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**Working Paper**

## The Superiority of Time-Varying Hedge Ratios in Turkish Futures

Working Papers in Economics, No. 09/07

**Provided in Cooperation with:**

Department of Economics, Izmir University of Economics

*Suggested Citation:* Olgun, Onur; Yetkiner, I. Hakan (2009) : The Superiority of Time-Varying Hedge Ratios in Turkish Futures, Working Papers in Economics, No. 09/07, Izmir University of Economics, Department of Economics, Izmir

This Version is available at:

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Working Papers in Economics

THE SUPERIORITY OF TIME-VARYING HEDGE RATIOS IN  
TURKISH FUTURES MARKET

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Working Paper No. 09/07  
November 2009

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## THE SUPERIORITY OF TIME-VARYING HEDGE RATIOS IN TURKISH FUTURES MARKET

### **Abstract**

This paper aims to compare the effectiveness of constant hedge ratio estimates (obtained through OLS and VECM methods) and time-varying hedge ratio estimates (obtained via M-GARCH method) for future contracts of ISE-30 index of TurkDEX. We use portfolio variance reduction as the measure of hedging effectiveness. We find that time-varying hedge ratios outperform the constant ratios for both in-sample and out-of-sample datasets and provide the minimum variance values.

**Keywords:** Futures Pricing, Hedging, M-GARCH, Hedging effectiveness

**JEL Classification:** G13, G17.

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## 1. INTRODUCTION

The demand for futures contracts has steadily expanded around the world over the last decade. One of the major reasons behind this growth has been the hedging opportunity provided by futures markets to cope with the adverse effects of volatility in asset prices. Common sense may lead one to assert that having the opposite but same magnitude positions in spot and future markets is the simplest and best way to hedge oneself against volatility in asset prices. Indeed, this is the traditional hedging approach. However, in reality, the spot and futures prices are not perfectly correlated. Hence, the magnitudes of the positions in spot and future markets would be different to follow an optimal hedging strategy. Determining the proper amount of futures position that perfectly covers the spot exposure is crucial in this context. The optimal hedge ratio, defined as the ratio of the size of portfolio taken in futures contracts to the size of the exposure in spot market under minimum risk constraint, is used to determine the amount of futures position that optimally covers the spot exposure (see Hull (2003)). Nevertheless, the computation of the optimal hedge ratio is not straightforward as there is a lack of consensus about the best empirical model for the estimation process. Different studies have documented contradictory results in this regard.

A significant amount of empirical research in the hedging literature has focused on estimating the optimal hedge ratio for a variety of futures contracts through various econometric techniques. It was firstly revealed by Johnson (1960) and Stein (1961) that a hedger can only maximize utility via minimizing the unconditional variance of the covered portfolio returns. Hence, the hedge ratio that provides the minimum portfolio variance ought to be the optimal hedge ratio. Extending the pioneering studies of Johnson (1960) and Stein (1961), Ederington (1979) adopted OLS regression method to derive risk-minimizing hedge ratio. He concluded that the OLS-based hedge ratio outperforms the naïve one-to-one hedging strategy in terms of hedging effectiveness.<sup>1</sup> The OLS regression method is commonly employed by numerous authors because of its simplicity in hedge ratio estimation. Amongst others, Hill and Schneeweis (1981), Figlewski (1984), Myers and Thompson (1989), Benet

(1992) and Lien (2005) all verified the robustness of hedge ratios calculated by the OLS regression method for different futures markets.

Even though the OLS approach has been widely applied in literature, it was subject to a number of theoretical criticisms (cf. Myers (1991)) stemming from the rigid assumptions of the process particularly and parallel to advances in financial econometrics. One of these challenges is highlighted with the serial correlation detected in residuals, which caused bias in hedge ratio estimates. To eliminate the serial correlation in residuals, Herbst *et al.* (1993) modelled the spot and future returns through a bivariate vector autoregressive (VAR) framework and gathered more realistic hedge ratios in the study. Further, the instantaneous feedback relation (mostly bidirectional) between spot and future markets is clearly documented under the lead-lag pattern, which has been taken into account by the bivariate VAR model as well in estimation of the hedge ratio (e.g., Stoll and Whaley (1990), Chan (1992), Abhyankar (1998), Brooks *et al.* (2001), and Kavussanos *et al.* (2007)).

Another structural viewpoint on hedge ratio estimation hinges upon the probable cointegration relationship between spot and futures prices. The existence of such a correlation would not allow prices to diverge extensively from the long-run equilibrium. Engle and Granger (1987) stated that the cointegration among variables might invalidate the findings of conventional methods, i.e., OLS and/or VAR. They suggested applying error-correction mechanisms in the case of cointegration. The error correction model (ECM) is initially used by Ghosh (1993) over the estimation of optimal hedge ratio. He reported that the hedging effectiveness is remarkably improved through the hedge ratio estimates of ECM, which incorporates the long-run equilibrium to the system and overcomes the misspecification problem.<sup>2</sup> Similar findings referring to superiority of ECM were also reported by Lien and Luo (1993), Chou *et al.* (1996) and Kenourgios and Samitas (2001) for the major currency and index futures contracts all around the world. However, Moosa (2003) revealed that consideration of cointegration had a negligible effect in terms of hedging effectiveness.

Since the most of the financial time-series have the feature of heteroskedasticity, the GARCH (Bollerslev (1986)) based models are also usually conducted with the aim of estimating hedge ratios. Myers and Thompson (1989) alleged that the hedge ratio should be adjusted continuously based on conditional information set. As a consequence, the conditional variance and covariances have to be taken into account jointly. Most researchers have chosen multivariate derivation of the GARCH model (called as M-GARCH) empirically in order to capture simultaneous interactions between spot and future prices. For instance, Yang (2001) employed a standard D-VEC M-GARCH (1, 1) model under the constant correlation hypothesis. He stressed that the hedging effectiveness is preceded via the M-GARCH hedge ratios for the Australian stock index futures. Choudhry (2004) implied that the time-varying (dynamic) hedge ratios of various M-GARCH derivations outperform the constant hedge ratios obtained from different estimation procedures for many stock markets and their corresponding future contracts. Despite the presence of a large amount of research for developed markets on the time varying (M-GARCH) hedge ratio concept, emerging markets have been insufficiently researched.<sup>3</sup> A small number of studies, such as Choudhry (2003) for Hong-Kong and South Africa, Floros and Voguas (2005) for Greece, and Bhaduri and Durai (2008) for India have emphasized the ability of M-GARCH framework to compute risk-minimizing hedge ratios for these markets.

This paper aims to estimate the optimal hedge ratio for ISE-30 stock index futures traded in Turkish Derivatives Exchange (TurkDEX hereafter), an emerging futures market, by utilizing a variety of empirical models just as OLS, VECM and M-GARCH. Hence, it aims to contribute the literature by revealing whether the simple (OLS regression or ECM) or complex models (M-GARCH) is superior for the estimation process, through associated hedging effectiveness evaluations within both in-sample and out-of-sample hedging horizons. Since there has been very limited scientific research on the hedging effectiveness of Turkish futures market, cf., Aksoy and Olgun (2009), this study may be seen as a significant contribution to the literature (by utilizing a M-GARCH model in estimation process, we diverge from Aksoy and Olgun (2009)).

The paper is organized as follows. Section 2 provides brief information on TurkDEX and ISE-30 index futures with selected statistics. Section 3 presents the data set and discusses empirical models conducted. Section 4 portrays hedge ratio estimates of models and the related comparison of hedging effectiveness. Section 5 draws concluding remarks.

## **2. A BRIEF NOTE ON TurkDEX and ISE-30 INDEX FUTURES**

TurkDEX is the first and unique derivatives market in Turkey, authorized by the Capital Markets Board (national regulatory agency). The opening bell for trading in the TurkDEX rang on 4<sup>th</sup> February 2005. Only futures contracts from the main categories of financials (currency, interest rate and equity index) and certain commodities (gold, cotton, wheat) have been traded in TurkDEX so far. Futures prices are determined by executing “multiple price-continuous auctions” method. A single trading session known as “normal session” is adopted in TurkDEX, holding between 9.30 a.m. and 5.10 p.m. As TurkDEX utilizes a fully electronic trading system with remote access, there are no geographical investment restrictions.<sup>4</sup>

There is a stable upward trend in total volume for the exchange during the four year period. Annual trading volume in the market soared more than 60 times and reached approximately \$138 billion at the end of 2008. Further, the daily average volume has recently covered 55%-65% of daily trading volume in Istanbul Stock Exchange (ISE). However, the breakdown of total trading volume in TurkDEX points out the presence of an abnormal structure for individual futures contracts. In particular, ISE-30 equity index futures have dominated the market since the beginning of 2006. This contract itself consisted of composed 60.71%, 91.16% and 90.51% of market trading volume for years 2006, 2007 and 2008 respectively.

The ISE-30 futures are quoted by simply dividing the underlying spot index (ISE-30) by 10. Six delivery months- February, April, June, August, October and December- are specified but only three are opened to trade at the same time considering expiration of previous contracts.<sup>5</sup> The ISE-30 future contracts are cash-settled as other futures in TurkDEX. Daily price limit is

+/-10%; position limits are 5000 contracts (absolute) and 10% of total open positions (proportional).

### **3. DATA and METHODOLOGY**

#### ***Data***

The data set employed in the study comprise daily spot and futures prices of the ISE-30 stock index with 1102 observations made during the period 2 May 2005 to 15 September 2009.<sup>6</sup> The spot and future data were collected from the official web sources of the Istanbul Stock Exchange (ISE) and the TurkDEX. The ISE-30 stock index consists of the shares of 30 largely capitalized firms from various sectors quoted on Turkish stock market accounting for approximately 60% of total value of stock market. To eliminate the possible effects of thin trading at expiration and discontinuities in the series, future data are rolled over by using nearby contract in particular. In this manner, the open position criterion as a proxy of trading volume is adopted to determine the actual switch (rollover) date among the futures contracts from various delivery months.<sup>7</sup> In addition, the last 180 observations (from 02 January 2009 to 15 September 2009) in the data set are excluded from the estimation process in order to evaluate out-of-sample forecasting abilities of the model.

Daily returns for ISE-30 index (spot and future) are calculated by the following equations:

$$R_{s,t} = \ln(S_t/S_{t-1}) \quad (1)$$

$$R_{f,t} = \ln(F_t/F_{t-1}) \quad (2)$$

where  $R_s$  and  $R_f$  represent daily spot and futures returns respectively. Closing values of ISE-30 index are shown by  $S_t$  for spot, and  $F_t$  for future, on the corresponding day  $t$ .

#### ***Methodology***

As stated previously, most of the researches in optimal hedge ratio estimation have been conducted by comparing various econometric models together and interpreting their results



in terms of hedging effectiveness. The appropriateness of an empirical model and the optimal hedge ratio for a specific future contract is determined through comparing the findings of these models respectively. This common application will also be adopted in this paper. Accordingly, an OLS Regression model, a Vector Error Correction model (VECM) and a D-VEC M-GARCH model are specified to estimate optimal hedge ratio for ISE-30 futures contracts.

The OLS regression model essentially relates the return on spot price (dependent) with the return on future prices (independent), as the interaction between spot and future prices is perceived the key principal of hedging. The following regression equation, developed by Ederington (1979), is used to estimate hedge ratio specifically;

$$R_{s,t} = c + \beta R_{f,t} + \varepsilon_t \quad (3)$$

where the slope coefficient  $\beta$  represents risk-minimizing hedge ratio and the constant term in the model is shown by  $c$  and  $\varepsilon$  is white noise.

Secondly, a VECM is derived by comprising an error correction mechanism out of a bivariate VAR model. The VECM has theoretical advantages (compared to OLS regression method) over calculation of optimal hedge ratio. It can eliminate serial correlation in residuals and helps to capture both short-run and long-run interactions between spot and future returns. The VECM specification of Yang (2001) is followed:

$$R_{s,t} = c_s + \sum_{i=1}^k \beta_{s,i} R_{s,t-i} + \sum_{i=1}^k \lambda_{s,i} R_{f,t-i} + \eta_s EC_{t-1} + \varepsilon_{st} \quad (4)$$

$$R_{f,t} = c_f + \sum_{i=1}^k \beta_{f,i} R_{s,t-i} + \sum_{i=1}^k \lambda_{f,i} R_{f,t-i} + \eta_f EC_{t-1} + \varepsilon_{ft} \quad (5)$$

$$EC_{t-1} = S_{t-1} - (a + bF_{t-1}) \quad (6)$$

$\beta_{s,i}$ ,  $\beta_{f,i}$ ,  $\lambda_{s,i}$  and  $\lambda_{f,i}$  are VECM parameters, and  $c_s$  and  $c_f$  indicate constant terms in the equations.  $EC_{t-1}$  represents lag-one error correction term and defined in equation (6). The optimal hedge ratio  $h$  is derived from the VECM as follows:

$$h = \frac{Cov(\varepsilon_{st}, \varepsilon_{ft})}{Var(\varepsilon_{ft})} \quad (7)$$

where  $\varepsilon_{st}$  and  $\varepsilon_{ft}$  are white noises from equation (4) and (5), respectively.

Since most of the financial time-series are characterized as heteroskedastic, the use of a GARCH derivation would be robust for estimating an optimal hedge ratio. Therefore, a D-VEC M-GARCH model (cf., Bollerslev *et al.* (1988)) is utilized in the paper for deriving time-varying hedge ratios. In fact, the distinctive feature of M-GARCH model, compared to univariate specifications, is using historical information from various markets together instead of concentrating in only one market, which helps to improve forecasts. Equations (4) and (5) are assigned as conditional mean equations for D-VEC M-GARCH model. Conditional volatility representations of the D-VEC M-GARCH (p, q) model are expressed through the following matrices in this manner.

$$A_i = \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \quad B_i = \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} h_{ss,t} \\ h_{sf,t} \\ h_{ff,t} \end{bmatrix} = \begin{bmatrix} c_{ss,t} \\ c_{sf,t} \\ c_{ff,t} \end{bmatrix} + A_i \times \begin{bmatrix} \varepsilon_{s,t-p}^2 \\ \varepsilon_{s,t-p}, \varepsilon_{f,t-p} \\ \varepsilon_{f,t-p}^2 \end{bmatrix} + B_i \times \begin{bmatrix} h_{ss,t-q} \\ h_{sf,t-q} \\ h_{ff,t-q} \end{bmatrix} \quad (9)$$

$A_i$  and  $B_i$  in equation (8) are diagonal and set to zero to ease complications due to the excessive number of parameters in the model. In equation (9),  $h_{ss}$  and  $h_{ff}$  exhibit conditional variance of the error terms ( $\varepsilon_{st}$ ,  $\varepsilon_{ft}$ ) from the mean equations of the model. Besides, the conditional covariance among daily spot and future returns is represented by  $h_{sf}$ .  $c_{ss}$ ,  $c_{sf}$  and  $c_{ff}$  represent constant parameters of the model. Once diagonal elements deducted from the process, conditional variances and covariance of the D-VEC M-GARCH (p, q) model in the study are found as:

$$h_{ss,t} = c_{ss} + \alpha_{ss} \varepsilon_{s,t-p}^2 + \beta_{ss} h_{ss,t-q} \quad (10)$$

$$h_{sf,t} = c_{sf} + \alpha_{sf} \varepsilon_{s,t-p}, \varepsilon_{f,t-p} + \beta_{sf} h_{sf,t-q} \quad (11)$$

$$h_{ff,t} = c_{ff} + \alpha_{ff} \varepsilon_{s,t-p}^2 + \beta_{ff} h_{ff,t-q} \quad (12)$$

After the estimation of parameters in the equations above, time-varying daily hedge ratios  $H_t$  are calculated by

$$H_t = h_{sf,t}/h_{ff,t} \quad (13)$$

We predicted the time-varying hedge ratios for out-of-sample period by using the estimated coefficients derived from equations (10)-(12) in this manner.

#### 4. EMPIRICAL RESULTS

##### *Basic Statistics*

Table 1 depicts various summary statistics related to univariate spot and future daily return series. The results show that both samples are very similar as presumed in terms of return, volatility and for other statistical measures such as skewness and kurtosis.

**Table-1: Descriptive Statistics**

	$R_s$	$R_f$
<b>Mean</b>	0.000566	0.000605
<b>Median</b>	0.000198	0.000367
<b>Maximum</b>	0.127255	0.105839
<b>Minimum</b>	-0.097398	-0.099722
<b>Standard Dev.</b>	0.021798	0.022253
<b>Variance</b>	0.000475	0.000495
<b>Skewness</b>	-0.009701	-0.023662
<b>Kurtosis</b>	5.533423	5.647846
<b>Jarque-Bera</b>	294.4537	321.7363

**Note:**  $R_s$  and  $R_f$  demonstrate daily spot and future returns respectively.

In order to analyze stationarity condition of the return series, Augmented Dickey Fuller (ADF) and Philips-Perron (PP) unit-root tests are applied. Test results are presented in Table 2. It is evidently denoted that spot and future return series are stationary at 1% significance level. However, the level forms of these series are likely to contain unit-root; hence they are indeed integrated of order one  $I(1)$ .

**Table-2: Unit Root Tests**

Variables	ADF Statistics	PP Statistics
$S_t$	0.774	0.795
$F_t$	0.809	0.839
$R_s$	-19.131*	-31.311*
$R_f$	-23.001*	-31.807*

**Note:**  $S_t$  and  $F_t$  represent logarithmic spot and future values for ISE-30 index (level) respectively. Tests are applied according to “intercept” and “trend” procedures as well; however we found identical results. Further, the optimal lag lengths for the unit root tests are determined by AIC and SIC criteria.

\* denotes 1% significance level.

Once the presence of  $I(1)$  process is detected, it is now possible to test for a cointegration relationship between non-stationary variables. We used Johansen (1988) procedure, which has precise strengths over other alternative tests, to observe interactions between spot and future markets.<sup>8</sup> Table 3 provides Johansen cointegration test results. Trace and eigenvalue statistics clearly indicate that there is a single cointegrating vector between spot and future series.

**Table-3: Johansen Cointegration Test**

	$H_0: r = 0$ and $H_1: r = 1$			$H_0: r \leq 1$ and $H_1: r = 2$		
	Statistics	Critical Values		Statistics	Critical Values	
	Value	1%	5%	Value	1%	5%
<b>Trace Test</b>	62.05*	31.15	25.87	6.21	16.55	12.51
<b>Maximum</b>	55.83*	23.97	19.38	6.21	16.55	12.51
<b>Eigenvalue Test</b>						

**Note:** VAR model employed in the process is specified with trend and constant terms according to log-likelihood statistics.

\* denotes 1% significance level.

### ***Hedge Ratio Estimates***

The hedge ratio results of our three empirical models are demonstrated in table 4 with estimated coefficients, standard errors, t-statistics and p-values and related diagnostic statistics in detail.

At first glance, the hedge ratio ( $\beta$ ) is found 0.9105 and significant through the regression method. Since the robustness of this model strongly depends on validity of OLS assumptions, required specification tests are applied to estimates of regression model. Contrary to assumptions of the model, we strongly reject normality and no serial correlation hypotheses for residual series through Shapiro-Wilk and Breusch-Godfrey tests. Moreover, the results of the ARCH-LM and White's tests state that the spot and future return series have time-varying variance in contradiction with OLS assumptions. Consequently, we argue that the OLS estimation is not unbiased.

Subsequently, we employ a bivariate VECM to estimate the hedge ratio. As presented in table 4, the robustness of future equation (5) is more confident than spot equation (4) by signalling univariate causality.<sup>9</sup> Whilst the error correction term is found as significant also just for future equation (5), we can suggest that the past prices in spot market give a clear expression of current movements in futures market. Further, the serial correlation problem of residuals is solved through the VECM as shown by LM test results. After predicting variance-covariance matrix of residual series for equations (4) and (5), we calculated the hedge ratio as 0.9358 from equation (7).

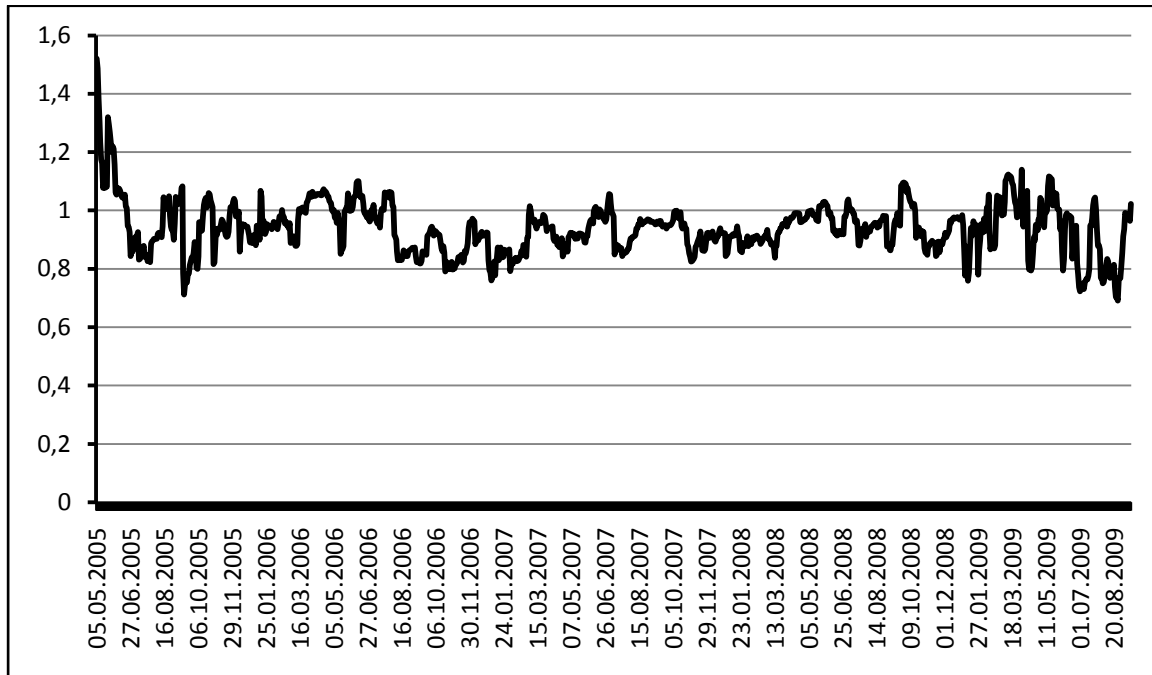
**Table-4: Estimates of Applied Models**

Model-1: OLS Regression				
Variable	Coefficient	Standard Error	t-statistics	p-value
c	-2.3 E-05	0.0002	-0.0818	0.9348
R <sub>f</sub>	0.9105	0.0127	71.5270	0.0000*
Diagnostic Check	Shapiro-Wilk	Breusch- Pagan	ARCH-LM	White
Test-statistics	170.58	90.98	33.84	12.70
Model-2: VECM				
Variable	Coefficient	Standard Error	t-statistics	p-value
c	9.67E-05	0.0007	0.1333	0.8165
	1.41E-05	0.0007	0.1924	0.7906
R <sub>s</sub> (-1)	-0.1316	0.0984	-1.3366	0.2051
	0.2717	0.0988	2.7505	0.0141**
R <sub>s</sub> (-2)	-0.0813	0.0938	-0.8669	0.4157
	0.0903	0.0941	0.9594	0.3663
R <sub>f</sub> (-1)	0.2069	0.0968	2.1374	0.0551**
	-0.2012	0.0971	-2.0716	0.0613**
R <sub>f</sub> (-2)	0.0701	0.0922	0.7602	0.4556
	-0.1101	0.0926	-1.1892	0.2512
ECT(-1)	0.0145	0.0562	0.2587	0.7685
	0.1287	0.0564	2.2806	0.0357**
Diagnostic Check	Lag-1	Lag-2	Lag-3	Lag-4
LM-Test	2.92 (0.56)	1.04 (0.90)	0.61 (0.96)	2.00 (0.73)
Model-3: D-VEC MGARCH				
Variable	Coefficient	Standard Error	z-statistics	p-value
C <sub>ss</sub>	8.39 E-06	2.93E-06	2.8588	0.0043*
C <sub>ff</sub>	9.73 E-06	2.93E-06	3.3172	0.0013*
C <sub>sf</sub>	8.36 E-06	2.60E-06	3.2139	0.0009*
α <sub>ss</sub>	0.0685	0.0142	4.8265	0.0000*
α <sub>ff</sub>	0.0693	0.0137	5.0641	0.0000*
α <sub>sf</sub>	0.0689	0.0135	5.0961	0.0000*
β <sub>ss</sub>	0.9139	0.0165	55.2517	0.0000*
β <sub>ff</sub>	0.9094	0.0170	55.2378	0.0000*
β <sub>sf</sub>	0.9116	0.0163	53.9045	0.0000*
Diagnostic Check	Spot (20 lags)	Future (20 lags)		
Ljung-Box Q Test	21.44 (0.25)	23.58 (0.19)		

**Note:** The first row is assigned for spot equation and second row is for future equation corresponding to coefficient estimates of Model-2. The optimal lag-lengths for Ljung-Box-Q test is defined by AIC for Model-3. \* denotes 1% significance level.

The heteroskedastic nature of return series emphasized previously has encouraged us to set a GARCH model in hedge ratio estimation. We prefer D-VEC MGARCH (1, 1) specification in this manner, which allows a joint consideration of the cointegration relationship between spot and futures prices.<sup>10</sup> To estimate coefficients in the model, BEKK parameterization is used particularly (cf., Engle *et al.* (1995)). The parameters in future mean equation (4) are all significant by consistent with theoretical wisdom, even if we could find only negligibly significant parameter for spot equation (5). Essentially, this consistency can be explained by random walk theory. Nonetheless, all coefficients of the conditional variance and covariance equations are highly significant and positive, which satisfies the precondition of model to calculate time-varying hedge ratios. Besides, the GARCH parameters' sum, i.e.,  $(c_{ss} + \alpha_{ss} + \beta_{ss})$  and  $(c_{ff} + \alpha_{ff} + \beta_{ff})$ , is close to unity for transformed variance equations. In other words, the persistence in volatility is high for the dataset. The sign of the covariance parameters  $(\alpha_{sf}, \beta_{sf})$  also corrects the positive interaction between the two prices. As a diagnostic check, Ljung-Box-Q test is applied to the results. These statistics confirm that there is no autocorrelation in residuals of both equations. Figure 1 plots the time varying hedge ratios calculated by the D-VEC MGARCH (1,1) model from equation (13). The estimated hedge ratios range from a minimum of 0.71 to a maximum of 1.52. The mean value for time varying hedge ratio series is determined as 0.9408.

**Figure-1: Time Varying Hedge Ratios**



### **Comparison of Models**

Ederington (1979) defines the effectiveness of hedging as the relative percentage reduction in the unhedged portfolio variance after the hedging transaction. Therefore, we first need to construct unhedged and hedged portfolios virtually.<sup>11</sup> The daily returns of unhedged ( $r_{u,t}$ ) and hedged ( $r_{h,t}$ ) portfolios are computed by the following equations respectively.

$$r_{u,t} = \ln(S_t) - \ln(S_{t-1}) \quad (14)$$

$$r_{h,t} = [\ln(S_t) - \ln(S_{t-1})] - h^*[\ln(F_t) - \ln(F_{t-1})] \quad (15)$$

$\ln(S_t)$  and  $\ln(F_t)$  indicate logged spot and future prices. The hedge ratio determining the weight of the futures position is shown by  $h^*$ . Consequently, the measure of hedging effectiveness (HE) that is used to evaluate the performances of the estimated hedge ratios is calculated as;

$$HE = \frac{Var(r_u) - Var(r_h)}{Var(r_u)} \quad (16)$$



Table 5 exhibits in-sample and out-of-sample hedging effectiveness (HE) results with portfolio returns and variances.

**Table-5: Hedging Effectiveness Results**

	in-sample				out-of-sample		
	Hedge Ratio	Variance	Mean Return	HE (%)	Variance	Mean Return	HE (%)
Unhedged	-	0,000485	0,000112	-	0,000422	0,00282	-
Traditional (one to one)	1	7,76E-05	-2,10E-05	83,98	6,80E-05	-4,8E-05	83,87
OLS	0,9105	7,36E-05	-9,08E-06	84,79	5,98E-05	<b>0,00021</b>	85,80
VECM	0,9358	7,40E-05	-1,24E-05	84,73	6,14E-05	0,00013	85,44
D-VEC MGARCH	Time varying	6,72E-05	<b>9,56E-06</b>	<b>86,13</b>	5,62E-05	0,00015	<b>86,66</b>

It is unsurprisingly that results indicate the traditional one-to-one hedging has the lowest mean return and hedging effectiveness value. Even though results among alternative methods are not dramatically dissimilar in terms of hedging effectiveness, time-varying hedge ratios of D-VEC MGARCH model outperform competing methods for both in-sample and out-of-sample data remarkably in terms of risk reduction. This implication is evidently consistent with the literature, such as Choudhry (2003) and Durai (2008). Hence, we can assert that D-VEC MGARCH model is the most appropriate model (as expected due to its strengths) to estimate risk-minimizing hedge ratios for ISE-30 index.

A small number of studies such as Howard and D'Antonio (1984) assert that the return after hedging is also important and should be taken into account when measuring the effectiveness of hedging. For this reason, the average daily returns of the constructed portfolios are also calculated and analyzed as a supportive tool in assessment process. When the return of the portfolios is taken into account, there is a slight difference between in-sample and out-of-sample datasets. While the highest return is provided by D-VEC-MGARCH model (only positive return) for in-sample data, the regression method is superior for out-of-sample data in particular. One possible explanation for this anomaly might be the reduced correlation between spot and future prices for the out-of-sample period.<sup>12</sup>

## **5. CONCLUSION**

This paper examines the optimal hedge ratio for ISE-30 index futures contracts, traded in TurkDEX, by running competing econometric models. In particular, the OLS, the VEC and the D-VEC MGARCH models are run to estimate the risk-minimizing hedge ratio. The appropriateness of the models is investigated under the hedging effectiveness criterion for each in-sample and out-of-sample data horizons.

The empirical results point out that time-varying hedge ratios determined by D-VEC MGARCH model provides the highest variance reduction along with both in-sample and out-of-sample datasets. This result supports the general wisdom in the paper since time-varying hedge ratios seem more realistic than constant hedge ratio estimates of other models.

Time-varying (MGARCH) hedge ratio concept has never been analyzed for Turkish futures markets thus far. In that respect, our study contributes on the newly established Turkish futures market. One important proposal for possible further research is changing the frequency of the data. To concentrate on high-frequency data might provide more realistic results as it captures a more detailed picture of the dynamics tick by tick between the spot and future markets in particular.

## Notes

1. The hedging effectiveness is specified by Ederington (1979) as the percentage variance reduction between hedged and unhedged positions.
2. By omitting the long run co-integration relationship from the estimation procedure, hedger would take a smaller than optimal futures position, which probably causes a relatively poor hedging performance.
3. See, for example, Baillie and Myers (1991), Park and Switzer (1995), Lypny and Powalla (1998), Brooks and Persaud (2002), Yang and Allen (2004).
4. The proportion of foreign investors in the market was 22% in 2008 (TurkDEX web site).
5. For instance, when February contract is expired August contract is activated.
6. As the ISE-30 index future contracts were not heavily traded during the first months of the exchange, the dataset is started from 02 May 2005 instead of the launching date, 4 February.
7. As Lien *et al.* (2002) stated the day when open position of the nearby contract exceeds outstanding futures is regarded as rollover day according to this method.
8. See Gonzalo (1994) for further information.
9. The optimal lag length for VECM is determined as 2 by AIC and SIC criteria.
10. Lag-lengths of  $p = 1$  and  $q = 1$  for the GARCH model provides the best combination corresponding to log-likelihood functions.
11. While the unhedged portfolio just contains the ISE-30 spot index, the hedged portfolios are composed from the ISE-30 spot index and the ISE-30 future index at different weights (using different hedge ratios) together.
12. Correlation between spot and future prices is approximately 0.9967 for in-sample period and 0.9632 for out-of-sample-period.

## REFERENCES

- [1]. Abhyankar, A. 1998. "Linear and nonlinear Granger Causality: Evidence from the UK stock index futures market." *Journal of Futures Markets*. 18, 519-540.
- [2]. Aksoy, G., and Olgun, O. 2009. "An Empirical Analysis on Estimation of the Optimal Hedge Ratio: the case of TurkDex (Turkish)." *İktisat, İşletme ve Finans*. 274, 33-50.
- [3]. Benet, B.A. 1992. "Hedge period length and ex-ante futures hedging effectiveness: The case of foreign-exchange risk crosses hedges." *Journal of Futures Markets*. 12, 163-175.
- [4]. Bhaduri, S., and Durai, S. 2008. "Optimal hedge ratio and hedging effectiveness of stock index futures: evidence from India." *Macroeconomics and Finance in Emerging Market Economies*. 1:1, 121-134.
- [5]. Bollerslev, T. 1986. "Generalized autoregressive conditional heteroscedasticity." *Journal of Econometrics*. 31, 307-327.
- [6]. Bollerslev, T.; Engle, R.F., and Woolridge, J.M. 1988. "A Capital Asset Pricing Model with Time-Varying Covariances." *Econometrica*. 96, 116-131.
- [7]. Brooks, C., and Persaud, G. 2002. "The Effect of Asymmetries on Optimal Hedge Ratios." *Journal of Business*. 75, 333-352.
- [8]. Chou, W.L.; Denis, K.K.F., and Lee, C.F. 1996. "Hedging with the Nikkei index futures: The conventional model versus the error correction model." *Quarterly Review of Economics and Finance*. 36, 495-505.
- [9]. Choudhry, T. 2003. "Short-Run deviations and optimal hedge ratio: evidence from stock futures." *Journal of Multinational Financial Management*. 13, 171-192.
- [10]. Choudhry, T. 2004. "The hedging effectiveness of constant and time-varying ratios using three Pacific Basin stock futures." *International Review of Economics and Finance*. 13, 371-385.
- [11]. Ederington, H. 1979. "The Hedging Performance of the New Futures Markets." *Journal of Finance*. 34, 157-170.
- [12]. Engle, R. F., and Granger, C. W. J. 1987. "Co-Integration and error-correction: Representation, estimation and testing." *Econometrica*. 55, 251—276.
- [13]. Engle, R.F., and Kroner, K.F. 1995. "Multivariate Simultaneous Generalized ARCH." *Econometric Theory*. 24, 122-150.
- [14]. Figlewski, S. 1984. "Hedging performance and basis risk in stock index futures." *Journal of Finance*. 36, 657-669.
- [15]. Floros, C., and Vougas, D.V. 2006. "Hedging effectiveness in Greek stock index futures market, 1999-2001." *International Research Journal of Finance and Economics*. 5, 7-18.
- [16]. Ghosh, A. 1993. "Hedging with stock index futures: Estimation and forecasting with error correction model." *Journal of Futures Markets*. 13, 743-752.

- [17]. Gonzalo, J. 1994. "Five Alternative Methods of Estimating Long-Run Equilibrium Relationships." *Journal of Econometrics*. 60, 203-223.
- [18]. Herbst, A.F.; Kare, D.D., and Marshall, J.F. 1993. "A Time-Varying Convergence Adjusted Minimum Risk Futures Hedge Ratio." *Advances in Futures and Options Research*. 6, 137-155.
- [19]. Hill, J., and Schneeweis, T. 1981. "The hedging effectiveness of foreign currency futures." *The Journal of Financial Research*. V, 95-104.
- [20]. Howard, C.T., and D'Antonio, L.J. 1984. "A risk-return measure of hedging effectiveness." *The Journal of Financial and Quantitative Analysis*. 19, 101-112.
- [21]. Hull, J.C. 2003. "Options, Futures and Other Derivatives." *Prentice Hall. Fifth Edition*.
- [22]. Johnson, L. 1960. "The Theory of Hedging and Speculation in Commodity Futures." *The Review of Economic Studies*. 27, 139-151.
- [23]. Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control*. 12, 231-254.
- [24]. Kavussanos, M., and Visvikis, I. 2008. "Hedging Effectiveness of the Athens Stock Index Futures Contracts." *The European Journal of Finance*. 14, 243-270.
- [25]. Lien, D., and Luo, X. 1993. "Estimating multi-period hedge ratios in cointegrated markets." *Journal of Futures Markets*. 13, 909-920.
- [26]. Lien, D. 2005. "A Note on the Superiority of the OLS Hedge Ratio." *Journal of Futures Markets*. 25, 1121-26.
- [27]. Lien, D.; Tse, Y.K., and Tsui, A.K.C. 2002. "Evaluating the Hedging Performance of the Constant-Correlation GARCH Model." *Applied Financial Economics*. 12, 791-798.
- [28]. Moosa, I. 2003. "The Sensitivity of the Optimal Hedge Ratio to Model Specification." *Finance Letters*. 1, 15-20.
- [29]. Myers, R.J., and Thompson, S.R. 1989. "Generalized Optimal hedge ratio estimation." *American Journal of Agricultural Economics*. 71, 858-867.
- [30]. Myers, R.J. 1991. "Estimating time-varying optimal hedge ratios on futures markets." *Journal of Futures Markets*. 11, 139-153.
- [31]. Park, T.H., and Switzer, L.N. 1995. "Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: A note." *Journal of Futures Market*. 15, 61-67.
- [32]. Stein, J.L. 1961. "The Simultaneous Determination of Spot and Future Prices." *American Economic Review*. 51, 1012-25.
- [33]. Yang, W., and Allen, D.E. 2004. "Multivariate GARCH hedge ratios and hedging effectiveness in Australian futures markets." *Accounting and Finance*. 45, 301-321.