Representativeness of news and exchange rate dynamics

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Abstract

Guided by psychological evidence, we develop a behavioral exchange rate model in which investors' perception of fundamental shocks switches between two states. According to the representativeness heuristic, agents underestimate the informational content of news in calm periods, whereas they overreact to news if they encounter a series of distinct exchange rate changes. Simulations indicate that the model mimics the behavior of actual exchange rates quite well. For instance, we observe fat tails for the distribution of the returns and volatility clustering.
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1. Introduction

This paper explores the relevance of news to exchange rate dynamics. As stated by the efficient market hypothesis, prices always reflect fundamental values (Fama, 1970). Such a view has, of course, severe implications: The statistical features of exchange rate changes are fully explained by those of the underlying fundamental

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process. For instance, the distribution of the returns has fat tails because meaningful news occurs more frequently than suggested by the Normal distribution. Volatility clustering arises since the intensity of news alternates over time.

Market microstructure theory (see Lyons (2001) for a recent survey) offers more promising insight into the complex behavior of the exchange rate. For instance, Fan and Lyons (2001) find that extreme price changes at high frequency are associated with large net flows from financial institutions, whereas low frequency trends are associated with secular net flows from non-financial corporations. Note that the flow of such orders conveys dispersed information. It contains, e.g., the trades of those who analyze information. Since informative trades are mixed with uninformative trades, market efficiency crucially depends on how markets accomplish the difficult task of aggregating dispersed information. As shown by Lyons (2002), even markets with many rational traders may display lasting misalignments and high exchange rate variability.

In contrast, the chartist-fundamentalist approach regards news as a less substantial origin of price fluctuations. Exchange rate dynamics are mainly driven by the trading activity of heterogeneous interacting agents. While Day and Huang (1990) and Farmer and Joshi (2002) generate complex price fluctuations from non-linear trading rules, Kirman (1991, 1993) investigates social interactions which may lead to herding behavior. In the framework of Brock and Hommes (1998), the traders switch between technical and fundamental predictors, depending on the rules' past performance. Lux and Marchesi (1999) generate realistic price movements by combining the latter two aspects. Osler (2003) investigates positive feedback dynamics resulting from stop-loss and take-profit orders. In a related framework, Hau (1998) shows that expectational errors tend to create excessive market entry and excess volatility.

However, exchange rates react to new information. Exploiting high frequency data, Andersen et al. (2003) conclude that announcement surprises trigger quick jumps in exchange rates. But how is news incorporated into exchange rates? Andersen et al. (2003) offer an intriguing channel of exchange rate determination: Traders change their investment positions due to the arrival of new information, and such a flow of orders causes exchange rates to adjust. Recent empirical studies support this mechanism. While Evans and Lyons (2002) report that the daily interdealer order flow explains an astonishing 60% of daily exchange rate movements, Evans and Lyons (2003) find that the order flow varies considerably with the macroeconomic news flow.

The aim of this paper is twofold: First, to propose a behavioral exchange rate model in which speculators' perception of news is based on robust psychological principles. Agents judge news as to whether it is similar to a typical class of news. Focusing on two regimes only, they think that if market historical volatility is high (low), current news must be important (unimportant). Over- and underreaction to news then drives the evolution of the exchange rate via the agents' orders. Second, to explore whether our model has the power to mimic actual exchange rate fluctuations. Among other things, simulations reveal fat tails for the distribution of the returns and volatility clustering. We thus conclude that the way in which speculators perceive news is essential to exchange rate dynamics.

The remainder of this paper is organized as follows: Next, we survey the relationship between news and exchange rates in further depth and sketch some psychological findings on how agents may perceive and process information. Section 3 develops a simple behavioral news model. In Section 4, we explore the extent to which the time series properties of exchange rates are reconcilable with our model. The last section concludes the paper.

2. The empirical background

2.1. News and exchange rates

What is news? According to Guillaume et al. (1997), news is a very broad concept covering events like a phone call of a customer who wants to make a large transaction, a conversation between foreign exchange dealers, forecasts of research centers, or general economic and political news releases. Although news is difficult to quantify, its impact on exchange rates is a heavily debated topic.

Goodhart et al. (1993) are among the first who relate movements in the exchange rate at high frequency to Reuters news announcements. These news messages appear in real time on the screen of professional traders. They detect an influence of news on the level of exchange rates, but the effect does not seem to be permanent. Andersen and Bollerslev (1998) find a somewhat stronger support. Largest returns appear to be linked to the release of public information such as certain macroeconomic announcements. More specifically, information arrivals induce abrupt price changes. The average price movement is typically attained within minutes. Using announcement surprises, defined as the difference between macroeconomic expectations and macroeconomic realizations, Andersen et al. (2003) are even more convinced that exchange rates obey news.

Empirical attempts to link exchange rate movements to news are hampered by the difficulty in extracting the unexpected component of news. For this reason, Cheung and Chinn (2001) try to derive the impact of news from a survey study conducted among professional foreign exchange traders. Their main findings are as follows. News is rapidly incorporated into exchange rates. For the majority of the respondents, the bulk of the adjustment takes place within 1 min. Moreover, traders believe that changes in fundamentals play a substantial role in the pricing of currencies.

Within our model, speculators trade on the basis of new information. The resulting order flow then decides the path of the exchange rate. This channel is backed up by two recent studies. Using order flow as a proximate determinant, Evans and Lyons (2002) develop a model which is strikingly successful in accounting for realized exchange rates. For the DEM/USD spot market, they find that $ 1 billion of net dollar purchase increases the DEM price of a dollar by about 0.5%. Estimates for daily changes in log exchange rates show R^2 statistics of above 60%.

Evans and Lyons (2003) disentangle how (macroeconomic) news enters exchange rates by distinguishing three sources of exchange rate variation: (1) News may be impounded directly into exchange rates, (2) news may induce order flow and thus

may have an indirect effect on exchange rates, and (3) transactions unrelated to news may affect the exchange rate. They find that all three sources are significant. The total effect of news accounts for about 30% of price variation. About two thirds of the price effect from news is transmitted via order flow, with the remaining one third being the direct impounding of news in prices. Given the many problems associated with news studies, we find this evidence quite remarkable.

2.2. Investor psychology

Experimental evidence supports the notion of bounded rationality (Simon, 1955; Tversky and Kahneman, 1974; Smith, 1991). People do not possess perfect knowledge, nor do they have the computational capacity to derive optimal actions. Instead, agents rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities or predicting values to simpler judgmental operations. In general, these heuristics are quite useful, but sometimes they lead to systematic errors. Since people share rather similar rules of thumb, their aggregated impact is significant. For surveys about heuristics compare, for instance, Kahneman et al. (1986), Shiller (1999) and Hirshleifer (2001).

Representativeness is one of the most salient heuristics. In the words of Tversky and Kahneman (1974, p. 1124): ''Many of the probabilistic questions with which people are concerned belong to one of the following types: What is the probability that object A belongs to class B? What is the probability that event A originates from process B? What is the probability that process B will generate event A? In answering such questions, people typically rely on the representativeness heuristic, in which probabilities are evaluated by the degree to which A is representative of B, that is by the degree to which A resembles B. For example, when A is highly representative of B, the probability that A originates from B is judged to be high. On the other hand, if A is not similar to B, the probability that A originates from B is judged to be low.''

Several aspects deserve our attention. Similarity is typically identified on the basis of small samples (Kahneman and Tversky, 1972). For instance, experiments by Grether (1980) reveal that individuals give too much weight to newly added evidence and too little to prior information. The use of the representativeness heuristic may therefore cause systematic errors, because people are too ready to believe that sequences of a certain type of events may have systematic causes. Put differently, people may perceive random clusters as reflecting a causal pattern. For instance, people mistakenly believe in 'hot hands' among sports players, even when actual performance is very close to serially independent (Gilovich et al., 1985). Such behavior is not limited to naive subjects. As reported by Tversky and Kahneman (1971), the statistical intuition of experienced researchers does not seem to be much better than that of other people.

In summary, individuals tend to classify things into discrete groups based on similar characteristics. Since the representativeness heuristic has been confirmed in various experimental settings, we adopt it for the foreign exchange market. Section 3 demonstrates that such behavior may lead to over- or underreliance on new information and thus may produce complex exchange rate dynamics.

3. A behavioral news model

3.1. Motivation

The foreign exchange market is the broadest, most active financial market in the world. For the BIS (2002), currency markets are highly speculative. The great majority of the trading volume reflects very short-term transactions. For example, intra-day operations account for 75% of the market volume. The prices that the main actors are prepared to bid and offer are observable from the relevant screen pages of financial news agencies such as Reuters. News is received quickly and plays a prominent role in the fast and hectic trading in currency markets.

Based on the empirical evidence, the model works as follows. The economy is continuously hit by random news that is incorporated into prices through the interplay of demand and supply. Our main focus is on speculators. If news is favorable, they will buy currency which drives prices up and vice versa. The dynamics of our model is driven by the agents' reactions to news. However, the exact meaning of new information is not clear. For simplicity, we consider two states only: Speculators either over- or underreact to new information depending on market historical volatility. If recent volatility exceeds a certain threshold, they overestimate the effects of news on exchange rates. In quite periods, news is underestimated. Note that such behavior is in line with the experimental finding mentioned above: Individuals form predictions based on how closely past outcomes fit certain categories. Periods of low volatility are associated with calm periods and vice versa.

Such behavior may create interesting dynamics. Suppose that a small number of large shocks hits the market at random. Since the agents pay too much attention to recent evidence, they conclude erroneously that these events are not random but have a fundamental cause. Since overreaction produces high volatility, the process is persistent. In fact, the behavior of the agents is self-fulfilling. A regime switching occurs only by chance. The arrival of a series of small shocks may, even in the case of overreaction, push the volatility below the threshold so that agents start to believe in a low volatility regime.[1]

3.2. Setup

The evolution of the fundamental exchange rate is due to the news arrival process and follows a random walk. Its log F is given by an arithmetic Brownian motion

$$F_t = F_{t-1} + \eta_t. \tag{1}$$

The news η is IID normally distributed with mean zero and (constant) variance σ_η^2.

The exchange rate is determined on an order driven market in which three types of agents are active: speculators, international firms and market makers. Speculators buy (sell) foreign currency if they expect a price increase (decrease). Their orders may

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[1]Theories of over- and underreaction for stock markets are proposed by Barberis et al. (1998), Daniel et al. (1998) and Odean (1998).

be expressed as

$$D_t^S = \alpha^S(E_t[S_{t+1}] - S_t),\tag{2}$$

where α^S is a positive reaction coefficient and S is the log of the exchange rate.[2]

Speculators watch the news arrival attentively. Expected exchange rate changes only depend on new information

$$E_t[S_{t+1}] = S_t + \delta_t \eta_t.\tag{3}$$

The perception of news is, however, biased. We consider two states: over- and underreaction. For instance, if market historical volatility exceeds a certain threshold K, speculators overreact to news. This aspect is formalized as

$$\delta_t = \begin{cases} \delta^O & \text{for } V_t(T) = \dfrac{1}{T} \sum_{i=1}^{T} |S_{t-i+1} - S_{t-i}| \geqslant K, \\[2mm] \delta^U & \text{else,} \end{cases}\tag{4}$$

where $\delta^O > 1$ stands for overreaction and $0 < \delta^U < 1$ denotes underreaction. Market historical volatility V (i.e. the memory of the agents) depends on the last T trading periods.

Relative to the transactions of the speculators, the demand from internationally operating firms plays a minor but still significant role. The firms' orders are given as

$$D_t^F = \alpha^F(F_t - S_t).\tag{5}$$

The reaction coefficient α^F is positive. Note that (5) reflects a standard current account principle: If the exchange rate is above (below) its fundamental value, then exports exceed (fall short of) imports. Put differently, a current account surplus (deficit) results in the selling (buying) of currency.

All orders are mediated by market makers who supply excess demand from their inventory or accumulate inventory when there is excess supply. Market makers quote the exchange rate for period $t+1$ as

$$S_{t+1} = S_t + \alpha^M(D_t^S + D_t^F),\tag{6}$$

where α^M is a positive reaction coefficient. Accordingly, buying drives prices up and selling drives them down.[3]

The solution of the model is obtained by combining (1)–(6). Defining changes in S as returns yields

$$r_{t+1} = S_{t+1} - S_t = x(F_t - S_t) + \begin{cases} y\eta_t & \text{for } V_t(T) \geqslant K, \\ z\eta_t & \text{else,} \end{cases}\tag{7}$$

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[2]Such a demand function is consistent with myopic mean-variance maximizers (Hommes, 2001). The reaction coefficient is then equal to the risk aversion times the conditional variance of the returns, the latter being exogenous.

[3]Note that (6) departs from the canonical price equation in microstructure finance (e.g. Kyle, 1985) in that the market makers here are not making inferences from public news directly. Changes in fundamentals are incorporated into exchange rates via the trading process.

where $x = \alpha^M \alpha^F$, $y = \alpha^M \alpha^S \delta^O$ and $z = \alpha^M \alpha^S \delta^U$ are dimensionless positive scaling factors. Since (7) precludes closed analysis, we proceed with numerical analysis.

3.3. Calibration

Experimenting with the coefficients shows that the following parameter setting delivers dynamics which comes close to the real behavior of exchange rates: $x = 0.001$, $y = 1.35$, $z = 0.65$, $K = 0.0075$, $T = 10$, $\sigma_\eta = 0.01$. With the help of these values, there should be no problem to replicate our findings. We regard this as a valuable advantage over more complicated contributions.

Some comments on the parameter setting seem to be appropriate. Since international trade transactions represent merely 1 percent of the total trading volume in foreign exchange markets (BIS, 2002), a low impact of firms' orders seems to be reasonable. Note that $x = 0.001$ also implies that each day 1/10th of 1% of any gap from the fundamental value dissipates. This translates into a half-life of about 2 years. Over- and underreaction are both equal to 35%. Speculators pay attention to the fluctuations of the last 10 trading days. Such a memory seems to be in accordance with the representativeness heuristic (Kahneman and Tversky, 1972; Grether, 1980). The threshold is assumed to be around 0.75%, which roughly corresponds to the average volatility observed in the simulated time series. As usual, the volatility is calibrated via the standard deviation of the exogenous variable. For $\sigma_\eta = 0.01$, we obtain extreme returns which are comparable to what is observed empirically. In addition, in a "fundamentals only" world, the news variable produces an annual volatility of about 15 percent, which is quite reasonable.

4. Simulation

In this section, we investigate the extent to which our model is able to generate typical exchange rate movements. The dynamics of the exchange rate is often characterized by five features: (1) the trajectory of log exchange rates resembles a random walk, (2) exchange rates occasionally deviate from fundamentals, (3) exchange rates fluctuate strongly, (4) the distribution of returns possesses fat tails, and (5) periods of low volatility alternate with periods of high volatility. Recent surveys on these features – including discussions of the relevant statistical techniques – include, for instance, Andersen and Bollerslev (1998), Guillaume et al. (1997) and Lux and Ausloos (2002).

We explore the dynamic behavior of actual and simulated exchange rates both numerically and graphically. Table 1 contains some statistics for DEM/USD and DEM/JPY exchange rates from 1974 to 1998. Both time series consist of 6264 daily observations. Table 1 also presents the minimum, median and maximum estimates of these statistics for 100 simulation runs. The top panel of Fig. 1 shows log DEM/USD exchange rates and the top panel of Fig. 2 displays simulated log exchange rates.

Several tests are in harmony with the random walk hypothesis. The penultimate panels of Figs. 1 and 2 reveal, for instance, the absence of any significant

Table 1
Numerical survey of stylized facts

Time series	$r_{\min}$	$r_{\max}$	V	D	$\gamma_{0.05}$	H_r	$H_{|r|}$
DEM/USD	−5.75	4.95	0.50	—	3.58	0.53	0.66
DEM/JPY	−3.84	8.94	0.44	—	3.69	0.57	0.63
Sim–Min	−3.68	3.62	0.59	2.99	3.37	0.50	0.60
Sim–Med	−4.43	4.47	0.66	5.48	3.89	0.53	0.66
Sim–Max	−6.21	5.91	0.74	10.27	4.74	0.56	0.70

Daily DEM/USD and DEM/JPY data from 1974 to 1998 (6264 observations). Sim–Min, Sim–Med and Sim–Max indicate the minimum, median and maximum estimates of the statistics obtained out of 100 simulated time series. All simulations are based on the same parameter setting and consist of 6264 observations. r, V, D, γ_α and H denote the return, the volatility, the distortion, the tail index and the Hurst exponent, respectively.

autocorrelation in the return series. From this perspective, exchange rates are unpredictable. The diffusion of a time series may be quantified by its Hurst exponent. Hurst exponents of around 0.5 suggest Brownian motion, whereas larger values indicate persistence and smaller values are a sign of anti-persistence. Applying the rescaled-range method, we find for simulated returns Hurst exponents between 0.5 and 0.56, which correlates well with estimates obtained for DEM/USD and DEM/JPY data.

Distortions are difficult to measure empirically. The second panel of Fig. 1 exposes strong current account imbalances between Germany and the USA. Especially during the increase of the DEM/USD exchange rate in the mid 1980s, German exports to the USA boomed. The second panel of Fig. 2 presents relative deviations between the exchange rate and its fundamental value. Our model may produce strong and lasting misalignments. The distance between the exchange rate and its fundamental may temporarily be larger than 20%. Let us define the distortion D as the average absolute deviation between the log exchange rate and its log fundamental value

$$D = \frac{100}{T} \sum_{t=1}^{T} |S_t - F_t|. \tag{8}$$

Table 1 reports that the model produces a median distortion of around 5.5%. In the extreme case, the average absolute distance between the exchange rate and its fundamental value may be as large as 10%.

The third panels of Figs. 1 and 2 exhibit the evolution of the returns in the time domain. Exchange rates fluctuate strongly. Largest daily returns are above 5%. During periods of overreaction, volatility is obviously excessive. The average relative absolute price change is 0.5% for the DEM/USD market and 0.44% for the DEM/JPY market. Calculating volatility for the simulated data yields values of $V = 0.59$–0.74.
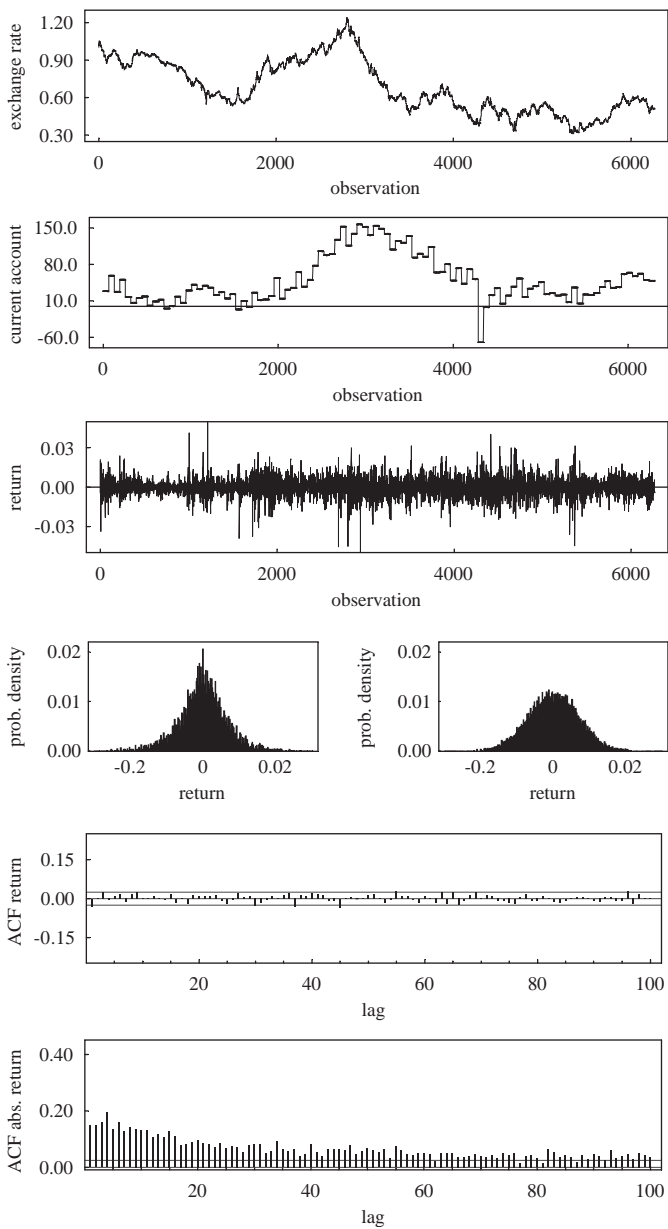
Fig. 1. Stylized facts of DEM/USD exchange rates. The first panel shows the log of the exchange rate (1974–1998, 6264 daily observations). The second panel displays the current account data in 1995 prices (1974–1998, 100 quarterly observations) and the third panel shows the distribution of the returns (left: DEM/USD, right: Normal distribution). The fourth panel depicts the autocorrelation function of raw returns and the last panel presents the autocorrelation function of absolute returns.
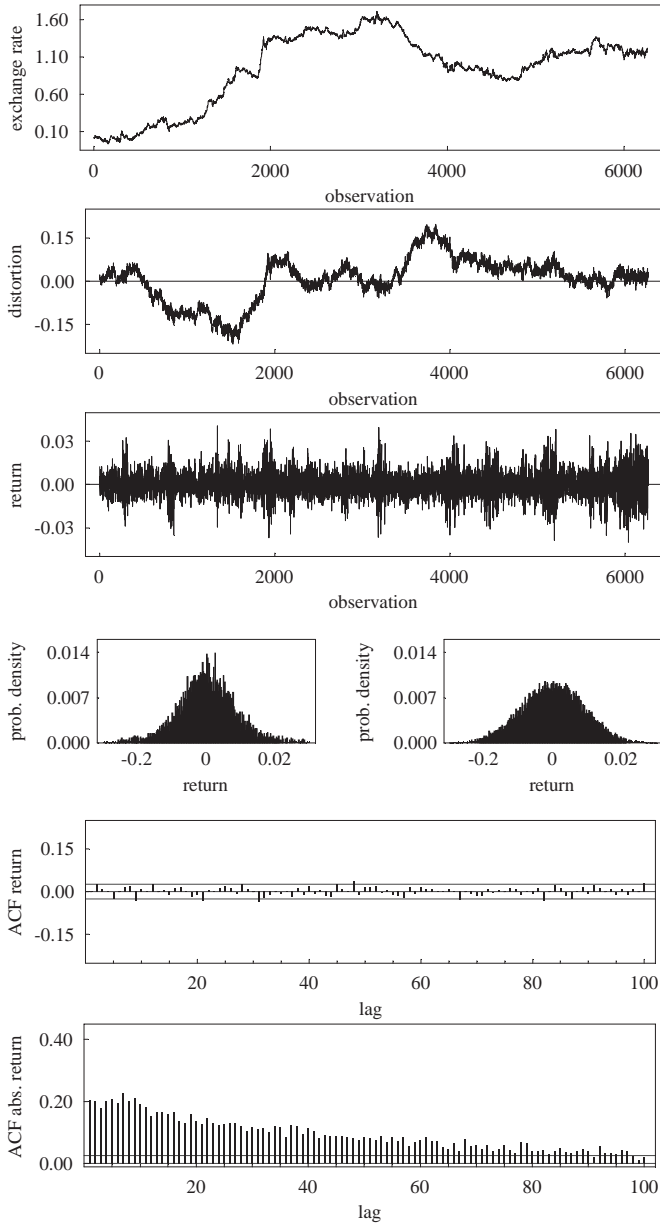
Fig. 2. Stylized facts of simulated exchange rates. The first panel shows the log of the exchange rate (6264 observations) and the second panel depicts relative deviations from fundamentals. The third panel shows the distribution of the returns (left: simulated returns, right: Normal distribution). The fourth panel displays the autocorrelation function of raw returns and the last panel presents the autocorrelation function of absolute returns.

The fourth panels of Figs. 1 and 2 visualize the fat tail property. The left-hand panels display the probability density function of our time series. The right-hand panels contain the probability density functions of Normal distributions. Relative to the Normal distribution, one typically observes a higher concentration around the mean, thinner shoulders and more probability mass in the tails. Using the Hill tail index estimator to quantify the tail size, we ascertain that the tail index of DEM/USD and DEM/JPY returns is in harmony with the tail indices of the simulated time series. For the largest 5% of the observations, $\gamma_{0.05}$ ranges mainly between 3.5 and 4. The tail indices for DEM/USD and DEM/JPY returns are computed as 3.58 and 3.69, respectively.

Volatility is strongly correlated over time. Using absolute returns as a proxy for volatility shows that temporal independence is strongly rejected (compare the bottom panels of Figs. 1 and 2). One finds significant positive autocorrelation coefficients over an extended time horizon. To be precise, the autocorrelation function displays a hyperbolic decline. Long-term dependence is also captured by Hurst exponents which scatter between 0.6 and 0.7.[4]

All in all, our model has the power to match the stylized facts of foreign exchange markets. Some popular statistical tests do not discriminate between real and artificial data. We find this noteworthy since our approach is relatively simple. Especially having fat tails and volatility clustering while having no autocorrelation in raw returns is for many behavioral finance models still a challenge. Finally, we investigate what is driving the dynamics and what is causing the stylized facts.

Let us first consider how the model functions. Suppose that the market is in a tranquil state so that the speculators underestimate the changes in fundamentals. As a result, volatility stays persistently low. But shocks are normally distributed and a series of large shocks will eventually appear. Although the agents underreact to news, volatility increases. If the threshold is crossed, they start to overreact to news. The high volatility regime continues until a series of minor shocks emerges.

Now, the time series properties are straightforward. Since the dynamics is dominated by speculators' responses to stochastic news, the exchange rate path appears as a random walk. Due to misperceptions, the exchange rate disconnects from its fundamental. Nevertheless, exchange rate changes are correlated with news.[5] The distortion is bounded by the current account reaction. The more the exchange rate is misaligned, the stronger the stabilizing impact of international trade transactions.[6] In the high volatility regime, exchange rate fluctuations are obviously

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[4]Several methods have been proposed to quantify long memory (see Kirman and Teyssière (2002) for a comprehensive survey). Note that for a time series with finite variance, the estimate of the Hurst exponent H is related to the estimate of the fractional differencing parameter d by the identity $H = d + 0.5$. Moreover, the rate of decay of the autocorrelation function is given as $y = 1 - 2d$.

[5]Which is in harmony with the findings of Evans and Lyons (2002, 2003). A model with state dependent levels of noise trading would not display this property.

[6]There seems to exist an analogy to the finding of Fan and Lyons (2001) mentioned in the introduction: International trade transactions govern the dynamics in the long run, preventing the system from exploding. In the short run, the erratic movements are mainly due to the behavior of the speculators.

excessive. The endogenous switching between the two regimes causes both fat tails and volatility clustering.

5. Conclusions

News is undoubtedly a major variable driving foreign exchange dynamics. However, even professional traders experience difficulties when evaluating the meaning of news. Experimental evidence suggests that agents tend to misperceive new information systematically. By judging in simple categories, news is identified as important in periods of high volatility, whereas it is underrated in periods of low volatility. Although the only exogenous variable of our model is normally distributed, the artificial market displays some features that are remarkably similar to those observed in real markets. Overall, our approach exposes the meaningfulness of news and its perception for understanding exchange rate dynamics. From a general perspective, the latter observation is also relevant for practical policy recommendations. If central authorities provide more reliable information about fundamentals, the degree of misperception may decrease. In addition, calming down the dynamics should further prevent periods of overreaction. We are convinced that these aspects deserve more attention.

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