Modeling the Time Varying Volatility of Housing Returns:
Further Evidence from the U.S. Metropolitan Condominium Markets

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ABSTRACT

This study extends the literature on modeling the volatility of housing returns to the case of condominium returns for five major U.S. metropolitan areas (Boston, Chicago, Los Angeles, New York, and San Francisco). Through the estimation of ARMA models for the respective condominium returns, we find volatility clustering of the residuals. The results from an ARMA-TGARCH-M model reveal the absence of asymmetry in the conditional variance. Dummy variables associated with the housing market collapse unique to each metropolitan area were statistically insignificant in the conditional variance equation, but negative and statistically significant in the mean equation. Condominium markets in Los Angeles and San Francisco exhibit the greatest persistence to volatility shocks.

Keywords: U.S. metropolitan areas; condominium returns; time-varying volatility; GARCH models

JEL Codes: R30; C22

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1.Introduction

The 2007-2008 global financial crisis certainly highlighted the importance of the housing market to the macroeconomy through its impact on household wealth, the financial system, and the real estate and construction sectors. The collapse in housing prices as a result also brought to the forefront the uncertainty associated with the volatility in housing prices and the transmission of such volatility to other sectors of the economy. Indeed, the leverage effect attached to declining house prices contributes to an increase in the debt to home equity ratio, thereby increasing the risk exposure associated with home ownership.[1] Hence, the greater house price volatility, the greater is the probability of negative home equity and mortgage foreclosure losses. As the probability of large losses are greater in highly volatile periods than standard mean-variance models would predict, the appropriate modeling of volatility is relevant for real estate portfolio management.

The presence of autoregressive conditional heteroscedasticity (i.e. ARCH effects) in condominium returns would indicate there is a much higher risk of large losses for returns with volatility clustering during such volatile periods than standard mean-variance analysis would predict. Thus, investors employing Value-at-Risk (VAR) models would be remiss to not identify and model volatility clustering as any failure to do so could potentially lead to sub-optimal portfolio management for investors in metropolitan condominium markets. Moreover, the presence of volatility clustering in the metropolitan condominium markets could have an impact on the local economy via wealth effects and the transmission of volatility shocks to other sectors of the housing market such as the mortgage markets (i.e. backed bonds and insurance).

[1] House price volatility also has impacts on the modeling of mortgage defaults, prepayment, and Value-at-Risk.

While the literature on modeling house price (returns) volatility has largely focused on aggregate house price indices (returns) and/or by geographic location, our study is the first to examine return volatility associated with condominium markets. With respect to metropolitan areas, the condominium markets serve an important segment of the housing market, as their location is generally more concentrated in the city-center where land values tend to be more expensive (Gil-Alana and Payne, 2019).[2] In this regard, Rappaport (2013) notes that the U.S. housing market is undergoing a shift from single-family to multi-family housing which can be attributed in part to the aging baby-boomer generation alongside a geographic shift from suburban to city living. With the condominium market a component of multi-family housing, such a change will have an impact on the decision-making of city planners and real estate developers in serving this population demographic.[3]

Building upon the existing literature on modeling the time varying volatility of housing returns, we address the following questions: Do condominium returns exhibit volatility clustering? If so, what is the degree of persistence in response to volatility shocks? Are shocks to volatility asymmetric? Does volatility have a direct impact on condominium returns? To what extent was the period leading up to the 'Great Recession' and the period immediately following the housing market collapse had an influence? Our empirical findings will address each of these questions.

Section 2 presents an overview of the literature on modeling house price (returns) volatility. Section 3 describes the data, methodology, and results while Section 4 provides concluding remarks.

[2] As preliminary analysis suggests, condominium prices are not stationary in levels, hence we focus on the first difference of the log of condominium prices (i.e. returns) which are stationary.

[3] Apergis and Payne (2019) reiterate this point in their analysis of the convergence in condominium prices of major metropolitan areas in finding distinct convergence clusters between the east and west coast condominium markets.

2. Literature Review

The literature on modeling the volatility in housing prices (returns) encompasses studies pertaining to the U.S. at both the aggregate and across geographical areas along with housing markets in a number of countries. Dolde and Tirtiroglu (1997) was one of the first studies to explore the spatial diffusion in house prices using a GARCH-M modelling framework applied to 15 labor market areas in Connecticut and 16 towns in San Francisco. Their results suggest there is an overreaction to local news within a quarter with a subsequent negative offsetting feedback at shorter lags and evidence of lagged positive information diffusion from neighboring towns, which is not the case for non-neighboring towns. Crawford and Fratantoni (2003) compare the forecasting performance of three univariate time series models (regime switching, ARIMA, and GARCH) associated with house prices for five U.S. states (California, Florida, Massachusetts, Ohio, and Texas) to find that while the regime switching model performs best in-sample, ARIMA models generally do better with respect to out-of-sample forecasting.

In forecasting U.S. house prices Guirguis et al. (2005) shows that a rolling GARCH model and Kalman filter performs well. In another study, Guirgius and Vogel (2006) use the dynamic conditional correlation multivariate GARCH model to investigate the asymmetric behavior of real house prices for San Jose, Oakland, and San Francisco while taking into account interdependence and spillover effects across the three cities. They find that real house prices are more responsive to positively lagged changes in house prices than to negative lagged changes, which they attribute to homeowners reacting to negative market changes by temporarily delaying the sale of homes. Miller and Peng (2006) employ GARCH modeling to capture house price volatility for 277 U.S. MSAs to find 17 percent of the house prices exhibit ARCH effects. The results from a panel VAR model of the determinants of house price volatility reveal an asymmetric impact of per capita GMP and home appreciation rate on house price volatility with decreases in per capita GMP and the home appreciation rate yielding longer lasting impacts. Furthermore, their findings show that house price volatility Granger-causes future house price volatility and per capita personal income growth while the unemployment rate and population do not Granger-cause house price volatility.

In a study of U.S. housing markets at the state level, Miles (2008) identifies ARCH effects in just over half (28) of the states. Miles (2008) proceeds with the estimation of GARCH-M models to show that volatility has a positive effect on returns in five states and a negative effect in three states. Using an augmented GARCH model that includes returns as a regressor in the conditional variance equation, Miles (2008) finds that higher returns decrease the variance in only two states. Finally, a threshold GARCH model is estimated with three states yielding positive effects (a negative shock raises volatility) and three states rendering negative effects. Miao et al. (2011) use the Case-Shiller U.S. home price indices for 16 U.S. metropolitan areas to investigate the transmission of excess returns and volatility. The 16 metropolitan areas were broken into five geographical regions: East, Florida, Central, Mountain, and West. With the exception of the Central and Mountain regions, there is significant return linkages with Boston, San Francisco, and Miami serving as the most influential markets within their respective regions. In terms of volatility, their results show significant volatility persistence in each market with some volatility dependence within each region. Moreover, Miao et al. (2011) find that geographical proximity has a significant impact on the degree of volatility linkages.

Miles (2011a) examines 62 U.S. MSAs to reveal long memory behavior with respect to conditional volatility in roughly half of the MSAs. In addition, MSAs located on the west coast exhibit the greatest persistence in conditional volatility. The results also indicate that the component GARCH models outperform the standard GARCH model in terms of forecasting performance. Elder and Villupuram (2012) investigate the long memory behavior of housing returns and volatility (defined as the absolute value of returns) for 14 U.S. cities and the 10-city Case/Shiller home price indices using several semi-parametric approaches to reveal that housing price volatility is highly persistent, which they attribute to the nonlinearities in the data generating process. Karoglou et al. (2013) allow for the presence of structural breaks in the mean and conditional variance equations of an asymmetric component GARCH model for five U.S. metropolitan areas using the Case-Shiller home price indices. Their results show that house prices exhibit asset market properties with respect to the risk-return relationship and asymmetric adjustment to shocks.

Barros et al. (2014) explore the long memory behavior of house price volatility for the 50 U.S. states and 20 metropolitan areas using parametric and semi-parametric fractional integration approaches to reveal in the majority of cases stationary long memory behavior in both squared and absolute housing returns. Antonakakis et al. (2015) employ a dynamic conditional correlation model to explain U.S. real housing returns based on the Case-Shiller 10-City Composite home price index. Their results indicate that increases in industrial production growth and decreases in the real federal funds rate have a positive impact on real housing returns, whereas an increase in economic policy uncertainty decreases real housing returns. Moreover, increases in lagged real housing returns reduce economic policy uncertainty when controlling for implied stock market volatility and industrial production growth. Likewise, an increase in implied stock market volatility and lower industrial production growth increases economic policy uncertainty. Furthermore, the results for the conditional variance equation support the presence of GARCH effects.

In addition to the numerous studies on U.S. house price volatility, there have been several studies pertaining to the U.K. Willcocks (2009) finds that an exponential GARCH-M model adequately captures the underlying data generating process for aggregate U.K. house prices while in the case of aggregate U.S. house prices various GARCH-type models fail to produce independent and identically distributed residuals. In another study on U.K. regional housing returns, Willcocks (2010) identifies ARCH effects in only seven of the 13 regions with the absence of volatility asymmetry in the exponential GARCH models estimated. Miles (2010) explores the volatility relationships in U.K. house prices by region using multivariate GARCH models to show that U.K. regions that exhibit GARCH effects have statistically significant conditional covariances with each other, and that conditional covariances are the greatest for regions with the closest geographical proximity. Tsai et al. (2010) examines the volatility properties of older and new house prices in the U.K. using a switching ARCH model to find that volatility states do not switch very often with respect to the older housing market and are less efficient than the new housing market.

Miles (2011b) investigates house price volatility across 12 U.K. regions to find that seven of the 12 regions exhibit volatility clustering. Of the seven regions with GARCH effects, the impact of the volatility of returns through a GARCH-M model is negative and statistically significant in only two regions (East Midlands and Wales). Likewise, an augmented GARCH model that includes returns in the conditional variance equation reveals the impact of returns as positive and statistically significant in these same two regions. Further analysis utilizing a threshold GARCH specification fails to reveal leverage effects in house price volatility. Morley and Thomas (2011) deploy the exponential GARCH-M model to examine the extent of the relationship between returns and volatility along with the influence of London house prices and interest rates with respect to 10 U.K. regions. With the exception of East Anglia, the South West, and Yorkshire there is a positive relationship between returns and volatility with positive asymmetry across the regions, except for the South East, East Anglia, West Midlands, and the South West regions. The presence of positive asymmetry suggests a speculative bubble, as an increase in house prices encourages speculators to enter the housing market in addition to ordinary homeowners, thereby creating excessive levels of volatility. Furthermore, the inclusion of lagged London house prices has a positive impact on both the mean level of returns and volatility, whereas the interest rate affects returns, but not volatility.

Begiazi and Katsiampa (2018) tests for the presence of structural breaks in U.K. regional house prices and those of different property types. Given the identification of structural break points, each region and property type are examined for ARCH effects, and for those time series exhibiting ARCH effects but no structural breaks, a multivariate GARCH model is estimated to investigate volatility spillovers. Begiazi and Katsiampa (2018) find structural breaks in the mean equation in seven of the 13 U.K. regions and in three of the four property types, along with structural breaks in the conditional variance equation for six regions and three property types. The results from the multivariate GARCH model reveal the covariances between London and other regions are more volatile relative to the covariances between the other U.K. regions.

While modeling house price volatility for the U.S. and U.K. has dominated the literature, several studies have investigated housing markets in Spain, Canada, and Australia. Guirguis et al. (2007) use a bivariate GARCH model to find a positive unidirectional spillover from house prices in Madrid to nearby Coslada; however, the absence of volatility spillovers between the two cities. Hossain and Latif (2009) estimate a GARCH model for aggregate Canadian house prices along with a VAR model of the determinants associated with the estimated volatility measures. Hossain and Latif (2009) find that both positive and negative GDP growth rates, house price appreciation, and the inflation rate impact house price volatility, while house price volatility influences negative GDP growth rates, negative house price appreciation, and future volatility. Variance decomposition analysis reveals that negative house price appreciation and current house price volatility are the most important variables that cause changes to house price volatility. Impulse response analysis shows that the magnitude of a negative shock to the GDP growth rate has a greater impact on house price volatility than a positive shock, while the same holds for a negative shock to house price appreciation. In addition, a positive shock to the inflation rate yields a greater impact on house price volatility than a negative shock.

Lin and Fuerst (2014) employ the exponential GARCH-M model to Canadian regional house prices to determine the risk-return relationship and the presence of leverage effects. In addition, Lin and Fuerst (2014) incorporate lagged Ontario housing returns and interest rates in the conditional variance equation in the examination of 11 Canadian provinces. They identify volatility clustering in all provinces with the exception of the thinly populated provinces of Manitoba, Nova Scotia, New Brunswick, Newfoundland, and Labrador. They also find a positive relationship between volatility and returns along with asymmetry in six provinces with the coefficient negative (i.e., leverage effects) for Ontario, British Columbia, and New Brunswick and a positive coefficient for Alberta, Quebec, and Saskatchewan. In terms of possible ripple effects, the coefficient on lagged Ontario returns is positive and statistically significant for the housing markets in the eastern provinces. Furthermore, the interest rate has a significant influence in the case of house price volatility for Ontario, New Brunswick, and British Columbia.

Lee (2009) examines house price volatility for eight Australian capital cities to find volatility clustering present in five cities. The results from an exponential GARCH model for the five cities with volatility clustering reveal the determinants of house price volatility varies across the five cities, but the presence of positive asymmetry. Lee and Reed (2014) examine the volatility of house prices in eight Australian cities by decomposing the conditional volatility of house prices into permanent and transitory components using a component GARCH model to ascertain the transmission of the long-run and short-run volatility dynamics along with potential determinants of each. Lee and Reed (2014) identify volatility clustering in six of the eight Australian cities with shocks more severe, but dissipating quickly with respect to the transitory volatility component. On the other hand, new information has a relatively minor impact on the permanent volatility component though the impact is more persistent. As for the determinants, inflation and real GDP growth yield strong spillover effects to the permanent volatility component while the other determinants of population growth, real income, the lending rate, the unemployment rate, and building approval rate less so. In regards to the transitory volatility component, population growth, the lagged growth rate of housing prices, real GDP growth, and the lending rate serve as strong drivers relative to inflation, the unemployment rate, the building approval rate, and real income.

3. Data, Methodology, and Results

The monthly data on condominium price indices for five major U.S. metropolitan markets (Chicago, Boston, Los Angeles, New York, and San Francisco), spanning covering the period 1995:1 to 2018:8, was obtained from the St. Louis Federal Reserve Bank database, FRED II.[4] The base year for the respective indices is 2000 = 100 and seasonally adjusted from the S&P/Case-Shiller home price indices. Returns are calculated as the first difference of the log of condominium prices. As in the case of single-family house prices, condominium prices also endured an extended decline due to the sub-prime mortgage crisis and ensuing 'Great Recession'. Figure 1 displays the monthly condominium price indices for the respective metropolitan areas. Though the NBER dates the 'Great Recession' from 2007:12 to 2009:6, condominium prices began to decline much sooner with prices depressed until early 2012: Boston (peak 2015:12, trough 2012:2), Chicago (peak 2007:3, trough 2012:4), Los Angeles (peak 2006:5, trough 2012:1), New York (peak 2006:2, trough 2012:2), and San Francisco (peak 2006:1, trough 2011:12). The monthly condominium returns for the respective metropolitan areas in Figure 2 show with a decline in returns in the mid-2000s and heighted volatility during the global financial crisis.

[Insert Figures 1 and 2 here]

[Insert Table 1 here]

Table 1 presents the descriptive statistics of the condominium returns for the respective metropolitan areas. Average monthly returns range from 0.220 percent (Chicago) to 0.547 percent (San Francisco), while the coefficient of variation shows that Chicago exhibits the highest relative variation (4.609) with Boston (1.461) the lowest. Monthly returns reveal negative skewness and kurtosis measures greater than 3 with the Jarque-Bera test rejecting the null hypothesis of normality in the returns data for Chicago, Los Angeles, and San Francisco. The

[4] Due to the availability of the data the time frame begins in 1995:1.

time series properties of the respectively monthly returns using the Phillips-Perron (1988) unit root test with and without a trend component clearly reject the null hypothesis of a unit root, implying that monthly returns for the respective metropolitan condominium markets are stationary.

To investigate the time-varying volatility associated with the respective metropolitan condominium markets, we follow Miller and Peng (2006) and Willcocks (2010) by first modeling the mean equation for monthly condominium returns for each metropolitan area via an ARMA (p,q) process as follows:

$$\phi(L)R_t = \mu_0 + \varphi DMETRO + \theta(L)\varepsilon_t, t = 1, \ldots T \quad (1)$$

where μ_0 is a constant term; L is the lag operator; $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$ and $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q$ are polynomials of p autoregressive terms and q moving average terms, respectively with ϕ and θ unknown parameters. As mentioned previously, returns, R_t, are calculated as the first difference of the log of condominium prices and ε_t is the error term. To account for the unique "peak-trough' behavior of prices, and thereby returns for the respective metropolitan condominium markets, we construct dummy variables unique to each metropolitan area. The period representing the 'peak to trough' is 1.0 and 0.0 otherwise as follows: Boston 1.0 for 2006:1-2012:2 and 0.0 otherwise, Chicago 1.0 for 2007:4-2012:4 and 0.0 otherwise, Los Angeles 1.0 for 2006:6-2012:1 and 0.0 otherwise, New York 1.0 for 2006:3-2012:2 and 0.0 otherwise, and San Francisco 1.0 for 2006:2-2011:12 and 0.0 otherwise.[5]

[Insert Table 2 here]

Table 2 displays the results of the ARMA model specifications for monthly condominium returns with respect to each metropolitan area. Each ARMA model satisfies the stationarity (AR

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[5] Upon the suggestion of the referee we have incorporated the collapse of the housing market in our modeling efforts in the construction of the respective dummy variables. The dummy variable designation as 1.0 begins in the period in which prices begin to fall following the peak price. For example, the peak price prior to the onset of the 'Great Recession' in the case of Boston occurred in 2005:12 with prices beginning to fall in 2006:1.

terms) and invertibility (MA terms) conditions.[6] The ARMA models are free of autocorrelation based on the Box-Pierce Q-statistic, Q(8), but the residuals exhibit autoregressive conditional heteroskedasticity (ARCH) based on the χ^2 distributed ARCH(8) statistic (Engle, 1982), indicative of volatility clustering.[7] The statistical significance of the overall F-statistic indicates each model has predictive power. The coefficient, DMETRO, is negative and statistically significant at the 1 percent level across the five metropolitan areas, reflecting the impact of the housing market collapse on condominium mean returns.

The ARMA models presented in Table 2 represent the mean equations for the respective monthly returns; however, with the presence of autoregressive conditional heteroskedasticity we proceed with examining the time-varying nature of the residual variance. We employ the TARCH-M model set forth by Glosten et al. (1993) and Zakoian (1994) in recognizing the possibility of asymmetry in the conditional variance and the direct influence of the conditional variance on mean returns. The ARMA-TGARCH-M model is specified as follows:

$$\phi(L)R_t = \mu_o + \varphi DMETRO + \lambda\sigma_t^2 + \theta(L)\epsilon_t \quad (2)$$

$$\sigma_t^2 = \omega + \delta \mathrm{DMETRO} + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 I_t + \beta\sigma_{t-1}^2 \quad (3)$$

where equation (2) represents the mean equation and includes the conditional variance, σ_t^2, and equation (3) is the TGARCH specification for the conditional variance equation. The conditional variance is a function of a constant term, ω, representing the long-run or average variance; the DMETRO dummy variable as previously defined; ϵ_{t-1}^2 represents news about volatility from the previous period (i.e. ARCH term); σ_{t-1}^2 is last period's forecast variance (i.e. GARCH term); and asymmetry is given by the indicator function, $I_t = 1$ if $\epsilon_{t-1} < 0$ and 0.0 otherwise. If $\gamma \neq 0$ the

[6] In the estimation of the respective ARMA models, we followed the principle of parsimony.

[7] Cosimano and Jansen (1988) reiterate that the absence of autocorrelation in the residuals is important before testing for the presence of autoregressive conditional heteroscedasticity (ARCH) in the residuals to avoid falsely identifying ARCH effects.

news impact of a shock is considered asymmetric, whereby $\gamma > 0$ suggests negative news increases volatility. For the leverage effect to hold negative news has a greater impact than positive news, such that $\alpha > 0$ and $\alpha + \gamma > 0$. With respect to housing markets, the leverage effect pertains to falling condominium prices that induce the debt to home equity ratio for condominium owners to rise, thereby increasing the risk (i.e. volatility) (Karoglou et al. 2013).[8]

[Insert Table 3 here]

Table 3 displays the results of ARMA-TGARCH-M models for the condominium returns of the respective metropolitan areas. Given the non-normality exhibited in condominium returns for a majority of metropolitan areas, the generalized error distribution is used in the estimation. Similar to the mean equation results reported in Table 2, the DMETRO dummy variable is negative and statistically significant at the 10 percent level or better along with the respective stationarity and invertibility conditions associated with the autoregressive and moving average terms being satisfied. The residuals for each model are free of autocorrelation and autoregressive conditional heteroscedasticity with the exception of New York, which fails to reject the null hypothesis of no autoregressive conditional heteroscedasticity at the 10 percent level of significance.[9] Contrary to the findings of Karoglou et al. (2013) for metropolitan housing returns, the conditional variance in the mean equation for condominium returns is statistically insignificant for all the metropolitan areas.

Focusing on the conditional variance equations, we do not find support for asymmetry in the conditional variance. The absence of support for the leverage effect in condominium returns parallels the results by Miles (2008) who finds limited evidence of asymmetry in volatility for housing markets at the state level. Also, the inclusion of the dummy variable, DMETRO, does

[8] Note the TGARCH-M model nests the GARCH, GARCH-M, and TGARCH models. The GARCH model results if $\lambda = 0$ and $\gamma = 0$, the GARCH-M model if $\gamma = 0$, and TGARCH model if $\lambda = 0$.

[9] The null hypothesis of no autoregressive conditional heteroscedasticity is rejected at 12 lags with $\chi^2 =$ 17.40 and probability value of 0.14.

not yield a statistically significant impact on the conditional variance. However, the impact of news and past volatility differ somewhat across metropolitan areas. In the cases of Boston and Chicago, the ARCH term, ϵ_{t-1}^2, is positive and statistically significant, yet the GARCH term, σ_{t-1}^2 is statistically insignificant. This result reveals that news about volatility rather than past volatility has an immediate impact on the conditional variance. In the case of Los Angeles, both the ARCH and GARCH terms are statistically significant whereas for New York and San Francisco only the GARCH term is statistically significant. Similar to the findings of Miles (2011a) for the housing markets of 62 MSAs, our results indicate the west coast metropolitan areas of Los Angeles and San Francisco, both relatively expensive housing marketing, exhibit the greatest volatility persistence associated with shocks.

4. Concluding Remarks

This study is the first to extend the literature on modeling the volatility of housing returns to the case of condominium returns for five major U.S. metropolitan areas. As is the case for single-family homes, identifying the presence of volatility clustering is relevant on several fronts. First, the volatility of condominium returns can be transmitted to other sectors of the housing market and the metropolitan economy. Second, in the event that declining condominium prices increases the debt to home equity, the leverage effect would increase the risk exposure to condominium ownership. Hence, the greater the volatility in condominium returns, the greater is the probability of negative home equity and mortgage foreclosure losses. Third, with the probability of large losses being greater in highly volatile periods than standard mean-variance models would predict, capturing the time-varying nature of volatility is pertinent for real estate portfolio management.

In this regard, we estimate an ARMA-TGARCH-M model to answer the following questions:[10] Do condominium returns exhibit volatility clustering? If so, what is the degree of persistence in response to volatility shocks? Are shocks to volatility asymmetric? Does volatility have a direct impact on condominium returns? To what extent has the period leading up to 'Great Recession' and the period immediately following the housing market collapse had an influence? Our analysis of ARMA models for metropolitan condominium returns reveals the presence of volatility clustering, evident by the residuals exhibiting autoregressive conditional heteroscedasticity. The degree of persistence varies across metropolitan areas with Los Angeles and San Francisco exhibiting the greatest persistence followed by Chicago, New York, and Boston. As is the case of other studies of U.S. housing markets, we do not find evidence of asymmetry in the conditional variance, hence the absence of a potential leverage effect associated with the volatility in returns. Moreover, volatility does not have a direct impact on returns. For each metropolitan area, condominium prices peaked some time prior to the onset of the 'Great Recession' with prices not recovering until early 2012, the inclusion of a dummy variable capturing the 'peak-trough' behavior in condominium prices reveals the housing market collapse affected mean returns, but not the conditional variance of returns.

While our study provides an initial investigation into modeling the volatility clustering associated with condominium returns, future research could extend the above analysis to the condominium markets of other metropolitan areas, as data becomes available, along with alternative modeling approaches to capture the time-varying volatility of returns.

[10] We explored alternative GARCH-type models such as exponential and component GARCH models, but the model diagnostics failed on several fronts, namely, with respect to the continued presence of autocorrelation and autoregressive conditional heteroscedasticity in the residuals.

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Figure 1
Metropolitan Condominium Prices
1995:1-2018:8

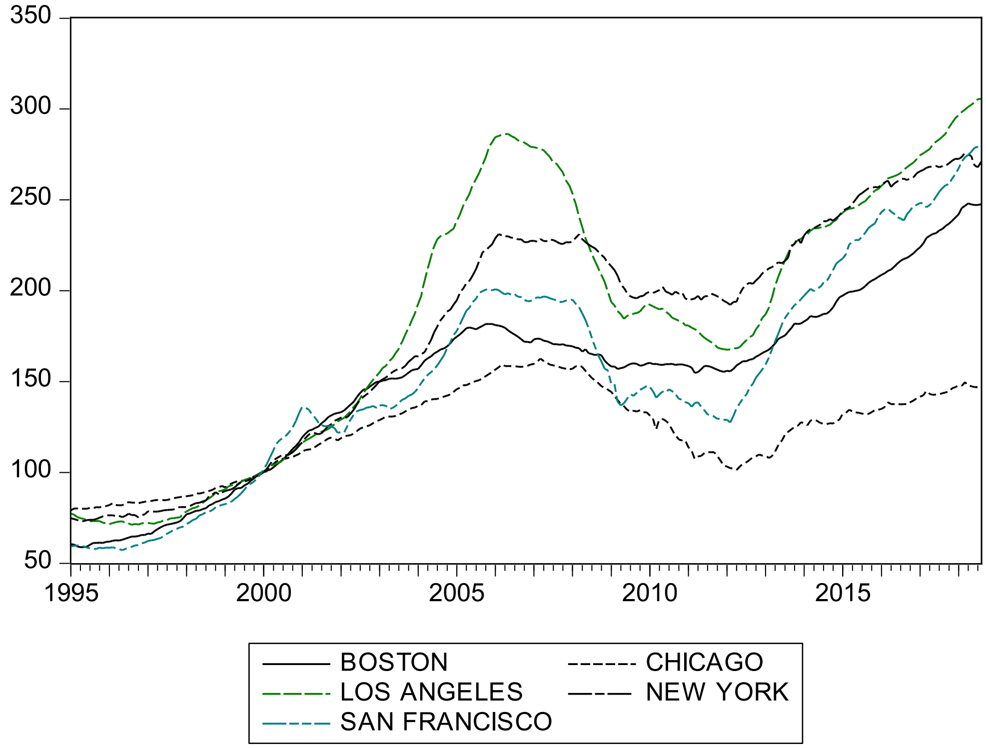

Figure 2
Metropolitan Condominium Returns
1995:1-2018:8

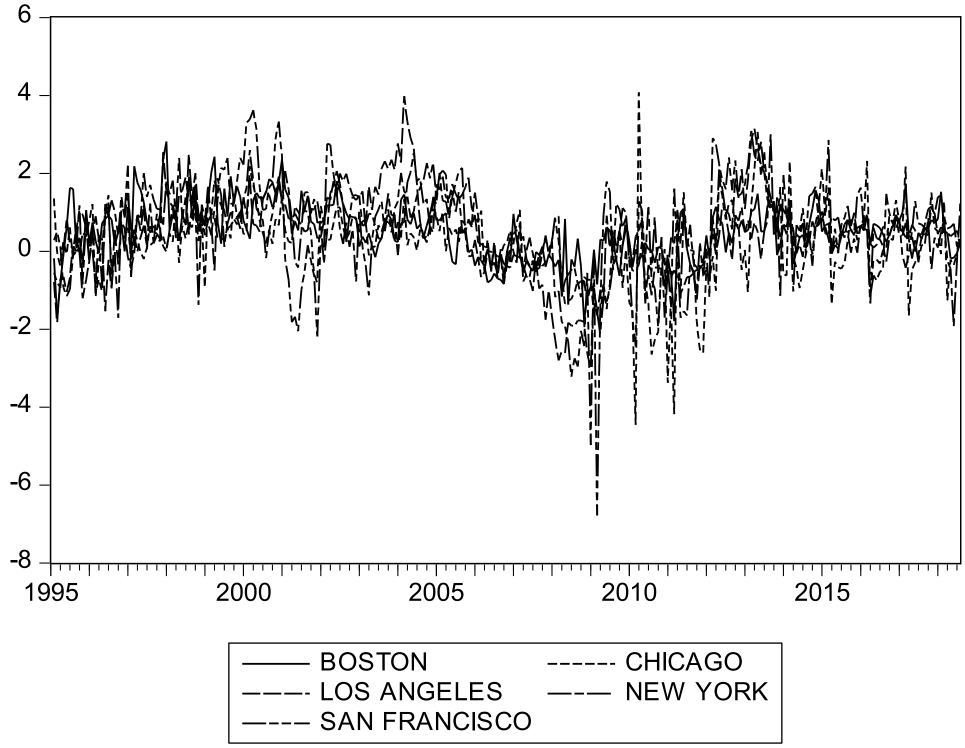

Table 1. Summary Statistics

Statistics	Boston	Chicago	Los Angeles	New York	San Francisco
Mean	0.499	0.220	0.485	0.455	0.547
SD	0.729	1.014	1.117	0.861	1.355
CV	1.461	4.609	2.303	1.892	2.477
Min	-1.798	-4.451	-3.014	-2.114	-6.778
Max	2.817	4.080	3.981	2.997	3.618
Skewness	-0.049	-0.792	-0.343	-0.146	-0.984
Kurtosis	3.608	6.487	3.656	3.204	6.204
JB	4.472	172.903	10.627	1.502	166.726
	[0.11]	[0.00][a]	[0.00][a]	[0.47]	[0.00][a]
PP(C)	-8.350[a]	-12.121[a]	-4.305[a]	-11.044[a]	-8.099[a]
PP(C+T)	-8.646[a]	-12.191[a]	-4.344[a]	-11.255[a]	-8.123[a]

Notes: SD denotes standard deviation. CV is the coefficient of variation. Min and Max are the minimum and maximum returns, respectively. JB is the Jarque-Bera test for normality. PP represents the Phillips-Perron (1988) unit root test statistics for the null hypothesis of unit root process in levels. Critical values with constant and without time trend, denoted PP(C), is 1% -3.453, 5% -2.872, and 10% -2.572. Critical values with constant and a linear time trend, denoted PP(C+T), is 1% -3.991, 5% -3.426, and 10% -3.136. Significance levels denoted as follows: 1% (a), 5% (b), and 10% (c). Probability values are in brackets.

Table 2. ARMA Models

Mean Equation:

Variables	**Boston**	**Chicago**	**Los Angeles**	**New York**	**San Francisco**
μ_0	0.745	0.502	0.784	0.741	0.870
	(0.068)[a]	(0.069)[a]	(0.214)[a]	(0.088)[a]	(0.194)[a]
DMETRO	-0.940	-1.304	-0.949	-1.012	-1.222
	(0.105)[a]	(0.190)[a]	(0.260)[a]	(0.161)[a]	(0.360)[a]
R_{t-1}			0.397	0.391	0.454
			(0.135)[a]	(0.057)[a]	(0.109)[a]
R_{t-2}			0.463	0.322	0.330
			(0.104)[a]	(0.052)[a]	(0.119)[a]
ϵ_{t-1}	0.476	0.211	0.249		
	(0.064)[a]	(0.081)[a]	(0.145)[c]		
ϵ_{t-2}	0.413	0.245			
	(0.066)[a]	(0.089)[a]			
ϵ_{t-3}			-0.286	-0.391	-0.276
			(0.067)[a]	(0.073)[a]	(0.060)[a]
Model Diagnostics:					
Adj. R^2	0.501	0.316	0.788	0.435	0.534
F-statistic	96.47	44.44	209.44	54.93	81.36
	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]
Q(8)	4.76	6.29	3.20	6.78	4.20
	[0.57]	[0.39]	[0.53]	[0.24]	[0.52]
ARCH(8)	32.52	23.42	15.43	16.99	93.04
	[0.00][a]	[0.00][a]	[0.05][b]	[0.03][b]	[0.00][a]
LL	-211.67	-349.63	-206.98	-273.25	-375.10

Notes: AR(.) represents the autoregressive terms and MA(.) the moving average terms. AR terms satisfy stationarity conditions and MA terms satisfy invertibility conditions. Coefficient estimates based on Newey-West heteroskedasticity-autocorrelation corrected standard errors and covariance. Q(8) is the Box-Pierce Q-statistic distributed as chi-square with 8 degrees of freedom to test the null hypothesis of no autocorrelation in the residuals up to 8 lags. ARCH(8) is distributed as chi-square with 8 degree of freedom to test the null hypothesis of no autoregressive conditional heteroscedasticity of the residuals. LL is the log likelihood. Significance levels denoted as follows: a(1%), b(5%), and c(10%). Standard errors are in parentheses and probability values in brackets.

Table 3. ARMA-TGARCH-M Models

Variables	Boston	Chicago	Los Angeles	New York	San Francisco
Mean Equation:					
μ_0	0.684 (0.070)[a]	0.531 (0.057)[a]	0.479 (0.280)[c]	0.732 (0.122)[a]	0.896 (0.257)[a]
DMETRO	-0.915 (0.112)[a]	-1.281 (0.166)[a]	-0.674 (0.362)[c]	-1.105 (0.198)[a]	-1.008 (0.350)[a]
R_{t-1}			0.438 (0.129)[a]	0.450 (0.073)[a]	0.541 (0.061)[a]
R_{t-2}			0.445 (0.108)[a]	0.284 (0.064)[a]	0.323 (0.060)[a]
ϵ_{t-1}	0.504 (0.067)[a]	0.296 (0.067)[a]	0.234 (0.133)[c]		
ϵ_{t-2}	0.407 (0.053)[a]	0.328 (0.052)[a]			
ϵ_{t-3}			-0.271 (0.076)[a]	-0.356 (0.060)[a]	-0.335 (0.070)[a]
σ^2	0.158 (0.279)	-0.014 (0.114)	-0.036 (0.063)	0.321 (0.329)	-0.019 (0.081)
Conditional Variance Equation:					
ω	0.114 (0.041)[a]	0.167 (0.039)[a]	0.005 (0.006)	0.120 (0.084)	0.028 (0.021)
DMETRO	-0.003 (0.030)	0.191 (0.119)	0.008 (0.011)	3.22E-3 (0.042)	0.023 (0.028)
ϵ_{t-1}^2	0.340 (0.203)[c]	0.762 (0.276)[a]	0.096 (0.065)[b]	0.235 (0.170)	0.071 (0.054)
$\epsilon_{t-1}^2 I_t$	-0.084 (0.237)	-0.329 (0.329)	0.020 (0.063)	-0.109 (0.167)	0.087 (0.086)
σ_{t-1}^2	0.262 (0.194)	0.141 (0.118)	0.866 (0.061)[a]	0.552 (0.279)[b]	0.837 (0.060)[a]

Table 3. ARMA-TGARCH-M Models (continued)

Model Diagnostics:					
Adj. R^2	0.498	0.303	0.786	0.426	0.526
Q(8)	4.46	9.73	3.88	5.42	5.30
	[0.61]	[0.14]	[0.42]	[0.37]	[0.38]
ARCH(8)	2.94	5.36	7.17	13.55	7.50
	[0.94]	[0.72]	[0.52]	[0.09][c]	[0.48]
LL	-193.04	-282.93	-184.90	-263.97	-330.38

Notes: AR(.) represents the autoregressive terms and MA(.) the moving average terms. AR terms satisfy stationarity conditions and MA terms satisfy invertibility conditions. Estimation method is maximum likelihood Berndt-Hall-Hall-Hausman using the Generalized Error Distribution with fixed parameter 1.5. Q(8) is the Box-Pierce Q-statistic distributed as chi-square with 8 degrees of freedom to test the null hypothesis of no autocorrelation in the residuals up to 8 lags. ARCH(8) is distributed as chi-square with 8 degree of freedom to test the null hypothesis of no autoregressive conditional heteroscedasticity of the residuals. LL is log likelihood. Significance levels denoted as follows: a(1%), b(5%), and c(10%). Standard errors are in parentheses and probability values in brackets.