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PRICE DISCOVERY EFFICIENCY IN BIST LIQUIDITY BANK INDEX USING DEFERRED FUTURES: A MULTILAYER PERCEPTRON NEURAL NETWORK APPROACH

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Abstract

The literature indicates that the process of price discovery in spot and futures can be bidirectional. This study novelty lies in its analysis of the spot data of the BIST liquid bank index, a relatively new index in Turkey, using futures contracts of different maturities with a multi-layer perceptron (MLP) artificial neural network model. The efficacy of the models is evaluated by examining the capacity of futures prices to inform spot price discovery. The effectiveness of the MLP models is measured by low mean squared error (MSE) ratios relative to the out-of-samples test series results. The findings indicate that the one- and two-next futures contracts of the liquid bank index are more effective than the nearest futures contracts in explaining spot prices. Additionally, the nearest expiry contracts are observed to exhibit higher variances than the others. The most efficient pricing model including both spot and futures as explaining variables, is autoregression with three lags for spot and two lags for the two next futures contracts. These results must be considered when implementing risk management strategies for individuals engaged in spot and futures transactions.

Keywords: BIST Liquid Bank Index, Multi-layer Perceptron Artificial Neural Networks, Futures Contracts, Spot Price Discovery, Financial Forecasting.

Jel Codes: G13, G17, C53.

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1. Introduction

A futures contract is an agreement to buy or sell a specific asset at a set price at a future date. The relationship between spot and futures prices is influenced by several factors, including transportation costs, interest rates, storage costs and the balance of supply and demand. Futures prices are derived from spot prices and are regulated by carrying costs and risk premiums. Risk premiums are demanded to hedge against future uncertainties. Uncertainties can arise from various factors, including price volatility, supply and demand imbalances and political risks. Carrying costs are the expenses associated with holding the underlying asset, such as storage, insurance, transport and financing costs. Spot price discovery is also affected by a number of other factors, including supply and demand, trading volume, futures expiry time, carrying costs, USDA announcements and market crashes (Hu et al., 2020).

Furthermore, numerous empirical studies in the literature demonstrate that futures or spot series lead each other. Bohl et al. (2011) investigate price discovery in European stock index futures markets and conclude that the increase in institutional trading volume triggers information flow from futures to spot markets. Gök and Kalaycı (2014) find that BIST30 futures prices drive spot prices with minute data. In the context of agricultural commodities, studies have indicated that the incorporation of futures prices into the process of price discovery has a positive effect on the accuracy of cash price forecasts (Xu & Zhang, 2021). Kumar and Pandey (2011) have also observed that the futures market exerts a significant influence on the spot market in certain periods within the Indian commodity futures market. Nicolau (2012) studied the dynamic relationship between spot and futures prices of crude oil. The findings revealed that futures prices can predict spot prices at the nearest maturities, but not for long-term futures prices. Fassas et al. (2020) examined the role of bitcoin futures in the price discovery process and found that futures markets play an important role in pricing new information. There are also studies where spot prices lead future prices. Different findings were observed due to variations in market dynamics, data periods and data frequencies. Yağcılar (2022), examined daily returns on BIST-30 Index futures contracts traded in Borsa Istanbul. Their findings indicated that the spot market leads the futures market in BIST-30 Index futures contracts. This result contrasts with those of Gök and Kalaycıya (2014), who used minute data.

The novelty of this study is that it analysed the BIST liquid bank index data, which is a relatively new stock index in Turkey, with a multi-level perception artificial neural network model with different deferred futures contracts. The performance of the models is compared by examining the impact of BIST liquid bank index futures prices on spot price discovery.

There are studies in the literature that support the validity of artificial neural networks as a useful tool for forecasting financial series, especially stock and futures prices. (Lasheras et al, 2015; Hsu, 2011; Wang & Li, 2018; Kulkarni & Haidar, 2009). Multilayer perceptron (MLP) artificial neural networks are one of the most widely used types of artificial neural networks, and usually refer to a nonlinear artificial neural network model with at least one hidden layer. This study compares the effectiveness of spot own lags and futures contract lags of different maturities in pricing spot data. Three different main models were constructed, i) models where only the autoregressive endogenous variables of the spot series are input, ii) models where the lags of futures contracts of different maturities are added to the model as exogenous variables, iii) models where spot and futures lags are used as inputs. The models were trained using the in-sample-series input through the training models. The trained models were then used for testing and the effectiveness of the models was measured with low MSE ratios according to the out-of-sample test series results. Results show that the one and two next futures contracts on the liquid bank index were found to explain spot prices better than the nearest futures contracts. In MLPNN models with lagged spot and forward, the most efficient pricing model is one with a three-lag autoregression of the spot and a two-lag of the two next futures contracts. Besides, the nearest expiring contracts have higher variances than the others

In the rest of the study, literature review, data and methodology, then findings and conclusions are presented.

2. Literature Review

After reviewing the literature on spot and futures price relations, the chapter concludes with an explanation of the effectiveness of artificial neural network models in finance.

Futures markets play a crucial role in financial and commodity markets, with futures contracts being a fundamental element of these markets. Futures contracts require a commitment to buy or sell a specific asset at a predetermined price for future delivery. The relationship between spot and futures prices is influenced by factors such as transport costs, interest rates, storage costs, and supply and demand balance. Futures prices are derived from spot prices and are regulated by carrying costs and risk premiums. Risk premiums are demanded to hedge against future uncertainties. Uncertainties can arise from various factors, including price volatility, supply and demand imbalances, and political risks. Carrying costs refer to the expenses associated with holding the underlying asset, such as storage, insurance, transport, and financing costs. Spot price discovery is also affected by factors such as supply and demand, trading volume, futures expiry time, transportation costs, USDA announcements and market crashes (Hu et al. 2020). Besides, in futures trading, the expectations theory holds that futures prices represent investors' expectations for future market circumstances as well as the expected values of future spot prices. There are many studies in the literature where futures or spot series lead each other. The originality of this study is that it has studied the BIST liquid bank index data, which is a new index in Turkey, and analysed it with a multi-level perception artificial neural network model. The performance of the models is compared by examining the impact of BIST liquid bank index futures prices on spot price discovery in futures contracts of different maturities.

2.1. Futures Effective

Xu and Zhang (2021) address the problem of forecasting on a data set of daily cash prices of corn from about 500 markets. They focus on univariate neural network (NN) modelling and bivariate NN modelling with futures prices on these data from different markets in sixteen states. To achieve high accuracy, simple NNs with twenty hidden neurons and two delays were used. Cash price predictions are positively affected by the inclusion of futures prices in the models. Bohl et al. (2011) examine price discovery in stock index futures and spot markets. They analyse time-varying spot-futures linkages in a VECM-DCC-GARCH framework to fill the gaps in the previous literature. The results suggest that an increase in institutional trading volume triggers information flows from the futures market to the spot market and increases the conditional correlation between the two markets, while the futures market does not contribute to price discovery in periods dominated by retail investors. Güzel (2020) examines the relationship between spot and futures markets in terms of price and volatility. He uses end-of-day data based on the BIST 30 index at the Borsa Istanbul, Turkey. He finds that futures, spot and options each have a price-discovery function. In other words, the futures market has priority, while the spot and options markets are second and third respectively. Gök and Kalaycı's (2014) study aims to investigate price discovery, Granger causality and volatility spillovers in BIST30 spot and futures markets. The study was carried out using 1-minute intraday data for the period between 2 January 2010 and 18 May 2012. Based on the results of the Johansen cointegration test, there is a long-run relationship between the index futures and spot market. The VECM model analysis shows that the index futures market contributes more to price discovery and that futures prices lead spot prices. The Granger causality block exogeneity test shows that there is a two-way causality relationship, but the causality from the futures market to the spot market is stronger. Using a GARCH(1,1)BEKK model, they found that there are two-way volatility transmissions between both markets, but that futures market shocks and volatility have a stronger impact on spot market volatility. The results suggest that information is mainly transmitted to the futures market and that the index futures market is more efficient than the spot market. Kalaycı and Gök (2013) reviewed the literature on price discovery in index futures and spot markets since 1982. The study aims to explain the factors that influence the role of markets in price discovery, considering both developed and emerging markets. The study also discusses the price discovery role of index futures and spot markets, as well as options markets. Most studies in the literature show that futures markets are more efficient in price discovery, but in some cases spot markets are found to lead futures markets. There is also evidence that options markets can be effective in price discovery. In summary, markets can play different roles in price discovery and it is important to examine the reasons. Factors such as the cost advantage of futures markets, leverage and liquidity are among the reasons for these differences. Kumar and Pandey (2011) investigated price and volatility spillovers between spot and futures in the Indian commodity futures market. The study covers different commodity groups. These include agricultural products, precious metals, energy and industrial metals. The results show that there is price discovery in both the spot and futures markets for agricultural commodities. During the harvesting season, the futures market is found to lead the spot market, and both markets tend to price together during periods of weak futures trading. In precious metals and energy markets, the futures market is found to lead price discovery. Nicolau (2012) focused on analysing the dynamic relationship between spot and futures prices of crude oil, an important commodity. The results confirm that futures prices are predictive of spot prices in the one and two nearest maturities. However, this is not the case for longer-term futures. Hu et al. (2020) examined price discovery between cash and futures contracts in storable and non-storable commodity futures markets. The study examined how contract maturity affects price discovery. For corn, near contracts tend to lead all deferred contracts, while for live cattle they are of lesser importance. The results of the regression analysis show that the level of price discovery is related to the volume of the nearest trade. However, price discovery is also affected by factors such as expiration time, carrying costs, USDA announcements and market crashes. Chen and Tongurai (2023) examine the impact of the US-China trade dispute on price discovery between China's futures and spot markets. Their empirical results, which reveal the relationships between futures contracts and spot prices, demonstrate that the futures and spot correlation in China's stock, copper and corn markets increased significantly during the periods of trade disputes between 2016 and 2019. The findings indicate that in periods of uncertainty, such as trade disputes, the correction of cointegrated relationships between futures and spot in the gold and corn markets occurred more rapidly, while the correction of deviations in the stock index and copper market was less pronounced. Katoch and Batra (2023) analyzed the volatility spillovers and co-movements between NIFTY spot and futures indices over the period 2011-2021. The researchers employed the wavelet coherence technique to illustrate the time-varying information transmission between markets at different time scales. The results indicate that index prices exhibit strong and significant dynamic conditional correlation across all time scales, with news propagation occurring both in the short and long term. Xie, Zhou and Zhang (2023) examined the role of nearby contracts in price discovery processes in the Chinese agricultural futures market. The findings indicate that the price discovery ability of near futures contracts declines as the maturity date approaches, exhibiting cyclical characteristics. The price discovery level of nearby contracts is observed to decrease as the expiry date approaches and to increase again when the contract rollover is completed. Furthermore, the price discovery efficiency of dominant contracts is found to peak at the end of the months and to fall to its lowest levels at the beginning of the months. However, the results show that futures contracts may be more effective in price discovery, especially during periods of increased liquidity and market volume. Fassas et al (2020) examined the role of Bitcoin futures in the price discovery process and found that futures markets play an important role in the process of pricing new information.

2.2. Futures Ineffective

Yağcılar (2022) analysed the relationships between BIST-30 Index futures contracts and Dollar TL futures contracts traded on Borsa Istanbul and the related spot markets. Using daily log returns for the period between August 2013 and April 2021, the study analysed the lead-lag relationships, price discovery function and volatility spreads between the spot and futures markets. The results obtained using VAR-BEKKGARCH and VAR-DCC-GARCH models show that the spot market leads the futures market in index futures contracts. The results of the study show that index futures contracts process new information more slowly than stock markets and that the spot market can predict the futures market and is therefore more efficient. Chan and Lien (2001) examined how the transition to cash settlement in futures markets affected price discovery. They find that after the transition to cash-settled contracts for feeder cattle in August 1986 and for pork in December 1996, spot price discovery in futures markets declined and more fragmentation between markets was observed. The study shows that the transition to cash-settled contracts affected the price discovery function of futures markets and changed the link between spot and futures markets. Chen et al (1999) found that the volatility of futures prices decreases as the maturity of the contract approaches. The Nikkei 225 index and futures are used in their empirical analysis. Kaur (2019) was conducted on 10 selected Sensex companies and BSE-Sensex, from 1 January 2011 to 31 December 2015 using daily spot and futures price data. The objective of the study is to identify the lead-lag relationship between spot and futures markets and their role in price discovery in India. Econometric techniques such as Johansen cointegration test, VECM and Granger causality test have been employed. The results suggest cointegration between spot and futures markets and the existence of long-run equilibrium between these two markets. Szczepańska-Przekota (2022) analysed futures prices on the CBOT exchange and the wheat producer price index. The data set spanned the period between January 2010 and January 2022. She employed granger causality tests and VAR models in her study. The results indicated a causality relationship from the spot market to the futures market, although this finding is not a common in the literature as she mentioned.

2.3. Artificial Neural Networks Model in Financial Series

There are studies in the literature that support the use of neural networks as a valid tool for the prediction of financial series, such as stock prices and futures prices. Hsu (2011) investigated the effectiveness of a systematic procedure based on backpropagation neural networks and feature selection techniques. The study demonstrates that this method is an appropriate and efficient instrument to forecast the TAIEX closing rate. Lasheras et al. (2015), in their study using public traded copper data from the COMEX market, found that MLP neural networks and Elman RNNs perform better than ARIMA concerning RMSE. In addition, the mean forecast error is lower than that of ARIMA for both the Elman RNN and the MLP. Wang and Li (2018) used a combination of neural network models to forecast the prices of a representative set of commodities, including agricultural products, industrial metals, and energy. They obtained experimental results showing that SSA and neural network models outperformed benchmarks in terms of certain metrics. Kulkarni and Haidar (2009) highlight the importance of utilizing artificial neural networks to predict short-term crude oil spot price trends. Their research findings demonstrate that futures prices provide new information about the direction of spot prices and confirm the performance of neural networks in forecasting crude oil prices. This study uses Multilayer Perceptrons (MLP) artificial neural network models to determine predictive effectiveness, like studies in the financial literature.

3. Data and Method

3.1. Data

On November 4, 2019, a liquid bank index was launched on the Borsa Istanbul in Turkey. The BIST Liquid Bank Index consists of bank stocks selected from companies traded on the

Stars Market with high market capitalization and trading volume of shares in active circulation. Futures contracts based on this index have been introduced to the market as well. The reliability of the results of the analysis is supported by the fact that the components of the index have not changed significantly since the beginning. In 2019, the index was launched with Akbank, Garanti Bankası, Türkiye Halk Bankası, İş Bankası, Vakıflar Bankası, Yapı ve Kredi Bankası. In March 2022, the Industrial Development Bank of Turkey (TSKB) was added to the index and in June 2023, Şekerbank and Albaraka Türk were added to the index. The only change related to TSKB joining the Index was considered. The study used weekend data (Friday close) of futures and spot prices, from early 2020 to late March 2023. Liquid bank futures contracts (F_XLBNK) are issued six times per year, with a two-month interval. The study examines the impact of the nearest maturity (t0), the next contract and two next contract maturity series on the spot price discovery. Price series were obtained from the Borsa Istanbul website, futures prices are Friday settlement prices. The daily settlement price is the price used to revalue open positions and update accounts at the end of the trading day for futures and options contracts. Table 1 shows the variables used in this research.

Table 1.
Return of the BIST Liquid BANK Indices

Series	**Description**
SPOT	Weekly Friday spot yields
Future.T.0	Weekly Friday nearest futures contract yields
Future.T.1	Weekly Friday next futures contract yields
Future.T.2	Weekly Friday two next futures contract yields

In artificial neural network models, appropriate transformations are usually applied to the data to make the results meaningful and reliable in studies using financial series (Hsu, 2011; Wang & Li, 2018; Kulkarni & Haidar, 2009). This study applies return transformations to price series (equation 1) both for establishing reliable neural network model and eliminating unit root problem.

$$\text{Return} = (\text{Price}_t/\text{Price}_{t-1}) - 1 \qquad (1)$$

3.2. Method

Multilayer perceptron (MLP) artificial neural networks are one of the most widely used types of artificial neural networks. It usually refers to a nonlinear neural network model with at least one hidden layer. An MLP consists of one or more input layers, one or more hidden layers, and an output layer with many connected nodes. Each node has connections to all nodes in the previous layer, and each connection has a weight. The learning process of the MLP is performed using a process called backpropagation. In this process, the network's predictions become closer to the true values as the error in the network's predictions is propagated backward and the weight of each connection is updated. As a result, MLP is widely used for its ability to model complex relationships and patterns and is often preferred for classification and regression problems. This study compares the effectiveness of proprietary spot lags and futures contract lags of different maturities in price discovery. In addition to the models constructed with the lags of spot data (equation 2), exogenous models are constructed in which the lags of futures series are included in the model (equation 3), too. Finally, both endogenous and exogenous models are constructed in which both spot and futures contracts are included in the model (equation 4).

$$Spot_t = f_k(Spot_{t-1}, Spot_{t-2}, \ldots, Spot_{t-k}) + \epsilon_t \quad (2)$$

$$Spot_t = g_k(Futures_{t-1}, Futures_{t-2}, \ldots, Futures_{t-k}) + \epsilon_t \quad (3)$$

$$Spot_t = h_{k,l}(Spot_{t-1}, \ldots, Spot_{t-k}, Futures_{t-1}, \ldots, Futures_{t-k}) + \epsilon_t \quad (4)$$

The empirical analysis was performed in R using the nnfor and neuralnet packages. As a performance measure for the MLP, the MSE was determined. The success of the model is measured by a low MSE. Another objective is to examine the hit rate. This is the accuracy of the model's predictions in terms of increases and decreases. The ratio (h) of the predicted (yhat) and observed (y) signs in the same direction indicates the success of the model (equation 5) (Kulkarni & Haidar, 2009).

$$h = \frac{1}{n}\sum_{n=1}^{n} z$$
$$\text{if } (y_{t+1} \cdot yhat_{t+1}) > 0,\ z = 1 \text{ and else, } z = 0. \quad (5)$$

Data normalization is critical to starting the MLP analysis. By taking the first difference of the selected weekly frequency spot and futures data, the unit root problem is effectively eliminated, and this transformation provides a more normalized form of the data on which artificial neural networks can perform better. When determining the architecture of an artificial neural network, factors such as number of layers, number of hidden neurons, and activation functions should be considered. A primary parameter affecting the computational cost and success of the model is the number of layers. The output layer is one and provides the prediction result. Input layers are the lags of the spot series itself and/or futures lags. As a result of the experiments, the appropriate number of hidden layers was determined to be 5 (Figure 1). Due to the nature of MLP, the backpropagation and gradient descent algorithms were preferred when selecting the optimization algorithms to be used in training the network. Stop training the network criteria set as Minus = 0.5, Plus = 1.2. A fixed number of iterations of 1000 and logarithmic activation functions were used. The training data was the basis for the testing of the network's performance and generalization ability. The first 83% of the data was used for in-sample training and the remaining 17% for out-of-the-sample testing. In the study, first the model was trained with the MLP neural network algorithm using spot returns with their own lags and 3 different futures contracts with their lags, then the performance of the same models was measured on test data. Models that achieve a low MSE and high hit rate in the test data are considered successful based on the low index constructed using equation 6. Finally, the spot series are re-estimated using the most successful spot lags and including the futures series with their respective lags.

Test.index = (Test.MSE/min(Test.MSE)) / (Test.hit rate/(min(Test.hit rate)) (6)

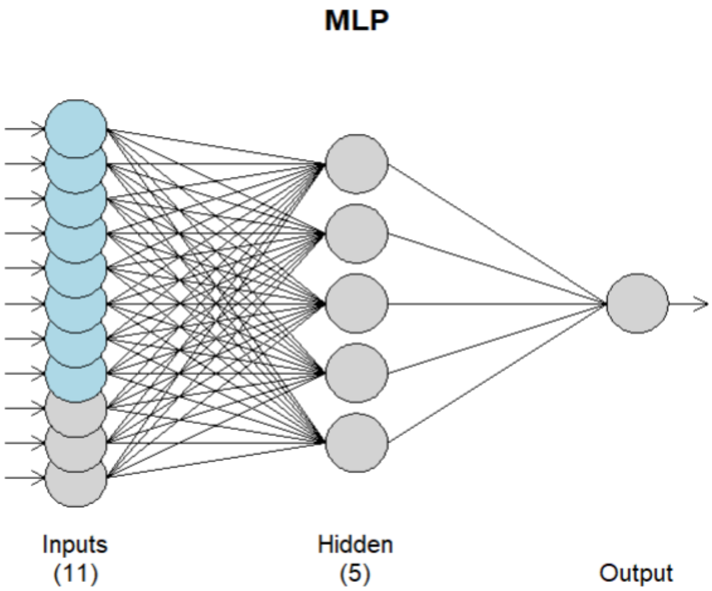

Figure 1.

An MLP network with 3 spot delays, 8 future delays and 5 hidden layers

4. Findings

Table 2 illustrates descriptive statistics for the weekly return transformed Liquid Bank Index’s spot and futures series. The average returns are positive. The fact that the mean is higher than the median and the skewness is greater than zero indicates that the series is right-skewed. A kurtosis greater than 3 is generally seen in financial return series with a high frequency of observations. The variance of the Future.T.0 series, which is the nearest maturity series, is higher than the other next one- and next two-contracts. The series are not normally distributed according to the Jarque-Berra statistics.

Table 2.

Descriptive Statistics

Series	**Min**	**Mean**	**Med**	**Max**	**Std**
SPOT	-0,2426	0,0085	0,0031	0,2710	0,0666
Future.T.0	-0,2349	0,0085	0,0059	0,2977	0,0686
Future.T.1	-0,2353	0,0085	0,0071	0,2751	0,0658
Future.T.2	-0,2000	0,0087	0,0010	0,2449	0,0650
Series	**Var**	**Skw**	**Kur**	**JB_x2**	**JB_p**
SPOT	0,0044	0,3312	5,8804	61,5113	0,0000
Future.T.0	0,0047	0,4445	6,1347	74,7600	0,0000
Future.T.1	0,0043	0,3405	6,1233	71,9578	0,0000
Future.T.2	0,0042	0,4783	5,1265	38,2861	0,0000

Models constructed with financial data generally require that there is no unit root in the series and that the series are stationary. The reason for the use of stationary series is to avoid misleading compatibility of models and spurious forecasting models. The use of non-stationary data allows the neural network to approximate the general characteristics of the data more quickly than real relationships in artificial neural network models. Thus, real relationships can be ignored (Refenes, 1995). A unit root test was applied to the price levels of the liquid bank indices at the level, thus series has unit root. After transforming the price data into return data as in equation 1, Augmented Dickey-Fuller and Phillips-Perron unit root tests were again applied and resulting the series has no unit root anymore (Table 3). The ARCH LM test is used to check whether the variances of the series vary or not. There is an ARCH effect in the series up to minimum 16-lags (Table 3). The MLP non-linear artificial neural network is able to model the series with different variances.

Table 3.

Unit Root and ARCH LM Tests Statistics

	ADF & PP Unit Root Test Results				**ARCH LM Test**		
Series	**ADF woTrend**	**ADF Drift**	**ADF wTrend**	**PP wTrend**	**ChiSq**	**Prob**	**Last.lag**
SPOT	**-8,1436 *****	**-8,2602 *****	**-8,5506 *****	**-12,1215 *****	**25,610**	**0,060**	**16**
Future.T.0	**-8,1769 *****	**-8,2943 *****	**-8,5588 *****	**-12,6536 *****	**28,330**	**0,057**	**18**
Future.T.1	**-8,1947 *****	**-8,3179 *****	**-8,5787 *****	**-11,9271 *****	**36,068**	**0,054**	**24**
Future.T.2	**-8,2538 *****	**-8,4231 *****	**-8,6570 *****	**-11,8110 *****	**45,984**	**0,052**	**32**

4.1. Univariate Input Models

In the study investigating the impact of spot or futures contract lags of different maturities on price discovery, series lags were included individually as input to the artificial neural network model. The number of hidden layers of the network was deployed as 5. First, the models were trained with the series individually included in the prediction model. Later, the in-sample trained models were used for testing out-of-sample data. As mentioned in the method section, the effectiveness of the models was measured by comparing the ratios of low MSE and high hit rate with those of other models. The results show that as the lag of the endogenous autoregressive variable and the number of exogenous variable lags increase together, the training MSEs of all models built with MLP artificial neural networks decrease, in line with the literature (Kulkarni & Haidar, 2009). This is due to the fact that the model forces itself to establish a relationship with each input variable provided to MLP artificial neural networks. Therefore, to determine the effectiveness of the main model, the study did not consider the calculated parameters of the train set, but primarily the low MSE and high hit rates calculated according to the results of the test set. In some cases, the performance results between the lagged models can be very close and it can be difficult to decide which model is more effective. To overcome this, the test.index parameter mentioned in the Methods section was created to interpret both test.MSE and test.hit rate together. Low test.index values were considered successful.

The test.index of the models constructed with auto-regressive spot variables in Table 4.1 shows that the three-lag model is the most efficient model among the other lags. In fact, although the test.MSE of the spot model with 2 lags is the lowest, the test.hit success rate is 69%, which is higher than the other models. When the two parameters are considered together, although the test.MSE of the two-lag model is the lowest, the three-lag model can be considered the most efficient due to the high hit rate.

Table 4.1.

MLP NN models with different lags of the auto regression of the Spot series

Serie	**Lag**	**Train.MSE**	**Test.MSE**	**Train.Hit**	**Test.Hit**	**Test.Index**
SPOT	1	0,0022	0,0080	0,5108	0,6429	0,8778
SPOT	2	0,0015	0,0067	0,6594	0,5556	0,8571
SPOT	**3**	**0,0011**	**0,0081**	**0,6642**	**0,6923**	**0,8315 ***
SPOT	4	0,0010	0,0088	0,7574	0,4800	1,2953
SPOT	5	0,0008	0,0082	0,7630	0,5000	1,1556
SPOT	6	0,0006	0,0086	0,8582	0,5652	1,0721

SPOT	7	0,0005	0,0092	0,8496	0,5455	1,1936
SPOT	8	0,0003	0,0073	0,9015	0,4762	1,0888

* *The most efficient lagged model among auto regressive models.*

Table 4.2.

MLP NN models with different exogenous lags of Futures.T.0

Serie	Lag	Train.MSE	Test.MSE	Train.Hit	Test.Hit	Test.Index
Future.T.0	1	0,0022	0,0085	0,5396	0,5714	1,1210
Future.T.0	2	0,0017	0,0101	0,6087	0,5926	1,2838
Future.T.0	3	0,0012	0,0091	0,6642	0,6154	1,1035
Future.T.0	4	0,0011	0,0091	0,7279	0,5600	1,2209
Future.T.0	5	0,0010	0,0079	0,7556	0,6667	0,8851
Future.T.0	6	0,0007	0,0087	0,8582	0,5652	1,1604
Future.T.0	**7**	**0,0005**	**0,0078**	**0,8797**	**0,6818**	**0,8542** *
Future.T.0	8	0,0004	0,0075	0,9091	0,5714	0,9800

** The most efficient model with lags of the exogenous nearest futures contract variable.*

Table 4.3.

MLP NN models with different exogenous lags of Futures.T.1

Serie	Lag	Train.MSE	Test.MSE	Train.Hit	Test.Hit	Test.Index
Future.T.1	1	0,0022	0,0084	0,4820	0,6071	0,9730
Future.T.1	2	0,0019	0,0078	0,5725	0,5185	1,0568
Future.T.1	3	0,0012	0,0088	0,6715	0,5385	1,1413
Future.T.1	4	0,0010	0,0095	0,7206	0,5600	1,1868
Future.T.1	**5**	**0,0008**	**0,0074**	**0,8074**	**0,6667**	**0,7778 ***
Future.T.1	6	0,0006	0,0108	0,8284	0,5652	1,3377
Future.T.1	7	0,0005	0,0103	0,8571	0,5455	1,3255
Future.T.1	8	0,0004	0,0075	0,8939	0,5714	0,9154

** The most efficient model with lags of the exogenous next futures contract variable.*

Table 4.4.

MLP NN models with different exogenous lags of Futures.T.2

Serie	Lag	Train.MSE	Test.MSE	Train.Hit	Test.Hit	Test.Index
Future.T.2	**1**	**0,0022**	**0,0079**	**0,4964**	**0,5714**	**0,8400** *
Future.T.2	2	0,0016	0,0086	0,5870	0,5926	0,8799
Future.T.2	3	0,0014	0,0086	0,6642	0,5385	0,9743
Future.T.2	4	0,0011	0,0120	0,7279	0,4800	1,5223
Future.T.2	5	0,0008	0,0086	0,7778	0,5833	0,9023
Future.T.2	6	0,0007	0,0086	0,7910	0,4783	1,0913
Future.T.2	7	0,0005	0,0099	0,8571	0,5000	1,2095
Future.T.2	8	0,0004	0,0078	0,8864	0,5238	0,9130

** The most efficient model with lags of exogenous next two futures contract variables.*

In order to understand the role of futures contracts in the spot price discovery process, separated non-linear neural network models were built using the lags of the nearest futures contract, the next futures contract, and the two next futures contracts. Among the models built using the lags of the nearest futures contract (Future.T.0), the seven-lag model had the second lowest MSE, while the hit rate was significantly higher than the others. We can say that the seven-lag model is the most efficient model for pricing the nearest futures contracts (Table 4.2). Table 4.3 shows the models generated with the lags of the next futures contract (Future.T.1). Amongst these, the five-lag model has the lowest test-mean and the highest test-hit. Among the models built using the lags of the next two futures contracts (Future.T.2), the one-lag model is more efficient than the others (Table 4.4).

The five-lag model constructed with Future.T.1 has the lowest test.MSE among the models constructed with the lags of the other futures contracts with different maturities. The fact that it is more efficient than the models constructed with the spot lags and the lags of the closest futures contract may be due to the higher variances and therefore higher volatilities of these series. According to the results, the contribution of the next futures contract to price discovery is more effective than that of the nearest futures contract.

4.2. Bivariate Input Models

The cases where spot and futures contract lags are included together as input to the MLP neural network models were also examined. This allowed the effectiveness of the forecasting models with both spot and futures contracts to be compared with the single input models. The results of the previous section showed that the most successful model when using spot lags was the three-lag model. With this information in mind, MLP neural network models were constructed with different lags of futures contracts of different maturities (Table 5). According to the training and test results, the lowest MSE was found in the two-lag model of the next futures contract (Future.T.2). The test MSE was 0.0062 and the hit rate was 77%. In the three-lag model with the next futures contract (Future.T.1), the MSE was 0.0064 and the hit rate was 73%. For the models constructed using the closest futures contract (Future.T.0), the test MSE of the single-lag model was 0.0071. The hit rate was 65%. These results show that futures contracts are more effective in the price discovery process when using spot data.

Table 5.

MLP NN models with 3 lags of the auto regression of Spot and exogenous different lags of Futures.T.X

Serie	Lag	Train.MSE	Test.MSE	Train.Hit	Test.Hit	Test.Index
Spot & Future.T.0	**3 & 1**	**0,0011**	**0,0071**	**0,7299**	**0,6538**	**0,6714 ***
Spot & Future.T.0	3 & 2	0,0009	0,0100	0,7372	0,5000	1,2361
Spot & Future.T.0	3 & 3	0,0008	0,0086	0,7956	0,5000	1,0568
Spot & Future.T.0	3 & 4	0,0006	0,0089	0,8162	0,4400	1,2496
Spot & Future.T.0	3 & 5	0,0006	0,0086	0,8222	0,5000	1,0556
Spot & Future.T.0	3 & 6	0,0005	0,0152	0,8657	0,4783	1,9520
Spot & Future.T.0	3 & 7	0,0003	0,0081	0,9323	0,5455	0,9147
Spot & Future.T.0	3 & 8	0,0002	0,0082	0,9167	0,3810	1,3237
Spot & Future.T.1	3 & 1	0,0010	0,0066	0,7153	0,6154	0,6625
Spot & Future.T.1	3 & 2	0,0008	0,0066	0,7518	0,6538	0,6235
Spot & Future.T.1	**3 & 3**	**0,0008**	**0,0064**	**0,7664**	**0,7308**	**0,5387 ****
Spot & Future.T.1	3 & 4	0,0006	0,0075	0,8088	0,6400	0,7197
Spot & Future.T.1	3 & 5	0,0005	0,0086	0,8963	0,5833	0,9052
Spot & Future.T.1	3 & 6	0,0004	0,0099	0,8657	0,4783	1,2802
Spot & Future.T.1	3 & 7	0,0003	0,0091	0,9248	0,5000	1,1229
Spot & Future.T.1	3 & 8	0,0002	0,0077	0,9015	0,6190	0,7646
Spot & Future.T.2	3 & 1	0,0010	0,0092	0,7226	0,6923	0,8195
Spot & Future.T.2	**3 & 2**	**0,0008**	**0,0062**	**0,7664**	**0,7692**	**0,4952 *****
Spot & Future.T.2	3 & 3	0,0006	0,0083	0,7883	0,6154	0,8316
Spot & Future.T.2	3 & 4	0,0006	0,0073	0,8235	0,6000	0,7480
Spot & Future.T.2	3 & 5	0,0004	0,0089	0,8741	0,6667	0,8209
Spot & Future.T.2	3 & 6	0,0003	0,0084	0,8731	0,4783	1,0837
Spot & Future.T.2	3 & 7	0,0003	0,0082	0,8947	0,5000	1,0071
Spot & Future.T.2	3 & 8	0,0002	0,0077	0,8864	0,4762	0,9981

*Among the models in the table, ***: the most efficient model, **: the second efficient model** and *: the third efficient model according to the Test.Index.*

The results show that futures prices lead spot prices for the BIST liquid bank index, in accordance with the findings of previous studies in the finance series. The one and two next futures contracts on the liquid bank index were found to explain spot prices better than the nearest futures contracts. The descriptive statistics show that the nearest expiring contracts have higher variances than the others. The fact that contracts issued at frequent intervals of 6 times a year are open to speculation by market participants at the nearest maturities may be the reason for the failure of these contracts in forecasting efficiency. Alternatively, when market participants want to hedge, they switch to futures contracts and do not wait until the last day, which may be one of the reasons why these one and two next contracts better explain spot prices.

5. Conclusion

Futures markets play a crucial role in financial and commodity markets, with futures contracts being a fundamental element of these markets. In addition to their role as a hedging tool, futures markets also contain valuable information relevant to the process of price discovery. The expectations theory in futures trading postulates that futures prices reflect the anticipated values of future spot prices and, consequently, incorporate investors' expectations about future market conditions. In the literature, the different stages of maturity of futures contracts can influence the accuracy of cash price forecasts through the price discovery process. Conversely, in certain instances, spot prices can influence the direction of futures prices. These findings underscore the intricate nature of the relationship between futures and spot markets and demonstrate that a range of factors, including market dynamics, data periods, and frequencies, can influence this relationship. A variety of models have been developed to facilitate the understanding of this relationship, including those that demonstrate the efficacy of artificial neural networks in the forecasting of financial series.

This research analyzes the BIST liquid bank index, a relatively new index in Turkey, using a multilayer perceptron (MLP) neural network model. The study evaluates the impact of the index on futures contracts pricing and spot price discovery. Two main models have been employed in empirical research: the univariate input model, in which spot and futures contracts are handled as single exogenous variables; and the bivariate input model, which includes both spot and futures as exogenous variables. Among the former models, two next-futures contracts have been identified as more effective in spot price discovery. The latter has been demonstrated to be the most efficient pricing model including spot autoregression with three lags and exogenous two-next futures contracts with two lags. Liquid bank index deferred maturity futures contracts are more effective in explaining spot prices than the most near-maturity contracts. Another finding is that contracts with the closest expiry have a higher variance than others. These results are consistent with literature indicating that futures prices can be used to predict spot prices. Moreover, futures with varying maturities may offer enhanced predictive efficacy than spot and nearby contract. These findings contribute to a deeper understanding of index price movements and the improvement of risk management strategies.

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