Computational Practice: Multivariate Parametric or Nonparametric Modelling of European Bond Volatility Spillover?

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Abstract

Previous research has documented the effectiveness of multivariate nonparametric radial basis function artificial neural networks to model the simultaneous bi-directional volatility spillover effects among European economies. As a nonparametric estimation method, artificial neural networks do not present researchers with the same confidence levels on weight estimation that are commonplace under the assumption of asymptotic normality under linear regression. This chapter considers extending prior research findings by examining the domain of applicability for linear multivariate parametric model when applied to the estimation of global government bond volatility spillover models. To this end the chapter examines both multivariate linear regression and canonical correlation techniques to establish a comparative set of findings to those presented from prior research using a multivariate radial basis function artificial neural network. The findings clearly demonstrate that linear parametric methods fail to adequately explain the correlation and cross-correlation structure of excess European bond returns. Further, for studies designed to map the continuity of cross-border bond volatility spillover, the research demonstrates the overall effectiveness of neural networks to map such real-valued measurable functions.

Keywords: Financial Econometrics, Volatility spillovers, Artificial neural networks.

JEL: C14, C45, C58

1 Introduction

In some research arenas the artificial neural network (ANN) topology is considered to be the “intriguing” empirical estimation alternative to choosing a classical linear model for the same task. Generally speaking, the ANN topology is designed to encompass artificial intelligence because of its similarity to problem solving by the human brain through the use of neuron connectivity. By contrast, classical linear models assume a linear functional relationship between a set of independent variables and at least one dependent variable. By its very cognitive inheritance, the ANN topology does not impose this structure on the modelling process. Nevertheless, despite any perceived advantages the ANN method offers to researchers who are faced with nonlinear and complex function rendering, many are reluctant to embrace the use of the method as it is too much of a “black box.” While some ANN algorithms do provide the researcher with information about the nature of the relationship between predictor (independent) and target (dependent) variables, many ANN algorithmic implementations do not make this relationship explicit. If that limitation were not enough to deter some researchers, nonparametric ANN techniques do not have wide scale support for metrics that reveal the strength of the relationship provided by each predictor variable to the mapping function.

The overall effectiveness of a multi-criteria radial basis function (RBF) artificial neural network (ANN) topology to estimate cross-border spillover effects in the European bond sector are detailed by Dash and Kajiji [7] in an application using the K4-RBF ANN (RANN). Subsequently, Dash and Kajiji [8] extended the RANN algorithm to a multivariate version, the K7-RBF ANN (MRANN). In an updated application to the estimation of bond volatility spillover effects, this paper discussed issues related to the multivariate estimation of mean-squared errors and related metrics needed to effectively evaluate modelling accuracy of MRANN. Additional elucidation of MRANN performance is provided in Kajiji and Dash [14]. Of equal importance, these research contributions provide the cognitive raison d’etre on how to effectively interpret (M)RANN estimates of quasi-elasticity metrics obtained from the double-log specification of the traditional micro-economic production theoretic model. Taken all together, the research contributions document “best effort” techniques by which to infer overall quality-of-fit in the evaluation of estimated quasi-elasticity parameters. Because it was not stated as
a specific research goal in either paper, the authors left unaddressed an assessment of what role classical linear parametric estimation should play as either a support tool, or as a stand-alone independent modelling tool, in the estimation of global bond volatility spillovers. In this chapter we close this gap as we determine the role of linear parametric multivariate models in the empirical investigation of cross-border volatility spillover among European government bond markets. Specifically, the chapter takes a position on how to combine both parametric and nonparametric modelling efforts.

2 Bond Volatility Spillover Modelling

The extraction of time-varying volatility of financial time series has largely been linked to the ARCH model of Engle [9] and Bollerslev [5] with recently updated literature and findings provided by Le and Kakinaka [15]. The latter contribution employs a two-stage GARCH methodology to provide evidence of how mean return and volatility spillover effects impact the stock markets of the U.S., Japan and China. Recent findings have shown that the artificial intelligence foundation of RANN methods is a viable alternative to the GARCH framework when modelling volatility spillover in European bond markets (Dash and Kajiji [7]) and when modelling the volatility of forex options (Dash, et. al. [6]). In this chapter the modelling process follows prior examples by implementing equation 1 to extract an AR(1) estimate of unexplained US government bond returns, $e_{US,t}$ over $T$ time periods. The associated idiosyncratic shock ($e_{US,t}$) is expected to be normally distributed with a variance of $\Sigma$, a mean of zero $E(\varepsilon) = 0$ and an uncorrelated structure, $(E(\varepsilon_i, \varepsilon_j) = 0; \forall i \neq j, i, j = 1...T)$:

$$R_{US,i} = b_{0,US} + b_{1,US} R_{US,i-1} + e_{US,i}.$$  \hspace{1cm} (1)

At this point, and following past practice, the modelling procedure moves to a RANN specification. In equation 2, conditional excess returns are captured for the aggregate European bond market by using the European total return government bond index, $R_E$. Specifically, equation 2 is formed as a multi-factor AR(1) by including $R_{US,i-1}$ and $e_{US,i-1}$:

$$R_{E,t} = b_{0,E} + b_{1,E} R_{E,t-1} + \gamma_{E} R_{E,i-1} + \phi_{E} e_{US,i-1} + \epsilon_{E,t}.$$  \hspace{1cm} (2)

In this form the conditional mean of the European excess bond return depends on its own lagged excess return as well as the spillover effects introduced by the lagged US excess return, $R_{US,i-1}$, and the US idiosyncratic shock, $e_{US,i-1}$. In equation 2 the idiosyncratic shocks ($e_{US,i-1}$ and $e_{E,t}$) are expected to be normally distributed with $E(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma$, and uncorrelated, $(E(\varepsilon_i, \varepsilon_j) = 0; \forall i \neq j; i, j = 1...T)$.

2.1 Multivariate RBF ANN Estimation of Stochastic Volatility

The univariate conditional excess return for $i^{th}$ country is specified in equation 3 as:

$$R_{i,t} = b_i + b_1 R_{i,t-1} + \gamma_{R_{US,i-1}} + \phi_{e_{US,i-1}} + \psi_{e_{E,t}} + \epsilon_{i,t}.$$  \hspace{1cm} (3)

For this model statement, the $i^{th}$ country conditional excess return depends upon the lagged performance of own country bond returns, $\{R_{i,t-1}\}$ as well as aggregate lagged bond returns generated by the US and European bond markets, $R_{US,i-1}$ and $R_{E,i-1}$, respectively. Conformable US and European volatility spillover effects are captured by $e_{US,i-1}$ and $e_{E,t}$. We note, however, that extant research does not provide evidence that univariate approaches to estimate global bond spillover effects consider the multivariate probability density that describes the joint interaction of the excess returns of the $i^{th}$ country with the aggregate European bond market. To counter this limitation modelling efforts should be expanded to a multivariate specification.

Equation 4 below presents an extension of the univariate European government bond spillover model to a multivariate formulation. For country $i$, the conditional excess return is determined not only by aggregate lagged returns and conforming spillover effects but within this specification it is now possible to express the simultaneous interaction dependency among local country risk:

$$(R_{i,t},...,R_{i,t}) = b_i \sum_{j} R_{j,t-1} + \gamma_{R_{US,i-1}} + \phi_{e_{US,i-1}} + \psi_{e_{E,t}} + \nu.$$  \hspace{1cm} (4)

Although not explored in this chapter, for parsimony with prior research we note that the specification of equation 4 permits a full examination of the vector $\nu$ for multivariate GARCH (MGARCH) effects (see Bauwens, et. al [4] for a survey of comparable MGARCH modelling characteristics). Lastly, because all subsequent references to equation 4 in this chapter are specific to the study of the European government bond market, we extrapolate model properties to the term “multivariate spillover model.”
3 Multivariate Modelling

The goal for this section of the chapter is to review three alternate approaches often used to execute multivariate modelling in realm of computational finance. The section begins with a statement on the purpose and use of the multivariate regression model. This is followed by an examination of the appointed task for the parametric linear canonical correlation model analysis; a task that is directed at establishing linear correlation among the variates of the multivariate spillover model. For parallel structure and comparative analytics the nonparametric MRANN multivariate spillover model is also re-introduced.

3.1 Generalized Parametric Multivariate Multiple Linear Regression

In this section we consider a generalized statement of the multivariate multiple linear regression model (MREGG). The model is a natural extension to the univariate multiple linear regression model. The model structure presented below forms the foundation statement for both parametric and nonparametric computational solutions. Specifically, we consider the model relationship between \( q \) responses \( y_1, \ldots, y_q \) and a single set of \( p \) predictor variables \( x_1, \ldots, x_p \). That is, it is possible to think of each \( q \) response as the excess return from each of the local European government bond market to explain the spillover effects. Within that context, each of the \( q \) responses is assumed to follow its own regression model as shown below.

\[
\begin{align*}
    y_1 &= \beta_{01} + \beta_{11}x_1 + \beta_{21}x_2 + \cdots + \beta_{p1}x_p + \varepsilon_1 \\
    y_2 &= \beta_{02} + \beta_{12}x_1 + \beta_{22}x_2 + \cdots + \beta_{p2}x_p + \varepsilon_2 \\
    &\vdots \\
    y_q &= \beta_{0q} + \beta_{1q}x_1 + \beta_{2q}x_2 + \cdots + \beta_{pq}x_p + \varepsilon_q
\end{align*}
\]

Restated, the multivariate linear regression model is:

\[
\mathbf{Y} = \mathbf{\beta X} + \mathbf{\varepsilon}, \quad \mathbf{E}(\mathbf{\varepsilon}) = \mathbf{0} \quad \text{and} \quad \text{Var}(\mathbf{\varepsilon}) = \mathbf{\Sigma}.
\]

Thus, the error terms associated with different responses may be correlated. We use multivariate regression routines from SAS [1] to estimate MREGG parameters.

3.2 The Canonical Correlations Model

The use of the multivariate multiple linear regression model specified in the section above assumes a linear multivariate normal relationship among the correlates. The solution for the \( \mathbf{\beta} \) matrix shown in equation 5 is a collection of estimates derived from solving a series of univariate least square solutions. Since one of the objectives of this chapter is to study the aforementioned linear interrelationships between the two sets of variables (e.g., excess bond returns and explanatory spillover effects) taken together we invoke canonical correlation analysis (CCA).

In this modelling method canonical variates\(^1\) are formed for both the dependent (target) and independent (predictor) variable sets. A canonical variate is similar to a linear composite of the set of variables. The CCA procedure extracts two variates – one representing the target set and another for the predictor set. The canonical procedure proceeds by developing orthogonal canonical functions that maximize the canonical correlation coefficient between the two variates. Canonical loadings are used to interpret each canonical variate. In a sense CCA is analogous to estimating a separate factor for each set of variables in order to maximize the correlation between factors. The orthogonal function extraction guarantees that CCA discriminates between the functions so that each function is representing a unique relationship between the variable sets. CCA also minimizes the Type I Error or the error that is related to finding a statistically significant result when none exist. Owing to the benefits of CCA as compared to MREGG we investigate its ability to uncover significant and meaningful linear relationships for the spillover effects.

We define the canonical algorithm by following and enhancing the algorithm proposed by Hardoon, et. al. [11]. Consider a multivariate random vector of the form \((x,y)\). Given sample observations as \( S = ((x_1,y_1), \ldots, (x_n,y_n)) \) of \((x,y)\), we can use \( S_x \) to denote \((x_1, \cdots, x_n)\) and similarly \( S_y \) to denote \((y_1, \cdots, y_n)\). Let us define a new coordinate for \( x \) by choosing a direction \( w_x \) and projecting \( x \) onto that direction \( x \to (w_x, x) \). We do the same for \( y \) by

\(^1\) A variate is similar to a latent variable that are routinely extracted by principal components analysis (PCA), except that a canonical variate also maximize the correlation between the two sets of variables.
choosing \( w_x \). As such, we obtain a sample of the new \( x \) coordinate as \( S_x, w_x = \{ (w_x, x_1), \ldots, (w_x, x_n) \} \) with the corresponding values of the new \( y \) coordinate being \( S_y, w_y = \{ (w_y, y_1), \ldots, (w_y, y_n) \} \).

The first stage of canonical correlation is to choose \( w_x \) and \( w_y \) to maximize the correlation between the two vectors (variates). The function to maximize is

\[
\rho = \max_{w_x, w_y} \text{corr}(S_x, w_x, S_y, w_y) = \max_{w_x, w_y} \frac{\text{corr}(S_x, w_x, S_y, w_y)}{\|S_x, w_x\| \cdot \|S_y, w_y\|} \tag{6}
\]

Denote \( \hat{E}[f(x, y)] \) as the empirical expectation of the function \( f(x, y) \) where \( \hat{E}[f(x, y)] = \frac{1}{m} \sum_{i=1}^{m} f(x_i, y_i) \).

We can then re-write the correlation expression as:

\[
\rho = \max_{w_x, w_y} \frac{\hat{E}\left[ (w_x, x) (w_y, y)^\top \right]}{\sqrt{\hat{E}\left[ (w_x, x)^2 \right] \hat{E}\left[ (w_y, y)^2 \right]}} = \max_{w_x, w_y} \frac{w_x^\top \hat{E}[xy] w_y}{\sqrt{w_x^\top \hat{E}[xx] w_x w_y^\top \hat{E}[yy] w_y}} \tag{7}
\]

Let’s define \( C \) as a covariance matrix of \((x, y)\). Then, \( C \) a block matrix can be written as:

\[
C(x, y) = \hat{E}\left[ \begin{pmatrix} x \\ y \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}^\top \right] = \begin{bmatrix} C_{xx} & C_{xy} \\ C_{yx} & C_{yy} \end{bmatrix} = C \tag{8}
\]

Hence, we can rewrite the function \( \rho \) as:

\[
\rho = \max_{w_x, w_y} \frac{w_x^\top C_{xx} w_x}{\sqrt{w_x^\top C_{xx} w_x w_y^\top C_{yy} w_y}} \tag{9}
\]

As seen from the derivation for \( \rho \), CCA maximizes the identification of linear relationship. CCA does not impose strict assumption of normality on the variables. However, multivariate normality is necessary for statistical inference of each canonical function.

### 3.3 The Multivariate Multi-Criteria MRANN Model

As in the univariate model, the multivariate version is generalized as a supervised least-squares method. The multivariate supervised learning function is stated as:

\[
Y = f(X), \tag{10}
\]

where \( Y \), the target matrix with \( q \) number of outputs, is a function of the input matrix \( X \) with \( p \) number of inputs. The function can be restated as:

\[
y_l = f(x_i) = \sum_{j=1}^{m} w_{lj} h_j(x), \tag{11}
\]

where, \( m \) is the number of basis functions, \( h \) is the number of hidden units, \( w \) is the weight vector, and \( i = 1..p \) where \( p \) is the number of input vectors; and \( l = 1..q \) where \( q \) is the number of output vectors.

The flexibility of \( f(x) \) and its ability to model many different functions across multiple targets is inherited from the freedom to choose different values for the weight matrix, \( w \). Within the RANN architecture, the multivariate weight matrix is found through optimization of an OLS objective function. This is equivalent to minimizing the multivariate sum of squared errors (SSE):

\[
\text{SSE}_q = \sum_{i=1}^{p} (\hat{y}_l - f(x_i))^2 \tag{12}
\]

Specifically, the MRANN algorithm invoked for this study extends the univariate derivation of Kajiji and Dash [7] to its multivariate multi-objective as summarized in the statement of equation 13:

\[
\arg \min_{k_l} \left[ \sum_{i=1}^{p} (y_l - f(x_i | k_l))^2 + \sum_{j=1}^{q} k_{lj} w_{lj}^2 \right]. \tag{13}
\]

For each of the \( l \) equations the computationally efficient Bayesian enhanced MRANN algorithm assures that \( q \) individual functions are mapped for smoothness and accuracy. In summary, as with its univariate counterpart, RANN, the multivariate MRANN incorporates the algorithmic enhancements evidenced to reconcile the twin evils that deter efficient ANN modelling: data dimensionality and an inflated residual sum of squares.
3.3.1 MRANN Data Scaling

ANN estimation requires input data to be scaled for efficient communication among neurons. For the MRANN estimation of the multivariate spillover model the data were scaled over the interval [0,1] by the Normalized Method 1. This method replaces an actual data point (D) with a normalized data value (Dv) based on the following transformation: \( D_v = \frac{(D - D_{L})}{(D_{U} - D_{L})} \). Here, \( D_L \) and \( D_U \) are computed as: \( D_L = D_{\text{min}} - \frac{(D_{\text{max}} - D_{\text{min}}) \times S_L}{100} \); and, \( D_U = D_{\text{max}} + \frac{(D_{\text{max}} - D_{\text{min}}) \times S_U}{100} \). The upper- (lower-) headroom percent, \( S_L \) and \( S_U \), are set separately at 0.00% and 1.01%, respectively, at the start of the model-building exercise.

3.3.2 MRANN Performance Characteristics Considerations

Lastly, minimization of the prediction error in all (M)RANN solutions is achieved by implementation of the generalized cross-validation (GCV) criterion. Because GCV is mathematically tractable and resembles a scaled SSE, when it is attached to the cost function, equation 13, it is possible to build the best possible model from a given training set (see Olivier and Olivier [16] for detailed properties).

4 Data and Alternate Modelling of European Government Bond Volatility Spillover

Weekly data for all government total return bond indices under study are obtained from Global Financial Data (GFD) 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. For the time period of this analysis, 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 with GFD extension) and Slovenia (10-year government bond yield index) define the individual country European local government bond markets. The USA effect is sampled by the inclusion of the Merrill Lynch U.S. government bond return index. Lastly, the J.P. 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. For presentation consistency, the return vector for the included indices are labelled as, Germany, Sweden, Spain, and Slovenia. Additionally, the USA Residual and EURO Residual derivations were provided by equations 1 and 2, respectively.

5 Results

Upon generating alternate parametric and nonparametric solutions to equation 5, this section develops a comparative analysis of computational results. Comparative analytics begin with a presentation of MRANN results. The MRANN results are obtained using WinORS e-AI [3]. These findings are followed with a presentation of MREGG computational results obtained from the SPSS software system [2]. Lastly, we complete the comparative examination of parametric linearity and additivity assumptions by conducting a CCA on the sample data. CCA computational results are obtained from the SAS statistical software system [1].

5.1 MRANN Model Weights

The weight matrix generated by applying the MRANN cognitive method to the multivariate spillover model is presented in Table 1. The weights are the estimated parameters attached to each predictor variable; or, stated differently they are estimated nonlinear regression parameters (see Hutchinson [12] an Kajiji [13] for details). The output performance measures generated by applying the K7-MRANN to equation 5 produced an R-square metric of 86.27%. As previously noted, a detailed discussion of these results is available in Dash and Kajiji [8].

<table>
<thead>
<tr>
<th>Return Generating Model</th>
<th>Lagged Germany</th>
<th>Lagged Sweden</th>
<th>Lagged Spain</th>
<th>Lagged Slovenia</th>
<th>Lagged Euro</th>
<th>Lagged USA</th>
<th>Euro Residual</th>
<th>USA Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>-0.7707</td>
<td>1.6275</td>
<td>1.7139</td>
<td>0.3434</td>
<td>1.5684</td>
<td>1.5771</td>
<td>-0.9211</td>
<td>-4.4926</td>
</tr>
<tr>
<td>Sweden</td>
<td>-1.2523</td>
<td>1.6448</td>
<td>1.6474</td>
<td>0.2934</td>
<td>1.2423</td>
<td>1.6652</td>
<td>-0.2510</td>
<td>-4.3313</td>
</tr>
<tr>
<td>Spain</td>
<td>-0.8412</td>
<td>1.9424</td>
<td>1.3946</td>
<td>0.2902</td>
<td>1.6484</td>
<td>1.5534</td>
<td>-0.9182</td>
<td>-4.4182</td>
</tr>
<tr>
<td>Slovenia</td>
<td>-0.5612</td>
<td>2.4429</td>
<td>1.8034</td>
<td>-0.0566</td>
<td>2.0115</td>
<td>1.3632</td>
<td>-1.6462</td>
<td>-4.7723</td>
</tr>
</tbody>
</table>

5.2 MREGG Model Weights

MREGG estimated parameter weights are presented in table 2. The statistical validity analysis is based on the computed Wilks’ Lambda (also shown in table 2). There are four (of eight) statically significant predictors for
the system of linear equations that define local country bond spillover effects. These are: a) lagged local bond returns from Slovenia; b) bond returns from the aggregate European market; c) the residual idiosyncratic spillover volatility from the aggregate European bond market; and, d) volatility spillover effects from the US government bond markets. Although spillover effects from both the European and US markets are confirmed by the solution to the MREGG model, these findings cast a shadow over a seemingly plausible weight structure produced by application of the cognitive MRANN algorithm. Before attempting to reconcile the two sets of results the next section invokes a CCA for the purpose of identifying and justifying any and all assumptions regarding a linear structure among the sets of variables. These confirmations are a necessary step in order to fully and accurately interpret the MREGG results.

Table 2: MREGG Spillover Weight Matrix

<table>
<thead>
<tr>
<th>Return Generating Model</th>
<th>Lagged Germany</th>
<th>Lagged Sweden</th>
<th>Lagged Spain</th>
<th>Lagged Slovenia</th>
<th>Lagged Euro</th>
<th>Lagged USA</th>
<th>Euro Residual</th>
<th>USA Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>0.2414</td>
<td>-0.7335</td>
<td>0.5400</td>
<td>-0.2735</td>
<td>0.5335</td>
<td>0.1144</td>
<td>0.0717</td>
<td>-0.5466</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.0017</td>
<td>-0.6272</td>
<td>0.6579</td>
<td>-0.2940</td>
<td>0.5502</td>
<td>0.1186</td>
<td>0.0237</td>
<td>-0.3247</td>
</tr>
<tr>
<td>Spain</td>
<td>0.3009</td>
<td>-0.6076</td>
<td>0.3375</td>
<td>-0.4600</td>
<td>0.7509</td>
<td>0.1225</td>
<td>-0.1108</td>
<td>-0.0572</td>
</tr>
<tr>
<td>Slovenia</td>
<td>0.1141</td>
<td>-1.0317</td>
<td>0.7513</td>
<td>-0.1488</td>
<td>0.6645</td>
<td>0.0870</td>
<td>-0.2209</td>
<td>0.2064</td>
</tr>
<tr>
<td>Wilks’ λ</td>
<td>0.9800</td>
<td>0.9200</td>
<td>0.9320</td>
<td>0.8760</td>
<td>0.8130</td>
<td>0.9920</td>
<td>0.8580</td>
<td>0.8770</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.8140</td>
<td>0.0850</td>
<td>0.2380</td>
<td>0.0330</td>
<td>0.0030</td>
<td>0.9550</td>
<td>0.0170</td>
<td>0.0350</td>
</tr>
</tbody>
</table>

Note: None of the individual parameters are significant

5.3 Canonical Structure

In this section the results of the CCA analysis are presented and interpreted. We begin the presentation by noting that, in general, the number of canonical functions (dimensions) is equal to the number of variables in the smaller set of variable under analysis. In this study the smaller set is defined by the excess returns of the local European countries. Stated differently, the analysis is defined by four (4) canonical functions.

5.3.1 Canonical Functions

Table 3: Canonical Functions

<table>
<thead>
<tr>
<th>Canonical Function</th>
<th>Canonical Correlation</th>
<th>Canonical R^2</th>
<th>Variability (%)</th>
<th>Approx. F-Value</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>0.6171</td>
<td>0.3808</td>
<td>50.23%</td>
<td>2.49</td>
<td>0.0001</td>
</tr>
<tr>
<td>F2</td>
<td>0.4712</td>
<td>0.2220</td>
<td>29.28%</td>
<td>1.70</td>
<td>0.0321</td>
</tr>
<tr>
<td>F3</td>
<td>0.3701</td>
<td>0.1370</td>
<td>18.07%</td>
<td>1.16</td>
<td>0.3138</td>
</tr>
<tr>
<td>F4</td>
<td>0.1408</td>
<td>0.0183</td>
<td>2.41%</td>
<td>0.33</td>
<td>0.8948</td>
</tr>
</tbody>
</table>

The CCA solution results report a statistically significant Wilks’ Lambda of 0.4075 (99% confidence level). However, it is imperative that the validity of each of the four functions that were extracted be studied. Table 3 presents the details of the sequentially extracted canonical functions. That is, F1 is extracted before F2, F3, and F4. F1 would therefore explain the highest proportion of the shared variance followed by F2, F3, and F4. For this analysis there is statistical significance at the 95% confidence level for F1 which explains 38.08% of the shared variance. F2 is also significant at the 95% confidence level and explains 22.20% of the shared variance. The significance values reported for F3 and F4 indicate that these are not likewise statistically significant. Thus taken together, the two functions (F1 and F2) account for a significant proportion of total variability at 79.51%. Based on the validity assessment, the remainder of the CCA analysis is restricted to an investigation of the first two canonical functions.

5.3.2 Redundancy Index

The redundancy index reports the amount of variance in a canonical variate (dependent or independent) that is explained by the other canonical variate in the canonical function [10]. The redundancy index for the set of dependent variables is very low when measured for the two statistically significant variates (0.1713). This measure is even lower (0.1158) when considering the first two variates of the independent variables. Because the hypothesized model structure was constructed within the context of a bond spillover model, where the cognitive separation between the sets of dependent and explanatory variables is clearly defined, the low redundancy value for the independent set is not considered problematic.
Table 4: Redundancy Analysis

<table>
<thead>
<tr>
<th>Canonical Variate</th>
<th>Avg. Loading Squared</th>
<th>Canonical R²</th>
<th>Variability Explained</th>
<th>Redundancy Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable Set</td>
<td>V1</td>
<td>0.0640</td>
<td>0.3808</td>
<td>0.0244</td>
</tr>
<tr>
<td>V2</td>
<td>0.6618</td>
<td>0.2220</td>
<td>0.1469</td>
<td></td>
</tr>
<tr>
<td>Independent Variable Set</td>
<td>W1</td>
<td>0.0714</td>
<td>0.3808</td>
<td>0.0272</td>
</tr>
<tr>
<td>W2</td>
<td>0.3992</td>
<td>0.2220</td>
<td>0.0886</td>
<td></td>
</tr>
</tbody>
</table>

As previously observed, the relatively low dependent set redundancy index value of 17.3% indicates a very small shared variance with the independent set. Given this observation, and by an alternative statement for this finding, the redundancy index values provide evidence that there is very little shared variance among the set of independent and dependent variates. This finding refutes the appropriateness assumption of applying a multivariate linear regression method to model a global bond spillover function. Nevertheless, because the basic canonical relationship was found to be statistically significant the analysis proceeds with an interrogation of the standardized canonical weights.

5.3.3 Canonical Weights

For comparative unification we report the standardized canonical coefficients in table 5.

Table 5: Canonical Weights

<table>
<thead>
<tr>
<th>Variable</th>
<th>W1</th>
<th>W2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Germany</td>
<td>1.055</td>
<td>0.3498</td>
</tr>
<tr>
<td>Lagged Sweden</td>
<td>1.7865</td>
<td>-3.9041</td>
</tr>
<tr>
<td>Lagged Spain</td>
<td>-3.3697</td>
<td>3.0452</td>
</tr>
<tr>
<td>Lagged Slovenia</td>
<td>-3.3383</td>
<td>1.3154</td>
</tr>
<tr>
<td>Lagged Euro</td>
<td>4.2509</td>
<td>-0.1718</td>
</tr>
<tr>
<td>Lagged USA</td>
<td>0.2140</td>
<td>0.0651</td>
</tr>
<tr>
<td>Euro Residual</td>
<td>-1.3391</td>
<td>0.2356</td>
</tr>
<tr>
<td>USA Residual</td>
<td>1.1507</td>
<td>-0.3428</td>
</tr>
</tbody>
</table>

Interpreting standardized canonical coefficients is analogous to interpreting standardized regression coefficients. For example, with a focus on Germany, a one standard deviation increase in the Lagged German bond return would be expected to produce a 1.055 standard deviation increase in the score on the first canonical variate (W1) within the independent variables set. This study has a clearly delineated set of independent and dependent variables; hence, the seemingly weak CCA analysis can focus primarily on the structure of the independent set.

The absolute magnitude of the weights provides additional insight into the linear correlation assumption embedded with the MREGG modelling statement. Stated succinctly, the absolute magnitude reflects the relative contribution of the variable to the variate. This definition suggests that Lagged Spain, Lagged Slovenia, and Lagged Euro make the greatest contribution to the first variate (W1), and Lagged Spain, and Lagged Sweden largely contribute to the definition of the second variate (W2). By way of emphasis, for the second variate, Lagged Spain has a high coefficient on both independent variates and thus makes the most contribution to defining the variates. The sign attached to the weights indicates the direction of the weighted contribution to the variate. For the first variate Lagged Euro has a positive weighting compared to the reported negative weights for Lagged Spain and Lagged Slovenia. Similarly, Lagged Spain makes a positive contribution to the second variate whereas Lagged Sweden makes an almost proportionate negative contribution.

Table 6: Correlation Matrix

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lagged Germany</th>
<th>Lagged Sweden</th>
<th>Lagged Spain</th>
<th>Lagged Slovenia</th>
<th>Lagged Euro</th>
<th>Lagged USA</th>
<th>Euro Residual</th>
<th>USA Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Germany</td>
<td>1.0000</td>
<td>0.9921</td>
<td>0.9966</td>
<td>0.9521</td>
<td>0.9472</td>
<td>0.8826</td>
<td>0.1680</td>
<td>-0.0762</td>
</tr>
<tr>
<td>Lagged Sweden</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.9888</td>
<td>0.9408</td>
<td>0.9362</td>
<td>0.8797</td>
<td>0.1708</td>
<td>-0.0788</td>
</tr>
<tr>
<td>Lagged Spain</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.9510</td>
<td>0.9429</td>
<td>0.8721</td>
<td>0.1783</td>
<td>-0.0645</td>
</tr>
<tr>
<td>Lagged Slovenia</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.9885</td>
<td>0.8198</td>
<td>0.1473</td>
<td>-0.0811</td>
</tr>
<tr>
<td>Lagged Euro</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.8261</td>
<td>0.1318</td>
<td>-0.0957</td>
</tr>
<tr>
<td>Lagged USA</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.2492</td>
<td>-0.0422</td>
</tr>
<tr>
<td>Euro Residual</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>-0.8818</td>
</tr>
<tr>
<td>USA Residual</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
Despite the interesting but conflicting CCA findings, the high correlations reported in table 6 among all of the “Lagged” variables as well as between the Euro Residual and the USA Residual render these findings unreliable and biased. While it appears the canonical weights adjust measurably when the combination of the variable set change, the high collinearity across the weight structure renders this finding unreliable.

5.3.4 Canonical Loadings

A canonical loading is linear correlation between the independent variable and its respective canonical variates. As previously stated, we limit the discussion of canonical loadings to the first two statistically significant functions and their associated independent set variates, W1 and W2. In table 7, we also present the variates, V1 and V2, of the dependent set.

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>W1</th>
<th>W2</th>
<th>Dependent Variable</th>
<th>V1</th>
<th>V2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Germany</td>
<td>0.2443</td>
<td>0.7240</td>
<td>Germany</td>
<td>0.2174</td>
<td>0.7986</td>
</tr>
<tr>
<td>Lagged Sweden</td>
<td>0.2596</td>
<td>0.6551</td>
<td>Sweden</td>
<td>0.2135</td>
<td>0.7622</td>
</tr>
<tr>
<td>Lagged Spain</td>
<td>0.2056</td>
<td>0.7433</td>
<td>Spain</td>
<td>0.2956</td>
<td>0.7751</td>
</tr>
<tr>
<td>Lagged Slovenia</td>
<td>0.2772</td>
<td>0.8176</td>
<td>Slovenia</td>
<td>0.2753</td>
<td>0.9097</td>
</tr>
<tr>
<td>Lagged Euro</td>
<td>0.3835</td>
<td>0.7936</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged USA</td>
<td>0.2151</td>
<td>0.6046</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Euro Residual</td>
<td>-0.3127</td>
<td>0.0556</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA Residual</td>
<td>-0.1832</td>
<td>-0.1433</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The first independent variate (W1) has relatively consistent and nearly all positive set of loadings across all variables except the Euro Residual and the USA Residual. These two variables exhibit a negative loading. The Lagged Euro and Euro Residual both have the loading with the highest magnitude with the other lagged variables having somewhat equal loading values. This latent variate is labelled a “Euro Zone” variable. The second variate, W2, is clearly defined by the “Lagged” variables in the study where each variable has a loading above 0.60. In practice, this variate can be labelled lagged country bond return dimension.

![Figure 1: BiPlot for F1 and F2](image)

Figure 1 presents a canonical Bi-Plot. Figure 1 provides a graphical relationship between the dependent and independent variates. With reference to figure 1, the encircled dependent and all lagged variables show strong positive correlation. This indicative of a substantial and positive interaction of excess bond returns across the sampled countries. The second dimension is defined by the two idiosyncratic risk metrics – Euro Residual and USA Residual. Each is displayed in quadrant II and III, respectively.
5.3.5 Canonical Cross Loadings

The CCA analysis concludes with the presentation of the canonical cross loadings. The purpose of canonical cross loadings is to display the simple linear correlation between the independent canonical variates and the dependent variables (local country bond returns).

<table>
<thead>
<tr>
<th>Variable</th>
<th>W1</th>
<th>W2</th>
<th>Variance Explained</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>W1</td>
</tr>
<tr>
<td>Germany</td>
<td>0.1341</td>
<td>0.3763</td>
<td>1.80%</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.1318</td>
<td>0.3591</td>
<td>1.74%</td>
</tr>
<tr>
<td>Spain</td>
<td>0.1824</td>
<td>0.3652</td>
<td>3.33%</td>
</tr>
<tr>
<td>Slovenia</td>
<td>0.1699</td>
<td>0.4286</td>
<td>2.89%</td>
</tr>
</tbody>
</table>

As shown by the data presented in Table 8, all dependent variables exhibit a relatively small correlation with the first independent variate (W1). By contrast, the correlations are somewhat higher on the second independent variate (W2). In either case, the relatively low linear correlations corroborate the earlier finding of a relatively low shared variance between the set of dependent variables and the two independent variates (previously labelled as “Euro Zone” and “Lagged”). For example, one results offered in table 8 shows that a low 1.80% of the variance in German government bonds is explained by the first, or “Euro Zone”, variate (W1). Continuing with a focus on the German bond market it is observed that the second variate “Lagged” effects, or W2, explains 14.16% of the variability in German government bond returns. Taken together, the total variance explained for German government bond market returns by the two canonical functions is a relatively low 15.96%. Only Slovenia (not an EMU member over the study time frame) is above 20% (21.26%).

5.4 Comparative Signed Model Weights: RANN, MRANN and MREGG

Table 9 is an updated version of table 3 from Dash and Kajiji [8]. The current updated presentation adds the signed spillover weights from the MREGG solution under the “G” designation. Designation “R” refers to the results of the RANN model while designation “M” is attached to interpretation of MRANN modelling results. The table data can be used to highlight important differences across alternate model structures. The purpose of table 9 is to assist in a direct comparison of the MREGG signed weights to those produced by MRANN solution.

For the Euro-stochastic volatility spillover effect the signed weights are negative and identical across MREGG and MRAN models for Spain and Slovenia. This finding suggests that volatility in the aggregate European government bond market tends to impact negatively the return generating process in local country government bond markets. Standing in contrast to this finding are the reversed signs for the two dominant economies in this study (Germany and Sweden). MRANN previously reported a positive effect in each case. Here, an increase in aggregate volatility of European government bonds would tend to add to the return structure of these two economies. MREGG, by contrast, suggests the impact of volatility in the aggregate European bond market has a negative impact on these same two economies. The results for the USA volatility spillover effect are a bit more uniform. Slovenia is the only country to report a reversed stochastic volatility contribution to the local government bond market. However, during the time period of this study the US economy and that of Slovenia explored a significant growth in relationship; a fact that could lend to this finding. For all other European countries the impact of volatility in the US government bond market is to impute negative effects on the returns generated in local country government bond markets.

<table>
<thead>
<tr>
<th>Return Generating Model</th>
<th>R/M/G</th>
<th>R/M/G</th>
<th>R/M/G</th>
<th>R/M/G</th>
<th>R/M/G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged</td>
<td>Lagged</td>
<td>Lagged</td>
<td>Euro</td>
<td>USA</td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>+ / - / +</td>
<td>- / + / +</td>
<td>+ / + / +</td>
<td>- / - / +</td>
<td>+ / - / -</td>
</tr>
<tr>
<td>Sweden</td>
<td>+ / + / +</td>
<td>+ / - / +</td>
<td>+ / + / +</td>
<td>+ / - / +</td>
<td>- / - / -</td>
</tr>
<tr>
<td>Spain</td>
<td>+ / + / +</td>
<td>+ / + / +</td>
<td>- / + / +</td>
<td>+ / - / +</td>
<td>- / - / -</td>
</tr>
<tr>
<td>Slovenia</td>
<td>+ / - / +</td>
<td>+ / + / +</td>
<td>- / + / +</td>
<td>- / - / -</td>
<td>- / - / -</td>
</tr>
</tbody>
</table>

R=K4-RANN; M=K4-MRANN; G=Multivariate Regression
The summarizing effect of the data in table 9 draws attention to the stated purpose of conducting a CCA on the model topologies available to extract estimates of global bond volatility spillover. The study of bond volatility spillover is a complex task where clearly there is significant interest in developing a descriptive solution from a properly specified estimation model. What is learned from the experiment presented above is that a nonparametric RBF ANN produces a very viable mapping of the volatility spillover function. Also learned is that there is a very weak linear correlation structure among the variates that describe the multiple dependent variables to the variates that describe lagged returns at both the country- and aggregate-level. There is little plausible reason to trust the weak statistical results generated by MRANN in a study of global bond volatility spillover.

6 Summary and Conclusions

This chapter combined computational statistics financial econometrics to investigate the structure of volatility spillover effects across EMU and non-EMU European government bond markets. The comparative results produced by alternate statistical models provided greater support for invoking the K7-MRANN computational method against the traditional multivariate linear regression method. Although both model topologies produced interpretable metrics, very clearly the impact of those metrics differed in direction and magnitude across the different model statements. That difference left open the question as to which model best replicated the reality of the local country government bond return generating process. CCA was invoked to examine the underlying assumptions of linearity and significant correlation structure between the dependent variates and the variates of the independent variables. Conclusively, CCA found weak to virtually non-existence linear correlation structure. This is a finding that points to the inappropriate use of linear multivariate regression methods to extract parameter estimates used to explain spillover effects across global government bond markets.

These finding raise additional questions that are left for future research projects. Knowing that linear multivariate regression is not a viable alternative to multivariate RBF ANN methods, one is left to reason that perhaps non-linear parametric and nonparametric regression methods should likewise be investigated and compared to cognitive MRANN. Of course, in such a study the comparative analytics of correlation structure should give way to the use of nonlinear CCA with its intended objective of comparing sets of data to an unknown compromise set that is defined by object scores. As the quest for improved modelling of bond spillover models advances, we envision a study of nonlinear modelling topologies with an increased set of local country variables, higher frequency data, and a time frame that reflects a more descriptive view of both the EU and EMU.
References

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Mission

Our responsibility is to provide strong academic programs that instill excellence, confidence and strong leadership skills in our graduates. Our aim is to (1) promote critical and independent thinking, (2) foster personal responsibility and (3) develop students whose performance and commitment mark them as leaders contributing to the business community and society. The College will serve as a center for business scholarship, creative research and outreach activities to the citizens and institutions of the State of Rhode Island as well as the regional, national and international communities.

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