

# Automatic Procedure of Building Congruent Dynamic Model in Gretl

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**Abstract.** In the last years we can observe intensive development of automatic model selection procedures. Best known are PcGets and RETINA. Such intensive work encourage to work on a new procedures. The concept of Congruent Modelling, formulated by Prof. Zygmunt Zieliński, is a very good framework for such development, including programming work, as well as many theoretical considerations. In the paper we present our concept of algorithm for automatic congruent modelling procedure and propose it's implementation in Gretl.

**Key words:** congruent dynamic modelling, automatic model selection, forecasting, PcGets, RETINA

## 1 Introduction

In article [3] there is a very interesting dialog between Prof. Granger and Prof. Hendry about PcGets – automatic model selection procedure described in [5]. Prof. Granger had formulated 20 questions concerning specification of GUM, simplification the GUM, testing economic theories, policy applications, nonstationarity, nonlinearity, multiple equation models and forecasting and asked Prof. Hendry how PcGets – automatic model selection procedure – handles with it.

That dialog shows how automatic model selection tools are important in contemporary econometrics, but also shows how difficult this area is. There are two major automatic model selection procedures – PcGets<sup>1</sup> and RETINA, described in [9]. The aim of this paper is formulation of algorithm for automatic

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<sup>1</sup> Since PcGive 12 and OxMetrics 5, PcGets is no longer available and current automatic model selection procedure is called Autometrics (see [2]). In this article we still use the former name, but all our considerations on PcGets refer to Autometrics as well.

model selection procedure based on congruent modelling approach and – as the next step – implementation that algorithm in Gretl<sup>2</sup>.

### 1.1 Idea of congruent modeling

The congruent modeling refers to building dynamic econometric models and was presented by Prof. Zygmunt Zieliński from Nicolaus Copernicus University from Toruń in 1984.

Many assumptions underlay the formulating of initial model specification. Some approaches refer to causal relationships, the other ones – to the internal structure of processes of interest with omission of causality, and others take both into account. The concept of congruent modeling, in Zieliński sense, refers to both approaches – casual relationship and internal structure of given processes<sup>3</sup>.

A model is congruent, according to Zieliński, if the harmonic structure of dependent process  $Y_t$  is the same as the joint harmonic structure of explanatory processes  $X_{it}$  ( $i = 1, 2, \dots, k$ ) and the residual process, which is independent of explanatory processes. This means that the variability of left side of model – ( $Y_t$ ) must be explained by the variability of right side of model – ( $X_{it}$ ). It is obvious that the model built for processes having white noise properties is always congruent:

$$\varepsilon_{yt} = \sum_{i=1}^k \rho_i \varepsilon_{x_{it}} + \varepsilon_t, \quad (1)$$

where  $\varepsilon_{yt}, \varepsilon_{x_{it}}$  and  $\varepsilon_t$  are white noises. Model (1) is congruent because harmonic structure of both sides of equation are equal or, in other words, the processes spectra are parallel to the frequency axis.

Let  $Y_t$  and  $X_{it}$  ( $i = 1, 2, \dots, k$ ) denote the endogenous process and explanatory processes respectively with the internal structure of:

- models describing non-stationary components:

$$\begin{aligned} Y_t &= P_{yt} + S_{yt} + \eta_{yt}, \\ X_{it} &= P_{x_{it}} + S_{x_{it}} + \eta_{x_{it}}, \end{aligned} \quad (2)$$

where  $P_{yt}, P_{x_{it}}$  are polynomial functions of variable  $t$ ,  $S_{yt}, S_{x_{it}}$  denote seasonal component with constant or changing in time amplitude of fluctuations and  $\eta_{yt}, \eta_{x_{it}}$  are stationary autoregressive processes for respective variables, and

<sup>2</sup> Any information about Gretl (Gnu Regression, Econometrics and Time-series), can be found in [1].

<sup>3</sup> More on congruent dynamic modelling one can find in: [13], [16], [14], [7], [11], [12].

– autoregressive processes:

$$B(u)\eta_{yt} = \varepsilon_{yt}, \quad (3)$$

$$A_i(u)\eta_{x_{it}} = \varepsilon_{x_{it}}, \quad (4)$$

where  $B(u)$ ,  $A_i(u)$  denote stationary autoregressive back shift operators for which all roots of equations  $|B(u)| = 0$  and  $|A_i(u)| = 0$  lie outside the unit root circle and  $\varepsilon_{yt}$ ,  $\varepsilon_{x_{it}}$  are white noises for respective processes.

Information about internal structure of  $Y_t$  and  $X_{it}$  processes enable to build the congruent dynamic econometric model by substituting  $\varepsilon_{yt}$  and  $\varepsilon_{x_{it}}$  in model (1) from models (3) and next for autoregressive processes in models (2). After transformations the congruent general dynamic econometric model is as follows:

$$B(u)Y_t = \sum_{i=1}^k A_i^*(u)X_{it} + P_t + S_t + \varepsilon_t, \quad (5)$$

where  $B(u)$ ,  $A_i^*(u)$  are autoregressive back shift operators,  $P_t$  is polynomial function of variable  $t$ ,  $S_t$  denotes seasonal component with constant or changing in time amplitude of fluctuations and  $\varepsilon_t$  is white noise. The white noise  $\varepsilon_t$  in model (5) has the same properties as white noise  $\varepsilon_t$  in model (1). Whole information of internal structure of all processes is taken into consideration. The variability of endogenous process  $Y_t$  is explained by variability of exogenous processes  $X_{it}$ , ( $i = 1, \dots, k$ ).

Described concept of building dynamic econometric model shows the necessity of including information about internal structure of given processes at the model specification stage.

## 1.2 Linear congruent model for intergrated processes

Let<sup>4</sup> assume that endogenous  $Y_t$  and exogenous  $X_{it}$  are intergrated processes with zero mean of order, respectively,  $d_y \geq 1$  and  $d_{x_i} \geq 1$ . It means, that:

$$\begin{aligned} Y_t^* &= (1 - u)^{d_y} Y_t = \Delta^{d_y} Y_t, \\ X_{it}^* &= (1 - u)^{d_{x_i}} X_{it} = \Delta^{d_{x_i}} X_{it}, \end{aligned} \quad (6)$$

are covariance stationary processes with zero mean, where  $u$  is such back shift operator, that  $u^s Z_t = Z_{t-s}$ . Processes  $Y_t^*$  and  $X_{it}^*$  can be expressed in AR notation:

$$\begin{aligned} B(u)Y_t^* &= \varepsilon_{yt}, \\ A_i(u)X_{it}^* &= \varepsilon_{x_{it}}, \end{aligned} \quad (7)$$

<sup>4</sup> This paragraph is based on [15] and [14].

where  $\varepsilon_{yt}$  and  $\varepsilon_{x_{it}}$  are white noises with zero mean,  $B(u)$  and  $A_i(u)$  are stationary autoregressive operators of order, respectively,  $p_y$  and  $q_{x_i}$ .

Operators:

$$\begin{aligned} B^*(u) &= B(u)(1-u)^{d_y} = 1 - \sum_{s=1}^{p_y+d_y} \alpha_s^* u^s = 1 - B_1^*(u), \\ A_i^*(u) &= A_i(u)(1-u)^{d_{x_i}} = 1 - \sum_{s=1}^{p_{x_i}+d_{x_i}} \gamma_s^* u^s = 1 - A_{i1}^*(u), \end{aligned} \quad (8)$$

are nonstationary autoregressive operators which satisfy condition, that  $d_y$  or  $d_{x_i}$  roots of  $B^*(z) = 0$  or  $A_i^*(z) = 0$  lie on a unit circle. Taking (8) into account, nonstationary processes  $Y_t$  and  $X_{it}$  can be expressed as:

$$\begin{aligned} Y_t &= B_1^*(u)Y_t + \varepsilon_{yt}, \\ X_{it} &= A_{i1}^*(u)X_{it} + \varepsilon_{x_{it}}. \end{aligned} \quad (9)$$

Linear congruent model (1), describing relationship between  $Y_t$  and  $X_{it}$ , can be write down in the following form:

$$Y_t = \sum_{i=1}^k \rho_i X_{it} - \sum_{i=1}^k \rho_i A_{i1}^*(u) X_{it} + B_1^* Y_t + \varepsilon_t, \quad (10)$$

Coefficient  $\rho$  in (10) is the same as in (1). Orders of autoregressions in model (10) are extended of orders of integration, which means, that lags of  $Y_t$  are equal to  $p_y + d_y$  and lags of  $X_{it}$  are equal to  $p_{x_i} + d_{x_i}$ .

## 2 General algorithm for automatic building congruent dynamic model

This is a very general algorithm for building congruent dynamic model, where only main stages are described without talking over any specific solutions, internal variables, used external functions and so on. This algorithm shows only a general idea of our procedure and it's compatibility with congruent dynamic econometric modelling procedure in Zieliński sense.

1. Getting outgoing data, setting following internal variables:
  - (a) Getting model variables: endogenous Y, list of explanatory X, list of deterministic (dummy) variables.
  - (b) Getting range of the sample and setting minimal degrees of freedom  $dfmin$  for starting general congruent model:

- i. if  $n < 200$ , then  $dfmin = round(0.1 \times n)$ ,
  - ii. if  $n \geq 200$ , then  $dfmin = 20$ .
- (c) Checking the frequency of time-series and setting:
  - i. deterministic cycle for consideration in pt. 2,
  - ii. maximum order  $pmax$  for autoregressive models in pt. 2c,
- 2. Analysis the internal structure of given processes:
  - (a) Checking, whether given processes have deterministic components.
  - (b) Checking, whether error terms after subtraction of deterministic components are integrated.
  - (c) Setting orders of autoregression for given processes, starting from a maximum order of  $pmax$ , after subtraction of deterministic components and differentiation if there was an integration.
- 3. Building starting specification of general unrestricted congruent model:
  - (a) Checking the degrees of freedom of starting general congruent model  $dfstart$ , taking into account all possible variables (lagged Y, current and lagged X, trend and/or cycle, deterministic variables):
    - i. if  $dfstart < dfmin$ , then maximum order of autoregressive model(s), specified in pt. 2c, is decreased by 1,
    - ii. if  $dfstart \geq dfmin$ , then the starting general model is stored in Gretl session.
- 4. Building congruent empirical model (specific):
  - (a) Specified in pt. 3 starting congruent general model is reduced according to a *posterior* procedure of variable selection with use of  $t$  statistics.
  - (b) Congruent empirical model is stored in Gretl session.

At **stage 1**, we just import dataset for model: endogenous Y, list of “normal” explanatory X and some deterministic (dummy) variables, which indicate some special moments, i.e. free days. For next stages, we check dataset structure.

At **stage 2** we perform the analysis of internal structure of explained process  $Y_t$  and explanatory processes  $X_{it}$ . We are looking for deterministic components: time trend and periodicity. We assume, that we only check presence of linear trend and “typical” periodicity for given data: seasonality for monthly or quarterly time-series, 1 year (52 weeks) cycle for weekly time-series and 1 week cycle for daily data. After that we subtract deterministic components from analyzed processes and perform ADF test. If there is an integration, we difference series and examine order of autoregression of all time-series.

At **stage 3** we formulate starting congruent general model and check, if we have sufficient degrees of freedom for running OLS estimation. This is crucial, that we want at least  $0.1 \times n$  degrees of freedom or, if series have more than 200 observations, at least 20. If we can’t meet this condition, maximum order

of autoregressive models is decreased by 1, so we earn at least 2 degrees of freedom at each reduction.

At **stage 4** we perform OLS estimation of coefficients of starting general congruent model with strategy of model reduction based on *a posterior* elimination with *t* statistics as a criterion. Empirical congruent model build on above algorithm always has white noise error terms.

### 3 Comparison of Congruent Modelling algorithm vs. PcGets vs. RETINA

In this section there are shown some similarities and differences between algorithm based on congruent dynamic modelling theory and approaches in PcGets and RETINA. PcGets and RETINA comparison one can find in [10] and tables (1)-(9) are based on it. There are just delivered suitable information about our approach, so comparison of that three automatic model selection procedures is now possible and easy. Comparison of General-to-Specific vs. Congruent Modelling one can find in [8].

**Table 1.** Goals

PcGets	RETINA	Congruent Modelling
1. Select a parsimonious undominated representation of an overly general initial model, the general unrestricted model (GUM).	1. Identify a parsimonious set of transformed attributes likely to be relevant for predicting out-of-sample.	1. Congruent general model is reduced parsimonious congruent model in Zieliński sense, which means error term of white noise properties.
2. Best model fit within sample.		2. Very good behavior in prediction out of the sample.
3. Congruent with theory.		3. Congruent with theory.

In congruent modelling we believe, that DGP is nested in the starting general model and reduction irrelevant variables can discover it. This is very similar to general-to-specific approach, but the starting general model is formulated in different ways. Starting specification is based on theory and extended of information about internal structure of given processes, including deterministic components, integration and autoregression. Autoregressive models can have different starting order, which is the biggest difference with general-to-specific approach.

In congruent modelling we start with congruent general model and step by step this model is reduced to congruent empirical model with white noise error

**Table 2.** Strategy

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
<ol style="list-style-type: none"> <li>1. General to specific.</li> <li>2. Formulate a GUM and reduce it to a parsimonious model using residual tests and hypothesis testing on coefficients.</li> </ol>	<ol style="list-style-type: none"> <li>1. Specific to general: Start from a model with a single transform. Add additional transforms only if they contribute to out-of-sample forecast ability.</li> <li>2. Flexible and parsimonious model.</li> <li>3. Selective search of transforms.</li> <li>4. Control for collinearity.</li> </ol>	<ol style="list-style-type: none"> <li>1. Congruent general model is reduced to congruent empirical model.</li> <li>2. Elimination insignificant variables using <i>a posterior</i> procedure based on <i>t</i> statistics.</li> <li>3. Empirical model is parsimonious.</li> </ol>

term. As a strategy we use *t* statistics which has sufficient power to discover DGP (see numerical experiment).

**Table 3.** Base Model

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
<ol style="list-style-type: none"> <li>1. GUM: specified by the researcher, usually based on theory. May use transforms of the original variables.</li> </ol>	<ol style="list-style-type: none"> <li>1. Based on original inputs and transforms, automatically selected from the first subsample by cross-validation in the second, controlling for collinearity.</li> </ol>	<ol style="list-style-type: none"> <li>1. Specification of starting general congruent is based on a theory and extended of information of internal structure of all included processes.</li> <li>2. Congruent model may use transformed processes.</li> </ol>

Base model is formulated on two basis: theory, which gives us causal relationships between variables and on the internal structure of all processes. This guarantee, that hole variability of  $Y_t$  and all  $X_{it}$  processes is included, so model is congruent (error term has white noise properties).

Congruent modelling assumes linear in parameters model, but variables can be log-transformed. Model can be nonlinear in variables, so congruent modelling gives maximum flexibility.

Starting congruent general model is unrestricted and, because of specification, based on the internal structure of all processes, overparametrized, but step by step model is being reduced with use of *t* statistics and *a posterior* procedure. Final (empirical) congruent model is parsimonious.

**Table 4.** Flexibility

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. The GUM determines maximum flexibility. May include transforms of the original variables.	1. The permitted transformations of the inputs determine maximum flexibility. 2. The actual flexibility of the candidate model is chosen by the procedure.	1. Congruent general model is unrestricted, so it gives maximum flexibility.

**Table 5.** Selective/Systematic Search

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. Starting from the GUM, performs a systematic search using multiple reduction paths. 2. Using diagnostics, checks the validity of each reduction until terminal selection. 3. When all paths are explored, repeatedly tests models against their union until a unique final model is obtained.	1. Uses a selective search to avoid the heavy task of evaluating all $2^m$ possible models and of applying some form of model selection. 2. A saliency feature of the transforms, such as the correlation with the dependent variable, is used to construct a natural order of the transforms in which they are considered. 3. Only a number of candidate models of order proportional to $m$ is considered.	1. Starting from congruent general model and reduce it by eliminating irrelevant variables with $t$ statistics.

**Table 6.** Colinearity

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. Seeks to formulate the GUM, in search for a relatively orthogonal specification. 2. A quick modeler option is available in PcGets for nonexpert users.	1. Controls for collinearity by adding an additional transform to the candidate list only if the collinearity is below a certain (user defined) threshold.	1. Collinearity is controlled by GRETL.

**Table 7.** Explanatory Variables

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. Original variables and transformations specified in the GUM.	1. Original variables and non-linear transformations allowed for by the procedure.	1. Original variables and handmade transformations specified at the beginning of procedure.



**Table 8.** Linearity

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. Linear or nonlinear in the parameters, as specified by the GUM.	1. Linear in the parameters.	1. Linear in the parameters.
2. Linear or nonlinear in the underlying variables, as specified by the GUM.	2. Linear or nonlinear in the underlying variables.	2. Linear or nonlinear in the underlying variables.

Congruent model assumes linearity in parameters, so computation is simple (we use OLS estimation). Transformations of variables are allowed, so starting general model can be nonlinear in the underlying variables.

**Table 9.** Types of Data Applicable So Far

<b>PcGets</b>	<b>RETINA</b>	<b>Congruent Modelling</b>
1. Time series or cross-section.	1. Mainly cross-section at present (no obstacles to its application in a time series context).	1. Time-series.

Congruent modelling is applicable to time-series and cross-section data as well, but our automatic procedure assumes time-series only. Congruent modelling approach is also applicable to multiple equation systems, including simultaneous equation models, but automatic procedure for it would be very complicated (but not impossible).

#### 4 Numerical experiment

To introduce the efficiency of model selection using the congruent modeling postulate there is numerical experiment presented. The experiment is based on Monte Carlo simulations. The scenario of experiment is summarized in table (10).

We assume situation (which is actually very common real case), that we do not have any observations of  $Z_t$  process, which is the component of DGP process. Because of autoregressive internal structure of  $X$  and  $Z$  processes ( $X_t, Z_t \sim AR(1)$ ), specification of starting congruent general model in table (10) was based on internal autoregressive structure of  $X_t \sim AR(1)$  and  $Y_t \sim AR(2)$  or  $AR(3)$ , as a result of combination of two  $AR(1)$  processes (see [4]).

For both scenarios following steps were realized:

**Table 10.** Experimental design

<b>DGP</b>	
$Y_t = 3X_t + 3Z_t + \varepsilon_{yt}$	$\varepsilon_{yt} \sim IN(0, \sigma_y^2)$
$X_t = \beta_x X_{t-1} + \varepsilon_{xt}$	$\varepsilon_{xt} \sim IID(0, 1)$
$Z_t = \beta_z Z_{t-1} + \varepsilon_{zt}$	$\varepsilon_{zt} \sim IID(0, 1)$
$\varepsilon_{xt} = \rho \varepsilon_{zt}$	$t = 1, 2, \dots, n$
<b>Congruent General Model</b>	
$Y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_{t-1} + \alpha_3 Y_{t-1} + \alpha_4 Y_{t-2} + \alpha_5 Y_{t-3} + \varepsilon_t$	$\varepsilon_t \sim IID$
<b>Experiment A</b> ( $\alpha = 0.01$ ) – table (11)	
<b>DGP:</b>	
$n = \{300, 120, 60, 20\}$	
$\rho = \{0.0, 0.2, 0.4, 0.6, 0.8\}, \sigma_y = \{1, 3\}$	
$\beta_x = \{0.6, 0.8, 0.95\}, \beta_z = \{0.6, 0.8, 0.95\}$	
<b>Experiment B</b> ( $\alpha = 0.05$ ) – table (12)	
<b>DGP:</b>	
$n = \{300, 120, 60, 20\}$	
$\rho = \{0.0, 0.2, 0.4, 0.6, 0.8\}, \sigma_y = \{1, 3\}$	
$\beta_x = \{0.6, 0.8, 0.95\}, \beta_z = \{0.6, 0.8, 0.95\}$	

1. Coefficients of the starting congruent general model, specified according to congruence postulate and formulated in table (10), was estimated by OLS method.
2. Elimination of insignificant processes was based on  $t$ -Student statistics and realized according to *a posterior* procedure at significance level of  $\alpha = \{0.01, 0.05\}$ .
3. Encompassing  $J$  test was run verifying the null hypothesis that the empirical model is special case of DGP. The number of not rejected null hypothesis was compared.

Tables (11) and (12) present percentage of non rejection the null hypothesis that the empirical congruent model is a special case of DGP. Results of  $J$  test show, that for samples of  $n = \{300, 120\}$  all cases of empirical congruent models, which were build without relevant process  $Z_t$  (one of the components of DGP process), was a special case of the data generating process. For samples  $n = 60$  and noise  $\varepsilon \sim N(0, 1)$  percentage of discover of DGP was 99%–100% and for noise  $\varepsilon \sim N(0, 9)$  it was 87%–100%. For samples  $n = 20$  percentage of discovering DGP was much lower and for noise  $\varepsilon \sim N(0, 1)$  it was 70%–95% and for noise  $\varepsilon \sim N(0, 9)$  it was 41%–88%.

So the conclusion is, that *a posterior* elimination procedure based on  $t$  statistics has sufficient power and even for small samples, percentage of discovering DGP is still relatively high and has a value of about 70%–80%.

**Table 11.** Percentage of not rejecting the null hypothesis assuming that congruent model is special case of DGP for  $\alpha = 0.01$ 

n	$\varepsilon_t$	$\rho$	$\beta_x=0,6$			$\beta_x=0,8$			$\beta_x=0,95$		
			$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$	$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$	$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$
n=300	$\varepsilon_t(0, 1)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
n=120	$\varepsilon_t(0, 1)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
n=60	$\varepsilon_t(0, 1)$	$\rho=0,0$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.87	0.98	1.00	0.98	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	0.92	0.98	1.00	0.99	1.00	1.00	0.99	1.00	1.00
		$\rho=0,4$	0.92	0.98	1.00	0.99	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	0.94	0.99	1.00	0.98	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.95	0.99	1.00	0.98	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.95	0.99	1.00	0.98	1.00	1.00	1.00	1.00	1.00
n=20	$\varepsilon_t(0, 1)$	$\rho=0,0$	0.85	0.85	0.92	0.83	0.89	0.93	0.88	0.91	0.96
		$\rho=0,2$	0.76	0.86	0.91	0.81	0.88	0.94	0.87	0.91	0.95
		$\rho=0,4$	0.75	0.83	0.87	0.82	0.88	0.92	0.85	0.92	0.95
		$\rho=0,6$	0.73	0.83	0.86	0.84	0.88	0.92	0.87	0.90	0.94
		$\rho=0,8$	0.70	0.80	0.83	0.82	0.88	0.90	0.84	0.90	0.93
		$\rho=0,8$	0.70	0.80	0.83	0.82	0.88	0.90	0.84	0.90	0.93
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.61	0.68	0.75	0.73	0.81	0.84	0.81	0.87	0.88
		$\rho=0,2$	0.54	0.66	0.72	0.67	0.78	0.79	0.77	0.82	0.85
		$\rho=0,4$	0.51	0.59	0.70	0.63	0.72	0.79	0.72	0.80	0.82
		$\rho=0,6$	0.47	0.56	0.67	0.59	0.67	0.75	0.72	0.80	0.79
		$\rho=0,8$	0.41	0.51	0.56	0.54	0.60	0.68	0.66	0.71	0.73
		$\rho=0,8$	0.41	0.51	0.56	0.54	0.60	0.68	0.66	0.71	0.73

**Table 12.** Percentage of not rejecting the null hypothesis assuming that congruent model is special case of DGP for  $\alpha = 0.05$

n	$\varepsilon_t$	$\rho$	$\beta_x=0,6$			$\beta_x=0,8$			$\beta_x=0,95$		
			$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$	$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$	$\beta_z=0,6$	$\beta_z=0,8$	$\beta_z=0,95$
n=300	$\varepsilon_t(0, 1)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
n=120	$\varepsilon_t(0, 1)$	$\rho=0,0$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
n=60	$\varepsilon_t(0, 1)$	$\rho=0,0$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,2$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,4$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.89	0.98	1.00	0.98	0.99	1.00	1.00	1.00	1.00
		$\rho=0,2$	0.91	0.98	1.00	0.98	1.00	1.00	0.99	1.00	1.00
		$\rho=0,4$	0.93	0.99	1.00	0.98	1.00	1.00	1.00	1.00	1.00
		$\rho=0,6$	0.93	0.99	1.00	0.98	1.00	1.00	0.99	1.00	1.00
		$\rho=0,8$	0.95	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00
		$\rho=0,8$	0.95	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00
n=20	$\varepsilon_t(0, 1)$	$\rho=0,0$	0.73	0.85	0.91	0.80	0.89	0.92	0.84	0.92	0.94
		$\rho=0,2$	0.73	0.81	0.87	0.78	0.89	0.93	0.88	0.91	0.91
		$\rho=0,4$	0.70	0.82	0.85	0.79	0.86	0.90	0.84	0.90	0.91
		$\rho=0,6$	0.72	0.77	0.84	0.77	0.88	0.89	0.81	0.90	0.92
		$\rho=0,8$	0.70	0.76	0.81	0.80	0.87	0.88	0.82	0.87	0.93
		$\rho=0,8$	0.70	0.76	0.81	0.80	0.87	0.88	0.82	0.87	0.93
	$\varepsilon_t(0, 3)$	$\rho=0,0$	0.53	0.61	0.70	0.62	0.72	0.77	0.76	0.79	0.82
		$\rho=0,2$	0.50	0.57	0.68	0.61	0.69	0.77	0.70	0.77	0.83
		$\rho=0,4$	0.51	0.57	0.65	0.57	0.69	0.77	0.68	0.75	0.83
		$\rho=0,6$	0.45	0.55	0.65	0.59	0.67	0.72	0.66	0.76	0.79
		$\rho=0,8$	0.41	0.47	0.56	0.52	0.55	0.64	0.64	0.70	0.70
		$\rho=0,8$	0.41	0.47	0.56	0.52	0.55	0.64	0.64	0.70	0.70

## 5 Summary

In the paper we discussed power of the congruent modelling concept and it is intrinsic features for being the base for automatic model selection procedure. Although we formulated full algorithm for such procedure, our considerations was theoretical. So the next stage of our work will be implementation this algorithm in Gretl. Our automatic procedure will:

1. Investigate internal trend-seasonal-autoregressive structure for all processes.
2. Formulate congruent general model on the basis of initial list of explanatory extended of it's internal components.
3. Run OLS estimation and eliminate insignificant variables according to a *posterior* procedure based on *t* statistics.
4. Store empirical congruent model in Gretl session.

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