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CAN WE FORECAST RETURN NATIONAL-FINANCIAL INDEX FOR ISTANBUL STOCK EXCHANGE?

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Abstract

Recently a substantial part of the macro-economic research has been underpinned by time series analysis. Two themes attract attention in time series analysis, which are examination of the data generating process and forecasting making use of the same data. In this study, we analyze the properties of univariate time series, unit root tests, and forecasting for the daily return of national financial index of Istanbul Stock Exchange (NFI). The unit root tests employed reveals that the daily return of national financial series are non-stationary. Afterwards, we estimated alternative ARIMA(p,d,q) models forecasting we calculated forecast accuracy measures. According to results of all of counted forecast performance measures are approximately equal to each other. But the more explicitly, we can say that if we compare to the four forecast accuracy measures together, ARIMA (1,0,0) model is the best.

Key Words: *Stock Index, Univariate Time Series Analysis, Unit Root Tests, Forecasting.*

Özet

Son zamanlarda makroekonomik araştımaların önemli bir kısmı zaman serisi analizleriyle desteklenmektedir. Zaman serilerinin veri üretme süreçlerinin belirlenmesi ve önraporlama zaman serileri analizinin iki önemli konusudur. Bu çalışmada İstanbul Menkul Kıymetler Borsasının Mali Endeksinin günlük getirileri (NFI) için tek değişenli zaman serisi özellikleri, birim kök testleri ve önraporlama

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analiz edilmiştir. Uygulanan birim kök testi mali endeksin günlük getiri serinin durağan olmadığını göstermiştir. Daha sonra alternatif ARIMA(p,d,q) modellerinin önraporlamaları tahmin edilmiştir. Bulunan sonuçlara göre tüm hesaplanan önraporlama doğruluk kriterleri yaklaşık olarak birbirlerine eşittir. Fakat daha açık olarak eğer dört önraporlama doğruluk kriteri bir arada değerlendirilirse ARIMA (1,0,0) modelinin en iyi model olduğu söylenebilir.

Anahtar Kelimeler: *İMKB, Tek Değişenli Zaman Serileri, Birim Kök Testleri, Önraporlama.*

1. INTRODUCTION

The aim of this study is forecasting and analysis of time series of Istanbul Stock Exchange (ISE) National-Financial Index (NFI), which is counted by share market. For least 20 years, one of the important reasons of univariate time series analysis to be such popular has been that it is easily constituted and efficiently estimated. Generally in univariate time series analysis is aimed taken a linear combination of past value of the financial or economic time series and forecasting.

This paper is organized as follows: We begin by reviewing literature on section 2. We then introduce the alternative ARIMA(p,d,q) models for using estimating and forecasting on section 3. In order to investigate whether or not the stationarity of the series is valid on section 4, we apply unit root test. For compare and finding the best model, we estimate alternative six ARIMA(p,d,q) models. Finally, conclusions and choice of the best model are presented in section 5.

2. LITERATURE OVERVIEW

Financial or economic time series can't be identified with certain function that has property random character. Therefore, this type of the series must be used stochastic time series (Chatfield 1980:6). Similarly, while using model of time series to future value is always added a disturbance term for all factors of effect events could not add models. Consequently disturbance term, which is added to models, is stochastic also time series will be shown stochastic property. When we wish to analyses a financial time series $\{Y_t\}$ using formal statistical methods, it is useful to regard the observed series $\{Y_1, Y_2 ..., Y_T\}$ as a particular realization of a stochastic process. This realization is often donated $\{Y_t\}_1^T$ while, in general, the stochastic process itself will be the family of random variables $\{Y_t\}_{-\infty}^{\infty}$ defined on an appropriate probability space (Mills 1999:8).

One an important simplifying assumption is that of stationary. If the characteristics of the stochastic process change over the time, the process is nonstationary. On the other hand, if stochastic process is fixed in time, it is stationary (Pindyck and Rubinfeld 1981:497). Stochastic property of stationary process is assumed fixed over the time. However, studies show that many financial and economic time series are not generated by stationary process. Consequently, in practical nonstationary series must be stationaried by some methods. Because developed and used stochastic models for time series analysis can be apply stationary series.

A stochastic process is said to be strictly stationary if its properties are invariant by a change of time origin. This very strong condition is hard to verify empirically. A weaker version of stationarity is often used weakly stationarity (Tsay 2002:23). If a stochastic process Y_t has a constant mean and finite variance, it is stationary process. More formally, a stochastic process Y_t is weakly stationary, if $E[Y_t] = \mu$ for all t, $Var(Y_t) = \sigma^2$ for all t, $Cov(Y_t, Y_{t+k}) = \gamma_k$ for all t and k (Judge, Hill, Griffiths, Lütkepothl and Lee 1988:679). Where estimate of mean of process can be obtained from sample mean of series and estimate of variance can be obtained from sample variance (Akgül 2002:08). Essentially stationary term is usually implying weakly stationary. In the literature, weakly stationary process is also referred to as a covariance stationary, second-order stationary, or wide-sense stationary process (Enders 1995:69). One another stationary term is trend stationarty. One of the cause nonstationarity at nonstationary time series is to be deterministic or stochastic trend (Maddala and Kim 1998:4). Generally, stochastic trend is described as random walk. Because nonstationary of time series is meaning to non constant mean (or zero mean) and indefinite variance. If a time series is plotted and there is no evidence of change in the mean over the time, then we say the series is stationary in the mean and if the plotted series shows no obvious in the variance over the time, then we say the series is stationary in the variance (Makridakis Wheelwright and Hyndman 1998:324). Stochastic trend structure also in the nonstationary time series from which is meaning of nonstationarity can be stationary with taken differences of time series. Differences stationary process is show scatter plot at around draw the center point. However, there is not one of such centerline draw in trend stationary process (Hatanaka 1996:17). Between differences stationary and trend stationary are go on effect of disturbance term to infinite. Occasionally, transformations other than differencing are useful in reducing a nonstationary time series to a stationary one. For example, in many economic time series the variability of the observations increases as the average level of the process increases; however, the percentage of change in the observations is relatively independent of level. Therefore, taking the logarithm of the original series will be useful in achieving stationarity (Montgomery and Johnson 1976:206).

In generally, linear stochastic models in time series analysis such as AR, MA, and ARMA are used (Harvey 1993:23). Linear stochastic models can be distinguished from linear stationary stochastic models (such as AR, MA, and ARMA) and nonlinear stationary models (such as pure random walk, random walk with drift, and ARIMA process). Because, ARIMA models are include integration form in nonstationary time series (Engle and Granger 1987:251-276). The practice of modeling co-integrated series is closely related to error-correction mechanism: error-correction behaviour on part of economic agents will induce co-integrating relationship among the corresponding time series and vice versa. A particular advantage of the error-correction mechanism is that the extend of adjustment in a given period to deviations from long-run equilibrium is given by the estimated equation without any further calculation (Banerjee, Dolado, Galbraith and Hendry 1993:6). To express stationary order of series at nonstationary time series is used integration term. If defined ARMA process model is stationary, it is modified to ARIMA to be integrated of model. A series which is stationary after differenced once is said to be integrated of order 1, and is donated I(1). In general a series which is stationary after being differenced d times is said to be integrated of order d, donated I(d). A series, which is stationary without differencing is said to be I(0) (Patterson 2000:220). Integrated models are showed ARIMA(p,d,q).

Box-Jenkins methodology is a popular approach at modeling ARIMA process. The Box-Jenkins approach to time series model building is a method of finding, for a given set of data an ARIMA model that adequately represents the data generating process. It is important, in practical, employed the smallest possible number of parameters for adequate representation at the foundation of Box-Jenkins methodology. The central role played by this principle of parsimony in the use of parameters will become clearer as we proceed (Box and Jenkins 1976:17). The method is customarily partitioned into four stages: model identification, estimation, diagnostic checking, and forecasting. At identification stage, a tentative ARIMA model is specified for data generating process based on the estimated autocorrelations and partial autocorrelations. At estimation stage, the parameters of ARIMA process can be estimated by regression methods. As the third step in the model building cycle, some checks on the model adequacy are suggested. At last stage if model is appropriate, it is used for forecasting. But if model is not appropriate, the process is repeated.

Now we must stand testing stationarity after standed stationarity, stationary process, and nonstationary process terms. Two essential approaches have for testing stationarity. First approach is testing stationarity with graphical approach. In this approach is used time series graph and correlograms. So computed autocorrelations and partial autocorrelations are tested for stationarity (Shumway and Stoffer 2000:19). Besides, if computed autocorrelations are stand in confidence interval, it is decided that the series to be random and autocorrelations to be zero (Işığıçok 1994:60). Second approach for testing nonstationarity is used unit root tests. Even though there is many unit root tests in the practical, there we will examine Augmented Dickey-Fuller test (ADF), ADF-GLS test (Point Optimal), KPSS test (Kawiatkowski-Philips-Schimidt-Shin), Philips-Perron test and Ng-Perron test.

Dickey and Fuller found with Monte Carlo study that performance of $\hat{\tau}$ were uniformly more powerful than Box-Pierce Q^*-statistics. Because $\hat{\tau}$ use the knowledge that the true value of the intercept in the regression (Dickey and Fuller 1979:427-431). Dickey and Fuller (1979, 1981) developed test for unit roots which based on approximation autoregression or moving average form and the ε_t assumed to have a zero mean and be independent and identically distributed, in shorthand this is $\varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$. However, mostly this assumption is not significant or not required for validity the Dickey-Fuller tests. If there is evidence of nonzero autocorrelations of ε_t, firstly we will add lagged Y_t terms by the time ε_t will have been white noise. We are attribution (ADF) Augmented Dickey-Fuller tests. Where, we are used alternative strategy for selection maximum lag length (Ng and Perron 1995:268-281). If order of lag length is not define correctly, its estimating parameter will be based. We can use strategy for selection of truncation lag by Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), General to specific or Specific to general approach. It is shown that a deterministic relationship between the truncation lag k and the sample size (Said and Dickey 1984:509-607).

The second motivation for alternative unit root test is to allow for disturbance process, ε_t, which are not $iid(0, \sigma_\varepsilon^2)$. Philips-Perron generalized the Dickey-Fuller tests to situations where, for example, the ε_t are serially correlated, other than by augmenting the initial regression with lagged dependent variables as in the ADF procedure (Phillips and Perron 1988:335-346). Their approach is nonparametric with respect to nuisance parameters and thereby allows for a very wide class of weakly dependent and possibly heterogeneously distributed data. The Philips-Perron versions of Dickey-Fuller tests are flexible in that the serial correlation between disturbances can be of an autoregressive or moving average form. However, where the autocorrelations of ε_t are predominantly negative the Philips-Perron tests suffer severe size distortions, with the actual size much grater than the nominal size. On correction for this distortion in size, it appears that the Philips-Perron tests can deliver more power than the ADF tests (Schwert 1989:147-160).

Conventional unit root tests are known to lose power dramatically against stationary alternatives with a low order moving average process: a characterization that fits well to a number financial and economic time series. Consequently, along the line of ADF tests, a more powerful variant is the ADF-GLS test proposed by ERS (Elliott, Rothenberg and Stock 1996:813-836). This test is similar to ADF tests, as performed by Dickey-Fuller, but has the best overall performance in term of small sample size and power, dominating the ordinary Dickey-Fuller tests. ADF-GLS test has substantially improved power when an unknown mean or trend is present.

Many unit root tests have been developed for testing the null hypothesis of a unit root against the alternative of stationarity. While the pretence or absence of a unit root has important implications, many remain skeptical about the conclusions drawn from tests. Many tests have low power, when the root of the autoregressive polynomial is close to but less than unity (DeJong, Nankervis, Savin, and Whiteman 1992: 323-343). Another alternative test is that proposed, which has a null hypothesis of stationarity (Kwiatkowski, Phillips, Schmidt and Shin 1992:159-178). The test may be conducted under the null of either trend stationarity or level stationarity. The aim of KPSS test is stationarity of time series from detrended. A testing strategy, which takes the null of stationarity against the alternative of nonstationarity, can be approached from the relation between structural and reduced form representations of time series models.

When the root of the error process is close to the unit circle, many commonly used unit root tests have size distortions. Ng-Perron test, particularly by now well documented fact that the Philips-Perron tests, as originally defined, suffer from severe size distortions when there are negative moving average errors (Perron and Ng 1996: 435-463). Although, the size of the Dickey-Fuller tests is more accurate, the problem is not negligible. Therefore, Ng-Perron test find that can be eliminate size distortions. It is widely known that when there are errors with a moving average root close to –1, a high order augmented autoregression is necessary for unit root tests to have good size, but that information criterias such as the AIC and SIC tend to select a truncation lag, k that is very small (Ng and Perron 2001:1519-1554). Construct four test statistics that are based upon the GLS detrended data. These test statistics are modified forms of Phillips-Perron Z_α tests, Bhargava's test, Philips-Perron Z_t tests and ERS Point

Optimal statistic. Consequently, these tests are attribution to M-tests by Ng-Perron. First test MZ_{α} is modified version of Z_{α}. The second statistics MSB is modified version of Bhargava's test statistics. This statistics is related to Bhargava's (1986) R statistic, which is built upon the work of Sargan and Bhargava (1983). MSB and Philips-Perron tests relation is modified and attribution to MZ_{t} statistics (Perron and Ng 1996:435-463). This result can be third statistics of Ng-Perron tests. The last test using Ng-Perron tests is modified ERS Point Optimal statistic, which is attribution to MPT statistic.

A forecast is a quantitive estimate (or set of estimates) about the likelihood of future events based on past and current information. This past and current information is embodied in the form of a model-a single-equation structural model, a multi equation model or a time series model. By extrapolating our models out beyond the period over which they were estimated, we can use the information contained in them to make forecasts about future events. The term forecasting is often thought to apply solely to time series problems in which we predict the future given information about the past and the present. Actually forecasting systems often use a combination of quantitive and qualitative methods. The statistical methods are used to routinely analyze historical data and prepare a forecast. We usually do not require the model to represent very old observations, as they probably are not characteristic of the present, or observations far into the future, beyond the lead time over which the forecast is made (Montgomery and Johnson. 1976:9). The best forecasting in time series are forecasting in which we are known mean and covariance function of the series (Fuller 1976:75). In many empirical studies, it appears that the models are tend to do best for within sample data do not necessarily forecast better out of sample. There is no strict rule for that, but empirical experience suggests that it may be better to select a few models based on the AIC and SIC, and to evaluate these on the out of data (Franses 1998:65). Perhaps no other univariate forecasting method has been more widely discussed than ARIMA model building, where an ARIMA model has three components: **A**uto**R**egressive, **I**ntegrated, and **M**oving **A**verage (DeLurgio 1998:273). The principle of forecasting from ARMA models is very simple. However, if using model has been intercept and deterministic trend, this intercept and deterministic trend must be directly add forecasting model (Clements and Hendry 1998:88).

3. THE ESTIMATING MODELS

After testing unit root of the NFI series of Istanbul Stock Exchange at Table 1 statistical measure, which will be used for appraise forecast accurate will be estimated. The accuracy of a forecasting method is determined by analyzing forecast errors experienced. Several methods have been devised to summarize the errors generated by a particular forecasting technique. Most of these measures involve averaging some function of the difference between an actual value and its forecast value. These differences between observed values and forecast value are often referred to as residual (Hanke and Reitsch 1998:112). These measures given as follows; RMSE: Root Mean Squared Error, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error, and Theil Inequality Coefficient. The model, forecast accuracy of which is the best, will be the model statistical measure of which the smallest. Just as from these measures are taken charge of forecast error. The meaning of this, the more accurately forecasts are calculated, the less forecast errors are calculated.

Table 1: Forecasting Models

ARIMA Tips	Model Equations	Model Definition
ARIMA(1,0,0)	$Y_t = \delta + \phi_1 Y_{t-1} + \varepsilon_t$	Autoregressive Process
ARIMA(0,0,1)	$Y_t = \mu + \theta_1 \varepsilon_{t-1} + \varepsilon_t$	Moving Average Process
ARIMA(1,1,0)	$\Delta Y_t = \delta + \phi_1 (Y_{t-1} - Y_{t-2}) + \varepsilon_t$	Autoregressive Integrated Process
ARIMA(0,1,1)	$\Delta Y_t = \mu + \theta_1 \varepsilon_{t-1} + \varepsilon_t$	Integrated Moving Average Process
ARIMA(1,0,1)	$Y_t = \delta + \phi_1 Y_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$	Autoregressive Moving Average Process
ARIMA(1,1,1)	$\Delta Y_t = \delta + \phi_1 (Y_{t-1} - Y_{t-2}) + \theta_1 \varepsilon_{t-1} + \varepsilon_t$	Autoregressive Integrated Moving Average Process

If Table 1 is examining, we can see that the Table 1 has been stationary models form and nonstationary models form. That is, while dependent variable of the three models describes first difference of series, the other three models describe level of series. So such as ARIMA(1,1,0) model, whose dependent variable is first difference, can be rewritten as follows.

$$\Delta Y_t = \mu + \phi_1 (Y_{t-1} - Y_{t-2}) + \varepsilon_t \qquad (1)$$

or

$$Y_t = \mu + (\phi_1 - 1) Y_{t-1} - \phi_1 Y_{t-2} + \varepsilon_t \qquad (2)$$

Note that this model (equation 2) now looks like an ARIMA(2,0,0) (Makridakis, Whellwright and Hyndman 1998:360). Where, equation (1) cannot show goodness of fit for forecasting value. Therefore, we will use equation (2) for forecasting of model. However, the parameters of equation (2) do not satisfy the conditions necessary to give a stationary series.

Similarly, ARIMA(0,1,1) model can be thought as nonstationary ($\phi_1 = 1$) ARIMA(2,0,0) and ARIMA(1,1,1) model can be thought as ARIMA(2,0,1).

4. RESULTS

The data, which were taken from the Central Bank of the Republic of Turkey's database, were daily evaluated between 02/01/1997 and 31/10/2006. The logarithm of the daily return of national financial index of Istanbul Stock Exchange is NFI.

4.1. Unit Root Tests

Whether or not the series are stationary helps to appraise of forecast performance. So firstly, we will research stationarity analysis of the series. In Table 2, the order of truncation lag using Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Lagrange Multiplier (LM) test while testing Augmented Dickey-Fuller (ADF) unit root tests of NFI series is described. If we add to model value of five lag of dependent variable using these three evaluation criterias, serial correlations in the disturbance term are to be ceased. After ADF unit root tests for NFI series are applied, we find NFI series include unit root. That is, NFI series is not stationary. Therefore, we take first differences of NFI series in Table 2 and again we applied ADF unit root test, and we see now NFI series is stationarity or does not include unit root.

Table 2: Unit Root Tests Results for ISE National-Financial Index

Unit Root Tests	Level of NFI	First Difference of NFI
ADF Test	-2.0555	-23.1183
ADF-GLS Test	1.6590	-8.4147 [a]
Phillips-Perron Test	-2.2704	-49.9525 [a]
KPSS Test	4.1261 [a]	0.1850
Ng-Perron Test [d]	0.9050, 1.3984, 1.5451 [a],154.209[a]	-9.6949 [b], -2.1872, [b] 0.2256 [a], 2.5857[a]

[a] indicates significance at 1 %,
[b] indicates significance at 5 %,
[c] indicates significance at 10 %.
[d] Ng-Perron construct four test statistics. These tests show order to MZ_a, MZ_t, MSB, and MPT tests results.
* Critical values of $\hat{\tau}_\mu$ also obtained using Cheung-Lai response surface coefficients, and we see NFI series is not stationary.

To determine order of lag length for ADF-GLS unit root tests we counted five lag length for disturbance terms for white noise. If Table 2 is examining, it can seen that results of ADF-GLS tests are similar to ADF unit root tests. That is NFI series include unit root or nonstationary. After taking first differences of NFI series, we find that the series is now stationary. Truncation lag parameter for Phillips-Perron unit root tests is to be taken $\ell = \circ(T^{1/3}) \cong 14$. Results of Phillips-Perron test show that NFI series include unit root and similarly if we take first differences of NFI series, we find that the series is now stationary. We counted truncation lag parameters $\ell = \circ(T^{1/2}) \cong 51$ for KPSS unit root tests. If examining Table 2, significance at 1% of tests can be seen. Where we must have been null hypothesis shows stationarity and alternatives shows nonstationarity. If we take first differences of NFI series, we do not find that significance of tests or the series is now stationary. The last test is Ng-Perron unit root test. Where we are also counted truncation lag parameters $\ell = \circ(T^{1/3}) \cong 14$ similar to Phillips-Perron unit root tests. Result of Ng-Perron test we also found support to other unit root tests. Where we must remind that although MZ_a and MZ_t test statistics are nonstationary for null hypothesis, MSB and MPT test statistics are stationary for null hypothesis. Tests results show that we cannot reject for MZ_a and MZ_t tests statistics. However, we can reject for MSB and MPT tests statistics. Therefore, we can conclude that NFI series has been unit root. Nevertheless, after taking first differences of NFI series, we find that the series is now stationary.

In results of five-unit root test we applied, we found that NFI series is not stationary or include unit root, and if we take first differences of the series, we can show the series is now stationary. That is, we can say that NFI series is to integrate of order 1. These result support that return series of Istanbul Stock Exchange (ISE) National-100 Index is said to integrate of order 1 (Nargeleçekenler 2005:98-136; Sevüktekin and Nargeleçekenler 2005:284).

4.2. Estimation of ARIMA (p,d,q) Models and Forecasting

Applied unit root test for NFI series say to us that we must constitute nonstationary model form. However, follows we estimated alternatives model form for comparing particularly such as AIC, SIC, SSE, and likelihood ratio etc., and find good forecasts.

Table 3: Estimated ARIMA (p,d,q) Models Results

	ARIMA (1,0,0)	ARIMA (0,0,1)	ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (1,0,1)	ARIMA (1,1,1)
Constant	10.7383 [a]	9.6004 [a]	0.0017 [b]	0.0017 [a]	10.7287 [a]	0.0015 [b]
ϕ_1	0.9985 [a]	-	0.0141	-	0.9985 [a]	0.9420 [a]
θ_1	-	0.9747 [a]	-	0.0128	0.0123	-0.9354 [a]
R^2	0.999	0.737	0.0002	0.0002	0.999	0.0034
SSE	2.6583	706.538	2.6624	2.6637	2.6578	2.6538
Likelihood	5113.45	-1979.643	5108.967	5110.869	5113.66	5113.068
AIC	-4.0232	1.5591	-4.0212	-4.0211	-4.0226	-4.0237
SIC	-4.0186	1.5637	4.0166	-4.0166	-4.0157	-4.0168
F	2556788 [a]	7120.431 [a]	0.5017	0.4566	1278101 [a]	4.3548 [b]

[a] indicates significance at 1 %.
[b] indicates significance at 5 %.
[c] indicates significance at 10 %.

Our evaluation among estimated models is as follows: estimated parameter and F-statistics must be significant, determination coefficient, R^2 and likelihood ratio must be possible high, AIC, SIC, and sum of squared resid, SSE must be possible low. If we take together all of these evaluation criterias for NFI series, we can see that the best model is ARIMA(1,1,1) process among all alternatives for the series. Because we found with applied unit root test that the series is nonstationary. These results also support to unit root test.

The second aim of our study is forecasting using estimated models for NFI series. However, before we must recall that accuracy forecast measures in Table 4 are counted by ex-post forecasting for NFI series and we can submit forecasting performance of estimated models in Table 4.

Table 4: Comparing Forecasting Results

	ARIMA (1,0,0)	ARIMA (0,0,1)	ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (1,0,1)	ARIMA (1,1,1)
RMSE	0.015000	0.798295	0.014521	0.014514	0.015044	0.014510
MAE	0.011301	0.797167	0.011083	0.011079	0.011355	0.011096
MAPE	0.101082	7.132696	90.52411	90.33825	0.101560	89.44933
Theil's U	0.000671	0.037038	0.877957	0.877053	0.000673	0.888266

If Table 4 is examine, all of counted forecast performance measures are approximately equal to each other.

5. CONCLUSIONS

We aimed time series analysis approach applied to Istanbul Stock Exchange NFI series in our study. So firstly, we tested unit root tests for NFI series and we found that the series has unit root or nonstationary. Afterwards, we estimated alternatives ARIMA(p,d,q) models for h-period forecasting of NFI series and among these alternatives we found that ARIMA(1,1,1) model is the best comparing estimated parameter, F-statistics, R^2, likelihood ratio, AIC, SIC, and SSE criterias. Later, with alternative ARIMA(p,d,q) models forecasting we calculated forecast accuracy measures. According to results of all of counted forecast performance measures are approximately equal to each other. But the more explicitly, we can say that if we compare to the four forecast accuracy measures together, ARIMA(1,0,0) model is the best.

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