Kalotychou, E., Staikouras, S. & Zhao, G. (2014). The role of correlation dynamics in sector allocation. Journal of Banking & Finance, 48, pp. 1-12. doi: 10.1016/j.jbankfin.2014.06.025

The Role of Correlation Dynamics in Sector Allocation

Elena Kalotychou [a,*], Sotiris K. Staikouras [a,**], Gang Zhao [b,***]

[a] *Cass Business School, City University, London EC1Y 8TZ, UK*
ALBA Graduate Business School, Athens 16671, Greece
[b] *School of Management, University of Bath, Bath BA2 7AY, UK*

Abstract

This paper assesses the economic value of modelling conditional correlations for mean-variance portfolio optimization. Using sector returns in three major markets we show that the predictability of models describing empirical regularities in correlations such as time-variation, asymmetry and structural breaks leads to significant performance gains over the static covariance strategy. Investors would be willing to pay a fee of up to 983 basis points to switch from the static to the dynamic correlation portfolio and about 100 basis points more for capturing asymmetries and shifts in correlations. The gains are robust to the crisis, transaction costs and are most pronounced for monthly rebalancing.

JEL Classification: *C32, C52, C53, F21, G11, G15*

Keywords: Correlation timing; Asymmetry; Structural break; Portfolio performance; Transaction costs.

* Corresponding author. Tel.: +44 – 20 7040 5259; *Email address*: e.kalotychou@city.ac.uk.
** Tel.: +44 – 20 7040 0165; *Email address*: sks@city.ac.uk.
*** Tel.: +44 – 1225 383968; *Email address*: gz249@bath.ac.uk.
The authors would like to thank participants at the IFABS Conference 2012, Valencia, the FMA European Meeting 2010, Hamburg, the FMA Annual Meeting 2009, Reno, the Multinational Finance Society Conference 2009, Crete, the FMA European Meeting 2009, Turin, the British Accounting Association Annual Conference 2009, Dundee, the 28th International Symposium on Forecasting 2008, Nice, and seminar participants at Cass Business School for useful comments on earlier versions of the paper. Special thanks to Spyros Mesomeris, Director of the Deutsche Bank Quantitative Strategy Team for constructive discussions and to the two anonymous referees for their helpful comments. The usual disclaimer applies.

1. INTRODUCTION

Volatility and correlation among asset returns are central to portfolio allocation and risk management. A burgeoning literature in financial economics has focused on time series models for asset return volatility and their comovement. Various Multivariate Generalized Autoregressive Conditional Heteroskedasitciy (MGARCH) models, such as the Dynamic Conditional Correlation (DCC) model of Engle (2002), have been developed to capture the well-documented time variation in correlations and other dynamic aspects of comovement between financial risks.

Correlation asymmetry is one regularity that has been widely found in the second moment of equity returns although the economic rationale behind the clustering of bad news is relatively less researched. Longin and Solnik (2001) show that correlations rise in bear markets. Ang and Bekaert (2002) document the presence of a high volatility-high correlation regime in the US, UK and Germany, which coincides with a bear market and refutes the benefits of international diversification. Cappiello et al. (2006) find support for asymmetry in the correlations of international equity and bond returns, while Bekaert et al. (2005) attribute jumps in cross-market correlations during crises to dependence on a common factor.

Structural breaks have also been documented in correlations and can have a fundamental impact on global markets. Billio and Pelizzon (2003) find that correlations of European markets increased following the European Monetary Union (EMU). Longin and Solnik (2001) suggest that the level and structure of global correlations shifted considerably over time. Cappiello et al. (2006) find significant correlation rise post-EMU not mirrored in conditional volatility indicating greater market integration.

There has been growing consensus that employing static long-term historical relationships between assets in portfolio management may lead to substantial underperformance in the face of increased market volatility, changing correlations and frequent regime shifts. This study assesses the economic merit of forecasting return correlation dynamics for sector allocation. We seek to generate profitable trading strategies through correlation predictability, that is, correlation timing, a notion introduced by Engle and Colacito (2006). The contribution to the literature is twofold. First, we investigate the economic value of capturing stylized facts of asset correlations such as time variation, asymmetry and structural breaks. To do so we employ a dynamic mean-variance framework, which incorporates investor risk aversion, transaction costs and different rebalancing frequencies. Second, as the value and viability of market timing strategies during the recent financial crisis has often been questioned, we empirically examine the benefits of correlation timing over the crisis period (2007 – 2009) and its aftermath (2009 – 2012).

The pertinent empirical literature mainly focuses on the economic value of volatility timing (Fleming et al., 2001; 2003; Della Corte et al., 2009). The evaluation of conditional correlation estimators has largely focused on statistical metrics and less attention has been paid to the economic value of capturing the empirical regularities in correlations. Engle and Sheppard (2001) show that the DCC model outperforms the industry standard RiskMetrics exponential smoother on the basis of residual normality and lower portfolio standard deviations. Engle and Colacito (2006) show that the efficiency loss of mean-variance portfolios decreases with correlation accuracy and that assuming constant correlation during volatile correlation phases is costly. But important issues such as the profitability of correlation predictability, the impact of transaction costs on active allocation and the value of the latter during market downturns or for different risk-aversions have not been examined as yet.[1]

Our analysis is based on daily prices from ten sector indices in three major markets (Japan, UK, US) over July 1996 to April 2012. The findings suggest that correlation timing is fruitful to sector investors. Dynamic correlation strategies deliver significant out-of-sample gains in risk-adjusted returns, which are more pronounced for monthly rebalancing and are robust to reasonable transaction costs. Risk-averse investors are willing to pay a fee of up to 983 basis points (bp) to switch from the static covariance portfolio to the dynamic DCC portfolio and up to an additional 100bp to also account for correlation asymmetries and regime shifts. The Sharpe Ratio (*SR*) accrual of dynamic portfolios can be as high as 0.48 and rises a further 0.08 when asymmetries and structural breaks are captured. Exploiting correlation dynamics appears more beneficial during the crisis: risk-adjusted returns rise to 0.60 in excess of the static portfolio and performance fees largely increase.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 delineates the conditional correlation models and the performance evaluation framework. Section 4 presents the empirical results. Section 5 concludes.

2. DATA

The empirical analysis is based on daily prices for ten sector indices from the Nikkei 225, FTSE-All and S&P500 obtained from Thomson Reuters DataStream International, namely, Energy (ENG), Basic Material (BML), Industrial (IND), Consumer Goods

[1] While DeMiguel et al. (2009) argue that the naïve *1/N* diversification strategy is able to outperform the mean-variance asset allocation, their findings have been questioned by Kirby and Ostdiek (2012) who document that active mean-variance timing is superior to naïve diversification but can be severely affected by transaction costs.

(CGS), Health Care (HCR), Consumer Service (CSV), Telecommunication (TEL), Utility (UTL), Financial (FIN) and Technology (TEC). The sample spans the period from July 1, 1996 to April 30, 2012, which amounts to a total of around 3900 daily logarithmic returns (in local currency) for each sector portfolio. The three-month Japanese interbank loan rate, the UK LIBOR, and the US Treasury bill rate proxy the risk free asset. The descriptive statistics in Table 1 show positive mean daily returns for most sectors.

[Insert Table 1]

All daily returns are non-normally distributed, particularly in the form of leptokurtosis. The extent and direction of skewness differs across sectors and equity markets. Most of the sector returns in the three markets are significantly negatively skewed. The Augmented Dickey-Fuller (ADF) test strongly rejects the hypothesis of a unit root for all return series. The Ljung-Box *Q*-statistic on raw/squared daily returns portrays serial dependence in all sectors. The strong evidence of volatility clustering supports the stylized fact that there is far more predictability in conditional volatility than in returns.

The analysis is based on domestic sector portfolios in each of the three markets and so within-country sector correlations are of relevance. The unconditional sector correlations over the sample period are significantly positive. The average sector correlation within Japan, UK and US is 59.7%, 48.1% and 62.9%, respectively.[2] Consumer services and industrials exhibit the highest correlation with other sectors in their respective markets at 65.8% and 64.7%, while utilities are the least correlated.

Our empirical framework is designed to assess the economic differences

[2] The three mean correlations are strongly significant with t-statistics 58.7, 39.6 and 65.8. The t-statistic is computed as $\rho\sqrt{(T-2)/(1-\rho^2)}$ and follows a Student-t distribution with $(T-2)$ degrees of freedom.

materializing from rival correlation forecasting approaches. The sample is divided into an in-sample estimation period from July 1, 1996 to June 30, 2005 (T= 2274, 2266, 2209 days, respectively, for the Japanese, UK and US sector portfolios) and a holdout evaluation period from July 1, 2005 to April 30, 2012 (T*= 1676, 1727, 1720 days, respectively, for the three domestic sector portfolios). The choice of out-of-sample period enables us to evaluate the performance of correlation timing over three distinctive phases of the recent global financial crisis, *i.e.* the pre-crisis (July 2005 – July 2007), crisis (August 2007 – February 2009), and post-crisis (March 2009 – April 2012) periods. The conditional correlation models are re-estimated over a rolling window of length-T to generate one-step-ahead covariance matrix forecasts.[3]

3. **METHODOLOGY**

The analysis builds upon the recursive construction of optimal mean-variance sector portfolios in the Japanese, UK and US markets and their out-of-sample performance based on incremental utility and risk-adjusted returns. For this purpose daily sector correlation and volatility forecasts, the main inputs alongside expected returns for active mean-variance allocation, are generated using the models outlined below.

(i) The Conditional Covariance Structure

Let r_t denote the day t logarithmic close-to-close return vector on n risky assets and $\xi_{t\text{-}1}$ be the information set available at the end of day t-1. The $[n \times 1]$ conditional expected return vector of r_t is defined as $\mu_t \equiv \mu_{t|t\text{-}1} = \mathrm{E}[r_t|\xi_{t\text{-}1}]$, while $H_t \equiv H_{t|t\text{-}1} = \mathrm{E}[(r_t - \mu_t)(r_t - \mu_t)'|\xi_{t\text{-}1}]$ is the symmetric $[n \times n]$ asset conditional covariance matrix. The return generating process is conceptualized as $r_t = \mu_t + H_t^{1/2}\varepsilon_t,\ \varepsilon_t \sim N(0,1)$. We characterize

[3] According to Clark and McCracken (2001), the ratio between the out-of-sample and in-sample period observations (π) should not be too large or small. In the current study, π is ranging from 0.74 to 0.78, thereby leaving a sizeable number of observations in each of the in-sample and out-of-sample portions.

the covariance dynamics H_t using variants of MGARCH models that account for correlation asymmetries and structural breaks.

Conditional correlation models rely on decomposing the conditional covariance into conditional standard deviations and conditional correlation. The simplest model is the Constant Conditional Correlation (CCC) introduced by Bollerslev (1990) which imposes time invariant correlation and covariance that changes over time proportionally to the time-varying volatilities. The CCC model is estimated in two steps. First, a univariate GARCH (p,q) model is fitted to each return series to obtain the conditional variance h_{it} , $i = 1,\ldots, n$. Second, the conditional covariance is specified as

$$H_t = D_t R D_t \tag{1}$$

, where $D_t = diag\left(\sqrt{h_{1t}},\ldots,\sqrt{h_{nt}}\right)$ and R is a positive definite $[n \times n]$ correlation matrix typically estimated by the unconditional in-sample correlation matrix.

The constant correlation assumption has been found to be too restrictive in several empirical studies (*e.g.* Ang and Bekaert, 2002), and so the covariance decomposition in (1) has been extended to allow for dynamics in the correlation matrix. Among the many specifications proposed for the evolution of R_t the DCC model of Engle (2002) is the most popular.[4] The DCC model has the same first step as the CCC approach, but for each series the standardized errors, ε_{it}, are generated alongside the conditional variance. In the second step, the ε_{it} are used to estimate the time-varying correlation matrix via

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \tag{2}$$

[4] The out-of-sample nature of the ensuing analysis and long evaluation period renders the recursive estimation and forecasting based on diagonal DCC models computationally intensive., thus, we focus on the scalar versions.

$$Q_t = (\overline{Q} - a^2\overline{Q} - b^2\overline{Q}) + a^2\, \varepsilon_{t-1}\, \varepsilon'_{t-1} + b^2\, Q_{t-1}$$

, where $\overline{Q} = E[\varepsilon_t \varepsilon_t']$ is the unconditional covariance of standardized innovations and $Q_t^{*} = \mathrm{diag}(\sqrt{q_{it}}, \ldots, \sqrt{q_{nt}})$ to ensure that R_t has the structure of a correlation matrix.

The Asymmetric DCC (A-DCC) of Sheppard (2002), extends (2) by allowing for asymmetries in the conditional covariance as follows

$$Q_t = C + a^2\, \varepsilon_{t-1}\, \varepsilon'_{t-1} + b^2\, Q_{t-1} + g^2\, \eta_{t-1}\, \eta'_{t-1} \tag{3}$$

, where $\eta_t = I[\varepsilon_t < 0] \otimes \varepsilon_t$, $\otimes$ indicates the element-by-element Hadamard product, $C = \overline{Q} - a^2\overline{Q} - b^2\overline{Q} - g^2\overline{N}$ and $\overline{N} = E[\eta_t \eta'_t]$, where the expectation is replaced by its sample analogue. Model (3) allows joint negative shocks to have a stronger impact on correlations than positive shocks of the same size and nests the symmetric DCC.

We also extend (3) to accommodate structural breaks in the long-run mean and dynamics of correlations (A-DCC-Break) as in Cappiello et al. (2006). The A-DCC-Break model accounts for three covariance regimes as follows

$$Q_t = d_1\, Q_{1t} + d_2\, Q_{2t} + (1 - d_1 - d_2)\, Q_{3t}$$

$$Q_{jt} = C_j + a^2_j\, \varepsilon_{t-1}\, \varepsilon'_{t-1} + b^2_j\, Q_{t-1} + g^2_j\, \eta_{t-1}\, \eta'_{t-1}; \text{ and } j = 1, 2, 3 \tag{4}$$

, where d_1 and d_2 are two structural break indicators defined as $d_1 = 1$ for $t \in$ [July 1996; December 1998] and 0 else, $d_2 = 1$ for $t \in$ [January 1999; July 2007] and 0 else.

Model estimation is by quasi maximum likelihood (QML). Inferences are based on Bollerslev-Wooldridge non-normality robust standard errors (Bollerslev and Wooldridge, 1992). Individual significance tests are based on *t*-statistics.

(ii) Dynamic Asset Allocation using Correlation Timing Strategies

We consider an investor with a short-term investment horizon who allocates funds across $n = 10$ risky assets (domestic sector indices) and a riskless security (3-month domestic interbank rate). Mean-variance optimization is deployed to construct a distinct domestic sector portfolio for each market using the conditional covariance matrix forecast and the expected return as inputs. We consider two portfolio optimization strategies: a) maximize expected return subject to a target expected volatility (Max-R), and b) minimize conditional variance subject to a target expected return (Min-V). The optimal portfolio weights vary through time as both μ_t and H_t change as follows

$$w_t = \frac{\sigma_p^* H_t^{-1}(\mu_t - r_f \mathbf{I})}{\sqrt{(\mu_t - r_f \mathbf{I})' H_t^{-1}(\mu_t - r_f \mathbf{I})}}, \text{ for the Max-R strategy,}$$

$$w_t = \frac{(\mu_p^* - r_f) H_t^{-1}(\mu_t - r_f \mathbf{I})}{(\mu_t - r_f \mathbf{I})' H_t^{-1}(\mu_t - r_f \mathbf{I})}, \text{ for the Min-V strategy,}$$

where σ_p* and μ_p* are the target expected volatility and return, respectively; w_t is an $[n \times 1]$ vector of weights on the risky assets, r_f is the return on the risk free asset, I is an $[n \times 1]$ vector of 1s, and the weight on the risk free asset is $(1 - w_t' \mathbf{I})$.

At the opening of each trading day, the conditional covariance matrix H_t is forecasted using price information up to day t-1 and used as input in the models to compute the optimal sector weights in each market. When the conditional expected return μ_t and conditional covariance H_t are perceived time varying, investors will rebalance their portfolio weights following the dynamic strategies outlined above to produce a daily sequence of optimal mean-variance portfolios spanning the out-of-sample period. Expected returns are notoriously hard to predict, and so we follow De Pooter et al. (2008) in assuming a constant expected return given by the average realized return over the three sample periods: pre-crisis, crisis and post-crisis. The target expected return and volatility (μ_p^*, σ_p^*) are set at 10% per annum.

The CCC model amounts to a volatility timing strategy and is adopted by investors who believe that changes in covariance are driven by changes in volatility, while correlations are constant through time. The DCC family can generate correlation timing strategies embedding various stylized facts of correlations such as time variation, asymmetry and structural breaks. The static benchmark strategy, adopted by an investor who believes that the covariance is constant over the out-of-sample period, is based on the realized unconditional covariance matrix and reflects the ex post optimal static allocation.

(iii) Performance Evaluation Framework

The adequacy of the dynamic strategies based on alternative covariance forecasts is judged on the basis of incremental utility relative to the static benchmark strategy. We follow the utility-based evaluation framework of Fleming et al. (2001) assuming that at a given point in time, one estimate of conditional covariance is better than another if it leads to higher average utility. The incremental value of correlation timing vis-a-vis the static benchmark is assessed by the return that would render an investor indifferent between the two strategies as follows

$$\sum_{t=0}^{T^*-1} \left| (R_{d,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{d,t+1} - \Delta)^2 \right| = \sum_{t=0}^{T^*-1} \left| R_{s,t+1} - \frac{\gamma}{2(1+\gamma)} R_{s,t+1}^2 \right| \qquad (5)$$

where $R_{d,t+1}$ and $R_{s,t+1}$ denote returns for the dynamic and static strategies. Equation (5) implies that the investor would incur a daily expense Δ for the dynamic strategy, which is the maximum performance fee (*PF*) in annualized basis points the investor is willing to pay to switch from the static to the dynamic strategy.

We statistically evaluate the risk-adjusted performance of the strategies by assessing the significance of the observed *SR* differential of the dynamic strategy and the static benchmark.[5] In order to test the null hypothesis H_0: (SR_d - SR_s) = 0 we

[5] We calculate the *SR* of the strategies using the mean and standard deviation of the realized portfolio excess

employ the asymptotic variance of the *SR* differential, $Var(SR_{diff}) = Var(SR_d - SR_s)$, derived by Opdyke (2007) under very general conditions of time-varying volatilities, serial correlation and non-*iid* returns. Since the *SR* statistic is asymptotically unbiased and normally distributed, the Central Limit Theorem implies that $\sqrt{T}(SR_{diff}) \overset{a}{\sim} N(0, Var(SR_{diff}))$.

(iv) Transaction Costs

Transaction costs play an important role when assessing the profitability of active trading strategies. Accurate estimation of the size of transaction costs is challenging since it requires information on the type of investor and broker and the value of transaction. In order to sidestep this issue we follow Han (2006) and compute break-even transaction costs (*BTC*) per trade as the proportional cost that renders the investor with quadratic utility function indifferent between the dynamic strategy at hand and the static strategy. We compute the average monthly turnover rate (*TO*) as the proportion of the portfolio value rebalanced each day, that is, $TO = (T^*)^{-1} \sum_{t=1}^{T^*} \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-1} \frac{1+r_{i,t}}{1+R_{p,t}} \right|$.

Sector index trading can be effectively replicated with Exchange Traded Funds (ETFs) at a relatively low cost. For frequent traders of ETFs the trading cost depends primarily on the bid-ask spread and the cost of market impact as the other cost components (total expense ratio and commission) are relatively small for large transactions (Jares and Lavin, 2004). Bid-ask spreads tend to be wider at the end of the trading day since traders face a higher risk that their order might not be executed (McInish and Wood, 1992).[6] This implies that using the end-of-day bid-ask spread

returns as in Fama and French (2002). It is worth noting that realized *SR* tends to overestimate the conditional risk as it uses the sample standard deviation of the realized portfolio returns.

[6] The higher bid-ask spread of the last trade can also be attributed to the introduction of the closing auction on

would inflate the actual trading cost. To circumvent this issue we use intraday price quotes and compute the bid-ask spread on day t as Bid-Ask$_t$ = min(ΔP_{jt})/LowP$_t$ for j = 1,…, M intraday intervals, where min(ΔP_{jt}) is the smallest intraday bid-ask spread observed during day t and LowP$_t$ is the lowest bid price. The estimated average Bid-Ask for SPDR US Sector ETFs ranges from 1.8 to 4.5bp, and is slightly higher for financials. The Daiwa JPN TOPIX Sector ETFs average Bid-Ask is found to be 28bp, whereas it is 48bp for the SPDR MSCI Europe Sector ETFs. The cost of market impact when trading large cap index ETFs is typically around 2bp.[7] Thus, the total trading cost of sector ETFs for traders in the US, Japan and UK markets, respectively, is approximately 7, 30 and 50bp per trade.

4. EMPIRICAL RESULTS

(i) The Dynamics of Sector Correlations

The covariance matrix for each of the three domestic sector portfolios is estimated over the entire sample period, July 1, 1996 to April 30, 2012. For each portfolio we use the fitted GARCH (1,1) conditional volatilities alongside equations (1) to (4) to estimate the conditional correlations.[8]

In order to account for potential structural breaks in the dynamics of sector correlations, we follow the pertinent literature (Baele, 2005; Billio and Pelizzon, 2003 *inter alios*) and introduce a structural break corresponding to the EMU introduction on January 1, 1999. Cappiello et al. (2006) provide evidence to support that the exchange rate harmonization of 1999 has increased national return correlations not

most of the exchanges. The bid-ask spread or terms of trade is determined by the number of informed traders in the market. If it the latter increases, the terms of trade will worsen especially when opinions are diversified. The closing auction will attract more informed traders into the price discovery process that possess more information about the underlying asset and could form a better strategy in the auction (Admati and Pfleiderer, 1988).

[7] See Frontier Investment Management report at *http://www.frontierim.com/files/file/download/id/592*.

[8] An EGARCH (1, 1) model was also fitted to the daily return series but no evidence of asymmetry was found.

only within EMU countries but also outside the EMU including the UK possibly signaling stronger economic ties. The increase in correlation between major European markets and other non-EMU markets implies that shocks to the underlying country fundamentals (*e.g.* business cycle and default risk) that drive sector comovements are now easier to transmit from EMU to non-EMU markets. The literature has also documented direct sector contagion effects between international equity markets (Baca et al., 2000; Phylaktis and Xia, 2009).

We also account for regime shifts in correlation dynamics triggered by the recent financial crisis by specifying a second break point on August 1, 2007.[9] Our focus on the EMU introduction and the recent crisis as structural break points is driven by their long-lasting and systemic impact on global financial markets. Multivariate conditional correlation models are quite data intensive due to the large number of parameters (our DCC models involve around 35 parameters) and so we need enough observations over both the pre- and post-break sub-periods in order to be able to estimate the models. Second, events that have a global impact would allow us to apply the same model across the markets/sectors considered.

Empirical likelihood ratio tests reported in Table 2 provide strong evidence for the presence of structural breaks in sector correlation dynamics in the three markets.

[Insert Table 2]

Asymmetry in sector correlations is also borne out by a significant increase in the value of the log-likelihood function upon inclusion of the asymmetric term. On the other hand, the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) that trade-off fit and parsimony point towards the DCC, the most

[9] The credit event of BNP Paribas in August 2007 is typically taken to mark the onset of the recent financial crisis by worsening global liquidity conditions.

parsimonious among the correlation models.

The parameter estimates for the conditional correlation models are set out in Table 3. Most parameters are statistically significant at the conventional levels.

[Insert Table 3]

We find evidence of correlation asymmetry in sector correlations in all three markets indicated by the significance of the asymmetry parameter g during the post-EMU period. The findings also indicate a change in the dynamic structure of conditional correlations following the introduction of the EMU and the recent financial crisis. Conditional correlations become more persistent after the introduction of the EMU, which implies that joint sector shocks have longer lasting effects on the conditional correlation. Short-run persistence increases in the crisis period, implying that recent news have a bigger impact on conditional correlations in the post-crisis period.

(ii) Timing the Correlation Signals

In order to investigate whether accurately characterizing the time varying correlations can be economically significant, mean-variance sector portfolios are recursively constructed based on the rolling one-day-ahead conditional covariance matrix forecasts obtained from models (1) to (4), while the static portfolio is based on the realized unconditional covariance matrix. Table 4 presents the out-of-sample evaluation of the correlation timing strategies against the static benchmark strategy.

[Insert Table 4]

First we appraise the standard portfolio performance measures. Reported for each sector portfolio is the annualized mean portfolio return (μ), return standard deviation (σ) and SR, and the associated p-values for Opdyke's (2007) test of equality of SR. A significant test statistic denotes rejection of H_0: $SR_d = SR_s$ in favour of the alternative that the dynamic strategy increases the *SR*. Bold denotes the best performing model under each criterion.

The results suggest that the dynamic strategies are able to deliver performance gains over the static benchmark strategy in all markets. The best model for the Japanese and UK sector portfolios is the A-DCC, which accrues significant *SR* gains of 0.62 (0.46) and 0.37 (0.09), respectively, in excess of the static Max-R (Min-V) strategy. For the US, structural breaks seem to matter as the A-DCC-Break model achieves the highest significant *SR* increase of 0.50 (0.25). The results based on Min-V strategy further underline the improvement in terms of lower portfolio volatility.

We now turn attention to the economic value of the covariance forecasting models on the basis of annualized *PF* of the strategy at hand vis-à-vis the static benchmark. We find large and positive performance fees across all portfolios providing overwhelming evidence that the dynamic strategies outperform the static constant covariance strategy in all three markets. Interestingly, the results provide evidence that accounting for correlation asymmetries and, in the US case also for breaks, enhance performance gains. A risk-averse Japanese sector investor would be willing to pay up to a maximum of 869bp per annum for the relative benefits of the dynamic A-DCC strategy. A US investor would opt for a dynamic strategy that accounts for asymmetries and also breaks and, in particular, she would willing to pay up to 596bp to switch from the static benchmark portfolio to the A-DCC-Break portfolio. When the focus is on minimizing risk the dynamic Min-V strategies produce relatively lower performance fees, but are able to reduce volatility, which implies accrued accuracy in the covariance matrix forecasts.

(iii) Turnover Rate and Break-Even Transaction Costs

The empirical results thus far suggest that the dynamic strategies outperform the static strategy in terms of *SR* and performance fees for risk-averse investors with quadratic utility. Active trading strategies, however, are prone to high turnover and so their performance can be substantially impeded by transaction costs. In order to demonstrate the trading intensive nature of the dynamic strategies, Figure 1 plots the weights derived from the A-DCC and the static covariance strategy for two indicative sectors (*i.e.* industrial and financial) and for the risk free asset.[10]

[Insert Figure 1]

As expected the weights of the dynamic strategies are very volatile. The monthly turnover (*TO*) for each strategy can be seen in Table 4. The *TO* of the static strategy that rebalances to maintain constant weights is 0.38 – 0.56 (Max-R) and 0.17 – 0.28 (Min-V), or equivalently 38% - 56% and 17% - 28% of total portfolio value. The monthly turnover for the conditional correlation strategies is considerable, ranging at 3.53 – 6.15 (Max-R) and 1.51 – 2.43 (Min-V) across models/portfolios. The strategy with the lowest *TO* employs the CCC model that responds only to volatility changes.

The differences in turnover rate among dynamic strategies have important implications for their post-transaction cost economic value, which is summarized by the break-even transaction costs (*BTC*). The results in Table 4 indicate that a highly risk-averse US sector investor using the least trade intensive CCC model faces economically plausible *BTC* of 7.20bp per trade under Max-R. For DCC-type models under Max-R the *BTC* are also higher than the assumed level of transaction costs for US sector ETFs. Therefore, US portfolio managers opting for conditional correlation models can get net performance gains. Nonetheless, in the UK and Japan the *BTC*

[10] In the interest of space, only the results based on the US domestic sector portfolio are illustrated. The graphs for the other two markets are available from the authors upon request.

are below the indicated trading costs for sector-linked ETFs. Thus, the gains of the dynamic strategies are wiped out by the high trading costs facing investors in these markets in line with DeMiguel et al. (2009) and Kirby and Ostdiek (2012).

(iv) Rebalancing Frequency and the Performance of Dynamic Strategies

Daily traders engaging in dynamic correlation strategies are confronted with high turnover, which casts doubt on the practical feasibility of the strategies. Lower rebalancing frequency can reduce the turnover allowing investors to effectively implement the dynamic strategies.

In order to investigate the impact of rebalancing frequency on the performance of the dynamic asset allocation strategies, we repeat the analysis for monthly and weekly investment horizons based on the overlapping rebalance approach. Portfolios are rebalanced daily based on the covariance matrix forecast and the new portfolio is held for an m-day holding period, where $m = 5$ for a weekly horizon and $m = 21$ for a monthly horizon. This overlapping approach assumes that, on each trading day, the investor will hold multiple portfolios simultaneously, each formed one day apart, but only one of the m portfolios will be revised.[11] The overall day-t return is calculated as the weighted average return of the m portfolios held on day t. The turnover ratio of the total asset holding on each day is equal to the turnover of the revised portfolio multiplied by its weight. The advantages of the overlapping approach is that it uses information from all the daily covariance forecasts and eliminates the bias arising from the day of the week/month effect and accounts for performance variability from the choice of rebalancing day.

Table 5 sets out the impact of lowering the rebalancing frequency from daily to

[11] The overlapping method to evaluate the performance of stock picking techniques with different rebalancing frequencies is inspired by Rouwenhorst's (1998) early work on portfolio trading strategies.

monthly on the out-of-sample performance of the dynamic strategies.

[Insert Table 5]

Portfolio volatility increases slightly when the investment horizon increases, in line with De Pooter et al. (2008). In terms of risk-adjusted performance, we find that the *SR* decreases with the investment horizon consistent with the evidence in Fleming et al. (2003), who use artificially generated returns. However, the incremental gains in risk-adjusted rewards over the static strategy are still significant and can be as high as 0.48. Furthermore, the benefits in risk-adjusted performance over the static strategy are robust to the different out-of-sample sub-periods: pre-crisis, crisis/post-crisis period and period excluding the crisis years (August 2007 to February 2009).[12] The incremental utility-based performance gains of dynamic strategies relative to the static benchmark are more pronounced at lower rebalancing frequencies. Monthly correlation timing generates *PF* of 1015bp, 420bp and 620bp (Max-R) for the Japanese, UK and US markets, respectively, which is an increase of 7% to 18% relative to daily rebalancing.[13] This can be attributed to the fact that dynamic portfolios benefit more than the static one from longer revision intervals, which implies that investors are prepared to pay higher fees to switch from static to dynamic strategies when rebalancing less often. Risk-averse investors are willing to pay a fee of up to 983bp to switch from the static covariance portfolio to the dynamic DCC- portfolio and up to100 bp more for correlation asymmetries and regime shifts.

The decrease in turnover rate when switching to monthly rebalancing is quite dramatic. The *TO* of monthly portfolios is less than a quarter of the *TO* of the daily

[12] The results for the three sup-periods are available from the authors upon request. Similarly, for the weekly rebalancing results which are qualitatively similar to the monthly ones.

[13] In our framework, lower rebalancing frequency does not imply lower sampling frequency as daily price information is still used in the correlation forecasting process in order to exploit the persistence of correlation and volatilities as investors move from daily to monthly frequencies.

portfolios. As an example, the daily dynamic strategy based on DCC forecasts under Max-R has a *TO* rate 5.41 for the US sector portfolio whereas the *TO* rate of the corresponding monthly portfolio is curtailed to 1.10.

A direct implication of enhanced performance fees and lower turnover is the higher *BTC* associated with lower rebalancing frequencies, which suggests that dynamic portfolios are more likely to maintain post-transaction cost benefits if they are revised less frequently. Depending on the model and risk-aversion, the *BTC* of conditional correlation models with monthly rebalancing range from 34bp to 104bp per trade (Max-R) and from 14bp to 33bp per trade (Min-V), notably higher than their daily counterparts. Thus, monthly correlation timing under Max-R becomes feasible and economically meaningful for investors in all three markets. Monthly Min-V correlation timing is also feasible for Japanese and US investors with *BTC* of about 30bp and 20bp, respectively. While in the UK the *BTC* of dynamic strategies are of similar magnitude, they do not exceed the rather high transaction costs; the gain from less frequent rebalancing is nonetheless noticeable.

In order to directly evaluate the effect of rebalancing frequency on the dynamic strategies we compute the maximum return an investor is willing to forfeit to switch from daily to monthly rebalancing. Table 6 presents these performance fees.

[Insert Table 6]

The largely positive *PF* (between 12bp and 140bp) suggest that monthly correlation-based rebalancing outperforms the daily one regardless of the risk-aversion level.[14]

(v) Economic Value of Correlation Asymmetry and Structural Breaks

In order to explicitly evaluate the economic value of capturing the well-documented

[14] The only exception pertains to Japan where the daily Min-V dynamic portfolios outperform their monthly counterparts possibly due to the slight decrease in return for the monthly Min-V dynamic portfolios.

stylized facts of correlation in the context of asset allocation, we further compute the *PF* and *BTC* of the correlation timing strategies with asymmetries and/or structural break features against those without.[15] The results for daily and monthly rebalancing are summarized in Table 7 for the high risk-aversion case (γ = 10).

[Insert Table 7]

The findings suggest that considering asymmetries and breaks in conditional correlation forecasts delivers performance gains, especially for monthly rebalancing.

Embedding structural breaks in the correlation process is economically most relevant for US investors - the break feature yields a performance fee of 100bp with *BTC* of 80bp. US investors can also benefit from substantial increase in the *SR* of 0.07 to 0.09 from incorporating structural breaks, while asymmetric effects do not seem to deliver any gains. On the other hand, the value of modelling structural breaks in correlations disappears in Japan, whereas exploiting correlation asymmetries alone amounts to a *PF* of 32bp per year and a *SR* increase of 0.02. In the UK both asymmetries and breaks improve portfolio performance, with *PF* of 18bp and 30bp, respectively. Finally, the *BTC* that render investors indifferent about asymmetric effects or structural breaks in the already time varying correlations by and large exceed the assumed levels of transaction costs.

The performance gains (unreported due to space constraints) of correlation timing appear more prevalent during the crisis, especially for the Min-V strategy, and are economically viable with *BTC* of around 50 - 100bp per trade.[16] The *SR* gains reach 0.48 in excess of the static strategy over the whole out-of-sample period, and

[15] For instance, in order to evaluate the effect of capturing correlation asymmetry, we contrast the A-DCC (or A-DCC-Break) portfolio against the DCC (or DCC-Break) portfolio.

[16] González-Hermosillo (2008) claims that investor risk-aversion increases dramatically under extreme market conditions, which indicates the relevance of minimum risk strategies during crisis periods.

0.64 during the crisis. The *PF* are also notably higher (twofold or threefold).

(vi) Robustness Tests

The results so far were based on assuming a certain level of target return or volatility in the mean-variance portfolio optimization. In the presence of a risk-free asset using an arbitrary target return/volatility has no qualitative impact on the *SR* performance of the dynamic portfolio against the static one as long as the capital market line (CML) of the former lies above that of the latter. Portfolios on the CML provide the highest possible *SR* among all efficient portfolios and different target settings simply change the allocation between the optimal risky portfolio and the risk-free asset along the CML. Figure 2 shows the risk-return performance of the daily optimal dynamic portfolios in Table 4 against the CML of the static strategy.

[Insert Figure 2]

The results suggest that correlation-timing portfolios outperform the static ones irrespective of the target settings, as they provide higher *SR*s than any portfolio on the static CML. We check the effect of changing the targets on the incremental utility of the dynamic portfolios by reproducing Table 4 using lower (5%) and higher (20%) levels of target return/volatility. The results (not reported due to space constraints) show that varying the target settings does not affect the value of correlation timing. Realized portfolio return and volatility change proportionally with the target so that their ratio remains constant and most portfolios outperform the static benchmark in terms of utility-based performance measures under the alternative target settings.[17]

We assess the asset allocation implication of the covariance matrix forecast accuracy by contrasting the frontiers from dynamic and static strategies in Figure 3.

[17] This is true if there are no transaction costs. In fact increasing the target return of the portfolio leads to higher turnover and, therefore, lowers the net risk-adjusted return. However, relative to the static benchmark the *BTC* of each of our dynamic portfolios remain the same across different target settings.

[Insert Figure 3]

The efficient frontiers of the best performing dynamic strategies embrace the static frontier, which implies that all efficient dynamic portfolios can achieve a better risk return trade-off than the efficient static portfolios and confirms that the outperformance of the dynamic strategies is attributed to more accurate covariance matrix forecasts and is not an artefact of the portfolio strategy.

5. CONCLUSIONS

Drawing on the growing realization that static, long-term correlation estimates are no longer appropriate in the rapidly changing financial markets this paper explores the economic value of correlation timing in sector allocation. We evaluate dynamic mean-variance strategies based on DCC-type forecasts that allow for time variation in both volatility and correlation against a static covariance strategy.

Our study offers important insights into the economic significance of correlation predictability with interesting industry implications. The findings suggest that the predictability of conditional correlation models leads to more efficient sector portfolios. Fund managers can enhance risk-adjusted returns by accurately capturing correlation time variation, especially during market downturns when asset correlations are the highest. Investors are willing to pay a fee up to 983bp to switch from the static to the dynamic strategy, and up to a further 100bp to capture asymmetric effects and breaks in correlations. The gains are more pronounced for monthly rebalancing, are robust to transaction costs and the choice of target return.

Diversification arguments imply that the risk of a well-diversified portfolio depends primarily on asset covariances. Therefore, exploring whether the value of modelling correlation dynamics increases with the number of assets in the portfolio would be an interesting avenue of further research.

REFERENCES

Admati, A.R. and P. Pfleiderer (1988), 'A Theory of Intraday Patterns: Volume and Price Variability', *Review of Financial Studies*, Vol. 1, pp. 3-40.

Ang, A. and G. Bekaert (2002), 'International Asset Allocation with Regime Shifts', *Review of Financial Studies*, Vol. 15, pp. 1137-87.

Baca, S. P., B.L. Garbe and R. A. Weiss (2000). 'The Rise of Sector Effects in Major Equity Markets'. *Financial Analysts Journal*, 34-40.

Baele, L. (2005), 'Volatility Spillover Effects in European Equity Markets', *Journal of Financial and Quantitative Analysis*, Vol. 40, pp. 373-401.

Bekaert, G., C. Harvey and A. Ng (2005), 'Market Integration and Contagion', *Journal of Business*, Vol. 78, pp. 39-69.

Billio, M. and L. Pelizzon (2003), 'Volatility and Shocks Spillover Before and After EMU in European Stock Markets', *Journal of Multinational Financial Management*, Vol. 13, pp. 323-40.

Bollerslev, T. (1990), 'Modeling the Coherence in Short-Run Nominal Exchange Rate: a Multivariate Generalized ARCH Approach', *Review of Economics and Statistic*, Vol. 72, pp. 498-505.

Bollerslev, T. and J. Wooldridge (1992), 'Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariance', *Econometric Reviews*, Vol. 11, pp. 143-72.

Cappiello, L., R. Engle and K. Sheppard (2006), 'Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns', *Journal of Financial Econometrics*, Vol. 4, pp. 537-72.

Clark, T.E. and M.W. McCracken (2001), 'Tests of Equal Forecast Accuracy and Encompassing for Nested Models', *Journal of Econometrics*, Vol. 105, pp. 85-110.

DeMiguel, V., L. Garlappi and R. Uppal (2009), Optimal versus Naïve Diversification: How Inefficient is the *1/N* Portfolio Strategy', *Review of Financial Studies*, Vol. 22, pp. 1915-53.

De Pooter, M., M. Martens and D. van Dijk (2008), 'Predicting the Daily Covariance Matrix for S&P 100 Stocks Using Intraday Data – but Which Frequency to Use?', *Econometric Reviews*, Vol. 27, pp. 199-229.

Della Corte, P., L. Sarno and I. Tsiakas (2009), 'An Economic Evaluation of Empirical Exchange Rate Models', *Review of Financial Studies*, Vol. 22, pp. 3491-530.

Engle, R. (2002), 'Dynamic Conditional Correlation: a Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models', *Journal of Business and Economic Statistics*, Vol. 20, pp. 339-50.

Engle, R. and R. Colacito (2006), 'Testing and Valuing Dynamic Correlations for Asset Allocation' *Journal of Business and Economic Statistics*, Vol. 24, pp. 238-53.

Engle, R. and Sheppard, K. (2001), '*Theoretical and Empirical Properties of Dynamic Conditional Correlation MVGARCH*', Working paper No. 2001-15 (University of California, San Diego).

Fama, E.F. and K.R. French (2002), 'The Equity Premium', *Journal of Finance*, Vol. 57, pp. 637-59.

Fleming, J., C. Kirby and B. Ostdiek (2001), 'The Economic Value of Volatility Timing', *Journal of Finance*, Vol. 56, pp. 329–52.

Fleming, J., C. Kirby and B. Ostdiek (2003), 'The Economic Value of Volatility Timing Using "Realized" Volatility', *Journal of Financial Economics*, Vol. 67, pp. 473–509.

González-Hermosillo, B. (2008), '*Investor Risk Appetite and Global Financial Market Conditions*', Working Paper No. WP/08/85 (International Monetary Fund).

Han, Y. (2006), 'Asset Allocation with a High Dimensional Latent Factor Stochastic Volatility Model', *Review of Financial Studies*, Vol. 19, pp. 237-71.

Jares, T.E. and A.M. Lavin (2004), 'Japan and Hong Kong Exchange-Traded Funds (ETFs): Discounts, Returns, and Trading Strategies', *Journal of Financial Services Research*, Vol. 25, pp. 57-69.

Kirby, C. and B. Ostdiek (2012), 'It's All in the Timing: Simple Active Portfolio Strategies that Outperform Naïve Diversification', *Journal of Financial and Quantitative Analysis*, Vol. 47, pp. 437-67.

Longin, F. and B. Solnik (2001), 'Extreme Correlation of International Equity Markets', *Journal of Finance*, Vol. 56, pp. 649-76.

McInish, T.H. and R.A. Wood (1992), 'An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks', *Journal of Finance*, Vol. 47, pp. 753-64.

Opdyke, J.D. (2007), 'Comparing Sharpe Ratio: So Where are the P-values', *Journal of Asset Management*, Vol. 8, pp. 308-36.

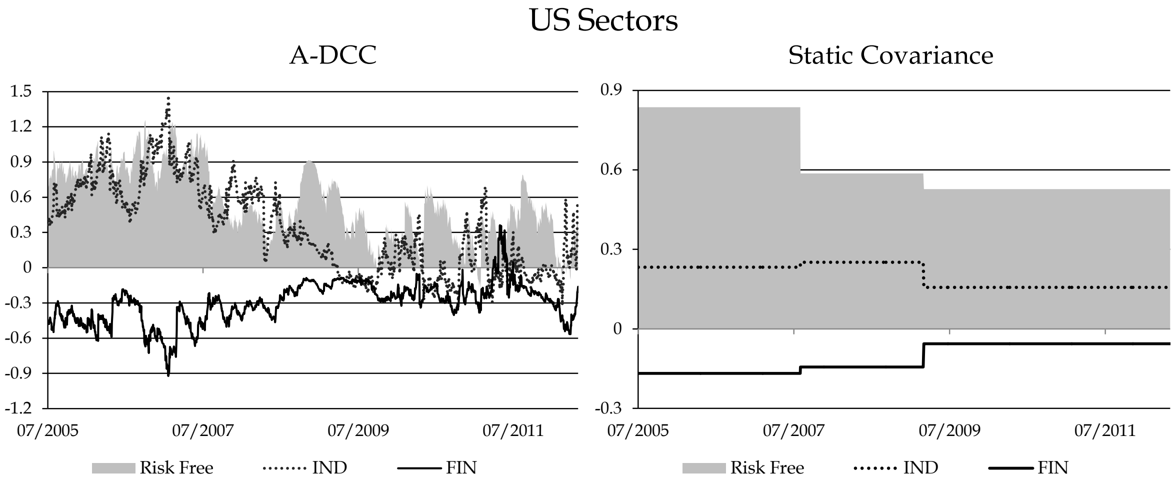
Phylaktis, K. and L. Xia (2009). Equity market comovement and contagion: A sectoral perspective. *Financial Management*, Vol. 38, pp. 381-409.

Rouwenhorst, K.G. (1998), 'International Momentum Strategies', *Journal of Finance*, Vol. 53, pp. 267-84.

Sheppard, K. (2002), '*Understanding the Dynamics of Equity Covariance*', Working Paper (University of California, San Diego).

Figure 1: Weighting schemes of the dynamic and static strategies
The graphs demonstrate the time varying weighting schemes for the risk free asset and the industrial (IND) and financial (FIN) sector indices under the dynamic A-DCC and the static allocation strategies for the US sector portfolio during the out-of-sample period (July 2005 – April 2012). Portfolios are rebalanced daily.

Panel A: Max-R Portfolio Construction Strategy



Panel B: Min-V Portfolio Construction Strategy

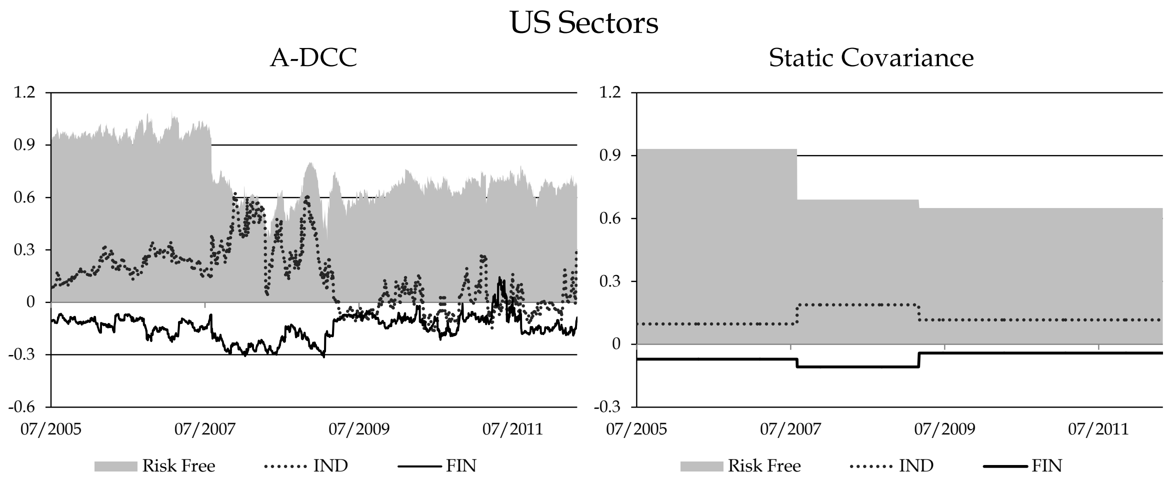


Figure 2: Dynamic correlation strategies and the static capital market line (CML)
The graphs demonstrate the relative performance of the correlation timing strategies based on MGARCH models against the CML derived from the ex post optimal static covariance benchmark. The annualized risk-return trade-off of the Max-R and Min-V correlation timing strategies reported in Table 4 is represented by the blue rectangles.

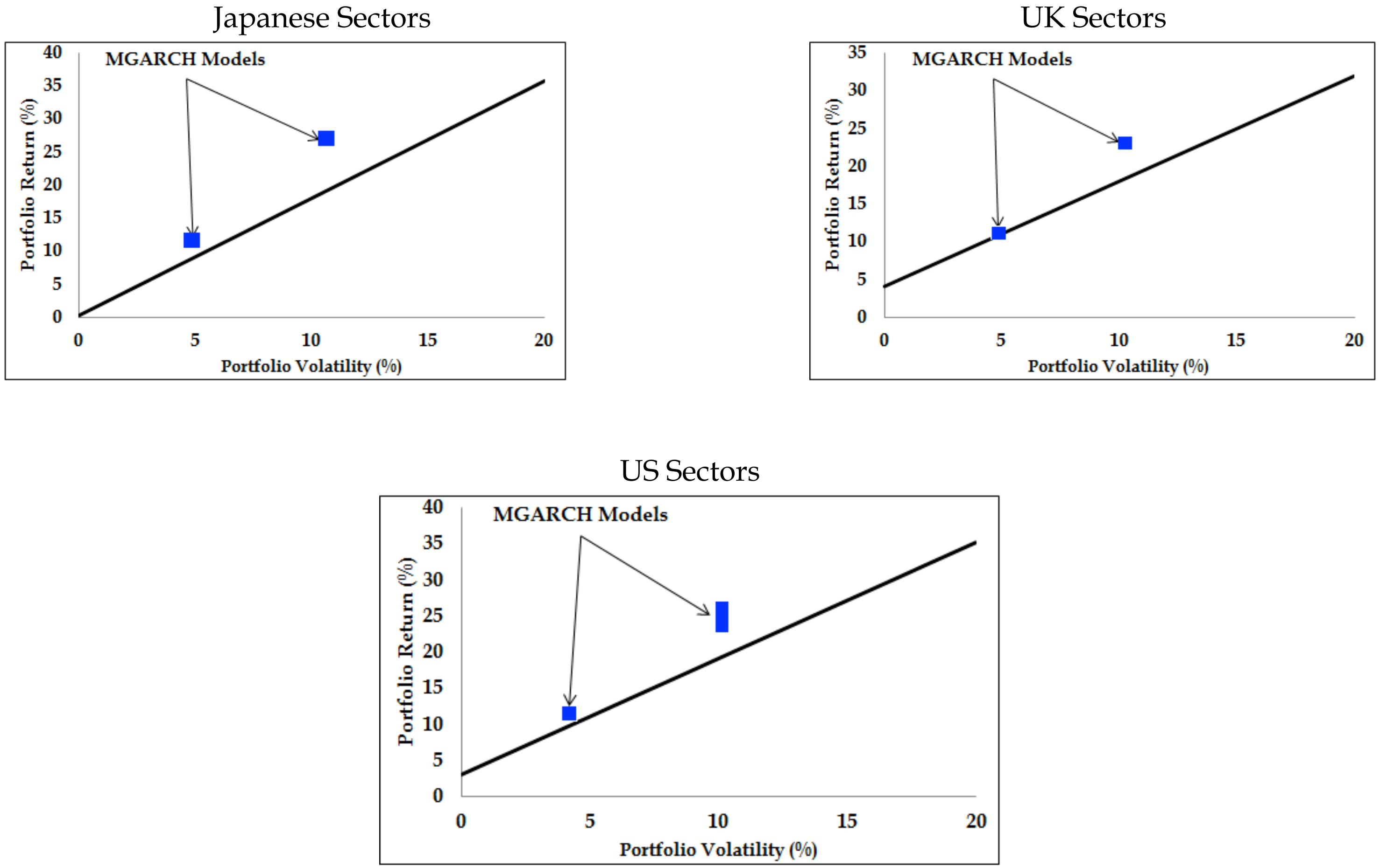


Figure 3: Efficient frontier of dynamic strategies and ex post optimal static strategy
The graphs illustrate the efficient frontier of the best performing dynamic strategy for each sector portfolio against that of the static strategy. Portfolios are aggregated over the out-of-sample period by averaging the daily portfolio volatilities for each level of expected return.

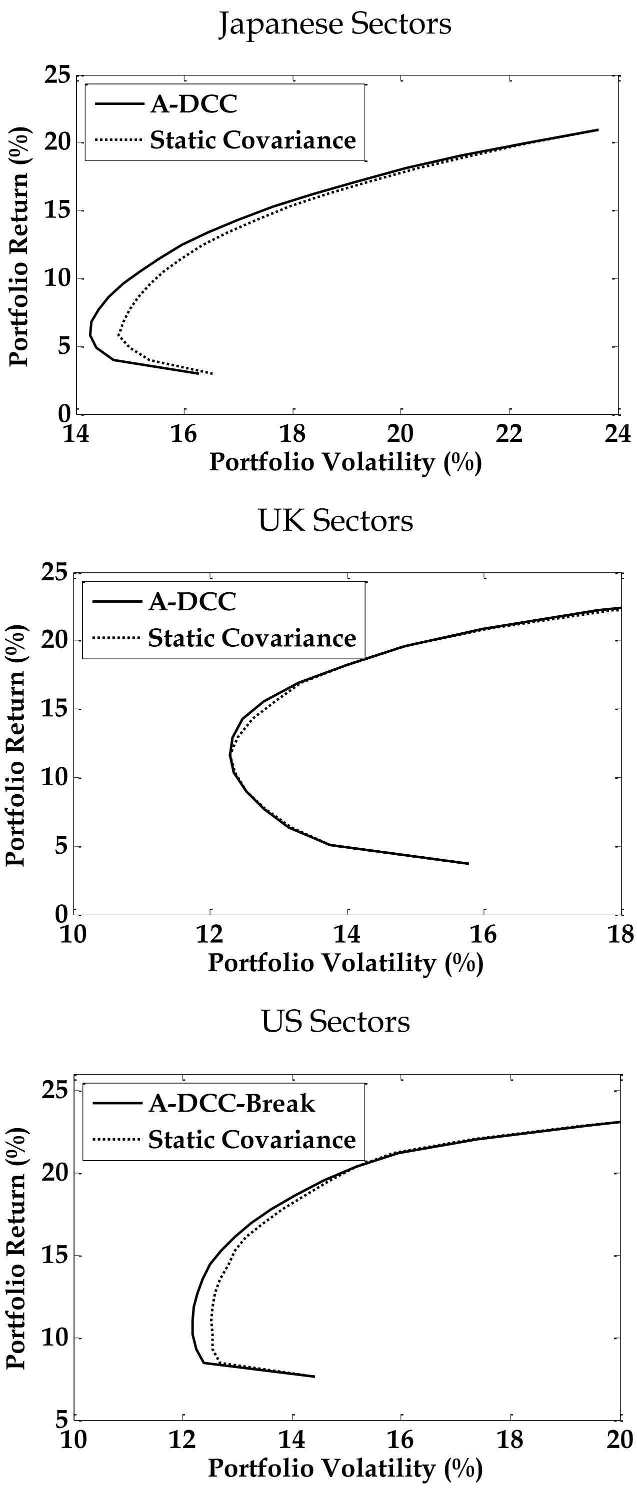


Table 1: Distributional properties of daily sector returns

	Sector Indices									
	ENG	BML	IND	CGS	HCR	CSV	TEL	UTL	FIN	TEC
Japan										
Mean	-0.018	-0.019	-0.006	-0.003	-0.002	-0.019	-0.008	-0.021	-0.045	-0.016
Maximum	0.126	0.159	0.143	0.130	0.102	0.105	0.103	0.091	0.145	0.134
Minimum	-0.142	-0.127	-0.136	-0.106	-0.117	-0.117	-0.127	-0.159	-0.126	-0.125
StDev	0.020	0.017	0.017	0.016	0.012	0.012	0.018	0.012	0.020	0.020
Skewness	-0.11***	-0.11***	-0.22***	-0.18***	-0.43***	-0.21***	-0.07**	-0.66***	0.15***	-0.11***
Kurtosis	6.06***	9.88***	8.42***	7.79***	12.12***	9.18***	6.99***	17.66***	7.01***	6.02***
JB test	1528***	7672***	4784***	3731***	13595***	6209***	2576***	35061***	2618***	1486***
ADF test	-46.53***	-59.41***	-45.61***	-46.13***	-48.65***	-62.94***	-46.16***	-60.26***	-56.47***	-56.49***
LB(5)	16.88***	19.71***	21.39***	22.72***	51.81***	26.19***	21.76***	27.60***	63.63***	48.70***
$LB^2(5)$	1288***	1730***	1982***	2153***	2345***	1205***	782***	613***	999***	1626***
UK										
Mean	0.024	0.020	0.006	0.017	0.017	0.000	0.013	0.031	0.000	-0.041
Maximum	0.111	0.187	0.083	0.139	0.078	0.067	0.090	0.109	0.173	0.150
Minimum	-0.088	-0.189	-0.156	-0.109	-0.080	-0.079	-0.121	-0.081	-0.131	-0.232
StDev	0.016	0.021	0.015	0.017	0.013	0.012	0.018	0.011	0.018	0.025
Skewness	0.07**	-0.17***	-0.55***	0.07**	-0.06**	-0.11***	0.03	-0.04	0.05	-0.48***
Kurtosis	6.81***	13.25***	9.58***	8.13***	6.79***	6.40***	5.75***	9.26***	10.93***	10.68***
JB test	2417***	17550***	7432***	4394***	2392***	1933***	1263***	6528***	10481***	9977***
ADF test	-32.57***	-62.03***	-59.14***	-48.10***	-63.02***	-61.25***	-42.34***	-66.54***	-28.61***	-60.98***
LB(5)	47.64***	22.28***	25.27	23.79***	28.00***	34.66***	59.82***	33.89***	38.83***	10.16***
$LB^2(5)$	1751***	1860***	344***	802***	1098***	1274***	808***	1433***	989***	220***
US										
Mean	0.034	0.020	0.022	0.011	0.021	0.023	0.002	0.011	0.011	0.028
Maximum	0.168	0.133	0.096	0.090	0.116	0.114	0.133	0.135	0.144	0.159
Minimum	-0.168	-0.139	-0.096	-0.124	-0.077	-0.106	-0.089	-0.090	-0.170	-0.101
StDev	0.017	0.018	0.015	0.013	0.011	0.014	0.015	0.013	0.020	0.020
Skewness	-0.27***	-0.29***	-0.26***	-0.20***	-0.10***	-0.12***	0.08**	0.03	-0.11***	0.17***
Kurtosis	12.17***	8.98***	7.51***	9.25***	10.63***	8.91***	9.46***	13.41***	13.64***	6.97***
JB test	14008***	5987***	3423***	6512***	9663***	5805***	6926***	17983***	18812***	2641***
ADF test	-50.64***	-64.48***	-64.54***	-66.25***	-49.10***	-47.49***	-47.81***	-65.19***	-68.19***	-47.55***
LB(5)	61.46***	15.68***	19.57***	25.41***	35.08***	26.33***	18.32***	18.18***	38.96***	15.09***
$LB^2(5)$	2133***	1859***	1185***	732***	1045***	849***	1180***	1712***	1508***	767***

Mean/Maximum/Minimum returns and StDev are in percentage points. JB denotes the Jarque-Bera test statistic for the null hypothesis of normality. ADF is the Augmented Dickey-Fuller test for the null of a unit root with 5% and 1% critical values -2.86 and -3.43, respectively. The truncation lag is chosen based on a max lag of $1/2\sqrt{T} = 30$ and a downward selection procedure based on the SIC until no serial correlation is present. LB(p) and $LB^2(p)$ are the Ljung-Box *Q*-statistics on the residuals and squared residuals, respectively, for the null of no serial correlation up to a lag of *p* days. *, **, *** indicate significance at the 10%, 5%, 1% level, respectively. The sample period is June 1, 2005 to April 30, 2012.

Table 2: Empirical likelihood ratio tests for correlation dynamics

Model (H_1)	LLF	AIC	SIC	LR test	Model (H_0)	Inference
			Japanese Sectors			
CCC	126300	126.51	568.55			
DCC	127938	**40.48**	**229.09**	3276	CCC	Time variation
A-DCC	127944	42.48	236.98	11	DCC	Asymmetry
DCC-Break$_{EMU\ \&\ Crisis}$	128169	48.48	260.66	461	DCC	Break (*a*, *b*)
A-DCC-Break$_{EMU\ \&\ Crisis}$	128183	54.48	284.34	478	A-DCC	Break (*a*, *b*, *g*)
			UK Sectors			
CCC	124222	126.54	570.71			
DCC	125329	**40.52**	**230.03**	2215	CCC	Time variation
A-DCC	125342	42.52	237.96	24	DCC	Asymmetry
DCC-Break$_{EMU\ \&\ Crisis}$	125546	48.52	260.70	433	DCC	Break (*a*, *b*)
A-DCC-Break$_{EMU\ \&\ Crisis}$	125547	54.52	284.38	410	A-DCC	Break (*a*, *b*, *g*)
			US Sectors			
CCC	133619	126.39	570.26			
DCC	135664	**40.36**	**229.75**	4091	CCC	Time variation
A-DCC	135672	42.36	237.67	16	DCC	Asymmetry
DCC-Break$_{EMU\ \&\ Crisis}$	135856	48.36	260.54	383	DCC	Break (*a*, *b*)
A-DCC-Break$_{EMU\ \&\ Crisis}$	135862	54.36	284.23	380	A-DCC	Break (*a*, *b*, *g*)

The table reports the Likelihood Ratio (LR) test result for the hypothesis that correlation dynamics is sufficiently characterized by the model under H_0 versus the model under H_1. AIC is the Akaike Information Criterion, $AIC = 2 \times k - 2 \times ln(LLF)$, k is the number of parameters and *LLF* the log-likelihood function value, SIC is the Schwarz Information Criterion, $SIC = k \times ln(LLF) - 2 \times ln(LLF)$. The EMU & Crisis subscript denotes the model that contains two structural breaks on January 1, 1999 and August 1, 2007. Break (*a*, *b*) indicates a structural break in the correlation persistence parameters, while Break (*a*, *b*, *g*) indicates a break in either correlation persistence or correlation asymmetry parameters. Bolded is the selected model under each criterion. All LR statistics are significant at the 1% level.

Table 3: Estimated parameters of dynamic conditional correlation models

	Pre-EMU (1996 - 1998)					Post-EMU (1999 - 2007)					Crisis (2007 - 2012)				
	a		***b***		***g***	***a***		***b***		***g***	***a***		***b***		***g***
Japanese Sectors															
DCC-Break$_{\text{EMU \& Crisis}}$	0.020	***	0.923	***		0.015	***	0.978	***		0.020	***	0.947	***	
A-DCC-Break$_{\text{EMU \& Crisis}}$	0.020	***	0.923	***	0.000	0.011	***	0.977	***	0.006 ***	0.018	***	0.947	***	0.003
UK Sectors															
DCC-Break$_{\text{EMU \& Crisis}}$	0.013	***	0.928	***		0.014	***	0.978	***		0.016	***	0.948	***	
A-DCC-Break$_{\text{EMU \& Crisis}}$	0.020	***	0.000		0.000	0.010	***	0.978	***	0.005 ***	0.013	***	0.948	***	0.005 ***
US Sectors															
DCC-Break$_{\text{EMU \& Crisis}}$	0.019	***	0.925	***		0.013	***	0.984	***		0.023	***	0.956	***	
A-DCC-Break$_{\text{EMU \& Crisis}}$	0.012	***	0.935	***	0.011 ***	0.011	***	0.984	***	0.002 **	0.022	***	0.957	***	0.001

The table presents parameter estimates for the DCC-Break and A-DCC-Break conditional correlation models. The full sample period is July 1, 1996 to April 30, 2012. The EMU & Crisis subscript denotes structural breaks on January 1, 1999 and August 1, 2007. *, **, *** indicate parameter significance at the 10%, 5%, 1% level, respectively.

Table 4: Performance of daily rebalancing portfolios

Strategy	Max-R								Min-V							
	μ	σ	*SR*	*TO*	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$	μ	σ	*SR*	*TO*	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
Japanese Sectors																
Static	19.18	10.78	1.75	0.56					10.00	5.31	1.82	0.28				
CCC	26.39	11.82	2.20 ***	4.24	715.54	16.33	710.71	16.22	11.07	5.03	2.13 ***	1.64	107.13	6.76	107.49	6.80
DCC	27.57	11.55	2.36 ***	4.83	834.87	16.40	831.36	16.33	11.28	4.84	2.26 ***	1.88	129.03	6.90	129.75	6.95
A-DCC	27.91	11.62	**2.37** ***	4.87	**869.04**	**16.90**	**865.19**	**16.83**	11.32	4.81	**2.28** ***	1.88	**133.43**	**7.11**	**134.18**	**7.17**
DCC-Break	26.51	11.36	2.30 ***	5.41	730.11	12.62	727.48	12.57	11.00	4.84	2.20 ***	2.29	101.08	4.31	101.85	4.35
A-DCC-Break	26.77	11.42	2.31 ***	5.44	755.40	12.98	752.50	12.93	11.04	4.82	2.22 ***	2.29	105.24	4.49	106.02	4.53
UK Sectors																
Static	20.09	10.58	1.51	0.38					10.00	5.10	1.15	0.17				
CCC	22.00	10.62	1.68 ***	3.53	190.81	4.72	190.25	4.71	10.32	5.36	1.15	1.51	31.02	1.89	30.40	1.79
DCC	23.77	10.48	1.87 ***	3.82	367.72	8.62	369.07	8.63	10.42	5.08	1.24 **	1.63	**41.84**	**2.33**	**41.80**	**2.32**
A-DCC	23.91	10.52	**1.88** ***	3.86	**381.26**	**8.85**	**382.48**	**8.85**	10.40	5.06	**1.24 ****	1.64	39.90	2.18	39.91	2.19
DCC-Break	23.51	10.62	1.83 ***	3.99	341.00	7.61	341.68	7.61	10.29	5.04	1.22 **	1.67	28.74	1.52	28.81	1.53
A-DCC-Break	23.68	10.66	1.83 ***	4.01	358.16	7.97	358.68	7.96	10.29	5.03	1.22 **	1.67	29.17	1.55	29.26	1.55
US Sectors																
Static	20.21	10.34	1.66	0.55					10.00	4.66	1.49	0.21				
CCC	23.74	10.77	1.92 ***	4.58	349.83	7.24	348.83	7.20	10.49	5.02	1.48	1.73	47.75	2.67	46.94	2.63
DCC	25.55	10.57	2.13 ***	5.41	531.80	9.18	532.11	9.16	10.79	4.58	1.69 ***	2.08	78.62	**3.58**	78.60	**3.58**
A-DCC	25.65	10.59	2.13 ***	5.43	541.30	**9.30**	541.53	**9.28**	10.78	4.57	1.69 ***	2.08	78.54	3.57	78.54	3.57
DCC-Break	26.12	10.69	2.16 ***	6.15	588.09	8.80	588.02	8.78	10.84	4.48	1.73 ***	2.43	83.85	3.21	84.00	3.22
A-DCC-Break	26.20	10.70	**2.16** ***	6.15	**596.07**	8.91	**595.97**	8.88	10.84	4.48	**1.74** ***	2.43	**84.13**	3.22	**84.29**	3.23

Reported are the portfolio annualized mean return (%μ), standard deviation (%σ) and Sharpe Ratio (*SR*) of the static strategy and the correlation timing strategies. *,**,*** indicates the *SR* of the dynamic strategy is significantly higher than that of the static strategy at the 10%,5%,1% level, respectively. Performance Fee (PF_γ) is the average annualized fee (in basis points) an investor with quadratic utility and constant relative risk-aversion γ is willing to pay to switch from the static to a dynamic strategy. Break-even Transaction Cost (BTC_γ) is the average cost per trade (in basis points) that renders the investor indifferent between static and dynamic strategies. *TO* is the average monthly turnover. Bold indicates the best performing model.

Table 5: Performance of monthly rebalancing portfolios

Strategy	Max-R								Min-V							
	μ	σ	SR	TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$	μ	σ	SR	TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
Japanese Sectors																
Static	18.26	10.89	1.64	0.15					9.38	5.31	1.70	0.08				
CCC	27.16	13.37	2.01 ***	0.84	875.06	**104.58**	862.75	**103.10**	10.19	5.11	1.93 ***	0.32	81.65	30.06	81.91	30.21
DCC	28.23	13.26	2.10 ***	1.01	983.31	95.43	971.60	94.29	10.50	5.01	2.03 ***	0.39	112.02	32.13	112.43	32.30
A-DCC	28.56	13.33	**2.12** ***	1.02	**1015.19**	97.58	**1003.09**	96.42	10.53	4.98	**2.04** ***	0.40	**115.21**	**32.75**	**115.66**	**32.93**
DCC-Break	27.80	12.99	2.11 ***	1.00	941.48	92.31	931.20	91.30	10.41	4.96	2.03 ***	0.40	103.35	28.53	103.86	28.71
A-DCC-Break	27.99	13.05	2.12 ***	1.00	960.08	93.60	949.51	92.57	10.44	4.95	2.04 ***	0.41	107.01	29.40	107.55	29.60
UK Sectors																
Static	20.89	10.80	1.55	0.11					10.26	5.07	1.21	0.05				
CCC	23.44	11.36	1.70 ***	0.73	251.75	34.54	248.71	34.20	10.77	5.30	1.25	0.30	49.74	**18.05**	49.14	**17.88**
DCC	24.67	11.28	1.82 ***	0.81	374.78	44.57	373.54	44.32	10.75	5.10	1.30 **	0.35	48.17	14.77	48.00	14.74
A-DCC	24.82	11.32	**1.83** ***	0.81	389.32	45.95	387.92	45.68	10.74	5.08	1.30 **	0.35	47.94	14.61	47.81	14.60
DCC-Break	24.95	11.46	1.82 ***	0.81	402.08	48.04	400.07	47.69	10.78	5.05	1.32 **	0.33	51.11	16.52	51.03	16.52
A-DCC-Break	25.14	11.51	1.83 ***	0.82	**420.34**	**50.01**	**418.13**	**49.63**	10.80	5.05	**1.32** ***	0.33	**53.45**	17.19	**53.38**	17.20
US Sectors																
Static	20.56	10.50	1.67	0.15					9.96	4.64	1.49	0.07				
CCC	24.21	11.46	1.85 ***	0.92	358.61	36.87	355.17	36.40	10.62	5.02	1.51	0.35	64.46	18.03	63.58	17.80
DCC	25.75	11.28	2.01 ***	1.10	513.22	43.05	510.96	42.74	10.77	4.62	1.67 ***	0.43	80.53	17.43	80.39	17.44
A-DCC	25.84	11.30	2.02 ***	1.10	522.71	43.77	520.37	43.45	10.77	4.61	1.67 ***	0.43	80.95	17.52	80.83	17.53
DCC-Break	26.76	11.36	2.09 ***	1.20	615.16	46.69	611.27	46.39	10.96	4.51	1.75 ***	0.47	99.86	19.57	99.90	19.62
A-DCC-Break	26.81	11.38	**2.09** ***	1.20	**620.24**	**47.01**	**616.27**	**46.69**	10.96	4.50	**1.75** ***	0.47	**99.97**	**19.60**	**100.01**	**19.65**

See note for Table 4.

Table 6: Performance of monthly rebalancing frequency relative to daily rebalancing

	Max-R						Min-V					
	Japanese Sectors		UK Sectors		US Sectors		Japanese Sectors		UK Sectors		US Sectors	
	$PF_{=1}$	$PF_{=10}$	$PF_{=1}$	$PF_{=10}$	$PF_{=1}$	$PF_{=10}$	$PF_{=1}$	$PF_{=10}$	$PF_{=1}$	$PF_{=10}$	$PF_{=1}$	$PF_{=10}$
CCC	66.85	58.76	139.54	135.94	43.10	39.89	-87.59	-87.92	45.17	45.20	13.01	12.98
DCC	55.78	47.02	85.65	81.93	15.74	12.53	-79.08	-79.59	32.77	32.66	-1.80	-1.88
A-DCC	53.50	44.70	86.66	82.89	15.73	12.52	-80.30	-80.80	34.49	34.37	-1.29	-1.36
DCC-Break	118.56	110.21	139.68	135.60	59.89	56.72	-59.71	-60.08	48.82	48.69	12.31	12.24
A-DCC-Break	111.89	103.54	140.77	136.67	56.98	53.79	-60.20	-60.57	50.73	50.59	12.13	12.06

The table reports for each strategy the Performance Fee (PF_{γ}), in annualized basis points, an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ is willing to pay to switch from monthly rebalancing to daily rebalancing.

Table 7: Economic value of asymmetry and structural breaks

Correlation Dynamics	Daily Rebalancing						Monthly Rebalancing					
	Max-R			Min-V			Max-R			Min-V		
	SR_{diff}	*PF*	*BTC*	SR_{diff}	*PF*	*BTC*	SR_{diff}	*PF*	*BTC*	SR_{diff}	*PF*	*BTC*
Asymmetry						**Japanese Sectors**						
A-DCC vs. DCC	0.02	31.82	60.42	0.02	4.45	84.00	0.01	31.49	312.61	0.02	3.24	119.65
A-DCC-Break vs. DCC-Break	0.01	23.27	69.76	0.02	4.20	NA	0.01	18.31	295.82	0.01	3.71	274.86
Structural Break												
DCC-Break vs. DCC	-	-	-	-	-	-	-	-	-	-	-	-
A-DCC-Break vs. A-DCC	-	-	-	-	-	-	-	-	-	-	-	-
Asymmetry						**UK Sectors**						
A-DCC vs. DCC	0.01	12.36	24.87	-	-	-	0.01	14.37	214.12	-	-	-
A-DCC-Break vs. DCC-Break	0.01	75.76	70.60	0.00	0.45	2.06	0.01	18.06	537.73	0.01	2.36	301.60
Structural Break												
DCC-Break vs. DCC	-	-	-	-	-	-	0.00	26.52	552.99	0.02	3.04	NA
A-DCC-Break vs. A-DCC	-	-	-	-	-	-	0.00	30.22	1464.57	0.02	5.59	NA
Asymmetry						**US Sectors**						
A-DCC vs. DCC	0.00	8.82	35.06	-	-	-	0.00	9.41	310.06	-	-	-
A-DCC-Break vs. DCC-Break	0.00	7.68	77.11	0.00	0.29	0.00	0.00	5.00	198.17	-	-	-
Structural Break												
DCC-Break vs. DCC	0.03	53.06	5.75	0.05	5.42	1.29	0.07	100.31	80.06	0.09	19.59	38.18
A-DCC-Break vs. A-DCC	0.03	51.92	5.72	0.05	5.77	1.38	0.07	95.90	76.80	0.08	19.26	37.78

The table reports for each pair of confronted models (*e.g.* A-DCC vs. DCC) the performance fee (*PF*), in annualized basis points, and break-even transaction costs (*BTC*) per trade an investor with quadratic utility and constant relative risk-aversion ($\gamma = 10$) is willing to pay to switch from the baseline dynamic correlation strategy (*e.g.* DCC) to a dynamic strategy with asymmetry and/or structural breaks in correlation (*e.g.* A-DCC). The difference in the Sharpe Ratio (SR_{diff}) between the two competing strategies is also reported. The "-" indicates that incorporating asymmetry/structural breaks in the conditional correlation fails to enhance the economic value of the dynamic strategy. "NA" refers to cases where the turnover ratio of the correlation timing strategy with structural breaks is lower than that of the baseline case.