STRUCTURAL BREAKS AND INTEREST RATES FORECAST: A SEQUENTIAL APPROACH

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ABSTRACT

The analysis of the future behaviour of economic variables can be biased if structural breaks are not considered. When these structural breaks are present, the in-sample fit of a model gives us a poor guide to ex-ante forecast performance. This problem is shared by univariate and multivariate analysis and can be extremely important when cointegration relationships are analysed. The main goal of this paper consists in analysing the impact of structural breaks on forecast accuracy evaluation. We are concerned in forecasting several interest rates from the Spanish interbank money market. In order to carry out the analysis, we perform two forecasting exercises: (1) without structural breaks and (2) when structural breaks are explicitly considered. We use new sequential methods in order to estimate change-points in an endogenous way. After which, we compare the out-of-sample forecast ability of these models. Our results may indicate scarce gains when the structural break is included in the models.

RESUMEN

El análisis del comportamiento futuro de las variables económicas puede estar sesgado si se ignora la presencia de cambios estructurales. Cuando se dan esos cambios, el ajuste de los modelos dentro de la muestra nos proporciona poca información ex-ante sobre el comportaiento en previsión. Este problema lo comparten el análisis univariante y multivariante y puede ser muy importante en el caso de que existan relaciones de cointegración. El objetivo principal de este trabajo consiste en analizar el impacto de los cambios estructurales en la evaluación de la capacidad predictiva. Estamos interesados en la previsión de los tipos de interés del mercado interbancario. Utilizamos nuevos métodos secuenciales para estimar los puntos de corte de manera endógena. Posteriormente, comparamos las previsiones hechas con los modelos que incorporan los cambios estructurales detectados con modelos en los que no se han tenido en cuenta. Nuestros resultados parecen indicar escasas ganancias cuando se incorpora la información sobre el cambio estructural.

KEYWORDS: Forecast accuracy comparison, Endogenous structural breaks, Sequential test, Interest rates forecast.

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1. INTRODUCTION

The literature on the theory and practice of economic forecasting is quite extensive [see Fildes and Makridakis (1995) or Clemens and Hendry (1998a)]. The reason is clear: forecasting the future behaviour of economic variables is a central matter in economics, business and finance. Beside, forecasting accuracy is an important tool in model validation. Thus, the search for the best forecasting model is a generalized and persistent phenomenon.

However, to achieve forecasting accuracy is not an easy task. As Clemens and Hendry have pointed out in several works, standard results on economic optimal forecasting are not appropriate in many cases. These results are based on the assumption of a constant, time-invariant and stationary Data Gererating Process (DGP) that coincides with the analysed forecasting model. Nevertheless, in the real world we have non-stationary and cointegrated processes, subject to intermittent regimes shifts and structural breaks of varying magnitudes. For this reason, empirical forecasting studies must be based on a theory that takes the appropriate aspects of the forecasted economy to be into account [Clemens and Hendry (1995, 1996, 1998a, 1998b, 1999)]. Fildes and Makridakis (1995) also indicate that the constancy of the model is usually the strongest assumption usually made and it could be the cause of the anomalies detected in empirical accuracy studies as well as in the standard theoretic framework.

In this paper we are concerned with the non-constancy of the DGP. In particular, our main goal is to analyse the impact of structural breaks on forecast accuracy evaluation from a empirical point of view. We analyse yields to maturity from the Spanish interbank money market at four maturities (1, 3, 6 and 12 months) from 1987 to 2000. Some important events related with the European monetary union process have been affecting the Spanish financial system during this period and they may have caused some structural changes. In this sense, one interesting question is to know whether these breaks had really happened.

Structural changes can take many forms: they can affect all the parameters of the model or only a subset of them; they can be abrupt or gradual; they can occur in a known or an unknown date; etc. On this last part, some authors have highlighted the differences in results achieved depending on the exogenous choice of break points [Christiano (1992), Zivot and Andrews (1992)]. They also stated that this choice can interfere with the power of the tests and the validation of the model.

For this reason, different procedures have been proposed to select the break point in an endogenous way, avoiding thus the pitfalls of any previous literature. Among these methods, researchers have considered a wide variety of rolling, recursive and sequential testing procedures. However, comparative studies by Banerjee, Lumsdaine and Stock (1992) and Montañes (1996) indicate that sequential procedures are generally more powerful, since they use all the sample information at once.

This is why, in order to aboard the problem of breaking point detection in an endogenous way, the sequential testing procedure proposed by Fernández-Serrano and Peruga-Urrea (1999a, 1999b) has been used. Once that the change point have been estimated, we add this information to the forecasting model. After which we compare the forecasting ability between two alternative modelling approaches: (1) without structural break and (2) with structural break explicitly considered. We also use two different forecasting approaches: univariate analysis using ARIMA models and multivariate, using VAR models. This way, we can study the effect of the breaks within a cointegration environment as well.

The answers we are looking for are: which is the best model to characterise the in-sample behaviour of interest rate when structural breaks are not considered?, can we achieve the same results when the structural break have been considered?, and most important of all, is it important to consider structural breaks to improve accuracy when both types of models are used in out-of sample forecasting?. We also can analyse whether the effects are different across maturities. We can anticipate that, certainly, when structural breaks are introduced, the models show better in-sample fit, however, this did not happen when forecasting performance was compared.

The paper is organised as follows. The sequential approach to analyse structural breaks is presented in Section 2. Section 3 describes the data set and shows the empirical results. The summary and some concluding comments are provided in Section 4. The paper ends with two appendixes where tables, figures and forecast error measures are shown.

2. A SEQUENTIAL APPROACH TO THE BREAK POINT ESTIMATION

To implant the structural change into forecasting models, previous structural stability analysis is very important in order to feature the statistical modelling of time series behaviour. Today's world economy is quite different from one in the past and the information gets to us steadily so, it is very important to know if the model will be capable of capturing all the relevant aspects that affect the variable to be forecasted. If the DGP changes and that change is ignored, the forecasting capacity of the model could be reduced.

Additionally, breaks can occur at any point of the sample so it is very important to locate them. Some authors have highlighted the effect over results achieved in an analysis of the exogenous choice of break points [Christiano (1992), Zivot and Andrews (1992)]. They also notice that this choice can reduce the power of the tests. That way, the researchers' efforts have been focused in developing appropriate and powerful tests to detect any structural instabilities as well as estimating the corresponding break point endogenously. We can find some examples in this line in the section "Break Points And Unit Roots" in *Journal of Business and Economic Statistics* (1992) where several tests to detect a break point, within the dataset, are presented. We can also mention the test procedures proposed by Andrews (1993) in a non-linear context, Bai (1994) and Bai and Perron (1996) for single and multiple change points in the mean of a general process respectively.

In this section, we present some sequential tests to analyse the instability in interest rates and to locate the change point. Our selection of the sequential approach is motivated by the results of the comparative studies by Banerjee, Lumsdaine and Stock (1992) and Montañes (1996). These authors find that sequential procedures are generally more powerful than recursive and rolling ones because they use all the sample information at once.

In a first stage, in order to test unit roots we use sequential ADF tests which allow us to detect any structural changes in the stochastic trend of the rates as well as changes in their degree of integration [Fernández-Serrano and Peruga-Urrea (1999a y 1999b)]. As we know, testing the null hypothesis of a unit root in a time series Y_t, the standard ADF test computes the pseudo t-ratio (t_δ) in the following regression:

$$\Delta Y_t = \mu + \beta t + \delta Y_{t-1} + \sum_{i=1}^{q} \gamma_i \Delta Y_{t-i} + \varepsilon_t, \qquad (1)$$

when no structural change is assumed in the parameters μ and β.

The sequential ADF test usually employed in the literature (Banerjee, Lumsdaine and Stock

(1992)], Zivot and Andrews (1992), Perron and Vogelsang (1992) and Montañés (1996)) involves estimating the following regressions:

$$\Delta Y_t = m + m' D_{t\,t} + d\, Y_{t-1} + \sum_{i=1}^{q} g_i \Delta Y_{t-i} + e_t, \tag{2}$$

where:

$$D_{t\,t} = \begin{cases} 0 & t < [t\, T] \\ 1 & t \geq [t\, T] \end{cases}, \quad t \in (0,1)$$

is a dummy variable that allows us to locate the break date in each one of the observations in the closed subset of (0,1). For each possible break date in the sample, τ, two statistics are computed from regression (2): t_δ and $|t_{\mu?}|$. t_δ is the standard pseudo t-ratio for testing the null hypothesis of a unit root $\delta = 0$, while $|t_{\mu?}|$ is the absolute value of the t statistic for testing the null hypothesis $\mu? = 0$ (i.e., it is a test of stability in the stochastic trend). If we impose the existence of a unit root in (2), we have the following restricted regression:

$$\Delta Y_t = m + m' D_{t\,t} + \sum_{i=1}^{q} g_i \Delta Y_{t-i} + e_t, \tag{3}$$

and, based on this, we can compute $|t_{\mu?}|$.

From regressions (2) and (3), we obtain a sequence of estimated values for each statistic. From this sequence, we take two summary values: the supreme and the mean one. Therefore we compute the following six statistics: Inft_δ, Mean t_δ, Sup $|t_{\mu?}|$, Mean $|t_{\mu?}|$, Sup $|t_{(\mu?)}|$ and Mean $|t_{(\mu?)}|$. Following Zivot and Andrews (1992), we consider the date associated with the corresponding supreme: Nsup $|t_{\mu?}|$, Ninf t_δ and Nsup $|t_{\mu?}|$ as the breakpoint estimation.

Until now, we have assumed that the time series follows a stochastic process that has always the same degree of integration (i. e., changes in the parameter δ in regression (1) are not allowed). To consider the possibility that such parameter may not be constant in the entire sample (and, therefore, the order of integration of the stochastic process could change depending on the subsample examined), we can study the following set of regressions:

$$\Delta Y_t = m + g_1 D_{t\,t} Y_{t-1} + g_2[1 - D_{t\,t}]Y_{t-1} + \sum_{i=1}^{k} d_i \Delta Y_{t-i} + u_t, \qquad (4)$$

$$\Delta Y_t = m + a_1[1 - D_{t\,t}]Y_{t-1} + \sum_{i=1}^{k} d_i \Delta Y_{t-i} + u_t, \qquad (5)$$

$$\Delta Y_t = m + a_2 D_{t\,t} Y_{t-1} + \sum_{i=1}^{k} d_i \Delta Y_{t-i} + u_t. \qquad (6)$$

Regression (4) simultaneously considers both resulting subsamples from the division of the sample. Since no restriction is imposed on any of them, this regression tries to test the null hypothesis of a unit root against the alternative hypothesis of stationarity simultaneously, in both subsamples. This way, for example, the time series could be integrated of order one in one subsample and integrated of order zero in the other. In the other two regressions, the existence of a unit root is imposed only in one subsample [the first one in regression (5) and in the second one in regression (6)], allowing the possibility of stationarity in the non-restricted subsample.

Afterwards, statistics $t_{\gamma1}$, $t_{\gamma2}$, $t_{\alpha1}$, and $t_{\alpha2}$ are computed for each possible break point in the sample. The first two statistics ($t_{\gamma1}$ and $t_{\gamma2}$) test for a unit root in the first and second subsamples, respectively. The statistic $t_{\alpha1}$ tests for a unit root in the first subsample separately, whereas $t_{\alpha2}$ does it in the second one. As in the previous case, after finishing this testing procedure, we will have four sequences of estimated statistics and from these sequences we will be able to compute the summary statistics: $Supt_{\gamma1}$, $Meant_{\gamma1}$, $Supt_{\gamma2}$, $Meant_{\gamma2}$, $Supt_{\alpha1}$, $Meant_{\alpha1}$, $Supt_{\alpha2}$ and $Meant_{\alpha2}$. In this case, the estimators of the break points are $Nsupt_{\gamma1}$, $Nsupt_{\gamma2}$, $Nsupt_{\alpha1}$ and $Nsupt_{\alpha2}$, respectively.

3. EMPIRICAL RESULTS

We consider daily continuously compounded yields to maturity from the Spanish interbank money market at four maturities: 1, 3, 6 and 12 months (r1m, r3m, r6m and r12m respectively).[1] The sample covers the period from 2/1/1987 to 3/3/2000, giving us 3436 observations.[2] The data come from Banco Bilbao Vizcaya-Argentaria (BBVA).

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1 Continuously compounded rates are computed from the following expression: $r_t \equiv \frac{360}{N} \mathrm{Ln}\left(1 + \frac{N}{360} s_t\right)$ where s_t, is 360 days basis, simple interest rates, corresponding to 1, 3, 6 and 12 months to maturity each time, and N indicates the maturity expressed in days.

2 Dates are expressed as dd/mm/yy.

In order to reduce the effect of extreme values[3] we construct non-overlapping weekly averages of the yields. The resulting sample size is 688 observations. Table 1 in Appendix 2 provides summary statistics of the yield levels and their first differences. As can be seen, all the weekly averaged rates have oscillated approximately between 22% at the beginning of the sample and 3% at the end, showing a decreasing behaviour (Figure 1). The Jarque-Bera test for joint normal kurtosis and skewness rejects the normality hypothesis.

Looking at figures 1 and 2, the averaged yields seem to be non-stationary, whereas their first differences seem to be I(0). The instability in rates is confirmed by ADF test [Table 2, Panel (a)]. Results are shown for the first differences and the levels of the variables. As can be seen, for the levels the ADF test cannot reject the null hypothesis of a unit root in any maturity at the 5% significance level. On the other hand, for the first differences the ADF test always rejects the null hypothesis of a unit root. The results are corroborated by the sequential statistics Inf t_δ and Mean t_δ, more robust than the ADF test in presence of structural breaks in the trend of the series.

3.1. Structural break detection

Table 2, Panel (a), reports the results for stability in the trend of the rates. The unrestricted statistic of change in the trend, Sup $|t_{\mu'}|$, suggests a structural break in the trend around the beginning of May 1993 for $r1m_t$, and around the end of April 1993 for $r3m_t$ and $r6m_t$. The same conclusion can be found for the statistic Mean $|t_{\mu'}|$, which also indicates a break in May 1993 and November 1992 for $r6m_t$ and $r12m_t$ respectively. These observations are consistent with the information obtained from a visual inspection of the graphs for those rates, as shown in Figure 3.

We proceed to test unit roots and trend structural breaks in the subsamples generated by each break point detected with Nsup $|t_{\mu'}|$ for all the period. As can be seen in Table 2, panels (b) and (c), all rates are I(1) in levels and I(0) in first differences and the sequential statistics do not suggest instability in all cases.

Table 3 shows the results for the degree of partial integration. Considering the results on this table, for the first differences there is no sign of change in the order of integration. However, for $r1m_t$ and

[3] Daily rates show extreme values at the beginning of the sample and between 1992 and 1993. In the last case, these outliers are related with the effect of the EMU crises over several European currencies, in particular over

$r3m_t$ yields, the results from the $Supt_{\gamma 1}$ and $Supt_{\alpha 1}$ statistics suggest a stationary behaviour until August 1992 and July 1993 respectively.

Summarising, we have found some evidence of structural breaks in the four rates analysed. Generally, the break in trend occurs in November 1992 for $r12m_t$ and May of 1993 for the rest of rates analysed. These breaks are directly related to the European Monetary Union (EMU) crises and the devaluations of the peseta made by Banco de España in November 1992 and May 1993.

In order to incorporate these breaks into the forecasting models analysed here we have selected 7/5/1993 as the break point for all series. This allows us to improve the estimation of all the models after May 1993, although some sources of bias are maintained in the first part of the sample period. Figure 3 shows the estimated break point in the levels of the rates.

In fact, since interest rates are I(1), a cointegration analysis has been made (Table 4) using Johansen (1988) procedure. A constant term is included in all auxiliary regressions. Different orders for the autoregressive process, p, have been considered (from 1 to 14). The results were always the same hence we only show them for p=1, 2, 4, 9. They indicate that rates are cointegrated with 2 cointegrating relationships. When we run the Johansen's test in the two subperiods defined by the break point detected above (7/5/1993) the result changes dramatically. Rates are cointegrated with two cointegrating relationships only after the break. After this break point, three cointegrating relationships are detected.[4] Theses results seem to indicate that if structural change is ignored, another source of missespecification is added: a wrong number of cointegrating relationships in the error correction model (ECM).

3.2. Forecasting models

We are concerned about the effect of the structural break detected over 1-step ahead forecast of interest rates with origin in T. Parameter values are estimated with the first 626 observations. After that, they are used to do 62 1-step ahead forecasts.

We consider two cases: (1) univariate analysis of the rates using ARIMA models, and (2)

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the Spanish peseta.

[4] This result is related with the Expectation Hypothesis (EH) of the Term Structure of Interest Rates. EH implies that in a vector of n rates n-1 cointegrating relationships must be found. This hypothesis has received a great deal of attention in empirical literature (see Pagan, Hall and Martin (1996) for a survey). Our results may indicate that the rejection of this EH implication can be related to the presence of structural break in the rates, but the

multivariate analysis using VAR-ECM models. In both cases, models are estimated with and without structural break in order to compare their out-of-sample forecasting accuracy. We analyse the effect of the break in different ways: in the trend of rates, in all the parameters of the model or in the parameters of the short run relationship in the multivariate case. The forecasting models considered are summarised below.

Forecasting Models

Models	**Description**	**Structural break**
Univariate		
US1	ARI(p), p=2 r12m, r6m, p=3 r1m, p=4 r3m	No
US2	ARI(p), p=2 r12m, r6m, p=3 r1m, p=4 r3m	Trend
US3	ARI(p), p=2 r12m, r6m, p=3 r1m, p=4 r3m	All parameters
Multivariate		
VAR-ECM1	VAR(3), 2 Cointegration relationships	No
VAR-ECM2	VAR(3), 3 Cointegration relationships	No
VAR-ECM3	VAR(3), 3 Cointegration relationships	Trend
VAR-ECM4	VAR(3), 3 Cointegration relationships	Trend Short run relationship
VAR-ECM5	VAR(3), 2 Cointegration relationships, first period VAR(2), 3 Cointegration relationships, second period	All parameters

US1 and VAR-ECM1 are restricted models for the non-change hypothesis. Besides, in order to evaluate the effect of the different number of cointegrating relationships detected after and before the break point, we estimate another restricted multivariate model (VAR-ECM2) with just a common trend. Models US3 and VAR-ECM5 are unrestricted models including the possibility of a change in all parameters, US2 and VAR-ECM3 only consider a break in the trend of the rates and VAR-ECM4 allows changes in trend and parameters of the short run relationship.

Table 5 shows univariate models estimation. US1 models are ARI(2) for $r6m_t$ and $r12m_t$, ARI(3) for $r1m_t$ and ARI(4) $r3m_t$, with a constant not being significant in all cases. As we can see, the Chow breakpoint test confirms a structural change in 7/5/1993 for all rates. In order to include the change in the models we define a dummy variable, D_t, equal to one before the break and zero otherwise. Models US2 show that the trend of all rates is significant decreasing in the second period, and the Adjusted R^2 of the models softly rises. In the case of US3 models the increase in the Adjusted R^2 is

analysis of this question is out of the scope of this paper.

bigger. For all rates the dynamic structure of the models seems to have changed. For instance, in $r3m_t$ model, the forth lag is not significant and $r12m_t$ seems to be ARI(2) before the break and ARI(1) after it.

The estimated multivariate models are shown in the six panels of Table 6. Panel F shows some diagnostic statistics for each equation of all models. The Adjusted R^2 shows that the best in-sample fit is achieved when three cointegration relationships are included. In general, the specification with no structural change is worse than the specifications that include structural break. In this case, the best in-sample performance is shown by VAR-ECM4 model followed by VAR-ECM5.

Summarising the main results, the inclusion of the structural break in both, univariate and multivariate models, may improve their in-sample goodness of fit and allows for better estimating their dynamic behaviour. In the same way, the comparison between univariate and multivariate models indicates a better behaviour of the latter in all cases.

3.3. Forecasting comparison

We report seven forecasting error statistics: Mean absolute error (MAE), Mean absolute percentage error (MAPE), root mean squared error (RMSE), root mean squared percentage error (RMSPE) and three different versions of the Theil?s U coefficient (UTHEIL1, UTHEIL2, UTHEIL3). The exact expressions of all of them are shown in Appendix 1.

The results obtained from them are shown in tables 7 and 8. In the first table we can find the forecasting accuracy results of univariate models. Surprisingly, for the four rates, the best forecasting models are US1 ones, followed by US2 and US3 in this order. All the statistics give us the same ranking of models. It seems to be that models without structural break are better in forecasting all the analysed rates.

In the multivariate case (Table 8) the main conclusion is the same: models VAR-ECM1 and VAR-ECM2 seem to be better than models that include the break explicitly. However, there are some remarkable facts. Firstly, considering a break in the trend of the model allow us to achieve better forecasts than considering a break in all parameters (in general). But in the cases of $r3m_t$ and $r6m_t$ VAR-ECM1 and VAR-ECM2 forecasts are more accurate than the VAR-ECM3 ones. It is very important to highlight that the ranking of models varies depending on the statistic used to measure accuracy. For example, for rates $r1m_t$, $r3m_t$ and $r6m_t$ the worst model with RECM is however the best one with

UTHEIL3. Only for $r1m_t$ the model with two cointegrating relationships is the best. For the remainder maturities it seems to be better to include three of them. Overall, the worst model is VAR-ECM5, which allows for a complete break.

To prove equality between two different forecast models, we use the Diebold and Mariano (1995) test. Such hypothesis of equality of forecast accuracy is:

$$H_0 : E[d_t] = 0 \text{ when } d_t \equiv g(e_t^i) - g(e_t^j) .$$

d_t is the loss-differential series and it is assumed that the loss function, $g(e_t^i)$, is a direct function of the model i forecast error, e^i_t.[5] The null hypothesis is that the population mean of the loss-differential is zero.

If the loss differential series is covariance stationary and short memory, then, its asymptotic distribution is:

$$\sqrt{T}\,(\bar{d} - m) \xrightarrow{d} N[0, 2p\, f_d(0)]$$

when $\bar{d}$ the sample mean loss differential d_t, the function $f_d(0) = \frac{1}{2p} \sum_{t=-\infty}^{\infty} g_d(t)$ is the spectral density of the loss differential at frequency 0 (see Diebold and Mariano (1995) for a detailed description). The statistic for testing the null hypothesis of equal forecast accuracy is:

$$S_1 = \frac{\bar{d}}{\sqrt{\frac{2p\, \hat{f}_d(0)}{T}}} \approx N(0,1)$$

The results with this test are similar to those obtained above. They are summarised in tables 9 and 10. In the univariate case (table 9), models US1 for all rates are significantly better than the other two, whereas US2 is significantly better than US3 only for $r1m_t$. In the case of $r12m_t$, is not rejected the equality between US1 and US3 forecast.

As we can see in Table 10, with the exception of $r1m_t$ forecast, the majority of the multivariate models are equal in terms of their forecasting accuracy. In the case of this rate, models without structural break are the best. It is remarkable that $r6m_t$ and $r12m_t$ models with 3 cointegrating relationships (VAR-ECM2) are significant better than the model VAR-ECM1, which includes only two.

[5] This test is also valid for loss function that will not be a direct function of this error.

In conclusion, the out-of-sample comparison of the different forecasting models analysed allows us to state that the information about structural changes does not improve the forecasting accuracy of the models.

4. SUMMARY AND CONCLUSIONS.

In this paper we address the issue of forecasting when structural breaks are present. We analyse yields to maturity from the Spanish interbank money market at four maturities from 1987 to 2000. Basically, we look for an answer the next question: is there any forecasting gain when structural breaks are considered in order to modelling the behaviour of time series?. To detect the break point, the sequential approach proposed by Fernández-Serrano and Peruga-Urrea (1999a, 1999b), has been used.

We detect a break in May 1993, coinciding with the last devaluation of the peseta during the EMU crises. Once the structural break has been located, we aboard our objective in a double perspective: (1) univariate and (2) multivariate. With these models we make several comparisons among correspondingly models in two ways: in-sample fit and out-of-sample forecasting analysis with and without structural break.

Although our results are preliminaries, they are remarkable in several ways. The most important of them are the next ones. As we expected, multivariate models are better than the univariate ones in the in-sample analysis. When the structural break is included into the historical behaviour of interest rates, the in-sample fit of all the models is improved. So, we would expect to find the same result in the out-of-sample forecasting analysis. We use several forecasting statistics (MAE, MAPE, RMSE, RMSPE and three different versions of the Theil's U coefficient) for the out-of-sample comparison. We also apply the procedure proposed by Diebold and Mariano (1995) to test the null of equal forecasting accuracy among different models. Surprisingly, the results seem to indicate that, in general, we have no significant gains when structural breaks are incorporated into the models. Indeed, the most contradictory results are found when short-run yields to maturity (1 and 3 months) are analysed. In these cases, the best forecasting models are the ones that ignore the structural break.

It is very important to remark the effects of ignoring structural breaks in the cointegration analysis. We find only two cointegrating relationships in the full sample whereas we find two before May 1993 but three after this date. The VAR-ECM model for the full sample with three cointegrating vectors is significant better than the one with only two both in the in-sample analysis and in the forecasting comparison.

ACKNOWLEDGEMENTS

We thank Mayte Ledo and BBVA who kindly provided us the data.

APPENDIX 1

The seven forecast error statistics reported are computed as follows. Considering the forecast sample $t = s, s+1, ..., s+N$, and denoting the actual and forecasted values in period t as r_s and $r^j_{\ s}$, respectively, the statistics are:

1. Mean absolute error: $MAE_j = \frac{1}{N}\sum_{s=1}^{N} | r^j_{t+s} \, r_{t+s} |$
2. Mean absolute percentage error: $MAPE_j = \frac{1}{N}\sum_{s=1}^{N} \frac{|r^j_{t+s} r_{t+s}|}{r_{t+s}}$
3. Root mean square error: $RMSE_j = \left(\frac{1}{N} \sum_{s=1}^{N} (r^j_{t+s} - r_{t+s})^2\right)^{1/2}$
4. Root mean square percentage e.: $RMSPE_j = \left(\frac{1}{N} \sum_{s=1}^{N} \left[(r^j_s - r_s) / r_{t+s}\right]^2\right)^{1/2}$
5. Theil's U coefficient: $UTHEIL\ 1_j = \left(\left[\sum_{s=1}^{N} (r^j_s - r_s)^2 \right] / \sum_{i=1}^{N} r^2_s \right)^{1/2}$
6. Theil's Inequality coefficient: $UTHEIL\ 2_j = \left(\frac{\sum_{s=1}^{N} (r^j_s - r_s)^2}{\left(\sum_{i=1}^{N} r^{j\,2}_s\right)^{1/2} + \left(\sum_{i=1}^{N} r^2_s\right)^{1/2}} \right)^{1/2}$
7. Theil's U for changes: $UTHEIL\ 3_j = \left(\left[\sum_{s=1}^{N} (r^j_s - r_s)^2 \right] / \sum_{s=1}^{N} \Delta r^2_s \right)^{1/2}$

APPENDIX 2

Figure 1. Weekly average yields to maturity: levels.

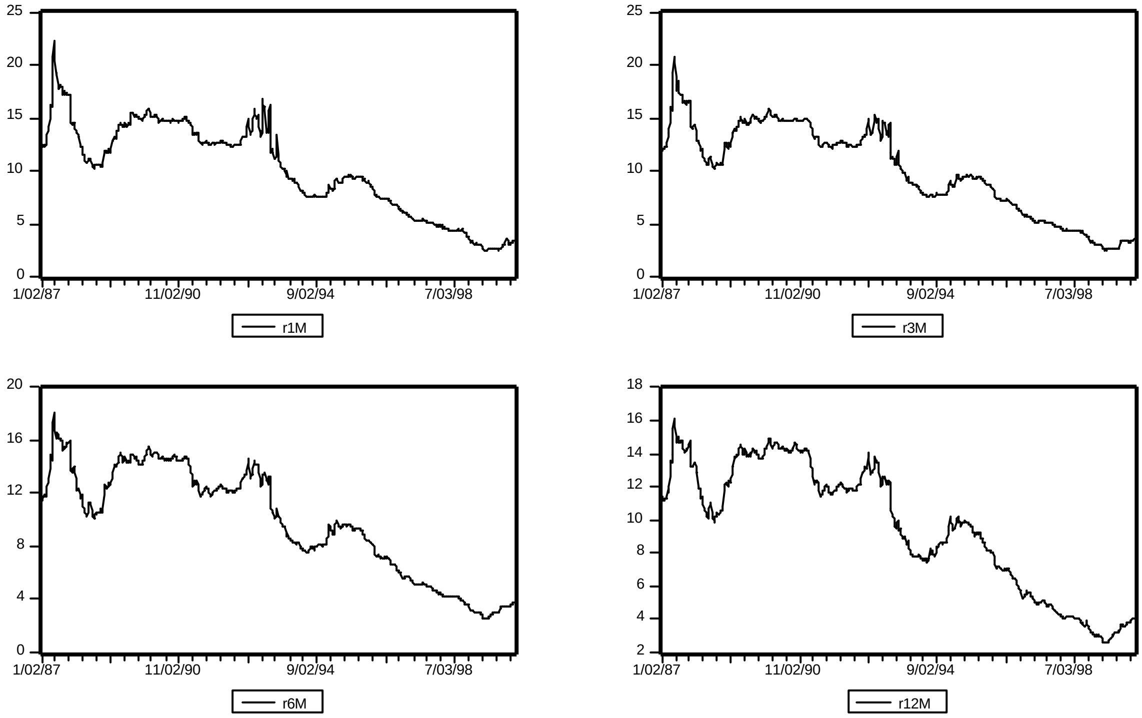

Figure 2. Weekly average yields to maturity: first differences.

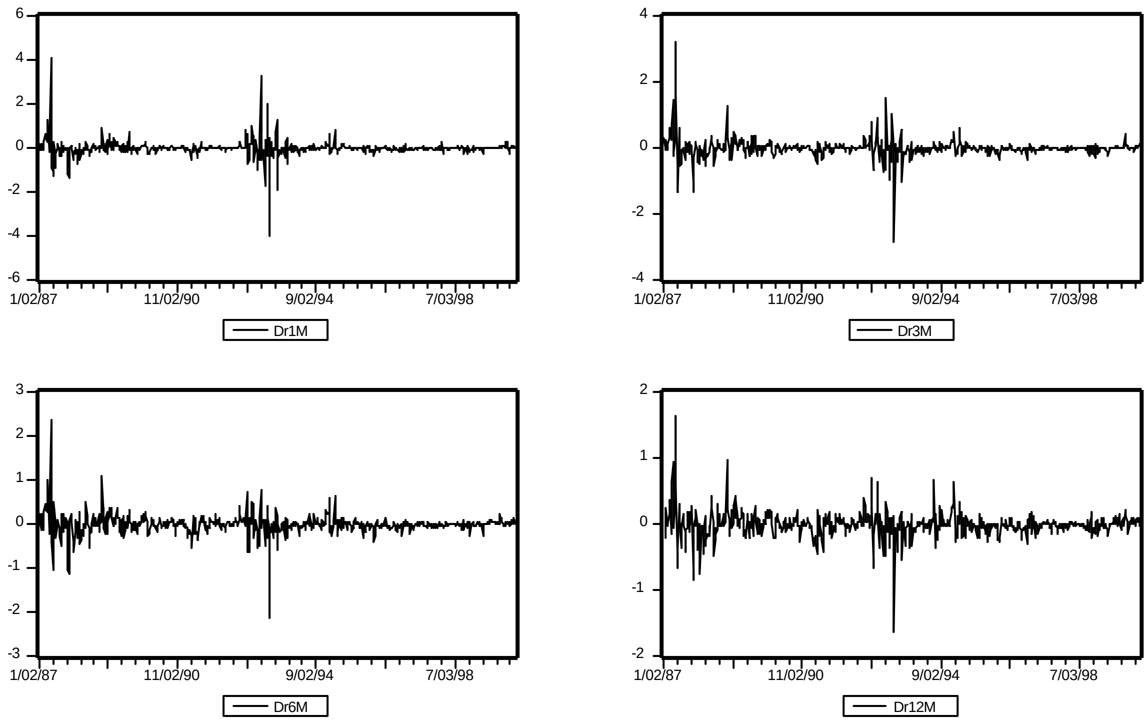

Table 1. Summary statistics

	r1m$_t$	D**r1m$_t$**	**r3m$_t$**	D**r3m$_t$**	**r6m$_t$**	D**r6m$_t$**	**r12m$_t$**	D**r12m$_t$**
Mean	10.834	-0.014	10.714	-0.014	10.485	-0.014	10.179	-0.013
Median	11.283	0.001	11.122	-0.009	10.778	-0.009	10.609	-0.011
Maximun	22.329	4.088	20.813	3.215	18.136	2.361	16.115	1.637
Minimun	3.289	-3.978	3.251	-2.814	3.190	-2.132	3.140	-1.615
Std. Dev.	3.884	0.379	3.800	0.298	3.651	0.235	3.439	0.197
Skewness	-0.076	1.197	-0.171	0.998	-0.295	0.464	-0.395	0.253
Kurtosis	2.105	55.301	1.979	42.410	1.912	32.914	1.949	20.644
Jarque-Bera	21.485	71269.8	30.171	40486.59	39.847	23287.98	44.938	8100.75
(probability)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2: Stability analysis of the stochastic trend

	$R1m_t$	$Dr1m_t$	$r3m_t$	$Dr3m_t$	$r6m_t$	$Dr6m_t$	$r12m_t$	$Dr12m_t$
				Full Sample				
ADF	-0.726	-7.345**	-0.691	-6.741**	-0.471	-6.649**	-0.193	-6.484**
Inf t_d	-3.803	-7.527**	-3.476	-6.869**	-3.034	-6.807**	-2.285	-6.697**
Ninf t_d	**07/05/93**	**05/02/93**	**23/04/93**	**20/11/92**	**30/04/93**	**18/09/92**	**07/05/93**	**18/09/92**
Mean t_d	-1.672	-7.368**	-1.656	-6.765**	-1.465	-6.689**	-1.291	-6.551**
Sup$\|t_{m?}\|$	4.025*	1.608	3.648	1.307	3.246	1.446	3.221	1.657
Nsup$\|t_{m?}\|$	**07/05/93**	**05/02/93**	**23/04/93**	**20/11/92**	**30/04/93**	**11/09/92**	**27/11/92**	**18/09/92**
Mean$\|t_{m?}\|$	1.636*	0.578	1.642*	0.577	1.606*	0.714	1.700*	0.886
Sup$\|t_{(m?)}\|$	1.693	0.683	1.367	0.759	1.489	0.854	1.807	0.755
Nsup$\|t_{(m?)}\|$	**19/02/93**	**07/05/93**	**04/12/92**	**07/05/93**	**25/09/92**	**07/05/93**	**02/10/92**	**07/05/93**
Meant_{a2}	0.616	0.134	0.625	0.156	0.759	0.173	1.031	0.148
				First period				
ADF	-2.298	-6.722**	-2.517	-5.949**	-2.481	-5.664**	-2.420	-5.381**
Inf t_d	-2.608	-6.789**	-2.797	-6.014**	-2.803	-5.725**	-2.800	-5.456**
Ninf t_d	**29/01/88**	**27/05/88**	**18/01/91**	**27/05/88**	**18/01/91**	**27/05/88**	**18/01/91**	**27/05/88**
Mean t_d	-2.293	-6.729**	-2.572	-5.954**	-2.517	-5.672**	-2.459	-5395**
Sup$\|t_{m?}\|$	1.245	1.029	1.329	0.984	1.396	1.008	1.504	1.069
Nsup$\|t_{m?}\|$	**29/01/88**	**27/05/88**	**28/12/90**	**27/05/88**	**28/12/90**	**27/05/88**	**04/01/91**	**27/05/88**
Mean$\|t_{m?}\|$	0.371	0.406	0.592	0.377	0.546	0.437	0.587	0.509
Sup$\|t_{(m?)}\|$	0.855	0.588	0.784	0.595	0.872	0.733	0.888	0.891
Nsup$\|t_{(m?)}\|$	**10/06/88**	**05/02/88**	**10/06/88**	**05/02/88**	**10/06/88**	**04/03/88**	**10/06/88**	**15/01/88**
Meant_{a2}	0.377	0.169	0.364	0.145	0.439	0.189	0.499	0.192
				Second period				
ADF	-0.817	-7.123**	-0.603	-7.964**	-0.006	-6.614**	-1.457	-6.119**
Inf t_d	-2.948	-7.729**	-2.816	-8.484**	-2.640	-6.980**	-3.223	-6.903**
Ninf t_d	**23/02/96**	**13/04/94**	**22/12/95**	**04/03/94**	**08/12/95**	**29/04/94**	**22/03/96**	**10/12/92**
Mean t_d	-1.347	-7.191**	-1.223	-8.015**	-0.738	-6.677**	-1.885	-6.186**
Sup$\|t_{m?}\|$	3.050	2.811	2.972	2.779	3.299	2.141	2.924	3.057
Nsup$\|t_{m?}\|$	**23/02/96**	**13/04/94**	**22/12/95**	**04/03/94**	**08/12/95**	**29/04/94**	**10/11/95**	**10/12/92**
Mean$\|t_{m?}\|$	1.621	0.790	1.502	0.842	1.312	0.802	1.687	0.688
Sup$\|t_{(m?)}\|$	2.794	1.143	2.489	1.596	2.112	1.556	3.119	1.369
Nsup$\|t_{(m?)}\|$	**20/04/94**	**06/01/95**	**18/03/94**	**28/10/94**	**11/03/94**	**23/12/94**	**24/12/93**	**23/12/94**
Meant_{a2}	0.744	0.384	0.713	0.554	0.877	0.530	0.698	0.394

Notes: *, **: signification levels at 10% and 5% respectively. The sample is divided according with the break point detected for each rate in Panel (a). Dates are expressed as dd/mm/yy.

Table 2b. Critical values

Confidence level	*Inft_d*	*Meant_d*	*Sup$\|t_{m'}\|$*	*Mean$\|t_{m'}\|$*	*Sup$\|t_{(m')}\|$*	*Mean$\|t_{(\mu')}\|$*
90	-4.082	-2.727	3.911	1.790	2.765	1.360
95	-4.347	-3.021	4.192	1.989	3.066	1.607

Table 3. Integration analysis.

	$r1m_t$	$Dr1m_t$	$r3m_t$	$Dr3m_t$	$r6m_t$	$Dr6m_t$	$r12m_t$	$Dr12m_t$
$Supt_{g1}$	-3.446*	-7.356**	-3.588*	-6.741**	-3.251	-6.649**	-2.925	-6.491**
$Nsupt_{g1}$	**07/08/92**	**03/04/87**	**07/08/92**	**06/03/87**	**07/08/92**	**06/03/87**	**06/11/92**	**10/04/87**
$Meant_{g1}$	-1.709	-2.873**	-2.050	-3.408**	-1.973	-3.560**	-1.769	-3.003**
$Supt_{g2}$	-3.034	-9.322**	-2.076	-7.975**	-1.693	-7.845**	-1.659	-7.876**
$Nsupt_{g2}$	**26/02/93**	**17/04/87**	**30/04/93**	**20/03/87**	**25/12/92**	**20/03/87**	**04/12/92**	**20/03/87**
$Meant_{g2}$	-0.254	-4.639**	-0.386	-3.418**	-0.326	-3.239**	-0.350	-3.796**
$Supt_{a1}$	-3.454*	-7.365**	-3.593*	-6.751**	-3.256	-6.692**	-2.921	-6.538**
$Nsupt_{a1}$	**30/07/93**	**24/11/95**	**30/07/93**	**10/11/95**	**30/07/93**	**15/12/95**	**16/04/93**	**06/01/95**
$Meant_{a1}$	-1.868	-6.569**	-2.287	-6.234**	-2.240	-6.132**	-2.057	-5.768**
$Supt_{a2}$	-3.017	-10.076**	-2.009	-8.421**	-1.682	-7.996**	-1.653	-8.151**
$Nsupt_{a2}$	**26/02/93**	**12/02/93**	**30/04/93**	**12/02/93**	**25/12/92**	**27/12/92**	**04/12/92**	**20/11/92**
$Meant_{a2}$	-0.573	-6.361**	-0.431	-5.617**	-0.393	-5.541**	-0.446	-5.902**

Note: *, **: signification levels at 10% and 5% respectively. Dates are expressed as dd/mm/yy.

Figure 3. Estimated break points.

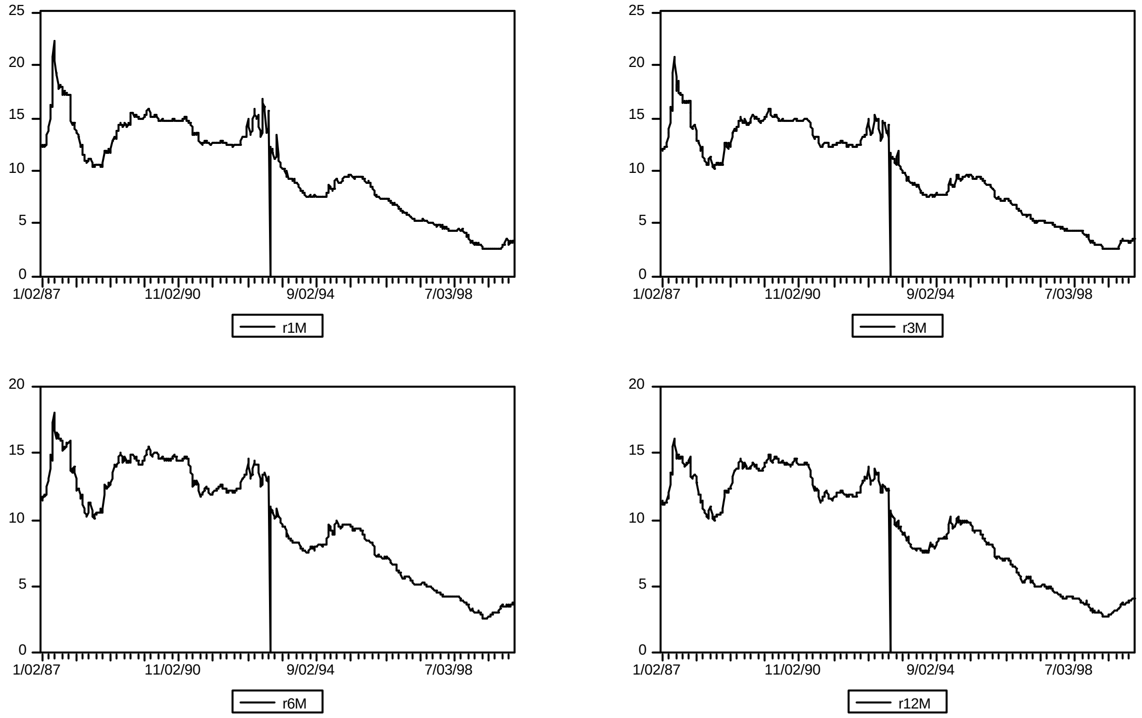

Table 4. Johansen (1988) LR Cointegration Test

ECM lags = 1	ECM lags = 2	ECM lags = 4	ECM lags = 6	H_O = Num. CR	5% CV
Full sample: 2/01/1987 25/12/1998					
193.697**	171.850**	113.667**	104.801**	None	47.21
90.686**	73.620**	54.577**	40.999**	At most 1	29.68
13.622	10.126	7.821	9.134	At most 2	15.41
0.000	0.001	0.070	0.116	At most 3	3.76
First period: 2/01/1987 7/05/1993					
133.067**	115.4556**	79.503**	81.839**	None	47.21
67.057**	53.851**	43.023**	45.580**	At most 1	29.68
13.703	11.647	11.494	14.131	At most 2	15.41
4.609	3.794	2.661	2.286	At most 3	3.76
Second period: 7/05/1993 25/12/1998					
152.160**	149.383**	115.115**	129.826**	None	47.21
85.706**	67.431**	63.115**	59.347**	At most 1	29.68
21.113*	16.719*	16.305*	17.786*	At most 2	15.41
0.077	0.179	0.318	0.367	At most 3	3.76

Note: * and ** denote rejection of the hypothesis at 5% and 1% significance level respectively. It is included a linear deterministic trend. Dates are expressed as dd/mm/yy.

Table 5. Univariate models

$$\Delta r_t = m + m' D_t + f_1 \Delta r_{t-1} + f_{1'} \Delta r_{t-1} D_t + f_2 \Delta r_{t-2} + f_{2'} \Delta r_{t-2} D_t + f_3 r_{t-3} + f_{3'} r_{t-3} D_t + f_4 \Delta r_{t-4} + f_{4'} \Delta r_{t-4} D_t + u_t$$

	US1				US2				US3			
	Dr1m	Dr3m	Dr6m	Dr12m	Dr1m	Dr3m	Dr6m	Dr12 m	Dr1m	Dr3m	Dr6m	Dr12m
m (x100)	-1.389	-1.155	-1.030	-0.965	-4.019	-2.992	-2.599	-2.395	-5.490	-3.758	-2.910	-2.551
	(1.482)	(1.108)	(0.866)	(0.752)	(2.162)	(1.620)	(1.265)	(1.098)	(2.162)	(1.675)	(1.280)	(1.107)
m? (x100)					4.962	3.666	2.947	2.689	6.287	4.173	3.242	2.832
	--	--	--	--	(2.972)	(2.226)	(1.736)	(1.501)	(2.947)	(2.257)	(1.737)	(1.501)
f_1	0.213	0.371	0.427	0.339	0.209	0.367	0.423	0.335	-0.031	0.164	0.196	0.110
	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)	(0.039)	(0.040)	(0.070)	(0.078)	(0.074)	(0.070)
f_1'									0.363	0.284	0.325	0.348
	--	--	--	--	--	--	--	--	(0.085)	(0.091)	(0.087)	(0.085)
f_2	-0.081	-0.121	-0.180	-0.098	-0.083	-0.123	-0.183	-0.103	-0.077	-0.050	-0.042	0.074
	(0.041)	(0.042)	(0.039)	(0.040)	(0.041)	(0.042)	(0.039)	(0.040)	(0.065)	(0.074)	(0.073)	(0.070)
f_2'									-0.077	-0.135	-0.214	-0.284
	--	--	--	--	--	--	--	--	(0.084)	(0.091)	(0.087)	(0.085)
f_3	-0.103	-0.147			-0.106	-0.151			-0.245	-0.203		
	(0.040)	(0.042)	--	--	(0.040)	(0.042)	--	--	(0.066)	(0.073)	--	--
f_3'									0.232	0.098		
	--	--	--	--	--	--	--	--	(0.081)	(0.091)	--	--
f_4		0.115				0.111				0.086		
	--	(0.040)	--	--	--	(0.040)	--	--	--	(0.074)	--	--
f_4'										0.013		
	--	--	--	--	--	--	--	--	--	(0.089)	--	--
Chow Test	7.322	2.990	6.462	8.647								
07/05/93	(0.00)	(0.01)	(0.00)	(0.00)	--	--	--	--	--	--	--	--
Adj. R^2	0.057	0.147	0.156	0.101	0.060	0.149	0.163	0.109	0.100	0.158	0.178	0.134
s_u	0.369	0.275	0.217	0.187	0.368	0.275	0.215	0.186	0.362	0.273	0.213	0.183
Q(6)	2.567	0.858	7.450	6.902	2.693	0.946	7.365	6.541	5.364	2.384	7.952	7.007
(p-val.)	(0.463)	(0.930)	(0.024)	(0.031)	(0.441)	(0.914)	(0.025)	(0.037)	(0.147)	(0.665)	(0.018)	(0.03)
Log Likel.	-260.5	-77.69	73.20	161.89	-259.15	-76.47	74.65	163.49	-247.4	-71.11	82.73	175.01

Note: D_t is a dummy variable equal to unity before the break and zero otherwise Standard deviations in parenthesis. Q(6) is the Ljun-Box tets for six order autocorrelation, the p-values have been adjusted by model order.

Table 6. VAR models

$$\Delta r_t = cte + \alpha'\beta \; r_{t-1} + d_1 \Delta r_{t-1} + d_2 \Delta r_{t-2} + d_3 \Delta r_{t-3} + e_t$$

$$(\Delta r_t)' = (\Delta r12m_t, \Delta r6m_t, \Delta r3m_t, \Delta r1m_t)$$

$$(\Delta r_{t-i})' = (\Delta r12m_{t-i}, \Delta r6m_{t-i}, \Delta r3m_{t-i}, \Delta r1m_{t-i}) \quad i = 1, 2, 3.$$

Panel A: VAR-ECM-1. Full sample and two cointegration relationships.

Rates	cte	a?		b				d1				d2				d3			
D**r12m$_t$**	-0.009	-0.122	0.152	1	0	-3.554	2.602	-0.164	0.880	-0.458	0.901	-0.107	0.052	-0.273	0.179	0.159	0.150	-0.211	-0.007
	(0.007)	(0.054)	(0.120)			(0.241)	(0.235)	(0.094)	(0.154)	(0.150)	(0.066)	(0.091)	(0.152)	(0.141)	(0.063)	(0.087)	(0.143)	(0.133)	(0.062)
D**r6m$_t$**	-0.010	0.001	-0.147	0	1	-2.318	1.331	-0.001	0.899	-0.519	0.108	-0.031	-0.117	-0.350	0.275	0.244	0.093	-0.314	0.043
	(0.008)	(0.065)	(0.144)			(0.111)	(0.108)	(0.112)	(0.185)	(0.180)	(0.079)	(0.109)	(0.182)	(0.169)	(0.075)	(0.104)	(0.170)	(0.159)	(0.074)
D**r3m$_t$**	-0.001	-0.119	0.080					0.077	1.054	-0.782	0.259	0.081	-0.204	-0.546	0.414	0.380	0.049	-0.483	0.118
	(0.011)	(0.081)	(0.191)					(0.140)	(0.231)	(0.225)	(0.099)	(0.137)	(0.227)	(0.211)	(0.094)	(0.131)	(0.213)	(0.199)	(0.092)
D**r1m$_t$**	-0.012	-0.232	0.117					0.153	0.807	-0.707	0.309	0.082	-0.628	-0.279	0.394	0.587	-0.235	-0.346	0.088
	(0.014)	(0.107)	(0.238)					(0.186)	(0.306)	(0.298)	(0.131)	(0.181)	(0.301)	(0.280)	(0.125)	(0.173)	(0.282)	(0.264)	(0.122)

Panel B: VAR-ECM2. Full sample and three cointegration relationships.

Rates	cte	a?							d1				d2				d3			
D**r12m$_t$**	-0.009	-0.106	0.153	0.057	1	0	0	-0.941	-0.176	0.881	-0.445	0.086	-0.117	0.057	-0.266	0.177	0.151	0.154	-0.204	-0.009
	(0.007)	(0.056)	(0.120)	(0.113)				(0.086)	(0.094)	(0.155)	(0.151)	(0.066)	(0.092)	(0.152)	(0.142)	(0.063)	(0.088)	(0.143)	(0.134)	(0.062)
D**r6m$_t$**	-0.009	0.032	-0.145	0.293	0	1	0	-0.980	-0.027	0.902	-0.495	0.099	-0.049	-0.109	-0.336	0.270	0.229	0.102	-0.301	0.040
	(0.008)	(0.067)	(0.143)	(0.135)				(0.056)	(0.113)	(0.185)	(0.180)	(0.079)	(0.110)	(0.182)	(0.169)	(0.075)	(0.105)	(0.170)	(0.159)	(0.074)
D**r3m$_t$**	-0.009	-0.073	0.083	0.170	0	0	1	-0.997	0.043	1.057	-0.747	0.247	0.053	-0.190	-0.525	0.407	0.358	0.059	-4.65	0.113
	(0.010)	(0.083)	(0.179)	(0.168)				(0.025)	(0.140)	(0.230)	(0.225)	(0.099)	(0.137)	(0.226)	(0.211)	(0.094)	(0.130)	(0.212)	(0.198)	(0.092)
D**r1m$_t$**	-0.012	-0.179	0.120	0.478					0.115	0.810	-0.666	0.295	0.050	-0.612	-0.255	0.386	0.562	-0.225	-0.324	0.083
	(0.014)	(0.110)	(0.237)	(0.223)					(0.186)	(0.305)	(0.298)	(0.131)	(0.182)	(0.301)	(0.280)	(0.125)	(0.174)	(0.281)	(0.263)	(0.122)

Panel C: VAR-ECM3. Structural change and three cointegration relationships

$\Delta r_t = cte + f_0 D_t + a'b\, r_{t-1} + d_1 \Delta r_{t-1} + d_2 \Delta r_{t-2} + d_3 \Delta r_{t-3} + e_t$

Rates	cte	f0	a?			b				d1				d2				d3			
Dr1m$_t$	-0.066 (0.029)	0.102 (0.048)	-0.159 (0.109)	0.082 (0.238)	0.463 (0.223)					0.103 (0.186)	0.833 (0.306)	-0.671 (0.298)	0.287 (0.131)	0.039 (0.182)	-0.585 (0.301)	-0.260 (0.280)	0.383 (0.125)	0.559 (0.173)	-0.205 (0.281)	-0.335 (0.263)	0.084 (0.122)
Dr12m$_t$	-0.041 (0.015	0.061 (0.024)	-0.079 (0.055)	0.127 (0.120)	0.032 (0.113)	1	0	0	-1.514 (0.459)	-0.193 (0.094)	0.897 (0.154)	-0.437 (0.151)	0.077 (0.066)	-0.132 (0.092)	0.077 (0.152)	-0.262 (0.142)	0.171 (0.063)	0.143 (0.088)	0.169 (0.142)	-0.205 (0.133)	-0.011 (0.062)
Dr6m$_t$	-0.059 (0.017)	0.095 (0.029)	0.063 (0.066)	-0.1841 (0.143)	0.265 (0.134)	0	1	0	-1.348 (0.301)	-0.047 (0.112)	0.925 (0.184)	-0.490 (0.179)	0.088 (0.079)	-0.067 (0.109)	-0.080 (0.181)	-0.335 (0.168)	0.264 (0.075)	0.221 (0.104)	0.123 (0.169)	-0.307 (0.158)	0.039 (0.073)
Dr3m$_t$	-0.067 (0.022)	0.109 (0.036)	-0.044 (0.082)	0.040 (0.179)	0.146 (0.169)	0	0	1	-1.154 (0.132)	0.025 (0.139)	1.082 (0.229)	-0.746 (0.224)	0.236 (0.099)	0.037 (0.136)	-0.159 (0.226)	-0.527 (0.210)	0.401 (0.094)	0.352 (0.130)	0.081 (0.211)	-0.474 (0.198)	0.113 (0.092)

Panel D: VAR-ECM4. Structural change in short run and three cointegration relationships.

Rates	cte	a?			b				d1				d2				d3			
Dr12m$_t$	-0.044 (0.014)	-0.056 (0.054)	0.088 (0.116)	0.051 (0.108)	1	0	0	-1.394 (0.276)	-0.397 (0.161)	0.705 (0.280)	0.418 (0.293	-0.488 (0.124)	-0.073 (0.162)	0.002 (0.278)	0.124 (0.297)	-0.078 (0.128)	0.092 (0.155)	0.445 (0.272)	-0.343 (0.285)	-0.114 (0.125)
Dr6m$_t$	-0.069 (0.017)	0.100 (0.065)	-0.242 (0.139)	0.286 (0.129)	0	1	0	-1.272 (0.184)	-0.301 (0.193)	0.661 (0.335)	0.415 (0.359)	-0.473 (0.149)	-0.056 (0.194)	-0.158 (0.333)	0.037 (0.355)	0.018 (0.154)	0.055 (0.186)	0.620 (0.326)	-0.490 (0.341)	-0.114 (0.149)
Dr3m$_t$	-0.085 (0.022)	0.018 (0.080)	-0.056 (0.172)	0.175 (0.161)	0	0	1	-1.124 (0.082)	-0.378 (0.239)	0.876 (0.416)	0.403 (0.435)	-0.519 (0.184)	-0.144 (0.240)	-0.147 (0.414)	-0.009 (0.441)	0.035 (0.191)	0.066 (0.231)	0.790 (0.404)	-0.645 (0.424)	-0.150 (0.185)
Dr1m$_t$	-0.085 (0.029)	-0.090 (0.107)	-0.029 (0.229)	0.500 (0.214)					-0.473 (0.319)	0.923 (0.555)	0.746 (0.580)	-0.761 (0.246)	-0.269 (0.321)	-0.474 (0.552)	0.351 (0.588)	-0.061 (0.254)	0.179 (0.307)	0.782 (0.539)	-0.616 (0.565)	-0.284 (0.247)

	f_0	f_1				f_2				f_3			
Dr12m$_t$	0.064 (0.023)	0.368 (0.188)	0.264 (0.308)	-1.218 (0.320)	0.812 (0.136)	-0.207 (0.190)	0.181 (0.314)	-0.373 (0.328)	0.205 (0.144)	0.099 (0.184)	-0.323 (0.308)	0.024 (0.318)	0.258 (0.141)
Dr6m$_t$	0.106 (0.028)	0.449 (0.225)	0.396 (0.369)	-1.350 (0.384)	0.833 (0.165)	-0.156 (0.228)	0.207 (0.376)	-0.379 (0.393)	0.203 (0.173)	0.269 (0.219)	-0.609 (0.369)	0.055 (0.381)	0.343 (0.170)
Dr3m$_t$	0.133 (0.035)	0.652 (0.279)	0.390 (0.458)	-1.766 (0.476)	1.122 (0.205)	0.074 (0.282)	0.155 (0.467)	-0.598 (0.488)	0.357 (0.215)	0.432 (0.273)	-0.863 (0.458)	0.002 (0.473)	0.515 (0.211)
Dr1m$_t$	0.129 (0.047)	0.903 (0.372)	0.033 (0.610)	-2.161 (0.635)	1.528 (0.273)	0.187 (0.376)	0.124 (0.622)	-0.744 (0.650)	0.431 (0.286)	0.543 (0.364)	-1.184 (0.611)	0.047 (0.630)	0.732 (0.281)

Panel E: VAR-ECM5. Structural change in short run and long run.

VAR-ECM5A: First period with two cointegration relationships

Rates	cte	a?		b				d1				d2				d3			
Dr12m$_t$	0.001	-0.196	0.242	1	0	-2.736	1.861	0.045	0.840	-0.739	0.311	-0.231	0.065	-0.191	0.119	0.213	0.038	-0.280	0.137
	(0.011)	(0.090)	(0.177)			(0.209)	(0.191)	(0.128)	(0.208)	(0.199)	(0.088)	(0.124)	(0.203)	(0.186)	(0.086)	(0.118)	(0.186)	(0.175)	(0.085)
Dr6m$_t$	0.002	0.021	-0.209	0	1	-2.022	1.073	0.189	1.011	-0.937	0.363	-0.187	-0.004	-0.327	0.221	0.330	-0.028	-0.427	0.227
	(0.013)	(0.112)	(0.220)			(0.116)	(0.105)	(0.159)	(0.259)	(0.248)	(0.109)	(0.154)	(0.252)	(0.232)	(0.107)	(0.147)	(0.231)	(0.217)	(0.106)
Dr3m$_t$	0.004	-0.100	0.024					0.342	1.184	-1.334	0.588	-0.024	-0.080	-0.563	0.375	0.516	-0.129	-0.620	0.348
	(0.017)	(0.140)	(0.276)					(0.199)	(0.325)	(0.310)	(0.137)	(0.193)	(0.315)	(0.290)	(0.134)	(0.184)	(0.289)	(0.272)	(0.132)
Dr1m$_t$	0.007	-0.304	0.173					0.559	0.784	-1.334	0.729	0.013	-0.511	-0.309	0.339	0.777	-0.505	-0.526	0.424
	(0.022)	(0.182)	(0.358)					(0.259)	(0.423)	(0.403)	(0.177)	(0.251)	(0.410)	(0.377)	(0.174)	(0.239)	(0.375)	(0.354)	(0.172)

VAR-ECM5B: Second period with three cointegration relationships

	cte	a?			b				d1				d2			
Dr12m$_t$	-0.028	-0.250	0.584	-0.214	1	0	0	-1.114	-0.277	0.152	0.674	-0.379	0.063	-0.256	-0.007	0.098
	(0.008)	(0.083)	(0.202)	(0.234)				(0.082)	(0.131)	(0.244)	(0.263)	(0.113)	(0.124)	(0.227)	(0.235)	(0.103)
Dr6m$_t$	-0.033	-0.199	0.441	-0.034	0	1	0	-1.074	-0.100	-0.032	0.724	-0.352	0.149	-0.5099	-0.101	0.227
	(0.009)	(0.092)	(0.224)	(0.259)				(0.048)	(0.145)	(0.271)	(0.292)	(0.125)	(0.137)	(0.251)	(0.261)	(0.115)
Dr3m$_t$	-0.039	-0.414	0.840	-0.084	0	0	1	-1.027	-0.101	0.005	0.673	-0.288	0.105	-0.586	-0.265	0.362
	(0.011)	(0.111)	(0.271)	(0.313)				(0.023)	(0.176)	(0.327)	(0.352)	(0.151)	(0.166)	(0.303)	(0.315)	(0.138)
Dr1m$_t$	-0.050	-0.619	0.781	0.809					-0.146	0.087	0.639	-0.257	0.016	-0.790	-0.379	0.533
	(0.015)	(0.156)	(0.382)	(0.441)					(0.247)	(0.461)	(0.496)	(0.213)	(0.233)	(0.428)	(0.443)	(0.195)

PANEL F: VAR Models Diagnosis

MODEL	VAR-ECM - 1				VAR-ECM - 2				VAR-ECM - 3				VAR-ECM - 4				VAR-ECM - 5			
	Dr12m	Dr6m	Dr3m	Dr1m	Dr12m	Dr6m	Dr3m	Dr1m	Dr12m	Dr6m	Dr3m	Dr1m	Dr12m	Dr6m	Dr3m	Dr1m	Dr12m	Dr6m	Dr3m	Dr1m
Adj. R^2	0.211	0.207	0.233	0.171	0.211	0.210	0.238	0.175	0.217	0.220	0.245	0.177	0.292	0.284	0.316	0.253	0.280	0.261	0.295	0.241
Q(6)	4.452	4.084	6.231	7.901	4.391	3.867	5.985	7.149	4.471	3.709	5.957	6.601	6.242	5.932	5.078	9.117	8.200	7.096	6.053	9.619
(p-value)	(0.62)	(0.66)	(0.40)	(0.24)	(0.62)	(0.69)	(0.42)	(0.31)	(0.61)	(0.71)	(0.43)	(0.36)	(0.397)	(0.42)	(0.53)	(0.17)	(0.22)	(0.32)	(0.42)	(0.15)
s$_u$	0.175	0.209	0.261	0.346	0.175	0.209	0.260	0.119	0.174	0.207	0.259	0.345	0.166	0.199	0.247	0.329	0.167	0.202	0.250	0.332
Log Likel.	208.21	97.83	-39.62	-214.8	208.94	99.68	-37.04	-212.8	211.86	104.07	-33.67	-211.4	249.45	137.20	3.072	-175.4	245.99	128.75	-5.489	-181.29

Note: D_t is a dummy variable equal to unity before the break and zero otherwise Standard deviations in parenthesis. Q(6) is the Ljun-Box tets for six order autocorrelation, the p-values have been adjusted by model order.

Table 7. Univariate models: Forecast accuracy

	r1m			r3m			r6m			r12m		
	US1	US2	US3	US1	US2	US3	US1	US2	US3	US1	US2	US3
MAE	0.051	0.067	0.080	0.046	0.056	0.061	0.042	0.048	0.051	0.056	0.061	0.062
MAPE	0.017	0.023	0.027	0.015	0.018	0.020	0.014	0.016	0.017	0.017	0.019	0.019
RMSE	0.080	0.089	0.105	0.077	0.083	0.088	0.060	0.066	0.067	0.075	0.080	0.079
REMSPE	0.026	0.029	0.034	0.025	0.027	0.028	0.020	0.022	0.022	0.024	0.025	0.024
UTHEIL1	0.027	0.030	0.036	0.025	0.027	0.029	0.019	0.021	0.022	0.023	0.025	0.024
UTHEIL2	0.014	0.015	0.018	0.013	0.014	0.015	0.010	0.011	0.011	0.012	0.012	0.012
UTHEIL3	0.916	0.922	1.045	0.945	0.976	1.025	0.961	0.971	0.983	1.032	1.061	1.029

Note: See Appendix A.

Table 8. VAR models: Forecast accuracy

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR1	VAR2	VAR3	VAR4	VAR5
			r1m					r3m		
MAE	0.0635	0.0660	0.0876	0.1070	0.1060	0.0629	0.0640	0.0840	0.0750	0.0904
MAPE	0.0216	0.0225	0.0303	0.0369	0.0365	0.0205	0.0210	0.0281	0.0252	0.0305
RMSE	0.0858	0.0882	0.1090	0.1470	0.1690	0.0947	0.0938	0.1080	0.0991	0.1170
RMSPE	0.0294	0.0303	0.0378	0.0508	0.0589	0.0305	0.0304	0.0358	0.0331	0.0394
UTHEIL1	0.0294	0.0302	0.0374	0.0503	0.0579	0.0313	0.0310	0.0356	0.0327	0.0388
UTHEIL2	0.0146	0.0150	0.0184	0.0249	0.0286	0.0156	0.0154	0.0176	0.0162	0.0192
UTHEIL3	0.7620	0.7770	0.8760	11.900	10.100	10.200	0.9760	0.9320	0.7790	0.6160
			r6m					r12m		
MAE	0.0532	0.0507	0.0558	0.0514	0.0594	0.0562	0.0553	0.0568	0.0604	0.0634
MAPE	0.0170	0.0162	0.0179	0.0165	0.0193	0.0174	0.0172	0.0178	0.0186	0.0199
RMSE	0.0738	0.0716	0.0771	0.0743	0.0828	0.0757	0.0746	0.0751	0.0779	0.0843
RMSPE	0.0239	0.0232	0.0251	0.0243	0.0270	0.0235	0.0232	0.0236	0.0239	0.0264
UTHEIL1	0.0237	0.0229	0.0247	0.0238	0.0265	0.0232	0.0229	0.0230	0.0239	0.0259
UTHEIL2	0.0118	0.0115	0.0123	0.0119	0.0132	0.0116	0.0115	0.0115	0.0119	0.0129
UTHEIL3	10.800	10.500	10.700	0.9340	0.9180	0.9950	0.9770	0.9650	0.8550	0.8680

Note: See Appendix A.

Table 9. Univariate models: Diebold and Mariano(1995) Test

	US1	US2	US1	US2
	R1m		r3m	
US2	2.685		2.583	
US3	3.368	3.318	2.429	1.887
	R6m		r12m	
US2	3.187		2.778	
US3	3.090	0.941	1.419	-0.685

Note: The null hypothesis is: $H_0: E[g(e_{it})] = E[g(e_{jt})]$, when $g(e_{it})$ is the loss function associated with the row i model forecast and $g(e_{jt})$ is the loss function associated with the column j model forecast

Table 10. VAR models: Diebold and Mariano (1995) Test

	VAR-ECM1	VAR-ECM2	VAR-ECM3	VAR-ECM4	VAR-ECM1	VAR-ECM2	VAR-ECM3	VAR-ECM4
		r1m				**r3m**		
VAR-ECM2	1.449				-0.427			
VAR-ECM3	4.397	4.975			2.332	3.381		
VAR-ECM4	2.438	2.409	1.735		0.343	0.457	-0.960	
VAR-ECM5	2.520	2.491	2.044	1.074	1.326	1.468	0.707	1.801
		r6m				**r12m**		
VAR-ECM2	-1.820				-1.699			
VAR-ECM3	0.809	1.715			-0.272	0.251		
VAR-ECM4	0.054	0.309	-0.366		0.273	0.413	0.376	
VAR-ECM5	0.759	0.970	0.555	1.375	1.009	1.169	1.224	1.277

Note: The null hypothesis is: $H_0 : E[g(e_{it})] = E[g(e_{jt})]$, when $g(e_{it})$ is the loss function associated with the row i model forecast and $g(e_{jt})$ is the loss function associated with the column j model forecast

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