A DYNAMIC KALMAN FILTERING APPROACH TO DETECT THE RELATIONSHIP BETWEEN FUTURES AND SPOT EQUITY MARKETS

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In this empirical paper, we design a dynamic Kalman filtering approach to investigate time-varying relationship between spot and futures equity markets. In addition to static bounds test from statistics, we revisit the econophysics discipline, and set up a dynamic Kalman filtering process that provides an iterative process for parameter estimation. The methodology is practically tested with a growing futures market in Turkey in the crisis period. Results of empirical evidence show that the prices of futures contracts can be predicted by spot prices indicating that the markets have not got information efficiency yet. The methodology based on econophysics discipline in the paper can be applied in other financial markets and macroeconomic indicators to detect time varying dynamic relationship between economic and financial variables.

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1. Motivation

The Kalman filter is a discrete, recursive linear filter to arrive at a conditional density function of the unobservable using the Bayes' Theorem [1]. The filter separates a time-series into two components as "signal" and "noise". It is assumed that there is a smooth trend line within the time series which represents the fundamental value of the price before it is perturbed by "market noise". The filter uses the current observation to predict the next period's value of unobservable and then uses the realization next period to update that forecast. As a recursive algorithm, it allows to upgrade model estimates using new information.

Though the Kalman filter was originally developed by Kalman in engineering field [2], it has been gaining popularity with other econophysics methodologies such as multi-fractal analysis and wavelet transformations applied in finance and economics. The preliminary application of the Kalman filtering in econophysics was based on defining unobservable parameters and state variables to predict financial time series. After successful implementation of Hamilton [3] and Harvey [4], the Kalman filter has been especially used for detecting regime switches in financial markets. In this empirical paper, we design an econophysics process via dynamic Kalman filtering to predict the prices of futures index contracts from their spot prices in Turkish equity markets. Though Turkish futures index contracts were started to trade in the beginning of 2005, the volume of the futures market has dramatically grown and is currently more than the volume of the spot market. The emerging Turkish futures markets, in that sense, present a valuable environment for empirical research on development of market efficiency, spot and futures markets interaction, and detecting regime switches in the financial time series. As the Turkish futures market is a newly emerging market, we think that it is worthy to examine if the prices in the futures market are predictable using a recent methodology allowing volatility clustering. The Kalman filter does not require that the deterministic dynamics have stationary properties.

There are certain researches based on econophysics including wavelets, multi-fractal analysis, time-varying copula, multi-scale causality and Markov chain processes to examine the price patterns in the stock markets. However, examining in this article the causality between the spot and futures markets with a dynamic Kalman filtering process is a contribution to the econophysics literature. In the empirical study, the time series of the Istanbul Stock Exchange National Index-30 (ISE-30 Index) along with time to maturity are used to construct a time series of futures contracts. Then, these futures prices are used to estimate the spot prices using the Kalman filter. Comparison of the spot prices and Kalman estimated spot prices shows how accurately the Kalman filter estimates the unobservable variable. The empirical findings show that the futures prices can be successfully predicted by their spot values using the Kalman filter in the Turkish stock markets. Therefore, the futures stock market has not got informational efficiency though it has been within a growing trend.

The rest of the paper is constructed as follows. In the next part, a literature survey focusing on the application of the Kalman filter in predicting financial time series is presented. Methodology and data used are overviewed in the third part. In that part, the Kalman filter is used, in particular, to our research interest. The descriptive statistics of the spot and futures time series are given in the same part. In the fourth part, the empirical findings are discussed in terms of their theoretical and practical implications. The fifth and the last part is the conclusion containing some suggestions for the future researches.

2. Literature review

As this paper examines the prediction of futures index with its underlying spot index using the Kalman filter, the literature review will include previous research on both interaction between spot and futures markets and also application of certain econophysics methods and the Kalman filtering in financial time series prediction.

Futures prices reflect expectations of the market participants in addition to the cost of carrying the position. The earlier researches on the relationship between spot and futures prices mainly relied on the cost of carry model [5–8]. The idea behind cost of carry model is based on the calculation of the opportunity cost in holding the position.

The recent literature, on the other hand, has relied on the time-varying dynamic models to analyze the interactions of price behaviours of the spot and futures markets. Some researchers are based on pure statistical and econometric processes. Routledge *et al.*, for example, state that the correlation between spot and futures prices might vary in time [9]. Najand uses linear and non-linear ARCH models to examine the time-varying effect of spot prices on futures [10]. He shows that EGARCH model, as a non-linear one, performs better than the other ARCH models. Tang and Shieih employ non-linear FIGARCH (1,d,1) and HYGARCH (1,d,1) models to model the futures index prices [11]. The research results show that the prediction success of the non-linear models is better than the linear ones. The effects of spot prices on futures prices or *vice versa* are examined in terms of the question if there exists co-integration between them. The empirical evidence shows that the spot and futures markets are cointegrated indicating that the markets have informational efficiency [12–15].

On the other hand, apart from pure econometrics models, recently dynamic models based on econophysics discipline have been applied in finance and economics. The current chaotic price behaviours in the financial markets have shown that the markets should be seen as dynamic organisms fed by the new information arrived into the market place. As it is theoretically accepted, the factor that changes the prices of the financial assets is the new information being related to those assets. Recent empirical evidence displays the fact that the prices in the financial markets have an asymmetric adjustment process [16, 17]. Dynamic and complex structures of the financial markets have encouraged the researchers for interdisciplinary studies combining physics with financial economics. Successful implementations of physics models into explanation of financial asset prices facilitated the popularity of the econophysics.

The main econophysics methods in the literature are based on adaptation of multi-fractal analysis, copula models, wavelet transformation and the Kalman filtering. For example, Oświęcimka *et al.* employs the multifractal model of asset returns (MMAR) where multifractality is carried by time deformation [18]. With inclusion of the Lux extension to MMAR, they showed that the model reproduces relevant aspects of the market dynamics in the Warsaw Stock Exchange. Oświęcimka *et al.* also investigate the fractal characteristics of the positive and the negative changes of the German DAX30 index by employing multifractal detrended fluctuation analysis. After calculating the singularity spectra $f(\alpha)$, they show that returns of both signs reveal multi-scaling, and conclude that a bear market is more persistent than the bull market irrespective of the sign of fluctuations [19]. Cifter and Ozun [20] tests the multi-scale capital asset pricing model (CAPM) in the Istanbul Stock Exchange-30 Index by wavelets based on the variance changing to the scale as a general risk indicator. They show that risk-return maximization of some stocks can be optimized at a level of 32 days. Cifter and Ozun also combine the wavelets with neural networks, and test whether the EUR–USD parity has any timescale impacts on Turkish lira and Russian ruble. They conclude that Russian ruble is impacted from EUR–USD parities in the long run based on wavelet network analysis [20]. Ozun and Ozbakis adopt a non-parametric copula analysis to examine the return distribution for a portfolio including the SP-500 (the US) and Bovespa (Brazil) stock markets. The results show that there exists a strong dependency in return distributions between two markets when non-parametric copula models based on Kendall‘s To and Sperman‘s Ro are used [21]. Ozun *et al.* successfully apply Grassberger and Procaccia‘s method into finance to predict stock returns in the Greek and Turkish stock markets. The estimations are based on correlation and minimum embedding dimensions of the corresponding strange attractor [22]. Recently, Ghosh *et al.* examines the time series for gold price from 1973 and detects degree of multifractality in the prices [23]. For a comprehensive and updated econophysics literature, the researchers can visit [24]. The Kalman filtering as another application of physics into finance discipline sees the markets as dynamic organisms and presents adaptive filtering for price adjustment process. When applying the Kalman filter in predicting returns, it is assumed that there is a smooth trend in the time series of the prices that inherent the real value of the price before it was perturbed by noise. By fitting the last few trend-line values to a suitable model, it is extended to the next time-value to reach a prediction.

The filter uses the current observation to predict the next periods value of unobservable and then uses the realisation next period to update that forecast. Cheung derives the Kalman filter algorithm for the state space model [25]. Harvey compares the Kalman filter approach to other estimation procedures, and concludes that it generates estimated parameters with better statistical properties in terms of efficiency and forecasting [26].

The Kalman filter started to be used to model the price behaviours in financial markets after its successful application to the engineering. Wells employs the Kalman technique to estimate beta parameters of the stocks traded in the Stockholm Stock Exchange [27]. Faff *et al.*, and Godbey and Hilliard successfully employ the Kalman filter to analyze the spot and futures markets interaction for different financial instruments [28, 29]. Arnold *et al.* have recently created an excel-based model to derive future prices from their spot prices. In the model, they show how the Kalman filter is combined with Expectation Maximization using an excel-based platform [30]. We use that combined model to predict future stock index using their underlying spot prices.

Before concluding the survey, it should be emphasized that the academic research on the price patterns in the futures markets in Turkey is scarce as it is newly growing market opened in 2005. Baklaci examines the volatility effects of futures prices of exchange rates on the spot prices and concludes that futures prices have structural change effects on the spot markets [31]. Baklaci argues that as the information is reflected on the futures prices more rapidly, the futures markets have a leading role in the price dynamics within the exchange rate markets. Ozun and Turk successfully use a stochastic process model set up [32] by Borovkova and Geman [33] to analyze the futures prices in the Turkish stock and exchange rate markets. In addition, the authors examine factor components of the futures prices by PCA factor loadings. That first academic work using data from the Turkish equity futures markets shows that the futures markets do not follow random walk process and have informational inefficiency as there exist arbitrage opportunities. What is more, in the literature, there are not any econophysics methods that examine the futures markets in Turkey. In this respect, this research article contributes also into applied finance as being the first research on econophysics application for futures markets in Turkey.

3. Data and methodology

3.1. Data and unit root tests

The study uses daily time series of spot and futures prices of ISE30 100 from January 2, 2009 to August 6, 2012. The period includes the global crisis environment with high volatility. Spot and future prices of ISE30 are measured in natural logarithms similar to the empirical literature and natural logarithms of spot and future prices are denoted as LS and LF respectively. Most of the studies in the literature investigate the relationship between spot and forward prices by employing co-integration and ARDL model assuming a static link. We distinguish our analysis from the existing literature by employing the Kalman filter to depict the time varying interaction between spot and forward prices.

In empirical analysis firstly, we investigate stationarity characteristics of the series. Investigating stationarity with conventional unit root tests does not consider the structural breaks. Our sample periods include shortly after the global financial crises period and structural breaks that could affect stationarity properties of our variables. In order to solve this problem, we employ both conventional unit root tests including ADF, PP and Ng–Perron tests and unit root tests with structural breaks including Zivot–Andrews test and Lee and Strazitch tests [34–38].

After stationarity check, we investigate the existence of the long term co-integration relationship between variables employing the bounds test developed by Pesaran *et al.* [39]. The bounds test approach has advantages of investigating co-integration relationship irrespective of whether the regressors are purely I(0) or I(1). In the bounds test, the existence of co-integration between spot and futures prices can be captured regardless of their stationarity levels. In that sense, it has superiority over the co-integration tests performed by Engle and Granger, Johansen and Johansen and Juselius [40]. Furthermore, the bounds test co-integration approach has superior properties in small sample sizes to other co-integration approaches [41].

We investigate stationarity properties of series by employing both conventional unit root tests including ADF, PP and Ng–Perron tests and unit root tests with structural breaks including the Zivot–Andrews test with one-break and Lee and Strazicich tests with two-breaks. Table I shows the results of conventional stationary tests.

According to Table I for ADF and PP tests, the null hypothesis indicates that the series include unit root. For both ADF and PP tests, the calculated t-statistics for all variables are lower than the critical values. Thus, the null hypothesis of unit root cannot be rejected; hence variables are non-stationary in levels. The results of first differenced variables shows that the calculated t-statistics both for ADF and PP tests are greater than critical values at 1% levels and the all variables are stationary after differencing, suggesting that all variables are integrated of order I(1) according to ADF and PP tests. In addition, for Ng–Perron test, according to MZ_a, MZ_t tests, the null hypothesis shows that the series have unit root and according to MSB and MPT tests the null hypothesis shows that the series are stationary [42]. For MZ_a, MZ_t tests, the calculated t-statistics are less and for MSB and MPT tests the calculated t-statistics are greater than the critical values for all

TABLE I

Conventional unit root test results.

ADF test results			
LS	-1.836	ΔLS	-29.504*
LF	-1.790	ΔLF	-29.442*
ADF critical values for LS 1% = -3.437		ADF critical values for ΔLS 1% = -2.567	
ADF critical values for LF 5% = -2.864		ADF critical values for ΔLF 5% = -1.941	

PP test results			
LS	-1.834	ΔLS	-29.509*
LF	-1.788	ΔLF	-29.443*
PP critical values for LS 1% = -3.437		PP critical values for ΔLS 1% = -2.567	
PP critical values for LF 5% = -2.864		PP critical values for ΔLF 5% = -1.941	

Ng–Perron test results

	MZ_a	MZ_t	MSB	MPT
LS	-1.842	-0.888	0.482	44.462
LF	-1.992	-0.930	0.466	41.641
ΔLS	-18.456**	-3.395**	0.149**	4.135**
ΔLF	-20.683**	-3.184**	0.153**	4.602**

Ng–Perron critical values for LS, LF, ΔLS and ΔLF series;
MZ_a, MZ_t, MSB, MPT, respectively;
1% significance level -23.80, -3.42, 0.14 and 4.03;
5% significance level for -17.30, -2.91, 0.17 and 5.48;
* denotes 1% significance level, ** denotes 5% significance level.

variables suggesting that LS and LF are non-stationary in their level forms. For the first differenced series, according to MZ_a, MZ_t tests, the calculated t-statistics are greater and for MSB and MPT tests the calculated t-statistics are lower than the critical values at 5% levels for all variables, suggesting that our series become stationary after differencing so that LS and LF series are I(1) according to Ng–Perron tests. The results of unit root tests with structural breaks are presented in Table II.

According to both the Zivot–Andrews and Lee–Strazicich tests, the null hypothesis shows that the series have unit root. For both the Zivot–Andrews and Lee–Strazicich tests, the calculated t-statistics for LS and LF variables are lower than the critical values in their level forms and greater than the critical values in their first difference at 5% significance levels. Moreover, both the Zivot–Andrews and Lee–Strazicich tests suggest that LS and LF variables become stationary after differencing, suggesting LS and LF series are I(1). In sum, both conventional unit root tests and unit root tests with structural breaks indicate that all the series used in the empirical analysis are integrated of order I(1).

TABLE II

Unit root tests with structural breaks.

Zivot–Andrews test				
	Level		First difference	
	Model A	Model C	Model A	Model C
LS	−1.63	−2.60	−30.91*	−31.10*
LF	−1.60	−2.57	−31.14*	−31.39*
Critical value (5%)	−4.80	−5.08	−4.80	−5.08
Lee–Strazitch test				
	Level		First difference	
	Model A	Model C	Model A	Model C
LS	−1.88	−4.15	−8.16*	−31.10*
LF	−1.81	−4.08	−6.05*	−31.17*
Critical value (5%)	−3.84	−5.71	−3.84	−5.71

3.2. Methodology

3.2.1. Bounds test approach

Before employing the Kalman filter approach, we first examine co-integration between spot and futures markets by the bounds test developed by Pesaran *et al.* [39] which has some superior properties explained above. In order to perform the bounds test, an unrestricted error correction model (UECM) should be created. UECM specification for our study is shown in Eq. (1)

$$\begin{aligned}\Delta \mathrm{LF}_t &= \alpha_0 + \sum_{i=1}^{m} \alpha_{1,i} \Delta \mathrm{LF}_{t-i} + \sum_{i=0}^{m} \alpha_{2,i} \Delta \mathrm{LS}_{t-i} \\ &\quad + \alpha_3 \mathrm{LF}_{t-1} + \alpha_4 \mathrm{LS}_{t-1} + \mu_t\,, \end{aligned} \tag{1}$$

where, LS is log of spot prices and LF log of forward prices. In UECM model in Eq. (1), m represents number of lags. For testing the existence of co-integration relationship, the statistics underlying the procedure is the Wald or F-statistics in a generalized Dickey–Fuller type regression, which is used to test the significance of lagged levels of the variables under consideration in a conditional UECM [41]. F-test is applied on first period lags of dependent and independent variables to test the existence of co-integration relationship.

Null hypothesis for F-test is established as

$$H_0 = \alpha_3 = \alpha_4 = 0$$

for our study and calculated F-statistics is compared with table bottom and upper critical levels in Pesaran *et al.* [39]. A lower than Pesaran bottom critical value F-statistics suggests the absence of co-integration relationship between the series. If the calculated F-statistics is between the bottom and top critical values, no exact opinion can be made and there is a need to apply supplementary co-integration tests [43]. Lastly, if the calculated F-statistics is higher than the top critical value, there is a co-integration relationship between the series [40]. The number of lags is determined according to Schwarz criteria and lag number is found 1[1]. After determining lag number of UECM model, we investigate co-integration relationship. We compared the computed F-statistics from UECM model with table bottom and upper critical levels in Pesaran *et al.* [39]. Table III shows the bounds test results.

TABLE III

Bounds test results. k is number of independent variable number in Eq. (1). Critical values are taken from Table C1(iii), Pesaran *et al.* [39], p. 300.

K	F-statistics	Critical value at 5% significance level	
		Bottom bound	Upper bound
1	7.27	4.94	5.73

According to Table III, F-statistics is higher than the upper bound of the critical values, and the null hypothesis of no co-integration is rejected. As a result, we found a significant long run co-integration relationship between spot and forward prices according to the bounds test analysis.

Finally, we followed a dynamic approach by employing the Kalman filter to depict the time varying interaction between spot and future prices. In time varying parameter (TVP) models, the parameters are allowed to change with each new observation [44].

3.2.2. State space form and dynamic Kalman filter approach

After static investigation of spot and forward price relationship, we finally examine this relationship dynamically by employing the Kalman filter approach to depict time varying interaction between spot and forward prices. A dynamic approach by employing the Kalman filter method based on recursive estimation is used to detect the statistically significant relationship between time series of spot and futures stock markets.

[1] Serial correlation for UECM model investigated by employing the Breusch–Godfrey serial correlation LM test and no serial correlation found in UECM model. Test results can be taken from the authors.

We base our dynamic approach on a classical reference of Harvey that introduces the Kalman filter approach. The Kalman filter approach is based on a form of state space representation. A linear state space of the dynamics of an equation can be represented as

$$
\begin{aligned}
y_t &= c_t + Z_t \alpha_t + \varepsilon_t\,, &(2)\\
\alpha_{t+1} &= d_t + T_t \alpha_t + \nu_t\,, &(3)
\end{aligned}
$$

where, in our case, α_t is a 2×1 vector of unobserved state variables, where c_t, Z_t, T_t, and d_t are adaptable vectors and matrices, and where ε_t and ν_t are vectors of mean zero, Gaussian disturbances. As stated in Eq. (3), unobserved state vector α_t is assumed to change over time as a first-order vector auto-regression. The Kalman filter recursively estimates the parameters by updating the estimation with every additional observation. The disturbance vectors ε_t and ν_t are assumed to be serially independent and with contemporaneous variance structure

$$
\mathit{\Gamma}_t = \mathrm{var}\begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix} = \begin{bmatrix} H_t & G_t \\ G_t' & Q_t \end{bmatrix}, \tag{4}
$$

where H_t and Q_t are the variance matrices, and G_t is the covariance matrix [45]. The mean and variance of the conditional distribution of the state vector available at time is defined as

$$
\begin{aligned}
a_{t|s} &\equiv E_s(\alpha_t)\,, &(5)\\
p_{t|s} &\equiv E_s\left[\;(\alpha_t - \alpha_{t|s}) \quad (\alpha_t - \alpha_{t|s})'\;\right]. &(6)
\end{aligned}
$$

Setting $s = t - 1$, we may obtain one step ahead mean and variance, $a_{t|t-1}$ and $P_{t|t-1}$ of the state α_t. Here, $a_{t|t-1}$ is the mean square estimator of α_t and $P_{t|t-1}$ is the mean square error. The Kalman filter is a recursive algorithm for sequentially updating the one step ahead estimate of the state mean and variance given new information/observation. Given the one step ahead state conditional mean, the one step ahead minimum mean square error estimate of y_t

$$
\tilde{y}_t = y_{t|t-1} \equiv E_{t-1}(y_t) = E_{y_t|a_{t|t-1}} = c_t Z_t a_{t|t-1}\,. \tag{7}
$$

The one step ahead, the prediction error is

$$
\tilde{\varepsilon}_t = \varepsilon_{t|t-1} \equiv y_t - \tilde{y}_{t|t-1} \tag{8}
$$

and the prediction error variance is defined as

$$
\tilde{F}_t = F_{t|t-1} \equiv \mathrm{var}(\varepsilon_{t|t-1}) = Z_t P_{t|t-1} Z_t' + H_t\,. \tag{9}
$$

Given that the initial values are specified, the Kalman filter may be used to compute one step ahead of state and the associated mean and variance matrix, thus, one step ahead prediction, prediction error and prediction error variance [45]. The increasing number of updates enable α_t and P_t to converge to steady state. The steady state condition can be accessed via maximizing the log likelihood function

$$\begin{aligned}\log L(\theta) &= -\frac{nT}{2}\log 2\pi - \frac{1}{2}\sum_t \log\left[\tilde{F}_t(\theta)\right] \\ &\quad -\frac{1}{2}\sum_t \tilde{\varepsilon}'_t(\theta)\tilde{F}_t(\theta)^{-1}\tilde{\varepsilon}_t(\theta)\,. \end{aligned} \tag{10}$$

The Kalman filter specification which employs level data is presented in Eqs. (11) and (12) below

$$LF_t = a_0 + a_{1,t}LS_t + \varepsilon_t\,, \tag{11}$$
$$a_{i,t} = a_{i,t-1} + \nu_{i,t}\,. \tag{12}$$

4. Empirical evidence

The time-varying parameter (TVP) estimations for the Kalman filter that used to analyzes the dynamic relationship between spot and futures stock markets with level data are presented in Fig. 1.

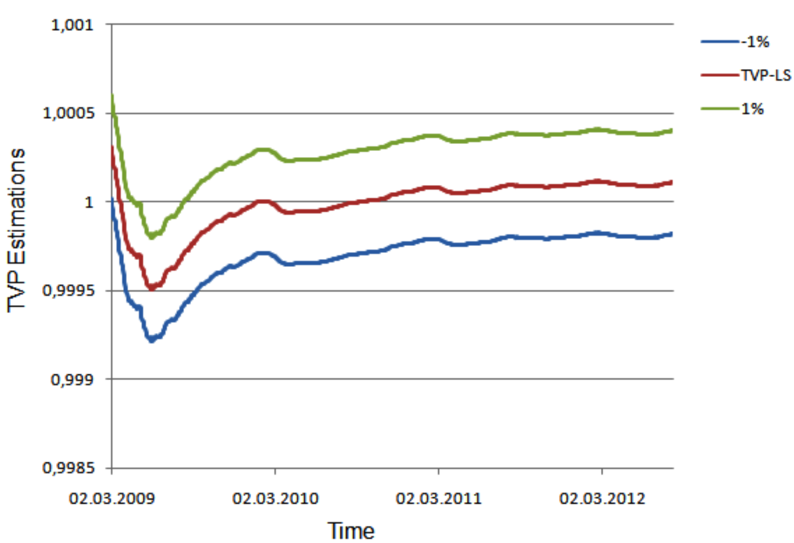

Fig. 1. Parameter estimates for the Kalman filter approach with level data.

The empirical evidence shows that the returns in futures market have significant impacts on returns in spot market at ISE-30 under high volatility. The futures markets have an decreasing impact on spot markets in the bearish market conditions. However, especially in recovery periods between Q2/09–Q1/10, the futures markets have significant increasing effect on spot market. In the market conditions where there exists a stable increasing trend, the impact of futures markets on the spot markets remains at stable magnitude.

In the empirical analysis, we also examine the volatility of futures markets on spot market prices by using differenced data. Therefore, the second Kalman filter specification which employs first differenced data (growth data) is presented in Eqs. (13) and (14).

$$\Delta LF_t = a_0 + a_{1,t}\Delta LS_t + \varepsilon_t \,, \tag{13}$$

$$a_{i,t} = a_{i,t-1} + \nu_{i,t} \,. \tag{14}$$

As presented in Fig. 2, the empirical results show similar results when difference data is employed.

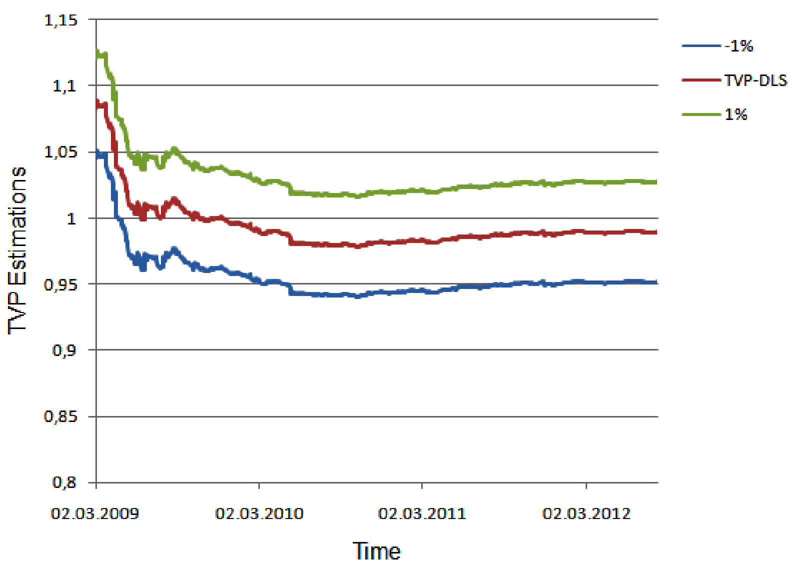

Fig. 2. Parameter estimates for the Kalman filter approach with difference data.

Empirical evidence points out the fact that the returns in spot and futures markets are interacted. There exists a dynamic relationship between spot and futures markets at ISE-30 Index. The causality is magnitude in recovery and bullish markets. The practical results and implications of the detected relationship is discussed in the next section.

5. Conclusion

We have tried to investigate spot and forward price interaction of ISE30 100 for the period of January 2, 2009 to August 6, 2012. In the empirical model, we firstly investigated stationarity properties of series employing both conventional unit root tests and unit root tests with structural breaks and according to all unit root tests, spot and futures prices series were found I(1).

After investigating stationarity properties of series, we examined co-integration relationship between spot and forward prices employing the bounds test approach developed by Pesaran *et al.* which has some advantages over the conventional co-integration models. According to the bound test results, we found a significant long run co-integration relationship between spot and forward prices.

Finally, we investigated dynamic relationship between spot and forward prices using a dynamic approach by employing the Kalman filter to depict the time varying interaction between spot and future prices.

The Kalman filter results show that the returns in futures market have significant impacts on returns in spot market at ISE-30 under high volatility. The futures markets have an decreasing impact on spot markets in the bearish market conditions. However, especially in recovery periods between Q2/09–Q1/10, the futures markets have significant increasing effect on spot market. Moreover, the empirical evidence points out the fact that the returns in spot and futures markets are interacted. There exists a significant asymmetric causality relationship from futures markets to spot markets at ISE-30. The causality is magnitude in recovery and bullish markets.

The findings are in line with the financial theory in that the futures market is able to fulfil its function in directing the spot markets. The increasing causality during the recovery periods can be interpreted that positive expectations are reflected in the prices with stronger impact.

Another conclusion that can be driven from the empirical results is related to market efficiency. Since the spot and futures markets have significant causality relationship, we can conclude there exists informational efficiency in the Turkish equity markets. The methodology in the paper could be applied in other markets for further researches in order to detect time varying dynamic relationship between the spot and futures markets.

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