The Predictability of Non-Overlapping Forecasts: Evidence from a New Market

Manolis G. Kavussanos*
Athens University of Economics and Business, Greece

Ilias D. Visvikis
ALBA Graduate Business School, Greece

This paper investigates the short-run forecasting performance, in the relatively new and fairly unresearched futures market of Greece. Forecasts from univariate (ARIMA) and multivariate (VAR, VECM and SURE-VECM) linear time-series models indicate that cash returns can be more accurately forecasted, for all forecast horizons, when forecast specifications contain information from both lagged cash and futures returns, than from specifications that utilize information only from lagged cash returns. On the other hand, futures return forecasts are not enhanced in accuracy when lagged cash returns are employed for almost all forecasts. This verifies that at almost all forecasting horizons futures returns contain significantly more and different information than that embodied in current cash returns. Moreover, all time-series models generate more accurate cash and futures forecasts than the forecasts obtained by the random walk model. (JEL: G13, G14, G15)

Keywords: Cointegration; VECM and ARIMA Models; Forecasting; Futures Markets; Emerging Markets; Predictability.

---

* Professor Manolis G. Kavussanos, Athens University of Economics and Business, 76 Patission St, 10434, Athens, Greece. Tel: 0030 210 8203167, Fax: 0030 210 8203196, Email: mkavus@aueb.gr.

The authors would like to thank the editor and an anonymous referee for their comments and suggestions, as well as participants of the following conferences, where earlier versions of this paper were presented: 12th Annual Conference of the Multinational Finance Society (MFS), Athens, Greece, July 2005; 14th European Financial Management Association (EFMA) Conference, Milan, Italy, June 2005; and 3rd Annual Conference of the Hellenic Financial and Accounting Association (HFAA), Athens, Greece, December 2004. Thanks are also due to Mr. Manolis Papadakis for research assistance. Any remaining omissions or errors are the responsibility of the authors.

(*Multinational Finance Journal*, 2011, vol. 15, no. 1/2, pp. 125–156)

DOI: 10.17578/15-1/2-4

I. Introduction

Emerging markets have become interesting alternatives for global investors (see Harvey, 1995; Bakaert and Harvey, 1997; and Kutan and Aksoy, 2004, amongst others). Furthermore, they have attracted a strong interest in the financial literature, as they are characterized by low liquidity, thin trading, higher sample averages, low correlations with developed market returns, non-normality, better predictability, higher volatility and short samples. In addition, market imperfections, high transactions and insurance costs, less informed rational traders and investment constraints may also affect the risks and returns involved. Less work has been carried on the behavior of emerging markets, in the period after their characterization as developed. The Athens Stock Exchange (ATHEX) in Greece is characterized as a developed market since May 2001.[1] However, questions remain as to whether the forecasting performance of this newly established derivatives market is in accordance with corresponding results from well-established derivatives markets. This paper examines empirically, for the first time, the forecasting performance of derivatives contracts trading in the fairly unresearched derivatives market of ATHEX.

The operation of the organised derivatives market in Greece rests with the Athens Derivatives Exchange (ADEX), founded in April 1998. The first stock index futures contract of ADEX was the FTSE/ATHEX-20 futures contract, introduced in August 1999, with the underlying asset being the FTSE/ATHEX-20 stock index, which consists of the 20 highest capitalization stocks listed in ATHEX. The FTSE/ATHEX Mid-40 index futures was created, a few months later, in January 2000 and is based on 40 medium capitalization stocks listed in ATHEX.[2]

---

1. There is a limited number of studies examining the ADEX market. Indicatively, Kavussanos *et al*. (2008) investigate the lead-lag relationship in daily returns and volatilities between price movements of the ADEX stock index futures and the underlying cash indices. Results show that futures prices (and volatilities) lead the cash index returns (and volatilities), by responding more rapidly to economic events than stock prices. Kavussanos and Visvikis (2008) show that risk can be hedged efficiently with the ADEX derivatives contracts. Kenourgios (2005) argues that the ADEX market is inefficient according to the unbiasedness hypothesis, in the sense that futures prices are biased predictors of future cash prices. Kenourgios (2004) presents evidence that there are spillover effects in the mean cash and futures returns in the ATHEX–ADEX markets.

2. Detailed contract specifications of the two futures contracts can be found on the ADEX website (www.adex.ase.gr), while the names of the companies, comprising each of the underlying indices, the ATHEX-20 and the ATHEX Mid-40 may be found on the ATHEX

Some “special properties” that differentiate the Greek capital market from other well-established markets are the following: (i) the Greek derivatives market is characterised by the absence of highly specialised traders, the absence of a respective large number of foreign derivatives traders and low value of trading in derivatives relative to the underlying cash market, in comparison to well-established derivatives exchanges; (ii) although liquidity has increased lately, for several listed companies, the market is thin. Due to low liquidity and the small size of the market, it may be dominated by the activities of hedgers rather than speculators. As a consequence, it cannot be taken for granted that all information relevant to future cash prices is automatically incorporated into futures prices; (iii) the privatization of the public sector entities that started in early 2000, continues today. ATHEX is a fully privatized group aiming at value maximization; (iv) the ownership structure in ATHEX is different to that of other more mature markets, such as those of the US and the UK. In Greece, the structure is family-owned, concentrated in block-holders, whereas in other markets the structure is diffused; (v) several reforms have taken place, in adopting the E.U. regulatory framework; and (vi) even though the Greek market is characterized as mature since 2001, some emerging market characteristics may still remain.

This paper assumes that stock index futures prices equal the expected value of cash index prices and therefore, in an effort to measure the forecasting performance of cash and futures prices in the FTSE/ATHEX-20 and the FTSE/ATHEX Mid-40 markets, it utilizes the Vector Error-Correction Model (VECM) of Johansen (1988), which uses information from both markets. The forecast evaluation procedures are designed in such a way so as to avoid biased overlapping forecasts, induced by serially correlated overlapping forecast errors. Thus, following Tashman (2000), independent out-of-sample N-period ahead forecasts are generated over the forecast period. The estimation period is augmented recursively by *N*-periods ahead every time (where *N* corresponds to the number of steps ahead). Then, the forecasting performance of the VECM model is compared against a number of alternative linear time-series models (Vector Autoregressive model – VAR and Autoregressive Integrated Moving Average – ARIMA model) and against the Random Walk (RW) model.[3]

---

website (www.athex.gr).

3. Beckers (1996) provides a good review of econometric time-series approaches for forecasting financial returns.

The remainder of this paper is organized as follows. Section II presents the methodology followed and the models used to generate the forecasts. Section III describes the data and presents their statistical properties. Section IV discusses the in-sample estimation results and the out-of-sample forecasting results and evaluates the forecasting performance of the alternative models. Finally, section V offers some concluding comments and implications of the results.

II. Methodology and Theoretical Considerations

The specifications used in this paper are the Box-Jenkings (1970) ARIMA model, the VAR model, the VECM model, and a restricted VECM model. Each model is estimated over the period 01 September 1999 to 31 December 2003 for the FTSE/ATHEX-20 market and 01 February 2000 to 31 December 2003 for the FTSE/ATHEX Mid-40 market, which leaves a test period of six months; from 02 January 2004 to 07 June 2004.

As most financial time-series prices tend to be non-stationary in levels, while stationary in first-differences, the order of integration of these series is examined first. Consider the following AR(1) model of a variable y_t:

$$y_t = \gamma + \rho y_{t-1} + \varepsilon_t, \quad t = 1,2,3,...,T \;\; ; \;\; \varepsilon_t \sim IN\left(0,\sigma^2\right) \qquad (1)$$

where, γ is a constant, ε_t are normally distributed error-terms with zero mean and finite variance σ^2 and T is the sample size. The variable y_t will be stationary or integrated of order zero, denoted $I(0)$, if $|\rho| < 1$ and non-stationary or integrated of order one, denoted $I(1)$, if $\rho = 1$.[4] Dickey and Fuller (1979), develop a unit root test to examine the stationarity property of a variable, by considering an AR(1) process as in equation (1). By subtracting y_{t-1} from both sides of equation (1) and adding on the right hand side of the equation enough lagged values of the dependent variable to account for the presence of autocorrelation in the residual series, the following Augmented Dickey-Fuller (ADF, 1981) equation is estimated:

4. The order of integration of a variable refers to the number of times that a series must be differenced to become stationary.

$$\Delta y_t = \mu\, y_{t-l} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t \;\; ; \;\; \varepsilon_t \sim iid\left(0, \sigma^2\right) \qquad (2)$$

This can be used to test for the existence of a unit root as the null hypothesis on the coefficient μ, where, $\mu = \rho - 1$ and the lag order, p, is determined though the Schwarz Bayesian Information Criterion (SBIC) (Schwarz, 1978). Conventionally, the order of integration of a series, y_t, is examined though the ADF test of equation (2) that uses t-tests to measure the statistical significance of the coefficient ρ, the lag order p, as well as the existence of constants/trends in the equation.

However, Campbell and Yogo (2006) argue that conventional t-tests of significance in regression equations may be misleading due to the possible persistence (non-stationarity) of the variables in case they are near-integrated $(\rho \rightarrow 1)$ and the sample size is small. In such a case, the use of the conventional t-tests of significance may not lead to correct inferences.[5] For example, the ADF test on ρ of equation (2) may fail to recognize persistence; that is, it may show stationarity, while the series has a unit root.

To correct for that, Campbell and Yogo (2006) develop a simple Bonferroni bounds test, based on the confidence interval for the largest autoregressive root (ρ) of the predictor (forecast) variable (in this case, the cash and futures returns of the two investigated markets). They argue that if the confidence interval indicates that the predictor variable is sufficiently stationary, which means that the predictor's innovations have low correlation with returns, then t-tests with conventional critical values can be safely applied. Otherwise, inferences based on first-order asymptotics could be invalid.

Inferences in this case can be made by utilizing the local-to-unity asymptotic theory.[6] This provides an asymptotic framework, where the largest autoregressive root of an AR(p) process, modeled as $\rho = 1 + c/T$ ($\rightarrow c = T(\rho - 1)$, where c is a fixed constant), is the parameter of

5. In general, in finite samples, a right-tailed t-test that uses conventional critical values tends to over-reject the null hypothesis while a left-tailed test tends to under-reject the null (see Campbell and Yogo, 2006).

6. Local-to-unity asymptotics provides an accurate approximation to the finite-sample distribution of test statistics when the predictor variable is persistent (Elliott and Stock, 1994). The asymptotic distribution theory is not discontinuous when y_t is non-stationary (i.e. when $c = 0$) and allows y_t to be stationary but nearly integrated (i.e. for $c < 0$) or even explosive (i.e. $c > 0$).

interest. ρ is close to one (nearly-integrated) in finite samples.[7] Such a test involves the computation of a unit root test statistic in the data and the use of the distribution of that statistic to construct the Bonferroni confidence interval for ρ (and c) and the estimation of δ, the latter being the correlation between the innovations to returns and the predictor variable.

Empirically, in order to construct a relatively accurate confidence interval for ρ, the Dickey-Fuller Generalised Least Squares (DF-GLS) unit root test of Elliott, *et al*. (1996) is used that exploits the knowledge of $\rho \approx 1$.[8] Under the null hypothesis of persistence, the Campbell and Yogo (2006) test considers whether the confidence interval for ρ contains the value of 1 (or its upper bound is close to 1), the confidence interval for c contains the value of zero and δ being negative and close to -1. When ρ is small in absolute value, c is large in absolute value and when $\delta = 0$, the test collapses to the conventional t-statistic. That is, a t-test that uses conventional critical values would have approximately the correct size. The size distortion of the t-test is maximized when $\delta = -1$ and $c \approx 1$.

This paper is concerned with the forecasting of cash and futures returns. Campbell and Yogo (2006) suggest that if the aim is to forecast the returns of a financial time-series, the following equations should be estimated, which test for the predictability of variables after correcting for persistence:

$$r_{c,t} = \alpha_c + \beta_c y_{f,t-1} + u_{c,t} \tag{3a}$$

$$r_{f,t} = \alpha_f + \beta_f y_{c,t-1} + u_{f,t} \tag{3b}$$

where, $r_{c,t}$ and $r_{f,t}$ are the cash and futures return variables that need to be forecasted, $y_{f,t-1}$ and $y_{c,t-1}$ are the lags of the futures and cash predictor variables, with coefficients β_c and β_f, respectively, in equations (3a) and (3b), and u_{ft} and u_{ct} are white noise error-terms. More specifically, in equation (3a), the FTSE/ATHEX-20 (FTSE/ATHEX Mid-40) lagged futures return $\left(y_{f,t-1}\right)$ is used as a predictor for the

7. When the predictor variable is an AR(p) process the regression is augmented by the addition of autoregressive terms up to order p determined by the SBIC (1978), as in equation (2).

8. Elliott *et al*., (1996) argue that the DF-GLS has the advantage of being more powerful than the ADF test, resulting in a tighter confidence interval for ρ.

FTSE/ATHEX-20 (FTSE/ATHEX Mid-40) cash return ($r_{c,t}$), while in equation (3b), the FTSE/ATHEX-20 (FTSE/ATHEX Mid-40) lagged cash return $\left(y_{c,t-1}\right)$ is used as a predictor for the FTSE/ATHEX-20 (FTSE/ATHEX Mid-40) futures return ($r_{f,t}$).

In this procedure, the degree of persistence is taken into account by constructing, for each value of ρ, a confidence interval for β_c and β_f given ρ and testing for predictability either by the Bonferroni t-test or by the Q-test of Campbell and Yogo (2006, page 32) that leads to valid inference regardless of the degree of persistence of the predictor variable.[9] In these tests the null hypothesis of no predictability [i.e. of β_c = 0 in equation (3a)] is rejected in favour of the alternative of predictability (i.e. of $\beta_c \neq 0$) if the confidence interval for β_c lies strictly above or below zero.

Once the order of integration of the series is determined, say to be $I(1)$, and that the series are predictable in the sense of Cambell and Yogo, the following models are considered as competing forecasting models.

The first model used to generate separately forecasts of cash and futures prices is the univariate ARIMA(p,d,q) model of the following form:

$$\Delta S_t = \mu_{S,0} + \sum_{i=1}^{p} a_{S,i}\Delta S_{t-i} + \sum_{j=1}^{q} b_{S,j}\varepsilon_{t-j} + \varepsilon_{S,t} \;\; ; \;\; \varepsilon_t \sim \text{iid}(0,\sigma_\varepsilon^2) \quad (4\alpha)$$

$$\Delta F_t = \mu_{F,0} + \sum_{i=1}^{p} a_{F,i}\Delta F_{t-i} + \sum_{j=1}^{q} b_{F,j}v_{t-j} + v_{F,t} \;\; ; \;\; v_t \sim \text{iid}(0,\sigma_v^2) \quad (4b)$$

where, ΔF_t and ΔS_t are changes in log futures and log cash prices, respectively, and ε_t and v_t are random white noise error-terms. For an ARIMA (p,d,q) model the terms p, d, q refer, respectively, to the lagged values of the dependent variable, the order of integration and the lagged values of the error-term.

The second model used, in a simultaneous cash-futures framework, is the following bivariate VAR(p,q) model:

9. Campbell and Yogo (2005) provide a detailed description of how to construct the Bonferroni confidence intervals.

$$\Delta S_t = \mu_{1,0} + \sum_{i=1}^{p} \mu_{1,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{1,i} \Delta F_{t-i} + \varepsilon_{1,t}$$

$$; \ \varepsilon_t \sim N(0,H) \quad (5)$$

$$\Delta F_t = \mu_{2,0} + \sum_{i=1}^{p} \mu_{2,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{2,i} \Delta F_{t-i} + \varepsilon_{2,t}$$

The bivariate VAR model takes into account the information content in cash price movements in determining futures price movements and vice versa (Sims, 1980). The (2 x 1) vector of residuals $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$ follow a conditional normal distribution with zero mean and variance-covariance matrix, H. Thus, the VAR model is estimated assuming that the variance-covariance matrix is homoskedastic. However, when the residuals of equation (5) exhibit heteroskedasticity, the *t*-statistics are adjusted by the White (1980) heteroskedasticity correction, which yields a consistent variance-covariance matrix with robust standard-errors (see also Al-Zoubi and Maghyereh, 2007). Nonetheless, the VAR model may be misspecified, as it ignores the possible cointegration (long-run) relationship between the cash and futures markets and, in such case, an Error-Correction Term (ECT) needs to be added (see Aggarwal and Zong, 2008).

Thus, the third and fourth models used to generate simultaneous out-of-sample forecasts for cash and futures prices are the unrestricted and restricted versions, respectively, of the following bivariate VECM(p,q) (Johansen, 1988) model:[10]

$$\Delta S_t = \mu_{10} + \sum_{i=1}^{p} \mu_{1,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{1,i} F_{t-i} + \alpha_1 (S_{t-1} - \beta_1 F_{t-1} - \beta_0) + \varepsilon_{1,t}$$

$$; \ \varepsilon_t \sim N(0,\mathrm{H}) \quad (6)$$

$$\Delta F_t = \mu_{20} + \sum_{i=1}^{p} \mu_{2,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{2,i} F_{t-i} + \alpha_2 (S_{t-1} - \beta_1 F_{t-1} - \beta_0) + \varepsilon_{2,t}$$

where, the term in parentheses represent the cointegrating (long-run) relationship between cash and futures prices of the previous period. This ECT represents the lagged disequilibrium term of the long-run relationship between cash and futures prices. The Johansen (1988)

10. The restricted VECM is estimated as a system of Seemingly Unrelated Regression Equations (SURE), derived by eliminating the insignificant variables from the unrestricted VECM and thus, yielding more efficient and consistent estimates (see Zellner, 1962).

VECM specification of equation (6), used to determine the existence of cointegration between cash and futures returns, can be written in matrix form as follows:[11]

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \;\; ; \;\; \varepsilon_t \sim N(0, \mathrm{H}) \tag{7}$$

where, X_t is the (2 x 1) vector $(S_t, F_t)'$ of log-cash and log-futures prices, respectively, Δ denotes the first difference operator, and ε_t is a (2 x 1) vector of residuals (as explained earlier). Once again, the VECM model of equations (6) and (7) is estimated assuming that the vector of residuals is homoskedastic, otherwise, when heteroskedasticity is present, the variance-covariance matrix is adjusted by the White (1980) correction. The VECM specification contains information on both the short- and long-run adjustment to changes in X_t, via the estimated parameters Γ_i and Π, respectively.

Johansen and Juselius (1990) show that the coefficient matrix Π contains the essential information about the relationship between S_t and F_t. Specifically, if rank(Π) = 0, then Π is the 2x2 zero matrix implying that there is no cointegration relationship between S_t and F_t. In this case the VECM reduces to a VAR model in first differences. If Π has a full rank, that is rank(Π) = 2, then all variables in X_t are $I(0)$ and the appropriate modelling strategy is to estimate a VAR model in levels. If Π has a reduced rank, that is rank(Π) = 1, then there is a single cointegrating relationship between S_t and F_t, which is given by any row of matrix Π and the expression ΠX_{t-1} is the ECT of equation (6). In this case, Π can be factored into two separate matrices α and β, both of dimensions (2 x 1), where 1 represents the rank of Π, such as $\Pi = \alpha\beta'$, where β' represents the vector of cointegrating parameters and α is the vector of error-correction coefficients (α_1 and α_2) measuring the speed of convergence of cash and futures prices to the long-run (equilibrium) steady state.[12]

---

11. The Johansen (1988) procedure is preferred because it provides more efficient estimates of the cointegration vector than the Engle and Granger (1987) two-step approach. Toda and Phillips (1993) argue that maximum-likelihood estimators based on Johansen's (1988, 1991) method (for large samples of more than 100 observations) are asymptotically median unbiased, have mixed normal limit distributions and take into account the information on the presence of unit roots in the system. Therefore, they are much better suited to perform inference.

12. Since rank(Π) equals the number of characteristic roots (or eigenvalues), which are different from zero, the number of distinct cointegrating vectors can be obtained by estimating

Finally, the forecasts are compared with those from the RW model. The latter is used as a benchmark model. In a RW model, the cash (futures) prices at time $t–n$, $S_{t–n}$ ($F_{t–n}$) are the most accurate predictors of cash (futures) prices at time t, S_t (F_t). Therefore, the RW process uses the current cash or futures prices to generate forecasts of these prices, and requires no estimation.

These alternative univariate and multivariate models are estimated over the estimation period and used to generate independent forecasts of the cash and futures prices up to 20-steps ahead in an out-of-sample period. Following Tashman (2000), independent out-of-sample N-period ahead forecasts are generated over the forecast (test) period; that is, from 02 January 2004 to 07 June 2004 for both contracts. In order to avoid the bias induced by serially correlated overlapping forecast errors, the estimation period is recursively augment by N-periods ahead every time (where N corresponds to the number of steps ahead). Then, the models are re-estimated each time a new observation is added in the set. For example, in order to compute 2 steps-ahead forecasts, the estimation period is augmented by $N = 2$ observations each time. This method yields 53 independent non-overlapping out-of-sample forecasts in the test period. Similarly, in order to compute 5 steps-ahead forecasts, the method yields 21 independent non-overlapping forecasts in the test period.

The forecast accuracy of each model is measured using the Root Mean Square Error (RMSE) that assumes a symmetric loss function:

$$\text{RMSE} = \sqrt{\frac{1}{K}\sum_{t=1}^{K}(R_t - Z_t)^2} \tag{8}$$

where, R_t are the realized values of the cash (futures) prices, Z_t are the forecast values of the cash (futures) prices, and K is the number of forecasts.

Following Batchelor *et al*. (2007), the Diebold and Mariano's (DM, 1995) pairwise tests of the hypothesis that the RMSEs from two competing models are equal are utilized. Let the average difference between the squared forecast errors from two models at time t, $u_{1,t}^2$ and $u_{2,t}^2$, be given by $\bar{d} = \frac{1}{K}\sum_{t=1}^{K}\left(u_{1,t}^2 - u_{2,t}^2\right)$, where K is the number of

---

the number of these eigenvalues, which are significantly different from zero (for more details see Johansen, 1998).

forecasts. Under the null hypothesis of equal forecast accuracy the following DM statistic has an asymptotic standard normal distribution:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{K}}} \sim N(0,1) \quad (9)$$

where, $f_d(0)$ is the spectral density of $\left(u_{1,t}^2 - u_{2,t}^2\right)$ at frequency zero. Following Diebold and Mariano (1995), a consistent estimate of $f_d(0)$ can be obtained by using a Bartlett weighting scheme as in Newey and West (1987). This test statistic is robust to the presence of non-normality and serial correlation in the forecast errors. Hypothesis tests for the equality of the RMSEs are conducted for each pair of models and the significance of the tests are indicated (as * and ** for the 5% and 10% significance levels, respectively) next to the RMSE ratios.

III. Data Description and Statistical Properties

The data used for the analysis are daily closing cash and futures prices for both the FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 markets, for the period August 1999 to June 2004 and February 2000 to June 2004, respectively. The data for the stock index futures are obtained from ADEX, and the data for the stock indices come from ATHEX. Stock index futures prices are always those of the nearby contract. All prices are transformed to natural logarithms. For forecasting evaluation purposes, the data are split into an estimation set and a test set. The various time-series models are initially estimated over the period 01 September 1999 to 31 December 2003 for the FTSE/ATHEX-20 market and 01 February 2000 to 31 December 2003 for the FTSE/ATHEX Mid-40 market – the first estimation period. The period from 02 January 2003 to 07 June 2004 is used to generate independent out-of-sample *N*-period ahead forecasts over the test data period.

Stock index futures prices are always those of the nearby contract because it is highly liquid and is the most active contract. To avoid thin markets and expiration effects (when futures contracts approach their settlement day, the trading volume decreases sharply) we rollover to the next nearest contract one week before the nearby contract expires. Moreover, a "perpetual" (constant maturity) 22-day ahead futures contract is used, which corresponds to the average number of trading days in a month, in order to avoid the potential problem of price-jumps

TABLE 1. Descriptive Statistics of Logarithmic First-Differences of Cash and Futures Prices

A. FTSE/ATHEX-20 Cash and Futures Price Series
(Sample Period: 01/09/99 to 07/06/04)

	T	Skew	Kurt	Q(36)	$Q^2(36)$	J-B
Cash	1185	0.183	6.527	70.33	230.30	620.53
Futures	1185	0.166	6.328	52.54	177.60	552.31

B. FTSE/ATHEX Mid-40 Cash and Futures Price Series
(Sample Period: 01/02/00 to 07/06/04)

	T	Skew	Kurt	Q(36)	$Q^2(36)$	J-B
Cash	994	–0.209	6.172	128.25	549.22	460.66
Futures	994	0.126	7.068	74.26	493.39	748.13

Note: All series are measured in logarithmic first differences. *T* is the number of observations. Skew and Kurt are the estimated centralized third and fourth moments of the data; their asymptotic distributions under the null are $\sqrt{T}\,\hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\,(\hat{\alpha}_4 - 3) \sim N(0,24)$, respectively. Q(36) and $Q^2(36)$ are the Ljung-Box (1978) Q statistics on the first 36 lags of the sample autocorrelation function of the raw series and of the squared series; these tests are distributed as $\chi^2(36)$. The critical values are 58.11 and 51.48 for the 1% and 5% levels, respectively. J-B is the Jarque-Bera (1980) test for normality, distributed as $\chi^2(2)$.

in the series at the date of the futures contracts rollover (Pelletier, 1983). The prices are calculated as a weighted average of a near and distant futures contract, weighted according to their respective number of days from maturity. However, when using the perpetual contract, the empirical results are qualitatively the same with those reported in the ensuing analysis and there is no evidence that the rollover of the futures contracts create a bias in the findings.

Summary statistics of logarithmic first-differences of daily cash and futures prices, for the whole period, are presented in table 1. The results indicate excess skewness and kurtosis in all price series. In turn, Jarque-Bera (1980) tests indicate departures from normality for cash and futures prices in both markets. The Ljung-Box Q(36) and $Q^2(36)$ statistics (Ljung and Box, 1978) on the first 36 lags of the sample autocorrelation function of the log-level series and of the log-squared series indicate significant serial correlation and existence of heteroskedasticity, respectively, in almost all cases.

Following the use of the Bonferroni bounds adjustment, the last two columns in Panel A of table 3 report the 95% confidence interval for the largest autoregressive root (ρ) and the corresponding local-to-unity parameter (c) – computed using the DF-GLS statistic – for the logarithmic cash and futures returns in the FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 markets, by treating each of the four return-series as a predictor variable (y_t). The estimated autoregressive lag lengths (p) for the predictor variables, the estimated correlations (δ) between the innovations to returns and the predictor variable and the DF-GLS statistic are reported in the third, fourth and fifth columns of the table, respectively.

As can be observed from the confidence intervals of ρ, the cash and futures price-series for the two markets are highly persistent, containing in three out of four cases a unit root in the confidence intervals. This is also confirmed from the confidence interval for c, where the value of zero (indication of non-stationarity) is included in all cases. Finally, the reported values of δ in the fourth column of Panel A are negative and large, and in accordance with the aforementioned results for ρ and c. According to Campbell and Yogo (2006), the high persistence in log levels of these predictor variables may suggest that first-order asymptotics could be misleading and as such, t-tests with conventional critical values could be invalid.

In order to test for the predictability of the persistent variables, adjusted confidence intervals for β given ρ, through the Bonferroni Q-test, are presented in Panel B of the same table. The second and third columns of the table indicate the t-statistic and the Ordinary Least Squares (OLS) point estimates of the coefficient $(\hat{\beta})$ of the predictor variable from equations (3a) and (3b). The last two columns report the 95% Bonferroni confidence intervals for β using the t-test and the Q-test, respectively. For all return-series, the results indicate that the confidence intervals for both the t-test and the Q-test lie strictly above or below zero, indicating predictability of returns. Hence, the null hypothesis of no predictability (i.e. of $\beta = 0$) is rejected in favor of the alternative of predictability at the 5% level of significance for all return-series.

Overall, it seems that even after taking into account the persistence of returns by the Bonferroni bounds correction, the cash and futures return-series of the ADEX market exhibit a degree of predictability and therefore, it is deemed important to empirically examine their forecasting performance knowing that inferences using t-statistics are valid.[13]

Panel C of table 2, reports ADF (1981), Phillips-Perron (PP, 1988)

---

13. The findings are in accordance with Liu and Maynard (2005) where after using Bonferroni bounds to test for the forward rate unbiasedness, report qualitatively the same results to the ones without the bounds correction.

TABLE 2. Bonferroni Bounds, Tests of Predictability and Unit Root Tests (sample periods as in table 1)

A. Parameter Estimates of the Predictive Regression Model: See (eq. 1)

Series	Obs.	P	Δ	DF-GLS	95% CI: ρ	95% CI: c
Futures-20	1,186	2	–0.997	–1.912	[0.998, 1.004]	[–2.033, 4.672]
Cash-20	1,186	2	–0.990	–2.014	[0.992, 1.001]	[–2.017, 4.675]
Futures-40	995	4	–0.909	–5.513	[0.863, 0.909]	[–3.934, 6.412]
Cash-40	995	4	–0.108	–2.371	[0.997, 1.002]	[–5.638, 4.097]

B. Predictability of Returns - Bonferroni t- and Q-tests on β: See (eq. 3a) and (eq. 3b)

Series		t-stat	95% CI: t-test	95% CI: Q-test
Futures-20	0.996 (β_f)	776.72	[0.993 , 0.998]	[0.995 , 0.997]
Cash-20	0.990 (β_c)	820.81	[0.987 , 0.993]	[0.988 , 0.991]
Futures-40	–0.146 (β_f)	–6.968	[–0.177, –0.108]	[–0.170, –0.115]
Cash-40	–0.104 (β_c)	–8.336	[–0.106, –0.102]	[–0.105, –0.102]

C. Unit Root Tests on logarithmic index levels and return series

Series	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Futures-20	–1.657 (2)	–1.653	–19.772 (2)	–31.621	0.815
Cash-20	–1.725 (2)	–1.682	–19.065 (2)	–29.642	0.736
Futures-40	–2.788 (2)	–2.672	–17.441 (2)	–28.123	0.415
Cash-40	–2.864 (2)	–2.623	–16.069 (2)	–24.648	0.325

(*Continued*)

TABLE 2. (Continued)

Note: Panel A: In order to examine the persistence of each logarithmic price series (e.g. Cash-20), an AR(p) version of equation (1) is estimated. The estimated autoregressive lag lengths p of the logarithms of variable (y_t) (determined through the Schwarz Bayesian Information Criterion – SBIC), the estimated correlation (δ) between ε_t and y_{t-1} and the DF-GLS statistic on ρ of Elliott, *et al*. (1996) are reported in the third, fourth and fifth columns of the table, respectively. The last two columns report the 95% confidence interval for the largest autoregressive root ρ (modeled as $\rho = 1 + c/T$ process, where c is a fixed constant and T is the sample size) and the corresponding local-to-unity parameter c for the logarithmic cash and futures prices of the two markets. Panel B: In order to examine the predictability of the persistent variables, equations (3a) and (3b) are estimated. The point estimates β_c and β_f and the corresponding t-statistics are reported in the second and third columns, respectively. The last two columns report the 90% Bonferroni confidence intervals for β_c and β_f using the t-test and the Q-test, respectively. The tests examine the non-existence of predictability (i.e., $\beta_c = 0$) against the alternative of predictability (i.e., $\beta_c \neq 0$). Panel C: Augmented Dickey Fuller (ADF, 1981) regressions including an intercept term are reported. The lag-length of the ADF tests (in parentheses) are determined by minimising the SBIC. PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses. Lev and 1st Diffs correspond to price series in log-levels and log-first differences, respectively. The 5% critical value for the ADF and PP tests is –2.89. The critical values for the KPSS test are 0.146 and 0.119 for the 5% and 10% levels, respectively.

TABLE 3. Johansen (1988) Tests for the Number of Cointegrating Vectors between Cash and Futures Prices

	Lags	Hypothesis (Maximal)		Test Statistic	Hypothesis (Trace)		Test Statistic	95% Critical Values		Cointegrating Vector	Hypothesis Test
		H_0	H_1	λ_{max}	H_0	H_1	λ_{trace}	λ_{max}	λ_{trace}	$\beta' = (1, \beta_1, \beta_0)$	$\beta' = (1, -1, 0)$
FTSE/ATHEX-20	2	$r = 0$	$r = 1$	106.46	$r = 0$	$r = 1$	110.99	15.67	19.96	(1, –0.988, –0.087)	26.828 [0.000]
		$r <= 1$	$r = 2$	4.54	$r <= 1$	$r = 2$	4.54	9.24	9.24		
FTSE/ATHEX Mid-40	2	$r = 0$	$r = 1$	83.37	$r = 0$	$r = 1$	94.16	15.67	19.96	(1, –0.997, –0.024)	2.745 [0.355]
		$r <= 1$	$r = 2$	5.73	$r <= 1$	$r = 2$	5.73	9.24	9.24		

Note: The lag length in the VAR model is determined using the SBIC (1978). Figures in square brackets [.] indicate exact significance levels. r represents the number of cointegrating vectors. The λ_{trace} tests the null that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r and the λ_{max} tests the null that the number of cointegrating vectors is r, against the alternative of $r + 1$. Critical values are from Osterwald-Lenum (1992), table 1*. Estimates of the coefficients in the cointegrating vector are normalised with respect to the coefficient of the cash rate, S_t. The statistic for the parameter restrictions on the coefficients of the cointegrating vector is $-T\,[\ell n(1-\lambda^*_1) - \ell n(1-\lambda_1)]$ where λ^*_1 and λ_1 denote the largest eigenvalues of the restricted and the unrestricted models, respectively. The statistic is distributed as χ^2 with degrees of freedom equal to the total number of restrictions minus the number of the just identifying restrictions, which equals the number of restrictions placed on the cointegrating vector. Only in the FTSE/ATHEX-20 model the cointegrating vector is not restricted and thus, is $z_t = \beta' X_t = (1\ F_t\ \beta_0)'$.

and Kwiatkowski, *et al*. (KPSS, 1992) unit root tests on the log-levels and log-first differences of the daily cash and futures price series. They indicate that all variables are log-first difference stationary, all having a unit root on the log-levels representation.[14] These preliminary results indicate that cash and futures series in first-differences should be used in the ARMA and VAR models, while cointegration tests should be performed to ascertain the long-run relationship between the series in the VECM model.

Table 3 presents the Johansen (1988) multivariate cointegration test results of equation (7), which indicate that cash and futures prices are cointegrated in both markets. As can be observed in the table, the results of the likelihood ratio tests for the over-identifying restrictions applied on the cointegrating vectors are: 26.828 [0.000] for the FTSE/ATHEX-20 market and 2.745 [0.355] for the FTSE/ATHEX Mid-40 market. The first figure is the test statistic, while the figure in square brackets is the corresponding *p*-value. As a consequence, the cointegrating vector $z_{t-1} = (S_{t-1} - \beta_1 F_{t-1} - \beta_0)$ is restricted to be the lagged basis $(S_{t-1} - F_{t-1})$ in the FTSE/ATHEX Mid-40 market, while in the FTSE/ATHEX-20 market it is the following unrestricted spread $(z_{t-1} = S_{t-1} - 0.98815 * F_{t-1} - 0.987635)$.

IV. Forecasting Performance of the Models

A. In-Sample Estimation Results

The results of the univariate and multivariate models for cash and futures prices for the FTSE/ATHEX-20 and the FTSE/ATHEX Mid-40 markets are presented in table 4, panels A and B, respectively. The lag length for the autoregressive and moving average parts are chosen to minimize the SBIC (Schwarz, 1978). Three lags are defined as the appropriate number of lag length for VAR models. All ARIMA models seem to be well-specified as indicated by relevant diagnostic tests for autocorrelation and heteroskedasticity (not shown). It can be seen that in both markets, the adjusted coefficient of determination for changes in cash prices (ranging from 0.0223 to 0.0599) are higher than those of futures prices (ranging from 0.0020 to 0.0329), indicating higher

---

14. It can be observed that the standard unit-root tests cannot capture the persistence found when using the DF-GLS test. This finding also confirms the use of the Bonferroni bounds correction.

TABLE 4. In-Sample Estimates of the Time-Series Models

A. FTSE/ATHEX-20 Market; Sample Period 01/09/99 to 31/12/03

	ARIMA		VECM		SURE-VECM		VAR	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	–	–	–0.075	0.149*	–0.082	0.168*	–	–
			(–1.15)	(2.13)	(–1.46)	(2.76)		
c_t	–0.001**	–0.001	–	–	–	–	–	–
	(–1.67)	(–1.54)						
ΔS_{t-1}	0.153*	–	–0.049	0.020	–	–	–0.096	0.115
	(5.02)		(–0.52)	(0.19)			(–1.13)	(1.25)
ΔS_{t-2}	–0.056**	–	0.033	0.081	–	–	–0.004	0.157**
	(–1.84)		(0.36)	(0.82)			(–0.05)	(1.69)
ΔS_{t-3}	–	–	0.185*	0.187*	0.184*	0.166**	0.158**	0.240*
			(2.17)	(2.03)	(2.27)	(1.90)	(1.93)	(2.70)
ΔF_{t-1}	–	0.088*	0.207*	0.085	0.159*	0.102*	0.254*	–0.009
		(2.89)	(2.33)	(0.89)	(5.61)	(3.32)	(3.22)	(–0.11)
ΔF_{t-2}	–	–	–0.068	–0.103	–	–	–0.032	–0.176*
			(–0.79)	(–1.09)			(–0.39)	(–2.01)
ΔF_{t-3}	–	–	–0.171*	–0.177*	–0.171*	–0.155**	–0.146**	–0.229*
			(–2.10)	(–2.02)	(–2.25)	(–1.89)	(–1.86)	(–2.71)
	0.0223	0.0068	0.0325	0.0137	0.0325	0.0149	0.0322	0.0104
Q(12)	10.241	12.162	8.669	11.053	9.864	11.434	9.501	10.386
	[0.509]	[0.352]	[0.652]	[0.439]	[0.543]	[0.408]	[0.576]	[0.496]

(*Continued*)

TABLE 4. (Continued)

B. FTSE/ATHEX Mid-40 Market; Sample Period 01/02/00 to 31/12/03

	ARIMA		VECM		SURE-VECM		VAR	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	–	–	0.140*	0.294*	0.126*	0.282*	–	–
			(2.889)	(5.046)	(2.917)	(5.469)		
c_t	–0.001*	–0.001**	–	–	–	–	–	–
	(–2.082)	(–1.948)						
ΔS_{t-1}	0.203*	–	–0.135	0.066	–0.085**	0.129*	–0.033	0.280*
	(6.331)		(–1.484)	(0.597)	(–1.935)	(3.368)	(–0.393)	(2.735)
ΔS_{t-2}	–0.087*	–	–0.152**	0.039	–0.058**	0.105*	–0.073	0.206*
	(–2.705)		(–1.700)	(0.366)	(–1.822)	(2.083)	(–0.853)	(1.983)
ΔS_{t-3}	–	–	0.134**	0.129*	–	–	0.180*	0.228*
			(1.697)	(1.965)			(2.332)	(2.423)
ΔF_{t-1}	–	–0.976*	0.318*	0.054	0.274*	–	0.221*	–0.151**
		(–3.882)	(4.137)	(0.583)	(9.861)		(3.181)	(–1.790)
ΔF_{t-2}	–	–0.603*	0.087	–0.068	–	–0.139*	0.013	–0.224*
		(–2.919)	(1.124)	(–0.723)		(–4.477)	(0.178)	(–2.501)
ΔF_{t-3}	–	–	–0.077	–0.109	–	–	–0.124**	–0.207*
			(–1.104)	(–1.295)			(–1.815)	(–2.498)
	0.0492	0.0020	0.0599	0.0329	0.0566	0.0319	0.0528	0.0083
Q(12)	16.285	10.435	15.397	10.489	15.498	11.286	16.096	10.630
	[0.131]	[0.492]	[0.165]	[0.487]	[0.161]	[0.420]	[0.138]	[0.475]

(*Continued*)

TABLE 4. (Continued)

Note: * and ** denote significance at the 5% and 10% levels, respectively. Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively. *t*-statistics are adjusted using the White (1980) heteroskedasticity consistent variance-covariance matrix. In the FTSE/ATHEX-20 model the cointegrating vector is not restricted and thus, is $z_t = \beta' X_t = (1\ \beta_1\ F_t)'$. In the FTSE/ATHEX Mid-40 model the cointegrating vector is restricted to be the lagged basis (see table 3). Q(12) is the Ljung-Box (1978) Q statistics for 12^{th} order serial correlation in the residuals.

explanatory power of cash series than futures prices.

The estimation results for the restricted VECM models are also presented in the same tables. Granger causality tests between cash and futures prices, as measured by the significance of lagged futures prices in the cash equation, and lagged cash prices in the futures equation, indicate that causality runs both ways between cash and futures markets.[15] In the FTSE/ATHEX-20 market, the 1-period and 3-periods lagged changes in futures prices are significant in the cash price equation, and the 3-periods lagged changes in cash prices are significant in the futures equation. In the FTSE/ATHEX Mid-40 market, the 1-period lagged change in futures prices is significant in the cash price equation, and the 3-periods lagged change in cash prices is significant in the futures equation. These results are in accordance with the results of Kavussanos *et al*. (2008), where after examining the price discovery function of the FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 markets, they argue that futures lead the cash index returns by responding more rapidly to economic events than stock prices. It seems then that new market information is disseminated faster in the futures market compared to the stock market.

B. Out-of-Sample Forecasting Results

The forecasting performance of each model for cash and for futures prices, across the different forecasting horizons, is presented in matrix form in tables 5 and 6 for the FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 markets, respectively. Different forecasting horizons are being used; from 1 day up to 20 days ahead. However, for the sake of brevity, results only up to 5 days ahead are reported. Figures in the principal diagonal of the tables are the RMSEs from each model and the off-diagonal figures are the ratios of the RMSE of the model in the column over the RMSE of the model in the row. The model in the column of the matrix provides a more precise forecast than the model in the row when this ratio is less than one.

The cash return forecasts of FTSE/ATHEX-20 are presented in Panel A of table 5. The RMSEs of the VECM and the SURE-VECM specifications are identical in almost all forecasting horizons. This is confirmed by the DM test, which indicates the non-significance of the difference between the RMSE from the two models, with the exceptions of the 3-day ahead forecasts. The results indicate that the RMSEs of the

---

15. Results on Granger causality tests are available upon request.

TABLE 5. FTSE/ATHEX-20 Cash and Futures Price Forecasts for Out-of-Sample Period

A. Cash Price Forecasts

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	106	VECM	0.01271				
		SURE-VECM	1.00633	0.01263			
		VAR	1.00079*	0.99448	0.01270		
		ARIMA	1.01194	1.00557	1.01114	0.01256	
		RW	0.76566	0.76084	0.76506	0.75662	0.01660
2	53	VECM	0.01193				
		SURE-VECM	0.99665	0.01197			
		VAR	1.00930**	1.01269*	0.01182		
		ARIMA	1.00590	1.00927	0.99662*	0.01186	
		RW	0.69766	0.70000	0.69122	0.69356	0.01710
3	35	VECM	0.01206				
		SURE-VECM	1.02813*	0.01173			
		VAR	0.99504	0.96782	0.01212		
		ARIMA	1.00583	0.97831*	1.01084	0.01199	
		RW	0.63809	0.62063	0.64127	0.63439	0.01890
4	26	VECM	0.01344				
		SURE-VECM	0.97603	0.01377			
		VAR	1.00523*	1.02991*	0.01337		
		ARIMA	0.98389	1.00805	0.97877*	0.01366	
		RW	0.67537	0.69196	0.67185	0.68643	0.01990

(*Continued*)

TABLE 5. (Continued)

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
5	21	VECM	0.01454				
		SURE-VECM	1.00414	0.01448			
		VAR	0.99931	0.99518	0.01455		
		ARIMA	1.00972	1.00555	1.01041	0.01440	
		RW	0.69172	0.68886	0.69219	0.68506	0.02102

B. Futures Price Forecasts

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	106	VECM	0.01356				
		SURE-VECM	1.00593	0.01348			
		VAR	0.99632	0.99044	0.01361		
		ARIMA	0.99559	0.98972	0.99926	0.01362	
		RW	0.70078	0.69664	0.70335	0.70388	0.01935
2	53	VECM	0.01259				
		SURE-VECM	0.99290	0.01268			
		VAR	0.98053	0.98753	0.01284		
		ARIMA	0.97824	0.98524	0.99766	0.01287	
		RW	0.68054	0.68540	0.69405	0.69567	0.01850

(*Continued*)

TABLE 5. (Continued)

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
3	35	VECM	0.01296				
		SURE-VECM	1.02208**	0.01268			
		VAR	1.00465*	0.98294	0.01290		
		ARIMA	0.99539	0.97388	0.99078	0.01302	
		RW	0.62974	0.61613	0.62682	0.63265	0.02058
4	26	VECM	0.01501				
		SURE-VECM	0.97215	0.01544			
		VAR	0.99206	1.02048*	0.01513		
		ARIMA	0.99404	1.02251*	1.00198*	0.01510	
		RW	0.66919	0.68836	0.67454	0.67320	0.02243
5	21	VECM	0.01612				
		SURE-VECM	0.99876	0.01614			
		VAR	1.00498*	1.00623*	0.01604		
		ARIMA	0.99629	0.99752	0.99134	0.01618	
		RW	0.71264	0.71352	0.70910	0.71529	0.02262

Note: Forecasts are generated by the models in table 4. *N* is the number of forecasts. * and ** denote significance at the 5% and 10% levels, respectively. Numbers on the principal diagonal are the RMSE from each model and the off-diagonal numbers are the ratios of the RMSE of the model on the column to the RMSE of the model on the row. The pairwise test of the hypothesis that the RMSEs from two competing models are equal is estimated.

VECM and SURE-VECM models are not significantly different than those of the VAR model for most forecast horizons. However, for the 1-day, 2-days and 4-days ahead, the VAR model produces superior forecasts than those produced by VECM and the SURE-VECM. Thus, it seems that the VAR model produces forecasts with either similar or superior as those produced by VECM and SURE-VECM models. Finally, the VAR, VECM and SURE-VECM models produce forecasts with similar accuracy as those produced by ARIMA in most of the forecast horizons, as the difference between the RMSEs is not significant according to the DM test. All specifications outperform the RW for all forecast horizons. These results demonstrate the additional power of information that the futures market is providing to the cash market. When futures returns are used in the various forecasting models of cash returns they significantly enhance the predictive accuracy of the model, leading to superior forecasts.

Following the previous results for the futures market, it is interesting to investigate if futures returns can also be forecasted with greater accuracy when the models utilize the information embedded in cash returns. It is expected that models that utilize information coming only from futures returns to exhibit at least the same if not greater forecasting accuracy than models which embody information from both futures and cash returns. This is expected for two reasons: firstly, due to the nature of cash returns, which are only able to assimilate market information up to the date of the actual cash return being reported, and secondly, since futures returns are able by design to reflect future market conditions and expectations and thus capture a greater set of information than cash returns.

The results of the FTSE/ATHEX-20 futures return forecasts, in Panel B of table 5, indicate that the difference between the RMSE from the VECM and SURE-VECM specifications is not significant, with the exception of the 3-day ahead forecasts, at the 10% significance level. However, the RMSEs of the VECM and SURE-VECM specifications are not significantly different from those of the VAR model for most forecast horizons, with the exception of the 4-day ahead forecasts. Finally, the differences between the RMSEs from the ARIMA and from the other time-series models are significant in 4-day ahead forecasts (which indicate that ARIMA based forecasts are superior from the other models). For all other forecasting horizons, lagged cash returns does not enhance the forecasting precision of futures returns. All specifications significantly outperform the RW model. Thus, it seems that the ARIMA model produces forecasts, which are as accurate as those produced by the other time-series models, verifying the a priori expectations for the

TABLE 6. FTSE/ATHEX Mid-40 Cash and Futures Price Forecasts for Out-of-Sample Period

A. Cash Price Forecasts

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	106	VECM	0.01327				
		SURE-VECM	1.00759**	0.01317			
		VAR	0.99549	0.98799*	0.01333		
		ARIMA	1.01298	1.00534	1.01755	0.01310	
		RW	0.77017	0.76436	0.77365	0.76030	0.01723
2	53	VECM	0.01361				
		SURE-VECM	1.00294*	0.01357			
		VAR	0.98480*	0.98191*	0.01382		
		ARIMA	1.00591	1.00296	1.02143	0.01353	
		RW	0.73927	0.73709	0.75067	0.73492	0.01841
3	35	VECM	0.01171				
		SURE-VECM	1.01123*	0.01158			
		VAR	0.99490*	0.98386*	0.01177		
		ARIMA	1.01298	1.00173	1.01817	0.01156	
		RW	0.72017	0.71218	0.72386	0.71095	0.01626
4	26	VECM	0.01539				
		SURE-VECM	1.00391*	0.01533			
		VAR	0.99547*	0.99159*	0.01546		
		ARIMA	1.04552	1.04144	1.05027	0.01472	
		RW	0.72186	0.71904	0.72514	0.69043	0.02132

(Continued)

TABLE 6. (Continued)

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
5	21	VECM	0.01349				
		SURE-VECM	1.01735**	0.01326			
		VAR	1.00898	0.99177**	0.01337		
		ARIMA	1.01429	0.99699	1.00526	0.01330	
		RW	0.81511	0.80121	0.80785	0.80363	0.01655

B. Futures Price Forecasts

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	106	VECM	0.01473				
		SURE-VECM	1.00068	0.01472			
		VAR	0.98925*	0.98858*	0.01489		
		ARIMA	0.97356	0.97290	0.98414*	0.01513	
		RW	0.69058	0.69011	0.69808	0.70933	0.02133
2	53	VECM	0.01407				
		SURE-VECM	0.99434	0.01415			
		VAR	0.96172*	0.96719*	0.01463		
		ARIMA	0.93302	0.93832	0.97015*	0.01508	
		RW	0.66368	0.66745	0.69009	0.71132	0.02120

(Continued)

TABLE 6. (Continued)

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
3	35	VECM	0.01328				
		SURE-VECM	1.00835	0.01317			
		VAR	0.98810*	0.97991**	0.01344		
		ARIMA	0.99476	0.98652	1.00674	0.01335	
		RW	0.69675	0.69098	0.70514	0.70042	0.01906
4	26	VECM	0.01571				
		SURE-VECM	0.98805	0.01590			
		VAR	0.98619*	0.99811*	0.01593		
		ARIMA	0.96380	0.97546	0.97730	0.01630	
		RW	0.68097	0.68920	0.69050	0.70655	0.02307
5	21	VECM	0.01523				
		SURE-VECM	1.00861	0.01510			
		VAR	1.01263	1.00399	0.01504		
		ARIMA	0.99542	0.98693	0.98301	0.01530	
		RW	0.78465	0.77795	0.77486	0.78825	0.01941

Note: See notes in table 5

superiority in information assimilation of futures returns.

Similar results to the FTSE/ATHEX-20 cash return forecasts are also reported for the FTSE/ATHEX Mid-40 cash return forecasts, in Panel A of table 6, indicating that the RMSEs of the SURE-VECM, the VECM and the VAR specifications are significantly different for all forecasting horizons, with the SURE-VECM producing the most enhanced forecasts. The ARIMA model produces forecasts with similar accuracy as those produced by the three bivariate models, as the difference between the RMSEs is not significant. Finally, all different time-series models outperform the RW model for all forecast horizons. It seems that using lagged futures returns and the restricted lagged basis on forecasting models of cash returns significantly enhances the predictive accuracy.

Finally, for the FTSE/ATHEX Mid-40 futures price forecasts, in Panel B of table 6, it can be argued that the RMSEs of the VECM and the SURE-VECM specifications are not significantly different for all forecasting horizons. Furthermore, the SURE-VECM and the VECM models significantly outperform the VAR model for up to 4-days ahead forecasts. However, for longer forecasts it seems that the VECM and the SURE-VECM specifications produce similar forecasts than those produced by VAR. Finally, the differences between the RMSEs from the ARIMA and from the other time-series models are not significant up to 5-days ahead forecasts, according to the DM test. For longer forecasts it seems that the ARIMA specification produces superior forecasts than those produced by all other specifications (not shown). For all forecast horizons, including lagged cash returns in the models does not enhance the forecasting accuracy of futures prices. All specifications significantly outperform the RW model. Thus, it seems that the ARIMA model produces forecasts as accurate as those by the other time-series models.

Overall, this paper examines empirically, for the first time, the forecasting performance of derivatives contracts trading in the developing and fairly unresearched derivatives market of ATHEX and tries to answer the question of whether the forecasting performance of this newly established derivatives market is in accordance with corresponding results from other well-established derivatives markets. Results indicate that models that utilize information coming only from futures returns exhibit at least the same if not greater forecasting accuracy than models which embody information from both futures and cash returns. Cash returns can be more accurately forecasted, for all forecast horizons, when forecast specifications contain information from both lagged cash and futures returns than from specifications that utilize information only from lagged cash returns. On the other hand, futures return forecasts are not enhanced in accuracy when lagged cash returns are employed for almost all forecasts. This suggests that for almost all forecasting horizons the futures returns contains significantly more and different information than that assimilated in the current cash returns. Finally, all time-series models generate more accurate cash and futures forecasts than the forecasts obtained by the random walk model in both markets.

V. Conclusion

The implication of the results in this paper for traders and analysts is that, since stock index futures returns provide useful information for the more accurate prediction of cash returns (but not the other way around), more efficient investment and trading strategies can be designed by incorporating this information coming from the futures market. For example, suppose that an investor holds a portfolio of shares – e.g. a mutual fund – which is designed to track the movements of the FTSE/ATHEX-20 or the FTSE/ATHEX Mid-40 indices. By incorporating into his trading strategy the daily information that comes from the stock index futures markets, together with the information that comes from the underlying stock index market, he can act quicker and obtain better target-returns in his portfolio of assets.

The above findings are also of interest to academics and policy-makers. First, it seems that futures markets play their role of price discovery. Second, their existence helps to complete the market. Third, the results are consistent with market efficiency, and as such, futures prices in the ATHEX market may be unbiased forecasts of future cash prices; that is, futures prices are influenced by the arrival of new news and not by the past information included in the lagged cash prices. Finally, the above are in accordance with the general literature on forecasting stock index returns in other well-developed derivatives markets. For example, Sarno and Valente (2005) report that exploiting information provided by the futures markets of the S&P500, NIKKEI 225 and FTSE100 indices lead to better stock return forecasts.

Accepted by: *Prof. P. Theodossiou*, *Editor-in-Chief*, *November* 2009

References

Aggarwal, R., and Zong, S. 2008. Behavioral biases in forward rates as forecasts of future exchange rates: Evidence of systematic pessimism and under-reaction, *Multinational Finance Journal*, 12: 241-277.

Al-Zoubi, H. A., and Maghyereh A. 2007. Stationary component in stock prices: A reappraisal of empirical findings, *Multinational Finance Journal*, 11: 287-322.

Bakaert, G., and Harvey, C. R. 1997. Emerging equity market volatility, *Journal of Financial Economics*, 43: 29-77.

Batchelor, R.; Alizadeh, A.; and Visvikis, I. D. 2007. Forecasting spot and forward prices in the international freight market, *International Journal of Forecasting*, 23: 101-114.

Beckers, S. 1996. A survey of risk measurement theory and practice, In Alexander, C. (eds), *The Handbook of Risk Management and Analysis*, New York, John Wiley & Sons.

Bera, A. K., and Jarque, C. M. 1980. Efficient tests for normality, heteroskedasticity, and serial independence of regression residuals, *Economics Letters*, 6: 255-259.

Box, G. E. P., and Jenkins, G. 1970. *Time series analysis, forecasting and control*, Holden-Day, San Francisco, CA.

Campbell, J. Y., and Yogo, M. 2006. Efficient tests of stock return predictability, *Journal of Financial Economics*, 81: 27-60.

Campbell, J. Y., and Yogo, M. 2005. Implementing the econometric methods in efficient tests of stock return predictability, *Unpublished Working Paper*, University of Pennsylvania.

Dickey, D. A., and Fuller, W. A. 1979. Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, 74: 427-431.

Dickey, D. A., and Fuller, W. A. 1981. Likelihood ratio statistics for autoregressive time series with a unit root, *Econometrica*, 49: 1057-1072.

Diebold, F. X., and Mariano, R. 1995. Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13: 253-263.

Elliott, G., and Stock, J. H. 1994. Inference in time series regression when the order of integration of a regressor is unknown, *Econometric Theory*, 10: 672-700.

Elliott, G.; Rothenberg, T. J.; and Stock, J. H. 1996. Efficient tests for an autoregressive unit root, *Econometrica*, 64: 813-836.

Engle, R. F., and Granger, C. W. 1987. Cointegration and error correction: Representation, estimation, and testing, *Econometrica*, 55: 251-276.

Harvey, C.R. 1995. Predictable risk and returns in emerging markets, *Review of Financial Studies*, 8: 773–816.

Johansen, S. 1988. Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, 12: 231-254.

Johansen, S. 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica*, 59: 1551-1580.

Johansen, S., and Juselius, K. 1990. Maximum likelihood estimation and inference on cointegration – with applications to the demand for money, *Oxford Bulletin of Economics and Statistics*, 52: 169-211.

Kavussanos, M. G., and Visvikis I. D. 2008. Hedging effectiveness of the Athens stock index futures contracts, *European Journal of Finance*, 14: 243-270.

Kavussanos, M. G.; Visvikis I. D.; and Alexakis, P. 2008. The lead-lag relationship between cash and stock index futures in a new market, *European Financial Management*, 14: 1007-1025.

Kenourgios, D. 2004. Price discovery in the Athens derivatives exchange: Evidence for the FTSE/ASE-20 futures market, *Economic and Business Review*, 6: 229-243.

Kenourgios, D. 2005. Testing efficiency and the unbiasedness hypothesis of the emerging Greek futures market, *European Review of Economics and Finance*, 4: 3-20.

Kutan, Al. M., and Aksoy, T. 2004. Public information arrival and emerging markets returns and volatility, *Multinational Finance Journal*, 8: 227-245.

Kwiatkowski, D. P.; Phillips, C. B.; Schmidt, P.; and Shin, Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root, *Journal of Econometrics*, 54: 159-178.

Liu, W., and Maynard, A. 2005. Testing forward rate unbiasedness allowing for persistent regressors, *Journal of Empirical Finance*, 12: 613-628.

Ljung, M., and Box, G. 1978. On a measure of lack of fit in time series models, *Biometrica*, 65: 297-303.

Newey, W. K., and West, K. D. 1987. A simple positive definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, 55: 703-708.

Pelletier, R. 1983. Contracts that don't expire aid technical analysis, *Commodities* (March): 71-75.

Phillips, P. C. B., and Perron, P. 1988. Testing for a unit root in time series regressions, *Biometrica*, 75: 335-346.

Sarno, L., and Valente, G. 2005. Modelling and forecasting stock returns: Exploiting the futures market, regime shifts and international spillovers, *Journal of Applied Econometrics*, 20: 345-376.

Schwartz, G. 1978. Estimating the dimension of a model, *Annals of Statistics*, 6: 461-464.

Sims, C. 1980. Macroeconomics and reality, *Econometrica*, 48: 1-48.

Tashman, L. J. 2000. Out-of-sample tests of forecast accuracy: An analysis and review, *International Journal of Forecasting*, 16: 437-450.

Toda, H. Y., and Phillips, P. C. B. 1993. Vector autoregressions and causality, *Econometrica*, 61: 1367-1393.

White, H. 1980. A Heteroskedastic-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica*, 48: 817-838.

Zellner, A. 1962. An efficient method of estimating seemingly unrelated regressions and tests of aggregation bias, *Journal of the American Statistical Association*, 57: 500-509.