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Explaining movements in UK stock prices: How important is the US market?

Abstract

This paper provides evidence on the causes of movements in monthly UK stock prices, examining the role of macroeconomic and financial variables in a nonlinear framework. We allow for time-varying effects through the use of smooth transition models. We find that past changes in the dividend yield are an important transition variable, with current US stock market price changes providing a second nonlinear influence. This model explains the declines in the UK market since 2000, whereas a competing model excluding current US prices does not. The conclusion is that the principal explanation of recent declines in the UK lies in the nonlinear influence of declines in the US, and not the domestic economic environment.

1. 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 returns across important world stock markets are time-varying; important recent contributions to understanding this phenomenon include Ang and Bekaert (2002), Hamilton and Susmel (1994), King, Sentana and Wadhwani (1994), Longin and Solnik (1995, 2001), and Ramchand and Susmel (1998). The overall conclusion from these studies is that inter-market correlations are higher in volatile periods than in periods of relative calm. This points to an important role for the return variances, with ARCH-type models typically used to capture time variation in the (conditional) variance.

However, in focusing on relationships across markets, this literature largely ignores the impact of domestic economic and financial information on stock market price movements; an exception is King *et al* (1994). The role of such information is also documented by (among others) Cochrane (1991), Fama (1990), McMillan (2001), and Pesaran and Timmermann (1995, 2000). Our purpose in this paper is to examine movements in monthly UK stock market prices in the light of both time-varying international stock market correlations and domestic conditions. In particular, we study the extent to which movements in the London market can be attributed to new domestic economic and financial information (including dividend yields) and the extent to which these movements can be attributed to the US market.

The central role played by models of the ARCH class over the 1990s in modelling time-varying correlations has begun to be questioned. In particular, Longin and Solnik (2001) use extreme correlations to establish that the time-variation in bivariate correlations between returns for important stock markets and that of the US are associated with the underlying direction of change in the markets, rather than their volatility. Specifically, correlations are higher during bear markets than bull markets. Further, Ang and Bekaert (2002) show that an asymmetric GARCH model cannot capture the correlation pattern documented by Longin and Solnik (2001), but a regime-switching model does.

Regime-switching models are now popular in empirical macroeconomics in the context of capturing phenomena associated with the business cycle. By allowing for distinct "states of the world" or regimes, these nonlinear models can represent situations where mean behaviour depends on the regime, with a positive mean during business cycle expansions and a negative mean during recessions. One key issue is the modelling of switches between the regimes. In the Markov switching model, originally employed in the business cycle context by Hamilton (1989), this switch is governed by a regime-dependent probability. Recent applications to stock price movements include Ang and Bekaert (2002), Perez-Quiros and Timmermann (2000), and Guidolin and Timmermann (2003).

A different approach is to explicitly model the regime as a continuous function of an explanatory variable. This approach explicitly allows interactions between variables, and also allows for the possibility of intermediate positions between the two regimes. These so-called smooth transition models have been developed primarily by Teräsvirta and his co-authors (Teräsvirta and Anderson, 1992; Teräsvirta, 1994, 1998), with these developments reviewed by van Dijk, Teräsvirta and Franses (2002). Applications of these models to financial data include McMillan (2001), Michael, Nobay and Peel (1997), and Sarantis (2001).

We follow this recent literature by adopting regime-switching models to characterise the time-varying correlations and strong nonlinearities in these series

(Abhyankar, Copeland and Wong, 1997; Qi, 1999). In doing so, we adopt the smooth transition models. We prefer these to Markov switching models in our context because we wish to explore the nature of the underlying regimes, so that the explicit modelling of these regimes is an attractive feature of the smooth transition models. Further, our experience in modelling macroeconomic variables (for example, Sensier, Osborn and Öcal, 2002; Simpson, Osborn and Sensier, 2001) has convinced us of the greater tractability of the smooth transition models in practice when estimating specifications with more than one or two explanatory variables.

From a statistical perspective, we take two different stances in examining the impact of movements in the US stock market on the UK. In one set of models we specify contemporaneous causation running from the US to the UK market, hence allowing current US stock price movements to be an explanatory variable in the models. Since information will be absorbed very quickly in these international stock markets, we do not expect to find any causality from lagged cross-market prices at the monthly data frequency we examine. Nevertheless, causality tests undertaken by Arshapanalli and Doukas (1993) and Gerrits and Yüce (1999) using daily data show unidirectional causality from the US to the UK market, which provides the basis for our causality assumption. For comparison purposes, we also develop a set of models that are not conditioned on contemporaneous price movements. However, both sets of models use the same set of current economic and financial indicators. By excluding contemporaneous movements in the US as an explanatory variable, this latter set of models essentially leaves the contemporaneous correlation with the US as part of the unexplained residual in our model for UK stock market prices and implicitly assumes that this correlation is constant over time.

The organization of this paper is as follows. In Section 2 we describe the smooth transition models and explain their desirable features for modelling stock market prices. This section also discusses the procedures we use for specifying, estimating and evaluating such models. In Section 3 we report our model estimation results, separately using contemporaneous and lagged US price movements. The recent (post-sample) performance of the estimated models is evaluated in Section 4. Conclusions in Section 5 complete the paper.

2. Smooth Transition Regression Models

As noted above, the smooth transition regression (STR) model is a form of regime-switching model. In the simplest case of two regimes, the model is given by (Teräsvirta, 1998)

$$y_t = \beta_0' w_t + F(s_t)\beta_1' w_t + u_t \qquad (1)$$

where w_t is a $(k + 1) \times 1$ vector of explanatory variables (including a constant), β_0 and β_1 are $(k + 1) \times 1$ coefficient vectors, the disturbance u_t is $iid(0, \sigma^2)$ and $F(s_t)$ is the transition function defining the regime. The transition function is bounded by zero and unity, with s_t being the transition variable that determines the regime. For any given value of $F(s_t)$, the STR model of (1) is linear, with coefficient vectors of β_0 and $\beta_0 + \beta_1$ at the extremes of $F(s_t) = 0$ and $F(s_t) = 1$ respectively. Therefore, the nonlinearity in (1) is evidenced as $F(s_t)$ changes as a function of s_t. A particular attraction of the STR model in our context is that different potential transition variables s_t can be considered for their role in generating nonlinearity in UK stock market price movements, which is the dependent variable y_t. Thus, for instance, business cycle indicators or changes in US stock prices can be examined in this light.

The transition function $F(s_t)$ is defined as the logistic function[1]

$$F(s_t) = \{1 + \exp[-\gamma(s_t - c)]\}^{-1} \qquad \gamma > 0 \qquad (2)$$

which is a monotonically increasing function of s_t. The parameter c is the threshold and locates the transition function in terms of the values of s_t, with $F(s_t) = 0.5$ when $s_t = c$, while γ defines the slope of the transition function. In practice, we allow the transition variable s_t to be any element of the vector of explanatory variables, w_t of (1), excluding the intercept.

In the stock market context, regimes might be bull versus bear markets. If the transition variable s_t is the lagged UK stock price change or the contemporaneous US change, the STR model of (1) and (2) can capture these regimes by $F(s_t)$ close to zero for negative s_t and $F(s_t)$ close to unity for positive s_t. Thus, the model is sufficiently flexible to capture the time-varying correlations documented by Longin and Solnik (2001) in terms of bull and bear markets. On the other hand, if s_t is an indicator of economic activity, the regimes can be business cycle recessions versus expansions. Notice also that the role of all explanatory variables in w_t can be potentially different in the two regimes through the coefficient vector β_1.

The slope parameter γ in (2) indicates the nature of the transition between 0 and 1 as a function of s_t. As $\gamma \rightarrow \infty$, $F(s_t)$ becomes a step function and the transition between the regimes is abrupt. In that case, the model approaches a threshold model of the type analysed by Tong (1990). More generally, however, intermediate values $0 < F(s_t) < 1$ can apply.

The two-regime STR model of (1) assumes that all nonlinearity in stock market prices is captured through a single transition variable. However, one transition variable

[1] McMillan (2001) and Sarantis (2001) both follow the general approach of Teräsvirta (1994, 1998) in considering an exponential, in addition to a logistic, transition function. However, the exponential form has no ready interpretation in terms of either bull versus bear markets or of business cycle regimes, so we prefer to use only the logistic form.

and its two associated regimes may not be sufficient to reflect the potentially complex nonlinearities in the determination of stock market prices (Qi, 1999). The analysis below also employs two transition functions, so that the model becomes

$$y_t = \beta_0^{'} w_t + F_1(s_{1t})\beta_1^{'} w_t + F_2(s_{2t})\beta_2^{'} w_t + u_t \tag{3}$$

where each transition function $F_i(s_{it})$, $i = 1, 2$, is a logistic function, defined analogously to (2). The transition variables s_{1t} and s_{2t} may be the same variable (with distinct locations c_1 and c_2, in order to ensure that F_1 and F_2 capture distinct regime behaviour) or different variables. Öcal and Osborn (2000) and Sensier *et al.* (2002) successfully use two transition function models as in (3) for modelling macroeconomic variables over the business cycle.

Our procedure for STR modelling is essentially that utilised in Sensier *et al.* (2002)[2]. This differs from the procedure of Teräsvirta (1994, 1998) in that we rely on grid search procedures for the selection of the appropriate transition variable and ordinary least squares (OLS) initial estimation of the STR model. More specifically, in order to select s_t in (1), we consider each element of w_t in turn (except the constant and the January dummy variable), using 40 potential values for c over the observed range of the variable and values[3] $\gamma = 1, 2, \ldots, 100$, with this latter range extended if $\gamma = 100$ minimises the residual sum of squares. The variable yielding the minimum residual sum of squares in this three dimensional grid search over w_t, c and γ is used as the transition variable.

Having selected s_t, and in order to obtain a more parsimonious model, OLS estimation is employed for the STR model, conditional on the transition function that

2 We use Gauss 3.2 for our nonlinear models. The linear models and graphs are computed in Givewin (Doornik and Hendry, 2001).

3 Following the recommendation of Teräsvirta (1994), we divide s_t by its sample standard deviation to avoid scaling problems.

minimises the residual sum of squares in the grid search. In this estimation, the elements of w_t and $F(s_t)w_t$ are treated as distinct variables. Beginning from a general model with all variables included, these are dropped sequentially (using the smallest t-ratio) to obtain the model that minimises the Akaike Information Criterion (AIC). The model with these selected variables is then estimated by nonlinear least squares, with the transition function parameters c and γ also estimated[4]. Further individual coefficients may be dropped at this stage if these are very insignificant.

Specification of the two transitions model of (3) takes the first transition variable as given from the single transition model, with each element of w_t (excluding the constant and the January dummy) considered as the second transition variable s_{2t}. For each variable, a four dimensional grid search is undertaken over γ_1, c_1, γ_2 and c_2, using $\gamma_1, \gamma_2 = 1, 2, \ldots, 50$ and ten values of c_1, c_2 over the ranges of the corresponding variables. After selection of the second transition variable from this grid search, an analogous modelling procedure is followed to the single transition case.

The validity of the assumptions underlying the STR model are investigated using the Lagrange multiplier tests of Eitrheim and Teräsvirta (1996). These are diagnostic tests for autocorrelation, additional nonlinearity and parameter constancy. The last of these is the most general test of the three proposed by Eitrheim and Teräsvirta. The test for additional nonlinearity considers each explanatory variable and time, with time included to examine whether any apparent nonlinearities may be due to unexplained time-variation. The residuals of all models are also checked for ARCH effects using a Lagrange multiplier test. The conventional RESET test (including squares and cubes of the predicted values) provides an overall test of possible nonlinearity in the context of the linear models. A parameter constancy test is also

[4] We intentionally use AIC here, as it is a conservative criterion in the retention of potentially relevant variables. Further, we always informally check that the γ and c from the nonlinear estimation are not too far from the values obtained in the initial grid search.

applied to the linear model, in an analogous way to the STR parameter constancy test. The normality test we report uses the Lomnicki-Jarque-Bera statistic.

3. Estimated Models: 1978-1999

We model movements in the monthly index of UK stock prices. More precisely, the dependent variable in our analysis is the end-of-month value of the Financial Times All Share Index (*FT*). Based on the UK analysis of Pesaran and Timmermann (2000), we consider a benchmark set of explanatory variables that may influence the UK stock market. These are[5]: the dividend yield of the FT Actuaries All Share Index (*DY*), the Standard and Poor's composite index (*S&P*) to measure the influence of the US market, UK industrial production (*IOP*) and retail sales (*RS*) volumes to represent domestic real economic activity, the average nominal 3-month prime bank bill discount rate as the short interest rate (*SR*), the average rate for 2.5% Consols for the long rate (*LR*), the exchange rate of US dollars to pounds sterling (*ER*), the nominal narrow money base (*M*0) and the oil price measured in US dollars (*OIL*). All these variables (including the dependent variable) are used as 100 times the first difference of the logarithms, apart from the interest rate series and the dividend yield for which we take only first differences. Data sources are detailed in Appendix 1. In addition, based on the UK results of Clare, Psaradakis and Thomas (1995) and Pesaran and Timmermann (2000), all models include a dummy variable for January.

In considering which variables may explain movements in monthly UK stock market prices, care must be taken in relation to the lag at which macroeconomic

[5] Our initial models also included the retail price index (RPI) to represent UK inflation, but this was not significant in any model and is excluded from the results presented. Pesaran and Timmermann (2000) do not include retail sales, but we do so in order to capture broader indications of domestic economic activity than are reflected in industrial production alone.

variables become available. While retail sales and $M0$ data relating to a specific month are released during the immediately subsequent month, that for industrial production is not. Therefore, lags of one month are employed for the first two variables, but *IOP* is lagged by two periods. Financial data on the exchange rate, oil prices, short and long interest rates are available continuously, and hence current average values for the month are used for these variables. The dividend yield is lagged by one month to avoid the simultaneity that would result if the current value was employed.

The sample period for model estimation is January 1978 to December 1999. We initially investigated models using data from the mid-1970s, but found evidence of parameter change around the end of 1977. During 1974 the UK stock market experienced a sequence of substantial monthly declines in stock market prices, followed by an extremely large positive value at the beginning of 1975. These dramatic movements may be explained by a series of special events (both international and domestic) that were associated with economic and political uncertainty during the early and mid-1970s. These were crisis years of 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. In order to focus on the recent past, we exclude this unusual historical period.

We reserve data from January 2000 to June 2002 for a genuine post-sample check on the models. Results relating to this period are discussed in Section 4.

Our sample period includes the effect of the stock market crash in October 1987, for both the UK and US series. To ensure this single event does not unduly influence the estimated models, we replace the single outlier in each series (ΔFT_t and $\Delta S\&P_t$) 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 1 for details).

As discussed in the Introduction, we estimate models using contemporaneous US stock market price changes, and also models using only lagged US values. We deal with these two sets of results in separate subsections below, with general discussion in subsection 3.3.

3.1 Models with contemporaneous US stock prices

The results for a linear model using all explanatory variables are presented in the second column of Table 1. This model explains half of the variation in UK stock market price movements, with the most significant single variable being contemporaneous US price changes. Nevertheless, domestic factors also play a substantial role, with changes in industrial production, long and short interest rates and the exchange rate all being individually significant at the 5 percent level and of the anticipated signs. An increase in *ER* represents an appreciation of the pound, and this has a very significant negative impact. At a 10 percent level, changes in the dividend yield enters with a positive coefficient. However, lagged changes in the UK stock market prices are not significant, in line with the weak form of the efficient market hypothesis. Further, changes in oil prices, retail sales and *M*0 have no significant effect in this specification.

Nevertheless, despite the overall plausibility of the estimated linear model, the diagnostic tests results indicate some inadequacies. Specifically, using the conventional 5 percent level, there is evidence of time varying conditional volatility (ARCH) in the residuals and of nonlinearity in the model (RESET test). At least in terms of the *p*-values, these two effects are equally strong.

As proposed by Teräsvirta (1994, 1998), we use the linear model as the null model for testing linearity against STR-type nonlinearity. According to the results, presented in the second column of Table 2, nonlinearity is evident particularly in relation to the dividend yield (p-value = .005), although there is also some evidence in relation to the short-term interest rate and US price movements. Using our grid search procedure (results are presented in Appendix Table A.3), the dividend yield is selected as the transition variable for the single transition model of (1). Our STR modelling procedure, outlined in Section 2, then yields the model in the third column of Table 1.

Figure 1 illustrates of the estimated transition function $F(\Delta DY_{t\text{-}1})$ over time and in relation to the value of $\Delta DY_{t\text{-}1}$. In effect, the transition function implies one regime when the dividend yield is falling and a smooth transition between regimes for positive changes, with $F(\Delta DY_{t\text{-}1}) = 1$ applying only for a small number of large increases in dividend yields. The "normal" regime corresponds to relatively small $F(\Delta DY_{t\text{-}1})$. Therefore, the estimated coefficients shown in the first block of column three (Table 1) capture the estimated "normal" responses of stock market price movements to the explanatory variables.

Comparing the single transition model with the linear one of Table 1, the broad pattern of the results is largely unchanged, although the exchange rate, oil prices, short interest rates and industrial production are now found to affect UK price movements only when changes in dividend yields are positive (and hence the value of the transition function is non-zero). The important impact of the US market remains, with an estimated coefficient that does not vary with the transition function and remains largely unchanged from that of the linear model. However, the diagnostic tests for this single transition model are not satisfactory. Although marginal at 5 percent, there remains some evidence of ARCH. Further, the tests for additional nonlinearity (presented in the third column of Table 2) indicate unexplained nonlinearity at the 5 percent level in relation to Time, short-term interest rates and retail sales.

To investigate this additional nonlinearity, we conduct a grid search taking the dividend yield as the first transition variable and searching over the explanatory variables for the second; the results of these are shown in Appendix Table A.4. This points to contemporaneous changes in the *S&P* index as the second transition variable, and our STR modelling procedure then results in the two transition model in the final column of Table 1.

Figures 2 and 3 illustrate the first and second transition functions for the contemporaneous S&P model. The first transition function, for dividend yields, has now moved to the left with a much steeper transition between regimes compared to Figure 1, with the location in Figure 2 centred on 0.19 percent. In effect, $F_1(\Delta DY_{t-1}) = 0$ for changes of less than 0.1 percent and $F_1(\Delta DY_{t-1}) = 1$ for changes above 0.3 percent. While $F_1(\Delta DY_{t-1}) = 0$ corresponds to the "normal" dividend yield regime, a nontrivial number of sample observations correspond to $F_1(\Delta DY_{t-1}) \approx 1$ or lie intermediate between these values. The second transition function, for $\Delta S\&P_t$, shown in Figure 3, is relatively abrupt with an estimated gamma of 10.8. For practical purposes, this effectively defines a threshold effect, with one regime defined by falls of more than 1.95 percent per month in US prices, and the other regime by less severe declines or rises in the US market. As can be observed from the upper panel of Figure 3, both regimes in the US market have been frequently observed during the sample period to the end of 1999.

To facilitate the interpretation of this last model, note that Figures 2 and 3 imply that the "normal" regime corresponds to $F_1(\Delta DY_{t-1}) = 0$ and $F_2(\Delta S\&P_t) = 1$. In this case, the two-transition model implies that the fitted value for the monthly change in *FT* (ignoring the January effect) is given by:

$$\begin{aligned}\Delta\hat{F}T_t &= 1.17 + 0.04\Delta FT_{t-1} + 0.27\,\Delta S\,\&\,P_t - 0.16\,\Delta ER_{t-1} - 5.19\,\Delta LR_t \\ &\quad + 0.47\,\Delta M0_{t-1} - 0.27\,\Delta RS_{t-1} + 4.70\,\Delta DY_{t-1}\end{aligned} \tag{4}$$

In comparison with the situation when the US market falls steeply, when $F_2(\Delta S\&P_t) = 0$ and the coefficients in the upper block of the final column of Table 1 apply, changes in *M*0 and *RS*, together with lagged ΔFT, are relatively unimportant[6] for the determination of changes in UK prices in (4). Thus, it is "normal" for these domestic UK variables to play little role.

Comparing the implications of the model when the *S&P* transition function moves from the normal regime $F_2(\Delta S\&P_t) = 1$ to the lower regime $F_2(\Delta S\&P_t) = 0$, the domestic variables $\Delta FT_{t\text{-}1}$, $\Delta M0_{t\text{-}1}$ and $\Delta RS_{t\text{-}1}$ all become more important (in terms of the magnitudes of their coefficients), whereas the dividend yield becomes less important and changes sign. The coefficients of neither the long rate nor *ER* are found to change with the *S&P* regime, with *LR* being highly significant in the model and *ER* marginally so (at 5 percent). Overall, however, the extent to which the UK market follows the US when the latter falls by a large amount will be influenced by domestic macroeconomic conditions.

We now turn to consider the implications of the model for the correlation between the UK and US markets. In comparison with the linear and single transition models of Table 1, the coefficient of $\Delta S\&P$ in the two transition model is approximately halved to 0.27 and its significance declines. There is, however, a further direct effect of this variable that operates through $F_2(\Delta S\&P_t)$. In a bull market, a fall in *S&P* by more

[6] The *p*–value is 0.43 for a test of the joint null hypothesis that the coefficients of $\Delta FT_{t\text{-}1}$, $\Delta M0_{t\text{-}1}$, $\Delta RS_{t\text{-}1}$ are equal in magnitude and opposite in sign when $F_2(\Delta S\&P_t) = 0$ and $F_2(\Delta S\&P_t) = 1$. This *p*-value also applies to a joint test that the coefficients on these variables in (4) are zero.

than the threshold of 1.95 percent in a month triggers an estimated decline of 3.6 percent in *FT*, in addition to the effects attributable to the other explanatory variables[7]. Thus, although the coefficient of $\Delta S\&P_t$ does not change between regimes, a very substantial effect is implied by this model for the impact on the UK market of large declines in the US. Through this, strong bear markets in the US are transmitted to the UK, which supports the findings of Longin and Solnik (2001) that the correlation between the US and UK markets is lower in bull than bear markets.

The highly significant negative coefficient of the activity indicator $\Delta RS_{t\text{-}1}$ when $F_2(\Delta S\&P_t) = 0$ is not anticipated. It may, however, reflect market concerns that high growth in retail sales could indicate increases in inflation in the future.

In relation to the first transition function $F_1(\Delta DY_{t\text{-}1})$, the results imply that when dividend yields in the previous month have risen sufficiently that $F_1(\Delta DY_{t\text{-}1}) = 1$, then compared with the normal regime where $F_1(\Delta DY_{t\text{-}1}) = 0$, the *FT* index increases by 1.76 percent through a shift in the intercept. In addition, economic and financial conditions generally become more relevant in the higher dividend yield regime. In particular, the negative effect of ΔER_t increases significantly, while short interest rates and industrial production become significant and of the expected signs. The coefficient for *M*0, however, effectively becomes zero. Nevertheless, the implication is that the market assesses a relatively large increase in the dividend yield in the light of current economic conditions.

Finally, the diagnostics of the two-transition model are satisfactory. Indeed, the evidence of ARCH effects in the linear and single transition models is now accounted for by the second ($\Delta S\&P$) transition function. As the linearity test results in the final

[7] The difference between the intercept of 1.17 in (4) for $F_2(s_{2t}) = 1$ and the estimated intercept of –2.46 corresponding to $F_2(s_{2t}) = 1$ in Table 1 is 3.63, which is the intercept shift that applies in moving from the upper to the lower regime.

column of Table 2 show, there is no evidence of further nonlinearity associated with any explanatory variable at even the 10 percent significance level.

3.2 Models with lagged US stock prices

Repeating the modelling strategy, but now conditioning only on lagged changes in *S&P* yields the estimated models of Table 3. Overall, except for the coefficient relating to Δ*S&P*, the linear and single transition models here are very similar to those of Table 1. Rather than repeat the discussion of subsection 3.1, subsection 3.3 below comments on the general patterns of the results across the two sets of models. Here we concentrate on points specific to Table 3.

Although the RESET test applied to the linear model in Table 3 does not strongly point to nonlinearity, the tests of Table 4 provide very strong evidence in relation to the dividend yield as the transition variable. This is confirmed by the grid search (results in Appendix Table A.5), and hence the single transition model of Table 3 again uses ΔDY_{t-1} as the transition variable.

There is, however, no clear evidence from the diagnostic test results for the single transition model in Table 3, or the additional nonlinearity tests for this model in Table 4, that there is substantial unexplained nonlinearity in this single transition model. Nevertheless, we explore a possible second transition function for comparability with the results of Table 1. Undertaking a grid search for a second transition variable (Appendix Table A.6) indicates that the lowest residual sum of squares is associated with Time as the transition variable. However, the residual sum of squares delivered by ΔER_t is only 0.3 percent higher. As we prefer an economic transition variable, the two transition model of Table 3 is based on ΔER_t as the second transition variable[8]. The estimated transition functions $F_1(\Delta DY_{t-1})$ and $F_2(\Delta ER_t)$ for this model are shown in Figures 4 and 5 respectively. The dividend yield transition function is very similar to that shown in Figure 2 for the single transition function model of Table 1 and (although it is not shown) to that for the single transition model of Table 3.

The transition function of Figure 5, together with the associated large estimated value of γ_2 and insignificant estimated c_2 in Table 3, point to a threshold model where exchange rate appreciations and depreciations induce different responses of the stock market to other financial variables. In particular, the model attributes responses to increases in oil prices and the dividend yield only to the appreciation regime, where $F_2(\Delta ER_t) = 1$, with these variables having no effect when $F_1(\Delta DY_{t-1}) = F_2(\Delta ER_t) = 0$. Further, changes in the long interest rate have a substantially greater impact in the appreciation regime. Nevertheless, we treat the two transition model of Table 3 with some caution, since the evidence of the need for the second transition function is not strong.

3.3 General Discussion

It is notable, but unsurprising, that the models of Table 1 using contemporaneous changes in *S&P* have greater explanatory power than those using only lagged *S&P* in Table 3. However, from another perspective, the estimated coefficients of the models in these tables are remarkably similar. In particular, the magnitudes and significance of the coefficients of the linear and single transition models are similar in the two tables[9]. As already noted, the estimated transition function $F_1(\Delta DY_{t-1})$ is also effectively the same

[8] Based on the similar residual sum of squares, we also specified and estimated a model using the change in oil prices as the second transition variable. However, AIC was lower for the model using exchange rates.

[9] Although the short interest rate is significant in the linear model of Table 1, but not in Table 3, it should be noted that the magnitude and significance of the long rate is higher in the latter.

across these models. Therefore, these results imply that contemporaneous changes in *S&P* have an effect on the UK stock market that can be considered as additional to that of domestic variables.

It should also be noted that when lagged (but not contemporaneous) $\Delta S\&P$ is considered, it is not significant in the linear model and does not enter the selected nonlinear model for either the single or two transition case in Table 3. Further, ΔFT_{t-1} plays a role here only in the relatively rare regime $F_1(\Delta DY_{t-1}) = 1$. In Table 1, similar comments apply in that ΔFT_{t-1} is significant only in the relatively unusual regime $F_2(\Delta S\&P_t) = 0$. Therefore, in general, past price changes do not provide any predictive information for current changes, as would be expected from an efficient market.

A further interesting feature of the results in Tables 1 and 3 relates to the characteristics of conditional heteroscedasticity and non-normality widely documented for stock market price changes, including changes in the *FT* index at the monthly frequency (Poon and Taylor, 1992). It has already been commented that the introduction of the *S&P* transition function in the models of Table 1 removes evidence of ARCH effects. Interestingly, none of the models of Table 3 demonstrate any evidence of ARCH. Therefore, at least at this monthly frequency, it appears that volatility clustering of the ARCH type in UK prices is not present once due account is taken of the effects of domestic macroeconomic and financial variables, together with US stock prices.

The results concerning non-normality are striking. The normality diagnostic test statistics of Table 3 show that all models excluding contemporaneous *S&P* exhibit highly significant non-normality. This is, however, much less marked in Table 1, with no model here having significant non-normality in the residuals at the 1 percent level. Indeed, the introduction of the second (*S&P*) transition function effectively removes any evidence of non-normality. Therefore, we conclude that non-normality in monthly UK stock market price movements can be attributed to the effects of the US market on the UK. Once these (contemporaneous) effects are adequately accounted for within the model, no significant non-normality remains.

4. Post-Sample Performance: 2000-2002

Table 5 provides an evaluation of the post-sample performance of the six estimated models of Tables 1 and 3. For this evaluation, the post-sample period from January 2000 to June 2002 is divided into two equal (and non-overlapping) periods of fifteen months. The second of these provides a severe post-sample test, since it represents a period of overall decline, in contrast to the substantial overall growth experienced during the sample period used for the estimation of the models. None of the models is re-specified or re-estimated during the post-sample period. Actual and predicted values over the entire post-sample period, January 2000 to June 2002, are shown in Figures 6 and 7 for the models of Table 1 and 3 respectively.

The first set of results in Table 5 provide tests of structural change based on the 2000-2001 and 2001-2002 sub-periods. These tests are based on a comparison of the squared prediction errors in relation to the sample residual variance, namely

$$\chi^2 = \sum_{t=n_1}^{n_2} e_t^2 / s^2 \qquad (5)$$

where e_t is the prediction error for period t, n_1 and n_2 are the first and last months (respectively) of the relevant sub-period, and s is the sample period estimate of the residual disturbance standard deviation, presented for each model in Table 1 or 3 as appropriate. The periods used for t in (5) are January 2000 to March 2001 or April 2001 to June 2002. If the disturbances of the (linear or nonlinear) model are normally distributed, then for each sub-period of 15 months, the statistic in (5) approximately follows a χ^2 distribution with 15 degrees of freedom under the null hypothesis of no structural change (Dufour, Ghysels and Hall, 1994)[10].

The models with contemporaneous *S&P* provide no evidence of any structural change over the sub-period to March 2001. Although the two transition model indicates some evidence of a structural break over the subsequent fifteen months, this is significant at the 5 percent but not the 1 percent level. Overall, these models generally perform well in this respect over the post-sample period, as can also be seen in Figure 6.

In contrast, the nonlinear models that exclude contemporaneous *S&P* do not. These cope less well with the period January 2000 to March 2001 than the nonlinear models with contemporaneous *S&P*, and fare much worse over the second sub-period, April 2001 to June 2002. The highly significant *p*-values for this latter case should be treated with some caution, however, as these models in Table 3 show clear evidence of non-normality. Nevertheless, Figure 7 indicates that the predictions of these models are poor in relation to actual movements in *FT*.

Table 5 also shows conventional predictive error statistics, namely the mean square prediction error (MSE) and statistics on the predicted compared with actual direction of change. In addition to the raw MSE value, this is shown divided by the sample residual variance for the corresponding estimated model, to order to measure post-sample accuracy in relation to that of the sample period. Direction of change statistics show the number of months where the direction is correctly predicted, separating months when the actual change is positive and negative. To sharpen the comparisons of the MSEs we compute the Diebold and Mariano (1995) predictive accuracy test for our competing models, in each case comparing the nonlinear model to

[10] This result is an asymptotic one in terms of the number of observations in the sample period used for model estimation.

the corresponding linear model (with contemporaneous or lagged *S&P*, as appropriate). The null hypothesis is that the models have the same underlying accuracy. To compare our direction of change results we calculate the Pesaran and Timmermann (1992) non-parametric test with the null hypothesis here that each set of forecasts and the actual values are independent. Such independence would indicate poor directional forecasts. Note that the Pesaran-Timmermann test statistic is not defined when one direction of change is not forecast by the model, as this involves division by zero.

A comparison of raw predictive accuracy statistics across models when contemporaneous *S&P* is used and when it is not are unfair, in the sense that the former use more information than the latter. Nevertheless, such comparisons also emphasise the extent of the information provided by movements in the US stock market for the UK market. The importance of $\Delta S\&P$ in explaining the six observed declines in *FT* between January 2000 and March 2001 is clear, since all contemporaneous models predict all of these declines, whereas the models without this information predict at most two declines. The better performance of the lagged *S&P* models (compared with the ones using the contemporaneous *S&P* value) in predicting increases in *FT* can effectively be discounted, since this better performance arises because these predicted values are essentially flat over this period; see Figure 7. Indeed, no model excluding current *S&P* predicts a decline in *FT* until mid-2001. The Pesaran-Timmermann test statistics emphasise this result, as all are significant for the current *S&P* models, but none are for the models using lagged *S&*P, in the sub-period from January 2000 and March 2001.

When we allow for the differing information content of the models of Tables 1 and 3 by measuring MSE in relation to the sample variance of the residuals, there is again evidence of a structural break in the models using only lagged *S&P*, especially after April 2001. In particular, the nonlinear lagged *S&P* models have MSE values 2.28

and 2.80 times the sample residual variance, respectively, for the one and two transition lagged *S&P* models over April 2001 to June 2002. Although the linear model does better in this respect, it is still performs poorly in relation to predicting declines in *FT*. The Diebold-Mariano test statistics do not indicate that any of the nonlinear models produce forecasts that are significantly different from the linear ones over either forecast sub-period[11].

Of the models using contemporaneous *S&*P it should be noted that although the two transition model tracks the post-sample values of ΔFT very well between January 2000 and March 2001, it is the least accurate of the contemporaneous *S&P* models over the period April 2001 to June 2002. Indeed, there is evidence of some deterioration in the performance of this model over the latter period in the predictive stability test, in the ratio of the MSE to sample residual variance and with the Pesaran-Timmermann test. However, we believe that analysis of this unusual period of decline in stock market prices will provide information additional to that of our sample period (ending December 1999) in terms of the nature of the relationship between international markets.

5. Concluding remarks

This paper contributes to the growing literature on the relationship between international stock markets by analysing monthly changes in UK prices in relation to both domestic variables and movements in the US market. Our results support two general conclusions. Firstly, the recent (January 2000 to June 2002) movements in the UK stock market cannot be understood without using information relating to

[11] The Diebold-Mariano statistics comparing the single and two transition models yield insignificant values of –0.5548 and –0.3659 in the first and second forecast sub-periods, respectively.

contemporaneous US prices. Models based on domestic variables and lagged price movements break down over this period, and fail to predict the declines that have actually occurred. In contrast, models using contemporaneous US prices generally do not show evidence of structural change and correctly predict the direction of almost all changes that have actually occurred. Therefore, it appears that the recent declines in the UK stock market have very little to do with the UK economy, and the underlying causes need to be sought in the US.

The second broad conclusion is that UK stock market prices respond in a nonlinear way to domestic macroeconomic information and to US price movements. Once these nonlinearities are modelled, we find no evidence for ARCH effects or non-normality in monthly price movements. Therefore, our results support the finding of Longin and Solnik (2001) that it is "regimes" or nonlinearities that are important, rather than changing volatility.

Nonlinearities in the response of UK stock market prices are most marked in relation to changes in the dividend yield for the market. In particular, increases in the dividend yield of around 2 percent lead to a different regime, in comparison with smaller increases or declines. These different regimes imply different responses for the UK stock market in response to other variables, including interest rates, oil prices and industrial production. The important role of dividends for the UK market is shown, in a different context, by Mills (1991). Although not explored further here, an interesting possibility is that news in dividend yield causes a nonlinear effect on the market due to the operation of "fads" (West, 1988).

However, dividend yields do not account for all the nonlinearity, with changes in the US market also contributing a second set of regimes. These latter regimes imply that substantial declines in the US market trigger different effects compared with increases or small declines. Although our approach is quite different and allows for the effect of domestic factors, our overall finding that the UK market follows the US when the latter declines by a large amount supports the implications of the extreme correlation analysis of Longin and Solnik (2001).

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Table 1: Estimated Models using Contemporaneous S&P

Variable	Linear Model	Single Transition Model	Two Transitions Model
Constant	0.0584 (0.20)	-0.5411 (-1.55)	-2.457 (-3.31)
January dummy	1.554 (2.13)	1.190 (1.93)	1.258 (2.10)
ΔFT_{t-1}	-0.0144 (-0.24)		-0.3027 (-2.46)
$\Delta S\&P_t$	0.5880 (11.3)	0.5177 (11.8)	0.2687 (3.75)
ΔER_t	-0.3251 (-4.01)		-0.1596 (-1.99)
ΔOIL_t	-0.0309 (-1.14)		
ΔSR_t	-1.186 (-2.66)		
ΔLR_t	-3.227 (-3.72)	-4.963 (-7.67)	-5.186 (-7.80)
$\Delta M0_{t-1}$	0.5495 (1.36)	1.459 (3.11)	2.159 (2.78)
ΔRS_{t-1}	-0.3393 (-1.77)	-0.7752 (-4.05)	-1.478 (-4.28)
ΔIOP_{t-2}	0.5837 (3.11)		
ΔDY_{t-1}	2.3220 (1.73)		-7.287 (-2.70)
$F_1(\Delta DY_{t-1})$		8.102 (2.54)	1.759 (1.25)
$F_1(\Delta DY_{t-1}) \times \Delta ER_t$		-3.432 (-2.32)	-1.236 (-3.81)
$F_1(\Delta DY_{t-1}) \times \Delta OIL_t$		-0.1818 (-1.57)	-0.2374 (-2.89)
$F_1(\Delta DY_{t-1}) \times \Delta SR_t$		-4.799 (-2.49)	-2.784 (-2.92)
$F_1(\Delta DY_{t-1}) \times \Delta M0_{t-1}$		-7.111 (-2.18)	-2.148 (-1.63)
$F_1(\Delta DY_{t-1}) \times \Delta RS_{t-1}$		4.344 (1.86)	
$F_1(\Delta DY_{t-1}) \times \Delta IOP_{t-2}$		4.891 (2.78)	2.264 (4.01)
γ_1		1.533 (3.68)	6.433 (0.93)
c_1		0.3482 (3.52)	0.1875 (8.34)
$F_2(\Delta S\&P_t)$			3.626 (3.97)
$F_2(\Delta S\&P_t) \times \Delta FT_{t-1}$			0.3409 (2.50)
$F_2(\Delta S\&P_t) \times \Delta M0_{t-1}$			-1.690 (-1.84)
$F_2(\Delta S\&P_t) \times \Delta RS_{t-1}$			1.213 (2.97)
$F_2(\Delta S\&P_t) \times \Delta DY_{t-1}$			11.99 (3.67)
γ_2			10.81 (1.50)
c_2			-1.951 (-5.63)
s	3.244	3.007	2.880
AIC	2.398	2.257	2.202
R^2	0.50	0.57	0.62
<u>*Diagnostic tests:*</u>			
Autocorrelation	0.0514	0.2056	0.2357
ARCH	0.0211	0.0509	0.2669
Normality	0.0378	0.0172	0.2879
RESET	0.0217		
Parameter Constancy:			
All coefficients	0.1274	0.2160	0.1417
Intercept	0.3966	0.3941	0.1134

Notes: Values in parentheses are *t*-values; results for the diagnostic tests are presented as *p*-values. Diagnostic tests for autocorrelation and ARCH are Lagrange multiplier tests using lags 1 to 6 inclusive.

Table 2: Linearity Tests for Contemporaneous S&P Models

Potential Transition Variable	**Linear Model**	**Single Transition Model**	**Two Transitions Model**
Time	0.2348	0.0422*	0.1049
ΔFT_{t-1}	0.4241	0.5915	0.5019
$\Delta S\&P_t$	0.0386*	0.1824	0.6259
ΔER_t	0.5074	0.8186	0.9252
ΔOIL_t	0.2017	0.4805	0.5368
ΔSR_t	0.0307*	0.0372*	0.5276
ΔLR_t	0.2428	0.2888	0.4582
$\Delta M0_{t-1}$	0.0613	0.0507	0.1010
ΔRS_{t-1}	0.3961	0.0296*	0.2144
ΔIOP_{t-2}	0.5309	0.7418	0.7081
ΔDY_{t-1}	0.0052*	0.7664	0.8078

Notes: All results are presented as *p*-values; * indicates significance at 5 percent.

Table 3: Estimated Models using Lagged S&P

Variable	Linear Model	Single Transition Model	Two Transitions Model
Constant	0.6235 (1.74)	0.6093 (1.95)	0.4904 (1.66)
January dummy	2.115 (2.37)	1.611 (2.10)	1.853 (2.68)
ΔFT_{t-1}	-0.0912 (-1.04)		
$\Delta S\&P_{t-1}$	0.0546 (0.69)		
ΔER_t	-0.3724 (-3.75)	-0.1777 (-1.91)	
ΔOIL_t	-0.0464 (-1.38)		
ΔSR_t	-0.751 (-1.37)		
ΔLR_t	-5.576 (-5.60)	-7.474 (-10.2)	-4.375 (-4.52)
$\Delta M0_{t-1}$	0.6814 (1.37)	1.339 (3.02)	1.342 (2.80)
ΔRS_{t-1}	-0.3967 (-1.68)	-0.7810 (-3.86)	-1.020 (-4.72)
ΔIOP_{t-2}	0.4818 (2.08)		
ΔDY_{t-1}	3.1981 (1.94)	4.117 (2.84)	
$F_1(\Delta DY_{t-1}) \times \Delta FT_{t-1}$		-0.8223 (-2.80)	-0.8459 (-2.88)
$F_1(\Delta DY_{t-1}) \times \Delta ER_t$		-4.633 (-2.68)	-5.597 (-2.92)
$F_1(\Delta DY_{t-1}) \times \Delta SR_t$		-7.336 (-2.72)	-6.427 (-2.66)
$F_1(\Delta DY_{t-1}) \times \Delta M0_{t-1}$		-7.287 (-2.50)	-6.340 (-2.67)
$F_1(\Delta DY_{t-1}) \times \Delta RS_{t-1}$		7.742 (2.50)	7.272 (2.36)
$F_1(\Delta DY_{t-1}) \times \Delta IOP_{t-2}$		6.925 (3.48)	7.386 (3.46)
γ_1		2.408 (3.80)	1.928 (4.56)
c_1		0.3503 (5.75)	0.3442 (5.10)
$F_2(\Delta ER_t) \times \Delta OIL_t$			-0.0759 (-2.11)
$F_2(\Delta ER_t) \times \Delta LR_t$			-6.578 (-4.56)
$F_2(\Delta ER_t) \times \Delta DY_{t-1}$			6.966 (3.72)
γ_2			1464 (0.01)
c_2			-0.3216 (-0.16)
s	3.977	3.587	3.447
AIC	2.805	2.610	2.541
R^2	0.25	0.40	0.45
Diagnostic tests:			
Autocorrelation	0.3263	0.4478	0.6317
ARCH	0.3923	0.2765	0.5440
Normality	0.0002	0.0000	0.0000
RESET	0.3558		
Parameter Constancy:			
All coefficients	0.4257	0.5146	0.6941
Intercept	0.5386	0.4744	0.7328

Notes: See Table 1.

Table 4: Linearity Tests for Lagged S&P Models

Potential Transition Variable	**Linear Model**	**Single Transition Model**	**Two Transitions Model**
Time	0.5952	0.3220	0.4897
ΔFT_{t-1}	0.1424	0.6991	0.2663
$\Delta S\&P_{t-1}$	0.0266*	0.0840	0.2406
ΔER_t	0.1338	0.3011	0.8426
ΔOIL_t	0.0183*	0.0772	0.1944
ΔSR_t	0.1387	0.4164	0.5481
ΔLR_t	0.0298*	0.1185	0.3251
$\Delta M0_{t-1}$	0.1227	0.0465*	0.2576
ΔRS_{t-1}	0.5359	0.0737	0.0706
ΔIOP_{t-2}	0.3849	0.4324	0.7688
ΔDY_{t-1}	1.3720e-05*	0.2487	0.3208

Notes: See Table 2.

Table 5. Post-Sample Model Comparisons

	Contemporaneous *S&P* Models			Lagged *S&P* Models		
	Linear	**One Transition**	**Two Transitions**	**Linear**	**One Transition**	**Two Transitions**
Predictive stability test (p-value)						
Jan 2000 – Mar 2001	0.9614	0.8586	0.9183	0.1542	0.0399	0.0469
Apr 2001 – Jun 2002	0.8452	0.4315	0.0341	0.0616	0.0032	0.0002
Predictive accuracy comparisons Jan 2000 – Mar 2001						
Mean square error (MSE)	4.813	5.635	4.497	21.5975	22.1490	19.9863
MSE/s^2	0.457	0.623	0.542	1.365	1.722	1.682
Diebold-Mariano statistic*		-0.2964	0.0640		-0.1538	0.2556
Direction of change:						
$\Delta FT > 0$	7/9	7/9	8/9	9/9	9/9	9/9
$\Delta FT < 0$	6/6	6/6	6/6	0/6	1/6	2/6
Pesaran-Timmermann statistic*	3.0619	3.0619	3.4993	N/A	1.3122	1.9258
Predictive accuracy comparisons Apr 2001 – Jun 2002						
Mean square error (MSE)	6.7240	9.2096	14.5923	25.5313	29.2858	33.2879
MSE/s^2	0.639	1.019	1.760	1.614	2.277	2.802
Diebold-Mariano statistic*		-0.3717	-0.4951		-0.3337	-0.5799
Direction of change:						
$\Delta FT > 0$	4/5	3/5	4/5	3/5	3/5	3/5
$\Delta FT < 0$	9/10	9/10	5/10	4/10	3/10	5/10
Pesaran-Timmermann statistic*	2.8062	2.1368	1.1573	0	-0.4009	0.3788

Note: The predictive stability test is a p-value obtained on the assumption of a normal distribution; see text. The value of s^2 is the sample residual variance, shown in Tables 1 or 3 as appropriate. The Diebold-Mariano test statistics relate to a MSE comparison of the single or two transition model to the corresponding linear specification. The direction of change statistics for $\Delta FT > 0$ show the number of months when an increase is correctly predicted, compared with the actual number of months where ΔFT is positive. The statistic for $\Delta FT < 0$ show the number of months when a decrease is correctly predicted, compared with the actual number of months where ΔFT is negative. *These statistics are asymptotically standard normal and the asymptotic 5% critical value is ± 1.96.

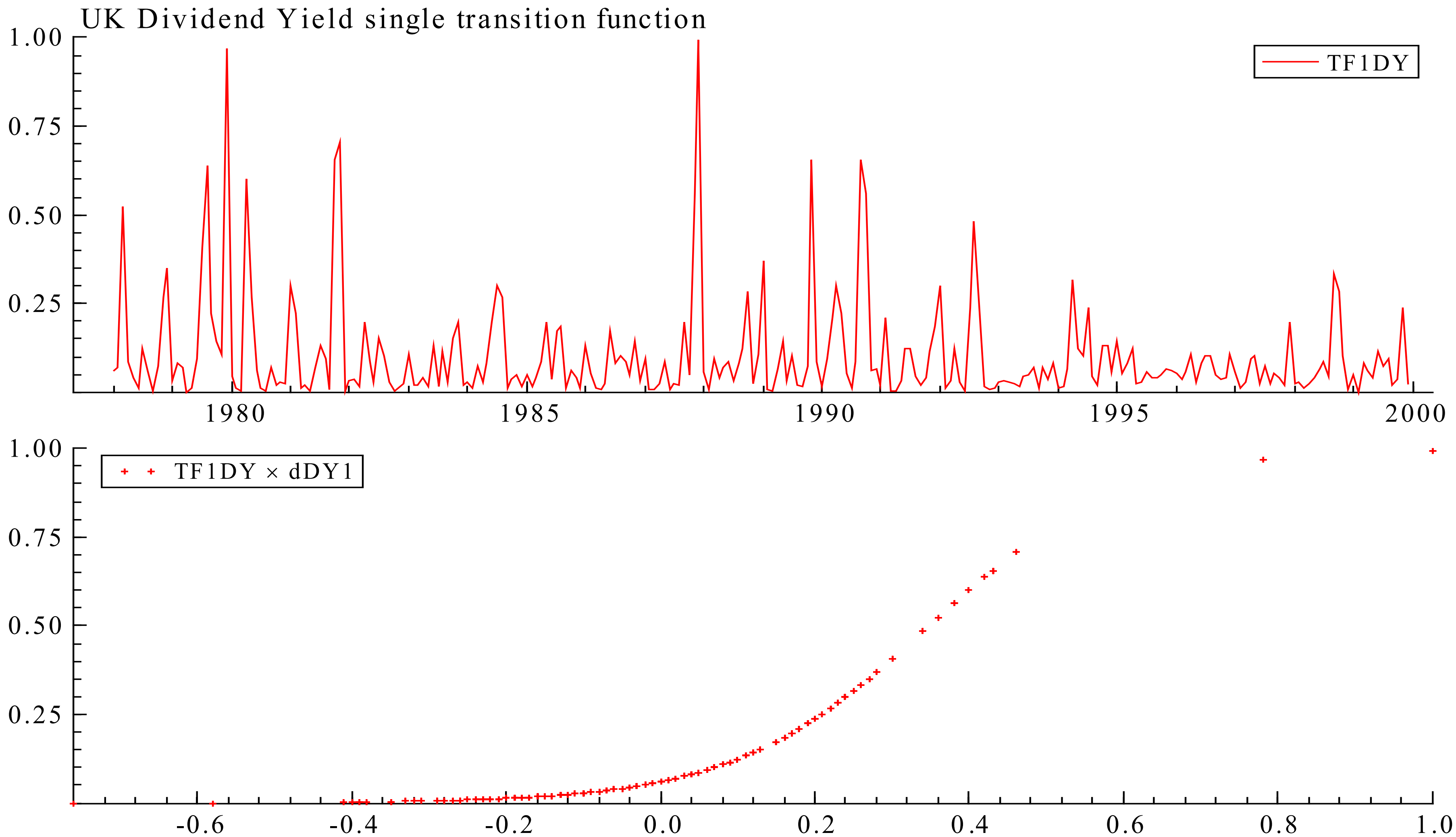

Figure 1: Dividend yield transition function for single transition functions model with contemporaneous *S&P*

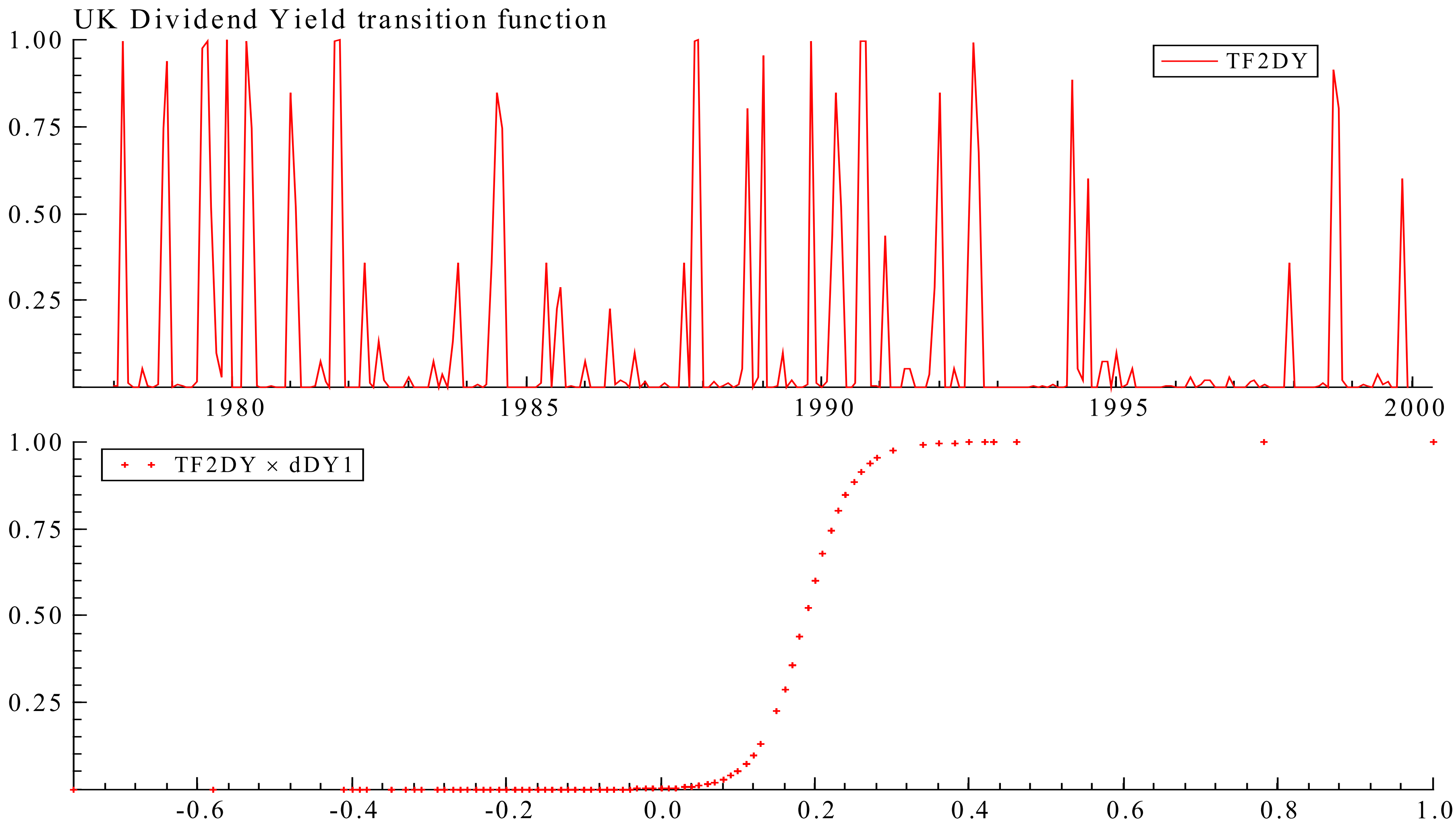

Figure 2: Dividend yield transition function for the two transition model with contemporaneous *S&P*

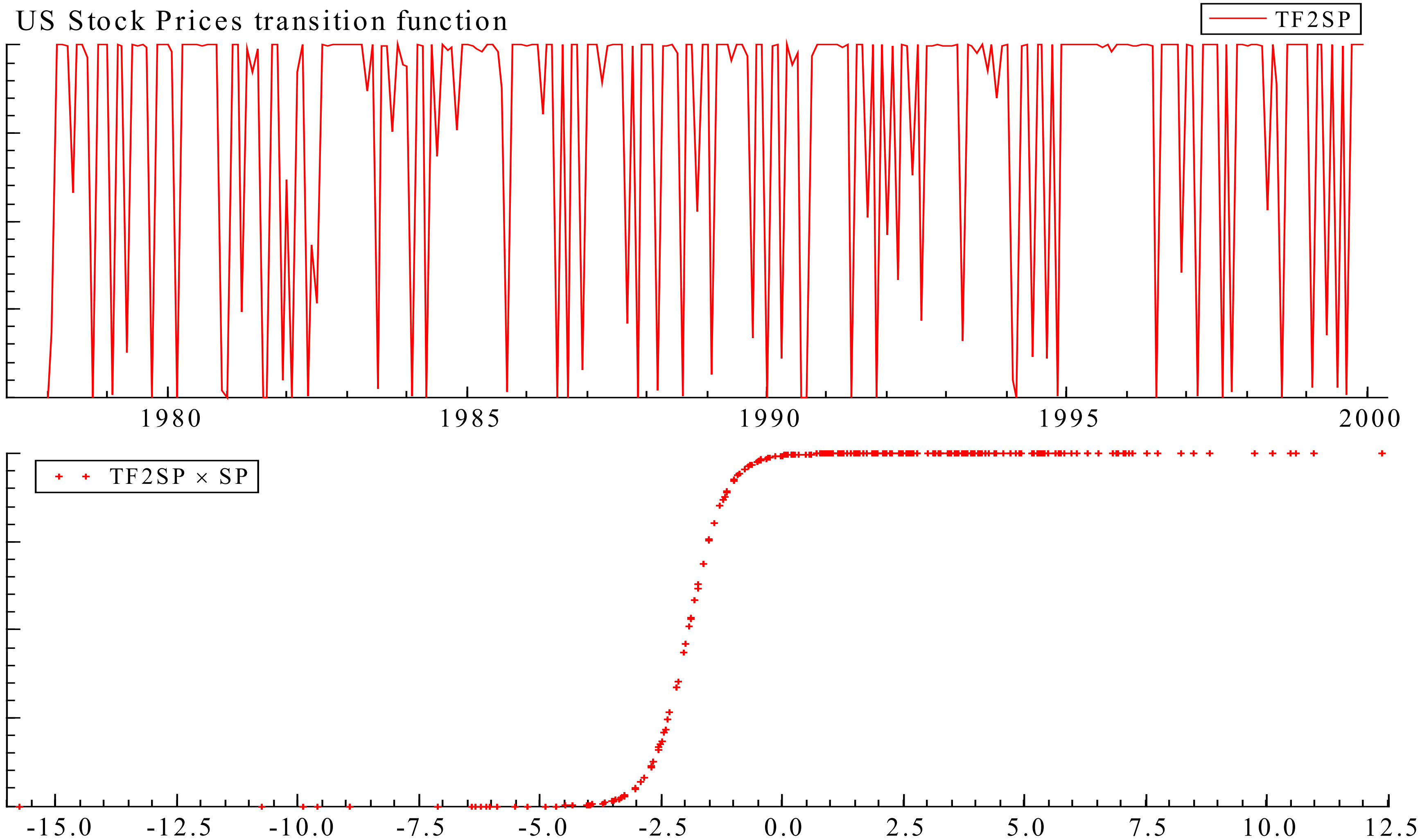

Figure 3: *S&*P transition function for the two transition model with contemporaneous *S&P*

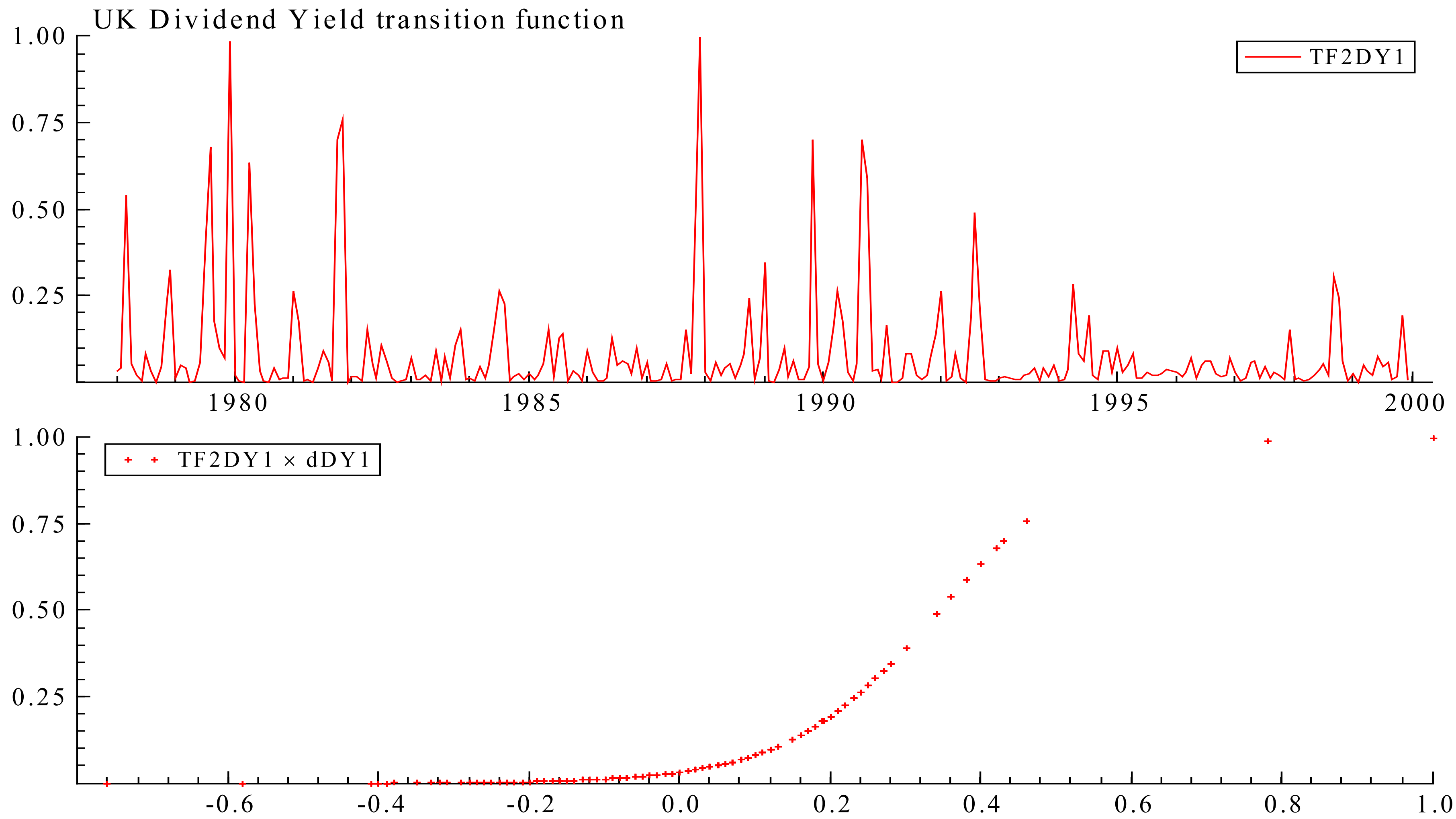

Figure 4: Dividend yield transition function for the two transition model using lagged *S&P*

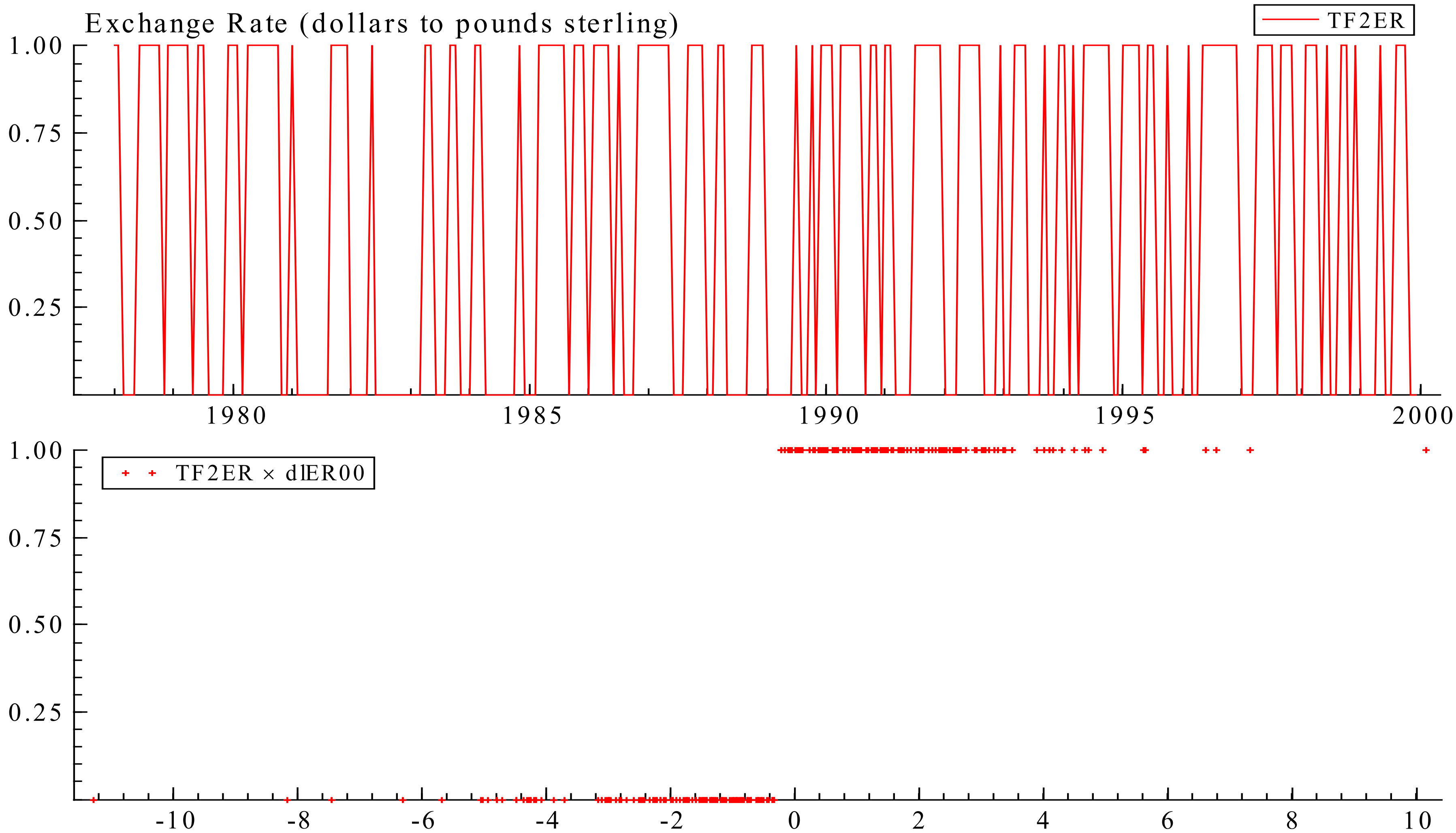

Figure 5: Real exchange rate transition function for the two transition model using lagged *S&P*

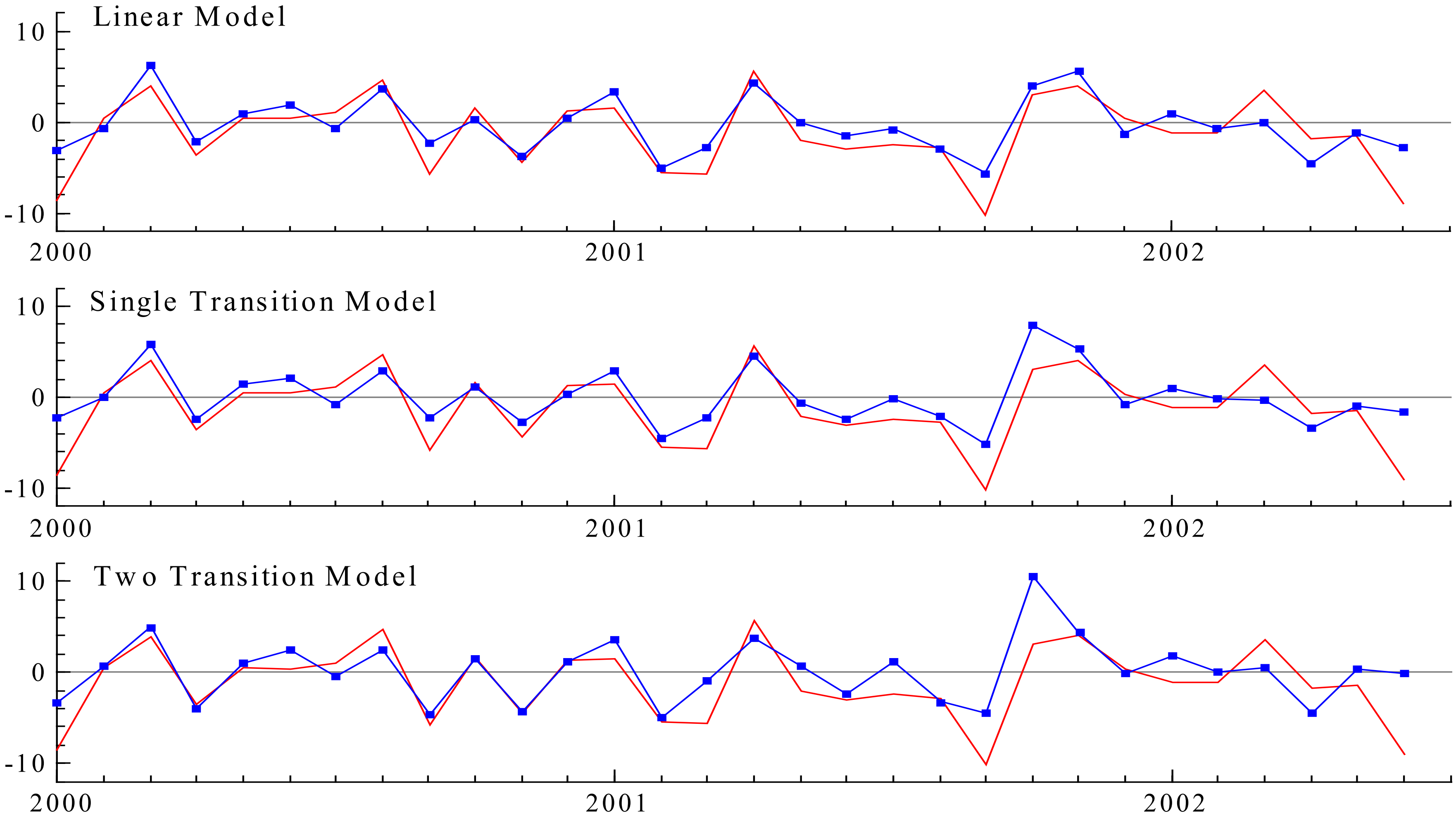

Figure 6: Post-sample predictions from linear, single and two transition models using contemporaneous *S&P*

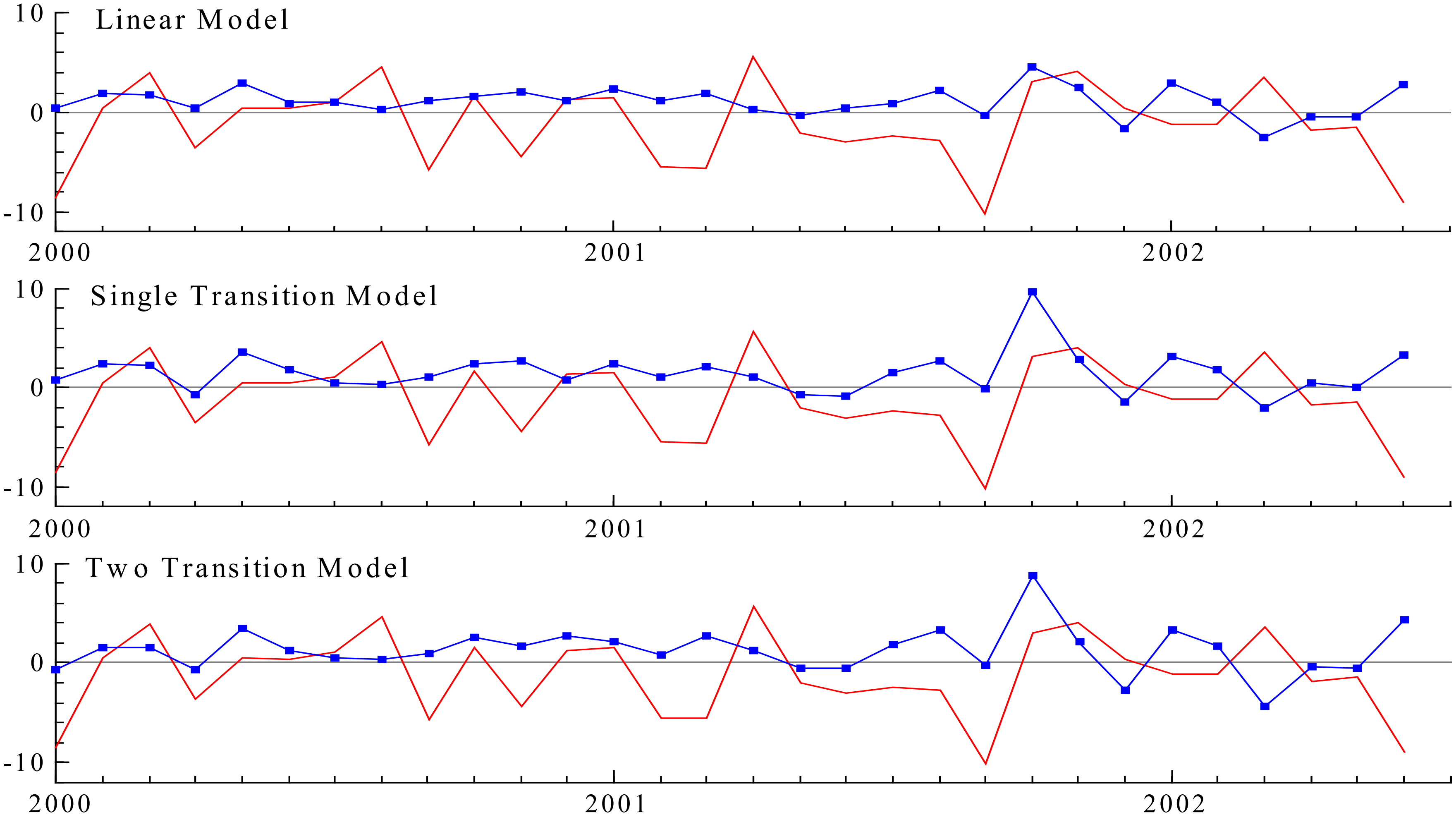

Figure 7: Post-sample predictions from linear, single and two transition models using lagged *S&P*

Appendix 1:
Data

Table A.1: Variable Descriptions and Sources

Name	Variable Description	Source	Code
FT	Financial Times all share index (EP), NSA	Datastream	UKFTALL.
DY	F.T. Actuaries all share index: dividend yield-monthly average, NSA	ONS	AJMD
S&P	Standard and Poors' composite index (EP), NSA	Datastream	USS&PCOM
ER	US $ TO £1, NSA	Datastream	UKXUS$..
OIL	Oil Price: Domestic West TX. Intermediate [Prior'82=Posted Price]($/Bbl), NSA	FRED	OILPRICE
SR	Bank bill rate - discount, 3 month, SA	Datastream	UK3MTHINE
LR	Average monthly gross flat yield on 2.5% Consols, NSA	Datastream	UKCNSYLD
*M*0	M0 wide monetary base (EP): level £M, SA	ONS	AVAE
RS	Retail sales volume index, SA	Datastream	UKRETTOTG
IOP	Industrial production volume index, SA	ONS	CKYW
RPI	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/).

Table A.2: Outliers Removed

	UK	US
Stock Market Prices	1987m10	1987m10
Industrial Production	1978m4; 1979m1	N/A
*M*0	1999m10-11	N/A
Retail Sales	1979m6	N/A

Appendix 2:
Grid Search Results

Table A.3: Grid Search Results for One Transition Contemporaneous S&P Model

Transition Variable	γ	c	RSS
ΔDY_{t-1}	3.000	0.2465	2233
$\Delta S\&P_t$	150.0	-2.518	2309
ΔER_t	130.0	2.865	2358
ΔOIL_t	23.00	0.5180	2388
$\Delta M0_{t-1}$	150.0	-0.2866	2417
ΔIOP_{t-2}	150.0	-0.4953	2424
ΔFT_{t-1}	5.000	-6.283	2425
ΔRS_{t-1}	90.00	-0.3680	2431
Time	150.0	109.2	2454
ΔSR_t	6.000	0.1925	2461
ΔLR_t	150.0	-0.2240	2466

Notes: RSS is the minimum residual sum of squares from the grid search when the named variable is used as the transition variable, with γ and c being the values yielding this RSS. All variables are included in the model.

Table A.4: Grid Search Results for Two Transitions Contemporaneous S&P Model (First Transition Variable ΔDY_{t-1})

γ_1	c_1	Second Transition Variable	γ_2	c_2	RSS
5	0.206	$\Delta S\&P_t$	15	-1.606	1938.26
3	0.206	*Time*	50	109.2	1989.10
4	0.206	ΔOIL_t	5	0.518	2038.71
4	0.206	$\Delta M0_{t-1}$	33	-0.287	2042.94
3	0.206	ΔRS_{t-1}	6	-0.697	2046.81
3	0.206	ΔER_t	15	-0.195	2052.85
3	0.206	ΔSR_t	5	0.050	2089.69
3	0.206	ΔLR_t	50	-0.224	2091.22
3	0.206	ΔFT_{t-1}	50	2.011	2107.99
3	0.206	ΔIOP_{t-2}	13	-0.661	2117.09

Note: See Notes for Table A.3.

Table A.5: Grid Search Results for One Transition Lagged S&P Model

Transition Variable	γ	c	RSS
ΔDY_{t-1}	3.000	0.2465	3197
ΔOIL_t	128.0	-2.179	3466
$\Delta S\&P_{t-1}$	5.000	-2.822	3526
ΔLR_t	150.0	0.2130	3561
ΔER_t	150.0	3.477	3589
ΔFT_{t-1}	3.000	-6.283	3609
ΔSR_t	150.0	0.4300	3627
ΔIOP_{t-2}	43.00	-0.5784	3644
$\Delta M0_{t-1}$	150.0	-0.1723	3664
Time	71.00	243.2	3724
ΔRS_{t-1}	108.0	-1.108	3726

Notes: See Table A.3.

Table A.6: Grid Search Results for Two Transitions Lagged S&P Model (First Transition Variable ΔDY_{t-1})

γ_1	c_1	Second Transition Variable	γ_2	c_2	RSS
5	0.206	*Time*	50	62.6	2852.23
3	0.206	ΔER_t	14	-0.195	2861.62
4	0.206	ΔOIL_t	4	0.518	2864.77
5	0.206	ΔLR_t	47	0.236	2873.53
4	0.206	$\Delta S\&P_{t-1}$	10	0.825	2908.60
4	0.206	$\Delta M0_{t-1}$	3	-0.287	2950.46
4	0.206	ΔFT_{t-1}	50	2.011	2954.63
4	0.206	ΔSR_t	50	0.430	3009.55
4	0.206	ΔRS_{t-1}	27	-1.354	3044.47
4	0.206	ΔIOP_{t-2}	50	-1.659	3064.74

Notes: See Table A.3.