**Volatility Clustering in U.S. Home Prices**

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Abstract

Generalized autoregressive conditional heteroscedasticity (GARCH) effects imply the probability of large losses is greater than standard mean-variance analysis suggests. Accurately capturing GARCH for housing markets is vital for portfolio management. Previous investigations of GARCH in housing have focused on narrow regions or aggregated effects of GARCH across markets, imposing one nationwide effect. This paper tests fifty state housing markets for GARCH, and develops individual GARCH models for those states, allowing for different effects in each. Results indicate there are GARCH effects in over half the states, and the signs and magnitudes vary widely, highlighting the importance of estimating separate GARCH models for each market.

Real estate investment, including holdings in the housing market, has become increasingly important not just for real estate investment trusts (REITs) and investment banks but also for pension funds and individuals. As with any investment, correctly understanding the volatility of returns is vital for portfolio management. House price volatility has been found to be a determinant of both mortgage default and prepayment (Foster and Van Order, 1984; Crawford and Rosenblatt, 1995; and LaCour-Little, Marschon, and Maxam, 2002).

In investigating house price volatility, it is important to test for and analyze the pattern of volatility clustering. This clustering, or autoregressive conditional heteroscedasticity (ARCH) effect, has been found in equity and bond markets. This is important, because a process exhibiting ARCH has a conditional volatility that is at times much larger than the unconditional variance. There is, accordingly, a much higher risk of large losses for a process with ARCH during volatile periods than standard mean-variance analysis would indicate. Thus investors employing Value-at-Risk (VAR) models would be remiss in not testing for and modeling ARCH if indeed the housing market of interest has such conditional variability. Failure to investigate ARCH effects will lead to sub-optimal portfolio management for housing market investors.

There have been some previous papers on ARCH in housing markets. Some have examined ARCH at the municipal or MSA level, (Dolde and Tirtiroglu, 1997; and Miller and Peng, 2006) and others at the state level for five U.S. states (Crawford and Fratantoni, 2003). Given that most investors are exposed to real estate risk across a wider region than just a municipality or metropolitan statistical area (MSA), this paper follows Crawford and Fratantoni and investigates ARCH at the state level. Moreover, some state governments tax property directly, or allow for state income tax exemptions based on local property taxes, so knowledge of house price, and thus tax revenue, volatility is of interest to government officials. Therefore, this study formally tests for ARCH effects in all fifty U.S. states. The findings reveal that there are ARCH effects in just over half of the states.

Individual ARCH models are estimated for those states exhibiting ARCH. These models are used to answer questions about volatility in housing markets. What, for instance, is the nature of house return variability? Does variability directly affect returns? How do returns affect variability? Do shocks have symmetric or asymmetric effects on volatility? These questions are answered by estimating a separate ARCH model for each of the states with ARCH effects. This is important, as the signs and magnitudes of the different effects vary across the states.

This paper proceeds as follows. The next section describes the previous literature on ARCH models in finance and their applications thus far in real estate. The third section describes the data and methodology to be employed in investigating time-varying volatility in the housing market. The fourth section describes the results of testing for and estimating ARCH models in the fifty U.S. states, and describes the various aspects of the very different ARCH processes that different states display. The final section concludes.

## Previous Literature

As noted, if ARCH effects are present, the conditional variance is, during certain periods, much larger than the unconditional variance. Thus risk can be much greater than standard mean-variance analysis would indicate. It is tiierefore important to understand the link between statistical ARCH processes and conditional volatility. The concept of ARCH modeling was first developed by Engle (1982) and has since been applied to countless financial assets. The idea can be understood through the hypothetical ARCH process displayed in

Exhibit 1. Many asset prices follow such a process, characterized by volatility clustering, or certain periods of tranquility followed by others of extremely high variability. The unconditional variance of the series is much lower than the conditional variance during the more volatile periods. Thus there is a much higher probability of high losses than standard mean-variance analysis would suggest. Value-at-risk models should thus incorporate ARCH effects, if they exist, for the assets in a given portfolio.

If time-varying volatility is suspected, one first estimates Equation 1, then regresses the squared residuals on their own lags. The null hypothesis of a constant variance can be tested with a LM test by comparing n Ã— R2 from this latter regression to a chi-square table. If the test statistic, n Ã— R2, exceeds the chi-square critical value (degrees of freedom equal to the number of lags in the regression), the null of a constant variance can be rejected and the ARCH model estimated. It is best to estimate Equations 1 and 2 simultaneously, using iterative maximum likelihood techniques, such as the Marquardt or BHHH algorithms. Successfully estimating an ARCH process requires convergence in the parameter estimates using such a technique.

The GARCH model thus allows for a more parsimonious specification than an ARCH process with many lags.

ARCH/GARCH estimation is clearly an improvement over constant variance models for asset markets with time-varying volatility. It is possible that the parameters, as well as volatility, may vary through time. These GARCH models could not capture such parameter instability. It is very difficult empirically to analyze coefficients that vary across both markets and time, but the possibility should be admitted.

It is important to note that a priori, there is no clear expected sign of the parameter Î». Glosten, Jaganathan, and Runkle (1993) apply GARCH-M to U.S. equities, and point out that while intuitively, a higher variance might induce investors to demand a greater risk premium (and thus the expected sign of Î» should be positive), there are theoretical reasons that indicate that Î» could be negative. For instance, periods that are risky may cause investors to believe that the future is more risky, and thus lead to greater savings, lowering risk premiums. The important point is that while the conditional variance may directly impact returns, the manner in which it does so may vary from market to market, and thus there are no theoretical restrictions that can be placed on the sign of Î». Indeed, for different markets, empirical studies have found differing signs of the parameter.

The middle term, Î³Îµ^sup 2^^sub t-1^d^sub t-1^ represents the asymmetric portion of the conditional variance. Here, the dummy variable, d^sub t-1^ is equal to one if Îµ^sub t-1^

There are important reasons to believe that housing markets may exhibit the volatility clustering modeled with GARCH processes. Cont (2006) theoretically shows that investor inertia can generate volatility clustering. case and Shiller (1989) point out that housing markets, unlike most financial assets, are usually traded by their owners. There are also high transactions costs, carrying costs, and tax considerations, which the authors believe may lead to inertia. Thus GARCH effects could well be present in housing markets. Gu (2002) notes that volatile real estate indices tend to have lower returns.

There have been three important papers that have investigated conditional volatility in real estate. Highlighting the importance of house price volatility, Crawford and Fratantoni (2003) investigated forecasting models for five states: California, Florida, Massachusetts, Ohio, and Texas. They employed three different types of models: ARMA, GARCH, and Markov Switching. Three different forecasting horizons for the five states, for a total of fifteen cases, were examined. While not formally testing for ARCH effects, the authors found that the GARCH models performed better, in terms of having lower root mean-squared error (RMSE) than the two alternatives in a plurality of seven of the fifteen cases.

Dolde and Tirtiroglu (1997) explore house price variability at the municipality level for towns in Connecticut and the San Francisco area. While not conducting formal LM tests for the existence of ARCH either, they find when GARCH models are run, the coefficients are statistically significant, thus indicating the presence of time-varying volatility in the towns under study.

Exploring potential ARCH effects at the MSA level, Miller and Peng (2006) examine data on 277 metropolitan statistical area home prices indices. The authors first estimate ARMA models, and then perform formal LM tests for the existence of ARCH effects in the squared residuals. Only about 17% of the MSAs have ARCH, according to the results of the LM tests. The authors then take the relatively few MSAs that exhibit ARCH, use the estimated variances, and aggregate them into a vector autoregression model to examine the interaction between volatility and other variables. The authors find, for instance, that negative shocks to home appreciation rates palpably raise the conditional variance (positive shocks to appreciation rates also have a positive, but much smaller effect). This approach, of collecting the estimated conditional variances for all the MSAs and aggregating them and estimating average effects certainly serves a purpose. For studying the relationship between volatility and other variables such as GDP, this type of analysis is probably optimal. A typical time series usually analyzed with GARCH may have less than one hundred observations, and thus by aggregating across ARCH models and pooling them into a panel VAR, Miller and Peng are able to analyze the relationship between volatility and other variables, such as output with lots of observations.

It is important to note, however, that by aggregating, the authors have imposed one response for all of the MSAs that exhibit time-varying variances. An advantage of GARCH modeling is that one can allow a different response for each time series unit under study. For instance, by using GARCH-M modeling, one can allow for a positive effect of the conditional variance on home price changes in some areas, and a negative effect on others. Using an augmented GARCH-M model, one can similarly allow for different effects of home price changes on the conditional variance. Thus for analyzing typical GARCH models-GARCH-M, T-GARCH, and augmented GARCH-the approach of allowing for different parameter estimates and effects may be more appropriate.

Note that the current study analyzes data at the state, rather than the MSA level, as Miller and Peng (2006) have done. There are several reasons for this approach. First and most obviously, most housing investors are exposed over a wider geographical area than just one MSA, so the results here are complementary to Miller and Peng.

Secondly, and more importantly, to anticipate the results, the ARCH effects are far more prevalent at the state level than Miller and Peng (2006) found for the MSA level. This suggests that ARCH rarely exists city-by-city, i.e., one may not hypothetically find ARCH for say the cities of Los Angeles, Sacramento, or San Diego, but the housing market of California as a state does exhibit ARCH. This suggests that investors who diversify across numerous MSAs, which most presumably do, may believe that ARCH is not a problem, since it rarely exists at the MSA level. However, finding that states have ARCH more often than not suggests that holdings across MSAs are more likely to exhibit time-varying volatility than an analysis of individual MSAs would indicate. Thus the probability of large losses is greater than investors would realize if they rely only on MSAlevel analysis. See Seiler, Chatrath, and Webb (2001) and Yan Lin and Yung (2004) for a discussion of how real estate affects mutual fund and shareholder portfolio returns.

Also, state government officials are interested in house price volatility. A number of states directly tax property at the state level. Other states allow a state income tax deduction for certain levels of municipal property taxes. So for tax-smoothing purposes, state officials will benefit from knowledge of state house price volatility.

## Data and Methodology

This study follows Crawford and Fratantoni (2003) and estimates state house price indices for signs of GARCH. Crawford and Fratantoni investigate home prices in five states. The current study will determine which among all fifty states have ARCH. The study employs the Office of Federal Housing Enterprise Oversight (OFHEO) quarterly home price index. It uses data from 1979 through the second quarter of 2006, for a total of 110 observations. The annual rate of appreciation is calculated for each quarter. This appreciation rate is the dependent variable.

The process begins by estimating an ARMA model for returns, as in Equation 1. The autocorrelation and partial autocorrelation functions are run for each return series to choose AR and MA lags. An assumption is made, as in Miller and Peng (2006) that for each state, agents use an ARMA model to rationally forecast returns. There are different criteria that could be used to choose optimal lag length, such as AIC, BIC, maximum likelihood, etc. A conservative strategy of adding AR and MA lags is used until there is no remaining autocorrelation in the residuals according to the results of a LM test for autocorrelation. It is always assumed in ARCH models that the residuals are uncorrelated (but there is of course autocorrelation among the squared residuals).

Once the ARMA model is estimated for each state, a LM test for ARCH effects is conducted. It is important to conduct such a test, as several previous papers have failed to do so. If the null hypothesis of a constant variance is rejected, then a GARCH model is estimated for die given state. A GARCH(1,1) model is used first. This is the most frequently employed specification in the literature, because it most often results in no remaining ARCH effects. The remaining residuals are tested for ARCH effects once the initial GARCH(1,1) model is estimated. If the null hypothesis of no remaining ARCH effects cannot be rejected, the analysis continues until a specification is found that leaves no remaining ARCH.

Once there is an adequate ARCH model, the study seeks to answer the following question: Does volatility affect average expected returns? As noted, Miller and Peng (2006) investigate the effect of volatility on home prices, as well as other impacts between volatility and house price variables, by aggregating all of the estimated conditional variances from those areas that displayed ARCH effects into a vector autoregression. They then use tests of Granger causality and in some cases impulse response analysis to discern the effects among the variables.

As noted, this can cause difficulties in inference if there are heterogeneous effects among the variables in different areas. For instance, in some areas, an increase in the variance may have no effect on the conditional mean return, in others it may have a positive impact, and in still others a negative effect. The same is true for other relations between the variance and housing returns.

The GARCH-M model of Equation 5 is used to investigate whether the conditional variance has a direct effect on mean returns. A test is conducted for the GARCHM term for each of the states in which ARCH effects are found. While intuitively, it may seem that greater risk should lead to greater returns, Glosten and Jagannathan (1987) have shown that the effect could be negative. Moreover, Dolde and Tirtiroglu (1997) find a positive effect of the conditional variance for towns near San Francisco, and a negative effect for Connecticut municipalities. Thus it is important to employ GARCH-M for each area to allow for different effects in diverse markets.

Another study question is whether returns affect volatility, following the direction of Miller and Peng (2006). Again, rather than aggregate across states and impose one effect on all areas, each state's GARCH model is augmented with returns to see whether higher returns raise or lower the conditional variance. Again, there is no a priori restriction based on financial theory that leads to expectation of a positive or negative sign.

Finally, there is an examination of whether unexpected positive and negative shocks to returns have symmetric effects on the conditional variance. The asymmetric effect of positive and negative shocks has been investigated in equity markets and such asymmetries may exist in housing. The T-GARCH model is applied to all the states that exhibit time-varying volatility. Again, there are no theoretical restrictions on the sign of the threshold term, and as will be displayed, it varies among the states.

## Results

### Testing for ARCH Effects

Exhibit 2 shows the results of the LM ARCH tests for the fifty states. Note, that given the presence of large shocks in financial markets, it is likely a strong assumption to believe the residuals are normally distributed. Accordingly, Bollerslev-Woodridge standard errors are employed in all of the ARCH models, which are robust to non-normality. As displayed, ARCH effects are significant in 29 of the 50 states. There was one state (Wisconsin) that had ARCH effects by the LM test, but for which a sensible ARCH model could not be estimated due to a lack of convergence in the estimates. Note that, for those states with feasible ARCH models, other regressors-mortgage rates and GDP were examined. However, the results (available upon request) were insignificant for both variables in a majority of cases. Moreover, the coefficients at times made no economic sense, with GDP in one case being negative and interest rates being positive. Therefore, such regressors may well be endogenous. It is likely the case that the time series is overly short to make both structural inference, as in Muellbauer and Murphy (1997), and also determine the nature of conditional volatility for optimal portfolio management. Thus the impact of such variables on the return-volatility relationship is a topic for future research. Hence in all, 28 of the 50 states had feasible ARCH effects.

It is notable that Massachusetts and Texas do not display ARCH effects. In the Crawford-Fratantoni (2003) paper, ARCH models were estimated for these two states, although ARCH effects were not formally examined. For both states, the estimated ARCH models yielded better forecasting performance than alternative ARMA and Markov-Switching estimates at one of three possible horizons. Indeed, for each of the five states in the paper, an ARCH model leads to the best forecasts for at least one of three possible horizons. Results here suggest that such results may be spurious, and should be treated with caution.

There is little pattern to which states have ARCH and which do not. In terms of unconditional variability, a t-test rejected the equality of variances between the two groups at the 10% level-those states without ARCH had, on average, larger variances than those states with ARCH effects. But it is important to keep in mind that for ARCH processes, a relatively low variance is deceiving, and not a good basis for portfolio decision-making. The conditional variance is much larger than the unconditional variance during volatile periods.

### Testing for GARCH-M Effects

Having established which states have ARCH, an analysis is conducted to determine whether, among those states with time-varying volatility, the conditional variance directly affects mean returns. To repeat, financial theory does not provide guidance as to whether to expect a positive or negative impact, and previous studies have found that some markets have a positive GARCH-M effect while others exhibit a negative effect (Dolde and Tirtiroglu, 1997).

A GARCH-M model examines all 28 of the ARCH-effect states. The conditional standard deviation is added to the estimated mean equation, as in Equation 5, to test for the significance of the Î» term. As displayed in Exhibit 3, 8 of the 28 states with ARCH have significant GARCH-M effects. Five of the states-Georgia, Minnesota, Nevada, Tennessee, and Virginia-have positive GARCH-M effects. The remaining three-Nebraska, Oklahoma, and South Carolina-get a decrease in mean returns from an increase in the conditional variance. Four of the 8 states exhibiting GARCH-M effects are located in the south, and in 3 of the 4 (Georgia, Tennessee, and Virginia) the effect of greater volatility is to raise returns. In Nevada and Oklahoma, the effect is also positive. Finally, in Minnesota the impact is positive while in Nebraska the impact is negative. Note that none of the states exhibiting GARCH-M effects is located in a coastal area, which is intuitive: investors in coastal areas are more used to volatility due to the frequent house booms, thus an increase in the conditional variance may not change average returns in such regions.

Testing for Augmented-GARCH Effects

The effect of returns on the variance is tested next by augmenting the conditional variance in Equation (4) with returns added as a regressor. That is, returns are added to Equation 4 for the 28 states exhibiting ARCH. This is a standard practice in many GARCH studies. Studies of inflation and inflation uncertainty, for instance, add die dependent variable-in this case the inflation rate-to the conditional variance to see if higher inflation raises inflation uncertainty, as measured by the GARCH process. Indeed, Engle's (1982) paper focused on inflation in the United Kingdom using 77 observations. The results, as displayed in Exhibit 4, indicate tiiat returns affect volatility significantly in only two cases: Iowa and Oklahoma. As with the case of GARCH-M, there is no theoretical restriction on the expected sign of the returns parameter. In both cases, higher returns decrease the conditional variance.

Testing for Asymmetric GARCH Effects

Next, the existence of an asymmetric response of the conditional variance to a negative shock is examined by employing a Threshold-GARCH, or T-GARCH model. This model was developed by Glosten, Jagannathan, and Runkle (1993). The rationale behind the model goes back to a finding by Black (1976) that equity price volatility rises more in response to negative than to positive shocks. Accordingly, the conditional variance process in Equation (4) is amended to that of Equation (6). It is important to note that this is distinct from testing whether the return has an impact on the conditional variance, as in Exhibit 4. The parameter of interest in a TARCH model is the coefficient on shocks to returns, not the returns themselves. That is, the coefficient y picks up the effect of the unexpected portion of returns, or the forecast error that investors make when predicting returns.

It is also important to note that in the literature, while there have been no theoretical restrictions on the sign of the threshold coefficient, the effect has typically been found to be positive (i.e., negative shocks typically cause greater volatility than positive), bolstering Black's (1976) finding. However, the real estate market has been found to exhibit different statistical properties than equity exchanges (case and Shiller, 1989) and thus we do not have any expectations as to the sign of the TARCH effect.

The results, as displayed in Exhibit 5, indicate that six of the twenty-eight states with time-varying volatility also have significant TARCH effects. Looking at the six states that exhibit TARCH effects, note mat the three states with positive TARCH effects (where a negative shock raises volatility) are in areas not traditionally associated with strong housing markets-Michigan, Montana, and Oklahoma. Thus a drop in returns, or a negative shock, could incur panic behavior, and raise uncertainty. New Jersey, one of the states with negative TARCH effects, is associated with a higher-priced housing market, and it is not surprising that a negative shock may make clear that prices are falling, and lower uncertainty (GARCH). To repeat, these particular properties will be of interest to investors for optimal portfolio management.

Comparing Unconditional Variances with GARCH Effects

Finally, while Exhibit 1 shows that GARCH processes are qualitatively different from standard constant-variance processes, it is useful to quantify this effect for the pertinent states in the sample. The variance of each home price index over the sample is computed and compared with the highest value for the GARCH series for all those states exhibiting GARCH. Again, the conditional variance GARCH process often leads to much larger variance during volatile periods than the unconditional variance. Thus, if the GARCH is greater then the unconditional variance, the probability of large losses is much larger than standard meanvariance analysis suggests, and value-at-risk models should take this into account. The results are displayed in Exhibit 6.

Here, it is clear that the conditional variance is, during the most volatile periods, much larger than the unconditional variance. In some states the GARCH process reaches a multiple of forty times the unconditional variance, as in Iowa. In all states, except New Jersey, the GARCH process reaches levels much higher than the unconditional. Even in New Jersey, the conditional variance reaches a level slightly higher than unconditional variability. Thus for portfolio management, it is vital to account for GARCH processes in house prices.

Conclusion

This study found ARCH effects in just over half of all U.S. states. It is important to note that while Miller and Peng (2006) found ARCH in only 17% of MSAs. Many real estate investors-banks, REITs, and pension funds-are exposed over wider regions than individual MSAs. It is thus crucial for such investors to know whether ARCH exists and the nature of the GARCH process in the given region of exposure for proper portfolio management.

The findings reveal that the conditional variance affects returns in eighteen of the twenty-six states exhibiting GARCH. However, in some states the effect was positive, and in others it was negative. Similarly, the effects of returns on the variance were positive for some states and negative in others, and the magnitudes varied widely; the same is true for the impact of asymmetric shocks (TARCH). Thus time-varying volatility is clearly important for the U.S. housing market, and estimating each individual state's particular GARCH process is vital to properly managing risk in housing investment.

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