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The Greek equity market in European equity portfolios

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ABSTRACT

The present paper emphasizes on the importance of the Greek equity market to European equity portfolios. The portfolio performance is higher for portfolios for which the Greek equity market is included. This result is consistent across a variety of variance–covariance matrix estimators, portfolio types, and evaluation measures as well. Results are also robust to the 2008 financial crisis. In terms of the variance–covariance matrix estimation, the realized volatility estimators result in higher portfolio performance than the daily squared returns estimator does. The realized volatility estimator which is optimally sampled and bias corrected is the most accurate variance–covariance matrix estimator. The Capital Market Line portfolio type is the portfolio type with the best portfolio performance. Overall, the inclusion of the Greek equity market to the European equity portfolios results in higher European equity portfolio performance.

1. Introduction

There are numerous papers trying to analyze the recent financial crises since 2008 in either a European or global financial markets. The latest financial crisis is attributed to the debt crisis in Europe, starting in Greece. So, a recent debate is: Should Greece continue to belong to the Eurozone? This question may be answered by examining the usefulness of either the debt or equity markets. As far as the global debt markets are quite problematic, question may be concerned on the usefulness of the Greek equity market to a European equity portfolio. Diamandis et al. (2012), among other results, provided evidence that diversification produces significant gains in terms of risk reduction in the Greek capital market. In specific, this paper investigates the economic value of the Greek equity market in a European equity portfolio. Its importance is increased when more accurate variance–covariance matrix estimates are used, based on a volatility-timing strategy.

This importance is also examined for different portfolio types: Efficient Frontier, Global Minimum Variance, Capital Market Line and Capital Market Line with only positive weights. It is also researched across different realized volatility estimators. The effect of accurate volatility estimation in a portfolio framework is examined in detail by Thomakos and Wang (2010). In the present paper, various non-parametric realized volatility estimators are employed to accurately estimate and forecast the variance–covariance matrix. These are the unrestricted realized volatility estimator, the realized optimally sampled volatility estimator and their bias-corrections against the benchmark of the daily squared returns. An influential study in parametric volatility modeling in the Athens Stock Exchange is Drakos et al. (2010). A more recent study on parametrically estimating comovements is Gjika and Horvath (2013). They examined the properties of the variance–covariances between the Central European and Euro-area stock markets. Gatfaoui (2013) is another recent study on parametrically examining time-varying conditional covariances and correlations as well as their asymmetric properties. Evaluation measures are the portfolio statistic measures (mean, standard deviation, Sharpe Ratio and Cumulative Return), the basis points that a risk averse investor is willing to pay per year in order to gain from the realized covariance estimates instead of the daily squared returns. The present paper is based on the methodology of volatility timing strategy in terms of portfolio construction. This was introduced by Flemming et al. (2003)—FKO (2003) hereafter. Another relative and more recent paper is Kyj et al. (2009).

Results reveal significant portfolio profits when the Greek equity market is included in a European portfolio. This is enhanced by more accurate realized volatility estimators in an out-of-sample as well as the economic value of the volatility timing strategy. This is also revealed in portfolio statistics. Moreover, the basis points that a risk-averse investor is willing to pay annually in order to profit from the realized volatility estimators of the variance–covariance matrix for a European portfolio are higher when the Greek equity market is included rather than those when it is not included. Also, portfolio statistics and performance fees are further improved when the sampling frequency of the variance–covariance estimates is optimally selected, as well as when the variance–covariance matrix is bias-corrected for the microstructure noise of the intraday data.

The plan of the rest of the paper is as follows. Section 2 presents the methodology concerning the volatility estimators, the portfolios and the criteria revealing the economic value of the variance–covariance forecasts. Section 3 describes the data used in this paper. Section 4 discusses the results with policy implications, and Section 5 concludes.

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2. Empirical methodology

The first step in the empirical methodology is to correctly estimate the variance–covariance matrix that determines the portfolio weights according to the volatility-timing strategy. The variance–covariance matrix is estimated by different realized volatility estimators apart from the daily squared returns. Firstly, the unrestricted 5-min realized variances and covariances are considered. Moreover, the optimally sampled variances and covariances as in Bandi and Russell (2006, 2008) are also included. The two above measures of the conditional covariance matrix are subjected to bias-corrections as detailed in Flemming et al. (2003). The bias-correction is important in correcting the unrestricted realized covariance estimates for the bias of the microstructure noise, which is attributed to various high-frequency data characteristics.[1] De Pooter et al. (2008) focus on the issue of determining the optimal sampling frequency as judged by the performance of mean-variance efficient S&P 100 stock portfolios.

The daily squared returns estimator is employed as a benchmark estimator to various realized volatility estimators. The same estimator was employed as a benchmark by FKO (2003). Portfolio weights are selected upon these estimators' performance forecasting the variance covariance matrix. Four different portfolio types are considered: the Efficient Frontier portfolio type (*EFR*), the Global Minimum Variance portfolio type (*GMV*), the Capital Market Line with no restrictions (*CML*), and the Capital Market Line portfolio type with the restriction for long (positive) weights only (*CML − Long*). The first two portfolio types are referred to FKO (2003). To the best of my knowledge, this paper is one of the first that studies the economic value of volatility forecasts for the *CML* and (*CML − Long*) portfolio types in the European equity market.

The following portfolio parameters are used: i) the annualized risk-free asset return (rf) is 2.5%; ii) the annualized portfolio target return (tr) is 30%; and iii) the number of days (d) used in bias-correction are 22 days. The returns and volatilities have been annualized on the basis of a 252-trading-day year, according to the scheme introduced by FKO (2003). The portfolio statistics as well as the performance fees (in basis points) are expressed in annualized percentages (year of 252 days). This section describes the methodology employed for the volatility timing strategy, the estimators of the variance–covariance matrix, the different portfolio types, and the portfolios' performance evaluation criteria.

2.1. Volatility timing

There is a set of N + 1 assets, from which the N are risky. Let R_t denote $N \times 1$ vector of logarithmic returns, with $\oint_{t-1}$ the day $t-1$ information set. In order to minimize the conditional volatility subject to a given expected return, the investor applies the risky asset weights

$$w_t = \frac{\mu_p \sum_t^{-1} \mu_t}{\mu_t' \sum_t^{-1} \mu_t} \tag{1}$$

where μ_t is the $N \times 1$ vector of conditional returns $\mu_t \equiv E[R_t | \oint_{t-1}]$, $\sum_t$ is the $N \times N$ vector of conditional covariance matrix $\sum_t \equiv E[(R_t - \mu_t)(R_t - \mu_t)' | \oint_{t-1}]$ and μ_p is the target portfolio expected return. The weight in cash is given by subtracting the sum of the elements of w_t from 1. The portfolio weights change through time by μ_t and $\sum_t$. The strategy that minimizes the conditional volatility subject to a target expected return (named volatility timing strategy) is employed. So, the usage of more precise estimates of the conditional covariance matrix will improve the performance of the volatility timing strategy.

2.2. Volatility estimators

According to the vast literature of realized volatility, realized volatility estimators estimate variances and covariances more accurately than daily squared returns. The present paper out-of-sample compares different realized volatility estimators to the daily squared returns. Following FKO (2003), the conditional covariance matrix $\sum_t$ is constructed by using the following backward-looking rolling estimator.

$$\hat{\Sigma}_t = \sum_{\varkappa=1}^{\infty} \Omega_{t-k} \odot e_{t-k} e_{t-k}' \tag{2}$$

where Ω_{t-k} is a symmetric $N \times N$ matrix of weights, $e_{t-k} = (R_{t-k} - \mu)$ is an $N \times 1$ matrix vector of daily return innovations and $\odot$ denotes the element-by-element multiplication. The reason for this, is that by applying a suitable set of weights to the squares and cross products of the lagged return innovations, the estimates of $\sum_t$ can be retrieved; these are by their very nature nonparametric.

As in FKO (2003), the weighting scheme is of the form $\Omega_{t-k} = a \cdot exp(-ak)$. So, the estimate of $\sum_t$ becomes

$$\hat{\Sigma}_t = exp(-a)\hat{\Sigma}_{t-1} + a \cdot exp(-a) e_{t-1} e_{t-1}' \tag{3}$$

where the a is the rate at which the weights decay with the lag length. It is estimated by maximizing the following likelihood function

$$max\left[L\left(e_t = \sum_t^{1/2} z_t\right)\right] \tag{4}$$

with

$$\Sigma_t = exp(-a)\Sigma_{t-1} + a \cdot exp(-a) e_{t-1} e_{t-1}' \tag{5}$$

[1] A detailed analysis of microstructure noise is not the purpose of this paper.