A panel data analysis for the greenhouse effects in fifteen countries of European Union.

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Abstract

This paper examines how some factors affect the greenhouse effect of fifteen countries in European Union with fixed and random effects, while we also investigate the case of the Arch effects presentation. Finally we estimate a neural network model to examine how all the factors affect the greenhouse effect and we compare the forecasting performance with that of fixed or random panel data estimation.

Keywords fixed and random effects, ARCH panel effects, panel unit root, cointegration, vector autoregressive models, vector error correction, principal components, neural networks

Introduction

Greenhouse effect is the increase in the temperature that Earth faces and experiences, because certain gases in the atmosphere trap the energy from the sun. These gases are called greenhouse gases, which absorb infrared radiation emitted by the earth's surface, by the atmosphere itself due to the same gases, and by clouds. So the greenhouse gases trap heat within the surface-troposphere system and this is called the natural greenhouse (Ledley et al., 1999). Without these gases the heat would escape back to the space and the average temperature of the Earth would be colder. The most important gas is the water vapor (H_2O) and then the carbon dioxide (CO_2) , which has a long lifetime in the atmosphere and then is ozone (O^3). Other important gases are the methane (CH_4) and nitrous oxide (N_2O) (Ledley et al., 1999). So one benefit of the greenhouse effect is that keeps Earth warm for human to live. But if the greenhouse effect become stronger , then it could increase the average temperature significant and make the Earth much warmer, while with an even little warming may be caused significant problems in the plants, animals and human. But besides the natural greenhouse gases there are the anthropogenic gases as such as the chlorofluorocarbons CFC-11 (CCl_3F) and CFC-12 (CCl_2F_2) and hydrofluorocarbons (HFCs) (Hansen et al., 1998), which are equivalent and theirs affection can be estimated using CO_2. Another important greenhouse gas is ammonia NH_3 which is an air pollutant contributing to the acidification and nitrogen eutrophication of the ecosystems, while its emissions are mainly caused by livestock manure (Pipatti, 1998)

Over the last century, according to statistical analysis and reports, the global temperature has increased by 0.3°–0.7°C. This warming has alternatively been linked to an increase in anthropogenic greenhouse gas CO_2 output (IPCC, 1996), but also and other gases , which thee most important are the nitrous oxide and the methane. Also others factor the growing urban heat island effect as the North American and European urban centres have grown in size (Karl et al., 1991) and natural processes as the changes in the solar radiation (Carslaw et al., 2002). Also a number of studies have determined that nitrous oxide (N_2O) fluxes into the atmosphere are high in croplands on which N fertilization and irrigation rates are also high (Goodroad and Keeney, 1984) and it's a very important factor to the greenhouse effect.

For the time-series analysis researchers used in the past decades the autoregressive moving average model (Karl et al., 1991) and regression models (Vincent, 1998) to evaluate climate change and inhomogeneites within climate data and records. Instead Prokoph and Patterson (2004) use wavelet analysis which present inhomogeneities in time series as the sum of temporal changes in the amplitude and phase of records over a wide sine-wave bandwidth.

In this paper we use a panel data analysis for fifteen countries of the European Union , which are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain, Sweden and United Kingdom. We use only the fifteen countries and not the 27, which are now , because in the period we examine only the above fifteen countries are members of the European Union, because of the data availability , but also because of the legal and the constitutional frames of the European Union. The period we examine is 1990 to 2004, the data are annually and we leave the year 2005 for forecasting. Then we compare the forecasting performance of traditional panel regression analysis with that of neural network modeling.

Methodology

Our dependent variable is the greenhouse effects records and the independent variables are the inflation rate, the economic sentiment indictor and the industrial production. We prefer to take the logarithms of the above variables. For the first model we examine with the Hausman test if there we have fixed or random effects. One hypothesis we can make is that we expect to have fixed effects as we take the whole population and not a sample because the period we examine is 2000-2004 so only fifteen countries belonged to European Union. Furthermore even if we accept the hypothesis that we have fixed effects we will estimate the model with one-way and two-way fixed. For the random effects we estimate only the one-way because we have unbalanced data.

We would like to consider In our analysis and economic variables to examine if they affect the greenhouse. Gross domestic product or environmental taxes are some variables among others. We propose the sixteen factors in table 1.

Table 1. Greenhouse effects factors

1. Sulphur oxides	9. Emission of tropospheric ozone precursors
2. Nitrogen oxides	10. Sulphur hexafluoride
3. Carbon monoxide	11. Ammonia
4. Methane	12. Environmental taxes
5. Nitrous oxide	13. Gross domestic product
6. Carbon dioxide	14. Taxes on production
7. Sum of air emissions of primary PM10	15. Capital formation
8. Emission of acidifying pollutants	16. Consumption

The next step is to apply a factor analysis to decide how many factors we can take and to find the b_k loadings. The methodology of the factor analysis application can be made with principal components or with maximum likelihood. The main point is that whatever method we apply we will obtain the same conclusions. Before we apply factor analysis we will estimate the greenhouse effects with Carbon dioxide, Nitrous oxide and Methane as factors, because these seems to contribute major in the greenhouse effect. Then we will estimate on the factors generated by principal components. Finally we will estimate a neural network model for all factors.

a. One-Way Fixed Effects

The one-way fixed model is defined as (Baltagi, 2001)

$$\mathrm{y}_{\mathrm{it}} = \alpha + \beta_j x_{jit} + \varepsilon_{it} \qquad (1)$$

$$\varepsilon_{it} = \mu_i + u_{it} \qquad (2)$$

, where

- x are independent of u
- μ_i are unobservable individuals-specific effects, correlated with x-variables, and $E(\mu_i|x_{ijt}) \neq 0$
- D_t are replaced with time dummies or time trend and part of the x-variable
- u_{it} are random error term assumed to be IIDN $(0,\sigma^2_u)$
- μ_i and u_{it} are independent among themselves and of x-variables.

b. Two-Way Fixed Effects

The two-way fixed effects error component model (Baltagi, 2001) is defined as

$$y_{it} = \alpha + \beta_j x_{jit} + \varepsilon_{it} \qquad (3)$$

$$\varepsilon_{it} = \mu_i + D_t + u_{it} \qquad (4)$$

, where

- x are independent of ε
- μ_i are unobservable individuals-specific effects, correlated with x-variables, and $E(\mu_i|x_{ijt}) \neq 0$
- D_t are unobservable time-specific effects, correlated with X-variables, $E(D_t|x_{ijt}) \neq 0$
- u_{it} are random error term assumed to be IIDN $(0,\sigma^2_u)$
- μ_i , D_t and u_{it} are independent among themselves and of x-variables.

Fixed effects are also known as least square dummy variables (LSDV).

c. One-Way Random Effects

The one-way random effects with GLS estimation (Baltagi, 2001) and is defined as:

$$y_{it} = \alpha + \beta_j x_{jit} + \varepsilon_{it} \qquad (5)$$

$$\varepsilon_{it} = \mu_i + u_{it} \qquad (6)$$

, where

- x are independent of u

- μ_i IIDN $(0,\sigma^2_\mu)$, homoscedastic and uncorrelated with x-variables, and $E(\mu_i|x_{ijt}) \neq 0$
- D_t are replaced with time dummies or time trend and part of the x-variable
- u_{it} are random error term assumed to be IIDN $(0,\sigma^2_u)$ and homoscedastic
- μ_i and u_{it} are independent among themselves and of x-variables.

Then we apply the Hausman's test for random or fixed effects and it is (Greene, 2003)

$$\hat{q} = \hat{\beta}_{WHN} - \tilde{\beta}_{GLS} \quad (7)$$

$$\text{and } \operatorname{var}(\hat{q}) = \operatorname{var}(\tilde{\beta}_{GLS}) - \operatorname{var}(\hat{\beta}_{WHN}) \quad (8)$$

, where WHN denotes within so it means fixed effects and GLS denotes the random effects. We test the hypothesis

H_0: $E(\mu_i|x_{ijt}) \neq 0$ against H_1: $E(\mu_i|x_{ijt}) = 0$, which means that under the null hypothesis within is most efficient and under the H_1 GLS is the proper estimation, so we have random effects. We must notice that within is consistent under both the two hypotheses.

d. ARCH Effects

The final model we estimate is the panel data with GARCH effects. Mazodier and Trognon (1978) suggest that the group-specific component u_i might be heteroscedastic. To solve the problem we know that pooled OLS are consistent, so we can use the residuals for the specific groups and we have:

$$\hat{\sigma}^2_{\varepsilon i} + \hat{u}^2_i = \frac{e'_i e_i}{T} \quad (9)$$

And the residuals from the dummy variable model are purged of the individual specific effect, u_i so we have:

$$\hat{\sigma}^2_{\varepsilon i} = \frac{e'^{lsdv}_i e^{lsdv}_i}{T} \quad (10)$$

, where $e_i^{lsdv} = y_{it} + x'_{it} b^{lsdv} - \alpha_i$. So combining all terms we have

$$\hat{\sigma}^2_u = \frac{1}{n}\sum_{i=1}^{n}[(\frac{e'^{ols}_i e^{ols}_i}{T}) - (\frac{e'^{lsdv}_i e^{lsdv}_i}{T})] \qquad (11)$$

We examine also for GARCH effects and if actually there are GARCH effects we estimate two models the GARCH (1,1) and the Nelson's EGARCH model. According to Bollerslev (1986) the GARCH (1,1) is:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i u^2_{t-i} + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} \qquad (12)$$

The EGARCH model , which was proposed by Nelson (1990), is defined as:

$$\log(\sigma_t^2) = a + \log\beta(\sigma_{t-1}^2) + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \delta\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] \qquad (13)$$

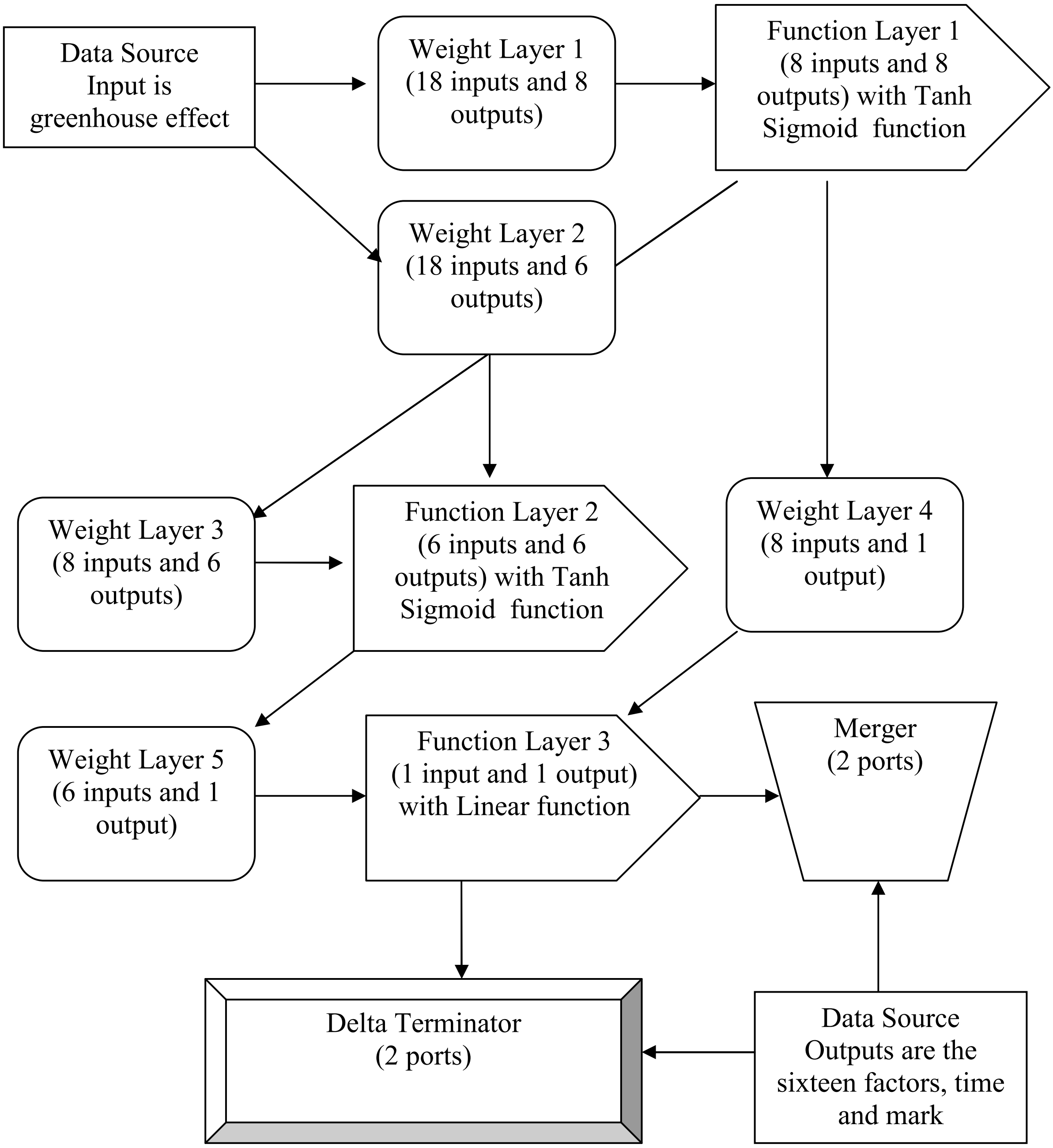
e. Neural networks panel model

The inputs are the sixteen factors we propose as we use two more inputs. One is variable 'time', where denotes the time period which is 1990-2005 and then we use variable 'mark', which denotes the countries, e.g. 1 denotes Belgium, 2 denotes Denmark and so on. The estimating period is the training set and the forecasting period is the validation set. Training set is referred to period 1990-2004 and validation set is referred on 2005, which is the year we would like to forecast the greenhouse effects for the fifteen countries of the European Union.

In the weight layers 1 to 4 we use as the back rule the quick propagation method with decay and step set up on 0.01, as in the weight layer 5 we use

Levenberg-Marquardt method and noise level equal with 0.4. In the first two function layers we use tanh sigmoid function as the transfer functions and as the back rule we use quick propagation and decay and step set up in the same levels with that of weight layers. In the thirds function layer we use linear function and Levenberg-Marquardt method.

Figure 1 . Neural networks modeling

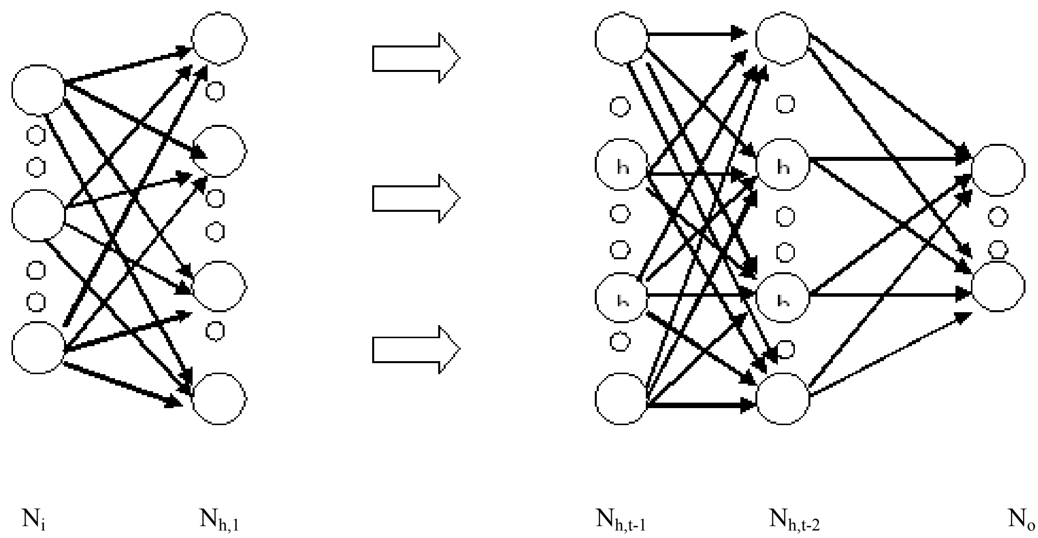


In the forecasting part of the paper we apply also feed-forward neural networks FNN model to VEqCM with no restrictions and with restrictions. FNN can be represented as:

$$f(x) = a_0 + \sum_{j=1}^{q} w_j \phi_{(\cdot)} (a_j + \sum_{i=1}^{p} w_{ij} x_i) \qquad (14)$$

, where f(x) is the output, x_i for i=1,2,3…p is the input patterns, α_j for j=1,2,3….q is the bias, w_{ij} for i=1,2,3…p and j=1,2,3….q is the weight connection between layers, p is the number of the input nodes, q is the umber of the hidden nodes and $\varphi_{(.)}$ is the transfer function of the hidden layer. A general feed forward multilayer neural networks illustration is resented in figure 2.

Figure 2. Feed-forward multilayer network architecture with t layers of units



Factor analysis results

In this part we apply factor analysis with principal components extraction. In table 2 in we present the results of the factor analysis with principal components. We used the Varimax rotation to improve the extractions of factors. Only two components have been extracted , as their eigenvalues are greater than unit.

Table 2 .Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.217	82.603	82.603	13.217	82.603	82.603	7.447	46.544	46.544
2	1.295	8.091	90.694	1.295	8.091	90.694	7.064	44.150	90.694
3	.823	5.146	95.841						
4	.381	2.383	98.224						
5	.099	.617	98.840						
6	.080	.500	99.340						
7	.041	.258	99.598						
8	.022	.135	99.733						
9	.015	.096	99.829						
10	.013	.081	99.910						
11	.007	.041	99.951						
12	.006	.037	99.988						
13	.002	.010	99.997						
14	.000	.003	100.000						
15	1.662E-5	.000	100.000						
16	2.281E-11	1.425E-10	100.000						

Extraction Method: Principal Component Analysis.

In table 3 we present the component matrix , which tells us how much each manifest variable loads onto each of the four latent variables before rotation. We set up in SPSS to suppress loadings less than 0.40 when running the analysis, therefore the blanks are actually small loadings. In table 4 we present the rotated components matrix, which gives the same information, as table 3, but after rotation. This is the table that tells us which variables map onto which factors most significantly and in size order. From this matrix we can see that factor one includes fifteen variables, and the second factor includes fourteen. So we propose to take the gross domestic product and the emissions of acidifying pollutants as the factors who contribute at most in the greenhouse effect.

Table 3 . Component Matrix

Variables	Component 1	Component 2
Sulphur oxides	.746	.530
Nitrogen oxides	.950	
Carbon monoxide	.918	
Methane	.958	
Nitrous oxide	.961	
Carbon dioxide	.969	
pm10	.949	
Emission of acidifying pollutants	.772	
Emission of tropospheric ozone precursors	.925	
Sulphur hexafluoride	.962	
Ammonia	.750	-.404
Environmental taxes	.940	
Gross domestic product	.908	
Taxes on production	.934	
Capital formation	.936	
Consumption	.915	

Table 4. Rotated Component Matrix

Variables	Component	
	1	2
Sulphur oxides	.529	.820
Nitrogen oxides	.472	.833
Carbon monoxide	.584	.774
Methane	.659	.700
Nitrous oxide	.798	.570
Carbon dioxide	.817	.521
pm10		.721
Emissions of acidifying pollutants	.433	.883
Emissions of tropospheric ozone precursors	.516	.850
Sulphur hexafluoride	.820	
Ammonia	.665	.665
Environmental taxes	.877	
Gross domestic product	.903	.410
Taxes on production	.885	.431
Capital formation	.872	.415
Consumption	.529	.820

Panel unit root test

As we decided which variables we will obtain in our analysis , we apply a panel unit root test for each variable. We test for the dependent variable, the greenhouse effect, and then for the repressors carbon dioxide , methane, nitrous oxide, ammonia, sulphurhexa fluoride, gross domestic product and emissions of acidifying pollutants. We provide different formulation of the augmented dickey fuller tests, beside Phillips-Perron, as Levin , Lin and Chu (2002) , Im and Pesaran (2003) and Breitung (2000). Levin and Lin test consider the following model

$$y_{it} = \rho_t y_{i,t-1} + z'_{i,t}\,\gamma + u_{it} \qquad (14) \qquad \text{, for i=1,2…,N and t=1,2,……,T}$$

We test the hypothesis H_0: ρ=1, that there is a unit root test against the alternative hypothesis H_1: ρ<1, that all individual series in the panel are stationary.

The coefficient ρ in Levin and Lin test requires to be homogenous across i, so Im ,Pesaran and Shin propose a test model, where allow for a heterogeneous coefficient of $y_{i,t-1}$. They propose a testing procedure based on the averaging individual unit root test statistics (Baltagi, 2001). The model is:

$$y_{it} = \rho_t y_{i,t-1} + \sum_{j=1}^{\rho_t} \phi_{ij} \Delta y_{i,t-j} + z'_{i,t} \gamma + u_{it} \qquad (15)$$

,and we test exactly the same hypotheses as in the case of Levin and Lin test. In the Breitung test we consider the following model:

$$y_{it} = \mu_t + \beta_{i,t} t + \varepsilon_{it} \qquad (16)$$

, where the unobserved error term ε_{it} follows

$$\varepsilon_{it} = \rho_i x_{i,t-1} + u_{it} \qquad (17)$$

Table 5.a. Panel unit root test for greenhouse effects in levels

Method	Statistics	Prob.	Cross-sections	Obs
Null: Unit				
Levin, Lin & Chu t	-0.83084	0.2030	15	210
Breitung t-stat	-0.55618	0.2890	15	195
Im, Pesaran and Shin W-stat	0.20720	0.5821	15	210
ADF - Fisher Chi-square	27.1510	0.6153	15	210
PP - Fisher Chi-square	33.3625	0.3070	15	225

Table 5.b. Panel unit root test for greenhouse effects in second differences

Method	Statistics	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-1.05067	0.1467	15	180
Breitung t-stat	-2.72198	0.0032	15	165
Im, Pesaran and Shin W-stat	-5.65101	0.0000	15	180
ADF - Fisher Chi-square	88.4548	0.0000	15	180
PP - Fisher Chi-square	255.446	0.0000	15	195

Table 6.a Panel unit root test for carbon dioxide in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t*	-1.70386	0.0442	15	210
Breitung t-stat	-0.37935	0.3522	15	195
Im, Pesaran and Shin W-stat	-0.19370	0.4232	15	210
ADF - Fisher Chi-square	29.4978	0.4916	15	210
PP - Fisher Chi-square	39.9800	0.1053	15	225

Table 6.b Panel unit root test for carbon dioxide in first differences

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-1.03082	0.1513	15	195
Breitung t-stat	-1.61699	0.0529	15	180
Im, Pesaran and Shin W-stat	-2.21450	0.0134	15	195
ADF - Fisher Chi-square	47.4128	0.0227	15	195
PP - Fisher Chi-square	150.995	0.0000	15	210

Table 7.a Panel unit root test for methane in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-1.35634	0.0875	15	210
Breitung t-stat	5.36278	1.0000	15	195
Im, Pesaran and Shin W-stat	3.12577	0.9991	15	210
ADF - Fisher Chi-square	11.4289	0.9991	15	210
PP - Fisher Chi-square	23.0050	0.8151	15	225

Table 7.b Panel unit root test for methane in first differences

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-3.58735	0.0002	15	195
Breitung t-stat	-1.42593	0.0769	15	180
Im, Pesaran and Shin W-stat	-1.83682	0.0331	15	195
ADF - Fisher Chi-square	47.2606	0.0235	15	195
PP - Fisher Chi-square	136.440	0.0000	15	210

Table 8.a Panel unit root test for nitrous oxide in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-0.48306	0.3145	15	210
Breitung t-stat	1.13876	0.8726	15	195
Im, Pesaran and Shin W-stat	0.79217	0.7859	15	210
ADF - Fisher Chi-square	27.4645	0.5988	15	210
PP - Fisher Chi-square	27.1189	0.6170	15	225

Table 8.b Panel unit root test for nitrous oxide in first differences

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-2.50646	0.0061	15	195
Breitung t-stat	-1.86310	0.0312	15	180
Im, Pesaran and Shin W-stat	-2.65212	0.0040	15	195
ADF - Fisher Chi-square	53.2606	0.0056	15	195
PP - Fisher Chi-square	100.159	0.0000	15	210

Table 9.a Panel unit root test for ammonia in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-0.08182	0.4674	15	210
Breitung t-stat	0.28176	0.6109	15	195
Im, Pesaran and Shin W-stat	0.01320	0.5053	15	210
ADF - Fisher Chi-square	31.9515	0.3698	15	210
PP - Fisher Chi-square	64.8330	0.0002	15	225

Table 9.b Panel unit root test for ammonia in first differences

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-4.44265	0.0000	15	195
Breitung t-stat	-2.16428	0.0152	15	180
Im, Pesaran and Shin W-stat	-2.83762	0.0023	15	195
ADF - Fisher Chi-square	56.3142	0.0025	15	195
PP - Fisher Chi-square	127.011	0.0000	15	210

Table 10.a Panel unit root test for sulphurhexa fluoride in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-1.00127	0.1583	12	168
Breitung t-stat	0.23009	0.5910	12	156
Im, Pesaran and Shin W-stat	-0.33725	0.3680	12	168
ADF - Fisher Chi-square	26.4745	0.3295	12	168
PP - Fisher Chi-square	25.5217	0.3779	12	180

Table 10.b Panel unit root test for sulphurhexa fluoride in second differences

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-1.90134	0.0286	12	144
Breitung t-stat	-0.28528	0.3877	12	132
Im, Pesaran and Shin W-stat	-3.08411	0.0010	12	144
ADF - Fisher Chi-square	51.0477	0.0010	12	144
PP - Fisher Chi-square	160.088	0.0000	12	156

Table 11.a Panel unit root test for gross domestic product in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-5.25154	0.0000	15	189
Breitung t-stat	0.43739	0.6691	15	174
Im, Pesaran and Shin W-stat	-1.14198	0.1267	15	189
ADF - Fisher Chi-square	50.6293	0.0107	15	189
PP - Fisher Chi-square	54.7437	0.0038	15	204

Table 11.b Panel unit root test for gross domestic product in first differences

Method	Statistics	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-8.73295	0.0000	15	174
Breitung t-stat	-3.95042	0.0000	15	159
Im, Pesaran and Shin W-stat	-2.25377	0.0121	15	174
ADF - Fisher Chi-square	59.7269	0.0010	15	174
PP - Fisher Chi-square	69.4068	0.0001	15	189

Table 12a Panel unit root test for emissions of acidifying pollutants in levels

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t	-0.78828	0.2153	15	210
Breitung t-stat	-0.43519	0.3317	15	195
Im, Pesaran and Shin W-stat	0.54054	0.7056	15	210
ADF - Fisher Chi-square	29.0032	0.5174	15	210
PP - Fisher Chi-square	63.9455	0.0003	15	225

Table 12.b Panel unit root test for emissions of acidifying pollutants in first differences

Method	Statistics	Prob.	Cross-sections	Obs
Null: Unit root				
Levin, Lin & Chu t*	-4.06591	0.0000	15	195
Breitung t-stat	-1.09579	0.1366	15	180
Im, Pesaran and Shin W-stat	-2.85065	0.0022	15	195
ADF - Fisher Chi-square	57.4951	0.0018	15	195
PP - Fisher Chi-square	156.040	0.0000	15	210

From tables 5-12 we conclude that neither time series are stationary in levels, so they aren't I(0), but are stationary in their first differences so they are I(1), except greenhouse effects and sulphurhexa fluoride , which are stationary in the second differences, so they are I(2). We

Panel cointegration tests and Vector Error-Equilibrium Correction model (VEqCM)

In this part of the paper we apply a cointegration panel test with Johansen methodology. We apply VAR-VECM model because in the previous part we found that SEPI is not stationary according to Im ,Pesaran and Shin test and Breitung test. So we estimate VECM model and also we apply forecasting for 2005 in next part of the paper. The basic steps to apply Johansen methodology are:

1. We specify and estimate a VAR(p) model based on the information criteria of Akaike and Schwarz, where the model with the minimum values of these criteria is preferred.
2. We apply likelihood ratio tests for the rank of Π to specify and determine the number of the co-integrating vectors.
3. We impose normalization and indentifying restrictions wherever this is necessary and possible.
4. Then we estimate the VEqCM by maximum likelihood.

Suppose we have the VAR(p) model.

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + Bx_t + u_t \quad (18)$$

Then we can rewrite the above VAR model as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{\iota=1}^{\rho-1} \Gamma_\iota y_{t-\iota} + Bx_t + u_t \qquad (19)$$

, where $\Pi = \sum_{\iota=1}^{\rho-1} \mathrm{A}_\iota - \mathrm{I}$ and $\Gamma_i = -\sum_{j=i+1}^{\rho} \mathrm{A}_j$

The best VAR(p) model according to the information criteria is VAR(5). We examine two tests (Johansen,1995) to determine the number of co-integrating vectors. The first is the Johansen trace statistic. We test the null hypothesis

H_0(r): r = r_0 against the alternative hypothesis H_1(r): r > r_0

The trace statistic is define as

$$LR_{trace}(r_0) = -T \sum_{i=r_0+1}^{n} \ln(1-\hat{\lambda}_\iota) \qquad (20)$$

The second LR statistic is known as the maximum eigenvalue statistic and is defined as:

$$LR_{maxeigen}(r_0) = -T \sum_{i=r_0+1}^{n} \ln(1-\hat{\lambda}_{r_0}+1) \qquad (21)$$

, and we test the null hypothesis

H_0(r_0): r = r_0 against the alternative hypothesis H_1(r_0): $r_0 > r_0+1$

In the beginning we suppose that first difference data have linear trends and the co-integrating equations have only intercepts. So we test the equation

$$\Pi \Delta y_{t-1} + Bx_t = a(\beta' y_{t-1} + \rho_0) \qquad (22)$$

We take the SEPI in the first differences as we concluded above that is not stationary. From table 13 we conclude that there are four cointegration equations with the LR trace statistic and three with the LR eigen maximum statistic at the α=0.05. In table 13 we present the VECM estimation with four cointegration equations for the period 1990-2004, while we leave year 2005 for forecasting.

Table 12. Johansen panel cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.750493	286.8114	159.5297	0.0000
At most 1 *	0.573458	181.3030	125.6154	0.0000
At most 2 *	0.449190	116.5475	95.75366	0.0009
At most 3 *	0.352061	71.22375	69.81889	0.0385
At most 4	0.260331	38.24294	47.85613	0.2915
At most 5	0.162710	15.32494	29.79707	0.7586
At most 6	0.022432	1.828525	15.49471	0.9969
At most 7	0.001371	0.104302	3.841466	0.7467

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.750493	105.5084	52.36261	0.0000
At most 1 *	0.573458	64.75546	46.23142	0.0002
At most 2 *	0.449190	45.32380	40.07757	0.0117
At most 3	0.352061	32.98081	33.87687	0.0637
At most 4	0.260331	22.91800	27.58434	0.1770
At most 5	0.162710	13.49642	21.13162	0.4077
At most 6	0.022432	1.724223	14.26460	0.9957
At most 7	0.001371	0.104302	3.841466	0.7467

So from table 14 we see, for the second cointegrating equation, that almost 1.50 % of disequilibrium "corrected" each month by changes in greenhouse effects, while for ACID, NH_3, CO_2, GDP, CH_4, N_2O and SF_6 are 42.07 %, 9.98 % , 7.85% ,2.78%, 30.10%, 18.99% and 81.65% respectively.

Next we estimate the impulse response functions (IRF). An impulse response function traces out the response of a variable of interest to an exogenous shock. We consider the following representation at time t+h

$$\begin{bmatrix} y_{1t+h} \\ y_{2t+h} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \theta_{11}^{(0)} \theta_{12}^{(0)} \\ \theta_{21}^{(0)} \theta_{22}^{(0)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t+h} \\ \varepsilon_{2t+h} \end{bmatrix} + \dots\dots\dots + \begin{bmatrix} \theta_{11}^{(h)} \theta_{12}^{(h)} \\ \theta_{21}^{(h)} \theta_{22}^{(h)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (23)$$

Table 14. VEqCM estimation

Cointegrating Eq:	CointEq1	CointEq2	CointEq3	CointEq4				
DDGREENHOUSE(-1)	1.000000	0.000000	0.000000	0.000000				
DACID(-1)	0.000000	1.000000	0.000000	0.000000				
DNH_3 (-1)	0.000000	0.000000	1.000000	0.000000				
DCO_2 (-1)	0.000000	0.000000	0.000000	1.000000				
DGDP(-1)	0.288427	0.170336	0.266009	0.347285				
	(0.21455)	(0.97876)	(0.43313)	(0.22111)				
	[1.34435]	[0.17403]	[0.61415]	[1.57061]				
DCH_4 (-1)	-0.104747	-0.928566	-0.972662	0.067342				
	(0.28065)	(1.28030)	(0.56657)	(0.28924)				
	[-0.37323]	[-0.72527]	[-1.71675]	[0.23283]				
DN_2O (-1)	0.278733	4.778955	2.428552	-0.007253				
	(0.31065)	(1.41717)	(0.62714)	(0.32016)				
	[0.89726]	[3.37219]	[3.87241]	[-0.02265]				
DSF_6(-1)	-0.237529	-0.743107	-0.430307	-0.219252				
	(0.04560)	(0.20803)	(0.09206)	(0.04700)				
	[-5.20880]	[-3.57207]	[-4.67415]	[-4.66521]				
C	0.020044	-0.075037	-0.007939	0.027335				
Error Correction:	D(DDGREENHOUSE)	D(DACID)	D(DNH_3)	D(DCO_2)	D(DGDP)	D(DCH_4)	D(DN_2O)	D(DSF_6)
CointEq1	-0.265904	1.484395	3.097776	-3.292534	1.507627	-4.483077	0.714958	4.970274
	(0.36072)	(2.04930)	(1.35812)	(2.33916)	(1.89864)	(1.27407)	(4.25752)	(16.8212)
	[-0.73715]	[0.72434]	[2.28092]	[-1.40757]	[0.79406]	[-3.51870]	[0.16793]	[0.29548]

Table 14. VEqCM estimation (cont.)

CointEq2	-0.015511	-0.420737	-0.099818	0.078520	0.027842	0.301270	-0.189981	-0.816536
	(0.02605)	(0.14798)	(0.09807)	(0.16891)	(0.13710)	(0.09200)	(0.30743)	(1.21462)
	[-0.59549]	[-2.84329]	[-1.01785]	[0.46487]	[0.20308]	[3.27475]	[-0.61797]	[-0.67226]
CointEq3	0.076932	0.672473	-0.528211	0.619044	-0.168655	0.013914	-0.314845	0.622370
	(0.04632)	(0.26314)	(0.17439)	(0.30036)	(0.24379)	(0.16360)	(0.54669)	(2.15993)
	[1.66095]	[2.55557]	[-3.02891]	[2.06101]	[-0.69179]	[0.08505]	[-0.57591]	[0.28814]
CointEq4	0.245710	-1.588238	-2.077189	1.815228	-1.347122	3.389698	0.056579	1.727090
	(0.26862)	(1.52608)	(1.01137)	(1.74193)	(1.41388)	(0.94878)	(3.17050)	(12.5265)
	[0.91471]	[-1.04073]	[-2.05383]	[1.04208]	[-0.95278]	[3.57269]	[0.01785]	[0.13788]
D(DDGREENHOUSE (-1))	-0.603012	-0.468685	-2.032598	3.964928	-2.553242	3.664778	-1.035292	-0.942183
	(0.39442)	(2.24075)	(1.48500)	(2.55769)	(2.07601)	(1.39310)	(4.65526)	(18.3927)
	[-1.52887]	[-0.20916]	[-1.36875]	[1.55020]	[-1.22988]	[2.63067]	[-0.22239]	[-0.05123]
D(DDGREENHOUSE (-2))	-0.319491	-0.393170	-1.523406	3.113372	-1.088833	2.852269	0.885286	-8.329635
	(0.35600)	(2.02251)	(1.34037)	(2.30858)	(1.87382)	(1.25742)	(4.20186)	(16.6013)
	[-0.89744]	[-0.19440]	[-1.13656]	[1.34861]	[-0.58108]	[2.26835]	[0.21069]	[-0.50175]
D(DDGREENHOUSE (-3))	-0.416911	-0.983631	-0.598221	2.442283	-0.099011	3.098838	0.568181	-4.981831
	(0.28429)	(1.61509)	(1.07036)	(1.84353)	(1.49634)	(1.00412)	(3.35542)	(13.2570)
	[-1.46651]	[-0.60903]	[-0.55890]	[1.32479]	[-0.06617]	[3.08614]	[0.16933]	[-0.37579]
D(DDGREENHOUSE (-4))	-0.015483	-0.211070	-0.100222	1.750061	0.652060	1.844213	-0.448287	4.081565
	(0.25110)	(1.42657)	(0.94542)	(1.62834)	(1.32169)	(0.88691)	(2.96376)	(11.7096)
	[-0.06166]	[-0.14796]	[-0.10601]	[1.07475]	[0.49335]	[2.07937]	[-0.15126]	[0.34857]
D(DDGREENHOUSE (-5))	-0.001492	-0.151809	0.215649	-0.262848	0.159407	-0.004313	0.085531	-0.965377
	(0.02085)	(0.11848)	(0.07852)	(0.13524)	(0.10977)	(0.07366)	(0.24615)	(0.97251)
	[-0.07153]	[-1.28131]	[2.74645]	[-1.94360]	[1.45220]	[-0.05856]	[0.34748]	[-0.99266]
D(DACID (-1))	-0.021685	-0.859448	-0.039447	-0.187157	-0.187966	-0.268288	-0.027184	1.392531
	(0.02657)	(0.15096)	(0.10005)	(0.17232)	(0.13986)	(0.09386)	(0.31363)	(1.23915)
	[-0.81605]	[-5.69309]	[-0.39428]	[-1.08612]	[-1.34391]	[-2.85852]	[-0.08667]	[1.12378]

Table 14. VEqCM estimation (cont.)

D(DACID (-2))	-0.043203	-0.579928	-0.249273	-0.214894	-0.012452	-0.273917	-0.049961	1.005151
	(0.03488)	(0.19815)	(0.13132)	(0.22618)	(0.18359)	(0.12319)	(0.41167)	(1.62650)
	[-1.23865]	[-2.92666]	[-1.89819]	[-0.95010]	[-0.06783]	[-2.22345]	[-0.12136]	[0.61798]
D(DACID (-3))	-0.045833	-0.371239	-0.254097	0.076576	0.110684	-0.214123	0.243480	1.237898
	(0.03228)	(0.18337)	(0.12152)	(0.20930)	(0.16989)	(0.11400)	(0.38095)	(1.50512)
	[-1.42002]	[-2.02457]	[-2.09096]	[0.36586]	[0.65152]	[-1.87825]	[0.63913]	[0.82246]
D(DACID (-4))	-0.027740	-0.252016	-0.174107	0.035692	-0.009719	0.006150	0.219566	-0.043291
	(0.02741)	(0.15573)	(0.10321)	(0.17776)	(0.14428)	(0.09682)	(0.32354)	(1.27830)
	[-1.01195]	[-1.61825]	[-1.68695]	[0.20079]	[-0.06736]	[0.06351]	[0.67863]	[-0.03387]
D(DACID (-5))	-0.024852	0.330894	0.054935	0.250962	0.013768	0.026601	0.198705	0.506897
	(0.02483)	(0.14104)	(0.09347)	(0.16098)	(0.13067)	(0.08768)	(0.29301)	(1.15766)
	[-1.00109]	[2.34617]	[0.58775]	[1.55892]	[0.10537]	[0.30338]	[0.67816]	[0.43787]
D(DNH_3 (-1))	-0.022740	-0.462333	-0.463658	-0.573613	0.331481	0.037512	0.225673	-0.040360
	(0.03944)	(0.22405)	(0.14848)	(0.25574)	(0.20757)	(0.13929)	(0.46547)	(1.83903)
	[-0.57663]	[-2.06356]	[-3.12267]	[-2.24299]	[1.59692]	[0.26930]	[0.48483]	[-0.02195]
D(DNH_3 (-2))	-0.039690	-0.263524	-0.220243	-0.101949	0.248562	0.139546	-0.076489	1.762616
	(0.03769)	(0.21413)	(0.14191)	(0.24442)	(0.19839)	(0.13313)	(0.44487)	(1.75765)
	[-1.05302]	[-1.23066]	[-1.55198]	[-0.41711]	[1.25290]	[1.04821]	[-0.17194]	[1.00282]
D(DNH_3 (-3))	-0.031854	-0.248836	-0.291295	-0.210581	0.228167	0.090009	-0.335431	0.648968
	(0.03593)	(0.20414)	(0.13529)	(0.23302)	(0.18914)	(0.12692)	(0.42412)	(1.67566)
	[-0.88646]	[-1.21892]	[-2.15310]	[-0.90371]	[1.20637]	[0.70919]	[-0.79089]	[0.38729]
D(DNH_3 (-4))	0.003668	-0.331285	-0.139023	-0.376480	0.030073	-0.005829	-0.330357	0.425392
	(0.03004)	(0.17065)	(0.11309)	(0.19478)	(0.15810)	(0.10609)	(0.35453)	(1.40072)
	[0.12211]	[-1.94134]	[-1.22928]	[-1.93280]	[0.19021]	[-0.05494]	[-0.93182]	[0.30369]
D(DNH_3 (-5))	-0.003319	-0.100166	0.051302	0.072897	0.171112	-0.105750	-0.197002	0.887683
	(0.02547)	(0.14471)	(0.09590)	(0.16518)	(0.13407)	(0.08997)	(0.30064)	(1.18782)
	[-0.13030]	[-0.69218]	[0.53494]	[0.44132]	[1.27628]	[-1.17542]	[-0.65527]	[0.74732]

Table 14. VEqCM estimation (cont.)

D(DCO$_2$ (-1))	0.575599	1.787664	2.368828	-2.479356	1.467338	-3.360485	0.286298	0.042976
	(0.27248)	(1.54801)	(1.02590)	(1.76696)	(1.43420)	(0.96241)	(3.21606)	(12.7064)
	[2.11244]	[1.15482]	[2.30902]	[-1.40317]	[1.02311]	[-3.49173]	[0.08902]	[0.00338]
D(DCO$_2$ (-2))	0.466480	0.872626	1.786567	-3.054249	2.069575	-2.660684	0.570504	-2.942638
	(0.30539)	(1.73496)	(1.14980)	(1.98036)	(1.60741)	(1.07864)	(3.60446)	(14.2410)
	[1.52750]	[0.50297]	[1.55380]	[-1.54227]	[1.28752]	[-2.46669]	[0.15828]	[-0.20663]
D(DCO$_2$ (-3))	0.245638	0.581614	1.287601	-2.685658	0.803371	-2.211726	-1.289966	3.470738
	(0.28176)	(1.60071)	(1.06083)	(1.82712)	(1.48302)	(0.99518)	(3.32554)	(13.1390)
	[0.87181]	[0.36335]	[1.21377]	[-1.46989]	[0.54171]	[-2.22245]	[-0.38790]	[0.26416]
D(DCO$_2$ (-4))	0.323495	0.669858	0.569824	-2.531208	0.291319	-2.647559	-0.844088	3.449027
	(0.23245)	(1.32060)	(0.87519)	(1.50739)	(1.22351)	(0.82103)	(2.74361)	(10.8398)
	[1.39167]	[0.50724]	[0.65108]	[-1.67920]	[0.23810]	[-3.22468]	[-0.30766]	[0.31818]
D(DCO$_2$ (-5))	0.005174	-0.343820	0.226589	-1.941177	-0.327713	-1.580488	0.064047	-3.753199
	(0.20943)	(1.18982)	(0.78853)	(1.35812)	(1.10235)	(0.73973)	(2.47191)	(9.76638)
	[0.02470]	[-0.28897]	[0.28736]	[-1.42932]	[-0.29729]	[-2.13659]	[0.02591]	[-0.38430]
D(DGDP (-1))	-0.064311	0.155501	-0.241720	0.093618	-0.697810	0.002213	-0.027726	-2.277619
	(0.02468)	(0.14020)	(0.09292)	(0.16004)	(0.12990)	(0.08717)	(0.29128)	(1.15084)
	[-2.60593]	[1.10910]	[-2.60146]	[0.58498]	[-5.37203]	[0.02539]	[-0.09519]	[-1.97910]
D(DGDP (-2))	-0.057940	-0.068637	-0.167606	0.171804	-0.532355	0.014294	-0.190167	-0.464496
	(0.02141)	(0.12163)	(0.08061)	(0.13884)	(0.11269)	(0.07562)	(0.25270)	(0.99840)
	[-2.70621]	[-0.56429]	[-2.07923]	[1.23745]	[-4.72402]	[0.18902]	[-0.75254]	[-0.46524]
D(DGDP (-3))	-0.052860	-0.105962	-0.202216	0.126819	-0.340134	-0.137335	-0.213602	-0.818445
	(0.02258)	(0.12827)	(0.08501)	(0.14641)	(0.11884)	(0.07975)	(0.26649)	(1.05287)
	[-2.34123]	[-0.82609]	[-2.37879]	[0.86618]	[-2.86213]	[-1.72214]	[-0.80155]	[-0.77735]
D(DGDP (-4))	-0.027388	-0.126086	-0.211521	-0.048660	-0.137772	-0.124116	-0.108005	-0.266309
	(0.01646)	(0.09350)	(0.06197)	(0.10673)	(0.08663)	(0.05813)	(0.19426)	(0.76751)
	[-1.66405]	[-1.34844]	[-3.41339]	[-0.45592]	[-1.59035]	[-2.13504]	[-0.55598]	[-0.34698]

Table 14. VEqCM estimation (cont.)

D(DGDP (-5))	-0.014164	-0.173856	-0.114104	-0.073912	-0.014270	-0.084195	-0.157969	-0.052135
	(0.01392)	(0.07907)	(0.05240)	(0.09026)	(0.07326)	(0.04916)	(0.16428)	(0.64905)
	[-1.01766]	[-2.19868]	[-2.17739]	[-0.81890]	[-0.19479]	[-1.71265]	[-0.96160]	[-0.08032]
$D(DCH_4 (-1))$	0.106677	0.605692	-0.178160	-0.069239	0.263606	-1.301596	0.099540	-2.654090
	(0.06963)	(0.39557)	(0.26215)	(0.45152)	(0.36648)	(0.24593)	(0.82181)	(3.24691)
	[1.53211]	[1.53120]	[-0.67961]	[-0.15335]	[0.71928]	[-5.29259]	[0.12112]	[-0.81742]
$D(DCH_4 (-2))$	0.135923	1.110853	0.473378	0.591989	0.707649	-0.862986	0.856919	-0.447965
	(0.08443)	(0.47969)	(0.31790)	(0.54753)	(0.44442)	(0.29823)	(0.99657)	(3.93739)
	[1.60981]	[2.31579]	[1.48908]	[1.08119]	[1.59230]	[-2.89373]	[0.85987]	[-0.11377]
$D(DCH_4 (-3))$	0.187999	0.924760	0.767911	0.664198	0.838217	-0.516960	0.684979	1.220886
	(0.08844)	(0.50244)	(0.33298)	(0.57350)	(0.46550)	(0.31237)	(1.04383)	(4.12412)
	[2.12576]	[1.84055]	[2.30620]	[1.15814]	[1.80069]	[-1.65496]	[0.65621]	[0.29604]
$D(DCH_4 (-4))$	0.122264	0.580608	0.574452	0.149229	0.608769	-0.426174	0.554473	-1.241876
	(0.07912)	(0.44947)	(0.29788)	(0.51305)	(0.41643)	(0.27944)	(0.93380)	(3.68938)
	[1.54538]	[1.29176]	[1.92849]	[0.29087]	[1.46189]	[-1.52509]	[0.59378]	[-0.33661]
$D(DCH_4 (-5))$	0.046432	-0.156232	0.093947	-0.005642	0.256587	-0.156866	0.619116	0.144896
	(0.05481)	(0.31137)	(0.20635)	(0.35541)	(0.28848)	(0.19358)	(0.64689)	(2.55582)
	[0.84719]	[-0.50175]	[0.45527]	[-0.01587]	[0.88944]	[-0.81033]	[0.95706]	[0.05669]
$D(DN_2O (-1))$	0.072633	-0.045251	0.836520	-0.982559	-0.190747	-0.420169	0.604230	0.497739
	(0.06196)	(0.35200)	(0.23328)	(0.40178)	(0.32612)	(0.21884)	(0.73129)	(2.88927)
	[1.17230]	[-0.12856]	[3.58597]	[-2.44550]	[-0.58490]	[-1.91999]	[0.82626]	[0.17227]
$D(DN_2O (-2))$	0.050009	-0.306276	0.532390	-1.107626	0.071776	-0.284954	0.560174	-0.476383
	(0.05886)	(0.33442)	(0.22163)	(0.38172)	(0.30983)	(0.20791)	(0.69477)	(2.74500)
	[0.84957]	[-0.91585]	[2.40218]	[-2.90167]	[0.23166]	[-1.37055]	[0.80627]	[-0.17355]
$D(DN_2O (-3))$	0.033101	-0.072751	0.488444	-0.658439	-0.060510	-0.208277	0.392773	0.811323
	(0.04695)	(0.26672)	(0.17676)	(0.30444)	(0.24711)	(0.16582)	(0.55412)	(2.18928)
	[0.70506]	[-0.27276]	[2.76332]	[-2.16277]	[-0.24487]	[-1.25604]	[0.70883]	[0.37059]

Table 14. VEqCM estimation (cont.)

D(DN_2O (-4))	0.037597	0.107130	0.402841	-0.445989	0.061635	-0.196167	0.441350	0.064449
	(0.03601)	(0.20456)	(0.13557)	(0.23350)	(0.18952)	(0.12718)	(0.42499)	(1.67912)
	[1.04415]	[0.52370]	[2.97146]	[-1.91003]	[0.32521]	[-1.54244]	[1.03849]	[0.03838]
D(DN_2O (-5))	-0.002942	-0.097686	0.160382	-0.379390	-0.132111	-0.063973	0.275793	-0.626640
	(0.02891)	(0.16425)	(0.10885)	(0.18748)	(0.15217)	(0.10211)	(0.34123)	(1.34817)
	[-0.10177]	[-0.59475]	[1.47342]	[-2.02366]	[-0.86818]	[-0.62649]	[0.80824]	[-0.46481]
D(DSF_6 (-1))	0.012262	-0.001189	-0.026300	-0.043717	0.025636	-0.054040	-0.043426	0.119141
	(0.00609)	(0.03460)	(0.02293)	(0.03949)	(0.03205)	(0.02151)	(0.07188)	(0.28399)
	[2.01348]	[-0.03436]	[-1.14703]	[-1.10702]	[0.79978]	[-2.51234]	[-0.60417]	[0.41953]
D(DSF_6 (-2))	0.012265	0.020281	0.003037	-0.002209	0.028169	-0.043267	-0.046729	0.149079
	(0.00534)	(0.03035)	(0.02011)	(0.03464)	(0.02812)	(0.01887)	(0.06305)	(0.24911)
	[2.29590]	[0.66826]	[0.15098]	[-0.06377]	[1.00182]	[-2.29312]	[-0.74113]	[0.59845]
D(DSF_6 (-3))	0.012732	0.039811	0.015075	-0.013763	0.003549	-0.020784	0.011110	-0.264847
	(0.00450)	(0.02556)	(0.01694)	(0.02918)	(0.02368)	(0.01589)	(0.05311)	(0.20982)
	[2.82963]	[1.55739]	[0.88987]	[-0.47169]	[0.14985]	[-1.30780]	[0.20920]	[-1.26224]
D(DSF_6 (-4))	0.005328	0.020876	-0.021653	-0.033134	0.009431	-0.020041	0.032547	-0.212082
	(0.00451)	(0.02561)	(0.01697)	(0.02923)	(0.02372)	(0.01592)	(0.05320)	(0.21019)
	[1.18201]	[0.81523]	[-1.27594]	[-1.13358]	[0.39753]	[-1.25884]	[0.61178]	[-1.00900]
D(DSF_6 (-5))	0.003894	0.021073	0.002327	0.032530	0.026482	-0.003727	0.022622	0.051961
	(0.00345)	(0.01960)	(0.01299)	(0.02237)	(0.01816)	(0.01219)	(0.04072)	(0.16088)
	[1.12874]	[1.07519]	[0.17911]	[1.45406]	[1.45836]	[-0.30583]	[0.55557]	[0.32298]
C	-0.001376	-0.015625	-0.009720	0.000767	-0.003681	0.008303	-0.012675	0.028224
	(0.00126)	(0.00717)	(0.00475)	(0.00818)	(0.00664)	(0.00446)	(0.01489)	(0.05882)
	[-1.09069]	[-2.18042]	[-2.04673]	[0.09379]	[-0.55445]	[1.86360]	[-0.85138]	[0.47983]
R-squared	0.996974	0.909147	0.859934	0.873326	0.838760	0.821372	0.600121	0.781039
Adj. R-squared	0.992678	0.780193	0.661131	0.693531	0.609904	0.567835	0.032550	0.470255
Sum sq. resids	0.000645	0.020829	0.009148	0.027138	0.017879	0.008051	0.089902	1.403369

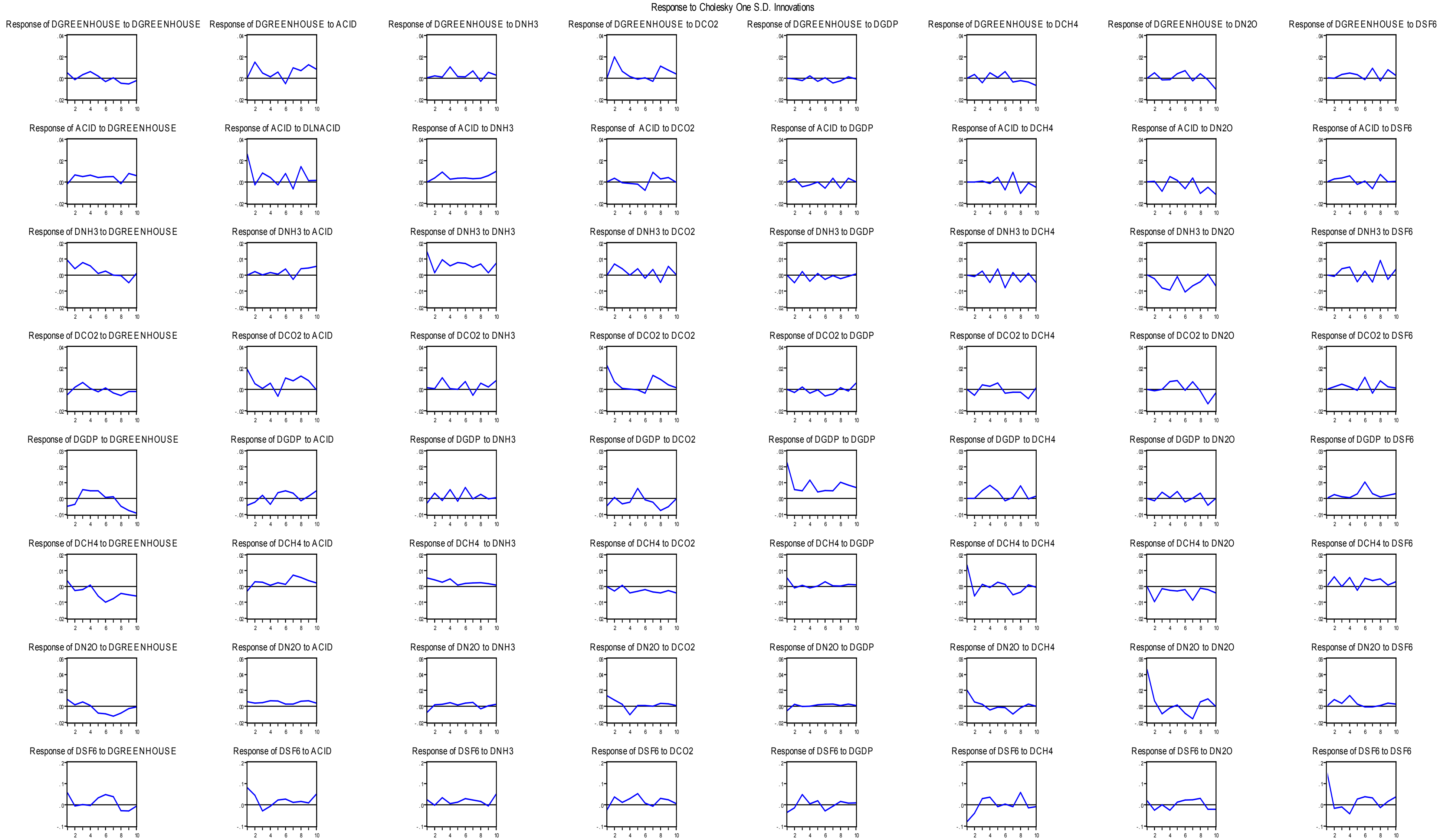
Table 14. VEqCM estimation (cont.)

S.E. equation	0.004563	0.025921	0.017179	0.029588	0.024015	0.016115	0.053852	0.212767
F-statistic	232.0906	7.050203	4.325552	4.857332	3.665007	3.239654	1.057349	2.513127
Log likelihood	335.8659	203.8420	235.1080	193.7877	209.6455	239.9633	148.2717	43.85127
Akaike AIC	-7.654367	-4.180052	-5.002843	-3.915465	-4.332777	-5.130613	-2.717677	0.030230
Schwarz SC	-6.274327	-2.800013	-3.622803	-2.535425	-2.952738	-3.750574	-1.337637	1.410269
Mean dependent	0.001124	-0.003170	0.002115	-0.001769	0.000555	0.000532	0.000167	0.004737
S.D. dependent	0.053321	0.055288	0.029510	0.053446	0.038451	0.024514	0.054751	0.292329
Determinant resid covariance (dof adj.)		7.50E-27						
Determinant resid covariance		5.74E-30						
Log likelihood		1695.798						
Akaike information criterion		-34.31048						
Schwarz criterion		-22.28880						

The dynamic multipliers are:

$$\frac{\partial y_{1t+h}}{\varepsilon_{1t}} = \theta_{11}{}^{(h)}, \frac{\partial y_{1t+h}}{\varepsilon_{2t}} = \theta_{12}{}^{(h)}, \frac{\partial y_{2t+h}}{\varepsilon_{1t}} = \theta_{21}{}^{(h)}, \frac{\partial y_{2t+h}}{\varepsilon_{2t}} = \theta_{22}{}^{(h)} \qquad (24)$$

Figure 3. Impulse response of the eight variables



In figure 3 we provide the impulse responses of the eight variables. Introducing positive shocks to ΔACID, ΔNH_3, ΔCO2 and ΔSF6 , we observe that there is positive response from greenhouse effects. The situation is the opposite for ΔGDP , while the situation for ΔCH_4 and ΔN_2O is

The situation is the same for ΔACID , expect from that positive shocks to ΔN_2O lead to negative response for ΔACID. Once again the situation for ΔNH_3 and ΔCO_2 is similar with that of ΔACID. For ΔGDP , introducing positive shocks to all variables , except ΔCO_2 , we see that there is positive response from ΔGDP , while response to ΔCO_2 is negative.

In the case of ΔCH_4, when we have positive shocks to ΔACID, ΔNH_3, ΔGDP and ΔSF_6, the response from is ΔCH_4 positive , while positive shocks to ΔGREENHOUSE, ΔCO_2 and ΔN_2O lead to negative response from ΔCH_4 .

Introducing now positive shocks to all variables except greenhouse , we observe that the response from ΔN_2O is positive, while the response to positive shocks to greenhouse is negative . Finally for DSF_6 positive shocks to all variables expect from ΔN_2O , lead to positive response from DSF_6 , while the situation for ΔN_2O

The next step is to examine for weak exogeneity. We consider the VEqCM model.

$$\Delta y_t = a\beta' y_{t-1} + \sum_{t=1}^{\rho-1} \phi_t \Delta y_{t-1} + Ax_t + \varepsilon_t \qquad (25)$$

And we divide process y_t , for example, into (y_{1t}, y_{2t}) with dimension m_1 and m_2 and Σ into

$$\Sigma = \begin{bmatrix} \Sigma_{11} \Sigma_{12} \\ \Sigma_{21} \Sigma_{22} \end{bmatrix}$$

The parameters can be decomposed as

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} , \quad \phi_i = \begin{bmatrix} \phi_{1i} \\ \phi_{2i} \end{bmatrix} , \quad A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}$$

So VEqCM(p) can be rewritten as

$$\begin{bmatrix}\Delta y_{1t}\\ \Delta y_{2t}\end{bmatrix}=\begin{bmatrix}\alpha_1\\ \alpha_2\end{bmatrix}\beta' y_{t-1}+\sum_{t=1}^{\rho-1}\begin{bmatrix}\phi_{1i}\\ \phi_{2i}\end{bmatrix}\Delta y_{t-1}+\begin{bmatrix}A_1\\ A_2\end{bmatrix}x_t+\begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix} \quad (26)$$

Finally the conditional model for y_{1t} given y_{2t} is:

$$\Delta y_{1t}=\omega\Delta y_{2t}+(a_1-\omega a_2)\beta' y_{t-1}+\sum_{t=1}^{\rho-1}(\phi_{1i}-\omega\phi_{2i})\Delta y_{t-1}+(A_1-\omega A_2)x_t+\varepsilon_{1t}-\omega\varepsilon_{2t} \quad (27)$$

And the marginal model of y_{2t} is:

$$\Delta y_t = a_2\beta' y_{t-1}+\sum_{t=1}^{\rho-1}\phi_{2t}\Delta y_{t-1}+A_2x_t+\varepsilon_{2t} \quad (28) \qquad \text{, where} \quad \omega=\Sigma_{12}\Sigma_{22}^{-1}$$

The test of weak exogeneity of $\mathbf{y}_{2t}$ for the parameters (α_1, β) determines whether α_2=0, which means that there is no information about β in the marginal model or that variables $\mathbf{y}_{2t}$ do not react in the disequilibrium. We test the hypothesis B=0 for only the first cointegrating equation, as for the others there isn't convergence.

Table 15. Hypothesis for weak exogeneity

Hypoth.	B(1,1)=0	B(1,2)=0	B(1,3)=0	B(1,4)=0	B(1,5)= 0	B(1,6)= 0	B(1,7)= 0	B(1,8)= 0	B(1,5)= B(1,6)= B(1,8)=0
X^2 (1)	35.250	19.270	15.662	37.585	0.0771	3.0586	27.719	0.1917	4.4725
Prob.	0.0000	0.00001	0.00007	0.0000	0.7811	0.0803	0.0000	0.6614	0.2147

Three variables out of eight are weak exogenous. These are ΔGDP, ΔDCH_4 and DSF_6. So we test also the hypothesis B(1,5)=B(1,6)=B(1,8)=0 and we accept the null hypothesis. So in other part of the paper we present the forecasting values generated by the VEqCM with no restrictions , but also by the VEqCM with imposed restrictions and we compare the models with the one-way random effects , according to RMSE and MAE measures.

Results

The first model we examine is

$$\text{lngreenhouse} = b_0 + b_1CO_2 + b_2CH_4 + b_3N_2O + b_4NH_3 + b_5SF_6 \quad (29)$$

In table 16 we estimate the greenhouse effect as the dependent variable and as factors and independent variables we take carbon dioxide (CO_2), methane (CH_4) ,nitrous oxide (N_2O) , ammonia (NH_3) and sulphurhexa fluoride (SF_6). We must mention that variables are expressed in logarithms. From table 15 we see that the best estimation, as referred to the statistically significance of the variables, is ARCH (1) effects model. In the other models all the coefficients, including the constant, are statistically significant except the coefficient of SF_6. But in the panel ARCH effect model all coefficient are significant, as the coefficients of the variance equation are. Also because we have ARCH(1) then we conclude that there is heteroscedasticity, so the other panel models, as the fixed and random effects models are not significant. Also we must mention that we examined GARCH (1,1), which GARCH (1) coefficient was found to be statistically insignificant. We've been led to the same conclusion with the other GARCH's models estimation, as GJR, EGARCH and others. Coefficients have the expecting sign, as the greatest contribution in the greenhouse effect has the CO_2, then CH_4 and N_2O and then follows with much lower contribution NH_3 and SF_6 according to the ARCH estimation . The situation is quite similar but with N_2O have greater contribution than CH_4. We will see also the contribution of all sixteen factors with the neural networks models.

From table 17 we see that $p<\alpha$ for $\alpha=0.05$ and $\alpha=0.01$, so we reject the null hypothesis, which means that we have random effects. So according to the Hausman test we prefer one-way random effect model. But even we chose the random effects , based on Hausman test , we conclude that there are ARCH effects, as we mentioned above as the ARCH (1) coefficient is statistically significant.

Table 16 . Estimation results with the four proposed models for equation (4)

	One-way[1] Fixed Effects	Two-way[1] Fixed Effects	One-way[1] Random Effects	ARCH(1)[2] effects
Constant	2.14	2.32	1.78	1.74
	(12.638)*	(13.14)*	(23.037)*	(141.66)*
CO_2	0.76	0.734	0.776	0.765
	(96.145)*	(63.78)*	(142.33)*	(537.41)*
CH_4	0.067	0.079	0.078	0.138
	(8.813)*	(9.337)*	(11.171)*	(92.92)*
N_2O	0.119	0.129	0.116	0.086
	(12.298)*	(12.074)*	(12.855)*	(43.08)*
NH_3	0.0272	0.0337	0.0267	0.0061
	(3.087)*	(3.73)*	(3.683)*	(4.52)*
SF_6	0.000245	0.000551	4.37e-05	0.0044
	(0.196)	(0.415)	(0.037)	(11.46)*
		Variance	**Equation**	
constant				6.78e-06
				(3.14)*
ARCH(1)				1.064
				(5.24)*
R^2 adjusted	0.9995	0.9995	0.9967	
Log-Likelihood				650.23
F-statistic	171,120.3	90,175.24	11,527.89	
Wald chi-square				7.70e+06

1.t-statistics in parentheses, 2. z-statistics in parentheses, *statistically significant in α=0.05

The second model is that was conducted by factor analysis and it is

$$\text{lngreenhouse} = b_0 + b_1\text{lngdp} + b_2\text{lnacid} \quad (30)$$

The results are presented in table 18 and we conclude that there are positive relationships between greenhouse effect and the independent variables. So if the gross domestic product is increasing then greenhouse effect is increasing too. In table 19 we present the Hausman's test results and we see that $p<\alpha$ for $\alpha=0.05$ and $\alpha=0.01$, so we reject the null hypothesis, so once again we have random effects.

Table 17. Hausman test for fixed and random effects and equation (4)

Coefficients	(b) fixed	(B)	(b-B) Difference	sqrt(diag(V_b-V_B))
CO_2	.7630119	.7766637	-.0136517	.0055354
CH_4	.0673658	.0781665	-.0108007	.0022909
N_2O	.1195187	.1164685	.0030501	.0023017
NH_3	.0272464	.0267069	.0005395	.004561
SF_6	.0002447	.0000435	.0002012	.0003

p = 0.0000

chi-square (5) = 50.78

From the neural networks results we found that there is a positive relationship between factors and the greenhouse effect expect variables emissions of acidifying pollutants and tropospheric ozone precursors, environmental taxes, taxes on production, capital formation and consumption. So countries with high capital formation and consumption, as the developed countries contribute less to the greenhouse effect, as countries with high environmental taxes and also taxes on the production. This is possible as the high capital formation is not necessary harmful to the environment , as this formation depends on the kind and also the measures , which these countries obtain. It is well know that usually developed countries obtain more drastic measures against the pollution as developing countries are not, because developing countries do what is necessary to reach the economic and social level that of developed countries. But the sign of the acidifying pollutants emissions is not the expected as we waiting to find a positive relationship between acid and greenhouse effects. This can be explained that acidifying pollutants have significantly reduced and decreased in Europe (Pipatti, 1998) Tropospheric ozone O^3 is produced as a result of photochemical processes, through reactions involving ozone precursors. These amounts are

Table 18 . Estimation results with the four proposed models for equation (5)

	One-way[1] Fixed Effects	Two-way[1] Fixed Effects	One-way[1] Random Effects	GARCH(1,1)[2] effects	EGARCH[2] effects
Constant	12.173	13.211	9.439	8.074	8.290
	(16.817)*	(19.037)*	(24.890)*	(168.01)*	(74.24)*
lnGDP	0.267	0.040	0.375	0.532	0.521
	(8.648)*	(0.973)*	(20.291)*	(55.16)*	(24.52)*
lnACID	0.332	0.509	0.465	0.403	0.398
	(8.912)*	(12.022)*	(21.844)*	(46.90)*	(20.03)*
		Variance	**Equation**		
constant				0.000721	-3.681
				(2.09)*	(-20.70)*
ARCH(1)				1.112	
				(5.81)*	
GARCH(1)				-0.0246	
				(-2.62)*	
EARCH(1)					-0.115
					(-0.42)
EGARCH(1)					1.282
					(5.17)
R^2 adjusted	0.9973	0.9981	0.728		
Log-Likelihood				144.7134	96.160
F-statistic	4,734.803	3036.741	289.282		
Wald chi-square				100,194.37	13,358.44

Table 19. Hausman test for fixed and random effects and equation (5)

Coefficients	(b) fixed	(B)	(b-B) Difference	sqrt(diag(V_b-V_B))
lnGDP	.2661098	.3776402	-.1115305	.0240997
lnACID	.3319776	.4670172	-.1350395	.030103

p = 0.0000

chi-square (2) = 20.11

increasing with the air pollution and the human-made sources, as the biomass burning, insudtry and transport. Tropospheric ozone can affect the atmospheric lifetimes of some greenhouse gases. The break down of tropospheric ozone in sunlight leads to the production of hydroxyl radicals, these help to mop up some other greenhouse gases, and so lessen their global warming potential. One possible reason for the negative relationship between tropospheric ozone and greenhouse effect is that there is the possibility of reducing the air pollution generated by human-made sources in Europe, as filters in industry and in the transport , alternative sources of energy "friendly" to the environment, decreasing in the biomass burning.

Forecasting

In table 20 we present the forecasting values of greenhouse effects for the fifteen countries of European Union in period 2005 with one-way random effects for equations (4) and (5) and with neural networks model obtaining all variables. The forecasting performance is very good for both models , even if MAE and RMSE for neural networks are only 8.58 and 12.25 respectively lower than the one way random effects GLS estimation counterparts. Also the missing forecasting values for Greece, Luxemburg and Portugal in columns (3) and (5) are due to in unavailability of data for one or some variables in the period we would like to estimate. But neural networks model is better because in the estimation process we obtain all the variables and we can examine how and much all the variables affect on the greenhouse effect.

Table 21 presents the forecasting values generated by VEqCM and VEqCM with imposed restrictions for the greenhouse effects in second differences for year 2005. Also we present the forecasting values by feed-forward neural networks for VEqCM and VEqCM with imposed restrictions.

As input data we have the forecasting values by VEqCM with no restrictions and as output variable we have the actual values of greenhouse effects in second differences. The same procedure we follow for the VEqCM with restrictions forecasting values , which we set up as the input variable, and the actual values of greenhouse effects as output. We decided to apply a feed-forward multilayer neural network model with 15 hidden layers, 1000 number of epochs. The train function is gradient descent with momentum and adaptive learning rate backpropagation, while the learning rate is set up at 0.5 and the momentum rate is set up at 0.6. The tranferr function to hidden layers is the hyperbolic tangent sigmoid and the transfer function to output layer is the linear. The MATLAB code , which is very simple, is:

Figure 4. MATLAB code for feed-forward multilayer neural network model training and simulation

```
net=newff(minmax(input),[10 1],{'tansig' 'purelin'},'traingdx');
net.trainParam.epochs = 1000;
net.trainParam.lr=0.5;   % learning rate
net.trainParam.mc=0.6; % momentum
net=train (net,input,output);
Y=sim(net,input);
```

We observe that forecasting performance with neural networks on forecasting values generated by VEqCM with restrictions are much better than that of simple VEqCM with both restrictions and no-restrictions, as is better than neural networks on VEqCM with no restrictions, a, as it was the expected result.

Table 20 . Forecasting results with one-way random effects for equation (4) and (5) and neural networks

Countries	Actual values of Greenhouse effects	Forecasting with One-way Random Effects Equation (4)	Forecasting with One-way Random Effects Equation (5)	Forecasting with Neural Networks obtaining all factors
Belgium	18.773	18.764	18.807	18.762
Denmark	17.967	17.960	18.074	18.972
Germany	20.728	20.718	20.674	20.715
Ireland	18.068	18.096	18.123	18.080
Greece	18.712	NA	18.776	NA
Spain	19.904	19.895	19.820	19.890
France	20.134	20.136	20.150	20.136
Italy	20.174	20.162	20.045	20.170
Luxemburg	16.402	NA	16.312	NA
Netherlands	19.170	19.185	19.207	19.190
Austria	18.350	18.335	18.318	18.341
Portugal	18.286	NA	18.221	NA
Finland	18.050	18.043	18.098	18.062
Sweden	18.018	18.012	18.089	18.014
United Kingdom	20.300	20.299	20.301	20.299
MAE		0.0099	0.0555	0.00905
RMSE		0.0120	0.0666	0.01053

Table 21 . Forecasting results with VEqCM and VEqCM with restrictions

Countries	Actual values of Greenhouse effects in second differences	Forecasting with VEqCM for Greenhouse effects in second differences	Forecasting with VEqCM and restrictions for Greenhouse effects in second differences	Forecasting with VEqCM and Neural VEqCM for Greenhouse effects in second differences	Forecasting with VEqCM and Neural VEqCM for Greenhouse effects in second differences
Belgium	0.0009	0.0037	0.0059	0.0063	-0.0030
Denmark	0.0835	0.0197	0.0260	0.0393	0.0641
Germany	0.0024	0.0331	0.0222	0.0018	0.0131
Ireland	-0.0007	-0.0099	-0.0023	0.0192	-0.0057
Greece	-0.0016	-0.0048	0.0152	0.0091	-0.0126
Spain	-0.0380	-0.0230	-0.0171	-0.0388	-0.0104
France	-0.0006	0.0191	0.0328	0.0394	0.0029
Italy	-0.0068	-0.0308	-0.0255	-0.0074	-0.0045
Luxemburg	-0.1388	-0.0476	-0.0467	0.1386	-0.1389
Netherlands	-0.0065	0.0101	0.0091	-0.0109	0.0003
Austria	0.0177	-0.0132	-0.0194	0.0155	-0.0104
Portugal	-0.0239	-0.0440	0.0400	-0.0239	-0.0246
Finland	0.0486	-0.0078	-7.0419e-05	0.0160	0.0522
Sweden	0.0147	0.0222	0.0231	0.0163	0.0253
United Kingdom	0.0020	0.0002	0.0125	-0.0053	0.0047
MAE		0.0261	0.0268	0.0114	0.0091
RMSE		0.0360	0.0354	0.0186	0.0126

Conclusion

We examined the effects of some factors on greenhouse effects of the fifteen countries of European Union. We took factors , which concern not only gases, but also we took and economic variables, as the gross domestic production, consumption and others. Then we applied principal components analysis to decide which variables to obtain in our estimation. We saw that we preferred one-way random effects than the fixed, according to Hausman test. From the other side we estimated a panel model with ARCH effects and we show that there is heteroscedasticity, and specifically we preferred the ARCH(1) model. So it's not sufficient to estimate only panel data with fixed and random effects , because the possibility of heteroscedasticity presence is strong. Then we estimated a panel vector error-equilibrium correction model with restrictions and with not. We estimated also a panel neural network model obtaining all factors and we discussed the advantage of neural networks , that we can obtain all variables, against traditional statistics and econometric estimations, where we forced to reduce all variables to obtain the proper estimation. Finally we applied forecasting for one-way fixed effects, neural network model we propose in figure 1, VEqCM with restrictions and with not, as with feed-forward multilayer network. We saw that forecasting performance is much more better with neural networks in both neural models, than traditional econometric methods.

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