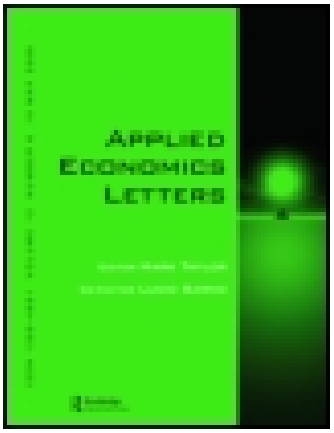

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Empirical evidence of joint nonlinearity in economic area and US economic variables using two modified multivariate nonlinearity tests

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Empirical evidence of joint nonlinearity in economic area and US economic variables using two modified multivariate nonlinearity tests

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This article examines the joint nonlinearity of 15 subsets of US and economic area (EA) economic variables using two modified multivariate nonlinearity tests recently developed in the literature. Clear evidence of joint nonlinearity in both US and EA economic variables is found. Our results thus cast doubts on the adequacy of using linear multivariate (VAR-type) models, structural or not, in applied economics.

Keywords: VAR models; principal component analysis; nonlinearity testing; TSAY test; ARCH test

JEL Classification: C12; C32

I. Introduction

Many central banks use various multivariate (VAR-type) models for forecasting and policy analysis simulations (see Kapetanios *et al.*, 2008 for an overview). However, when developing these models, the researchers face an ultimate dilemma whether to construct a linear or a nonlinear version of the model. This question is of much practical importance since any model misspecification may lead to misleading inference (e.g. hypothesis testing, impulse-response functions, forecast error variance decompositions, point and interval forecasts) and serious mistakes in economic policy (e.g. setting the interest rates). On the one hand, nonlinear (economic) models can capture empirically observed phenomena (e.g. a zero-lower bound of the interest rates, business cycle asymmetry in output, etc.) without breaking theoretical concepts or imposing unrealistic assumptions (see Davig, 2007; Liu *et al.,* 2009, 2011; or Rudebusch and Swanson, 2008, for example). On the other hand, all modelling steps (i.e. identification, estimation, bias correction, indeterminacy/stability, forecasting) of nonlinear models are far more complex and complicated as compared to linear counterparts.

Therefore, using appropriate nonlinearity testing procedures is desirable in order to establish the adequacy or otherwise of a linear data representation before exploring more complicated nonlinear structures. The problem is that although there exist many univariate nonlinearity tests (see, e.g. Tong, 1990; Teräsvirta *et al.*, 2010), it can be shown that these tests applied to individual components of a multiple time series may easily lack power to detect a nonlinear structure (see Psaradakis and Vávra, 2014). The aim of this note is to fill the gap in the literature and examine joint nonlinearity of the economic area (EA) and US economic variables using two modified multivariate (and hence adequate) nonlinearity test statistics. In addition, special attention is paid to: (i) the sensitivity of the modified tests to a model size; and (ii) the stability of the test results over time.

The article is organized as follows. The modified multivariate tests are discussed in Section II. An empirical application to US and EU data is provided in Section III. Section IV summarizes and concludes.

II. Null Hypothesis of Linearity and Principal Component Multivariate Nonlinearity Tests

Without loss of generality, let us consider a linear finite-order real-valued vector autoregressive model for k-variate time series $\{\boldsymbol{x}_t\}$ under the null hypothesis of linearity[1]:

$$\boldsymbol{x}_t = \boldsymbol{\mu} + \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \qquad t = -p+1, \ldots, 0, \ldots, T \tag{1}$$

where $p \geq 1$ is a fixed integer, $\boldsymbol{\mu}$ is a $k \times 1$ vector of real constants, $\boldsymbol{A}_j$ $(j = 1, \ldots, p)$ are $k \times k$ matrices of real constants, and $\{\boldsymbol{u}_t\}$ is a sequence of independent, identically distributed k-dimensional random vectors with $\mathbb{E}(\boldsymbol{u}_t) = \boldsymbol{0}$, $\det \mathbb{E}(\boldsymbol{u}_t \boldsymbol{u}_t') \neq 0$, and $\mathbb{E}(\|\boldsymbol{u}_t\|^4) < \infty$. It is also assumed that $\det\left(\boldsymbol{I}_k - \sum_{j=1}^{p} \boldsymbol{A}_j z^j\right) \neq 0$ for all complex z such that $|z| \leq 1$, where $\boldsymbol{I}_k$ denotes the identity matrix of order k. We are interested in testing the hypothesis that there is no neglected nonlinearity in the conditional mean (hence the TSAY test) and conditional volatility (hence the ARCH test) in Equation 1.

The multivariate TSAY test for neglected nonlinearity considered by Harvill and Ray (1999) may be implemented as a test for the hypothesis $\boldsymbol{B}_2 = \boldsymbol{0}$ in the auxiliary multivariate regression:

$$\hat{\boldsymbol{u}}_t = \boldsymbol{b}_0 + \boldsymbol{B}_1 \boldsymbol{v}_t + \boldsymbol{B}_2 \boldsymbol{w}_t + \boldsymbol{\eta}_t, \qquad t = 1, 2, \ldots, T \tag{2}$$

where $\hat{\boldsymbol{u}}_t$ is the $k \times 1$ vector of least-squares residuals from Equation 1, $\boldsymbol{v}_t$ is the $kp \times 1$ vector defined as $\boldsymbol{v}_t = (\boldsymbol{x}_{t-1}', \ldots, \boldsymbol{x}_{t-p}')'$, $\boldsymbol{w}_t$ is the $\frac{1}{2}kp(kp+1) \times 1$ vector defined as $\boldsymbol{w}_t = \operatorname{vech}(\boldsymbol{v}_t \boldsymbol{v}_t')$, $(\boldsymbol{b}_0, \boldsymbol{B}_1, \boldsymbol{B}_2)$ are artificial parameters and $\boldsymbol{\eta}_t$ is an artificial error term. Putting $m = \frac{1}{2}kp(kp+1)$, the linearity hypothesis is rejected for large values of the likelihood-ratio statistic:

$$\Lambda = T(\ln \det \boldsymbol{S}_0 - \ln \det \boldsymbol{S}_1) \tag{3}$$

where $\boldsymbol{S}_1$ and $\boldsymbol{S}_0$ are the least-squares residual sum of squares matrices from Equation 2 with $\boldsymbol{B}_2$ unrestricted and $\boldsymbol{B}_2 = 0$, respectively.

An obvious difficulty with the application of a nonlinearity test based on Equation 3 in practice is the large dimension m of the squares and cross-products vector $\boldsymbol{w}_t$. As a result, long time series are required for the implementation of the test procedure. In addition, the components of $\boldsymbol{w}_t$ are likely to be highly collinear, something which can have adverse effects on the finite-sample performance of the test.

However, Psaradakis and Vávra (2014) show that the dimensionality and collinearity problems may be effectively alleviated by the use of principal components Specifically, they suggest replacing $\boldsymbol{w}_t$ in Equation 2 by the n-dimensional vector $\boldsymbol{y}_t = (Y_{1t}, \ldots, Y_{nt})'$, $1 \leq n \leq m$, consisting of the first n sample principal components of $\boldsymbol{w}_t$. Letting $\lambda_1 \geq \cdots \geq \lambda_m$ denote the eigenvalues of the Pearson correlation matrix of $(\boldsymbol{w}_1, \ldots, \boldsymbol{w}_T)$, the ith principal component is computed as $Y_{it} = \boldsymbol{\xi}_i' \boldsymbol{w}_t^*$ $(i = 1, \ldots, m)$, where $\boldsymbol{\xi}_i$ is the normalized eigenvector associated with λ_i and $\boldsymbol{w}_t^*$ is the standardized version of $\boldsymbol{w}_t$. A modified multivariate TSAY test of neglected nonlinearity may then

[1] It is worth mentioning that even some structural economic models (e.g. dynamic stochastic general equilibrium (DSGE) models) can allow for a VAR representation under mild conditions (see Alvarez-Lois *et al.*, 2008 for details).

be implemented as a test for the hypothesis $\boldsymbol{C}_2 = \boldsymbol{0}$ in the auxiliary multivariate regression:

$$\hat{\boldsymbol{u}}_t = \boldsymbol{c}_0 + \boldsymbol{C}_1 \boldsymbol{v}_t + \boldsymbol{C}_2 \boldsymbol{y}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, 2, \ldots, T \tag{4}$$

where $(\boldsymbol{c}_0, \boldsymbol{C}_1, \boldsymbol{C}_2)$ are artificial parameters and $\boldsymbol{\varepsilon}_t$ is an artificial error term. Linearity is thus rejected for large values of the likelihood-ratio statistic:

$$\Lambda_{\text{TSAY}} = (T - \bar{\tau})(\ln \det \boldsymbol{S}_0 - \ln \det \boldsymbol{S}_2) \tag{5}$$

where $\bar{\tau} = kp + \frac{1}{2}(k + n + 3)$ and $\boldsymbol{S}_2$ is the least-squares residual sum of squares matrix from Equation 4. For large T, Λ_{TSAY} may be approximately treated as χ^2_{kn} under the null hypothesis that $\{\boldsymbol{x}_t\}$ satisfies the linear model (Equation 1). The authors demonstrate that a significant reduction in the dimension of the set of relevant test variables through the use of principal components can be achieved. In addition, the resulting test Λ_{TSAY} displays no systematic level distortion or power loss relative to the original test.

Based on these arguments, the multivariate ARCH test considered by Lütkepohl (2005, Chap. 16) is modified in a similar fashion. In this case, the principal component-based ARCH test is based on the hypothesis that $\boldsymbol{C}_1 = \boldsymbol{0}$ in the auxiliary multivariate regression:

$$\hat{\boldsymbol{e}}_t = \boldsymbol{c}_0 + \boldsymbol{C}_1 \boldsymbol{y}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, 2, \ldots, T \tag{6}$$

where $(\boldsymbol{c}_0, \boldsymbol{C}_1)$ are artificial parameters, $\hat{\boldsymbol{e}}_t = \operatorname{diag}(\hat{\boldsymbol{u}}_t \hat{\boldsymbol{u}}_t')$ and $\boldsymbol{\varepsilon}_t$ is an artificial error term. In this case, $\boldsymbol{y}_t = (Y_{1t}, \ldots, Y_{nt})'$, $1 \leq n \leq m$, represents the first n sample principal components of $\boldsymbol{w}_t = (\operatorname{vech}(\hat{\boldsymbol{u}}_{t-1}\hat{\boldsymbol{u}}_{t-1}')', \ldots, \operatorname{vech}(\hat{\boldsymbol{u}}_{t-p}\hat{\boldsymbol{u}}_{t-p}')')'$ and $m = \frac{1}{2}kp(k+1)$. As in the previous case, linearity is thus rejected for large values of the likelihood-ratio statistic:

$$\Lambda_{\text{ARCH}} = (T - \bar{\tau})(\ln \det \boldsymbol{S}_0 - \ln \det \boldsymbol{S}_3) \tag{7}$$

where $= kp + \frac{1}{2}(k + n + 3)$ and $\boldsymbol{S}_3$ is the least-squares residual sum of squares matrix from Equation 6. For large T, Λ_{ARCH} may be approximately treated as χ^2_{kn} under the null hypothesis that $\{\boldsymbol{x}_t\}$ satisfies the linear model (Equation 1).

A decision, however, needs to be made in the implementation of the test based on Λ_{TSAY} and Λ_{ARCH} on the number of principal components to be used. Among the various methods available in the literature (see Jolliffe, 2005, Chap. 6 for details), the following rules for selecting n are popular in applied work:

R1: n is the smallest integer such that $m^{-1}\sum_{i=1}^{n}\lambda_i \geq 0.9$ (proportion-of-variance rule);
R2: n is the smallest integer such that $\lambda_{n+1} \leq \tilde{\lambda}$ for $\tilde{\lambda} = 0.7$ (average-root rule).

III. Data and Empirical Results

The principal component multivariate TSAY and ARCH tests defined in Equations 5 and 7 are used to test for joint linearity in US and EA data. The following economic indicators are considered: the growth rate of real GDP (Y), the growth rate of real consumption (C), the growth rate of real investment (I), the CPI inflation rate (P), the 3-month treasure bill rate (RS), the 10-year government bond rate (RL), the growth rate of nominal wage (W), the growth rate of employment (L), the growth rate of Euro per USD (ER) and the growth rate of commodity price index (COM).[2] Since many real economic variables share a common stochastic trend (e.g. due to a nonstationary technology shock), the first differences are used to make them stationary. All variables span the period 1971Q2 to 2010Q4 (i.e. $T = 159$ obs.). The selected data sample overlaps with time periods usually used for the estimation of economic models.[3] In order to check the robustness of the multivariate tests against a model size (i.e. a number of economic variables in a model), 15 scenarios of economic variables are considered (see Table 1). A linear VAR model as in Equation 1 is

[2] The data-sets come from the St. Louis Federal Reserve Economic Database and the Area Wide Model Database. All relevant variables are seasonally adjusted. The data-sets are available from the author upon request.
[3] For example, Smets and Wouters (2007) used a data-set spanning the period 1966Q1–2000Q4 (156 obs.), Adolfson *et al.* (2007) used the period 1970Q1–2002Q4 (132 obs.) and Liu and Mumtaz (2011) used the period 1970Q1–2009Q1 (157 obs.).

Table 1. Selected scenarios of economic variables

Scenario 1	Y, P, RS
Scenario 2	Y, P, RS, ER
Scenario 3	Y, P, RS, RL
Scenario 4	Y, P, RS, COM
Scenario 5	Y, P, RS, RL, ER, COM
Scenario 6	Y, P, RS, W, L
Scenario 7	Y, P, RS, W, L, ER
Scenario 8	Y, P, RS, W, L, RL
Scenario 9	Y, P, RS, W, L, RL
Scenario 10	$Y, P, RS, W, L, RL, ER, COM$
Scenario 11	Y, P, RS, W, L, C, I
Scenario 12	Y, P, RS, W, L, C, I, ER
Scenario 13	Y, P, RS, W, L, C, I, RL
Scenario 14	$Y, P, RS, W, L, C, I, COM$
Scenario 15	$Y, P, RS, W, L, C, I, RL, ER, COM$

considered as an adequate model under the null hypothesis of linearity with the automatically selected lag order p using the Hannan–Quinn (HQ) information criterion.[4]

The empirical p-values of the principal component multivariate nonlinearity tests Λ_{TSAY} and Λ_{ARCH} are presented in Table 2. The results suggest the following:

(i) The null hypothesis of linearity is clearly rejected by the modified multivariate TSAY test in all 15 scenarios for both US and EA variables at the usual significance level 0.05, regardless the stopping rules (i.e. R1 and R2). Very similar results are obtained from

Table 2. *p*-Values of the multivariate nonlinearity tests

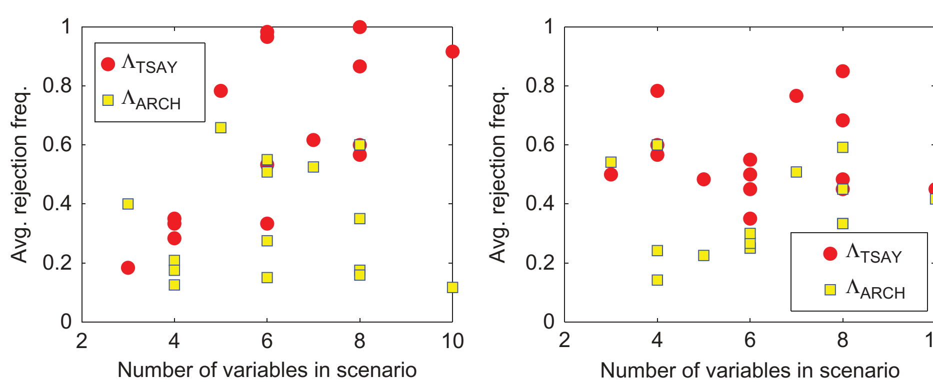
		Λ_{TSAY}(R1)	n	Λ_{TSAY}(R2)	n	Λ_{ARCH}(R1)	n	Λ_{ARCH}(R2)	n
EA	Scenario 1	0.001	4	0.002	5	0.000	7	0.000	5
	Scenario 2	0.000	8	0.000	10	0.000	13	0.000	9
	Scenario 3	0.008	3	0.017	5	0.000	11	0.000	8
	Scenario 4	0.000	6	0.001	8	0.000	10	0.000	8
	Scenario 5	0.000	10	0.000	14	0.020	19	0.033	16
	Scenario 6	0.003	6	0.000	10	0.000	16	0.000	13
	Scenario 7	0.000	11	0.000	14	0.001	23	0.001	19
	Scenario 8	0.005	6	0.000	11	0.076	20	0.035	17
	Scenario 9	0.000	9	0.001	13	0.003	19	0.031	16
	Scenario 10	0.000	14	0.000	20	0.741	31	0.816	27
	Scenario 11	0.000	11	0.000	17	0.000	19	0.000	17
	Scenario 12	0.000	17	0.000	24	0.000	28	0.000	24
	Scenario 13	0.001	11	0.000	18	0.000	25	0.001	22
	Scenario 14	0.000	15	0.000	21	0.000	23	0.000	22
	Scenario 15	0.001	10	0.000	12	0.000	21	0.000	18
US	Scenario 1	0.000	6	0.000	8	0.004	8	0.004	8
	Scenario 2	0.000	10	0.000	10	0.020	9	0.007	7
	Scenario 3	0.000	4	0.000	6	0.000	7	0.000	6
	Scenario 4	0.000	8	0.000	9	0.036	7	0.087	8
	Scenario 5	0.000	6	0.000	6	0.256	8	0.529	7
	Scenario 6	0.003	4	0.000	5	0.000	6	0.000	4
	Scenario 7	0.000	7	0.000	7	0.000	9	0.000	7
	Scenario 8	0.000	5	0.000	6	0.000	8	0.000	5
	Scenario 9	0.000	6	0.000	6	0.000	8	0.000	6
	Scenario 10	0.000	8	0.000	9	0.000	13	0.000	11
	Scenario 11	0.000	6	0.000	7	0.000	10	0.000	9
	Scenario 12	0.000	9	0.000	9	0.000	13	0.000	11
	Scenario 13	0.000	7	0.000	8	0.000	11	0.000	11
	Scenario 14	0.000	8	0.000	9	0.000	12	0.000	11
	Scenario 15	0.000	10	0.000	12	0.000	18	0.000	16

[4] The maximum lag order is restricted to 6. Note that the HQ is a little bit more benevolent in determining the lag order of VAR models as compared to the BIC. Additional lags may eliminate remaining serial correlation in residuals which is desirable when using neglected nonlinearity tests (see Lumsdaine and Ng, 1999 for details).

the modified multivariate ARCH test. In this case, the null is rejected (at least) in 13 out of 15 scenarios. Interestingly, we find that including either more macroeconomic variables (e.g. W or L) or financial variables (e.g. ER or COM) into the model under the null does not alter the results at all. Overwhelming and robust evidence of nonlinearity in both conditional mean and variance indicates that linear VAR-type models, structural or not, seem not to be an adequate representation for any subset of US and EA variables.[5]

(ii) Although the stopping rules R1 and R2 slightly differ in determining the number of principal components (see n in Table 2), they offer a tremendous dimensionality reduction in practice. For example, in case of EA Scenario 14, the R1 stopping rule determines to use the first 15 principal components (i.e. $n = 15$) for running the modified multivariate TSAY test, whereas the original multivariate TSAY test would require $m = 136$ additional variables (for $k = 8$ economic variables and $p = 2$ the selected lag order of a VAR model), which represents a dimensionality reduction around 90%! A similar dimensionality reduction is achieved for the multivariate ARCH test as well. More importantly, a different number of principal components determined by the stopping rules has no significant impact on the finite sample properties of the modified tests. Finally, it is worth remarking that even in subsets consisting of a sizable number of economic variables (e.g. Scenarios 10–15), no more than 31 principal components are needed to run the modified multivariate tests. This fact indicates some potential of the modified multivariate tests for testing joint nonlinearity even in large-scale economic models with limited number of observations.

Although the null hypothesis of linearity is clearly rejected in almost all scenarios for both economic regions, it may still be interesting to assess the stability of the results over time. For this purpose, a rolling-window approach is applied here – the full sample is split into 60 consecutive time windows with 100 observations in each window. The principal component multivariate nonlinearity tests are then applied to each window altogether with the automatically selected lag order p. The rejection frequencies of the multivariate tests (using both stopping rules altogether) for the selected scenarios of nominal level 0.05 are reported in Fig. 1.[6] It may be concluded from the results that we find stronger evidence of nonlinearity in the conditional mean using the TSAY test than in conditional volatility using the



(a) US (b) EA

Fig. 1. Sensitivity analysis

[5] Note that although both nonlinearity tests fall into a category of nonconstructive tests, which means that after rejecting the null, they do not give us any indication about the correct (nonlinear) model, Vávra (2013) shows that these tests have reasonable power against, for instance, regime-switching VAR/DSGE models.

[6] The rejection frequency is calculated as $\left(\frac{1}{2}\right)\left(\frac{1}{60}\right)\sum_{i=1}^{60}\sum_{j=1}^{2} I(\hat{\alpha}_{ij} \leq 0.05)$, where $\hat{\alpha}_{ij}$ is the p-value of a given test statistic obtained in the ith time window and using the jth stopping rule, and $I(\cdot)$ is an indicator function. So, the rejection frequency equal to 1 means that a given test statistic rejects the null hypothesis of linearity in all 60 time windows, regardless of the stopping rule.

ARCH test. Although the EA results are slightly more homogeneous as compared to the US ones, the average rejection frequencies of the tests (over all scenarios) are actually very similar. In particular, the average rejection frequency of the TSAY test is around 0.60 for both US and EA, whereas only 0.35 when using the ARCH test. Put differently, conditional mean nonlinearity (caused very likely by business cycle movements) seems to be statistically more relevant component as compared to conditional volatility in both economic regions.

IV. Conclusion

This article has focused on examining joint nonlinearity in 15 subsets of US and EA economic variables using the principal component multivariate TSAY and ARCH tests. Although the results for US and EA slightly differ, clear and robust evidence of nonlinearity (especially in the conditional mean) in both economic regions is found. Our results thus cast doubts on the adequacy of using linear multivariate VAR-type models, structural or not, for forecasting and/or policy analysis simulations. Put differently, we are of the opinion that our results call for implementing suitable regime-switching models in applied macroeconomics.

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