Multivariate Analysis of the European Economic and Defence Structure

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In this paper we model the defence and economic structure of 39 European countries using cluster and factor analytic methods. Initial results from standard cluster analysis performed on the original variables are compared with the results obtained from a confirmatory factor model estimated with maximum likelihood method within the general LISREL framework. Namely, a K-means cluster analysis is performed on latent scores calculated from the LISREL model. The results indicate that general clustering patters do not cut across East-West or transitional/non-transition division lines, rather it is found that a more subtitle grouping of countries exists where the more developed transitional countries clearly cluster closer to some West European countries than to the other transitional countries. It is subsequently found that noted differences exist also among the EU countries, which generally do not belong to a single cluster, regardless of the methods used.

Key words: economic development, military expenditures, factor analysis, cluster analysis, linear structural equation modelling

1. Introduction

Models of defence spending are widely present in the literature. Dunne (1996) classified these models into public choice, bureaucratic behaviour, alliances, arms-race, and general models of aggregate defence spending (see also Dunne, 1990). Models based on simple demand often find a positive correlation between defence spending and country income (e.g., Smith, 1980; Dunne and Mohamed, 1995). Dunne and Nikolaidon (2001) estimate a simple demand model for Greek economy and defence spending following Smith (1980, 1989) and Dunne and Mohamed (1995). They find negative direct effect of defence spending on economic growth and negative indirect effects through savings and trade balance. Benoit (1973, 1978) investigated the defence-growth relationship and found positive correlation between defence spending and economic growth. These results were unexpected and subsequently criticised in the literature (e.g., Ball, 1983; Faini et al. 1984; Grobar and Porter, 1989). Biswas and Ram (1986) present an example of an alternative modelling approach that starts from the neoclassical supply-side framework. The problem of assumed exogeneity of defence spending was to some degree resolved by Smith and Smith (1980) who used structural equation modelling to account for possible demand-side effects in aggregate demand framework and the supply-side effects in the growth equation. Deger and Sen (1983), Deger and Smith (1983) and Dunne and Mohammed (1995) further extended this. Other aspects of defence spending models are covered inter alia in Brzoska (1981), Deger (1981), Hartley and Sandler (1995), Mintz and Stevenson (1995), Ram (1995) and Sandler and Harley (1995). Faini et al. (1984) analyses dynamic relationships between defence spending and economic growth using a time-series cross section (panel) data. Most of these models, however, make explicit and theoretically unjustified structural assumptions without first exploring them empirically. Furthermore, these models allow mainly investigation of relationships among military and economic variables, but are less useful in classification and comparative analysis of countries. In addition, causal relationships among defence and

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economic indicators are assumed and measured without allowing for a possibility that there is an underlying latent structure, namely, that the observed defence and economic data present indicators of unobserved latent dimensions, which are the actual focus of the research on the defence-economic relationships.

The main aim of this paper is comparative classification of European countries and we develop a structured methodology that allows grouping of countries on the bases on their relative proximity in the general variable space, given the available defence and economic characteristics.

We develop a multivariate model of defence spending and economic structure of 39 European countries. We make no *a priori* exogeneity assumptions regarding causality of implied relationships and develop an empirical measurement model for underlying military and economic latent variables. The analysis starts from purely exploratory factor analysis and then estimates a confirmatory factor model using general LISREL methodology (Jöreskog, et al. 2000; Bollen, 1989). That way we test for the implied structure statistically and subsequently evaluate validity of parsimonious simplifications. The model is used in subsequent cluster analysis performed on computed latent scores, which is contrasted with the cluster analysis performed on the original variables. Our results suggest that differences in patterns of defence and economic structure in Europe do not cut strictly on the lines of East-West or transition/non-transition distinctions. Rather, there is a finer division into clusters of countries that place some more advanced transitional countries together with Western ones, and further division of Western countries into separate clusters.

2. Data and descriptive analysis

The data consist of the main macroeconomic, demographic and military expenditure indicators for 39 European countries (Mahečić, 2002, NATO Office for Information and Press, 2000a; 2000b). We use the 1997 data in order to avoid the effect of NATO membership on Hungary, the Czech Republic and Poland. The variable definitions are given in Table 1.

Fig. 1 shows empirical densities and QQ plots (distribution) for each variable. With the possible exception of *GDP per capita* and *share of soldiers*, all variables sharply deviate from normality displaying mainly right-skewness and excess kurtosis.

Formal tests for normality and descriptive statistics (Table 2) confirm the graphical analysis, namely the normality chi-square statistic is highly significant for all variables except *GDP per capita* ($p = 0.069$). Normality of the *number of soldiers* variable can be rejected on 1% level, though it holds on 5% level. For details on these tests see D'Agustino, 1970, 1971, 1986; Bowman and Shenton, 1975; Doornik and Hansen, 1994; Shenton and Bowman, 1977 and Mardia, 1980; Hendry and Doornik, 1999).

The found deviation from normality indicates caution in the use of maximum likelihood (ML) based multivariate techniques. This specially relates to the method of extraction in factor analysis, which for the non-normally distributed data should be principal components. However, as we intend to apply more powerful inferential techniques that are based on maximum likelihood and the assumption of multivariate normality, the original data must be transformed to approximately normal (Gaussian) distribution. If successful, such transformation will enable model evaluation and selection based on overall measures of fit.

For this purpose we apply the *normal scores* technique (Jöreskog *et al.*, 2000, Jöreskog, 1999). The technique can be summarised as follows. Given a sample of N observations on the j^{th} variable, $\mathbf{x}_j = \{x_{j1}, x_{j2}, \ldots, x_{jN}\}$, the normal scores transforma-

Table 1
Definitions of the variables

Variable name	Description	LISREL notation
Population	Total population	x_1
Area	Area in km^2	x_2
GDP	Gross domestic product	x_3
GDP per capita	Gross domestic product per capita	x_4
Number of soldiers	Total number of soldiers	x_5
Share of soldiers	Share of soldiers in the population	x_6
Military share	Share of the military expenditures in the national budget	x_7
Expenses per soldier	Total annual expenses spend per soldier	x_8

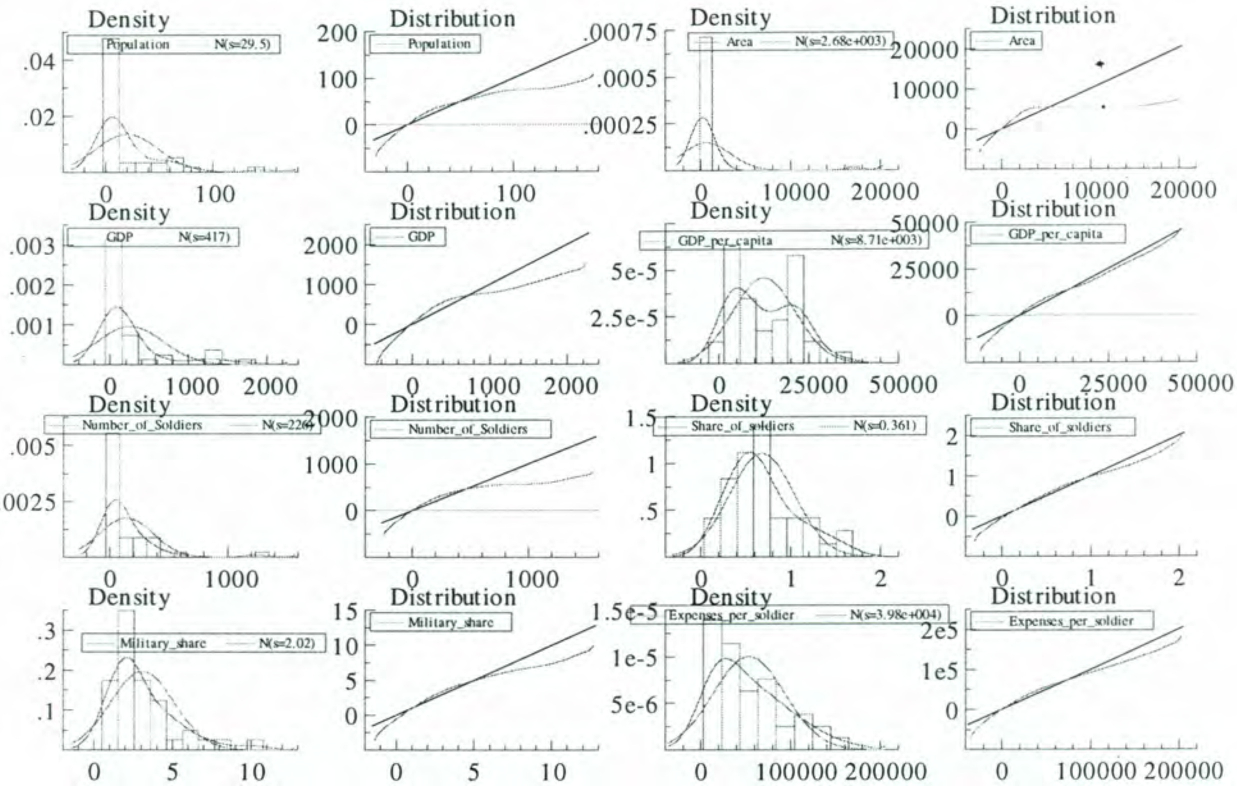


Figure 1. Empirical density (Gaussian kernel estimate) and QQ plots

tion is computed in the following way. First define a vector of k distinct sample values, $\mathbf{x}_j^k = \{x_{j1}', x_{j2}', \ldots, x_{jk}'\}$ where $k \leq N$ thus $\mathbf{x}^k \subseteq \mathbf{x}$. Let f_i be the frequency of occurrence of the value x_{ji} in $\mathbf{x}_j$ so that $f_{ji} \geq 1$ and. Then normal scores x_{ji}^{NS} are computed as $x_{ji}^{NS} = (N/f_{ji})\{\phi(\alpha_{j,i-1}) - \phi(\alpha_{ji})\}$ where ϕ is the standard Gaussian density function, a is defined as

$$(1) \qquad \alpha_{ji} = \begin{cases} -\infty, & i = 0 \\ \Phi^{-1}\left(N^{-1}\sum_{l=1}^{i} f_{jl}\right) & i = 1, 2, \ldots, k-1 \\ \infty, & i = k \end{cases},$$

and Φ^{-1} is the inverse of the standard Gaussian distribution function. The normal scores are further scaled to have the same mean and variance as the original variables.

The resulting empirical distributions after normalisation are shown in Fig. 2. It is apparent that the transformation was successful, showing no visible deviations from normality of the empirical densities and QQ plots (distribution).

Table 2

Univariate normality tests (original variables)

	Population	Area	GDP	GDP per capita	Number of Soldiers	Share of soldiers	Military share	Expenses per soldier
Mean	20.32	606.52	257.64	12555.90	138.93	.68	3.07	53530.13
Std.Devn.	29.49	2678.03	417.16	8712.51	226.37	.36	2.02	39780.07
Skewness	2.411	5.956	2.20	.39	3.25	.81	1.55	.84
Excess Kurtosis	6.38	33.66	3.85	−.99	12.11	.01	2.44	−.07
Minimum	.40	.30	2.00	960.00	.80	.15	.80	5513.00
Maximum	146.00	17074.00	1740.00	33700.00	1240.00	1.60	10.20	162657.00
Normality X^2	51.54	1337.40	88.14	5.33	93.60	7.03	20.04	9.03
X^2 p-value	.000	.000	.000	.069	.000	.029	.000	.011

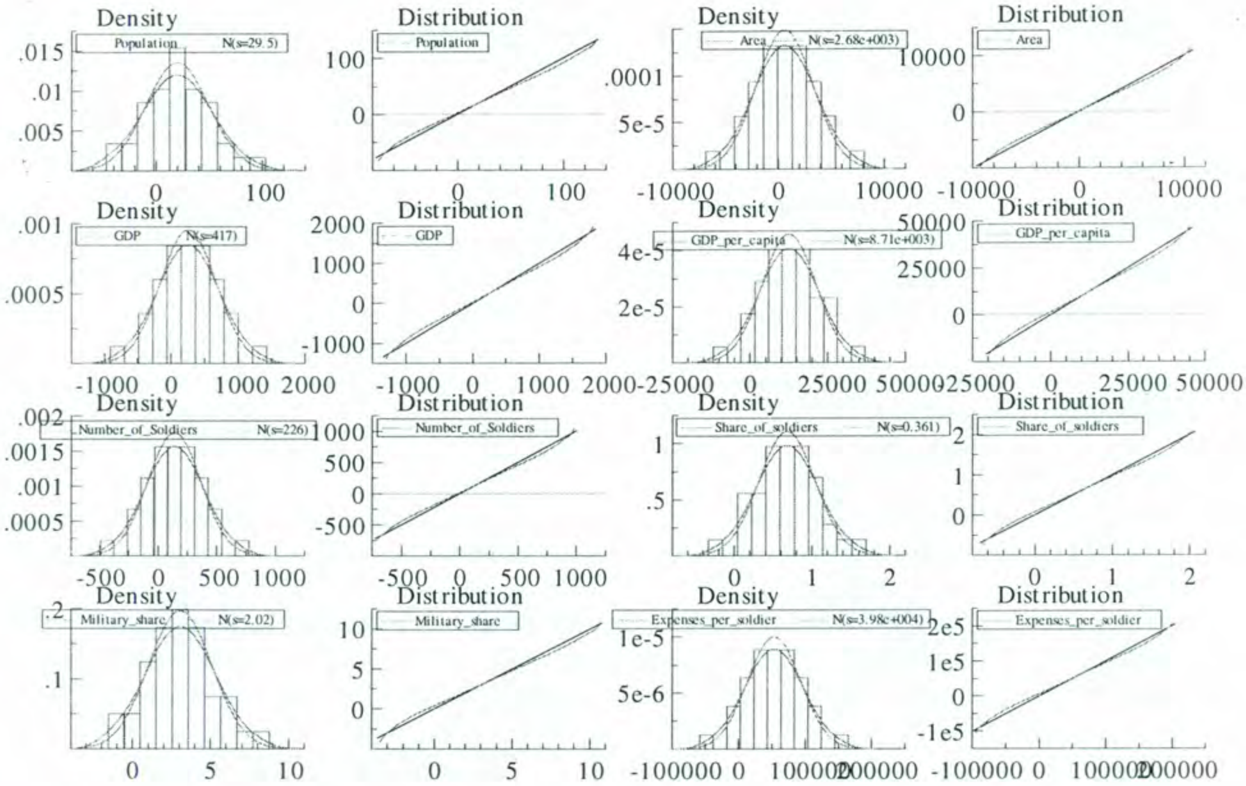


Figure 2. Empirical density (Gaussian kernel estimate) and QQ plots after transformation

Formal tests (Table 3) confirm that normality can no longer be rejected for the transformed variables. Note that we normalised all variables in the sample, even the two border cases mentioned above because given the small sample size (N = 39) the power of these tests is severely reduced.

3. Multivariate analysis

The multivariate methodology is used to classify variables and countries. We wish to model the underlying structure of demographic, economic and military indicators, postulating two main (latent) dimensions underlying the observed variables. These two (latent) dimensions indicate military (defence) and economic factors, respectively. First we use factor analysis with principal components extraction applied to the original (untransformed) data in order to reduce the variable space (see Anderson and Rubin, 1956; Anderson, 1958; Lawley, 1971; Mulaik, 1972). Then we perform cluster analysis (Everitt, 1993) aimed at distinguishing grouping patterns of countries. Finally, using normalised data, we use confirmatory factor analysis framed within general LISREL approach (Jöreskog, 1973; Jöreskog *et al.* 2000) to further test for specification of the estimated model. This enables computing latent scores for the underlying latent variables and subsequently ranking of all countries in the analysis based on the estimated latent scores.

Table 3

Univariate normality tests (transformed variables)

	Population	Area	GDP	GDP per capita	Number of Soldiers	Share of soldiers	Military share	Expenses per soldier
Mean	20.32	606.52	257.64	12555.90	138.93	.68	3.07	53530.13
Std.Devn.	29.50	2678.04	417.16	8712.51	226.37	.36	2.02	39780.07
Skewness	.03	.00	.00	.00	.00	.01	.02	.00
Excess Kurtosis	− .28	− .20	− .20	− .20	− .20	− .21	− .28	− .20
Minimum	− 40.57	− 5651.09	− 717.10	− 7804.86	− 390.03	− .16	− 1.11	− 39425.45
Maximum	89.40	6864.14	1232.38	32916.66	667.89	1.52	7.81	146485.70
Normality X^2	.12	.23	.23	.23	.23	.22	.12	.23
X^2 p-value	.944	.890	.890	.891	.890	.895	.944	.890

3.1 Factor analysis with principal components extraction

For descriptive purposes Table 4 gives Pearson product-moment correlation matrix (upper part) and their accompanying p-values (bottom part). A clear pattern can be observed in the correlation matrix, namely, country size and economic performance variables (*population*, *area*, *GDP*) correlate stronger (and significantly) among themselves then with the military expenditure data (*share of soldiers*, *military share*, *expenses per soldier*). The *number of soldiers* is the only "military" variable that strongly correlates with demographic and economic variables, which was expected.

Exploratory factor analysis extracted 8 factors two of which have an eigenvalue greater then one (Keiser criteria). The total variance explained by the first two factors (Table 5), however, is only 72% which is indicative or a larger number of noise factors. The eigenvalue scree plot (Fig. 3) shows a sharp fall and flattening starting with the third factor further supporting the hypothesis that there are only two true factors present.

The extracted components (Table 6) show a clear two-factor pattern, classifying *population*, *area*, *GDP* and *number of soldiers* into one factor, and *GDP per capita*, *share of soldiers*, *military share* and *expenses per soldier* into another factor. Somewhat ambiguous are the loadings of *GDP*, which appears to belong, to some degree, also in the second factor. This ambiguity of *GDP* variable requires confirmatory factor analysis and testing the hypothesis that *GDP* loads to both underlying latent variable against the alternative that it loads only on the first one. To implement such test we need to estimate the model in the maximum likelihood framework, which will be done in section 3.3 below.

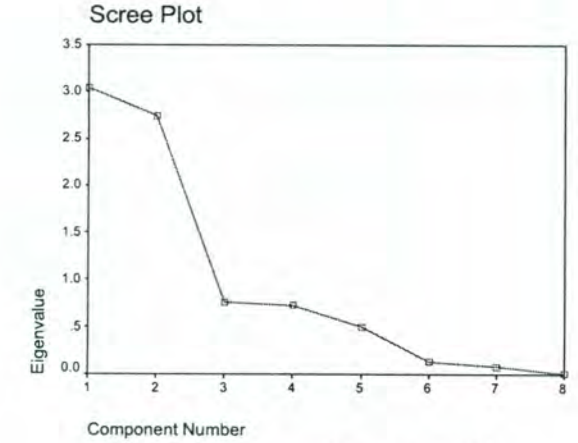


Figure 3. Eigenvalue scree plot

It can also be observed that the first factor includes positive loadings of variables describing country's size (*population*, *area*, *GDP*) and the *number of soldiers*, which should normally be closely related to the population size of a country. On the other hand, the second factor combines positive loading of *GDP per capita*, a common measure of country's economic welfare, with negative loadings on *share of soldiers* and *military share*. The *expenses per soldier* also load negatively on this second factor. Thus, it appears that this second factor measures degree of economic development and relative defence spending. It can be expected that countries with higher level of economic development spend smaller shares of their national budgets on military expenses. Also, more developed countries might have smaller number of soldiers per capita.

Assuming orthogonality of the two factors in the population we apply the Verimax rotation with Kaiser normalisation. Rotated loadings are shown in Table 7. The rotated solution confirms the previous without removing ambiguity related to the loading of *GDP*.

Table 6

Component Matrix[a]

	Component	
	1	2
Population	.975	.156
Area	.833	-.125
GDP	.625	.544
GDP per capita	-.090	.844
Number of soldiers	.974	-.061
Share of soldiers	.129	-.736
Military share	.197	-.684
Expenses per soldier	-.027	.826

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

3.2 Cluster analysis

We apply non-hierarchical cluster analysis procedure (*K*-means) to form mainly descriptive groupings of countries allowing for the existence of 2, 3 and 4 possible groupings. It is interesting to pay special attention on division between East and West European countries, as well as on internal divisions within each group. Also interesting would be to com-

Table 4

Correlation Matrix

		Population	Area	GDP	GDP per capita	Number of soldiers	Share of soldiers	Military share
Correlation	Population	1.000	.728	.734	.010	.947	.006	.053
	Area	.728	1.000	.203	-.140	.824	.080	.210
	GDP	.734	.203	1.000	.377	.509	-.181	-.165
	GDP per capita	.010	-.140	.377	1.000	-.131	-.388	-.598
	Number of soldiers	.947	.824	.509	-.131	1.000	.163	.161
	Share of soldiers	.006	.080	-.181	-.388	.163	1.000	.475
	Military share	.053	.210	-.165	-.598	.161	.475	1.000
	Expenses per soldier	.066	-.086	.396	.660	-.106	-.621	-.269
Sig. (1-tailed)	Population		.000	.000	.476	.000	.486	.374
	Area	.000		.108	.197	.000	.314	.099
	GDP	.000	.108		.009	.000	.136	.158
	GDP per capita	.476	.197	.009		.214	.007	.000
	Number of soldiers	.000	.000	.000	.214		.161	.164
	Share of soldiers	.486	.314	.136	.007	.161		.001
	Military share	.374	.099	.158	.000	.164	.001	
	Expenses per soldier	.344	.301	.006	.000	.261	.000	.049

Table 5

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumula
1	3.047	38.091	38.091	3.047	38.091	38.091	3.044	38.050	3
2	2.745	34.307	72.398	2.745	34.307	72.398	2.748	34.348	7
3	.755	9.434	81.832						
4	.727	9.093	90.925						
5	.498	6.227	97.152						
6	.138	1.729	98.880						
7	.083	1.035	99.915						
8	.007	.085	100.000						

Extraction Method: Principal Component Analysis.

Table 7

Rotated Component Matrix[a]

	Component	
	1	2
Population	.986	.053
Area	.815	-.212
GDP	.678	.476
GDP per capita	-.001	.849
Number of soldiers	.962	-.163
Share of soldiers	.051	-.745
Military share	.124	-.701
Expenses per soldier	.059	.824

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

pare clustering of NATO members and non-NATO members.

Extraction of two factors after convergence produced the final cluster centres shown in Table 8. The first cluster has higher centres in *area* and *number of soldiers* (though the later is only slightly larger). The second cluster appears to average higher on *population*, *GDP*, *GDP per capita* and *expenses per soldier* while is similar to the first cluster in other variables.

Table 8

Final Cluster Centers

	Cluster	
	1	2
Population	17.9	25.8
Area	785	206
GDP	126.6	552.5
GDP per capita	9081	20374
Number of soldiers	145	124
Share of soldiers	.8	.4
Military share	3.4	2.4
Expenses per soldier	31109	103977

The two-cluster solution classified 27 cases in the first and 12 in the second cluster. The distribution of countries into clusters (Table 14) classified most CEE and Baltic countries into the first cluster leaving Western countries in the second cluster. However, the solution places Austria, Cyprus, Denmark, Finland, Greece, Ireland, Malta, Portugal and Turkey together with the former communist countries. Extraction of three clusters enabled a finer distinction among smaller more developed countries in respect to *expenses per soldier* variable (Table 9).

Table 9

Final Cluster Centers

	Cluster		
	1	2	3
Population	20.9	19.0	21.1
Area	1004	214	144
GDP	116.1	384.1	445.3
GDP per capita	6603	18812	18841
Number of soldiers	179	96	98
Share of soldiers	.9	.6	.3
Military share	3.7	2.2	2.7
Expenses per soldier	21957	66678	121198

Classification into three clusters (Table 14) still placed several Western countries in the CEE cluster, namely Greece, Malta and Turkey. Given that these are not particularly developed countries this finding is more interpretable, but now the Baltic countries enter non-CEE cluster giving a more interesting picture. The three-cluster extraction classified altogether 20 countries into first cluster (mainly CEE countries), 12 countries into second cluster (manly Western countries) and 7 countries in third cluster (France, Latvia, Lithuania, Luxemburg, Switzerland and United Kingdom).

Allowing for even finer distinction and extracting four clusters produced virtually identical solution in regard to East-West classification to the three-cluster solution.

The cluster centres (Table 10) do not offer clear division that makes substantive sense or that provides further inside into inter-country differences. Again, most CEE countries were placed into the first cluster which includes 20 countries (with Austria, Greece, Malta and Turkey as non-CEE outliers), the second cluster included Luxembourg and the United Kingdom which is rather problematic, two of the three Baltic states were grouped into the third cluster together with Switzerland leaving Estonia and most West European countries in the fourth cluster. The extraction of four clusters clearly introduced lots of noise and provided no better solution from the three-cluster extraction.

So far we separately analysed patterns of variables and cases (countries) by performing factor and cluster analysis, respectively. In the following section we estimate a latent variable model (confirmatory factor analysis) using maximum likelihood (ML) technique and compute latent scores for the underlying latent variables. Using ML will allow model evaluation on inferential grounds and subsequent

Table 10

Final Cluster Centers

	Cluster			
	1	2	3	4
Population	20.9	29.8	17.6	19.0
Area	1004	124	152	214
GDP	116.1	627.8	372.4	384.1
GDP per capita	6603	27450	15398	18812
Number of soldiers	179	107	95	96
Share of soldiers	.9	.3	.3	.6
Military share	3.7	1.9	3.1	2.2
Expenses per soldier	21957	148729	110186	66678

guidance and criteria for possible model modification. The final model will be used to calculate latent scores, which, in turn, will be used in a secondary cluster analysis.

3.3. Maximum likelihood factor analysis

Confirmatory maximum likelihood factor analysis has a major advantage over the non-parametric procedures insofar it allows statistical evaluation and testing of the postulated model. The requirement of multivariate normal distribution for the analysed variables is rather strong in this technique; however, we use normalised data so this requirement is formally satisfied. The model we wish to estimate can be specified as a special case of the general linear structural equations model with latent variables (LISREL) given in the form

$$\text{(2)} \qquad \mathbf{x} = \Lambda_x \xi + \boldsymbol{\delta},$$

where Λ_x is the matrix of factor loadings and **x** and ξ are vectors of observed and latent variables, respectively and $\boldsymbol{\delta}$ is the residual vector that allows for the measurement error in the observed variables (see Jöreskog *et al.*, 2000). The above performed exploratory factor analysis on the untransformed data using principal components as the factor extraction method indicated a two-factor solution with possibly ambiguous loadings of the *GDP* variable. The application of confirmatory maximum likelihood factor analysis will allow formally testing this two-factor solution and possibly resolving the problem with the ambiguous loading. First we estimate the unrestricted model (M_1), which allows GDP (x_3) to load on both latent variables (i.e., factors). Second, we estimate a restricted model (M_2) where each indicator is allowed to load only on one latent variable. In LISREL notation the general model (M_1), corresponding to the conceptual path diagram shown in Fig. 4, is specified as

$$\text{(3)} \qquad \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{pmatrix} = \begin{pmatrix} \lambda_{11} & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & \lambda_{32} \\ 0 & \lambda_{42} \\ \lambda_{15} & 0 \\ 0 & \lambda_{62} \\ 0 & \lambda_{72} \\ 0 & \lambda_{82} \end{pmatrix} \cdot \begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \end{pmatrix}.$$

The restricted model (M_2) sets λ_{32} in Eq. (3) to zero (Fig. 5). It can be shown that both models are overidentified with 19 and 18 degrees of freedom, respectively. The covariance structure implied by the Eq. (2) is given by

$$\text{(4)} \qquad \begin{aligned} \Sigma(\boldsymbol{\theta}) &= E(\xi\xi^{T}) = E[\Lambda_x\xi + \boldsymbol{\delta})(\Lambda_x\xi + \boldsymbol{\delta})^{T}] \\ &= \Lambda_x \Phi \Lambda_x^{\ T} + \Theta_\delta, \end{aligned}$$

where Φ is the covariance matrix of the latent variables defined (by writing only the lower triangular elements) as

$$\text{(5)} \qquad \Phi = \mathrm{E}(\xi\xi^{T}) = \begin{pmatrix} 1 & \\ \phi_{21} & 1 \end{pmatrix},$$

and Θ_δ is the covariance matrix of the residuals. Note that Eq. (5) assumes that latent variables are standardised. Note that a null hypothesis on ϕ_{21} tests for orthogonality of the two latent variables—the assumption we made in exploratory factor analysis that justified the use of the Verimax rotation.

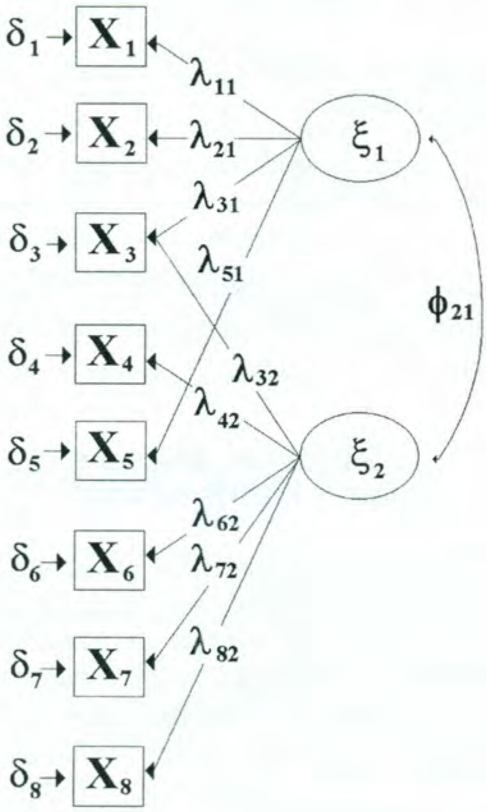
Assuming multivariate Gaussianity, the model parameters can be estimated using full information maximum likelihood (FIML) technique by maximising the multivariate likelihood function

$$(6) \quad F_{ML} = ln|\boldsymbol{\Sigma}(\boldsymbol{\theta})| + tr\{\mathbf{S}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\} - ln|\mathbf{S}| - p,$$

where **S** denotes empirical covariance matrix (i.e., computed directly from data), and p is the number of the observed variables.

We first estimate the more general model and then test for the validity of the reduction from M_1 to M_2. Estimation of the model M_1 produced the following results (standard errors are in the parentheses and "NE" stands for not estimated, i.e., fixed to zero):

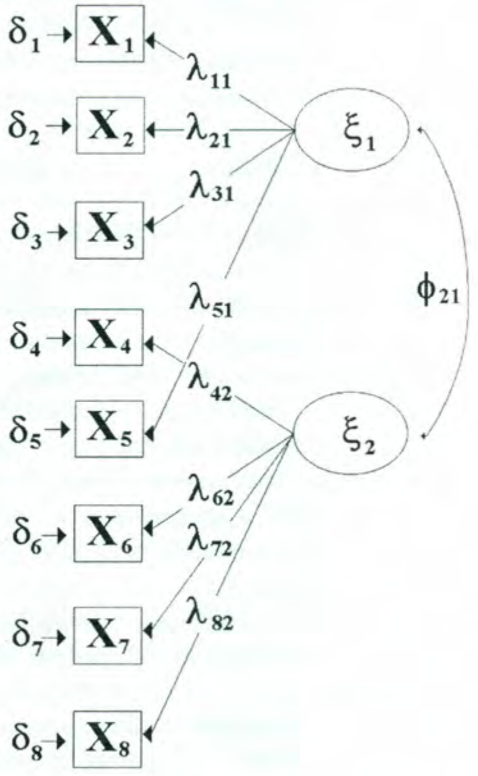
Figure 4.
Conceptual path diagram for model M_1



$$\Lambda_x^{(2)} = \begin{pmatrix} .96\,(.12) & NE \\ .84\,(.13) & NE \\ .89\,(.11) & .70\,(.08) \\ NE & .99\,(.14) \\ .98\,(.12) & NE \\ NE & -.58\,(.14) \\ NE & -.72\,(.14) \\ NE & .78\,(.13) \end{pmatrix}$$

As it can be observed, all coefficients are significant and have expected signs. The magnitudes of the estimated coefficients are reasonably close to those obtained from principal components extraction in the exploratory factor analysis (Table 7).

Figure 5.
Conceptual path diagram for model M_2



The chi-square statistic of overall fit for M_1 is 9.4 with 19 degrees of freedom, which shows good fit of the model. Imposing the restriction on the loadings matrix by fixing the coefficient of GDP (λ_{32}) to zero produced the following results (M_2):

$$\Lambda_x^{(1)} = \begin{pmatrix} 1.02\,(.11) & NE \\ .80\,(.13) & NE \\ .83\,(.13) & NE \\ NE & .99\,(.14) \\ .92\,(.12) & NE \\ NE & -.37\,(.16) \\ NE & -.72\,(.15) \\ NE & .69\,(.15) \end{pmatrix}$$

It can be observed that the coefficient estimates are close to those obtained in the unrestricted model, however the chi-square now increased to 47.2 with 18 degrees of freedom. The chi-square difference is thus 37.08 with one degree of freedom, which strongly rejects the restriction on λ_{32}. We note that in both models the on ϕ_{21} coefficient was insignificant which supports the assumptions of orthogonality between the two factors. Moreover, in this model *GDP* is not causally related to defence spending, rather, it is an observed indicator of both the "size" and "economic development" latent variables, which are themselves uncorrelated.

3.4 Latent scores

Of particular interest in this application are methods for estimation of latent scores in the general structural equation models (Jöreskog, 2000). Such methods also allow structural recursive and simultaneous relationships among latent variables. Estimation of factor scores in the pure measurement (factor) models is just a special case of the general procedure (see Lawley and Maxwell, 1971).

We describe a technique capable of computing scores of the latent variables based on the maximum likelihood solution of the Eq. (4) following Jöreskog (2000). Given the measurement model $\mathbf{x} = \Lambda_x \mathbf{x} + \boldsymbol{\delta}$, the latent scores $\boldsymbol{\xi}_i$ can be computed for each observation x_{ij} in the $(6 \times N)$ sample matrix whose rows are observations on each of the six observed variables, i.e.,

$$(7) \qquad \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ x_{31} & x_{32} & \cdots & x_{3N} \\ x_{41} & x_{42} & \cdots & x_{4N} \\ x_{51} & x_{52} & \cdots & x_{5N} \\ x_{61} & x_{62} & \cdots & x_{6N} \end{pmatrix} = (\mathbf{x}_1\ \mathbf{x}_2\ \cdots\ \mathbf{x}_N).$$

Once the coefficients of $\boldsymbol{\Lambda}_x$ are estimated they can be treated as fixed and the latent scores can be computed by maximising

$$(8) \qquad \sum_{i=1}^{N} (\mathbf{x}_i - \boldsymbol{\Lambda}_x \boldsymbol{\xi}_i)^T \Theta_\delta^{-1} (\mathbf{x}_i - \boldsymbol{\Lambda}_x \boldsymbol{\xi}_i),$$

subject to constraint $(1/N)\sum_{i=1}^{N} \xi_i \xi_i^T = \boldsymbol{\Phi}$.

It can be shown that the solution to this constrained maximisation problem is given by

$$(9) \qquad \boldsymbol{\xi}_i = \mathbf{D}^{1/2}\mathbf{U}^T\mathbf{H}\mathbf{K}^{-1/2}\mathbf{H}^T\mathbf{U}\mathbf{D}^{1/2}\boldsymbol{\Lambda}_x^{\ T}\Theta_\delta^{-1}\mathbf{x}_i \ ,$$

where $\mathbf{UDU}^T$ and $\mathbf{HKH}^T$ are singular value decompositions of $\boldsymbol{\Phi}$ and

$$\mathbf{D}^{1/2}\mathbf{U}^T\boldsymbol{\Lambda}_x^{\ T}\Theta_\delta^{-1} \sum_{i=1}^{N} x_i x_i^T \ \Theta_\delta^{-1}\boldsymbol{\Lambda}_x\mathbf{U}\mathbf{D}^{1/2},$$

respectively. The derivation of Eq. (9) follows the approach of Jöreskog (2000) and Lawley and Maxwell (1971).

3.5 Cluster analysis using latent scores

The above computed latent scores can be subsequently used in secondary analysis such as cluster analysis. We apply the *K*-means cluster method extracting again 2, 3 and 4 clusters by using two criteria variables, latent Size and Development factors calculated from Eq. (9) using coefficient estimates from model M_1. Extraction of two clusters produced cluster centres shown in Table 11. This solution is rather clear, the two groups of countries classified into two clusters differ insofar the first cluster is low in size and high in development and the second is the opposite.

Table 11

Final Cluster Centers

	Cluster	
	1	2
Size	52.95	-460.22
Development	2263.72	10116.86

The first cluster included 17 and the second 22 cases. This division differs from the two-cluster solution based on the original variables (Table 8). Specifically, Austria, Croatia, Hungary, Ireland, Moldova, Poland and Spain no longer belong to the first (dominantly transitional countries) cluster (Table 14), while Luxembourg and Norway changed their place from the second to the first cluster. This solution no longer offers clear East-West cut and suggests relevance of other than geo-political factors. The first cluster centres higher on latent *Size* variable and lower on *Development* while the second centres in the opposite way (Table 11). Thus, we would expect the first cluster to include larger and less developed countries, while the second cluster should include smaller, more developed countries. According to the classification in Table 14 (two-cluster solution with latent scores), the first cluster indeed included less developed, though not necessarily larger countries. For example Albania, BiH, Cyprus, Macedonia are less developed but small. On the other hand, Luxemburg is a very small but highly developed country despite its classification in the first cluster. Similar ambiguities exist for Greece, Norway, Poland and Turkey. Moldova, a small underdeveloped country was also apparently wrongly included into the second cluster. Therefore, we cannot accept the two-cluster solution and need to look for further refinements.

The three-cluster solution (Table 12) distinguishes large and underdeveloped cluster (first), and two clusters of small countries: more and less developed (clusters two and three, respectively). However, some small countries nevertheless ended up in the first cluster (Albania, Cyprus and Luxembourg) while Norway, Poland, Spain and Turkey ended up in the second cluster (small and underdeveloped). Moldova and Russia are also clear outliers in the third cluster, first because it is an underdeveloped country, and second due to its large size.

Table 12

Final Cluster Centers

	Cluster		
	1	2	3
Size	190.85	-219.52	-554.66
Development	54.34	6163.49	11983.52

The three-cluster extraction classified 9 countries into the first, 17 into the second and 13 into the third cluster, while the four-cluster division included 9/14/9/11 division.

Table 13

Final Cluster Centers

	Cluster			
	1	2	3	4
Size	219.76	-323.76	-671.02	22.58
Developmen	-1343.19	7992.02	12963.67	3564.44

Nevertheless, the three-cluster solution using latent scores as criteria variables indicated that while the most underdeveloped CEE and fSU countries have similar economic and defence structure, some more advanced CEE countries seem to cluster closer to a group of West European countries. For example, Croatia, Czech Republic, Estonia, Hungary, Poland, Slovakia and Slovenia (also Romania, which is less clear), belong to a same defence-economic structure group countries with e.g., Austria, Denmark, Germany, Spain and Sweden.

The four cluster solution (Table 13) offers perhaps clearer picture. The cluster centres indicate that the first extracted cluster should include medium-sized very poor countries. Table 14 shows that the first cluster indeed groups medium-sized underdeveloped countries with only one noted exception, Luxembourg. The second cluster should be small and relatively well developed countries, however France, Germany, Russia, and Sweden stand out as clear outliers. The third cluster, according to cluster centres (Table13) should group very small and very well developed countries, which holds in most cases with the clearest exception of Moldova. The fourth cluster should apparently include medium-sized relatively developed countries. Norway and Romania present outliers.

Further refinements would most likely be unable to supply any additional useful information, thus we accept the four-cluster solution with latent scores as substantively most acceptable, with least obvious outliers.

Table 14

Country Clusters

	Using original variables			Using latent scores		
	2-clusters	3-clusters	4-clusters	2-clusters	3-clusters	4-clusters
Albania	1	1	1	1	1	1
Austria	1	1	1	2	2	2
Belgium	2	2	4	2	3	3
Belarus	1	1	1	1	1	4
BiH	1	1	1	1	1	1
Bulgaria	1	1	1	1	1	4
Croatia	1	1	1	2	2	2
Cyprus	1	2	4	1	1	1
Czech Republic	1	1	1	2	2	2
Denmark	1	2	4	2	2	2
Estonia	1	2	4	2	2	2
Finland	1	2	4	2	3	3
France	2	3	3	2	3	2
Germany	2	2	4	2	2	2
Greece	1	1	1	1	2	4
Hungary	1	1	1	2	2	2
Ireland	1	2	4	2	3	2
Italy	2	2	4	2	3	3
Latvia	2	3	3	2	3	3
Lithuania	2	3	3	2	3	3
Luxembourg	2	3	2	1	1	1
Macedonia	1	1	1	1	2	4
Malta	1	1	1	1	2	4
Moldova	1	1	1	2	3	3
Netherlands	2	3	3	2	3	3
Norway	2	2	4	1	2	4
Poland	1	1	1	2	2	2
Portugal	1	2	4	1	1	4
Romania	1	1	1	1	2	4
Russia	1	1	1	2	3	2
Slovakia	1	1	1	1	2	4
Slovenia	1	1	1	1	2	2
Spain	1	2	4	2	2	2
Sweden	2	2	4	2	3	2
Switzerland	2	3	3	2	3	3
Turkey	1	1	1	1	2	4
Ukraine	1	1	1	1	1	1
United Kingdom	2	3	2	2	3	3
Yugoslavia	1	1	1	1	1	4

5. Conclusion

Using multivariate techniques we analysed defence and economic pattern similarities among 39 European countries. We identified two underlying latent dimensions in the analysed data accounting primarily for defence and economic factors. Furthermore, these two factors are found to be insignificantly mutually correlated, which contradicts much of the findings in the literature on modelling the military-economic relationships. Gross domestic product, as often used indicator of country's overall income, was modelled as an indicator of country's latent "size" and "economic development" factors, which themselves proved to be uncorrelated. This approach allows further reinterpretation of Benoit (1973, 1978) findings as possible model misspecification. Namely, GDP appears to be an indicator of both economic and defence spending factors but, unlike Benoit, we assumed no causality in our model.

The country classification using two alternative approaches, *K*-means cluster analysis on original variables and on latent scores computed from an estimated LISREL model, indicate a more refined European groupings in respect to general similarity patterns in the defence and economic structure of countries. In particular, the results suggest that the common differentiation between transition and non-transition countries does not hold in respect to the general defence and economic patterns. Furthermore, the West European countries themselves do not cluster into a single coherent group thus displaying specific differences not fully accountable by the East-West status. The main policy relevance of this analysis lies in the observation that, in an attempt to classify countries on the basis of their defence and economic structure, more emphases should be placed on the analysis of individual properties of particular countries and less on their political or geographical status. ■

REFERENCES

Anderson, T.W. (1958), "An Introduction to Multivariate Statistical Analysis", New York: John Wiley.

Anderson, T.W. and Rubin, H. (1956), "Statistical Inference in Factor Analysis", *Proceedings of the Third Berkley Symposium*, Vol. V. Berkley: University of California Press.

Ball, N. (1983), "Defence and Development: A Critique of the Benoit Study", Economic Development and Cultural Change, ***31**, pp. 507-524.*

Benoit, E. (1973), Defence and Economic Growth in Developing Countries. *Boston: Lexington Books.*

Benoit, E. (1978), "Growth and Defence in LDCs", Economic Development and Cultural Change, ***26**, pp. 271-280.*

Biswas, B. and Ram, R. (1986), "Military Expenditure and Economic Growth in LDCs", Economic Development and Cultural Change, ***34**, pp. 361-372.*

Bollen, K.A. (1989), *Structural Equations with Latent Variables*. New York: Wiley.

Bowman, K.O. and Shenton, L.R. (1975), "Omnibus Test Contours for Departures from Normality based on Öb_1 and b_2", *Biometrika*, **62**, pp. 243-50.

Brzoska, M. (1981), "The Reporting on Military Expenditure", Journal of Peace Research ***18**, pp. 261-275.*

D'Agostino, R.B. (1970), "Transformation to Normality of the Null Distribution of g_1", *Biometrika*, **57**, pp. 679-681.

D'Agostino, R.B. (1971), "An Omnibus Test of Normality for Moderate and Large Sample Size", *Biometrika*, **58**, pp. 341-348.

D'Agostino, R.B. (1986), "Tests for Normal Distribution", in D'Agostino, R.B. and Stephens, M.A. (Eds.), *Goodness-of-fit Techniques*. New York: Marcel Dekker, pp. 367-419.

Deger, S. (1981), Investment, Defence and Growth in LDCs. *Birkbeck Colledge Discussion Paper 105.*

Deger, S. and Sen, S., (1983), "Military Expenditure, Spin-off and Economic development", Journal of Development Economics, ***13**, pp. 68-83.*

Deger, S. and Smith, R. (1983), "Military Expenditure and Growth in LDCs", Journal of Conflict Resolution, ***27**, pp. 335-353.*

Doornik, J.A., and Hansen, H. (1994), *A Practical Test for Univariate and Multivariate Normality*, Discussion paper, Nuffield College, Oxford.

Dunne, P. (1990), "The Political Economy of Military Expenditure: An Introduction", Cambridge Journal of Economics, ***14**, pp. 395-404.*

Dunne, P. (1996), "Economic Effects of Military Expenditures in Developing Countries: A Survey", in Gletitsch, N.P. (Ed.), The Peace Divident. *Amsterdam: Elsevier, pp. 439-464.*

Dunne, P., and Nikolaidon, E. (2001), "Military Expenditure and Economic Growth: A Demand and Supply Model for Greece, 1960-96", Defence and Peace Economics ***12**, pp. 47-67.*

Dunne, P., and Mohammed, N. (1995), "Military Expenditure in Sub-Saharan Africa: Some Evidence for 1967-85", Journal of Peace Research, ***32**, pp. 331-343.*

Faini, R., Annez, P. and Taylor, L. (1984), "Defence Spending, Economic Structure and Growth: Evidence Among Countries and over Time", Economic Development and Cultural Change*; **32**, pp. 487-498.*

Grobar, L. and Porter, R.C. (1989), "Benoit Revised: Defence Spending and Economic Growth in LDCs", Journal of Conflict Resolution, ***33**, pp. 318-345.*

Hartley, K. and Sandler, T. (1995), Handbook of Defense Economics, *Vol.I. Amsterdam: Elsevier.*

Hendry, D.F. and Doornik, J.A. (1999), *Empirical Econometric Modelling Using PcGive*, Vol. I. West Wickham: Timberlake Consultants.

Jöreskog, K.G. (1969), "Factoring the Multitest-multioccasion Correlation Matrix", *Research Bulletin* 62. Princeton: Educational Testing Service.

Jöreskog, K.G. (1973), "A General Method for Estimating a Linear Structural Equation System", in Goldberger, A.S. and Duncan, O.D. (Eds.), *Structural Equation Models in the Social Sciences*. New York: Seminar Press.

Jöreskog, K.G. (1999), "Formulas for skewness and kurtosis", Scientific Software International, http://www.ssicentral.com/lisrel.

Jöreskog, K.G. (2000), "Latent variable scores and their uses". Scientific Software International, http://www.ssicentral.com/lisrel.

Jöreskog, K.G., Sörbom, D. du Toit, S. and du Toit, M. (2000), *LISREL 8: New Statistical Features*. Chicago: Scientific Software International.

Everitt, B.S. (1993), *Cluster Analysis*. New York: John Wiley.

Lawley, D.N. and Maxwell, A.E. (1971), *Factor Analysis as a Statistical Method*. 2nd ed. London: Butterworths.

Mahečić, Z., Ed., (2002), *Hrvatska u 21. stoljeću: Nacionalna Sigurnost*. Zagreb: Ured za strategiju razvitka Republike Hrvatske.

Mardia, K.V. (1980), "Tests of Univariate and Multivariate Normality", in Krishnaiah, P.R. (Ed.), *Handbook of Statistics*, Vol. I. Amsterdam: North Holland, pp. 279-320.

McDonald, R.P. and Burr, E.F. (1967), "A Comparison of Four Methods of Constructing Factor Scores", *Psychometrika*, **32**, 381-397.

Mintz, A. and Stevenson, R. (1995), "Defence Expenditures, Economic Growth and the 'Peace Dividend': A Longitudinal Analysis of 103 Countries", Journal of Conflict Resolution, ***39**, pp, 283-305.*

Mulaik, S.A. (1972), *The Foundation of Factor Analysis*. New York: McGraw-Hill.

NATO Office of Information and Press (2000a), *Financial and Economic Data Relating to NATO Defence, 2000*. Defence Expenditures of NATO Countries (1980 - 2000). Brussels: NATO.

NATO Office of Information and Press (2000b), *NATO Communiques and Statements 1999*. Brussels: NATO.

Ram, R. (1995), "Defence Expenditure and Economic Growth", in Hartley, K. and Sandler, T. (Eds.), Handbook of Defense Economics, *Vol.I. Amsterdam: Elsevier.*

Sandler, T. and Hartley, K. (1995), The Economics of Defence. *Cambridge: Cambridge University Press.*

Shenton, L.R. and Bowman, K.O. (1977), "A Bivariate Model for the Distribution of Öb_1 and b_2", Journal of the American Statistical Association, **72**, pp. 206-211.

Smith, R. (1980), "The Demand for Military Expenditure", Economic Journal, ***90**, pp. 811-820.*

Smith, R. (1989), "Models of Military Expenditure", Journal of Applied Econometrics, ***4**, pp. 345-359.*

Smith, R. and Smith, D. (1980), Military Expenditure, Resources and Development. *Birkbeck College Discussion Paper 87, London: University of London.*