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Volatility transmission across the term structure of swap markets: international evidence

PILAR ABAD and ALFONSO NOVALES‡*

Departamento de Economía Aplicada, Universidad de Vigo. Spain and ‡*Departamento de Economía Cuantitativa, Universidad Complutense, Campus de Somosaguas, 28223 Madrid, Spain*

The behaviour of volatility across the term structure of interest rate swaps is characterized in three currencies (Deutsche mark, Japanese yen and US dollar). For that purpose, a modified GARCH-in mean model is used allowing for seasonal patterns in the mean and variance of interest rates and asymmetric responses to interest rate surprises. Daily interest rate changes are found (a) to be predictable, following autoregressive structures, and (b) to display weekly seasonality. Additionally, interest rate volatility is shown to (a) decrease with maturity, (b) be very persistent and hence, somewhat predictable, which is important when pricing derivatives on swap products, (c) show a tendency to be lower at the beginning of the week, increasing later on, and (d) to respond asymmetrically to interest rate innovations. These properties could clearly be used in risk management with interest rate swaps. Finally, significant transmission of volatility is found from the very short-term to longer-term interest rates. This evidence supports the importance attributed by most central banks to achieving stability in short-term interest rates.

I. INTRODUCTION

The dynamic behaviour of volatility is examined over the term structure of interest rates in swap markets denominated in US dollars, Deutsche marks and Japanese yens between April 1987 and January 1999, paying special attention to the possible transmission of volatility from the very short-term interest rates in money markets, to the longer maturities in swap markets.

Whether money market volatility is specific to that market or rather, it gets transmitted to other interest rate markets trading in longer term maturities, is a central question for monetary policy design, since consumption and investment decisions are affected by interest rates at longer maturities, which are not directly under the control of the monetary authority. It is also a crucial issue when designing immunization strategies for fixed income portfolios and for pricing interest rate derivatives. However, the literature has offered limited empirical evidence on this transmission, and the available results are not very conclusive. The results suggest that there is, in fact, significant transmission of volatility from money markets to the longer maturities in swap markets, which is consistent with interest rate stabilization policies followed by most central banks.

To search for possible patterns of volatility transmission across maturities, volatility variables must be first constructed. Careful specification search becomes crucial, since the results might be biased by inappropriate volatility modelling. One is particularly interested in capturing all volatility characteristics in the models: first, since there is ample evidence of intra-week seasonality when working

*Corresponding author. E-mail: anovales@ccee.ucm.es.

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with high-frequency financial data, one starts by characterizing the seasonal patterns in the conditional mean and variances of interest rates. Even the possibility that serial correlation in interest rates might display some day-of-the week effect is allowed. Second, one also needs to appropriately capture the strong evidence on asymmetric effects of volatility innovations in the data. Third, a relationship is allowed for between the level and the volatility of interest rates at each individual maturity. In addition to these effects, we incorporate the volatility transmission effect, the main focus of this research.

The paper is structured as follows: Section II presents the most relevant characteristics of *IRS* interest rates and their volatilities, which are taken into account when specifying conditional volatility models in Section III. Section IV shows estimation results for these models, and discusses their most relevant characteristics. Section V tests for volatility transmission across the term structure of interest rates. Finally, Section VI presents the more relevant conclusions.[1]

II. GENERAL PROPERTIES OF *IRS* INTEREST RATES

The data

The study started by estimating a term structure of interest rates by the bootstrapping method, using data from two markets: short-term interest rates (1-, 3-, 6- and 12-month maturities) were obtained from either the interbank market (for the US dollar and yen), or the euromarket for deposits (for the Deutsche mark), whereas medium- and long-term rates (between 2- and 10-year maturities) were obtained from the fixed arm of a generic interest rate swap (*IRS*). The term structure is made up by 13 vertices observed daily, from 1 April 1987, 3 April 1987 and 18 September 1989 for the Deutsche mark, US dollar and Japanese yen, respectively, to 31 December 1998. Quotes for daily interest rates from money markets and *IRS* markets were obtained[2] from *Datastream*^{TM}. From them, the volatility of the unpredictable component of each interest rate was estimated, using the more appropriate model of the autoregressive conditional heteroscedasticity family in each case, as discussed below.

Interest rates

Augmented Dickey-Fuller and Phillips-Perron unit root tests indicate that interest rates are $I(1)$ processes for all maturities in the three currencies considered (first two columns in Table 1). The possibility of two unit roots is rejected for all currencies and maturities. Descriptive statistics for daily interest rate changes for the whole sample, as well as for each day of the week, provide a clear suggestion of daily seasonality in interest rates. To formally test for this type of seasonality, a regression of interest rate changes on day-of-the week dummy variables was estimated, testing for statistical significance of individual coefficients, as well as for the null hypothesis that all coefficients are equal to each other, which would amount to lack of daily seasonality. The joint analysis of these statistics, using standard deviations robust to the possible presence of autocorrelation and heteroscedasticity (Newey and West, 1987), leads to rejecting the null hypothesis of absence of daily seasonality in interest rate changes in the three currencies. Specifically, evidence of a positive Monday effect on interest rate changes at the longer maturities in the Deutsche mark and the US dollar, and a possible negative Thursday effect on the Japanese yen were found.[3]

These tests suggest the use of autoregressive processes for the first difference of interest rates, including daily dummy variables. An autoregressive process should be able to capture any serial correlation in interest rate changes, as well as some seasonality effects. Multiplicative dummy variables were also included for the autoregressive term, to test for possible seasonality in the autoregressive component of interest rate changes. As will be later seen, these dummy variables turned out to be significant just for the Deutsche mark.

Volatility

To represent the dynamic behaviour of conditional variances, GARCH specifications were used. To identify the orders p,q of the process, traditional Box-Jenkins techniques were used, together with more formal Lagrange multipliers tests.[4] When these tests were not conclusive, different specifications were considered, performing a battery of tests on estimated coefficients and the corresponding

[1] In all figures and tables, ISO codes for each currency are displayed in parentheses (USD: US dollar; DEM: Deutsche mark, JPY: Yen).
[2] Medium and longer term rates (those between 2- and 10-year maturities) are obtained from the fixed rate payment stream of a generic *IRS*, the variable rate being the equivalent rate from LIBOR. Quoted rates were obtained from *DataStream*^{TM}, which collects them daily at 18:00 hours GMT. They are the average of *bid* and *ask* rates, as provided by *Dark Limited*, from *Intercapital Brokers Limited.*
[3] This preliminary analysis is not shown to save space, but it is available from the authors upon request.
[4] Tests on the simple and partial autocorrelation functions were used for squared standardized residuals from the conditional mean model, as well as Ljung–Box statistics (see Bollerslev, 1987). To test for the null hypothesis of no heteroscedasticity, against the alternative of an ARCH(p) structure for the error term, the Lagrange multiplier statistic is TR^2, R^2 being the R-squared from a regression of the squared residuals from the model for the mean, on a constant and its own first p lags. That statistic is asymptotically distributed as a χ^2_p.

Table 1. *Specification tests*

	DEM						USD						JPY					
	ADF	PP	Sign bias	−size bias	+size bias	Joint	ADF	PP	Sign bias	−size bias	+size bias	Joint	ADF	PP	Sign bias	−size bias	+size bias	Joint
r 1 month	−0.944	−0.986	−0.387*	0.021	6.369*	16.951*	−1.448	−1.397	−0.107	−4.001	16.992*	2.236	−1.345	−1.292	0.231	−2.993	9.536	2.053
	−13.783*	−62.585*	(−3.531)	(0.032)	(3.586)	[0.00]	−13.455*	−60.173*	(−0.520)	(−0.935)	(2.125)	[0.33]	−13.097*	−48.738*	(0.836)	(−1.398)	(1.498)	[0.36]
r 3 month	−0.596	−0.514	0.124	−6.089*	12.593*	1.692	−0.998	−0.911	−0.427*	0.056	43.594	9.509*	−0.019	−0.874	0.315	−9.505*	13.992*	2.055
	−12.646*	−61.759*	(1.021)	(−3.186)	(2.698)	[0.43]	−13.106*	−59.571*	(−2.419)	(0.049)	(1.669)	[0.01]	−12.533*	−46.448*	(1.145)	(−3.330)	(2.407)	[0.36]
r 6 month	−0.637	−0.495	0.093	−7.304*	9.056*	0.232	−1.096	−1.037	−0.928*	1.576	153.063*	8.251*	−1.095	−0.945	0.415	−26.996*	7.468*	2.802
	−11.994*	−63.028*	(0.789)	(−3.191)	(3.155)	[0.89]	−13.358*	−76.132*	(−1.916)	(1.030)	(2.354)	[0.02]	−11.667*	−47.152*	(1.601)	(−2.526)	(2.012)	[0.25]
r 1 year	−0.649	−0.465	0.204*	−7.963*	4.195*	1.817	−1.252	−1.136	−0.166	−3.676	32.626	1.849	−1.279	−1.079	−0.894	−4.811	7.652*	3.903
	−11.466*	−62.477*	(1.739)	(−4.140)	(2.599)	[0.40]	−13.619*	−62.282*	(−0.605)	(−1.209)	(1.505)	[0.40]	−11.852*	−42.906*	(−1.608)	(−0.837)	(2.194)	[0.14]
r 2 year	−0.687	−0.417	−0.259*	−7.790*	11.353*	3.644	−1.347	−1.100	−0.219	−2.358	5.127*	1.261	−1.428	−1.098	0.032	−3.700	18.287*	5.392*
	−11.660*	−51.799*	(−1.939)	(−1.711)	(5.028)	[0.16]	−12.711*	−55.373*	(−0.886)	(−1.484)	(1.760)	[0.53]	−11.214*	−46.832*	(0.229)	(−1.466)	(2.656)	[0.07]
r 3 year	−0.650	−0.334	−0.159	−5.711	13.196*	2.838	−1.310	−1.023	−0.224	−2.367	2.468	4.365	−1.367	−1.016	−0.092	−4.701	19.182*	3.289
	−11.740*	−52.124*	(−1.520)	(−1.372)	(4.672)	[0.24]	−12.711*	−56.032*	(−0.894)	(−1.449)	(1.661)	[0.11]	−11.126*	−47.032*	(−0.624)	(−1.466)	(2.800)	[0.19]
r 4 year	−0.555	−0.194	−0.219*	−4.196	12.550*	5.494*	−1.195	−0.949	−0.122	−2.950*	0.976	8.040*	−1.224	−0.920	−0.255*	−4.687	15.191*	4.074
	−11.459*	−53.830*	(−2.217)	(−1.165)	(5.725)	[0.06]	−12.801*	−56.320*	(−0.589)	(−1.803)	(1.047)	[0.02]	−10.991*	−48.289*	(−1.826)	(−1.594)	(3.044)	[0.13]
r 5 year	−0.407	−0.113	−0.182*	−3.579	11.486*	4.886*	−1.125	−0.900	0.075	−2.560*	1.059	0.762	−1.116	−0.844	−0.307*	−0.101	11.640*	7.792*
	−11.893*	−53.961*	(−2.011)	(−1.243)	(5.291)	[0.09]	−12.897*	−55.663*	(0.838)	(−2.052)	(1.058)	[0.68]	−10.787*	−48.759*	(−2.466)	(−0.051)	(3.041)	[0.02]
r 6 year	−0.271	0.003	−0.251*	−1.423	12.934*	11.233*	−1.076	−0.842	0.100	−3.169*	1.046	1.443	−1.036	−0.766	−0.234*	0.338	10.411*	5.988*
	−11.942*	−53.119*	(−2.895)	(−0.748)	(5.379)	[0.00]	−13.098*	−55.837*	(1.118)	(−2.419)	(1.008)	[0.49]	−10.474*	−48.854*	(−2.056)	(0.158)	(3.120)	[0.05]
r 7 year	−0.120	0.086	−0.282*	−0.564	12.436*	13.853*	−1.024	−0.796	0.078	−4.308*	1.350	2.171	−0.967	−0.695	−0.370*	0.254	11.425*	11.184*
	−12.245*	−55.278*	(−3.347)	(−0.358)	(5.197)	[0.00]	−13.402*	−57.368*	(0.865)	(−3.080)	(1.129)	[0.34]	−10.332*	−50.673*	(−3.339)	(0.112)	(3.257)	[0.00]
r 8 year	−0.038	0.124	−0.269*	−0.424	13.736*	13.651*	−0.985	−0.772	0.049	−3.845*	1.549	1.314	−0.891	−0.658	−0.328*	0.021	10.479*	8.821*
	−12.342*	−54.851*	(−3.128)	(−0.249)	(5.200)	[0.00]	−13.456*	−56.772*	(0.551)	(−2.873)	(1.159)	[0.52]	−10.295*	−50.190*	(−3.032)	(0.009)	(3.466)	[0.01]
r 9 year	0.041	0.141	−0.242*	−1.502	13.695*	10.746*	−0.947	−0.757	0.027	−3.185*	1.909	0.379	−0.834	−0.628	−0.325*	−0.031	9.134*	9.281*
	−12.531*	−55.088*	(−2.798)	(−0.736)	(5.197)	[0.01]	−13.541*	−56.738*	(0.300)	(−2.394)	(1.271)	[0.83]	−10.352*	−50.272*	(−3.077)	(−0.013)	(3.196)	[0.01]
r 10 year	0.111	0.124	−0.219*	−3.856	12.849*	6.663*	−0.914	−0.752	−0.040	−2.459*	2.533	0.225	−0.779	−0.608	−0.246*	−0.700	8.031*	5.482*
	−12.825*	−56.074*	(−2.484)	(−1.259)	(5.166)	[0.04]	−13.654*	−57.352*	(−0.450)	(−1.827)	(1.550)	[0.89]	−10.522*	−51.014*	(−2.343)	(−0.312)	(2.767)	[0.07]

Note: The first two columns show Augmented Dickey-Fuller(ADF) and Phillips-Perron (PP) tests for levels and first differenced interest rates. Critical values at 90% confidence: ADF = −2.582, PP = −2.568. An asterisk denotes significance at 90% confidence. The remaining columns contain statistics for *size* and *sign test*, as proposed by Engle and Ng (1993). The *sign bias* test is the significance test for S^-_{t-1} ($S^-_{t-1} = 1$ when $\varepsilon_{t-1} < 0$, being equal to 0 otherwise) in a regression of squared standardized residuals ($z_t^2 = a + bS^-_{t-1} + u_t$).The tests of *positive and negative bias*, are significance tests for S^-_{t-1} and S^+_{t-1} (where $S^+_{t-1} = 1 - S^-_{t-1}$) in: $z_t^2 = a + bS^-_{t-1}\epsilon_{t-1} + u_t$ and $z_t^2 = a + bS^+_{t-1}\epsilon_{t-1} + u_t$. The table contains estimated coefficients together with the t statistic in parentheses. The last column contains the value of the Wald statistic to test the joint hypothesis: $b_1 = 0$, $b_2 = -b_3$ in: $z_t^2 = a + b_1 S^-_{t-1} + b_2 S^-_{t-1}\epsilon_{t-1} + b_3 S^-_{t-1}\epsilon_{t-1} + u_t$. Its p-value is shown in square brackets.

residuals. A model was required to leave no evidence of autocorrelation or conditional variance in the residuals. In addition, the possibility that volatility might be affected asymmetrically by positive and negative innovations was searched for.

To test for the possible existence of this *leverage effect* in volatility, the behaviour of standardized residuals was examined from the estimation of the conditional mean model, using the *bias* and *sign* tests proposed by Engle and Ng (1993). Denoting by ε_t those residuals, defined as dummy variable S_{t-1}^- to be equal to 1 when $\varepsilon_{t-1} < 0$, being equal to 0 otherwise. The *sign bias* test is the significance test for S_{t-1}^- in a regression of squared standardized residuals $[z_t^2 = a + b\,S_{t-1}^- + u_t]$, to check if the average size of positive and negative residuals is the same. To evaluate the different impact on volatility of positive and negative surprises, Engle and Ng propose the tests of *positive and negative bias,* as the significance of S_{t-1}^- and S_{t-1}^+ (where $S_{t-1}^+ = 1 - S_{t-1}^-$ in: $z_t^2 = a + bS_{t-1}^-\,\varepsilon_{t-1} + u_t$ and $z_t^2 = a + bS_{t-1}^+\,\varepsilon_{t-1} + u_t$. Finally, they propose to jointly test for both effects through a Lagrange multipliers test for joint significance of b_1, b_2 and b_3 in: $z_t^2 = a + b_1 S_{t-1}^- + b_2 S_{t-1}^-\,\varepsilon_{t-1} + b_3 S_{t-1}^+\,\varepsilon_{t-1} + u_t$.[5] Under the null, there is no effect from last period's innovations on the size of current innovations. Here, since the test is performed at the identification stage, we propose testing for the weaker null hypothesis: $b_1 = 0$, $b_2 = -b_3$, that the effect of last period's innovations on squared current innovations does not depend on sign.

The joint analysis of these statistics (last four columns in Table 1) suggests some evidence of asymmetric effects for the three currencies. For the Deutsche mark and Japanese yen, the *sign bias* test shows the average squared normalized residual to be smaller following negative interest rate surprises, suggesting that volatility could be higher after positive interest rate innovations. This is what should be expected in interest rate markets, where an increase in zero coupon rates implies a lower price for the *IRS* and hence, it is perceived as *bad news*. The *size bias* tests show that, at least for the Deutsche mark and Japanese yen, large positive interest rate innovations (*bad news*) increase volatility by significantly more than small positive innovations. For the US dollar, significant evidence is obtained for the size effect only in the case of *good news* (negative interest rate surprises). That these preliminary results are not fully consistent for the three currencies and maturities may be due to the fact that these tests are being run in a model estimated under the assumption of a constant variance. Nevertheless, the evidence is important enough to consider the possibility of *leverage effects*, as explained in next section.

III. MODEL SPECIFICATION

When the possibility of a *leverage effect* was detected, a GJR-GARCH model was estimated (Glosten *et al.*, 1993), which is able to capture such effect. It is a linear model which in this application does not show excessive convergence problems in estimation, and it is not too sensible to the presence of extreme values. Model specification is,

$$\Delta r_t = E[\Delta r_t/\Omega_{t-1}] + \varepsilon_t, \quad \varepsilon_t/\Omega_{t-1} = N(0, \sigma_t)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\,\varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i\,\varepsilon_{t-i}^2\,S_{t-i}^- + \sum_{j=1}^{p} \beta_j\,\sigma_{t-j}^2$$

where Δr_t are daily changes in interest rates, and ε_t their unanticipated component, independent over time and assumed to follow Normal distribution, with zero mean and conditional variance σ_t^2.

This model allows for a different reaction of volatility to positive and negative surprises, although maintaining the assumption that the minimum volatility level is attained when there are no news of any sign. Then, $\varepsilon_t = 0$, and volatility is given by $\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j\,\sigma_{t-j}^2$. The impact of news on volatility depends on the sign of the estimated parameters. When the γ_i coefficients are positive, negative interest rates surprises produce bigger increases in volatility than positive surprises of the same size. Alternatively, when a *leverage effect* was not detected, a GARCH model was estimated (Bollerslev, 1986), a particular case of the previous specification when the γ_i coefficients are equal to zero.

Lagrange multiplier tests were also implemented for the existence of a *trade-off* between return and volatility.[6] When such a relationship was detected, GARCH or GJR-GARCH was estimated in mean models (Engle *et al.*, 1987). In line with Baillie and Bollerslev (1989), possible seasonal effects were also considered in conditional variance, including dummy variables for each day of the week in the equation for the variance.

To test for possible transmission of volatility from short to long maturities, the conditional standard deviation of the 1-month money market interest rate was introduced as an explanatory variable in the conditional variance equation for longer maturities. This way, coefficients associated to this variable measure the extent to which volatility gets transmitted from the shortest maturity to all other

[5] The Lagrange multiplier statistic is TR^2, R^2 being the *R*-squared obtained when estimating the model, and *T* the sample size. It is asymptotically distributed as a χ_3^2.

[6] To test for existence of a GARCH in the mean structure, an omitted variable test was performed in the equation for the conditional mean for interest rate changes. The statistic is TR^2, R^2 being the *R*-squared from a regression of the residuals from the equation for the mean, on a constant and the omitted variable. It is asymptotically distributed as a χ_1^2.

maturities. The conditional variance of the 1-month rate short-term maturity was previously obtained from its own model, as described above. The final specification for interest rates other than the shorter maturity, is

$$\Delta r_t = \sum_{j=1}^{5} \varphi_j \Delta ri_{t-j} + \omega_M M_t + \omega_T T_t + \omega_W W_t + \omega_{Th} Th_t + \omega_F F_t + \kappa\sigma_t + \varepsilon_t, \quad \varepsilon_t/\Omega_{t-1} = N(0, \sigma_t)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 S_{t-i}^- + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \varphi_M M_t + \varphi_W W_t + \varphi_{Th} Th_t + \varphi_F F_t + \lambda\sigma_{t,\,1\text{month}}$$

where M_t, T_t, W_t, Th_t, F_t denote day of the week dummy variables[7] and $\sigma_{t,\,1\,\text{month}}$ denotes the conditional standard deviation of the 1-month rate.

IV. EMPIRICAL RESULTS

Interest rates

Maximum likelihood estimates of the conditional mean and variance equations for the three currencies at all maturities considered are shown in Table 2, where the standard deviations suggested by Bollerslev and Wooldridge (1992) have been used, which are robust to deviations from Normality in the residuals. Daily changes in interest rates follow autoregressive processes, especially at the shorter maturities. The order of these structures is never greater than 5, the number of lags which would be needed to capture the possible presence of significant weekly seasonality. Autoregressive structures imply some predictability for interest rates in swap markets, even at the daily frequencies used in the estimation, contradicting the random walk hypothesis. In the US dollar, Deutsche mark and the longer maturities of the Japanese yen, first order autoregressive coefficients are often negative, reflecting mean reversion in interest rates. For the Deutsche mark there is some evidence that the autoregressive structure may be specific of the day of the week. This type of nonlinear seasonal structure has been observed in other financial markets and macroeconomic variables (see Flores and Novales, 1997a, b; Ghysels and Osborne, 2001 among others), and could be captured through the use of periodic models. That would be an interesting issue for further research, since seasonal autocorrelation might have significant implications for interest rate forecasting as well as for risk management in fixed income portfolios.

Daily dummy variables show significant weekly seasonality in interest rate changes: in consistency with the results of the preliminary analysis of interest rates in Section II, there is a tendency for Mondays to show increases[8] in interest rates in the US dollar and Deutsche mark, which is corrected later in the week. In some cases, this characteristic is observed in the form of negative coefficients for the remaining days. For the Japanese yen, Mondays also show, on the average, higher interest rate changes than any other day. But interest rates on the yen maintained a negative trend over the sample period,[9] so that this effect comes in the form of a negative coefficient of smaller absolute size on Mondays. This corresponds with the well known fact that in fixed income markets, portfolio returns[10] for the last day of negotiation in the week are significantly higher than those obtained any other day, sometimes called the *week-end effect*. In swap markets, this same effect was detected, although one day later. The reason could well be due to the fact that hedging adjustments usually take place at the end of the negotiation date, after *Datastream*^{TM} data are gathered 18 hours *GMT*.

Conditional volatility

The specification search for a model for the variance of interest rates at different maturities and currencies led to GARCH(1,1) or GJR-GARCH(1,1) models in all cases. Except for 1-month rates, estimates of the autoregressive parameter in the variance equation are quite high in all maturities and currencies, showing a strong inertial behaviour in volatility. This high persistence indicates a slow response of volatility to interest rate surprises, a standard observation in most high-frequency financial time series.

The last columns in Table 2 show Lagrange multiplier tests for first order autocorrelation in variance, together with Ljung-Box statistics of order 10 on the residuals and squared residuals, not detecting any significant indication of remaining autocorrelation structures in the mean or in the variance of interest rates. Only for the Deustche mark are these statistics sometimes significant, but it is due to the presence of extreme values, rather than to any systematic misspecification problem. Hence, the specification seems to adequately capture the dynamic structure in the first two moments of daily interest rate changes.[11]

[7] In the specification of the model for the conditional variance, Tuesdays were used as the benchmark.
[8] Indeed, a positive coefficient for the Monday dummy suggests a value for interest rate changes above their mean, which is essentially zero.
[9] In fact, average interest rate changes were negative and statistically significant for each day of the week.
[10] One must bear in mind the negative association between interest rate movements and returns in fixed income markets.
[11] Nelson (1992) shows that GARCH models are quite robust to some types of misspecification errors. Specifically, if the process generating prices can be approximated by a diffusion, and enough high frequency data is available, these models provide consistent estimates of the conditional variance even under an incorrect specification.

Table 2a. *(DEM). Estimated GJR-GARCH models with volatility transmission*

$$\Delta ri_t = \varphi_1 \Delta ri_{t-1} + \varphi_2 \Delta ri_{t-2} + \varphi_3 \Delta ri_{t-3} + \varphi_4 \Delta ri_{t-4} + \varphi_5 \Delta ri_{t-5} + \omega_M M_t + \omega_T T_t + \omega_W W_t + \omega_{Th} Th_t + \omega_F F_t + \eta_M (M_t \cdot \Delta ri_{t-1}) + \eta_T (T_t \cdot \Delta ri_{t-1})$$
$$+ \eta_W (W_t \cdot \Delta ri_{t-1}) + \eta_{Th} (Th_t \cdot \Delta ri_{t-1}) + \eta_F (F_t \cdot \Delta ri_{t-1}) + \kappa \sigma_t + \varepsilon_t$$
$$\sigma_t^2 = \nu + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 S_{t-1}^- + \beta \sigma_{t-1}^2 + \varphi_M M_t + \varphi_W W_t + \varphi_{Th} Th_t + \varphi_F F_t + \lambda \sigma_{t,\,1\mathrm{month}}$$

	φ_1	φ_2	φ_3	φ_4	φ_5	ω_M	ω_T	ω_W	ω_{Th}	ω_F	η_M	η_T	η_W	η_{Th}	η_F	κ	ν	α	γ	β	φ_{Th}	λ	Q(10)	LM(1)	$Q^2(10)$
r 1 month	−0.130*	–	–	–	–	–	–	–	–	–	−0.115*	–	–	–	–	–	0.559*	0.553*	−0.521*	0.232*	–	–	0.12	16.58	3.60
	(0.027)										(0.071)						(0.096)	(0.204)	(0.202)	(0.099)			[0.73]	[0.08]	[0.96]
r 3 month	−0.126*	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	−0.011	0.080*	–	0.895*	–	0.241**	2.38	19.43	7.03
	(0.023)																(0.016)	(0.017)		(0.020)		(0.177)	[0.12]	[0.04]	[0.72]
r 6 month	−0.133*	–	−0.058*	–	–	–	–	–	–	–	–	–	–	–	–	–	−0.015	0.079*	–	0.877*	–	0.334*	5.69	21.92	13.22
	(0.021)		(0.021)														(0.017)	(0.019)		(0.024)		(0.197)	[0.02]	[0.02]	[0.21]
r 1 year	−0.155*	−0.061*	−0.044*	–	–	–	–	–	−0.729*	–	0.179*	–	–	–	–	–	−0.021	0.102*	–	0.842*	–	0.451*	0.38	16.20	5.93
	(0.024)	(0.022)	(0.022)						(0.224)		(0.057)						(0.021)	(0.022)		(0.029)		(0.239)	[0.54]	[0.09]	[0.82]
r 2 year	–	–	–	–	0.054*	0.575*	–	–	–	–	0.145*	–	–	–	0.201*	−0.042*	−0.008**	0.099*	–	0.879*	0.053*	0.036	0.38	23.06	15.34
					(0.023)	(0.188)					(0.046)				(0.048)	(0.019)	(0.006)	(0.019)		(0.018)	(0.018)	(0.058)	[0.54]	[0.01]	[0.12]
r 3 year	–	–	–	–	0.061*	0.640*	–	–	–	–	0.163*	–	–	–	0.163*	−0.054*	−0.015*	0.075*	–	0.904*	0.074*	0.051	0.18	26.65	9.17
					(0.021)	(0.202)					(0.044)				(0.043)	(0.020)	(0.006)	(0.018)		(0.018)	(0.021)	(0.056)	[0.67]	[0.01]	[0.52]
r 4 year	0.061*	–	–	–	–	0.635*	–	–	–	–	–	–	–	–	–	−0.060*	−0.009	0.100*	–	0.852*	0.084*	0.024	0.02	22.59	7.71
	(0.021)					(0.195)										(0.019)	(0.007)	(0.019)		(0.024)	(0.022)	(0.063)	[0.88]	[0.01]	[0.66]
r 5 year	–	–	–	–	0.037*	0.650*	–	–	–	–	0.100*	–	–	–	–	−0.065*	−0.012*	0.084*	–	0.889*	0.067*	0.046	0.01	19.47	13.08
					(0.021)	(0.195)					(0.045)					(0.020)	(0.006)	(0.016)		(0.019)	(0.019)	(0.051)	[0.92]	[0.04]	[0.22]
r 6 year	0.047*	–	–	–	–	0.559*	–	–	–	–	–	–	–	–	–	−0.054*	−0.008**	0.111*	−0.051*	0.883*	0.051*	0.040	0.11	18.97	8.79
	(0.020)					(0.181)										(0.021)	(0.005)	(0.018)	(0.026)	(0.021)	(0.015)	(0.044)	[0.74]	[0.04]	[0.55]
r 7 year	–	–	–	–	–	0.459*	–	–	–	–	0.069*	–	–	–	–	−0.048*	−0.007**	0.098*	−0.053*	0.897*	0.044*	0.042	0.09	13.02	4.06
						(0.181)					(0.041)					(0.020)	(0.005)	(0.016)	(0.022)	(0.018)	(0.016)	(0.040)	[0.76]	[0.22]	[0.95]
r 8 year	–	–	–	–	–	0.434*	–	–	–	–	–	–	–	–	–	−0.049*	−0.007**	0.095*	−0.051*	0.902*	0.037*	0.046	0.01	13.40	2.91
						(0.175)										(0.020)	(0.005)	(0.016)	(0.020)	(0.017)	(0.014)	(0.039)	[0.93]	[0.20]	[0.98]
r 9 year	–	–	–	–	–	0.401*	–	–	–	–	–	–	–	–	–	−0.048*	−0.007**	0.091*	−0.047*	0.904*	0.027*	0.067**	0.35	8.72	2.12
						(0.176)										(0.020)	(0.005)	(0.017)	(0.020)	(0.018)	(0.014)	(0.043)	[0.55]	[0.56]	[0.99]
r 10 year	–	–	–	–	–	0.347*	–	–	–	–	–	–	–	–	–	−0.043*	−0.008**	0.097*	−0.053*	0.896*	0.025*	0.094*	1.93	5.27	2.41
						(0.180)										(0.020)	(0.005)	(0.018)	(0.022)	(0.020)	(0.016)	(0.049)	[0.17]	[0.87]	[0.99]

Note: Sample period: 4/3/1987 to 12/31/1998. Bollerslev–Wooldridge (1992) robust standard deviations in parentheses. M, T, W, Th and F are dummy variables to capture possible day-of-the week effects. Estimated values for ω_L, ω_X, ω_J, ω_V, φ_L, φ_X, φ_J, φ_V, ν and λ have been multiplied by 10^2. The dummy variable S_t^- is equal to 1 when $\varepsilon_t < 0$ and equal to 0 otherwise. An (two) asterisk(s) denotes statistical significance at 90% (80%) confidence. LM(1) is the Lagrange multiplier test for ARCH(1) effects on the residuals. Q(10) and $Q^2(10)$ are the Ljung-Box autocorrelation statistics for the residuals and squared residuals. p–values are included in square brackets.

Table 2b. *(USD). Estimated GJR-GARCH models with volatility transmission*

$$\Delta r\, i_t = \delta + \varphi_1\, \Delta r\, i_{t-1} + \varphi_2\, \Delta r\, i_{t-2} + \varphi_3\, \Delta r\, i_{t-3} + \varphi_4\, \Delta r\, i_{t-4} + \varphi_5\, \Delta r\, i_{t-5} + \omega_M\, M_t + \omega_T\, T_t + \omega_W\, W_t + \omega_{Th}\, Th_t + \omega_F\, F_t + \kappa\, \sigma_t + \varepsilon_t$$

$$\sigma_t^2 = \nu + \alpha\, \varepsilon_{t-1}^2 + \gamma\, \varepsilon_{t-1}^2\, S_{t-1}^- + \beta\, \sigma_{t-1}^2 + \varphi_M\, M_t + \varphi_W\, W_t + \varphi_{Th}\, Th_t + \varphi_F\, F_t + \lambda\, \sigma_{t,\,\mathrm{1month}}$$

	δ	φ_1	φ_2	φ_3	φ_4	φ_5	ω_M	ω_T	ω_W	ω_{Th}	ω_F	κ	ν	α	γ	β	φ_M	φ_W	φ_{Th}	φ_F	λ	Q(10)	LM(1)	$Q^2(10)$
r 1 month	–	–	0.065*	–	–	–	–	–	–	–	–	–	–0.158	0.204*	–	0.422*	1.020*	0.705*	1.177*	–	–	0.05	5.12	1.77
			(0.027)										(0.163)	(0.099)		(0.121)	(0.401)	(0.273)	(0.347)			[0.82]	[0.88]	[0.99]
r 3 month	0.092	–	–	–	–	–	–	–	–	–	–	–	–0.035	0.083*	–	0.912*	–	–	–	–	0.472**	1.78	10.30	2.32
	(0.191)												(0.028)	(0.034)		(0.023)					(0.339)	[0.18]	[0.42]	[0.99]
r 6 month	–0.068	–	–	–	–	–	–	–	–	–	–	–	–0.122	0.314*	–	0.365*	–	–	–	1.327*	2.225*	0.05	13.47	1.20
	(0.120)												(0.090)	(0.120)		(0.148)				(1.000)	(0.786)	[0.83]	[0.20]	[1.00]
r 1 year	–	–0.065*	–	–0.077*	–	–	–	–	–	–	–	–	0.104**	0.089*	–	0.846*	–	–0.430*	–	–	0.432	1.45	9.44	3.17
		(0.030)		(0.038)									(0.078)	(0.041)		(0.036)		(0.202)			(0.487)	[0.23]	[0.49]	[0.98]
r 2 year	–	–	–	–	–0.031*	–	–	–	–	–0.671*	–	–	–0.010	0.085*	–0.054*	0.912*	–0.307*	–	0.110*	0.242*	0.177*	0.03	12.28	3.98
					(0.020)					(0.266)			(0.020)	(0.026)	(0.025)	(0.014)	(0.075)		(0.049)	(0.079)	(0.106)	[0.88]	[0.27]	[0.95]
r 3 year	–	–	–	–	–0.031*	–	0.443*	–	–	–	–	–0.031**	–0.014	0.073*	–0.050*	0.914*	–0.357*	–	0.123*	0.309*	0.185**	0.13	11.09	3.32
					(0.019)		(0.264)					(0.021)	(0.020)	(0.022)	(0.023)	(0.016)	(0.109)		(0.048)	(0.119)	(0.132)	[0.72]	[0.35]	[0.97]
r 4 year	–	–	–	–	–0.039*	–	0.444*	–	–	–	–	–0.034*	–0.004	0.068*	–0.042*	0.924*	–0.321*	–	0.143*	0.279*	–0.022	0.06	7.40	3.46
					(0.020)		(0.262)					(0.021)	(0.017)	(0.018)	(0.020)	(0.012)	(0.098)		(0.043)	(0.104)	(0.034)	[0.81]	[0.69]	[0.97]
r 5 year	–	–	–	–	–	–	0.545*	–	–	–	–	–0.033*	–0.004	0.064*	–0.035*	0.917*	–0.228*	–	0.133*	0.181*	0.019	0.31	8.37	13.99
							(0.254)					(0.020)	(0.018)	(0.015)	(0.016)	(0.019)	(0.057)		(0.042)	(0.054)	(0.044)	[0.58]	[0.59]	[0.17]
r 6 year	–	–	–	–	–	–	0.484*	–	–	–	–	–0.032**	0.001	0.067*	–0.036*	0.914*	–0.198*	–	0.137*	0.138*	–0.016	0.45	8.76	17.50
							(0.249)					(0.020)	(0.017)	(0.015)	(0.016)	(0.018)	(0.052)		(0.041)	(0.048)	(0.032)	[0.51]	[0.56]	[0.06]
r 7 year	–	–	–	–	–	–	0.456*	–	–	–	–	–0.030**	0.002	0.064*	–0.031*	0.921*	–0.173*	–	0.133*	0.098*	–0.005	0.16	7.35	18.12
							(0.252)					(0.020)	(0.017)	(0.015)	(0.016)	(0.017)	(0.051)		(0.042)	(0.046)	(0.033)	[0.69]	[0.69]	[0.05]
r 8 year	–	–	–	–	–	–	0.446*	–	–	–	–	–0.031*	0.001	0.068*	–0.039*	0.919*	–0.158*	–	0.132*	0.086*	–0.006	0.26	7.55	19.66
							(0.246)					(0.020)	(0.017)	(0.016)	(0.016)	(0.017)	(0.049)		(0.040)	(0.043)	(0.031)	[0.61]	[0.67]	[0.03]
r 9 year	–	–	–	–	–	–	0.507*	–	–	–	–	–0.033*	0.004	0.069*	–0.041*	0.921*	–	–	–	–	0.076**	0.02	10.54	17.95
							(0.247)					(0.020)	(0.005)	(0.017)	(0.018)	(0.016)					(0.052)	[0.90]	[0.40]	[0.06]
r 10 year	–	–	–	–	–	–	0.524*	–	–	–	–	–0.034*	0.001	0.068*	–0.045*	0.923*	–	–	–	–	0.121*	0.11	10.60	12.12
							(0.249)					(0.021)	(0.006)	(0.017)	(0.019)	(0.016)					(0.068)	[0.75]	[0.39]	[0.28]

Note: Sample period: 4/3/1987 to 12/31/1998. Bollerslev–Wooldridge (1992) robust standard deviations in parentheses. *M*, *T*, *W*, *Th* and *F* are dummy variables to capture possible day-of-the week effects. Estimated values for δ, ω_L, ω_X, ω_J, ω_V, φ_L, φ_X, φ_J, φ_V, ν and λ have been multiplied by 10^2. The dummy variable S_t^- is equal to 1 when $\varepsilon_t < 0$ and equal to 0 otherwise. An (two) asterisk(s) denotes statistical significance at 90% (80%) confidence. LM(1) is the Lagrange multiplier test for ARCH(1) effects on the residuals. Q(10) and $Q^2(10)$ are the Ljung-Box autocorrelation statistics for the residuals and squared residuals. *p*-values are included in square brackets.

Table 2c. *(JPY). Estimated GJR-GARCH models with volatility transmission*

$$\Delta r\, i_t = \varphi_1\, \Delta r\, i_{t-1} + \varphi_2\, \Delta r\, i_{t-2} + \varphi_3\, \Delta r\, i_{t-3} + \varphi_4\, \Delta r\, i_{t-4} + \varphi_5\, \Delta r\, i_{t-5} + \omega_M\, M_t + \omega_T\, T_t + \omega_W\, W_t + \omega_{Th}\, Th_t + \omega_F\, F_t + \kappa\, \sigma_t + \varepsilon_t$$

$$\sigma_t^2 = \nu + \alpha\, \varepsilon_{t-1}^2 + \gamma\, \varepsilon_{t-1}^2\, S_{t-1}^- + \beta\, \sigma_{t-1}^2 + \varphi_M\, M_t + \varphi_W\, W_t + \varphi_{Th}\, Th_t + \varphi_F\, F_t + \lambda\, \sigma_{t,\,1\text{month}}$$

	φ_1	φ_2	φ_3	φ_4	φ_5	ω_M	ω_T	ω_W	ω_{Th}	ω_F	κ	ν	α	γ	β	φ_M	φ_W	φ_{Th}	φ_F	λ	Q(10)	LM(1)	$Q^2(10)$
r 1 month	0.154*	0.123*	−0.122*	–	–	−0.573*	–	–	–	–	–	0.095*	0.483*	–	0.552*	–	–	–	–		0.23	14.14	1.08
	(0.067)	(0.059)	(0.071)			(0.348)						(0.024)	(0.100)		(0.049)						[0.63]	[0.17]	[1.00]
r 3 month	0.162*	–	–	0.078*	–	−0.337*	–	–	–	–	–	−0.035*	0.216*	–	0.737*	–	–	0.067*	0.029*	0.537*	0.35	8.87	4.81
	(0.026)			(0.023)		(0.089)						(0.001)	(0.010)		(0.004)			(0.002)	(0.002)	(0.018)	[0.55]	[0.55]	[0.90]
r 6 month	0.194*	–	0.085*	–	–	–	–	–	–	–	–	0.038*	0.139*	–	0.847*	−0.112*	−0.072*	–	–	0.089*	1.66	9.38	9.66
	(0.033)		(0.028)									(0.000)	(0.025)		(0.022)	(0.000)	(0.003)			(0.025)	[0.20]	[0.50]	[0.47]
r 1 year	0.242*	–	–	–	–	−0.275*	–	–	–	–	–	−0.081	0.106*	–	–	–	–	–	–	3.774*	0.01	14.23	0.50
	(0.035)					(0.147)						(0.119)	(0.066)							(2.141)	[0.91]	[0.16]	[1.00]
r 2 year	0.054*	–	–	0.046*	–	−0.372*	–	–	−0.437*	−0.392*	–	0.016*	0.079*	–	0.903*	−0.026*	–	–	−0.047*	0.053*	0.00	15.12	4.99
	(0.022)			(0.024)		(0.150)			(0.178)	(0.176)		(0.006)	(0.016)		(0.018)	(0.014)			(0.020)	(0.038)	[0.98]	[0.13]	[0.89]
r 3 year	0.041*	–	–	0.046*	–	−0.332*	–	−0.379*	−0.473*	−0.395*	–	0.023*	0.094*	–	0.884*	−0.036*	–	–	−0.065*	0.051**	0.00	17.27	5.35
	(0.023)			(0.023)		(0.155)		(0.228)	(0.198)	(0.180)		(0.007)	(0.019)		(0.020)	(0.016)			(0.023)	(0.040)	[0.98]	[0.07]	[0.87]
r 4 year	–	0.040*	–	0.055*	–	−0.422*	–	−0.398*	−0.518*	−0.382*	–	0.028*	0.095*	–	0.873*	−0.075*	–	−0.053*	–	0.086**	0.05	15.87	5.62
		(0.023)		(0.022)		(0.162)		(0.218)	(0.194)	(0.198)		(0.011)	(0.021)		(0.025)	(0.025)		(0.029)		(0.059)	[0.83]	[0.10]	[0.85]
r 5 year	–	–	–	0.066*	–	−0.323*	–	−0.381*	−0.492*	−0.369*	–	0.035*	0.092*	–	0.877*	−0.059*	–	−0.052*	−0.050*	0.072**	0.81	16.32	5.22
				(0.023)		(0.161)		(0.212)	(0.193)	(0.189)		(0.010)	(0.021)		(0.025)	(0.021)		(0.028)	(0.020)	(0.050)	[0.37]	[0.09]	[0.88]
r 6 year	–	–	–	0.059*	–	−0.406*	–	−0.618*	−0.694*	−0.523*	1.071*	0.033*	0.095*	–	0.877*	−0.050*	–	−0.042*	−0.054*	0.048**	1.95	15.31	6.55
				(0.023)		(0.182)		(0.246)	(0.227)	(0.204)	(0.647)	(0.010)	(0.019)		(0.023)	(0.019)		(0.026)	(0.018)	(0.036)	[0.16]	[0.12]	[0.77]
r 7 year	−0.049*	–	–	0.042*	–	−0.354*	–	−0.589*	−0.724*	−0.521*	1.229*	0.015*	0.122*	−0.048*	0.876*	–	–	–	−0.051*	0.018	1.47	16.13	5.80
	(0.023)			(0.023)		(0.198)		(0.234)	(0.227)	(0.197)	(0.626)	(0.005)	(0.024)	(0.026)	(0.021)				(0.018)	(0.028)	[0.23]	[0.10]	[0.83]
r 8 year	−0.044*	–	–	0.037*	–	−0.517*	−0.422*	−0.721*	−0.902*	−0.631*	2.301*	0.013*	0.122*	−0.049*	0.875*	–	–	–	−0.042*	0.021	2.57	12.81	7.91
	(0.022)			(0.023)		(0.205)	(0.215)	(0.243)	(0.240)	(0.207)	(0.810)	(0.005)	(0.024)	(0.027)	(0.022)				(0.018)	(0.030)	[0.11]	[0.24]	[0.64]
r 9 year	−0.051*	–	–	–	–	−0.576*	−0.490*	−0.763*	−0.974*	−0.679*	2.634*	0.011*	0.117*	−0.043*	0.875*	–	–	–	−0.032*	0.026	3.45	14.20	10.37
	(0.022)					(0.208)	(0.216)	(0.241)	(0.238)	(0.213)	(0.860)	(0.005)	(0.023)	(0.026)	(0.023)				(0.019)	(0.033)	[0.06]	[0.16]	[0.41]
r 10 year	−0.060*	–	–	–	–	−0.592*	−0.484*	−0.763*	−0.947*	−0.690*	2.458*	0.004**	0.085*	–	0.886*	–	–	–	–	0.031	2.39	13.43	10.20
	(0.022)					(0.223)	(0.223)	(0.245)	(0.241)	(0.236)	(0.898)	(0.003)	(0.015)		(0.021)					(0.035)	[0.12]	[0.20]	[0.42]

Note: Sample period: 9/19/1989 to 12/31/1998. Bollerslev–Wooldridge (1992) robust standard deviations in parentheses. *M*, *T*, *W*, *Th* and *F* are dummy variables to capture possible day-of-the week effects. Estimated values for ω_L, ω_X, ω_J, ω_V, φ_L, φ_X, φ_J, φ_V, ν and λ have been multiplied by 10^2. The dummy variable S_t^- is equal to 1 when $\varepsilon_t < 0$ and equal to 0 otherwise. An (two) asterisk(s) denotes statistical significance at 90% (80%) confidence. LM(1) is the Lagrange multiplier test for ARCH(1) effects on the residuals. Q(10) and $Q^2(10)$ are the Ljung-Box autocorrelation statistics for the residuals and squared residuals. *p*-values are included in square brackets.

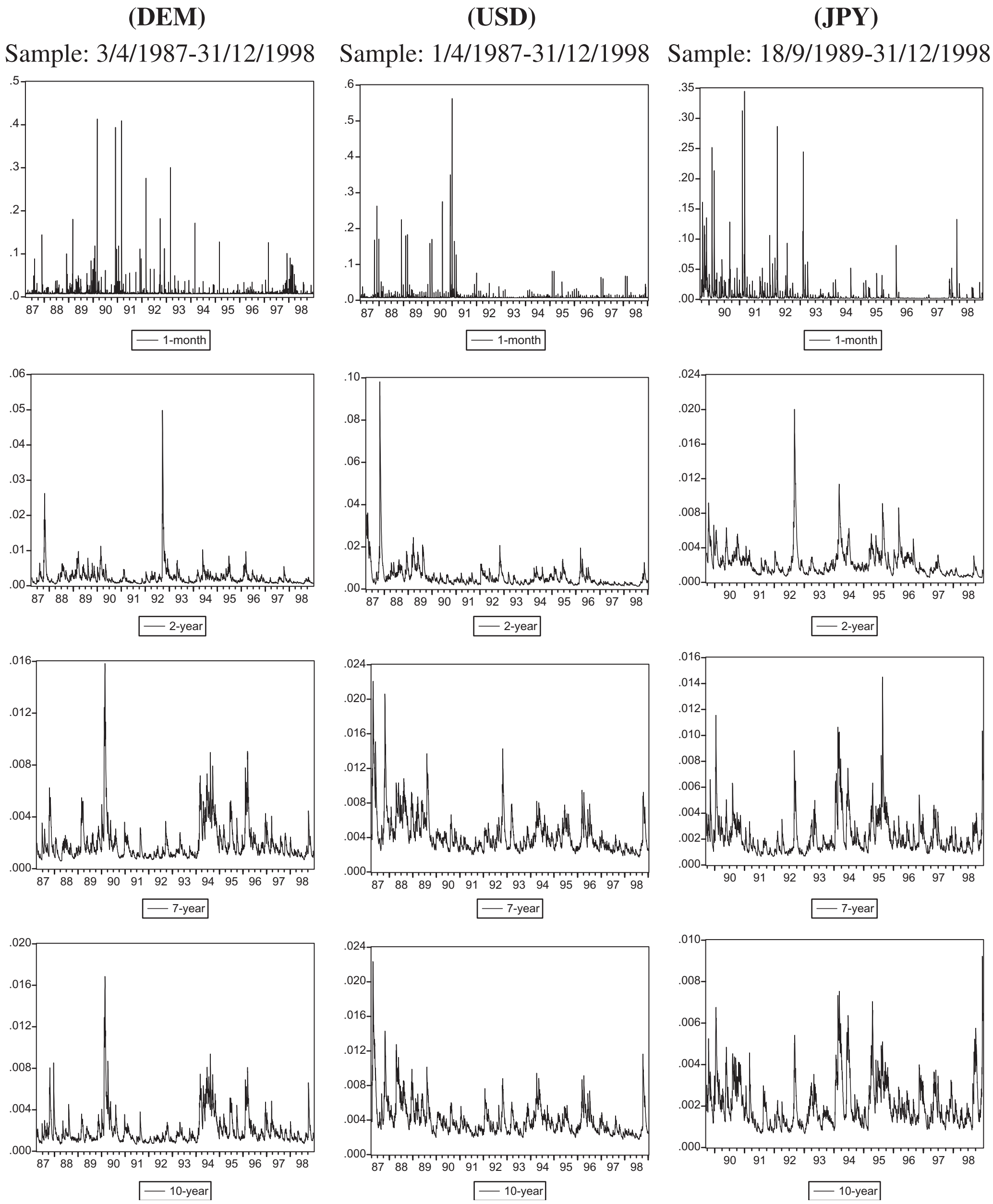

Fig. 1. *Daily volatility estimated from GARCH, GARCH-M or GJR-GARCH for 1-month and 2-, 7- and 10-year rates*

Figure 1 shows estimated daily conditional standard deviations for zero coupon rates from swap markets in the three currencies, for the 1-month, 2-, 7- and 10-year maturities. Although the range of values in the vertical axis is not kept constant in the graphs for the different maturities, it is easy to see that volatility decreases with maturity, as observed in most analysis of the term structure of interest rates. Even though swap rates show few changes in their level, they exhibit important variations over time in their conditional variance. The estimates show that interest rate volatility in swap markets was rather high over some periods of time. Specifically, high volatility levels are seen in the Deutsche mark at the beginning of 1990, as a consequence of increased uncertainty about the economic consequences of the German reunification. A similar process arose after 1992, reflecting the crisis in currency markets. The *black October* of 1987 in Wall Street led to a sharp increase in volatility in US dollar interest rates, while the several successive crises in Asia increased volatility in interest rates in yens.

Asymmetry in volatility: the leverage effect

Even though the *sign* and *size bias* tests proposed by Engle and Ng (1993) already detected some asymmetric responses of volatility to innovations on some interest

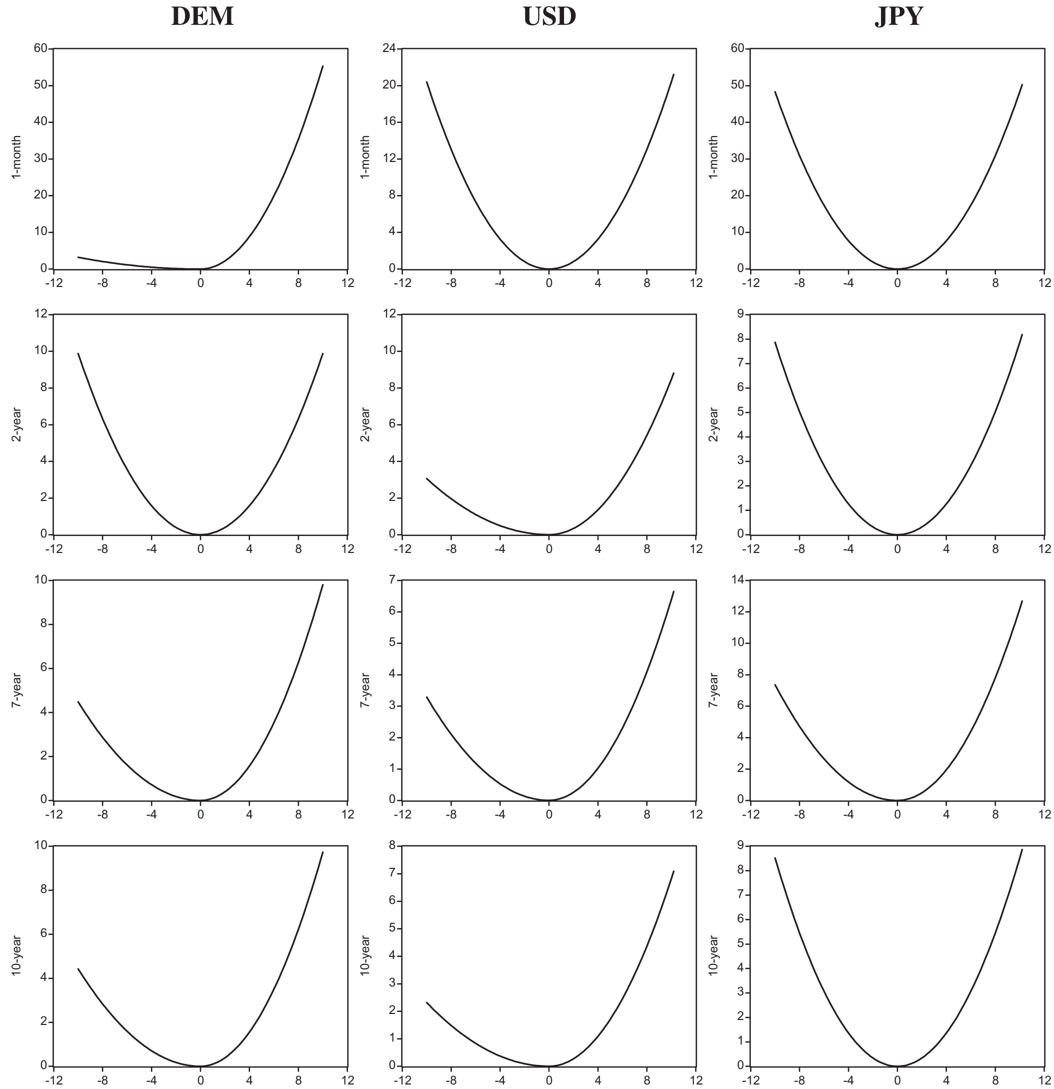

Fig. 2. *News impact curves for 1-month and 2-, 7- and 10-year zero coupon rates from IRS markets (Engle and Ng (1993))*

rates in Table 1, it is interesting to question whether they are strong enough to be statistically significant. In fact, the leverage effect turns out to be significant for the longer maturities in the three currencies. In those cases, the impact of surprises on interest rate volatility is positive with independence of the sign of the innovation, but positive surprises have a bigger impact than negative surprises of the same size. As mentioned above, this is consistent with the fact that an increase in zero coupon rates leads to lower *IRS* prices and hence, it is perceived as *bad news*. In fact, estimated coefficients in Table 2 suggest that the effect of a positive surprise on interest rate volatility in the swap market can easily be twice as large as the effect on volatility of a negative surprise of the same size. That the evidence on asymmetric effects is now more consistent and widespread that in the preliminary tests in Table 1 is due to the fact that one now has a detailed specification for the variance equation, which incorporates the dynamics in the conditional variance through the presence of its lagged value.

This asymmetric response of volatility to surprises of different sign can be illustrated in the form of *news impact curves*, as proposed by Engle and Ng (1993). These curves, shown in Fig. 2, capture next period response of conditional variance to an innovation in zero coupon rates.[12]

[12] The news impact curve relates the conditional variance (σ_t^2) to past observations of the unanticipated component of interest rates (ε_t). Since the conditional variance in GARCH and GJR-GARCH models also depends on its own past, previous conditional variance (σ_{t-i}^2) was given a value equal to the average conditional variance $\overline{\sigma}^2$ over the sample period. Hence, the function represented in Figure 2 for a GJR-GARCH (1,1) model obeys the analytical expression: $\sigma_t^2(\varepsilon_{t-1}) = \hat{\omega} + \hat{\alpha}\,\varepsilon_{t-1}^2 + \hat{\gamma}\,\varepsilon_{t-1}^2\, S_{t-1}^- + \hat{\beta}\,\overline{\sigma}^2$, with ε_{t-1} taking values in $(-10, 10)$.

The news impact curves for the 1-month, 2-, 7- and 10-year zero coupon rates are presented for each currency. Isolating the effects of news on volatility, the impact of an innovation of a given size on short-term interest rate volatility can be seen to be well higher than that on volatility at longer maturities. As expected, Fig. 2 also shows that the impact of news on volatility in maturities for which a GJR-GARCH model was estimated clearly depends on the sign of the news arriving to the market, bad news having a significantly higher impact on volatility. At the 1-month maturity, it is striking the extreme asymmetry observed in Deutsche mark rates.

Interaction between volatility and the level of IRS interest rates

There is also significant evidence on a relationship between the level of interest rates and their conditional variance in the longer maturities for the three currencies. These are almost the same maturities for which asymmetric responses of volatility to interest rates surprises were found. The effect of conditional volatility on average interest rates in marks and dollars is negative, so that increases in conditional volatility tend to produce smaller interest rate changes. Since daily variations have a mean close to zero, this effect suggests that higher volatility tends to produce a fall in interest rates. This is consistent with the fact that *IRS* are derivative products extensively used for hedging portfolios so that their demand will be higher in periods of high market volatility. The increased demand will generally put an upward pressure on prices, lowering zero coupon rates.

The opposite relationship is found for the Japanese yen, in which increased volatility tends to produce higher interest rates. It can also be seen that the size of the effect of volatility on interest rate changes is much higher in this currency. It is clear that the presence of the conditional volatility in the equation for interest rate changes is capturing an effect of a different kind in the case of the yen.

Daily seasonality in volatility

Significant coefficients in the daily dummy variables included in the variance equation, show that most maturities present weekly seasonal effects in volatility. Since a constant term is included in the equation for the variance, we have excluded the dummy variable for Tuesdays, to avoid perfect multicolinearity, estimated coefficients then measuring differential effects relative to Tuesdays.

Estimated seasonal patterns are not identical across currencies, being linked to some market characteristics. The market in Deutsche mark *IRS* is the one with a more stable intra-week volatility, with just an indication that interest rate volatility tends to be higher on Thursdays. Volatility shows a well-defined pattern in the market for US dollar *IRS* rates, increasing as the week moves along. Finally, average volatility in interest rates in Japanese yen show significant differences at the beginning and the end of the week, relative to Tuesdays. Specifically, average volatility in interest rates on yen denominated *IRS* seems to peak precisely on Tuesdays, since most estimated coefficients are negative.

A good reason to expect higher volatility towards the end of the week is the well-known practice that large traders generally tend to adjust their portfolios at that moment. French and Roll (1986), who obtain descriptive measures for the New York Stock Exchange and American Stock Exchange prices over the trading week, weekends and holiday periods, detect a daily effect in volatility similar to the one presented here, considering that it is produced in part by negotiation patterns. These authors focus on the difference between trading and non-trading periods, proposing three reasons why volatility can be higher during trading periods: (a) private information affect prices just when negotiation takes place, (b) only then public information circulates across the market, and (c) possible pricing errors committed in infrequent negotiation. Being the *IRS* an *over the counter* financial product, with some liquidity limitations, information does not flow easily or continuously, so that it is perfectly natural that as information circulates over the trading week, volatility increases, as it is the case in the Deutsche mark and US dollar *IRS* markets.

V. VOLATILITY TRANSMISSION ACROSS THE TERM STRUCTURE OF INTEREST RATES

The estimates also provide some evidence suggesting that conditional volatility for the 1-month rate is a significant explanatory variable for conditional volatility in interest rates at other maturities in the Deutsche mark and the US dollar. Coefficients associated to the *contemporaneous* transmission of volatility are significant for the shorter and the 9- and 10-year maturities in these two currencies, being positive in all cases, as it should be expected.[13]

It is interesting that it is the shorter end of the curve, together with the 9- and 10-year maturities the ones that are influenced by the 1-month rate volatility that could be produced by monetary policy interventions. The 10-year bund yield, as well as the 10-year rate in the US have for a long time been followed as an indicator of monetary policy stance. The spread between them is a standard

[13] Significance is sometimes achieved just at the 80% confidence level.

reference for the relative degree of monetary restriction in the two regions. Hence, although the results hardly constitute a proof, they are consistent with the interpretation that monetary policy implementation is behind the volatility transmission that has been found in the data.

There is also statistically significant evidence of volatility transmission in the term structure for the Japanese yen up to the 7-year maturity. Finding the true cause for the different response of volatility among these currencies should make an interesting issue for further research.

These results are robust to the choice of volatility indicator. The same models were estimated as in Table 2 for each maturity and currency, except for using a times series of the standard deviation on a rolling window of one week of data as the volatility indicator for the 1-month rate. In all cases, estimates for all coefficients were essentially unchanged,[14] so qualitative results in the previous sections go through. The correlation coefficient between the GARCH and the rolling window volatility indicators is 0.75 over the whole sample, so it is not surprising that most results are robust to the volatility indicator used. The main difference is that coefficients are then estimated with higher precision, so significance tests gain power and the evidence on volatility transmission is even more clear-cut. Since estimates of the remaining coefficients are barely affected by the measure of volatility being used, Table 3 reports estimates of the volatility transmission effect, to be compared with estimates of the same parameter in the three panels of Table 2.

It is important to point out that the reported volatility transmission goes beyond what should be expected from the structure of *IRS* markets: in an *IRS*, two counterparts exchange payment streams with the same principal but different interest rates, one of them fixed, variable the other one. The term structure has been estimated from quoted rates for the fixed arm of the swap, while the variable rates are typically pegged to the 6- or 12-month interbank rate of the issuer country. The significant effects of variations in 1-month rate volatility on volatility at longer maturities that have been detected in the estimation must be due to something more than just the natural connection existing between rates from both streams in an *IRS*.

The evidence of volatility transmission that are brought forward should not necessarily be interpreted in terms of the ability of monetary policy to influence the longer end of the yield curve, since the connection between intervention rates and 1-month rates is less than perfect. However, since the correlation between these two rates is usually tight, such an interpretation is possible. From that point of view, the results are interesting because working with a short term structure derived from interbank market rates, Ayuso *et al.* (1997) did not find the same evidence on volatility transmission from the 1-day rate, as a proxy for monetary policy interventions, to the remaining maturities up to 1 year, which was present in other currencies.[15]

Table 3. *Volatility transmission: Standard deviation on a rolling window*

	DEM λ	USD λ	JPY λ
r 3 month	5.308*	1.237*	2.454*
	(0.628)	(0.359)	(0.446)
r 6 month	3.755*	0.584*	1.401*
	(0.678)	(0.338)	(0.233)
r 1 year	0.274*	11.464*	4.226*
	(0.112)	(0.140)	(1.424)
r 2 year	0.042*	0.146*	0.047*
	(0.025)	(0.061)	(0.030)
r 3 year	0.025	0.139*	0.043**
	(0.024)	(0.076)	(0.033)
r 4 year	0.030	0.046**	0.073**
	(0.034)	(0.035)	(0.051)
r 5 year	0.044*	0.031	0.052**
	(0.027)	(0.028)	(0.040)
r 6 year	0.031**	0.010	0.037
	(0.023)	(0.020)	(0.031)
r 7 year	0.025	0.021	0.016
	(0.020)	(0.021)	(0.029)
r 8 year	0.022	0.021	0.020
	(0.019)	(0.021)	(0.032)
r 9 year	0.027**	0.057*	0.024
	(0.020)	(0.031)	(0.037)
r 10 year	0.038*	0.079*	0.028
	(0.022)	(0.039)	(0.039)

Note: Estimated models are the same as in Table 2 (·), except for using the standard deviation on a 1-week rolling window as the volatility indicator for the 1-month rate. Bollerslev–Wooldridge (1992) robust standard deviations in parentheses. Estimates of λ have been multiplied by 10^2. An (two) asterisk(s) denotes statistical significance at 90% (80%) confidence.

VI. CONCLUSIONS

The main characteristics of the term structure of interest rates swap markets (*IRS*) have been analysed in US dollars, Deutsche marks and Japanese yen, paying special attention to volatility transmission across the term structure. After estimating zero coupon rates from quoted *IRS* rates, daily

[14] Except for those in the dummy variables, as a consequence of the implied change in the average level of volatility.
[15] Analysing daily quotes for the money market for 1-day, 1-, 3- and 12-month rates, from January 1988 to January 1993, these authors do detect volatility transmission from the 1-day rates across the term structure in the markets in the UK, Spain and France, rejecting the existence of volatility transmission just for Germany.

changes in interest rates have been shown to be serially correlated, so that the random walk hypothesis is not fully appropriate in these markets. There is a consistent tendency in the three currencies for interest rates at all maturities to increase on Mondays, this effect correcting itself later on in the week. There is also some indication of weekly seasonality in the autocorrelation pattern for Deutsche mark swap rates.

GARCH(1,1) or GJR-GARCH(1,1) models have been found to adequately represent the main characteristics of interest rate volatility in *IRS* markets. The estimates capture the main episodes of market turbulence that occurred during the sample period. Conditional volatility for interest rates displays interesting properties: (1) it decreases with maturity; (2) it is very persistent, responses to interest rate surprises decaying very slowly; (3) consequently, it is somewhat predictable, which should be of interest when pricing swap derivatives; (4) it tends to be lower on Mondays, increasing later on in the week; and (5) responses of volatility at longer maturities to changes in interest rates are asymmetric, interest rate increases (the *bad news* in fixed income markets) bringing about twice as large an effect on volatility, as interest rates falls of the same size.

There is a significant and negative effect of volatility on interest rate changes in the *IRS* markets in US dollars and Deutsche marks at almost the same maturities at which an asymmetric response of volatility to interest rate surprises is detected. The sign of the estimated relationship between interest rate changes and volatility is consistent with the use of swaps as a hedging instrument. The large and positive effect of volatility on interest rate changes estimated for the yen clearly captures a different feature whose interpretation requires some specific analysis.

Finally, special attention has been paid to possible evidence consistent with the extended belief that shorter term interest rates must be kept stable, for their volatility affects volatility over the whole term structure. This is an issue of utmost importance on monetary policy, calling for using a short-term interest rate as a policy instrument, maybe jointly with a monetary aggregate or some other alternative. Indeed, in addition to volatility transmission among interbank rates, statistically significant evidence has been found of volatility transmission from the 1-month rate to the 9- and 10-year rates in the case of the Deutsche mark and the US dollar. It is believed that the fact that 10-year rates in these two countries, as well as their spread, have traditionally been followed as indicators of monetary policy stance explains its connection to the 1-month rate.

Although the 1-month rate is not a perfect indicator of monetary policy, it is close enough to the intervention rate to allow for an interpretation of the results as being consistent with the maintained hypothesis in most central banks that the volatility in shorter maturities gets transmitted to other interest rates. That supports the recommendation to maintain stability mechanisms for interest rates at the shorter maturities.

The results have a clear potential for practical use in risk management, since characterizing the dynamic behaviour of volatility and its transmission between fixed income spot and derivative markets is essential for portfolio managers. Indeed, to design an efficient hedging strategy for an *IRS*, one must explicitly consider the effect of shorter term interest rate volatility on the volatility of *IRS* rates. In fact, models for evaluating market risk, as Value at Risk (VaR), take into account the correlations between interest rates at different maturities when estimating volatilities. An example is the *Riskmetrics™* methodology, developed by *J. P. Morgan*, which provides the historical volatilities and correlations with this goal in mind.

Finally, the evidence presented on the volatility transmission mechanism suggests an interesting extension of this work, to analyse the possibility of volatility transmission across different currencies. In that case, it would be very interesting to identify the fundamental factors acting as the leaders in this transmission process.

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Financial support from the Spanish Ministry of Science and Technology and from European Regional Development Fund (BEC2002-01995, DGICYT PB98-0831), and from the Xunta de Galicia (PGIDIT03PXIC30001PN) is acknowledged.

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