Table of Contents

Go Back

AUTOREGRESSIVE MODELS AND SYSTEM DYNAMICS. A CASE STUDY FOR THE LABOR MARKET IN SPAIN.

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Extended Abstract

A general description of the autoregressive models (AR) could be given by saying that these models explain, partially at least, the values of a variable or set of variables, based on the past values of this variable or set of variables. Lately, AR models have increased their presence and importance within the field of economic and econometric analysis. It has been found that this kind of simple models, with a small number of variables and parameters, can seriously compete in terms of their prediction capabilities, with the large macroeconomic models with hundreds of variables and parameters, developed during the fifties and sixties.

This paper tries to show how System Dynamics (SD) models may easily incorporate fundamental elements of AR models. We first review the different elements of AR models with increasing complexity: a single variable AR model; vector autoregressive models (VAR) considering a vector with several variables; and structural vector autoregressive (SVAR) models, where several economy theory elements can be considered. As an illustration, we present a case study for the labor market in Spain. We explain the fundamentals of the problem and the formulation of the corresponding SVAR model. Finally, we develop the model within the framework of system dynamics.

We do believe this work is a good example of how system dynamics and econometric models can be considered as complementary analysis tools, in order to deal effectively with these complex problems.

Keywords: Autoregressive models, system dynamics, labor market .

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1. Introduction to AR models

As we have mentioned above, the more simple AR models have only one variable, where the value of the variable is expressed as a function of the previous values of the variable. This can be formulated as follows:

$$y_t = f_1\, y_{t-1} + f_2\, y_{t-2} + \ldots + f_p\, y_{t-p} + c + e_t \qquad [1]$$

where $y_t, y_{t-1}, \ldots, y_{t-p}$ are the values of the variable y in periods $t, t\text{-}1, \ldots, t\text{-}p$; $f_1, f_2, \ldots, f_p$ and c are parameters and a constant that can be estimated; and e_t is a random perturbation term, also called *innovation,* as this is the only new information that enters in period t, with respect to what it is already available from previous periods. The model in [1] is denoted $AR(p)$, where the *order* p is the number of time lags of the model. Using the lag operator L defined as follows:

$$L\, x_t \equiv x_{t-1}; \quad L^2\, x_t \equiv x_{t-2}; \ldots; \quad L^p\, x_t \equiv x_{t-p}; \qquad [2]$$

equation [1] can be written:

$$(1 - f_1 L - f_2 L^2 - \ldots - f_p L^p)\, y_t = f(L)\, y_t = c + e_t \qquad [3]$$

where $f(L)$ is a polynomial in the lag operator:

$$f(L) = 1 - f_1 L - f_2 L^2 - \ldots - f_p L^p \qquad [4]$$

AR models are very closely related to moving average *MA(q)* models:

$$y_t = e_t + y_1 e_{t-1} + y_2 e_{t-2} + \ldots + y_q\, e_{t-q} + m = y(L)\, e_t + m \qquad [5]$$

where $e_t, e_{t-1}, e_{t-2}, \ldots, e_{t-q}$ denote the innovations in $t, t\text{-}1, \ldots, t\text{-}q$; $y_1, y_2, \ldots, y_q$ and m are parameters and a constant to be estimated, q is the order of the *MA* model and $y(L)$ is the following polynomial in the lag operator:

$$y(L) = 1 + y_1 L + y_2 L^2 + \ldots + y_q L^q \qquad [6]$$

Mixed (autoregressive-moving average) models *ARMA(p, q)* can also be formulated as follows:

$$f(L)\, y_t = c + y(L)\, e_t \qquad [7]$$

where $f(L)$ and $y(L)$ are polynomials in the lag operator of orders p and q, respectively.

Under suitable conditions, *AR* (*MA*) models can be transformed in *MA* (*AR*) infinite-order models. Then, comparing [3] and [5], the following should apply:

$$y(L) = f(L)^{-1} \qquad [8]$$

ARMA models, also under suitable conditions, can be transformed too in either autoregressive, or moving average models.

Autoregressive models (or *ARMA* models, in general) of just one variable, have obtained good results in predictions of variables showing a persistent temporal pattern like, for instance, seasonal inward and outward station movements in a telephone company.

2. Introduction to VAR and SVAR models

VAR models can be interpreted as a vector generalization of AR models. Considering a vector of *n* variables, denoted $\mathbf{y}_t$, equation [3] is now transformed into:

$$\mathbf{F}(\mathrm{L})\,\mathbf{y}_t = \mathbf{c} + \mathbf{e}_t \qquad [9]$$

where $\mathbf{y}_t$, $\mathbf{c}$ y $\mathbf{e}_t$ are vectors (n x 1) and $\mathbf{F}(\mathrm{L})$ is a matrix polynomial in the lag operator with (n x n) matrices $\mathbf{F}_j$:

$$\mathbf{F}(L) = \mathbf{I}_n - \mathbf{F}_1 L - \mathbf{F}_2 L^2 - \ldots - \mathbf{F}_p L^p \qquad [10]$$

where $\mathbf{I}_n$ represents the identity matrix of order *n*. Notice that, as I_n is the identity matrix, in the VAR model in equation [9] each element of the vector $\mathbf{y}_t$ (endogenous variables determined within the system) is expressed as a function of lagged values of all the elements in the same vector (variables predetermined in previous periods). However, they do not appear contemporaneous relations between the variables, that is, each variable is not related to the values of the others in that same period. Thus, equation [9] can be viewed as the reduced autoregressive form that could be obtained from a SVAR model in which there would be a relationship among endogenous variables for the current time period:

$$\mathbf{B}(\mathrm{L})\,\mathbf{y}_t = \mathbf{k} + \mathbf{u}_t \qquad [11]$$

where $\mathbf{k}$ is a vector (n x 1) with constants, $\mathbf{u}_t$ a vector (n x 1) of perturbations, that in this structural model are called structural shocks, and $\mathbf{B}(\mathrm{L})$ is a matrix polynomial in the lag operator with (n x n) matrices $\mathbf{B}_j$:

$$\mathbf{B}(L) = \mathbf{B}_0 - \mathbf{B}_1 L - \mathbf{B}_2 L^2 - \ldots - \mathbf{B}_p L^p \qquad [12]$$

Notice how $\mathbf{B}_0$ denotes the contemporaneous relationships among the endogenous variables $\mathbf{y}_t$.

Equation [11] is the structural autoregressive form of the model. If we pre-multiply both members of the equation by $\mathbf{B}_0^{-1}$ we would obtain [9] (reduced autoregressive form) and, vice versa, known the matrix $\mathbf{B}_0$, the structural autoregressive form of the model can be obtained by pre-multiplying $\mathbf{B}_0$ in both members of [9]. However, it can be demonstrated that the information contained in $\mathbf{y}_t$ is not enough to identify the matrix $\mathbf{B}_0$ and some additional restrictions are required.

These additional restrictions can be obtained from the implications that theoretical models have on the expected behavior of the variables $\mathbf{y}_t$. In this sense, it can be affirmed that whereas in the VAR model of the equation [9] the theoretical requirements are minimum (a set of variables whose interaction is going to be analyzed and number of time lags to be included), in the SVAR model a greater theoretical content can be found, given by the model from which the above mentioned additional restrictions are obtained.

Like the models of a single variable, vector autoregressive models in its reduced [9] or structural [11] form, under suitable conditions, can be transformed into the reduced or structural moving average forms, just by premultiplying both equations by $\mathbf{F}(L)^{-1}$ and $\mathbf{B}(L)^{-1}$, respectively.

$$\mathbf{y}_t = \mathbf{Y}(L)\,\mathbf{e}_t + \mathbf{d} \qquad [13]$$

$$\mathbf{y}_t = \mathbf{C}(L)\,\mathbf{u}_t + \mathbf{h} \qquad [14]$$

where **d** and **h** are vectors (n x 1) of constants, and:

$$\mathbf{Y}(L) = \mathbf{F}(L)^{-1} \qquad [15]$$

$$\mathbf{C}(L) = \mathbf{B}(L)^{-1} \qquad [16]$$

3. SVAR models and System Dynamics

We will now show how it is possible to implement a SVAR model within the framework of SD. In order to do so, we consider a concrete application of a SVAR model to the labor market in Spain, developed by Dolado and Gómez (1997) that, in turn, takes as reference the study carried out by Blanchard and Diamond (1989). We will explain how we have implemented this model constructing two basic SD models, the model 1 and the model 2, each of which corresponds to different phases of the process of analysis, as it will be later exposed closely.

3.1. The initial SVAR model

Dolado and Gómez (1997) SVAR model centers on the quarterly series of three variables: unemployment (U), vacancies (V), and labour force (L). In this model the vector $\mathbf{y}_t$ is obtained from a few previous transformations, and it is composed by the variables Δ(v-u), Δu y Δl, where v, u and l are the logarithms of V, U and L, and where Δx indicates the first difference of the corresponding x variable. These three transformed variables correspond respectively to the rates of growth of the unemployment/vacancies ratio, unemployment and labour force.

Relating each of these three transformed variables with the lagged values (up to 4 quarters) of all of them, the reduced autoregressive form [9] is obtained, in which it is included also a vector of dummy quarterly variables $\mathbf{d}_t$ with its coefficients matrix **D**, that were not included in the generic form [9], and that serve to control the seasonal effects:

$$\mathbf{F}(L)\,\mathbf{y}_t = \mathbf{c} + \mathbf{D}\,\mathbf{d}_t + \mathbf{e}_t \qquad [17]$$

As it was mentioned in section 2, in this reduced autoregressive form, contemporaneous relations do not appear among the variables, that is, each variable is not related to the values of the others in the same period. These contemporaneous relations do appear in the structural autoregressive form [11]:

$$\mathbf{B}(\mathrm{L})\ \mathbf{y}_t = \mathbf{u}_t + \ldots \qquad [18]$$

where other terms, corresponding to the constants and seasonal variables, have been omitted. The matrix $\mathbf{B}_{0,}$ within the polynomial in the lag operator $\mathbf{B}$(L), reflects the contemporaneous relations among the variables. As it was also exposed in section 2, the information contained in the time series $\mathbf{y}_t$ it is not sufficient to identify the elements of $\mathbf{B}_0$, and therefore it is necessary to add restrictions. These restrictions can be obtained from the implications that theoretical models may have on the expected behavior of the variables $\mathbf{y}_t$.

Dolado and Gómez (1997) use a theoretical model, using a flow approach to labour market, constituted by four blocks: the flows of job creation and job destruction, the hiring process through a matching function between vacancies and unemployment, the wage determination based on the excess demand in the labor market, and the labour supply or labour force as a function of wages and of unemployment. This is used to obtain a relation among the transformed variables that compose the vector $\mathbf{y}_t$ in the structural autoregressive form [18]. At the same time, the structural shocks $\mathbf{u}_{t,}$ are identified using three types of disturbances in the economy: *aggregate activity shocks,* due to disturbances in the different components of aggregate demand, *reallocation shocks*, due to disturbances affecting the efficiency in the matching process between vacancies and unemployed (skill mismatch, geographical mismatch …) and *labour force shocks,* due to disturbances that affect directly this variable (women participation in the labor market …). The additional restrictions for the identification of $\mathbf{B}_{0,}$ obtained as implications of this theoretical model, are that a labour force shock does not have permanent effects on unemployment and vacancies and that a reallocation shock does not have permanent effects on the vacancies/unemployment ratio.

3.2. General approach followed to build the SD models.

In order to accomplish the SVAR analysis and its application to the labor market within the SD framework, we have built using VENSIM software two basic models: model 1 and model 2. Each of which corresponds to a different phase of the analysis process, that will be exposed in detail later on. In Figures 1 and 2, stock and flow diagrams of both models are presented.

The common nucleus of both models is the prediction of the variables in every period from its values in the previous periods, according to the reduced autoregressive form of the equation [17]. The main difference between both models is that model 1 uses the real data of the variables in the previous periods, whereas model 2 uses the values predicted for the previous periods by the model. For this reason, we can say that the prediction horizon is of a single period in the first model, and multi-period in the second.

Figure 1 : Model 1, stock and flow diagram.

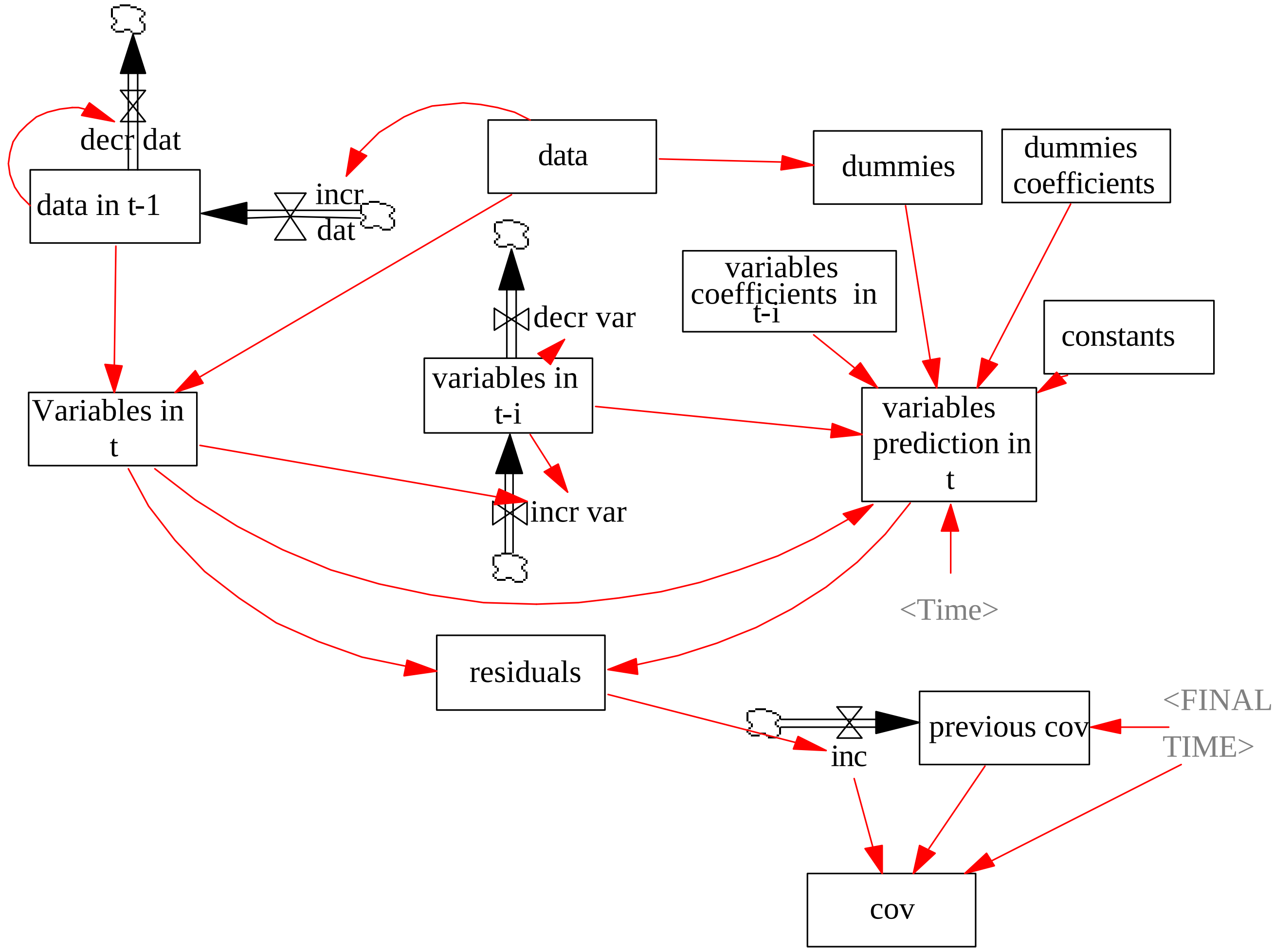
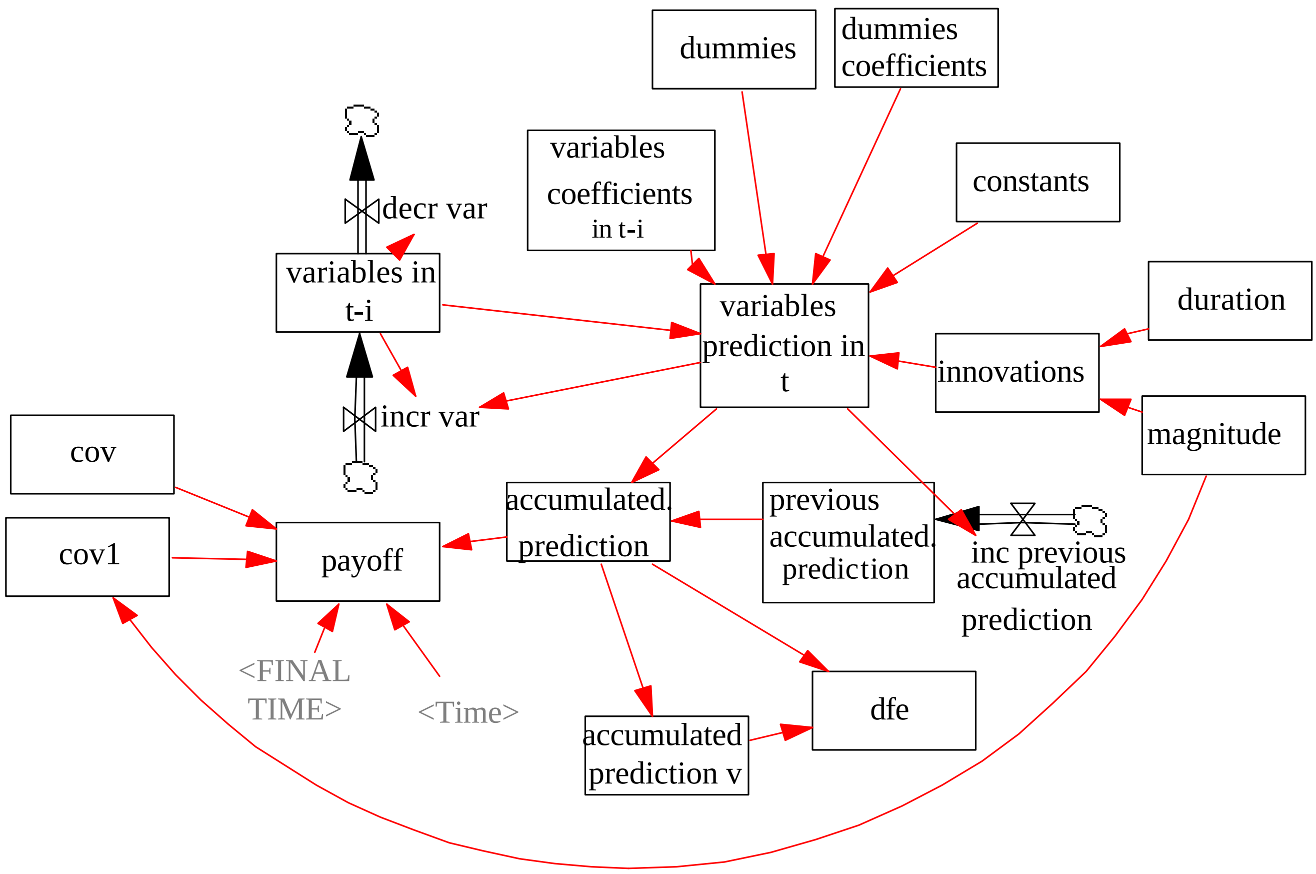


Figure 2 : Model 2, stock and flow diagram



Model 1 is used to estimate the parameters of the model in the reduced autoregressive form [17] from a series of real values of the variables. With the same model, it is studied the adjustment obtained between the predictions of the estimated model and the series of real values of the variables, calculating the differences between both of these residuals (or estimated values of innovations $\mathbf{e}_t$) and their variance-covariance matrix.

With the values of the estimated parameters, model 2 is used to calculate the $\mathbf{B}_0$ matrix. By doing that we can obtain the structural autoregressive form from the reduced autoregressive form, with the additional restrictions that the theoretical model imposes on the long-term values of the variables. Model 2 also allows simulating the response of the variables to different impulses (in innovations $\mathbf{e_t}$ or in structural shocks $\mathbf{u}_t$), known as impulse-response functions. These functions are also related to the moving average forms of the model. In order to obtain all these results model 2 is used in three versions differing only in the magnitude of the innovations.

In the next two sections, we present in detail the analysis process that both models follow, divided in six steps, two for model 1 and four more for model 2.

3.3. Detailed explanation of model 1

The model 1 is in the figure 1 (the names of the variables will be indicated within quotation marks as they are explained).

1) Data input and initial transformations.

First, there is a reading of the "data" imported from an external file: quarterly series of values for corrected vacancies (V), unemployment (U) and labour force (L), together with the quarterly dummy variables.

Later, several data initial transformations are made, obtaining "variables in t " and the "dummies". The obtained variables are Δ(v-u), Δu and Δl, composing the $\mathbf{y}_t$ vector, where Δx is the first difference of the corresponding x variable. In order to calculate these differences, the level variables "data in t-1" need to be calculated first, and are updated at the end of every period with an input flow "incr dat" that stores the data of this period as lagged information for the following period, and an output flow "decr dat" that eliminates the data stored previously. Besides this, the four seasonal dummies (d1, d2, d3, d4) are reduced to three (dum1, dum2, dum3), to avoid the problem of perfect collinearity among them, by doing:

$$
\begin{aligned}
&dum1=d1-d4\\
&dum2=d2-d4 \qquad [19]\\
&dum3=d3-d4
\end{aligned}
$$

2) Estimation of the model in reduced autoregressive form, the residuals, and the variance–covariance matrix.

The VAR model is based on the relation that the vector of variables $\mathbf{y}_t$ in a period, holds with the same vector in previous periods. In a similar way to what we did with the data in the step 1, the level variables "variables in t-i" (where i indicates the lag order; i = 1..., 4 in our application to the labor market) are generated, and updated at the end of every period as previously explained.

As we said before, the core of the model 1 is the prediction of the variables for every period ("variables prediction in t ") from their values in the previous periods, in accordance with the model in reduced autoregressive form [17], which includes also a vector of "constants" $\mathbf{c}$, and the term corresponding to the seasonal "dummies" $\mathbf{d}_t$. The model parameters to estimate are "variable coefficients in t-i", "dummies coefficients" and the "constants". The variable "Time" is used to control the periods in which the model is initialized, introducing the real values of the variables as first lags.

The estimation of the model parameters, starting from the series of variables' real values, is done using a modified Powell Method[1] included in the "calibration" option of VENSIM. By doing so, the values obtained for the parameters minimize the sum of the squared residuals (real values of the variables minus predictions of the model) for all the periods that compose the estimation interval. A joint estimation is done for all three equations that compose [17], corresponding to each variable in the vector $\mathbf{y}_t$, giving the same weight to the sums of the squares of every equation residuals in the global payoff function to minimize.

With the estimated values of the parameters, we obtain the estimated "residuals", and by multiplying those values we obtain the estimate of the variance–covariance matrix "cov". The flow variable "inc" increases in every period the accumulated level "previous cov" of the sum of the residuals products for all the previous periods. Finally, the variable "FINAL TIME" provides the number of periods that it is necessary to take into account in this process.

3.4. Detailed explanation of model 2

The model 2 stock and flow diagram can be observed in figure 2.

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[1] Among the numerical optimization techniques, the direct-search method that does not evaluate the gradient, is most suitable for the analysis of dynamics of complex nonlinear control systems. The Powell method (Powell, 1964), is well known to have an ultimate fast convergence among direct-search methods. The basic idea behind Powell's method is to break the *N* dimensional minimization down into *N* separate one-dimensional (1D) minimization problems. Then, for each 1D problem a binary search is implemented to find the local minimum within a given range. Furthermore, on subsequent iterations, an estimate is made of the best directions to use for the 1D searches.

Some problems, however, are not always assured of optimal solutions because the direction vectors are not always linearly independent. To overcome this difficulty, the method was revised (Powell,1968) by introducing new criteria for the formation of linearly independent direction vectors. This revised method, which is the one used in this paper, is called "The Modified Powell Method"

3) Obtaining the polynomial matrix $\mathbf{Y}(L)$ *corresponding to the reduced or structural moving average form , and the impulse-response functions (non orthogonalized).*

The impulse-response functions (non orthogonalized) are obtained as a result of the simulation[2] of the response of the vector of variables $\mathbf{y}_t$ to impulses in the innovations $\mathbf{e}_t$. The specification "non orthogonalized" refers to the fact that innovations appear contemporaneously correlated among them, as shown by the variance-covariance matrix obtained in step (2). The response obtained as a result of the simulation is "variables prediction in t", which corresponds to the vector $\mathbf{y}_t$, obtained by means of the model in reduced autoregressive form of the equation [17], with "variables coefficients in t-i" estimated also in the step (2). The "variables in t-i", in this model 2, are generated from the prediction in t[3], them updating at the end of every period with an input flow "incr var", that stores as lagged data (lags 1 to 4) for the following period the prediction and the variables with 1, 2 and 3 lags in this period, and an output flow "decr var" which eliminates the information stored previously.

The impulse are the "innovations" $\mathbf{e}_{t,}$ that are made equal to 1 in the initial period for the corresponding variable of the vector $\mathbf{y}_t$, whereas they are made equal to zero for the remaining variables in this period and for all variables in the following periods. Three simulations are done, therefore, according to which of these three variables experiences the unitary initial impulse. Nevertheless, it is possible to carry out three simulations at the same time by using subscripts. The innovations are obtained as the product of "duration", which establishes the time that the innovation lasts (in this case, an initial impulse that then disappears) by the "magnitude" of the same innovation (in this case, which is the first version of the model 2, the "magnitude" is 1 for the variable that experiences the impulse and 0 for the others).

From the impulse-response functions, we can obtain the matrix $\mathbf{Y}(L)$ corresponding to the moving average reduced form [13]:

$$\mathbf{y}_t = \mathbf{Y}(L)\, \mathbf{e}_t + \dots \qquad [20]$$

where other terms corresponding to constants and seasonal dummies have been omitted. It is just required to take into account that in $\mathbf{Y}(L)$, the term corresponding to the lag s, is composed by the elements of the impulse-response functions corresponding to the period s of simulation. In the case of our application to the labor market, the terms of $\mathbf{Y}(L)$ are 3x3 matrices and their elements correspond to the response of each one of the three variables to each one of the three simulated impulses.

4) Obtaining the matrix $\mathbf{S} = \mathbf{B}_0^{-1}$*, the structural autoregressive form, the structural moving average form, and the structural shocks.*

As previously exposed in section 2, pre-multiplying both members of the reduced autoregressive form [9] by $\mathbf{B}_{0,}$ the structural autoregressive form [11] can be obtained and, vice versa, known the matrix $\mathbf{S} = \mathbf{B_0}^{-1}$, it is possible to obtain [9] from [11], pre-multiplying both members of this equation by $\mathbf{S}$. As the $\mathbf{u}_t$ are standardized

[2] See Hamilton (1994).
[3] Initially, its values are made equal to 0.

structural shocks, not contemporaneously correlated to each other, their variance-covariance matrix is the identity ($E\,(\mathbf{u}_t\,\mathbf{u}_t') = \mathbf{I}$) and $\mathbf{e}_t = \mathbf{S}\,\mathbf{u}_t$, then:

$$E\,(\mathbf{e}_t\,\mathbf{e}_t') = \mathbf{W} = \mathbf{S}\,\mathbf{S}' \qquad [21]$$

where **W** is the variance-covariance matrix of the residuals $\mathbf{e}_t$ estimated in step (2). As **W** is a 3 x 3 symmetric matrix, the equation [21] provides 6 conditions to identify the nine elements of **S**. The other three conditions, as it was exposed in the section 3.1, are obtained as implications of the theoretical model. These conditions are that a labour force shock does not have permanent effects on unemployment and vacancies, and that a reallocation shock does not have permanent effects on the vacancies/unemployment ratio.

Since the model 2 corresponds to the reduced autoregressive form, we must consider that, according to the equation $\mathbf{e}_t = \mathbf{S}\,\mathbf{u}_t$, an unitary value of one of the shocks $\mathbf{u}_t$ is equivalent to a vector of innovations $\mathbf{e}_t$ of magnitude equal to the respective column of the matrix **S**. Therefore, the matrix **S** that we look for will be formed by the values that the variable "magnitude" takes in our model (of each innovation in each of the three simulations).

The properties of the theoretical model refer to the values of u, v and v-u in the long term. As the variable "variables prediction in t” corresponds to the first differences Δ(v-u), Δu y Δl, the model recovers v-u, u and l accumulating the prediction in the variable "accumulated prediction”. The level “previous accumulated prediction” is updated at the end of every period with the input flow “inc previous accumulated prediction”, that is equal to the prediction of the variables obtained in this period, and "accumulated prediction" is obtained by adding this prediction to the one accumulated previously (notice that this is required since the updating of the level variables at the end of every period is not registered in the output of the model until the following period, and therefore only the accumulated prediction in the previous period would be registered). "Accumulated prediction v" is then obtained adding the levels v-u and u.

The numerical optimization is guided by the fulfillment of the aforementioned conditions, that are reflected in a vector of nine variables "payoff", maximized giving the same weight to all these variables. The first three are the square of the prediction in the final period (long term) of u and v, responding to an unitary labour force shock, and the square of the prediction in the final period of v-u responding to an unitary reallocation shock, all of them with negative sign. The other six are the square of the differences among all six non identical elements of the symmetrical matrices S S ' and **W,** also with negative sign. Initially, in the second version of the model 2, we give initial unitary values to all the elements of "magnitude", and therefore to all the elements of S. After that, the process of optimization continues until are found the values of the above mentioned elements that approximates the payoff sufficiently to its maximum possible value, which is zero. That value is reached when $\mathbf{W} = \mathbf{S}\,\mathbf{S}'$, and the prediction of u and v in the final period responding to an unitary labour force shock, and the prediction of v-u responding to an unitary reallocation shock in that final period are all them zero. In the variables "cov" y "cov1" (with the corresponding subscripts) are respectively the elements of the matrix **W** estimated in the step 2) and the elements of the product **= S S’**, obtained from the values of "magnitude" forming the matrix **S**. The variables “Time” and “FINAL TIME" are used to control that the payoff is calculated in the final period.

Once the matrix $\mathbf{S} = \mathbf{B_0}^{-1}$ has been obtained, pre-multiplying both members of the reduced autoregressive form [9] by $\mathbf{B}_0$, the structural autoregressive form [11] and the structural shocks $\mathbf{u}_t = \mathbf{B}_0\mathbf{e}_t$ are obtained. The structural moving average form [14] can also be obtained from the moving average reduced form [20], obtained in step number 3), multiplying $\mathbf{Y}$(L) by $\mathbf{S}$, since, as $\mathbf{e}_t = \mathbf{S}\,\mathbf{u}_t$, we get:

$$\mathbf{y}_t = \mathbf{Y}(\mathrm{L})\,\mathbf{e}_t + \ldots = \mathbf{Y}(\mathrm{L})\,\mathbf{S}\,\mathbf{S}^{-1}\,\mathbf{e}_t + \ldots = \mathbf{C}(\mathrm{L})\,\mathbf{u}_t + \ldots \qquad [22]$$

where $\mathbf{C}(\mathrm{L}) = \mathbf{Y}(\mathrm{L})\,\mathbf{S}$ is the polinomial matrix corresponding to the structural moving average form.

5) Obtaining the orthogonalized impulse-response functions

In the third version of model 2, the elements of "magnitude" are made equal to the values obtained for S in the previous step. As it was already explained, each of the parallel simulations thus carried out with the reduced autoregressive form corresponds to unitary values in the initial period of each one of the structural shocks. Therefore, the values obtained in the simulations of the variables u and l in "accumulated prediction", and of v in "accumulated prediction v", represent the orthogonalized impulse-response functions for these variables, recovered from their first differences. The specification "orthogonalized" refers to the fact that the structural shocks are not contemporaneously correlated among each other.

6) Variance of the forecast error decomposition

From the values, in each period, of u and l in "accumulated prediction" and of v in "accumulated prediction v" in the orthogonalized impulse-response functions of the previous step, we can obtain the decomposition of the variance of the forecast error "dfe" in the same period. This error is originated by the responses to each of the structural shocks. So, for the variables v, u and l, the percentage that supposes the square of their value in each of the three simulations is calculated in relation to the sum of these three squares.

4. Conclusions

The central topic of this work has been the comparison between SVAR and System Dynamics methodologies. With this purpose we have considered both, their theoretical foundations and the general procedures that they use, and we have applied them to the study of the labor market in Spain.

Within the System Dynamics framework, we have adapted a labor market SVAR model, originally developed in the fields of economic theory and econometrics. This is a good example, in our opinion, of the high capacity that system dynamics has to "import" from other fields and methodologies. Since the model was already defined and formalized, the initial phases of the SD model construction have been omitted. The main effort has been done searching for the correspondence, in system dynamics, of the main formal concepts and procedures that appear in the SVAR model.

To develop this SD version of the SVAR model, we have built two models using the VENSIM simulation environment. Each of these models corresponds to different phases of the process of the SVAR analysis. The lagged variables, essential in the SVAR analysis, are now treated as SD level variables. The calculation procedures have been similar to those of the original econometric SVAR analysis, although the analytical resolution of some of the steps of the problem has been done through simulation within the SD models.

The results obtained (estimations of the parameters, impulse-response functions, decomposition of the variance of the forecast error) with the SD models reproduce faithfully those of the original application of the SVAR analysis. Likewise, the adjustment between the real series of the considered variables, and the predictions of the models, is good for the period of estimation. A possible extension of this research might study the ex-ante predictive capacity of these models beyond the period of estimation. On the other hand, the core of the SD models built is the reduced autoregressive form of the SVAR analysis. The responses to the structural shocks have been obtained transforming them into non orthogonalized innovations, by means of the corresponding matrix, which also has been estimated with the second one of these SD models. Another possible extension of our work might consist in the construction of a SD model directly from the structural autoregressive form.

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Back to the Top