Valuing volatility spillovers in European stock markets*

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ABSTRACT

Allowing for volatility spillovers in covariance forecasts produces small, significant reductions in mean-variance portfolio risk. We demonstrate reductions in the order of 1-1.5% of standard deviation for portfolios of European equities at daily, weekly, and monthly rebalancing horizons. We estimate and forecast the conditional second moment matrix of (synchronized) daily index returns for the London, Frankfurt and Paris stock markets via two asymmetric dynamic conditional correlation models (A-DCC): the unrestricted model includes volatility spillover effects and the restricted model does not. We combine covariance forecasts from the restricted and unrestricted models with a wide range of assumed returns relatives via a polar co-ordinates method, and compute out-of-sample realized portfolio returns and variances for testing. Diebold-Mariano tests confirm that risk reductions are significant in most portfolios. Stochastic dominance tests indicate that portfolios accounting for volatility spillover would be preferred by risk averse agents.

Introduction

We incorporate volatility spillovers into covariance forecasts for mean-variance portfolios of European equities, and quantify any resulting benefits to investors. There are many empirical studies of time-varying second moments but fewer studies which actually measure whether new models will benefit investors. Since a key ingredient in successful portfolio selection is an accurate prediction of covariance between asset returns, better forecasting models should generate measurably lower portfolio risk. Volatility spillovers, for example, have been extensively documented as a feature of financial data but their importance for efficient investment has not been evaluated.

A volatility spillover occurs when changes in price volatility in one market produce a lagged impact on volatility in other markets, over and above local effects. They are a common feature of financial markets. We find that portfolios which are optimized using conditional covariance forecasts that account for volatility spillovers show small but significant improvements in efficiency, relative to benchmark. The efficiency gains arising from modelling volatility spillovers range from a 0.02 to a 1.51 per cent reduction in portfolio standard deviation. For a portfolio returning, say, 10 per cent per year, this represents a small risk-adjusted improvement of at most 0.15 per cent, however tests confirm that, in the majority of cases, these risk reductions are statistically significant at all forecasting horizons. In addition, stochastic dominance tests point to significant improvements in investor utility arising from volatility spillover forecasting.

The overall impact of volatility spillover may not be large by commercial standards, but it is statistically significant, and since including volatility spillover effects in the portfolio selection process does not necessarily incur any additional transactions costs, even small gains can represent improvement for investors.

Volatility spillover patterns appear to be widespread in financial markets. There is evidence for spillovers between equity markets (see for example Hamao, Masulis and Ng 1990, and Lin, Engle and Ito 1994), bond markets (Christiansen 2003), futures contracts (Abrhyankar 1995, Pan and Hsueh 1998), exchange rates (Engle, Ito and Lin 1990, and Baillie and Bollerslev 1990), equities and exchange rates (Apergis and Rezitis 2001), various industries (Kaltenhauser 2002), size-sorted portfolios (Conrad, Gultekin and Kaul 1991), commodities (Apergis and Rezitis 2003), and swaps (Eom, Subrahmanyam and Uno 2002). Despite the interest that investors might have in these pervasive spillover effects, we are not aware of any study that investigates the question of their impact on efficient asset allocation.

Our first step towards answering this question is to construct a covariance model which comprehensively captures the data while isolating the impact of volatility spillovers. In this study, investors hold mean-variance portfolios allocated among the risk-free asset and equities in two of three major European stock markets, London, Frankfurt and Paris. Portfolio weights therefore depend on forecasts of the bivariate conditional covariance matrix of stock market returns. To isolate the impact of volatility spillovers on portfolio efficiency, we estimate two nested forecasting models of returns volatility via Asymmetric Dynamic Conditional Correlation (A-DCC) models (Cappiello, Engle and Sheppard 2004). The benchmark (restricted) model captures time-varying volatility and correlation, including asymmetric effects, but omits volatility spillover terms, which we add to the unrestricted model.[i] We estimate the models over the first part of the sample and then forecast the conditional covariance matrix over remaining data at a range of horizons, computing optimal portfolio weights at each forecast.

Mean-variance portfolio weights depend on expected returns as well as expected second order moments, and it is well known that out-of-sample portfolio performance is often degraded by a poor choice of expected returns (Chopra and Ziemba 1993). A new approach, developed by Engel and Colacito (2004), offers a method for minimizing the impact of expected return choice on out-of-sample portfolio efficiency: In a two-asset portfolio, relative, rather than absolute, returns matter to optimal portfolio weighting, so by computing weights for a wide range of returns ratios, we can better identify the effects of covariance forecasting separately from returns forecasting. Finally, using optimal weights, we compute realized portfolio returns and variances, and then test for significant difference between the volatility spillover formulation and the benchmark. Section 5 below reports standard deviations of optimal portfolio returns, Diebold and Mariano (1995) tests of forecasting performance, and gives evidence of significant second degree stochastic dominance among portfolios via a time-series adaptation of the Barrett and Donald (2003) tests.

The next section (Section 2) reviews some of the relevant features of volatility spillover literature. We outline the benchmark and alternative models in Section 3, followed by portfolio construction in Section 4. Section 5 presents an outline of the data and estimated parameters, followed by tests comparing the performance of portfolios constructed from the benchmark and volatility spillover models. Section 6 concludes.

2 Literature Review

Interest in volatility spillovers across international equity markets intensified after the October 19, 1987 stock market crash when a sharp drop in the US equity markets appeared to create a widespread volatility ripple across international markets. In an attempt to explain this, King and Wadhwani (1990) put forward a 'market contagion' hypothesis, arguing that stock price turbulence in one country is partly driven by turbulence in other countries, beyond the influence of fundamentals. Identifying and testing the transmission of turbulence between markets has been the focus of the volatility spillover literature.

Early studies of volatility spillovers typically focus on developed country equity markets, and the transmission of volatility from larger to smaller country markets in particular. For example, Hamao, Masulis and Ng (1990) find unidirectional volatility spillovers from US markets to the UK and Japan, and the UK to Japan, while Theodossiou and Lee (1993) argue for additional transmissions from the US market to Canada and Germany.

Further, the large-small country effect appears to be mirrored within equity markets on a firm-size level. Studies document volatility spillover from large to small firms (Conrad, Gultekin and Kaul 1991, and Reyes 2001), although bad news may cause spillover in the reverse direction as well (Pardo and Torro 2003).

More recent studies investigate spillover effects between developed and emerging markets, and among emerging markets themselves. A typical finding (see, for example, Wei et al, 1995) is that volatility transmits from developed to emerging markets, and that the smaller, less developed markets are likely to be more sensitive to transmitted shocks.

Geographic locality, regardless of market size, is also likely to be a factor in volatility spillover. Bekaert and Harvey (1997) are able to distinguish between local and global shocks, studying volatility spillovers across emerging stock markets. Regional factors are important for Pacific Basin markets, over and above the world-market effects of spillovers from the US (Ng 2000). In a related study, Miyakoshi (2003) goes further, arguing that regional effects are stronger than world market influence for markets in the Asian region.

Europe represents a particularly interesting geographic area for volatility spillover studies since it encompasses a number of developed markets with common economic and financial features, and overlapping trading hours. Thirteen European markets and the US are studied by Baele (2003), who decomposes volatility spillovers into country specific, regional and world shocks. (The model also allows for regime switches in the spillover effects.) Both regional and world effects are reported as significant. Further, spillovers appear to have intensified over the 1980s and 1990s, with a more pronounced rise among European Union (EU) markets. In a related study, Billio and Pelizzon (2003) find that volatility spillovers to most European stock markets from both the world index and the German index have increased since the European Monetary Union (EMU) came into effect.

The importance of regional spillovers for Europe is not restricted to equity markets. Testing for volatility spillover effects in European bond markets, Christiansen (2003) finds evidence of spillover from both the US and Europe to individual country's bond markets. The European volatility spillover effects are stronger than the US volatility spillovers in bond markets, as in equity markets.

An important methodological issue for transmission studies is whether volatility spillovers can be identified separately from lags in information transfer due to non-overlapping trading hours between markets. For example, in the foreign exchange market Engle, Ito and Lin (1990) investigate volatility spillovers across Tokyo and New York for the Yen/USD exchange rate. Since these two markets trade a common security, but operate in different time zones, the authors argue for a 'Meteor Shower' effect, whereby surprises in one market while the other is closed show up as soon as the second market opens. In addition, by studying open-to-close against close-to-open equity returns, Lin, Engle and Ito (1994) find that shocks to New York daytime equity returns are correlated with overnight Tokyo returns and vice versa. In the latter case they conclude that information revealed during the trading hours of one market has a simultaneous impact on the returns of the other market. Any study of volatility spillovers needs to distinguish between contemporaneous shocks that appear lagged because of staggered trading hours, and real-time lead-lag effects between security markets (Martens and Poon 2001).

Existing empirical research provides evidence of volatility spillovers both across and within various markets. Our choice of equity markets (London, Frankfurt and Paris) facilitates investigation of larger-smaller market effects as well as the interesting intra-regional influences which appear to be strengthening in Europe. In addition, we restrict the study to synchronous price observations, avoiding the confusion which can arise from trading lags.

3 Model Specification and Estimation

We build bivariate M-GARCH models with asymmetry to capture time-varying volatility and asymmetric effects while also allowing correlations between security returns to vary over time. Recent studies (Cappiello, Engle and Sheppard 2003, Kearney and Poti 2005) have established the importance of correctly modelling time-varying correlation, particularly among European security markets. Variance targeting ensures long-run stationarity.

Consider a vector of returns for two equity markets, $\mathbf{r}_t = [r_{1t} \quad r_{2t}]'$ such that

$$\mathbf{r}_t = \mathbf{c} + \mathbf{u}_t \tag{1}$$

$$\mathbf{u}_t = \mathbf{D}_t \varepsilon_t, \tag{2}$$

where $\mathbf{c}$ is the unconditional mean vector of $\mathbf{r}_t$, $\mathbf{D}_t$ contains conditional standard deviations on the main diagonal and zeros elsewhere, ε_t are the innovations standardized by their conditional standard deviations, and Ψ_{t-1} represents the conditioning information set at time t such that

$$\varepsilon_t \mid \Psi_{t-1} \sim \left(0, \mathbf{R}_t\right). \tag{3}$$

Observe that $E_{t-1}\left(\varepsilon_t \varepsilon_t'\right) = \mathbf{R}_t$ is also the conditional correlation matrix of the standardized innovations. We can therefore specify the conditional covariance matrix for the returns vector $\mathbf{r}_t$ as

$$\begin{aligned} Var(\mathbf{r}_t \mid \Psi_{t-1}) = Var_{t-1}(\mathbf{r}_t) &= E_{t-1}\left[\left(\mathbf{r}_t - \mathbf{c}\right)\left(\mathbf{r}_t - \mathbf{c}\right)'\right] \\ &= E_{t-1}\left[\mathbf{D}_t \varepsilon_t \left(\mathbf{D}_t \varepsilon_t\right)'\right] \\ &= E_{t-1}\left[\mathbf{D}_t \varepsilon_t \varepsilon_t' \mathbf{D}_t\right], \end{aligned} \tag{4}$$

and since D_t is a function only of information at $t-1$, we can write the conditional covariance matrix as

$$\begin{aligned} \mathbf{H}_t &\equiv Var_{t-1}(\mathbf{r}_t) \\ &= \mathbf{D}_t E_{t-1}\left(\varepsilon_t \varepsilon_t'\right) \mathbf{D}_t \end{aligned} \tag{5}$$

$$= \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t. \tag{6}$$

The elements of the $\mathbf{D}_t$ matrix are the conditional standard deviations, where

$$\mathbf{D}_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix}. \tag{7}$$

We use two different specifications of conditional variances to capture the effects of asymmetric dynamics and volatility spillover separately:

Asymmetric GJR(1,1,1)[ii]:

$$h_{ii,t} = \omega + \left(\alpha + \delta I_{t-1}\right) u_{ii,t-1}^2 + \beta h_{ii,t-1} \tag{8}$$

where $I_t = \begin{cases} 1 \mid u_t < 0 \\ 0 \mid u_t \geq 0 \end{cases}.$

Asymmetric GJR(1,1,1) with volatility spillover:

$$h_{ii,t} = \omega + \left(\alpha + \delta I_{t-1}\right) u_{ii,t-1}^2 + \beta h_{ii,t-1} + \gamma u_{jj,t-1}^2 \tag{9}$$

where $I_t = \begin{cases} 1 \mid u_t < 0 \\ 0 \mid u_t \geq 0 \end{cases}$ and $ii \neq jj.$[iii]

Next we model the conditional correlation matrix $\mathbf{R}_t$ following Cappiello, Engle and Sheppard (2004). From (1) and (2) above, the standardized residuals can be calculated as

$$\mathbf{D}_t^{-1}\mathbf{u}_t = \varepsilon_t, \tag{10}$$

where the elements of $\mathbf{D}_t^{-1}$ have been derived from estimated equations for each of the formulations for $h_{ii,t}$ above. By using these standardized residuals we are able to estimate a conditional correlation matrix of the form:

$$\mathbf{R}_t = diag\left[\mathbf{Q}_t\right]^{-1} \mathbf{Q}_t \; diag\left[\mathbf{Q}_t\right]^{-1} \tag{11}$$

$$\mathbf{Q}_t = \bar{\mathbf{Q}}(1-\phi-\eta) - \varphi\bar{\mathbf{m}} + \phi\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \varphi\mathbf{m}_{t-1}\mathbf{m}_{t-1}^{'} + \eta\mathbf{Q}_{t-1}$$

where ϕ, φ and η are scalar parameters. The vector $\mathbf{m}_t = I\left[\varepsilon_t < 0\right] \circ \varepsilon_t$ (where $\circ$ is the Hadamard product) isolates observations where standardized residuals are negative.

Notice that $\mathbf{Q}_t$ resembles a GJR(1,1,1) process in the standardized volatilities. Finally, we implement variance targeting, where $\bar{\mathbf{Q}} = \frac{1}{T}\sum \varepsilon_t \varepsilon_t'$ and $\bar{\mathbf{m}} = \frac{1}{T}\sum \mathbf{m}_t \mathbf{m}_t'$ to enforce stationarity. Combining estimates for (6) and (10) results in a conditional covariance matrix for the returns vector $\mathbf{r}_t$ which can be used, along with a vector of expected returns, to predict optimal portfolio weights t periods ahead:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t . \tag{12}$$

4. Portfolio construction

In this study, investors use short-horizon mean-variance strategies to create portfolios from two equity market indices and the (zero-return) risk-free asset, relying on forecasts of conditional covariance from dynamic models. On one hand, mean-variance portfolios are not ideal for equity investors, since they maximise utility only when asset returns are elliptically distributed, but on the other hand, mean-variance modelling is a well-understood analytic tool that maps into the portfolio performance literature, is commonly applied in funds management practice, and can be simply adapted to changing levels of risk aversion.

4.1 Weight selection

A single-horizon investor chooses portfolio weights to minimize portfolio variance subject to a required return μ_0.

$$\min_{w_t} \mathbf{w}_t' \mathbf{H}_t \mathbf{w}_t \tag{13}$$

$$s.t. \quad \mathbf{w}_t' \mu = \mu_o \tag{14}$$

deriving an optimal weighting vector:

$$\mathbf{w}_t = \frac{\mathbf{H}_t^{-1}\mu}{\mu' \mathbf{H}_t^{-1}\mu}\mu_o , \tag{15}$$

where μ is an assumed vector of expected returns to be described below, and μ_o is the required rate of return to the portfolio, here set to unity. $\mathbf{H}_t$ is the expected (forecasted) covariance matrix of returns. We do not impose full investment or short-sales constraints on the portfolio allocations, so any wealth not accounted for by $\mathbf{w}_t$ is implicitly invested in the risk-free (assumed zero return) asset, and the weight vector may include negative values.

The individual variance formulations described by equations (8) and (9), in combination with the A-DCC correlation estimates, generate two sets of conditional covariance matrices for each pair of market returns, $\{\mathbf{H}_t\}_{i=1}^{2}$, where model *i=2* includes volatility spillover effects and model *i=1* does not. We forecast $\mathbf{H}_t$ and rebalance the portfolio at daily, weekly (5 days) two-weekly (10 days) and monthly (20 days) frequencies, using the A-DCC models described above, testing to see if the impact of volatility spillover tapers off over longer rebalancing horizons.

4.2 Expected Returns

Engle and Colacito (2004) propose a solution to the intractable problem of forecasting expected returns. Expected return estimation errors are not only usually large, but also amplified in the mean-variance optimization process, causing poor out-of-sample portfolio performance. Engle and Colacito point out that, for two-asset portfolios, optimal weights are functions of *relative* returns, not of the absolute size of expected return to each asset. Since it is the *return ratio* that matters, a wide spectrum of relative returns between two assets can be mapped out over the zero-one interval. By applying their method, we can test for the impact of volatility spillover on portfolio efficiency without jointly testing a peripheral hypothesis about expected returns.

We can span a wide range of returns relatives by choosing pairs of expected returns as polar co-ordinates, $\mu = \left[\sin\frac{\pi j}{20}, \cos\frac{\pi j}{20}\right]$ and allowing *j* to vary from 0 to 10, $j \in \{0,\ldots,10\}$. The resulting values (listed in Table 1) range from zero to one for each asset, including a mid-point where the expected return of both assets are equal. Combined with forecast covariance matrices $\left\{H_t^i\right\}_{i=1}^{2}$, these eleven expected return pairs $\left\{\mu_t^k\right\}_{k=1}^{11}$ allow us to compute optimal portfolio weights from (15). If one conditional covariance model performs better for all eleven expected returns relatives, we can be confident that it is a better model for any choice of return.

[INSERT TABLE 1 HERE]

Since comparison between eleven portfolios is cumbersome we also derive a Bayesian probability for each value of *j* and compute a probability-weighted summary measure of portfolio risk and return. Again following Engle and Colacito (2004), we compute non-overlapping sample means (using 40 observations) $\left\{\bar{\mu}_1^l, \bar{\mu}_2^l\right\}_{l=1}^{L}$, from the sample data for each market pairing. Any mean pair where either value is negative is dropped, leaving a subset of size $d = 1,...D.$ From this sample we back out D values of $\theta_d = \frac{2}{\pi} a\cos\left(\frac{\bar{\mu}_{2,d}}{\sqrt{\bar{\mu}_{2,d}^2 + \bar{\mu}_{1,d}^2}}\right)$ and use these values of θ to calculate maximum likelihood parameters of the Beta distribution $\hat{a}$ and $\hat{b}$. Finally, we infer the empirical probability of each pair of the eleven polar co-ordinate returns $\mu^k = \left(\sin\frac{\pi j}{20}, \cos\frac{\pi j}{20}\right)$ by computing the value

$$\Pr\left(\theta = \theta_j\right) = \frac{1}{\Upsilon} \frac{\theta_j^{\hat{a}-1}(1-\theta_j)^{\hat{b}-1}}{\int_0^1 t^{\hat{a}-1}(t)^{\hat{b}-1}dt}. \tag{16}$$

where $\frac{1}{\Upsilon}$ is a normalizing constant and $\int_0^1 t^{\hat{a}-1}(t)^{\hat{b}-1}dt = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$ for each pair of markets.

Figure 1 graphs the probability density functions for θ computed from this procedure, with all showing some skewness across the range of relative returns. Skewness in the London-Paris distribution, for examples, indicates that returns are likely to be higher in London than in Paris. A similar observation applies to Frankfurt and Paris, with the London-Frankfurt pair likely to be more equal. All but the most extreme values of θ have some weight in the density, so focusing on the most likely value may be misleading.

[INSERT FIGURE 1 HERE]

4.3 Performance measurement

Portfolio performance is a guide to forecasting accuracy, since the best model of covariance will generate the least risk. Engle and Colacito (2004) show that, for a given required rate of return μ_0, the portfolio with the smallest realised standard deviation will be the portfolio constructed from the most accurate covariance forecast. This result holds because the covariance forecasting model that is closest to the underlying data generating process (DGP) predicts better, and generates portfolio weights which minimise realised risk. So if σ^* is the portfolio standard deviation achieved using the true covariance matrix, and $\hat{\sigma}$ is the standard deviation from an inefficiently estimated covariance matrix, then σ^* will be less than for $\hat{\sigma}$, such that

$$\frac{\sigma^*}{\mu_o} < \frac{\hat{\sigma}}{\mu_o}. \qquad (17)$$

Consequently, if including volatility spillover effects improves conditional covariance forecasts then portfolios constructed from the better forecasts will have lower realized standard deviations. Another way of expressing this efficiency gain is by computing the required rate of return we would need in order to maintain a constant risk-to-reward ratio. Let μ_0^* be the required rate of return associated with the true covariance matrix and $\hat{\mu}_0$ be the required rate of return associated with an inefficient covariance matrix, and rewrite (17) as an equality:

$$\frac{\sigma^*}{\mu_0^*} = \frac{\hat{\sigma}}{\hat{\mu}_0} \qquad (18)$$

where $\mu_0^* < \hat{\mu}_0$. Equivalently we can write (18) as:

$$\frac{\hat{\mu}_0}{\mu_0^*} = \frac{\hat{\sigma}}{\sigma^*} \qquad (19)$$

The ratio on the left hand side of equation (19) measures the addition to returns which would compensate the investor for a less efficient covariance matrix. (We report estimates of these ratios in Tables 4 –6 below.)

5. Empirical Results

5.1 Data and estimation

We estimate[iv] the A-DCC models using daily returns from three major European stock market price indices, valued in US dollars: FTSE 100 (London); DAX 30 (Frankfurt); and CAC 40 (Paris). Returns are calculated as log differences and do not include dividends. No currency hedging is implemented. Trading hours for the London, Frankfurt and Paris stock exchanges overlap imperfectly, so to ensure synchronous prices we take index values at London 16:00 time (Frankfurt and Paris 17:00 time).[v] The models were estimated using the first 2700 observations of the 3523 size sample, leaving the remaining 823 observations for testing. The estimation period runs from 1 January 1992 to 6 May 2002, and predictive power for portfolio formation is tested over the three years from 7 May 2002 to 4 July 2005.

Martens and Poon (2001) point out the importance of synchronous data for studies of daily conditional correlation and volatility spillover. Substantial mis-estimation of returns correlation and spillovers can result from a failure to account for timing differences at the daily level. Correlations will be under-estimated, and estimated spillover patterns changed, if non-synchronous daily data are used in correlation models. By synchronizing prices we ensure that estimated spillovers and correlations more accurately expose real-time interactions, rather than representing lags in information flows, misalignments in trading, or mismatched data collection.

Table 2 reports key features of the data sample. Average returns are highest for the DAX 30 index, which also displays the largest standard deviation and degree of skewness. The FTSE 100 has annualized returns around two per cent lower than the DAX 30 and the least variance of the three markets. CAC 40 exhibits medium level of average return and volatility compared with the two. All three daily returns series show considerable non-normality manifested in negative skewness and excess kurtosis. Average skewness is -0.11, and kurtosis, 5.35.

[INSERT TABLE 2 HERE]

A graph of the daily returns in Figure 2 clearly shows clusters of volatility, where groups of large or small changes persist for a number of periods. More frequent periods of turbulence are evident from 1998 to 2003 (when volatility begins to drop off) and volatility patterns are clearly related, as might be expected among such closely-aligned equity markets.

[INSERT FIGURE 2 HERE]

Table 3 reports estimates for a total of six bivariate A-DCC models: two for each of the three pairs of returns series (London-Frankfurt, London-Paris and Frankfurt-Paris). We compute a benchmark without volatility spillover and an alternative with volatility spillover for each market pair.

[INSERT TABLE 3 HERE]

The top portion of Table 3 reports parameter estimates and standard errors for the variance equations, and the lower portion reports estimates of the parameters of the correlation matrices. With the exception of statistically insignificant volatility spillover parameter from Paris to Frankfurt, all parameters have the expected (positive) sign. All models show evidence of high levels of volatility persistence, with parameters on lagged variables summing to just below one. Estimates from the benchmark model (GJR (1,1,1)) show significant asymmetry effects (δ) in all three market. Furthermore, the asymmetric effect is strongest for the UK market, dominating the symmetric volatility shock component.

In terms of volatility spillover (γ), we find significant transmission from Frankfurt and Paris to London, and from Frankfurt to Paris, so we observe that Frankfurt is unaffected by lagged news shocks from the other markets in this sample. Although all volatility spillover coefficients are small in magnitude, Frankfurt to Paris shocks are greatest in magnitude. Estimates of volatility spillover effects from London to the continental markets are positive, but smaller and poorly estimated, a surprising result given the relative sizes of the markets.[vi]

Figure 3 presents graphs of estimated conditional variance series for the volatility spillover model. Conditional variances confirm earlier observations (Figure 2) that the three markets have become increasingly volatile since early 1997, possibly in connection with the beginning of the Asian crisis. The German market shows the most, and the UK market, the least, volatility over the whole sample.[vii]

[INSERT FIGURE 3 HERE]

Conditional correlation parameter estimates (ϕ, η, φ) for the benchmark and alternative models differ only slightly. This result should help us isolate the effects of volatility spillovers on the portfolio selection process. The Frankfurt-Paris combination displays the most persistence (η) in conditional correlations[viii]. Asymmetric effects in conditional correlations are smaller than their symmetric counterparts in all three combinations, with the London-Frankfurt pair exhibiting the largest asymmetric effect and London-Paris the smallest. Kearney and Poti (2005) report weak asymmetry effects for conditional correlations among Euro-zone equity markets.

Figure 4 graphs the conditional correlation series from the volatility spillover model, showing that time-variation in conditional correlation is an important feature of the second-moment dynamics.

[INSERT FIGURE 4 HERE]

5.2 Portfolio Standard Deviations

We forecast from estimated benchmark and volatility spillover models, generate predicted covariances $\left\{H_t^i\right\}_{i=1}^2$ at 1, 5, 10 and 20-step horizons, and compute optimal portfolio weights $\left\{\mathbf{w}_t^{i,k}\right\}$, from equation (15), for two equity markets and the risk-free asset. This procedure simulates realized portfolio returns from the remaining (823) observations of the data set:

$$\pi_t^{i,k} = \mathbf{w}_t^{i,k'}\mathbf{r}_t. \tag{20}$$

where $i = 1, 2$ corresponds to the benchmark and alternative portfolios and k indicates the vector of expected returns.

As outlined in Section 4, we expect the more efficient covariance model to produce a lower portfolio risk for any required return. (Here, $\mu_o = 1.$) Tables 6-8 set out realized standard deviations for the benchmark and volatility spillover models for London-Frankfurt, London-Paris and Frankfurt and Paris, respectively. We report volatility ratios for daily, weekly, ten-day and monthly forecasting and rebalancing horizons. In each row, we set the least standard deviation equal to 100, and then report the larger standard deviation as a proportional increase over the smaller. The last row in each column reports the probability weighted average of the whole column of standard deviations, where the weighting applied to each row is given by the Bayesian probabilities associated with each return relative for that data. (These are graphed in Figures 1.) For example, in Table 4, which gives the standard deviations for the London-Frankfurt market pairing, the last row under 10-steps-ahead forecasts shows that the portfolio standard deviation for the benchmark model was 1.52 per cent bigger than the standard deviation for portfolios computed using the volatility spillover model.[ix] On a weighted average basis, the volatility spillover model performs better than the benchmark at every forecast horizon, and for all market pairs.

[INSERT TABLES 4,5 AND 6 HERE]

In terms of economic value, the relative efficiency gains are not large. The greatest efficiency gain for the volatility spillover model on a weighted average basis is for the 5-step-ahead forecast model for London-Frankfurt, where the benchmark model standard deviation is 101.52, meaning that neglecting volatility spillover effects increases portfolio risk by about 1.52 per cent of standard deviation. Or, in terms of risk-adjusted returns, if investors who allow for volatility spillover (σ^*) are receiving 10 per cent returns $(\mu^* = 10)$, then investors who forecast using the benchmark $(\hat{\sigma})$ would need $\hat{\mu} = 10.152$ per cent returns to equalize the return to risk ratio such that $\frac{\mu_0^*}{\sigma^*} = \frac{\hat{\mu}_0}{\hat{\sigma}}$. The efficiency gains to predicting covariance using the volatility spillover model thus represent risk-free return improvements around 15 basis points on a ten per cent return portfolio. Nevertheless these small efficiency improvements do not disappear at longer forecast horizons, as can be seen from weekly, fortnightly and monthly portfolio standard deviations. In fact as Figures 2. 1 – 2. 4. (in Appendix 2) suggest, gains seem to peak between weekly and monthly rebalancing forecasting horizons before they start to diminish at longer horizons where the forecasts converge to unconditional values.

5.3 Diebold-Mariano Tests

We test the statistical significance of any risk reductions by the Diebold and Mariano (1995) method for distinguishing between forecasted volatilities. The Diebold-Mariano test statistic is the estimated difference between realised variance for the benchmark symmetric and alternative asymmetric models, calculated as

$$v_t^k = \left(\pi_t^{1,k}\right)^2 - \left(\pi_t^{2,k}\right)^2, \tag{21}$$

forming 11 series for each market pairing, $\left\{v_t^k\right\}_{k=1}^K$. Under the null hypothesis the expected value of $\left\{v_t^k\right\}_{k=1}^K$ is zero, such that including volatility spillover effects in covariance models does not reduce portfolio variance[x].

We conduct a joint test of this null hypothesis using a GMM estimate of the parameter β from the regression $V_t = \beta\iota + \varepsilon_t$. We first stack all values of $\left\{v_t^k\right\}_{k=1}^K$ and estimate a single moment condition for the coefficient β. We also construct a system of $k = 11$ moment conditions, one for each v_t^k, again restricting the system to a single estimate of β. We report t-tests of the null hypothesis that $\beta = 0$, using the robust Newey-West standard errors from the GMM estimation. Table 7 reports results for each market pairing and forecast horizon. The volatility spillover model does not get unqualified support, with significant *negative* values for β at the longer horizon tests of the London-Paris pair. But the majority of tests of β (including short-horizon forecasts for London and Paris) reject the null hypothesis and confirm that portfolio variances are significantly lower when volatility spillover model is modelled in the conditional covariance matrix.

[INSERT TABLE 7 HERE]

5.5 Stochastic dominance tests

Tests for second-degree stochastic dominance can tell us whether risk-reductions are likely to matter to any risk averse investor. Consider two samples of portfolio returns $\{Y_I\}_{I=1}^{M}$ and $\{X_I\}_{I=1}^{M}$ with cumulative distributions (CDFs) G and F. Second degree stochastic dominance (SD2) establishes the conditions under which any risk averse agent prefers one portfolio to another: Portfolio Y will be preferred to portfolio X by any agent whose utility over portfolio returns $U(\pi)$ obeys $U^{'}(\pi) \geq 0$, $U^{''}(\pi) \leq 0$ when $\int_{o}^{\pi} G(t)dt \leq \int_{o}^{\pi} F(t)dt$ for all π.

Barrett and Donald (2003) derive a Kolmogorov-Smirnov style test for stochastic dominance of any degree, evaluating the CDFs at all points in the support. This technique avoids the problem of choosing an arbitrary set of comparison points which can result in inconsistency.[xi] The null hypothesis to be tested is that G (weakly) dominates F to the second degree, against the alternative that it does not. From random samples of equal size, the test statistic is given by:

$$\hat{S}_2 = (\frac{M}{2})^{1/2} \sup_{\pi}(I_2(\pi;\hat{G}_M) - I_2(\pi;\hat{F}_M)), \qquad (22)$$

where $I_2(\pi;\hat{G}_M) = \frac{1}{M}\sum_{i=1}^{M} 1(Y_i \leq \pi)(\pi - Y_i), \quad I_2(\pi;\hat{F}_M) = \frac{1}{M}\sum_{i=1}^{M} 1(X_i \leq \pi)(\pi - X_i),$ and $1(\cdot)$ is the indicator function, returning the value 1 when $(X_i \leq \pi)$ and zero otherwise. Under the null hypothesis, the test statistic is no greater than zero. Bald comparisons between CDFs or their integrals are subject to non-trivial sampling error when the population density is unknown, so we need some approximation to the sampling distribution, here derived by block bootstrapping.

We follow Linton, Maasoumi and Whang (2002), and Lim, Maasoumi and Martin (2004), and adjust the bootstrapping method to keep underlying serial dependence intact. Block size is set at $B = 28$ where $B = \alpha\sqrt{T}$, α is a positive constant and T is sample size, here 823.[xii] Each set of portfolio returns is divided into overlapping blocks of size B, then a random selection is made, choosing sufficient (contemporaneous) blocks to create a distribution of size T. Bootstrap samples are used to build an empirical distribution of the test statistic.

We report results for one-step-ahead forecasts and two-steps-ahead forecasts, since 5 and other multi-step forecasting generates samples too small for reliable testing. We conduct the test on a weighted average of returns to the k portfolios, where weights are the Bayesian probabilities shown in Figure 1. Results in Table 8 show that the null hypothesis that the benchmark model dominates the volatility spillover model can be rejected in all but one of six tests.

[INSERT TABLE 8 HERE]

6. Conclusions

We present a valuation of one aspect of time-varying volatility, volatility spillover, from the perspective of an investor choosing a two-asset equity portfolio from among equity markets in London, Frankfurt and Paris. By studying the conditional second moments of the London, Frankfurt and Paris equity markets in an A-DCC set-up, we isolate portfolio risk reductions that can be attributed to forecasting volatility spillovers between these markets. We combine these covariance forecasts with an encompassing range of expected returns relatives and isolate the impact of spillover effects on portfolio performance.

Although relatively small in magnitude, volatility spillover estimation improves the out-of-sample covariance forecasts and, consequently, portfolio performance. Standard deviations of realized portfolio returns are lower for volatility spillover models, across all market choices and forecast horizons. Further, estimates of lower portfolio risk are confirmed by Diebold-Mariano tests, which show that, for the majority of cases, reductions in portfolio risk in the volatility spillover model are statistically significant and do not disappear as the forecasting horizon increases from daily to monthly. In addition, the distributions of realized portfolio returns from the volatility spillover models stochastically dominate returns from the benchmark model in five of six cases according to Barrett-Donald (2003) tests.

Failing to incorporate volatility spillover effects in variance equations makes portfolio standard deviations about 1-1.5% per cent higher. While such losses are not dramatic, they could be eliminated without necessarily incurring higher rebalancing costs and without additional portfolio risk.

Appendix 1

A-DCC Estimation

We follow Engle (2002) and estimate the models in two steps. Assuming that the standardized residuals ε_t are conditionally normally distributed so that $\varepsilon_t \mid \boldsymbol{\psi}_{t-1} \sim N(0, \mathbf{R}_t)$, the log likelihood function for the vector of returns $\mathbf{r}_t$, can be expressed as

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + \log|H_t| + \mathbf{u}_t' H_t^{-1}\mathbf{u}_t\right). \tag{1.1}$$

Now let the mean parameters, $\mathbf{c}$, and the univariate GARCH parameters in $\mathbf{D}_t$ be represented by ψ, and the conditional correlation parameters in $\mathbf{R}_t$ by ζ. The log likelihood can be written as the sum of a volatility part and a correlation part:

$$L(\psi, \zeta) = L_V(\psi) + L_C(\zeta \mid \psi), \tag{1.2}$$

where the volatility term is

$$L_V(\psi) = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|\mathbf{D}_t| + \mathbf{u}_t'\mathbf{D}_t^{-2}\mathbf{u}_t\right), \tag{1.3}$$

and the correlation component is

$$L_C(\zeta \mid \psi) = -\frac{1}{2}\sum_{t=1}^{T}\left(-\varepsilon_t'\varepsilon_t + \log|\mathbf{R}_t| + \varepsilon_t'\mathbf{R}_t^{-1}\varepsilon_t\right). \tag{1.4}$$

The procedure is further simplified by recognizing that the volatility part of the log likelihood is just the sum of the individual univariate GARCH likelihoods:

$$L_V(\psi) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n}\left(\log(2\pi) + \log(h_{i,t}) + \frac{u_{it}^2}{h_{i,t}}\right). \tag{1.5}$$

The two-step estimation method involves maximizing each univariate GARCH term separately, standardizing the returns by estimated standard deviations and then jointly estimating elements of $\mathbf{R}_t$ by maximizing the correlation component of the log likelihood $L_C(\psi, \zeta)$. We maximize log likelihoods numerically using the Max SQP procedure in OX 3.4. This procedure implements a sequential quadratic programming technique to maximise a non-linear function subject to non-linear constraints.

Although the assumption of normality in ε_t is convenient for estimation, it is not necessary for consistency, since quasi-maximum likelihood arguments apply as long as the conditional mean and variance equations are correctly specified (Hamilton, 1994, p.126). However the standard errors need to be adjusted according to the method described for the univariate GARCH volatility equations. Standard errors for the correlation parameters require a more complicated process explained in Engle (2002).

APPENDIX 2

[INSERT FIGURES 2.1-2.3 HERE].

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TABLES and GRAPHS

Table 1: Pairs of expected returns

Range of expected returns used to calculate portfolio weights where $\mu = \left[\sin\frac{\pi j}{20}, \cos\frac{\pi j}{20}\right]$

j	μ(1)	μ(2)	θ
0	0.000	1.000	0
1	0.156	0.988	0.1
2	0.309	0.951	0.2
3	0.454	0.891	0.3
4	0.588	0.809	0.4
5	0.707	0.707	0.5
6	0.809	0.588	0.6
7	0.891	0.454	0.7
8	0.951	0.309	0.8
9	0.988	0.156	0.9
10	1.000	0.000	1

Table 2: Summary statistics- daily stock index returns, % p.a.

Daily returns calculated as $r_t = 100\ln(p_t / p_{t-1})$ from price indices synchronized at London 16:00 time, 2 January 1992 to 4 July 2005. All indices are in USD, unhedged. Data supplied by Datastream.

	FTSE 100	DAX 30	CAC 40
Mean	5.1	7.3	6.1
Std. Dev.	16.4	21.6	20.0
Skewness	0.03	-0.23	-0.08
Kurtosis	5.6	5.8	5.0
Jarque-Bera	957.6	1205	570.8
Observations	3523	3523	3523

Table 3: Parameter estimates, A-DCC models.

Columns show estimated parameters for GJR ADCC and GJR-ADCC with Volatility Spillover conditional covariance models. P-values are in brackets. GJR and GJR(volatility spillover) equations were computed for every market using de-meaned returns, and then standardised residuals were used to compute estimates for the ADCC and ADCC(volatility spillover) models. Estimated over 2700 daily returns, sampling 2/1/1992 – 6/5/2002.

Parameter	London-Frankfurt				London-Paris				Frankfurt-Paris			
	GJR (1,1,1)		GJR (1,1,1) Volatility spillover		GJR (1,1,1)		GJR (1,1,1) Volatility spillover		GJR (1,1,1)		GJR (1,1,1) Volatility spillover	
	UK	DE	UK	DE	UK	FR	UK	FR	DE	FR	DE	FR
ω	0.0272 (0.079)	0.0251 (0.028)	0.0259 (0.018)	0.0248 (0.048)	0.0272 (0.079)	0.0246 (0.099)	0.0236 (0.044)	0.0259 (0.220)	0.0251 (0.028)	0.0246 (0.099)	0.0259 (0.042)	0.0297 (0.079)
α	0.0162 (0.304)	0.0428 (0.001)	0.0017 (0.894)	0.0431 (0.002)	0.0162 (0.304)	0.0210 (0.006)	0.0021 (0.862)	0.0186 (0.063)	0.0428 (0.001)	0.0210 (0.006)	0.0436 (0.004)	0.0013 (0.887)
β	0.9242 (0.000)	0.9220 (0.000)	0.9160 (0.000)	0.9212 (0.000)	0.9242 (0.000)	0.9426 (0.000)	0.9168 (0.000)	0.9397 (0.000)	0.9220 (0.000)	0.9426 (0.000)	0.9223 (0.000)	0.9341 (0.000)
δ	0.0595 (0.000)	0.0352 (0.042)	0.0665 (0.000)	0.0334 (0.053)	0.0595 (0.000)	0.0363 (0.011)	0.0660 (0.000)	0.0329 (0.020)	0.0352 (0.042)	0.0363 (0.011)	0.0362 (0.036)	0.0461 (0.0018)
γ			0.0133 (0.033)	0.0021 (0.819)			0.0151 (0.077)	0.0088 (0.374)			-0.0021 (0.803)	0.0185 (0.026)
ϕ	0.0229		0.0216		0.0317		0.0317		0.0318		0.0321	
η	0.9391		0.9412		0.9149		0.9115		0.9609		0.9600	
φ	0.0241		0.0278		0.0143		0.0182		0.0161		0.0187	

Table 4: Portfolio standard deviations, London – Frankfurt

Notes: Smallest portfolio standard deviation for each pair of expected returns is scaled to 100. Values over 100 represent proportional increases in standard deviations. The final row is a weighted average of the preceding rows where weights are the Bayesian probabilities reported in Figure 1.

	One-step-ahead forecasts		**Five-steps-ahead forecasts**		**Ten-steps-ahead forecasts**		**Twenty-steps-ahead forecasts**	
J	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER
0.00	100.00	100.35	102.12	100.00	101.24	100.00	100.00	100.30
1.00	100.00	100.24	100.90	100.00	100.23	100.00	100.00	100.03
2.00	100.52	100.00	100.00	100.22	100.17	100.00	100.74	100.00
3.00	100.85	100.00	100.37	100.00	101.17	100.00	100.43	100.00
4.00	100.12	100.00	102.68	100.00	103.10	100.00	100.00	100.02
5.00	100.00	100.06	103.10	100.00	102.58	100.00	100.31	100.00
6.00	100.13	100.00	101.31	100.00	100.49	100.00	100.62	100.00
7.00	100.35	100.00	100.37	100.00	100.36	100.00	100.77	100.00
8.00	100.59	100.00	100.40	100.00	101.27	100.00	100.99	100.00
9.00	100.83	100.00	100.78	100.00	102.20	100.00	101.32	100.00
10.00	101.03	100.00	101.25	100.00	102.92	100.00	101.67	100.00
	100.31	**100.00**	**101.39**	**100.00**	**101.52**	**100.00**	**100.49**	**100.00**

Table 5: Portfolio standard deviations, London – Paris

Notes: Smallest portfolio standard deviation for each pair of expected returns is scaled to 100. Values over 100 represent proportional increases in standard deviations. The final row is a weighted average of the preceding rows where weights are the Bayesian probabilities reported in Figure 1.

	One-step-ahead forecasts		**Five-steps-ahead forecasts**		**Ten-steps-ahead forecasts**		**Twenty-steps-ahead forecasts**	
J	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER
0.00	100.00	100.17	104.04	100.00	102.27	100.00	101.81	100.00
1.00	100.00	100.31	102.37	100.00	101.39	100.00	100.74	100.00
2.00	100.07	100.00	100.00	100.25	100.00	100.38	100.00	100.22
3.00	100.70	100.00	100.00	101.51	100.00	101.37	100.00	100.55
4.00	100.38	100.00	100.48	100.00	100.00	100.62	100.00	100.27
5.00	100.01	100.00	102.41	100.00	100.72	100.00	100.50	100.00
6.00	100.19	100.00	101.83	100.00	100.93	100.00	100.70	100.00
7.00	100.32	100.00	100.15	100.00	100.09	100.00	100.07	100.00
8.00	100.49	100.00	100.00	101.23	100.00	100.90	100.00	100.84
9.00	100.70	100.00	100.00	101.99	100.00	101.71	100.00	101.63
10.00	100.89	100.00	100.00	102.24	100.00	102.27	100.00	102.16
	100.28	**100.00**	**100.73**	**100.00**	**100.02**	**100.00**	**100.05**	**100.00**

Table 6: Portfolio standard deviations, Frankfurt – Paris

Notes: Smallest portfolio standard deviation for each pair of expected returns is scaled to 100. Values over 100 represent proportional increases in standard deviations. The final row is a weighted average of the preceding rows where weights are the Bayesian probabilities reported in Figure 1.

	One-step-ahead forecasts		**Five-steps-ahead forecasts**		**Ten-steps-ahead forecasts**		**Twenty-steps-ahead forecasts**	
J	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER	GJR(1,1,1)	GJR(1,1,1) VOLATILITY SPILLOVER
0.00	100.66	100.00	100.41	100.00	103.17	100.00	100.64	100.00
1.00	100.62	100.00	100.18	100.00	102.84	100.00	100.35	100.00
2.00	100.53	100.00	100.00	100.09	102.17	100.00	100.00	100.05
3.00	100.34	100.00	100.00	100.26	100.87	100.00	100.00	100.42
4.00	100.00	100.00	100.32	100.00	100.06	100.00	101.17	100.00
5.00	100.00	100.00	101.02	100.00	103.64	100.00	103.59	100.00
6.00	100.91	100.00	100.24	100.00	100.92	100.00	100.13	100.00
7.00	100.13	100.00	100.14	100.00	100.32	100.00	101.33	100.00
8.00	100.42	100.00	100.90	100.00	101.38	100.00	102.16	100.00
9.00	100.58	100.00	101.19	100.00	102.12	100.00	102.21	100.00
10.00	100.64	100.00	101.27	100.00	102.57	100.00	102.09	100.00
	100.36	**100.00**	**100.51**	**100.00**	**101.40**	**100.00**	**101.48**	**100.00**

Table 7: Diebold-Mariano tests for portfolio variance equality.

GMM estimates of coefficients and robust p-values for the test that difference in portfolio variances (u) is jointly zero for all expected returns. An asterisk indicates rejection at the 1% (***), 5 % (**) or 10 % (*) level. Significant positive values for β indicate that portfolio variances are less under the volatility spillover model, negative values indicate that they are more.

	Single moment condition				Multiple moment conditions			
Market pairing	1 step ahead	5-steps ahead	10 steps ahead	20-steps ahead	1 step ahead	5-steps ahead	10 steps ahead	20-steps ahead
London – Frankfurt	0.009** (0.02)	0.152* (0.07)	0.315** (0.01)	0.174* (0.10)	0.002** (0.02)	0.060*** (0.00)	0.122* (0.06)	0.130 (0.00)
London - Paris	0.0079** (0.05)	0.047 (0.34)	-0.030 (0.44)	-0.023 (0.72)	0.001* (0.10)	0.031*** (0.00)	-0.02*** (0.00)	-0.017*** (0.00)
Frankfurt - Paris	0.010** (0.021)	0.047 (0.34)	0.291*** (0.01)	0.552* (0.10)	0.006*** (0.00)	0.032*** (0.00)	0.159*** (0.01)	0.386*** (0.00)

Table 8: Stochastic Dominance relations, one-step-ahead and two-steps-ahead forecasts. Bootstrapped P-values for tests of second degree stochastic dominance relations between pairs of portfolio returns where portfolios are formed on the basis of one- or two-step-ahead forecasts from the benchmark and volatility spillover models. Portfolio returns are a weighted average over all values of θ where weights are the Bayesian probabilities reported in Figure 1. An asterisk indicates rejection at the 1%(***), 5 % (**) or 10 % (*) level when the reverse null is not rejected. Failure to reject both nulls is inconclusive.

	1-step-ahead		2-steps ahead	
	Null Hypothesis		Null Hypothesis	
Market pairing	Volatility Spillover dominates Benchmark	Benchmark dominates Volatility Spillover	Volatility Spillover dominates Benchmark	Benchmark dominates Volatility Spillover
London Frankfurt	0.92	0.07*	0.92	0.07*
London Paris	0.93	0.00***	0.88	0.04**
Frankfurt Paris	0.06*	0.95	0.74	0.00***

Figure 1: Probability density functions

Empirical Bayesian estimate of the probability of assumed expected returns such that each pair is $\cos(\frac{\pi}{2}\theta)$ and $\sin(\frac{\pi}{2}\theta)$. Numerical values are listed in Table 5.

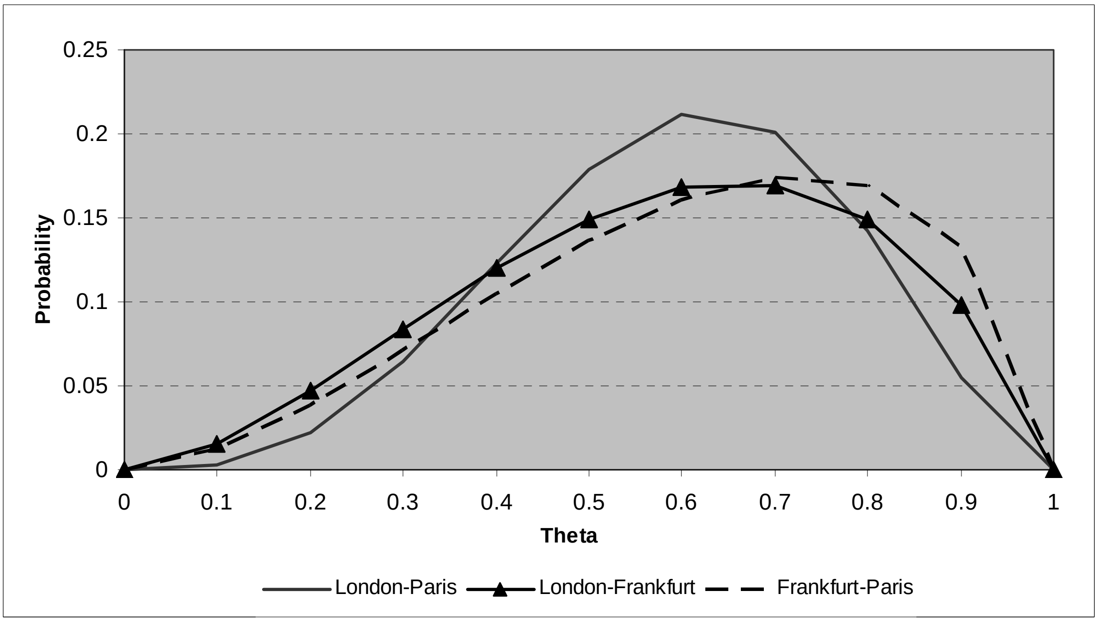


Figure 2: Daily stock index returns, 2 January 1992 – 4 July 2005.
De-meaned daily equity index returns: London (FTSE), Frankfurt (DAX), Paris (CAC)

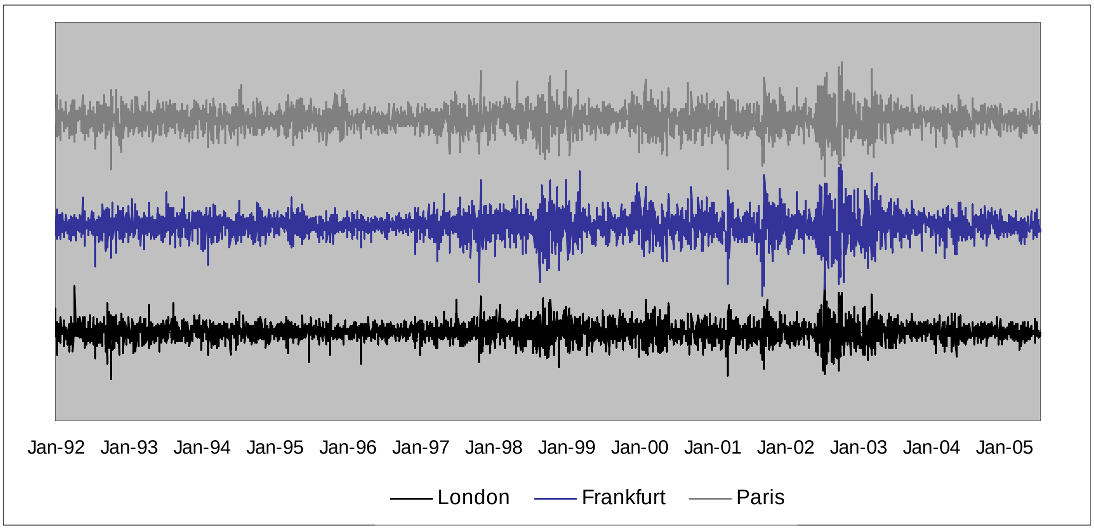


Figure 3: Daily conditional variances, 2 January 1992 – 8 May 2002.
In-sample conditional variance predictions from GJR(1,1,1) model.

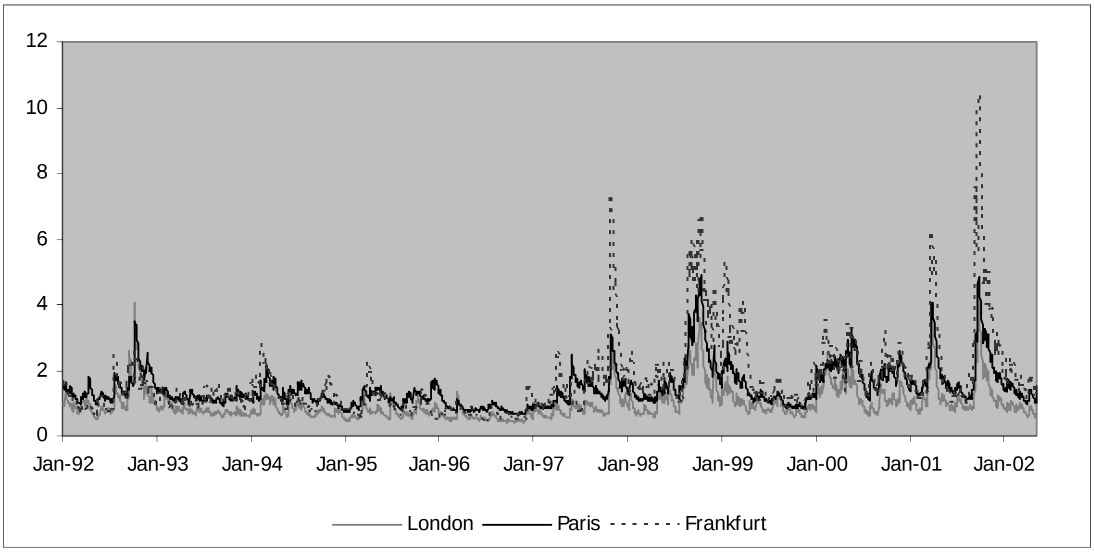


Figure 4: Daily conditional correlations, 2 January 1992 – 8 May 2002.
In sample conditional correlation predictions from GJR(1,1,1) ADCC model.

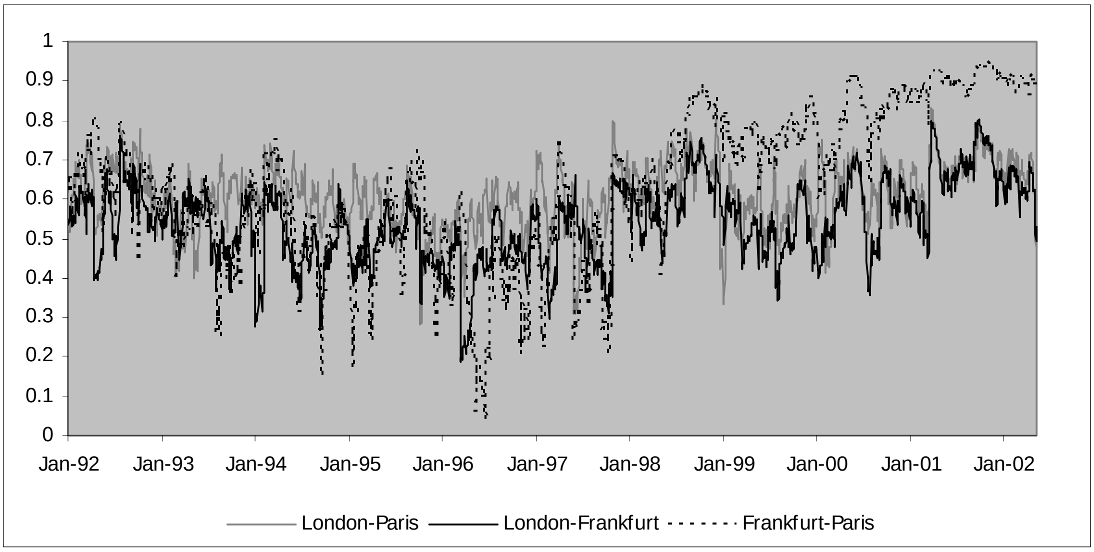


Figure 2.1: Loss of portfolio efficiency as forecasting horizon increases, London-Frankfurt.

Columns measure increase in portfolio standard deviation for benchmark over volatility spillover model, where the volatility spillover portfolio standard deviation is scaled to 100, and the benchmark is a proportional increase.

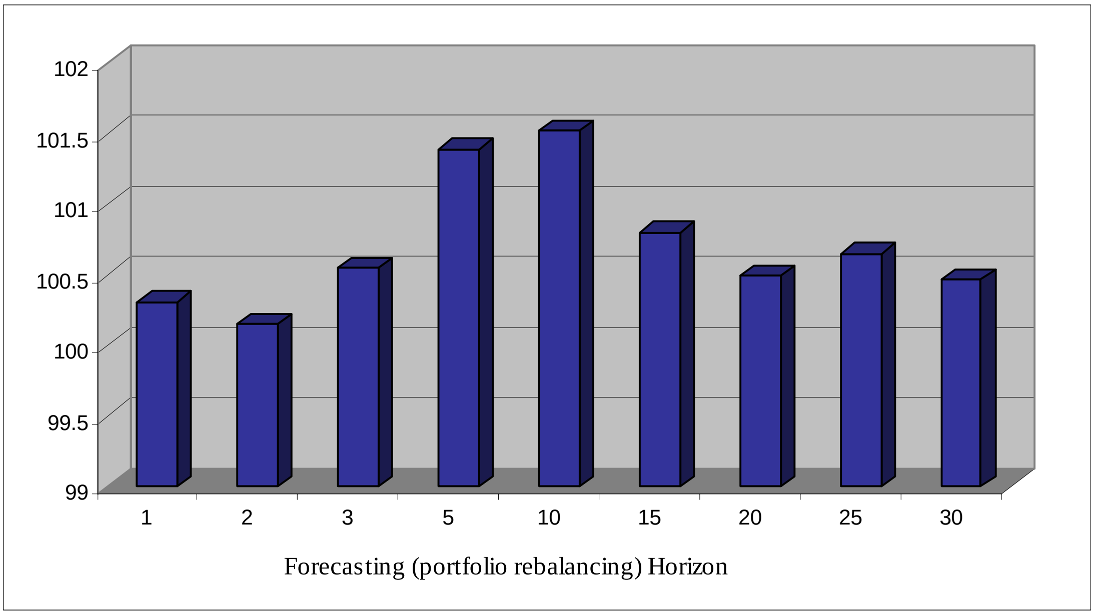


Figure 2.2: Loss of portfolio efficiency as forecasting horizon increases, London-Paris.

Columns measure increase in portfolio standard deviation for benchmark over volatility spillover model, where the volatility spillover portfolio standard deviation is scaled to 100, and the benchmark is a proportional increase.

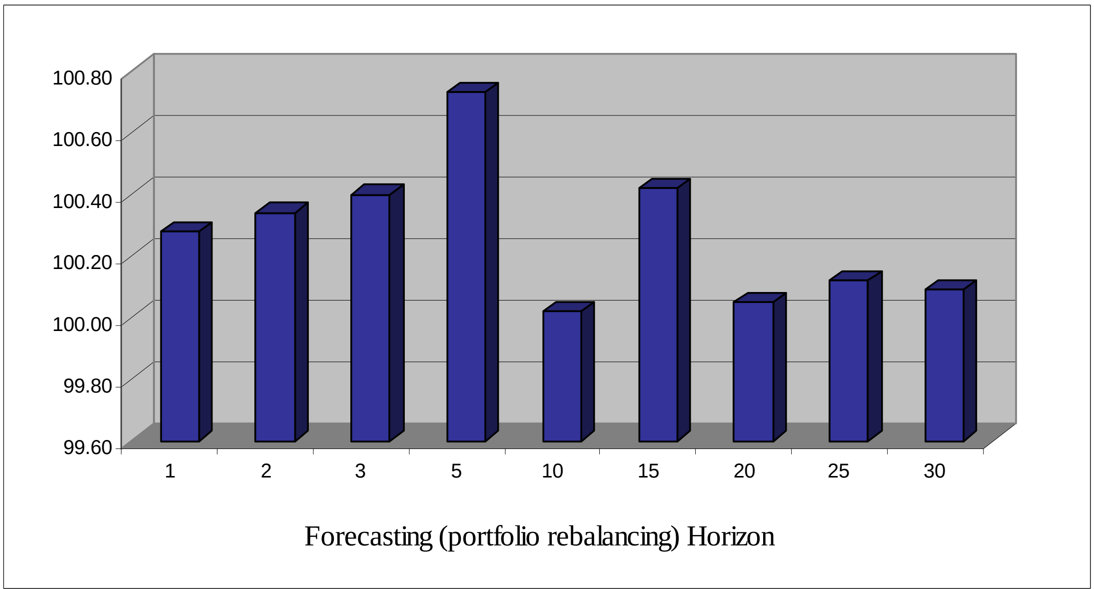
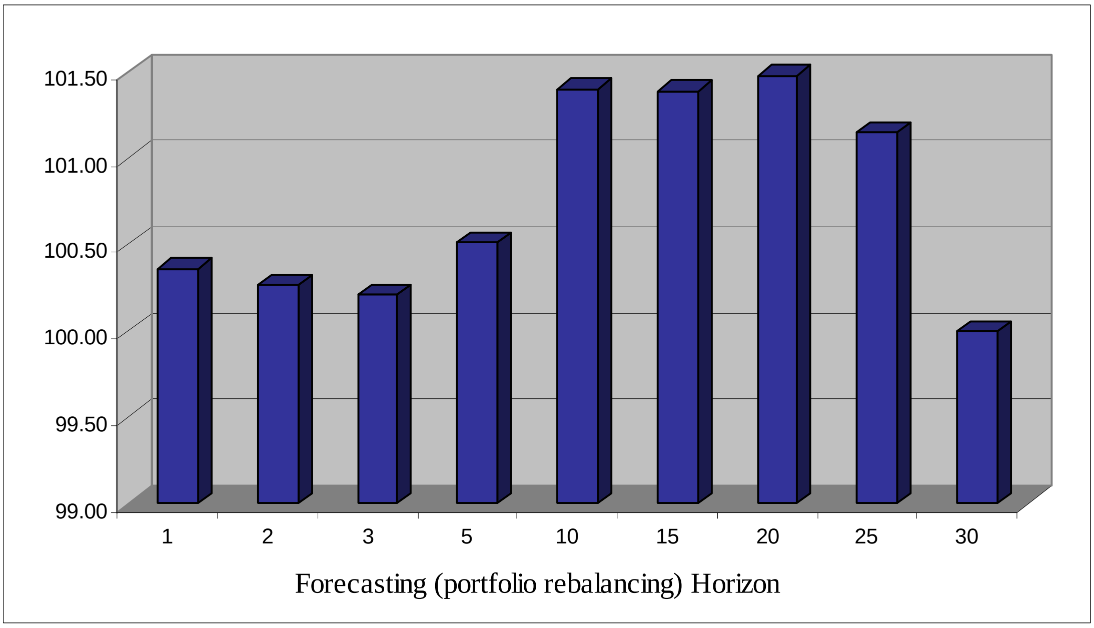


Figure 2.3: Loss of portfolio efficiency as forecasting horizon increases, Frankfurt-Paris.

Columns measure increase in portfolio standard deviation for benchmark over volatility spillover model, where the volatility spillover portfolio standard deviation is scaled to 100, and the benchmark is a proportional increase.



Notes

[i]Volatility asymmetry was first introduced to the financial literature by Black (1976), and has since become a well-documented feature of volatility patterns hence a failure to account for asymmetries may result in distorted estimates of volatility spillover. See, for example, Nelson (1991), Koutmos (1992), Poon and Taylor, (1992), Campbell and Hentschel (1992), Bekaert and Wu (2000), and Wu (2001).

[ii] Glosten, Jagannathan and Runkle (1993).

iii Engle (2002) shows that a Bollerslev-Wooldridge (1992) covariance matrix gives consistent standard errors for the estimates.

[iv] We use a two-step estimation process following Engle (2002). Appendix 1 sets out details of the maximum likelihood procedure.

v Datastream supplies London 16:00 data for a group of major markets. Codes for the series described here are FOOTC16(PI) , DAXIN16(PI), and CAC4016(PI).

[vi] Harju and Hussain (2005) find that the UK and German markets respond to each other's innovations using intra-daily data.

viiWe note that daily returns to the DAX 30 have the largest unconditional variance of the three indices.

[viii] Estimated unconditional correlations are London-Frankfurt 0.77, London-Paris, 0.69 and Frankfurt-Paris, 0.66.

[ix] Appendix 2 presents results for forecasting horizons of 15, 25 and 30 days.

[x] Following Engle and Colacito (2004), we also calculated a heteroscedasticity-adjusted measure of the Diebold-Mariano test-statistic and conduct the same hypothesis tests. Results, not reported here, were substantially unchanged.

xiTo make the test tractable, each pairing of returns distributions was shifted to the right by the same fixed positive amount, sufficient to ensure a lower bound of zero for a support $\pi[0,\tilde{\pi}]$ where $\tilde{\pi} < \infty$.

xii Before forming the blocks, the returns from each portfolio are weighted to adjust for the number of times they are sampled in the overlapping blocks. The weights that follow the rule:

$$\omega_t = \begin{cases} t/B : t < B \\ 1 : B \le t \le T - B + 1 \\ (T - t + 1)/B : T - B + 2 \le t \le T \end{cases},$$

where ω_t is the weight and *B* is block size.