THE PREDICTABILITY OF NON-OVERLAPPING FORECASTS: EVIDENCE FROM THE DERIVATIVES MARKET IN GREECE

MANOLIS G. KAVUSSANOS* AND ILIAS D. VISVIKIS+

* *Department of Accounting and Finance, Athens University of Economics and Business, 76 Patission St, 10434, Athens, Greece.*

+ *Athens Laboratory of Business Administration, Athinas Ave. & 2A Areos Str, 16671, Vouliagmeni, Athens, Greece.*

Emails: mkavus@aueb.gr, elias10@otenet.gr

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***Corresponding Author:**
Professor Manolis G. Kavussanos, Athens University of Economics and Business, 76 Patission St, 10434, Athens, Greece. Tel: +30 210 8203167, Fax: +30 210 8228816, Email: mkavus@aueb.gr

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ABSTRACT

This paper investigates the performance of alternative univariate (ARIMA) and multivariate (VAR, VECM, and SURE-VECM) linear time-series models in generating short-term forecasts in the cash market and in the recently developed emerging derivatives market of the Athens Exchange. The forecasts from these models indicate that conditioning cash returns on lagged futures returns generates more accurate forecasts of the cash prices for all forecast horizons. However, conditioning futures returns on lagged cash returns does not enhance the forecasting accuracy of futures prices; the univariate ARIMA model produces forecasts as accurate as those from more complex time-series models. This verifies that at almost all forecasting horizons the futures price contains significantly more and different information than what is embodied in the current cash price. Moreover, all time-series models generate more accurate cash and futures forecasts than the forecasts obtained by the random walk model.

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1. INTRODUCTION

Emerging markets have received massive inflows of capital in the past and have become interesting alternatives for investors seeking diversification. Indeed, Harvey (1995) shows that emerging markets provide investment opportunities for world investors. In general, emerging markets offer high expected returns with an associated high risk. This study investigates the performance of alternative time-series models in generating short-term forecasts of cash and corresponding futures prices in the stock and emerging derivatives market of the Athens Exchange in Greece. Stock return forecasting is central to active asset allocation. Short-run return forecasting, however, is widely viewed as difficult. This view stems from both introspection and observation. That is, financial economic theory suggests that asset returns should not be easy to forecast using readily-available information and forecasting techniques, and a broad interpretation of four decades of empirical work suggests that the data support the theory (e.g., Fama, 1970, 1991). For different countries the literature has found mixed empirical evidence depending on the time frequency, country, and time span among other characteristics. This could be due to differences in market microstructure or to other characteristics of these countries.

Since the seminal work of Bachelier (1900) and Fama (1965), the Random Walk Hypothesis (RWH) has been an integral part of theories pertaining to financial time series. In particular, this hypothesis can be framed in a statistical framework to model the concept of market efficiency in the sense that the best predictor of future prices are current ones (Fama, 1970, 1991). If a stock price does satisfy the RWH, it follows that future equity prices are not predictable based on past prices. This has important implications for asset price modeling, especially for traders and practitioners that are searching for patterns in prices. Lo and MacKinlay (1988), in a seminal paper, present evidence that the RWH is strongly rejected for the US equity market for the sample period 1962–1985 and for different subperiods. Since their seminal work, a variety of papers have found mixed evidence for a number of countries and sample periods. Urrutia (1995) tests the RWH for Latin American emerging equity markets and rejects it for some of these countries, suggesting that there is predictability. In another paper, Huang

(1995) also shows that we can reject the RWH for Korea, Malaysia, Hong Kong, Singapore and Thailand.

Many studies have considered testing the null hypothesis of a random walk for prices against a variety of alternative hypotheses. Some specify a time series representation different from the random walk (e.g., a stationary autoregressive process or the sum of a permanent and transitory component; see Fama and French, 1988; Poterba and Summers, 1988; Lo and Mackinlay, 1988). Others attempt to assess whether some regressors have a predictive power for returns at some horizon (e.g., lagged returns, interest rates or the dividend–price ratio; Hansen and Hodrick, 1980; Fama and French, 1988).

The approach of this study is to recognise that futures prices may be considered as the expected value of spot prices and to estimate a Vector Error-Correction (VECM) model linking cash and futures prices for two stock index futures contracts of the emerging derivatives market of the Athens Exchange; namely the FTSE/ASE-20 contract and the FTSE/ASE Mid-40 contract. The structure and performance of this model is then used to make inferences about the efficiency and usefulness of futures derivatives prices. For example, if futures prices are expectations of cash prices we would expect (a) there to be a cointegrating vector linking cash and futures prices, and (b) the cointegrating vector to be the basis (that is, cash price – futures price = 0), and (c) this equilibrium to be established by cash prices to converging on futures prices, but not vice versa.

The performance of the VECM model is tested by benchmarking it against a number of alternative linear time-series models (VAR and ARIMA), and against the random walk[1]. Even if two price series are cointegrated, incorporating the information contained in the cointegrating relationship in the model is not guaranteed to improve the predictability of the prices (Engle and Yoo, 1987). However, the balance of existing evidence does favour the VECM approach. Zeng and Swanson (1998) estimated VECM and other models for cash and futures prices on the S&P500 index, the US 30-year T-bond, gold and oil. They

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

found that the VECM did predict better than simpler models, including the random walk, especially if the cointegrating vector incorporated the cost of carry.

Emerging capital markets have long posed a challenge for finance. High transaction costs, low liquidity, high volatility, thin trading, possibly less informed and rational investors and investment constraints are associated with emerging market investments. Emerging market investors may either place too much faith in their own forecasts, thus introducing bias to their actions, or may not respond instantaneously to information. That is, uniformed traders may delay their response to see how informed market participants behave, because either their information is not reliable or they do not have the resources to fully analyse the information. Thus, emerging market returns have different characteristics than the ones in developed countries. According to Bakaert and Harvey (1997) emerging market returns are characterised by higher sample average returns, low correlations with developed market returns, more predictable returns, higher volatility, and they are highly non-normal (too fat-tailed) with short samples. The periods with high volatility are found to be associated with important events in each country rather than global events. In addition, market imperfections, such as transactions costs and insurance costs, induced by regulatory rules may also affect the risks and returns involved. Standard models are often ill suited to deal with the specific circumstances arising in these markets. However, the interest in emerging markets has provided impetus for both the adaptation of current models to new circumstances in these markets and the development of new models.

These developments raise a number of intriguing questions. From the perspective of investors in developed markets, what are the financial benefits of investing in emerging markets? And from the perspective of the developing countries themselves, what are the effects of increased foreign capital on domestic financial markets and ultimately on economic growth? As foreigners are allowed to access the local market, liquidity may increase along with trading volume. There could also be some structural changes in the market. For example, if the cost of capital decreases, new firms may present initial public offerings (IPOs). Market concentration may decrease as a result of these new entrants. In addition, individual stocks may become less sensitive to local information and more sensitive to world events (as stock markets are largely characterised by frequent, sudden changes in variance). This may cause the cross-correlation of individual stocks within a market to change.

The cash market of the Athens Exchange has experienced rapid growth in the last twelve years and played a major role in economical development of the country. The Greek economy has been characterised by the emergence of a strong security market that attracted increasing attention from both domestic and foreign investors. The period 1993-1996 was characterised by the influx of construction companies to the stock exchange and by the great volatility in prices and indices. From the beginning of 1997, the value of turnover showed signs of revitalisation and prices began tending upwards. During the period 1997-2000, the Greek economy was characterised by its attempt at readjusting its macroeconomic, achieving the criteria to become the 12 member of the Euro Zone. In 1992 there were 158 securities on the Athens Exchange, while in 2004 there are 366 securities. This growth is mainly attributed to the fact that Greece managed to become a member of the European Union, and the institutional reforms, structural changes, and deregulation measures taken in the monetary and capital sectors of the economy during the last twelve years[2]. As one of the emerging European stock markets, the Athens Exchange constitutes an excellent opportunity for international investors, since it combines both diversification benefits and profit opportunities (Foreign investors participation is 32% in total capitalization; 38% in 20 large caps accounting for 57% of total capitalization). Greece is officially included in the Morgan Stanley Capital International (MSCI) developed market index and declared as mature market since 2001 and the Euro has replaced the Greek Drachma (eliminating the associated foreign exchange risk). Moreover, the Athens Exchange attracts special interest for empirical

[2] The 1892/91 Law made the Athens Exchange an independent corporation, with new regulations regarding the transmission of confidential information and the information disclosure in company prospectuses. Other reforms involve the introduction of an electronic trading system that replaced the open-outcry system and the 2324/95 Law that transformed the legal entity of the Athens Exchange and allowed amendments to stock exchange legislation, such as public offers and brokerage commissions. Other important reforms include the introduction of remote and off-exchange trading, the incorporation of European Union directives regarding capital adequacy, and the legal provisions for the dematerialization of stocks (Apergis and Eleptheriou, 2001).

work in light of the reforms that have taken place over the last few years, aimed at restructuring and regulating the market (Dockery and Kavussanos 1996).

The current study is of great importance for market agents in the derivatives market of the Athens Exchange (ADEX henceforth), which need to cover the risk exposure that they face. The introduction of a derivatives exchange in an emerging capital market with the above characteristics can be seen as a beneficial attempt, in the sense that derivatives can complete the market and improve efficiency. However, it is deemed important to empirically examine the forecasting performance, using derivatives contracts with underlying assets with the aforementioned characteristics. Moreover, for the Greek derivatives market this implies an absence of highly specialised traders, an absence of a respective large number of foreign derivatives traders and that the volume traded during a normal day in the ADEX represents only a very small fraction of that traded in well-established derivatives exchanges (i.e. of US and UK). The ratios of the value of the stock index futures transactions over the value of the underlying cash market transactions in Greece, Italy, London and Germany, over the average period January-April 2004, are 0.84, 0.95, 1.35, and 7.17, respectively (according to Federation of European Securities Exchanges – FESE data). Furthermore, in developed markets, stocks and derivatives can be traded in many Stock and Derivatives Exchanges, while in Greece trading can only be done in the Athens Exchange; this fact makes arbitrage more difficult. These issues, among others, differentiate the Greek market with respect to non-emerging ones. Finally, most of the studies in the literature are concentrated on well-established derivatives markets.

This paper contributes to the literature in the following aspects. First, a data set from a country not previously considered in the literature is used. To the best of our knowledge there are no studies that investigate the forecasting performance of the contracts traded on the relatively new derivatives market of the Athens Exchange. Thus, our findings can reveal some new evidence of the forecast performance of newly traded derivatives instruments. There is practical value to users of the market in knowing whether and how futures rates can best be used to predict cash rates. Second, unlike the large established markets in commodities and financial futures the emerging derivatives market of the Athens Exchange is small and may be dominated by the activities of hedgers rather than speculators. Due to low liquidity, it cannot therefore be taken for granted that all information relevant to future cash rates is automatically incorporated into the futures price[3]. In these circumstances we should expect to observe certain characteristics in the time-series of cash and futures prices. In speculatively efficient markets, futures prices are unbiased forecasts of future cash prices, and changes in futures prices for fixed target dates are close to being random, reflecting the arrival of news. The thinness of the Athens Exchange derivatives market and the absence of a strong speculative interest mean that futures prices may exhibit neither of these properties. Third, most studies use overlapping forecast intervals, which Tashman (2000) argues may bias forecast evaluation. In this paper the forecast evaluation procedures are designed is such a way so as to avoid this problem. Following Tashman (2000), independent out-of-sample *N*-period ahead forecasts are generated over the forecast period. In order to avoid the bias induced by serially correlated overlapping forecast errors, the estimation period is augmented recursively by *N*-periods ahead every time (where *N* corresponds to the number of steps ahead).

The study is organised as follows. Section 2 presents the characteristics and the operations of the derivatives market of the Athens Exchange. Section 3 presents the methodology followed and the models that are used to generate the forecasts. Section 4 describes the data and presents their statistical properties. Section 5 discusses the in-sample and out-of-sample estimation results and evaluates the forecasting performance of the alternative models. Finally, section 6 summarises this study.

2. THE DERIVATIVES MARKET OF THE ATHENS EXCHANGE

The operation of the organised derivatives market in Greece rests with the ADEX and the Athens Derivatives Exchange Clearing House (ADECH). ADEX and ADECH were founded in April 1998 as autonomous companies and their operations are controlled and

[3] Thin trading may have consequences on the hedging effectiveness and on the price discovery of the traded contracts (for more see Alexakis, Kavussanos and Visvikis, 2002, 2004).

supervised by the Hellenic Capital Markets Commission. ADEX is responsible for the organisation and support of the derivatives market and for the supervision of trading, as well as for the overall development of the derivatives exchange. ADECH is responsible for the recording and clearing of the trades, as it acts as the central counter-party in all trades concluded in ADEX. Transactions are conducted electronically (screen trading) via the Integrated Electronic Trading System (OASIS), see Kavussanos and Phylaktis (2001).

The first stock index futures contract of ADEX was the FTSE/ASE-20 futures contract (released for trading in August 1999) with the underlying asset being the blue chip FTSE/ASE-20 stock index[4]. The FTSE/ASE-20 index was created in September 1997 by FTSE International and the Athens Stock Exchange (ASE), and is based on 20 highly capitalised and liquid companies listed on the ASE[5]. The constituents of the FTSE/ASE-20 index are subject to revision by the Advisory Committee twice a year, in April and October. From September 1999 to June 2004, its volume (Figure 1) and open interest (Figure 2) have steadily increased from 238 contracts per month (September 1999) to 10,869 (June 2004) and from 124 contracts per month (September 1999) to 22,175 (June 2004), respectively. The FTSE/ASE Mid-40 index futures was created, a few months later, in January 2000 and is based on the 40 medium capitalisation stocks listed in Athens Exchange[6]. The volume and the open interest of the contract can be seen in Figures 3 and 4, respectively. From the figures we can notice that the volume and open interest of the FTSE/ASE Mid-40 futures contract have declined steadily from mid 2002

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[4] The FTSE/ASE-20 constituent stocks as of 01/12/04 are the following: National Bank of Greece S.A., EFG Eurobank Ergasias Bank S. A., Alpha Bank S.A., Piraeus Bank S.A., Elliniki Technodomiki TEB S.A.., Emporiki Bank of Greece S.A, Titan Cement Company. S.A., Hellenic Petroleum S.A., Coca-Cola EEE S.A., OPAP S.A., Motor Oil (Hellas) Refineries S.A., Hellenic Telecom Organisation, Intracom S.A., Cosmote-Mobile Telecommunications S.A., Folli-Follie S.A., Hyatt Regency S.A., Viohalco, Germanos Ind. & Com. Co S.A., Public Power Corp. S.A., Duty Free Shops S.A.

[5] The Greek capital market has been upgraded to mature market status as from May 31 2001.

[6] The FTSE/ASE Mid-40 constituent stocks as of 01/12/04 are the following: Attica Holdings S.A., Elbisco Holding S.A., F.G. Europe S.A., Fourlis S.A., Goody's S.A., J. & P. Avax S.A., Marfin Financial Group S.A., Notos Com Holdings S.A., S & B Industrial Minerals S.A., Heracles Gen. Cement Company S.A., Aktor S.A., Aluminium of Greece S.A., Astir Palace Vouliagmeni S.A., General Construction Company S.A., General Bank of Greece S.A., Delta Singular S.A., Delta Holdings S.A., Lambrakis Press S.A., Egnatia Bank S.A., N.B.G. Real Estate Development Co., Elais oleaginous Prod S.A., Elval S.A., Hellenic Sugar Industry S.A., Hellenic Exchanges Holdings S.A., Athens Water Supply & Sewerage S.A., Ethniki S.A. General Insurance Co., Iaso S.A., Intralot S.A., Metka S.A., M. J. Maillis S.A., Babis Vovos Inter/nal

onwards. The exact opposite situation exists in the FTSE/ASE-20 futures market. Thus, it seems that investors of the ADEX market may concentrate on large capitalisation stocks in the cash market, and therefore, use more frequently the FTSE/ASE-20 futures market for their hedging needs.

The most considerable difference between traditional futures contracts and stock index futures is the replacement of the traditional delivery mechanism by cash settlement. When stock index futures contracts expire, they are settled in cash by transferring funds into or out of the contract holder's margin account based on the value of the underlying index. The futures contracts are traded in index points, while the monetary value of the contracts is calculated by multiplying the futures price by a multiplier which is 5 EUR per point for the FTSE/ASE-20 futures contract and 50 EUR per point for the FTSE/ASE Mid-40 futures contract. The tick size of the FTSE/ASE-20 futures is 0.25 points, equivalent to 1.25 EUR and the tick size of the FTSE/ASE Mid-40 futures is 0.25 points, equivalent to 12.5 EUR[7]. Table 1 provides the detailed contract specifications of the two futures contracts.

For every long and short position resulting from a transaction, the counter-party to every investor is ADECH. Open positions on the futures are subject to daily settlement (mark-to-market), a procedure through which, at the end of each day investors whose positions show a loss, pay the respective amount to investors whose positions are profitable. Moreover, ADECH calculates initial margin requirements per clearing account. This amount is pledged to ADECH as an escrow account in the name of the end-investor, and is credited or debited via orders by the clearing member of the investor. The initial margin is used when the end-client cannot meet his/her daily settlement obligations. The final settlement procedure is applied on positions, which remain open up to the expiration day and are subject to cash settlement. During the final settlement there is a final

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Technical S.A., Mytilineos Holdings S.A., P.P.A. S.A., Plaisio Computers S.A., Sidenor S.A., Terna S.A., Technical Olympic S.A., Teletipos S.A., Bank of Attica S.A., Halkor S.A.

[7] Up until February 2004, for the FTSE/ASE Mid-40 futures contract, the multiplier was 25 EUR and the tick size was equivalent to 6.25 EUR.

debit/credit of the investors' accounts based on the open positions according to the closing price of the index on the expiration date of the contract.

3. METHODOLOGY AND THEORETICAL CONSIDERATIONS

We use five time-series models to identify the model that provides the most accurate short-term forecasts of cash and futures prices in each market. It is important to note that the specification of the evaluation model may affect the findings. Although it is not the only model specification issue, stationarity is an important concern. Price-level models assume that prices are stationary in levels. However, most financial prices tend to be non-stationary in levels, implying that price-level models may generate inappropriate hypothesis tests. Clearly, alternative choices for the order of integration need to be assessed in studies of the forecasting performance of financial prices. The specifications used in this paper are the Box-Jenkings (1970) Autoregressive Integrated Moving Average (ARIMA) model, the Vector Auto-regressive (VAR) model, a Vector Error-Correction (VECM) model, and a restricted VECM model. Each model is estimated over the period 01 September 1999 to 31 December 2003 for the FTSE/ASE-20 market and 01 February 2000 to 31 December 2003 for the FTSE/ASE Mid-40 market, which leaves a *test period* of six months; from 02 January 2004 to 07 June 2004.

Box-Jenkings (1970) or univariate ARIMA(p,d,q) models of the following form are used to generate forecasts of cash and futures prices:

$$\Delta S_t = \mu_0 + \sum_{i=1}^{p} \mu_i \Delta S_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} + \varepsilon_t \qquad ; \qquad \varepsilon_t \sim \text{iid}(0, \sigma_\varepsilon^2) \tag{1a}$$

$$\Delta F_t = \mu_0 + \sum_{i=1}^{p} \mu_i \Delta F_{t-i} + \sum_{j=1}^{q} \gamma_j v_{t-j} + v_t \qquad ; \qquad v_t \sim \text{iid}(0, \sigma_v^2) \tag{1b}$$

Where ΔF_t and ΔS_t are changes in log futures and cash prices, respectively, and ε_t and v_t are the white noise random error-terms. For an ARIMA (p,d,q) model the terms p, d, q

refer to the lagged values of the dependent variable, the order of integration[8], and the lagged values of the error-term, respectively, in the specification of the model.

The bivariate VAR(*p,q*) model of the following form is also used to produce forecasts of cash and futures prices in a simultaneous cash-futures framework:

$$\begin{aligned} \Delta S_t &= \mu_{10} + \sum_{i=1}^{p} \mu_{1,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{1,i} F_{t-i} + \varepsilon_{1,t} \qquad \varepsilon_{i,t} \sim IN(0, \mathrm{H}_t) \\ \Delta F_t &= \mu_{20} + \sum_{i=1}^{p} \mu_{2,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{2,i} F_{t-i} + \varepsilon_{2,t} \end{aligned} \tag{2}$$

The use of VAR models for economic forecasting was proposed by Sims (1980). The main advantage of the bivariate VAR model over the univariate ARIMA model is that it takes into account the information content in cash price movements in determining futures price movements and vice versa.

Finally, the unrestricted and restricted versions of the bivariate VECM(*p,q*) model of the following form is used to generate simultaneous out-of-sample forecasts for cash and futures prices:

$$\begin{aligned} \Delta S_t &= \mu_{10} + \sum_{i=1}^{p} \mu_{1,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{1,i} F_{t-i} + \alpha_1 (S_{t-1} - \beta_1 F_{t-1} - \beta_0) + \varepsilon_{1,t} \\ \Delta F_t &= \mu_{20} + \sum_{i=1}^{p} \mu_{2,i} \Delta S_{t-i} + \sum_{i=1}^{q} \gamma_{2,i} F_{t-i} + \alpha_2 (S_{t-1} - \beta_1 F_{t-1} - \beta_0) + \varepsilon_{2,t} \end{aligned}$$

where the term in brackets represent the cointegrating (long-run) relationship between the cash and futures prices. Alternatively, this error-correction term (ECT) represents the lagged disequilibrium term of the long-run relationship between cash and futures prices. The error-terms follow a normal distribution with mean zero and time-varying covariance matrix, H_t. The VECM model is argued by the economic literature to be more appropriate than the univariate ARIMA and bivariate VAR models in modelling the cash and futures

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

prices as it takes into account both the short-run dynamics and the long-run relationship between the variables. In Equation (3) the coefficients α_1 and α_2 measure the speed of adjustment of cash and futures prices to their long run equilibrium.

The VAR model may be considered a restricted version of the VECM, where the two ECTs are zero. The VAR model therefore may require a larger number of parameters compared to the VECM to capture the dynamic behaviour of the variables. This lack of parsimony in the VAR may cause problems when the model is used for forecasting. One potential problem is that the collinearity between the different lagged variables may lead to imprecise coefficient estimates. A second and more important problem is that the large number of parameters may lead to a good within-sample fit but poor forecasting accuracy (Litterman, 1986). Furthermore, there is an omitted variable problem (the ECT) which leads to biased and inconsistent parameter estimates.

Finally, we use a restricted bivariate VECM, which is simply a parsimonious version of the VECM, derived by eliminating the insignificant variables from the original VECM. The selected model is estimated as a system of Seemingly Unrelated Regression Equations (SURE) since this method yields more efficient and consistent estimates than the Ordinary Least Squares (OLS) (see Zellner, 1962).

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. The forecasts are then compared with those from the Random-Walk (RW) model as a benchmark model. Based on a RW model, the cash (futures) prices at time t-n, $S_{t\text{-n}}$ ($F_{t\text{-n}}$) 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.

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, we recursively augment our estimation period by N-periods ahead every time (where N corresponds to the number of steps ahead). For example, in order to compute 2 steps-ahead forecasts, we augment our estimation period by $N = 2$ observations each time. This method yields 53 independent non-overlapping forecasts. Similarly, in order to compute 5 steps-ahead forecasts, the method yields 21 independent non-overlapping forecasts. This methodology provides two desirable characteristics for an out-of-sample test; *adequacy* (enough forecasts for each forecasting horizon), and diversity (desensitising forecast error measures to special events and specific phases of business).

The forecast accuracy of each model is assessed using the Root Mean Square Error (RMSE) metric. This assumes a symmetric loss function for forecast users, which seems reasonable given the bilateral buyer-seller nature of the market. The RMSE is calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\mathrm{R}_t - \mathrm{Z}_t)^2} \tag{4}$$

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

Finally, the Diebold and Mariano's (1995) pairwise test of the hypothesis that the RMSEs from two competing models are equal is employed. This statistic is constructed as follows. Let the average difference between the squared forecast errors from two models at time t, $u_{1,t}^2$, $u_{2,t}^2$, be given by $\bar{d} = \frac{1}{N}\sum_{t=1}^{N}(u_{1,t}^2 - u_{2,t}^2)$ where N is the number of forecasts.

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

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{N}}} \sim N(0,1) \tag{5}$$

where $f_d(0)$ is the spectral density of $(u_{1,t}^2 - u_{2,t}^2)$ at frequency 0. Following Diebold and Mariano (1995), a consistent estimate of $f_d(0)$ can be obtained by calculating the weighted sum of the sample autocovariances of $(u_{1,t}^2 - u_{2,t}^2)$ using a Bartlett weighting scheme (the sum is truncated at a lag equal to 1/3 of the out-of-sample observations) 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.

4. DATA DESCRIPTION AND THEIR STATISTICAL PROPERTIES

The data available are daily closing cash and futures prices for both the FTSE/ASE-20 and FTSE/ASE 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 ASE. 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/ASE-20 market and 01 February 2000 to 31 December 2003 for the FTSE/ASE 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. However, 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.

Combining information from futures contracts with different times to maturity may create breaks in the series at the date of the futures rollover since futures returns for that day are calculated between the price of the expiring contract and the price of the next nearest contract (Pelletier, 1983). To account for possible systematic relationships in the data associated with the retention of the last week of a contract (to account for the statistical effect of including the delivery period in the data set) we experimented with a series of synthetic prices for a “perpetual” 22-day ahead futures contract. 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. This procedure generates a series of futures prices with constant maturity and avoids the problem of price-jumps caused by the expiration of a particular futures contract (Pelletier, 1983). Herbst *et al*. (1989) suggest a *perpetual* contract 22-days horizon, which corresponds to the average number of trading days in a month, by taking a weighted average of the rates of contracts that expire before and after the 22-day period. Let S and P denote the days to expiry of the spot and prompt month futures contracts, with $S \leq 22 \leq P$. The price of a 22-days *perpetual* contract is calculated as follows:

$$F_{22} = F_S\,[(P-22)/(P-S)] + F_P\,[(22-S)/(P-S)] \qquad (6)$$

where F_S and F_P denote the prices of the spot and prompt month futures contracts, respectively. However, use of this data yields empirical results, which are qualitatively the same as those reported below, so there is no evidence that the futures contract rollover biases our findings.

Summary statistics of logarithmic first-differences of daily cash and futures prices, for the whole period, are presented in Table 2. 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.

Augmented Dickey-Fuller (ADF, 1981) and Phillips-Perron (PP, 1988) tests unit root tests on the log-levels and log-first differences of the daily cash and futures price series indicate that all variables are log-first difference stationary, all having a unit root on the log-levels representation. This means that the first differences of cash and futures series should be used in the ARMA and VAR models, while cointegration tests should be performed to ascertain the long run relationship between the series if the VECM model is going to be used. ADF and PP tests are sometimes criticised for lack of power in rejecting the null hypothesis of a unit root when it is false (Lee, *et al*., 2000). This lack of power is addressed by the KPSS test proposed by Kwiatkowski, *et al.* (1992), which has stationarity as the null hypothesis. However, results from applying the KPSS test on the series confirm the ADF and PP test findings.

Table 3 presents the Johansen (1988) multivariate cointegration test results which indicate that cash and futures prices are cointegrated in both markets. 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/ASE Mid-40 market, while in the FTSE/ASE-20 market is the following unrestricted spread: $(z_{t-1} = S_{t-1} - 0.98815*F_{t-1} - 0.987635)$. The results of the likelihood ratio tests for the over-identifying restrictions applied on the cointegrating vector are: 26.828 [0.000] for the FTSE/ASE-20 market and 2.745 [0.355] for the FTSE/ASE Mid-40 market. The first figure is the test statistic while the figure in square brackets is the corresponding *p*-value.

4. FORECASTING PERFORMANCE OF THE TIME-SERIES MODELS

4.1. In-Sample Estimation Results

Results of VAR, VECM, SURE-VECM and ARIMA models for cash and futures prices for the FTSE/ASE-20 and the FTSE/ASE Mid-40 markets are presented in Tables 4 and 5, respectively. The lag length for the autoregressive and moving average parts are chosen to minimise the Schwarz Bayesian Criterion (Schwarz, 1978). All ARIMA models seem to be well-specified as indicated by relevant diagnostic tests for autocorrelation and heteroskedasticity (not shown). It can be noted that in both markets, the adjusted coefficient of determination for changes in cash prices (ranging from 0.0599 to 0.0223) are higher than those of futures prices (ranging from 0.0329 to 0.0020), indicating higher explanatory power of cash series than futures prices. Three lags are defined as the appropriate number of lag length for VAR models.

The estimation results for the restricted VECM models are also presented in the same tables. “Granger-Causality” 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, seems to run both ways. In the FTSE/ASE-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/ASE 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. Alexakis, Kavussanos and Visvikis (2002) investigate the lead-lag relationship (causality) in daily returns and volatilities between price movements of stock index futures and the underlying cash index in the FTSE/ASE-20 and FTSE/ASE 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. Moreover, they find that futures volatility spills some information over to the cash market volatility in both investigated markets (FTSE/ASE-20 and FTSE/ASE Mid-40). These findings indicate that the futures markets can be used as price discovery vehicles.

4.2. Out-of-Sample Test Results

The forecasting performance of each model (VAR, VECM, SURE-VECM, ARIMA, RW) for cash and for futures prices, across the different forecasting horizons, is presented in matrix form in Tables 6 to 8 for the FTSE/ASE-20 and FTSE/ASE Mid-40 markets. Different forecasting horizons are being used; from 1 day up to 20 days ahead. Figures in the principal diagonal of the tables are the RMSEs from each model and the off-diagonal numbers are the ratios of the RMSE of the model in the column to the RMSE of the model in the row. When this ratio is less than one, the model in the column of the matrix provides a more accurate forecast than the model in the row.

Consider first the **FTSE/ASE-20 cash price** forecasts in Table 6. The RMSEs of the VECM and the SURE-VECM specifications are identical in almost all forecasting horizons. This is confirmed by Diebold and Mariano's (1995) test which indicates that the difference between the RMSE from the two models is not significant, with the exceptions of the 3- and 10- and 20-days ahead forecasts. The results indicate that the RMSEs of the 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, 4-days, 10-days, and 15-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 accuracy as those produced by VECM and SURE-VECM models. These results are in accordance with earlier cointegration results which reject the hypothesis that the cointegrating vector is restricted to be the lagged basis in the FTSE/ASE-20 market. The failure to restrict the cointegrating vector to be the lagged basis may explain why forecasts produced by the VAR model are superior than those produced by VECM and SURE-VECM models. Finally, the VAR, VECM and SURE-VECM produces forecasts with either similar or superior accuracy as those produced by ARIMA, and outperform the RW for all forecast horizons. Overall, it seems that conditioning cash returns on lagged futures returns significantly enhances the predictive accuracy of the model. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 23.43% (i.e. 1 – 0.76566).

Turning next to the **FTSE/ASE-20 futures** price forecasts in Table 7, the results indicate that the difference between the RMSE from the VECM and SURE-VECM specifications is not significant, with the exception of the 3-days and 10-days 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 and 20-days ahead forecasts. Finally, the differences between the RMSEs from the ARIMA and from the other time-series models are significant in 4-days, 10-days, and 20-days ahead forecasts (which indicate that ARIMA based forecasts are superior from the other models). For all other forecast horizons conditioning futures returns on lagged cash returns 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. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 29.92% (i.e. 1 – 0.70078).

For the **FTSE/ASE Mid-40 cash** price forecasts in Table 8, the results indicate that the the RMSEs of the SURE-VECM and the VECM specifications are significantly different for all the forecast horizons, with the SURE-VECM to produce superior forecasts than those produced by VECM. The results also indicate that the RMSEs of the SURE-VECM and the VAR specifications are significantly, with the SURE-VECM to produce superior forecasts than those produced by VAR, with the exception of the 10-days and 2- days ahead forecasts. These results are in accordance with earlier cointegration results which accept the hypothesis that the cointegrating vector is restricted to be the lagged basis in the FTSE/ASE Mid-40 market. Restricting the cointegrating vector to be the lagged basis may explain why forecasts produced by the SURE-VECM specifications are superior to the VAR model. Moreover, it seems that conditioning cash returns on lagged futures returns and on the restricted lagged basis significantly enhances the predictive accuracy of the model. All different time-series models outperform the RW model for all forecast horizons. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 22.98% (i.e. 1 – 0.77017). This is in accordance with the order of magnitude found in commodity markets but greater than what is found in stock markets. Tse (1995) for example finds that the ECM outperforms the naive model by 3% in the Nikkei stock index market.

Turning next to the **FTSE/ASE Mid-40 futures** price forecasts in Table 9, it can be seen that the RMSEs of the VECM and the SURE-VECM specifications are not significantly different for all the forecast horizons. Furthermore, the SURE-VECM and the VECM models significantly outperform the VAR model 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 Diebold and Mariano’s (1995) test. For longer forecasts it seems that the ARIMA specification produce superior forecasts than those produced by all other specifications. For all forecast horizons conditioning futures returns on lagged cash returns 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. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 30.94% (i.e. 1 – 0.69058), much larger than for cash rates.

5. CONCLUSION

In this study we investigate the performance of alternative univariate and multivariate linear time-series models in generating short-term forecasts in the cash market and in the recently developed derivatives market of the Athens Exchange. The forecasts from these models are benchmarked against the random walk. Our findings can be summarised as follows: First, conditioning cash returns on lagged futures returns generates more accurate forecasts of the cash prices for all forecast horizons. But conditioning futures returns on lagged cash returns does not enhance the forecasting accuracy of futures prices in almost all forecasts. Thus, it seems that the univariate Box-Jenkins (1970) ARIMA model produces forecasts as accurate as those by the other time-series models in both markets. This suggests that at almost all horizons the futures rate does contain significantly more and different information than is embodied in the current cash rate.

Second, restricting the cointegrating vector to represent the exact lagged basis significantly affects the forecast performance of the VECM model. In the FTSE/ASE Mid-40 market (where the restriction is accepted) the VECM provides more accurate forecasts than the VAR specification. In contrast, in the FTSE/ASE-20 market (where the restriction is not accepted) the VAR provides more accurate forecasts than the VECM specification at almost all horizons. This may be evidence that the market is working more efficiently in some contracts (FTSE/ASE Mid-40) than in others (FTSE/ASE-20).

Third, all time-series models generate more accurate cash and futures forecasts than the forecasts obtained by the random walk model in both markets. So while the futures rate does contain some forward-looking information, it behaves very differently from – and is more predictable than – futures rates in the speculatively efficient markets for currencies and mainstream commodity futures.

Finally, the reduction in the RMSE achieved by the VECM over the Random Walk for the 1-day ahead cash forecasts is lower than the reduction achieved for the 1-day ahead futures forecasts in both markets. This compares favourably to the findings in other markets. For example, Ghosh (1993) reports reductions in RMSE for the 1-day ahead cash forecasts ranging from 15% to 34% for the S&P500 and the Commodity Research Bureau (CRB) spot indices, respectively. Corresponding reductions for the 1-day ahead futures forecasts range from 24% and 39%. However, the studies of Ghosh (1993) and Tse (1995) use only 1-step ahead forecasts and do not formally test the equality of the RMSEs. Consideration of longer forecast horizons does seem important, since in several markets, market dynamics only become apparent for rates set more than 10 days ahead. Rigorous tests for comparative accuracy, as performed in our study, also appear important. At a practical level, they allow market agents in the futures market to find the appropriate time-series specification in order to generate accurate forecasts of the cash and the futures prices, and hence design more efficient investment and speculative trading strategies.

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Figure 1. FTSE/ASE-20 Futures Volume (No. of Contracts) (Sep-99 to Jun-04)

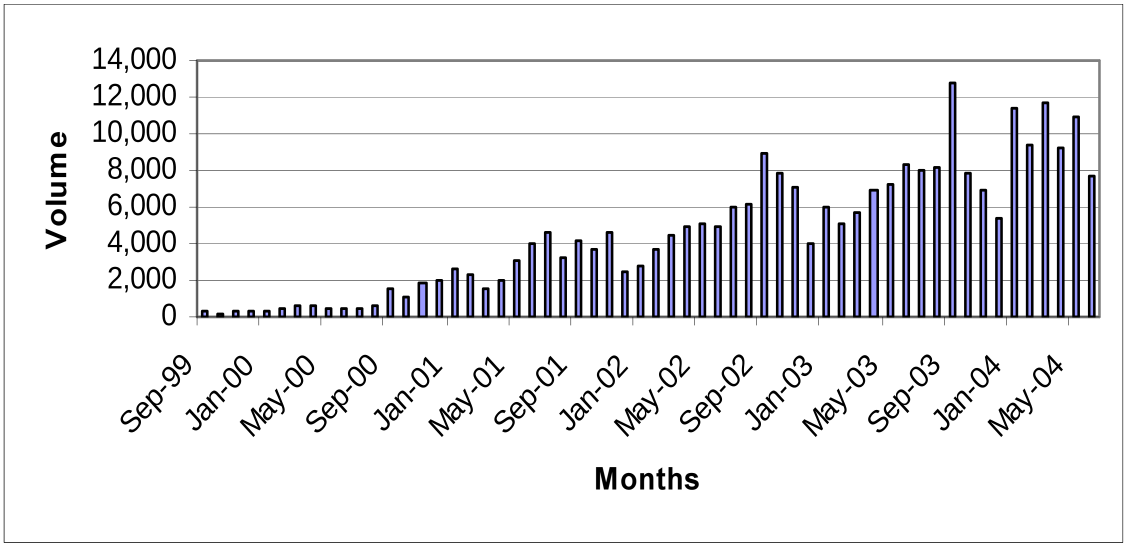

Figure 2. FTSE/ASE-20 Futures Open Interest (No. of Contracts) (Sep-99 to Jun-04)

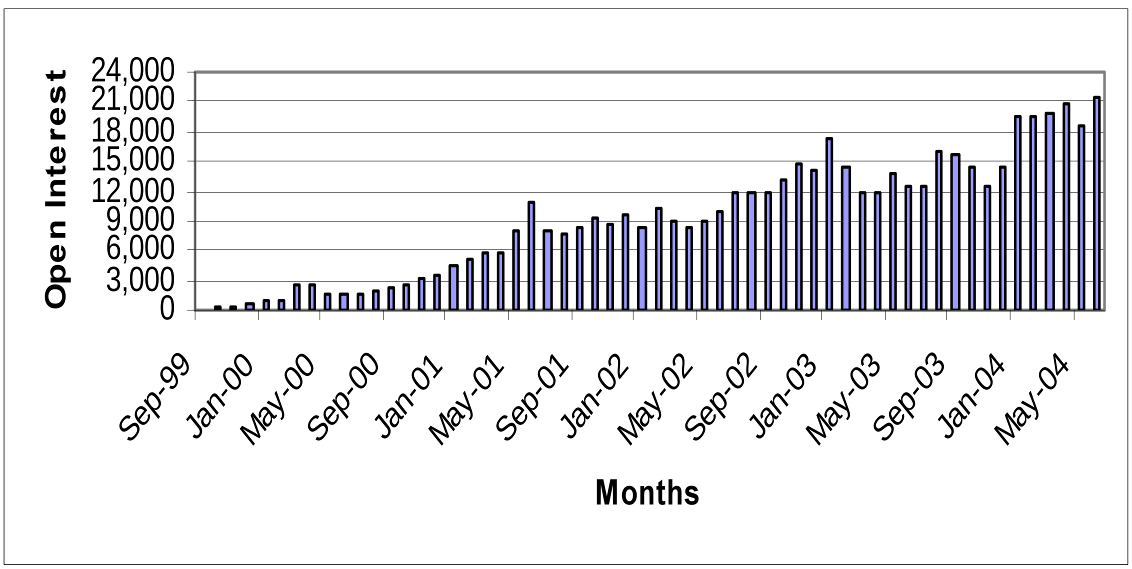

Figure 3. FTSE/ASE Mid-40 Futures Volume (No. of Contracts) (Feb-00 to Jun-04)

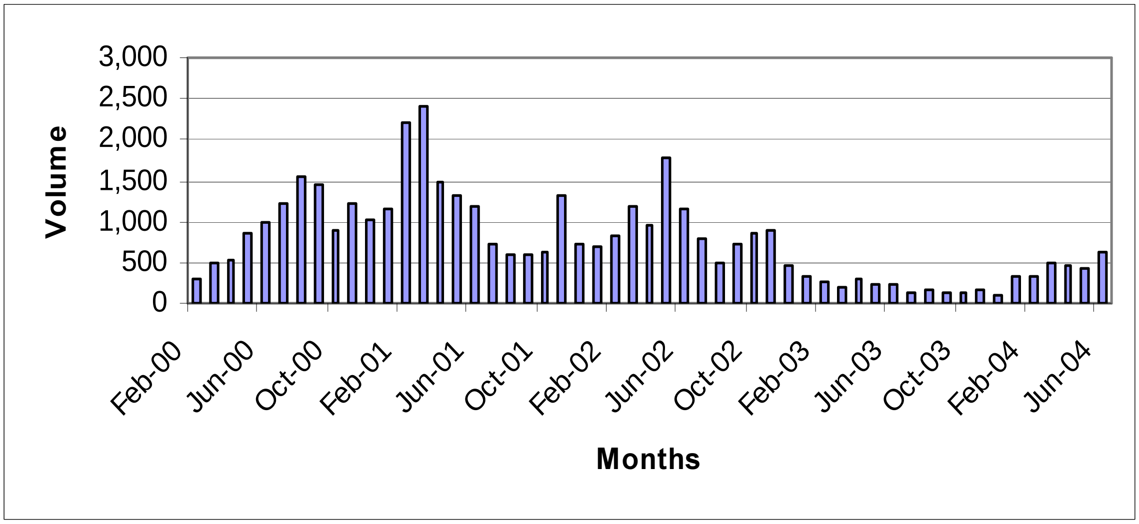

Figure 4. FTSE/ASE Mid-40 Futures Open Interest (No. of Contracts) (Feb-00 to Jun-04)

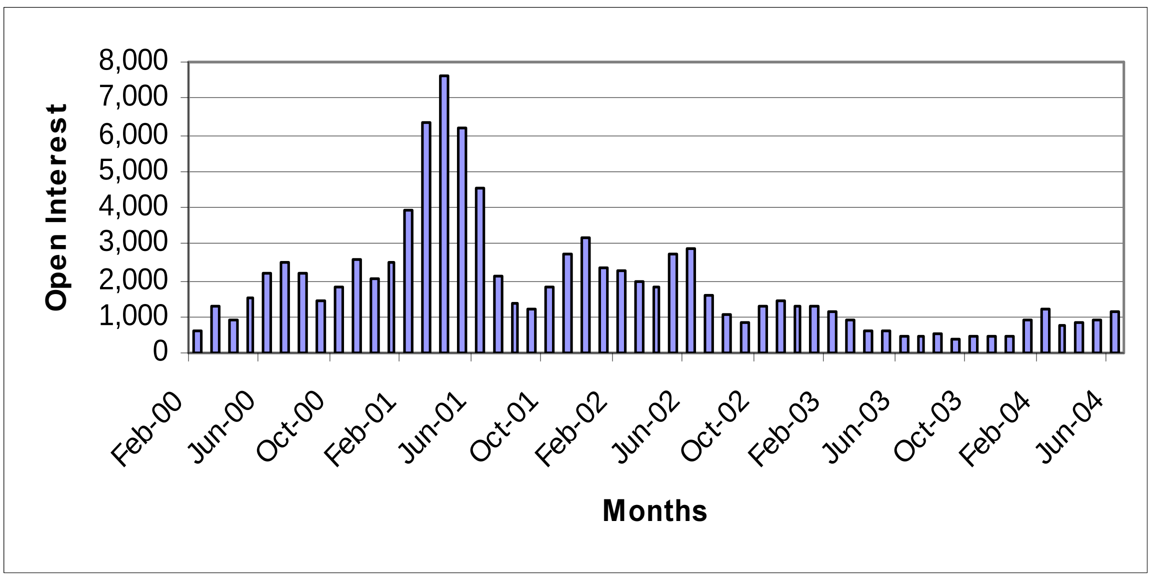

Table 1. FTSE/ASE-20 and FTSE/ASE Mid-40 Contract Specifications[*]

Underlying Asset	FTSE/ASE-20 Index[a] / FTSE/ASE Mid-40 Index[b]
Settlement	Cash Settlement
Minimum Lot Size	Single Market: x1 contract, Block Market: x100 contracts
Multiplier	5 EUR[a] / 50 EUR[b]
Quote Unit	Index Points
Minimum Tick	0.25
Tick Value	1.25 EUR[a] / 12.5 EUR[b]
Price Limits	No Price Limits
Trading Hours	10:45am to 16:15 pm
Margin Requirements	12% of the Position
Position Limits	No Position Limits
Last Trading Day	3rd Friday of the Expiration Month
Settlement Day	First Working Day Following the Last Trading Day
Listing Rules	3 Closest Consecutive Months Plus 3 Closest from the Mar-Jun-Sep-Dec Quarter Cycle.
Contract Rollover Date	First Working Day Following the Last Trading Day
Exchange Fees	0.10 - 0.75 EUR (Market Makers B) and 1.20 EUR (Other Members)

Notes:

- [a] FTSE/ASE-20 futures contract, [b] FTSE/ASE Mid-40 futures contract, [*] as of 01/11/03.

Table 2. Descriptive Statistics of Logarithmic First-Differences of Cash and Futures Prices

	N	Skew	Kurt	Q(36)	$Q^2(36)$	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Panel A: FTSE/ASE-20 Cash and Futures Price Series (01/09/99 to 07/06/04)											
Cash	1185	0.183	6.527	70.33	230.30	620.53	-1.725 (2)	-1.682	-19.065 (2)	-29.642	0.736
Futures	1185	0.166	6.328	52.54	177.60	552.31	-1.657 (2)	-1.653	-19.772 (2)	-31.621	0.815
Panel B: FTSE/ASE Mid-40 Cash and Futures Price Series (01/02/00 to 07/06/04)											
Cash	994	-0.209	6.172	128.25	549.22	460.66	-2.864 (2)	-2.623	-16.069 (2)	-24.648	0.325
Futures	994	0.126	7.068	74.26	493.39	748.13	-2.788 (2)	-2.672	-17.441 (2)	-28.123	0.415

Notes:

- All series are measured in logarithmic first differences.
- N is the number of observations.
- Skew and Kurt are the estimated centralised 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 $\chi^2(2)$.
- ADF is the Augmented Dickey Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is 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}	$\beta' = (1, \beta_1, \beta_2)$	$\beta' = (1, 0, -1)$
FTSE/ASE-20	2	r = 0	r =1	106.46	r = 0	r >=1	110.99	15.67	19.96	(1, -0.087, -0.988)	26.828 [0.000]
		r <=1	r =2	4.536	r <=1	r =2	4.536	9.24	9.24		
FTSE/ASE Mid-40	2	r = 0	r =1	83.367	r = 0	r >=1	94.160	15.67	19.96	(1, -0.024, -0.997)	2.745 [0.355]
		r <=1	r =2	5.729	r <=1	r =2	5.729	9.24	9.24		

Notes:

- 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.
- $\lambda_{max}(r,r+1) = -T\,\ell n(1-\hat{\lambda}_{r+1})$ and $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ell n(1-\hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in Equation (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 $-T\,[\ell n(1-\hat{\lambda}^*_1) - \ell n(1-\hat{\lambda}_1)]$ where $\hat{\lambda}^*_1$ and $\hat{\lambda}_1$ 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.
- In both the FTSE/ASE-20 and the FTSE/ASE Mid-40 models the cointegrating vector is not restricted and thus, is $z_t = \beta' X_t = (1\ \beta_1\ F_t)'$.

Table 4. In-Sample Estimates of the Time-Series Models in the FTSE/ASE-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*	-	-
			(-1.145)	(2.134)	(-1.455)	(2.758)		
c_t	-0.001**	-0.001	-	-	-	-	-	-
	(-1.670)	(-1.544)						
ΔS_{t-1}	0.153*	-	-0.049	0.020	-	-	-0.096	0.115
	(5.018)		(-0.521)	(0.199)			(-1.130)	(1.247)
ΔS_{t-2}	-0.056**	-	0.033	0.081	-	-	-0.004	0.157**
	(-1.841)		(0.363)	(0.822)			(-0.051)	(1.696)
ΔS_{t-3}	-	-	0.185*	0.187*	0.184*	0.166**	0.158**	0.240*
			(2.165)	(2.027)	(2.268)	(1.902)	(1.927)	(2.701)
ΔF_{t-1}	-	0.088*	0.207*	0.085	0.159*	0.102*	0.254*	-0.009
		(2.889)	(2.326)	(0.887)	(5.610)	(3.318)	(3.218)	(-0.110)
ΔF_{t-2}	-	-	-0.068	-0.103	-	-	-0.032	-0.176*
			(-0.787)	(-1.099)			(-0.397)	(-2.011)
ΔF_{t-3}	-	-	-0.171*	-0.177*	-0.171*	-0.155**	-0.146**	-0.229*
			(-2.101)	(-2.016)	(-2.249)	(-1.899)	(-1.856)	(-2.712)
$\overline{R}^2$	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]

Notes:

- * 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/ASE-20 model the cointegrating vector is not restricted and thus, is $z_t = \beta' X_t = (1\ \beta_1\ F_t)'$. In the FTSE/ASE Mid-40 model the 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.

Table 5. In-Sample Estimates of the Time-Series Models in the FTSE/ASE 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)
$\overline{R}^2$	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]

See Notes of Table 4.

Table 6. FTSE/ASE-20 Cash Price Forecasts for Out-of-Sample Period

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
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
10	10	VECM	0.01275				
		SURE-VECM	1.03658**	0.01230			
		VAR	1.00314*	0.96774**	0.01271		
		ARIMA	1.08695	1.04859	1.08354	0.01173	
		RW	0.78268	0.75506	0.78023	0.72007	0.01629
15	7	VECM	0.00789				
		SURE-VECM	0.98256	0.00803			
		VAR	1.01806*	1.03612*	0.00775		
		ARIMA	0.96691*	0.98406*	0.94975*	0.00816	
		RW	0.75792	0.77137	0.74447	0.78386	0.01041
20	5	VECM	0.01077				
		SURE-VECM	1.04563*	0.01030			
		VAR	0.97466	0.93212*	0.01105		
		ARIMA	1.19269	1.14064	1.22369	0.00903	
		RW	0.85408	0.81681	0.87629	0.71609	0.01261

Notes:

- Forecasts are generated by the models in Tables 3 and 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 Diebold and Mariano (1995) pairwise test of the hypothesis that the RMSEs from two competing models are equal is estimated using a Newey-West (1987) covariance estimator with a truncation lag equal to 1/3 of the corresponding out-of-sample observations each time.

Table 7. FTSE/ASE-20 Futures Price Forecasts for Out-of-Sample Period

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
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
10	10	VECM	0.01334				
		SURE-VECM	1.04300**	0.01279			
		VAR	1.00451*	0.96310	0.01328		
		ARIMA	1.02536**	0.98309	1.02075*	0.01301	
		RW	0.75495	0.72382	0.75155	0.73627	0.01767
15	7	VECM	0.00962				
		SURE-VECM	1.02777	0.00936			
		VAR	0.99896	0.97196	0.00963		
		ARIMA	0.95816	0.93227	0.95916	0.01004	
		RW	0.65576	0.63803	0.65644	0.68439	0.01467
20	5	VECM	0.01380				
		SURE-VECM	1.05102	0.01313			
		VAR	1.05585*	1.00459*	0.01307		
		ARIMA	1.09177*	1.03876*	1.03401*	0.01264	
		RW	0.92123	0.87650	0.87249	0.84379	0.01498

See Notes in Table 6.

Table 8. FTSE/ASE Mid-40 Cash Price Forecasts for Out-of-Sample Period

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
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
10	10	VECM	0.01202				
		SURE-VECM	1.02911*	0.01168			
		VAR	1.03710	1.00777	0.01159		
		ARIMA	1.17040	1.13729	1.12853	0.01027	
		RW	1.00083	0.97252	0.96503	0.85512	0.01201
15	7	VECM	0.00751				
		SURE-VECM	1.02736*	0.00731			
		VAR	0.99867*	0.97207*	0.00752		
		ARIMA	1.27939	1.24532	1.28109	0.00587	
		RW	0.89833	0.87440	0.89952	0.70215	0.00836
20	5	VECM	0.01070				
		SURE-VECM	1.03782*	0.01031			
		VAR	1.12988	1.08870	0.00947		
		ARIMA	1.37179	1.32179	1.21410	0.00780	
		RW	0.92162	0.88802	0.81567	0.67183	0.01161

See Notes in Table 6.

Table 9. FTSE/ASE Mid-40 Futures Price Forecasts for Out-of-Sample Period

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
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
10	10	VECM	0.01128				
		SURE-VECM	1.02639	0.01099			
		VAR	1.04930	1.02233	0.01075		
		ARIMA	1.13939*	1.11010*	1.08586*	0.00990	
		RW	0.82577	0.80454	0.78697	0.72474	0.01366
15	7	VECM	0.00827				
		SURE-VECM	0.99279	0.00833			
		VAR	1.00364	1.01092	0.00824		
		ARIMA	1.05619*	1.06385*	1.05236*	0.00783	
		RW	0.96612	0.97313	0.96261	0.91472	0.00856
20	5	VECM	0.00923				
		SURE-VECM	0.95253	0.00969			
		VAR	1.37556	1.44411	0.00671		
		ARIMA	1.44898*	1.52119*	1.05338*	0.00637	
		RW	0.86262	0.90561	0.62710	0.59533	0.01070

See Notes in Table 6.