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Co-movements between US and UK stock prices: the roles of macroeconomic information and time-varying conditional correlations

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Abstract
We provide evidence on the sources of co-movement in monthly US and UK stock returns by investigating the role of macroeconomic and financial variables in a model with time-varying correlations. Cross-country communality in response is uncovered, with changes in US Federal Funds rate, UK bond yields and oil prices having negative effects in both markets. These effects do not, however, explain the marked increase in correlations from around 2000, which we attribute to time variation in the correlations of shocks to these markets. A regime-switching model captures this time variation well and shows the correlations increase dramatically around 1999-2000.

I. Introduction

There is a great deal of interest, and a correspondingly large literature, on the relationship between international financial markets. In particular, it is now well established that the correlations of returns across international stock markets are not only strong, but also time-varying. Important contributions to understanding the nature of this phenomenon include Ang and Bekaert (2002), Cappiello, Engle and Sheppard (2006), King, Sentana and Wadhwani (1994), Longin and Solnik (2001), and Ramchand and Susmel (1998).

Nevertheless, the question of what drives temporal changes in cross-country correlations remains largely unanswered, since few studies incorporate explanatory variables in models designed to capture international stock market linkages. This omission is surprising, since investors need to understand the causes of co-movements in order to evaluate the potential benefits of international portfolio diversification. For example, it is often observed that stock markets have become more integrated over time. Two plausible explanations are, firstly, that the macroeconomic policies and business cycles of countries have become more closely aligned or, secondly, that common shocks have become relatively more important over time. In the former case, international diversification offers protection against both idiosyncratic shocks and changing economic prospects in individual countries. On the other hand, international diversification offers less advantage if common shocks play an increasingly dominant role over time. In the light of this, the present paper aims to shed light on the drivers of changing correlations between stock market price movements in the US and UK since 1980, focusing on the role of macroeconomic effects and, conditional on these, on the patterns of conditional shock correlations.

A long and continuing stream of research, initiated by Fama (1981), has examined the role of macroeconomic variables (particularly real activity, inflation and interest rates) for stock returns. However, this research has almost exclusively considered domestic economic conditions, and hence sheds little light on cross-country linkages. Nevertheless, there are some important exceptions, including Bonfiglioni and Favero (2005), Campbell and Hamao (1992), Canova and De Nicoló (2000), and Nassah and Strauss (2000), all of whom allow foreign economic variables to affect domestic stock returns. While these studies document the importance of international market linkages, especially with the US, and frequently find that foreign macroeconomic variables play a role for domestic stock returns, only Bonfiglioni and Favero (2005) focus primarily on explaining the changing nature of such links.

Bonfiglioni and Favero (2005) study monthly German and US (log) stock market indices in relation to bond yields and (log) analysts' forecasts of earnings. They propose an innovative methodology that distinguishes between short-run stock market interdependence and contagion through the significance, in the equation for German stock returns, of dummy variables representing extreme changes in the US market. While an incisive contribution, their analysis is nevertheless based on the crucial assumption that, after allowing for a small number of periods of extreme change, the vector of shocks to the markets is normally distributed with a constant covariance matrix. However, in the light of the recent literature concerned with time-varying conditional correlations across international financial markets, this is a strong assumption. Baele (2005) takes a different approach, by focusing on time-varying correlations between the US and European markets through a Markov-switching approach, and then, in a second stage, considering the role of economic variables in explaining the switches between high and low spillover regimes. Although recognising time-varying correlations, this approach does not readily allow analysis of the extent to which this time-variation is due to changing economic circumstances or to changing levels of stock market integration. Further, the treatment of the regimes as observed for the second stage is not valid econometrically[1].

Despite their different methodologies and different sample periods, a common finding of both Baele (2005) and Bonfiglioni and Favero (2005) is that cross-market spillovers between major markets have generally increased over time, with this being indicated in the latter case by the preponderance of identified contagion instances occurring at the end of the 1990s and early in the new century. The present paper investigates these issues further by directly modelling changes in stock market price indices in an international context in terms of their economic determinants, using a richer set of explanatory variables than Bonfiglioni and Favero (2005), while explicitly considering the existence and nature of time-varying conditional correlations using the recent approaches of dynamic conditional correlations (Engle, 2002)[2] and smooth transition conditional correlations (Berben and Jansen, 2005, Silvennoinen and Teräsvirta, 2005). The latter is preferred to the Markov-switching approach of Ang and Bekaert (2002) and Pelletier (2006), among others, since it allows the regime to be modelled as a continuous function of one or more so-called transition variables, and hence avoids the two-step approach of Baele (2005). It

[1] As Pagan (1984) proves that the standard errors need adjustment in regressions with constructed regressors.

[2] A similar methodology is proposed by Tse and Tsui (2002).

should also be noted that, in modelling conditional correlations, we do not make any assumption of causal ordering between the US and UK markets. This contrasts with the strong assumption explicitly made by Bonfiglioni and Favero (2005), and implicitly by (for example) Canova and De Nicoló (2000)[3], that there is no contemporaneous feedback from stock market growth in other major countries to that in the US[4].

To preview our results, we find substantial communality in responses of US and UK stock markets to changes in short-term interest rates, bond yields and oil price inflation. In addition, the UK market reacts to exchange rate movements and dividend yields from both markets, effects we associate with the role of international investors in this market. Nevertheless, these economic determinants fail to explain the increase in correlations across these markets in the period from 2000. We also find strong statistical evidence for time-varying conditional correlations, which are adequately captured by a smooth transition conditional correlation model that implies a strong increase in correlations around 2000.

The organisation of this paper is as follows. Sections II and III, respectively, describe the econometric methodology and data we use. Substantive results are then reported and discussed in Section IV. Conclusions in Section V complete the paper, with some additional results presented in an Appendix.

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[3] This assumption is implicit in the variable ordering used in a triangular variance decomposition used to compute impulse responses.

[4] Such as assumption is more plausible in the context of small open economies, as examined by Bredin and Hyde (2008).

II. Econometric Methodology

After outlining our approach for the mean and volatility equations (Section II.A), Section II.B describes the time-varying conditional correlation models. Specification testing and estimation are then discussed in Sections II.C and II.D.

A. Mean and Volatility Equations

We model monthly changes in the logarithm of the US and UK stock market price indices, which are the corresponding variables to those of Bonfiglioni and Favero (2005). Richards (1995) argues that the concept of, and testing for, cointegration across international stock markets is problematic, with the econometric issues further complicated by the possible presence of a non-constant conditional covariance matrix. Therefore, we examine short-run stock price movements, with the consequences of economic integration on stock markets captured through the inclusion of appropriate variables in the mean equations.

The mean equation for the two-dimensional vector (y_t) of stock price growth for the US and UK can be written as

(1) $$y_t = Bx_t + u_t, \qquad t = 1, 2, \ldots, T$$

where the explanatory variables x_t include the relevant macroeconomic information set. Following Bonfiglioni and Favero (2005), Campbell and Hamao (1992), Canova and De Nicoló (2000), and Nassah and Strauss (2000), foreign as well as domestic variables are allowed to enter both equations, so that no *a priori* zero restrictions are imposed on the matrix B. However, based on the findings of Bonfiglioni and Favero (2005), the macroeconomc indicators in x_t are assumed weakly exogenous for y_t.

In line with recent literature on international stock market returns, the conditional covariances of the shocks in equation (1) are time-varying, such that

(2) $$u_t|\Im_{t-1} \sim (0, H_t)$$

where $\Im_{t-1}$ is all available information at t-1. From equation (2), each univariate error process can be written

(3) $$u_{i,t} = h_{ii,t}^{1/2}\,\varepsilon_{i,t},\; i = 1, 2$$

where $h_{ii,t} = E(u_{i,t}^2 / \Im_{t-1})$ and $\varepsilon_{i,t}$ is a sequence of independent random variables with mean zero and variance one. As common in empirical analyses, each conditional variance is assumed to follow the univariate GARCH(1,1) process

(4) $$h_{ii,t} = \alpha_{i0} + \alpha_{i1}u_{i,t-1}^2 + \beta_{i1}h_{ii,t-1}$$

with non-negativity and stationarity restrictions imposed.

Rather than modelling the off-diagonal elements of H_t directly, the definition

(5) $$\rho_t = h_{12,t}(h_{11,t}h_{22,t})^{-1/2}$$

allows the focus to be placed on the conditional correlations ρ_t. The constant conditional correlation (CCC) model assumes that ρ_t is constant over time, while the dynamic conditional correlation (DCC) and smooth transition conditional correlation (STCC) models allow distinct patterns of time-variation in ρ_t.

B. Time-Varying Conditional Correlations

Engle (2002) specifies the DCC model through the GARCH(1,1)-type process

(6) $$q_{ij,t} = \bar{\rho}_{ij}(1-\alpha-\beta) + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta q_{ij,t-1}, \quad i, j = 1, 2$$

where $\bar{\rho}_{12}$ is the (assumed constant) unconditional correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, α is the news coefficient and β is the decay coefficient. The quantity $q_{12,t}$ from equation (6) is normalized using

(7) $$\rho_t = \frac{q_{12,t}}{(q_{11,t}\,q_{22,t})^{1/2}}$$

in order to ensure a conditional correlation between -1 and +1. The model is mean-reverting provided $\alpha+\beta<1$, while the conditional correlation process in equation (6) is integrated when the sum equals 1. However, the latter case violates the assumption of a constant unconditional correlation $\bar{\rho}_{12}$, which is embedded in equation (6).

Rather than assuming a constant unconditional correlation, the STCC model developed by Berben and Jansen (2005) and Silvennoinen and Teräsvirta (2005)[5] assumes the presence of two extreme states (or regimes) with state-specific correlations. These correlations are, however, allowed to change smoothly between the two regimes as a function of an observable transition variable s_t. More specifically, the conditional correlation ρ_t follows

(8) $$\rho_t = \rho_1\left(1 - G_t\left(s_t;\gamma,c\right)\right) + \rho_2 G_t\left(s_t;\gamma,c\right)$$

in which the transition function $0 \le G_t\left(s_t;\gamma,c\right) \le 1$ is a continuous function of s_t, while γ and c are parameters.

Since equation (8) implies $\rho_t = \rho_1$ when $G_t = 0$ and $\rho_t = \rho_2$ when $G_t = 1$, extreme values of the transition function identify the distinct correlations that apply in these regimes. A weighted mixture of these correlations applies when $0 < G_t < 1$. A plausible and widely used specification for the transition function is the logistic function

(9) $$G_t\left(s_t;\gamma,c\right) = \frac{1}{1+\exp[-\gamma(s_t - c)]}, \quad \gamma > 0$$

where the parameter c locates the midpoint between the two regimes. The slope parameter γ determines the smoothness of the change in G_t as a function of s_t. When

[5] The model of Berben and Jansen (2005) is bivariate with a time trend as the transition variable, while the framework of Silvennoinen and Teräsvirta (2005) is multivariate and their transition variable can be deterministic or stochastic.

$\gamma \to \infty$, $G_t(s_t;\gamma,c)$ becomes a step function ($G_t(s_t;\gamma,c)=0$ if $s_t \le c$ and $G_t(s_t;\gamma,c)=1$ if $s_t > c$), and the transition between the two extreme correlation states becomes abrupt. In that case, the model approaches a threshold model in correlations.

An important special case of the STCC model uses time as the transition, $s_t = t/T$, which gives rise to the time-varying conditional correlation (TVCC) model employed by Berben and Jansen (2005)[6]. This allows one (smooth) change between correlation regimes, and as $\gamma \to \infty$ captures a structural break in the correlations. This transition variable may be particularly relevant in order to capture the effects of increasing integration of financial markets over the last twenty years.

C. Specification Tests

Before applying either the DCC or STCC model, tests are applied to investigate the constancy of the conditional correlations in equation (5). Two residual-based tests of Bollerslev (1990) are particularly suitable for testing against a DCC specification. The first is the Ljung-Box statistic for testing autocorrelation up to *m* lags in the cross product of the standardised residuals (r_{1t} and r_{2t}) from the GARCH(1, 1) model of equation (4), which under the null hypothesis is asymptotically distributed as χ^2 with *m* degrees of freedom (we use m = 18). The second is an *F* test of the significance from a regression of the sample values of $r_{1t}r_{2t}h_{12,t}^{-1}-1$ on $h_{12,t}^{-1}$, $r_{1,t-1}^{2}h_{12,t}^{-1}$, $r_{2,t-1}^{2}h_{12,t}^{-1}$ and lags $r_{1,t-k}r_{2,t-k}h_{12,t}^{-1}$ (in which we include k = 1, …, 12). In addition, we apply the Lagrange Multiplier (*LM*) test of Tse (2000), which considers the null hypothesis δ = 0 in the ARCH-type structure

(10) $$\rho_{12,t} = \rho_{12} + \delta\, r_{1,t-1}\, r_{2,t-1}$$

[6] The scaling implied by defining $s_t = t/T$ aids interpretation; see Berben and Jansen (2005).

Under the null hypothesis, the statistic is distributed as χ^2 with 1 degree of freedom[7]. We perform the Tse (2000) test in an estimation of the complete system (including mean equations).

Silvennoinen and Teräsvirta (2005) derive a Lagrange Multiplier test LM_{CCC} for the constancy of the correlations against a particular transition variable by applying a first-order Taylor series expansion to the STCC transition function (9) and then testing the significance of the additional terms that arise compared to a CCC specification. After allowing for the effects of macroeconomic variables through the mean equation (1), this test is applied using a time transition in the correlations to investigate changing conditional correlations associated with globalisation[8].

After estimation, the adequacy of the DCC and STCC models are checked using diagnostic tests applied to the standardised residuals from the bivariate system. Following Engle (2002), the required standardised residuals $v_t = H_t^{-1/2} r_t$ are computed through the triangular decomposition of H_t, so that

$$v_{1,t} = r_{1,t} / h_{11,t}^{1/2}$$

[7] Tse (2000) notes that it may be more natural to use standardised values of $r_{i,t-1}$ in equation (10), but prefers the unstandardised form for analytical tractability. Nevertheless, this choice may affect the power of the test. Power may also be affected by applying this two-sided test, in a context where δ is positive under the alternative.

[8] Based on previous studies that find co-movements to be stronger in volatile times than in more tranquil periods (Ang and Bekaert, 2002; Baele, 2005; Longin and Solnik, 2001; Ramchand and Susmel, 1998, among others), we also tested constancy of conditional correlations against a model with the conditional variance of the US stock returns as the transition variable. However, constancy was rejected more strongly using time and, when the volatility transition model was estimated, it resulted in relatively modest improvements in the log likelihood compared with the CCC model.

$$v_{2,t} = r_{2,t}\,\frac{1}{(h_{22,t}(1-\rho_{12,t}^2))^{1/2}} - r_{1,t}\,\frac{\rho_{12,t}}{(h_{11,t}(1-\rho_{12,t}^2))^{1/2}} \tag{11}$$

in which unknown parameters are replaced by their sample analogues. Since v_{2t} depends on the (estimated) dynamic correlations, tests on this are more revealing than those on v_{1t} (Engle, 2002, p.344). We apply the Ljung-Box test to both the standardised residuals and the squares of these standardised residuals.

D. Estimation

We estimate the CCC, DCC and STCC models by quasi-maximum likelihood (QML), with robust standard errors (Bollerslev and Wooldridge, 1992) used for the parameter estimates. All equations (that is, for the conditional means, volatility and conditional correlation) are estimated jointly. Although Engle (2002) and Cappiello *et al*. (2006) use a two step approach for estimation of DCC models, this does not allow for computation of QML standard errors that are robust to the violation of the assumption of normality in equation (1). Furthermore, through joint estimation taking account of (changing) cross-market conditional correlations, we aim for efficiency gains in the estimation of the impact of economic information on stock returns[9].

Nevertheless, nonlinear estimation of the resulting models is not always easy to achieve and specification of starting values plays a crucial role. The procedure we use to obtain starting values is discussed in Appendix 1.

[9] In practice we estimate the CCC and DCC models using the GARCH wizard in RATS 6.3. The reported STCC estimates are obtained using GAUSS, where our programs are adapted from code supplied to us by Christos Savva.

III. Data

We simultaneously model movements in the monthly index of US and UK stock prices using data over the sample 1980m1-2006m6. More precisely, the US stock price is the Standard and Poor's composite index (*SP*) and the UK stock price is the Financial Times All Share Index (*FT*), with end-of-month values employed for each. The starting date of 1980 is selected as it is subsequent to the financial liberalisations that occurred during the latter part of the 1970s[10].

As discussed in the Introduction, we investigate interdependence of the markets arising from available international information by allowing the macroeconomic variables for each country to enter the linear mean equations for both countries. The US and UK analyses of Pesaran and Timmermann (1995, 2000) provide the benchmark set of explanatory variables we use. More specifically, we consider the dividend yield for the corresponding market (*SPDY*, *FTDY*), industrial production (*USIP*, *UKIP*), retail sales volumes (*USRS*, *UKRS*), a short interest rate (the US Federal Funds Rate, *USFF*, and the UK 3-month Treasury Bill Rate, *UKTB*) a long bond rate (*USLR* and *UKLR*), nominal money stock (*USM*1 and *UKM*0), the Consumer Price index (*USCP* and *UKRP*) and the oil price measured in US dollars (*OIL*). In addition, the exchange rate of US dollars to pounds sterling (*ER*) is considered as an explanatory variable for the UK to reflect the open nature of its economy, while one month lagged returns for both markets are also considered as possible variables entering the two mean equations. The set of variables is therefore sufficiently broad to capture monetary policy and business cycle influences, as well as

[10] Also, the early/mid-1970s were crisis years in the UK, with accelerating inflation, rising unemployment, massive industrial unrest and the first oil price shock (Dow, 1998). In their Markov switching model for UK returns, Guidolin and Timmermann (2003) associate one regime, with negative mean returns and a large variance, primarily with this period.

spillovers between markets and other dynamics. While we aim to use the corresponding series for the US and UK, a precise matching is not always possible due to data availability. Appendix 2 provides details of the series and data sources.

Most variables (including stock market prices) are used as growth rates, computed as 100 times the first difference of the logarithms. Exceptions are the interest rate series and the dividend yield, for which we take first differences, and the consumer price indices which are transformed to annual inflation rates. The decision to difference the explanatory variables was based on the results of prior unit root tests.

To match the timing of our monthly stock price data, we also use end-of-month values for the explanatory variables. Nevertheless, care must be taken in relation to the lag at which macroeconomic variables become available. While retail sales, consumer prices, money, and US industrial production data for a specific month are released during the immediately subsequent month, this is not the case for UK industrial production. On the other hand, while contemporaneous oil prices are known, in practice we found a lag of one month to have higher significance. Therefore, lags of one month are employed for most real activity variables, with *UKIP* lagged by two periods. Financial data on the exchange rate, short and long interest rates are available continuously, and contemporaneous end-of-month values are used for these variables. Dividend yields are lagged by one month to avoid the simultaneity that would result if the current value was employed.

By using latest data available to the stock market at the end of the month, we assume that the macroeconomic indicators are weakly exogenous for stock market returns. This assumption is in line Bonfiglioni and Favero (2005) and the timing of explanatory variables for regime changes in Baele (2005), as well as with the causal ordering made in variance decompositions by Nassah and Strauss (2000) and many others.

Our sample period includes the stock market crash in October 1987, which affects both UK and US stock prices and the corresponding dividend yield series. The effect of the Long Term Capital Management crisis in 1998 is marked for the US stock price index. To ensure these events do not unduly influence the estimated models, we replace these outliers by the average value of the series over the sample period, computed excluding the outlier observation. We also remove outliers associated with extreme events in the industrial production, retails sales and money series (see Appendix 2 for details).

The column labelled sample cross correlations in Table 4 provides some descriptive evidence on the changing correlations of the monthly stock market growth series that we model. Over our entire sample period, these markets exhibit a strong positive correlation, but over (approximately) five year sub-samples, this correlation varies between 0.45 and 0.87. Indeed, the contrast between the correlations for the second half of the 1990s and the high correlation in first part of the new century is particularly marked[11].

IV. Results

Section IV.A discusses initial results for the mean equations, including the variables that survive our selection process, while Section IV.B provides a summary comparison of results for different conditional correlation specifications. The final Section IV.C then discusses the results obtained using the preferred STCC model.

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[11] Goetzmann, Li and Rouwenhorst (2005) examine the correlation structure of world equity markets for a period of 150 years and find that correlations between stock markets were relatively high during the late nineteenth century, the Great Depression and the late twentieth century.

A. Mean Equations

As already discussed, one aspect of interest in this study is co-movement across the US and UK markets that arises from similar responses to available information. However, a disadvantage of allowing variables from the other country to influence domestic stock market prices is the consequent possible over-parameterisation of the mean equations. To avoid this, the set of explanatory variables in each equation is reduced by adopting a general to specific approach and eliminating the least significant variables one by one in order to achieve the minimum Akaike information criteria (AIC). Although undertaken in a single equation setting for each market, the possible presence of heteroscedasticity is recognised by using robust standard errors to judge the least significant variable.

For comparison with later results, the OLS estimates of the resulting linear models are presented in Table 1[12], together with heteroscedasticity robust standard errors. The UK model explains almost a quarter of the variation in the growth of stock market prices. The strongest significance is from the exchange rate, where an appreciation of the pound against the dollar (an increase in *ER*) has a negative impact. The implication that a depreciation of the pound is associated with a growth rate of UK stock market prices is compatible with international investors requiring higher price growth to compensate for the adverse effects of a depreciation on returns

[12] We also considered using the unanticipated changes in the variables as regressors in our models, where the unanticipated component for each series was extracted using an AR(12) model, and including the residuals in the linear model. Then we followed a general to specific approach based on the AIC to select the specific model. The selected specific model was very similar that obtained using the original series, and hence we proceeded with the model based on observed values.

measured in dollars[13]. Another indicator of the role of international investors for the UK market is the significance of the US dividend yield, with the opposing signs of $\Delta SPDY_{t-1}$ and $\Delta FTDY_{t-1}$ implying that potential investors compare these when considering where to invest.

Nevertheless, domestic economic conditions also play a substantial role for the UK market, with changes in the long and short rates and industrial production all being individually significant at the 5 percent level and of the anticipated signs. However, the presence of lagged UK and US stock price growth is not in line with the weak form of the efficient market hypothesis, where it might be noted in particular that the former (ΔFT_{t-1}) has a strong positive and significant coefficient. The US model, on the other hand, contains fewer variables and explains a substantially lower proportion of total variation (around 14 percent), with no role for either past price growth or dividend yields. Indeed, unlike the UK, industrial production does not survive the variable selection process. Although retail sales does appear, it is not significant at even 10 percent, and this variable is consequently dropped from subsequent models. Overall, real variables appear to play only a minor role in explaining movements in US stock prices.

However, our main focus of interest is not individual markets but rather their co-movements. In this context, two aspects of the results in Table 1 are of interest. The first is the negative influence of oil prices, where the almost identical (and significant) coefficients imply that co-movement will be stronger when oil price changes are large.

[13] Note, however, that the coefficient on ΔER_t is also significantly different from -1, and hence it is inappropriate in this model to measure UK stock market price growth net of exchange rate effects.

The second aspect is the strong role played by interest rate changes for both markets. Not only do both domestic long and short-rates appear (with negative signs) in the respective equations, but UK bond rates are highly significant for the US while US short-rates have marginal significance of around 6 percent for the UK. Once again, the similarity of the coefficients for $\Delta UKLR_t$ and $\Delta USFF_t$ across the two equations implies that the common responses of the markets to changes in these variables will give rise to co-movement. Indeed, Laopodis (2002) documents stronger international correlations for bond prices during the 1990s than the 1980s, and such increased correlation for US and UK long rates would further enhance the implied communality of stock price movements in Table 1[14].

The diagnostic tests for the linear model in Table 1 provides strong evidence of time varying conditional volatility (ARCH) in the residuals of the US model. There is also evidence of non-normality, especially for the UK, although this is not unexpected when modelling stock returns.

Before moving to the time-varying volatility models we eliminate ΔSP_{t-1} from the FT equation as this is insignificant. Detailed results for the parsimonious linear model can be obtained from the authors on request.

B. Model Comparisons

The CCC, DCC and STCC models outlined in Section III take account of time-varying volatility, but make differing assumptions about the temporal nature of the cross-market conditional correlations. The impact of these differing assumptions are summarised in Tables 2, 3 and 4.

[14] To be specific, the aggregate of the coefficients on US and UK long-term rates in the US equation is -3.76, compared with -3.50 in the UK equation (with the latter arising from UK long-term rates alone). When the two long-term rates move together, only this aggregate is relevant.

Table 2 shows that taking account of volatility in the mean specifications of Table 1 through a GARCH(1,1) specification for each market, in conjunction with constant cross-market conditional correlations, is not satisfactory. More specifically, the Ljung-Box and (particularly) the Bollerslev residual diagnostic tests reject the assumption of constant conditional correlations. Although the Tse (2000) test is less decisive, it also rejects this assumption at a marginal significance level of 6 percent. However, the CCC model is particularly strongly rejected against the STCC model with a time transition[15].

In line with these results, the statistics in Table 3, and especially AIC and BIC, point to the use of the STCC model in preference to a CCC or DCC specification. Further, and not surprisingly, the models with explanatory variables in the mean equations are preferred to constant mean specifications, which underlines the importance of (domestic and international) macroeconomic conditions in explaining movements in the US and UK markets. However, these results shed little light on the extent to which these variables explain the apparently time-varying correlation of the movements in these markets.

To gain further insight into this question, Table 4 shows, firstly, the correlations between the fitted values from the mean equations of (1) and, secondly, the corresponding conditional correlations for each of the CCC, DCC and STCC

[15] This test was computed using the Ox programs supplied by Annastiina Silvennoinen. The test is performed on the residuals from a linear regression including the explanatory variables as the programs do not allow all equations of our model to be estimated simultaneously. All the explanatory variables were tested as possible STCC transitions for the constant mean model and the results are presented in Table A.3.1. However, testing the explanatory variables from the mean model of equation (1) as possible STCC transitions in this way is not asymptotically valid, as there may exist conditional mean estimation effects that are not accounted for by the test, see Halunga and Orme (2007).

models, over both the whole sample period and five year sub-samples. Although these do not provide a simple decomposition, nevertheless they provide information about the relative contributions of the mean equations and the residual conditional correlations to modelling the observed sample cross-correlations.

Interestingly, over the whole period and irrespective of the particular conditional correlation model employed, the mean equation fitted values yield correlations around 0.65-0.70, which is similar to the observed correlation. Nevertheless, common shocks are also important, with these having a correlation of 0.61, so that the overall sample correlation of 0.65 cannot be clearly attributed to either economic conditions or to conditional correlations unexplained by these. Until around 1999, the sub-sample correlations implied by the mean equations remain fairly constant, but then fall to around 0.5 in the post-2000 period. In other words, the fitted means do quite poorly in capturing the large increase in correlations at the end of the sample. The high correlation unexplained by economic conditions is consequently manifested by a large increase in the conditional correlations. Despite the CCC model being estimated under the assumption of constant conditional correlations, the residual series from this model nevertheless show a similar pattern of temporal change in the conditional correlations as the time-varying DCC and STCC specifications.

The conditional correlations shown in Figure 1 for the DCC and STCC specifications provides further information on these temporal patterns. In particular, the implied correlations grow fairly dramatically from around 0.4 at the beginning of the sample to around 0.9 in 2002, which may reflect increasing globalisation and integration of stock markets not captured by the explanatory variables in the mean equations. Although Cappiello *et al*. (2006) associate an increase in correlations of stock markets in the recent past with the introduction of the euro currency, the increase in the bivariate correlation between the US and UK cannot be attributed to this source and appears to be a consequence of broader international financial market integration; see also Savva *et al*. (2005).

Although the DCC model is not designed to capture a systematic temporal pattern in conditional correlations, Table 4 and Figure 1 indicate that, in practice, it does so quite well in our case. Nevertheless, the clear pattern in the DCC conditional correlations indicates that the STCC model may be a more appropriate specification, a conclusion compatible with the AIC and SIC values in Table 2.

Detailed estimation results are not presented for the CCC or DCC models[16]. In the former case, this is because the CCC assumption is rejected by the data. In the DCC case, the estimate for $\alpha + \beta$ in (6) is on the border of nonstationarity, at 0.9999, which appears to violate the assumption of an underlying correlation of shocks that is constant over time. Indeed, it is only through this effective nonstationarity that the DCC model is able to capture the temporal pattern indicated in Figure 1. It may also be noted that the estimated mean equation coefficients and their significance are very similar across the CCC, DCC and STCC specifications.

4.3 STCC Results

The discussion of the previous subsection points to the STCC specification as being the most appropriate model for capturing the time-varying conditional correlations between the growth rates in US and UK stock market prices.

The importance of time for capturing the correlations between these markets is reinforced by Appendix Table A.3.1, which shows the results of tests for constant correlations against time-varying correlations in a constant-mean model. Therefore, in this specification, all co-movement is captured by the correlations of the disturbances,

[16] These may be obtained from the authors on request.

even when such co-movements could be due to related responses common macroeconomic information. Although Table A.3.1 indicates that interest rate variables and US consumer price inflation (which is, of course, correlated with interest rates) as possible transition variables, nevertheless the *p*-values point to the dominant role of time if a single transition variable is to be selected.

Therefore, in conjunction with effects of interest rates and other observed variables captured through the mean equations, Table 5 presents the estimates of the STCC model, described by equations (1), (4), (8) and (9). As shown by the diagnostic statistics, this model satisfactorily accounts for the temporal patterns in these returns and their correlations.

By comparing corresponding estimates in Tables 1 and 5, it can be seen that modelling change over time in the conditional correlations has some impact on the estimated effects and significance of the economic variables in the mean equations. In particular, although the lagged value of *FT* remains significant in the UK equation in Table 5, the magnitude of this coefficient is substantially lower than for the OLS estimates of Table 1. Further, the US long-term interest rate is now highly significant for the US equation in Table 5. Overall, however, the substantive implications of this model for the mean remain as for Table 1.

In terms of the temporal pattern of the conditional correlations, *c* in Table 5 defines the middle of the transition period, with this value expressed as a fraction of the sample size, and the corresponding estimated mid-point date of May 2000 is also indicated[17]. The results show that the conditional correlation between the two markets increases from 0.52 at the beginning of the sample to the substantially higher value of

[17] It is worth mentioning that Berben and Jansen (2005) for their US-UK model estimate a mid-point of March 1983. However, their estimation period is 1980-2000, and hence they apparently do not pick up the large increase in correlation we find around 2000.

0.90 in the latter part. Indeed, similar conditional correlations are obtained in a constant-mean STCC specification (see Appendix Table A.3.2), indicating once again that macroeconomic variables account for relatively little of this temporal pattern.

This temporal pattern for STCC estimated conditional correlations has already been noted in relation to Figure 1. It might also be noted that the slope parameter of the transition function of 13.4 in Table 5 results in the relatively smooth change over time in the cross-market conditional correlations evident in Figure 1.

V. Concluding remarks

This paper provides two contributions to understanding the nature and causes of co-movements in monthly US and UK stock prices. Firstly, we examine the role of macroeconomic and financial variables for explaining stock price growth and find substantial communality in the responses to these variables. In particular, not only are domestic variables important, but some interest rate changes affect both markets irrespective of the country in which these changes apply. It is plausible that the US Federal Funds rate is important for the UK market as a signal of movements in world interest rates. Although the role of UK bond rates for the US market is less evident *a priori*, nevertheless it indicates that the US market is open to international influences. In general, however, the UK market is affected more by international influences, with other significant variables including the dividend yield for the US market, US inflation and changes in the dollar/pound exchange rate. Perhaps not surprisingly, both markets react significantly to oil price inflation.

In addition to these cross-country effects, domestic short and long interest rates also play a role in explaining stock market returns, while there is a negative effect in both markets from oil prices increases. The communality of these effects results in positive correlations between movements in the stock markets in both countries. Nevertheless, our results also imply that the increase in correlations between these markets in the post-2000 period cannot be explained in terms of their responses to economic information. Indeed, our models indicate that economic variables alone would point to the cross-market correlations being lower in this period than previously, whereas the observed correlations substantially increase.

The second contribution of this paper is to explore the usefulness of time-varying conditional correlation models in this context. Although other recent studies (including Cappiello et al. 2006, Savva et al., 2005) employ time-varying conditional correlation models, to our knowledge the present study is the first that does so while also allowing for mean effects due to known macroeconomic information. In our context, the dynamic conditional correlation model of Engle (2002) points to increasing correlations in the latter part of the sample, but the parameter estimates are not compatible with the stationarity assumption that underlies this specification. This situation is handled well by the smooth transition conditional correlation specification of Silvennoinen and Teräsvirta (2005) using time as the transition variable. The resulting STCC specification indicates that the correlations of shocks (unexplained by the macroeconomic and financial variables) increase dramatically from around 1999.

The robustness of our results is verified using constant-mean models that do not admit explanatory variables in the mean equations. These yield similar results, confirming the high degree of co-movement between the US and UK equity markets in recent years. Since the increase in co-movement remains largely unexplained after exploring the implications of common responses to observed economic information through the mean equations, the increased correlations of shocks appears to be a manifestation of increased globalisation.

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Table 1: OLS Estimates of Mean Models for US and UK Stock Prices

Variable	ΔSP_t	ΔFT_t
Constant	0.7213 [0.2299]	-0.0244 [0.4599]
$\Delta USRS_{t-1}$	0.3275 [0.2121]	
$\Delta USLR_t$	-1.1260 [0.5731]	
$\Delta USFF_t$	-0.4121 [0.2140]	-0.3547 [0.1910]
$\Delta USCP_{t-1}$		0.1555 [0.0968]
ΔOIL_{t-1}	-0.0621 [0.0252]	-0.0697 [0.0275]
$\Delta UKLR_t$	-2.6305 [0.7597]	-3.5021 [0.8712]
$\Delta UKTB_t$		-1.0649 [0.4688]
ΔFT_{t-1}		0.4523 [0.1790]
ΔSP_{t-1}		-0.1404 [0.1167]
$\Delta FTDY_{t-1}$		11.9207 [3.7722]
$\Delta SPDY_{t-1}$		-6.7356 [2.7762]
$\Delta UKIP_{t-2}$		0.5662 [0.2294]
ΔER_t		-0.3148 [0.0695]
s	3.7569	3.7772
AIC	5.5038	5.5328
SIC	5.5747	5.6748
R^2	0.1392	0.2413
Diagnostics		
Autocorrelation	0.5495	0.8237
ARCH	0.0000	0.1634
Normality	0.0655	0.0016

Notes: Values in square brackets are heteroscedasticity-robust standard errors; results for the diagnostic tests are presented as p-values. Diagnostic tests for autocorrelation and ARCH are (single equation) Lagrange multiplier tests using lags 1 to 12 inclusive.

Table 2: Tests of Constant Conditional Correlations

<u>Tests against DCC model</u>	
Ljung Box test	32.29 (0.020)
Bollerslev test	2.923 (0.0003)
Tse LM statistic	3.476 (0.062)
<u>Test against STCC model</u>	
t/*T* transition	19.47 (0.0000)

Notes: The Ljung-Box statistic tests autocorrelation up to 18 lags in the cross products of the GARCH standardised residuals, distributed as χ^2 with 18 degrees of freedom. Bollerslev's (1990) residual based diagnostic is the *F* test from a regression of $r_{i,t}r_{j,t}h_{i,j,t}^{-1}-1$ on $h_{i,j,t}^{-1}$, $r_{i,t-1}^{2}h_{i,j,t}^{-1}$, $r_{j,t-1}^{2}h_{i,j,t}^{-1}$ and $r_{i,t-1}r_{j,t-1}h_{i,j,t}^{-1},\ldots,r_{i,t-12}r_{j,t-12}h_{i,j,t}^{-1}$. The Tse (2000) test is the Lagrange Multiplier statistic for constant correlations, distributed as χ^2 with 1 degree of freedom. Figures in the parentheses are *p*-values. Tests against a single transition STCC model are those of Silvennionen and Teräsvirta (2005), distributed as χ^2 with 1 degree of freedom.

Table 3: Log Likelihood and Information Criteria Values

	Log-Likelihood	AIC	SIC
Models with explanatory variables			
CCC	-1645.14	10.492	10.764
DCC	-1631.31	10.411	10.695
STCC	-1626.40	10.393	10.434
Constant mean models			
CCC	-1706.69	10.791	10.897
DCC	-1695.12	10.724	10.842
STCC	-1688.76	10.697	10.716

Table 4: Mean Equation and Conditional Correlations over Sub-Samples

			Fitted Mean Correlations			Conditional Correlations		
	No. of obs	Sample Cross Correlations	CCC	DCC	STCC	CCC	DCC	STCC
1980m1-2006m6	318	0.656	0.662	0.651	0.693	0.619	0.602	0.606
1980m1-1984m12	60	0.509	0.680	0.662	0.710	0.457	0.492	0.518
1985m1-1989m12	60	0.668	0.721	0.691	0.741	0.606	0.522	0.518
1990m1-1994m12	60	0.664	0.737	0.728	0.754	0.582	0.634	0.518
1995m1-1999m12	60	0.449	0.716	0.713	0.742	0.459	0.497	0.596
2000m1-2006m6	78	0.867	0.501	0.495	0.528	0.855	0.804	0.864

Notes: All models are estimated using data over the sample 1980m1-2006m6, using the same variables in the mean equations (see Section IV.A), but making different assumptions about conditional correlations. Mean equation correlations are computed using the fitted values from (1), over the indicated sub-sample periods. Conditional correlations for the CCC model are computed as the simple correlations of the residuals from the mean equations, standardized using the estimated conditional volatility. The DCC model conditional correlations are the sub-sample average of the estimated conditional correlations ρ_t of (7). The STCC conditional correlations are obtained using the estimated values from (8) and (9) with time as the transition variable.

Table 5: Model Estimates with Smooth Transition Conditional Correlations in Time

	ΔSP_t	ΔFT_t
a. Mean equations		
Constant	0.8443 [0.1904]	0.3128 [0.3186]
ΔFT_{t-1}		0.2526 [0.1093]
$\Delta FTDY_{t-1}$		8.0769 [2.6158]
$\Delta SPDY_{t-1}$		-3.5870 [1.4812]
$\Delta UKTB_t$		-1.0225 [0.4228]
$\Delta UKLR_t$	-2.4112 [0.7343]	-3.6162 [0.8274]
$\Delta USLR_t$	-1.7081 [0.5716]	
$\Delta USFF_t$	-0.4584 [0.2255]	-0.3781 [0.1767]
ΔOIL_{t-1}	-0.0507 [0.0243]	-0.0613 [0.0257]
ΔER_t		-0.2778 [0.0511]
$\Delta UKIP_{t-2}$		0.4078 [0.1627]
$\Delta USCP_{t-1}$		0.1355 [0.0711]
b. Volatility equations		
Constant	0.4760 [0.2402]	1.4469 [0.8443]
$r_{i,t-1}^2$	0.0639 [0.0222]	0.0658 [0.0320]
$h_{i,t-1}$	0.8959 [0.0236]	0.8281 [0.0613]
c. Correlation equation (*time transition*)		
ρ_1	0.5175 [0.0527]	
ρ_2	0.8997 [0.0340]	
γ	13.431 [6.5918]	
c	0.7701 [0.0220] (Date: 2000:m5)	
AIC	10.393	
SIC	10.434	
<u>*Diagnostics*</u>		
$LB(v_{i,t}, 18)$	16.38 (0.566)	18.69 (0.411)
$LB(v_{i,t}^2, 18)$	17.23 (0.507)	14.51 (0.695)

Notes: Values in square brackets are robust standard errors (Bollerslev-Wooldridge, 1992). The sample period is January 1980 to June 2006 (318 observations). *LB*(., 18) is the Ljung-Box statistic for testing autocorrelation up to 18 lags calculated for both the standardized residuals $v_{i,t}$, see equation (11), and the squared standardized residuals, both distributed as χ^2 with 18 degrees of freedom under the null hypothesis (where 18 is approximately the square root of 318). Figures in parentheses are *p*-values.

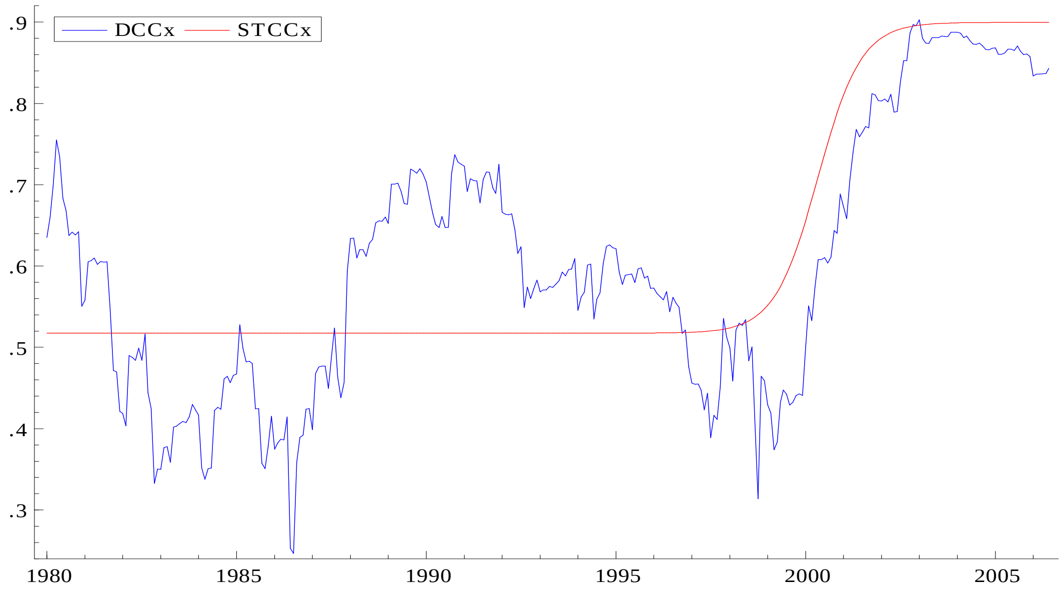

Figure 1: Monthly time-varying conditional correlations from DCC specification (DCCx) and fitted time transition for STCC model (STCCx), both with explanatory variables in mean equation.

Appendix 1: Initialisation of the Nonlinear Estimation

An important practical issue in nonlinear modelling is the selection of starting values for the estimation. Starting values for the DCC models are based on linear estimates for the mean equations with all parameters in the GARCH part of the equation initialised as 0.05. For the correlation parameters, the news parameter α is initialised at 0.05. While we experimented with different values for the decay parameter, the likelihood maximum was achieved with β initialised at 0.05.

As far as the (single transition) STCC models are concerned, we use starting values from OLS estimation of the mean equations (1) and initial univariate estimates of the volatility equation (4) to obtain estimates of the respective parameters and also the associated series $r_{1,t}$, $r_{2,t}$, $h_{11,t}$ and $h_{22,t}$. Using these, we perform a grid search[18] where we select initial values for the remaining parameters as those that minimise the square of the distance between the cross products of the standardised residuals and the implied correlations, namely

$$\text{(A.1)} \qquad \min_{\gamma,c,\rho_1,\rho_2}\left\{\left[\frac{\hat{r}_{1,t}\hat{r}_{2,t}}{(\hat{h}_{11,t}\hat{h}_{22,t})^{1/2}}\right]-\rho_1(1-G_t(s_t;\gamma,c))-\rho_2 G_t(s_t;\gamma,c)\right\}^2$$

We also estimate the STCC-GARCH models conditional on OLS results for the mean equations and then apply the iterative procedure of Silvennoinen and Teräsvirta (2005) that separates the parameters of the GARCH, correlation volatility and transition function(s)[19]. For the STCC model without explanatory variables in the mean equations, the results reported are obtained using these initial values, as this resulted in the higher log likelihood values than other initialisations[20].

[18] See Sensier, Osborn and Öcal (2002) for an example of grid search techniques applied to nonlinear estimation.

[19] This procedure was applied using Ox programs supplied by Annastiina Silvennoinen. These programs are written such as that the returns are the residuals from a filtered time series, they do not allow for the computation of QML standard errors.

[20] For instance, the grid search gave a first best initial estimate for the time threshold of 0.15. However, the highest log likelihood value was obtained using 0.75, which was the estimate obtained from the Ox program.

Appendix 2: Data

Table A.1: Variable Descriptions and Sources

Name	Variable Description	Source	Code
SP	Standard and Poors' composite index (EP), NSA	Datastream	USS&PCOM
SPDY	Standard and Poors' 500 composite: dividend yield (EP), NSA	Datastream	S&PCOM(DY)
USFF	Federal Funds Rate Market Rate, (EP), NSA	GFD	_FFYD
USLR	10-year Bond Constant Maturity Yield, (EP), NSA	GFD	IGUSA10D
USIP	Industrial production index, SA	FRED	INDPRO
USRS	Total retail trade (Volume), SA	OECD	SLRTTO01 .IXOBSA
USM1	M1 Money Stock, SA	FRED	M1SL
USCP	Consumer Price Index for All Urban Consumers: All Items, NSA	FRED	CPIAUCNS
FT	Financial Times all share index (EP), NSA	Datastream	UKFTALL.
UKDY	F.T. all share index: dividend yield-(EP), NSA	Datastream	FTALLSH(DY)
ER	US $ TO £1 (WMR), exchange rate (EP), NSA	Datastream	USDOLLR.
OIL	West Texas. Intermediate Oil Price (EP), US$/Barrel, NSA	GFD	__WTC_D
UKTB	Treasury bills: average discount rate, NSA	ONS	AJNB
UKLR	Gross interest yield on 2.5% Consols, (EP) NSA	Datastream	UKCONSOL
UKM0	M0 wide monetary base (EP): level £M, SA	ONS	AVAE
UKRS	Retail sales volume index, SA	Datastream	UKRETTOTG
UKIP	Industrial production volume index, SA	ONS	CKYW
UKRP	Retail price index, NSA	Datastream	UKCONPRCF

Notes: EP – end of period; SA – seasonally adjusted; NSA – not seasonally adjusted; ONS – Office for National Statistics; FRED – Federal Reserve Economic Data (http://research.stlouisfed.org/fred/); GFD – Global Financial Database (http).

Table A.2: Outliers Removed

	UK	**US**
Stock Market Prices	1981m9, 1987m10	1987m10, 1998m8
Dividend Yields	1981m9, 1987m10, 1998m1	1987m10
Industrial Production	2002m6	N/A
M0/1	1999m12, 2000m1	2001m9
Retail Sales	1979m6	1987m1, 2001m10

Appendix 3: Additional Results

Table A.3.1: Tests of Constant Conditional Correlations in Constant Mean Model

Test	Statistic	p-value
Tests against DCC model		
Ljung Box test	29.56	0.042
Bollerslev test	2.007	0.017
Tse test	8.866	0.003
Tests against STCC model		
ΔFT_{t-1} transition	1.424	0.232
ΔSP_{t-1} transition	0.007	0.932
$\Delta FTDY_{t-1}$ transition	0.260	0.610
$\Delta SPDY_{t-1}$ transition	0.003	0.952
$\Delta UKTB_{t}$ transition	9.393	0.002
$\Delta UKLR_{t}$ transition	9.200	0.002
$\Delta USLR_{t}$ transition	0.449	0.502
$\Delta USFF_{t}$ transition	4.490	0.034
ΔOIL_{t-1} transition	0.002	0.962
ΔER_{t} transition	0.846	0.357
$\Delta UKIP_{t-2}$ transition	3.475	0.062
$\Delta USCP_{t-1}$ transition	10.01	0.001
$\Delta USRS_{t-1}$ transition	0.289	0.590
t/T transition	15.53	8.0904e-005

Notes: See Table 2.

Table A.3.2: Constant Mean STCC-GARCH Model

	ΔSP_t	ΔFT_t
a. Mean equations		
Constant	0.9423 [0.2168]	1.0714 [0.2205]
b. Volatility equations $E(r_{i,t}^2 / \Im_{t-1}) = h_{i,t}$		
Constant	0.6487 [0.3512]	1.6799 [0.8645]
$r_{i,t-1}^2$	0.0679 [0.0230]	0.0813 [0.0367]
$h_{i,t-1}$	0.8887 [0.0235]	0.8236 [0.0554]
c. Correlation equation $\rho_t = \rho_1(1 - G_t(t/T;\gamma,c)) + \rho_2 G_t(t/T;\gamma,c)$		
ρ_1	0.5633 [0.0468]	
ρ_2	0.8813 [0.0210]	
γ	31.739 [22.759]	
c	0.7600 [0.0152] (Date: 2000:m2)	
AIC	10.697	
SIC	10.716	
Diagnostics		
$LB(v_{i,t}, 18)$	16.44 (0.562)	8.989 (0.960)
$LB(v_{i,t}^2, 18)$	17.92 (0.461)	16.72 (0.542)

Notes: See Table 5.