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Lead Lag Relationship and Price Discovery in Turkish Stock Exchange and Futures Markets

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In perfectly efficient financial markets, new information should be impounded simultaneously into the cash and futures markets. Real world institutional factors, however, often create an emprical lead-lag relationship between alternative securities price changes. Current futures prices in one futures market would lead the change of current spot prices. Price discovery can be defined as lead-lag relationship and information flows between two markets. This study examines the price discovery and lead-lag relationship between stock index (ISE 100) and stock index futures markets in Turkey over the period 2006-2011. We test our hypotheses with daily data in the context of a Vector Error Correction model that also incorporates possible co-integration between the futures and spot market. The evidence supports that the futures market in Turkey is a useful price discovery tool.

Key words: Causality, error correction, price discovery, futures, stock exchange.

INTRODUCTION

Under perfectly efficient markets, new information is impounded simultaneously into cash and futures markets. However, in reality, institutional factors such as liquidity, transaction costs, and other market restrictions may produce an empirical lead-lag relationship between price changes in two markets.

Futures prices are naturally highly related to spot prices, current futures prices (F_t) and the expected future spot prices (S_T), because futures are derivatives of spot assets. Because futures prices represent the prices at which market participants agree to transact on a set date in the future, a conclusion seems natural that current futures prices F_t should be the prediction of future spot prices S_T in an efficient market, which is defined as the function of "price discovery" of futures. Here, T is the time until delivery date in a futures contract and t denotes the current time point. In the futures market's literature, this argument is expressed as "futures prices are unbiased estimates of future spot prices".

Some researchers define the lead-lag relationship, current futures prices (F_t) and current spot prices (S_t), and information flows between futures and spots markets as "price discovery". The market absorbing and reflecting new information more rapidly is said to have the function of price discovery. If F_t changes more rapidly than S_t when new information arrives and S_t changes after F_t, we would say the futures market has the function of "price discovery" (Chen and Zheng, 2008).

The lead-lag relation between price movements of stock index futures and the underlying cash market illustrates how fast one market reflect new information relative to the other, and how well the two markets are linked. In a perfectly frictionless world, price movements of the two markets are contemporaneously correlated and not cross-autocorrelated. However, if one market reacts faster to information, and the other market is slow

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to react, a lead-lag relation is observed. Identification of the nature and direction of the lead-lag relationship between stock indices and stock index futures markets has been the subject of long-standing debate among researchers and policy-makers. Research on the price discovery role of futures markets and their possible volatility implications for the spot market generally focuses on the US and a few other developed markets. This paper examines the case for Turkey that has recently established index futures trading.

Theoretical framework and literature review: Relationship between spot and futures markets

Theoretical underpinnings underlying the lead-lag relationship between the spot and futures markets are the cost of carry model, the price discovery and market efficiency hypotheses.

The central tenet of the cost of carry model hypothesized that, in a perfect capital market with non-stochastic interest rates and dividend yields, prices of futures contracts and the underlying spot prices are perfectly contemporaneously correlated and no lead-lag relationship would exist.

The efficient market hypothesis states that financial markets efficiently process all relevant information to be reflected simultaneously into both the spot and futures prices and that the price movements in each market are identically and independently distributed.

In an informationally efficient market, financial asset prices reflect information available to market participants. Price discovery is the process by which markets incorporate this information to arrive at equilibrium asset price. If a single financial asset or multiple highly related financial assets are traded on more than one market, each market may be involved in the price discovery process but one that provides a combination of the greatest liquidity, lowest execution costs and greatest leverage opportunities should dominate. Price discovery is typically documented by nothing the speed at which prices react to new information. This is a direct outcome of the assertion that price discovery (informed trading) occurs in the market in which the smallest overall transaction costs are incurred.

In perfectly efficient financial markets, new information should be impounded simultaneously into the cash and futures markets. Real world institutional factors, however, often create an empirical lead-lag relationship between alternative securities price changes. The market that provides the greater liquidity, the lower transaction costs, and less restriction is likely to play a more important role in price discovery. Futures markets, accordingly, are more likely to incorporate information more efficiently than cash market due to their inherent leverage, low transaction costs, and lack of short sell restrictions. Two main, but not mutually exclusive, models of futures prices exist, i.e. (i) the cost-of-carry model and (ii) the expectations model (Laws and Thompson, 2004). The theoretical relation between the price of an index futures contracts and the price level of the underlying index, according to the cost-of-carry model is;

$$F_t = S_t e^{(r_t - q_t)(T-t)} \qquad (1)$$

where F_t is the index futures price at time t; S_t is the spot index price at t; r_t is the continuously compounded cost of carrying the spot index basket from the present t, to time T which is the expiration date of the stock index futures contract and q_t is the average yield per annum on the spot during the life of the futures contracts with continuous compounding.

If Equation (1) does not hold, arbitrageurs will execute arbitrage strategies until Equation (1) holds again and the market reaches equilibrium (Chen and Zheng, 2008).

If Equation (1) is transformed into a model in log-returns rather than levels, we obtain;

$$R_{S,t} = (r_t - q_t) + R_{F,t} \qquad (2)$$

Where

$$R_{S,t} = ln\left(\frac{S_t}{S_{t-1}}\right) \text{ and } R_{F,t} = ln\left(\frac{F_t}{F_{t-1}}\right)$$

Under market efficiency and in the absence of market frictions, the relationship in Equation (2) implies that: (i) The expected rate of return of price appreciation on the stock index portfolio equals the net cost of carry plus the expected rate of return on the futures contract, (ii) The standard deviation of the rate of return of the futures contract equals the standard deviation of the rate of return of the underlying stock index, (iii) the contemporaneous rates of return of the futures and the cash are perfectly, positively correlated while the non-contemporaneous rates of return are uncorrelated and no lead-lag relationship would exist (Abhyankar, 1995).

However, there are several reasons why, in the presence of market imperfections, there may be a lead-lag relationship between the index futures and cash market returns.

Under perfectly efficient markets, new information is impounded simultaneously into cash and futures markets. However, in reality, institutional factors such as liquidity, transaction costs, and other market restrictions may produce an empirical lead-lag relationship between price changes in the two markets. Future markets could incorporate new information more quickly than do cash market given their inherent leverage, low transaction costs, and lack of short-sale restrictions (Tse, 1999; So and Tse, 2004).

The lead-lag relationship illustrates how well two markets are linked, and how fast one market reflects new information from the other (Herbst et al., 1987). It investigates whether the spot market leads the futures market, whether the futures market leads the spot market or whether the bi-directional feedback between the two markets exists.

Empirical research aimed at testing the lead-lag relationship between the index futures and the underlying spot market produced mixed results. Empirical evidence indicates that, (a) future prices tend to influence spot prices, (b) spot prices tend to lead futures prices, and (c) a bi-directional feedback relationship exists between spot and futures prices.

Argument (a) predicts that futures prices lead spot prices when informed traders, hedgers and speculators react to new information by indulging in futures rather than spot transactions due to lower transaction costs, capital requirements and short-selling restrictions in the derivative markets. Since spot transactions require a greater deal of initial outlay and may take a longer time to implement, spot prices tend to react with a lag (see, Grossman and Miller, 1998; Miller, 1990).

Houthakkar (1992) argued that futures trading influences inter-temporal allocation of production and consumption decisions by holding inventories. Suppose that futures prices of distant deliveries are far higher than those of early deliveries. The relative difference between the futures and spot prices will trigger action with the postponement of current consumption and the subsequent change in spot prices arising from the change in demand in the spot market.

Moosa and Al-Loughani (1995) in a theoretical model assert that futures prices are jointly determined by arbitrageurs’ and speculators’ demand for futures contracts. Arbitrageur demand depends on the difference between the arbitrage price as determined by the cost of carry model and the actual futures price. Speculator demand depends on the difference between the expected future spot price and actual futures prices. It is the futures price rather than the spot price that acts as a yardstick in both cases.

Argument (b) predicts that spot prices lead to futures prices. Moosa (1996) argued that a change in spot price would trigger action from arbitrageurs and speculators leading to a subsequent change in futures prices. Firs, the index arbitrageurs will respond to the violation of the cost of carry condition by participating in the spot market. Second, speculators would react following the discrepancy between the current futures price and the expected spot price and to the discrepancy between the current futures prices and the expected futures prices. In both cases spot prices lead futures prices.

Furthermore, Subrahmanyam (1991), Chan (1992) and Abhyankar (1995) argued that when informed traders have firm-specific information, they find it optimal to trade in the shares of firms in the spot market rather than trading index futures in the derivatives market.Kawaller et al. (1987) and Srinivasan (2009) postulate a bi-directional feedback relationship between spot and futures prices when spot prices are affected by their past history, current and past futures prices, and futures prices are affected by their past history, current and past spot prices and other market information.

The preceding argument of Subrahmanyam (1991), Chan (1992) and Abhyankar (1995) in conjunction with the leading indicator property of futures prices also indicates the possibility of a bi-directional lead-lag relationship between spot and futures prices.

Several studies suggest that futures markets play a critical role in price discovery for the underlying spot market (Chatrath et al., 1999; Yang et al., 2001; Lien and Tse, 2002; Chen and Zheng, 2008). This price discovery function implies that the prices in the future and spot markets are systematically related in the short run and /or in the long run. In the co-integration jargon, the price discovery function implies the presence of an equilibrium occurs, prices in one or both markets should adjust to correct the disparity.

Other studies which have examined cross-listed futures contracts have found an association between better price discovery and those exchanges which are characterized by lower transaction costs (Chen et al., 2002; Roope and Zurbruegg, 2002; Hsieh, 2004)

Recently, Lien and Zhang (2008) summarise theoretical and empirical research on the roles and functions of emerging derivatives markets. They report that empirical result from a few emerging countries suggest a price discovery function of emerging futures markets.

DATA AND METHODOLOGY

Our data consist of daily observations starting from the inception of index futures trading of the Istanbul Stock Exchange – ISE in Turkey. Specifically, the analysis covers the period 2 January 2006–17 March 2011 (a total of 1309 daily observations). The ISE 100 index is the broadest indicator of the overall performance of the Turkish stock market. The ISE 100 index futures contracts are traded in Turkish Derivatives Exchange – TurkDEX in Turkey.

The TurkDEX lists daily closing prices for the ISE 100 index and daily settlement prices for the ISE 100 futures. The index futures contract of the most immediate maturity is generally the most heavily traded until the beginning of the delivery month when the market interest shifts over to the contract with the next most immediate maturity. We use futures price data for the most immediate contracts, except during the delivery month when we use instead the next most immediate contract (Zhong et al., 2004). Zhong et al. (2004) have suggested that using of data in such a way that eliminates abnormal price variability which may occur during the delivery month. We express the ISE 100 index and the index futures prices in natural logarithms, where logarithmic first-differences represent continuously compounded returns.

Stationarity and unit root tests

Before the lead lag relationship between the ISE 100 index and the ISE 100 index futures is examined in a causality framework of several simultaneous equation models, it is important to test the unit roots prior to testing the casual relationships, as Granger causality tests require the data to be stationary.

A series is said to be integrated of order one (or to be *I(1)*) if it has to be differentiated once before becoming stationary (Vogelvang 2005). Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979; 1981) unit root test and the Phillips-Perron (Perron, 1988; Phillips and Perron, 1988) nonparametric tests (Enders 2004). Instead of choosing between either one of these test methods, Enders (2004) considers a safe choice is to use both types of unit roots tests, since they reinforce each other.

Since most financial data contain stochastic trends, these trends need to be detected and detrended if, and as, necessary (Wilkinson, 1999). The test statistics can be based on the ordinary least squares (OLS) to determine a suitable specified regression equation for a time series y_t for the ADF test for each series:

$$\Delta y_t = \alpha_0 + \beta_1 y_{t-1} + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

with the number of lags being determined by the residuals free from autocorrelation. This could be tested for in the standard way such as by Lagrange Multiplier (LM) test. In practice many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here we are going to use the AIC to test the optimal lag number.

The Phillips-Perron (PP) test involves incorporating lagged values of the dependent variable into the following equation:

$$y_t = \alpha_0 + \beta_1 y_{t-1} + \varepsilon_t \tag{4}$$

Cointegration

The concept of co-integration was first introduced by Granger (1981) and elaborated further by Engle and Granger (1987), Engle and Yoo (1987; 1991), Phillips and Ouliaris (1990), Stock and Watson (1988), Phillips (1991) and Johansen (1988; 1991; 1995), among others. Two series can be tested for co-integration using the Phillips-Ouliaris test.

Two non-stationary time series s_t and f_t are co-integrated if some linear combination as_t + bf_t, with a and b constant, is a stationary series.

As an example consider a random walk μ_t given by $\mu_t = \mu_{t-1} + w_t$, where w_t is white noise with zero mean, and two series x_t and y_t given by $x_t = \mu_t + w_{x,t}$ and $y_t = \mu_t + w_{y,t}$, where $w_{x,t}$ and $w_{y,t}$ are independent white noise series with zero mean. Both series are non-stationary, but their difference $x_t - y_t$ is stationary since it is a finite linear combination of independent white noise terms. Thus the linear combination of x_t and y_t, with a = 1 and b = −1, produced a stationary series, $w_{x,t} - w_{y,t}$. Hence x_t and y_t are co-integrated and share the underlying stochastic trend μ_t.

Error correction model and casuality

Co-integration analysis is important, because if two non-stationary variables are cointegrated, a vector auto-regression (VAR) model in the first difference is mis-specified, due to the effect of a common trend. If a co-integration relationship is identified, the model should include residuals from the vectors, lagged at one period, in a dynamic vector error correction mechanism (VECM). Granger (1986) and Engle and Granger (1987) have demonstrated, if Y and X are both I (1) variables and are co-integrated, an error correction model exists.

The error correction model can be interpreted as showing there often exists a long-run equilibrium relationship between two economic variables, but in the short run, however, there may be disequilibrium. With the error correction mechanism, a proportional disequilibrium in one period is corrected in the next period.

The testing procedure for causal relationships between variables uses VAR and VECM modeling. The VECM will be used, as sources of causality cannot be detected by the VAR technique (Li, 2001; O'Connor, 1999). The VECM equation requires the time series to be non-stationary or integrated of an order bigger than zero, as well as being co-integrated.

Hypotheses

Our hypotheses characterize the dynamic relation between ISE 100 stock index (IX) and ISE 100 stock index futures (FX). The first hypothesis surrounds the price discovery function of the index futures market, and contends that prices in the futures market are a useful predictor of subsequent spot prices. In this paper, we distinguish between short-run prediction (H_1) and long-run prediction (H_2). Short-run prediction implies that a given change in futures prices can only predict temporary (one time) change in spot prices. On the other hand, long-run prediction implies that a given change in futures prices can predict the persistent (long-lasting) change in spot prices. Clearly, long-run predictions require the presence of a long-run (equilibrium) relation binding prices in the two markets.

According to the cost-of-carry model (e.g., Koutmos and Tucker, 1996), the logarithms of futures price, f_t, and the logarithms of the underlying cash price, s_t, are co-integrated with a common stochastic trend. Let the co-integrating relation between the two price-series be:

$$f_t = \beta_0 + \beta_1 s_t + \beta_2 m_t \tag{5}$$

where m_t is the number of days to maturity of the futures contract at time *t* (Ng and Pirrong, 1996). Following Tse (1999), a vector error correction model can represent the bivariate co-integrated series (s_t; f_t), that is:

$$\Delta s_t = \mu_1 + \alpha_1(f_{t-1} - \beta_0 - \beta_1 s_{t-1} - \beta_2 m_{t-1}) + \sum_{i=1}^{k} \Gamma_i^{11} \Delta s_{t-i} + \sum_{i=1}^{k} \Gamma_i^{12} \Delta f_{t-i} + \varepsilon_{1t} \tag{6}$$

$$\Delta f_t = \mu_2 + \alpha_2(f_{t-1} - \beta_0 - \beta_1 s_{t-1} - \beta_2 m_{t-1}) + \sum_{i=1}^{k} \Gamma_i^{21} \Delta s_{t-i} + \sum_{i=1}^{k} \Gamma_i^{22} \Delta f_{t-i} + \varepsilon_{2t} \tag{7}$$

The lagged *ec* term, $ec_{t-1} = (f_{t-1} - \beta_0 - \beta_1 s_{t-1} - \beta_2 m_{t-1})$ represents the dynamics of the long-run relation linking the two series, so that disequilibria in any period are corrected in the next. The loading α_1 (α_2) is the speed of adjustment of index (futures) returns toward equilibrium.

The short-run prediction hypothesis contends that lagged futures prices have significant predictive power for spot prices over finite forecasting horizons. This hypothesis is akin to the Granger-causality concept and can be tested in the above vector error correction model system by:

$$H_1 : \Gamma_1^{12} = \Gamma_2^{12} = \cdots = \Gamma_k^{12} = 0 \tag{8}$$

Rejecting H_1 implies that futures prices lead spot prices and is

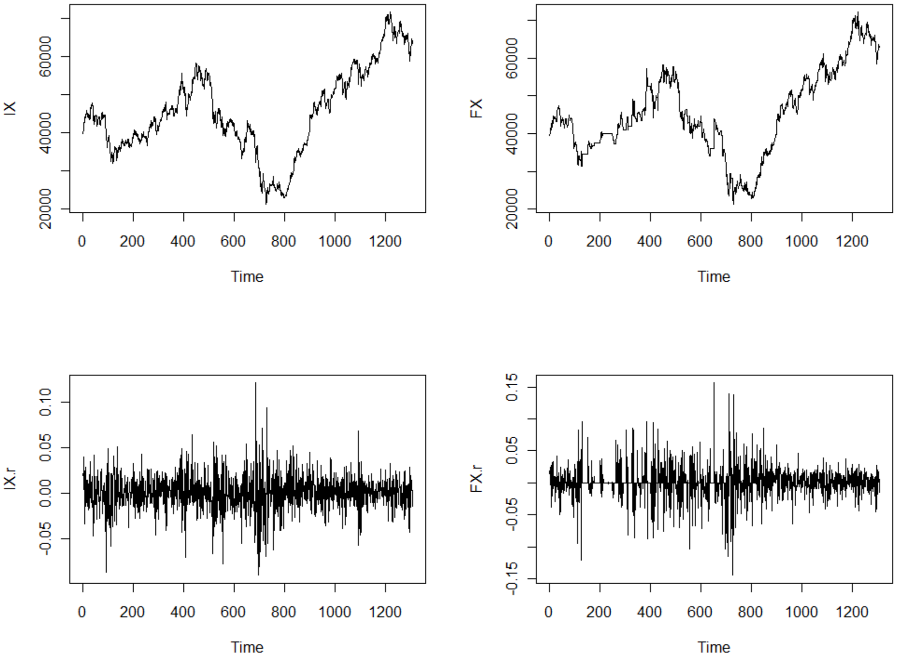

Figure 1. Index prices – IX (top-left), Futures prices – FX (top-right), Index log returns – IX.r (bottom-left) and Futures log returns – FX.r (bottom-right).

consistent with the short-run prediction hypothesis. A similar hypothesis can test for a reverse Granger causality from spot to futures prices. As to testing the long-run prediction hypothesis, we focus on the long-run speed of adjustment (α_i) in models (4) and (5) above. This hypothesis will be supported if the lagged error-correction term $(f_{t-1} - \beta_0 - \beta_1 s_{t-1} - \beta_2 m_{t-1})$ can effectively predict current changes in spot prices (Zapata and Rambaldi, 1997; Yang et al., 2001).

Under this long-run prediction hypothesis, deviations from the long-run spot/futures market equilibrium help predict subsequent movements in spot prices. Thus, the null hypothesis of no long-run prediction is:

$$H_2 : \alpha_1 = 0 \tag{9}$$

This long-run prediction hypothesis posits that index futures prices impact spot price changes through the long-run price equilibrium channel. Rejecting H_2 (that is, a non-zero α_1) is consistent with the long-run interpretation of the prediction hypothesis.

This hypothesis posits that the long-term prediction that the long-term price stability through the impact of index futures prices, spot price changes. H_2 rejection (that is, a non-zero α_1) estimate the long-term interpretation is consistent with the hypothesis.

EMPIRICAL RESULTS

Descriptive statistics are presented for our series before we proceed to model estimations. We display in Figure 1 the ISE 100 index prices and the ISE 100 index futures prices, and Figure 2 the price discrepancies between these two. Both series rise and fall together, hence a possible strong linear relationship. The two series indicate the existence of co-movements between the prices. This co-movement indicates the possible existence of co-integration between the index prices and index futures prices. One market will be useful in predicting the other market's returns; hence a valid error correcting presentation will exist.

Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) Dickey and Fuller 1979, 1981) unit root test and the Phillips-Perron (Perron, 1988; Phillips and Perron 1988) nonparametric tests. We run the ADF test with a linear trend on level and first differences of spreads of up to five lags in order to control for serial correlation. The Akaike Information criterion (AIC) was used to determine the optimal number of lags for both the tests. We also run the PP test diagnostic corrected by Newey-West autocorrelation consistent variance estimator. For both tests we employ MacKinnon (1996) critical values for rejection of the unit root null hypothesis. We further test for statistically significant residual autoregressive effects on the basis of the Ljung-Box Q statistic.

Significant excess kurtosis statistics in Table 1 and the Jarque–Bera test statistics in Table 2 indicate that the two return series diverge from the bivariate normal distribution. This suggests that a generalized distribution with conditional variance–covariance matrix may better represent the time-series behavior of prices and returns in the Turkish market than could an unconditional normal distribution. The Ljung–Box Q statistics (Ljung and Box, 1978; Brockwell and Davis, 2002) of serial correlation (up

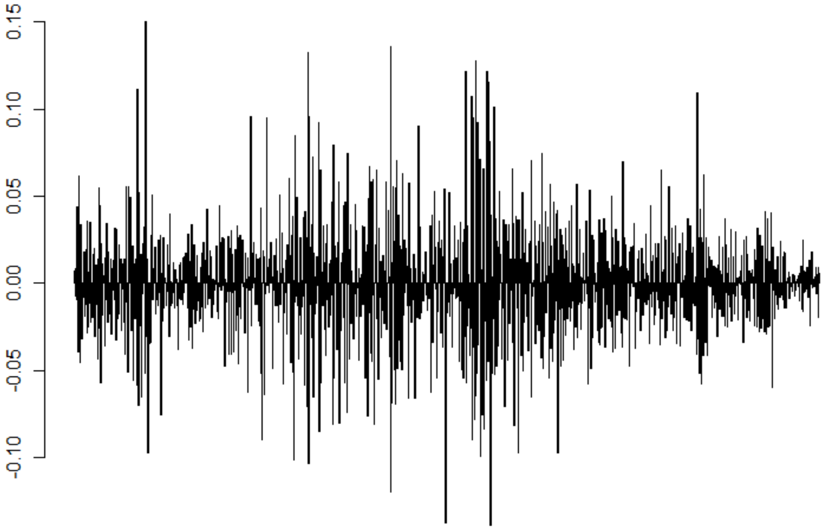

Figure 2. Price discrepancies between index prices (IX) and index futures prices (FX).

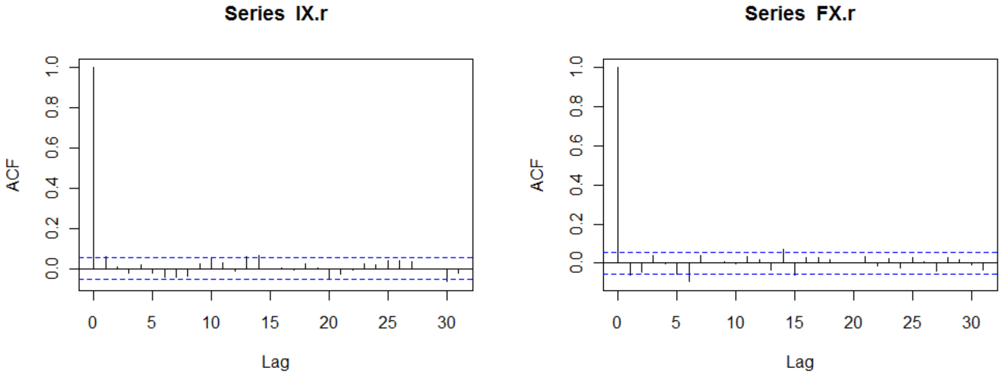

Figure 3. The auto correlation function of the index prices log returns – IX.r (left) and the auto correlation function of futures prices log returns – FX.r (right).

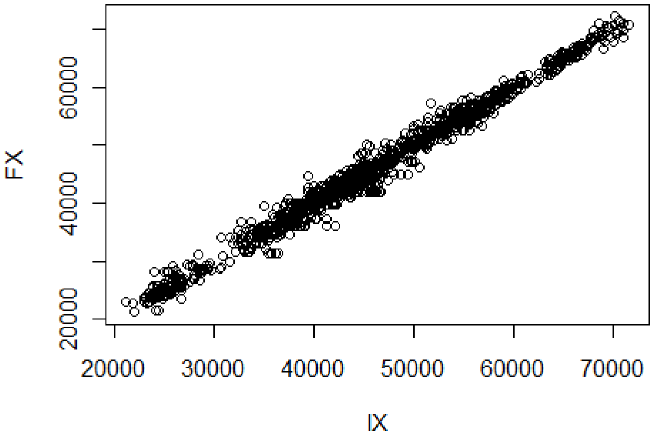

Figure 4. Scatter plot of the index (IX) and the futures prices (FX).

Table 1. Descriptive statistics.

	Mean	Median	Std. dev.	Min.	Max.	Skewness	Excess Kurtosis
Index prices	45370.2100	44371.9700	11269.3600	21228.2700	71543.2600	0.1439	-0.4650
Futures prices	45265.9900	43925.0000	11321.4300	21200.0000	72150.0000	0.1557	-0.4889
Index returns	-0.00003	0.0007	0.0196	-0.0901	0.1213	-0.1164	2.9009
Futures returns	-0.0002	0.0000	0.0242	-0.1447	0.1559	-0.0547	7.1327

Table 2. Unit root and cointegration tests.

	JB	Q(20)	ADF (lag order = 10)	JB	KPSS (lag param. = 8)	PP
Index prices	16.1265[a]	1299.1640[a]	0.4866	16.1265[a]	4.3625[a]	-2.4703[a]
Futures prices	18.1350[a]	1295.8330[a]	0.3940[a]	18.1351[a]	4.3999[a]	-3.0053[a]
Index returns	464.4592[a]	4.5552[b]	-24.5242[a]	464.4592[a]	0.1500[a]	-1207.020[b]
Futures returns	2785.4730[a]	4.6912[b]	-27.5508[a]	2785.4730[a]	0.1272[a]	-1316.713[b]

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

Table 3. Results of Engle-Granger procedure.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.91427	23.43921	0.295	0.768
ec_{t-1} (α_i)	0.18146	0.01806	10.050	< 2e-16[a]
Δs_{t-1}	0.67837	0.02931	23.148	< 2e-16[a]
Δf_{t-1}	-0.11350	0.02313	-4.908	1.04e-06[a]

to 20 lags) approach significance, supporting the notion that index and index futures returns in Turkey are autocorrelated.

Finally, we also examine the stationarity of the data using four unit root tests; namely,

- the Augmented Dickey–Fuller test discussed in Elliott et al. (1996), Greene (2002), Said and Dickey (1984),
- the Jarque Bera test discussed in Jarque et al. (1980; 1981;1987),the Kwiatkowski-Phillips-Schmidt-Shin KPSS) test discussed in Kwiatkowski et al. (1992) and Bhargava (1986),
- the Phillips–Perron test discussed in Phillips and Perron (1988).

The test results in Table 1 and Table 2 suggest that index and index futures prices are first difference stationary [I(1)].

[a] indicates statistical significance at the 1% level. [b] indicates statistical significance at the 5% level. [c] indicates statistical significance at the 10% level. ADF: Augmented Dickey-Fuller test, JB: Jarque Bera test, Q: Ljung-Box test, KPSS: Kwiatkowski-Phillips-Schmidt-Shin test, PP: Phillips-Perron test.

A necessary condition for co-integration is each of the time series integrates in the same order greater than zero, i.e. I(1). We conducted the Engle-Granger co-integration test to determine if the return series of the ISE 100 index and the ISE 100 index futures are co-integrated of order 1. Table 3 and Table 4 report the co-integration vectors and Engle-Granger tests. We reject the null hypothesis the two series cannot be co-integrated. Since both the series are co-integrated with co-integration vector (1,-0.9936).

Table 5 presents results from the Johansen Co-integration test and reports the number of co-integrating relations among the variables. There are two types of test statistics reported. The first is trace statistics and the second is eigenvalue statistics. The first column in Table 5 is the number of co-integrating relations under the null hypothesis (the null hypothesis is stated no co-integrating relationship exists). The second column is the ordered eigenvalues of the Π matrix. The third column is the test statistic and the last column is the 5% and 1% critical values. Both the trace test and the eigenvalue tests indicate there is one co-integrating relationship among the variables at 5% significant level. Both the series are co-integrated with co-integration vector (1, -0.9935617).

In Table 5 the price series in each market are co-

Table 4. Granger causality test.

			IX ~ FX		FX ~ IX	
Order	**Res.Df.**	**Df**	**F**	**Pr(>F)**	**F**	**Pr(>F)**
1	1306	-1	0.8434	0.3586	823.8300	< 2.2e-16^{a}
2	1304	-2	0.0551	0.9464	440.1900	< 2.2e-16^{a}
3	1302	-3	1.7172	0.1616	302.3100	< 2.2e-16^{a}
4	1300	-4	2.7130	0.0287^{b}	227.4300	< 2.2e-16^{a}
5	1298	-5	2.5743	0.0251^{b}	182.0400	< 2.2e-16^{a}
6	1296	-6	2.4784	0.0218^{b}	151.2200	< 2.2e-16^{a}
7	1294	-7	2.1904	0.0327^{b}	128.1700	< 2.2e-16^{a}
8	1292	-8	1.7021	0.0935^{c}	112.2500	< 2.2e-16^{a}
9	1290	-9	1.7980	0.0643^{c}	99.6500	< 2.2e-16^{a}
10	1288	-10	1.6291	0.0930^{c}	89.5650	< 2.2e-16^{a}

^{a} indicates statistical significance at the 1% level. ^{b} indicates statistical significance at the 5% level. ^{c} indicates statistical significance at the 10% level.

Table 5, Johansen cointegration test.

Eigenvalues (lambda)		**Values of teststatistic and critical values of test**				
0.5516458	0.2479247		test	10pct	5pct	1pct
		r <= 1	372.10	6.50	8.18	11.65
		r = 0	1047.64	12.91	14.90	19.19
	Eigenvectors				Loading matrix	
	IX.lr.l2	FX.lr.l2			IX.lr.l2	FX.lr.l2
IX.lr.l2	1.0000000	1.0000000		IX.lr.l2	-0.417520	-0.5275762
FX.lr.l2	-0.9935617	0.6474762		FX.lr.l2	1.190527	-0.2072201

^{a} indicates statistical significance at the 1% level. ^{b} indicates statistical significance at the 5% level. ^{c} indicates statistical significance at the 10% level.

integrated with one common stochastic factor. The co-integrating vector is (1, -0.9935617) indicating the index market and the futures market value the same underlying information differently over the long run.

In Table 5, we present the price discovery results of the index market and the futures market. The common factor weights for the index market and for the futures market, suggesting that the index market contributes the most to the price discovery process. The factor weights are a measure of the markets contribution to permanent information and a greater factor weight assigned to a market, the slower its speed of adjustment to equilibrium and the bigger its role in discovering equilibrium prices.

We report the lower bound, upper bound, and average of all permutations of the Cholesky factorisation of information shares. The index market dominates and the futures market yields.

The lower and the upper bounds differ considerably, but Martens (1998), Baillie et al. (2002) and Booth et al. (2002) also report a substantial difference in their Hasbrouck (1995) upper and lower bounds of information shares. Baillie et al. (2002) shows in a bivariate case, using various examples, that the average of the information shares given by the two permutations is a reasonable estimate of the markets role in price discovery.

Both the Hasbrouck (1995) and Gonzalo and Granger (1995) results indicate the index market plays the primary role in the price discovery. The information share is significantly larger than the futures market and the price discovery is predominately in the index market.

CONCLUSION

This paper investigates for the Turkish market the hypotheses that the futures market effectively serves the price discovery function. Our findings are helpful to traders, speculators and financial managers dealing with emerging stock markets and index futures markets. We define the function of price discovery of futures markets as the leading role in the reactions to new information. We test both hypotheses simultaneously with daily data that incorporates short-run dynamics while preserving the underlying cointegrating relation between the two markets in both the conditional means and conditional variances. Results are consistent with the above arguments.

Our empirical results have important implications for traders and speculators. First, we show that both series, ISE 100 spot and futures are cointegrated. The existence of cointegration implies that one of the variables can be used to predict the other one. The results are consistent with both hypotheses, suggesting that the futures market in Turkey is a useful price discovery tool. The evidence of cointegration between the markets implies that prices cannot move far away from each other. The presence of cointegration suggests a violation of weak form market efficiency and possibility of an arbitrage opportunity.

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