A re-examination of volatility spillovers in European government bond markets using a multi-objective artificial network

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Abstract

In this paper we extend prior efforts to engineer an efficient mapping of volatility transmission across various western- and central-European government bond markets. Prior research efforts report that the closed-form derivation of the regularization parameter embodied by the Kajiji-4 RBF ANN results in an efficient minimization of the ill-effects of multi-collinearity while attaining maximum smoothness in nonparametric time series analysis. This computational innovation provides the raison d'être for a comparative re-examination of volatility spillover effects obtained from the study of parametric-based conditional volatility investigations. The current research calibrates the Kajiji-4 ANN to produce new evidence on volatility flows. The two step research method focuses first on the art of ANN engineering of financial time-series. The method then focuses on the resultant modelling efficiency by introducing an investigatory ARCH-framework as well as a classification-directed ANN. The post-modelling efficiency tests certify the ex-ante expectation for the Kajiji-4 RBF ANN to produce residuals that are devoid of latent economic covariance and conditional volatility effects. Moreover, we find that the estimated Kajiji-4 network parameters yield corroborative evidence that supports the broader findings in the extant literature on bond volatility-spillover effects. However, the non-parametric approach also produced results that challenge some contemporary findings. Most notably, the research findings contradict the view of a weak US volatility-spillover into EMU countries with a correspondingly strong spillover effect for non-EMU countries.
Keywords: volatility, spillovers, bond markets, neural networks, radial basis functions, artificial neural networks.

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1 Introduction

The recent convergence of two allogeneous disciplines, financial and computational engineering, has created a new mode of scientific inquiry. In this paper, we seek to utilize the innovation inherent in financial engineering to provide a new and expanded window into the structure of volatility spillovers in European government bond markets. The specific aim of this research is to re-examine reported findings that describe the effects of volatility spillovers from the United States (US) and aggregate European government bond markets into the government bond markets of two EMU countries (Germany in the west and Spain in the south) and two non-EMU countries (northerly Sweden and central European member Slovenia). The analytical examination is developed in two stages. The initial stage focuses on the process of engineering a complex nonlinear artificial neural network (ANN) mapping of government bond excess returns. To accomplish this step the current research exploits the Kajiji-4 radial basis function (RBF) ANN. The algorithm has proven to be a fast and efficient topology for mapping financial instrument volatility across various time intervals [for example, Dash and Kajiji [10] use the algorithm to successfully model daily volatility asymmetries of FX futures contracts and, similarly, Dash, et al. [9] employ the method to forecast hourly futures options ticks]. The second stage establishes the overall effectiveness of the ANN to control for the known conditional volatility properties that define transmission linkages among government bond excess returns. The testable volatility spillover model preferred for the research inquiry can be traced to a panoptic review on market contagion by Christiansen [7]. The ANN models formulated here are further influenced by the linear regression-based methods of Bekaert and Harvey [2, 3], the VAR methods of Clare and Lekkos [8], and associated extensions offered by Ng [16]. We also take into consideration associated refinements detailed in Bekaert, et al. [4], and in Baele [1]. However, it is the Christiansen approach that sets a foundation for the two-stage modelling experiment that defines this research.

1.1 The volatility spillover model

The issues of time-varying volatility of financial time series are well documented. The ARCH model process of Engle [11] exploited this autoregressive property where historical events leave patterns behind for a certain time after some initial action. The GARCH model of Bollerslev [5] introduced the ability to examine volatility in terms of conditional heteroscedasticity in that the variance, which is now conditional on the available information, varies and also depends on old values of the process. The existence of volatility leverage effects in financial time series, the observation that bad news has a larger impact on volatility than does good news, is also a well-known phenomenon (e.g. Koutmos and Booth [13] and Booth, et al. [6]). The EGARCH model of Nelson [14] and Nelson and Cao [15] has proven to be nearly ideal for capturing the leverage effects that define the overall market behaviour of financial instruments. Recent results provide new evidence that

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own bond-market effects are significant and exhibit asymmetric impacts in the volatility generating process. The generation of this new knowledge was inextricably linked to the innovative use of new modelling methodology

Within the context of the Christiansen methodology, we engineer a nonlinear ANN approach that is not unwieldy, over-parameterized, nor difficult to test within the temporal of bond volatility. We begin by defining the conditional return on the US government bond index as an AR(1) process:

$$R_{US,t} = b_{0,US} + b_{1,US} R_{US,t-1} + \varepsilon_{US,t} . \tag{1}$$

In this model, the idiosyncratic shock ($\varepsilon_{US,t}$) is normally distributed with a mean of zero ($E \mid \varepsilon_{i,t} \mid = 0$), is uncorrelated $(E \mid \varepsilon_{i,t} \varepsilon_{j,t} \mid = 0;\ \forall i \neq j)$, and the conditional variance follows an asymmetric EGARCH(1,1) specification;

$$\sigma^2_{US,t} = \omega_{US} + \alpha_{US} e^2_{US,t-1} + \gamma_{US} \sigma^2_{US,t-1} . \tag{2}$$

Specifically, the generalized EGARCH model implemented for all excess bond return generating models presented in this section is represented by:

$$\ln(\varepsilon^2{}_{US,t}) = \varpi + \sum_{k=1}^{q} \alpha_k g(z_{t-1}) + \sum_{j=1}^{p} \gamma_j \ln(h^2{}_{t-j}) , \tag{3}$$

where

$$g(z_t) = \theta z_t + \gamma \left[\left| z_t \right| - E \left| z_t \right| \right] \tag{4}$$

and

$$z_t = \frac{\varepsilon_t}{\sqrt{h_t}} . \tag{5}$$

and the

$$E \left| z_t \right| = \left(\frac{2}{\pi} \right)^{0.5} ;\ \ z_t \sim N(0,1) . \tag{6}$$

In our formulation, the parameter γ is set to 1. In this research we re-estimate the degree to which economic shocks in the aggregate European government bond market influence the return-generating process of individual European countries by the application of the ANN econometric model. The conditional excess return on the European total return government bond index is assumed to be a multi-factor AR(1). The model is specified as:

$$R_{E,t} = b_{0,E} + b_{1,E} R_{E,t-1} + \gamma_{E,t-1} R_{US,t-1} + \phi_{E,t-1} \varepsilon_{US,t} + \varepsilon_{E,t} . \tag{7}$$

In this system, the conditional mean of the European bond excess return depends on its own lagged return as well as the spillover effects introduced by the lagged US excess return, $R_{US,t-1}$, and the US idiosyncratic risk shock, $\varepsilon_{US,t}$. Following the previous assumption, the conditional variance of the idiosyncratic risk shock ($\varepsilon_{E,t}$) is assumed to follow an asymmetric EGARCH(1,1) specification:

$$\ln(\varepsilon^2{}_{E,t}) = \varpi + \sum_{k=1}^{q} \alpha_k g(z_{t-1}) + \sum_{j=1}^{p} \gamma_j \ln(\varepsilon^2{}_{t-j}) \tag{8}$$

subject to the usual restrictions (e.g. eqns. 4-6).

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The second ANN econometric specification described here is a model that is capable of describing the conditional return generating process for the *i-th* individual European country government bond market from among the *N* markets included in the study. That is, for country *i*, the conditional excess return is determined by:

$$R_{i,t} = b_{0,i} + b_{1,i} R_{i,t-1} + \gamma_{i,t-1} R_{US,t-1} + \delta_{i,t-1} R_{E,t-1} + \phi_{i,t-1} \varepsilon_{US,t} + \psi_{i,t-1} \varepsilon_{E,t} + \varepsilon_{i,t} \qquad (9)$$

Within this model statement the conditional excess return depends upon the lagged performance of own country return as well as that of the US and aggregate European bond markets. More specifically, the US and European spillover to the *i*-th country is captured by the lagged returns $R_{US,t-1}$ and $R_{E,t-1}$, while volatility spillover effects are captured by $\varepsilon_{US,t}$ and $\varepsilon_{E,t}$, idiosyncratic shocks from the regional conditional return estimations, respectively. Finally, and for completeness, again we note that the idiosyncratic shocks for all *N* country models are subject to the same EGARCH(1,1) distributional assumptions as shown in eqn. (10) and associated constraints shown in eqn (4) to eqn. (6) as previously defined for the expected behaviour of the regional return index.

$$\ln(\varepsilon^2_{i,t}) = \varpi + \sum_{k=1}^{q} \alpha_k g(z_{t-1}) + \sum_{j=1}^{p} \gamma_j \ln(\varepsilon^2_{t-j}) . \qquad (10)$$

With the return generating process identified for all bond indices associated with expected volatility spillover effects, the emphasis shifts directly to the nonlinear modelling features provided by the application of a neural network methodology.

2 Data

Weekly data for all government total return bond indices under study are obtained from Global Financial Data for the period May 2003 to January 2005 inclusive (a total of 90 observations). Non-synchronous data issues are partially reduced by the use of weekly data. The two EMU-member countries, Germany (REX government bond performance index) and Spain (Spain 10-year government bond total return index), and the two non-EMU countries, Sweden (government bond return index w/GFD extension and the Slovenia 10-year government bond yield index) define the European local market. The US effect is sampled by the inclusion of the Merrill Lynch U.S. government bond return index. Lastly, the JP Morgan European total return government bond index samples the aggregate European government bond market. Total return indices are preferred as they are derived under the assumption that all received coupons are invested back into the bond index. The descriptive statistics for these indices are presented at: http://www.nkd-group.com/research/cf2006/cf2006-exhibits.pdf in table A. All further mention of online tables refers to the URL presented.

3 ANN estimation of volatility spillover

In this section of the paper we estimate bond market spillover effects by applying the Kajiji-4 RBF ANN to the aggregate European bond model of eqn. (7) and to the individual country model as shown in eqn. (9). However, before the exact estimation of spillover effects is presented, we provide algorithmic detail as it pertains to the ANN modelling methodology. Section 3.1 differentiates the enhanced dual objective Kajiji-4 algorithm from the more traditional uni-objective RBF ANN. Section 3.2 is devoted specifically to data transformation and scaling. Section 3.3 to 3.5 relate to the specifics of generalizing the application of the Kajiji-4 RBF ANN to modelling of European government bond returns and their associated volatility. Section 3.6 discusses the policy implications.

3.1 The multiple-objective RBF ANN architecture

Kajiji [12] reasoned that some modelling problems are best examined by considering at least two objectives: smoothness and accuracy. To achieve these dual objectives, Kajiji augmented the generalized RBF to include a modified Tikhonov and Arsenin [17] regularization equation. Tikhonov regularization adds a weight decay parameter to the error function to penalize mappings that are not smooth. By adding a weight penalty term to the SSE optimization objective, the modified SSE is restated as the following cost function:

$$C = \sum_{i=1}^{p} \left(\hat{y}_i - f(x_i) \right)^2 + \sum_{j=1}^{m} k_j w_j^2 \tag{11}$$

where k_j are regularization parameters or weight decay parameters. Under this specification the function to be minimized is stated as:

$$C = \frac{\text{argmin}}{k} \left(\varsigma \sum_{i=1}^{p} (y_i - f(x_i \mid \bar{k}))^2 + \sum_{j=1}^{m} k_j w_j^2 \right) \tag{12}$$

3.2 Data scaling by transformation

Neural networks learn more efficiently with lower prediction errors when the distribution of input variables is modified to better match outputs. The point to emphasize here is the importance of data scaling by one of any number of recognized transformations as an integral part of the neural network engineering process. The Kajiji-4 RBF ANN supports several alternative data transformation algorithms. For the bond volatility modelling application described herein, we choose to scale the data by the *Normalized Method 1* which scales the data to [0, 1.01] when S_L = 0% and S_U = 1%. For the definition and algorithmic details of the *Normalized Method 1* see the online tables B and C.

3.3 Algorithmic parameterization and efficient supervised learning

The parameterization of the RBF network begins with the judicious choice of a transfer function. Neural network researchers understand that sigmoidal functions may be better estimates for some data, while Gaussian functions may be better approximators for other kinds of data. RBF ANN algorithms are trained to predict the target variable by supervising the use of an increasing number of cases (observations) on the input variables up to the point where modelling improvements become redundant. Overfitting occurs at the point where the ANN ceases to learn about the underlying process but, instead, it begins to memorize the peculiarities of the training cases. The results of solving a simulation to determine the optimal number of cases over which to train individual country models is exemplified by Figure 1.

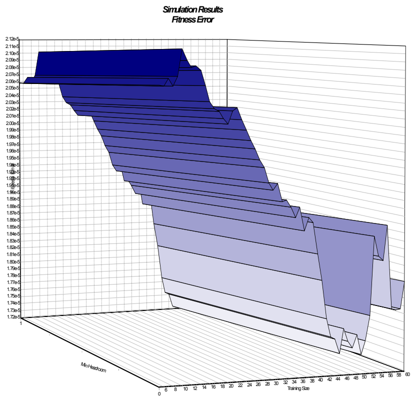

Figure 1: Simulation results.

3.4 The estimated Kajiji-4 RBF ANN spillover model

The output measures generated by an application of the Kajiji-4 RBF ANN for the individual European country government bond spillover models show interesting results. We note the value of R-square is evenly reported across countries, ranging from a low of 86.27% (Germany) to a high of 87.37% (Sweden). Additionally, the two ANN performance measures defined as *Direction* and *Modified Direction* each report accuracy and consistency across all countries. The Direction measures range from a low of 0.71 for Slovenia to a high of 0.77 for Spain and Sweden. Similarly, the modified directions measure ranges from a low of 0.61 for Slovenia to a high of 0.76 for Sweden. Further details are available online in table D. Fig. 2 presents a visual reference of overall prediction accuracy.

3.5 Characteristics of the RBF generated residuals

Descriptive statistics for country-level idiosyncratic residual returns obtained by the application of the Kajiji-4 spillover model were calculated (see online table E). The Shapiro-Wilkes' test for normality (W-statistic) confirmed the expectation of non-normality. The autocorrelation patterns among the residuals are somewhat mixed. In summary, we find that applying the Kajiji-4 RBF ANN to the government bond spillover model for European markets results in a solution where the idiosyncratic residual returns exhibit moderate nonlinear dependence, an absence of skewness at the individual country level, and, except for Germany, moderately heavy-tails.

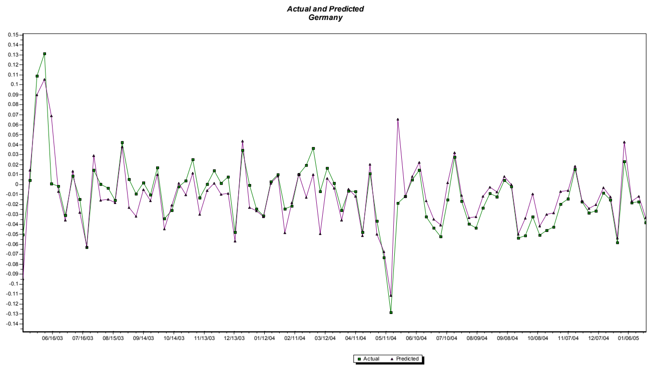

Figure 2: Kajiji-4 RBF-ANN actual and predicted values (Germany).

We also note that the reported EGARCH results (online table F) fail to identify significant residual return dependence and leverage effects among the EMU countries. That is, none of the explanatory variables are jointly significant for any of the bond indices. This finding does not hold for the two non-EMU countries – Sweden and Slovenia; a finding that augers for a corroborating interrogation of the ANN generated residuals.

The residual analytics were expanded to test for statistical independence. Specifically, we applied a principal components analysis (PCA) to the European residuals in order to uncover whether the observed distributional properties are related by latent hidden factor(s). The results produced one-factor dominance. A single dominant factor from the PCA analysis provides evidence that the RBF ANN spillover model removed a significant amount of any linearly related economic volatility from the excess returns of all country specific European government bonds. The factor loading structure is presented online in table G.

Nonlinear diagnostics were also employed to test for statistical independence. In this case a Kohonen self-organizing map (K-SOM) was applied to the RBF generated residuals. Unlike the PCA solved above, the K-SOM method does not impose any distributional assumptions on the components. Based on a accumulated review of the parametric analysis of the RBF ANN residuals as well as the non-parametric optimal solution from the K-SOM (online figure A), it is factually apparent that the Kajiji-4 RBF ANN spillover model achieved its appointed task – to model the time-dependent sources of volatility spillover effects in a cross-section of European government bond markets.

3.6 Policy implications

For the most part, the empirical results for individual government bond markets corroborate extant findings for post Euro-conversion (Christiansen [7]). Inferences drawn from the signed weights produced by solving the RBF ANN model are consistent in their identification of a larger US mean-spillover effect into the German market than that caused by the aggregate European bond market

(0.2520 and –0.1692, respectively). This finding is contrasted by the results for the other EMU country, Spain. In this case the US mean spillover effect is about 100 times smaller than that generated by the aggregate European bond markets (–0.1560 and 15.4974, respectively). The results for non-EMU members Sweden and Slovenia also offer some contrasts. For northern neighbour Sweden, the impact of the aggregate European spillover effect is 27 times that of the US mean spillover effect (6.203 and 0.2249, respectively). Whereas in the case of eastern-bloc Slovenia the result is a small inverse spillover effect to the US bond markets (-0.1393) with a moderate domestic effect recorded in Slovenia from the aggregate European bond markets (0.6621). Clearly, for the time period of this study, Slovenia's post-communism transition to World Bank donor status, near membership in NATO and the EU along with its close relationship with trading partners Germany, Italy, Austria and other EU countries is accurately reflected in the metrics as estimated by the RBF ANN spillover model.

Table 1: RBF ANN spillover model weights.

Return Generating Model	Lagged Country $(b_{1,t})$	Lagged Euro $(\delta_{i,t-1})$	Lagged USA $\gamma_{i,t-1}$	Euro Residual $\psi_{i,t-1}$	USA Residual $\phi_{i,t-1}$
USA	n/a	n/a	0.4137	n/a	n/a
Euro	n/a	0.1470	0.1328	n/a	0.1385
Germany	0.2670	–0.1692	0.2520	–0.0760	0.1629
Sweden	2.0330	6.2023	0.2249	1.8278	–9.7189
Spain	3.5540	15.4974	–0.1560	3.6120	–21.8662
Slovenia	0.1146	0.6621	–0.1393	–0.1347	–0.0863

4 Summary and conclusions

This paper investigated the structure of volatility spillover effects across EMU, non-EMU, western- and central-European government bond markets by the application of innovative computational financial engineering analytics. The Kajiji-4 RBF ANN network produced an efficient separation of global, regional and local volatility effects. The econometric significance of these findings was interrogated by applying both a parametric and non-parametric examination to the estimated time series residuals. In each case, PCA for the linear and K-SOM for the nonlinear analytics, the search for independence within the residuals was confirmed. The econometric modelling experiment produced several important policy findings that provide a foundation for future consideration in research that relies upon nonlinear mappings of economic time series by intelligent networks. Key among these findings was the presentation of evidence that clearly highlighted the perceived differences between the government bond markets of EMU, non-EMU and central-European countries. Among other findings, this fact alone suggests that as EMU affiliated countries expand policymakers should take immediate and ongoing actions to address the practical aspects of the planned changeover to the euro. Such actions range from meeting the euro-zone 2 % inflation rate to effective control of ethical decision-making in all aspects of business and government decision-making.

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