ASYMMETRY IN THE EMS: NEW EVIDENCE BASED ON NON-LINEAR FORECASTS *

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ABSTRACT

In this paper we provide new evidence on the hypothesis of German leadership and asymmetric performance in the EMS, in the framework of causality tests, using daily data. Given the evidence about non-linearity in financial series, we propose applying non-linear forecasting methods based on the literature on complex dynamic systems. Our analysis covers nine countries, and the sample period runs until 30 April 1998, so including the more recent events in the EMS history. A comparison of our results with those obtained from standard linear econometric techniques leads us to conclude that inference on causality based on our non-linear predictors would be preferable to that based on the standard linear approach.

JEL codes: C53, E43, F33

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Key words: Interest rates, European Monetary System, Non-linear forecasting

1. Introduction

As it is well known, fixed exchange rate systems face the so-called *n*-1 problem: there are *n* countries pegging their exchange rates but only *n*-1 exchange rates among them, which gives the system one degree of freedom when setting money supply and the interest rate. This degree of freedom can be used either in an asymmetric (i. e., hegemonic) way, by enabling one country to become the leader and settle monetary policy independently, with the other countries following its stance; or, alternatively, in a symmetric (i. e., cooperative) way, so that all countries are allowed to decide jointly over the implementation of monetary policy (see De Grauwe, 1997).

The European Monetary System (EMS) means no exception to this problem. However, and despite the initial objectives of the founders of the EMS, a general consensus has emerged that the system works in an asymmetric way, with Germany assuming the leading role and the remaining countries passively adjusting to German monetary policy actions. In its turn, the follower countries may find beneficial to behave in such a way, since they can take advantage of the firmly established anti-inflation credibility of the German Bundesbank (see, e. g., Giavazzi and Pagano, 1988, or Mélitz, 1988). On the other hand, these countries would have retained some degree of monetary autonomy by resorting to capital controls, which would have allowed them to dissociate the evolution of domestic (i. e., onshore) interest rates from those prevailing in the Euromarket (i. e., offshore) (see Rogoff, 1985, or Giavazzi and Giovannini, 1989).

Some evidence along these lines was provided by Giavazzi and Giovannini (1987,1989), who found a higher volatility for French and Italian offshore interest rates as compared to the German ones during the EMS period, reflecting the higher autonomy of

German monetary policy. Similarly, Mastropasqua, Micossi and Rinaldi (1988) analysed foreign exchange intervention and sterilization for four EMS countries (Germany, Belgium, France and Italy) along the period 1979-1987, and obtained that interventions were fully sterilized only in Germany, which was again interpreted in terms on Germany's leadership in the system. Also, by means of Granger-causality tests, Karfakis and Moschos (1990) concluded that interest rate changes for Belgium, France, Italy, and the Netherlands could be predicted using information on the past evolution of German interest rates, but not conversely.

Other authors, however, have challenged these conclusions; see, for instance, Cohen and Wyplosz (1989), Fratianni and von Hagen (1990), von Hagen and Fratianni (1990), Cherubini, Ciampolini, Hamaui and Sironi (1992), Kutan (1992), Hassapis, Pittis and Prodromidis (1999), or Bajo and Montávez (1999). In these papers, equations for monetary aggregates or interest rates in several EMS countries are estimated, finding that monetary variables in every country depend on German variables, but also on those concerning the other countries. Using different methods, comparable results have been also obtained by De Grauwe (1989) and Koedijk and Kool (1992).

A common result to most of the above quoted studies is the finding that, both in terms of size and persistence, the effect is stronger from German variables to the other EMS countries' variables, rather than the other way round. In other words, whereas monetary policy in the other EMS countries would be affected not only by German actions but also by the other EMS partners also, German monetary policy would operate rather independently. This would point to a special role of Germany within the EMS, even though the hypothesis of German leadership or dominance might appear too strong. In von Hagen and Fratianni's words: "(I)n the short run, the EMS is best portrayed as an interactive web of monetary policies, where Germany is an important player, but not the dominant one (...) (I)t is tempting to conclude that many observers have mistaken German dominance with the relative strength of Germany and the relative weakness of France in the EMS" (von Hagen and Fratianni, 1990, p. 373).

Unlike the previous papers, which make use either of quarterly or monthly data, we can quote two more recent studies which use instead high-frequency (i. e., daily) data on interest rates, and also address the issue of the influence of the German reunification on the hypothesis of the asymmetric behaviour of the EMS. However, a common feature to both papers is that they only deal with the cases of France and Germany.

So, by computing the impulse effects of unit shocks to interest rates from VAR estimates, Gardner and Perraudin (1993) find the effect of French innovations on Germany to be significant, although smaller than the German effect on France. They also detect the presence of a structural break coinciding with German reunification, with Germany losing its leadership role after then but recovering it thereafter.

Finally, by using several concepts of causality, Henry and Weidmann (1995) confirm the hypothesis of German dominance *vis-à-vis* France in the short-run dynamics, unlike the long run where some evidence of interdependence is found for the period before the German reunification. Again, according to their results, after that date German dominance would have become even stronger.

In this paper we will try to provide some additional evidence on the hypothesis of

German leadership and asymmetric performance in the EMS, by using high frequency (i. e., daily) data. Unlike the above mentioned papers, we will propose using non-linear forecasting methods based on the literature on complex dynamic systems, which can be justified given the evidence about non-linearity present in financial series (see, e. g., Mills, 1996). At the same time, we extend the analysis to nine countries, and include in our sample the more recent events in the EMS history, such as the German reunification, the monetary turmoil at the end of 1992, and the broadening of fluctuation bands in 1993. We also perform a comparison of our results with those obtained from standard linear econometric techniques, which leads us to suggest that inference on causality based on our non-linear predictors would be more appropriate than that based on the standard linear approach.

The rest of the paper is organised as follows. Our testing strategy is discussed in section 2, whereas the main empirical results are presented in section 3. Next, the comparison of our results using the non-linear approach with those obtained from standard linear econometric techniques is reported in section 4. The main conclusions are summarised in section 5.

2. A procedure for testing causality using non-linear forecasting methods

The traditional method for testing causality in economic time series makes use of the well-known Granger's definition of causality (Granger, 1969). Given two variables, x and y, x is said to Granger-cause y if the latter can be predicted better by past values of x and y, rather than by past values of y alone. From this definition, the test proceeds by using both x and y as dependent variables, so that four results are possible: x Granger-causes y, y Granger-causes x, two-way Granger-causality, and no Granger-causality.

In practice, the criterion for assessing Granger-causality consists of comparing the prediction errors (PE) from both information sets. Formally, denoting by y_t^f the prediction of y_t, if

$$\mathrm{PE}(y_t^f \mid Y_{t-1} \cup X_{t-1}) < \mathrm{PE}(y_t^f \mid Y_{t-1})$$

then x_t Granger-causes y_t, where X_{t-1} and Y_{t-1} are, respectively, the sets of all past information on variables x and y available at time t.

Starting from this approach, we will make predictions for the variable y_t by means of the nearest neighbour forecasting technique proposed by Farmer and Sidorowich (1987), together with the bivariate case presented in Fernández, Sosvilla and Andrada (1999).

The basic idea behind these predictors, inspired in the literature on forecasting in non-linear dynamic systems, is that pieces of time series sometime in the past might have a resemblance to pieces in the future. In order to generate predictions, similar patterns of behaviour are located in terms of nearest neighbours, and the time evolution of these nearest neighbours is exploited to yield the desired prediction. Therefore, the procedure only uses information local to the points to be predicted and makes no attempt to fit a function to the whole time series; the general ideas behind this procedure can be found in Bajo, Fernández and Sosvilla (1992), and Fernández, Sosvilla and Andrada (1999). Notice that these predictors have shown, for financial time series, a higher efficiency than a random walk in several studies, where, in many cases, evidence on some kind of deterministic behaviour has been found; see, among others, Diebold and Nason (1990), Bajo, Fernández and Sosvilla (1992), Mizrach (1992), Fernández, Sosvilla and Andrada (1999), or Soofi and Cao (1999).

More specifically, the procedure runs as follows. Beginning with the univariate case, let z_t (t=1,...,n) be a finite time series. To detect behavioural patterns in this series, segments of equal length are considered as vectors Z_t^m of m observations sampled from the original time series:

$$Z_t^m = (z_t, z_{t-1}, ..., z_{t-(m-1)}) \qquad t = m, m+1, ..., n \tag{1}$$

with m referred to as the embedding dimension. These m-dimensional vectors are often called m-histories, while the m-dimensional space $\Re^m$ is referred to as the phase space of time series.

The sequence of m-histories makes up a m-dimensional object that can, for a big enough m, mimic the data generation process (Takens, 1981). The proximity of two m-histories in the phase space $\Re^m$ allows us to talk of “nearest neighbours” in the dynamic behaviour of two segments in the time series z_t (t=1,...,n).

This approach does not require stationarity in the time series z_t (t=1,...,n), the local predictions being generated by analysing the historical paths of the vectors around the last available vector

$$Z_n^m = (z_n, z_{n-1}, z_{n-2}, ..., z_{n-(m-1)}) \qquad (2)$$

Segments with similar dynamic behaviour are detected and used to produce the forecast, which is computed as some average of the actually observed terms next to the segments involved. Therefore, in order to construct a local predictor we have considered the *k* *m*-histories

$$Z_{i_1}^m, Z_{i_2}^m, Z_{i_3}^m, ..., Z_{i_k}^m \qquad (3)$$

most similar to Z_n^m. The future short-term evolution of the time series will then be obtained using the information contained in the nearest neighbours found in the past.

In order to establish nearest neighbours to Z_n^m, we look for the closest *k* vectors (3) in the phase space $\Re^m$, which maximise the function:

$$\rho(Z_i^m, Z_n^m)$$

so that the chosen *m*-histories Z_i^m present the highest serial correlation with respect to the last one, Z_n^m.

Once the nearest neighbours to Z_n^m have been established, we consider predictors of the future evolution of Z_n^m. A predictor is simply a rule for obtaining an estimate of z_{n+1}^f, i. e., a prediction of the next observation z_{n+1}. This is made by using some extrapolation of the observations

$$z_{i_1+1}, z_{i_2+1}, ..., z_{i_k+1} \qquad (4)$$

subsequent to the *k* nearest neighbours *m*-histories chosen, that is to say:

$$z_{n+1}^{f} = F(z_{i_1+1}, z_{i_2+1}, ..., z_{i_k+1}) \qquad (5)$$

When generating nearest neighbours predictions, locally adjusted linear autoregressive predictions are usually employed. The procedure involves the regression by ordinary least squares of the future evolution of the *k* nearest neighbours chosen on their preceding *m*-histories, that is, regressing z_{i_r+1} from (4) on $Z_{i_r}^{m} = (z_{i_r}, z_{i_r-1}, z_{i_r-2}, ..., z_{i_r-(m-1)})$ from (3), for r=1,...,k. Then, the fitted coefficients are used to generate predictions for any z_{n+1} as follows:

$$z_{n+1}^{f} = \hat{a}_0 z_n + \hat{a}_1 z_{n-1} + ... + \hat{a}_{m-1} z_{n-(m-1)} + \hat{a}_m \qquad (6)$$

The above approach has been extended to the bivariate case by Fernández, Sosvilla and Andrada (1999). Let us consider a set of two time series, z_t (t=1,...,n) and w_t (t=1,...,n).

We are interested in making predictions for an observation of one of these series (e. g., z_{n+1}), by simultaneously considering nearest neighbours in both series. To that end, we embed each of these series in the vectorial space $\Re^{2m}$, paying attention to the following vector:

$$(Z_n^m, W_n^m) \in \Re^m \times \Re^m$$

which gives us the last available *m*-history for each time series.

To establish nearest neighbours to the last *m*-histories (Z_n^m, W_n^m), we can look for the closest *k* points that maximise:

$$\rho(Z_i^m, Z_n^m) + \rho(W_i^m, W_n^m) \qquad i = m, m+1, ..., n$$

In this way, we obtain a set of *k* simultaneous *m*-histories in both series:

$$Z_{i_1}^m \ , W_{i_1}^m$$

$$Z_{i_2}^m \ , W_{i_2}^m$$

$$. \ . \ . \ . \ . \ . \ . \ . \ . \tag{7}$$

$$Z_{i_k}^m \ , W_{i_k}^m$$

The predictions for z_{n+1} and w_{n+1} can be obtained by ordinary least squares as in (6):

$$z_{n+1}^f = \hat{a}_0 z_n + \hat{a}_1 z_{n-1} + ... + \hat{a}_{m-1} z_{n-(m-1)} + \hat{a}_m \tag{8a}$$

$$w_{n+1}^f = \hat{b}_0 w_n + \hat{b}_1 w_{n-1} + ... + \hat{b}_{m-1} w_{n-(m-1)} + \hat{b}_m \tag{8b}$$

from a linear regression of z_{i_r+1} on $Z_{i_r}^m = (z_{i_r}, z_{i_r-1}, z_{i_r-2}, ..., z_{i_r-(m-1)})$, and a linear regression of w_{i_r+1} on $W_{i_r}^m = (w_{i_r}, w_{i_r-1}, w_{i_r-2}, ..., w_{i_r-(m-1)})$, for r=1,...,k. The difference between this predictor and that presented in (6) is that now the nearest neighbours are established using information from both series.

3. Empirical results

The above local predictors have been applied to daily three-month interbank interest rates of the seven countries participating at the exchange rate mechanism (ERM) of the EMS from its start: Belgium, Denmark, France, Germany, Ireland, Italy, and the Netherlands. Notice that the correct application of the methodology based on non-linear dynamic systems requires using very long time series (see, e. g., Abarbanel, 1996), so that daily data are the natural choice[1]. The sample period for this group of countries runs from 13 March 1979 (the date the ERM started to operate) to 30 April 1998 (just before the announcement of the countries participating in the European monetary union); therefore, we have more than 7000 observations in the sample. In its turn, the forecasting period starts from the last realignment in the EMS before the monetary turmoil at the end of 1992, i. e., 13 January 1987, to the end of the sample. In addition, we have also made the exercise for the three newcomers to the ERM of the EMS: Spain, the United Kingdom (UK) and Portugal, with the forecasting period in these cases running from the date of their accession: 19 June 1989 for Spain, 8 October 1990 for the UK, and 9 April 1992 for Portugal. Finally, we have computed our test for the whole sample, and also before and after the German reunification.

It should be noticed that multi-country analysis of financial series requires a special treatment for high-frequency (daily) data. Despite the relatively large number of observations, holiday effects, which differ across countries, may distort the outcomes. To avoid such a possibility, the data have been purged of this holiday effect, matching day by day the interest rate series and eliminating observations when there is no trading in any of

1 Following the referee's suggestion, the computations performed in this section have been still replied using weekly data for the two *a priori* more interesting cases, i. e., France and Italy. However, the results (not shown here, but available from the authors upon request) did not change with respect to those for our sample of daily data.

the countries under study. Therefore, the univariate prediction results for Germany change according to the sample size used for the reference country.

We begin by testing for unit roots, by means of the non-parametric tests proposed by Phillips and Perron (1988). These test statistics are particularly appropriate for testing for unit roots if a non-linear data generating mechanism is feasible *a priori*, since they are robust in the presence of a heterogeneous non-independent error process. The results are reported in Table 1 for both the levels and first differences of the series, with a truncation lag equal to 4 according to the Newey and West (1994) procedure. The test statistics are highly supportive of a single unit root in each of the series under study.

[Table 1 here]

Before computing our local predictors, we have tested for the presence of non-linear dependence in the series, since evidence of non-linearity would support our approach to forecasting. To that end, we have made use of the well-known BDS test statistic (see Brock, Dechert, Scheinkman and LeBaron, 1996):

$$\mathrm{BDS}(m,\varepsilon)=\frac{\sqrt{T_N}\,[C_m(\varepsilon)-(C_1(\varepsilon))^m]}{\hat{\sigma}_m(\varepsilon)}$$

where $T_N=n-m+1$ is the number of m-histories that can be made from a sample size n, $C_m(\varepsilon)$ is the fraction of all m-histories in the series that are "close" to (within ε of) each other, and $\hat{\sigma}_m(\varepsilon)$ is an estimate of the standard deviation of $[C_m(\varepsilon)-(C_1(\varepsilon))^m]$. Brock, Dechert, Scheinkman and LeBaron (1996) show that, under the null hypothesis of an independent and identical distribution (*iid)*, the BDS statistic is asymptotically N(0,1).

As for the practical implementation of the BDS test, the series were first-differenced given the presence of a unit root. After that, we used the residual of an AR(p) model as inputs in order to remove any linear dependence in the time series. Using the Schwarz information criterion, the appropriate lag length p was set equal to 4 for Denmark, France, the Netherlands, Ireland and Spain; 3 for Belgium, Germany, Italy and Portugal; and 1 for the UK. On the other hand, since the BDS test statistic depends on the values of the embedding dimension and the chosen distance related to the standard deviation of the data (m and ε, respectively), we followed Hsieh (1989) and Brock, Hsieh and LeBaron (1991) in Table 2 to show the results for values of m from 2 and 7, and for values of ε ranging from 0.5σ to 2σ, where σ denotes the standard deviation of the series. With over 5000 observations, we can use the normal standard tables to assess significance, since the small sample properties only become important for sizes lower than 500 (see Brock, Hsieh and LeBaron, 1991). As can be seen, the null hypothesis of *iid* is rejected at the 1% marginal significance level for all the series under study.

[Table 2 here]

In order to reinforce our previous results, we followed Scheinkman and LeBaron's (1989) suggestion, and recreated the data series by sampling them randomly, with replacement from the data until one has a "shuffled" series of the same length as the original. The shuffled series should be completely random (though preserving the original distribution). Applying the BDS test to the shuffled residuals series, the null hypothesis of *iid* is retained, because all the BDS test values are less than the critical values (see Table 3). Therefore, there is evidence that some non-linear structure present in the original series has been removed by shuffling.

[Table 3 here]

Based on this preliminary evidence of non-linearities previously reported, we proceeded to compute our local non-linear predictors. Since they depend on the values of the embedding dimension *m* and the number of *k* closest points in the phase space $\Re^m$, the latter were chosen according to Casdagli´s (1991) algorithm, obtaining in our case an embedding dimension *m*=6 and a number of nearest neighbourhood points equal to 2% of the sample. Notice that the results are robust to the choice of *m* and *k*, since other values for these parameters gave similar qualitative results.

As we said before, in the case of the seven founding members the forecasting period runs from 13 January 1987 to the end of the sample. Our local predictors are then used to produce forecasts for every change in interest rates since 14 January 1987. Every time a forecast is produced after a change in interest rates, the observation for this date is added to the sample, the models are re-estimated, and new forecasts are recursively generated for the next change in all the series until the end of the sample. In the case of Spain, the United Kingdom and Portugal, the same recursive process is performed from their respective joining dates.

The forecasting performance is measured by the root mean square error (RMSE), which is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{T} (z_i^f - z_i)^2}{T}}$$

where z_i is the current value of the variable to be predicted (in our case the interest rate), z_i^f is the predicted value, and T is the number of forecasts in the prediction period.

Table 4 shows the forecasting performance, measured by the RMSE, of our predictors in both versions (univariate and bivariate), for the whole period. In the bivariate case, the interest rate of Germany is used for establishing occurring analogues for each of the remaining countries, and *vice versa*. Then, by comparing the RMSEs, the last column reports the result of the causality test, so that if the RMSE in the bivariate case is lower (higher) than the RMSE in the univariate case, there is (there is not) causality from the first country to the second.

[Table 4 here]

As can be seen in that table, the interest rates in all the countries considered can be predicted better by adding German interest rates to the past values of the interest rates in every country, rather than by past values of national interest rates alone. On the other hand, causality is also found running from interest rates in Belgium, Denmark and the Netherlands to those in Germany.

Note also that, when two-way causality is found, the reduction in RMSEs is greater for forecasts of national interest rates using information about German interest rates than in the cases of German interest rates using information about other national rates. This could be taken as a first indication that, in these cases, the German influence on the other country is stronger than the other way round.

In order to further evaluate forecasting accuracy, in the sense of testing whether the differences between RMSEs obtained in Table 4 are statistically significant or not, we have used a test recently proposed by Diebold and Mariano (1995). Let z_{ut}^{f} and z_{bt}^{f} denote forecasts of the variable z_t based on the univariate and bivariate local predictors, respectively, and let $d_t=[(z_{ut}^{f}-z_t)^2-(z_{bt}^{f}-z_t)^2]$ denote the loss differential between the two forecasting errors. In this way, Diebold and Mariano suggest a test of the null hypothesis that the mean loss differential $\bar{d}$ is zero with an appropriate correction for serial correlation in the d_t series:

$$S = \frac{\bar{d}}{\sqrt{\dfrac{2\pi \hat{f}_d(0)}{T}}}$$

where $\hat{f}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency 0, T is the number of forecasts and S is asymptotically distributed as a N(0,1). Therefore, a significant and positive (negative) value for S would indicate a significant difference between the two forecasting errors, which would mean a better accuracy of the bivariate (univariate) predictor.

The results are shown in Table 5. As can be seen, we reject the hypothesis of equal expected squared error (i. e., bivariate local predictors would be statistically significant better predictors than univariate local predictors) when predicting interest rates in all the countries considered by adding the information content of the German interest rates. On the other hand, except for Belgium, Denmark and the Netherlands, we do not reject the hypothesis of equal expected squared error when predicting German interest rates based on national interest rates (i. e., bivariate local predictors would not be statistically significant better predictors than univariate local predictors), which would suggest that forecasting accuracy for German interest rates cannot be gained by considering also the information content of national interest rates. Therefore, these results reinforce our earlier conclusions from Table 4.

[Table 5 here]

As in Gardner and Perraudin (1993) and Henry and Weidmann (1995), we have checked the possible effects on the previous results following the German reunification. To this end, we have divided the sample in two parts, the breaking point being 29 November 1990 (as in Henry and Weidmann, 1995). The reason for taking this particular point is that, although the German reunification process actually started in the end of 1989, it was only in late November 1990 when German interest rate series registered a jump.

Tables 6 and 7 offer the results for the RMSEs and the Diebold-Mariano test, respectively. Notice that Portugal is not included, since she entered into the ERM of the EMS after the breaking point. As can be seen in Table 6, for the first subperiod we obtain similar results than those for the whole period. A different picture emerges, however, after the German reunification. Now, causality is only found running from Germany to all other countries, except for the Netherlands, where two-way causality is still detected. Again, these results are supported when performing the Diebold-Mariano test, as shown in Table 7.

[Tables 6 and 7 here]

According to these results, it would seem that German leadership in the EMS would have increased after reunification. In this way, we confirm, using different methods, earlier findings using French data by Gardner and Perraudin (1993) and Henry and Weidmann (1995), at the same time that we extend the analysis to the rest of the EMS member countries.

4. A comparison with the linear approach

The purpose of this section is to check the appropriateness of our approach to testing for asymmetry in the EMS, based on non-linear forecasting methods, by performing a comparison of our results with those obtained from standard linear econometric techniques, again in the context of Granger-causality tests.

As it is well known, the results from causality tests are highly sensitive to the order of lags, so that selecting the appropriate lag lengths becomes crucial. Otherwise, the model estimates will be inconsistent and, therefore, likely to draw misleading inferences. In this paper, we will make use of Hsiao's (1981) sequential method, which combines Akaike's final predictive error (FPE) and the definition of Granger's causality.

Briefly, Hsiao's method proceeds as follows. Consider the models

$$x_t = \alpha_0 + \sum_{j=1}^{m} \delta_j x_{t-j} + \varepsilon_t \tag{9}$$

$$x_t = \alpha_0 + \sum_{j=1}^{m} \delta_j x_{t-j} + \sum_{i=1}^{n} \gamma_i y_{t-i} + \eta_t \tag{10}$$

where x_t and y_t are stationary variables [i. e., they are I(0) variables]. The following steps are used to apply Hsiao's procedure for testing causality:

(i) Treat x_t as a one-dimensional autoregressive process as in (9), and compute its FPE with the order of lags m varying from 1 to M. Choose the order which yields the smallest FPE, say m, and denote the corresponding FPE as $\mathrm{FPE}_X(m,0)$.

(ii) Treat x_t as a controlled variable with m lags, and y_t as a manipulated variable as in (10). Compute again the FPEs of (10) by varying the order of lags of

y_t from 1 to N, and determine the order that gives the smallest FPE, say n, and denote the corresponding FPE as $FPE_X(m,n)$.

(iii) Compare $FPE_X(m,0)$ with $FPE_X(m,n)$ [i. e., compare the smallest FPE in step (i) with the smallest FPE in step (ii)]. If $FPE_X(m,0) > FPE_X(m,n)$, then y_t is said to Granger-cause x_t; whereas, if $FPE_X(m,0) < FPE_X(m,n)$, then x_t is an independent process.

(iv) Repeat steps (i) to (iii) for the y_t variable, treating x_t as the manipulated variable.

When x_t and y_t are not stationary variables, but they are first-difference stationary [i. e., they are I(1) variables] and they are cointegrated, it is possible to investigate the causal relationships between Δx_t and Δy_t using the following error correction models:

$$\Delta x_t = \alpha_0 + \beta u_{t-1} + \sum_{j=1}^{m} \delta_j \Delta x_{t-j} + \varepsilon_t \tag{11}$$

$$\Delta x_t = \alpha_0 + \beta u_{t-1} + \sum_{j=1}^{m} \delta_j \Delta x_{t-j} + \sum_{i=1}^{n} \gamma_i \Delta y_{t-i} + \eta_t \tag{12}$$

where u_t is the OLS residual of the cointegrating regression $x_t = \mu + \lambda y_t$. Note that, if x_t and y_t are I(1) variables, but they are not cointegrated, then β in (11) and (12) is assumed to be equal to zero.

In both cases [i. e., when x_t and y_t are I(1) variables, and whether they are cointegrated or not], we can use Hsiao's sequential procedure by replacing expressions (9) and (10) with equations (11) and (12), as well as x_t with Δx_t and y_t with Δy_t in steps (i) to (iv).

As we saw in the previous section, Table 1's results suggest that all the variables could be treated as first-difference stationary. Hence, the next step is to test for cointegration between each national interest rate and that of Germany. As can be seen in Table 8, both the Phillips-Perron test applied to the cointegrating residuals and Johansen's (1991,1995) likelihood test indicate that the null hypothesis of no cointegration can be rejected in all cases at the 1% significance level, except for Portugal and the UK.

[Table 8 here]

Therefore, for Belgium, Denmark, France, Ireland, Italy, the Netherlands and Spain, we tested for Granger-causality in first differences of the variables, with an error-correction term added [i. e., equations (11) and (12)]; whereas, for the cases of Portugal and the UK, we tested for Granger-causality in first differences of the variables, with no error-correction term added [i. e., equations (11) and (12), with $\beta=0$]. The resulting FPE statistics for the whole sample are reported in Table 9.

[Table 9 here]

As can be seen, for Belgium, Denmark, France, Ireland, Spain and the UK, FPEs decrease when German interest rates are added in the explanation of national interest rates, but not the other way round, suggesting Granger-causality running from German interest rates to national interest rates. Only for the Netherlands we find that FPEs decrease when either German or Dutch interest rates are added to an autoregressive process for their respective interest rates, so that two-way Granger-causality would appear between them. Finally, the opposed result is found for Italy and Portugal, so that no Granger-causality would be present between German and both Italian and Portuguese interest rates. When comparing these results with those from our non-linear predictors in Table 4, we can see that now causality from Belgian and Danish interest rates to those of Germany vanishes, as well as causality from German interest rates to those of both Italy and Portugal. These results are again supported when performing the Diebold-Mariano test, as shown in Table 10.

[Table 10 here]

As in the previous section, we have also computed causality tests before and after the German reunification. Tables 11 and 12 offer the results for the FPE and the Diebold-Mariano test, respectively. As can be seen in the tables, the results for the first subperiod are again the same than for the whole period (see Tables 9 and 10); whereas for the second subperiod causality from German to Italian interest rates disappears as compared with the results using our non-linear predictors (see Tables 6 and 7).

[Tables 11 and 12 here]

Summarizing, the results from the standard linear approach look somewhat different than those obtained from the non-linear predictors proposed in this paper. In order to discriminate between them, we have computed Diebold-Mariano tests to assess the forecasting accuracy of these two predictors, in both the univariate and bivariate cases. The test results, shown in Table 13, suggest that our non-linear predictors outperform in all cases the standard linear predictors at the 1% significance level. In this way, the evidence of non-linearity found in Tables 2 and 3, taken together with the results in Table 13, would indicate that the inference about causality obtained using the non-linear predictors proposed in this paper would be preferable to that obtained using the standard linear predictors.

[Table 13 here]

To conclude, and from the methodological point of view, this paper tries to make a contribution, particularly relevant once economists are becoming more aware of the importance that non-linearities could have on their analysis. In this sense, this paper illustrates how the formal consideration (through adequate statistical procedures) of the presence of non-linearities in the data may be a useful tool for a more correct detection of causality relationships.

5. Conclusions

In this paper we have provided some new evidence on the hypothesis of German leadership and asymmetric performance in the EMS, by applying Granger-causality tests to interest rates data. To that end, we have used comparisons of out-of-sample forecasts to determine whether the German interest rate has some predictive power in the explanation of national interest rates. So, in a first stage, forecasts of the national interest rates have been constructed, firstly using a model that excludes the German interest rate (a variable with presumed predictive content), and secondly including it. Then, in a second stage, given the two sequences of forecast errors, we conducted tests of equal forecast. The out-of-sample approach adopted in this paper is explicitly advocated, e. g., by Ashley, Granger and Schmalensee (1980), who argue that using post-sample forecast tests is more in the spirit of the definition of Granger-causality than using the standard full-sample causality test.

The main contribution of this paper has been the use of non-linear forecasting methods when performing causality tests, which is justified given the non-linear behaviour detected in the series according to standard BDS tests. On the other hand, we have used daily data on the interest rates of nine ERM members, extending the number of countries considered as compared with previously available studies. Moreover, we have analysed a longer period, covering from the start of the EMS until 30 April 1998, the day before the announcement of the countries participating in the European monetary union.

Our results suggest that, for the whole period of analysis, there is two-way causality between, on the one hand, interest rates in Belgium, Denmark and the Netherlands, and, on the other hand, those in Germany. However, for the cases of France, Ireland, Italy, Portugal, Spain and the UK, causality is only found running from Germany to those countries. It is also interesting to note that, when two-way causality is found, the forecasting improvement is greater when national interest rates are predicted adding information on German interest rates, than when German interest rates are predicted adding information on other national rates. Overall, these results could be taken as a first indication of the special role played by Germany within the EMS, even though we cannot talk of "dominance" in a strict sense.

Next, and following previous studies on the subject, we have analysed the robustness of our results by dividing the sample in two parts, before and after the German reunification. Although our conclusions are not modified for the first half of the sample, they do change after the German reunification, since two-way causality is only found in the case of the Netherlands. Therefore, this would indicate a reinforcement of German leadership in the working of the EMS following this major asymmetric shock. Overall, our results would suggest a relatively low cost of giving up monetary sovereignty by the non-German EMS countries, as implied by the European monetary union.

On the other hand, we have compared the results from our non-linear predictors with those obtained from an alternative approach, namely, standard linear econometric techniques. The standard approach led to somewhat different results; in particular, both causality from Belgian and Danish interest rates to those of Germany, and from German interest rates to those of Italy and Portugal, no longer hold. However, when computing Diebold-Mariano tests to assess the forecasting accuracy of both predictors, our non-linear predictors clearly outperformed in all cases the standard linear predictors. In other words, and recalling the caution with which any empirical results should be taken, our methodology would reveal itself as an improvement over the conventional one, in terms of forecasting accuracy. Taken together with the evidence of non-linearity obtained from BDS tests, the results of this paper would suggest that inference on causality based on our non-linear predictors would be more appropriate for the issues analysed in the paper, and preferable to that based on the standard linear approach[2].

2 In addition, the fact that our main results did not change when replied using weekly data (see note 1), would mean that this conclusion is robust to the frequency of the data.

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Table 1: Phillips-Perron test statistics

	First differences I(2) vs. I(I)			Levels I(I) vs. I(0)		
	Phillips-Perron test			Phillips-Perron test		
	$Z(t_{\tilde{\alpha}})$	$Z(t_{\alpha^*})$	$Z(t_{\hat{\alpha}})$	$Z(t_{\tilde{\alpha}})$	$Z(t_{\alpha^*})$	$Z(t_{\hat{\alpha}})$
Belgium	-7.65[a]	-7.22[a]	-7.23[a]	-2.21	-1.39	-1.42
Denmark	-7.32[a]	-7.35[a]	-7.42[a]	-2.27	-1.53	-1.18
Germany	-7.43[a]	-7.35[a]	-7.15[a]	-2.16	-1.52	-0.63
France	-7.10[a]	-7.49[a]	-7.01[a]	-1.60	-1.11	-1.21
Ireland	-7.82[a]	-7.79[a]	-7.61[a]	-2.24	-1.50	-1.12
Italy	-7.85[a]	-7.26[a]	-7.83[a]	-2.32	-2.21	-1.39
Netherlands	-7.27[a]	-7.29[a]	-7.35[a]	-0.73	-0.64	-0.72
Portugal	-6.17[a]	-6.19[a]	-6.03[a]	-1.17	-1.21	-1.17
Spain	-6.38[a]	-6.41[a]	-6.25[a]	-1.32	-1.34	-1.53
UK	-7.87[a]	-7.82[a]	-7.43[a]	-2.17	-1.18	-0.69

Notes:

(i) $Z(t_{\tilde{\alpha}})$, $Z(t_{\alpha^*})$ and $Z(t_{\hat{\alpha}})$ denote the Phillips-Perron statistics with drift and trend, with drift, and without drift, respectively (see Dolado, Jenkinson and Sosvilla-Rivero, 1990).

(ii) a denotes significance at the 1% level, according to MacKinnon´s (1991) critical values.

Table 2: BDS test on ARIMA(p,1,0) residuals

(A) Belgium

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	28.77[a]	15.47[a]	21.98[a]	22.37[a]	21.76[a]	24.61[a]	24.68[a]
m=3	34.06[a]	19.81[a]	24.77[a]	23.85[a]	22.81[a]	25.06[a]	24.94[a]
m=4	39.32[a]	22.76[a]	26.68[a]	25.20[a]	23.62[a]	25.23[a]	24.63[a]
m=5	45.42[a]	25.50[a]	27.54[a]	26.03[a]	24.09[a]	25.23[a]	24.33[a]
m=6	53.78[a]	28.64[a]	29.53[a]	26.56[a]	24.31[a]	25.01[a]	23.88[a]
m=7	65.54[a]	32.84[a]	31.24[a]	27.29[a]	24.61[a]	24.90[a]	23.58[a]

(B) Denmark

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	25.24[a]	23.51[a]	22.63[a]	22.21[a]	21.27[a]	20.56[a]	20.86[a]
m=3	32.93[a]	29.02[a]	27.52[a]	26.52[a]	25.51[a]	25.07[a]	25.30[a]
m=4	38.82[a]	31.84[a]	29.48[a]	28.06[a]	26.92[a]	26.64[a]	26.91[a]
m=5	45.67[a]	34.55[a]	30.85[a]	29.02[a]	27.54[a]	27.17[a]	27.59[a]
m=6	54.66[a]	37.56[a]	32.09[a]	29.76[a]	28.03[a]	27.64[a]	27.75[a]
m=7	66.10[a]	40.74[a]	33.21[a]	30.24[a]	28.19[a]	27.71[a]	27.79[a]

(C) Germany

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	18.94[a]	27.94[a]	24.24[a]	23.47[a]	25.85[a]	23.08[a]	22.01[a]
m=3	24.87[a]	34.46[a]	27.39[a]	26.24[a]	27.89[a]	24.96[a]	23.57[a]
m=4	33.53[a]	39.30[a]	30.39[a]	28.40[a]	28.95[a]	25.42[a]	23.83[a]
m=5	47.15[a]	44.48[a]	33.42[a]	31.31[a]	29.88[a]	26.33[a]	24.36[a]
m=6	68.82[a]	50.38[a]	36.65[a]	34.03[a]	30.49[a]	26.89[a]	24.76[a]
m=7	102.53[a]	57.40[a]	40.17[a]	37.25[a]	31.10[a]	27.57[a]	24.98[a]

Table 2 (continued)

(D) France

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	21.19[a]	21.02[a]	22.22[a]	22.14[a]	22.58[a]	21.01[a]	20.39[a]
m=3	25.06[a]	24.32[a]	25.51[a]	24.63[a]	25.12[a]	23.15[a]	22.26[a]
m=4	29.33[a]	26.56[a]	27.12[a]	25.24[a]	25.68[a]	23.74[a]	22.86[a]
m=5	33.55[a]	28.54[a]	28.24[a]	26.28[a]	26.32[a]	24.08[a]	23.14[a]
m=6	39.59[a]	31.12[a]	29.74[a]	27.08[a]	26.74[a]	24.21[a]	23.24[a]
m=7	45.94[a]	33.65[a]	31.04[a]	27.60[a]	26.91[a]	24.27[a]	23.35[a]

(E) Ireland

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	23.16[a]	23.54[a]	23.85[a]	24.44[a]	26.05[a]	26.64[a]	25.92[a]
m=3	26.04[a]	25.15[a]	25.12[a]	25.30[a]	26.69[a]	27.61[a]	26.73[a]
m=4	28.15[a]	25.80[a]	25.16[a]	25.34[a]	26.32[a]	27.09[a]	26.06[a]
m=5	30.06[a]	25.91[a]	24.82[a]	24.79[a]	25.71[a]	26.23[a]	25.41[a]
m=6	32.24[a]	26.35[a]	24.64[a]	24.33[a]	24.85[a]	25.27[a]	24.23[a]
m=7	34.53[a]	26.83[a]	24.54[a]	24.02[a]	24.23[a]	24.44[a]	23.61[a]

(F) Italy

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	21.31[a]	28.14[a]	27.61[a]	26.46[a]	25.02[a]	25.09[a]	25.12[a]
m=3	24.25[a]	30.97[a]	29.61[a]	27.72[a]	26.31[a]	26.04[a]	26.25[a]
m=4	27.09[a]	33.39[a]	30.68[a]	28.77[a]	26.67[a]	25.93[a]	25.83[a]
m=5	30.97[a]	35.86[a]	32.29[a]	29.28[a]	26.45[a]	25.41[a]	25.09[a]
m=6	35.08[a]	38.09[a]	33.12[a]	29.43[a]	26.34[a]	24.73[a]	24.11[a]
m=7	40.33[a]	41.08[a]	34.39[a]	29.85[a]	26.35[a]	24.37[a]	23.41[a]

Table 2 (continued)

(G) Netherlands

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	15.56[a]	20.38[a]	21.11[a]	16.94[a]	19.69[a]	19.57[a]	18.16[a]
m=3	20.48[a]	24.37[a]	24.83[a]	20.87[a]	20.69[a]	21.96[a]	20.22[a]
m=4	24.36[a]	26.33[a]	26.27[a]	22.63[a]	23.20[a]	22.60[a]	20.98[a]
m=5	28.77[a]	28.74[a]	27.66[a]	23.78[a]	23.73[a]	22.90[a]	21.29[a]
m=6	35.04[a]	31.82[a]	29.33[a]	24.75[a]	23.97[a]	22.91[a]	21.32[a]
m=7	42.95[a]	35.88[a]	31.30[a]	26.21[a]	24.41[a]	23.12[a]	21.53[a]

(H) Portugal

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	13.27[a]	10.18[a]	11.83[a]	9.95[a]	7.66[a]	5.78[a]	4.43[a]
m=3	15.43[a]	11.94[a]	12.62[a]	10.40[a]	8.83[a]	7.35[a]	6.82[a]
m=4	16.91[a]	12.46[a]	13.13[a]	10.82[a]	9.20[a]	7.45[a]	7.48[a]
m=5	18.79[a]	13.54[a]	13.54[a]	10.93[a]	9.13[a]	7.24[a]	7.57[a]
m=6	21.01[a]	15.01[a]	13.62[a]	11.11[a]	9.15[a]	7.13[a]	7.48[a]
m=7	23.25[a]	16.18[a]	14.82[a]	11.54[a]	9.30[a]	7.26[a]	7.70[a]

(I) Spain

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	29.22[a]	29.78[a]	28.15[a]	27.32[a]	25.34[a]	20.43[a]	15.90[a]
m=3	33.37[a]	33.20[a]	31.90[a]	31.81[a]	30.91[a]	27.72[a]	23.51[a]
m=4	35.01[a]	34.23[a]	32.63[a]	32.65[a]	35.18[a]	29.43[a]	25.41[a]
m=5	36.44[a]	34.73[a]	32.82[a]	32.59[a]	32.32[a]	30.26[a]	27.14[a]
m=6	37.53[a]	34.75[a]	32.63[a]	31.82[a]	31.73[a]	30.06[a]	27.35[a]
m=7	38.99[a]	34.96[a]	31.98[a]	31.31[a]	31.26[a]	29.78[a]	27.35[a]

Table 2 (continued)

(J) UK

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	23.14[a]	33.77[a]	22.42[a]	25.35[a]	23.47[a]	21.64[a]	22.78[a]
m=3	37.40[a]	39.91[a]	28.06[a]	29.25[a]	27.04[a]	24.66[a]	25.33[a]
m=4	52.08[a]	44.73[a]	32.15[a]	31.58[a]	28.65[a]	25.98[a]	25.83[a]
m=5	71.52[a]	50.01[a]	35.91[a]	33.60[a]	29.71[a]	26.51[a]	25.72[a]
m=6	101.02[a]	56.92[a]	39.97[a]	35.78[a]	30.86[a]	27.13[a]	25.62[a]
m=7	144.56[a]	65.20[a]	44.41[a]	37.85[a]	31.83[a]	27.46[a]	25.33[a]

Notes:

(i) The BDS statistic is applied to the ARIMA(p,1,0) residuals of the original series. Using the Schwarz information criterion, the appropriate lag length p is set equal to 4 for Denmark, France, the Netherlands, Ireland and Spain; 3 for Belgium, Germany, Italy and Portugal; and 1 for the UK.

(ii) We report the results for several values of the embedding dimension (m) and the distance (ε), where the latter is related to the standard deviation of the data (σ).

(iii) BDS statistics are distributed N(0,1) under null hypothesis of *iid* residuals; and a, b and c denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: BDS test on shuffled ARIMA(p,1,0) residuals

(A) Belgium

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	-0.26	-0.41	0.27	0.21	0.29	0.37	0.45
m=3	-0.98	-0.97	-0.55	-0.27	-0.05	0.38	0.62
m=4	-0.65	-0.47	-0.16	0.04	0.18	0.71	0.97
m=5	-0.33	-0.35	-0.17	0.09	0.25	0.75	1.01
m=6	-0.24	-0.31	-0.07	0.26	0.45	0.84	1.08
m=7	-0.44	-0.46	-0.11	0.22	0.45	0.77	0.98

(B) Denmark

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	0.70	-0.05	-0.43	0.17	0.43	0.56	1.15
m=3	-0.17	-0.67	-0.73	-0.37	-0.33	-0.16	0.46
m=4	-0.36	-0.81	-0.84	-0.63	-0.58	-0.39	0.31
m=5	-0.42	-0.77	-0.78	-0.55	-0.47	-0.22	0.47
m=6	-0.34	-0.71	-0.82	-0.64	-0.48	-0.14	0.58
m=7	-0.581	-0.882	-0.982	-0.796	-0.615	-0.228	0.52

(C) Germany

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	0.04	-0.40	-0.11	-0.94	-1.24	-0.71	-1.09
m=3	-0.12	-0.48	-0.42	-1.03	-1.20	-1.14	-1.26
m=4	-0.09	-0.93	-0.72	-1.23	-1.21	-1.28	-1.17
m=5	0.13	-1.06	-0.76	-1.21	-1.34	-1.25	-1.29
m=6	0.48	-0.63	-0.65	-1.11	-1.15	-1.13	-1.25
m=7	0.91	-0.36	-0.38	-0.78	-1.16	-1.17	-1.14

Table 3 (continued)

(D) France

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	-0.57	-1.15	-1.12	-1.13	-1.18	-1.22	-1.10
m=3	0.16	-0.55	-1.19	-1.16	-1.07	-0.55	-0.27
m=4	-0.21	-1.19	-1.16	-1.22	-0.87	-0.38	-0.32
m=5	-0.25	-1.16	-1.15	-1.17	-1.01	-0.49	-0.31
m=6	-0.28	-1.18	-1.19	-1.15	-1.06	-0.57	-0.42
m=7	-0.16	-0.92	-1.22	-1.24	-1.13	-0.61	-0.47

(E) Ireland

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	0.37	0.36	0.11	0.475	1.04	0.63	0.86
m=3	1.21	1.28	1.29	1.28	1.23	1.17	1.27
m=4	1.22	1.24	1.25	1.23	1.17	1.26	1.23
m=5	1.14	1.24	1.27	1.23	1.24	1.21	1.23
m=6	0.84	1.13	1.21	1.26	1.21	1.22	1.26
m=7	0.51	0.92	1.26	1.27	1.18	1.21	1.04

(F) Italy

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	-0.25	0.26	0.39	0.02	0.66	0.77	1.09
m=3	0.83	1.17	1.21	1.20	1.23	1.27	1.26
m=4	1.10	1.27	1.18	1.12	1.25	1.28	1.27
m=5	1.17	1.22	1.24	1.23	1.14	1.29	1.23
m=6	1.26	1.24	1.25	1.22	1.26	1.23	1.29
m=7	1.24	1.27	1.26	1.17	1.27	1.26	1.24

Table 3 (continued)

(G) Netherlands

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	-0.59	-0.68	-0.67	-0.35	0.10	0.72	1.28
m=3	-1.21	-1.17	-1.03	-0.56	0.09	0.84	1.27
m=4	-1.20	-1.21	-1.23	-0.87	0.01	0.87	1.12
m=5	-1.21	-1.18	-1.24	-0.79	0.12	0.92	1.11
m=6	-1.22	-1.23	-0.98	-0.47	0.39	1.16	1.27
m=7	-1.11	-0.89	-0.58	-0.21	0.83	1.26	1.28

(H) Portugal

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	0.32	0.55	-0.47	-1.11	-1.14	-1.12	-1.56
m=3	0.44	0.53	-0.19	-0.49	-0.44	-0.26	-0.69
m=4	0.18	0.43	0.12	-0.27	-0.19	-0.03	-0.26
m=5	0.27	0.32	0.18	0.12	0.26	0.45	-0.12
m=6	0.11	0.22	0.10	0.09	0.25	0.57	0.15
m=7	-0.12	-0.13	-0.32	-0.12	0.33	0.72	0.21

(I) Spain

	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	0.12	-0.11	-0.24	-0.44	-0.53	-0.71	-0.41
m=3	0.83	0.37	-0.27	-0.42	-0.43	-0.48	-0.49
m=4	0.89	0.59	-0.19	-0.29	-0.19	-0.22	-0.24
m=5	0.63	0.54	-0.14	-0.32	-0.12	0.12	0.23
m=6	0.74	0.71	0.12	-0.11	0.21	0.51	0.76
m=7	0.72	0.75	0.13	-0.12	0.20	0.57	0.90

Table 3 (continued)

(J) UK	ε=0.5σ	ε=0.75σ	ε=σ	ε=1.25σ	ε=1.5σ	ε=1.75σ	ε=2σ
m=2	1.11	-0.12	-0.10	-0.67	-0.44	-0.45	-0.43
m=3	0.33	0.10	0.17	-0.34	-0.12	0.24	0.16
m=4	0.11	0.34	0.33	-0.14	0.09	0.43	0.45
m=5	-0.12	0.37	0.39	0.12	0.21	0.42	0.44
m=6	0.16	0.43	0.32	0.09	0.12	0.36	0.42
m=7	-0.10	0.49	0.27	-0.04	-0.02	0.17	0.28

Notes: See Table 2.

Table 4: Non-linear predictors. Root mean square error (whole sample)

	Univariate	Bivariate	Causality
Germany→Belgium	0.1851	0.1762	yes
Belgium→Germany	0.1138	0.1125	yes
Germany→Denmark	0.5897	0.5426	yes
Denmark→Germany	0.1121	0.1099	yes
Germany→France	0.2052	0.2008	yes
France→Germany	0.1111	0.1119	no
Germany→Ireland	0.5821	0.5690	yes
Ireland→Germany	0.1134	0.1143	no
Germany→Italy	0.3006	0.2962	yes
Italy→Germany	0.1173	0.1182	no
Germany→Netherlands	0.1085	0.0990	yes
Netherlands→Germany	0.1121	0.1014	yes
Germany→Spain	0.1289	0.1261	yes
Spain→Germany	0.1046	0.1051	no
Germany→UK	0.1488	0.1351	yes
UK→Germany	0.0920	0.0930	no
Germany→Portugal	0.5026	0.4148	yes
Portugal→Germany	0.0903	0.0910	no

Note: The forecasting period is 13-1-87 to 30-4-98 for Belgium, Denmark, France, Ireland, Italy, and the Netherlands, 19-6-89 to 30-4-98 for Spain, 08-10-90 to 30-4-98 for the United Kingdom, and 9-4-92 to 30-4-98 for Portugal.

Table 5: Non-linear predictors. The Diebold-Mariano test statistic (whole sample)	
Germany→Belgium	5.9958[a]
Belgium→Germany	4.2211[a]
Germany→Denmark	3.9243[a]
Denmark→Germany	3.2901[a]
Germany→France	4.1630[a]
France→Germany	-1.3016
Germany→Ireland	2.8128[a]
Ireland→Germany	-1.2625
Germany→Italy	4.8235[a]
Italy→Germany	-1.2524
Germany→Netherlands	5.3246[a]
Netherlands→Germany	4.8949[a]
Germany→Spain	3.8694[a]
Spain→Germany	-1.3038
Germany→UK	3.8547[a]
UK→Germany	-1.2537
Germany→Portugal	3.8635[a]
Portugal→Germany	-1.1724

Note: a denotes significance at the 1% level. The critical values are 2.58 (1%), 1.96 (5%), and 1.64 (10%).

Table 6: Non-linear predictors. Root mean square error (before and after German reunification)						
	Until 29-11-90			After 30-11-90		
	Univariate	Bivariate	Causality	Univariate	Bivariate	Causality
Germany→Belgium	0.1409	0.1327	yes	0.2149	0.2077	yes
Belgium→Germany	0.1299	0.1254	yes	0.0911	0.0943	no
Germany→Denmark	0.2537	0.2433	yes	0.8067	0.7395	yes
Denmark→Germany	0.1299	0.1267	yes	0.0883	0.0909	no
Germany→France	0.1549	0.1506	yes	0.2345	0.2276	yes
France→Germany	0.1280	0.1290	no	0.0902	0.0913	no
Germany→Ireland	0.2348	0.2305	yes	0.7256	0.7124	yes
Ireland→Germany	0.1283	0.1296	no	0.0906	0.0921	no
Germany→Italy	0.2303	0.2295	yes	0.3238	0.3184	yes
Italy→Germany	0.1315	0.1364	no	0.0899	0.0915	no
Germany→Netherlands	0.1364	0.1164	yes	0.0870	0.0861	yes
Netherlands→Germany	0.1280	0.1251	yes	0.0902	0.0884	yes
Germany→Spain	0.1264	0.0808	yes	0.1357	0.1293	yes
Spain→Germany	0.1359	0.1364	no	0.0905	0.0921	no
Germany→UK	0.2947	0.2869	yes	0.1404	0.1371	yes
UK→Germany	0.1310	0.1423	no	0.0906	0.0909	no

Note: See Table 4.

Table 7: Non-linear predictors. The Diebold-Mariano test statistic (before and after German reunification)

	Until 29-11-90	After 30-11-90
Germany→Belgium	4.4705[a]	6.5709[a]
Belgium→Germany	3.7474[a]	-1.2875
Germany→Denmark	3.2635[a]	3.9372[a]
Denmark→Germany	2.7215[a]	-1.3558
Germany→France	3.5524[a]	3.2761[a]
France→Germany	-1.3657	-1.2154
Germany→Ireland	2.7229[a]	3.1792[a]
Ireland→Germany	-1.3556	-1.3217
Germany→Italy	3.6033[a]	5.1439[a]
Italy→Germany	-1.3492	-1.5324
Germany→Netherlands	3.2865[a]	5.8368[a]
Netherlands→Germany	3.5312[a]	4.0279[a]
Germany→Spain	3.5183[a]	3.8427[a]
Spain→Germany	-1.2523	-1.3329
Germany→UK	3.4901[a]	4.0257[a]
UK→Germany	-1.2519	-1.3802

Note: See Table 5.

Table 8: Cointegration tests			
	Phillips-Perron	Johansen	Cointegration
Belgium	-4.98[a]	9.87[a]	yes
Denmark	-5.73[a]	16.98[a]	yes
France	-4.66[a]	8.39[a]	yes
Ireland	-4.37[a]	7.93[a]	yes
Italy	-4.29[a]	6.79[a]	yes
Netherlands	-5.13[a]	24.92[a]	yes
Portugal	-2.52	1.43	no
Spain	-4.62[a]	8.56[a]	yes
UK	-2.11	0.55	no

Notes:

(i) The cointegrating regression is $i_t = \mu + \lambda i_t^G$, where i_t is the national interest rate and i_t^G is the German interest rate.

(ii) a denotes significance at the 1% level.

Table 9: Linear predictors. FPE statistics (whole sample)

	FPE(m,0)x10^{-3}	FPE(m,n)x10^{-3}	Causality
Germany→Belgium	1.7214(1,0)	1.6327(1,3)	yes
Belgium→Germany	4.5921(1,0)	4.6246(1,1)	no
Germany→Denmark	0.1524(3,0)	0.1282(3,2)	yes
Denmark→Germany	4.6117(1,0)	4.6312(1,1)	no
Germany→France	2.1735(2,0)	2.1207(2,2)	yes
France→Germany	4.5155(2,0)	4.5316(2,1)	no
Germany→Ireland	0.1058(3,0)	0.0869(3,3)	yes
Ireland→Germany	4.5345(1,0)	4.5587(1,1)	no
Germany→Italy	4.6234(3,0)	4.6593(3,1)	no
Italy→Germany	4.5400(1,0)	4.5609(1,1)	no
Germany→Netherlands	5.2049(2,0)	4.9461(2,2)	yes
Netherlands→Germany	4.5305(2,0)	4.4227(2,1)	yes
Germany→Spain	10.8639(1,0)	10.8334(1,2)	yes
Spain→Germany	3.4703(2,0)	4.1373(2,1)	no
Germany→UK	7.3032(2,0)	7.2802(2,1)	yes
UK→Germany	2.5413(1,0)	2.5417(1,1)	no
Germany→Portugal	9.5227(1,0)	9.5490(1,2)	no
Portugal→Germany	1.4622(2,0)	1.4813(2,1)	no

Note: The figures in brackets are the number of lags in every equation yielding the smallest FPE, estimated from the entire sample for each pair of countries.

Table 10: Linear predictors. The Diebold-Mariano test statistic (whole sample)

Germany→Belgium	3.2561[a]
Belgium→Germany	-1.0053
Germany→Denmark	3.3951[a]
Denmark→Germany	-1.2740
Germany→France	3.1968[a]
France→Germany	-1.3771
Germany→Ireland	2.6722[a]
Ireland→Germany	-1.1931
Germany→Italy	-1.8994[c]
Italy→Germany	-1.1807
Germany→Netherlands	3.2353[a]
Netherlands→Germany	2.6513[a]
Germany→Spain	2.7879[a]
Spain→Germany	-1.2385
Germany→UK	2.3642[b]
UK→Germany	-1.1336
Germany→Portugal	-1.9541[c]
Portugal→Germany	-0.9968

Notes:

(i) The forecasts have been computed recursively from the dates shown in the note to Table 4, in order to allow comparisons with the non-linear case.

(ii) a, b and c denote significance at the 1%, 5% and 10% levels, respectively. The critical values are 2.58 (1%), 1.96 (5%), and 1.64 (10%).

Table 11: Linear predictors. FPE statistics (before and after German reunification)

	Until 29-11-90			After 30-11-90		
	FPE(m,0)x10^{-3}	FPE(m,n)x10^{-3}	Causality	FPE(m,0)x10^{-3}	FPE(m,n)x10^{-3}	Causality
Germany→Belgium	1.1369(1,0)	1.1244(1,2)	yes	0.7898(1,0)	0.7708(1,2)	yes
Belgium→Germany	2.0182(1,0)	2.0193(1,1)	no	2.3810(1,0)	2.3943(1,1)	no
Germany→Denmark	0.4212(1,0)	0.4023(1,2)	yes	0.2346(1,0)	0.2341(1,2)	yes
Denmark→Germany	0.7989(1,0)	0.8055(1,1)	no	0.2397(1,0)	0.2643(1,1)	no
Germany→France	0.9721(2,0)	0.9484(2,2)	yes	0.2937(2,0)	0.2801(2,2)	yes
France→Germany	0.7788(2,0)	0.7922(2,1)	no	0.2371(2,0)	0.2375(2,1)	no
Germany→Ireland	2.0080(3,0)	2.0012(3,3)	yes	0.7808(3,0)	0.7283(3,1)	yes
Ireland→Germany	0.1454(1,0)	0.1557(1,1)	no	0.2381(1,0)	0.2393(1,1)	no
Germany→Italy	0.1404(2,0)	0.1995(2,1)	no	0.7861(3,0)	0.7942(3,1)	no
Italy→Germany	0.6337(1,0)	0.6512(1,1)	no	0.2361(1,0)	0.2471(1,1)	no
Germany→Netherlands	0.5635(2,0)	0.5522(2,2)	yes	0.4073(2,0)	0.4001(2,3)	yes
Netherlands→Germany	0.1823(1,0)	0.1720(1,2)	yes	0.2351(3,0)	0.2195(3,1)	yes
Germany→Spain	0.3197(1,0)	0.3015(1,2)	yes	0.3212(1,0)	0.3013(1,2)	yes
Spain→Germany	0.8055(1,0)	0.8112(1,1)	no	0.2887(1,0)	0.2892(1,1)	no
Germany→UK	0.1142(2,1)	0.1101(2,1)	yes	0.2677(2,0)	0.2389(2,1)	yes
UK→Germany	0.0955(1,0)	0.0995(1,1)	no	0.0724(2,0)	0.0799(2,1)	no

Note: The figures in brackets are the number of lags in every equation yielding the smallest FPE, estimated from the entire sample (before and after German reunification, in every case) for each pair of countries.

Table 12: Linear predictors. The Diebold-Mariano test statistic (before and after German reunification)

	Until 29-11-90	After 30-11-90
Germany→Belgium	3.0053[a]	3.0231[a]
Belgium→Germany	-1.2641	-1.3237
Germany→Denmark	3.1426[a]	3.2410[a]
Denmark→Germany	-1.5742	-1.8270[c]
Germany→France	3.0121[a]	2.9591[a]
France→Germany	-1.1168	-1.1267
Germany→Ireland	2.9748[a]	3.1469[a]
Ireland→Germany	-1.4064	-1.4303
Germany→Italy	-2.3567[b]	-2.3413[b]
Italy→Germany	-1.7210[c]	-1.5083
Germany→Netherlands	3.1559[a]	2.7601[a]
Netherlands→Germany	2.6330[a]	2.8988[a]
Germany→Spain	2.8320[a]	2.9308[a]
Spain→Germany	-1.3915	-1.3773
Germany→UK	3.0421[a]	2.6867[a]
UK→Germany	-1.0145	-1.3636

Note: See Table 10.

Table 13: Linear versus non-linear predictors forecast accuracy. The Diebold-Mariano test statistic (whole sample, and before and after German reunification)

	Whole sample		Until 29-11-90		After 30-11-90	
	Univariate	Bivariate	Univariate	Bivariate	Univariate	Bivariate
Germany→Belgium	2.9104[a]	2.6387[a]	4.7483[a]	3.9802[a]	3.5611[a]	3.0153[a]
Belgium→Germany	3.1197[a]	3.6352[a]	3.4957[a]	3.7108[a]	3.0081[a]	4.8342[a]
Germany→Denmark	3.3868[a]	3.2570[a]	3.6032[a]	3.7869[a]	3.7878[a]	4.2017[a]
Denmark→Germany	3.1014[a]	3.9871[a]	3.4957[a]	3.8150[a]	3.9871[a]	4.4108[a]
Germany→France	3.1568[a]	3.2397[a]	3.5745[a]	4.1886[a]	3.4771[a]	3.9304[a]
France→Germany	3.2366[a]	4.0212[a]	3.3189[a]	3.9740[a]	3.6598[a]	4.2810[a]
Germany→Ireland	3.8012[a]	4.1425[a]	3.5390[a]	3.8689[a]	3.0342[a]	3.4405[a]
Ireland→Germany	2.8590[a]	3.1593[a]	3.2608[a]	3.6197[a]	3.4634[a]	3.6005[a]
Germany→Italy	3.2129[a]	3.1716[a]	3.6540[a]	3.6247[a]	3.8662[a]	3.7055[a]
Italy→Germany	3.7096[a]	4.5706[a]	3.1805[a]	3.8353[a]	3.6438[a]	3.8566[a]
Germany→Netherlands	3.7746[a]	3.7236[a]	3.1116[a]	3.1935[a]	3.2583[a]	3.3142[a]
Netherlands→Germany	3.2998[a]	4.0034[a]	3.3189[a]	3.6831[a]	3.7293[a]	4.3000[a]
Germany→Spain	3.0120[a]	3.4943[a]	3.9223[a]	4.1825[a]	3.5370[a]	3.7544[a]
Spain→Germany	3.7012[a]	4.0103[a]	3.8683[a]	3.9016[a]	3.5437[a]	3.8367[a]
Germany→UK	3.0203[a]	3.2602[a]	3.0350[a]	3.0416[a]	3.7581[a]	4.2262[a]
UK→Germany	3.5499[a]	3.4053[a]	3.4923[a]	3.0133[a]	3.5127[a]	3.3572[a]
Germany→Portugal	3.5135[a]	3.9532[a]	-	-	-	-
Portugal→Germany	3.4194[a]	3.4668[a]	-	-	-	-

Notes:

(i) A significant and positive (negative) value indicates a significant difference between the two forecasting errors, which would mean a better accuracy of the non-linear (linear) predictor.

(ii) a denotes significance at the 1% level. The critical values are 2.58 (1%), 1.96 (5%), and 1.64 (10%).