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**TARGET ZONES AND CONDITIONAL VOLATILITY:
THE ROLE OF REALIGNMENTS**

Christopher J. Neely*

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Abstract: This paper examines the relationship between the conditional volatility of target zone exchange rates and realignments of the system. To investigate this question, modified jump-diffusion Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and absolute value GARCH models are fit to six exchange rates of the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS). Time-varying jump probability and absolute value GARCH models are effective in improving the fit of jump-diffusion models on target zone data. There is some evidence that conditional volatility is higher around the periods of realignments.

Keywords: Conditional variance, Forecasting, Jump-diffusion, Exchange Rate Mechanism

JEL subject numbers: C22, C53, F31

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TARGET ZONES AND CONDITIONAL VOLATILITY:
THE ROLE OF REALIGNMENTS

1. INTRODUCTION

Since March 1979, most of the nations of the European Union have participated in a "target zone" system of exchange rate management known as the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS). Realignments of these target zones have been common; the United Kingdom and Italy suspended their participation in the ERM on September 17, 1992, after speculative attacks. After August 1993, the bands were broadened sufficiently to functionally alter the character of the system. These episodes, the Mexican peso crisis, and the more recent Asian currency turmoil have focused attention on the importance of realignments of target zone systems.

Because of the importance of exchange rates in economic decisions, various authors (e.g. Baillie and Bollerslev 1989, 1991, Lastrapes 1989, Hsieh 1988, 1989, and Jorion 1988) have studied the empirical properties of floating exchange rates, emphasizing measurement of conditional volatility. The ERM target zone system, however, complicates the study of European exchange rate volatility. Diebold and Pauly (1988) used ARCH models to conclude that the ERM reduced conditional volatility but ignored the most prominent characteristic of ERM rates, realignments of the ERM bands. Vlaar and Palm (1993) were the first to model this feature of ERM exchange rates with "jump-diffusion" (G)ARCH processes. They concentrated on investigating the optimal jump mixture and producing a multivariate model. In similar work, Nieuwland, Verschoor and Wolff (1994) focused on the mean reversion properties of ERM exchange rates and the excess kurtosis found in the data and concluded that the model which most successfully fitted the EMS exchange rate returns "is a combined jump-GARCH model with conditionally t-distributed innovations."

This paper extends the work of Vlaar and Palm (1993) and Nieuwland, Verschoor and Wolff (1994) by considering the interaction of realignments and conditional volatility in three ways. First, information about the credibility of the target zones is incorporated into the model to allow for a time-varying jump probability for the jump-diffusion GARCH models. The data generally reject constant jump intensity in favor of a time-varying parametrization that better forecasts conditional volatility during periods of speculative pressure. Second, to provide a more robust estimate of the forecast conditional variance, the absolute value GARCH models of Taylor (1986) and Schwert (1989), as well as standard GARCH models, are fit to the data. Time-varying realignment probability and absolute value GARCH models are employed to reduce bias in the estimated GARCH parameters. Third, study of the periods around realignments suggests conditional volatility is higher than normal at these times.

2. THE DATA

The data consist of weekly exchange and interest rates from seven ERM countries – Belgium, Denmark, France, Germany, Ireland, Italy, and the Netherlands – from March 14, 1979, to July 31, 1992 (698 observations). The end of the sample was chosen to exclude the speculative attacks of September 1992. Weekly rates were used to facilitate comparison with previous results and avoid problems with day-of-the week effects in the data. Wednesday dollar spot exchange rates were obtained from the Federal Reserve Board of Governors and converted to deutsche mark rates by assuming the absence of triangular arbitrage. Target zone central parities of each

ERM currency, and the three-month and 12-month Euromarket interest rates, were obtained from the Bank of International Settlements (BIS). Bilateral target zones were normally ±2.25% but more volatile currencies used ±6.0% target zones some of the time. Figure 1 depicts the time series of the French franc per deutsche mark (FF/DM) exchange rate, from March 1979 through July 1992. The most striking feature of Figure 1 is the realignments of the FF/DM target zone.

Three stylized facts emerge from the literature on weekly floating exchange rates: they are martingales, they are conditionally heteroskedastic, and they exhibit excess kurtosis. Target zone exchange rates are different, however. They are normally constrained within bands which are occasionally realigned. Some of their statistical properties are quite different from those of managed floating rates. For example, target zone exchange rate changes are more predictable than those of floating rates in the short term.[1]

Target zone exchange rates do exhibit the second stylized fact of high frequency financial time series: they are conditionally heteroskedastic. Figure 2 shows the weekly changes in the French francs per deutsche mark (FF/DM) exchange rate. These changes appear to contain time-varying volatility (ARCH). Previous work, as well as formal tests not reported here, confirm the presence of ARCH in the data.

Consistent with conditional heteroskedasticity is the third stylized fact: exchange rate changes are characterized by "fat tailed distributions," i.e., excess kurtosis. Table 1 displays summary statistics of the exchange returns ($100*\ln(e_t/e_{t-1})$). The skewness statistics are uniformly

[1] In this context, predictability means predictability from fundamentals or time series models. Neely, Weller and Dittmar (1997) and Neely and Weller (1998) discuss predictability of returns from technical signals for dollar and target zone exchange rates, respectively.

positive, reflecting the weakness of these currencies versus the deutsche mark during these periods. Five of the six ERM rates' skewness statistics reject symmetry at the 5% level. The target zone exchange rate returns are also extremely kurtotic, more kurtotic than floating rates, with kurtosis statistics of at least ten. These very high skewness and kurtosis statistics are partly due to the realignments in the target zone exchange rates.

3. MODELS OF EXCHANGE RATE CHANGES

There are three major issues involved in the modeling of target zone exchange rates. The first issue is how to model the expected changes in the exchange rate—within the target zone and with realignments. The second issue is how to model conditional heteroskedasticity of the target zone exchange rate processes. Finally, the "fat tails" and possible discontinuities in the data must be confronted. This section describes the log likelihood function for exchange rate changes and explains how its features model the data.

3.1 The Basic Model

The basic model for high frequency target zone exchange rate changes is the jump-diffusion GARCH model that assumes the returns are drawn from a mixture of distributions—a diffusion process and a jump process. The continuously compounded rate of return is:

$$\begin{aligned} 00 \cdot \ln\left(\frac{e_t}{e_{t-1}}\right) &= \mu_{1t} + \sqrt{h_t}\varepsilon_{1t}\,, \qquad \textit{with probability } (1-\lambda_t) \\ &= \mu_{1t} + \sqrt{h_t}\varepsilon_{1t} + \mu_2 + \delta\varepsilon_{2t}\,, \quad \textit{with probability } \lambda_t \end{aligned} \qquad \textbf{(1)}$$

where ε_{1t} and ε_{2t} are mean-zero errors and the number of jumps per period is drawn from a

Bernoulli distribution with parameter λ_t. In this case, the log likelihood function for $\ln(e_t/e_{t-1})$ with conditionally t-distributed innovations is:

$$L_T(\theta,e_t) = T\cdot\ln\left[\frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})\cdot\sqrt{\pi\cdot(v-2)}}\right]$$

$$+\sum_{1}^{T}\ln\Bigg[\;(1-\lambda_t)\cdot(\frac{1}{\sqrt{h_t}})\cdot\Big[1+\frac{(100\cdot\ln(\frac{e_t}{e_{t-1}})-\mu_{1t})^2}{(v-2)\cdot h_t}\Big]^{-(\frac{v+1}{2})} \tag{2}$$

$$+\;\lambda_t\cdot(\frac{1}{\sqrt{h_t+\delta^2}})\cdot\Big[1+\frac{(100\cdot\ln(\frac{e_t}{e_{t-1}})-\mu_{1t}-\mu_2)^2}{(v-2)\cdot(h_t+\delta^2)}\Big]^{-(\frac{v+1}{2})}\;\Bigg]$$

where μ_{1t} is the time-varying mean of the diffusion process, μ_2 is the mean of the jump distribution, h_t is the variance of the diffusion process, δ^2 is the variance of the jump distribution, and λ_t is the time-varying probability of a jump. The following subsections describe the rationale for the features of this log likelihood.

3.2 Jump-Diffusion Models

The very high kurtosis statistics for the ERM exchange rates are symptomatic of discrete discontinuities or "jumps" in the data, caused partially by realignments. To manage this feature of the data, Vlaar and Palm (1993) and Nieuwland, Verschoor and Wolff (1994) applied “jump-diffusion" GARCH models in which the change in the exchange rate is assumed to be drawn from a mixture of distributions with the number of jumps per period drawn from a Poisson or Bernoulli distribution. Nieuwland, Verschoor and Wolff used the Poisson specification of Jorion

(1988), but Vlaar and Palm (1993) specifically investigated the use of Poisson and Bernoulli specifications and found "...there are no strong reasons to prefer the Poisson mixture to the Bernoulli-normal model."   Modeling the probability of a jump as a Bernoulli trial is simpler computationally and perhaps more realistic for modeling ERM realignments; more than one "jump" in a week would indicate a breakdown of the ERM. Therefore, the Bernoulli specification is used here.

The distribution of the error terms in the jump-diffusion models is another tool to treat the kurtosis in the data. Vlaar and Palm (1993) used the simpler normal and multivariate normal distributions as the underlying distributions for their jump-diffusion models. However, if allowance for the GARCH process and a mixture of normal distributions cannot fully account for the kurtosis in the data, one can mix from fat-tailed distributions, such as conditional t-distributions. Nieuwland, Verschoor and Wolff (1994) found this strategy to be useful in reducing kurtosis in the standardized residuals. Therefore, the models in this study were estimated with the conditional t-distribution as well as the normal distribution.

3.3 Mean Reversion Within the Target Zone

A problem with applying the simple jump-diffusion model to target zone exchange rates is that it assumes that future movements of the exchange rate are completely unpredictable. In target zones, however, mean reversion within the target zone is expected because of central bank intervention. The expected change within the band should be dependent on the current position of the exchange rate within the band. Therefore, the mean of the diffusion process, μ_{1t} (from (2)), is parametrized as:

$$\mu_{1t} = \mu_0 + \mu_{lx}(\ln(e_{t-1}) - \ln(c_{t-1})) \tag{3}$$

where e_t and c_t are the position of the exchange rate and the central parity at time t. If the exchange rate is currently greater (less) than the center of the band, it is reasonable to expect that it will decline (increase), that is, μ_{lx} is expected to be negative. This parametrization is more intuitive and more consistent with the literature on target zone credibility (see Mizrach, 1993, and Rose and Svensson, 1994) than an ARMA specification.

3.4 Modeling the Jump Probability

The simple jump-diffusion model assumes a constant probability of a jump. This ignores the literature on the realignments of target zones that suggests the structure of Eurocurrency interest rate differentials and the domestic yield curve should provide information about the likelihood of realignments. Specifically, uncovered interest parity requires the interest differential to measure expected depreciation against the deutsche mark. Further, expectations of a devaluation should steepen the weak currency's yield curve because a devaluation changes the rate of return over short horizons much more than it does over longer horizons.

Because all the realignments have been devaluations with respect to the deutsche mark, the probability of realignment (λ_t in (2)) is modeled as a probit function of the three-month interest differential with Germany and the yield curve in the other country. For example, the realignment probability for France, at time t, would be:

$$= \int_{-\infty}^{z_t} \varphi(u)\, du, \qquad z_t = \lambda_0 + \lambda_{id}(i_t^{ff3} - i_t^{ge3}) + \lambda_{yc}(i_t^{ff3} - i_t^{ff1} \tag{4}$$

where $(i_t^{ff3} - i_t^{ge3})$ is the interest rate differential on three-month Euromarket rates of France with Germany; $(i_t^{ff3} - i_t^{ff12})$ is a measure of the French yield curve (the three-month interest rate minus the 12-month interest rate) and φ(*) denotes the standard normal distribution function.

3.5 Conditional Heteroskedasticity

Because conditional heteroskedasticity may also contribute to excess kurtosis, GARCH(1,1) and absolute value GARCH models are used to model the conditional variance of the diffusion process as a function of past errors. For example, the absolute value GARCH(1,1) model used in this work parametrizes current conditional variance as a function of the magnitude of the last shock and the last estimated conditional variance. In this case, the conditional standard deviation $(h_t^{1/2})$ at time t is expressed as:

$$h_t^{\frac{1}{2}} = \alpha_0 + \alpha_1 \cdot |\varepsilon_{t-1}| + \beta \cdot h_{t-1}^{1/2}, \qquad \alpha_0,\ \alpha_1,\ \beta \geq 0. \tag{5}$$

where ε_{t-1} is the residual from the model of the spot exchange rate at time "t-1."[2]

The GARCH(1,1) and absolute value GARCH(1,1) model have the advantages of simplicity and parsimony while allowing long correlation among the magnitudes of the shocks. While most studies of exchange rates have used Bollerslev's GARCH(1,1) parametrization to estimate conditional heteroskedasticity, Nelson and Foster (1994) showed that the absolute value

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[2] Nelson and Cao (1992) show the constraints on α_1 and β in (5) are sufficient but not necessary to ensure positive conditional variance forecasts. For cases in which the estimated conditional variance process was explosive ($\alpha_1 + \beta > 1$), the model was reestimated using the IGARCH model that imposes $\alpha_1 + \beta = 1$.

GARCH model is a superior filter for series with discrete changes or excess kurtosis and only slightly inferior to the standard GARCH model for true diffusion processes.

4. RESULTS

To investigate the interaction of conditional volatility and realignments, a variety of general and restricted jump-diffusion GARCH models were estimated using the likelihood function (2) as the baseline model. Two issues are examined:

1) Is time-varying jump intensity an appropriate way to model the data? If so, how does it affect the choice of GARCH model and the estimated conditional volatility series?

2) What is the behavior of the actual and forecast volatility around realignments?

4.1 Time Varying Realignment Probability and Maximum Likelihood Results

Confirming the work of Vlaar and Palm (1993) and Nieuwland, Verschoor and Wolff (1994), the data are supportive of elaborate models of target zone exchange rates. For example, heteroskedasticity and mean reversion in the diffusion process and a conditional t distribution are generally preferred by likelihood ratio and non-nested tests to restricted models. Also in accord with previous findings, estimates of the degrees of freedom parameter (ν) in Table 2 are very low, consistent with very fat tails. Even allowing for absolute value GARCH and time-varying jumps, ν was estimated to be less than 4 for four of the six rates, indicating infinite kurtosis.

Extending previous results, however, substantial support was found for time-varying jump intensity. Likelihood ratio tests reject a constant jump probability for at least half the exchange rates over a variety of model specifications and likelihood functions. The Akaike information criterion was even more supportive of the time-varying parametrization. Justification for this model was especially pronounced for the standard—rather than absolute value—GARCH models and the normal—rather than t—distributions. Given the highly parametrized models and relatively few periods of speculative pressure, this is substantial evidence in favor of the time-varying jump intensity.

A priori, it was expected that the absolute value GARCH model of Taylor (1986) and Schwert (1989) would be preferred to the standard GARCH model of Bollerslev (1986) because ARCH specifications are not robust to discontinuities in the data such as realignments (Nelson, 1992). Essentially, the problem is the process that produces the "jump" discontinuities is not the same as the diffusion process whose conditional variance is being modeled by the (G)ARCH process; the "jumps" bias the (G)ARCH parameters. The data, however, proved indifferent between the GARCH and absolute value GARCH models of conditional volatility for the models with mean reversion and time-varying realignment probabilities. The time-varying realignment probability, in particular, sometimes offset the discontinuities in the data that bias the GARCH parameters. For more parsimonious models, however, the absolute value GARCH model was generally preferred.

In light of the theoretical advantages of the absolute value GARCH parametrization, results from the most general jump-diffusion absolute value GARCH model with both time-varying mean in the diffusion process (3) and a time-varying jump frequency (4) are presented in Table 2. The time series of conditional standard deviations produced by this model is shown in Figure 3. Generally, volatility is quite low but tends to spike upward, especially around realignment periods.

The fourth column of Table 2 shows the estimates of the within-the-band mean reversion parameter (μ_{lx}) are always of the correct sign and likelihood ratio tests of the hypothesis that μ_{lx} = 0 reject the null for four of the six rates. These results support modeling the mean reversion within the target zone as a function of position in the band.

It was expected, a priori, that the parameter λ_τ would capture the probability of a realignment in any given period, μ_2 would capture the mean size of the realignments,δ^2 would capture the variance of the realignments, etc. But, as noted in Vlaar and Palm (1993) and Nieuwland, Verschoor and Wolff (1994), the jump models did not pick up only the realignments as jumps; large movements within the bands also affected the jump parameters. The use of time varying realignment probabilities mitigated this tendency. For example, the mean implied jump intensity (see column 6 of Table 3) is much lower with the time-varying realignment parametrization. The model was much better able to pick out realignments as jumps.

All of the estimated interest differential (λ_{id}) parameters and four of the six the yield curve (λ_{yc}) parameters were of the expected sign. The correlation among the time-varying realignment probability parameters makes their standard errors uninformative as to individual significance but likelihood ratio tests of the restriction that the time-varying realignment probability parameters are jointly zero ($\lambda_{id} = \lambda_{yc} = 0$) reject that hypothesis for three of the six exchange rates (the Belgian Franc, Danish Kroner and Dutch Guilder). These results are conservative in the sense that the use of a normal distribution and/or the standard GARCH(1,1) model yielded even more positive results for this parametrization, as did use of the Akaike information criterion rather than likelihood ratio tests.

The time series of the probability of "jumping" for the FF/DM exchange rate is shown in

Figure 4. The decline in the average probability of jump in Figure 4 affirms the previous conclusion of Frankel and Phillips (1992) and Mizrach (1993) that the ERM had been getting more credible from 1985 to 1992. The eighth column of Table 3 shows the correlation between the probability of jump and the absolute value of the error. Not surprisingly, they are all positive and the correlation is highest for the three rates – Belgium, Denmark and the Netherlands – for which the likelihood ratio test rejects that the time-varying realignment probability parameters are jointly zero (λ_{id}=λ_{yc}= 0). Figure 3 shows that by permitting jump-intensity to vary with interest rate differentials and the yield curve, forecast conditional volatility rises during periods of speculative pressure, often *before* realignments of the system. Weeks of realignment are represented by dashed lines in the figure. A constant probability of jump model would not pick up this uncertainty. Also, to the extent this feature reduces the bias in GARCH parameter estimates, it will more accurately forecast conditional volatility in "normal" periods. Time-varying realignment probability is an important characteristic of ERM exchange rates.

4.2 Conditional Variance Around Realignment Periods

What was the relationship between the periods of realignments and the conditional volatility of the series? To answer this question, the series must be aggregated to study their common tendencies. Figure 5 displays such an aggregation: The natural logs of a normalized measure of the behavior of the magnitude of the residuals and the conditional standard deviations for twelve weeks before and after realignments. These data were constructed as follows: for each of the six ERM rates, 25 (2×12 + 1) weeks of residuals from the model were picked out around each actual realignment. For each of the 37 realignments, the 25 observations on the absolute value of the residuals were normalized by dividing them by their respective mean values for each exchange rate over the whole sample. This left 37 normalized series of length 25 weeks or 25 vectors – indexed by the length of time from the realignment – 37 rows long. Each of the 25 vectors were sorted in order of magnitude and the 4th, 18th and 33rd elements (10th, 50th and 90th percentiles) of each were picked out to be graphed. Finally, the magnitude of the residuals during the realignment periods necessitated taking natural logs of the two time series in order to make the graph more readable. Conditional standard deviations were handled in a similar manner.

Figure 5 provides some evidence that conditional volatility was moderately high in the two weeks before and after realignments. A formal test of the hypothesis that the mean magnitude of the residuals and conditional standard deviation is different in the weeks around realignments was done by comparing the means of the series of natural logs of residual magnitudes and conditional standard deviations in the four weeks around realignments to the means of the same series four to 25 weeks around realignments. The fourth and fifth columns of Table 4 show the t statistics and the p-values for these tests for the four periods before and after realignments. The t statistics suggest that the mean residual magnitudes are higher than normal in the two weeks before and after realignments. Because these tests assume the series have equal variance, F tests for equality of variances are shown in columns two and three. The F tests fail to reject the equal variance restriction for most of the cases. The t statistics should be interpreted cautiously because they ignore the possible correlation between the volatility of different exchange rates during the same realignment. Despite these caveats, these tests suggest that conditional volatility is high in the two weeks around realignments and that this volatility may even be marginally useful in forecasting realignments of target zones.

5. CONCLUSIONS

This paper focused on the interaction of conditional volatility and realignments of a target zone exchange rate system (the ERM). Three conclusions are drawn. First, information about the credibility of the target zones is useful in allowing for a time-varying realignment probability of jump for the ERM exchange rate jump-diffusion GARCH models. Second, the absolute value GARCH models of Taylor (1986) and Schwert (1989) provide a more robust estimate of the forecast conditional variance. Absolute value GARCH models, time-varying realignment probability and the conditional t distribution all proved useful in modeling the realignments found in ERM data. The data suggest these specifications can substitute for one another, to some extent, in reducing the bias in GARCH parameters caused by realignments. Finally, there is some evidence that conditional volatility is higher in the weeks around realignments.

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Table 1: Summary Statistics from the ERM Exchange Rate Returns [$100*\ln(e_t/e_{t-1})$]

1979-1992

Series	Obs	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis
BE	698	0.038	0.429	-3.008	7.768	8.417	156.531
DK	698	0.046	0.376	-1.345	3.908	2.723	21.270
FR	698	0.055	0.439	-2.121	6.041	7.496	87.237
IE	698	0.050	0.437	-1.247	6.233	6.063	74.448
IT	698	0.073	0.515	-4.427	5.005	1.773	27.185
NL	698	0.006	0.178	-0.792	1.413	1.261	10.379

Notes: The skewness and kurtosis statistics would be distributed N(0,1) if the data were drawn identically and independently from a normal distribution. These summary statistics include the full sample on the Irish pound.

Table 2: Parameter Estimates from the Jump-Diffusion Absolute Value GARCH Model with Time-varying Mean and Jump Probability for the ERM Rates

1979-1992

Rate	Obs	μ_0	μ_{lx}	α_0	α_1	β	μ_2	δ^2	λ_0	λ_{id}	λ_{yc}	ν
BE	697	.010	-.017	.036	.379	.503	.029	.054	-2.934	1.063	1.096	3.490
		*	*	*	*	*	*	*	*	*	*	*
DK	697	.018	-.024	.228	.147	.000	.510	.864	-2.397	.139	.126	9.362
		(.011)	(.008)	(.017)	(.052)	(.001)	(.243)	(.348)	(.388)	(.066)	(.187)	(4.979)
FR	697	.006	-.011	.043	.184	.700	4.540	1.832	-2.948	.071	-.083	3.305
		(.007)	(.006)	(.015)	(.059)	(.084)	(.558)	(2.131)	(.424)	(.053)	(.115)	(.519)
IE	560	.015	-.027	.107	.249	.423	5.347	1.488	-3.208	.075	.160	3.979
		(.009)	(.010)	(.028)	(.061)	(.107)	(.809)	(1.887)	(.770)	(.107)	(.388)	(.707)
IT	697	-.040	-.008	.127	.448	.326	.265	.126	-1.002	.063	.022	3.034
		(.018)	(.006)	(.041)	(.101)	(.109)	(.095)	(.064)	(.436)	(.039)	(.114)	(.534)
NL	697	-.000	-.051	.001	.073	*	.079	.064	-5.028	2.342	-1.967	6.570
		(.003)	(.011)	(.000)	(.024)	*	(.053)	(.030)	(1.872)	(.947)	(.999)	(1.321)

Table 3: Conditional Volatility and Jump Statistics

ERM: 1979-1992

Rate	Mean Cond Std Deviation	Unconditional Standard Deviation	Corr.	Estimated Frequency of Jumps (%)	Estimated Size of Jumps	Estimated Jump Std Dev	Corr2	Number of Realignments	Frequency in %	Mean Size of Realignment	Estimated Realignment Std Dev
BE	0.338	0.429	0.292	56.648	0.029	0.232	0.210	7	1.003	3.883	2.677
DK	0.343	0.377	0.219	5.717	0.510	0.929	0.222	8	1.148	3.765	1.217
FR	0.282	0.439	0.096	0.591	4.540	1.353	0.062	6	0.860	6.218	3.198
IE	0.289	0.424	0.105	0.361	5.347	1.220	0.081	5	0.893	5.466	2.934
IT	0.499	0.515	0.258	31.233	0.265	0.355	0.118	9	1.291	5.470	2.554
NL	0.142	0.178	0.501	5.876	0.079	0.252	0.226	2	0.287	1.947	0.047

Notes: Corr = Correlation of Residual Magnitude and Forecast Standard Deviation. Corr2 = Correlation of Residual Magnitude and Estimated Jump Probability.

Table 4: Tests for whether mean residual magnitude and mean conditional standard deviation are of unusual magnitude around periods of realignments.

Tests of Distribution of Estimated Residual Error Magnitude Around Realignments

Periods After Realignments	F statistic for equality of variances	F statistic p-value	t statistic for equality of means	t statistic p-value
-4	1.387	0.069	-1.278	0.101
-3	1.479	0.038	-0.228	0.410
-2	0.844	0.728	2.156	0.016
-1	0.691	0.915	2.029	0.021
0	0.827	0.755	9.730	0.000
1	1.084	0.341	0.090	0.464
2	0.765	0.838	0.889	0.187
3	1.539	0.025	-0.420	0.337
4	1.476	0.038	-1.960	0.025

Tests of Distribution of Estimated Conditional Standard Deviation Around Realignments

Periods After Realignments	F statistic for equality of variances	F statistic p-value	t statistic for equality of means	t statistic p-value
-4	0.853	0.714	-0.899	0.184
-3	0.638	0.951	-0.787	0.216
-2	0.639	0.951	0.032	0.487
-1	0.796	0.798	1.754	0.040
0	0.678	0.925	1.308	0.096
1	2.547	0.000	9.382	0.000
2	1.619	0.014	4.892	0.000
3	1.093	0.329	3.145	0.001
4	0.939	0.573	1.414	0.079

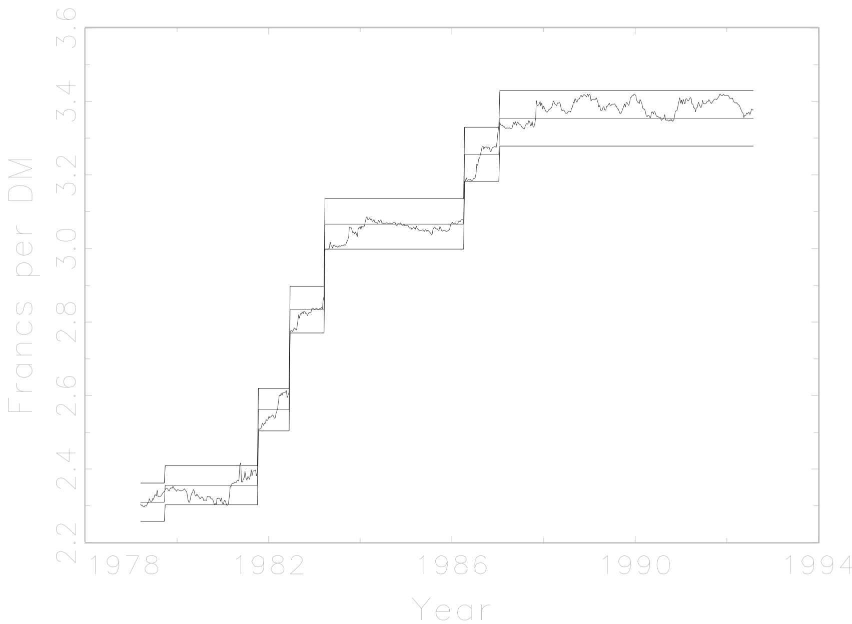

Figure 1: Target Zone Exchange Rate Behavior

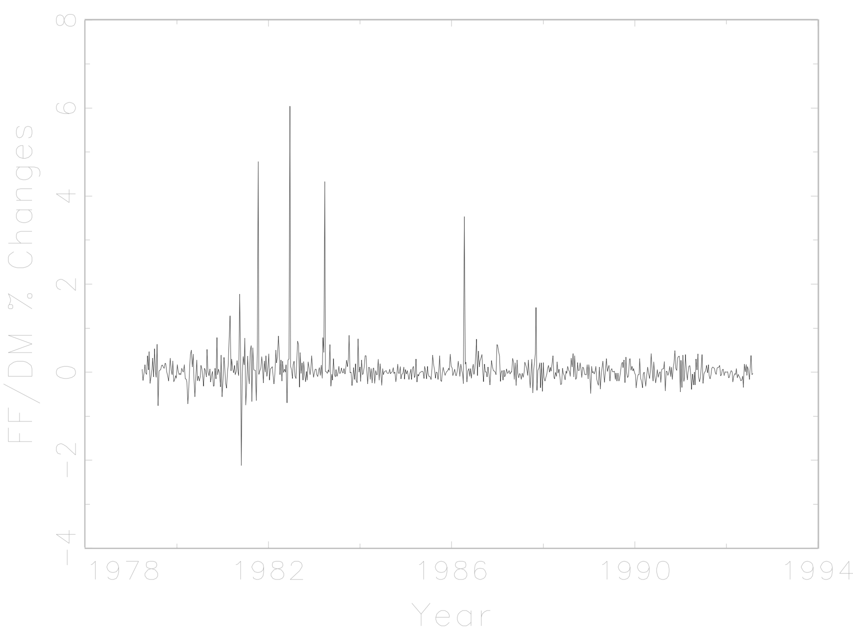

Figure 2: Percentage Changes in the Exchange Rate

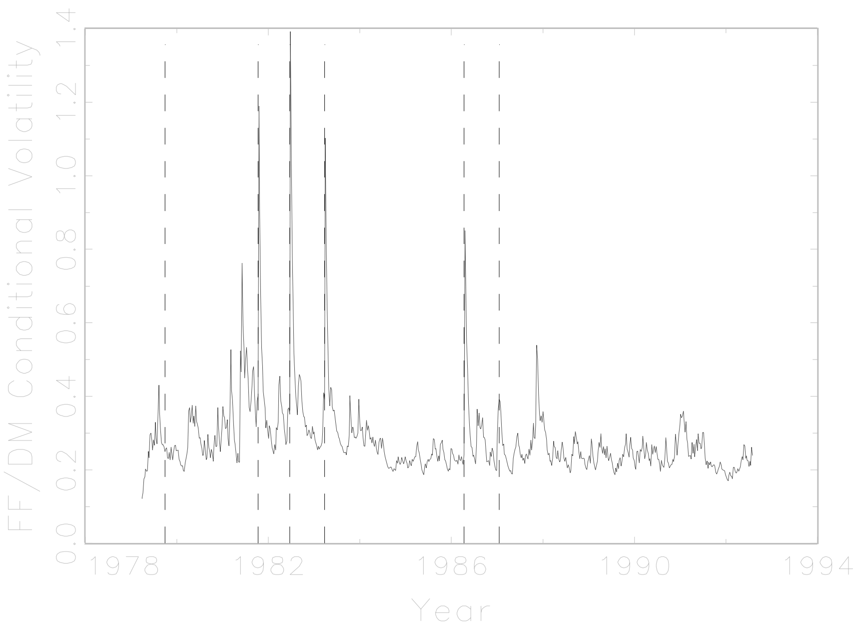

Figure 3: Conditional Standard Deviation Over Time

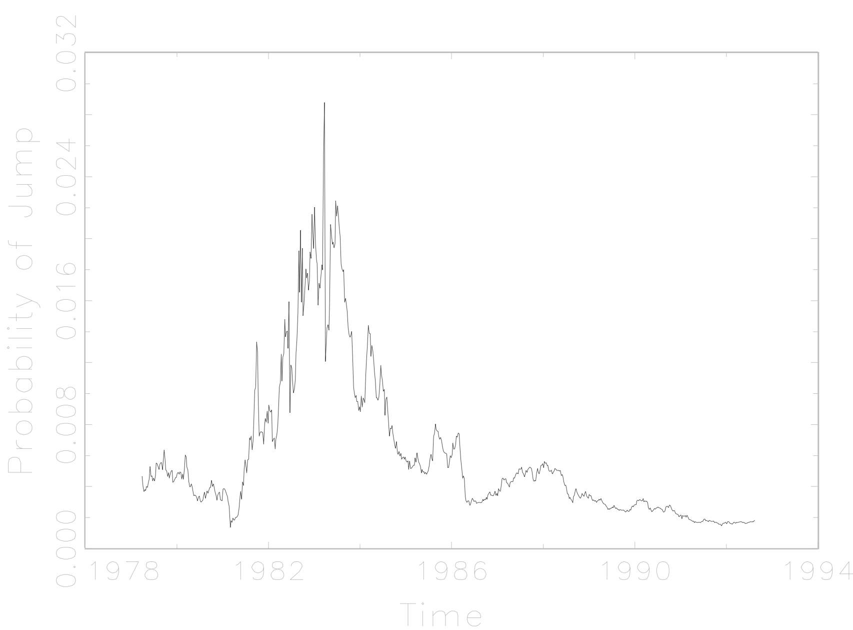

Figure 4: Time Varying Jump Probability

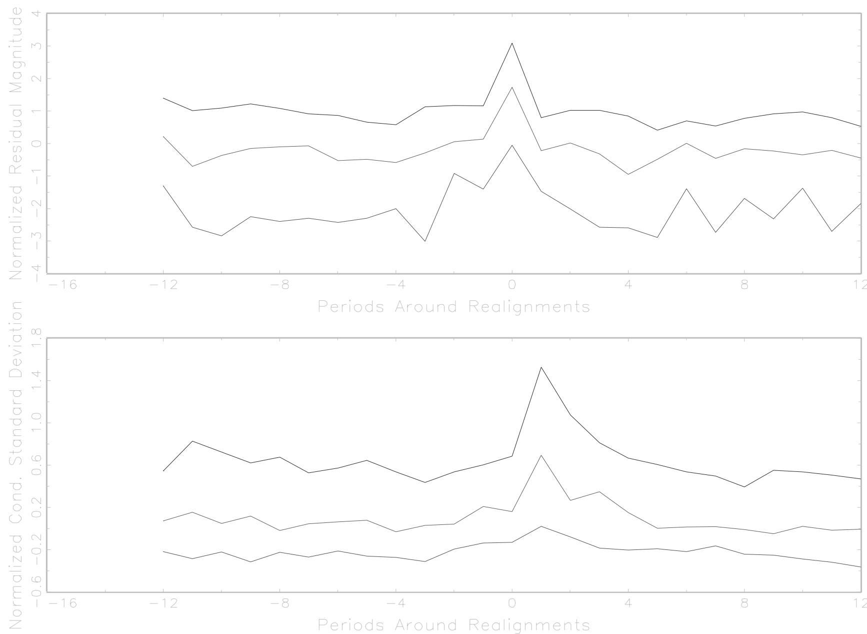

Figure 5: 10th, 50th and 90th Percentiles of Normalized Residual Magnitudes and Forecast Conditional Standard Deviation Around Realignments.