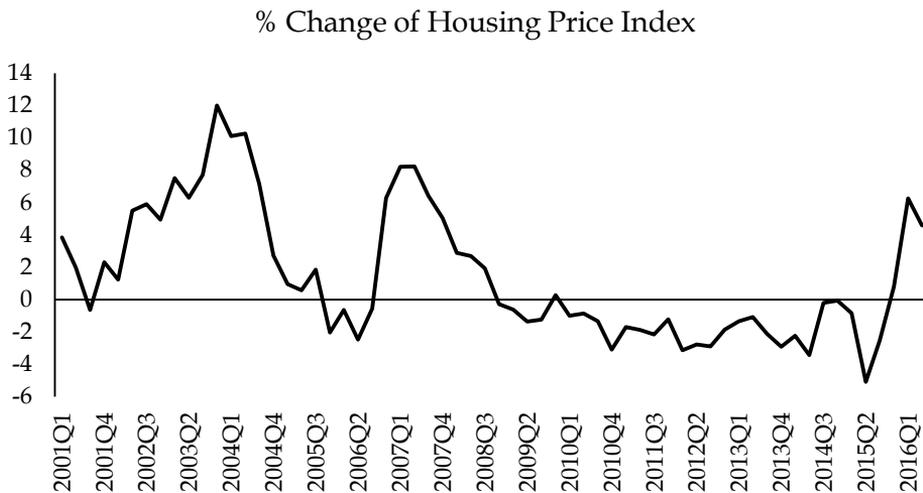
FIGURE 1

Plots of the Variables

Panel a



Panel b



3. Empirical Findings

3.1 GARCH family models

The first step in the estimation process is to determine the appropriate lag order for the mean equation taking into account various (G)ARCH specification orders. According to the Akaike and Schwartz Information Criteria (not reported but available upon request) the appropriate order is set to one.³ As for the variance equation, the ARCH and GARCH models are used to estimate the volatility of the series at a particular point in time. We estimate the ARCH and GARCH models to determine the most appropriate model for the volatility of the series. More specifically we estimate the AR(1)-ARCH(1), AR(1)-ARCH(2), and AR(1)-GARCH(1,1) models. The estimation results are shown in Table 2.

TABLE 2

Empirical results of ARCH family

Model	ARCH(1)	ARCH(2)	GARCH(1,1)
Mean Equation			
φ_0	0.274*	0.345*	-0.130
φ_1	0.850***	0.884***	0.880***
Variance Equation			
ω_0	5.303***	0.835*	0.248*
a_1	0.631***	0.857***	0.3143**
a_2		0.432**	
β_1			0.706**

Notes: * Indicates significance at 10% level, ** at 5% and *** at 1% using Bollerslev-Wooldridge s.e.

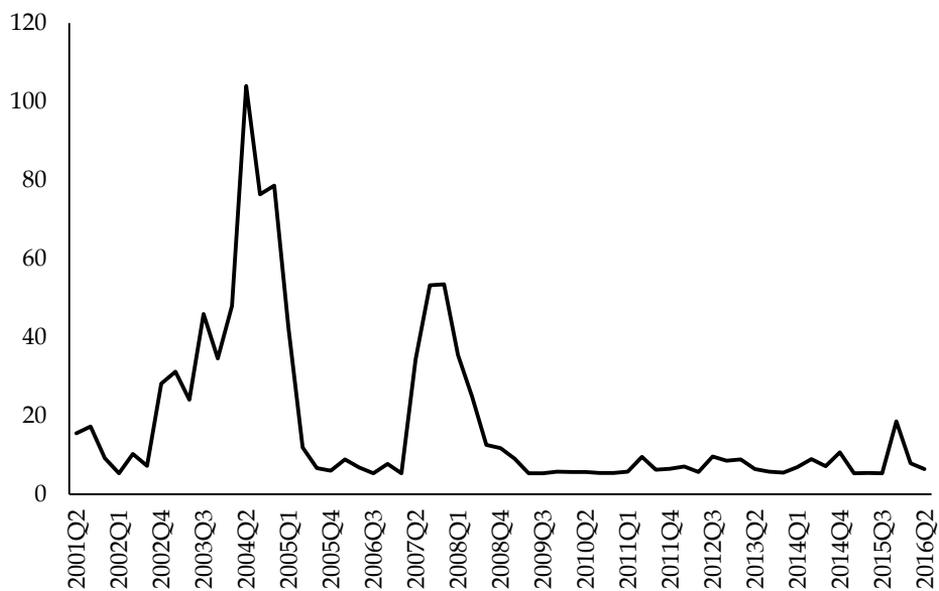
The estimated coefficients of ARCH and GARCH effects are highly significant in each series. The sum of ARCH and GARCH coefficients in both the AR(1)-ARCH(2) and the AR(1)-GARCH(1,1) model are larger than one, suggesting that shocks to the conditional variance are highly persistent, and that the two models are inappropriate for estimating the volatility.⁴ Lamoureux and Lastrapes (1990) argued that high persistence might reflect regime switch in the variance process. Therefore, different volatility states might also occur in housing market.

³ This is in line with the lag order chosen by Hamilton and Susmel (1994) and Tsai et al. (2010).

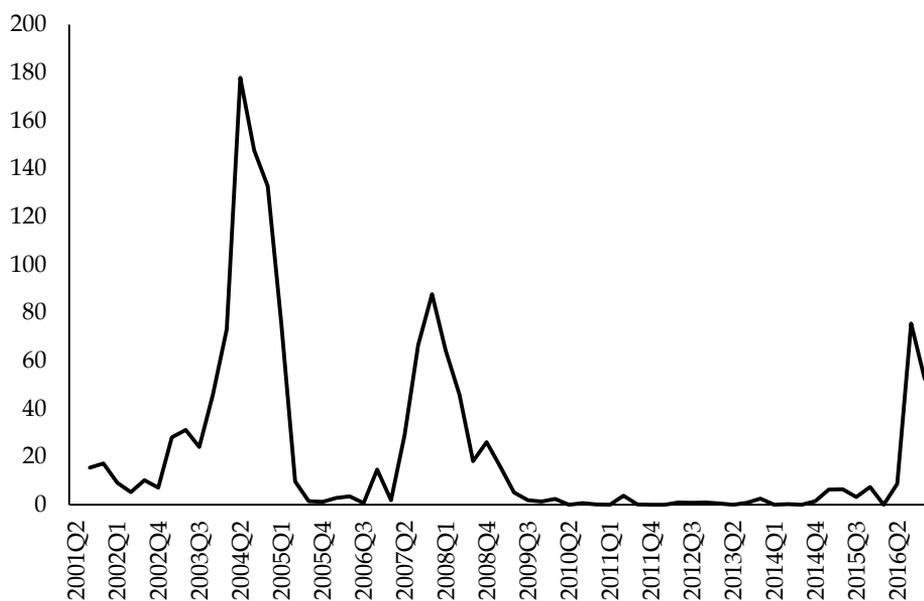
⁴In fact, they violate the stationarity condition of the traditional ARCH, GARCH models.

FIGURE 2
Plots of Conditional Variances

Panel a. ARCH(1)



Panel b. ARCH(2)



Panel c. GARCH(1,1)

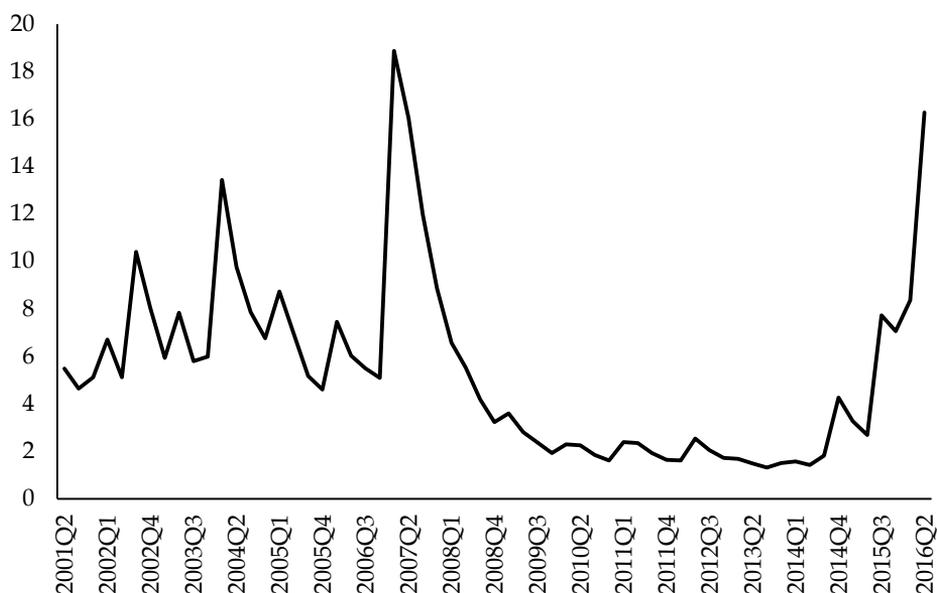


Figure 2 presents the conditional variances for these models (panel a corresponds to AR(1)-ARCH(1), panel b to AR(1)-ARCH(2), and panel c to AR(1)-GARCH(1,1)). According to the figure, there appears to be different states of volatility and several high volatility periods can be seen. Volatilities are greater before 2009 and after 2015 but low in-between. Consequently, we continue to model these volatility states by using a SWARCH model.

3.2 Do house prices exhibit different volatility states?

To determine whether or not the conditional volatilities of house prices switch stochastically and to endogenously capture the switching points, we use an AR(1)-SWARCH(2,1) model to estimate the variance of housing prices. Since the results of Table 2 suggests that the sum of the ARCH and GARCH coefficients in both AR(1)-ARCH(2) and AR(1)-GARCH(1,1) are greater than unity, these two models are inappropriate for estimating the volatilities of the two housing market regimes (see Tsai et al, 2010). Hence, we choose the AR(1)-ARCH(1) to estimate the switching of the ARCH model, which is also the relatively more parsimonious model.

TABLE 3

Empirical Results of SWARCH(2,1) model

Mean Equation	
φ_0	-0.262
φ_1	0.843***
Variance Equation	
ω_0	0.936**
α_1	0.085***
Transition Probabilities	
p_{11}	0.993***
p_{21}	0.007
p_{12}	0.017
p_{22}	0.983***
State Variable	
g_2	7.521***

Notes: * Indicates significance at 10% level, ** at 5% and *** at 1% using Bollerslev-Wooldridge standard errors.

Table 3 presents the empirical results of the estimation. The first result which should be pointed out is that the state variable, g_2 , is significant, suggesting that housing prices exhibit two different volatility states. The coefficient of g_2 is 7.5 suggests that volatility in the high volatility state is 7.5 times larger than volatility in low-volatility state. Consequently, we find that volatility differences across the two states are large.

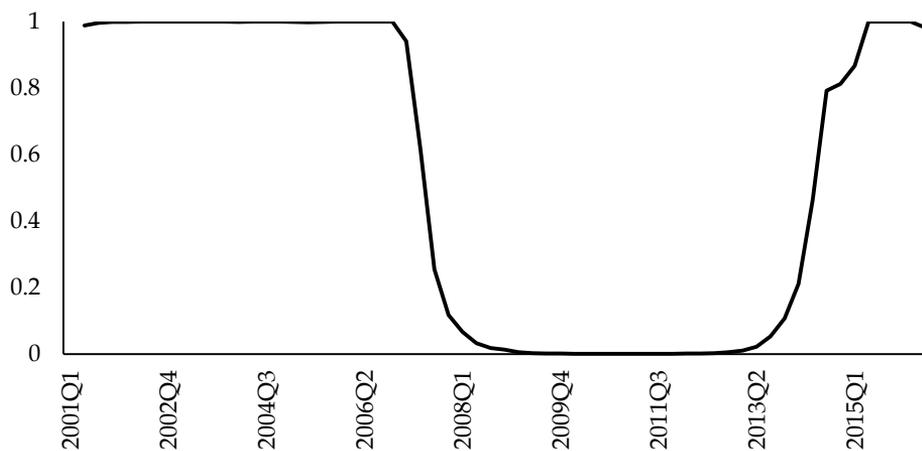
According to the model assumptions, which dictate that states are governed by a first-order Markov chain with a transition probability p_{ij} , the probability of switching to different states depends on the transition probability. The housing market has two significant transition probabilities, both of which suggest that there a large probability that the market will remain in the high or low volatility state once it gets there. In other words, there is high persistence in each probability state. Accordingly, both probability states are also found to have high duration.

The smoothed probabilities of transitions are depicted in Figure 3. The results show that starting from the period in which Cypriot housing prices were relatively undervalued (late nineties) and continuing until the housing boom period (2004-2008) the volatility of prices is higher with its corresponding probability of remaining in high state being large (close to

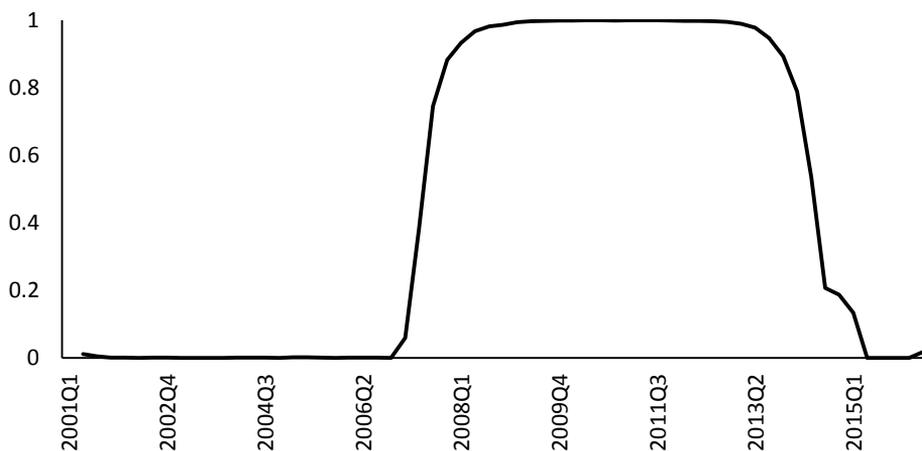
unity). This probability starts to decline, dropping approximately to 10% in 2007q4.

FIGURE 3

Probabilities of Transition - State 1 (High Volatility)



Probabilities of Transition - State 2 (Low Volatility)



Although housing prices were rising until late 2009, price volatility remained declined, and therefore the probability of being in the high volatility state decreased to values close to zero. The departure from the high volatility state is also likely to have had an impact on bank capital needs: projections of higher volatility (which mainly assumed an increasing trend in housing prices) may have had an impact on lending practices and thus could be related to lowering capital adequacy following the boom period.

From that period onwards house prices entered their low volatility state. The probability of the low state (p_{22}) is quite high for the years following the housing boom, suggesting that this state is also persistent. The housing market started its move towards the high volatility state again in 2013, mainly due to the increased uncertainty in the economy followed by the bail-in of the unsecured depositors in March of that year. This development also coincides with the gradual easing of credit conditions from 2014 onwards. The high volatility market appears to have been dominating since 2015, however these results should be interpreted with caution since the late sample increase in volatility can be attributed to the low number of housing sales.

4. Conclusions

Higher volatility is usually associated with boom and bust cycles in housing prices. These cycles distort housing choices, increase risk and consequently drive mortgage arrears and repossession rates. In addition, they affect housebuilding and intergenerational equity and well as the certainty of household income. Even though home-owners are more exposed to issues arising from high volatility, private renting households are also prone to these; for example, in the UK, buy-to-let properties were repossessed by lenders at an almost identical rate to owner-occupied properties in the 2007-2009 period (Stephens, 2011). Following these, it is thus not surprising that increased housing price volatility can decrease macroeconomic stability and raise systemic risks in the banking and mortgage sectors as they are vulnerable to fluctuations in the housing sector due to their exposures (OECD, 2011).

The results for the Cyprus housing market, based on the ARCH-type models suggest that volatility is significant and persistent. Further analysis using the SWARCH model indicates that house price behaviour in Cyprus can be divided into a high volatility and a low volatility regime; the former's volatility is more than 7.5 times higher than the latter's. High

volatility was dominant during the period before the housing boom reached its peak mainly because of the rapid adjustment of housing properties. Low volatility is evident for the period 2010-2013 where housing prices remained rather stable (although high) for a few years. The departure from the high volatility state is also likely to have had an impact on bank capital needs: projections of higher volatility (which mainly assumed an increasing trend in housing prices) may have had an impact on lending practices and thus could be related to lowering capital adequacy following the boom period.

An important conclusion reached is that volatility states do not change very often. This apparent persistence of the volatility states suggests that changes in housing prices could be re-enforcing with high volatility states creating more volatility in the housing market, with all the consequences this implies. In addition, higher volatility can also be associated with higher credit growth during the period, suggesting that credit expansion can bring more investors to the housing market and increase speculation therein. These provide support to the idea that more regulation regarding the practices in the housing market could be enforced and a closer look should be given to the dynamics of the market, and more specifically to the link between banking supervision and housing volatility, in order to avoid future mishaps. Given that this is beyond the scope of the paper, we leave this very interesting point for future research.

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