KJCEM 25. 4. 053~065
July 31, 2024
www.kicem.or.kr (pISSN 2005-6095 / eISSN 2465-9703)
https://dx.doi.org/10.6106/KJCEM.2024.25.4.053

Macroeconomic Determinants of Housing Prices in Korea VAR and LSTM Forecast Comparative Analysis During Pandemic of COVID-19

Starchenko, Maria[1] · Jangsoon Kim[2] · Namhyuk Ham[3*]· Jae-Jun Kim[4]

[1]Grauduate Student, Department of Architectural Engineering, Hanyang University
[2]Grauduate Student, Department of Architectural Engineering, Hanyang University
[3]Professor, Department of Digital Architecture and Urban Engineering, Hanyang Cyber University
[4]Professor, Department of Architectural Engineering, Hanyang University

Abstract : During COVID-19 the housing market in Korea experienced the soaring prices, despite the decrease in the economic growth rate. This paper aims to analyze macroeconomic determinants affecting housing prices in Korea during the pandemic and find an appropriate statistic model to forecast the changes in housing prices in Korea. First, an appropriate lag for the model using Akaike information criterion was found. After the macroeconomic factors were checked if they possess the unit root, the dependencies in the model were analyzed using vector autoregression (VAR) model. As for the prediction, the VAR model was used and, besides, compared afterwards with the long short-term memory (LSTM) model. CPI, mortgage rate, IIP at lag 1 and federal funds effective rate at lag 1 and 2 were found to be significant for housing prices. In addition, the prediction performance of the LSTM model appeared to be more accurate in comparison with the VAR model. The results of the analysis play an essential role in policymaker perception when making decisions related to managing potential housing risks arose during crises. It is essential to take into considerations macroeconomic factors besides the taxes and housing policy amendments and use an appropriate model for prices forecast.

Keywords : COVID-19, Housing Prices, Macroeconomic Determinants, VAR, LSTM

1. Introduction

Since 2020, there have been some major events in the Korean economy, including the pandemic of COVID-19. This phenomenon has led to a policy of quantitative easing and stricter mortgage lending rules (Stefanski, 2023). All these factors have impacted the Korean economy in general and the housing market specifically. During the pandemic, the housing prices soared by 25.5% according to the Bank of International Settlement (BIS, 2022). However, in August 2022, selling price of houses in Korea started decreasing and by February 2023 diminished by 5% (KOSIS, 2023). The reasons for this fluctuation can be analyzed according to location factors (Gao et al., 2022), or by using urban approach analyzing size and location of the apartment (Glaeser et al., 2014). Another approach is the analysis of macroeconomic determinants of the housing market (Panagiotidis & Printzis, 2016; Grum & Govekar, 2016). Macroeconomic determinants are fiscal or monetary events that change the economic and financial country conditions and outlook. Macroeconomic factors considerably influence housing prices as they reflect the country economic conditions, impact on goods and services price level, and determine aggregate demand structure (Gasparėnienė et al., 2016).

There are different methodologies that can be used for time-series macroeconomic and real estate data analysis:

* **Corresponding author:** Namhyuk Ham, Department of Digital Architecture and Urban Engineering, Hanyang Cyber University, Seoul 04763, Republic of Korea
E-mail: nhham@hycu.ac.kr
Received November 15, 2023; **revised** January 11, 2024
accepted February 22, 2024

time-series regression analysis, vector autoregression analysis, structural equation modeling, and machine learning (ML) techniques. However, since every country has its own economic conditions and features of the economic policy, there is a lack of consensus on the data models to use for analysis and forecasting of housing prices. Vector autoregression (VAR) and vector error corrected (VECM) models were applied when analyzing housing prices in Greece, China, Malasia, etc.. (Panagiotidis & Printzis, 2016; Trofimov et al., 2018; Duan et al., 2021). There is also no common opinion even on the determinants to be analyzed. Moreover, the period of analysis of housing market price is different and dependent on the unique feature of every country. Thus, it is important to find appropriate economic variables to conduct the analysis, build a model and get holistic view of Korean real estate price changes to see the dependencies between macroeconomic factors and housing price index during December 2019 – February 2023.

This study includes selected variables according to macroeconomic monetary theory – inflation, interest and mortgage rates, economic growth and money supply. In comparison with previous research that didn't include international economy factors, the present research analyzes the impact of the US federal funds effective rate (FED rate) on housing prices. The FED rate included in the research highlights the close economic ties between Korea and the USA and opens opportunities for analyzing cross-border policy impacts on housing market in Korea. The research captures the period of COVID-19, which allows to analyze the shock of COVID-19 to housing prices and compare it with the situation during the same period in other countries. Moreover, the VAR model applied in the research gives causality insights about the variables. In addition, the research contains forecasting conducted with both VAR and long-short time memory (LSTM) model with the comparison of the prediction performance for both models. This research could contribute to a deeper comprehension of housing price fluctuation in Korea during the unique circumstances of the pandemic.

The present research aims to capture the factors determining the housing prices in Korea and find the appropriate model to forecast the changes in the housing price index (HPI). The research questions of the paper were formulated as follows:

1. What macroeconomic factors impact the HPI in Korea?
2. What are the relationships between FED rate and the Korean HPI?
3. What forecast model is more accurate when predicting housing prices in Korea during recession caused by the pandemic?

2. Research Background

2.1 Macroeconomic Factors and Housing Market

Housing market is an area of great interests of policy makers around the globe. Housing prices being the part of the market are essential to study as it is related to the supply side of the economy reflecting the overall economic stability and growth, as well as the demand side affecting the consumer spending and saving behavior (Asadov et al., 2023; Goel et al., 2023). There are a lot of macroeconomic factors that influence the housing sector, and that it impacts in response; therefore, it is crucial to understand what macroeconomic variables impact housing prices. In addition, this cause-and-effect analysis is essential during economic crises. Policymakers need to respond effectively to mitigate the negative consequences for housing market.

From the demand side, housing prices are dependent on the purchasing power of the population. Thus, consumer price index (CPI), interest rate, unemployment, broad money (M2) can be listed among variables affecting people's saving and spending behavior. Anari and Kolari (2002); Sipos & Buglea (2015); Cohen and Karpavičiūtė (2017); Pinjaman and Kogid (2020); Pommeranz & Steininger (2020); Kartal et al. (2023) studied the impact of inflation on housing prices, that were closely related through population's purchasing power and interest rate adjustment to target the inflation level set by the government.

Apart from that, unemployment was considered one of the variables determining the housing prices in the research of Jacobsen and Naug (2005), Grum and Govekar

(2016), Cohen and Karpavičiūtė (2017), Irandoust (2019).

The impact of either policy interest rate or mortgage rate on the real estate was observed in the studies of Apergis (2003), Otrok and Terrones (2005), Nneji et al. (2013), Cohen and Karpavičiūtė (2017), Mohan et al. (2019), Pinjaman and Kogid (2020).

M2 was analyzed by Greiber and Setzer (2007), Adalid and Detken (2007), and Tripathi (2019). Authors found strong relationship between money supply growth and increase in housing prices.

From the supply side, housing prices are dependent on overall economic stability and growth. These two characteristics can be reflected by index of industrial production (IIP), which tracks the volume of production measuring the physical output in various industries. The impact of IIP on housing prices was analyzed in studies of Marfatia (2020), Colak (2021), Akça (2023).

In this paper, several macroeconomic factors such as CPI, unemployment rate, interest rate, mortgage rate, IIP, M2 were chosen to analyze the dependent variable – HPI. The reason for choosing these variables were the importance of this factors both for the economy and for the housing market. Accounting for close economic ties between Korea and the US, FED rate was also chosen as independent variable.

2.2 US Federal Funds Effective Rate and Korean Housing Market

FED rate is median of the interest rate that is used by the depositary institutions in the US to issue a short-term, usually one-day, loan to other banks and credit unions. The targeted range of this rate is decided by the US Federal Reserve System (FED). The FED rate can impact on inflation rate, cost of borrowed funds and yield of securities.

〈Fig. 1〉 demonstrates the growing volume of trade between the USA and Korea with the drastic growth of export from Korea to the USA. It represents strong economic ties between the two countries.

As the USA is the country with the biggest economy in the world, changes in FED rate may influence the Korean economy. Its economy is small and open, so it can be affected by the external shocks caused by the changing global interest rates (Son & Park, 2019). Changes in FED rate may indirectly influence international borrowing cost and investors' behavior. Therefore, the investors change their focus, which leads to increase in demand for housing and consecutively, housing price index.

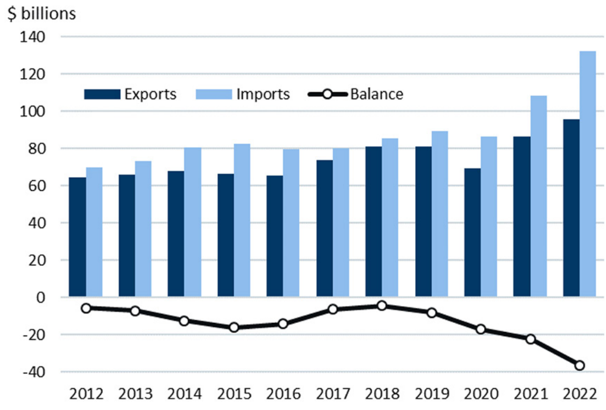


Fig. 1. The USA total trade with the Republic of Korea

2.3 COVID-19 and Korean Housing Market

COVID-19 has weakened investors' confidence about investment in housing in Korea because of the paralyzed economic activities around the globe and in Korea. Inability to constantly reduce interest rates due to soaring inflation in the US led to hawkish monetary policy in the US and in Korea that conducted its monetary policy in line with the States (Chang, 2021; IMF, 2023). Growing inflation in Korea and growing interest rates led to the situation when people who ventured to buy a new housing during COVID-19 crises will be forced to sell it at a cheaper price than they bought. Nevertheless, during the first half of 2020, the demand for housing was growing due to favorable financial conditions and the lowest mortgage rate, which resulted in boiling housing market. At the same time, low-income class was under threat of housing instability as social inequality increased drastically during the COVID-19 (Kang et al., 2020).

The present paper analyzes the crucial factors impacting HPI changes during COVID-19, taking into consideration synchronical policy of Korea and the US as well as projecting the forecast of housing prices during the unique circumstances of the pandemic to find an appropriate model for the forecasts of housing prices in the similar contingencies.

3. Methodology

3.1 Methodology Overview

This study aims to examine the macroeconomic determinants of housing price index in Korea during the outbreak of COVID-19 and build a prediction model for forecasting the changes in HPI to let politicians make efficient decisions concerning housing market.

The dependencies between HPI and macroeconomic variables are analyzed using a VAR model, and afterwards two prediction models of housing price index are made with VAR and LSTM. Initially VAR models were introduced by Christopher Sims (1980) to examine the dynamics and causal relations between macro-economic variables composing linear function from the past values of the model variables. VAR model allows to analyze multivariate time series both describing and forecasting the data. It indicates the evolution of set of endogenous variables changing over time. VAR is used for the time series that are related to each other. VAR model enables to analyze the effects of the shocks to the variables in question by other variables, showing the interrelationship between multivariate time series (Adenomon and Oyejola, 2014). In addition, VAR model appeared to be a flexible and usable model for the analysis related to monetary policy providing economic interpretability (Jacobson et al., 2001). Bagliano and Favero (1998) used VAR model to examine monetary policy shocks. VAR model was also applied to analyze macroeconomic determinants of housing prices in Iacoviello (2000), Hossain and Latif (2009), Kim (2013), Mohan et al. (2019) Ahmed (2020), Benazić, and Učkar, (2023).

VAR surpasses prediction performance in comparison with structural models and ARIMA when dealing with economic forecasts (Bentour, 2015). It did better performance than ARIMA for data with higher correlation (Khan & Kahn, 2020). VAR methodology is considered one the most convenient for the capture of the dynamic relationship between the variables and the housing prices (Iacoviello, 2000).

The next model applied for the analysis is LSTM model that is a type of a recurrent neural network (RNN) that deals with temporal data and is capable of learning long-term relationships between variables. The model was introduced by Hochreiter and Schmidhuber (1997). LSTM contains memory units with a fixed-weight self-connection. An input gate unit protects the constant error from turmoil inside the memory cell. An output gate protects the memory units from turmoil caused by irrelevant content within another memory unit. The LSTM has an ability to capture complex patterns, even those that are nonlinear and have long term dependencies. LSTM tends to be an appropriate model for time series as it can model long-run relations in the data (Chattha, 2021).

LSTM is applicable model for house prices forecast (Yu et al., 2018). However, LSTM is likely to perform better with a small dataset of predictors than with a large one (Chu & Qureshi, 2022). LSTM can be used for monetary policy factors forecast. Thus, it was used for the forecast of broad money supply using the training dataset of 15 months (Zhai et al., 2021).

Kim et al. (2012) noticed that it is important to use different statistical techniques when analyzing macroeconomic determinants of housing prices in Korea. As studies using both methods for the analysis of the Korean housing market during the pandemic are rare, this study will cover both gaps: analyze the macroeconomic variables impacting the housing market in Korea, taking into consideration the economic features during the pandemic and compare the forecasting performance of VAR and LSTM. The analysis presented in this paper will be valuable as it can influence the politician's decision making when another external shock would appear. In addition, it could help evaluate what way is more effective to predict the housing prices during recessions.

3.2 Vector Autoregression Model

3.2.1 Data Preprocessing

The time series data of HPI and macroeconomic variables were collected from International Monetary Fund Database and Bank of Korea Database. The monthly dataset covers the period from December 2019 to February 2023. The data preprocessing as well as model development were done using Python 3.10 along with time series analysis package. The data were divided into train and test ones, containing 33 and 6 samples each.

The first step of the analysis is to check data series for stationarity as the variables used in the VAR model should be stationary. The Augmenter Dickey-Fuller (ADF) test can be employed to confirm stationarity (Dickey & Fuller, 1979). The null hypothesis of the test is that there is a unit root in the time series, which means that the data are non-stationary. The stationarity is important assumption of the VAR model as it proves that the correlation between the data is not spurious. However, this assumption is allowed to be omitted in the time series model where the macroeconomic data are used as the comovements in the data are genuine (Enders, 2004).

After the stationary test for the data in levels, the differencing was conducted. Differencing is the common way to eliminate trends, seasonality and other non-stationary patterns presenting in the data used for the analysis. The simple differencing implies the subtraction of the previous observation from the current one.

3.2.2 VAR Model Development

VAR model is composed of n-dimension of the vector equal to the number of variables to the model. Apart from this, it is essential to select an appropriate lag order of VAR model because it allows to ensure the statistical soundness of the model chosen for the analysis. The lag can be chosen by analyzing information criteria to measure the goodness fit of the statistical model. Akaike information criterion (AIC) was selected to find the best fit for VAR model (Akaike, 1987).

VAR model allowed analysis of whether there are interdependencies and interactions between housing price index time series and independent macroeconomic variables. This model showed what kind of dependencies there were between the dependent variable – HPI and independent variables at a certain lag – fixed amount of passing time.

VAR model presented in the current study is depicted by the following equation:

$$\begin{aligned} HPIt = c &+ \sum_{i=1}^{2} \beta_1 {*} HPI_{t-i} + \sum_{i=1}^{2} \beta_2 {*} CPI_{t-i} + \sum_{i=1}^{2} \beta_3 {*} MRG_{t-i} + \\ &\sum_{i=1}^{2} \beta_4 {*} INT_{t-i} + \sum_{i=1}^{2} \beta_5 {*} M2_{t-i} + \sum_{i=1}^{2} \beta_6 {*} IIP_{t-i} + \\ &+ \sum_{i=1}^{2} \beta_7 {*} UNEMP_{t-i} + \sum_{i=1}^{2} \beta_8 {*}\ FED_{\ t-i} + \varepsilon t \end{aligned} \tag{1}$$

Where HPIt-n is a variable for an autoregressive effect to be captured in the model. CPIt-i, MRGt-i, INTt-i, M2t-i, UNEMPt-i, FEDt-i are lagged values of independent variables, and c, β1, β2, β3, β4, β5, β6, β7, β8 are coefficients to be estimated.

VAR model was build using statsmodels.tsa.api module in Python 3.10. It is important to note that when developing the VAR model for multivariate series, it includes a number of equations similar to the number of time series variables. However, as this paper is concentrated on HPI analysis, only this very model is assessed and evaluated.

After the model is developed, the coefficients of those variables whose probability is higher than 0.05 considered to be insignificant at 95% level. Insignificant variables are not included in the final equation describing the model, and the impact of these independent variables on HPI is omitted. Only coefficients of significant variables are included in the final model equation.

Finally, the forecast was proceeded utilizing the estimated model to predict future values of HPI. This is achieved by iteratively applying the lagged values and the estimated coefficients to generate forecasts for six-time steps ahead the training series period.

3.2.3 VAR Forecast Performance Evaluation

The forecasting performance of the VAR model was evaluated with the actual data using a range of metrics including mean absolute error (MAE),

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{2}$$

y_i : actual value
x_i : predicted value
n : number of observations

root mean square error (RMSE) (Willmont & Matsuura, 2005),

$$RSE = \sqrt[2]{\frac{\sum_{i=1}^{n} |y_i - x_i|^2}{n}} \tag{3}$$

y_i : actual value
x_i : predicted value
n : number of observations

mean absolute percentage error (MAPE) (Makridakis, 1993).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right| \tag{4}$$

y_i : actual value
x_i : predicted value
n : number of observations

The VAR model is appropriate to analyze the dependencies and forecast the change in variables. This could be useful for making future decisions concerning housing price; however, it is not the only model suitable for forecasting. LSTM was also used to make predictions to compare the forecasting performance.

3.3 Long-short Term Memory Model

3.3.1 Data Preprocessing

Before developing LSTM model, the data were preprocessed. The data were divided into train and test datasets, containing 33 and 6 samples each, which is similar to the split of data of VAR model. Additionally, the data were standardized to facilitate the model convergence using StandardScaler from scikit-learn package. Next, the input sequences of 10-time steps were created along with their next time step's HPI value. The sequences and the targets were converted into NymPy arrays for efficient model training. The input array was reshaped into 3D format (samples, time steps, features) to meet the requirements for LSTM model input.

3.3.2 LSTM Model Development

The model for HPI prediction was developed with Python 3.10. The model consisted of two LSTM layers with 50 units each to learn temporal patterns. Two dropout layers with a rate of 0.2 were included in the model after each LSTM layer to prevent outfitting. The output layer was a single dense neuron to predict HPI value for the next time step. The model was compiled with the Adam optimizer. For the loss function, the mean squared error (MSE) was chosen to measure the average squared difference between the prediction values and the actual ones.

After the model was created, the test data were prepared for prediction. First, the test dataset was created by combination of the last 10 rows of train dataset with the test data to secure the consistency in data structure for prediction. The data from a new dataset were scaled. Next, the input sequences for the test dataset were prepared, following the structure similar to the training dataset. Sequences of 10 consecutive time steps from the new dataset for the model to process temporal patterns. The extracted sequences were converted into NumPy array.

Next, the trained LSTM model was used to make predictions for the input test sequences. Then the received model's predictions were transformed inversely to revert to the original scale of the HPI. These predictions were integrated into the original dataset to compare with the actual values of HPI visually.

3.3.3 LSTM Forecast Performance Evaluation

Finally, the predicted data were compared with the actual ones during the same period, using quantification means such as MAE, MAPE, RMSE. It was essential to make comparison of the forecasting performance of both LSTM and VAR models to find an appropriate model with the least quantification means for prediction of housing prices during economic recession.

4. Results

4.1 Data Preprocessing

It is important to secure the stationarity of the data to conduct the analysis and build VAR model. Non-stationary data can lead to spurious results of the analysis and deceptive correlation between the variables. There is unit root in the unstable time series of data, thus ADF test was used to check for the stationarity of all the time series. The results are shown in 〈Table 1〉.

Table 1. Augmented Dickey-Fuller tests results

Lag order	Level		1st Differencing		2nd Differencing	
	t-statistics	p-value	t-statistics	p-value	t-statistics	p-value
HPI	-2.97	0.06	-2.30	0.17	-.30	0.92
CPI	0.99	0.99	-3.11	0.03	-4.08	0.00
MTG	1.23	0.99	-2.80	0.06	-4.58	0.00
INT	0.90	0.99	-0.79	0.82	-9.83	0.00
M2	-0.93	0.77	-3.65	0.01	-6.51	0.00
IIP	-0.54	0.88	-3.56	0.01	-2.89	0.04
UNP	-1.63	0.47	-4.84	0.00	-3.10	0.03
FED	-1.16	0.69	2.04	0.99	-3.15	0.03

The t-statistics of all the variables at levels showed a higher significance level in comparison with 1%, 5% and 10%; therefore, it is impossible to reject the null hypothesis of non-stationary data at level. There were done two differencing of data when the null hypothesis was rejected at 1%, 5% and 10% for all the variables apart from HPI. The null hypothesis of the existence of unit root was at 10%.

The time series at levels are all non-stationary; therefore, all the variables were differenced. After first round of differentiation, CPI, M2, IIP and unemployment rate became stationary. As there were non-stationary data in the model, they were differenced for the second time. The p-value of most the data was below 0.05 that allowed to reject the null hypothesis of unit root presence, which means that all the data apart from HPI were found to be stationary. However, the analysis was proceeded further as HPI is a macroeconomic variable and the dependencies between such kind of variables are not spurious, so the model could be built.

4.2 VAR Model Development

To determine the appropriate lag order for the VAR model, the AIC is employed as the criterion for selection 〈Table 2〉.

Table 2. VAR lag selection results based on AIC criterion

Lag order	AIC	BIC	FPE	HQIC
0	-8.056	-7.678	0.0003174	-7.937
1	-8.804	-5.409	0.0001779	-7.740
2	-10.95	-4.535	-6.932e-05	-8.939

Based on the AIC criterion from 〈Table 2〉, the VAR model with a lag order of 2 yields the lowest AIC value, indicating a better fit compared to other lag orders. Therefore, the estimation of the VAR model was proceeded with a lag order of 2.

The VAR model was estimated using the ordinary least squares (OLS) method. The summary of regression results for the VAR model at a lag order of 2 is presented in 〈Table 3〉. 〈Table 3〉 shows the VAR model equation for the housing price index (HPI) at Lag 2, which demonstrates the relationships between the independent lagged variables at lag 1 and 2 – HPI, CPI, mortgage rate, policy interest rate, M2, IIP unemployment rate and FED rate, and the dependent unlagged variable – HPI. 〈Table 3〉 includes coefficients of the variables, standard error, t-statistics, and probability level.

Table 3. Summary of regression results for HPI VAR model at lag 2

Lag order	Coefficient	Standard Error	T-statistics	probability
Const	-0.00061	0.04394	-0.014	0.989
L1.HPI	0.36290	0.34361	1.056	0.291
L1.CPI	-0.42997	0.19266	-2.232	0.026*
L1.MRG	-1.45319	0.73486	-1.977	0.048*
L1.INT	-0.61242	0.60414	-1.014	0.311
L1.M2	0.00294	0.00507	0.580	0.562
L1.IIP	-0.01776	0.00810	-2.193	0.028*
L1.UNP	-0.00061	0.09602	1.187	0.235
L1.FED	0.36290	0.31985	2.095	0.036*
L2.HPI	-0.42997	0.27653	1.186	0.235
L12.CPI	-1.45319	0.19198	-0.379	0.705
L2.MRG	-0.61242	0.99888	-0.766	0.444
L2.INT	0.00294	0.71881	-1.955	0.051
L2.M2	-0.01776	0.00437	0.415	0.678
L2.IIP	0.11396	0.00819	-1.701	0.089
L2.UNP	0.66997	0.109165	-0.202	0.840
L2.FED	0.32808	0.288988	2.485	0.013*

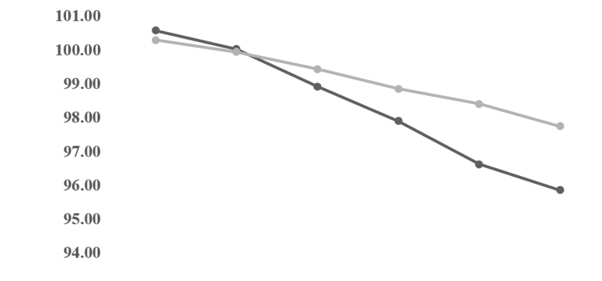
There is a condition for the probability to be less than 0.05 for the independent variable to be significant in the equation. Judging by the probability, significant variables of the HPI equation are CPI at lag 1, mortgage interest rate at lag 1, IIP at lag 1, FED rate at lags 1 and 2. The coefficients of the significant variables are -0.429967 (t-statistic: -2.232, p-value: 0.026) for CPI at lag 1, -1.453192 (t-statistic: -1.977, p-value: 0.048) for mortgage rate at lag 1, -0.017759 (t-statistic: -2.193, p-value: 0.028) for IIP at lag 1, 0.362896 (t-statistic: 2.095, p-value: 0.036) for FED rate at lag 1 and 0.328080 (t-statistic: 2.485, p-value: 0.013) for FED rate at lag 2. This suggests a statistically significant inverse relationship between the CPI and the dependent variable in the equation, which means that an increase in CPI by 1 will lead to the decrease in housing price index by 0.4 at lag of 1 month. The growth of the mortgage rate by 1 will reduce HPI by 1.45 at lag of 1 month. The increase in the IIP by 1 will diminish HPI by 0.018 at lag of 1 month. However, there is direct relationship between FED rate one and two periods ago and HPI; therefore, an increase in the FED rate by will crease HPI by 0.36 at lag of 1 month and 0.32 at lag of 2 months. Consequently, the equation for HPI could be written as:

$$HPI = -0.429967 * L1.CPI - 1.453192 * *L1.MRG - - 0.017759 * L1.IIP + 0.362896 * L1.FED + + 0.328080 * L2.FED \quad (5)$$

According to the model, HPI has negative relationships with CPI, mortgage rate and IIP at lag 1 and positive relationships with FED rate both at lag 1 and 2. In the equation, HPI is affected by the lagged variables indicating that the model is taking into account the effect of the past values of independent variables on the current dependent HPI. Apart from that, this equation demonstrates the strength and direction of the relationship between significant variables and HPI. Mortgage rate may be the most important variable influencing HPI as the magnitude of its coefficient is the highest. This equation can be potentially used for the forecast of HPI using the lagged independent variables mentioned in the equation.

4.3 VAR Model Forecast

After the VAR model for HPI was built, the forecast was proceeded utilizing the estimated model to predict future values of the variable in question – HPI. The forecast for six-time steps ahead the training series period was generated. The HPI prediction results are presented in 〈Fig. 2〉.



	1	2	3	4	5	6
Actual	100.57	100.01	98.91	97.89	96.61	95.85
Prediction	100.29	99.93	99.42	98.84	98.39	97.74

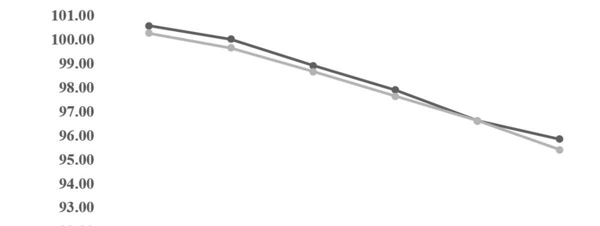
Fig. 2. HPI forecast for six time steps using VAR model

The HPI prediction has the same trend with the actual HPI. The prediction results are lower than the actual data up to the second period, and after the second period the prediction results showed slower decline in comparison with the actual one, that was sharper.

The forecasting performance of the VAR model was evaluated with MAE, RMSE and MAPE to quantify the predictive capacity of the model. MAE is equal to 0.9169, RMSE accounts for 1.1543. MAPE is equal to 0.0094. The relatively small values of MAE, RMSE and MAPE mean that the model has a high capacity to forecast the HPI trends and attests to the reality.

4.4 LSTM Model Forecast

Apart from VAR model, there is another model built with the deep learning method – LSTM. First, the LSTM model was trained to capture temporal dependencies within the sequences. Then the model was built, and the prediction results of six-time period of housing price index were compared with the actual ones. The predicted results are shown in 〈Fig. 3〉.



	1	2	3	4	5	6
Actual	100.57	100.01	98.91	97.89	96.61	95.85
Prediction	100.26	99.65	98.65	97.63	96.61	95.40

Fig. 3. HPI forecast for six time steps using LSTM model

The built LSTM model demonstrates that the actual results are higher than the prediction up to the 5th time series period when the actual and the predicted data become equal.

To evaluate the forecasting performance of the model the means such as MAE, RMSE and MAPE were used. MAE accounts for 0.2711. RMSE is equal to 0.3036, and MAPE – 0.0027. This is because the LSTM model, which is the ML technique, is effective for prediction of the trends in the time series, especially for short-time period. Same as in the case of VAR model relatively small values of the means prove that the model has a high capacity to forecast the HPI.

5. Discussion

The key findings of the previous papers are various, strongly dependent on the period of analysis, country and selected macroeconomic variables. For example, Al-Masum and Lee (2018) found that gross disposable income, housing supply, unemployment rate and GDP are statistically significant for housing prices in Greater Sydney. Tripathi (2019) found that inflation, per-capita GDP, GDP growth rate and money supply impact positively on housing prices from cross-country perspective. While Cohen and Karpavičiūtė (2017) noted that among macroeconomic factors determining housing prices there are GDP, unemployment and lagged housing prices.

VAR model let identify macroeconomic determinants that influence housing price significantly during COVID-19 pandemic: CPI, IIP, mortgage rate and FED rate. These variables are bounded with the COVID-19 monetary policy in Korea. Inflation at lag 1 negatively impacts housing prices in Korea causing dampening effect on housing prices. During COVID-19 CPI increased by 10% in 3 years from December 2019 to February 2023, which is higher than the inflation targets of 2% per year. Despite the downward trend of the inflation in Korea in the years preceding the pandemic, during COVID-19 there were disruptions in supply chains and increased demand for essential goods that cause the faster increase of CPI (Oh et al., 2020).

Inflation was the cause of the growth of housing prices in several Turkish regions that are close to industrial or agricultural areas with high economic and social opportunities (Korkmaz, 2019). Laurinavičius et al. (2022) found positive relation between inflation and housing prices in Vilnus.

Next, the Bank of Korea was the first central bank among central banks in the developed countries that rose the policy interest rate in August 2020 for the first time showing the policy intention for housing price stabilization (Cho, 2022). Changes in interest levels affect both affordability and demand for residential properties. A hike in these rates would imply higher borrowing costs through growing mortgage rate that could make it harder for potential buyers to afford homes at current market prices – ultimately dampening demand while simultaneously putting downward pressure to housing prices. The same finding was reflected in the studies of Apergis (2003), Mohan et al. (2019), Akkay (2021), Yiu (2021).

The relations between IIP and HPI turned out to be negative during the pandemic. This could be due to shifted consumer preferences. The pandemic made consumer spending shift from non-essential goods to essential goods (groceries and healthcare), which caused the decline in IIP as well as in housing supply since the pandemic retarded housing construction and caused problems with housing supply chains (Kang et al., 2020).

During the pandemic the housing prices increased overseas as well as in Korea. In Turkey, the most effective factors appeared to be the outbreak of COVID-19, housing rent changes and weighted average cost of funding of Central Bank of the Republic of Turkiye (Kartal et al., 2023). The housing prices increased during the pandemic in Australia, Canada, New Seland, the UK and the USA due to a common economic shock, not because of the shortage of land supply. The cut of interest rates in the above-mentioned countries led to an increase in housing prices, providing evidence for effectiveness of expansionary monetary policy (Yiu, 2021). In China, Brazil, South Africa, Thailand and Turkey, the housing prices increased due to spillover effects of the FED's policy in the US. That is why the actions of the FED should be accounted for while conduction the policy of quantitative easing, proven to be an alternative tool to mitigate housing market shock during COVID-19 (Nguyen and Le, 2023).

The same spillover effects of the US monetary policy were examined in Korea where FED rate growth temporary positively influenced housing prices. At the beginning of the pandemic the FED rate was decreased, and Koreans expected the decrease in base interest rate and mortgage rate as well, so according to their expectations it was favorable to buy a house immediately without postponement (Jacobsen & Naug, 2005). Therefore, the housing demand soared and prices hiked based on the expectations concerning the decrease in the FED rate.

During the pandemic, the necessity of a dwelling affordability became fundamental. Inflation-targeted policy could stabilize housing prices along with the growth of policy interest rate; however, it will not make houses affordable, especially for low-income class (Kang et al., 2020). Low interest rate policy as well as high interest rate policy may be not effective as it causes property speculations. It is possible to set the borrowing restriction for people having vast portfolio of real estate, and the debt obligations can be assessed before lending (Trofimov et al., 2018). With that, the policy to curb investment demand could be a solution for the government to control housing prices through mortgage loan ratio or the total debt repayment ratio limits, which may be effective measures to prevent the surge of housing prices (Hwang et al., 2010). Apart from that, the liquidity injections into the market during COVID-19 were extensive; therefore, the decrease in the deposit reserve ratio for the banks may be helpful (He & Wang, 2022). In the short term, there could be changes in tax policy for instant response to solve the problem of unaffordability of housing. Also, there is a necessity to increase the existing housing stock to increase supply so as the price for housing would go down.

It is essential to delve into a comprehensive analysis and make a comparison of VAR and LSTM models built and analyzed in the previous section. Both models used the same datasets for training and testing. However, the results are different due to the difference in underlying principles of each model. The relative changes of the prediction of both models can be seen in ⟨Fig. 4⟩.

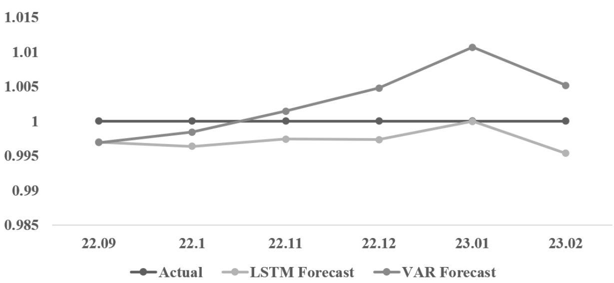


Fig. 4. Changes in the forecast in comparison with actual data

The ⟨Fig. 4⟩ demonstrates that up to November 2022 the VAR forecast was relatively more precise as the residuals of VAR model as can be seen visually less than those of LSTM model. Starting from December 2022 the LSTM forecast is considered to be more accurate. Apart from visual interpretation this could be proven by analyzing MAE, MAPE and RMSE for 2 periods: September 2022 ¬– November 2022, December 2022 – February 2023. The results are shown in ⟨Table 4⟩.

Table 4. VAR and LSTM models prediction performance

Means	VAR		LSTM	
	09/22-11/22	12/22-02/23	09/22-11/22	12/22-02/23
MAE	0.0500	1.5400	0.3066	0.2355
RMSE	0.3427	1.5960	0.3098	0.2973
MAPE	0.0029	0.0159	0.0031	0.0024

The smaller MAE of VAR model demonstrates that the VAR forecast is more accurate than LSTM prediction. However, judging by RMSE the LSTM model is more precise. Moreover, the RMSE is a preferred metric to use when evaluating the prediction performance as it is desirable to reduce the impact of outliers on the model performance. Therefore, despite the lower value of MAE of VAR model, the LSTM model prediction is more accurate.

There are several reasons behind the fact the LSTM model is more accurate than VAR model. First of all, the VAR model assumes a linear relationship between variables and examines the relationship with the lagged values of the same variables. LSTM model admits that the relationship between the variables can be not linear, which allows the model to capture complex temporal patterns. Secondly, LSTM model can capture temporal dependencies better than VAR model that allows the former to produce more accurate forecast. LSTM accuracy outweighs VAR in terms of accuracy (Shetty et al., 2023). The higher accuracy of the LSTM model was observed when predicting cumulative reported incidences and mortality based on the lowest RMSE and MAE values that the model achieved (Mishra et al., 2023). Therefore, LSTM model is a more reliable model for policy makers in Korea, especially when changing the housing policy.

6. Conclusion

There is no unanimous agreement over what factors should be analyzed when examining the macroeconomic determinants of the housing price index. To address these discrepancies, a VAR model reliant upon monthly economic data during COVID-19's onset path was employed to evaluate macroeconomic variables' relationship with HPI. Besides, VAR and LSTM were used to make a prediction on HPI. Subsequently, an opposite correlation was discovered between lagged mortgage rate, CPI and IIP, and HPI. FED rate was found to have a positive impact on HPI both at Lag 1 and 2. Besides, LSTM model is better for the prediction of the value of HPI during the pandemic of COVID-19. This is due to different specifications and assumptions of each model.

There are some limitations that could appear during the present analysis. The models used in this research are appropriate only for the housing price predictions in terms of economic shocks and high improbability events, such as COVID-19. Exogeneity of shocks is another problem that could arise in the analysis because apart from coronavirus pandemic there was another shock – the Russia's invasion to Ukraine started in February 2022, that affected the economy conditions in the whole world and in Korea, particularly. In addition, the characteristics of COVID-19 may be unique, and it may be hard to fully capture its effects on the housing market in Korea.

The results of the analysis presented in the paper, play an essential role in policymaker perception when making decisions related to managing potential housing risks like those inflicted by pandemics such as Covid-19. This is because the housing sector started playing a more important role starting from 2020 when people were locked down in their houses. Therefore, it is essential for the policy makers to forecast the movement of housing prices during crises correctly taking into considerations macroeconomic factors besides the taxes and housing policy amendments.

Acknowledgments

The authors express their gratitude to Construction Management and Computer Integrated Construction Lab of Hanyang University for help and consideration while making the research, conducting the data analysis and writing this paper.

References

Adalid, R., and Detken, C. (2007). Liquidity shocks and asset price boom/bust cycles. ECB Working paper, 732.

Adenomon, M., and Oyejola, B. (2014). "Forecasting Meteorological Time Series Data with a Reduced Form Var Model and Three Univariate Time Series Techniques: A Comparative Study." *Social and Basic Sciences Research Review*, 2(3), pp. 139-152.

Akça, T. (2023). "House price dynamics and relations with the macroeconomic indicators in Turkey." *International Journal of Housing Markets and Analysis*, 16(4), pp. 812-827.

Akkay, R.C. (2021). "The macroeconomic determinants of the housing prices in Turkey." *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 58, pp. 241-264.

Al-Masum, M.A., and Lee, C.L. (2019). "Modelling housing prices and market fundamentals: evidence from the Sydney housing market." *International Journal of Housing Markets and Analysis*, 12(4), pp. 746-762.

Anari, A., and Kolari, J. (2002). "House prices and inflation." *Real Estate Economics*, 30(1), pp. 67-84.

Apergis, N. (2003). "Housing prices and macroeconomic factors: prospects within the European Monetary Union." *International real estate review*, 6(1), pp. 63-74.

Asadov, A., Ibrahim, M., and Yildirim, R. (2023). "Impact of house price on economic stability: some lessons from OECD countries." *The Journal of Real Estate Finance and Economics*, pp. 1-31.

Bagliano, F.C., and Favero, C.A. (1998). "Measuring monetary policy with VAR models: An evaluation." *European Economic Review*, 42(6), pp. 1069-1112.

Bank of international settlements (2022). BIS residential property price statistics in Q2 2022, BIS, pp. 1-8.

Benazić, M., and Učkar, D. (2023). "The impact of selected macroeconomic variables on house prices in Croatia." *Ekonomska misao i praksa*, pp. 1-24.

Bentour, E.M. (2015). A ranking of VAR and structural models in forecasting.

Chang, Y. (2021). "Monetary policy synchronization of Korea and United States reflected in the statements." *The Korean Journal of Applied Statistics*, 34(1), pp. 115-126.

Chattha, Muhammad Ali (2021). DeepLSF: Fusing Knowledge and Data for Time Series Forecasting.

Cho, D. (2022). "The Korean Economy in the Swirl of Pandemic." *Korea's Economy*, 32, pp. 1-8.

Chu, B., and Qureshi, S. (2023). "Comparing out-of-sample performance of machine learning methods to forecast US GDP growth." *Computational Economics*, 62(4), pp. 1567-1609.

Cohen, V., and Karpavičiūtė, L. (2017). "The analysis of the determinants of housing prices." *Independent journal of management & production*, 8(1), pp. 049-063.

Colak, Z. (2021). "A causality analysis on factors affecting housing prices: case of Turkey." *Journal Of Business Economics and Finance*, 10(2), pp. 58-71.

Dickey, D., and Fuller, W. (1979). "Distribution of the estimators for autoregressive time series with a unit root." *Journal of the American Statistical Association*, 74(366), pp. 427-431.

Duan, J., Tian, G., Yang, L., and Zhou, T. (2021). "Addressing the macroeconomic and hedonic determinants of housing prices in Beijing Metropolitan Area, China." *Habitat International*, 113, pp. 1-11.

Enders, W. (2004). *Applied econometric time series*, 2nd ed., Ames, Wiley, p. 301.

Gasparėnienė, L., Remeikienė, R., and Skuka, A. (2016). "Assessment of the impact of macroeconomic factors on housing price level: Lithuanian case." *Intellectual Economics*, 10(2), pp. 122-127.

Glaeser, E., Gyourko, J., Morales, E., and Nathanson, C. (2014). "Housing dynamics: An urban approach." *Journal of Urban Economics*, 81, pp. 45-56.

Goel, S., Leishman, C., and MacLennan, D. (2023). "How does the housing market affect financial and economic stability?" *Economic Observatory*.

Greiber, C., and Setzer, R. (2007). Money and Housing: Evidence for the Euro Area and the US. Bundesbank Series 1 Discussion Paper No. 2007, 12.

Grum, B., and Govekar, D. (2016). "Influence of Macroeconomic Factors on Prices of Real Estate in Various Cultural Environments: Case of Slovenia, Greece, France, Poland and Norway." *Procedia Economics and Finance*, 39, pp. 5987-604.

He, Y., and Wang, Y. (2022). "Macroeconomic effects of COVID-19 pandemic: Fresh evidence from Korea." *Sustainability*, 14(9), 5100.

Hochreiter, S., and Schmidhuber, J. (1997). "Lstm can solve hard long time lag problems." *Advances in neural information processing systems*, pp. 473-479.

Hossain, B., and Latif, E. (2009). "Determinants of housing price volatility in Canada: a dynamic analysis." *Applied Economics*, 41(27), pp. 3521-3531.

Hwang, S., Park, M., Lee, H., and Yoon, Y. (2010). "Analysis of the Korean Real Estate Market and Boosting Policies Focusing on Mortgage Loans: Using System Dynamics." *Korean Journal of Construction Engineering and Management*, KICEM, 11(1), pp. 101-112.

Hochreiter, S., and Schmidhuber, J. (1997). "Long Sort-Term Memory." *Neural Computation*, 9(8), pp. 1735-1780.

Iacoviello, M. (2000). House prices and the macroeconomy in Europe: results from a structural VAR analysis.

International Monetary Fund (2023). IMF Executive Board Concludes 2023 Article IV Consultation with Republic of Korea. https://www.imf.org/en/News/Articles/2023/11/16/pr23397-republic-of-korea-imf-exec-board-concludes-2023-art-iv-consult (January 8, 2024).

Irandoust, M. (2019). "House Prices and Unemployment: An Empirical Analysis of Causality." *International Journal of Housing Markets and Analysis*, 12(1), pp. 148-164.

Jacobson, T., Jansson, P., Vredin, A., and Warne, A. (2001). "Monetary policy analysis and inflation targeting in a small open economy: a VAR approach." *Journal of Applied Econometrics*, 16(4), pp. 487-520.

Jacobsen, D., and Naug, B. (2005). "What drives house prices?" *Penger of Kreditt Economic Bulletin 05 Q1*, pp. 29-41.

Kang, M., Choi, Y., Kim, J., Lee, K.O., Lee, S., Park, I.K., and Seo, I. (2020). "COVID-19 impact on city and region: what's next after lockdown?." *International Journal of Urban Sciences*, 24(3), pp. 297-315.

Kartal, M.T., Kılıç Depren, S., and Depren, Ö. (2023). "Housing prices in emerging countries during COVID-19: evidence from Turkey." *International Journal of Housing Markets and Analysis*, 16(3), pp. 598-615.

Khan, Md. S., and Khan, U. (2020). "Comparison of forecasting prsormance with VAR vs. ARIMA models using economic variables of Bangladesh." *Asian Journal of Probability and Statistics*, 10(2), pp. 33-47.

Kim, J.G. (2013). "An empirical analysis on the relationship between stock price, interest rate, price index and housing price using VAR model." *Journal of Distribution Science*, 11(10), pp. 63-72.

Kim, H., Chin, K., and Lee, K. (2012). "A study on Relationship between House Rental Price and Macroeconomic Variables." *Korean Journal of Construction Engineering and Management*, KICEM, 13(2), pp. 128-136.

Korean Statistical Information Service (2023). Housing sales price index by scale. KOSIS. 〈https://www.kosis.kr/eng〉 (Oct. 25, 2023).

Korkmaz, Ö. (2019). "The relationship between housing prices and inflation rate in Turkey: Evidence from panel Konya causality test." *International Journal of Housing Markets and Analysis*, 13(3), pp. 427-452.

Laurinavičius, A., Laurinavičius, A., and Laurinavičius, A. (2022). "Macroeconomic variables influencing housing prices in Vilnius." *International Journal of Strategic Property Management*, 26(1), pp. 23-34.

Makridakis, S. (1993). "Accuracy measures: theoretical and practical concerns." *International Journal of*

Forecasting, 9(4), pp. 527-529.

Marfatia, H. (2021). "Time-frequency linkages of international housing markets and macroeconomic drivers." *International Journal of Housing Markets and Analysis*, 14(4), pp. 652-679.

Mishra, S, Singh, T., Manish, K., and Satakshi. (2023). "Multivariate time series short term forecasting using cumulative data of coronavirus." *Evolving Systems*, 15, pp. 811-828.

MOFA. (2020). All about Korea's response to COVID-19. Government of the Republic of Korea. Retrieved 〈https://www.mofa.go.kr/〉 (Oct. 27, 2023).

Mohan, S., Hutson, A., MacDonald, I., and Lin, C.C. (2019). "Impact of macroeconomic indicators on housing prices." *International Journal of Housing Markets and Analysis*, 12(6), pp. 1055-1071.

Nguyen, T.B., and Le, C.V. (2023). "Impacts of monetary policy on housing prices in five emerging economies during the Covid-19 pandemic." International Journal of Housing Markets and Analysis.

Nneji, O., Brooks, C., and Ward, C.W. (2013). "House price dynamics and their reaction to macroeconomic changes." *Economic Modelling*, 32, pp. 172-178.

Oh, S., Moon, H.C., and Zhong, Y. (2020). "Contingency management and supply chain performance in Korea: A covid-19 pandemic approach." *Sustainability*, 12(23), p. 9823.

Otrok, C., and Terrones, M.E. (2005). "House prices, interest rates and macroeconomic fluctuations: international evidence." International Monetary Fund, mimeo.

Panagiotidis, T., and Printzis, P. (2016). "On the macroeconomic determinants of the housing market in Greece: a VECM approach." *International Economics & Economic Policy*, 13(3), pp. 387-409.

Pinjaman, S., and Kogid, M. (2020). "Macroeconomic determinants of house prices in Malaysia." *Jurnal Ekonomi Malaysia*, 54(1), pp. 153-165.

Pommeranz, C., and Steininger, B. (2020). "What drives the premium for energy-efficient apartments – green awareness or purchasing power?" *Journal of Real Estate Finance and Economics*, 62(2), pp. 220-241.

Shetty, J., Cottur, K., Shobha, G., and Prajwal, Y. (2023). "A weighted ensemble of VAR and LSTM for multivariate forecasting of cloud resource usage." *Journal of Advances in Information Technology*, 14(2), pp. 264-270.

Sims, C. (1980). "Macroeconomic and reality." *Econometrica*, 48(1), pp. 1-48.

S,ipos C., and Buglea, A. (2015). "An analysis of the evolutions of real estate market and purchasing power within the European Union." *Theoretical and Applied Economics*, 22, p. 8.

Son, J., and Park, H. (2019). "U.S. interest rate and household debt *sustainability*: the case of Korea." Sustainability, 11(3759), pp. 1-16.

Stefanski, M. (2023). "Quantitative easing during the COVID-19 pandemic: a cross-country study." *SGH KAE Working Papers Series,* 088, pp. 1-80.

Trofimov, I., Aris, N., and Xuan, D. (2018). "Macroeconomic and demographic determinants of residential property prices in Malaysia." *Zagreb International Review of Economics and Business*, 21(2), pp. 71-96.

Willmont, C., and Matsuura, K. (2005). "Advantages of the mean absolute error (MAE) over mean square error (RMSE) in assessing average model performance." *Climate Research*, 30(1), pp. 79-82.

Yiu, C.Y. (2021). "Why house prices increase in the COVID-19 recession: A five-country empirical study on the real interest rate hypothesis." *Urban Science*, 5(4), p. 77.

Yu, L., Jiao, C., Xin, H., Wang, Y., and Wang, K. (2018). "Prediction on housing price based on deep learning." *International Journal of Computer and Information Engineering*, 12(2), pp. 90-99.

Zhai, W., Wu, G., Xin, L., and Niu, L. (2021). "Forecast of Broad Money Supply Based on Long Short-term Memory Neural Network (LSTM-NN)." In 2021 7th International Conference on Big Data and Information Analytics, pp. 406-412.