Forecasting Assessment

DSC5122C

Quantitative Risk Management

Group Project 1

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Motivation and project overview

Japan equity market is one of the biggest financial markets in the world and largest among Asia market. The Nikkei 225 or more commonly known as Nikkei Index is a price-weighted index composed of Japan's top 225 blue-chip companies traded on the Tokyo Stock Exchange (TSE), and is often used to identify opportunities and risks in the market. To understand how Japan equity market will perform in 2019, we conduct six months forecast for Nikkei Index. Adjusted Closing Value is chosen as the index monthly performance.

In the later part of the discussion, we will further study the relationship of Hang Seng Index, Nikkei and S&P 500. Any of the index is the main driver and leading the other two? Is Japan highly affected by US or Hong Kong market?

Data description

For time series analysis, we collected 20 years (1999.1-2019.1) of **Nikkei 225, Hang Seng Index**, and **S&P 500 Stock Index** data on monthly frequency (a total of 240 observations) from Yahoo Finance, which can be downloaded here. The **Adjusted Closing Value** is selected for our analysis.

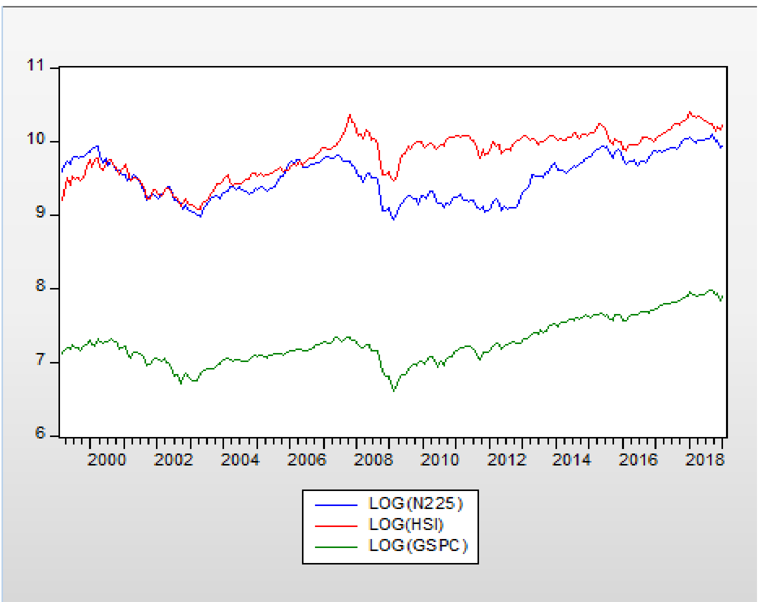


Figure 1 Monthly trend of Hang Seng Index , S&P 500 Stock Index and Nikkei 225 from 1999 Jan to 2019 Jan

Theoretical explanation for the forecasting model

Model Identification

The forecast series must be stationary so that Auto Regressive Integrated Moving Average can be performed. Thus, it's necessary for us to check the stationarity first before the model building.

We can see that Nikkei time series has instances of both positive and negative trend. Overall, it is very volatile, which tells us that we will have to transform the data for the Box-Jenkins Methodology to predict with better accuracy.

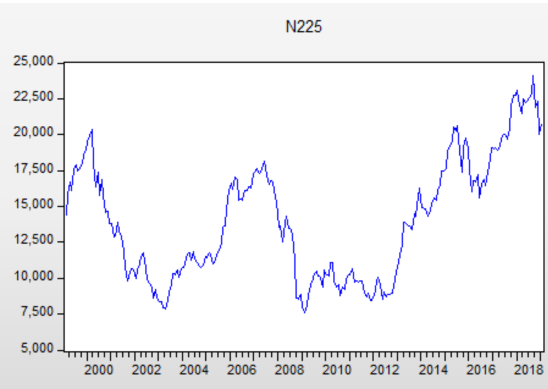


Figure 2 Monthly trend of Nikkei Index from 1999 Jan to 2019 Jan

Augmented Dickey-Fuller Unit Root Test on N225

Null Hypothesis: N225 has a unit root
Exogenous: None
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.245269	0.7566
Test critical values:	1% level	-2.574674	
	5% level	-1.942159	
	10% level	-1.615814	

*MacKinnon (1996) one-sided p-values.

Figure 3 Augmented Dickey-Fuller Unit Root Test on N225

From the result above, the p value of DF test is 0.76, higher than 0.05 threshold, thus we cannot reject the null hypothesis that N225 has a unit root and we can conclude that Nikkei 225 is not stationary.

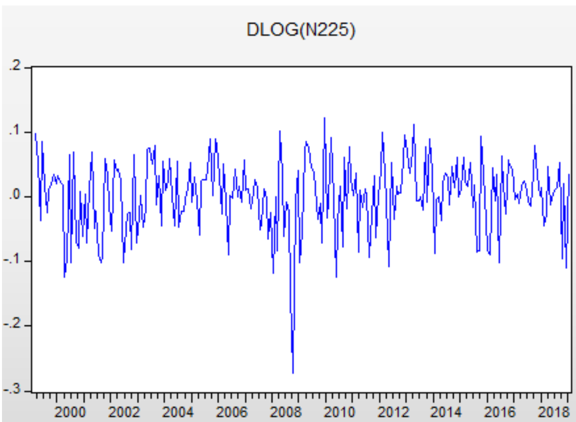


Figure 4 Monthly trend of DLOG(N225) from 1999 Jan to 2019 Jan

Augmented Dickey-Fuller Unit Root Test on DLOG(N225)

Null Hypothesis: DLOG(N225) has a unit root
Exogenous: None
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.64196	0.0000
Test critical values:	1% level	-2.574714	
	5% level	-1.942164	
	10% level	-1.615810	

*MacKinnon (1996) one-sided p-values.

Figure 5 Augmented Dickey-Fuller Unit Root Test on DLOG(N225)

After DLOG transformation, the series graph looks stationary. Dickey-Fuller Test is further conducted to verify the stationarity. The t-Statistics is now significant and null hypothesis can be rejected, thus DLOG(N225) is stationary.

Estimation of the model parameters

Correlogram of DLOG(N225)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.125	0.125	3.7877	0.052
		2	0.055	0.040	4.5262	0.104
		3	0.081	0.071	6.1279	0.106
		4	0.016	-0.004	6.1887	0.185
		5	-0.001	-0.009	6.1891	0.288
		6	-0.074	-0.080	7.5332	0.274
		7	0.022	0.041	7.6587	0.364
		8	0.010	0.010	7.6839	0.465
		9	0.046	0.055	8.2152	0.513
		10	0.028	0.012	8.4124	0.589
		11	0.021	0.011	8.5270	0.665
		12	0.006	-0.015	8.5348	0.742
		13	-0.006	-0.006	8.5452	0.806
		14	-0.016	-0.017	8.6089	0.855
		15	0.011	0.024	8.6383	0.896
		16	-0.017	-0.018	8.7094	0.925
		17	-0.057	-0.052	9.5547	0.921
		18	-0.011	-0.004	9.5850	0.945
		19	0.057	0.065	10.433	0.941
		20	0.028	0.020	10.636	0.955
		21	-0.028	-0.034	10.840	0.966
		22	0.010	0.002	10.865	0.977
		23	-0.005	-0.016	10.871	0.984
		24	-0.011	-0.004	10.906	0.990
		25	-0.024	-0.010	11.063	0.993
		26	-0.041	-0.030	11.524	0.994
		27	0.011	0.020	11.560	0.996
		28	-0.027	-0.028	11.764	0.997
		29	0.033	0.040	12.071	0.998
		30	0.016	0.006	12.139	0.998
		31	-0.049	-0.055	12.791	0.998
		32	0.007	0.011	12.803	0.999
		33	-0.056	-0.053	13.693	0.999
		34	-0.018	-0.006	13.786	0.999
		35	-0.054	-0.039	14.618	0.999
		36	-0.064	-0.036	15.783	0.999

Figure 6 Correlogram of DLOG(N225)

As shown in the correlogram of DLOG(N225), the PACF and ACF function have a significant spike at period one and then cut-off. Therefore, we start our model by using AR (1).

Analysis of the model results

ARIMA models

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 13:52
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.151876	0.065767	2.309285	0.0218
R-squared	0.021405	Mean dependent var		0.002092
Adjusted R-squared	0.021405	S.D. dependent var		0.056392
S.E. of regression	0.055786	Akaike info criterion		-2.930101
Sum squared resid	0.703321	Schwarz criterion		-2.915013
Log likelihood	333.5665	Hannan-Quinn criter.		-2.924013
Durbin-Watson stat	1.997658			
Inverted AR Roots	.15			

Figure 7 Summary of AR (1)

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 13:59
Sample: 1999M03 2018M01
Included observations: 227
Estimation settings: tol= 0.00010
Initial Values: C(1)=0.14097, C(2)=0.02383
Convergence achieved after 5 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.148378	0.066646	2.226361	0.0270
AR(2)	0.024198	0.066657	0.363023	0.7169
R-squared	0.021970	Mean dependent var		0.002092
Adjusted R-squared	0.017623	S.D. dependent var		0.056392
S.E. of regression	0.055893	Akaike info criterion		-2.921862
Sum squared resid	0.702916	Schwarz criterion		-2.891686
Log likelihood	333.6313	Hannan-Quinn criter.		-2.909686
Durbin-Watson stat	1.995073			
Inverted AR Roots	.25	-.10		

Figure 8 Summary of AR (1) AR (2)

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 13:48
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.554610	0.314500	1.763465	0.0792
MA(1)	-0.418790	0.343108	-1.220579	0.2235
R-squared	0.024058	Mean dependent var		0.002092
Adjusted R-squared	0.019720	S.D. dependent var		0.056392
S.E. of regression	0.055834	Akaike info criterion		-2.923967
Sum squared resid	0.701415	Schwarz criterion		-2.893792
Log likelihood	333.8703	Hannan-Quinn criter.		-2.911791
Durbin-Watson stat	1.975590			
Inverted AR Roots	.55			
Inverted MA Roots	.42			

Figure 9Summary of AR (1) MA (1)

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 13:56
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.126335	0.062845	2.010260	0.0456
AR(3)	-0.384964	0.274644	-1.401683	0.1624
MA(3)	0.516890	0.257832	2.004756	0.0462
R-squared	0.035909	Mean dependent var		0.002092
Adjusted R-squared	0.027301	S.D. dependent var		0.056392
S.E. of regression	0.055617	Akaike info criterion		-2.927017
Sum squared resid	0.692898	Schwarz criterion		-2.881753
Log likelihood	335.2164	Hannan-Quinn criter.		-2.908752
Durbin-Watson stat	1.947664			
Inverted AR Roots	.41+.63i	.41-.63i	-.69	
Inverted MA Roots	.40+.70i	.40-.70i	-.80	

Figure 10 Summary of AR (1) AR (3) MA (3)

Among all the models above, AR (1) model has the lowest AIC, Schwarz criterion and Hannan-Quinn criter. The coefficient of AR (1) is also significant at level 0.05. As with regression, residuals should have zero mean, fixed variance, no autocorrelation, we further conduct the residual test. Here, we cannot use DW when lag is an explanatory variable.

Residual test

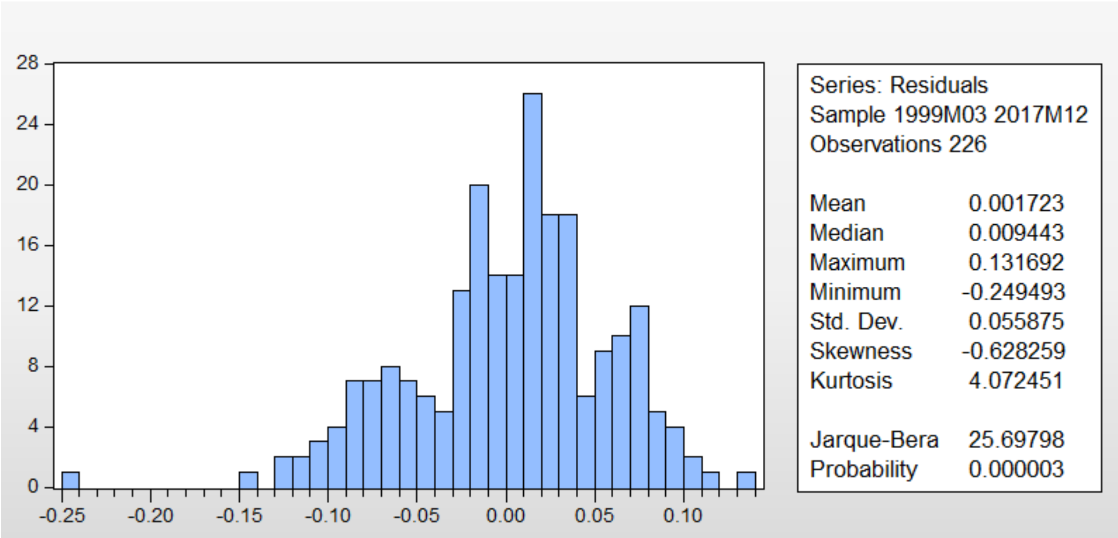
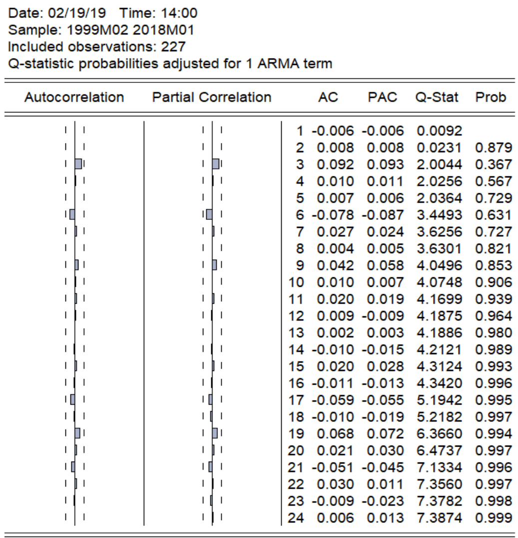


Figure 11 Normality test

Figure 12 AR (1) Residual Plot


Date: 02/19/19 Time: 14:00
Sample: 1999M02 2018M01
Included observations: 227
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0092	
		2	0.008	0.008	0.0231	0.879
		3	0.092	0.093	2.0044	0.367
		4	0.010	0.011	2.0256	0.567
		5	0.007	0.006	2.0364	0.729
		6	-0.078	-0.087	3.4493	0.631
		7	0.027	0.024	3.6256	0.727
		8	0.004	0.005	3.6301	0.821
		9	0.042	0.058	4.0496	0.853
		10	0.010	0.007	4.0748	0.906
		11	0.020	0.019	4.1699	0.939
		12	0.009	-0.009	4.1875	0.964
		13	0.002	0.003	4.1886	0.980
		14	-0.010	-0.015	4.2121	0.989
		15	0.020	0.028	4.3124	0.993
		16	-0.011	-0.013	4.3420	0.996
		17	-0.059	-0.055	5.1942	0.995
		18	-0.010	-0.019	5.2182	0.997
		19	0.068	0.072	6.3660	0.994
		20	0.021	0.030	6.4737	0.997
		21	-0.051	-0.045	7.1334	0.996
		22	0.030	0.011	7.3560	0.997
		23	-0.009	-0.023	7.3782	0.998
		24	0.006	0.013	7.3874	0.999

Figure 13 : AR (1) Residual Correlogram

To verify the assumptions of residual, we did a residual diagnosis in EViews. From figure 12 and figure 13, we can conclude that the residual of our model satisfies the three assumptions:

- normally distributed
- independent (no autocorrelation)
- same variance (no heteroscedasticity)

Forecast

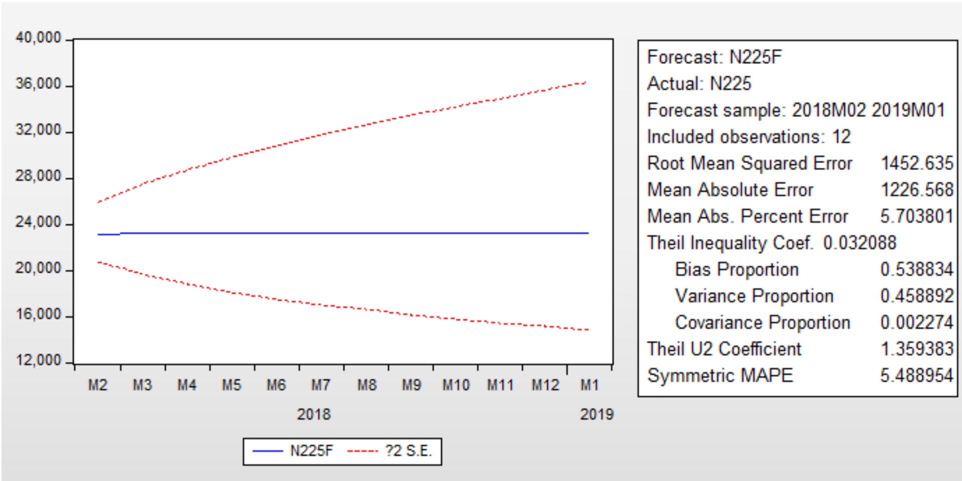


Figure 14 In-sample forecast for one year(dynamic)

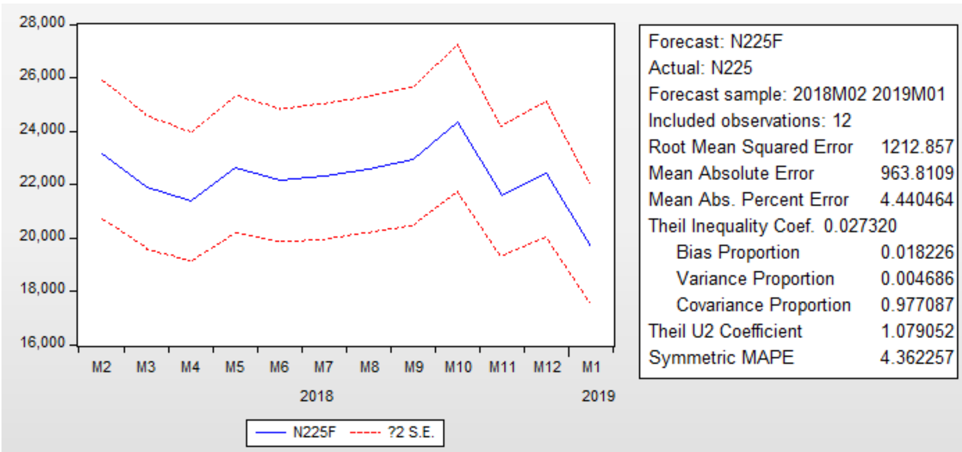


Figure 15 In-sample forecast for one year(static)

To evaluate our static forecast result, we can have a look at the index. The Theil Inequality Coefficient is 2.7%, which indicates it's a very good fit. For Bias Proportion, 1.8% tells us that the forecast for the mean are very close to the actual values. For the Variance Proportion, 0.4% tells us the variance of the forecasts is almost perfect. For Covariance Proportion, 97.7% tells us that a big proportion of forecasting errors are unsystematic. Overall, this is a very good model.

Mixed ARIMA model

To further improve the model, Japan Unemployment Rate (Aged 15 and Over), Consumer Purchase Index and the Long-Term Government Bond interest rate are included in our Mixed

Arima Model, we also run multiple regressions to select the best model to do the forecast.

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 15:23
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003272	0.004239	0.771870	0.4410
DLOG(UER)	0.051407	0.120166	0.427797	0.6692
DLOG(CPI)	1.019345	1.213828	0.839777	0.4019
DLOG(LTGB+0.3)	0.125705	0.028965	4.339931	0.0000
AR(1)	0.152039	0.066941	2.271248	0.0241

R-squared	0.101984	Mean dependent var	0.002092
Adjusted R-squared	0.085803	S.D. dependent var	0.056392
S.E. of regression	0.053919	Akaike info criterion	-2.980788
Sum squared resid	0.645409	Schwarz criterion	-2.905348
Log likelihood	343.3194	Hannan-Quinn criter.	-2.950347
F-statistic	6.302875	Durbin-Watson stat	1.990627
Prob(F-statistic)	0.000080		
Inverted AR Roots	.15		

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 15:26
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(UER)	0.043387	0.119536	0.362963	0.7170
DLOG(CPI)	1.031767	1.212787	0.850741	0.3958
DLOG(LTGB+0.3)	0.124479	0.028881	4.310149	0.0000
AR(1)	0.154849	0.066733	2.320416	0.0212

R-squared	0.099581	Mean dependent var	0.002092
Adjusted R-squared	0.087467	S.D. dependent var	0.056392
S.E. of regression	0.053870	Akaike info criterion	-2.986922
Sum squared resid	0.647136	Schwarz criterion	-2.926571
Log likelihood	343.0157	Hannan-Quinn criter.	-2.962569
Durbin-Watson stat	1.990216		
Inverted AR Roots	.15		

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 15:27
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 4 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(UER)	0.036608	0.119105	0.307360	0.7589
DLOG(LTGB+0.3)	0.123842	0.028842	4.293767	0.0000
AR(1)	0.158252	0.066287	2.387378	0.0178

R-squared	0.096646	Mean dependent var	0.002092
Adjusted R-squared	0.088580	S.D. dependent var	0.056392
S.E. of regression	0.053837	Akaike info criterion	-2.992474
Sum squared resid	0.649246	Schwarz criterion	-2.947210
Log likelihood	342.6458	Hannan-Quinn criter.	-2.974209
Durbin-Watson stat	1.991587		
Inverted AR Roots	.16		

Dependent Variable: DLOG(N225)
Method: ARMA Generalized Least Squares (BFGS)
Date: 02/19/19 Time: 15:28
Sample: 1999M03 2018M01
Included observations: 227
Convergence achieved after 4 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(LTGB+0.3)	0.123782	0.028782	4.300724	0.0000
AR(1)	0.159456	0.066107	2.412094	0.0167

R-squared	0.096266	Mean dependent var	0.002092
Adjusted R-squared	0.092249	S.D. dependent var	0.056392
S.E. of regression	0.053728	Akaike info criterion	-3.000862
Sum squared resid	0.649519	Schwarz criterion	-2.970686
Log likelihood	342.5978	Hannan-Quinn criter.	-2.988686
Durbin-Watson stat	1.989215		
Inverted AR Roots	.16		

Figure 16: Mixed Arima Model

Among all the models above, the fourth model which consists of AR (1) and DLOG (LTGB+0.3) has the lowest AIC, Schwarz criterion and Hannan-Quinn criter. The coefficient of AR (1) and DLOG (LTGB+0.3) are all significant at level 0.05. As with regression, residuals should have zero mean, fixed variance, no autocorrelation, we further conduct the residual test. Here, we cannot use DW when lag is an explanatory variable.

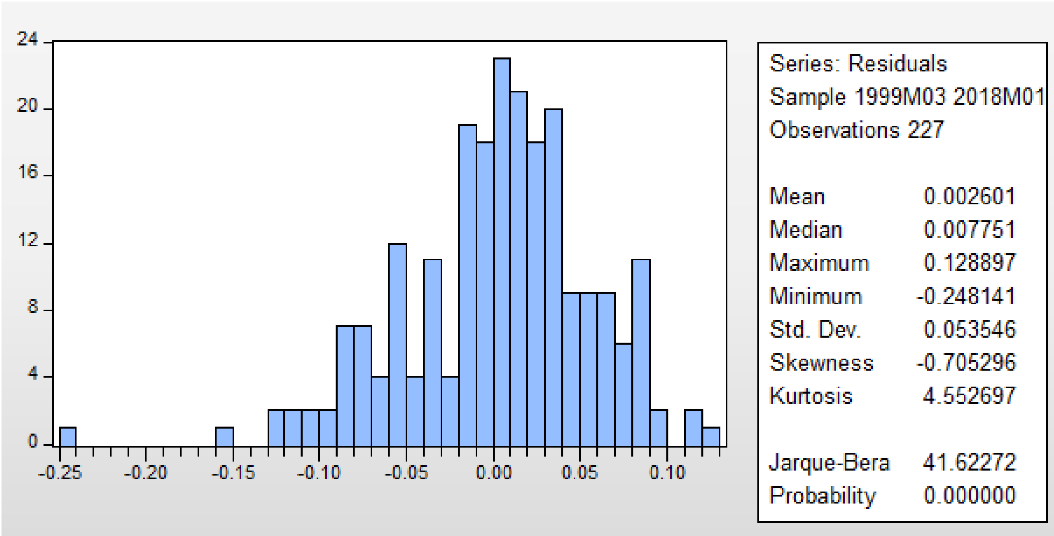


Figure 17 Residual Plot Histogram

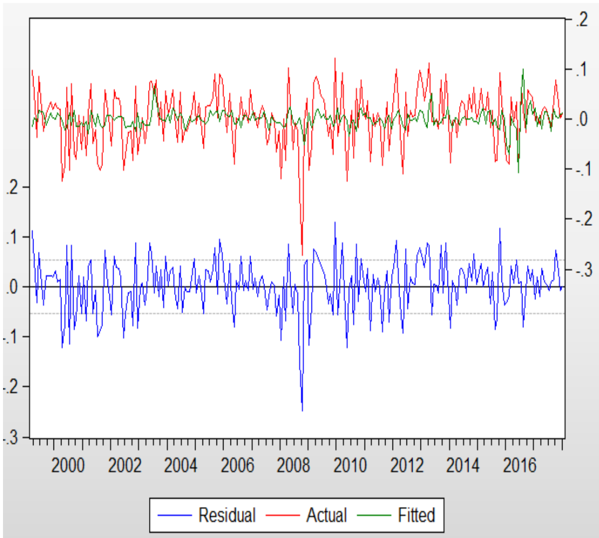
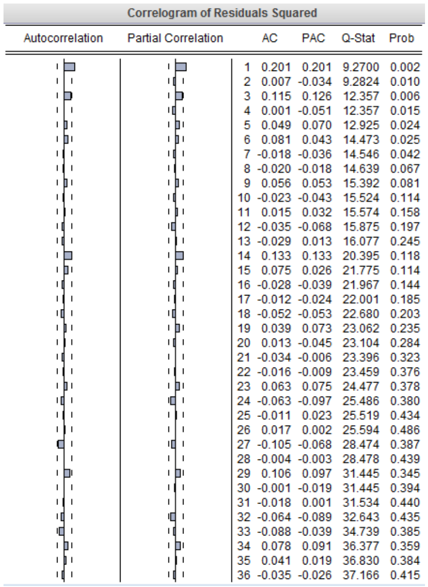


Figure 18 Residual Correlogram



Correlogram of Residuals Squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.201	0.201	9.2700	0.002
		2	0.007	-0.034	9.2824	0.010
		3	0.115	0.126	12.357	0.006
		4	0.001	-0.051	12.357	0.015
		5	0.049	0.070	12.925	0.024
		6	0.081	0.043	14.473	0.025
		7	-0.018	-0.036	14.546	0.042
		8	-0.020	-0.018	14.639	0.067
		9	0.056	0.053	15.392	0.081
		10	-0.023	-0.043	15.524	0.114
		11	0.015	0.032	15.574	0.158
		12	-0.035	-0.068	15.875	0.197
		13	-0.029	0.013	16.077	0.245
		14	0.133	0.133	20.395	0.118
		15	0.075	0.026	21.775	0.114
		16	-0.028	-0.039	21.967	0.144
		17	-0.012	-0.024	22.001	0.185
		18	-0.052	-0.053	22.680	0.203
		19	0.039	0.073	23.062	0.235
		20	0.013	-0.045	23.104	0.284
		21	-0.034	-0.006	23.396	0.323
		22	-0.016	-0.009	23.459	0.376
		23	0.063	0.075	24.477	0.378
		24	-0.063	-0.097	25.486	0.380
		25	-0.011	0.023	25.519	0.434
		26	0.017	0.002	25.594	0.486
		27	-0.105	-0.068	28.474	0.387
		28	-0.004	-0.003	28.478	0.439
		29	0.106	0.097	31.445	0.345
		30	-0.001	-0.019	31.445	0.394
		31	-0.018	0.001	31.534	0.440
		32	-0.064	-0.089	32.643	0.435
		33	-0.088	-0.039	34.739	0.385
		34	0.078	0.091	36.377	0.359
		35	0.041	0.019	36.830	0.384
		36	-0.035	-0.026	37.166	0.415

Figure 19: Residual Plot over Time

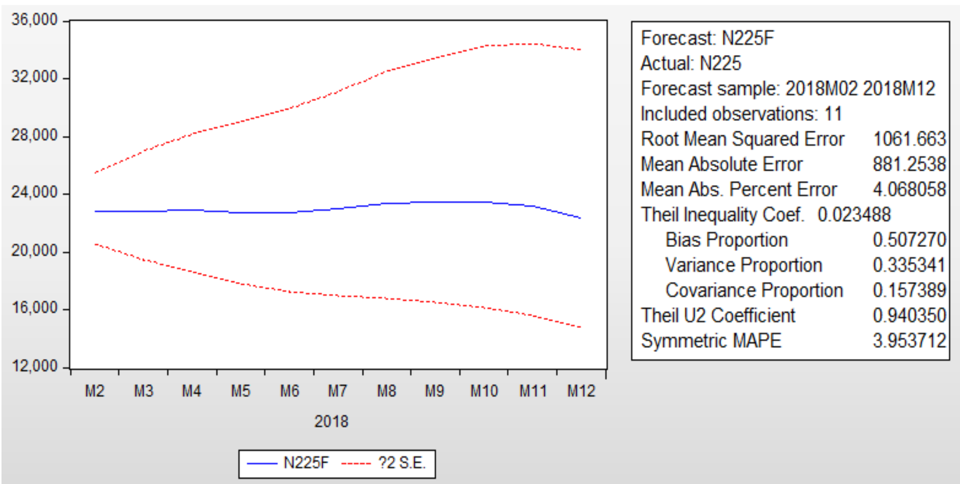


Figure 20: In-sample dynamic forecast

From the in-sample dynamic forecast, we can see that there is a slightly upward trend from M6 to M9, followed by a downward trend from M10 to M12.

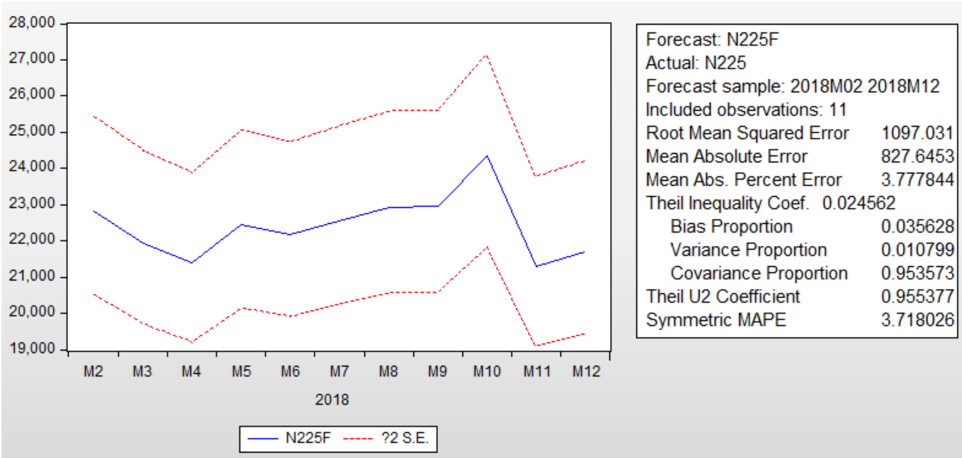


Figure 21 In-sample static forecast

Vector Autoregression Estimates

Vector Autoregression Estimates
Date: 03/05/19 Time: 14:20
Sample (adjusted): 1999M04 2019M01
Included observations: 238 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DLOG(HSI)	DLOG(N225)	DLOG(GSPC)
DLOG(HSI(-1))	0.115910	0.098460	0.094858
	(0.09330)	(0.08247)	(0.06262)
	[1.24236]	[1.19382]	[1.51472]
DLOG(N225(-1))	0.078961	0.045906	0.083354
	(0.09686)	(0.08563)	(0.06502)
	[0.81517]	[0.53612]	[1.28203]
DLOG(GSPC(-1))	-0.144239	0.032805	-0.096427
	(0.14688)	(0.12984)	(0.09859)
	[-0.98201]	[0.25265]	[-0.97805]
C	0.003787	0.000580	0.002907
	(0.00409)	(0.00361)	(0.00274)
	[0.92692]	[0.16066]	[1.06003]
R-squared	0.012942	0.026251	0.026805
Adj. R-squared	0.000288	0.013767	0.014328
Sum sq. resids	0.923792	0.721884	0.416207
S.E. equation	0.062832	0.055543	0.042174
F-statistic	1.022727	2.102753	2.148346
Log likelihood	322.9258	352.2739	417.8050
Akaike AIC	-2.680049	-2.926672	-3.477353
Schwarz SC	-2.621691	-2.868314	-3.418996
Mean dependent	0.003939	0.001140	0.003122
S.D. dependent	0.062841	0.055929	0.042480

Figure 22 Vector Autoregression Estimates

VAR Model with lag 1 is estimated as above. All three index have no significant impact on each other. There is no major influencer in the model.

Johansen Cointegration Test

Date: 02/19/19 Time: 14:16
Sample (adjusted): 1999M04 2019M01
Included observations: 238 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: LOG(N225) LOG(HSI) LOG(GSPC)
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.043732	19.49388	35.19275	0.7578
At most 1	0.029258	8.851237	20.26184	0.7501
At most 2	0.007467	1.783848	9.164546	0.8203

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Figure 23 Cointegration test

Cointegration test shows that none of the hypothesis can be rejected at significance level 0.05. No cointegration equation can be establish among Nikkei, S&P500 and Heng Seng Index. Thus, Vector Error Correction Models (VECM) cannot be applied in this case.

Out-of-sample forecasts for at least five periods.

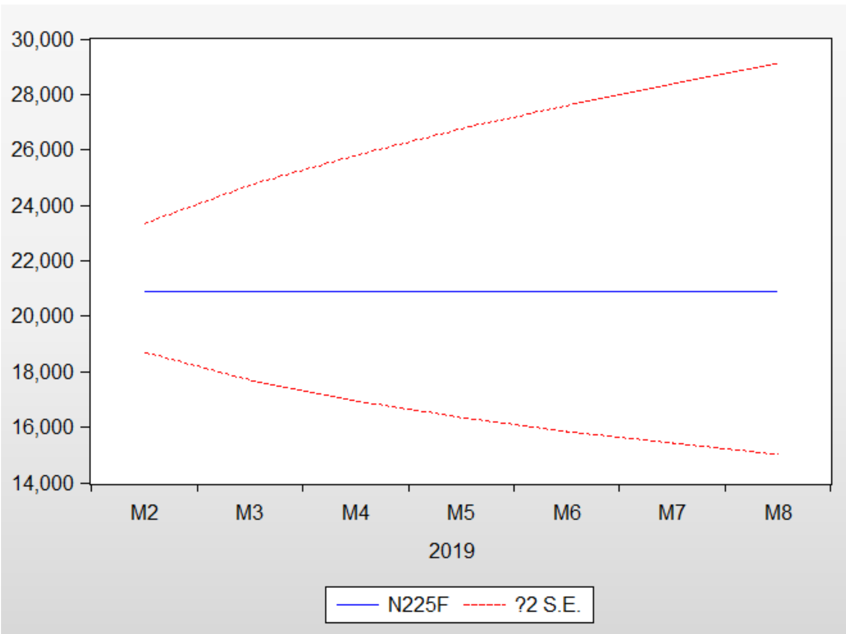


Figure 24 Out-of-sample forecasts(dynamic)

AR(1) is selected to perform out of sample forecast. The out of sample forecast result shows a flat trend for the following 6 months. This suggest that Nikkei will keep fluctuate with 21,000 level.

The standard error widens up over the time. The suggests that the ARIMA model can compete reasonably well in short-term prediction, but not in the long run.

Conclusions

Stock price prediction is an important topic in finance and economics which has attracted the interest of researchers over the years to develop better predictive models. This paper presents extensive process of building ARIMA model for Nikkei price prediction. The results obtained with best ARIMA model demonstrated that the simpler model perform better. Even though the prediction result doesn't have high degree of accuracy, time series model is still good to predict the overall trend of the stock price movement.

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