5 Forecasts using econometric models

Even today, the basic workhorse tool for forecasting in economics is the large structural econometric model. These models are developed in specialized institutions, government agencies, and banks. They often consist of hundreds of equations. It is interesting that econometric theory has not been focusing on these models for almost thirty years. Following the general failure of these macroeconometric models to cope with the economies of the 1970s following the OPEC crisis, theory has discarded them. This attitude was supported by several empirical studies that generally concluded that time-series models yield better forecasts than structural models. An important contribution was the article by Sims who, from the angle of economic as well as econometric theory, recommended multivariate time-series modeling instead of structural models. In the lengthy discussion contained in that article, Sims explicitly refers to the many ‘incredible’ exclusion restrictions of macroeconometric models, while he also concedes that ‘large-scale models do perform useful forecasting ... functions’. Chatfield’s assertion that ‘econometric models are often of limited value to forecasters’ sounds much harsher and may miss the point, as many large-scale models are built with the purpose of forecasting in mind.

5.1 The classical macroeconometric model

The classical approach to macroeconometric modeling consists of several steps. Model building is indeed \textit{guided by theory} but the model specification is not really \textit{determined by theory}. I distinguish the following phases:

1. choosing the variables to be included in the model;
2. separating the variables into \textit{endogenous} and \textit{exogenous} variables;
3. sketching \textit{a priori} causal relationships among the variables, in the style of a flow chart;
4. specification of estimable equations;
5. estimation;
6. forecasting.
Step 1 is guided by the intended purpose of the model. A model for the Austrian economy may include various Austrian economic variables and a lesser variety of foreign variables, together with possibly some non-economic variables such as population or weather conditions. An important restriction is the availability of data. For example, a quarterly model could include macroeconomic subaggregates with respect to consumer demand or capital formation, while several government expenditure categories are available on an annual basis only. Mixing different periodicities is sometimes considered but many modelers find this option inconvenient.

Step 2 is crucial. Philosophers of science have named the classification of variables into endogenous and exogenous variables as a characteristic of econometric research (Cartwright). In many other fields of science, an analogous classification rests on firm a priori beliefs, while such beliefs are rare in economics. No generally accepted theory can tell whether saving causes investment or investment causes saving. Similarly, there is no accepted causal ordering between the interest rate and real output. Deterministic variables, such as constants and time trends, are always exogenous. If the model is designed to represent the domestic sector of a small open economy, foreign variables are also usually regarded as exogenous. This may change if a world model is targeted. Typical such foreign variables would be world demand and price indexes for the world market, while export prices and even import prices may respond to the domestic price structure. Many macroeconomic models also view fiscal variables as exogenous. This decision is often dictated by institutional reasons, such as the preference of a government institution who pays for the forecasting project and does not want to be seen as a reaction node without a free will. One may, however, also choose that option to allow for conditional forecasting, i.e. scenarios that respond to alternative government policies. Some macroeconomic models choose an intermediate solution and keep aggregate tax revenues as endogenous, while they impose exogenous tax rates and long-range conditions such as a tendency of the budget to be balanced. Non-economic variables are usually modeled as exogenous.

Step 3 determines the internal structure of the model. Often, the often large amount of variables is broken down into blocks of variables, such as real demand variables, price indexes, labor market variables etc. Influences across these blocks or sectors then may run in both directions, though the number of such relationships may be restricted to very specific effects. For example, the labor market may respond to the price sector via a Phillips-
curve only. Causal orderings among blocks or variables are often not meant to specify dynamic causal orderings. Rather, they indicate which variables will appear on the right-hand side of regression equations for specific left-hand side variables. While the explanatory variables may be accepted as lags in further specifications, some model builders have a skeptical view on such time lags and may regard them as weak spots of their models. The economic science finds it difficult to specify dynamic interaction and has to justify it by arguments of habit persistence, adjustment costs, delivery lags etc. There is little information on the exact form of these features, hence coefficients that describe dynamic interaction are difficult to interpret. On the other hand, dynamic rather than static relationships in equations help in forecasting as well as in stabilizing the system. In the extreme case of an $n$-variable static model, a ‘solution’ for a given time point is calculated by solving a system of $n$ often nonlinear equations. Forecasting will not be possible, unless assumptions are made on extrapolating $n - 1$ of the variables at a different (future) time point. The other extreme is a VAR or VARX system, where all influences are dynamic. A forecast for future time points is calculated by simple insertion of the current observed values.

Step 4 consists in a cursory search for equation specifications. In most macroeconometric models, this search is conducted on a single-equation basis, in spite of persistent theoretical criticism. The dependent variable is specified, for example private consumption of durable goods, and various combinations of explanatory variables are tried as regressors. The specification search is guided by the set of possible influences that was specified in step 3. Functional forms, such as linear or double-log specifications, are selected according to statistical criteria or, less often, to theory arguments. Possible nonlinear forms in some equations are among the advantages of econometric modeling relative to linear VAR systems. Usually, the final specification is required to fulfil the following criteria:

1. regressors should be statistically significant;
2. coefficients should have an economically interpretable size and sign whenever such interpretation is possible;
3. influences that are deemed to be important for theoretical reasons should exist, which often implies ‘keeping’ insignificant regressors;
4. residuals should not show substantial autocorrelation;
5. if inserted into the whole model, the equation should not de-stabilize the model. A solution should be possible in a ‘range’ of values around the observed data and for a reasonable ‘range’ of possible residuals without obtaining inadmissible values, such as negative unemployment rates;

6. measures such as $R^2$ should be conveniently large, the required values ranging between 0.3 and 0.95;

7. more general statistical tests of misspecification should not indicate severe violations of assumptions.

In many cases, these different targets are in conflict with each other. Modelers decide on their preferences among targets on an ad-hoc basis. It is no wonder that model building is called a ‘science and art’ in the literature (Pindyck & Rubinfeld).

Step 5 demands for detailed comments. According to the classical model-building framework, as set out by the Cowles Commission, linear econometric models can be written in the form

$$Y \Gamma = XB + U.$$ 

Many econometric models are nonlinear but this form may even serve as a basis for estimation for nonlinear structures. $Y$ is a matrix of dimension $T \times G$ and contains the observations on the $G$ ‘endogenous’ variables, while $\Gamma$ is a $G \times G$ matrix of estimable coefficients. $X$ is a matrix of dimension $T \times K$ and contains the ‘exogenous’ variables, including lags of endogenous variables. Due to their similar estimation properties, exogenous (again including lagged ones) and lagged endogenous variables are summarized as predetermined variables. Note that the wording ‘predetermined’ does not refer to a forecasting application, as data on current exogenous variables are usually not available before the data on endogenous variables. $B$ is a $K \times G$ coefficient matrix, while $U$ contains regression errors.

Clearly, the matrix $\Gamma$ cannot be estimated without further restrictions. It contains information on simultaneous relationships among the endogenous variables and represents the completely ‘static’ aspect of the model. Without restrictions, the system contains $G$ different equations that look all alike. The extreme case $\Gamma = I$ is called the reduced form of the system. In a certain context, systems with $\Gamma = I$ are also called SUR models (seemingly unrelated...
regressions), as the only connection among equations is by common regressors and by possible correlation of errors, which two aspects may be ignored at first sight. Reduced form systems can always be estimated by regression methods. They are convenient for forecasting but economists avoid them, as they do not reflect interdependencies that were developed in economic theory. Another argument against their usage is that their parameters are difficult to interpret. This argument again reflects the ‘hybrid’ aims of econometric modeling; even when the model is built exclusively for prediction, economists require its interpretability in economic terms.

The conditions on $\Gamma$ that have to be imposed in order to make the model ‘identified’, i.e. to allow its sensible empirical estimation, are rather complex. Most applied econometric models fulfil these conditions anyway, due to their tendency to include ‘many unbelievable restrictions’, as Sims has put it. In these systems with general $\Gamma$, regression estimation of single equations yields inconsistent parameter estimates. The literature recommends variants of instrumental variables estimation procedures, such as two-stage least squares (2SLS), in order to overcome this deficiency of least squares in ‘simultaneous systems’. In empirical model building, this advice is not always followed. Many large-scale econometric models are estimated by least squares methods, while in other models 2SLS estimation is restricted to some sensitive sub-systems. An informal argument in favor of this practice is that the inconsistency of least squares plays a lesser role in larger models. This may not be true in general.

Finally, step 6 consists in substituting estimates for the unknown parameters and to predict the endogenous variables via

$$\hat{Y}_t(1) = X_{t+1}\hat{B}\hat{\Gamma}^{-1},$$

which poses difficulties if $X_{t+1}$ is not available. Unless $X$ contains only lagged endogenous variables—this is a special case of VAR modeling—$X_{t+1}$ will not be available and has to be guessed or extrapolated. Other forecasters avoid this ‘zero-residual’ forecasting and prefer

$$\hat{Y}_t(1) = X_{t+1}\hat{B}\hat{\Gamma}^{-1} + \hat{U}_{t+1}\hat{\Gamma}^{-1},$$

where $\hat{U}_{t+1}$ are so-called ‘add factors’ that are guessed and inserted by the forecaster. This may make sense when the model has an annual frequency and the current year is to be forecasted. Although the endogenous variables are not yet available, some information has spread on the current economic
situation, which may discourage the automatic usage of zero residuals. In practice, the calibration of add factors according to informal information is the principal and most time-consuming task of economic model forecasters. The above formulae are too simplistic, as they are valid for linear models only. With nonlinear models, simple multiplication by the inverted $\hat{\Gamma}$ is replaced by a numerical solution of a high-dimensional system of nonlinear equations. In former times, this step required a large amount of computer time, which was a binding constraint to forecasters. Nowadays, computers have become so powerful that even high-dimensional systems can be solved within a few seconds.

5.2 An example

A prototypical example for a macroeconometric model is the national income model by Granger:

\[
\begin{align*}
C_t &= a_1 + b_1 Y_t + e_{Ct}, \\
I_t &= a_2 + c_2 P_{t-1} + e_{It}, \\
T_t &= d_3 GDP_t + e_{Tt}, \\
P_t &= a_4 + b_4 Y_t + f_4 I_{t-1} + e_{Pt}, \\
GDP_t &= C_t + I_t + G_t, \\
Y_t &= GDP_t - T_t.
\end{align*}
\]

The endogenous variables are: consumption $C$, investment $I$, taxes $T$, profits $P$, gross domestic product $GDP$, disposable income $Y$. Apparently, the original Granger called $Y$ the ‘national disposable income’ out of a misunderstanding, thus excluding the government sector from the national economy. Rather, $Y$ appears to be a disposable income of the household and firm sectors. The exogenous variables are: government expenditure on goods and services $G$ and the constant. There are four structural or behavioral equations with error terms and two identities. The economy is closed, which is clear from the GDP definition. There are two simultaneous feedback cycles: $C$ depends on $Y$, $Y$ depends on $GDP$, and $GDP$ depends on $C$; $T$ depends on $GDP$, $GDP$ depends on $C$, $C$ depends on $Y$, and $Y$ depends on $T$. Therefore, least-squares estimation will yield inconsistent estimates of all parameters (coefficients).

By substitution, for example $GDP$ can be expressed by the predetermined
variables

\[ GDP_t = A + \frac{G_t}{H} + c_2 \frac{P_{t-1}}{H} + e_{Gt}, \]

where \( A = (a_1 + a_2) / H, \) \( H = 1 - b_1 + b_1 d_3, \) and \( e_{Gt} = (e_{Ct} + e_{It} - b_1 e_{T_t}) / H. \)

Analogous substitution yields the reduced form of the system, which expresses all six endogenous variables by predetermined variables and error terms. Note that the error structure of the reduced form necessarily has a singular covariance matrix. The equations of the reduced form can be estimated consistently by least squares. Econometric textbooks consider the option of retrieving estimates for the original ‘structural’ coefficients ‘backward’ from these reduced form estimates by algebraic operations and call it \textit{indirect least squares}. This method is rarely used in practice.

In order to forecast \( GDP_{t+1}, \) one may use

\[ GDP_t (1) = A + \frac{G_{t+1}}{H} + c_2 \frac{P_t}{H}, \]

which assumes that approximations to the reduced-form coefficients \( A, H^{-1}, \)
and \( c_2 / H \) are available in any case, either from least squares on the reduced form or from two-stage least squares on the structural model and simple ‘forward’ algebraic operations. While \( P_t \) is available at \( t, \) \( G_{t+1} \) is not. Either one inserts a ‘plausible value’ for \( G_{t+1}, \) for example from the government’s budget plan, or one uses an additional time-series or econometric equation for predicting \( G. \) The latter option ‘essentially completes the system by treating \( G \) as if it were endogenous’ \( \text{(Granger)}, \) i.e. by endogenizing government policy. \text{Granger} suggests ‘to use a model to forecast \( G \) and then to alter this forecast subjectively if relevant extra information is available to the forecaster. The success or lack thereof of such adjustments clearly depends on the quality of the information being utilized and the abilities of the forecaster who tries to use it’.
References


