Chartist Prediction in the Foreign Exchange Market

Evidence from the Daily Dollar/DM Exchange Rate

RALF AHRENS*

INSTITUT FÜR KAPITALMARKTFORSCHUNG-CENTER FOR FINANCIAL STUDIES (IFK-CFS), TAUNUSANLAGE 6, 60329 FRANKFURT AM MAIN, GERMANY

STEFAN REITZ

DEPARTMENT OF ECONOMICS, JUSTUS-LIEBIG-UNIVERSITY GIESSEN, LICHER STRASSE 66, 35394 GIESSEN, GERMANY

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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 empirical results suggest that this model does successfully explain daily DM/Dollar forward exchange rate dynamics from 1982 to 1998. Moreover, our findings turned out to be relative robust by estimating the model in subsamples. A particular focus of this study is on testing the c&f model against alternative regime switching specifications applying likelihood ratio tests. The results are striking. Nested atheoretical models like the popular segmented trends model suggested by Engel and Hamilton (1990) are rejected in favour of the c&f model. Finally, the c&f regime switching model seems to describe the data much better than a competing regime switching GARCH(1,1) model.

JEL classification: F31, F37; C32; G12, G15

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* Corresponding author. Tel.: -49-69-24294112, fax: -49-69-24294177. E-mail address: ahrens@ifk-cfs.de

1. Introduction

The standard text book model in exchange rate economics interprets the spot rate as the weighted sum of current and expected future market fundamentals. Although this asset market approach can mimic a broad set of exchange rate models, numerous empirical studies produced overwhelming evidence that it performs poorly in explaining short term movements of the exchange rate.[1] 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.[2] Subsequent research has proceeded in two directions. One direction tries to explain the puzzle with time-varying risk premiums, peso-problems and bubbles while maintaining the rational (homogeneous) expectation hypothesis. The other direction takes into account heterogeneous beliefs of foreign exchange market participants. This is typically done within the chartist and fundamentalist (c&f) framework which was originally suggested by Frankel and Froot (1986). As a crucial feature, c&f models have included chartist forecasting techniques in order to explain the exchange rate behaviour in the 1980s. While providing substantial improvement in understanding the exchange rate movements, the implementation of chartism in exchange rate models – although common practice in foreign exchange markets - was dismissed by the academia. This stems partly from the argument that under certain circumstances destabilising (chartist) speculation cannot be profitable,[3] and partly because these univariate prediction rules proof statistically illusive in the traditional sense.[4] The main reason for having not confronted c&f models with actual exchange rate data, however, has been the difficult task to find an appropriate econometric specification. Hence, only anecdotal support for c&f models was found in studies of micro survey data, which show that chartist techniques dominate the forecasts of market participants up to one week, whereas beyond this horizon more weight is given to fundamentals.[5]

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1 See Lewis (1995), pp. 1916 ff. and Taylor (1995), pp. 14 ff.

2 Regime-dependence of the exchange rate is discussed in Baxter and Stockman (1989), Flood and Rose (1993), and Eichengreen (1988).

3 Friedman (1953).

4 See Diebold and Nason (1990).

5 See Dominguez (1986), Allen and Taylor (1989), and Menkhoff (1995). An overview is provided by Takagi (1991).

In a recent study, Vigfusson (1997) overcomes this serious drawback by testing for the presence of chartist forecasting techniques while still allowing for economic fundamentals driving the exchange rate, too. Using the standard markov regime switching approach proposed by Hamilton (1989), he finds evidence in daily data of the Canada-US exchange rate from 1983 to 1992 supporting the c&f model. Relying on this promising result, the purpose of our paper is to investigate whether c&f regime switching behaviour can also be found in the daily German-US exchange rate. 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 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, as suggested by Vigfusson (1997, p. 300), we investigate whether the classification of our models might be driven by high- and low-variance 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).

The paper is organised as follows. Section 2 introduces the basic c&f-model and outlines some extensions that has 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 concludes the paper.

2. The standard chartist and fundamentalist model

In Frankel and Froot (1986) the (log of the) exchange rate s_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 $E_t[\Delta s_{t+1}]$ and a set of contemporaneous variables included in a vector $\mathbf{z}_t$. Thus the exchange rate can then be written as

$$s_t = aE_t[\Delta s_{t+1}] + \mathbf{bz}_t \qquad (1)$$

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 briefly described in the introduction of this paper. In contrast to this, Frankel and Froot (1986) assumed that portfolio managers generate their exchange rate expectations using a weighted average of chartist $E_t^c[\Delta s_{t+1}]$ and fundamentalist $E_t^f[\Delta s_{t+1}]$ forecasts:

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

ω_t, denoting the weight given to fundamentalist views at date t, is dynamically updated by the portfolio managers in a rational Bayesian manner:

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

with

$$\omega_{t-1}^* = \frac{\Delta s_t - E_{t-1}^c[\Delta s_t]}{E_{t-1}^f[\Delta s_t] - E_{t-1}^c[\Delta s_t]}$$

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 proofs responsible for the exchange rate dynamics. For simulation purposes Frankel and Froot set δ equal to 0.03 implying that portfolio managers give substantial weight to prior information and are learning slowly.

So far, nothing has been said about how forecasts are generated. In Frankel and Froot fundamentalist have some kind of long run equilibrium s^* (for example the purchasing power parity, a terms of trade-measure or a simple constant) in mind, to which the exchange rate reverts with a given speed γ over time, i.e. $E_t^f[\Delta s_{t+1}] = \gamma(s^* - s_t)$. Believing that the exchange rate follows a random walk, Chartists are using the actual spot rate to predict the future rate. Hence, their forecasting rule is reduced to $E_t^c[\Delta s_{t+1}]$ = 0, which simplifies the difference equation (3) dramatically. In addition the random walk modelling chartist techniques by itself has no destabilising effect on the exchange rate dynamics. So within this setting 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 s_t and ω_t.

The standard c&f-model has been extended in different ways. De Grauwe (1994) uses an AR(4) 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 result 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.

In a more realistic environment market participants have incomplete knowledge of the true set of fundamental variables driving the exchange rate. In addition, new information about these variables are available only with considerable lags. Lewis (1989) concludes that an appropriate exchange rate model should cover these issues by introducing learning processes in which changes of the underlying fundamentals cause fundamentalist forecast errors that appear systematically wrong ex post. Learning processes are applied to c&f-models by Frenkel (1994).

De Long *et al.* (1990) argue that trading on chartist forecasts (noise trading) enlarges the exchange rate 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 selfcreated risks. This means that destabilising speculators were not always driven out of the market. Empirical evidence for these findings is provided by Pilbeam (1995) and Dewachter (1997), who compare the predictive power of chartist and fundamentalist forecasts using a profitability measure or the sign of the predicted exchange rate change, respectively.

3. Model specification and estimation method

3.1 The basic regime-switching model

In order to describe the stochastic process of the exchange rate 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). In these models, the conditional mean μ and the conditional variance h of (log) exchange rate changes Δy are allowed to follow two different processes. The behaviour of the series depends on the value of an unobserved state variable S_t. Thus, under conditional normality, the observed realisation y_t is presumed to be drawn from a $N(m_{1t}, h_{1t})$ distribution when $S_t = 1$, whereas y_t is distributed $N(m_{2t}, h_{2t})$ 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:

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

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

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

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. Supposed 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 equation (2) and the mixture of normal distributions becomes obvious. Following Vigfusson (1997), it is exactly this relation which should be exploited by modelling and testing c&f regime switching behaviour in the Dollar/DM exchange rate.

Note, however, that the Bayesian updating of the weights in regime switching models differs from the updating process (3) in the Frankel and Froot model, that is $\omega_t \neq p_{1t}$. 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 $f_{1t} = f(y_t|S_t = 1, \Phi_{t-1})$ and $f_{2t} = f(y_t|S_t = 2, \Phi_{t-1})$. 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. Discussing simultaneous effects of chartism, peso problems and learning within a theoretical framework, however, goes beyond this study and is left for further research. Technically, specification (6) is very similar to a GARCH model where unobserved conditional variances follow a recursive structure with unknown parameters. The recursive representation of the regime-switching model allows us to construct the log-likelihood function conveniently as

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

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 briefly 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:

$$m_{1t} = f$$
$$m_{2t} = c$$

(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 Δy_t is not conditional on past regimes but the autoregressive term is assumed to be regime dependent, too.

$$m_{1t} = f + f_1 \Delta y_{t-1}$$
$$m_{2t} = c + f_2 \Delta y_{t-1}$$

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

As discussed above, the main focus of this study is on the c&f regime switching model which is labelled as RS-CF-AR(0). The mean equation of the first regime includes the deviation of the exchange rate from its fundamental value $\tilde{y}_t$ as the independent variable and thus represents the fundamentalist regime. In the chartist regime, 14 d and 200 d moving averages of the exchange rate are supposed to explain future exchange rate changes. The RS-CF-AR(0) specification corresponds almost exactly with the approach suggested by Vigfusson (1997). However, Vigfusson additionally includes the spread between domestic and foreign money market interest rates in both equations. Though such a proceeding might be reasonable when taking into account uncovered interest rate parity, we directly use the forward exchange rate which should be able to capture forward looking behaviour of market participants, too.

$$m_{1t} = f + q\left(\tilde{y}_{t-1} - y_{t-1}\right)$$
$$m_{2t} = c + y_{14} ma_{14} + y_{200} ma_{200}$$

(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 a regime dependent autoregressive term. Note, that this specification nests all three models described above.

$$m_{1t} = f + q\left(\tilde{y}_{t-1} - y_{t-1}\right) + f_1 \Delta y_{t-1}$$

$$m_{2t} = c + y_{14} ma_{14} + y_{200} ma_{200} + f_2 \Delta y_{t-1}$$

4. Empirical Results

4.1 Estimation results and specification tests

All models described in subsection 3.2 were estimated by 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 estimates are derived from the daily DM/Dollar forward exchange rate series which was kindly supplied by the Deutsche Bundesbank. [interpolation, I(2), ma etc.] The sample extends from January 1982 to November 1998. The series of the forward exchange rate, the PPP relation and the 200 d moving average are presented in Figure 1.

[Figure 1]

Table1 contains the whole sample estimates of the four models described in subsection 3.1. 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 as high as 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 $\overline{\mathrm{P}} = \dfrac{1-\mathrm{Q}}{2-\mathrm{P}-\mathrm{Q}}$ 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 daily DM/$ exchange rate is successfully described by two-state regime-switching processes. However, the most important question has not been addressed yet: Is there evidence in favour of exchange rate dynamics driven by both chartists 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 significant estimates of the parameters θ, ψ_{14} and ψ_{200} which heavily support the c&f model in explaining exchange rate movements. 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. Of course, this implies that volatility is much higher when the exchange rate is driven by fundamentals which has already been reported by Vigfusson (1997). To complement this intuitive argumentation, subsection 4.2 discusses the performance of a GARCH model as an alternative variance specification.

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 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,

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

is reported in the third column of Table 3.[6] 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. To 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 than 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

6 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.

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 chartists behaviour explains the exchange rate even in a period when PPP holds on average, while fundamentalists do play a role even when exchange rate is driven far away from PPP. Unfortunately, the estimated conditional mean dynamics of the exchange rate process do not unanimously support this finding. In the first subsample, only the chartist parameter estimates are significantly different from zero, while in the second estimation period only θ is significant at 10 %. Note, however, that the coefficients have reasonable values and correct signs.

[Table 5, Table 6]

5. Conclusion

Though common practice in foreign exchange markets, only anecdotal support for chartist forecasting techniques were found in studies of micro survey data. Up to Vigfusson (1997) it has been difficult to find an appropriate econometric specification to confront the chartist and fundamentalist (c&f) models with actual exchange rate data. Relying on these promising results, we use the regime switching framework to investigate whether chartist and fundamentalist forecasting techniques can also be found in the daily German-US exchange rate. The empirical results suggest that this model does successfully explain forward exchange rate dynamics from 1982 to 1998. Moreover, our findings turned out to be relative robust by estimating the model in subsamples. In addition 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.

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

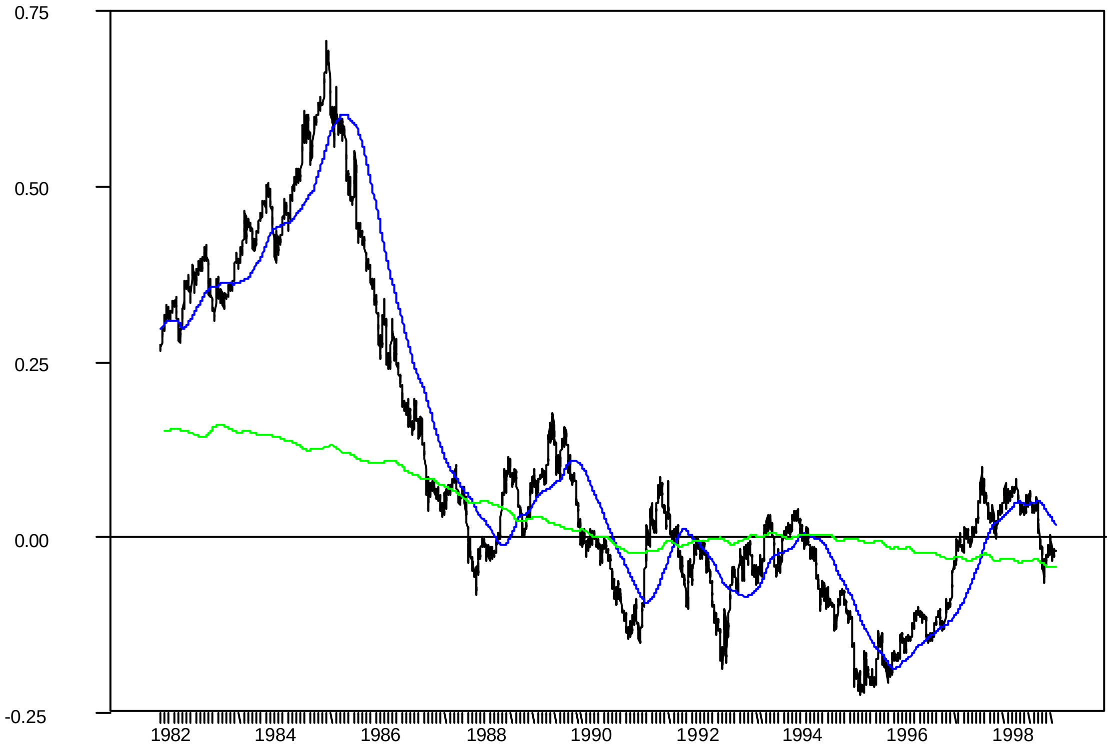

Table 1

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)
q	-	-	$3{,}42 \cdot 10^{-3}$ (2,17)	$3{,}51 \cdot 10^{-3}$ (2,23)
y_{14}	-	-	$6{,}27 \cdot 10^{-3}$ (2,92)	$6{,}65 \cdot 10^{-3}$ (2,80)
y_{200}	-	-	$-5{,}56 \cdot 10^{-3}$ (2,62)	$-5{,}89 \cdot 10^{-3}$ (2,53)
f_1	-	- 0,0394 (1,49)	-	- 0,0408 (1,55)
f_2	-	- 0,0364 (2,14)	-	- 0,0409 (2,14)
s_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)
s_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. t-statistics in parentheses are based on heteroskedastic-consistent standard errors. The likelihood ratio test statistics 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

	RS-CF-GARCH(1,1) ***1982 – 1998***
F	$6{,}83 \cdot 10^{-5}$ (0,60)
C	$-5{,}39 \cdot 10^{-4}$ (0,52)
q	$1{,}14 \cdot 10^{-3}$ (1,32)
y_{14}	$-3{,}12 \cdot 10^{-3}$ (0,18)
y_{200}	$9{,}20 \cdot 10^{-3}$ (0,60)
f_1	- 0,0507 (3,00)
f_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. 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)
q	$3{,}76 \cdot 10^{-3}$ (1,51)	$7{,}15 \cdot 10^{-3}$ (1,66)
y_{14}	$8{,}76 \cdot 10^{-3}$ (2,96)	$2{,}02 \cdot 10^{-3}$ (0,60)
y_{200}	$-7{,}24 \cdot 10^{-3}$ (2,40)	$-3{,}43 \cdot 10^{-3}$ (1,05)
s_1^2	$9{,}88 \cdot 10^{-5}$ (6,46)	$8{,}06 \cdot 10^{-5}$ (7,10)
s_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)
$\bar{P}$	0,36	0,42
$\bar{Q}$	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 December 1988 and from January 1989 to November 1998 respectively. 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.