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Heterogeneous Expectations in the Foreign Exchange Market Evidence from the Daily Dollar/DM Exchange Rate

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Heterogeneous Expectations in the Foreign Exchange Market Evidence from the Daily Dollar/DM Exchange Rate[1]

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Abstract:
In this study a regime switching approach is applied to estimate the chartist and fundamentalist (c&f) exchange rate model originally proposed by Frankel and Froot (1986). The c&f model is tested against alternative regime switching specifications applying likelihood ratio tests. Nested atheoretical models like the popular segmented trends model suggested by Engel and Hamilton (1990) are rejected in favour of the multi agent model. Moreover, the c&f regime switching model seems to describe the data much better than a competing regime switching GARCH(1,1) model. Finally, our findings turned out to be relatively robust when estimating the model in subsamples. The empirical results suggest that the model is able to explain daily DM/Dollar forward exchange rate dynamics from 1982 to 1998.

JEL Classification: F31, F37, C32, G12, G15

Keywords: exchange rates, multi agent models, regime-switching

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1. Introduction

Numerous empirical studies produced evidence that the asset market approach in exchange rate economics performs poorly in explaining short term movements of the exchange rate (Lewis, 1995 and Taylor, 1995). Particularly, the property of the forward rate to be a biased predictor of the future spot rate as well as the dependence of the volatility on exchange rate regimes cannot be captured within the standard asset market approach.[3] Subsequent research has proceeded in two directions. One direction tries to explain the puzzle with time-varying risk premia, peso-problems and bubbles while maintaining the rational (homogeneous) expectation hypothesis (Lewis, 1995). The other direction takes into account heterogeneous beliefs of foreign exchange market participants. These models explain the exchange rate by a time varying convex combination of lagged chartist and fundamentalist (c&f) forecasts as originally suggested by Frankel and Froot (1986) and developed further by – among others – De Long *et al.* (1990), Lux (1995) and Sethi (1996). While providing substantial improvement in understanding exchange rate movements, c&f models have not been confronted with actual exchange rate data. Hence, only anecdotal support for c&f models was found in studies of micro survey data like Dominguez (1986), Allen and Taylor (1989), and Menkhoff (1995).

Following Vigfusson (1997) we try to overcome this serious drawback using the standard markov regime switching approach proposed by Hamilton (1989). We approximate fundamentalist forecasts by the deviation of the lagged exchange rate from purchasing power parity. The chartist forecasts are constructed by the deviation of a short term from a long term moving average, which is a trading rule commonly used in foreign exchange markets. In four respects, this study goes beyond Vigfussons analysis. First, our sample extends from January 1982 to November 1998 and thus includes more than 4400 observations of daily German-US exchange rates providing reliable estimates and allowing for valuable subsample experiments. Second, because in the 1980s the US-Dollar was apparently overvalued relative to the DM when looking at fundamentals, the German-US exchange rate of this period is an ideal candidate for testing the presence of chartism. Third, we investigate whether the classification of our models might be driven by high- and low-volatility regimes, rather than chartist and fundamentalist elements. Fourth, we statistically compare the c&f regime switching model with the less complex segmented trend model. This competing but nested specification was originally suggested by Engel and Hamilton (1990) and has recently been applied by Dewachter (1997). Likelihood ratio tests, statistically significant coefficients in chartist and fundamentalist regimes, as well as the ability to capture ARCH-effects in daily exchange rates provide evidence in favour of multiagent model of foreign exchange markets.

The paper is organised as follows. Section 2 introduces the basic c&f-model and outlines some extensions that have been made in the literature. The c&f regime switching specification and the estimation method are described in section 3. Section 4 reports and discusses the estimation results and the test statistics. Section 5 provides the conclusions of the paper.

2. The chartist and fundamentalist exchange rate model

In Frankel and Froot (1986) the (log of the) exchange rate e_t is driven by the decisions of portfolio managers. They buy and sell foreign currency in response to changes in the expected rate of depreciation $E_t[\Delta e_{t+1}]$ and a set of contemporaneous variables included in a vector $\mathbf{z}_t$. Thus the exchange rate can be written as

$$e_t = aE_t[\Delta e_{t+1}] + \mathbf{b}\mathbf{z}_t \qquad (1)$$

where the vector of elasticities of the contemporaneous variables **b** and the elasticity of exchange rate expectation a should be constant over time. Under the rational expectations hypothesis equation (1) has the well known forward looking solution. In contrast to this, it is assumed that portfolio managers generate their exchange rate expectations using a weighted average of chartist $E_t^c[\Delta e_{t+1}]$ and fundamentalist $E_t^f[\Delta e_{t+1}]$ forecasts:

$$E_t[\Delta e_{t+1}] = \omega_t E_t^f[\Delta e_{t+1}] + (1 - \omega_t)E_t^c[\Delta e_{t+1}]. \qquad (2)$$

The parameter ω_t denotes the weight given to fundamentalist views at date t and is dynamically updated by the portfolio managers in a rational Bayesian manner:

[3] Exchange rate regime-dependence is discussed in Baxter and Stockman (1989), Flood and Rose (1993), and Eichengreen (1988).

$$\Delta\omega_t = \delta\left(\omega^*_{t-1} - \omega_{t-1}\right) \tag{3}$$

with

$$\omega^*_{t-1} = \frac{\Delta e_t - E^c_{t-1}[\Delta e_t]}{E^f_{t-1}[\Delta e_t] - E^c_{t-1}[\Delta e_t]}$$

where ω^*_{t-1} is the ex post calculated weight that must have been assigned to fundamentalist forecast in order to predict the current exchange rate change accurately. The value of δ reflects the extend to which portfolio managers enclose new information in this adaptive process and proves responsible for the exchange rate dynamics. Since portfolio managers always maintain a positive weight for both chartist and fundamentalist forecasts, $\Delta\omega$ has to be restricted so that ω stays in the range between 0 and 1. To make sure that the empirical analysis remains tractable, another feedback rule is introduced. Similar to Lewis (1989), portfolio managers are supposed to optimize the weight assigned to fundamentalist forecasts by means of a Bayesian learning process:

$$\omega_t = \frac{\omega_{t-1} \cdot \varphi_f\left(\Delta e_t \middle| E^f_{t-1}[\Delta e_t]\right)}{\omega_{t-1} \cdot \varphi_f\left(\Delta e_t \middle| E^f_{t-1}[\Delta e_t]\right) + \omega_{t-1} \cdot \varphi_c\left(\Delta e_t \middle| E^c_{t-1}[\Delta e_t]\right)} \tag{3'}$$

where $\varphi_c\left(\Delta e_t \middle| E^c_{t-1}[\Delta e_t]\right)$ and $\varphi_f\left(\Delta e_t \middle| E^f_{t-1}[\Delta e_t]\right)$ are the density functions of Δe_t conditional on the forecasts of chartists and fundamentalists, respectively.

So far, nothing has been said about how forecasts are generated. In Frankel and Froot (1986) fundamentalist have in mind some kind of long run equilibrium $\tilde{e}$, for example the purchasing power parity, a terms of trade-measure or a simple constant, to which the exchange rate reverts with a given speed θ over time, i.e. $E^f_t[\Delta e_{t+1}] = \theta(\tilde{e} - e_t)$. Chartists are assumed to believe that the exchange rate follows a random walk implying that they are using the actual spot rate to predict the future rate. Hence, their forecasting rule is reduced to $E^c_t[\Delta e_{t+1}] = 0$. The advantage of employing this assumption is to simplify the difference equation (3) permitting analytical solutions in theoretical models. In addition, this proceeding may be intended to focus on the destabilising effect of a decreasing weight of fundamentalist expectations on the exchange rate dynamics: An initial positive shock on the exchange rate is merely magnified by the portfolio managers subsequent revisions of their exchange rate expectations according to (2) and (3), which enforces them to further purchases of foreign currency. The occurrence of an exchange rate bubble can be explained technically by some kind of „overshooting", namely by different adjustment speeds of the two endogenous variables e_t and ω_t. Obviously, the random walk modelling is not a realistic description of chartist techniques for reasons of the lack of profitability, so it cannot be used in empirical models.

The standard c&f-model has been extended in different ways. De Grauwe (1994) uses an AR(4) time series process as a proxy for chartist behaviour. Reflecting the uncertainty about the true model of the foreign exchange market, fundamentalists are assumed to form heterogeneous expectations. Aggregation of these beliefs results in a normal distribution around the long run equilibrium value of the exchange rate. Consequently, fundamentalist views compensate almost completely in the case of a small deviation so that the weight ω assigned to their forecast should be low. By the same argument a high value of ω appears when this deviation is large and most of the fundamentalists forecasts point into the same direction. The implementation of this nonlinearity allows for both a range of fundamentalist agnosticism where the exchange rate can be easily driven away from its long run equilibrium and a range of large positive or negative deviations where the exchange rate exhibits mean reversion properties.

De Long *et al.* (1990) argue that trading on chartist forecasts (noise trading) enlarges the asset price volatility. Facing additional risk, utility-maximising speculators with sufficient risk aversion will limit their positions against noise traders. In this stock market model with overlapping generations noise traders earn higher expected profits for bearing self-created risks. This means that destabilising speculators were not always driven out of the market. Empirical evidence for these findings is provided by Kho (1996) who explains trading rule profitability by a time varying risk premium. Excess returns of moving average (MA) trading rules of daily U.S. dollar quotes for the DM, yen, pound sterling and swiss franc is reported in Neely (1997) and LeBaron (1999, 2000). Lee et al. (2001) found MA trading rule profitability for Latin American currencies applying out of sample-tests. European cross rates seem to exhibit no MA trading rule profitability, which may be due to the presence of the EMS (Lee and Mathur, 1996). However, Neely and Weller (1999) constructed trading rules by a genetic programming approach generating excess return for EMS exchange rates. Pilbeam (1995) and Dewachter (1997) compare the predictive power of chartist and fundamentalist forecasts using a profitability measure or the sign of the predicted exchange rate change, respectively.

In the models developed so far, excess demand of agents is based solely on exchange rates and it's fundamentals denying an important feature of financial markets. If markets are best described by heterogeneous interacting agents, asymmetric information distribution might lead to learning by observing other traders investment decisions or communication. These herding effects are introduced by the work of e.g. Banerjee (1992), Kirman (1993), and Lux (1995).

3. Model specification and estimation method

In order to confront the basic chartist and fundamentalist model with actual exchange rate data we estimate markov regime switching models with two states as suggested originally by Engel and Hamilton (1990) and developed further by, among others, Kaminsky (1993), Engel (1994) and Dewachter (1997). We first outline the general econometric methodology and then discuss the mean and variance specifications of the exchange rate models in detail.

3.1 The Markov regime-switching methodology

In Markov regime switching models, the conditional mean μ and the conditional variance h of (log) exchange rate changes Δe are allowed to follow two different processes. The behavior of the series depends on the value of an unobserved state variable S_t. Thus, under conditional normality, the observed realisation Δe_t is presumed to be drawn from a $N(\mu_{1t}, h_{1t})$ distribution when $S_t = 1$, whereas Δe_t is distributed $N(\mu_{2t}, h_{2t})$ when $S_t = 2$. The regime indicator S_t is parameterised as a first-order Markov process and the switching or transition probabilities P and Q have the typical Markov structure:

$$\begin{aligned}
&\Pr\left[S_t = 1 | S_{t-1} = 1\right] = P \\
&\Pr\left[S_t = 2 | S_{t-1} = 1\right] = (1 - P) \\
&\Pr\left[S_t = 2 | S_{t-1} = 2\right] = Q \\
&\Pr\left[S_t = 1 | S_{t-1} = 2\right] = (1 - Q) \quad .
\end{aligned} \tag{4}$$

Under the assumption of conditional normality for each regime, the conditional distribution of Δe_t is a mixture of normal distributions,

$$\Delta e_t | \Phi_{t-1} \sim \begin{cases} N(\mu_{1t}, h_{1t}) & \text{w. p. } p_{1t} \\ N(\mu_{2t}, h_{2t}) & \text{w. p. } p_{2t} = (1 - p_{1t}) \end{cases}, \tag{5}$$

where $p_{1t} = \Pr(S_t = 1 | \Phi_{t-1})$ is the probability that the analysed process is in regime 1 at time t conditional on information available at time t-1. Of course, p_{1t} can also be regarded as a weight assigned to regime dependent forecasts by market participants. Suppose the regime-dependent conditional distributions in (5) represent chartists and fundamentalists forecasting approaches, respectively, a conceptual similarity between the theoretically motivated c&f model's forecasting equations (2) and (3') and the mixture of normal distributions becomes obvious.

In the regime switching literature the probability p_{1t} is called 'ex ante regime probability', because it is based solely on information already available and because it forecasts the prevailing regime in the next period. Following Hamilton (1994) and Gray (1996) the unobserved regime probability is formulated as a recursive process,

$$p_{1t} = P\left[\frac{f_{1t-1}\, p_{1t-1}}{f_{1t-1}\, p_{1t-1} + f_{2t-1}(1 - p_{1t-1})}\right] + (1 - Q)\left[\frac{f_{2t-1}(1 - p_{1t-1})}{f_{1t-1}\, p_{1t-1} + f_{2t-1}(1 - p_{1t-1})}\right], \tag{6}$$

with the regime-dependent conditional distributions $f_{1t} = f(\Delta e_t | S_t = 1, \Phi_{t-1})$ and $f_{2t} = f(\Delta e_t | S_t = 2, \Phi_{t-1})$. The process described in (6) is well founded by asset pricing theory. Kaminsky (1993) and Evans (1996) demonstrate that (6) is implied by peso problem behaviour in combination with rational learning of market participants. Thus, our empirical approach is able to capture or even unify competing theories in exchange rate economics. The recursive representation of the regime-switching model allows us to construct the log-likelihood function conveniently as

$$L=\sum_{t=1}^{T}\log\left[p_{1t}\frac{1}{\sqrt{2\pi h_{1t}}}\exp\left\{\frac{-(\Delta e_t-\mu_{1t})^2}{2h_{1t}}\right\}\right.$$
$$\left.+(1-p_{1t})\frac{1}{\sqrt{2\pi h_{2t}}}\exp\left\{\frac{-(\Delta e_t-\mu_{2t})^2}{2h_{2t}}\right\}\right] \qquad . \tag{7}$$

3.2 Conditional mean specification

As mentioned in the introduction, the c&f regime switching model is tested against alternative regime switching specifications. The c&f model and his competitors are described below with reference to their alternative mean dynamics. Their common characteristic is the volatility assumed to be constant *within* regimes:

$$h_{1t}=\sigma_1^2 \text{ and } h_{2t}=\sigma_2^2$$

That is, the only source of conditional heteroskedasticity is regime switching behaviour. Note, that in subsection 4.2 below it will be discussed if this assumption is appropriate.

(1) Segmented Trend Model: RS-AR(0)

This most simple specification was introduced by Engel and Hamilton (1990) to model long swings in quarterly exchange rates. It can be easily interpreted as a random walk model with drift. However, it has the special feature that the drift term is subject to discrete shifts. Ideally, the drift term of one regime should be negative thereby characterising exchange rate decreases, while the drift term of the other regime is expected to be positive. If regimes turn out to be persistent, longer periods of appreciation followed by longer periods of depreciation can be captured by this model. Because it does not allow for autocorrelation or exchange rate dependence on other variables, it is denoted as a RS-AR(0) model. For comparison purposes, let f denote the drift in regime 1 and c be the drift in regime 2:

$$\mu_{1t}=f$$
$$\mu_{2t}=c$$

(2) Regime switching-AR(1) model: RS-AR(1)

A natural extension of the Segmented Trend model is the RS-AR(1) specification which allows for short run autocorrelation in exchange rate changes. Following Hamilton (1993), the distribution of Δe_t is not conditional on past regimes but the autoregressive term is assumed to be regime dependent, too:

$$\mu_{1t} = f + \phi_1 \Delta e_{t-1}$$
$$\mu_{2t} = c + \phi_2 \Delta e_{t-1}.$$

(3) Regime switching-c&f model: RS-CF-AR(0)

As discussed above, the main focus of this study is to explain daily exchange rate changes by the interaction of chartist and fundamentalist forecasts, so that the mean equations of the empirical model driving today's exchange rate change have to include lagged forecasts. In the first regime the deviation of the exchange rate from its fundamental value at date t-1 is used as the independent variable and thus represents the fundamentalist regime. The second regime includes the chartist forecasts at date t-1. As outlined in Neely (1997) chartist analysis is based on the idea that charting methods and mechanical trading rules can identify trends in the exchange rate movements. Because charting methods, i.e. searching for regularities in the graph of past exchange rates, require the interpretation of the analyst and are not suitable for theoretical and empirical modelling, we approximate chartist forecasting by means of a mechanical trading rule. To reduce the impact of data snooping biases brought on by searching for the best performer we follow Vigfusson (1997) and employ a commonly used and simple type of trading rule: Chartists are supposed to expect that a future exchange rate increase is predicted by the proportion ψ of the positive difference between the 14 day moving average (ma14) and 200 day moving average (ma200) and vice versa, i.e. $E^C_{t-1}[\Delta e_t] = \psi(ma_{14,t-1} - ma_{200,t-1})$. From an econometric point of view, this trading rule imposes a restriction on the moving averages ma_{14} and ma_{200}, which can be exploited to apply another specification test: We estimate a coefficient for both moving averages separately and denote them ψ_{14} and ψ_{200}, respectively. Evidence of the trading rule we only be provided, if the restriction ψ_{14} = -ψ_{200} in the chartist mean equation cannot be rejected by means of a likelihood ratio test. Thus, the mean equations of the *RS-CF-AR(0)* are:

$$\mu_{1t} = f + \theta(\tilde{e}_{t-1} - e_{t-1})$$
$$\mu_{2t} = c + \psi_{14} ma_{14,t-1} + \psi_{200} ma_{200,t-1} \ .$$

(4) Regime switching-c&f-AR(1) model: RS-CF-AR(1)

The last model we consider is the RS-CF-AR(0) model augmented by regime dependent autoregressive terms. Note, that this specification nests all three models described above:

$$\mu_{1t} = f + \theta(\tilde{e}_{t-1} - e_{t-1}) + \phi_1 \Delta e_{t-1}$$
$$\mu_{2t} = c + \psi_{14} ma_{14,t-1} + \psi_{200} ma_{200,t-1} + \phi_2 \Delta e_{t-1} \ .$$

4. Empirical Results

4.1 Estimation results and specification tests

The theoretical model outlined above focus on the role of heterogeneous exchange rate expectations and does not account for risk considerations. Under these circumstances any spot market speculation consists of a covered interest transaction and a forward market speculation so that the forward exchange rate can be used to approximate the expected future spot rate.[4] The estimates are derived from the daily DM/Dollar (three month) forward exchange rate series which was kindly supplied by the Deutsche Bundesbank. The fundamental value of the exchange rate is described by purchasing power parity (PPP) which was derived by interpolating monthly observed price indexes to a daily frequency.[5] Moving averages of the exchange rate (ma_{14} and ma_{200}) are constructed in t by using unweighted data up to t-1. All models described in subsection 3.2 were estimated by (quasi) maximum likelihood. Parameter estimates were obtained using the BFGS algorithm, and the reported t-statistics are based on heteroskedastic-consistent standard errors (White, 1982). The sample extends from January 1982 to November 1998. The series of the forward exchange rate, the PPP relation and the 200 day moving average are presented in Figure 1.

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[4] Of course, on the daily basis the results are not change much when spot exchange rates are used.

[5] According to the results of standard unit root tests, both the German and the US price index are reasonably modelled as I(2) processes. Relying on this information, the interpolation procedure was done with the RATS routine INTERPOL.

[Figure 1]

Table1 contains the whole sample estimates of the four models described in subsection 3.2. For a better interpretation of regimes, the unconditional (stationary) regime probabilities and the expected durations $(1-\mathrm{P})^{-1}$ and $(1-\mathrm{Q})^{-1}$ of the regimes are also reported. As regards the constant terms, variances and transition probabilities, all models under consideration differ slightly at best. While the constants are not significantly different from zero, highly significant estimates of variances point to regime dependent heteroskedasticity capturing periods of high and low volatility: The second moment in the first regime is almost three times higher than the variance in the second regime. The transition probabilities are significant, too, and range above 0.95 thereby indicating high persistence of regimes. The unconditional probability of the high volatility regime $\overline{\mathrm{P}} = \frac{1-\mathrm{Q}}{2-\mathrm{P}-\mathrm{Q}}$ is with 0.37 substantially less than the one assigned to the second regime. This is also reflected in the expected durations of regimes. The high volatility regime is expected to last 25 trading days whereas regime two has a much longer duration of 45 trading days.

So far, we can conclude that the two-state regime-switching model is suitably specified. However, the most important question has not been addressed yet: Is there evidence in favour of exchange rate dynamics driven by both charts and fundamentals? The answer is given by the values of the log-likelihood functions and the derived likelihood ratio test statistics reported in the last two lines of Table 1.

[Table 1]

Note that the RS-AR(0) model is nested in all three remaining specifications whose relative power thus can be examined under the null hypothesis of segmented trends. Furthermore, the RS-CF-AR(1) model can be tested against all three simpler models which can be regarded as restricted RS-CF-AR(1) specifications. As the LRT statistics suggest, richer mean dynamics captured by the CF- and AR-terms do explain significant improvements in the log-likelihood function when moving from the parsimonious RS-AR(0) to the most complex RS-CF-AR(1) specification.

The most important finding, however, are statistically significant estimates of the parameters θ, ψ_{14} and ψ_{200} with correct signs and meaningful magnitudes. A given deviation of the actual exchange rate from the purchasing power has an only small effect on the daily exchange rate change implying that fundamentalist forecasting provides only long run stability of the exchange rate dynamics. In the chartist regime the sign of the estimated coefficient ψ_{14} is positive whereas that of ψ_{200} is negative. Moreover, ψ_{14} and ψ_{200} are of comparable size so that the restriction $\psi_{14} = -\psi_{200}$ cannot be rejected by means of a likelihood ratio test. This can be interpreted as additional evidence in favour of the moving average trading rule as an approximation of chartist analysis. Against their atheoretical competitors, RS-CF models are performing best. Hence, it can be concluded that the exchange rate is indeed driven by the fudamentalist and chartist regimes. The fact that regime classification might be driven by state-dependent heteroskedasticity does not weaken this conclusion. A typical finding in the regime switching literature is that coefficients in the mean equations become insignificant when additionally allowing for variances depending on regimes. This phenomenon can be explained by the dominance of second moments in characterising the distribution of high frequency data. As Table 1 suggests, the case in our study is completely different: Because θ, ψ_{14} and ψ_{200} are significant even in the presence of strong state dependent volatility, empirical support for the c&f model is strong.[6] Of course, this implies that volatility is much higher when the exchange rate is driven by fundamentals, which is at first sight contradictory to the economic intuition. A possible explanation for this is provided by Sethi (1996). In a nonlinear disequilibrium model of speculative markets he show that if information about economic fundamentals is costly, chartism is the superior forecasting strategy in the stable regime, and fundamentalist forecasting performs better in the unstable regime. Corresponding to our empirical results he concludes that fundamentalism may be most profitable in an unstable market and should dominate high volatility periods. Conversely, chartism may be rather lucrative in a stable market thereby dominating low volatility periods.

Those models which allow for autoregressive dependence explain the data better than the segmented trend and the basic c&f specification, respectively. However, the AR(1)-coefficients are only significant in the second regime revealing that chartists forecasts are not

[6] To complement this intuitive argumentation, subsection 4.2 discusses the performance of a GARCH model as an alternative variance specification.

purely based on moving averages. In contrast, the fundamental exchange rate is sufficiently described by PPP, leaving no room for autocorrelation in regime one.

[Table 2]

Table 2 reports Ljung-Box statistics relating to the residuals as well as to the squared standardised residuals of the estimated models thereby testing for serial correlation and autoregressive conditional herteroskedasticity. While all models under consideration are able to capture conditional heteroskedasticity by regime switching, significant serial correlation in the residuals is found for higher lag orders. Nevertheless, it can be concluded that particularly the c&f models do a good job in modelling the DM/Dollar exchange rate.

4.2 Regime dependent versus autoregressive conditional heteroskedasticity

In his original contribution, Vigfusson (1997) suggests to re-estimate the c&f regime switching model by using a Markov-switching specification whose variance is restricted to be independent of regimes but is instead described by an ARCH process. This should be done in order to analyse whether the classification of regimes might be driven by high- and low-variances, rather than chartist and fundamentalist elements. Vigfusson argues as follows: "Ideally, this would allow one to rule out variance induced-switching and isolate the chartist and fundamentalist influences on the exchange rate". Obviously, the underlying argument is that conditional heteroskedasticity can be either described by regime switching or alternatively by ARCH. However, extensive analyses provided by Gray (1996) show that this is not necessarily true. Instead, there are several options to combine both approaches, and the econometrican has to examine carefully which specification is most adequate. Nevertheless, parameter estimates of a regime switching GARCH(1,1) model imposing the restriction of a constant variance process across regimes,

$$h_{1t} = h_{2t} = h_t = b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1},$$

is reported in Table 3.[7] Table 4 includes Ljung-Box statistics testing for remaining serial correlation and ARCH effects. Though the RS-CF-AR(1)-GARCH(1,1) model captures exchange rate volatility successfully (the GARCH parameters are highly significant indicating strong volatility persistence), the value of the log-likelihood function is substantially below the ones reported in Table 1. This is remarkable, because the RS-CF-AR(1)-GARCH(1,1) model has twice as much parameters than the RS-AR(0) and even one more parameter than the RS-CF-AR(1) specification. Hence, the discouraging estimates of the mean dynamics in the RS-CF-AR(1)-GARCH(1,1) model should not raise any doubt on the empirical success of the c&f approach documented in Table 1. In our opinion, the insignificant estimates of θ, ψ_{14} and ψ_{200} are due to an inadequate model specification restricting the exchange rate volatility to be constant across regimes instead of allowing it to be state dependent and thereby directly linked to fundamentalist and chartist regimes.

[Table 3, Table 4]

4.3 Subsample estimates

When looking at Graph 1, two periods which are characterised by different exchange rate behaviour can roughly be distinguished. Most time in the 1980s, the Dollar was persistently above the level implied by purchasing power parity. In contrast, in the 1990s, the actual exchange rate was fluctuating cyclically around its fundamental value. Thus, to assess the c&f model more deeply, subsample estimations of the RS-CF-AR(1) model are obvious exercises. The estimates relying on observations from 1982 to 1988 and from 1989 to 1998, respectively, are shown in Table 5 and point to some interesting findings. First, the estimated subsample variances do not differ much from each other and have the same magnitude as the ones estimated for the whole sample. Second, for the first subsample, the transition probabilities and thus also the unconditional regime probabilities and expected durations are similar to those reported in Table 1. As already expected when looking at Graph 1, the fundamentalists regime is more important in explaining the exchange rate in the 1989 to 1998 period. The unconditional probability is above forty percent and the duration exceeds the fundamentalist whole sample duration by ten trading days. As a central finding, one can conclude from Table 1 that chartist behaviour has some explanatory power even in a period when PPP holds on

[7] As regards the model specification and the construction of the conditional variance, we basically follow Gray (1996) who introduces a convenient framework for formulating regime switching GARCH(1,1) models.

average, while fundamentalists do play a role even when exchange rate is driven far away from PPP. Of course, the estimated conditional mean dynamics of the exchange rate process do not unanimously support this finding. The chartist parameter estimates are significantly different from zero only in the first subsample, which is compatible with recent findings in the literature on technical trading suggesting a significant decline of it's profitability in the 1990th (LeBaron, 2000).

[Table 5, Table 6]

4.4 Graphical examination of regime probabilities

In Section 3.1 it was shown that regime probabilities can be regarded as weights assigned to either chartist or fundamentalist forecasts. Therefore it should be possible to examine whether the Frankel and Froot (1986) explanation of the 1980s exchange rate dynamics finds support in the data. For this purpose we estimate a parsimonious RS-CF model using monthly forward exchange rates.

[Table 7]

As can be seen from Table 7 the fundamentalist regime estimates remain unchanged relative to the findings reported in section 4.1, whereas an autoregression term sufficiently describes chartist behaviour. The t-statistics of θ and ϕ indicate high significance of both regimes. In addition, the estimates of the regime specific volatilities suggest that heteroskedasticity is fading with the transition to the lower data frequency. For the purpose of inferring if an increasing weight assigned to chartist forecasts have driven the exchange rate in the past, we look at the smoothed probabilities $\Pr(S_t = 1 | \Phi_T)$ which are calculated ex post using the entire information set of the whole sample. Together with the forward exchange rate the smoothed probabilities of the fundamentalist regime are plotted in graph 2.[8]

[Graph 2]

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[8] Remember that the chartist regime probabilities are defined as $\Pr(S_t = 2 | \Phi_T) = 1 - \Pr(S_t = 1 | \Phi_T)$.

The following aspects are worth mentioning. Contrary to Frankel and Froot (1986) the figure shows unambiguously that the RS-CF-model does not explain the large dollar appreciation with a gradually rising weight assigned to chartist behaviour. The chartist regime probabilities were already high when the dollar started its roller coaster in the end of 1980. This is due to the significant autoregressive term in the chartist regime. It leads to chartist dominance whenever a trend is established that drives the exchange rate away from purchasing power. Furthermore the exchange rate's turnaround in early 1985 coincides with a sharp rise of the fundamentalist regime probability. In the following years, it declines only gradually, showing that both the chartist and the fundamentalist regime were driving the exchange rate back to it's purchasing power value. Although the estimated regime probabilities provide a useful graphical interpretation supporting the general c&f-approach, it must be stated that the weight assigned to fundamentalist forecasts seems not to be the main driving force of the exchange rate in the 1980s.

5. Conclusion

The purpose of this paper is to apply the regime switching framework to investigate the empirical evidence of the chartist and fundamentalist (c&f) model originally proposed by Frankel and Froot (1986). As is shown in studies of micro survey data (e.g., Takagi, 1991), chartist analysis dominate the forecasts of market participants up to one week, whereas beyond this horizon more weight is given to fundamentals. Consistent with these findings we follow Vigfusson (1997) and approximate chartist and fundamentalist forecasting techniques by a moving average trading rule and the deviation of the exchange rate from purchasing power, respectively. The c&f model was tested against alternative regime switching specifications applying likelihood ratio tests. Nested atheoretical models like the popular segmented trends model suggested by Engel and Hamilton (1990) as well as the competing regime switching GARCH(1,1) model are rejected in favour of the c&f model. These findings turned out to be relatively robust by estimating the model in subsamples. Moreover, the calculated Ljung-Box Q-statistics suggest that the c&f model captures sufficiently the observed conditional heteroskedasticity in daily exchange rates by regime switching. So our empirical results provide evidence that the heterogeneous expectations exchange rate model is able to explain daily German-US forward rates from 1982 to 1998.

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Graph 1: DM/Dollar Exchange Rate, PPP, 200 d moving averages
Daily observations, 1982 - 1998

Table 1

Parameter estimates of regime-switching models for the Dollar/DM forward exchange rate (1982 – 1998)

	RS-AR(0)	*RS-AR(1)*	*RS-CF*	*RS-CF-AR(1)*
f	$-3.43 \cdot 10^{-4}$ (1.16)	$-3.59 \cdot 10^{-4}$ (1.27)	$-4.38 \cdot 10^{-5}$ (0.17)	$-5.56 \cdot 10^{-5}$ (0.20)
c	$1.02 \cdot 10^{-4}$ (0.91)	$1.06 \cdot 10^{-4}$ (0.90)	$5.38 \cdot 10^{-5}$ (0.50)	$5.57 \cdot 10^{-5}$ (0.49)
$\boldsymbol{\theta}$	-	-	$3.42 \cdot 10^{-3}$ (2.17)	$3.51 \cdot 10^{-3}$ (2.23)
$\boldsymbol{\psi_{14}}$	-	-	$6.27 \cdot 10^{-3}$ (2.92)	$6.65 \cdot 10^{-3}$ (2.80)
$\boldsymbol{\psi_{200}}$	-	-	$-5.56 \cdot 10^{-3}$ (2.62)	$-5.89 \cdot 10^{-3}$ (2.53)
$\boldsymbol{\phi_1}$	-	- 0.0394 (1.49)	-	- 0.0408 (1.55)
$\boldsymbol{\phi_2}$	-	- 0.0364 (2.14)	-	- 0.0409 (2.14)
$\boldsymbol{\sigma_1^2}$	$9.14 \cdot 10^{-5}$ (8.84)	$9.14 \cdot 10^{-5}$ (8.78)	$9.08 \cdot 10^{-5}$ (9.18)	$9.10 \cdot 10^{-5}$ (10.48)
$\boldsymbol{\sigma_2^2}$	$2.57 \cdot 10^{-5}$ (13.36)	$2.57 \cdot 10^{-5}$ (12.90)	$2.54 \cdot 10^{-5}$ (14.25)	$2.54 \cdot 10^{-5}$ (13.94)
P	0.9619 (75.62)	0.9616 (73.15)	0.9607 (70.90)	0.9601 (280.00)
Q	0.9778 (177.05)	0.9778 (195.07)	0.9769 (179.39)	0.9768 (177.32)
$\overline{\mathbf{P}}$	0.37	0.37	0.37	0.37
$\overline{\mathbf{Q}}$	0.63	0.63	0.63	0.63
$\mathbf{(1-P)^{-1}}$	26.25	26.04	25.45	25.06
$\mathbf{(1-Q)^{-1}}$	45.05	45.05	43.29	43.10
Log-Likelihood	15830.78	15833.74	15838.16	15841.64
LRT	-	5.92* (2 df)	14.76*** (3 df)	21.72*** (5 df)
	-	-	-	15.78*** (3 df)
	-	-	-	6.96** (2 df)

Notes: The sample contains daily observations of the DM/Dollar forward exchange rate from January 1982 to November 1998. F, C, θ, ψ_{14}, ψ_{200}, ϕ_1, ϕ_2 indicate the estimated parameters of the mean equations, σ^2_1 and σ^2_2 the estimated regime dependent variances, P and Q the estimated conditional transition probalilities, $\overline{P}$ and $\overline{Q}$ the unconditional (stationary) regime probabilities, $(1-P)^{-1}$ and $(1-Q)^{-1}$ the expected regime durations. t-statistics in parentheses are based on heteroskedastic-consistent standard errors. LRT indicate the likelihood ratio test statistics which are asymptotically χ^2 (df)-distributed with df indicating the number of restrictions. * (**. ***) denotes significance at the 10% (5%. 1%) level.

Table 2

Specification Tests (Ljung-Box Q-Statistic)

	RS-AR(0)	***RS-AR(1)***	***RS-CF***	***RS-CF-AR(1)***
AR(1)	1.11 (0.29)	1.64 (0.20)	1.67 (0.20)	1.43 (0.23)
AR(5)	9.79 (0.08)	10.68 (0.06)	8.40 (0.14)	8.28 (0.14)
AR(10)	25.66 (0.00)	27.52 (0.00)	22.34 (0.01)	22.89 (0.01)
ARCH(1)	1.69 (0.19)	1.60 (0.21)	0.90 (0.34)	0.86 (0.35)
ARCH(5)	8.48 (0.13)	8.58 (0.13)	7.23 (0.20)	7.39 (0.19)
ARCH(10)	13.38 (0.20)	13.81 (0.18)	11.90 (0.29)	12.37 (0.26)

Notes: AR(p) denotes the Ljung-Box statistic for serial correlation of the residuals out to p lags. ARCH(q) denotes the Ljung-Box statistic for serial correlation of the standardized squared residuals out to q lags. p-values are in parentheses.

Table 3

Parameter estimates of the c&f-regime-switching-GARCH(1,1) model with constant variances across regimes for the Dollar/DM forward exchange rate (1982 – 1998)

	RS-CF-GARCH(1.1) ***1982 – 1998***
f	$6.83 \cdot 10^{-5}$ (0.60)
c	$- 5.39 \cdot 10^{-4}$ (0.52)
θ	$1.14 \cdot 10^{-3}$ (1.32)
ψ_{14}	$- 3.12 \cdot 10^{-3}$ (0.18)
ψ_{200}	$9.20 \cdot 10^{-3}$ (0.60)
$\phi 1$	- 0.0507 (3.00)
ϕ_2	- 0.6347 (4.15)
b_0	$1.17 \cdot 10^{-6}$ (3.76)
b_1	0.0452 (4.14)
b_2	0.9109 (83.33)
P	0.9940 (325.32)
Q	0.8645 (17.19)
Log-Likelihood	15806.34

Notes: The sample contains daily observations of the DM/Dollar forward exchange rate from January 1982 to November 1998. F, C, θ, ψ_{14}, ψ_{200}, ϕ_1, ϕ_2 indicate the estimated parameters of the mean equations, b_0, b_1, b_2 the estimated GARCH(1,1) parameters of the regime independent variance, P and Q the estimated conditional transition probalilities. t-statistics in parentheses are based on heteroskedastic-consistent standard errors.

Table 4

Specification Tests (Ljung-Box Q-Statistics)

	RS-CF-GARCH(1.1) ***1982 – 1998***
AR(1)	0.08 (0.78)
AR(5)	8.29 (0.14)
AR(10)	27.09 (0.00)
ARCH(1)	1.96 (0.16)
ARCH(5)	3.03 (0.69)
ARCH(10)	6.50 (0.77)

Notes: AR(p) denotes the Ljung-Box statistic for serial correlation of the residuals out to p lags. ARCH(q) denotes the Ljung-Box statistic for serial correlation of the standardized squared residuals out to q lags. p-values are in parentheses.

Table 5

Parameter estimates of regime-switching models for the Dollar/DM forward exchange rate

	RS-CF* *1982 – 1988	***RS-CF* *1989– 1998***
f	$2.18 \cdot 10^{-4}$ (0.33)	$-2.52 \cdot 10^{-4}$ (0.73)
c	$-2.24 \cdot 10^{-4}$ (0.74)	$-1.15 \cdot 10^{-5}$ (0.06)
θ	$3.76 \cdot 10^{-3}$ (1.51)	$7.15 \cdot 10^{-3}$ (1.66)
ψ_{14}	$8.76 \cdot 10^{-3}$ (2.96)	$2.02 \cdot 10^{-3}$ (0.60)
ψ_{200}	$-7.24 \cdot 10^{-3}$ (2.40)	$-3.43 \cdot 10^{-3}$ (1.05)
σ_1^2	$9.88 \cdot 10^{-5}$ (6.46)	$8.06 \cdot 10^{-5}$ (7.10)
σ_2^2	$2.62 \cdot 10^{-5}$ (9.95)	$2.38 \cdot 10^{-5}$ (10.63)
P	0.9601 (86.04)	0.9713 (46.68)
Q	0.9774 (120.07)	0.9791 (95.25)
$\overline{P}$	0.36	0.42
$\overline{Q}$	0.64	0.58
$(1-P)^{-1}$	25.06	34.84
$(1-Q)^{-1}$	44.25	47.85
Log-Likelihood	6420.59	9296.02

Notes: The sample contains daily observations of the DM/Dollar forward exchange rate from January 1982 to November 1998. F, C, θ, ψ_{14}, ψ_{200}, indicate the estimated parameters of the mean equations, σ^2_1 and σ^2_2 the estimated regime dependent variances, P and Q the estimated conditional transition probalilities, $\overline{P}$ and $\overline{Q}$ the unconditional (stationary) regime probabilities, $(1-P)^{-1}$ and $(1-Q)^{-1}$ the expected regime durations. t-statistics in parentheses are based on heteroskedastic-consistent standard errors.

Table 6

Specification Tests (Ljung-Box Q-Statistics)

	RS-CF ***1982 – 1988***	***RS-CF*** ***1989– 1998***
AR(1)	0.32 (0.57)	1.59 (0.21)
AR(5)	5.71 (0.34)	5.41 (0.37)
AR(10)	18.58 (0.05)	17.31 (0.07)
ARCH(1)	0.04 (0.84)	0.71 (0.40)
ARCH(5)	6.33 (0.28)	4.26 (0.51)
ARCH(10)	13.30 (0.21)	7.40 (0.69)

Notes: AR(p) denotes the Ljung-Box statistic for serial correlation of the residuals out to p lags. ARCH(q) denotes the Ljung-Box statistic for serial correlation of the standardized squared residuals out to q lags. p-values are in parentheses.

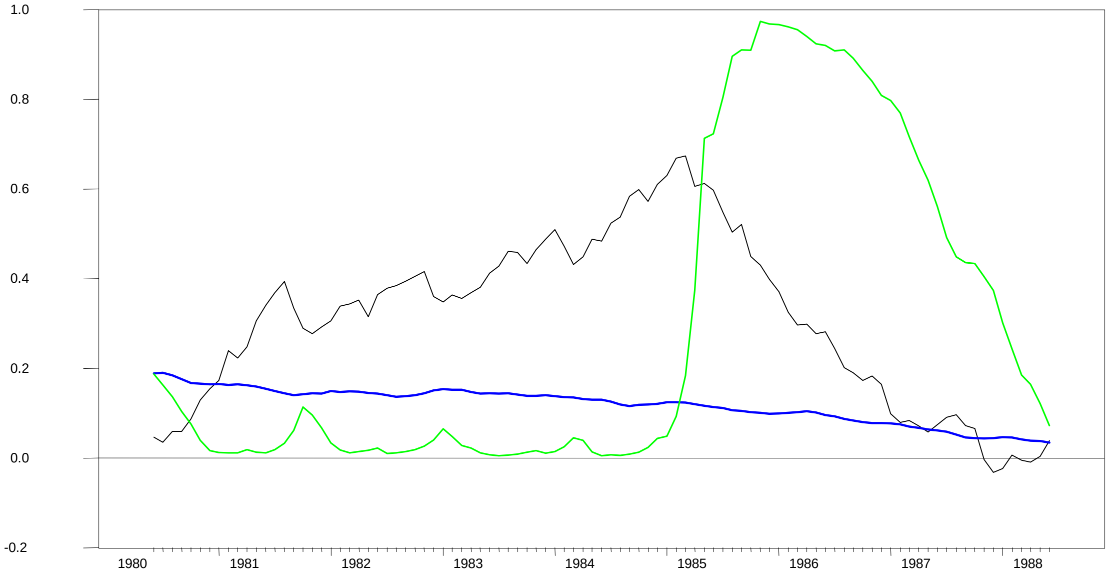
Table 7

Parameter estimates of the c&f-regime-switching model for the monthly Dollar/DM forward exchange rate

	RS-CF-AR(1) ***1980 – 1998***
f	$- 1.12 \cdot 10^{-2}$ (1.99)
c	$3.41 \cdot 10^{-3}$ (1.28)
θ	$5.22 \cdot 10^{-2}$ (2.93)
ϕ	0.293 (4.41)
σ_1^2	$5.16 \cdot 10^{-4}$ (3.54)
σ_2^2	$6.73 \cdot 10^{-4}$ (7.20)
P	0.9234 (20.60)
Q	0.9770 (40.08)
Log-Likelihood	492.01

Notes: The sample contains monthly observations of the DM/Dollar forward exchange rate from April 1980 to August 1998. F, C, θ, ϕ indicate the estimated parameters of the mean equations, σ^2_1 and σ^2_2 the estimated regime dependent variances, P and Q the estimated conditional transition probalilities.t-statistics in parentheses are based on heteroskedastic-consistent standard errors.

Graph 2: **DM/Dollar Exchange Rate, PPP and Smoothed Fundamentalist Regime Probabilities**
Monthly observations 1980 - 1998



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