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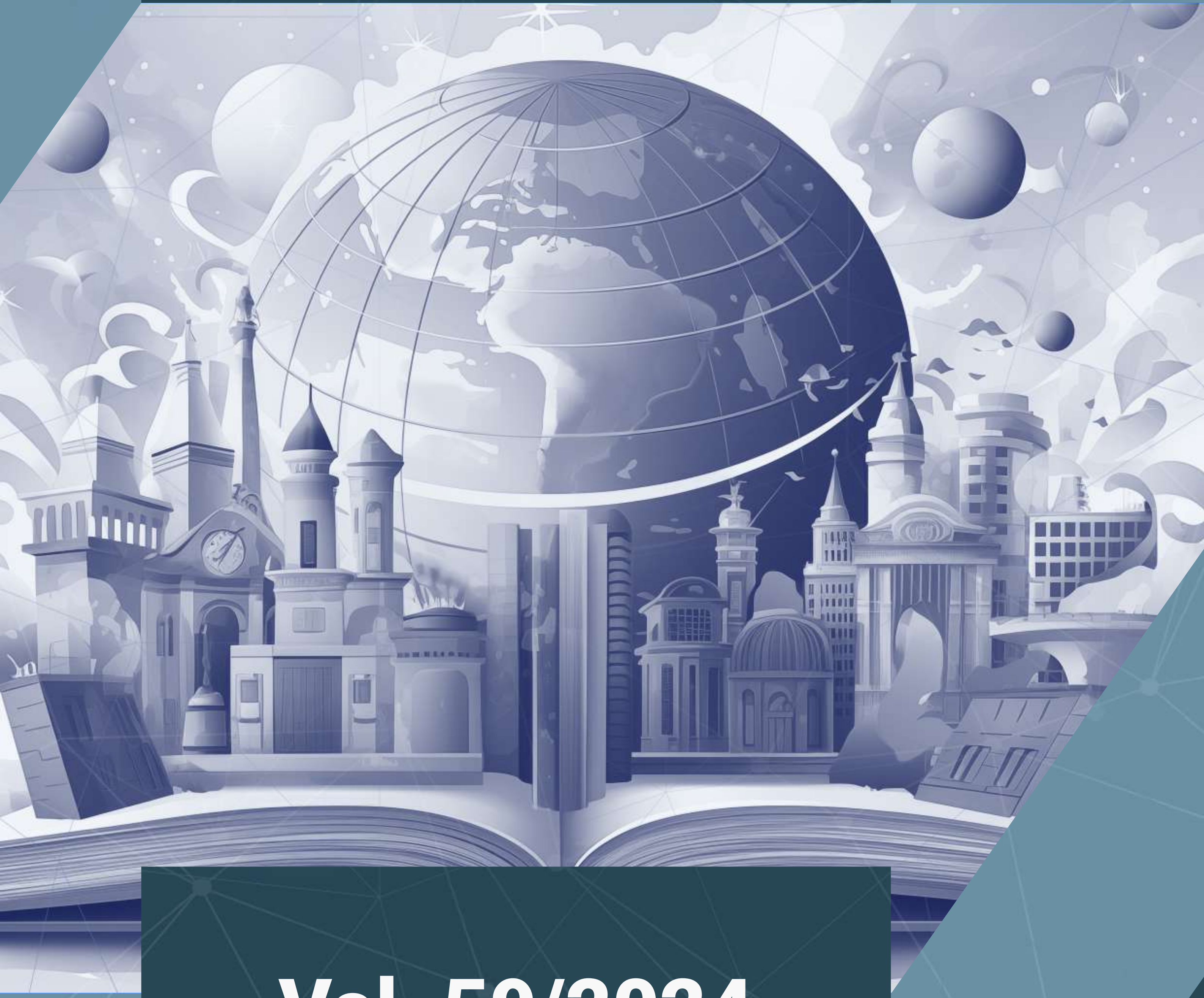

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Will the Release of Presale Housing moderate or exacerbate residential price volatility? - Taking Apartmemt complexes Units in Taichung City as an Example

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Abstract. During periods of economic prosperity, increased profit opportunities lead to active transactions in the existing housing market and heightened consumer risk preferences. At this time, developers increase the launch of presale housing projects to expand business opportunities, indirectly filling the supply gap of existing homes and alleviating housing demand. However, in reality, prices in both the presale and existing housing markets mutually drive each other up, further delaying the stabilization of housing prices. Therefore, whether the launch of presale housing projects can alleviate the demand for existing homes and achieve the function of price moderation becomes a research-worthy question. This study aims to investigate whether the volume of presale housing projects moderates or exacerbates housing prices. We focus on the volatility of aggregate residential housing prices in Taichung City, Taiwan, using transaction data of monthly average prices for Apartmemt complexes Units (high-rise buildings and high-rise apartments) from August 2012 to June 2023. We employ the ARCH/GARCH models to analyze the impact of presale housing project volumes on housing price volatility. Stability and convergence indicate a moderating effect of presale housing project volumes on housing prices; otherwise, it indicates exacerbation. After model testing, this study selects the most appropriate model as the ARIMA(3,1,0)-GARCH(1,0) model. This study finds that during periods of economic prosperity, the volume of presale housing projects does not aid in stabilizing or converging residential housing prices; instead, it exacerbates market disruption.

Keywords. Volatility clustering; conditional heteroskedasticity; ARCH/GARCH model; Taichung City

1. Introduction

Since the global financial crisis, monetary easing policies have facilitated a home-buying environment characterized by ample funds and low interest rates, resulting in heightened housing prices. However, ordinary homebuyers have encountered income growth that lags behind the rapid rise in housing costs. Research indicates that declining natural interest rates in advanced economies over recent decades have coincided with significant increases in housing price volatility. Moreover, recent Taiwanese government tax policies targeting interest rates and land holding costs have proven ineffective in curbing housing price escalation (Wang et al., 2022). Traditionally, during economic booms, an increase in presale housing launches is expected to moderate housing demand and stabilize price fluctuations. Contrary to expectations, this has not been the case, prompting further investigation. The primary aim of this study is to explore whether the volume of presale housing projects moderates price fluctuations in Apartmemt complexes Unitsresidential buildings.

The presale housing promotion system is widespread in Taiwan, Hong Kong, and China, serving as a prevalent method for home acquisition. It helps alleviate demand pressures on existing housing, thereby establishing a dynamic where supply and demand act as substitutes. Previous research in these regions has delved into various aspects, including the futures-like nature of presale housing and its impact on market dynamics (Li & Yang, 2010; Jiang et al., 2019). Wang et al. (2022) utilized spider web and forward contract pricing models, demonstrating that immediate responses in housing spot demand markets may divert demand to forward pre-sold housing markets due to supply lag in existing housing markets, potentially overheating the presale housing market.Studies in mainland China by Wang et al. (2007) and Qi & Wang (2010) on Shanghai and Yunnan Province housing prices suggest that presale housing stabilizes existing housing markets. Similarly, in Hong Kong, Wong et al. (2006) found that the presale housing market stabilizes existing housing price fluctuations. Most studies agree that the volume of presale housing projects can moderate and stabilize housing prices.Presale housing exhibits a supply lag characteristic akin to the cobweb theory, resulting in a price-volume asymmetry. This arises because the volume of presale housing is based on existing home prices from the previous period. Due to prices leading quantities, each period's price undergoes a correction process resembling a spider web shape, gradually achieving equilibrium. If the slope of the demand curve exceeds that of the supply curve, prices and quantities gradually converge towards equilibrium. Conversely, if the slope of the supply curve exceeds that of the demand curve, price divergence occurs.

Housing types in Taiwan include apartmemt complexes units, townhouses, and apartments. The Actual Price Registration System revealed that from August 2021 to June 2023, Taichung City recorded a total of 242,681 residential housing transactions. The city tends to adopt a high-density approach to land use in the face of high land costs, thereby making apartmemt complexes units its mainstream residential housing type. In this study, a total of 153,452 housing transactions are included.Housing not only is a consumer commodity that can hedge against price falls but can also be regarded as an asset product with the following major price-volatility-related features: 1) housing price volatility shows a leptokurtic distribution; 2) the conditional variance tends to be time-varying. Volatility occurs with great persistence. In other words, a large fluctuation tends to immediately follow a large fluctuation, and a small fluctuation tends to immediately follow a small fluctuation. Heavy tails (suggesting the existence of numerous residuals) are observed in the empirical distribution of the asset price series. These phenomena are called volatility clustering (Chen, 2020) and are features of the conditional variance equation σ_t^2, which is used to replace risk and uncertainty. σ_t^2 of an economic variable is regarded as the quantitative indicator for the change in risk, namely, volatility.Most research in this aspect was conducted based on the average or median of the transaction prices. Since $\sigma_t^2$is the standardized fourth moment and therefore a non-observable variable, its estimation can rely on the ARCH/GARCH (autoregressive conditional heteroskedasticity/generalized autoregressive conditional heteroskedasticity) model. As the short-term impact comes from the residual ε_{t-1} and is the forecast error in the equation of the mean of residuals in the previous period, the coefficient of this unexpected impact that denotes the degree of volatility can be estimated. Meanwhile, σ_{t-1}^2 is the conditional variance under the progressive effect of lags. When there are more lags, the impact is more persistent. If the coefficient $|\beta_1||<1$, a geometric progressive decrease occurs. A smaller coefficient indicates a faster progressive decrease and a smaller impact. In such a case, the coefficient can be used as an indicator for the risk impact. If the coefficient |β1| is greater than 1, the opposite is true.

Most previous studies have adopted the ARCH/GARCH model for analyzing housing price volatility. Some studies focused on different property types such as residential housing, office buildings, retail buildings, and factories, or different apartment types such as one-bedroom and two-bedroom units. Other studies estimated the impact of policy interventions and their effect on volatility as a leverage factor. These studies commonly used monthly average or median transaction prices to develop the optimal ARCH/GARCH model for estimation and interpretation.To achieve the objective of exploring housing price volatility, this study developed a housing price model based on the GARCH model. It measures whether the increments in presale homes in Taichung City, the second-largest city in Taiwan, had a significant impact on the volatility of residential housing prices in Taichung City. The Actual Price Registration system, launched in 2012 by the Ministry of the Interior, focuses on the prices of Multi Dwelling Units (high-rise residential buildings and high-rise apartments).This study focuses on analyzing volatility in residential housing prices in Taichung City, specifically in Multi Dwelling Units. Data from August 2012 to June 2023, comprising 242,681 transactions, was filtered to 153,452 transactions for high-rise residential buildings and high-rise apartments, and compiled into monthly averages over 131 periods. The number of presale housing proposals was derived from monthly average changes in building usage permit statistics from the Ministry of the Interior. Initial assessments of data attributes indicated non-stationarity, necessitating first-order differencing to achieve stationarity. Model selection criteria identified ARIMA(3,1,0)-GARCH(1,0) as the most suitable model.

Research findings confirm that incorporating the volume of presale housing proposals into housing price volatility models shifts the model from convergence to divergence, leading to continued price escalation in Multi Dwelling Units This exacerbates instability rather than stabilizing volatility.

2. Literature Review

Random price volatility is common in the operation of market mechanisms, such as in the high-frequency trade of stocks, exchange rates and gold on a daily basis in the asset market. Consequently, a large fluctuation tends to immediately occur after a large fluctuation and a small fluctuation tends to immediately occur after a small fluctuation; this is known as volatility clustering. Transactions in the real estate market are conducted at a low frequency, and the relevant data are recorded at a monthly basis. Relevant literature is presented as follows.

Wang and Hartzel (2020) studied the real estate price volatility of Hong Kong. Specifically, they analyzed the monthly data on the prices of residential homes, office buildings, retail buildings, and factory buildings in Hong Kong from February 1993 to February 2019 to verify the existence of volatility clusters. The results showed that volatility clusters existed in all the four types of real estate. The determinants of housing price volatility depended on the real estate type. In general, the housing price volatility of Hong Kong was mainly affected by exchange rates (with CNY and USD), while the price volatility of commercial properties was mainly affected by the unemployment rate. Dufitinema (2020) examined the prices in the Finnish housing market, and found that significant clustering effects were found in over half of the cities/sub-areas in all studied types of apartments. Moreover, the asymmetric impacts of shocks were observed in the residential real estate markets of almost all cities and sub-areas. Furthermore, the forecasting performances on volatility in the study were noted to vary across cities and sub-areas, and by apartment types. Miles (2020) studied the residential real estate markets of 50 states of the US and found that the GARCH effects with volatility clustering existed in more than half of the studied states. Kaulihowa and Kamiti (2019) explored the impact of macroeconomic factors on the housing price volatility of Namibia from Q1 2007 to Q2 2017. Their results supported the hypothesis that the housing price volatility of Namibia was persistent. Fan et al. (2022) argued that the uncertainty in economic policies was a significant determinant of housing price volatility. Wang et al. (2022) developed two theoretical models to analyze the long-term equilibrium and short-term changes in the presale home market. In summary, most of these studies were based on the ARIMA/GARCH models, while some of them were based on other theories such as the cobweb theory and the forward contract pricing. Within the scope of these studies, the price volatility under the impact of various subjects, including housing area, housing type, financial assets, macroeconomic factors and policy intervention, was explored. The above-mentioned literature was summarized by scope, subject, method and result as follows.

Author	Research Purpose: To study the real estate price volatility of Hong Kong.

Wang, Hartzel (2020)	Data Scope:	Real estate price volatility of Hong Kong from February 1993 to February 2019.
	Data Object:	Monthly data on the prices of residential homes, office buildings, retail buildings, and factory buildings in Hong Kong.
	Research Method:	The ARIMA/GARCH model.
	Research Results:	1. Volatility clusters existed in all the four types of real estate, and the determinants of housing price volatility depended on the real estate type. 2. The housing price volatility of Hong Kong was mainly affected by exchange rates, while the price volatility of commercial properties was mainly affected by the unemployment rate. 3. The exponential GARCH model indicated that no asymmetric effects existed in the real estate market of Hong Kong.
Author	Research Purpose:	To check if the prices in the Finnish housing market has similar financial features with stocks and other assets.
Dufitinema (2020)	Data Scope:	The research areas were the 15 major areas of Finland from Q1 1988 to Q4 2018.
	Data Object:	The studied residential type was blocks of flats, which could be categorized into one-bedroom units, two-bedroom units and three-or-more-bedroom units.
	Research Method:	The ARIMA/GARCH model.
	Research Purpose:	1. The results showed that clustering effects were found in over half of the cities/sub-areas in all studied types of apartments. 2. Mixed results on the sign of the significant risk-return relationship were observed across cities and sub-areas in all three apartment types. 3. The forecasting performances on volatility in the study were noted to vary across cities and sub-areas, and by apartment types. 4. The asymmetric impacts of shocks were observed in the residential real estate markets of almost all cities and sub-areas.
Author	Data Scope:	To identify the model that has the best forecasting performance on price returns and price volatility in the Finnish housing market.
Dufitinema (2021)	Data Object:	The quarterly housing price indexes of the 15 major areas of Finland from Q1 1988 to Q4 2018.
	Research Method:	The Finnish housing market.
	Research Results:	The ARMA, ARFIMA and EGARCH models.
	Research Purpose:	GARCH models (CGARCH and FIGARCH) had better forecasting performance on housing price volatility than the EGARCH model, indicating that housing price volatility was characterized by long-range dependence. The models could capture and forecast the feature of housing price volatility.
Author	Data Scope:	To explore the macroscopic factors in the housing price volatility of Namibia.
Kaulihowa and Kamiti (2019)	Data Object:	The housing prices in Namibia from Q1, 2007, to Q2, 2017.
	Research Method:	The ARIMA/GARCH model.
	Research Results:	The results supported the hypothesis that the housing price volatility of Namibia was persistent.

Author	Research Purpose:	To test the residential real estate markets of 50 states by developing unique GARCH models for each state.
Miles (2020)	Data Scope:	The housing prices of 50 states of the US.
	Data Object:	ARIMA/GARCH models.
	Research Method:	The results showed that the GARCH effects with volatility clustering existed in more than half of the studied states.
Author	Research Purpose:	To explore the relationship between housing price volatility and the uncertainty in economic policies in G7 countries.
Fan et al. (2022)	Data Scope:	The housing prices of G7 countries.
	Data Object:	The application of the GARCH-MIDAS model, a newly introduce econometric technique, for samples collected from January 1998 to May 2021.
	Research Method:	The uncertainty in economic policies was a significant determinant of housing price volatility. The out-of-sample test also indicated that the uncertainty in economic policies was an effective forecasting factor, and the GARCH-MIDAS model had a good forecasting performance.
Author	Research Purpose:	To develop two theoretical models to explain the frequent over-heating of presale home market within a short term by taking the Taiwan's housing market as an example.
Wang, Lin, Tsai(2022)	Data Scope:	The data for this study focused on Taipei City, New Taipei City, Taichung City, and Kaohsiung City. The data on presale home prices was the data on possible transaction prices from Q1 2000 to Q1 2021, provided by Cathay Real Estate Development and Center for Real Estate Research, College of Social Sciences, National Chengchi University.
	Data Object:	The cobweb theory and the spot contract pricing model were adopted.
	Research Method:	The forward contract pricing model was used to explain the short-term volatility in the presale home market, and it was recommended that the government could tackle with the overheated presale home market by increasing the interest rates and the land holding costs.

This section presents the model for random price volatility and its economic implications. Random Walk (RW) models are time series models that have the following economic implications: (1) A RW model without drift economically implies that, while there is no change in the conditions for the supply-demand relation of any market and market players can directly forecast the future prices based on the previous-period prices. The creation process of any time series data on prices (or even trade volume) may not include a RW model without drift. (2) A RW model with drift economically implies that, while the market supply encourages the stable demand growth due to the continuous progress in technological innovation or the continuous population growth, the creation process of any time series data on prices (or even trade volume) may include a RW model with drift. (3) A RW model with a random disturbance economically implies that, while factor inputs and technological progress and innovation are random, but create enduring and accumulative influences and interest, the creation process of any time series data on returns or prices may include a RW model with a random disturbance (Yang, 2017). In conclusion, asset products may exhibit volatility clustering. In terms of the housing market characterized by low-frequency trade, the major factors in the price volatility include the housing type, exchange rates, interest rates and economic policies. In terms of its nature, housing price volatility is random. Therefore, RW models can be used to interpret the significance of relevant economic activities.

3. Data Sources

(1) Size of the transaction data

A total of 489,448 transactions of residential housing in Taichung City registered in The Actual Price Registration system from August 2012 to June 2023 were used as the data.

(2) Selection and categorization

As shown in Table 2, a total of 242,681 transactions were selected as the effective data after the exclusion of missing values and deviations.

Table 2 Data-generating Process

Step	Excluded transactions	Effective data (transactions)
(1) Population	-	489,448
(2) Housing-land integration	142,999	346,449
(3) Residential products	100,453	245,996
(4) Exclusion of missing values	3,015	242,705
(5) Exclusion of deviations (three SDs)	24	242,681
Total	246,491	242,681

By type, the housing involved in the data can be categorized into “high-rise apartments” (high-rise buildings of 6-10 stories with elevators), “high-rise buildings” (at least 11 stories with elevators), “townhouses” (each has its own house numbers) and apartments (buildings of at most five stories without elevators). As different types of Apartmemt complexes Units (high-rise apartments and high-rise buildings) only differ in the number of stories, they were grouped together for analysis. As shown in Table 3, among the 242,681 transactions, 153,452 were transactions of Apartmemt complexes Units, including 39,106 transactions of high-rise buildings and 114,346 transactions of high-rise apartments, 71,881 were transactions of townhouses, and 17,348 were transactions of apartments.

Table 3 Residential Housing Types

Residential housing type	Transactions
1.Apartmemt complexes Units (high-rise apartments and high-rise buildings)	153,452
(1) High-rise apartments (below 10 stories with elevators)	39,106
(2) High-rise buildings (of at least 11 stories with elevators)	114,346
2. Townhouses (with a unique house number)	71,881
3. Apartments (of at most five stories without elevators)	17,348
Total	242,681

(3) Data source of presale homes:

The data on the issued building construction licenses for residential buildings was collected from the building statistics for the period from August 2012 to June 2023 issued by the National Land

Management Agency of the MOI. In summary, a total of 244,116 licenses were granted for presale homes from August 2012 to June 2023, with a monthly minimum of 413 recorded on February 2016, a monthly maximum of 6,792 recorded on January 2021, and a monthly average of 1,864. The monthly statistics are shown in Table 4.

To address the issue of different calculation units and the disparity in volume of this variable, we use the absolute value of the monthly rate of change: |(Current month quantity - Previous month quantity) / Previous month quantity|. This represents the absolute monthly increment of pre-sold houses.

Table 4 The Monthly Statistics on Residential Building Construction Licenses

Period	2012M8	2012M9	2012M10	2012M11	2012M12	2013M1	2013M2	2013M3	2013M4	2013M5	2013M6	2013M7	2013M8	2013M9	2013M10	2013M11	2013M12
number of households	1244	2199	1018	1248	1837	2076	1012	1391	1700	1965	1184	1486	1550	2498	2241	1082	1493
Period	2014M1	2014M2	2014M3	2014M4	2014M5	2014M6	2014M7	2014M8	2014M9	2014M10	2014M11	2014M12	2015M1	2015M2	2015M3	2015M4	2015M5
number of households	876	1099	960	1471	954	1137	1561	1190	604	1113	822	940	879	1099	967	1471	954
Period	2015M6	2015M7	2015M8	2015M9	2015M10	2015M11	2015M12	2016M1	2016M2	2016M3	2016M4	2016M5	2016M6	2016M7	2016M8	2016M9	2016M10
number of households	1137	1561	1190	604	1113	822	940	1131	413	1228	616	864	611	1280	1862	799	860
Period	2016M11	2016M12	2017M1	2017M2	2017M3	2017M4	2017M5	2017M6	2017M7	2017M8	2017M9	2017M10	2017M11	2017M12	2018M1	2018M2	2018M3
number of households	770	2224	1258	963	684	1076	1997	1123	1419	1711	1501	920	1333	1400	1628	797	2097
Period	2018M4	2018M5	2018M6	2018M7	2018M8	2018M9	2018M10	2018M11	2018M12	2019M1	2019M2	2019M3	2019M4	2019M5	2019M6	2019M7	2019M8
number of households	1573	1590	1897	938	2098	1241	2459	2109	2851	4376	792	3642	2068	1144	913	2805	2187
Period	2019M9	2019M10	2019M11	2019M12	2020M1	2020M2	2020M3	2020M4	2020M5	2020M6	2020M7	2020M8	2020M9	2020M10	2020M11	2020M12	2021M1
number of households	2433	4080	1472	3130	2410	3498	2531	1456	1831	4002	3291	2633	3519	2505	2710	3655	6792
Period	2021M2	2021M3	2021M4	2021M5	2021M6	2021M7	2021M8	2021M9	2021M10	2021M11	2021M12	2022M1	2022M2	2022M3	2022M4	2022M5	2022M6
number of households	1527	2550	1996	1849	2765	3364	1067	1096	2050	3362	4066	1433	1603	2729	3403	2522	4312
Period	2022M7	2022M8	2022M9	2022M10	2022M11	2022M12	2023M1	2023M2	2023M3	2023M4	2023M5	2023M6					
number of households	2173	2792	3226	2772	4308	2374	1549	3241	1083	1438	1185	4397					

4. Results of the Empirical Analysis and Discussion

In order to study the housing price volatility, ARCH/GARCH models are developed in this paper. Furthermore, the absolute increments in presale homes are included as the exogenous variable to measure the housing price volatility under an impact. In this study, the equations for the volatility model are as follows:

$$y_t|\Omega_t \sim N(x\mathrm{a}, \sigma^2)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq (4-1)}$$

$$\varepsilon_t = y_t - X_t\mathrm{a}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq(4-2)}$$

$$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2\ldots\ldots\ldots\ldots\text{Eq (4-3)}$$

where X_t is the regressive independent variable vector; a is the coefficient vector of the regression equation; q is the order of the lag;
X_ta is the linear combination of the acquired variable Ω_t, $(a_0 + a_1X_{1t} + a_2X_{2t} + \cdots + a_kX_{kt})$. Eq. 4-2 is the mean equation, and Eq. 4-3 is the variance equation. In the mean equation, X_t is the ARMA of a single time series, which includes the lag y_t and the moving-average lag n. To include the heteroskedasticity ARCH(q), the mean equation and the ARCH variance equation can be integrated into an ARMA(m,n)-ARCH(q) form:

$$y_t = a_0 + \sum_n^m a_i\, y_{t-i} + \varepsilon_t + \sum_n^m b_i\, \varepsilon_{t-1}\ \ldots\ldots\ldots\ldots\ldots\ldots\text{Eq(4-4)}$$

$$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2\ldots\ldots\ldots\ldots\ldots\text{Eq (4-5)}$$

A GARCH is a generalized ARCH model. A typical GARCH(p,q) model takes the form as

$$y_t|\Omega_t \sim N(X_t\mathrm{a}, \sigma^2)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq(4-6)}$$

$$\varepsilon_t = y_t - X_t\mathrm{a}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq (4-7)}$$

$$\sigma^2 = \alpha_0 + \sum_{i=1}^q a_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i\, \sigma_{t-i}^2\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq (4-8)}$$

where p and q are the orders of the GARCH. If q = 0, the model takes an ARCH(q) form. As ARMA(0,2) is AR(2), the AR(2)-GARCH(1,1) model is expressed as follows:

$$y_t = a_0 + a_1y_{t-1} + a_2y_{t-2} + \varepsilon_t\ldots\ \ \varepsilon_t \sim N(0, \sigma^2)\ldots\ldots\ldots\text{Eq (4-9)}$$

$$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{i-1}^2 + \beta_1\sigma_{i-1}^2\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Eq (4-10)}$$

where σ^2 is the conditional variance, which is not observable, but can be estimated based on the GARCH model. As the variable is normally regarded as an alternative variable for risk or uncertainty, σ^2 is used as a quantitative indicator for changes in risk, or volatility; ε_{t-1}^2 is the square of the expected error of the mean equation for the previous period; α_1 denotes the short-term, unexpected volatility. A large α_1 indicate greater impact of the corresponding short-term, and unexpected factor, and vice versa; $a_0 + a_1\beta_{i}{}_i$ as the sum of the coefficients β_i and a_i, or the accumulation of short-term volatility, denotes the long-term, persistent volatility. Therefore, considering the hypothesis that the impact is weak stationary as it exhibits a geometric progressive decrease when $\beta_i < 1$, the long-term variable $\sigma^2 = \frac{a_0}{1-(a_1+\beta_1+\beta_2)}$ (Yang, 2017).

In summary, the mean equation $y_t = a_0 + a_1y_{t-1} + a_2y_{t-2} + \ldots\ldots + \varepsilon_t$

and the GARCH-in-Variance Regressors model

$$\sigma^2=\alpha_0+\sum_{i=1}^{p} a_i\ \varepsilon_{t-1}^2+\sum_{i=1}^{p}\beta_i\ \sigma_{t-i}^2+\theta\lceil\Delta x_t\rceil \text{ ....Eq(4-11)}$$

(1) The development of the empirical model

To develop the empirical model, the first step is to determine whether the time series variable is stationary or non-stationary, for which the most common method is the unit root test. In this study, time series data include the monthly average prices of Apartmemt complexes Units and the number of construction licenses. Their respective procedures are as follows:

As the trend in the prices of Apartmemt complexes Units shown in Figure 1 does not seem to represent a RW model with significant drift, whether the drift is significant should be determined by the unit root test.

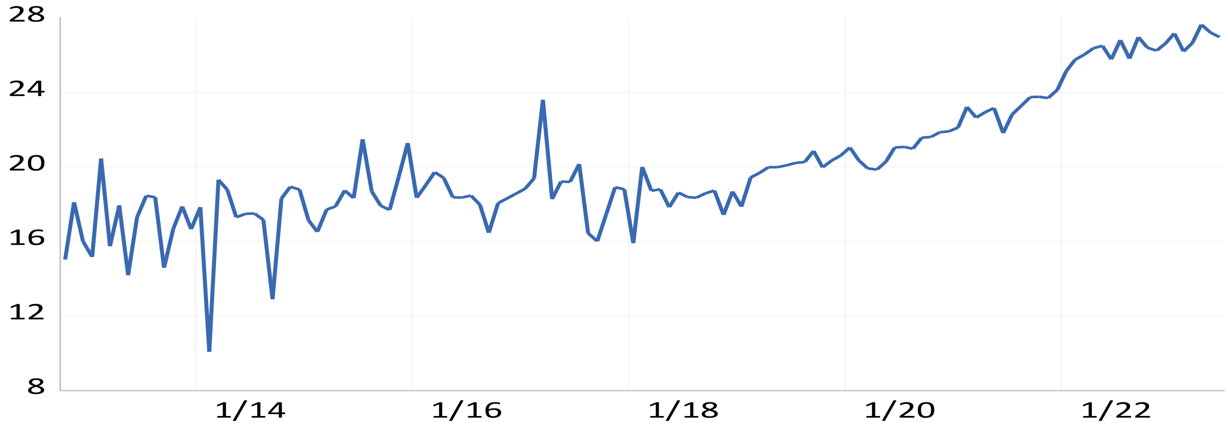


Figure 1 Housing price trend of Multi-dwelling Units

1. Test for stationarity

For H_0 (the null hypothesis) is that a unit root is present in the model, and H_1 is that the null hypothesis is rejected. While there are no lags, no conditions as the exogenous variable, and no drift, the ADF test (as a unit root test) is performed to determine whether the time series variable is stationary. After the original variable data are subject to the ADF test for variable data with drift, the data on Apartmemt complexes Units are all non-stationary in which a unit root is present, and could be transformed into stationary data by differencing. The relevant results are shown as follows:

(1) As shown in Table 5, the ADF test statistic for the data on the monthly transactions of Apartmemt complexes Units is -1.603769, which is larger than the value of the 5% level, -3.446464, indicating that the H0 is accepted.

Table 5. The Test for the Stationarity of the Data on Apartmemt complexes Units

Augmented Dickey-Fuller test statistic		Test critical values:		
t-Statistic	-1.603769	1% level	5% level	10% level
Prob	0.7862	-3.482879	-2.884477	-2.57908

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

(2) Transformation of non-stationary data into stationary data

As shown in Figure 2 and Table 6, the above-mentioned non-stationary data can be differenced into stationary data, and the results of the unit root test for the differenced data indicate that the H_0 is rejected.

(3) As shown in Table 6, the ADF test statistic for the differenced data on the monthly transactions of Apartmemt complexes Units is -7.066043, which is larger than the value of the 5% level, -3.446464, indicating that the H_0 is rejected.

Table 6. The Test for the Stationarity of the Differenced Data on Apartmemt complexes Units

Augmented Dickey-Fuller test statistic		Test critical values:		
t-Statistic	-7.066043	1% level	5% level	10% level
Prob.*	0.0000***	-3.482879	-2.884477	-2.579080

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

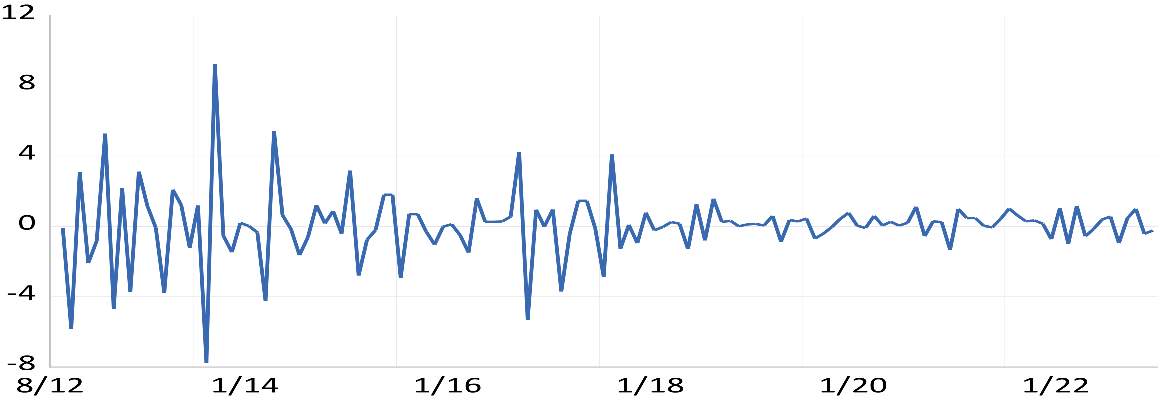


Figure 2 stationary diagram of housing transaction prices

2. The residual test and model estimation

Based on the statistics on the differenced variable that the null hypotheses for the data on Apartmemt complexes Units are all rejected, the data should be correct, stationary variable data. The autocorrelation within the residuals of the ADF test estimators is observed. It is a common method for estimating the lag length by increasing the lag length to make the residuals become white noise. While the drift and trend are included, whether the hypotheses are accepted is determined through the residual test. Furthermore, to find the best fit model, various model selection criteria, including Schwarz Criterion (S.C), Akaike information criterion(A.I.C) and R^2, are adopted in this paper. Based on whether the equation includes drift, the trend is tested, and whether the results reach the 5% significance level, the models with an insignificant explanatory power are excluded to improve the goodness-of-fit of the equation.

(1) Table 7 shows the residuals of the ADF test estimators for the data on Apartmemt complexes Units. They are observed to determine the lag length with which the variable would become white noise. It can be seen that the t-statistics with a lag length of 2 and a lag length of 3 are 2.858569 and 1.758495, respectively. While the $\mathcal{P}$-value for the former is 0.0050**, exceeding the 5% significance level, the $\mathcal{P}$-value for the latter is 0.0813, failing to reach a significance level. Additionally, the drift is -0.639256 and the trend is 1.750377, both failing to reach the 5% significance level and therefore being excluded from the equation.

Table 7 Residuals of the ADF Test Estimators for the Data on Apartmemt complexes Units

variable	coefficient	t-statistic	$\mathcal{P}$−VALUE
D(AP(-1))	-3.409923	-7.066043	0.0000***

D(AP(-1),2)	1.636391	3.738451	0.0003**
D(AP(-2),2)	1.027189	2.858569	0.0050**
D(AP(-3),2)	0.465990	1.758495	0.0813
D(AP(-4),2)	0.239352	1.424836	0.1569
D(AP(-5),2)	0.203844	2.532370	0.0127*
C	-0.171425	-0.639256	0.5239
@TREND	0.006228	1.750377	0.0827*
AIC	3.536626	SBC	3.718580
R^{2}	0.838540	Log likelihood	-211.2708

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

(2) Estimation of the lag length

As shown in Table 7, the statistics with a lag length of 2 or 3 reach the 5% significance level. Therefore, the estimator with a lag length of 3 is derived based on a general ordinary least squares estimator (OLSE), which is presented in Table 8:

$(APt) = \gamma AP_{t-1} + \beta_1 d(AP_{t-1}) + \beta_2 \mathrm{d}(AP_{t-2}) + \beta_3 \mathrm{d}(AP_{t-3}) + \varepsilon_t$…….….. Eq. (4-12)

By inputting various variable coefficients shown in Table 7 into Eq. 4-12, Eq. 4-13 is derived:

$(APt) = 0.008777 AP_{t-1} - 0.744893 \Delta(AP_{t-1}) - 0.478469 \Delta(AP_{t-2})$
$- 0.295752 \Delta(AP_{t-3}) + \varepsilon_t$ ……………………………………… Eq. (4-13)

Table 8 Statistics of the General OLSEs for the Data on Apartmemt complexes Units

variable	coefficient	t-statistic	$\mathcal{P}$−VALUE
AP(-1)	0.008777	1.290024	0.1995
D(AP(-1))	-0.744893	-8.614009	0.0000***
D(AP(-2))	-0.478469	-4.996329	0.0000***
D(AP(-3))	-0.295752	-3.609528	0.0004**
A.I.C	3.729644	S.C	3.819225
R^{2}	0.380516	Log likelihood	-232.8324

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

In terms of residual diagnostics, whether there is autocorrelation within the model series is tested by using the Box-Pierce test against 36 periods of the time series data with the H_0 (null hypothesis) that there is no autocorrelation within any time series. The results of the BOX-Pierce test are shown in Table 9.

Table 9 The Results of the Box-Pierce Test (Only a Part is Presented)

NO	AC	PAC	Q-Stat	Prob
1	-0.080	-0.080	0.8264	0.363
2	-0.084	-0.091	1.7571	0.415
3	-0.145	-0.162	4.5494	0.208
4	-0.018	-0.057	4.5921	0.332
5	0.097	0.063	5.8613	0.320
6	-0.168	-0.191	9.6667	0.139

7	0.048	0.019	9.9776	0.190
8	-0.011	-0.017	9.9930	0.266
9	0.086	0.042	11.030	0.274

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

Additionally, the Jarque-Bera Test for residual normality is performed with the H_0 that the residuals are normally distributed. As shown in Table 10, the results indicate that the 5% critical level is exceeded and the 0.0000*** significance level is reached, rejecting the H_0. Therefore, the data are not normally distributed. Subsequently, the GARCH model is to be estimated.

Table 10 The Jarque-Bera Test for Residual Normality

Normality Test Jarque Bera			
Jarque Bera	125.0427	Prob.	0.000***

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

3. The model estimation

Based on the estimation results in Table 11 for ARIMA(2,1,0)-GARCH(1,1), ARIMA(3,1,0)-GARCH(1,0), and ARIMA(3,1,0)-GARCH(0,1) models, the mean equations of ARIMA(3,1,0) and ARIMA(2,1,0) are significant at the 5% critical level. The residual equations for all three models are also significant at the 5% critical level.

Table 11 The estimated models

equation	ARIMA(2,1,0)-GARCH(1,1)			ARIMA(3,1,0)-ARCH(1,0)			ARIMA(3,1,0)-GARCH(0,1)		
variable	Coefficient	z-Statistic	Prob.	Coefficient	z-statistic	Prob.	Coefficient	z-statistic	Prob.
AP(-1)	0.010331	2.7934	0052**	0.013321	3.4364	0.0006**	0.009665	2.466762	.014*
D(AP(-1))	0.563285	-6.7409	.000***	-0.642482	-9.3524	0.000***	-0.636398	-7.474947	.000***
D(AP(-2))	0.265928	-2.7800	0054**	-0.429457	-3.9179	0.0001**	-0.514430	-10.74481	.000***
D(AP(-3)	-	-	-	-0.289093	-3.1335	0.0017**	-0.509727	-12.23662	.000***
C	0.002244	0.230993	.8173	0.003383	0.5524	0.5805	0.615536	4.226127	.000***
RESID(-1)^2	0.051925	2.270550	.0232*	-	-	-	1.269451	4.805210	.000***
GARCH(-1)	0.925327	43.49438	0.000***	0.967571	183.0407	0.000***	-	-	-
R-squared		0.318442			0.369399		0.323082		
Log likelihood		-208.761300000			-196.30800000		-215.755600000		

Akaike info criterion	3.355646	3.185952	3.492214
Schwarz criterion	3.489335	3.320323	3.626585

(2) The GARCH-in-Variance-Regressors model and the residual test

As shown in Table 12, increments in presale homes are included in the residual equation as the exogenous variable for observation. For the ARIMA(3,1,0)-GARCH(1,1) residual equation, the GARCH coefficient $|\beta_1|$=1.022081 > 0, the statistic of the absolute increments in presale homes (PREDQ) is 0.0000353 with a coefficient of 0.000170, and the p-value=0.5060, failing to reach the 5% significance level. For the ARIMA(3,1,0)-GARCH(1,0) residual equation, the GARCH coefficient $|\beta_1|$=1.006139>0, the PREDQ is 79.25583 with a coefficient of 0.000152, and the p-value=0.000***, reaching the 5% significance level. For the ARIMA(3,1,0)-GARCH(0,1) residual equation, the GARCH coefficient $|\beta_1|$=1.141443 > 0, the PREDQ is -1.151049, and the p-value=0.2497, failing to reach the 5% significance level.

Table 12 The GARCH-in-Variance-Regressors Models

Equation	ARIMA(3,1,0)-GARCH(1,1)			ARIMA(3,1,0)-GARCH(1,0)			ARIMA(3,1,0)-GARCH(0,1)		
Variable	Coefficient	z-Statistic	Prob.	Coefficient	z-statistic	Prob.	Coefficient	z-statistic	Prob.
AP(-1)	0.011184	3.138322	0.0017*	0.010092	3.277602	0.001**	0.009770	2.256954	0.024
D(AP(-1))	-0.630877	-9.260191	0.000***	-0.696821	-9.731782	0.000***	-0.614817	-6.417993	0.000***
D(AP(-2))	-0.387608	-3.967475	0.0001**	-0.394377	-4.457328	0.000***	-0.501282	-8.998950	0.000***
D(AP(-3))	-0.275214	-3.619340	0.0003**	-0.222384	-5.368992	0.000***	-0.501601	-10.53896	0.000***
C	-0.040693	-0.589908	0.5553	-0.198331	-9.3E+101	0.000***	0.751017	4.199439	0.000***
RESID(-1)^2	-0.042865	-3.661275	0.0003**				1.141443	4.470757	0.000***
GARCH(-1)	1.022081	3907.398	0.000***	1.006139	4.3E+103	0.000****			
PREDQ	3.53E-05	0.665133	0.5060	0.000152	79.25583	0.000***	-7.76E-05	-1.151049	0.2497
R-squared	0.369397			0.374829			0.320391		
Log likelihood	-189.7452			-193.6138			-215.1745		
Akaike info criterion	3.114097			3.159272			3.498811		
Schwarz criterion	3.293258			3.316039			3.655577		

Note: $\mathcal{P}^* \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

As shown in Table 13, the results of the residual tests for the three models are as follows:

Table 13 Residual Tests for the GARCH-in-Variance-Regressors Models

Model Test	ARIMA(3,1,0) -GARCH(1,1)	ARIMA(3,1,0) -GARCH(1,0)	ARIMA(3,1,0) -GARCH(0,1)
Correlogram squared Residual Test	0.279-0.999	0.264-0.997	0.031~0.817
Normality Test Jarque Bera Probability	0.666453	0.276666	0.000^{***}
ARCH-LM F-statistic Probability F -statistic/Obs*R-square	0.0170/0.0171	0.1439/0.1416	0.2804/0.2767

Note: $\mathcal{P}* \leq 0.05$; $\mathcal{P}** \leq 0.01$; $\mathcal{P}*** \leq 0.000$

1.Correlogram Squared Residual test

Whether there was autocorrelation within the series data is tested based on 36 periods of the time series data (lag length=1-36). For both the ARIMA(3,1,0)-GARCH(1,1) model, the p-value=0.279~0.999, all failing to reach a significance level. For the ARIMA(3,1,0)-GARCH(1,0) model, the p-value=0.264~0.997, all failing to reach a significance level. The residuals of both models accept the H_0 (there is no autocorrelation within the series data) and appears to be white noise. For the ARIMA(3,1,0)-GARCH(0,1) model, the p-value=0.031~0.817, indicating that only the results of the model with a part of lag lengths rejects the H_0 and exhibits autocorrelation.

2.The Jarque-Bera Test for probability normality

Only the results for the ARIMA(3,1,0)-GARCH(0,1) model indicate that the H_0 (the probability is normally distributed) is rejected. The results for the other two models accept the H_0.

3.The ARCH-LM test

The test is conducted for detection of autoregressive heteroskedasticity existed in the series data, and the null hypothesis H_0 is that there are not ARCH effects. For the ARIMA(3,1,0)-GARCH(0,1) model, the p-value=0.0170^*, exceeding the 5% significance level and rejecting the H_0. For either of the other two models, the p-value fails to reach the 5% significance level and the H_0 is accepted.

(3) Model Selection Criteria

The optimal model is selected from the three models above based on criteria shown in Table 14. For the ARIMA(3,1,0)-GARCH(1,0) model, the R-squared = 0.374829, indicating that it has the best explanatory power. The ARIMA(3,1,0)-ARCH(1,1) model ranks second in terms of the R-squared (0.369397), which has almost the same explanatory power as the previous model had. In terms of the Akaike Information Criterion (A.I.C)and the Schwarz Criterion S.C, the smaller the statistic, the better the model. In terms of the statistic for either of the two criteria, the ARIMA(3,1,0)-GARCH(1,1) has the best performance, followed by the ARIMA(3,1,0)-ARCH(1,0) model that was almost the same as that of the previous model. After comprehensive consideration based on the test results and the model selection results, the ARIMA(3,1,0)-ARCH(1,0) model is selected as the optimal model.

Table 14 Test Results for Candidate Models based on Various Model Selection Criteria

Model Good of fit Test	ARIMA(3,1,0)-GARCH(1,1)	ARIMA(3,1,0)-GARCH(1,0)	ARIMA(3,1,0)-GARCH(0,1)
R-squared	0.369397	0.374829	0.320391
Log likelihood	-189.7452	-193.6138	-215.1745
Akaike info criterion	3.114097	3.159272	3.498811
Schwarz criterion	3.293258	3.316039	3.655577

(4) Summary

In this study, the optimal model for explaining the price volatility of Apartmemt complexes Units is estimated to be the ARIMA(3,1,0)-GARCH(1,0) model. The relevant coefficients of the model are shown in Table 15.

Table 15 The Optimal ARCH/GARCH Model

Equation	Variable	AP(-1)	D(AP(-1))	D(AP(-2))	D(AP(-3)	C	GARCH(-1)	PREDQ
ARIMA(3,1,0)-GARCH(1,0)	Coefficient	0.010092	-0.696821	-0.394377	-0.222384	0.198331	1.006139	0.000152
	z-statistic	3.277602	-9.731782	-4.457328	-5.368992	-9.30E+101	4.3E+103	9.25583
	Prob.	0.001^{**}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}

Note: $\mathcal{P}^{*} \leq 0.05$; $\mathcal{P}^{**} \leq 0.01$; $\mathcal{P}^{***} \leq 0.000$

The impact of an exogenous variable can be included in a residual equation, thereby transforming Eq. 4-12 into Eq. 4-13, in order to observe and explore the impact of the volatility. In this study, increments in the supply of presale homes are included as the exogenous variable. The variable's absolute value is denoted as $|\Delta\chi_t|$ to measure the impact of the exogenous variable on the current-period volatility, so that the current-period volatility σ_t^2 increases when the variable's coefficient θ>0, and decreases when θ<0.

The GARCH(1,0) residual equation is $\sigma_t^2=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\beta_1\sigma_{t-1}^2+\theta|\Delta\chi_t|$……...Eq.(4-12)

and, after the input of the coefficients shown in Table 17, transforms into σ_t^2=0.010092+1.006139σ_{t-1}^2+0.000152$|\Delta\chi_t|$ ……………Eq (4-13)

Based on the results of the empirical analysis above, this paper further explores the price volatility of Apartmemt complexes Units under a short-term impact, the volatility under a long-term impact, and the impact of the exogenous variable. While the data on the prices of Apartmemt complexes Units are non-stationary and made stationary by single differencing, the ARIMA(3,1,0)-GARCH(1,0) model is selected as the optimal model. Specifically, ARIMA(3,1,0) indicates that the mean equation for the prices of Apartmemt complexes Units is related to a solution by iteration at a lag length of 3, and MA(0) means that no modification is needed. In terms of Eq. 4-12, ε_{t-1}^2 is the square of the previous-period expected error, which is used to denote the variance of the residual and represent the impact of short-term, unexpected shocks on volatility. When the unexpected shocks are more severe, the coefficient α_1 is larger. In order to measure the short-term risk, the short-term shock $\alpha_1\varepsilon_{t-1}^2$=0 for this model.

Moreover, for Eq. 4-12, the condition variance equations ($\sigma_{t-1}^2, \sigma_{t-2}^2, \sigma_{t-3}^2 \ldots.$) are additive. When the absolute values of β_1 and β_1 are smaller than 1, there is a progressive decrease in the persistent period of volatility under long-term shocks, otherwise, there is a progressive increase. In terms of the persistent impact of volatility under shocks, as shown in Table 15, the GARCH(-1) coefficient $|\beta_1|$=1.006139***>1, indicating that the volatility under shocks is divergent and increasing progressively. Therefore, the residual equation in this study is GARCH(1,0), with p=1 and q=0, meaning that there is short-term volatility without expected errors, while the volatility at a lag length of 1 exhibits a significant persistent and delayed impact.

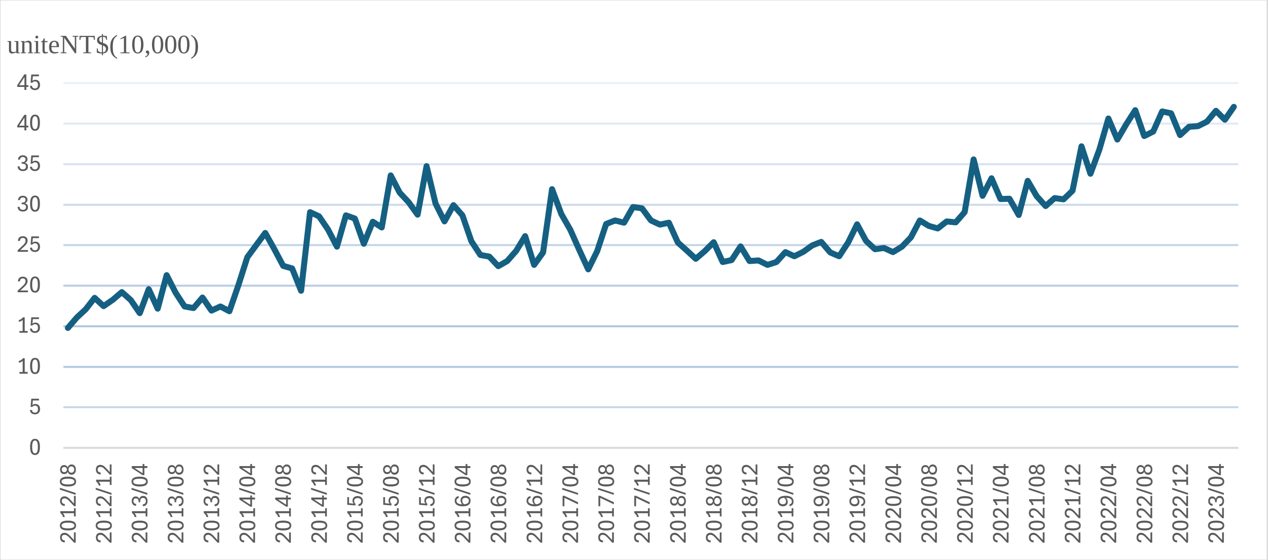
Previous studies mentioned that volatility clustering of housing prices is a unique property of residual volatility. In this study, the conditional variance σ_t^2 has a coefficient $|\beta_1|$=1.006139***>1, which exceeds the 5% significance level, indicating that the marginal impact of the volatility under shocks is increasing progressively. While some previous studies adopted exchange rates, interest rates, policies and other housing-price-related factors as the exogenous variables, the same approach can be taken for the measurement of the impact of the volatility under shocks. As in Eq. 4-13, the absolute increments in presale homes $|\Delta\chi|$ are adopted as the exogenous variable, and the variable's coefficient θ=0.000152***>0, which exceeds the 5% significance level, indicating that the increments in the supply of presale homes amplifies the price volatility of Apartmemt complexes Units. Therefore, based on the results of the empirical analysis in this study, the increments in the supply of presale homes do not conduce to the moderation of the price volatility of Apartmemt complexes Units.

5. Conclusion

Based on the established ARIMA(3,1,0)-GARCH(1,0) model, the results show: **1.**The mean equation does not include an intercept term. This implies that if the market's supply and demand conditions remain unchanged, market participants can directly reference the previous period's price when forming future price expectations**.** **2**.Without including the exogenous variable of presale housing volume, the GARCH(-1) coefficient $|\beta_1|$ is 0.967571***, which is less than 1. When the exogenous variable of presale housing volume is included, the GARCH(-1) coefficient $|\beta_1|$ is 1.006139***, which is greater than 1. This shift from less than 1 to greater than 1 indicates that volatility changes from convergent to divergent. **3.**The impact of presale housing volume on housing price volatility is significant. The exogenous variable $|\Delta\chi|$ has a coefficient θ=0.000152***, which is greater than 0 and significant. This significance does not help stabilize the price volatility of high-rise residential buildings; instead, it exacerbates the instability of housing price volatility.

The discussion of this study in comparison with the existing literature is as follows: **1.**This study uses the GARCH model to capture the volatility of housing prices in Taichung City and finds evidence of volatility clustering risk. Similar risk attributes have been found in the literature for the real estate markets in Hong Kong, 15 regions of Finland, and over half of the U.S. states. This indicates that housing in Taichung City, like in major metropolitan areas abroad, exhibits the financial asset characteristic of volatility clustering. **2.**Regarding how exogenous variables affect price volatility, the literature presents various options such as unemployment rates, exchange rates, and other macroeconomic factors, including the impact of presale housing. This study also finds a significant impact of presale housing volume on housing price volatility. **3.**The results of this study have several similarities with the research by Wang et al. (2022) on housing price volatility in four metropolitan areas in Taiwan. The comparison is as follows:Differences in Perspective: Wang et al. (2022) studied the impact of the shift in demand from the existing home market to the presale housing market, whereas this study examines the impact of presale housing volume on the existing home market.Differences in Methodology: Wang et al. (2022) used the cobweb model and forward contract pricing model, while this study employs the GARCH model to analyze housing price volatility.Differences in Research Scope: Wang et al. (2022) investigated the price index volatility in four metropolitan areas in Taiwan, whereas this study focuses on the transaction price volatility of high-rise residential buildings recorded in Taichung City's Actual Price Registration. Similar Results: During periods of economic prosperity, the existing home market and the presale housing market mutually influence each other, which does not stabilize housing price volatility but rather exacerbates it.

We have compiled the transaction price trends of presale homes in Taichung City from The Actual Price Registration, as shown in Figure 3. The price period ranges from August 2012 to June 2023, encompassing 79,098 residential transactions and 131 monthly average transaction prices. The data reveals that housing prices escalated from NT$147,900 per ping in August 2012 to NT$420,700 per ping in June 2023, marking a price difference of NT$272,800 and a growth rate of 184%. Comparing this with the price trends of apartmemt complexes units in Figure 1, it is evident that both price trends have shown consecutive increases. In an active housing market, heightened risk appetite and increased supplier expectations gradually drive up presale housing prices, which interact with existing home prices, further exacerbating market price volatility and divergence, thereby disrupting market function.



Figue3 Average Price Trend of Presale Homes in Taichung

The contributions of this paper are as follows: 1.The verification results show that presale housing projects in Taichung City have not moderated housing prices but have instead driven them up. 2.Empirical findings reveal that the volume of presale housing projects fails to stabilize housing price fluctuations and, instead, exacerbates instability.

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