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Modelling the sectoral structure of the final output

Abstract

This paper examines the modelling complications that appear when some macroeconomic behavioral relationships interact with structural variables, even under a given A matrix. The main problem is concretized for the situation when, a) the final consumption, gross fixed capital formation, inventory changes, export, import (all of them at the market prices), and gross value added (at the production prices) are estimated as macro-indicators, and b) the output (at production prices) is determined on a disaggregated level. The so-called demand-side or supply-side approaches are possible; here, the supply-side approache is especially researched.

With such a goal, the regression and linear weighted average (in the Fisher version) techniques are discussed as the main tools for estimating sectoral weights of the final output. For the linear weighted average method, the paper sketches – as a discussion proposal – a methodology for the optimal selection of the length (number of terms) of the moving average. As a primary database, the Romanian input-output tables for 1989–2009, aggregated into 10 sectors were used.

JEL Classification: C32, C36, C43, C67
Key-words: final output, sectoral structure, regression, moving average

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I. **The problem**

1. The models combining the main behavioral macroeconomic relationships (of Keynesian or post-Keynesian types) with variables related to the structural profile of economy (as in Dobrescu 2006, for instance) have to solve a challanging problem. Technically, the difficulty of such an attempt results from the fact that some indicators are defined at the global level, while others, at the sectoral one. We shall discuss this question under the following assumptions:

• The final consumption, gross fixed capital formation, inventory changes, export, import (all at the market prices), and gross value added (at production prices) are estimated as macro-indicators.

• The output (evidently, at production prices) is determined on the sectoral basis, according to the adopted branch classification; an aggregate indicator in this case also can be computed, but only through summation of sectoral data.

In such an analysis, the input-output (I-O) tables are irreplaceable searching tools (the main coordinates can be found, for instance, in Leontief, 1970; 1986; Stone, 1961; United Nations, 1999; Miller and Blair, 2009). More concretely, if the A matrix is given, a consistent interaction between the mentioned levels could be obtained by different ways. Two such methods already were implemented in the Romanian modelling activity. First, termed as the demand-side approach, in essence consists of an econometric estimation of utilization of resources. Symmetrically, the other focuses attention on final outputs and it is termed as the supply-side approach.

2. As an example, the demand-side approach was applied in the 2005 version of the Romanian macromodel (Dobrescu, 2006). The leading relationships involved in such a case are described below.

$$C_{ij} = Q_i * a_{ij} \qquad (I.1)$$

C_{ij} – intermediary consumption from sector i in sector j, current prices
Q_i - output in the sector i, current prices
a_{ij} – technical coefficients, current prices - exogenous

$$\mathrm{GVA} = \mathrm{GDP} - \mathrm{NIT} \qquad (I.2)$$

GVA – total gross value added, current prices
GDP - gross domestic product, current prices; defined by macroeconomic relationships
NIT – total net indirect taxes; defined by macroeconomic relationships

$$\mathrm{UF} = \mathrm{GDP} + \mathrm{M} \qquad (I.3)$$

UF – total final resources, current prices
M - import of goods and services, current prices; defined by macroeconomic relationships

$$\mathrm{GVA} = \sum \mathrm{GVA_i} \qquad (I.4)$$

GVA_i - gross value added in sector i, current prices

$$\mathrm{GVA_i} = \mathrm{Q_i} * (1 - \sum \mathrm{a_{ij}}) \text{ for i fixed} \quad \text{(I.5)}$$

$$\mathrm{Q_i} = \mathrm{DR_i} - (\mathrm{wm_i} * \mathrm{M} + \mathrm{NIT} * \mathrm{wn_i}) \quad \text{(I.6)}$$

DR_i – total resources of the sector i, current prices
wm_i – weight of the sector i in import; econometric estimation
wn_i - weight of the sector i in total of net indirect taxes, econometric estimation

$$\mathrm{DR_i} = \mathrm{UF_i} + \sum \mathrm{a_{ij}} * \mathrm{Q_j} \text{ for i fixed} \quad \text{(I.7)}$$

UF_i - final resources of the sector i, current prices

$$\mathrm{UF_i} = \mathrm{cw_i} * \mathrm{FC} + \mathrm{fw_i} * \mathrm{GFCF} + \mathrm{xw}_i * \mathrm{X} + \mathrm{sw_i} * \mathrm{STOCK} \qquad \text{i=1, 2...10} \quad \text{(I.8)}$$

cw_i – weight of the sector i in final consumption; econometric estimation
FC – total final consumption, current prices; defined by macroeconomic relationships
fw_i – weight of the sector i in gross capital formation; econometric estimation
GFCF – total gross capital formation, current prices; defined by macroeconomic relationships
xw_i – weight of the sector i in export of goods and services
X – total export of goods and services, current prices; defined by macroeconomic relationships
sw_i – weight of the sector i in change of inventories; econometric estimation
STOCK – total change of inventories, current prices; defined by macroeconomic relationships.

The demand-side approach involves, therefore, a very difficult operation of consistently determining six sectoral distributions, wm_i, wn_i, cw_i, fw_i, wx_i, and ws_i, under the restriction $\Sigma wm_i = \Sigma wn_i = \Sigma cw_i = \Sigma fw_i = \Sigma wx_i = \Sigma ws_i = 1$.

3. The supply-side approach was applied in the integrated system of the 2012 version of the Romanian macro-model (National Commission for Prognosis, 2013). This is centered on the final output (NY_i) as a difference between output (production) of each sector and its total deliveries for intermediate consumption in the whole economy (respectively $Q_i - \Sigma a_{ij} Q_j$, i=fixed, at the sectoral level, and $NY = \Sigma NY_i$, at the aggregate level). According to NY, the newly created resources of the economy are determined in basic prices (as the output itself), and under the restriction of null foreign trade balance. Several algebraic transformations drive us to an important accounting equality. Therefore,

$$\mathrm{NY}_i = \mathrm{FC}_i + \mathrm{GFCF}_i + \mathrm{STOCK}_i + \mathrm{X}_i - \mathrm{M}_i - \mathrm{NIT}_i \quad \text{(I.9)}$$

$$\mathrm{NY} = \sum \mathrm{FC}_i + \sum \mathrm{GFCF}_i + \sum \mathrm{STOCK}_i + \sum \mathrm{X}_i - \sum \mathrm{M}_i - \sum \mathrm{NIT}_i \quad \text{(I.10)}$$

$$\mathrm{FC} = \sum \mathrm{FC}_i \quad \text{(I.11)}$$

$$\mathrm{GFCF} = \sum \mathrm{GFCF}_i \qquad \text{(I.12)}$$

$$\mathrm{STOCK} = \sum \mathrm{STOCK}_i \qquad \text{(I.13)}$$

$$\mathrm{X} = \sum \mathrm{X}_i \qquad \text{(I.14)}$$

$$\mathrm{M} = \sum \mathrm{M}_i \qquad \text{(I.15)}$$

$$\mathrm{NIT} = \sum \mathrm{NIT}_i \qquad \text{(I.16)}$$

$$\mathrm{NY} = \mathrm{FC} + \mathrm{GFCF} + \mathrm{STOCK} + \mathrm{X} - \mathrm{M} - \mathrm{NIT} \qquad \text{(I.17)}$$

$$\mathrm{GDP} = \mathrm{FC} + \mathrm{GFCF} + \mathrm{STOCK} + \mathrm{X} - \mathrm{M} \qquad \text{(I.18)}$$

Finally,

$$\mathrm{NY} = \mathrm{GDP} - \mathrm{NIT} = \mathrm{GVA} \qquad \text{(I.19)}$$

As already mentioned, in our set of adopted assumptions, the total gross value added results (as in the previous approach) from the macroeconomic relationships. Note, however, that the equality NY=GVA is valid only at the macroeconomic level. At the sectoral level significant differences are possible, depending on the external and internal competitiveness of different branches. If the sectoral distribution wny_i ($wny_i = NY_i/NY$) is approximated, then the following deductions are evident:

$$\mathrm{Q}_i = \sum \mathrm{a}_{ij}\mathrm{Q}_j + \mathrm{NY}_i = \sum \mathrm{a}_{ij}\mathrm{Q}_j + \mathrm{wny}_i * \mathrm{NY} \quad \text{i=fixed} \qquad \text{(I.20)}$$

$$\mathrm{Q}_j = \sum \mathrm{a}_{ij}\,\mathrm{Q}_j + \mathrm{GVA}_j \quad \text{j=fixed} \qquad \text{(I.21)}$$

$$\mathrm{GVA}_j = \mathrm{Q}_j - \sum \mathrm{a}_{ij}\,\mathrm{Q}_j = \mathrm{Q}_j * (1 - \sum \mathrm{a}_{ij}) = \mathrm{Q}_j * (1 - \mathrm{sca}_j) \quad \text{j=fixed} \qquad \text{(I.22)}$$

in which sca_j represent the colSums of technical coefficients a_{ij}. Consequently,

$$\mathrm{GVA_i} = (1 - \mathrm{sca_i}) * (\sum \mathrm{a_{ij}} \frac{\mathrm{GVA_j}}{1-\mathrm{sca_j}} + \mathrm{wny_i} * \mathrm{NY}) \quad \text{i=fixed} \qquad \text{(I.23)}$$

Hereinafter, it is simple to determine the global output of sectors. The supply-side approach needs, therefore, to estimate (econometrically or by another procedure) only the distribution wny_i.

We must outline that this entire discussion relates to the sectoral structure of output (production and gross value added) and not to other sectoral indicators. For such a limited purpose, the supply-side approach is simpler and reduces the necessary sectoral distribution vectors from six (as in the demand-side approach) to only one.

4. The target of our paper is to illustrate the supply-side approach using Romanian input-output tables (annual data for the period 1989-2009). The extended classification, comprising 105 branches (INSEE, 2012), was aggregated into 10 sectors (Dobrescu, 2009; National Commission for Prognosis, 2012), according to the following codification:

- Agriculture, forestry, hunting and fishing (suffix 1)
- Mining and quarrying (suffix 2)
- Production and distribution of electric and thermal power (suffix 3)
- Food, beverages and tobacco (suffix 4)
- Textiles, leather, pulp and paper and furniture (suffix 5)
- Machinery and equipment, transport means and other metal products (suffix 6)
- Other manufacturing industries (suffix 7)
- Constructions (suffix 8)
- Transports and post and telecommunications (suffix 9)
- Trade, business and public services (suffix 10)

The first three positions belong to the primary mega-field. The following four constitute the manufacturing industry, which – together with construction – configure the secondary mega-sector. The last two positions can be considered as the tertiary mega-field. The series wny_i is detailed in the Annex A1.

5. The rest of the paper is organized as follows. The possibilities to estimate the set of wny_i by using, on the one hand, econometric regressions and, on the other hand, a weighted linear moving average are discussed in the sections II and III. Their specific advantages and limits are outlined. The final part of this paper presents several concluding remarks.

II. Econometric Regressions

1. The series wny_i was submitted to two tests of stationarity: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) in three variants concerning exogenous (none, constant and constant and linear trend) and three forms of series (primary data and first-order and second-order differences). The results are detailed in the Annex A2. Although some series are I(0), in the proposed specification the first-order differences are used as dependent variables in all the 10 equations.

2. Concerning the right side of the regressions, different solutions are possible. In order to avoid irrelevance and complications for our analysis, the paper does not involve other variables besides the statistical series of wny_i themselves.

A careful examination of the data shows, however, that it would be risky to use only the simple auto regressions (that is, exclusively, lags and differences of every estimated variable). Table 1 presents the Galtung-Pearson correlations (in module) registered during 1990-2009 between all the wny_i.

Table 1
Galtung-Pearson correlations

Module	wny9	wny4	wny10	wny6	wny5	wny7	wny1	wny3	wny2	wny8
wny9	1	0.8128	0.8422	0.9044	0.8972	0.6993	0.3771	0.6471	0.6596	0.038
wny4	0.8128	1	0.847	0.6246	0.7033	0.808	0.6167	0.4632	0.5524	0.4459
wny10	0.8422	0.847	1	0.7993	0.7509	0.9068	0.6226	0.5157	0.5068	0.1508
wny6	0.9044	0.6246	0.7993	1	0.9471	0.5643	0.1522	0.6281	0.7181	0.2427
wny5	0.8972	0.7033	0.7509	0.9471	1	0.5238	0.1286	0.6217	0.7345	0.0891
wny7	0.6993	0.808	0.9068	0.5643	0.5238	1	0.6592	0.3948	0.2471	0.3068
wny1	0.3771	0.6167	0.6226	0.1522	0.1286	0.6592	1	0.218	0.0759	0.7079
wny3	0.6471	0.4632	0.5157	0.6281	0.6217	0.3948	0.218	1	0.2256	0.016
wny2	0.6596	0.5524	0.5068	0.7181	0.7345	0.2471	0.0759	0.2256	1	0.1383
wny8	0.038	0.4459	0.1508	0.2427	0.0891	0.3068	0.7079	0.016	0.1383	1

Legend		
	0.8-1	(blue)
	0.6-0.8	(green)
	0.4-0.6	(red)
	0.2-0.4	(yellow)
	<0.2	(white)

Therefore, from 45 bilateral coefficients, 8 exceed 80% and 15 are situated between 60-80%; the group between 40-60% includes 7 positions as well. In other words, the registered co-movements in the evolution of different sectoral weights of the final output cannot be ignored.

3. The final retained specification contains 35 estimators. In many cases lags and differences of other wny_i than that estimated are involved. More formally, the solved system shows as follows (SySw):

$$d(wny1) = c(1) + c(2) * wny1(-1) + c(3)\frac{t}{t+1} \quad \text{(II.1)}$$

$$d(wny2) = c(4) + c(5) * wny2(-1) + c(6) * wny6(-1) \quad \text{(II.2)}$$

$$d(wny3) = c(7) + c(8) * wny3(-1) + c(9)wny6(-1) \quad \text{(II.3)}$$

$$d(wny4) = c(10) + c(11) * wny4(-1) + c(12) * wny1(-1) + c(13) * wny2(-1) \quad \text{(II.4)}$$

$$d(wny5) = c(14) + c(15) * wny5(-1) \quad \text{(II.5)}$$

$$d(wny6) = c(16) + c(17) * wny6(-1) + c(18) * d(wny10) \quad \text{(II.6)}$$

$$d(wny7) = c(19) + c(20) * wny7(-1) + c(21) * wny4 + c(22) * d(wny6,2) + c(23) * d(wny10(-1)) \quad \text{(II.7)}$$

$$d(wny8) = c(24) + c(25) * wny8(-1) + c(26) * wny4(-1) \quad \text{(II.8)}$$

$$d(wny9) = c(27) + c(28) * wny9(-1) + c(29) * wny2(-1) \quad \text{(II.9)}$$

$$d(wny10) = c(30) + c(31) * wny10(-1) + c(32) * d(wny2,2) + c(33) * d(wny6) + c(34) * d(wny6,2) + c(35) * d(wny9(-1)) \quad \text{(II.10)}$$

According to the symbolism of EViews, d(wny_i) represents the first order difference and d(wny_i, 2) the second order.

4. The system SySw was solved by six techniques (Annex A3): ordinary least squares (OLS), weighted least squares (WLS), seemingly unrelated regression (SUR), two-stage least squares (2SLS), weighted two-stage least squares (W2LS),, and three-stage least squares (3SLS). Two circumstances concerning the obtained estimators are important:
a) in all cases the null hypothesis is significantly rejected; and
b) the algebraic signs of all the estimators are independent on the applied technique.

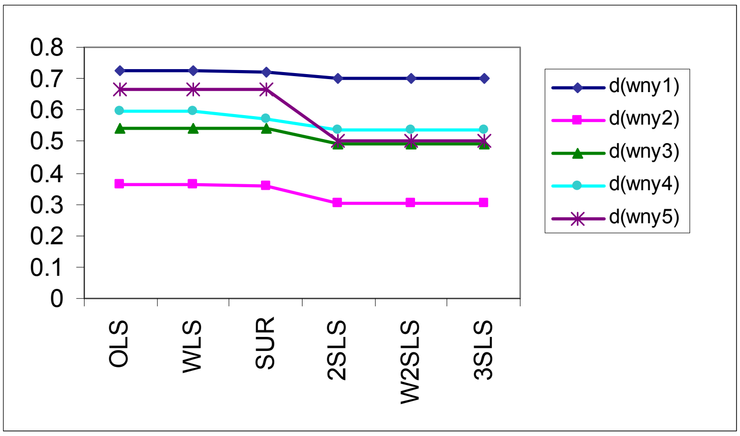
Under these conditions, the R-squared coefficient was used as a discriminating criterion (Table 2)

Table 2.
Coefficients of determination

Equation		OLS	WLS	SUR	2SLS	W2SLS	3SLS
d(wny1)	R-squared	0.754063	0.754063	0.751292	0.731128	0.731128	0.731128
	Adjusted R-squared	0.72513	0.72513	0.722032	0.699496	0.699496	0.699496
d(wny2)	R-squared	0.428807	0.428807	0.424202	0.377581	0.377581	0.377581
	Adjusted R-squared	0.361608	0.361608	0.356461	0.304355	0.304355	0.304355
d(wny3)	R-squared	0.591066	0.591066	0.588717	0.548066	0.548066	0.548066
	Adjusted R-squared	0.542956	0.542956	0.540331	0.491574	0.491574	0.491574
d(wny4)	R-squared	0.659118	0.659118	0.640439	0.61548	0.61548	0.61548
	Adjusted R-squared	0.595203	0.595203	0.573021	0.538576	0.538576	0.538576
d(wny5)	R-squared	0.683628	0.683628	0.68317	0.527534	0.527534	0.527534
	Adjusted R-squared	0.666052	0.666052	0.665569	0.499742	0.499742	0.499742
d(wny6)	R-squared	0.813574	0.813574	0.809646	0.782508	0.782508	0.782508
	Adjusted R-squared	0.791641	0.791641	0.787252	0.755321	0.755321	0.755321
d(wny7)	R-squared	0.686302	0.686302	0.68297	0.6795	0.6795	0.6795
	Adjusted R-squared	0.596674	0.596674	0.592389	0.587929	0.587929	0.587929
d(wny8)	R-squared	0.451842	0.451842	0.450727	0.305167	0.305167	0.305167
	Adjusted R-squared	0.387352	0.387352	0.386107	0.223422	0.223422	0.223422
d(wny9)	R-squared	0.577444	0.577444	0.570186	0.521291	0.521291	0.521291
	Adjusted R-squared	0.527732	0.527732	0.51962	0.461452	0.461452	0.461452
d(wny10)	R-squared	0.881757	0.881757	0.862468	0.873684	0.873684	0.873684
	Adjusted R-squared	0.83628	0.83628	0.809572	0.825101	0.825101	0.825101

GraphR1 sketches the comparative levels of the adjusted R-squared coefficients for the first five equations (d(wny1)-d(wny5).

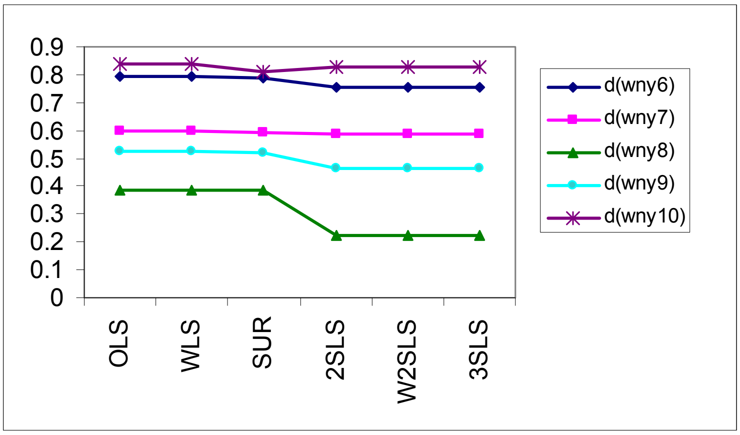
GraphR1



Generally, the coefficients of determination are equal in the case of OLS and WLS and higher than those provided by other procedures.

The situation is identical for the second half of equations (d(wny6)-d(wny10)) represented in GraphR2.

GraphR2



Consequently, our application uses the OLS econometric results.

5. Moreover, the coefficient, residual, and stability diagnostics do not invalidate them.
5.1. The variance inflation-factor test is presented in Table 3.

Table 3
Variance inflation factors (VIF)

Equation	Variable	Coefficient variance	Centered VIF	Equation	Variable	Coefficient variance	Centered VIF
d(wny1)	c	0.002482	Na	d(wny7)	c	0.000256	na
	wny1(-1)	0.00855	1.041996		wny7(-1)	0.016891	2.247643
	t/(t+1)	0.002674	1.041996		wny4	0.017399	2.187514
d(wny2)	c	2.42E-05	na		d(wny6,2)	0.028301	1.36685
	wny2(-1)	0.023048	1.217922		d(wny10(-1))	0.004816	1.297817
	d(wny6(-1))	0.010297	1.217922	d(wny8)	c	0.000612	na
d(wny3)	c	5.16E-05	na		wny8(-1)	0.017393	1.156796
	wny3(-1)	0.053487	1.649276		wny4(-1)	0.014873	1.156796
	wny6(-1)	0.002156	1.649276	d(wny9)	c	0.000121	na
d(wny4)	c	3.77E-05	na		Wny9(-1)	0.003289	1.789711
	wny4(-1)	0.005824	2.590451		Wny2(-1)	0.034893	1.789711
	wny1(-1)	0.001921	1.742686	d(wny10)	c	0.001541	na
	wny2(-1)	0.032865	1.746076		wny10(-1)	0.005785	2.672029
d(wny5)	c	8.80E-06	na		d(wny2,2)	0.105386	1.2726
	wny5(-1)	0.002551	1		d(wny6)	0.196036	2.507426
d(wny6)	c	1.06E-05	na		d(wny6,2)	0.087827	1.707267
	wny6(-1)	0.002009	1.045802		d(wny9(-1))	0.374786	2.074322
	d(wny10)	0.001357	1.045802				

The centered VIF represent 1-1.5 for 13 variables and 1.5-2.25 for the other 9. Only in 3 cases it is larger, but it does not exceed 2.7. It seems reasonable, therefore, to admit that the collinearity syndrome does not significantly alter the system SySw.

5.2. According to the Breusch-Pagan-Godfrey test (Table 4), the probability for the rejection of heteroscedasticity hypothesis is significant in all cases.

Table 4
Breusch-Pagan-Godfrey heteroscedasticity test

d(wny1)	F-statistic	0.3673	Prob. F(2,17)	0.698	d(wny6)	F-statistic	1.2336	Prob. (2,17)	0.316
	Obs*R-squared	0.8283	Prob. Chi-Square(2)	0.6609		Obs*R-squared	2.5348	Prob. Chi-Square(2)	0.2816
	Scaled expl. SS	0.7401	Prob. Chi-Square(2)	0.6907		Scaled expl. SS	1.0414	Prob. Chi-Square(2)	0.5941
d(wny2)	F-statistic	1.4749	Prob. F(2,16)	0.2583	d(wny7)	F-statistic	0.0205	Prob.F(4,14)	0.9991
	Obs*R-squared	2.9576	Prob. Chi-Square(2)	0.2279		Obs*R-squared	0.1107	Prob. Chi-Square(4)	0.9985
	Scaled expl. SS	2.4937	Prob. Chi-Square(2)	0.2874		Scaled expl. SS	0.0879	Prob. Chi-Square(4)	0.9991
d(wny3)	F-statistic	2.0411	Prob. F(2,17)	0.1605	d(wny8)	F-statistic	0.3716	Prob.F(2,17)	0.6951
	Obs*R-squared	3.8726	Prob. Chi-Square(2)	0.1442		Obs*R-squared	0.8378	Prob. Chi-Square(2)	0.6578
	Scaled expl. SS	2.1847	Prob. Chi-Square(2)	0.3354		Scaled expl’ SS	0.3734	Prob. Chi-Square(2)	0.8297
d(wny4)	F-statistic	0.6824	Prob. F(3,16)	0.5756	d(wny9)	F-statistic	0.2003	Prob.F(2,17)	0.8204
	Obs*R-squared	2.2688	Prob. Chi-Square(3)	0.5185		Obs*R-squared	0.4605	Prob. Chi-Square(2)	0.7943
	Scaled expl. SS	1.4144	Prob. Chi-Square(3)	0.7022		Scaled expl. SS	0.3738	Prob. Chi-Square(2)	0.8295
d(wny5)	F-statistic	0.0282	Prob. F(1,18)	0.8684	d(wny10)	F-statistic	0.275	Prob.F(5,13)	0.9187
	Obs*R-squared	0.0313	Prob. Chi-Square(1)	0.8595		Obs*R-squared	1.8176	Prob. Chi-Square(5)	0.8738
	Scaled expl. SS	0.0256	Prob. Chi-Square(1)	0.8728		Scaled expl. SS	0.8202	Prob. Chi-Square(5)	0.9757

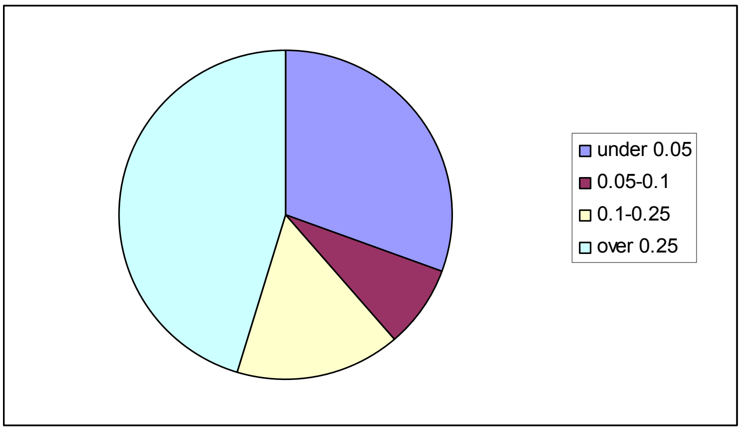
5.3. The OLS residuals were submitted to both unit root tests ADF and PP, in all the available options for exogenous conditions (Table 5).

Table 5
Unit root tests for residuals (res)

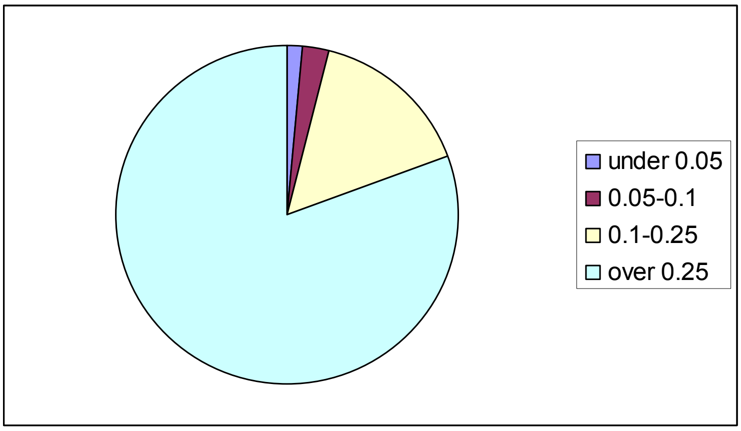
Series	Exogenous	ADF		PP	
		t-Statistic	Prob.	Adj. t-Stat	Prob.
reswny1	None	-4.64555	0.0001	-4.64555	0.0001
	Constant	-4.51013	0.0024	-4.51013	0.0024
	Constant, linear trend	-4.4027	0.0128	-4.4027	0.0128
reswny2	None	-3.83592	0.0007	-3.83146	0.0007
	Constant	-3.72723	0.013	-3.70252	0.0137
	Constant, linear trend	-3.69561	0.0496	-3.85037	0.0376
reswny3	None	-4.32818	0.0002	-4.67667	0.0001
	Constant	-4.20564	0.0046	-4.4892	0.0025
	Constant, linear trend	-4.10338	0.0226	-4.73247	0.0068
reswny4	None	-4.4433	0.0001	-4.4433	0.0001
	Constant	-4.3169	0.0036	-4.3169	0.0036
	Constant, linear trend	-4.20967	0.0185	-4.20926	0.0185
reswny5	None	-5.02309	0	-5.9537	0
	Constant	-4.88165	0.0011	-5.72604	0.0002
	Constant, linear trend	-4.08859	0.0244	-5.15	0.0031
reswny6	None	-5.07258	0	-5.11736	0
	Constant	-4.94774	0.001	-4.9896	0.0009
	Constant, linear trend	-3.17295	0.1244	-14.2635	0.0001
reswny7	None	-5.5984	0	-5.47931	0
	Constant	-5.42818	0.0004	-5.32661	0.0005
	Constant, linear trend	-5.26999	0.0027	-5.18459	0.0032
reswny8	None	-2.92002	0.0059	-2.92002	0.0059
	Constant	-2.84165	0.0713	-2.84165	0.0713
	Constant, linear trend	-2.7104	0.2434	-2.7104	0.2434
reswny9	None	-3.75772	0.0008	-3.78099	0.0007
	Constant	-3.66193	0.0142	-3.68954	0.0134
	Constant, linear trend	-3.4935	0.0689	-3.53176	0.0644
reswny10	None	-3.95378	0.0005	-3.94569	0.0005
	Constant	-3.83568	0.0105	-3.82305	0.0107
	Constant, linear trend	-3.71337	0.048	-3.69565	0.0496

5.4. Finally, on the OLS residuals, the BDS (Brock–Dechert–Scheinkman) test was applied as a powerful tool to identify an extended spectrum of possible serial correlations (Annex A4). Five embedding dimensions (2, 3, 4, 5, and 6) and three options related to the distance (fraction of pairs, the standard deviations, and the fraction of range) were adopted. The p-value for the tested null hypothesis was estimated for both the sample data (normal probability), and their random repetitions (bootstrap probability). Consequently, 30 p-values were computed for each wny_i. Grouped in four categories (under 0.05; 0.05-0.1; 0.1-0.25; and 0.25-1), these 300 resultant p-values are represented in Graph BDSn for normal probability and Graph BDSb for the bootstrap.

GraphBDSn



GraphBDSb



Overall, therefore, 63% of the BDS p-values exceed 0.25 and almost 16% are situated between 0.1-0.25. The distribution of bootstrap p-values – considered more relevant for small samples, as it is in our case – attests clearly the absence of the serial correlation in the $reswny_i$ series (81% over 0.25 and 15% in the group 0.1-0.25).

Summarizing, the tests for collinearity, heteroscedasticity, stationarity and serial correlation of residuals confirm the adequacy of the OLS estimations.

6. Nevertheless, a question must be supplementarily examined. Based on the OLS estimators, wny_i were projected for the following 5 years after statistical sampling.

This operation was developed in two stages.

• During the first stage, the econometric relationships were computed, obtaining $ewny_i$. Their sum is noted as sew.

• In the second stage, the $ewny_i$ were multiplied by 1/sew in order to observe the compulsory equality of $\Sigma wny_i=1$.

The resultant values are presented in Table 6.

Table 6
Forecasted OLS values for 5 post-sampling years

Year	1	2	3	4	5
wny1	0.05798	0.06425	0.0581	0.06981	0.05469
wny2	-0.0287	-0.0272	-0.02747	-0.0274	-0.0291
wny3	0.01937	0.02542	0.01697	0.03079	0.01078
wny4	0.05512	0.05419	0.04599	0.05247	0.04187
wny5	0.02525	0.0269	0.02418	0.02888	0.0231
wny6	0.036	0.07069	0.02091	0.10739	-0.0025
wny7	-0.0687	-0.0472	-0.06362	-0.0323	-0.0742
wny8	0.20896	0.26311	0.26333	0.3608	0.30692
wny9	0.10775	0.11328	0.10198	0.12126	0.09736
wny10	0.58695	0.45665	0.55963	0.28826	0.57107
Sum	1	1	1	1	1

The registered volatility for some wny_i cannot be neglected. Besides, beginning with the sixth year, the forecasts even induce dubious values. Consequently, an alternative solution was also investigated.

III. Moving average attempt

To find an alternative solution, the moving average method was considered as a possible competitor. However, in which variant should the moving average be: simple or weighted? In economics, the recent lags of time series are involved more frequently than those that are far-off. This means an implicit preference for the weighted moving average. We shall apply it in the so-called Fisher version (Fisher, 1937).

1. As it is known, the weights of different sample's observations included in computations depend on the adopted length (number of terms, noted k) of the moving average. According to Fisher's formula, beginning with the 13-th anterior observation, such a weight becomes insignificant (lower than 1%). This is why the searched interval in the present paper is comprised between 2 and 12 terms (Annex A5). Even under this limitation, the pallet of possible options remains large enough (11 variants). Usually, the concrete choice of the moving average's length is based on empirical reasons. In our opinion, however, some guidance rules in this sense could be established.

1.1. Among them, the degree at which the properties of the given statistical series are reflected in the estimated corresponding moving averages (ma_k) must be taken into consideration. Our trials have showed that – for such a purpose – the information criterion (IC_k) could be useful. There are several such measures, the most frequently used being Akaike - AIC (Akaike, 1973, 1974), SIC - Schwarz (Schwarz, 1978), and Hannan-Quinn - HQC (Hannan and Quinn, 1979). An extensive mathematical and interpretative background for these statistical tools can be found in (Burnham and Anderson, 2002 and 2004; Gagne and Dayton, 2002; Lukacs at al, 2007, Claeskens and Hjort, 2008). As a discussion proposal, our applicative procedure will be exemplified involving only AIC_k variant in the following numerical determination:

$$\text{AIC} = \left(\frac{1}{n}\sum_{t=1}^{n} u_t^2\right) \cdot e^{\frac{2(k+1)}{n}} \quad \text{(III.1)}$$

where n is the sample size, u is the differences between primary data and the corresponding moving average results, and k is the number of terms included in computations.

1.2. Extrapolating the here examined series, at one time, the moving average generates very small first-order successive differences (under a given conventionally established level), which could be interpreted as a symptom that the given computational algorithm ceases to adequately reflect the original data. Consequently, the post-sampling interval in which the results of the moving average do not yet reach the mentioned treshold can be considered as a sort of temporal relevance of the examined procedure (noted τ_k). If n is the last sample observation, then τ_k=(n+1), (n+2),…,(n+m). In practice, it is necessary to numerically define the conventional threshold, to which the temporal relevance of the compared moving average's lengths is defined. In principle, a higher τ could be considered as a sign of a more adequate reflection of the primary series.

1.3. The behavior of calculated data within the τ_k interval is also of interest. Which resulted series reproduces the original information more faithfully? The one that is relatively flattened or the other that is more volatile? In our opinion, it is the second, as both the involved methods originate from the same statistics and their only difference is in the number of terms included in the moving average. The coefficient of variation that was determined for the post-sampling estimated data (noted CV_k) could approximate such a structural inertiality of extrapolation.

2. In the case of series wny_i the above mentioned parameters - AIC_k, τ_k , and CV_k - were determined for all compared lengthes (respectively k=2, 3…12). Annex A6 contains these results. In order to facilitate their interpretation, we shall adopt a transformed variant that is more familiar to economists.

2.1. So, AIC_k is recomputed as an information criterion index, denoted ICI_k. If AIC_{max} represents the maximum AIC among the k registered values, then:

$$\text{ICI}_k = 1 - \frac{\text{AIC}_k}{\text{AIC}_{max}} \quad \text{(III.2)}$$

For positive values (as in our application), this index observes the inequality $0 \le ICI_k \le 1$. A higher ICI_k would be interpreted as reproducing better the respective statistical data, and vice-versa. Table 7 details the information criterion indices for all wny_i.

Table 7
Informational criterion indices

Number of terms	Wny1	wny2	wny3	wny4	wny5	wny6	wny7	Wny8	wny9	wny10
2	0.98676	0.93491	0.8543	0.99645	0.96434	0.98316	0.98316	0.99527	0.98843	0.98979
3	0.98807	0.83505	0.66041	0.99016	0.90446	0.94253	0.94253	0.9873	0.96336	0.96779
4	0.9793	0.73139	0.50081	0.9801	0.83302	0.91632	0.91632	0.98112	0.91016	0.94969
5	0.96125	0.57673	0.6256	0.96462	0.81457	0.88755	0.88755	0.96709	0.82559	0.92217
6	0.94511	0.65523	0.48987	0.94415	0.69562	0.81553	0.81553	0.94597	0.69287	0.88338
7	0.9115	0.70766	0.30351	0.91632	0.5077	0.67274	0.67274	0.9172	0.54805	0.82346
8	0.85808	0.63068	0.12138	0.89422	0.50896	0.55237	0.55237	0.86979	0.41354	0.7411
9	0.77393	0.54011	0	0.83951	0.35864	0.45156	0.45156	0.79279	0.44329	0.6269
10	0.64295	0.22413	0.70702	0.71165	0.07761	0.18299	0.18299	0.66365	0.38815	0.39487
11	0.41296	0	0.60981	0.46113	0	0	0	0.43742	0.16785	0.10126
12	0	0.29144	0.35344	0	0.36579	0.22732	0.22732	0	0	0

It must be noted that, generally, the informational criterion index preponderantly decreases under increasing number of terms used in the Fisher linear moving average. Only for two series - wny2 and wny3 – it fluctuates.

2.2. In the case of the second property, a temporal persistence index (TPI_k) is approximated by

$$\mathrm{TPI}_k = \frac{\tau_k}{\tau_{max}} \qquad \text{(III.3)}$$

in which τ_{max} is the maximum τ

This index also observes the restriction $0 \leq TPI_k \leq 1$.

In our application, we use as a limit of the post-sampling extrapolation ϵ=0.0001 for at least 5 successive values. If ma_j represent the moving average estimations, ϵ is defined as follows: ϵ=((ma_j/ma_{j-1}-1)^2)^0.5; (n+1)≤j≤n+m). The obtained results for the temporal relevance indices are given in Table 8.

Table 8
Temporal relevance indices

Number of terms	wny1	wny2	wny3	wny4	wny5	wny6	wny7	wny8	wny9	wny10
2	0.27273	0.42857	0.42857	0.28571	0.35294	0.35294	0.27273	0.21053	0.25	0.23529
3	0.36364	0.42857	0.5	0.33333	0.33333	0.35294	0.31818	0.36842	0.375	0.23529
4	0.40909	0.5	0.64286	0.42857	0.42857	0.41176	0.40909	0.47368	0.4375	0.29412
5	0.5	0.64286	0.64286	0.52381	0.52381	0.52941	0.45455	0.57895	0.5	0.47059
6	0.59091	0.71429	0.71429	0.57143	0.57143	0.58824	0.54545	0.68421	0.5625	0.52941
7	0.63636	0.78571	0.78571	0.66667	0.66667	0.64706	0.5	0.73684	0.5625	0.58824
8	0.72727	0.85714	0.85714	0.71429	0.71429	0.88235	0.68182	0.84211	0.625	0.64706
9	0.77273	0.92857	0.92857	0.80952	0.80952	0.88235	0.77273	0.89474	0.6875	0.70588
10	0.86364	1	1	0.85714	0.85714	0.88235	0.81818	1	0.75	0.82353
11	0.90909	0.92857	0.92857	0.95238	0.95238	1	0.90909	0.89474	0.875	0.88235
12	1	1	1	1	1	0.94118	1	0.94737	1	1

Without some minor deviations, the temporal relevance indices, in all cases, are positively correlated with the number of terms implied in the Fisher linear moving average, which means a comparatively converse situation with ICI.

2.3. We shall proceed in a similar way in the case of the third discussed property. If mma represents the mean of the resultant moving averages during τ, and τ includes m values, then the coefficient of variation (CV_τ) is approximated by

$$C_{V\tau} = \sqrt{\frac{\sum_\tau \left(\frac{ma_\tau}{mma} - 1\right)^2}{m}} \qquad \text{(III.4)}$$

On this basis, a structural inertiality index (SII_k) can be determined:

$$SII_k = \frac{CV_k}{CV_{max}} \qquad \text{(III.5)}$$

where CV_{max} is the maximum CV_τ. Again, the limits $0 \le SII_k \le 1$ are valid.

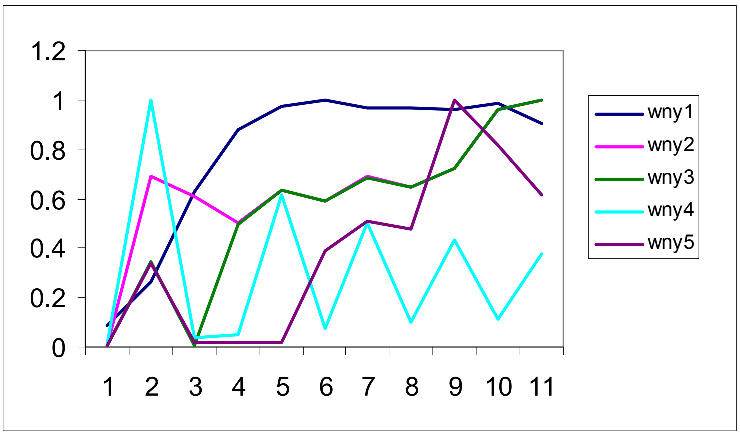
For the here examined wny_i series, these indices are given in Table 9.

Table 9
Structural inertiality indices

Number of terms	wny1	wny2	wny3	wny4	wny5	wny6	wny7	wny8	wny9	wny10
2	0.0852	0.00436	0.00415	0.01202	0.0049	0.00451	0.01102	1	0.88905	0.66662
3	0.26458	0.68798	0.34336	1	0.3392	0.94549	0.58212	0.37575	0.66656	1
4	0.62947	0.61167	0.00876	0.03815	0.02132	0.84091	0.01807	0.0239	0.59239	0.88901
5	0.87703	0.50056	0.49916	0.05121	0.02093	0.6884	0.42423	0.02881	0.72707	0.5456
6	0.97483	0.63539	0.63368	0.61693	0.01664	0.8741	0.35934	0.03134	0.82037	0.61561
7	1	0.59015	0.58862	0.07759	0.38731	0.81237	1	0.03333	0.95229	0.5717
8	0.96483	0.68838	0.68692	0.50556	0.50864	0.23136	0.29387	0.03292	1	0.62536
9	0.96491	0.64771	0.64661	0.09965	0.47895	0.43266	0.04925	0.03199	0.94132	0.58871
10	0.96113	0.72409	0.72327	0.43139	1	0.77187	0.25403	0.02941	0.98287	0.50789
11	0.98401	0.96255	0.96216	0.11167	0.81383	0.55163	0.08336	0.4398	0.80071	0.484
12	0.90759	1	1	0.37717	0.61652	1	0.08742	0.53326	0.72811	0.45529

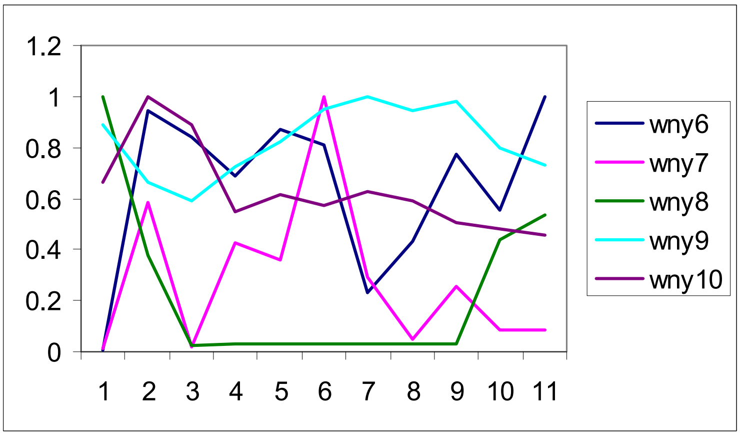
In comparison with ICI_k and TPI_k, the structural inertiality index (SII_k) depicts a more complicated picture. Graph SII1 refers to the series wny1-wny5.

Graph SII1



The situation does not change significantly for the series wny6-wny10, described in the Graph SII2.

Graph SII2



2.4. The indices of informational criterion, temporal relevance, and structural inertiality provide, therefore, contradictory signals. As a result, based on ICI_k, TPI_k, and SII_k as individual parameters, it would be difficult to consistently choose an optimal length of the moving average. Hereinafter, we shall try to aggregate them into a single composite selecting length index (SLI_k).

3. For such a goal, it is necessary to define the summation weights $s1_i$ (for ICI_k), $s2_i$ (for TPI_k), and $s3_i$ (for SII_k), under the restrictions $0 \le s1_i \le 1$, $0 \le s2_i \le 1$, $0 \le s3_i \le 1$, and $s1_i + s2_i + s3_i = 1$; obviously, i refers to the corresponding wny_i series (i=1, 2…10).

3.1. In order to estimate these summation weights, for each series wny_i, the following system is built:

$$SLI_{ki} = s1_i * ICI_{ki} + s2_i * TPI_{ki} + s3_i * SII_{ki} \quad k=2, 3 \ldots 12 \qquad (III.6)$$

$$\mathrm{MSLI_i} = \frac{1}{11} * \sum_k \mathrm{SLI_{ki}} \qquad \text{(III.7)}$$

$$\mathrm{VSL_i} = \frac{1}{11} * [\sum_k (\mathrm{SLI_{ki}} - \mathrm{MSLI_i})^2] \qquad \text{(III.8)}$$

$$\mathrm{STD}_i = \sqrt{\mathrm{VSL}_i} \qquad \text{(III.9)}$$

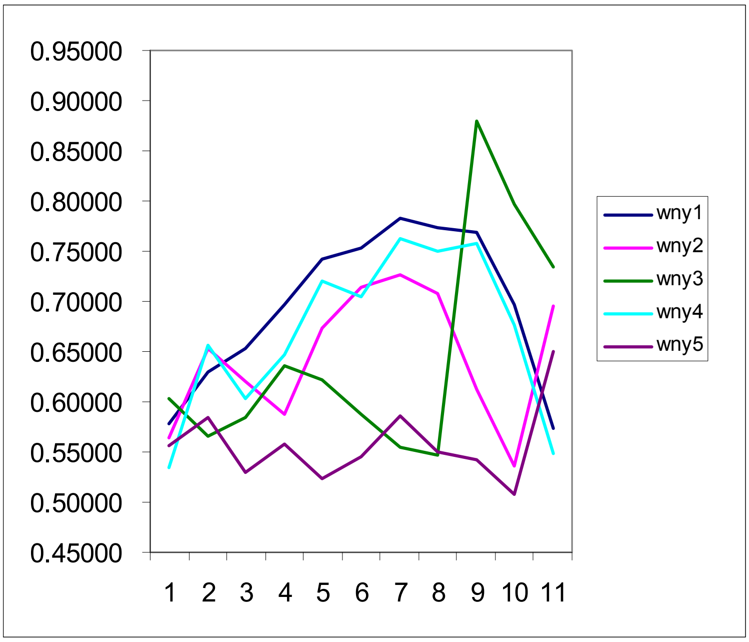
Our proposal is to solve the system by adding the minimization of the standard deviation as an objective function. The resultant summation weights s by this procedure are detailed in Table 10.

Table 10
Estimated summation weights s

Series	wyn1	wyn2	wyn3	wyn4	wyn5
ICI (s1)	0.42668	0.42953	0.41179	0.38829	0.43897
TPI (s2)	0.57332	0.37633	0.58821	0.51083	0.37517
SII (s3)	0	0.19414	0.00000	0.10089	0.18587
Series	wyn6	wyn7	wyn8	wyn9	wny10
ICI (s1)	0.38974	0.38227	0.32074	0.34398	0.22502
TPI (s2)	0.54771	0.56507	0.42645	0.49398	0.46296
SII (s3)	0.06255	0.05266	0.25281	0.16204	0.31202

3.2. Using these summation weights, the selecting length indices ($\mathrm{SLI_k}$) were determined for all $\mathrm{wny_i}$ (Annex 7). These are plotted on Graph SLI1 for wny1-wny5.

Graph SLI1

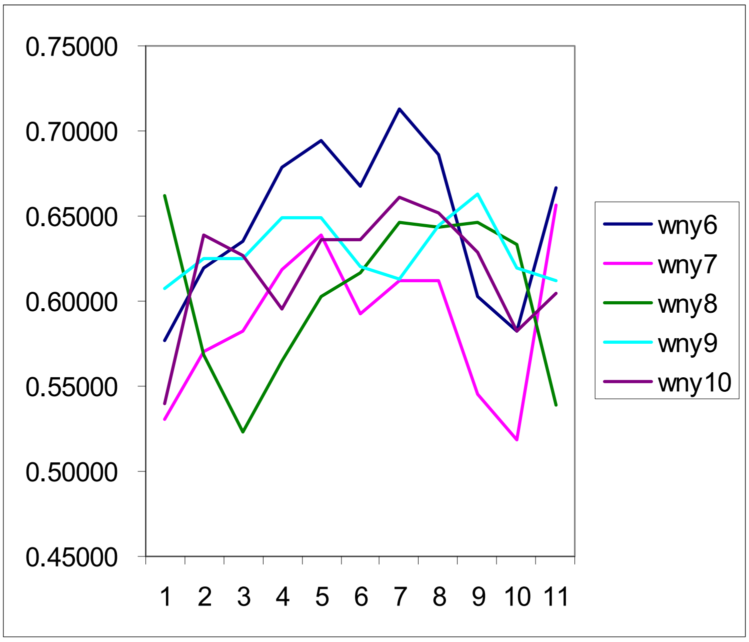


According to the proposed methodology, therefore, the preferable lengths of a Fisher weighted moving average would be

• 8 terms for wny1, wny2, and wny4;
• 10 terms for wny3; and
• 12 terms for wny5.

The selecting length indices for wny6-wny10 are presented in the Graph SLI2.

Graph SLI2



Now, in a better position are the moving averages with

• 8 terms for wny6 and wny10;
• 12 terms for wny7;
• 2 terms for wny8; and
• 10 terms for wny9.

3.3. Similar to the OLS application, the moving averages were also prolonged five years after sampling. The restriction $\Sigma wny_i=1$ was applied in the same manner as in the previous exercise.

Table 11
Forecasted wny_i by moving average for 5 post-sampling years

t	1	2	3	4	5
wny1	0.071049	0.068838	0.067093	0.065959	0.065802
wny2	-0.02955	-0.03001	-0.03026	-0.03047	-0.03054
wny3	0.022274	0.022474	0.022563	0.022587	0.022539
wny4	0.061389	0.060845	0.060416	0.060091	0.059997
wny5	0.030815	0.031238	0.031459	0.031466	0.031363
wny6	0.054259	0.055117	0.055817	0.056259	0.056392
wny7	-0.0567	-0.05813	-0.05898	-0.05969	-0.06002
wny8	0.187372	0.184453	0.183708	0.183274	0.183304
wny9	0.117852	0.118737	0.119181	0.11953	0.119601
wny10	0.541248	0.546442	0.549005	0.550994	0.551564
Sum	1	1	1	1	1

As expected, the projected evolution is more stable when compared with OLS estimations.

IV. Some concluding remarks

1. Under a given A matrix, the structure of the economy – represented by its sectoral output – can be approximated by starting from the I-O quadrant of resources utilization (demand-side approach), or from the sectoral final output vector (supply-side approach). If we have macroeconomic estimations for final (private and public) consumption, gross fixed capital formation, inventory changes, export, import, and gross value added, in order to determine the structure of the output, sectoral distributions are necessary:

- for six mentioned aggregates in the case of demand-side approach, and;
- only for final outputs, for the supply-side approach.

If the modelling objective refers preponderantly to the sectoral structure of output, then the supply-side approach seems to be more accessible.

2. In both cases, we can involve expert exogenous data or different statistical procedures. In terms of statistical procedures, the present paper has illustrated, on the one hand, the applicability of the regression technique and on the other hand, of linear weighted average (Fisher version). As a primary database, the Romanian I-O tables for 1989-2009 aggregated into 10 sectors were used.

3. The econometric specification referred to the weights of these sectors in the final output of the economy. The retained relationships were submitted to a large battery of tests concerning collinearity, heteroscedasticity, stationarity, and serial correlation. Several estimating techniques were also involved.

4. The paper sketches – as a discussion proposal – a methodology for the selection of optimal number of terms included in the moving average. This attempt takes into consideration the measure in which the resultant values reproduce the properties of the original statistical series. Further researches are necessary in this field.

5. Our application shows that - concerning the dynamic behavior of the estimated indicators - the econometric technique seems to be more sensitive than the moving average. Consequently, their possible combinations could be taken into consideration.

Annex 1 – Primary data

	wny1	wny2	wny3	wny4	wny5	wny6	wny7	wny8	wny9	wny10	Sum
1989	0,048262	-0,0527	0,012775	0,150968	0,147187	0,150087	-0,00015	0,178946	0,030189	0,334442	1
1990	0,168653	-0,05838	0,009659	0,133226	0,110923	0,137788	-0,02274	0,130723	0,048014	0,342128	1
1991	0,163945	-0,04206	0,004601	0,146278	0,089337	0,09898	-0,01931	0,097833	0,042035	0,41836	1
1992	0,167268	-0,04839	0,027633	0,140971	0,062975	0,085371	-0,00117	0,107102	0,052165	0,40608	1
1993	0,192613	-0,02476	0,017988	0,128219	0,066108	0,088558	0,019899	0,117318	0,059063	0,334998	1
1994	0,175469	-0,02455	0,010386	0,118841	0,059742	0,097298	0,033051	0,135045	0,080752	0,313964	1
1995	0,162887	-0,0311	0,022485	0,101425	0,034247	0,064415	-0,00502	0,12864	0,097971	0,42405	1
1996	0,155846	-0,04385	0,02543	0,104314	0,037467	0,050052	-0,03048	0,131919	0,118795	0,45051	1
1997	0,140337	-0,03904	0,032751	0,123863	0,035899	0,053298	-0,02317	0,114477	0,118364	0,443212	1
1998	0,132471	-0,027	0,019152	0,116699	0,024033	0,036631	-0,02006	0,108243	0,116542	0,493285	1
1999	0,120979	-0,02162	0,019357	0,102362	0,017935	0,02339	-0,04732	0,106375	0,123671	0,554869	1
2000	0,103072	-0,02981	0,021493	0,09348	0,028984	0,033551	-0,03166	0,105409	0,123697	0,551783	1
2001	0,137851	-0,02633	0,021078	0,094425	0,029625	0,041231	-0,05821	0,112644	0,125483	0,522205	1
2002	0,122762	-0,0243	0,021464	0,083853	0,036269	0,053189	-0,04913	0,117855	0,116775	0,521259	1
2003	0,111937	-0,02952	0,026023	0,073832	0,03965	0,045003	-0,05781	0,115624	0,120897	0,554363	1
2004	0,11768	-0,02642	0,023421	0,076871	0,039964	0,046082	-0,05545	0,120787	0,125531	0,531537	1
2005	0,08144	-0,03057	0,025577	0,069404	0,034704	0,053403	-0,05565	0,134625	0,127652	0,559409	1
2006	0,074536	-0,02922	0,024819	0,065893	0,03501	0,056554	-0,0554	0,142902	0,123876	0,561037	1
2007	0,059881	-0,02989	0,022166	0,059101	0,033058	0,058143	-0,06542	0,176494	0,123324	0,563143	1
2008	0,061008	-0,03183	0,020379	0,053667	0,024648	0,057437	-0,07251	0,203408	0,114925	0,568862	1
2009	0,056857	-0,03308	0,022693	0,060121	0,026784	0,060857	-0,0621	0,188315	0,119829	0,559727	1

Annex 2 – Unit root tests

	ADF		ADF		ADF		PP		PP		PP	
Exogenous	none		constant		constant, linear trend		none		constant		constant, linear trend	
Series	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
wny1	-0,49757	0,4877	-1,85453	0,3453	-8,82642	0	-0,49757	0,4877	-2,11812	0,2401	-8,95694	0
d(wny1)	-8,78457	0	-9,10973	0	-8,6088	0	-8,88132	0	-10,2238	0	-9,69526	0
d(wny1,2)	-7,88116	0	-7,71818	0	-8,05288	0	-17,3099	0,0001	-20,1353	0	-28,2034	0,0001
wny2	-1,44873	0,1328	-3,5946	0,0163	-3,00223	0,1569	-1,23316	0,1921	-2,6268	0,1043	-2,48099	0,3325
d(wny2)	-3,50489	0,0016	-3,57342	0,0185	-4,51826	0,0119	-5,28847	0	-5,33599	0,0004	-7,79111	0
d(wny2,2)	-5,82122	0	-5,83729	0,0003	-5,95033	0,0011	-18,6282	0,0001	-23,2492	0	-23,781	0,0001
wny3	-0,54466	0,4682	-3,04431	0,0486	-3,35893	0,0871	-0,23673	0,5883	-3,15783	0,0382	-3,65854	0,05
d(wny3)	-6,10752	0	-5,98995	0,0001	-5,92534	0,0007	-8,50594	0	-10,2451	0	-13,0772	0
d(wny3,2)	-5,60414	0	-5,31553	0,0008	-5,06679	0,0057	-16,7268	0,0001	-15,8331	0	-15,1331	0,0001
wny4	-2,38998	0,0197	-1,14369	0,6769	-3,97456	0,0288	-7,15596	0	-1,21447	0,6468	-2,96958	0,164
d(wny4)	-4,07833	0,0004	-4,65097	0,002	-4,51403	0,0111	-4,07883	0,0004	-6,00802	0,0001	-5,74147	0,001
d(wny4,2)	-4,61277	0,0002	-4,43228	0,0042	-4,20478	0,024	-10,3869	0,0001	-9,98937	0	-13,746	0
wny5	-1,11361	0,23	-6,23659	0,0001	-1,41598	0,8175	-5,1666	0	-18,0733	0	-10,0982	0
d(wny5)	-4,57211	0,0001	-4,18976	0,0055	-3,13714	0,1295	-3,92387	0,0005	-4,23813	0,0043	-5,03481	0,0038
d(wny5,2)	-5,45953	0	-5,63665	0,0003	-6,53563	0,0003	-7,72718	0	-8,93326	0	-12,4608	0
wny6	-2,78768	0,0079	-3,36236	0,0253	-1,89819	0,618	-2,79601	0,0077	-3,9569	0,0073	-2,91524	0,1786
d(wny6)	-3,15639	0,0033	-3,22737	0,0341	-5,22045	0,003	-3,11006	0,0037	-3,17357	0,0379	-6,21969	0,0004
d(wny6,2)	-5,85327	0	-5,77085	0,0003	-5,62966	0,0017	-7,26922	0	-9,19339	0	-11,5825	0
wny7	-0,2891	0,5689	-1,33336	0,593	-2,52211	0,3151	-0,20281	0,6006	-1,34804	0,5861	-2,58102	0,2911
d(wny7)	-4,66468	0,0001	-3,44427	0,0238	-3,23003	0,1116	-4,66445	0,0001	-4,61616	0,0019	-4,5236	0,0102
d(wny7,2)	-6,72343	0	-6,52754	0	-6,28587	0,0004	-16,9189	0,0001	-16,4021	0	-16,396	0,0001
wny8	-0,14912	0,6197	-1,28678	0,6146	-2,71697	0,2406	-0,2264	0,592	-1,792	0,3733	-2,69394	0,2487
d(wny8)	-3,61069	0,0011	-3,61859	0,0155	-3,05806	0,1435	-3,61069	0,0011	-3,68561	0,0135	-2,9579	0,1682
d(wny8,2)	-3,67769	0,001	-3,58325	0,0213	-2,63415	0,2728	-3,60864	0,0012	-3,4321	0,0235	-3,75512	0,0446
wny9	0,670172	0,8519	-2,7656	0,0811	-0,99212	0,9225	0,868327	0,8893	-2,65938	0,0984	-1,0224	0,9175
d(wny9)	-3,21374	0,0029	-3,4575	0,0215	-3,9309	0,0312	-3,26938	0,0025	-3,53678	0,0183	-3,95982	0,0296
d(wny9,2)	-7,96223	0	-7,65911	0	-7,45452	0,0001	-7,73633	0	-7,44974	0	-7,43856	0,0001
wny10	0,940482	0,9009	-1,47369	0,5258	-2,22116	0,4536	2,016917	0,9861	-1,45735	0,5338	-2,17269	0,4779
d(wny10)	-5,11521	0	-5,59069	0,0003	-5,39855	0,0022	-3,79103	0,0007	-5,16063	0,0006	-6,4748	0,0003
d(wny10,2)	-6,94631	0	-6,70584	0	-6,4562	0,0004	-8,59672	0	-9,0317	0	-8,64329	0

Annex 3 – System SySw

OLS

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,347946	0,049816	6,984678	0
c(2)	-0,420552	0,092465	-4,548209	0
c(3)	-0,331256	0,051712	-6,405835	0
c(4)	-0,015687	0,005449	-2,879071	0,0045
c(5)	-0,776813	0,221071	-3,513867	0,0006
c(6)	-0,141417	0,068127	-2,075803	0,0395
c(7)	0,033237	0,007182	4,627793	0
c(8)	-1,146095	0,231273	-4,955593	0
c(9)	-0,140158	0,046434	-3,018427	0,0029
c(10)	-0,014292	0,006137	-2,328897	0,0211
c(11)	-0,39046	0,076313	-5,11655	0
c(12)	0,155279	0,043831	3,542659	0,0005
c(13)	-0,897608	0,181288	-4,951277	0
c(14)	0,009537	0,002966	3,215898	0,0016
c(15)	-0,315006	0,050509	-6,236592	0
c(16)	0,011526	0,003254	3,541524	0,0005
c(17)	-0,201363	0,04482	-4,492747	0
c(18)	-0,230093	0,03684	-6,245803	0
c(19)	-0,056252	0,015986	-3,518716	0,0006
c(20)	-0,416294	0,129967	-3,203069	0,0016
c(21)	0,44973	0,131906	3,409474	0,0008
c(22)	0,520374	0,168229	3,093243	0,0023
c(23)	-0,219588	0,069397	-3,164221	0,0019
c(24)	0,089253	0,024743	3,607261	0,0004
c(25)	-0,362136	0,131883	-2,74588	0,0067
c(26)	-0,411774	0,121955	-3,376452	0,0009
c(27)	0,052974	0,011017	4,808415	0
c(28)	-0,276179	0,057352	-4,815548	0
c(29)	0,626097	0,186798	3,351736	0,001
c(30)	-0,110826	0,039257	-2,823086	0,0053
c(31)	0,223586	0,076059	2,93964	0,0038
c(32)	-1,311648	0,324631	-4,040423	0,0001
c(33)	-1,984356	0,44276	-4,481788	0
c(34)	-1,093953	0,296356	-3,691343	0,0003
c(35)	1,836526	0,612198	2,999891	0,0031

Annex 3 continued

Equation: d(wny1) = c(1) + c(2)*wny1(-1) + c(3)*T/(T+1)			
Observations: 20			
R-squared	0,754063	Mean dependent var	0,00043
Adjusted R-squared	0,72513	S.D. dependent var	0,032122
S.E. of regression	0,016841	Sum squared resid	0,004821
Durbin-Watson stat	2,100397		
Equation: d(wny2) = c(4) + c(5)*wny2(-1) + c(6)*wny6(-1)			
Observations: 20			
R-squared	0,428807	Mean dependent var	0,000981
Adjusted R-squared	0,361608	S.D. dependent var	0,008661
S.E. of regression	0,00692	Sum squared resid	0,000814
Durbin-Watson stat	2,12604		
Equation: d(wny3) = c(7) + c(8)*wny3(-1) + c(9)*wny6(-1)			
Observations: 20			
R-squared	0,591066	Mean dependent var	0,000496
Adjusted R-squared	0,542956	S.D. dependent var	0,007809
S.E. of regression	0,005279	Sum squared resid	0,000474
Durbin-Watson stat	1,882006		
Equation: d(wny4) = c(10) + c(11)*wny4(-1) + c(12)*wny1(-1) + c(13)			
*wny2(-1)			
Observations: 20			
R-squared	0,659118	Mean dependent var	-0,004542
Adjusted R-squared	0,595203	S.D. dependent var	0,009702
S.E. of regression	0,006173	Sum squared resid	0,00061
Durbin-Watson stat	2,088532		
Equation: d(wny5) = c(14) + c(15)*wny5(-1)			
Observations: 20			
R-squared	0,683628	Mean dependent var	-0,00602
Adjusted R-squared	0,666052	S.D. dependent var	0,012413
S.E. of regression	0,007173	Sum squared resid	0,000926
Durbin-Watson stat	2,333812		
Equation: d(wny6) = c(16) + c(17)*wny6(-1) + c(18)*d(wny10)			
Observations: 20			
R-squared	0,813574	Mean dependent var	-0,004462
Adjusted R-squared	0,791641	S.D. dependent var	0,014019
S.E. of regression	0,006399	Sum squared resid	0,000696
Durbin-Watson stat	2,157002		
Equation: d(wny7) = c(19) + c(20)*wny7(-1) + c(21)*wny4 + c(22)			
*d(wny6,2) + c(23)*d(wny10(-1))			
Observations: 19			
R-squared	0,686302	Mean dependent var	-0,002072
Adjusted R-squared	0,596674	S.D. dependent var	0,01692
S.E. of regression	0,010745	Sum squared resid	0,001616
Durbin-Watson stat	2,565741		

Annex 3 continued

Equation: d(wny8) = c(24) + c(25)*wny8(-1) + c(26)*wny4(-1)			
Observations: 20			
R-squared	0,451842	Mean dependent var	0,000468
Adjusted R-squared	0,387352	S.D. dependent var	0,01886
S.E. of regression	0,014762	Sum squared resid	0,003705
Durbin-Watson stat	1,240255		
Equation: d(wny9) = c(27) + c(28)*wny9(-1) + c(29)*wny2(-1)			
Observations: 20			
R-squared	0,577444	Mean dependent var	0,004482
Adjusted R-squared	0,527732	S.D. dependent var	0,009142
S.E. of regression	0,006283	Sum squared resid	0,000671
Durbin-Watson stat	1,648142		
Equation: d(wny10) = c(30) + c(31)*wny10(-1) + c(32)*d(wny2,2) +			
c(33)*d(wny6) + c(34)*d(wny6,2) + c(35)*d(wny9(-1))			
Observations: 19			
R-squared	0,881757	Mean dependent var	0,011453
Adjusted R-squared	0,83628	S.D. dependent var	0,041859
S.E. of regression	0,016937	Sum squared resid	0,003729
Durbin-Watson stat	1,916046		

Annex 3 continued

WLS

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,347946	0,045928	7,575947	0
c(2)	-0,420552	0,085249	-4,933226	0
c(3)	-0,331256	0,047676	-6,948103	0
c(4)	-0,015687	0,005023	-3,122791	0,0021
c(5)	-0,776813	0,203817	-3,811324	0,0002
c(6)	-0,141417	0,06281	-2,251525	0,0257
c(7)	0,033237	0,006621	5,019546	0
c(8)	-1,146095	0,213223	-5,375096	0
c(9)	-0,140158	0,04281	-3,273944	0,0013
c(10)	-0,014292	0,005489	-2,603786	0,0101
c(11)	-0,39046	0,068257	-5,720476	0
c(12)	0,155279	0,039204	3,960813	0,0001
c(13)	-0,897608	0,162149	-5,535696	0
c(14)	0,009537	0,002814	3,389854	0,0009
c(15)	-0,315006	0,047917	-6,573945	0
c(16)	0,011526	0,003	3,841322	0,0002
c(17)	-0,201363	0,041322	-4,873069	0
c(18)	-0,230093	0,033964	-6,774525	0
c(19)	-0,056252	0,013723	-4,09918	0,0001
c(20)	-0,416294	0,111563	-3,731463	0,0003
c(21)	0,44973	0,113227	3,971917	0,0001
c(22)	0,520374	0,144407	3,603519	0,0004
c(23)	-0,219588	0,05957	-3,686206	0,0003
c(24)	0,089253	0,022811	3,912624	0,0001
c(25)	-0,362136	0,12159	-2,978325	0,0033
c(26)	-0,411774	0,112437	-3,662276	0,0003
c(27)	0,052974	0,010157	5,215458	0
c(28)	-0,276179	0,052876	-5,223196	0
c(29)	0,626097	0,172219	3,635468	0,0004
c(30)	-0,110826	0,032472	-3,412945	0,0008
c(31)	0,223586	0,062914	3,553851	0,0005
c(32)	-1,311648	0,268525	-4,884633	0
c(33)	-1,984356	0,366238	-5,418217	0
c(34)	-1,093953	0,245137	-4,462617	0
c(35)	1,836526	0,506392	3,626692	0,0004

Annex 3 continued

Equation: d(wny1) = c(1) + c(2)*wny1(-1) + c(3)*T/(T+1)			
Observations: 20			
R-squared	0,754063	Mean dependent var	0,00043
Adjusted R-squared	0,72513	S.D. dependent var	0,032122
S.E. of regression	0,016841	Sum squared resid	0,004821
Durbin-Watson stat	2,100397		
Equation: d(wny2) = c(4) + c(5)*wny2(-1) + c(6)*wny6(-1)			
Observations: 20			
R-squared	0,428807	Mean dependent var	0,000981
Adjusted R-squared	0,361608	S.D. dependent var	0,008661
S.E. of regression	0,00692	Sum squared resid	0,000814
Durbin-Watson stat	2,12604		
Equation: d(wny3) = c(7) + c(8)*wny3(-1) + c(9)*wny6(-1)			
Observations: 20			
R-squared	0,591066	Mean dependent var	0,000496
Adjusted R-squared	0,542956	S.D. dependent var	0,007809
S.E. of regression	0,005279	Sum squared resid	0,000474
Durbin-Watson stat	1,882006		
Equation: d(wny4) = c(10) + c(11)*wny4(-1) + c(12)*wny1(-1) + c(13)			
*wny2(-1)			
Observations: 20			
R-squared	0,659118	Mean dependent var	-0,00454
Adjusted R-squared	0,595203	S.D. dependent var	0,009702
S.E. of regression	0,006173	Sum squared resid	0,00061
Durbin-Watson stat	2,088532		
Equation: d(wny5) = c(14) + c(15)*wny5(-1)			
Observations: 20			
R-squared	0,683628	Mean dependent var	-0,00602
Adjusted R-squared	0,666052	S.D. dependent var	0,012413
S.E. of regression	0,007173	Sum squared resid	0,000926
Durbin-Watson stat	2,333812		
Equation: d(wny6) = c(16) + c(17)*wny6(-1) + c(18)*d(wny10)			
Observations: 20			
R-squared	0,813574	Mean dependent var	-0,00446
Adjusted R-squared	0,791641	S.D. dependent var	0,014019
S.E. of regression	0,006399	Sum squared resid	0,000696
Durbin-Watson stat	2,157002		
Equation: d(wny7) = c(19) + c(20)*wny7(-1) + c(21)*wny4 + c(22)			
*d(wny6,2) + c(23)*d(wny10(-1))			
Observations: 19			
R-squared	0,686302	Mean dependent var	-0,00207
Adjusted R-squared	0,596674	S.D. dependent var	0,01692
S.E. of regression	0,010745	Sum squared resid	0,001616
Durbin-Watson stat	2,565741		

Annex 3 continued

Equation: d(wny8) = c(24) + c(25)*wny8(-1) + c(26)*wny4(-1)			
Observations: 20			
R-squared	0,451842	Mean dependent var	0,000468
Adjusted R-squared	0,387352	S.D. dependent var	0,01886
S.E. of regression	0,014762	Sum squared resid	0,003705
Durbin-Watson stat	1,240255		
Equation: d(wny9) = c(27) + c(28)*wny9(-1) + c(29)*wny2(-1)			
Observations: 20			
R-squared	0,577444	Mean dependent var	0,004482
Adjusted R-squared	0,527732	S.D. dependent var	0,009142
S.E. of regression	0,006283	Sum squared resid	0,000671
Durbin-Watson stat	1,648142		
Equation: d(wny10) = c(30) + c(31)*wny10(-1) + c(32)*d(wny2,2) +			
c(33)*d(wny6) + c(34)*d(wny6,2) + c(35)*d(wny9(-1))			
Observations: 19			
R-squared	0,881757	Mean dependent var	0,011453
Adjusted R-squared	0,83628	S.D. dependent var	0,041859
S.E. of regression	0,016937	Sum squared resid	0,003729
Durbin-Watson stat	1,916046		

Annex 3 continued

SUR

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,355425	0,038901	9,136695	0
c(2)	-0,460663	0,068483	-6,726651	0
c(3)	-0,333842	0,04213	-7,924038	0
c(4)	-0,017512	0,004511	-3,88223	0,0002
c(5)	-0,855068	0,155632	-5,494149	0
c(6)	-0,153611	0,048905	-3,141018	0,002
c(7)	0,03429	0,005205	6,588489	0
c(8)	-1,157882	0,160009	-7,236336	0
c(9)	-0,152763	0,038156	-4,003652	0,0001
c(10)	-0,015306	0,004849	-3,156866	0,0019
c(11)	-0,406511	0,051271	-7,928749	0
c(12)	0,188159	0,02799	6,722277	0
c(13)	-0,855844	0,135204	-6,329996	0
c(14)	0,009895	0,002771	3,571364	0,0005
c(15)	-0,323059	0,046704	-6,917199	0
c(16)	0,010985	0,002925	3,755611	0,0002
c(17)	-0,18959	0,039602	-4,78741	0
c(18)	-0,251489	0,030759	-8,176094	0
c(19)	-0,055918	0,011672	-4,790862	0
c(20)	-0,390748	0,092767	-4,21214	0
c(21)	0,450151	0,097443	4,619622	0
c(22)	0,496568	0,125003	3,972431	0,0001
c(23)	-0,210551	0,050693	-4,153487	0,0001
c(24)	0,086636	0,020614	4,202776	0
c(25)	-0,359571	0,105044	-3,423038	0,0008
c(26)	-0,390103	0,106642	-3,658052	0,0003
c(27)	0,05878	0,008357	7,033287	0
c(28)	-0,306302	0,045404	-6,746212	0
c(29)	0,708455	0,142846	4,959583	0
c(30)	-0,085789	0,02735	-3,136727	0,002
c(31)	0,175736	0,053433	3,28893	0,0012
c(32)	-1,201476	0,214677	-5,596677	0
c(33)	-1,970749	0,296757	-6,640948	0
c(34)	-0,773446	0,201248	-3,843257	0,0002
c(35)	1,363127	0,384794	3,542485	0,0005

Annex 3 continued

Equation: d(wny1) = c(1) + c(2)*wny1(-1) + c(3)*T/(T+1)			
Observations: 20			
R-squared	0,751292	Mean dependent var	0,00043
Adjusted R-squared	0,722032	S.D. dependent var	0,032122
S.E. of regression	0,016935	Sum squared resid	0,004876
Durbin-Watson stat	1,929745		
Equation: d(wny2) = c(4) + c(5)*wny2(-1) + c(6)*wny6(-1)			
Observations: 20			
R-squared	0,424202	Mean dependent var	0,000981
Adjusted R-squared	0,356461	S.D. dependent var	0,008661
S.E. of regression	0,006948	Sum squared resid	0,000821
Durbin-Watson stat	2,013371		
Equation: d(wny3) = c(7) + c(8)*wny3(-1) + c(9)*wny6(-1)			
Observations: 20			
R-squared	0,588717	Mean dependent var	0,000496
Adjusted R-squared	0,540331	S.D. dependent var	0,007809
S.E. of regression	0,005294	Sum squared resid	0,000476
Durbin-Watson stat	1,841925		
Equation: d(wny4) = c(10) + c(11)*wny4(-1) + c(12)*wny1(-1) + c(13) *wny2(-1)			
Observations: 20			
R-squared	0,640439	Mean dependent var	-0,004542
Adjusted R-squared	0,573021	S.D. dependent var	0,009702
S.E. of regression	0,00634	Sum squared resid	0,000643
Durbin-Watson stat	1,989437		
Equation: d(wny5) = c(14) + c(15)*wny5(-1)			
Observations: 20			
R-squared	0,68317	Mean dependent var	-0,00602
Adjusted R-squared	0,665569	S.D. dependent var	0,012413
S.E. of regression	0,007178	Sum squared resid	0,000927
Durbin-Watson stat	2,311227		
Equation: d(wny6) = c(16) + c(17)*wny6(-1) + c(18)*d(wny10)			
Observations: 20			
R-squared	0,809646	Mean dependent var	-0,004462
Adjusted R-squared	0,787252	S.D. dependent var	0,014019
S.E. of regression	0,006466	Sum squared resid	0,000711
Durbin-Watson stat	2,155728		
Equation: d(wny7) = c(19) + c(20)*wny7(-1) + c(21)*wny4 + c(22)			
*d(wny6,2) + c(23)*d(wny10(-1))			
Observations: 19			
R-squared	0,68297	Mean dependent var	-0,002072
Adjusted R-squared	0,592389	S.D. dependent var	0,01692
S.E. of regression	0,010802	Sum squared resid	0,001634
Durbin-Watson stat	2,57415		

Annex 3 continued

Equation: d(wny8) = c(24) + c(25)*wny8(-1) + c(26)*wny4(-1)			
Observations: 20			
R-squared	0,450727	Mean dependent var	0,000468
Adjusted R-squared	0,386107	S.D. dependent var	0,01886
S.E. of regression	0,014777	Sum squared resid	0,003712
Durbin-Watson stat	1,226536		
Equation: d(wny9) = c(27) + c(28)*wny9(-1) + c(29)*wny2(-1)			
Observations: 20			
R-squared	0,570186	Mean dependent var	0,004482
Adjusted R-squared	0,51962	S.D. dependent var	0,009142
S.E. of regression	0,006336	Sum squared resid	0,000683
Durbin-Watson stat	1,599359		
Equation: d(wny10) = c(30) + c(31)*wny10(-1) + c(32)*d(wny2,2) +			
c(33)*d(wny6) + c(34)*d(wny6,2) + c(35)*d(wny9(-1))			
Observations: 19			
R-squared	0,862468	Mean dependent var	0,011453
Adjusted R-squared	0,809572	S.D. dependent var	0,041859
S.E. of regression	0,018267	Sum squared resid	0,004338
Durbin-Watson stat	1,873431		

Annex 3 continued

2SLS

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,321759	0,056781	5,666681	0
c(2)	-0,304126	0,13946	-2,180742	0,0307
c(3)	-0,318185	0,055234	-5,760646	0
c(4)	-0,019364	0,008316	-2,328488	0,0212
c(5)	-1,03625	0,414401	-2,500596	0,0134
c(6)	-0,217042	0,113599	-1,910598	0,0579
c(7)	0,042299	0,009976	4,239927	0
c(8)	-1,415679	0,293991	-4,815382	0
c(9)	-0,195047	0,074334	-2,623925	0,0095
c(10)	-0,014634	0,008475	-1,726762	0,0862
c(11)	-0,458196	0,179313	-2,555282	0,0116
c(12)	0,210405	0,11555	1,820895	0,0705
c(13)	-0,895211	0,354586	-2,524668	0,0126
c(14)	0,00904	0,003811	2,372293	0,0189
c(15)	-0,30444	0,077146	-3,946277	0,0001
c(16)	0,016649	0,004372	3,808547	0,0002
c(17)	-0,278596	0,069738	-3,994873	0,0001
c(18)	-0,296052	0,104044	-2,845464	0,005
c(19)	-0,062866	0,02877	-2,185108	0,0304
c(20)	-0,459766	0,23433	-1,962041	0,0515
c(21)	0,505896	0,228943	2,209704	0,0286
c(22)	0,560651	0,213097	2,630969	0,0094
c(23)	-0,235236	0,074473	-3,158688	0,0019
c(24)	0,105522	0,038867	2,714966	0,0074
c(25)	-0,565262	0,236625	-2,388852	0,0181
c(26)	-0,313641	0,1542	-2,033993	0,0436
c(27)	0,064503	0,016696	3,863421	0,0002
c(28)	-0,313138	0,078413	-3,993439	0,0001
c(29)	0,873124	0,298082	2,929142	0,0039
c(30)	-0,116095	0,044712	-2,596484	0,0103
c(31)	0,234122	0,086419	2,709163	0,0075
c(32)	-1,042519	0,371276	-2,807934	0,0056
c(33)	-2,036676	0,465497	-4,375271	0
c(34)	-1,051822	0,307666	-3,418716	0,0008
c(35)	1,815241	0,713547	2,54397	0,0119

Annex 3 continued

Equation: d(wny1) = c(1) + c(2)*wny1(-1) + c(3)*T/(T+1)			
Instruments: wny8(-1) T/(T+1) c			
Observations: 20			
R-squared	0,731128	Mean dependent var	0,00043
Adjusted R-squared	0,699496	S.D. dependent var	0,032122
S.E. of regression	0,017609	Sum squared resid	0,005271
Durbin-Watson stat	2,395875		
Equation: d(wny2) = c(4) + c(5)*wny2(-1) + c(6)*wny6(-1)			
Instruments: d(wny9) wny5 c			
Observations: 20			
R-squared	0,377581	Mean dependent var	0,000981
Adjusted R-squared	0,304355	S.D. dependent var	0,008661
S.E. of regression	0,007224	Sum squared resid	0,000887
Durbin-Watson stat	1,802511		
Equation: d(wny3) = c(7) + c(8)*wny3(-1) + c(9)*wny6(-1)			
Instruments: d(wny3,2) wny9 c			
Observations: 19			
R-squared	0,548066	Mean dependent var	0,000686
Adjusted R-squared	0,491574	S.D. dependent var	0,007975
S.E. of regression	0,005686	Sum squared resid	0,000517
Durbin-Watson stat	1,376179		
Equation: d(wny4) = c(10) + c(11)*wny4(-1) + c(12)*wny1(-1) + c(13)			
*wny2(-1)			
Instruments: wny4(-2) d(wny9,2) d(wny9(-1)) c			
Observations: 19			
R-squared	0,61548	Mean dependent var	-0,00385
Adjusted R-squared	0,538576	S.D. dependent var	0,009443
S.E. of regression	0,006415	Sum squared resid	0,000617
Durbin-Watson stat	1,994574		
Equation: d(wny5) = c(14) + c(15)*wny5(-1)			
Instruments: wny5(-2) c			
Observations: 19			
R-squared	0,527534	Mean dependent var	-0,00443
Adjusted R-squared	0,499742	S.D. dependent var	0,010447
S.E. of regression	0,007389	Sum squared resid	0,000928
Durbin-Watson stat	2,34044		
Equation: d(wny6) = c(16) + c(17)*wny6(-1) + c(18)*d(wny10)			
Instruments: wny6(-2) wny10 c			
Observations: 19			
R-squared	0,782508	Mean dependent var	-0,00405
Adjusted R-squared	0,755321	S.D. dependent var	0,014278
S.E. of regression	0,007062	Sum squared resid	0,000798
Durbin-Watson stat	2,317022		

Annex 3 continued

Equation: d(wny7) = c(19) + c(20)*wny7(-1) + c(21)*wny4 + c(22)			
*d(wny6,2) + c(23)*d(wny10(-1))			
Instruments: wny7(-2) wny4(-1) d(wny10,2) d(wny10) c			
Observations: 19			
R-squared	0,6795	Mean dependent var	-0,00207
Adjusted R-squared	0,587929	S.D. dependent var	0,01692
S.E. of regression	0,010861	Sum squared resid	0,001652
Durbin-Watson stat	2,520842		
Equation: d(wny8) = c(24) + c(25)*wny8(-1) + c(26)*wny4(-1)			
Instruments: IP10(-1) wny9(-1) c			
Observations: 20			
R-squared	0,305167	Mean dependent var	0,000468
Adjusted R-squared	0,223422	S.D. dependent var	0,01886
S.E. of regression	0,01662	Sum squared resid	0,004696
Durbin-Watson stat	0,825886		
Equation: d(wny9) = c(27) + c(28)*wny9(-1) + c(29)*wny2(-1)			
Instruments: wny9(-2) d(wny2) c			
Observations: 19			
R-squared	0,521291	Mean dependent var	0,00378
Adjusted R-squared	0,461452	S.D. dependent var	0,008821
S.E. of regression	0,006473	Sum squared resid	0,00067
Durbin-Watson stat	1,476797		
Equation: D(WNY10) = C(30) + C(31)*WNY10(-1) + C(32)*D(WNY2,2) + C(33)*D(WNY6) + C(34)*D(WNY6,2) + C(35)*D(WNY9(-1))			
Instruments: WNY10(-2) D(WNY2) D(WNY6(-1)) D(WNY6) D(WNY9,2) C			
Observations: 19			
R-squared	0,873684	Mean dependent var	0,011453
Adjusted R-squared	0,825101	S.D. dependent var	0,041859
S.E. of regression	0,017506	Sum squared resid	0,003984
Durbin-Watson stat	2,081652		

Annex 3 continued

W2SLS

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,321759	0,052349	6,146378	0
c(2)	-0,304126	0,128576	-2,365347	0,0192
c(3)	-0,318185	0,050923	-6,248298	0
c(4)	-0,019364	0,007667	-2,5256	0,0125
c(5)	-1,03625	0,382059	-2,712277	0,0074
c(6)	-0,217042	0,104733	-2,072334	0,0399
c(7)	0,042299	0,009155	4,620353	0
c(8)	-1,415679	0,269785	-5,247441	0
c(9)	-0,195047	0,068214	-2,859356	0,0048
c(10)	-0,014634	0,00753	-1,943407	0,0537
c(11)	-0,458196	0,159324	-2,875875	0,0046
c(12)	0,210405	0,102669	2,04935	0,0421
c(13)	-0,895211	0,315058	-2,841421	0,0051
c(14)	0,00904	0,003605	2,507961	0,0132
c(15)	-0,30444	0,072973	-4,171957	0
c(16)	0,016649	0,004012	4,150268	0,0001
c(17)	-0,278596	0,063996	-4,353312	0
c(18)	-0,296052	0,095477	-3,100772	0,0023
c(19)	-0,062866	0,024696	-2,545574	0,0119
c(20)	-0,459766	0,201148	-2,285709	0,0236
c(21)	0,505896	0,196523	2,574228	0,011
c(22)	0,560651	0,182921	3,064986	0,0026
c(23)	-0,235236	0,063927	-3,67976	0,0003
c(24)	0,105522	0,035834	2,944794	0,0037
c(25)	-0,565262	0,218158	-2,591073	0,0105
c(26)	-0,313641	0,142165	-2,206175	0,0288
c(27)	0,064503	0,015321	4,210065	0
c(28)	-0,313138	0,071957	-4,35175	0
c(29)	0,873124	0,273539	3,191958	0,0017
c(30)	-0,116095	0,036985	-3,138997	0,002
c(31)	0,234122	0,071483	3,275218	0,0013
c(32)	-1,042519	0,307109	-3,394626	0,0009
c(33)	-2,036676	0,385045	-5,289444	0
c(34)	-1,051822	0,254492	-4,133027	0,0001
c(35)	1,815241	0,590225	3,075509	0,0025

Annex 3 continued

Equation: d(wny1) = c(1) + c(2)*wny1(-1) + c(3)*T/(T+1)			
Instruments: wny8(-1) T/(T+1) c			
Observations: 20			
R-squared	0,731128	Mean dependent var	0,00043
Adjusted R-squared	0,699496	S.D. dependent var	0,032122
S.E. of regression	0,017609	Sum squared resid	0,005271
Durbin-Watson stat	2,395875		
Equation: d(wny2) = c(4) + c(5)*wny2(-1) + c(6)*wny6(-1)			
Instruments: d(wny9) wny5 c			
Observations: 20			
R-squared	0,377581	Mean dependent var	0,000981
Adjusted R-squared	0,304355	S.D. dependent var	0,008661
S.E. of regression	0,007224	Sum squared resid	0,000887
Durbin-Watson stat	1,802511		
Equation: d(wny3) = c(7) + c(8)*wny3(-1) + c(9)*wny6(-1)			
Instruments: d(wny3,2) wny9 c			
Observations: 19			
R-squared	0,548066	Mean dependent var	0,000686
Adjusted R-squared	0,491574	S.D. dependent var	0,007975
S.E. of regression	0,005686	Sum squared resid	0,000517
Durbin-Watson stat	1,376179		
Equation: d(wny4) = c(10) + c(11)*wny4(-1) + c(12)*wny1(-1) + c(13)			
*wny2(-1)			
Instruments: wny4(-2) d(wny9,2) d(wny9(-1)) c			
Observations: 19			
R-squared	0,61548	Mean dependent var	-0,00385
Adjusted R-squared	0,538576	S.D. dependent var	0,009443
S.E. of regression	0,006415	Sum squared resid	0,000617
Durbin-Watson stat	1,994574		
Equation: d(wny5) = c(14) + c(15)*wny5(-1)			
Instruments: wny5(-2) c			
Observations: 19			
R-squared	0,527534	Mean dependent var	-0,00443
Adjusted R-squared	0,499742	S.D. dependent var	0,010447
S.E. of regression	0,007389	Sum squared resid	0,000928
Durbin-Watson stat	2,34044		
Equation: d(wny6) = c(16) + c(17)*wny6(-1) + c(18)*d(wny10)			
Instruments: wny6(-2) wny10 c			
Observations: 19			
R-squared	0,782508	Mean dependent var	-0,00405
Adjusted R-squared	0,755321	S.D. dependent var	0,014278
S.E. of regression	0,007062	Sum squared resid	0,000798
Durbin-Watson stat	2,317022		

Annex 3 continued

Equation: d(wny7) = c(19) + c(20)*wny7(-1) + c(21)*wny4 + c(22)			
*d(wny6,2) + c(23)*d(wny10(-1))			
Instruments: wny7(-2) wny4(-1) d(wny10,2) d(wny10) c			
Observations: 19			
R-squared	0,6795	Mean dependent var	-0,00207
Adjusted R-squared	0,587929	S.D. dependent var	0,01692
S.E. of regression	0,010861	Sum squared resid	0,001652
Durbin-Watson stat	2,520842		
Equation: d(wny8) = c(24) + c(25)*wny8(-1) + c(26)*wny4(-1)			
Instruments: IP10(-1) wny9(-1) c			
Observations: 20			
R-squared	0,305167	Mean dependent var	0,000468
Adjusted R-squared	0,223422	S.D. dependent var	0,01886
S.E. of regression	0,01662	Sum squared resid	0,004696
Durbin-Watson stat	0,825886		
Equation: d(wny9) = c(27) + c(28)*wny9(-1) + c(29)*wny2(-1)			
Instruments: wny9(-2) d(wny2) c			
Observations: 19			
R-squared	0,521291	Mean dependent var	0,00378
Adjusted R-squared	0,461452	S.D. dependent var	0,008821
S.E. of regression	0,006473	Sum squared resid	0,00067
Durbin-Watson stat	1,476797		
Equation: D(WNY10) = C(30) + C(31)*WNY10(-1) + C(32)*D(WNY2,2) + C(33)*D(WNY6) + C(34)*D(WNY6,2) + C(35)*D(WNY9(-1))			
Instruments: WNY10(-2) D(WNY2) D(WNY6(-1)) D(WNY6) D(WNY9,2) C			
Observations: 19			
R-squared	0,873684	Mean dependent var	0,011453
Adjusted R-squared	0,825101	S.D. dependent var	0,041859
S.E. of regression	0,017506	Sum squared resid	0,003984
Durbin-Watson stat	2,081652		

Annex 3 continued

3SLS

	Coefficient	Std. Error	t-Statistic	Prob.
c(1)	0,321759	0,052349	6,146378	0
c(2)	-0,304126	0,128576	-2,365347	0,0192
c(3)	-0,318185	0,050923	-6,248298	0
c(4)	-0,019364	0,007667	-2,5256	0,0125
c(5)	-1,03625	0,382059	-2,712277	0,0074
c(6)	-0,217042	0,104733	-2,072334	0,0399
c(7)	0,042299	0,009155	4,620353	0
c(8)	-1,415679	0,269785	-5,247441	0
c(9)	-0,195047	0,068214	-2,859356	0,0048
c(10)	-0,014634	0,00753	-1,943407	0,0537
c(11)	-0,458196	0,159324	-2,875875	0,0046
c(12)	0,210405	0,102669	2,04935	0,0421
c(13)	-0,895211	0,315058	-2,841421	0,0051
c(14)	0,00904	0,003605	2,507961	0,0132
c(15)	-0,30444	0,072973	-4,171957	0
c(16)	0,016649	0,004012	4,150268	0,0001
c(17)	-0,278596	0,063996	-4,353312	0
c(18)	-0,296052	0,095477	-3,100772	0,0023
c(19)	-0,062866	0,024696	-2,545574	0,0119
c(20)	-0,459766	0,201148	-2,285709	0,0236
c(21)	0,505896	0,196523	2,574228	0,011
c(22)	0,560651	0,182921	3,064986	0,0026
c(23)	-0,235236	0,063927	-3,67976	0,0003
c(24)	0,105522	0,035834	2,944794	0,0037
c(25)	-0,565262	0,218158	-2,591073	0,0105
c(26)	-0,313641	0,142165	-2,206175	0,0288
c(27)	0,064503	0,015321	4,210065	0
c(28)	-0,313138	0,071957	-4,35175	0
c(29)	0,873124	0,273539	3,191958	0,0017
c(30)	-0,116095	0,036985	-3,138997	0,002
c(31)	0,234122	0,071483	3,275218	0,0013
c(32)	-1,042519	0,307109	-3,394626	0,0009
c(33)	-2,036676	0,385045	-5,289444	0
c(34)	-1,051822	0,254492	-4,133027	0,0001
c(35)	1,815241	0,590225	3,075509	0,0025

Annex 3 continued

Equation: D(WNY1) = C(1) + C(2)*WNY1(-1) + C(3)*T/(T+1)			
Instruments: WNY8(-1) T/(T+1) C			
Observations: 20			
R-squared	0,731128	Mean dependent var	0,00043
Adjusted R-squared	0,699496	S.D. dependent var	0,032122
S.E. of regression	0,017609	Sum squared resid	0,005271
Durbin-Watson stat	2,395875		
Equation: D(WNY2) = C(4) + C(5)*WNY2(-1) + C(6)*WNY6(-1)			
Instruments: D(WNY9) WNY5 C			
Observations: 20			
R-squared	0,377581	Mean dependent var	0,000981
Adjusted R-squared	0,304355	S.D. dependent var	0,008661
S.E. of regression	0,007224	Sum squared resid	0,000887
Durbin-Watson stat	1,802511		
Equation: D(WNY3) = C(7) + C(8)*WNY3(-1) + C(9)*WNY6(-1)			
Instruments: D(WNY3,2) WNY9 C			
Observations: 19			
R-squared	0,548066	Mean dependent var	0,000686
Adjusted R-squared	0,491574	S.D. dependent var	0,007975
S.E. of regression	0,005686	Sum squared resid	0,000517
Durbin-Watson stat	1,376179		
Equation: D(WNY4) = C(10) + C(11)*WNY4(-1) + C(12)*WNY1(-1) + C(13) *WNY2(-1)			
Instruments: WNY4(-2) D(WNY9,2) D(WNY9(-1)) C			
Observations: 19			
R-squared	0,61548	Mean dependent var	-0,00385
Adjusted R-squared	0,538576	S.D. dependent var	0,009443
S.E. of regression	0,006415	Sum squared resid	0,000617
Durbin-Watson stat	1,994574		
Equation: D(WNY5) = C(14) + C(15)*WNY5(-1)			
Instruments: WNY5(-2) C			
Observations: 19			
R-squared	0,527534	Mean dependent var	-0,00443
Adjusted R-squared	0,499742	S.D. dependent var	0,010447
S.E. of regression	0,007389	Sum squared resid	0,000928
Durbin-Watson stat	2,34044		
Equation: D(WNY6) = C(16) + C(17)*WNY6(-1) + C(18)*D(WNY10)			
Instruments: WNY6(-2) WNY10 C			
Observations: 19			
R-squared	0,782508	Mean dependent var	-0,00405
Adjusted R-squared	0,755321	S.D. dependent var	0,014278
S.E. of regression	0,007062	Sum squared resid	0,000798
Durbin-Watson stat	2,317022		

Annex 3 continued

Equation: D(WNY7) = C(19) + C(20)*WNY7(-1) + C(21)*WNY4 + C(22) *D(WNY6,2) + C(23)*D(WNY10(-1))			
Instruments: WNY7(-2) WNY4(-1) D(WNY10,2) D(WNY10) C			
Observations: 19			
R-squared	0,6795	Mean dependent var	-0,00207
Adjusted R-squared	0,587929	S.D. dependent var	0,01692
S.E. of regression	0,010861	Sum squared resid	0,001652
Durbin-Watson stat	2,520842		
Equation: D(WNY8) = C(24) + C(25)*WNY8(-1) + C(26)*WNY4(-1)			
Instruments: IP10(-1) WNY9(-1) C			
Observations: 20			
R-squared	0,305167	Mean dependent var	0,000468
Adjusted R-squared	0,223422	S.D. dependent var	0,01886
S.E. of regression	0,01662	Sum squared resid	0,004696
Durbin-Watson stat	0,825886		
Equation: D(WNY9) = C(27) + C(28)*WNY9(-1) + C(29)*WNY2(-1)			
Instruments: WNY9(-2) D(WNY2) C			
Observations: 19			
R-squared	0,521291	Mean dependent var	0,00378
Adjusted R-squared	0,461452	S.D. dependent var	0,008821
S.E. of regression	0,006473	Sum squared resid	0,00067
Durbin-Watson stat	1,476797		
Equation: D(WNY10) = C(30) + C(31)*WNY10(-1) + C(32)*D(WNY2,2) + C(33)*D(WNY6) + C(34)*D(WNY6,2) + C(35)*D(WNY9(-1))			
Instruments: WNY10(-2) D(WNY2) D(WNY6(-1)) D(WNY6) D(WNY9,2) C			
Observations: 19			
R-squared	0,873684	Mean dependent var	0,011453
Adjusted R-squared	0,825101	S.D. dependent var	0,041859
S.E. of regression	0,017506	Sum squared resid	0,003984
Durbin-Watson stat	2,081652		

Annex 4 – BDS test

Series		Fraction of pairs		Standard deviation		Fraction of range	
	Dimension	Normal prob.	Bootstrap prob.	Normal Prob.	Bootstrap Prob.	Normal Prob.	Bootstrap Prob.
reswny1	2	0,4509	0,806	0,9224	0,756	0,3806	0,954
	3	0,7819	0,676	0,1026	0,148	0	0,425
	4	0,8107	0,824	0,1403	0,168	0	0,5734
	5	0,7163	0,892	0,1824	0,21	0	0,4698
	6	0,3884	0,956	0,3184	0,218	0,0004	0,6426
reswny2	2	0,9251	0,726	0,8717	0,8816	0,1769	0,4322
	3	0,9028	0,698	0,0246	0,3058	0,1661	0,5318
	4	0,4821	0,436	0,3668	0,8308	0,8811	0,8068
	5	0,2433	0,278	0,4682	0,959	0,6261	0,5406
	6	0,2362	0,234	0,7458	0,644	0,4891	0,4798
reswny3	2	0,2121	0,3532	0,0339	0,1676	0,2695	0,7798
	3	0,0319	0,1414	0,0655	0,2088	0,1325	0,8038
	4	0,0074	0,076	0,0448	0,1878	0,2937	0,6636
	5	0,0114	0,0836	0,0132	0,1506	0,05	0,5392
	6	0,0065	0,066	0,0064	0,1186	0,0026	0,4254
reswny4	2	0,287	0,612	0,3238	0,8546	0,4561	0,9518
	3	0,2893	0,6552	0,0063	0,3806	0,2189	0,9958
	4	0,0786	0,4136	0,0068	0,4052	0,0681	1
	5	0,7163	0,9144	0,2637	0,9814	0,0006	0,703
	6	0,9548	0,6608	0,459	0,822	0	0,5588
reswny5	2	0,9014	0,7896	0,2118	0,4314	0,2479	0,863
	3	0,2914	0,7592	0,0415	0,1662	0,1257	0,8872
	4	0,8544	0,7008	0,0668	0,2204	0,8084	0,813
	5	0,1853	0,3396	0,4533	0,6722	0,0008	0,4694
	6	0,0695	0,2264	0,5072	0,669	0	0,3308
reswny6	2	0,009	0,178	0,6802	0,7383	0,0072	0,299
	3	0,0176	0,178	0,0002	0,3049	0,0159	0,3164
	4	0,1587	0,348	0,0289	0,8648	0,0111	0,2884
	5	0,9005	0,734	0,0001	0,5097	0,0059	0,2432
	6	0,0588	0,598	0,0001	0,4663	0,8711	0,7288
reswny7	2	0,9371	0,812	0,9516	0,853	0,4017	0,7998
	3	0,4296	0,482	0,9793	0,7796	0,7405	0,9002
	4	0,4075	0,468	0,2934	0,6954	0,9035	0,726
	5	0,8205	0,634	0,2829	0,633	0,1987	0,8662
	6	0,9807	0,728	0,4201	0,709	0,6341	0,8816
reswny8	2	0,0234	0,186	0,0543	0,252	0,707	0,7938
	3	0,7986	0,6972	0,001	0,1018	0,0366	0,5974
	4	0,0654	0,4482	0,0001	0,0794	0	0,2214
	5	0,9411	0,7688	0	0,0392	0,0264	0,6182
	6	0,1194	0,2268	0	0,042	0,9257	0,8136
reswny9	2	0,3908	0,7458	0,8916	0,7846	0,551	0,9904
	3	0,0828	0,4018	0,1517	0,5666	0,0077	0,7732
	4	0,2073	0,6124	0,4613	0,9318	0,6748	0,8074
	5	0,2543	0,6926	0,8752	0,5644	0,0045	0,591
	6	0,1725	0,5836	0,5844	0,9856	0	0,491
reswny10	2	0,1613	0,5	0,0476	0,1074	0,397	0,77
	3	0,1003	0,42	0,1292	0,167	0,0906	0,5964
	4	0,2338	0,54	0,3645	0,2732	0,0262	0,5116
	5	0,2738	0,74	0,6691	0,948	0,0153	0,492
	6	0,0568	0,62	0,6955	0,8866	0,0146	0,5018

Annex 5 - Weights in Fisher linear moving average

t	Number of terms										
	2	3	4	5	6	7	8	9	10	11	12
t	0,66667	0,5	0,4	0,33333	0,28571	0,25000	0,22222	0,20000	0,18182	0,16667	0,15385
t-1	0,33333	0,33333	0,3	0,26667	0,23810	0,21429	0,19444	0,17778	0,16364	0,15152	0,14103
t-2		0,16667	0,2	0,20000	0,19048	0,17857	0,16667	0,15556	0,14545	0,13636	0,12821
t-3			0,1	0,13333	0,14286	0,14286	0,13889	0,13333	0,12727	0,12121	0,11538
t-4				0,06667	0,09524	0,10714	0,11111	0,11111	0,10909	0,10606	0,10256
t-5					0,04762	0,07143	0,08333	0,08889	0,09091	0,09091	0,08974
t-6						0,03571	0,05556	0,06667	0,07273	0,07576	0,07692
t-7							0,02778	0,04444	0,05455	0,06061	0,06410
t-8								0,02222	0,03636	0,04545	0,05128
t-9									0,01818	0,03030	0,03846
t-10										0,01515	0,02564
t-11											0,01282
Sum	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000	1,00000

From Jula, D. and N-M Jula, p. 50-54 for 4, 5, and 12 terms; the rest of weights have been completed by D. Jula in 2013

Annex 6 - AIC_k, τ_k , and CV_k parameters

	Number of terms	2	3	4	5	6	7	8	9	10	11	12
wny1	AIC	0,00015	0,00013	0,00023	0,00043	0,00061	0,00098	0,00158	0,00251	0,00396	0,00652	0,0111
	τ	6	8	9	11	13	14	16	17	19	20	22
	CV	0,0014	0,00436	0,01037	0,01445	0,01607	0,01648	0,0159	0,0159	0,01584	0,01622	0,01496
wny2	AIC	1,08E-05	2,7E-05	4,5E-05	7E-05	5,7E-05	4,9E-05	6,1E-05	7,7E-05	0,00013	0,00017	0,00012
	τ	6	6	7	9	10	11	12	13	14	13	14
	CV	0,00159	0,25019	0,22244	0,18203	0,23107	0,21461	0,25034	0,23555	0,26332	0,35004	0,36366
wny3	AIC	8,73E-06	2E-05	3E-05	2,2E-05	3,1E-05	4,2E-05	5,3E-05	6E-05	1,8E-05	2,3E-05	3,9E-05
	τ	6	7	9	9	10	11	12	13	14	13	14
	CV	0,00151	0,12495	0,00319	0,18165	0,2306	0,2142	0,24997	0,23531	0,2632	0,35014	0,36391
wny4	AIC	1,65E-05	4,6E-05	9,2E-05	0,00016	0,00026	0,00039	0,00049	0,00075	0,00134	0,0025	0,00465
	τ	6	7	9	11	12	14	15	17	18	20	21
	CV	0,0015	0,12495	0,00477	0,0064	0,07708	0,00969	0,06317	0,01245	0,0539	0,01395	0,04713
wny5	AIC	2,74E-05	7,3E-05	0,00013	0,00014	0,00023	0,00038	0,00038	0,00049	0,00071	0,00077	0,00049
	τ	6	9	9	11	13	12	13	14	12	14	17
	CV	0,0018	0,12494	0,00785	0,00771	0,00613	0,14266	0,18734	0,17641	0,36833	0,29975	0,22708
wny6	AIC	3,1E-05	0,00011	0,00015	0,00021	0,00034	0,0006	0,00082	0,00101	0,0015	0,00184	0,00142
	τ	6	6	7	9	10	11	15	15	15	17	16
	CV	0,00119	0,25011	0,22245	0,1821	0,23123	0,2149	0,0612	0,11445	0,20418	0,14592	0,26453
wny7	AIC	4,3E-05	0,00011	0,00021	0,00033	0,00043	0,00052	0,00079	0,001	0,00159	0,0028	0,00397
	τ	6	7	9	10	12	11	15	17	18	20	22
	CV	0,00237	0,12507	0,00388	0,09115	0,0772	0,21485	0,06314	0,01058	0,05458	0,01791	0,01878
wny8	AIC	5,1E-05	0,00014	0,0002	0,00035	0,00058	0,00089	0,0014	0,00222	0,00361	0,00604	0,01073
	τ	4	7	9	11	13	14	16	17	19	17	18
	CV	0,33331	0,12524	0,00797	0,0096	0,01045	0,01111	0,01097	0,01066	0,0098	0,14659	0,17774
wny9	AIC	1,5E-05	4,7E-05	0,00012	0,00022	0,0004	0,00058	0,00076	0,00072	0,00079	0,00107	0,00129
	τ	4	6	7	8	9	9	10	11	12	14	16
	CV	0,33335	0,24993	0,22211	0,27261	0,30759	0,35706	0,37495	0,35294	0,36852	0,30022	0,273
wny10	AIC	0,00026	0,00081	0,00126	0,00195	0,00292	0,00442	0,00649	0,00935	0,01516	0,02251	0,02505
	τ	4	4	5	8	9	10	11	12	14	15	17
	CV	0,33331	0,5	0,4445	0,2728	0,3078	0,28585	0,31268	0,29435	0,25394	0,242	0,22765

Annex 7 – SLI

Number of terms	wny1	wny2	wny3	wny4	wny5	wny6	wny7	wny8	wny9	wny10
2	0,57739	0,56370	0,60388	0,53407	0,55663	0,57677	0,53052	0,66181	0,60756	0,53965
3	0,63007	0,65353	0,56606	0,65563	0,58513	0,61979	0,57075	0,56877	0,62463	0,63872
4	0,65239	0,62107	0,58437	0,60333	0,53042	0,63525	0,58240	0,52273	0,62519	0,62725
5	0,69681	0,58683	0,63575	0,64729	0,55797	0,67894	0,61847	0,56436	0,64879	0,59561
6	0,74204	0,67360	0,62187	0,72074	0,52283	0,69470	0,63889	0,60312	0,64913	0,63596
7	0,75376	0,71422	0,58715	0,70417	0,54496	0,66741	0,59236	0,61684	0,62069	0,63601
8	0,78308	0,72711	0,55416	0,76309	0,58593	0,71303	0,61190	0,64642	0,61302	0,66145
9	0,77324	0,70719	0,54619	0,74955	0,55016	0,68633	0,61186	0,64393	0,64462	0,65155
10	0,76948	0,61317	0,87935	0,75770	0,54151	0,60287	0,54566	0,64675	0,66326	0,62859
11	0,69740	0,53632	0,79731	0,67682	0,50857	0,58222	0,51809	0,63305	0,61971	0,58230
12	0,57332	0,69565	0,73375	0,54888	0,65033	0,66664	0,65657	0,53882	0,61196	0,60502

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