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A Study on the Housing Price Forecasting Models of Korea, the USA, and Japan

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Abstract. This study comparatively analyzed the housing price forecasting performance of Korea, the USA, and Japan by in-sample and out-of-sample forecasting period using ARIMA, GARCH, and regime-switching (RS) models. Root mean squared errors (RMSE) and mean absolute percentage errors (MAPE) were performed to test the fitness of the estimated model and forecasting. To analyze the housing price forecasting performance, each country's housing price time series data from June 1993 until December 2021 were used. In the case of in-sample forecasting, the forecasting performances of the ARIMA (2, 1, 2) model in Korea and the ARIMA (1, 1, 1) model in the USA were higher compared to GARCH models or RS models. In Japan, the ARIMA (2,1,0)-EGARCH (1, 1) model's forecasting performance was higher than the ARIMA and RS models'. As for the out-of-sample forecast (from January until December 2021), the forecasting performance of the ARIMA (1,1,0)-RS model in Korea and the ARIMA (2,1,0)-RS model in Japan was higher, respectively, and the forecasting performance of the ARIMA (1, 1, 1) model in the USA was higher. The forecasting performance of the in-sample and the out-of-sample ARIMA model was higher in the USA. However, in Korea and Japan, the forecasting performance of the in-sample ARIMA models and GARCH models was higher, but the RS models' forecasting performance was higher, each, in the out-of-sample. This means that as the housing price forecasting period becomes longer, the regime-switching models, by which a structural change possibility including stagnant market and boom market can be grasped, can be an alternative prototype for forecasting performance improvement.

Keywords: housing price, forecasting, ARIMA model, GARCH model, regime switching model

1. Introduction

The housing market is an incomplete market ceaselessly changing based on internal and external market shocks. Housing owners, people who want to buy housing, and housing suppliers are all interested in the direction of housing prices. Due to high correlations between business volatility and housing prices, policymakers and scholars are paying attention to the housing price trends. Consequently, the importance of housing price forecasting ability is on the rise. The theoretical basis for forecasting housing prices depends on whether the housing market can establish an efficient market hypothesis like the stock market. Therefore, studies on the initial stage housing price forecasting models focused on examining whether efficient market hypotheses can be established in the housing market. Gau (1984) verified whether the housing market is an efficient market using Vancouver's commercial real estate price index. According to the analysis result, Gau could not present that the housing market is inefficient. Hamilton and Schwab (1985) empirically analyzed whether housing prices can be forecasted using the capitalization rate of housing in cities using a hedonic model, but the result showed that the research hypothesis of single variable forecasting models was rejected. However, Guntermann and Smith (1987) made a critical assertion on an efficient housing market hypothesis of Hamilton and Schwab (1985) that housing prices cannot be forecasted using the housing price data of detached house markets in 57 large cities. Case and Shiller (1989) presented that the housing market does not follow a random walk process like the stock market through data built using the weighted repeated sales method of detached houses in San Francisco, Oakland, Dallas, Chicago, and Atlanta from 1970 until 1986. Capozza and Seguin (1996) showed an empirical analysis result that the housing market has differences from the complete and efficient market like stock market using the ratio data of rent to housing price. This means that the housing price change rate is time variable and has a fairly persistent pattern, so housing prices can be forecasted. Since then, it has been shown that housing prices can be forecasted using various models such as Crawford and Fratantoni (2003), Mills (2008), Plaza et al. (2010), Chen and Yu).

Crawford and Fratantoni (2003) identified forecasting models like autoregressive integrated moving average(ARIMA) models, generalized autoregressive conditional heteroscedasticity(GARCH) models, and regime-switching(RS) models using each quarter data from 1Q 1979 until 4Q 2001 and comparatively analyzed forecasting ability. As a result of the analysis, the forecasting ability of RS models was higher in the in-sample, and the forecasting ability of ARIMA models was higher in the out-of-sample. Mills (2008) analyzed with the same data that Crawford and Fratantoni (2003) used to test the forecasting ability of housing prices using the generalized autoregressive (GAR) model that considers non-linearity in the autoregressive (AR) models. According to the analysis result, GAR models were higher in housing price forecasting ability than the forecasting ability of the ARIMA, GARCH, and RS models used by Crawford and Fratantoni (2003). Plazzi et al. (2010) estimated a real estate price forecasting model using a generalized method of moments (GMM) model. According to the estimation, they reported that capitalization rate could forecast office rent growth rate, but there is a limitation in forecasting the rent growth rate of apartments, retail stores, and industrial real estate. Chen and Yu (2010) identified the ARIMA models using the S&P/Case-Shiller housing price index and analyzed forecasting ability tests. The ARIMA models could not forecast the housing price bubble in the 2008 global financial crisis but could forecast housing price decline after June 2006. Jadevicius and Huston (2015) presented a study result that housing price change of Lithuania can be greatly forecasted with the ARIMA models.

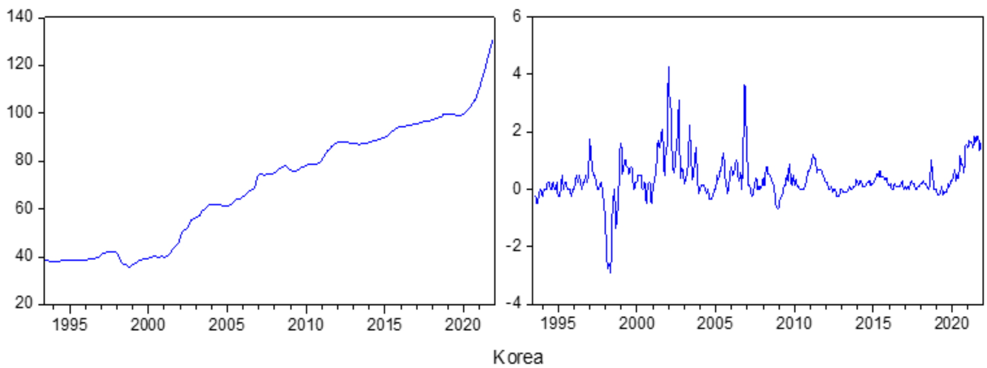
Kim (1998) identified the housing sale price and rent price forecasting models using the ARIMA and state-space models and comparatively analyzed the forecasting ability of the two models. According to the analysis, the ARIMA model's housing sale price forecasting ability was higher than the state-space model's. Meanwhile, the state-space model was higher than the ARIMA model in rent's price forecasting ability. Yun and Kim (2000) identified the housing sale and rent price forecasting models using the ARIMA model and carried out forecasting ability tests. As a result of the analysis, the model's forecasting ability by quarter was identified to be higher. Choi (2005) and Choi (2021) identified the USA real estate investment trusts(REIT) price models using the vector autoregressive (VAR) and ARIMA models. According to the forecasting ability analysis result, the root mean squared error (RMSE) of the VAR model was smaller than that of the ARIMA model, so the forecasting ability of the VAR model was higher. Lee and Kim (2012) identified models to apply to land, housing sale, and rent prices using the ARIMA, (VAR), and autoregressive distributed lag (ARDL) models and comparatively analyzed the forecasting performance. According to the analysis result, the RMSE of the ARDL model was the smallest in terms of goodness-of-fit, so it was better than the ARIMA model or VAR model. Kim (2014) identified the forecasting models of Korean housing sale prices and rent prices and analyzed forecasting ability. As a result of the analysis, the forecasting ability of the ARIMA models was higher in housing sale and rent price forecasting.

However, these existing studies are limited results mainly targeting the housing market in the country, and international comparative analysis studies have not yet been found. In addition, it cannot be said to be the identification of the forecasting performance model of the universal housing market due to the opening of the housing market. Therefore, the purpose of this study is to estimate the housing price forecasting model in Korea, the United States, and Japan using the ARIMA, GARCH, and RS models on the research results of Crawford and Fratantoni (2003), identify which model is better, and present implications to evaluate the forecasting performance. Such an analysis has academic significance in that it can help to dynamically understand the housing market and make rational housing policies, as well as contribute to establishing a useful housing market outlook system. This study has differentiation from previous studies as it is a starting point for comparative analysis of international forecasting performance of housing prices and a model presentation for abundant research. As for the composition of this study, the ARIMA, GARCH, and RS models are explained as an analysis method in Chapter 2. In Chapter 3, analysis results are presented. In Chapter 4, the analysis results are discussed, and in Chapter 5, implications are stated in conclusions.

2. Data and Analysis Model

2.1. Data

The housing price variables of Korea, the USA, and Japan were used. Korea's nationwide apartment price index released by Kookmin Bank, the American monthly FHFA single house price index released by the Federal Housing Finance Agency (FHFA), and the Japanese JREI condominium home price index released by the Japan Real Estate Institute (JREI) were used by log differencing after seasonal adjustment. The data analysis period was from June 1993 until December 2021, given that the available time of Japanese data was from June 1993. Figure 1 shows the housing price indices and increased rate trends compared to the previous month, and basic statistics are shown in Table 1. The rate of change in housing prices was calculated like $R_i = ln(P_t/P_{t-1})$ using Taylor expansion. The skewness of housing price volatility in Table 1 shows the biased distribution in the USA and Japan's negative (-) direction except for Korea. The kurtosis shows a sharper cusp distribution in Korea, the USA, and Japan. The Jarque-Bera statistic rejects a null hypothesis that housing price volatility distribution is normal distribution at a 1% significance level. Therefore, it can be seen that it is necessary to apply the ARCH series model to this data.



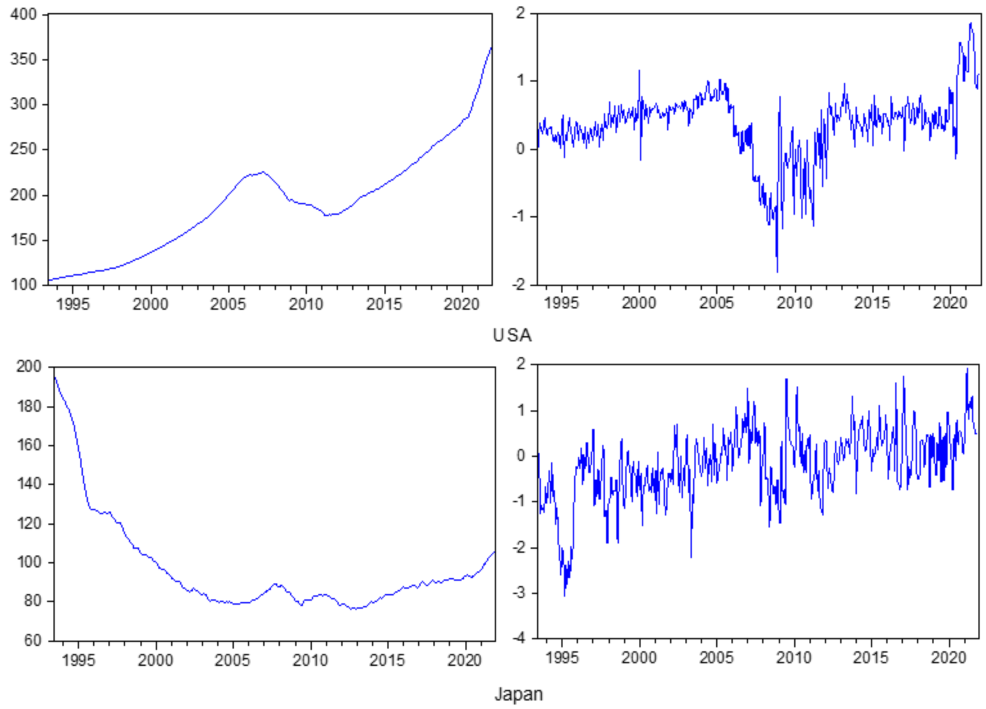


Fig. 1: Housing price indices and price volatility rates of Korea, the USA, and Japan

Table 1: Basic statistics

	KOREA	USA	JAPAN
Mean	0.3572	0.3613	-0.1783
Std. Dev.	0.7400	0.4996	0.7868
Skewness	0.6483	-0.8223	-0.5855
Kurtosis	9.6675	5.3444	4.0716
Jarque-Bera	657.46 (0.000)	116.87 (0.000)	35.90 (0.000)
Obse	342	342	342

Note: ( ) is the significance level that can reject the null hypothesis.

Meanwhile, a time series analysis is based on stationary attributes. A unit root test was carried out using the Augmented Dickey-Fuller test and a PP test to test the stationary attributes of variables. The time-series data through the first-phase log differencing of each index was stationary at a 1% significance level in Korea, the USA, and Japan. Table 2 reveals the results.

Table 2: Unit root test results

		Index	Log Differencing
	Korea	1.3000	-5.5479***

ADF (lag 1)	USA	2.3108	-3.7510***
	Japan	-7.1546	-4.7694***
PP (lag 1)	Korea	1.8711	-5.4022***
	USA	2.5523	-5.2405***
	Japan	-6.4344	-9.2327***

*Note) 1. p<0.01***, p<0.05**, p<0.1*   2. Threshold of 1% significance level when the constant term is included: -3.45*

2.2. Analysis model

This study centered on ARIMA, GARCH, and RS models. The ARIMA model is a basic single-variable time series model that assumes changes in housing prices linearly. Housing prices are known to have the characteristics of volatility clustering. The GARCH model is suitable for analyzing time series with the characteristics of volatility clustering. The forecasting power of housing prices may vary depending on the business situation. The RS model is suitable for analyzing forecasting power according to the business regime. Therefore, this study aims to confirm whether the RS model considering the regime a model with better is forecasting power than the ARIMA or GARCH model. Various factors decide housing prices, and economic variables' characteristics in each country are different. To minimize the bias of the analysis result depending on economic variable characteristics and to overcome difficulties in obtaining data, this study analyzed forecasting performance using single time series models that do not include economic variables

2.2.1. ARIMA model

The prediction model using the single time series model is generally widely used by the ARIMA model suggested by Box and Jenkins (1976). The ARIMA model uses a theory in which the previous period's time series data observation and residual affect the next period. The ARIMA model is different from the method to compare past trend curves of time series data to forecast the future through modeling. The ARIMA (p, 1, q) models can be indicated as shown in the following equation:

$$\Delta X_t = \mu(1 - \sum_{k=1}^{p} \alpha_k) + \sum_{k=1}^{p} \alpha_k * \Delta X_{t-k} + \sum_{k=0}^{q} \beta_k * \varepsilon_{t-k}) \quad (1)$$

$$\varepsilon_t \sim N(0, \sigma^2) \quad (2)$$

Equation (1) Δ indicates differencing, in which α_k is the coefficient of AR and β_k is the coefficient of MA. This study examines eight models from ARIMA (1, 1, 0) to ARIMA (2, 1, 2) to identify the models applicable to Korea, the USA, and Japan.

2.2.2. GARCH model

The GARCH model is the model that added the lag of conditional variance to the autoregressive conditional heteroscedasticity (ARCH) model of Eagle (1982) by Bollerslev (1986). As a result of the ARCH/GARCH models' preliminary estimation result, the conditional variance was confirmed to be nonstationary, so this study chose the IGARCH (1, 1) model. The integrated GARCH (IGARCH) model indicating the mean equation in the ARIMA type is shown in the following equation:

$$\Delta X_t = \phi + \sum_{k=1}^{p} \alpha_k * \Delta X_{t-k} + \sum_{k=0}^{q} \beta_k * \varepsilon_{t-k} \quad (3)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, {\sigma_t}^2) \quad (4)$$

$${\sigma_t}^2 = c + a * {\varepsilon_{t-1}}^2 + b * {\sigma_{t-1}}^2 \quad (5)$$

Equation (3) is a mean equation indicating the ARIMA process, β_0=1. Equation (4) is the variance of the error term and indicates the time-varying term. Equation (5) is a conditional variance equation and indicates GARCH (1, 1) model. IGARCH follows the constraint of a+b=1. Meanwhile, the exponential GARCH EGARCH model adopts a revised conditional variance equation presented by Nelson (1991).

$${\sigma_t}^2 = \exp[c + a * |\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| + d * \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b * \log({\sigma_{t-1}}^2)] \quad (6)$$

However, $c = c_0 - a\sqrt{\frac{2}{\pi}}$

The EGARCH (1,1) model has eased constraints on parameters. If $|b| \prec 1$, the estimated variance equation becomes stationary. In Equation (6), the parameter measuring an asymmetric effect is d. Namely, if $(\varepsilon_{t-1}/\sigma_{t-1}) < 0$, it becomes a-d, and if $(\varepsilon_{t-1}/\sigma_{t-1}) > 0$it becomes a+d. Volatility in the EGARCH (1, 1) model asymmetrically responds to news shock.

2.2.3. RS model

The RS model is a model in which the random process of an observation variable x_t is dependent on the non-observation state variable S_t. Because the state variable cannot be observed in reality, a measuring technique to process it is necessary, and one of the techniques is the Markov regime-switching model of Hamilton (1989). This study uses the RS model of Hamilton. One may assume that the mean is μ, stable p term's autoregressive process is complied with, and 2-state exists. In this case, the Hamilton model can be indicated as follows:

$$=\Delta X_t - \mu(S_t) = \sum_{k=1}^{p} \alpha_k * (\Delta X_{t-k} - \mu(S_{t-k})) + \varepsilon_t \quad (7)$$

In Equation (7), S_t indicates a regime (situation): $S_t = 1$ means stagnant regime and $S_t = 2$ means boom regime. Specifically, X_t has mutually different methods (μ_1 or μ_2) depending on the business regime. This means that deviation from each regime's unique mean value ($z_t = \Delta X_t - \mu(S_t)$) complies with the autoregressive process (AR(p)). If the regime (situation) S_t is set to have Markov feature, the transition matrix or transition probability,p_{kj}, is as follows:

$$p_{kj} = p = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \quad (8)$$

In Equation (8),$p_{kj} = Pr(S_{t+1} = j|S_t = k)$, so switching probability p_{11} means that the probability of a stagnant regime continues in t period. p_{22} is the probability that the boom regime during t-1 period can continue in t period $1 - p_{12}$ and $1 - p_{21}$ indicate the probability for the regime in t-1 period to be switched to the different regimes in t period. As for the probability process of X_t in the regime-switching model, two models, namely two ARIMA (1, 1, 0)-RS, and ARIMA (2, 1, 0)-RS models, were set.

2.2.4. Forecasting method

Harvey (1990) presented seven model setting criteria for parsimony, identifiability, data admissibility, theoretical consistency, predictive power, and encompassing. In this paper, each forecasting model was set focusing on parsimony, theoretical consistency, and predictive power. Before estimating the model, first, a unit root test is performed on all analysis variables to test whether each variable is stable, and then the model is estimated. As for identifying each model's lag conformity, the model with the smallest AIC value was identified depending on the principle of parsimony, stationary, invertible, and AIC and BIC standards. For each model estimation, a maximum likelihood method was used. Finally, among the estimated models, RMSE and MAPE are used to test whether the model has better predictive power. It is judged that the smaller the value of the RMSE, MAPE, the better the predictive power. Here, the equation of RMSE is as follows:

$$RMSE = \sqrt{\sum_{t=T+1}^{T+n} (\hat{X}_t - X_t)^2 / n} \tag{9}$$

In Equation (9), the actual value is x_t , the forecasted value is $\hat{x}_t$ of the dependent variable, the forecasting error is $\hat{x}_t - x_t$, and n is the number of forecasting values. If the sum of forecasting square errors is divided by n, the mean value is calculated, and taking the square root of it is RMSE. The equation of mean absolute percentage errors(MAPE) is as follows:

$$MAPE = (\sum_{t=T+1}^{T+s} |\hat{y}_t - y_t / y_t| / s) \times 100(\%) \tag{10}$$

Equation (10) is a value obtained by averaging the absolute values of the ratio of the residual to the actual data. Unlike RMSE, MAPE divides the residuals by y_t. This is to measure the relative fluctuations of endogenous variables so that it is possible to compare predictive power regardless of the unit of measurement. MAPE has a value between 0-100%, and it is judged that the closer to 0, the better the prediction model.

3. Analysis Results

3.1. Analysis results

Table 3 shows the estimated results of the ARIMA models of Korea, the USA, and Japan. In this study, ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (1,1,1) and ARIMA (2,1,1) models were applied. ARIMA (0,1,0) is applied in that it provides a standard for forecasting a general ARIMA model as a random walk model, and ARIMA (1,1,0) is applied in that it was a basic model. When looking at ARIMA (0,1,0) to ARIMA (2,1, 2) on the Korean, the USA, and Japan housing price time series, the goodness-of-fit of the models is judged based on the minimum of AIC and high value of R2, and log L. In the case of Korea, the AIC value of the ARIMA (2,1,2) model is the smallest at 1.270, the R2 is 0.632, and log L is -211.189, which are high, so it was judged to the best model. In the USA, the AIC value of the ARIMA (1,1,1) model is the smallest at 0.406, the R2 is 0.656, and log L is -65.460, which are high, so it was judged to the best model. In Japan, the AIC value of the ARIMA (2,1,1) model is the smallest at 1.752, the R2 is 0.470, and log L is -294.611, which are high, so it was found to be an excellent model.

Table 3: Estimated Results of ARIMA Models

	ARIMA(0,1,0)	ARIMA(1,1,0)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(2,1,2)
Korea					
μ	0.357(0.040)***	0.351(0.128)***			0.352(0.116)***
α1		0.787(0.018)***			-0.194(0.050)***
α2					0.687(0.048)***
β1					1.051(0.062)***
β2					0.163(0.048)***
R^2	0.000	0.622			0.632
AIC	2.238.	1.279			1.270
log L	-381.832	-215.779			-211.189
USA					
μ	0.361(0.027)***	0.357(0.079)***	0.391(0.218)*		
α1		0.747(0.026)***	0.972(0.009)***		
α2					
β1			-0.657(0.029)***		
β2					
R^2	0.000	0.561	0.656		
AIC	1.453	0.642	0.406		
log L	-247.492	-106.897	-65.460		
Japan					
μ	-0.178(0.042)***	-0.172(0.088)**		-0.169(0.115)	
α1		0.618(0.037)***		0.054(0.104)	
α2				0.563(0.069)***	
β1				0.405(0.123)***	
β2					
R^2	0.000	0.382		0.470	
AIC	2.361	1.891		1.752	
log L	-402.813	-320.487		-294.611	

*Note: ( ) is the standard error and ***, **, and * indicate that the coefficients are significant at levels 1%, 5%, and 10%, respectively.*

This study analyzed the ARIMA (1,1,0)-ARCH (1), ARIMA (1,1,0)-GARCH (1, 1), ARIMA (1,1,0)-EGARCH, ARIMA (2,1,0)-ARCH (1), ARIMA (2,1,0)-GARCH (1, 1), and ARIMA (2,1,0)-EGARCH (1,1) models of GARCH model series, and Table 4 shows the analysis results. The AIC values was smaller and log L and R2 values was relatively higher in the ARIMA (1,1,0)-GARCH (1, 1) model in Korea, in the ARIMA (2,1,0)-GARCH (1, 1) model in the USA, and in the ARIMA (2,1,0)-EGARCH model in Japan; therefore, they were identified as suitable models. Consequently, the coefficients of ARCH/GARCH of Korea and the USA ('a' and 'b' respectively) are significant, so the ARCH/GARCH effects exist in the housing price indices of Korea and the USA. However, the ARCH effect of Japan was unclear because the coefficient of ARCH 'a' was not significant.

Table 4: Estimated Results of ARIMA-IGARCH Models

	Korea			USA			Japan		
	ARIMA (1,1,0)-ARCH (1)	**ARIMA (1,1,0)-GARCH (1,1)**	**ARIMA (1,1,0)-EGARCH (1,1)**	**ARIMA (2,1,0)-ARCH (1)**	**ARIMA (2,1,0)-GARCH (1,1)**	**ARIMA (2,1,0)-EGARCH (1,1)**	**ARIMA (1,1,0)-GARCH (1)**	**ARIMA (1,1,0)-GARCH (1,1)**	**ARIMA (2,1,0)-EGARCH (1,1)**
θ	0.111** (0.058)	0.183** (0.086)	0.224** (0.097)	0.344*** (0.101)	0.425*** (0.065)	0.415*** (0.065)	-0.167** (0.087)	-0.147* (0.084)	-0.172 (0.132)
α1	0.809*** (0.014)	0.826*** (0.034)	0.845*** (0.028)	0.588*** (0.028)	0.388*** (0.043)	0.400*** (0.043)	0.625*** (0.040)	0.605*** (0.043)	0.404*** (0.054)
α2				0.274*** (0.028)	0.442*** (0.047)	0.414*** (0.046)			0.351*** (0.053)
c	0.053*** (0.005)	0.010*** (0.001)	-0.689*** (0.104)	0.055*** (0.003)	0.003*** (0.000)	-0.298*** (0.051)	0.364*** (0.032)	0.133 (0.165)	-1.615 (0.653)
a	1.425*** (0.132)	0.495*** (9.972)	0.606*** (0.084)	0.538*** (0.105)	0.173*** (0.037)	0.285*** (0.043)	0.043 (0.062)	0.051 (0.060)	0.082 (0.116)
b		0.574*** (0.047)	0.883*** (0.021)		0.804*** (0.033)	0.967*** (0.012)		0.599 (0.462)	-0.409 (0.619)
d			0.099** (0.048)			-0.040 (0.035)			0.074 (0.076)
R^2	0.618	0.619	0.618	0.611	0.612	0.613	0.382	0.382	0.456
AIC	0.881	0.691	0.694	0.376	0.143	0.155	1.894	1.899	1.781
log L	-146.795	-113.324	-112.697	-59.307	-18.493	-19.673	-319.992	-319.785	-297.597

*Note: ( ) is the standard error and ***, **, and * indicate that the coefficients are significant at levels 1%, 5%, and 10%, respectively.*

This study estimated the housing price forecasting performance of Korea, the USA, and Japan by applying the ARIMA (1, 1, 0)-RS and ARIMA (2, 1, 0)-RS models in terms of the probability process of X_t in the regime-switching models for simplification and efficiency of analysis. Table 5 shows the estimated results. In Korea, the estimated coefficients of the ARIMA (1, 1, 0)-RS model were all significant at 5% significance level. The AIC and log L values were relatively better than those of the ARIMA (2, 1, 0)-RS models. Therefore, the ARIMA (1, 1, 0)-RS model was suitable. When looking at the Korean housing price volatility characteristics through the ARIMA (1,1,0)-RS model's estimated results, the mean price increase rate in the stagnant regime was 0.044%, and that in the boom regime was 0.189. The p11 and p22, the regime-switching probability, indicate the probability that stagnant regime and boom regime were maintained, respectively. The probability of a stagnant regime (p11) to be maintained was 96.36%, and the mean persistency period was 1/(1-p11) =27.479 months. The probability of boom regime (p22) to be maintained was 92.33%, and the mean persistency period was 1/(1-p22) =13.047 months. Therefore, the possibility for a stagnant regime to continue was higher.

In the USA, all coefficients of ARIMA (2, 1, 0)-RS model were significant at 1% significance level, and the AIC and log L values were estimated to be better than those of the ARIMA (1, 1, 0)-RS model; consequently, the ARIMA (2, 1, 0)-RS model was suitable. When looking at the housing price volatility characteristics of the USA through estimated results of the ARIMA (2, 1, 0)-RS model, the mean price increase rate was 0.120% in the stagnant regime, and that in the boom regime was 0.019%. The regime-switching probability, p11 and p22, indicates the probability of the stagnant regime and boom regime continuing. The probability of the stagnant regime (p11) was 98.69%, and the mean persistency period was 1/(1-p11) =76.646 months. The probability for the boom regime (p22) was 96.83%, and the mean persistency period was 1/(1-p22) =31.585 months. Consequently, the possibility for the stagnant regime to continue was higher.

In Japan, all estimated coefficients of the ARIMA (2, 1, 0)-RS model except μ1 and μ2 were significant at 1% significance level. Compared to the ARIMA (1, 1, 0)-RS model, the AIC and log L values were better, so the ARIMA (2, 1, 0)-RS models were suitable. When looking at the Japanese housing price volatility characteristic through the estimate results of the ARIMA (2, 1, 0)-RS model, the mean price increase rate in the stagnant regime was 0.063%, and that in the boom regime was -0.040%. The regime-switching probabilities, p11 and p22, indicate the probability of the stagnant regime and boom regime continuing. The probability for the stagnant regime (p11) to be maintained was 92.25%, and the mean persistency period was 1/(1-p11) =17.416 month. The probability for the boom regime (p22) to be maintained was 98.07%, and the mean persistency period was 1/(1-p22) =52.055 months. Consequently, the probability for the boom regime to continue was higher.

Table 5: Estimated results of ARIMA-RS models

Parameter	Description	Korea	USA	Japan
		Coefficient	Coefficient	Coefficient
ARIMA(1,1,0)-RS model				
α1	Regime 1 AR	0.743(0.044)***	0.510(0.060)***	0.744(0.054)***
α2	Regime 2 AR	0.759(0.064)***	0.759(0.069)***	0.723(0.056)***
μ1	Regime 1 Mean	0.044(0.015)***	0.228(0.31***)	0.340(0.056)***
μ2	Regime 2 Mean	0.189(0.088)**	0.020(0.057)	-0.402(0.055)***
σ1	Regime 1 std. dev.	-1.672(0.072)***	-1.645(0.049)***	-0.743(0.065)***

σ2	Regime 2 std. dev.	-0.282(0.082)***	-0.619(0.077)***	-0.638(0.062)***
p11		3.276(0.435)***	4.349***	-2.620(1.420)*
p21		-2.488(0.466)***	-3.459***	-1.915(0.725)***
	Av. duration Regime 1	27.479	78.405	1.072
	Av. duration Regime 2	13.047	32.793	1.147
AIC		0.627	0.251	1.780
Log L		-98.924	-34.839	-295.651
ARIMA(2,1,0)-RS model				
α11	Regime1 AR	0.744(0.064)***	0.290(0.057)***	0.357(0.129)***
α12	Regime 1 AR	0.133(0.060)**	0.446(0.056)***	0.606(0.128)***
α21	Regime 2 AR	0.841(0.111)***	0.543(0.105)***	0.3401(0.070)***
α22	Regime 2 AR	-0.124(0.113)	0.288(0.106)***	0.223(0.098)**
μ1	Regime 1 mean	0.031(0.016)**	0.120(0.028)***	-0.047(0.100)
μ2	Regime 2 mean	0.179(0.097)*	0.019(0.056)***	-0.021(0.052)
σ1	Regime 1 std. dev.	-1.628(0.066)***	-1.755(0.047)***	-0.782(0.138)***
σ2	Regime 2 std. dev.	-0.231(0.92)***	-0.654(0.078)***	-0.543(0.057)***
p11		3.128(0.409)***	4.326(0.621)***	2.798(1.141)***
p21		-2.129(0.483)***	-3.420(0.681)***	-3.932(1.641)***
	Av. duration Regime 1	23.843	76.646	17.416
	Av. duration Regime 2	9.411	31.585	52.055
AIC		0.640	0.082	1.754

Log L		-98.935	-4.027	-288.259

*Note: ( ) is the standard error and ***, **, and * indicate that the coefficients are significant at levels 1%, 5%, and 10%, respectively.*

3.2. Analysis results of forecasting performance

This study carried out in-sample and out-of-sample forecasting to compare the models' forecasting performance. The in-sample forecast is the estimated result of the models during the entire data period (June 1993-December 2021). The out-of-sample forecast was carried out by dividing the entire period (June 1993-December 2021) in which data was estimated into a 6-month period (January to June 2021) and the 12-month period (January to December 2021). For comparison of forecasting performance by models, RMSE and MAPE were calculated in each forecasting period and as shown in Equation (9), (10), and the results are presented in Table 6.

Table 6: Comparison of forecasting ability by models

Korea		USA		Japan	
Model	RMSE / MAPE	Model	RMSE / MAPE	Model	RMSE / MAPE
In-sample testing: 1993:6-2021:12					
ARMA(2,1,.2)	0.736	ARMA(1,1,1)	0.499	ARMA(2,1,1)	0.779
	0.874		1.340		1.357
ARIMA(1,1,0)-GARCH(1,1)	0.758	ARIMA(2,1,0)-GARCH(1,1)	0.503	ARIMA(2,1,0)-EGARCH(1,1)	0.777
	0.662		1.577		1.397
ARIMA(1,1,0)-RS	0.736	ARIMA(2,1,0)-RS	0.500	ARIMA(2,1,0)-RS	0.784
	0.898		1.519		1.134
Out-of-sample testing: 1993:6-2020:12 data, 2021:1-2021:12 forecast (12 months)					
ARMA(2,1,2)	1.031	ARMA(1,1,1)	0.431	ARMA(2,1,1)	1.056
	0.584		0.381		1.098
ARIMA(1,1,0)-GARCH(1,1)	1.010	ARIMA(2,1,0)-GARCH(1,1)	0.581	ARIMA(2,1,0)-EGARCH(1,1)	1.078
	0.581		0.412		1.128
ARIMA(1,1,0)-RS	0.857	ARIMA(2,1,0)-RS	0.912	ARIMA(2,1,0)-RS	1.010
	0.464		0.586		1.022
Out-of-sample testing: 1993:6-2020:12 data, 2021:1-2021:6 forecast (6 months)					
ARMA(2,1,2)	0.898	ARMA(1,1,1)	0.508	ARMA(2,1,1)	1.193
	0.485		0.240		0.959
ARIMA(1,1,0)-GARCH(1,1)	0.827	ARIMA(2,1,0)-GARCH(1,1)	0.710	ARIMA(2,1,0)-EGARCH(1,1)	1.206
	0.455		0.351		1.000
ARIMA(1,1,0)-RS	0.702	ARIMA(2,1,0)-RS	1.044	ARIMA(2,1,0)-RS	1.152
	0.381		0.537		0.935

Note: For each forecasting horizon, the case with the smallest forecasting error is indicated darkly.

Regarding the forecasting performance by models, the models with the highest forecasting performance by countries were compared from the ARIMA models' estimations in Table 2, the ARIMA-IGARCH models estimations in Table 3, and the ARIMA-RS models estimations in Table 4. For the in-sample forecast, the forecasting ability of the ARIMA (2,1,2) model in Korea was 0.736, which was higher than the forecasting ability of the ARIMA (1,1,0)-GARCH (1, 1) or ARIMA (1,1,0)-RS model. In the USA, the forecasting ability of the ARIMA (1, 1, 1) model was 0.499, which was higher than that of the ARIMA (2,1,0)-GARCH (1, 1) model and the ARIMA (2,1,0)-RS model. In Japan, the forecasting ability of the ARIMA (2,1,0)-EGARCH (1, 1) model was 0.777, which was the highest in comparison with that of the ARIMA (2, 1, 1) model and the ARIMA (2,1,0)-RS model.

For the out-of-sample forecast, the forecasting performance of the ARIMA (1,1,0)-RS model was 0.857 (12-month) and 0.702 (6-month), and it was higher than that of the ARIMA or GARCH. The forecasting performance of the ARIMA (1,1,0)-RS model was found to be 6 months higher than that of 12 months. This means that the short-term forecasting ability is higher than the long-term forecasting performance. In the USA, the forecasting performance of the ARIMA (1, 1, 1) model was 0.431 (12-month) and 0.508 (6-month), and thus its forecasting performance was higher than that of the GARCH or RS model. The 12-month forecasting performance of the ARIMA (1,1,1) model was higher than the 6-month forecasting performance. This means that long-term forecasting performance is higher than short-term forecasting performance. In Japan, the forecasting performance of the ARIMA (2,1,0)-RS model was 1.010 (12-month) and 1.152 (6-month), and it was higher than that of the ARIMA model or the EGARCH model. The 12-month forecasting performance of the ARIMA (2,1,0)-RS model was higher than the 6-month forecasting performance, and thus this means that the long-term forecasting performance is higher than the short-term forecasting performance, which deserves special mention.

Meanwhile, the in-sample forecasting performance of the ARIMA models was higher in Korea, but the forecasting performance of the RS models was higher in the out-of-sample forecast. The in-sample and the out-of-sample ARIMA models' forecasting performances in the USA were high. Although the in-sample EGARCH models' forecasting performance was higher in Japan, the out-of-sample forecasting performance of the RS models was higher. In other words, the out-of-sample RS models' forecasting performance was higher in Korea and Japan, and the in-sample and the out-of-sample ARIMA models' forecasting performances were higher in the USA. This means there is a need to apply the RS models through which a structural change possibility, including the stagnant and boom markets, can be grasped as the housing price forecasting period is longer.

4. Discussion

This study comparatively analyzed the housing price forecasting performance in Korea, the USA, and Japan using the ARIMA, GARCH, and RS models. The three countries' housing price time series data from June 1993 until December 2021 was used to analyze the housing price forecasting performance. The in-sample and the out-of-sample forecasting performances were analyzed with the forecasting period.

For the in-sample forecast, the forecasting performance of the ARIMA (2, 1, 2) model was higher than that of the ARIMA (1,1,0)-GARCH (1, 1) model or ARIMA (1,1,0)-RS model in Korea. The forecasting performance of the ARIMA (1, 1, 1) model was higher than that of the ARIMA (2,1,0)-GARCH (1, 1) model or ARIMA (2,1,0)-RS model in the USA. The forecasting performance of the ARIMA (2,1,0)-EGARCH (1, 1) model was higher than that of the ARIMA (2, 1, 1) and the ARIMA (2,1,0)-RS model in Japan. In Korea and the USA, the forecasting performance of the ARIMA model was higher than that of the GARCH or RS models. Meanwhile, the forecasting performance of the EGARCH model was higher than that of the ARIMA model or RS model in Japan.

Regarding the out-of-sample forecast, first, the 6-month (Jan.-Jun. 2021) and 12-month (Jan.-Dec. 2021) forecasting performances of the ARIMA (1,1,0)-RS model were higher than those of the ARIMA model or GARCH model in Korea. For the forecasting performance in terms of the forecasting period model, the 6-month forecasting ability was higher than the 12-month forecasting performance, so the short-term forecasting performance was higher than the long-term forecasting performance, which is consistent with a general theory. The 6-month model (Jan.-Jun. 2021) and the 12-month model (Jan.-Dec. 2021) forecasting performances of the ARIMA (1, 1, 1) were higher than those of the GARCH models or RS models in the USA. The 6-month (Jan.-Jun. 2021) and the 12-month (Jan.-Dec. 2021) forecasting performances of the ARIMA (2,1,0)-RS model were higher than those of the ARIMA model or EGARCH model in Japan. The 12-month model forecasting performance was higher than the 6-month model forecasting performance in the USA and Japan. This means that the long-term forecasting performance is higher than the short-term forecasting performance, which deserves special mention. Second, concerning in-sample forecast, the forecasting performance of the ARIMA model and EGARCH model was higher in Korea and Japan, respectively. However, the RS model's forecasting performance of the out-of-sample was higher in Korea and Japan. This means that the RS model that can grasp a structural change possibility, including stagnant and boom markets, can be a helpful alternative for forecasting performance improvement, as the housing price forecasting term is longer. The results of this analysis are somewhat consistent with the results of Kim Dong-hwan (2014). Meanwhile, the in-sample and the out-of-sample ARIMA model forecasting performances were higher in the USA. This is different from the research results of Crawford and Fratantoni (2003) that the forecasting power of the RS model is excellent in the sample. The difference between the results of this study and the results of Crawford and Fratantoni (2003) can be due to the difference between the data and the analysis period. Therefore, there is a need to identify a model, data, and research periods suitable for each market for housing price forecasting power improvement.

5. Conclusions

Each country's housing price forecasting performance examined in this study may vary depending on the forecasting period, method, and model. Because a vast change may occur to forecasting performance depending on each forecasting model and method, there is a need to devise a method to control the effect properly. Nonetheless, this study has academic significance in that the study identified the forecasting models that can help dynamically understand the housing market, make a rational decision, and analyze forecasting performance internationally for the first time. In addition, a practical meaning can be awarded because this study presented leading models for rich study. Housing price volatility is affected by various economic variables. However, this study analyzed forecasting performance with a single time series model, which can limit research. Research using more sophisticated models for robust forecasting performance and economic variables can be the task of further study.

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