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Speculative behavior, exchange rate volatility, and central bank intervention

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Summary: The aim of this paper is twofold. First, to develop a model which helps to explain the high exchange rate volatility observed empirically. Second, to study under which conditions central bank interventions may calm down the foreign exchange market. Based on empirical observations, a model is presented where the agents select in each trading period a trading rule to determine their speculative positions. The agents have the choice between technical and fundamental trading rules. Simulations produce a high variability of the exchange rates, fat tails for returns, and weak evidence of mean reversion. Whithin this framework, the effectiveness of some intervention strategies is analysed. One result is: "leaning against the wind" may reduce the volatility as long as the dynamics are influenced by trend-following trading strategies. In periods when the agents are uncertain about the fundamental exchange rate, however, supporting a target exchange rate may be the preferable strategy for the central bank to stabilize the market.

Keywords: exchange rate theory, technical and fundamnetal trading rules, central bank intervention

1 Introduction

Since the development of real time information systems and the decline in transaction costs following the liberalisation of the capital markets in the mid 80's, both daily foreign exchange turn-over and volatility of exchange rates have sharply increased. The trading volume reflects more and more short-term transactions indicating a highly speculative component. By contrast, international trade transactions account for merely one percent of the total (BIS 1999).

When determining their speculative positions, the market participants rely on both technical and fundamental trading rules. Technical analysis is a trading method that attemps to identify trends and reversals of trends by inferring future price movements from those of the recent past whereas fundamental concepts look at the underlying reasons behind that action.[1] As reported by Taylor and Allen (1992) most foreign exchange dealers place at least some weight on technical analysis, especially in the short run.

Based on such evidence, the noise trader approach (Shleifer and Summers 1990) is a research direction which focuses on modelling speculative behavior. The noise trader approach assumes that not all market participants are fully rational and that arbitrage possibilities are limited. Consequently, shifts in investor sentiment are an important determinant of high exchange rate volatility. The more specific chartists-fundamentalists models are a special branch within this research program (among them Frankel and Froot 1986, de Grauwe et al. 1993, Lux 1997). Central for these papers is the interaction between chartists (technical traders) and fundamentalists. This area of research is very promising because some basic stylized facts of the empirical data are replicated.

The aim of this paper is twofold. First, to develop a realistic, yet simple exchange rate model in the spirit of the chartists-fundamentalists models to get a deeper understanding of the driving forces behind foreign exchange dynamics. Second, to evaluate whether typical intervention strategies of central banks will be able to calm down disorderly markets dominated by speculative transactions.

The model presented in this paper is similar to models found in the chartists-fundamentalists literature. Rather than deriving the results from a well defined utility maximization problem, details from the market microstructure and psychological evidence are used to describe the behavior of the traders. Clearly, the traders rely on simple decision rules to determine their investment positions. The interaction of these rules generates, even in a simple setting, a realistic behavior of exchange rates: In their first moments the simulated time series resemble a stochastic trend. Evidence of mean reversion is observable if the behavior of the chartists is trend-following. The returns of the generated time series display a high kurtosis which declines under time aggregation. Fat tails are also identified by the scaling behavior of the returns which roughly follow a power law.

The volatility is mostly caused endogenously through the interaction between the traders. The news arrival process plays a role in the sense that changes in fundamentals are amplified by technical trading. Although the dynamics in the foreign exchange market are very complex, simple nonlinear models may suffice to explain and understand them. Such models preclude predictions but invite to investigate how the underlying system may be controlled. Thus, we introduce a central bank into the model and analyse the effectiveness of some well-known intervention strategies. Note that we are not searching for an optimal intervention strategy. Rather we ask what the conditions for a successful intervention operation are and when it is likely that the intervention operation fails. The

[1] For an introduction into technical analysis see Neely (1997). A deeper discussion is found in Murphy (1999). The latter is sometimes referred to as the "bible" of technical analysis.

results are: If the dynamics are dominated by trend-following trading strategies, a leaning against the wind intervention where the central bank operates against the trend is able to reduce the volatility. The strategy becomes less successful when the chartists trade rather unsystematically. However, in periods where the fundamentalists are uncertain about the fundamental value of the exchange rate leaning against the wind is likely to increase the variability of the market. This explains why in empirical studies the effectiveness of central bank intervention changes in sign across time. In such a situation the central bank may be better off by directly supporting the target rate.

This paper is organised as follows: Section 2 presents the model and some simulation results. In section 3, a central bank is introduced into the model to study the consequences of some intervention strategies. The last section offers some conclusions.

2 A Simple Nonlinear Exchange Rate Model

2.1 Setup of the Model

The basic idea of the model is that the market participants have to choose at the beginning of each trading period a specific trading rule to determine their speculative positions. The selection of the rules depends somehow on expected performance possibilities, which are derived from past observations. The agents have the choice between technical and fundamental trading rules. The former are called chartists and the latter fundamentalists.

Simple technical trading rules use only past movements of the exchange rate S as an indicator of market sentiment and extrapolate these into the future, thus adding a positive feedback to the dynamics. The excess demand of chartists in period t resulting from such rules might be expressed as

$$d_t^C = a^{C,1}(0.6(LogS_{t-1} - LogS_{t-2}) + 0.4(LogS_{t-2} - LogS_{t-3})) + a^{C,2}\delta_{t-1}. \quad (1)$$

The first bracket of (1) describes a simple moving average rule to capture the usual behavior of the chartists. In general, chartists buy (sell) foreign currency if the exchange rate rises (declines). Since more attention is paid to the most recent trend, a larger coefficient is selected for the first extrapolating term than for the second term (0.6 versus 0.4). The second bracket represents additional random demand to allow for more complicated behavior, where δ is an in-dependently and identically distributed normal random variable with mean zero and time invariant variance. With the (positive) coefficients $a^{C,1}$ and $a^{C,2}$ the relation between the systematic and unsystematic demand components is calibrated. For simplicity, these coefficients are not time dependent. Note that by (1) chartists place a market order today in response to past price changes, i.e. price changes between period t and t–1 are disregarded. Such a lag structure is typical for technical trading rules, because only the past movements of the exchange rates are taken into account (Murphy 1999).

Fundamental trading rules depend on the expected future exchange rate. The expectation formation process of the agents is modeled in a typically regressive way, i.e. when the exchange rate deviates from its equilibrium value S^F, the fundamentalists expect it to return. Therefore, $E^F_t[S_{t+1}]=\gamma S^F_{t-1}+(1-\gamma)S_{t-1}$, where γ stands for the expected adjustment speed of the exchange rate towards its fundamental. Since the expectation formation for the trading period t has to be made in advance, the last available fundamental value is from t–1. The excess demand of fundamentalists can be written as follows

$$d_t^F = a^F (E_t^F[S_{t+1}] - S_t)/S_t = a^F(\gamma S_{t-1}^F + (1-\gamma)S_{t-1} - S_t)/S_t, \tag{2}$$

where a^F is a positive reaction coefficient. The fundamental trading rule delivers a buy (sell) signal, if the expected future exchange rate is above (below) the spot rate. The corresponding demand depends on the relative distance between the expected rate and the spot rate.[2]

The agents form their expectations of the fundamental exchange rate on the basis of a structural model. The development of the fundamental value is due to the news arrival process and behaves like a jump process. The logarithm of S^F is given by

$$LogS_t^F = LogS_{t-1}^F + p\varepsilon_t. \tag{3}$$

The news ε_t (the jump size) is identically and independently distributed according to a Normal distribution with mean zero and time invariant variance. The news hits the market with *prob* (p=1)=0.2 (the jump arrival time intensity). On average, a shock hits the market every 5 periods.

The selection of the rules depends on expected future performance possibilities. Fundamentalism, compared to chartism, becomes more popular the wider the spot rate deviates from the expected future exchange rate. This might be justified as follows: the chance that the exchange rate returns to its expected value increases as its relative distance rises. We define the weight of chartists as

$$m_t = 1/(1+\beta^1+\beta^2\sqrt{\left|(E_t^F[S_{t+1}]-S_{t-1})/S_{t-1}\right|}, \tag{4}$$

and the weight of fundamentalists as $(1-m_t)$, respectively. The coefficient β^1 represents the basic influence of the fundamentalists. If, for example, β^1 is 0.25, then 20 percent of the agents are always fundamentalists. Nevertheless, most traders adjust their trading strategies with respect to the relevant conditions. As assumed by (4), the weight of fundamentalists increases, though at a declining rate, as the relative distance between $E^F_t[S_{t+1}]$ and S_{t-1} rises. In such a situation, more and more agents realize that the exchange rate does not reflect its fundamental value any more. Consequently, fundamental analysis is prefered to chartism. Note that the influence is determined with a time lag since the selection of the rules has to be repeated at the beginning of each new trading period.

Demand from international trade is neglected since trade transactions, in contrast to speculative transactions, are small in absolute magnitude. Using the market clearing condition

$$m_t d_t^C + (1-m_t)d_t^F = 0, \tag{5}$$

the solution of the model is a four dimensional stochastic difference equation system

[2] Due to the time structure of the model the fundamentalists function as market makers.

$$S_t = \frac{\gamma S_{t-1}^F + (1-\gamma)S_{t-1}}{1 - \dfrac{a^{C,1}(0.6LogS_{t-1} - 0.2LogS_{t-2} - 0.4LogS_{t-3}) + a^{C,2}\delta_{t-1}}{a^F(\beta^1 + \beta^2\sqrt{|(\gamma S_{t-1}^F + (1-\gamma)S_{t-1} - S_{t-1})/S_{t-1}|})}}. \tag{6}$$

Since (6) cannot be solved explicitly, some simulations are done to demonstrate that the underlying structure gives rise to complex exchange rate behavior as it is typically observed empirically.[3, 4]

2.2 Simulations

Figure 1 contains in the top the simulated dynamics for the exchange rate (solid line) and the stochastic development of its fundamental (dashed line), the bottom presents the weights of chartists. Even a low probability of fundamental shocks suffices to generate complex exchange rate movements, where the exchange rate fluctuates around its fundamental value. Moreover, the volatility of the exchange rate is far greater than the volatility of its equilibrium value. The influence of chartists is concentrated in the range from 40 to 60 percent with some peaks going down to 20 or up to 80 percent. Such a behavior is pretty close to what is reported in survey studies (Taylor and Allen 1992).

Simplified, the dynamics can be explained as follows. Technical trading rules always produce some kind of buy or sell signal. On the basis of a feedback process, a self-reinforcing run might emerge. But such a run cannot last because investment rules based on fundamentals work like a center of gravity. The more the exchange rate departs from the fundamental exchange rate, the stronger the influence of the fundamentalists, until eventually their increasing net position triggers a mean reversion. However, this indicates a new signal for the chartists and directly leads to the next momentum. The exchange rate overshoots the fundamental exchange rate because chartism dominates the market near the fundamental. Heavy outliers occur when the chartists have a clear trading signal and the influence of the fundamentalists is low. Since the exchange rates move several periods in one direction, chartism may be profitable temporarily.

Note that the simulations indicate that the volatility of the foreign exchange market need not be solely caused by exogenous shocks; it might be explained at least partially by an endogenous nonlinear law of motion. The trading signals needed to keep the process going are generated by the agents themselves.

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[3] If a low proportion of fundamentalists is confronted with a huge demand of chartists, a large price reaction is needed in order to match the demand. However, a stability problem in (6) never occured in our simulations.

[4] Westerhoff (2001) shows that in the absence of any shocks, i.e. $\delta=\varepsilon=0$, the model can generate chaotic motion (positive Lyapunov exponents, low dimensional attractors). This finding is observed for different parameter settings and functional specifications of (1), (2), and (4). The mechanics of the system are best described by an endogenous stretching and folding of the exchange rate around its fundamental value. Although the dynamics are very complex, we allow for some shocks in order to mimic empirical exchange rate fluctuations more closely.

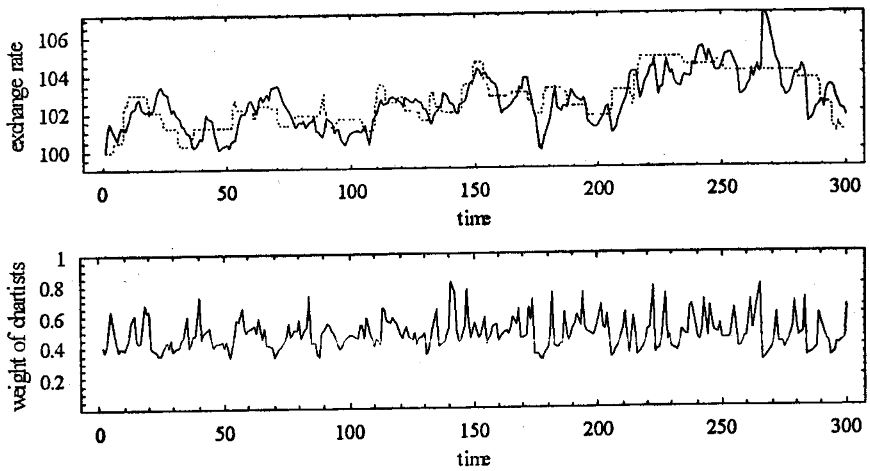

Figure 1: Simulated Exchange Rates and Weights of Chartists. The solid line in the top is the exchange rate, the dashed line its fundamental, $S_1^F=100$, $S_1=100$, $S_2=101$, $S_3=101.5$, $a^{C,1}=0.4$, $a^{C,2}=0.003$, $a^F=1$, $\beta^1=0.1$, $\beta^2=30$, $\gamma=0.2$, $\delta \sim N(0, 1)$, $prob(\text{p}=1)=0.2$, $\varepsilon \sim N(0, 0.0075)$, T=300.

A lot of empirical work is done on describing the distribution of the returns. Figure 2 compares the distribution of the returns and the scaling behavior for the simulated data (top) with normally distributed returns (bottom). An important stylized fact says that the distribution of the returns reveals fat tails (Guillaume et al. 1997). In contrast to a Normal distribution one finds a stronger concentration around the mean, more probability mass in the tails of the distribution and thinner shoulders. Estimations of the kurtosis are able to reveal fat tails. Table 1 displays estimates of the kurtosis under time aggregation for 20,000 data points. In comparison, the kurtosis of a Normal distribution is given with 3. Since the random variables are normally distributed, the high kurtosis is caused through the model. Stronger outliers do not only occur as a consequence of normally distributed shocks. If, for instance, a medium demand by chartists is matched by a low weight of fundamentalists, the price reaction is also strong. Furthermore, the empirically observed kurtosis declines under time aggregation.[5] This is also true for the kurtosis of the computed time series.

time aggregation	1	2	5	10	25	50
kurtosis	14.1	6.9	3.4	3.6	3.4	3.5

Table 1: Kurtosis under Time Aggregation. The same parameter setting as in figure 1, T=20,000.

[5] A time aggregation of d means that the returns are calculated as $r_t = LogS_t - LogS_{t-d}$.

An alternative way to identify fat tails is to determine the tail index. The tail index α, given as $F(|\text{return}| > x) \approx c\,x^{-\alpha}$, is estimated from the cumulative distribution of the positive and negative tails for normalized log-returns. The returns are normalized by dividing by the standard deviation. A regression on the largest 30 percent of the observations delivers a significant tail index of 3.29 which is in good agreement with results obtained from empirical data. According to Lux and Ausloos (2000), the tail index has mostly been found to hover between 2.5 and 4. The tail index of a Normal distribution, as can be seen at the slope in the bottom right part of figure 2, is clearly higher.[6]

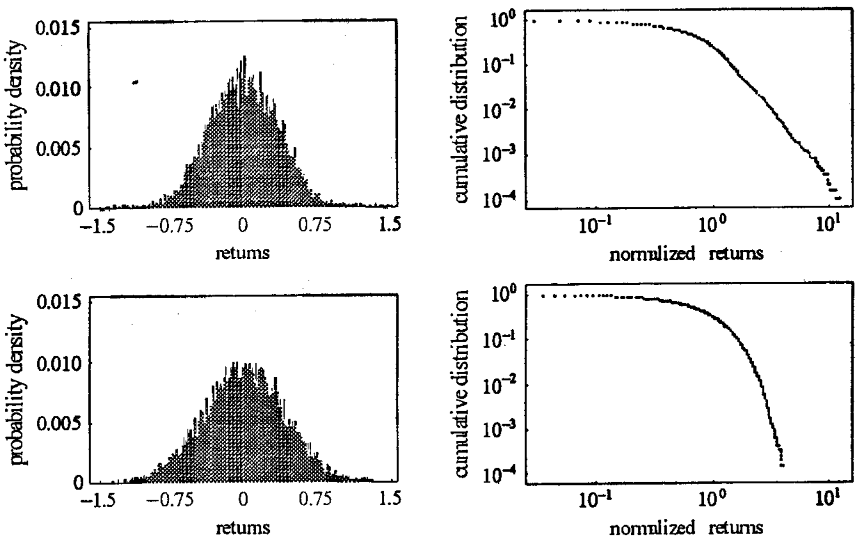

Figure 2: Distribution of Returns and Scaling Behavior. The top contains the distribution of returns and the scaling behavior of the cumulative distribution of the positive and negative tails for normalized log-returns, the bottom the same for a Normal distribution with identical variance, the same parameter setting as in figure 1, T=20,000

Empirical results concerning serial autocorrelation of the returns of the exchange rates are not uniform. Cutler et. al. (1990) found that returns tend to be positively correlated at high frequencies and are weakly negatively correlated over longer horizons, thus exhibiting a mean reversion tendency. For other financial data, the mean reversion tendency is much stronger. Figure 3 displays the autocorrelation function of the returns for three different numerical specifications of equation (1): in the top the systematic demand is roughly 55 percent of total transactions, in the middle 30 percent, and in the bottom 15 percent. The middle part contains the autocorrelation function for the earlier

[6] Note that the moments of a distribution higher than its tail index are not bounded (Guillaume et al. 1997).

simulations. Depending on the extent to which the demand of the chartists is correlated, the simulated time series may reveal some kind of mean reversion tendency. Clearly, the empirically observed autocorrelation function lies somehow between the ones shown in the middle and the bottom part of the figure. Ninety-five percent confidence intervals are given as $\pm 2/\sqrt{T}$, with T as the number of observations and the assumption of white noise of the returns.

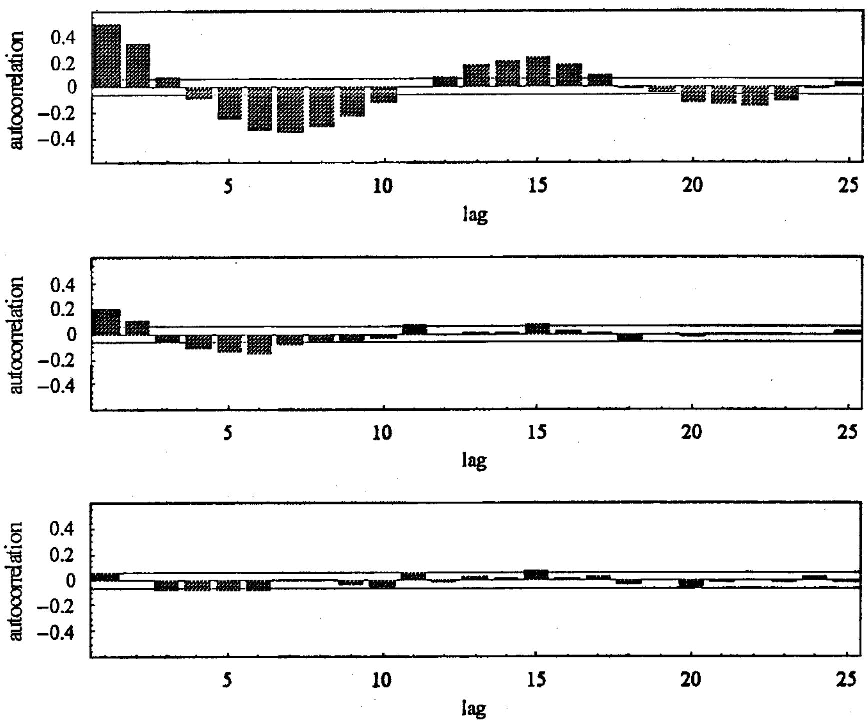

Figure 3: Autocorrelation Function of Returns. The same parameter setting as in figure 1, but in the top $a^{C,1} = 0.7$, $a^{C,2} = 0.002$, in the middle $a^{C,1} = 0.4$, $a^{C,2} = 0.003$, and in the bottom $a^{C,1} = 0.2$, $a^{C,2} = 0.004$, T = 1,000, ninety-five percent confidence intervals are plotted as $\pm 2/\sqrt{T}$ (assumption of white noise).

All in all, the model presented generates complex exchange rate movements and replicates some well-known stylized facts. On the one hand, the computed time series looks apparently random. On the other hand, some (deterministic) pattern like mean reversion is also observable. These features are the outcome of the nonlinear structure in the model. Evidence of nonlinearities in financial data is, for instance, strongly supported by Barnett and Serletis (2000). We argue that the forces driving the dynamics are at least partially endogenous. Although the dynamics are highly complex, simple models may suffice to explain and understand them. Such models preclude predictions but invite to control the underlying system.

3 The Effectiveness of Central Bank Intervention

3.1 Central Bank Intervention

Central bank intervention is the practice of monetary authorities buying and selling currency in the foreign exchange market to influence the exchange rate. Our focus will be on sterilized interventions and not on ordinary monetary policy. Sterilized interventions are intervention operations that are accompanied by an offsetting open market operation that restores the domestic monetary base to its original size.[7]

One aim of central bank interventions could be to influence the level of the exchange rate, for instance to achieve policy goals or to limit misalignments of the exchange rate. There are two channels through which official interventions might affect the foreign exchange market. Under the assumption that domestic and foreign assets are imperfect substitutes, the portfolio balance approach states that investors allocate their portfolios to balance their risk against expected rates of returns. If intervention operations change the relative supplies of assets denominated in different currencies, investors must be compensated to hold the relatively more numerous asset with a higher expected return. This higher expected return must result from a change in either the price of the asset or the exchange rate (portfolio balance channel). Through the signalling channel, sterilized interventions can have an effect on exchange rates if the interventions provide the market with relevant information previously not known or not fully incorporated in the current exchange rate. However, there is little empirical evidence that interventions have an influence on the level of the exchange rate.

Another aim of central bank interventions could be to reduce the exchange rate volatility, since exchange rate risk has a negative impact on the international trade. Although financial markets provide some hedge instruments, these only allow a limited elimination of the risk. A necessary condition for volatility decreasing intervention is that the variability is caused at least partially endogenously and is not solely justfied by exogenous shocks. Then, intervention might work through the noise trader channel: In our model the exchange rate is determined by the demand and supply flowing through the foreign exchange market. These transactions are considerably affected by noise trader activity. In such a short-run flow equilibrium, a central bank is able to manipulate the exchange rate at least at the moment the intervention takes place. Since the chartists assign much heavier weight to the most recent exchange rate movements when taking positions, the effect of the intervention is not only transistory by itself, but also amplified and prolonged by noise trader activity. Through this channel, a central bank intervention can slow down the momentum of an exchange rate trend or even reverse the direction of the trend.[8]

[7] For surveys on central bank interventions see Edison (1993) or Dominguez and Frankel (1993).

[8] To evaluate the welfare implications correctly, one has to take into account the costs of intervention operations. But as empirical studies show, US intervention operations were cost free in the past (Neely 1997, LeBaron 1999).

The noise trader channel may also explain the high degree of secret interventions. As mentioned by Murphy (1999) the philosophy behind technical trading rules is that if prices rise, the fundamentals must be "bullish". Thus, technicians claim to study the fundamentals indirectly. As long as it is unknown that the central bank is responsible for an exchange rate movement, chartists believe in the trend. If they know that the market reaction is caused by an intervention, they will become suspicious and may even counter it.

Until recently, empirical research examining the impact of sterilized intervention on exchange rate volatility barely existed. However, a promising study from Hung (1997) identifies periods where intervention operations significantly decreased the volatility via the noise trader channel. In addition, periods where intervention operations have increased the volatility are also detected. According to Hung, these operations have not to be unsuccessful intervention periods, since the central banks may have used, in order to reach a target exchange rate, the chartists by inducing a momentum in the desired direction. But volatility-enhancing operations, compared to volatility-decreasing operations, are less often used. Nevertheless, the noise trader channel allows the explanation of the phenomenon that the impact of intervention operations on the exchange rate volatility changes signs across time.

In the following we try to develop a deeper understanding of some intervention mechanism in the noise trader framework by introducing a central bank into the model. To start, we look at how intervention operations are executed in practice. Recently some studies became available which have access to daily intervention data (Neely 1998, LeBaron 1999, Saacke 1999). The decision of central banks whether and how to intervene seems to be made on a day to day basis. For example, both the Federal Reserve Bank and the Bundesbank intervened in the period between 1979 and 1996 on one day in four. The interventions tend to be clustered together in time. The probability of intervention for a day strongly increases if there has been an intervention the day before. If intervention did occur, it was small – in absolute value – relative to the size of total transactions. Nevertheless, at the very moment the intervention takes place its volume hits a considerably thinner market. In addition, the interventions are typically sterilized, on average relatively balanced and performed secretely. Finally, regression studies about the intervention reaction function of a monetary authority indicate that interventions are significantly influenced by past changes in the spot exchange rate or by deviations of the exchange rate from a target rate. More clearly, the central banks engage in the so called "leaning against the wind" operations, that is, they buy (sell) foreign currency if the exchange rate declines (rises) in order to reduce the momentum of a trend, or the central banks intervene to support a target exchange rate.

3.2 Strategies and Goals

In this section the intervention strategies and the aims of the central bank are formalized. We concentrate on the two most common strategies empirically identified. Interventions take place every period. The decision about the intervention volume for period t has to be made before the trading starts. This seems reasonable since the decision process needs time and is based on recent deviations from a desired exchange rate path.

The first strategy is called the leaning against the wind strategy (LAW) and may be expressed as

$$d_t^{CB} = \alpha^{CB,L}\,(LogS_{t-2} - LogS_{t-1}), \tag{7}$$

where the intervention volume in period t depends on the difference between the logarithm of the exchange rates in t–1 and t–2. The reaction coefficient $\alpha^{CB,L}$ is constant and positive. Applying this strategy, the central bank always trades against past trends.

With the second strategy, the central bank supports a target exchange rate. The TARGET strategy is formalized as

$$d_t^{CB} = \alpha^{CB,T}\,(S_{t-1}^F - S_{t-1})/S_{t-1}, \tag{8}$$

where the intervention volume in period t depends on the relative distance between the target rate and the exchange rate in t–1. Again, the reaction coefficient $\alpha^{CB,T}$ is constant and positive. For simplicity, we assume that the target rate is equal to the fundamental exchange rate. By this strategy the central bank aims at moving the exchange rate towards its fundamental, but does not influence the value of the fundamental exchange rate itself.

To evaluate the succes of an intervention two measures are considered. One is directly concerned with the variability of the exchange rate, the other one more with deviations from a target rate. The volatility measure is defined as

$$V = \frac{100}{n-1}\sum_{t=2}^{n}\left|LogS_t - LogS_{t-1}\right|, \tag{9}$$

where the volatility is meassured as the average of the absolute returns. As suggested by Guillaume et al. (1997), we prefer the absolute value of the returns to the more usual squared values. Due to the nonexistens of the forth moment in the distribution of the returns, the former quantity has a greater capacity to reflect the structure in the data.

Although the volatility measure is the most common measure it should not be the only one. For instance, it is not desirable that the central bank stabilizes the exchange rate far away from its fundamental value. Therefore, we suggest an additional measure to capture the distortion in the foreign exchange market. A distortion in the sense of deviations of the exchange rate from the target rate may be defined as

$$D = \frac{100}{n}\sum_{t=1}^{n}\left|(S_t - S_t^F)/S_t^F\right|. \tag{10}$$

The distortion measures the extend to which the exchange rate fluctuates around the fundamental exchange rate. Again, absolute values are used. Clearly, if two measures are used, a trade-off may exist. This problem has to be solved by the central bank, for instance by minimizing a loss function combined out of (9) and (10).

3.3 Simulations

Taking into account the central bank operations, market clearing requires

$$m_t d_t^C + (1-m_t) d_t^F + d_t^{CB} = 0. \tag{11}$$

Solving (11) for the exchange rate yields

$$S_t = \frac{E_t^F[S_{t+1}]}{1-(m_t d_t^C + d_t^{CB})/a^F(1-m_t)}, \tag{12}$$

where the demand of the central bank is due to its applied intervention strategy.

To understand how intervention operations affect exchange rate dynamics, we first present an example and then discuss the results more generally. Figure 4 shows an example in the time domain for 300 periods. The top part of the figure contains a simulation run without intervention. The relation between the systemantic and the unsystematic demand of the chartists is roughly equal. For 1,000 observations the volatility is computed as 0.31 and the distortion as 0.70.

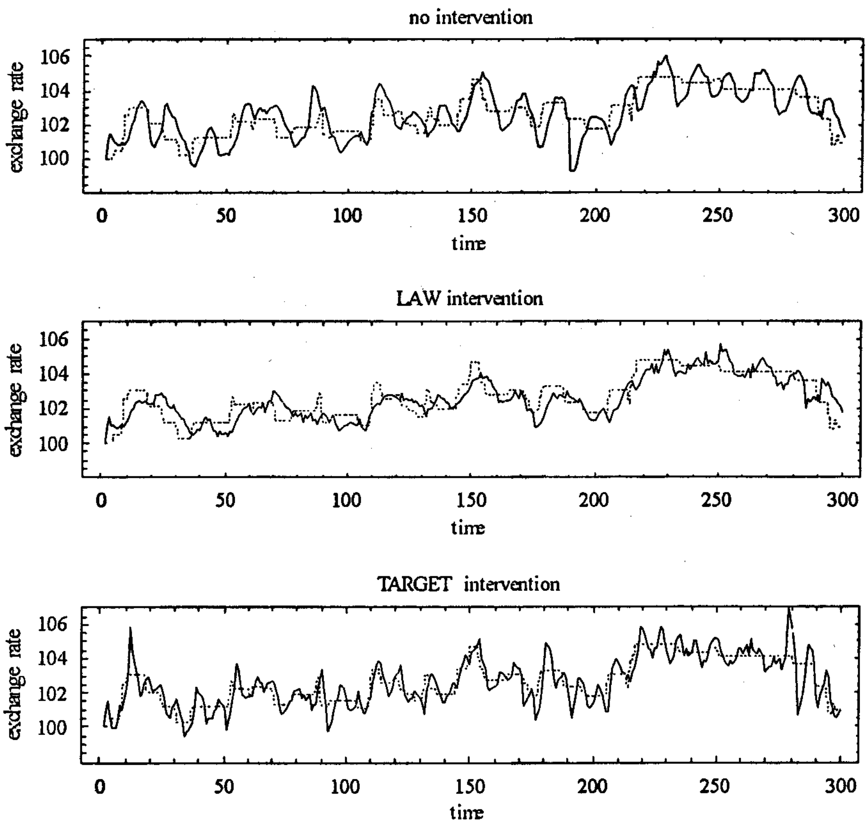

Figure 4: Example of Intervention Operations. The solid line is the exchange rate, the dashed line its fundamental, the same parameter setting as in figure 1, but $a^{C,1} = 0.7$, $a^{C,2} = 0.002$, LAW intervention: $a^{CB,L}$=0.25, TARGET intervention: $a^{CB,T}$=0.3.

The middle part of figure 4 displays a time series generated with the LAW strategy. For this regime the volatility is 0.25 and the distortion 0.54. The reduction of the volatility is a consequence of the specific intervention strategy. By leaning against the wind the central bank reduces the momentum of the exchange rate movement. In addition, the distortion also declines.

The bottom part of figure 4 contains a simulation run for the TARGET intervention. On the one hand the intervention operation has reduced the distortion (D=0.52), but on the other hand the volatility has increased (V=0.51). The TARGET intervention is in an environment dominated by trend-following chartists not successful. The reason is that if the exchange rate trends toward the fundamental exchange rate, chartists and the central bank trade in the same direction. In such a situation, the central bank rises the momentum of the exchange rate movement.

Note that intervention operations may also have an impact on the finer structure of the exchange rate path. Figure 4a compares the autocorrelation functions for the above time series. As can be seen, the LAW strategy clearly reduces the mean reversion tendency. In addition, if periods of intervention alternate with periods of no intervention the central bank obviously causes volatility clustering.

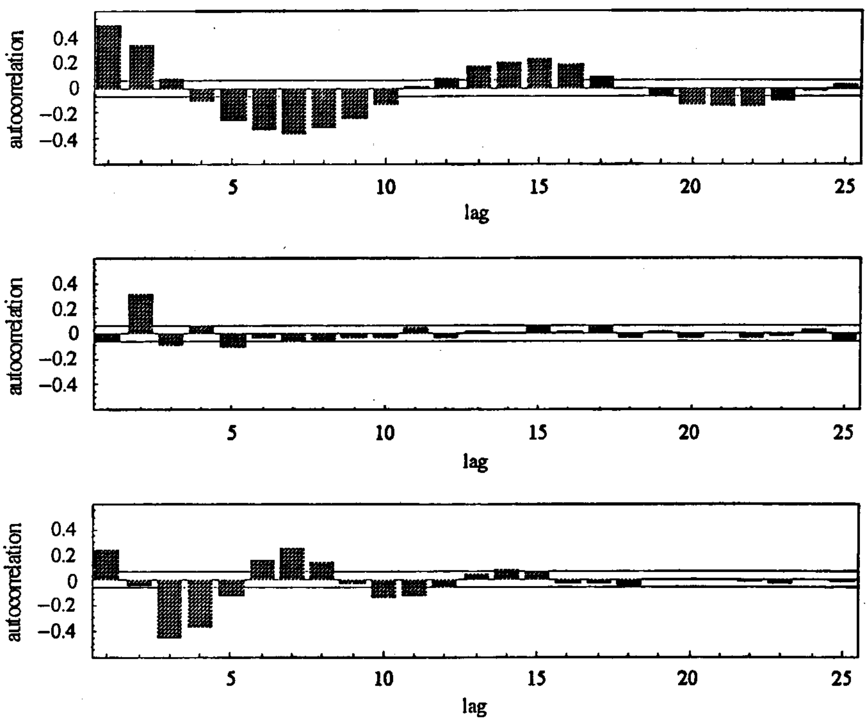

Figure 4a: Mean Reversion and Intervention Operations. The same parameter setting as in figure 4, top (middle, bottom): no (LAW, TARGET) intervention, T=1,000, ninety-five percent confidence intervals are plotted as $\pm 2/\sqrt{T}$ (assumption of white noise).

Figure 5 shows the simulation results in more detail. Each part of figure 5 is constructed as follows. On the one axis the intervention volume, that is the coefficient a^{CB}, is increased in 20 discrete steps starting from zero. On the other axis the noise level $a^{C,2}$ is increased. To hold the volatility constant, the influence of the first part of the technical trading rule, as given by $a^{C,1}$, is lowered. In this way the volatility is fixed around 0.3 (no intervention!).[9] The initial noise level is zero and increased in 20 discrete steps. The maximum (medium) noise level results in an unsystematic trading volume that is roughly 2/3 (1/2) of the total. Thus, the figure displays regimes where the chartists trade rather unsystematically as well as regimes where the trading positions are correlated. The volatility and the distortion are calculated on the basis of 1,000 observations.

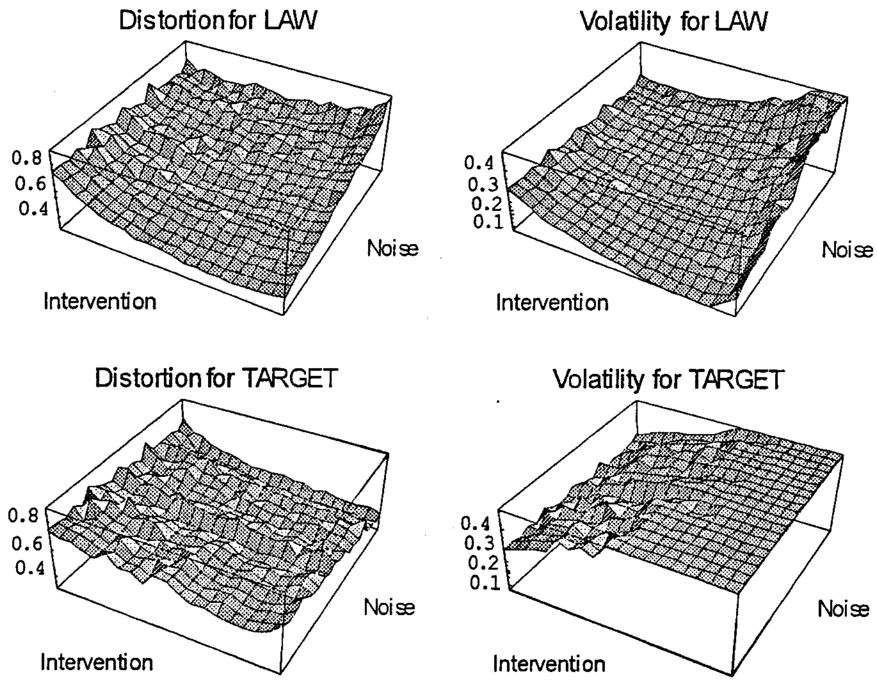

Figure 5: Intervention Results. Distortion and volatility are calculated on the basis of 1,000 observations, the same parameter setting as in figure 1, the intervention level is increased in 20 steps from 0 to 0.475, the noise level in 20 steps from 0 to 0.00285, β^2 is identified so that for $a^{C,1}=1$ and $a^{C,2}=0$ the volatility is approximately 0.3, to hold the volatility constant while increasing the noise level, $a^{C,1}$ is appropriately reduced.

[9] The volatility is set somewhat lower than observed empirically to demonstrate that the effectiveness is not a consequence of disorderly markets but rather works in calm periods. However, if the volatility is fixed at a higher level, the qualitative results remain stable.

As can be seen, the LAW strategy is in a trend-following environment very effective. The volatility can be reduced depending on the noise level. The reason is that the central bank by leaning agaist the wind reduces the momentum of the exchange rate movement and therefore the power of the trading signals. When the noise level rises, the effectiveness declines. Note that whenever the direction of the trend changes, the central bank, due to their decision lag, intervenes in the wrong direction. Hence, if the behavior of the chartists becomes less trend-following, the success of LAW intervention diminishes. As a byproduct, the distortion declines also, especially when the noise level is low.

The TARGET intervention does not reduce the volatility. The main reason is that if the exchange rate moves in the direction of the fundamental exchange rate, chartists and the central bank typically trade in the same direction. This strategy is able to reduce the distortion, yet at the cost of higher volatility. Therefore, the LAW strategy seems to be preferable, especially if the central bank is sure that the exchange rate trend prevails.

3.4 Periods of High Uncertainty

If the environment is extremely uncertain, the agents allow themselves to be guided by past values of the exchange rate when forming new expectations. These function as "anchors" in the individual judgement of the future exchange rate. This phenomenon is called anchoring heuristics and well documented in the psychological literature (Tversky and Kahneman 1974). In such periods the expectation formation process, with respect to the exchange rate, is not only regressive but also anchored to the last few observations of the exchange rate. Assuming $E^F_t[S_{t+1}]=\gamma S^F_{t-1}+(1-\gamma)(S_{t-1}+S_{t-2})/2$, equation (2) modifies according to

$$d_t^F = \alpha^F(\gamma S_{t-1}^F + (1-\gamma)(S_{t-1}+S_{t-2})/2 - S_t)/S_t, \tag{13}$$

where the fundamentalists now use the exchange rate in t–1 and t–2 as an orientation for expectation formation.

The top of figure 6 displays the implications of anchor expectations for the exchange rate behavior. The main difference is that after a stronger outlier occures, for instance triggered by a shock, the exchange rate stays near the new exchange rate for a while before reversion sets in. This is a consequence of the anchoring behavior, since the agents stick to the past when forming expectations. For the first 1,000 observations the volatility is 0.30 and the distortion is 0.54.

What are the implications for central bank interventions in such an environment? The middle part of figure 6 shows a simulation run for LAW interventions. Through the intervention operation the volatility is increased. The distortion is not influenced (V=0.41, D=0.53). In this regime, the LAW intervention is not successful since the market is not trending. In contrast to regressive expectations, the anchor heuristic together with the high uncertainty often leads to reversals of the exchange rate movement with the result that the central bank intervenes in the wrong direction. Moreover, in some cases the adjustment of the exchange rate towards its fundamental is slowed down: Instead of smoothing the exchange rate path, the exchange rate fluctuates more strongly and in a greater distance to its fundamental value. Hence, the distortion is not reduced.

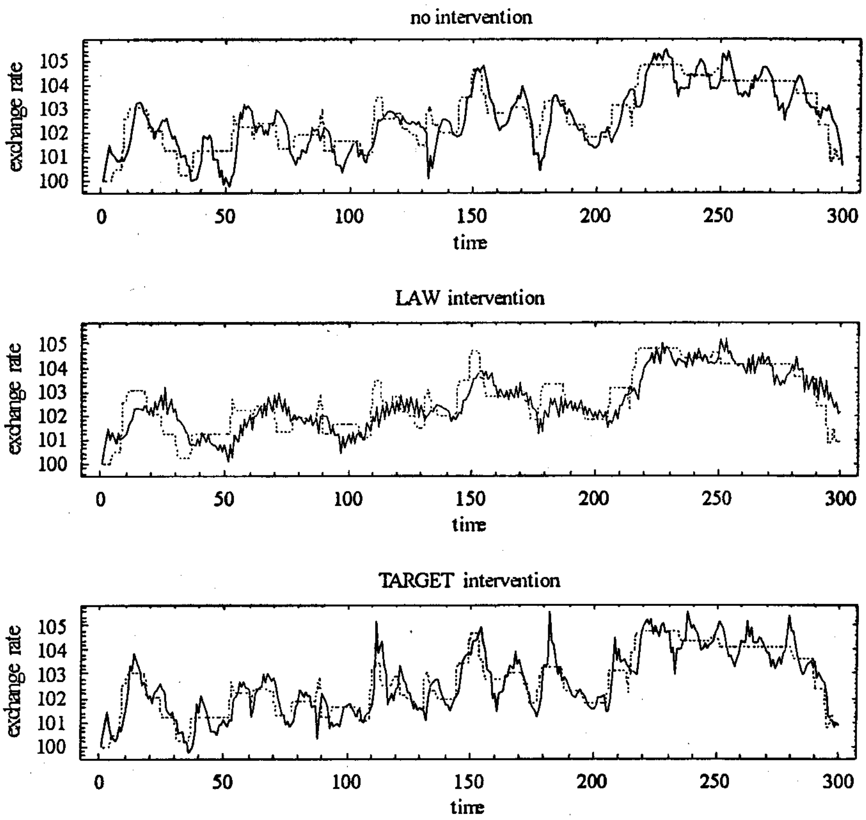

Figure 6: Example of Intervention Operations for Anchor Expectations. The solid line is the exchange rate, the dashed line its fundamental, $S_1^F=100$, $S_1=100$, $S_2=101$, $S_3=101.5$, $a^{C,1}=0.6$, $a^{C,2}=0.0012$, $a^F=1$, $\beta^1=0.1$, $\beta^2=15$, $\gamma=0.2$, $\delta \sim N(0, 1)$, $prob(p=1)=0.2$, $\varepsilon \sim N(0, 0.0075)$, T=300, LAW intervention $a^{CB,L}=0.25$, TARGET intervention $a^{CB,T}=0.11$.

The bottom displays the impact of the TARGET intervention. The results are mixed. The volatility has increased up to 0.35, but the distortion has dropped down to 0.40. In periods of high uncertainty the central bank seems to be able to improve the distortion at the cost of a higher volatility. Since the exchange rate is always pushed towards its fundamental value, the volatility automatically rises.

Figure 7 shows the consequences of the intervention operations in more detail. The figure is constructed in the same way as before. In general, the LAW operations have not the power to reduce the volatility. Only if the noise level is low, the distortion might be reduced. But it seems natural that in periods of high uncertainty chartists do not rely on trend-following trading rules. In such times, their behavior is better described as unsystematic.

Although TARGET operations increase the volatility they allow to reduce the distortion. By using this volatility-enhancing strategy the central bank stabilizes the exchange rate near its fundamental value. In a broader sense, the central bank takes over the role of the fundamentalists.

Note that our model replicates the empirical findings of Hung (1997). On the one hand, central bank interventions are able to reduce the volatility, but on the other hand the opposite effect is also observable. An increase in the volatility may be the price for less distorted markets. However, volatility decreasing interventions seem to be the more used strategy.[10, 11]

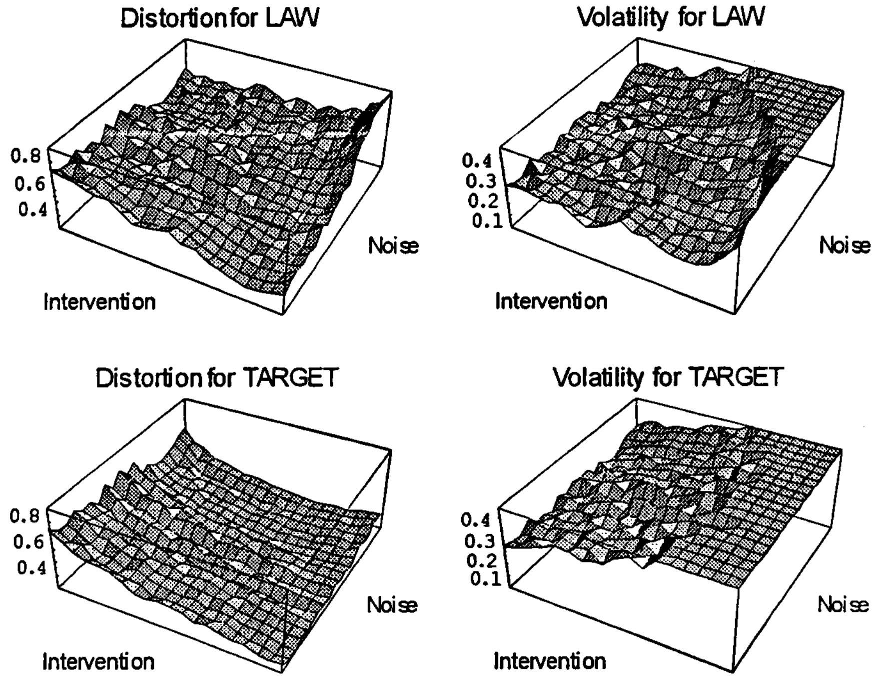

Figure 7: Intervention Results for Anchor Expectations. Distortion and volatility are calculated on the basis of 1,000 observations, the same parameter setting as in figure 6, the intervention level is increased in 20 steps from 0 to 0.475, the noise level in 20 steps from 0 to 0.0019, β^2 is identified so that for $a^{C,1} = 1$ and $a^{C,2} = 0$ the volatility is approximately 0.3, to hold the volatility constant while increasing the noise level, $a^{C,1}$ is appropriately reduced.

[10] To check the robustness of the intervention outcome, we repeated the simulations with other functional and numerical specifications. For instance, we used in (1) a double crossover method (instead of the moving average rule), or in (4) a quadratic weighting scheme (instead of the square root). The qualitative results remain stable under such modifications.

[11] In reality, central banks intervene, of course, less frequently. Thus, we modified (7) and (8) so that an intervention is only triggered if $|LogS_{t-1}-LogS_{t-2}|$ or if $|(S^F_{t-1}-S_{t-1})/S_{t-1}|$ exceeded a certain threshold. Varying these thresholds, we found that the intervention operation works the best, if the central bank permanently intervenes as specified by (7) and (8).

3.5 Support of Fundamentalism

So far, the means of the central bank may be evaluated rather pessimistically. Only if the chartists behave trend-following, LAW can be successful. The TARGET strategy may decrease the distortion, but leads to a higher volatility. In addition, the costs of the intervention operations are unclear. Another problem could be that for a successful operation the intervention volume is unreasonably high. Finally, if it is not possible to sterilize these transactions other markets may be disturbed.

Besides direct intervention operations, the central bank may wish to control the dynamics indirectly. In our model this can be reached by encouraging fundamental trading. Remember that the influence of the fundamentalists is controlled by two parameters: β^1 reflects the ground proportion of fundamental traders and β^2 the popularity of fundamental trading rules. Now, if the central bank provides better information about the fundamental exchange rate, β^1 and β^2 might increase. Figure 8 shows that such a support of the fundamentalists reduces both the distortion and the volatility. This holds independently of the noise level.

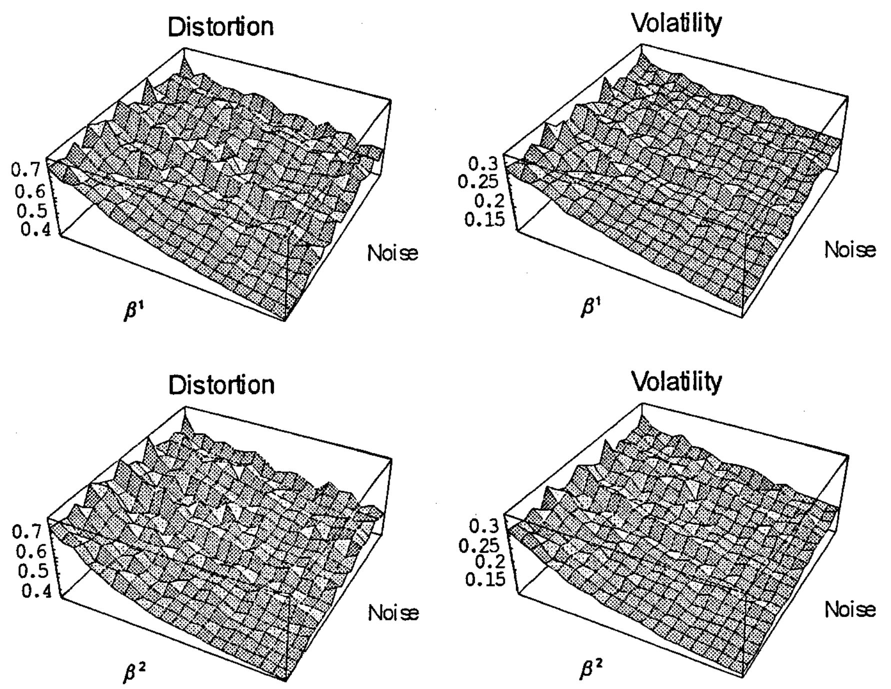

Figure 8: Support of Fundamentalism. Distortion and volatility are calculated on the basis of 1,000 observations, the same parameter setting as in figure 1, but β^1 (β^2) is increased in 20 steps from 0.1 to 0.48 (from 30 to 58.5), the noise level in 20 steps from 0 to 0.00285, to fix the volatility around 0.3 while increasing the noise level, $a^{C,1}$ is reduced.

4 Conclusions

The aim of this paper is, firstly, to develop a better understanding of the driving forces of exchange rate dynamics, and secondly, to study whether typical intervention strategies are able to reduce the high volatility. Guided by empirical observations, the focus of our analysis is on the speculative behavior of the traders. To conclude, we have identified four main forces responsible for the complex dynamics:

- First, technical trading rules typically destabilize the market. Especially when the demand of chartists is correlated, i.e. if they trade systematically into one direction, stronger trends in the exchange rate path are observed.
- Second, fundamental trading rules typically stabilize the market. But when the agents are uncertain about the fundamental value of the exchange rate, these strategies may also contribute to a distortion in the foreign exchange market.
- Third, another source is, of course, the news arrival process. Although the news arrival process is the classical argument explaining foreign exchange dynamics it is only one factor among others. Our model shares even for a low probability of fundamental shocks some important stylized facts of the empirical data: a high variability of the exchange rates, fat tails for returns, and weak evidence of mean reversion.
- Fourth, central bank interventions also have an impact on the dynamics. By leaning against the wind, the autocorrelation of the returns may be reduced. In contrast, other financial markets exhibit a stronger tendency of mean reversion although the speculative investment positions of the agents are derived in a similar way. Moreover, if periods of intervention alternate with periods of no intervention, the central bank induces a volatility clustering.

Depending on what drives the dynamics, the central bank may be able to stabilize the market by intervention.

- If the investment positions of the chartists are correlated, a leaning against the wind strategy is able to reduce the volatility.
- If the market is uncertain about the fundamental value of the exchange rate, the central bank has the opportunity to reduce the distortion by supporting its target exchange rate.

Apart from direct interventions, the central bank may also encourage the fundamentalists to take more risk by providing better information about the fundamental value of the exchange rate.

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