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Predicting the Total Construction Spending of Health Care by Using SARIMA Model: United States Case

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ABSTRACT

This study aims to determine the optimal model to predict the Total Construction Spending of Health Care by using Seasonal Autoregressive Integrated Moving Average Model (SARIMA). SARIMA Model was performed during 22 years from January 2002 to December 2023 of Total Construction Spending of HealthCare (SHC), Millions of Dollars, from Federal Reserve Economic Data. The researcher concluded that the estimated model of the first order difference for the logarithm of SHC (DLSHC) series is SARIMA (1,1,2) $(0,1,2)_{12}$. With coefficients: C = 0.003845, AR (1) = 0.970015, MA (1) = -1.147784, MA (2) = 0.219215, MA (12) = -0.89710 & MA (24) = -0.227258. This Model has more than 50% of the coefficients are statistically significant at 5% level. The jointly significant F-statistic value equals (3.893122) with P-value (0.000981), S.E. of regression equals (0.019284). The ability to predict SARIMA (1, 1, 2) $(0,1,2)_{12}$ Model is satisfactory, with a highly predictive power, with Theil Inequality Coefficient equals (0.000898) and Biaproportion equals (0.000087).

Keywords: Predicting, Construction spending, Spending, Health care, and SARIMA model.

INTRODUCTION:

Health care is the core of community. It is the most significant among other things as it gives genuine and true benefits to people. Health care requires a substantive expansion in its utilities from clinics to hospitals and so on. Health systems are organizations established to meet the health needs of targeted populations. According to the World Health Organization (WHO), a well-functioning healthcare system requires a monetary mechanism, a tight and a sufficient well-arranged paid workforce, authentic database on which to base decisions and policies, and well-maintained health facilities particularly to deliver high quality medicines and technologies. A competent healthcare system can contribute to a significant part in a country's economy, development, and industrialization. Health care is conventionally regarded as the most important determinant in promoting the general physical and mental health and serves in the well-being of people around the world (WHO, 2019). Healthcare facilities may vary across nations and communities according to several factors that are influenced by socio-economic conditions as well as political factors. Providing health care services means "the timely use of personal health services to achieve the best possible health outcomes" (Millman M., 1993; Sultan MA., 2023).

Many empirical papers have applied the SARIMA model: Prista N. *et al.* (2011) "Use of the SARIMA Models to Assess Data-Poor Fisheries: A Case Study with A Sciaenid Fishery Off Portugal", conclude that the SARIMA model was able to find adequately fitted and has forecasted the time series of meagre landings (12-month forecasts; mean error: 3.5 tons (t); annual absolute percentage error: 15.4%), in spite of its limited sample size. Therefore, we derive model-based prediction intervals and demonstrate the idea of how they can be used to detect problem-atic situations in the fishery Chhabra *et al.,* (2023). “A Comparative Study of ARIMA and SARIMA Models to Forecast Lockdowns due to SARS-CoV-2”, a brief comparison between trained ARIMA & SARIMA models which are the presented, where ARIMA model gained an upper hand due to its accuracy. Additionally, the models are able to pre-dict confirmed death and confirmed cases of COVID Liu *et al.,* (2023). “Application of SARIMA model in forecasting and analyzing inpatient cases of acute mountain sickness”, conclude that AMS inpatients have an evident periodicity and seasonality. The SARIMA model has a perfect ability and is accurate in predicting on the short-term. It helps in exploring various characteristics of AMS disease & provide any relevant medical resources for AMS inpatients.

MATERIALS AND METHODS:

Monthly data of the Total Construction Spending of Health Care in United State (SHC), Millions of Dollars, were obtained from the Federal Reserve Economic Data https://fred.stlouisfed.org/series/ TLHLTHCONS). SARIMA Model was performed during 22 years from January 2002 to December 2023 by using Stationary test (Unit Root of Augmented Dickey-Fuller) which was performed on the SHC series, as well as autocorrelation and partial autocorrelation function graphs was performed to determine the laying of difference and the appropriate transformation that should be used to convert it to stationary series. The researcher will determine the appropriate model of SARIMA (p, d, q) (P, D, Q)$_S$, by selecting the model that has a larger significant coefficient and the highest R-squared value along with the smallest values of Akai Info. Criterion, Schwarz Criterion and SIGMASQ (Box *et al.,* 2015; Gujarati *et al.,* 2009; Fan *et al.,* 2009).

SARIMA is an extended algorithm that has a sea-sonal component along with the ARIMA (Auto Regressive Integrated Moving Average) method. The model assumes that the Total Construction Spending of Health Care in the United States (SHC) data comprises trends, seasonal components, and irregular terms. For ARMA (p, q) equation we will use L operator, which denotes the lag operator,

Where $L^n x_t = x_{t-n}$

$$x_t = \alpha + \sum_{i=1}^{p} \alpha_i L^i x_t + \mu + \sum_{i=1}^{q} \theta_i L^i \varepsilon_t + \varepsilon_t \quad (1)$$

Which can be represented as follow:

$$x_t = \alpha(L)^p x_t + \theta(L)^q \varepsilon_t + \varepsilon_t \quad (2)$$

It can be assumed that ARIMA (p, d, q) equation will turn out to be:

$$\Delta^d x_t = \alpha(L)^p \Delta^d x_t + \theta(L)^q \Delta^d \varepsilon_t + \Delta^d \varepsilon_t \quad (3)$$

By using seasonal lags and an ARMA (P, Q) model on the different values, we can extract any remaining structure. In other words, we use L^S rather than the standard lag operator L. Once more, P and Q are seasonal time lags.

$$\Delta_S^D x_t = A(L^S)^P \Delta_S^D x_t + \vartheta(L^S)^Q \Delta_S^D \varepsilon_t + \Delta_S^D \varepsilon_t \quad (4)$$

We can now apply another ARIMA(p, d, q) model to $\Delta_S^D x_t$ by multiplying the seasonal model by the new ARIMA model in order to remove any remaining seasonality and obtain a mathematical representation of SARIMA(p,d,q)(P,D,Q)$_S$

$$\Delta^d \Delta_S^D x_t = \alpha(L)^p A(L^S)^P \Delta^d \Delta_S^D x_t + \theta(L)^q \vartheta(L^S)^Q \Delta^d \Delta_S^D \varepsilon_t + \Delta^d \Delta_S^D \varepsilon_t \quad (5)$$

(Gujarati *et al.,* 2009; Carter *et al.,* 2011) Seasonal Auto-Regressive Integrated Moving Average (SARIMA) was established to:

- Analyze and explore the intrinsic structure of the series
- Determine the seasonal variations.
- Determine the optimum model for prediction.
- Analyze the performance of SARIMA Model.
- Forecasting for the next year during the months using the SARIMA Model.

The data were analyzed with Econometrics Views (EViews) Release 10.

RESULTS AND DISCUSSION:

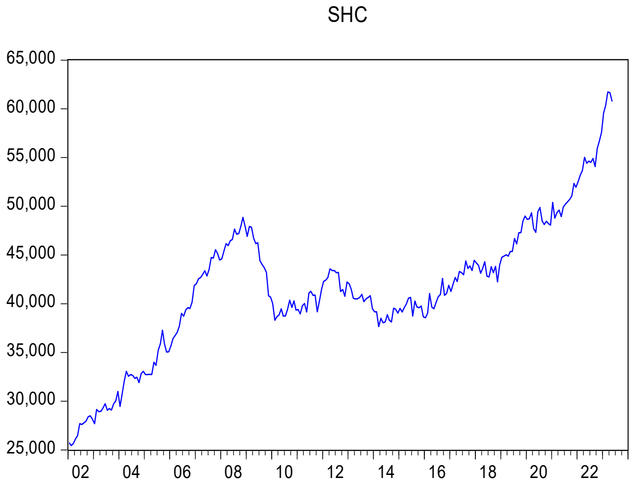


Fig. 1: Monthly Data of the Total Construction Spending of Health Care in USA during January 2002 - December 2023.

The above figure shows that the SHC series has exponential shape and have some seasonality affect.

Table 1: Descriptive Statistics for Monthly Data of the Total Construction Spending of Health Care in USA during January 2002 – December 2023.

Mean	**41570.63**
Median	41262.00
Maximum	61749.00
Minimum	25438.00
Std. Dev.	7122.802
Observations	257

According to the above table, the Total Construction Spending of Health Care in millions of dollars is range between (25438 - 61749) with mean value (41570.63), median value (41262) and std. Dev. (7122.802).

Table 2: Augment Dickey-Fuller Unit Root Test on SHC.

Null Hypothesis: SHC has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=15)			
Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-0.287389	0.9235
Test critical values	1% level	-3.455786	
	5% level	-2.872630	
	10% level	-2.572754	

Table 2 shows that the Augment Dickey-Fuller statistic is (-0.287389) with P-value (0.9235) which is not a statistically significant value at level 1%, 5%, 10% respectively. Therefore, we wouldn't be able to reject the null hypothesis; that SHC has a unit root, and we conclude that the series of SHC is non-stationary. As in **Fig. 1**, the original series has exponential shape, so we should try to eliminate its non-stationary by using the logarithm of the SHC.

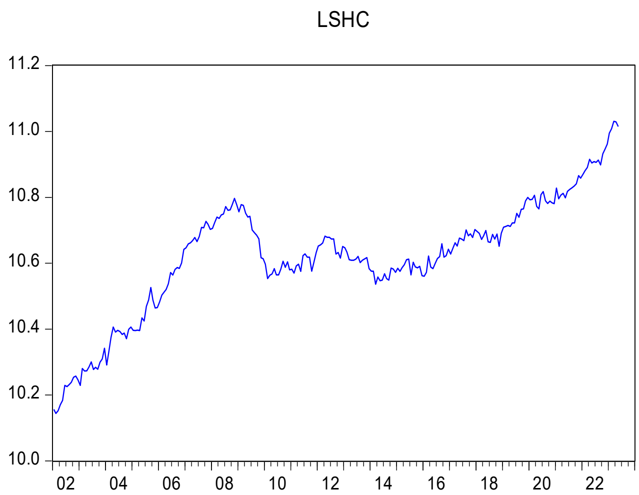


Fig. 2: The LSHC Data During January 2002 - December 2023: is Plotted in Fig. 2.

Table 3: Augment Dickey-Fuller Unit Root Test on LSHC.

Null Hypothesis: LSHC has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=15)			
Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-1.437988	0.5634
Test critical values	1% level	-3.455786	
	5% level	-2.872630	
	10% level	-2.572754	

According to **Fig. 2** and **Table 3**, the results show that the Augment Dickey-Fuller statistic of LSHC is (-1.437988) with P-value (0.5634) which is not statistically significant value at level 1%, 5%, 10% respectively. Therefore, we wouldn't be able to reject the null hypothesis; that LGDP has a unit root, and we conclude that the series of LSHC is still non stationary. Further, the first order difference is performed and the D (LSHC) series is obtained as in the following table:

Table 4: Augment Dickey-Fuller Unit Root Test on D (LSHC).

Null Hypothesis: D(LSHC) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=15)			
Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*
		-18.57187	0.0000
Test critical values	1% level	-3.455887	
	5% level	-2.872675	
	10% level	-2.572778	

The Augment Dickey-Fuller statistic of D (LSHC) is (-18.57187) with P-value (0.0000) and is a statistically significant value at level 1%, 5%, 10% respecttively. Therefore, we wouldn't be able to reject the null hypothesis; that D (LSHC) has a unit root, and we conclude that the series of D (LSHC) is the stationary. The autocorrelation and the partial correlation function graphs of D (LSHC) series are plotted in the figure below.

In the above **Table 5** the autocorrelation of the D (LSHC) series is significantly non zero when the lag order is q=1 or q=2, as it is basically in confidence band when the lag order is greater than 2. The same goes as well for partial autocorrelation where we take p=1 or p=2, hence the final order with 0, 1, 2 in autoregressive moving average pre-estimation is performed on sample series. In the seasonal part, we can take q=1 or q=2 as the same as p=1 or p=2.

Table 5: Correlogram of D (LSHC).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.154	-0.154	6.1123	0.013
		2	0.003	-0.021	6.1143	0.047
		3	0.048	0.046	6.7116	0.082
		4	0.068	0.084	7.9075	0.095
		5	0.036	0.062	8.2465	0.143
		6	0.057	0.074	9.1182	0.167
		7	0.018	0.033	9.2059	0.238
		8	0.013	0.011	9.2505	0.322
		9	0.055	0.046	10.060	0.346
		10	0.060	0.064	11.019	0.356
		11	0.019	0.031	11.118	0.433
		12	-0.011	-0.016	11.153	0.516
		13	0.059	0.038	12.098	0.520
		14	-0.051	-0.058	12.816	0.541
		15	0.005	-0.031	12.821	0.616
		16	0.009	-0.013	12.844	0.684
		17	0.071	0.066	14.256	0.649
		18	0.069	0.098	15.570	0.623
		19	0.010	0.037	15.595	0.684
		20	-0.135	-0.143	20.707	0.415
		21	0.096	0.030	23.271	0.330
		22	0.023	0.021	23.424	0.378
		23	0.051	0.063	24.151	0.395
		24	-0.140	-0.126	29.737	0.194
		25	0.033	-0.015	30.044	0.223
		26	-0.007	-0.022	30.058	0.265
		27	0.027	0.015	30.267	0.302
		28	-0.061	-0.071	31.344	0.302
		29	0.054	0.054	32.206	0.311
		30	-0.065	-0.034	33.426	0.304
		31	0.002	-0.003	33.427	0.350
		32	0.010	0.002	33.458	0.396
		33	-0.038	-0.010	33.889	0.424

Table 6: Automatic ARMA Forecasting.

Automatic ARMA Forecasting
Selected dependent variable: D(LSHC)
Sample: 2002M01 2023M12
Included observations: 256
Forecast length: 0
Number of estimated ARMA models: 81
Number of non-converged estimations: 0
Selected ARMA model: (1,2)(0,2)
AIC value: -5.02625776141

According to Akaike Information Criteria in **Fig. 3** and Automatic ARMA Forecasting in **Table 5**, the selected ARMA Model is (1,2)(0,2) with AIC* value (-5.026258), which is the best one out from 81 estimated ARMA Models that have significant parameters with the highest R-squared value and the lowest values of Akai Info. Criterion, Schwarz Criterion and SIGMASQ.

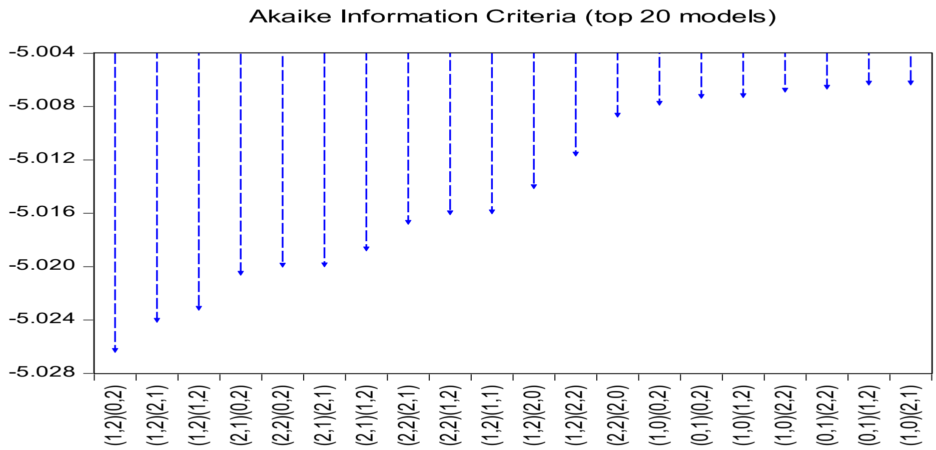


Fig. 3: Akaike Information Criteria.

Table 7: The Estimated Results of SARIMA (1, 1, 2) (0, 1, 2)$_{12}$ Model.

Dependent Variable: D(LSHC)				
Method: Least Squares				
Sample: 2002M02 2023M05				
Included observations: 256				
Convergence achieved after 17 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003845	0.001892	2.031539	0.0433
AR(1)	0.970015	0.030383	31.92642	0.0000
MA(1)	-1.147784	0.069909	-16.41819	0.0000
MA(2)	0.219215	0.064498	3.398800	0.0008
SMA(12)	-0.089710	0.078744	-1.139266	0.2557
SMA(24)	-0.227258	0.066969	-3.393472	0.0008
SIGMASQ	0.000362	3.12E-05	11.60168	0.0000
R-squared	0.085765	Mean dependent var		0.003354
Adjusted R-squared	0.063735	S.D. dependent var		0.019929
S.E. of regression	0.019284	Akaike info criterion		-5.026258
Sum squared resid	0.092594	Schwarz criterion		-4.929319
Log likelihood	650.3610	Hannan-Quinn criter.		-4.987269
F-statistic	3.893122	Durbin-Watson stat		1.967391
Prob(F-statistic)	0.000981			

According the above results shown in **Table 7**, the estimated model is SARIMA (1, 1, 2) $(0, 1, 2)_{12}$ has more than 50% of the coefficients that are statistically significant at level 5%. R-squared value is equal to (0.085765), and the jointly significant F-statistic value equals (3.893122) with P-value (0.000981). Durbin-Waston statistic (1.967391) is found to be 2, so there is no first-order autocorrelation neither positive nor negative. In addition to it, Durbin-Waston statistic is more than R-squared, which emphasize that this model is not spurious. So, the estimated model of the D (LSHC) series SARIMA (1, 1, 2)$(0, 1, 2)_{12}$ is:

$$\mathrm{DLSHC} = 0.003845 + 0.970015\mathrm{AR}(1) - 1.147784\mathrm{MA}(1) + 0.219215\mathrm{MA}(2) - 0.089710\mathrm{SMA}(12) - 0.227258\mathrm{SMA}(24)$$

with S.E. of the regression equals (0.019284) By the using residual diagnostics, we examine the normality of the Model SARIMA (1, 1, 2)$(0, 1, 2)_{12}$ as shown in the following figure:

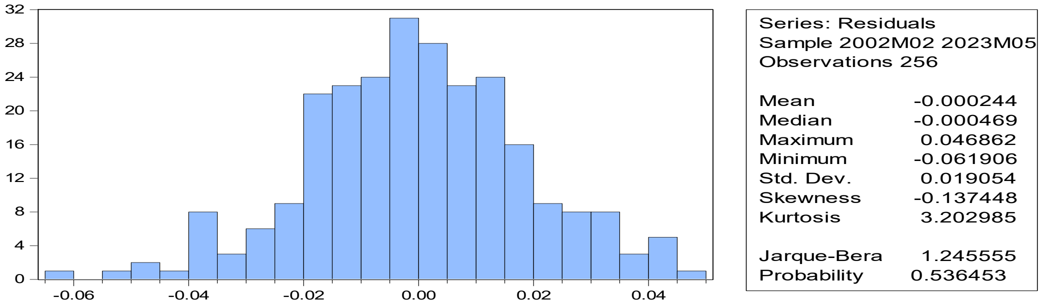


Fig. 4: Normality Test of the Model SARIMA (1, 1, 2) $(0, 1, 2)_{12}$.

The P-value of Jarque-Bera Normality Test is equal to (1.245555) and is not statistically significant at level 5%; so we accept the null hypothesis; that the residuals are normally distributed.

The autocorrelation and the partial autocorrelation function graphs of residual series in the above figure show that the residuals are the white noise which indicates that the model is valid.

Table 8: Correlogram of the Residuals of SARIMA (1, 1, 2) $(0, 1, 2)_S$.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0032	0.955
		2	-0.043	-0.043	0.4925	0.782
		3	0.049	0.050	1.1248	0.771
		4	0.034	0.032	1.4346	0.838
		5	-0.074	-0.071	2.8808	0.718
		6	0.022	0.023	3.0032	0.808
		7	0.012	0.003	3.0431	0.881
		8	-0.078	-0.071	4.6531	0.794
		9	-0.012	-0.008	4.6928	0.860
		10	0.044	0.032	5.2231	0.876
		11	-0.061	-0.055	6.2397	0.857
		12	-0.107	-0.098	9.3158	0.676
		13	0.018	0.002	9.4048	0.742
		14	-0.031	-0.035	9.6628	0.786
		15	-0.037	-0.018	10.031	0.818
		16	0.019	0.008	10.126	0.860
		17	-0.022	-0.037	10.258	0.892
		18	-0.029	-0.014	10.494	0.915
		19	0.080	0.070	12.261	0.874
		20	0.045	0.026	12.839	0.884
		21	-0.015	-0.001	12.900	0.912
		22	-0.050	-0.057	13.594	0.915
		23	0.092	0.070	16.019	0.854
		24	-0.018	-0.020	16.112	0.884
		25	0.003	0.012	16.114	0.911
		26	0.013	-0.007	16.162	0.932
		27	0.008	0.006	16.179	0.949
		28	-0.096	-0.081	18.857	0.903
		29	0.035	0.019	19.222	0.915
		30	-0.068	-0.084	20.588	0.900
		31	-0.002	0.036	20.589	0.922
		32	-0.067	-0.070	21.929	0.909
		33	0.051	0.044	22.712	0.911
		34	0.054	0.062	23.589	0.909
		35	0.025	0.041	23.783	0.925
		36	-0.079	-0.095	25.670	0.899

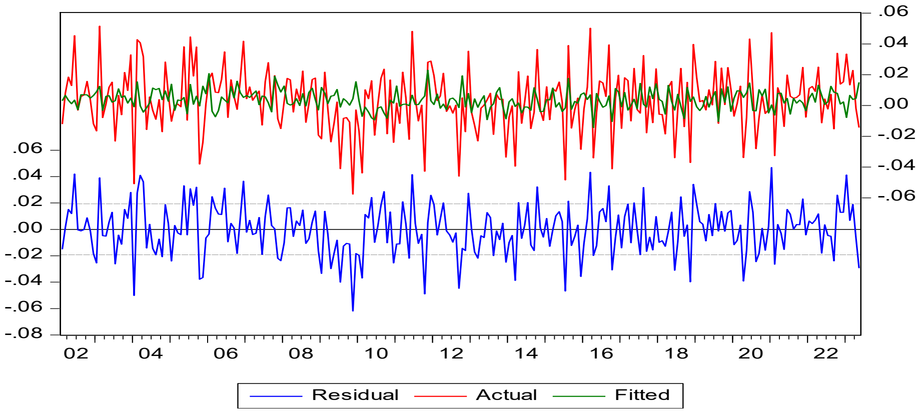


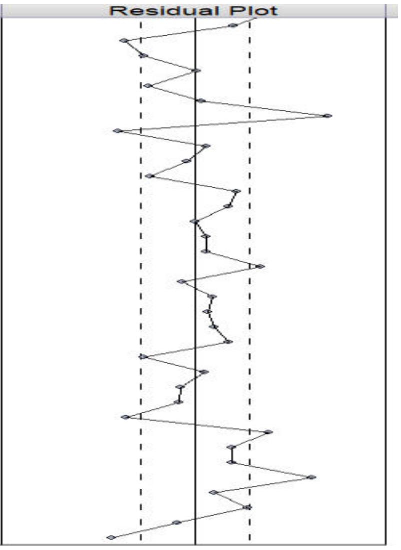
Fig. 5: Actual, Fitted, Residual Graph.

As shown in **Fig. 5**, the actual & fitted series are passing through 50% confidence interval, so the forecasting of D (LSHC) is significant and the ability of forecasting the model is satisfactory. Firstly, we do the forecast inside the sample to check the power of the model in forecasting (Hossain *et al*., 2020).

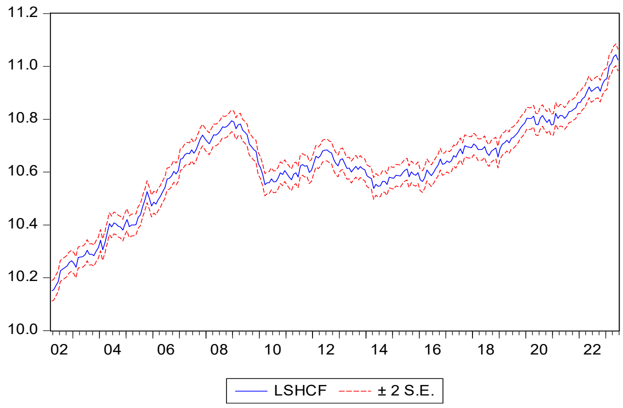
Table 9: Forecast inside the Sample.

obs	Actual	Fitted	Residual
2020M07	0.00969	-0.00337	0.01306
2020M08	-0.02801	-0.00350	-0.02451
2020M09	-0.00786	0.01030	-0.01816
2020M10	0.00694	0.00616	0.00078
2020M11	-0.00519	0.01057	-0.01577
2020M12	-0.00274	-0.00490	0.00215
2021M01	0.04724	0.00038	0.04686
2021M02	-0.03256	-0.00619	-0.02637
2021M03	0.01149	0.00783	0.00367
2021M04	0.00517	0.00801	-0.00284
2021M05	-0.01366	0.00150	-0.01516
2021M06	0.01973	0.00465	0.01508
2021M07	0.00599	-0.00554	0.01153
2021M08	0.00475	0.00460	0.00014
2021M09	0.00520	0.00155	0.00365
2021M10	0.00701	0.00346	0.00356
2021M11	0.02470	0.00161	0.02308
2021M12	-0.00754	-0.00339	-0.00414
2022M01	0.01101	0.00470	0.00631
2022M02	0.01235	0.00795	0.00440
2022M03	0.00912	0.00211	0.00700
2022M04	0.02495	0.01320	0.01175
2022M05	-0.01129	0.00662	-0.01792
2022M06	0.00416	0.00073	0.00343
2022M07	-0.00225	0.00238	-0.00463
2022M08	0.00717	0.01243	-0.00527
2022M09	-0.01516	0.00864	-0.02380
2022M10	0.03385	0.00793	0.02592
2022M11	0.01390	0.00090	0.01300
2022M12	0.01536	0.00240	0.01296
2023M01	0.03341	-0.00776	0.04117
2023M02	0.01339	0.00655	0.00684
2023M03	0.02272	0.00394	0.01878
2023M04	-0.00183	0.00459	-0.00642
2023M05	-0.01436	0.01503	-0.02939

Residual Plot



The above graph shows that the forecasting value of LSHC in 2023M05 is (0.01503) while the actual value is equal to (-0.01436) with a poor relative error 2.93%, so the forecasted value is close to the actual value. Hence, it signifies that the model has a good fitting effect.



Forecast: LSHCF	
Actual: LSHC	
Forecast sample: 2002M01 2023M12	
Adjusted sample: 2002M03 2023M06	
Included observations: 256	
Root Mean Squared Error	0.019092
Mean Absolute Error	0.014945
Mean Abs. Percent Error	0.140841
Theil Inequality Coefficient	0.000898
Bias Proportion	0.000087
Variance Proportion	0.001780
Covariance Proportion	0.998120
Theil U2 Coefficient	0.944876
Symmetric MAPE	0.140834

Fig. 6: Forecast LSHC.

As shown in the above figure, the root mean squared error equals (0.019092), while Theil Inequality Coefficient equals (0.000898), which is close to zero, this means that the predictive power of this model is very strong. Bia proportion equals (0.000087), which means there is no obvious gap between the actual LSHC and the predictive value and they are moving closely, and passing through 50% confidence interval so, the forecasting of LSHC is significant and the ability of forecasting SARIMA (1, 1, 2)(0, 1, 2)$_{12}$ Model is satisfactory. Secondly, by using Box-Jenkies for forecasting SHC during the upcoming year from 2024M01 to 2024M12, the results are shown in the table below:

Table 10: Forecasting of the Total Construction Spending of Health Care in USA: Outside the Sample from January 2024 to December 2024.

Month	Forecasting of LSHC values	Forecasting of SHC values
January	11.14408996309091	69153.916
February	11.14793441593948	69420.286
March	11.15177887237625	69687.683
April	11.15562333229362	69956.111
May	11.15946779558723	70225.572
June	11.16331226215585	70496.071
July	11.16715673190127	70767.613
August	11.17100120472823	71040.201
September	11.17484568054434	71313.839
October	11.17869015925996	71588.531
November	11.18253464078816	71864.282
December	11.18637912504459	72141.094

CONCLUSION:

Seasonal Autoregressive Integrated Moving Average Model SARIMA (1, 1, 2) $(0, 1, 2)_{12}$ is acceptable to the predictive purpose of forecasting the Total Construction Spending of Health Care in USA (SHC):

$$DLSHC = 0.003845 + 0.970015AR(1) - 1.147784MA(1) + 0.219215MA(2) - 0.089710SMA(12) - 0.227258SMA(24)$$

with S.E. of regression equals (0.019284), Durbin-Waston statistic (1.967391) and the probability of F-statistic equals (0.000981). The ability of forecasting SARIMA (1, 1, 2) $(0, 1, 2)_{12}$ Model is satisfactory and carries a highly predictive power, with Theil Inequality Coefficient equals (0.000898) and Bia proportion equals (0.000087).

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CONFLICTS OF INTEREST:

The author confirms that have no conflict of interest.

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