The Model Object in EViews

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Foreword

- A "logical picture" differs from an ordinary picture in that it need not look the least bit like its object. Its relation to the object is not that of a *copy*, but of *analogy*.
- …The great value of analogy is that by it, and it alone, we are led to seeing a single "logical form" in things which may be entirely discrepant as to content.

Langer (1967)

Topics

1. What is a Model?
   - Definition
   - Example
2. Specification
3. Parameter Estimation
4. Model Set-Up and Solution
5. Types of Simulations
6. Scenario Implementation
7. Hands-On Exercise

What is a Model?

- Definition of Model
  - A model is a logical picture (structural expression) of a phenomenon. A quantitative model is usually represented by a set of equations that jointly describe relationships among a group of variables.
  - In EViews, the model object combines such equations into a single entity that may be used to create a joint forecast or a simulation of all endogenous variables of the model.

What is a Model?

- Example: Keynesian Model of Income Determination (A framework for analyzing the interaction between the financial and the real sides of the economy).
  - Aggregate demand determines the equilibrium level of output.
  - Real economy determines level of income which affects the demand for money, a financial variable.
  - The financial sector determines the interest rates which affect investment in the real economy.
  - A static IS-LM model is a reduced-form representation of macroeconomic balance through a simultaneous equilibrium of the goods and the money markets.

Specification

- An Expression of a Simple Dynamic IS-LM (Pindyck and Rubinfeld 1998: 390)
  - Consumption

$$C_t = \alpha_1 + \alpha_2 Y_t + \alpha_3 C_{t-1} + \varepsilon_{1t}$$

  - Investment

$$I_t = \beta_1 + \beta_2 (Y_{t-1} - Y_{t-2}) + \beta_3 Y_t + \beta_4 R_{t-4} + \varepsilon_{2t}$$

  - Money Market

$$R_t = \gamma_1 + \gamma_2 Y_t + \gamma_3 (Y_t - Y_{t-1}) + \gamma_4 (M_t - M_{t-1}) + \gamma_5 (R_{t-1} + R_{t-2}) + \varepsilon_{3t}$$

  - GNP Accounting Identity

$$Y_t = C_t + I_t + G_t$$

Specification

- Equation list and key variables
  - First equation describes an autoregressive consumption function.
  - Investment is related to GNP and interest rate in the second equation.
  - The third equation represents the money market. It relates interest rate to GNP and the money supply.
  - Last equation may be interpreted as equilibrium condition for the goods market.
- Typical economic models include two categories of equations: (1) behavioral; (2) equilibrium conditions

Parameter Estimation

- Numerical implementation requires that we assign numerical values to structural parameters of the model.
- For econometric models we resort to estimation.
- Appropriate method of estimation depends on underlying stochastic structure of the model and the desirable properties we would like the estimator to have.
- Recall the benchmark case of the classical linear model:
  - Identification condition (Greene 2000): lack of multicollinearity, and there are at least as many observations as parameters to be estimated.

Parameter Estimation

- Classical case
  - Strict exogeneity (Hayashi 2000) holds (i.e. no observations on any explanatory variable convey information of the expected value of the random disturbance). Hence the expectation of the disturbance conditional on observables is zero. So, strict exogeneity implies that, for all observations, the explanatory variables are orthogonal to the random disturbances.
  - Spherical error variance (Greene 2000): Homoskedasticity (constant variance) and no correlation between observations.
  - Under these circumstances, OLSE is a feasible and optimal method of estimation among all linear estimators. Identification ensures feasibility, while the rest of the assumptions brings optimality in terms of unbiasedness (hitting the target on average) and efficiency (minimum variance).

Parameter Estimation

- Also, in large samples, OLSE is consistent in the sense that it converges, in probability to the true value of the parameter. (Both unbiasedness and consistency hinge on the assumption of strict exogeneity).

- Implications of Simultaneity
  - Consider a very simple model of national income determination where variables are measured in deviations from sample means (Pindyck and Rubinfeld 1998:341)

$$c_t = \beta y_t + \varepsilon_t; \quad y_t = c_t + i_t + g_t$$

The OLSE for the marginal propensity to consume is:

$$b = \frac{\sum_t c_t y_t}{\sum_t y_t^2} = \beta + \frac{\sum_t y_t \varepsilon_t}{\sum_t y_t^2}$$

Parameter Estimation

- Implications of Simultaneity
  - Above reveals that explanatory variable y_t is related to the disturbance ε_t via c_t. Hence strict exogeneity is lost and we can no longer claim that the OLSE is unbiased and consistent. Any remedy?
- Identification
  - Identification is a prerequisite for estimation
  - Posed in terms of the relationship between structural and reduced-form parameters, the issue is whether we can obtain values of the structural parameters from reduced-form estimates.
  - An equation is unidentified if there is no way of estimating all the structural parameters from reduced-form estimates, otherwise the equation is identified.

Parameter Estimation

- Identification
  - It is exactly identified if there is a unique set of values for structural parameters in terms of the reduced-form ones. If more than one value is obtainable for some parameters, then the equation is overidentified.
  - Order condition for identification (necessary, but not sufficient): The number of predetermined variables (exogenous and lagged endogenous variables) excluded from the equation must be at least equal to the number of included endogenous variables minus one (Pindyck and Rubinfeld 1998:245).

Parameter Estimation

- Identification
  - The rank condition extends the order condition to include both necessary and sufficient conditions. It ensures that there is only one solution for the structural parameters given reduced-form ones.
  - Terminology also applies to parameters (Beals 1972): a structural parameter is said to be identified if it can be written as a function of reduced-form coefficients. In a system of equations mapping structural parameters to reduced-from coefficients, the rank condition states that the rank of the relevant sub-matrix of reduced-form coefficients must equal the number of included endogenous variables minus one (Intriligator 1978: 346-348).

Parameter Estimation

- Instrumental Variable Method of Estimation
  - Principle
    - Consider this expression of the OLSE of β

$$b = \frac{\sum_t c_t y_t}{\sum_t y_t^2} = \beta + \frac{S_{y\varepsilon}}{S_y^2}$$

    - Last term is ratio of sample covariance between y_t and ε_t, and the variance of y_t.
    - It suggests a way of recovering orthogonality and hence consistency in estimation.

Parameter Estimation

- Instrumental Variable Method of Estimation
  - If there is a variable x_t highly correlated with yt but uncorrelated with εt, then use it as instrument to get:

$$b_{IV} = \frac{\sum_t c_t x_t}{\sum_t y_t x_t} = \beta + \frac{S_{x\varepsilon}}{S_{yx}}$$

- Choice of Instruments
  - Most common practice: use 2SLS with predetermined variables as instruments.
  - Predetermined variables are assumed uncorrelated with error terms. Their inclusion in model means they are correlated with endogenous variables.

Parameter Estimation

- Instrumental Variable Method of Estimation
  - 2SLS
    - Regress included endogenous variable on predetermined variables.
    - Use fitted value of endogenous as instrument in IV expression or regress the dependent variable on fitted value of included endogenous and the relevant predetermined variables.

$$b_{2sls} = \frac{\sum_t c_t \hat{y}_t}{\sum_t y_t \hat{y}_t} = \frac{\sum_t c_t \hat{y}_t}{\sum_t \hat{y}_t^2}$$

Parameter Estimation

- Instrumental Variable Method of Estimation
  - Generalized Method of Moments (GMM)
  - Member of the IV family of estimators that relies on a set of orthogonality conditions and does not require specification of the distribution of error terms.
  - For a valid instrument x_t, the orthogonality condition is:

$$E[x_t(c_t - \beta y_t)] = 0$$

Parameter Estimation

- Instrumental Variable Method of Estimation
  - Generalized Method of Moments (GMM)
  - Sample analogue:

$$\frac{1}{n}\sum_t [x_t(c_t - b_{GMM}\ y_t)] = 0$$

  - Hence

$$b_{GMM} = \frac{\sum_t c_t x_t}{\sum_t y_t x_t} = b_{IV}$$

  - When

$$x_t = \hat{y}_t$$

  - We get 2SLS

Parameter Estimation

- Instrumental Variable Method of Estimation
  - Generalized Method of Moments (GMM)
    - General Expression
      - Given the orthogonality conditions

$$E[Z'f(\theta)] = 0$$

      - The GMME of θ selects parameter estimates so that the sample correlations between the instruments Z and some function f(θ) is as close to zero as possible based on the following distance function

$$J(\theta) = [m(\theta)' W m(\theta)]; \quad m(\theta) = Z' f(\theta)$$

      - Where W is weighing matrix. Any symmetric positive definite matrix will yield consistent estimates of θ.

Parameter Estimation

- Full Information Estimation
  - When applied to one equation at the time, above methods lead to consistent estimates.
  - Single equation estimation known as limited information methods because they fail to account for cross-equation correlation among error terms, and the fact that some predetermined variables are excluded from other equations.
  - Full information methods (SUR, 3SLS, GMM and FIML) are designed treat all equations and parameters jointly and apply the principle of Generalized Least Squares to deal with cross-equation correlation.
  - The FIML approach relies on the assumption that error terms follow the normal distribution. It produces estimates that are asymptotically efficient.

Parameter Estimation

- Full Information Estimation
  - Focus on 3SLS
    - Applies generalized least-squares estimation to a system of equations each of which has first been estimated by 2SLS.
    - Steps:
      - Estimate reduced-form of model
      - Use fitted values of endogenous variables to obtain 2SLSE of all the equations in the system
      - Use residuals from 2SLS to estimate cross-equation variances and covariances and obtain generalized least-squares estimates of the parameters.

Parameter Estimation

- Full Information Estimation
  - Focus on 3SLS
    - Link to GMM (Hayashi 2000)
      - Under heteroskedasticity, GMM is equivalent to Full Information Instrumental Variable Estimator (FIVE).
      - Which in turn is the 3SLSE if the set of instruments is common to all equations.
      - If all regressors are predetermined, then 3SLSE=SURE.
      - Which reduces to the multivariate regression when all equations have the same regressors.

Parameter Estimation

- Two-Stage Least Squares estimates of Dynamic IS-LM (workfile:PINDYCKTAB135.WF1)
  - The system is block recursive with consumption, investment and GNP determined simultaneously. The interest rate enters only the investment equation with a four-quarter lag.
  - Hence we use Two-Stage Least Squares to estimate the consumption and investment equation, and OLS to estimate the interest rate equation. We also correct for autocorrelation in the investment equation:

Parameter Estimation

- Two-Stage Least Squares estimates of Dynamic IS-LM
  - EQUATION EQCN.TSLS APC=ALPHA(1) + ALPHA(2)*GNP +ALPHA(3)*APC(-1) @ APC(-1) (GNP(-1) -GNP(-2)) GNP(-1) GVX (RMNY -RMNY(-1)) (IRATE(-1) +IRATE(-2)) IRATE(-4)
  - EQUATION EQI.TSLS INV=BETA(1) + BETA(2)*(GNP(-1) -GNP(-2)) +BETA(3)*GNP +BETA(4)*IRATE(-4) + [AR(1)=BETA(5)] @ APC(-1) (GNP(-1) -GNP(-2)) GNP(-1) GVX (RMNY -RMNY(-1)) (IRATE(-1) +IRATE(-2)) IRATE(-4)

Parameter Estimation

- EQUATION EQR.LS IRATE=GAMMA(1) +GAMMA(2)*GNP +GAMMA(3)*(GNP -GNP(-1)) +GAMMA(4)*(RMNY -RMNY(-1)) +GAMMA(5)* (IRATE(-1) +IRATE(-2))

Parameter Estimation

Dependent Variable: APC
Method: Two-Stage Least Squares
Date: 10/10/05 Time: 23:04
Sample (adjusted): 1951Q1 1985Q4
Included observations: 140 after adjustments
APC=ALPHA(1) + ALPHA(2)*GNP +ALPHA(3)*APC(-1)
Instrument list: APC(-1) (GNP(-1) -GNP(-2)) GNP(-1) GVX (RMNY
-RMNY(-1)) (IRATE(-1) +IRATE(-2)) IRATE(-4)

	Coefficient	Std. Error	t-Statistic	Prob.
ALPHA(1)	-6.792841	5.348433	-1.270062	0.2062
ALPHA(2)	0.037400	0.018913	1.977544	0.0500
ALPHA(3)	0.951434	0.028085	33.87718	0.0000

R-squared	0.999476	Mean dependent var	1430.531
Adjusted R-squared	0.999469	S.D. dependent var	479.7035
S.E. of regression	11.05918	Sum squared resid	16755.84
Durbin-Watson stat	1.561832	Second-stage SSR	17594.26

Parameter Estimation

Dependent Variable: INV
Method: Two-Stage Least Squares
Date: 10/10/05 Time: 23:04
Sample (adjusted): 1951Q2 1985Q4
Included observations: 139 after adjustments
Convergence achieved after 15 iterations
INV=BETA(1) + BETA(2)*(GNP(-1) -GNP(-2)) +BETA(3)*GNP
+BETA(4)*IRATE(-4) + [AR(1)=BETA(5)]
Instrument list: APC(-1) (GNP(-1) -GNP(-2)) GNP(-1) GVX (RMNY
-RMNY(-1)) (IRATE(-1) +IRATE(-2)) IRATE(-4)
Lagged dependent variable & regressors
added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
BETA(1)	-62.75639	20.68087	-3.034514	0.0029
BETA(2)	0.086076	0.048132	1.788322	0.0760
BETA(3)	0.205110	0.009691	21.16394	0.0000
BETA(4)	-6.284993	1.523252	-4.126036	0.0001
BETA(5)	0.765456	0.054908	13.94070	0.0000

R-squared	0.985826	Mean dependent var	389.1424
Adjusted R-squared	0.985403	S.D. dependent var	130.2811
S.E. of regression	15.74032	Sum squared resid	33199.53
Durbin-Watson stat	1.811167		
Inverted AR Roots	.77		

Parameter Estimation

Dependent Variable: IRATE
Method: Least Squares
Date: 10/10/05 Time: 23:04
Sample (adjusted): 1950Q3 1985Q4
Included observations: 142 after adjustments
IRATE=GAMMA(1) +GAMMA(2)*GNP +GAMMA(3)*(GNP -GNP(-1))
+GAMMA(4)*(RMNY -RMNY(-1)) +GAMMA(5)* (IRATE(-1)
+IRATE(-2))

	Coefficient	Std. Error	t-Statistic	Prob.
GAMMA(1)	-0.559804	0.314896	-1.777747	0.0777
GAMMA(2)	0.000514	0.000235	2.187794	0.0304
GAMMA(3)	0.013447	0.003172	4.239166	0.0000
GAMMA(4)	-0.085370	0.014963	-5.705259	0.0000
GAMMA(5)	0.425824	0.025847	16.47489	0.0000
R-squared	0.932255	Mean dependent var		5.210286
Adjusted R-squared	0.930277	S.D. dependent var		3.256572
S.E. of regression	0.859904	Akaike info criterion		2.570585
Sum squared resid	101.3026	Schwarz criterion		2.674663
Log likelihood	-177.5115	Durbin-Watson stat		1.359228

Model Set-Up and Solution

- Declaration Statement
  MODEL ISLMD 'A Dynamic IS-LM Model
- Bring in linked equations

```
FOR %EQ EQCN EQI EQR
      ISLMD.MERGE {%EQ}
NEXT
```

Add inline identity

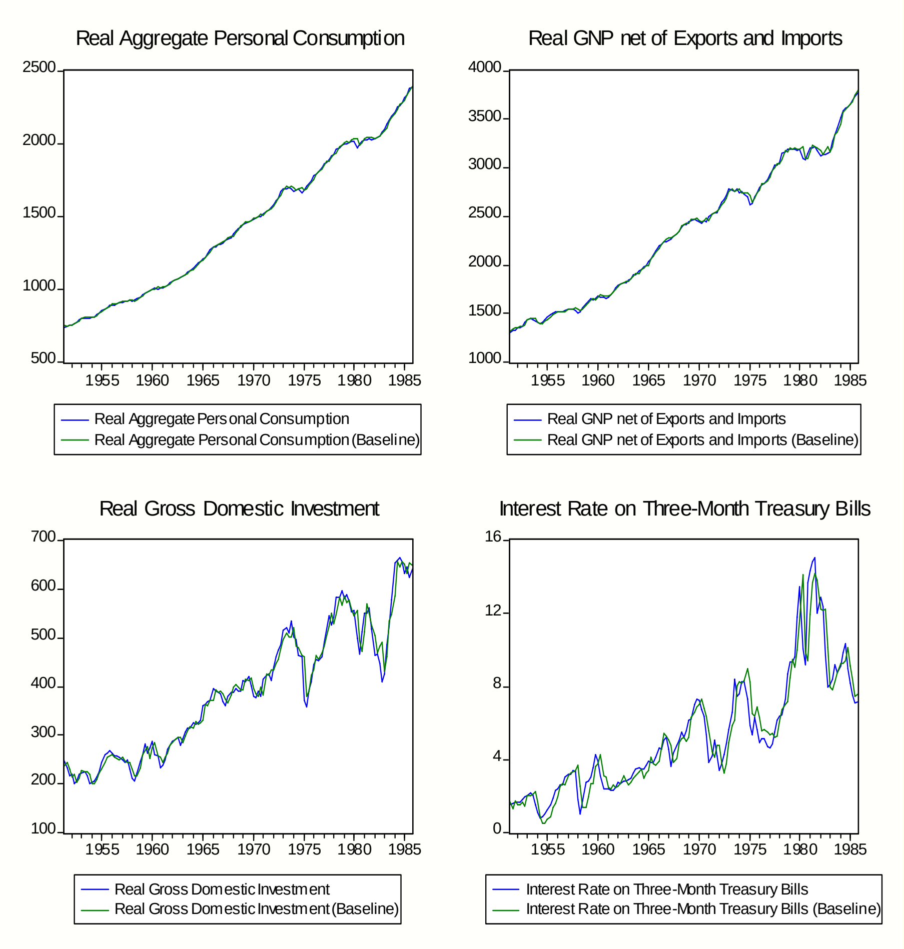
```
ISLMD.APPEND GNP=APC + INV +GVX
```

- Note: must assign a unique endogenous variable to each equation; any non-assigned variable is considered exogenous to the model.
- A linked equation gets its specification from an external object e.g. estimation object (equation or system). Inline equation is specified as text in the model.

Model Set-Up and Solution

- Solution Sample (Tracking History)
  SMPL 1951Q2 1985Q4
  - Chosen in a way that accommodates the lags involved in instruments.
- Baseline solution
  ISLMD.SCENARIO BASELINE
  ISLMD.SOLVE(s=d,d=s)
  - s=d: solution type=deterministic (not stochastic).
  - d=s: solution dynamics=static i.e. model prediction based on actual values of exogenous and lagged endogenous variables.
  - Default Solver: Gauss-Seidel ; Alternative: Newton
- Create a Graph called HISTORY
  ISLMD.MAKEGRAPH(a) HISTORY @ENDOG
  - Option a means include actuals in the graph.
  - Could use MAKEGROUP to create a table

Tracking History



Types of Simulations

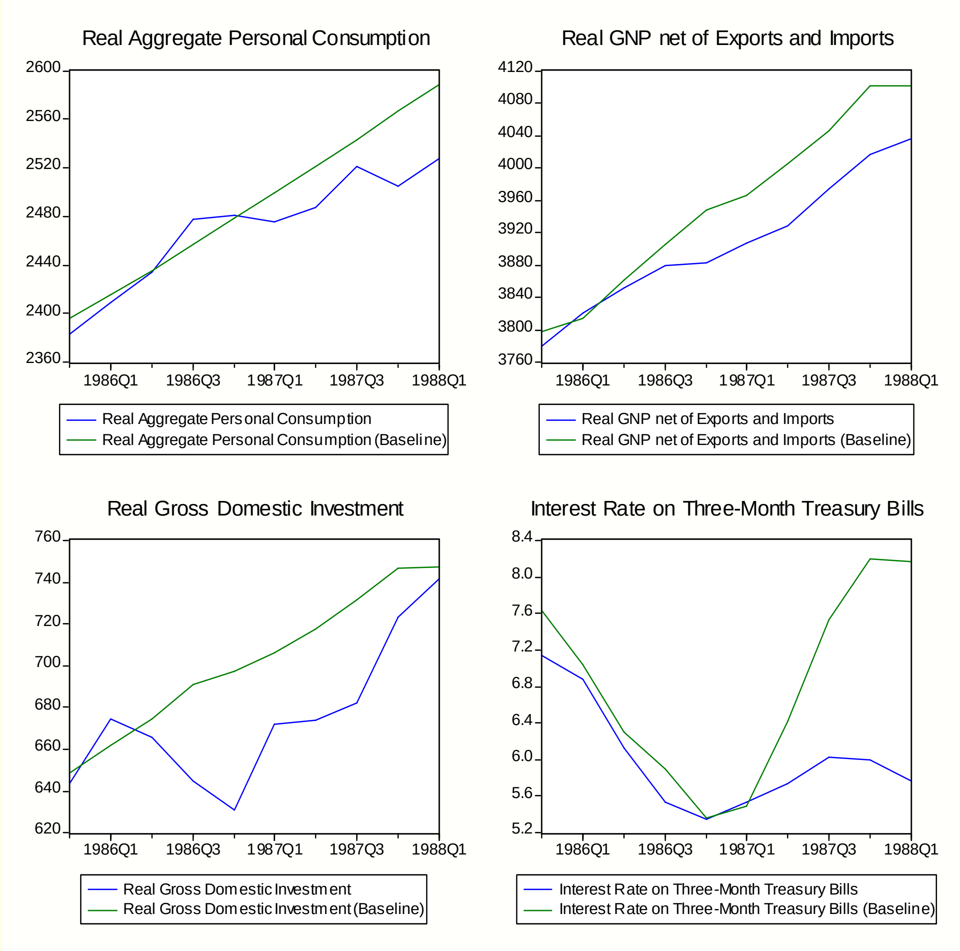
- Historical or ex post simulation: static solution based on estimation sample (see case above).
- Ex post forecast: dynamic based on observations outside estimation sample:

  SMPL 1985Q4 1988Q1

  ISLMD.SOLVE(s=d,d=d)

  - d=d invokes a dynamic simulation: values for lagged endogenous variables are obtained from previous period forecasts and not from actual historical data.
- Both types of simulations (historical and ex post forecast) help evaluate ability of model to replicate actual data.

Ex Post Forecast



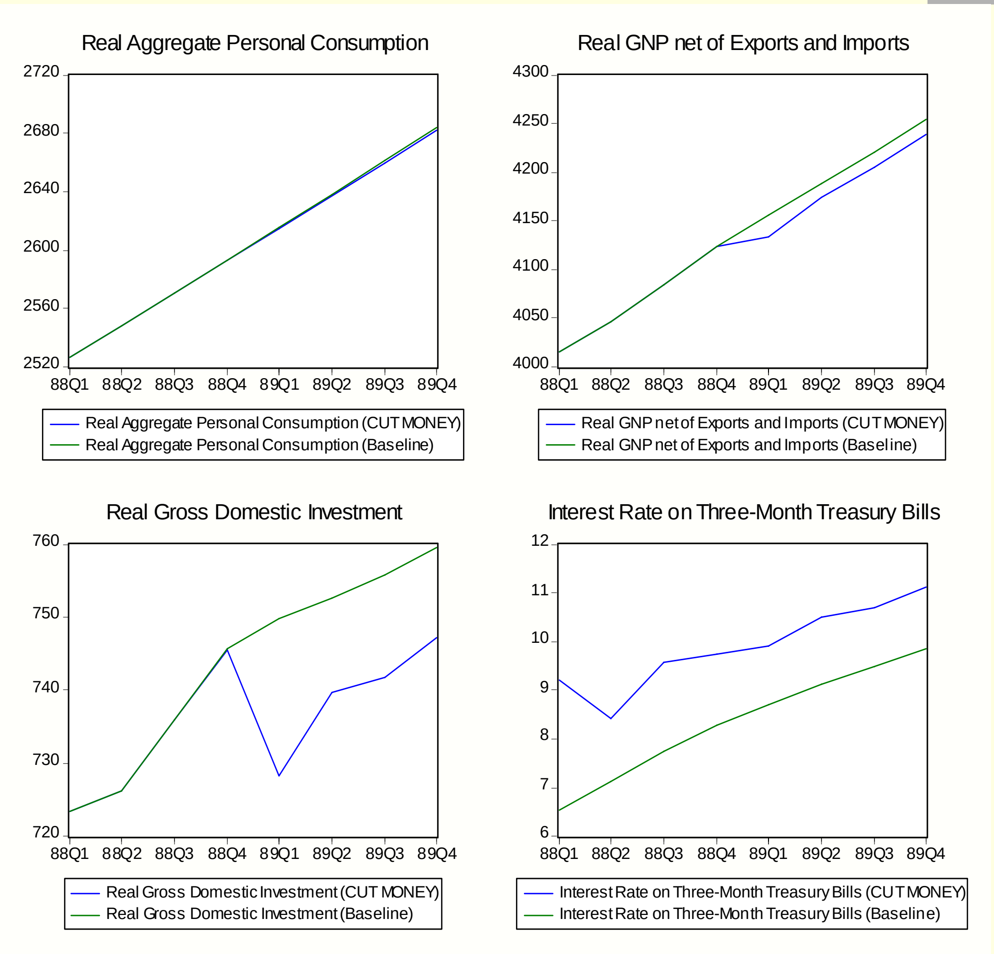
Ex Ante Policy Simulation

- Baseline Forecast (Counterfactual) :
  - Between 1988Q1 and 1989Q4 (forecast horizon) government spending would grow at 3.2 percent per year and money supply at 1 percent per year.
  - Take this as baseline or counterfactual
- Tight Monetary Policy
  - Starting in 1988Q1 maintain money supply at 600.

Ex Ante Policy Simulation

- 'Create Series to hold relevant values for policy instrument.
  SMPL @ALL
  SERIES RMNY_mnp=RMNY
- 'Solve for Policy Outcomes
  SMPL 1988Q1 @LAST
  RMNY_mnp=600
  ISLMD.SCENARIO(n, a=mnp) CUT MONEY
  ISLMD.OVERRIDE RMNY
  ISLMD.SOLVE(s=d, d=d)
- 'Draw a Graphical Comparison with the Baseline
  SMPL 1988:1 1989:4
  ISLMD.MAKEGRAPH(c) MPOLICY @ENDOG

Tight Monetary Policy



Tight Monetary Policy

- A substantial increase in interest rate.
- Causes a sharp reduction in real gross domestic investment in 1989Q1. Real investment stays below the base path for the rest of the horizon.
- This leads to small reduction in GNP, and a very small decrease in real consumption.

Scenario Implementation

- Definition: *A set of assumptions about exogenous variables.*
- Scenario implementation greatly facilitated by aliasing: Mapping of model variables into different sets of workfile series without having to alter equations of the model. This protects historical data from being overwritten

Scenario Implementation

- For exogenous variables, aliasing works in conjunction with the OVERRIDE procedure which allows one to change the path of an exogenous variable.
  - Values of the overridden variables are fetched from workfile series specific for that scenario.
- EXCLUDE procedure specifies excluded endogenous variables in the active scenario.

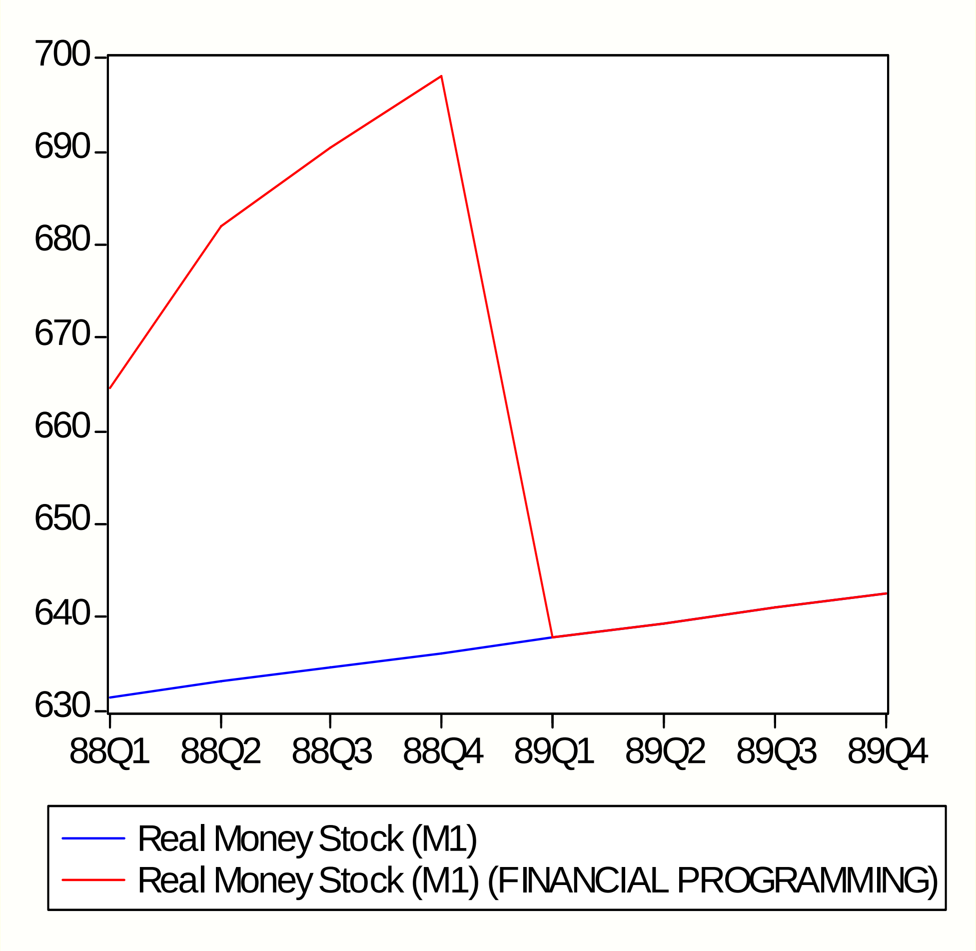
Scenario Implementation

- Solve Control for a Target
  - The CONTROL procedure solves for values on an exogenous variable so that a target endogenous variable follows a chosen trajectory.
  - Syntax: model_name.control control_var target_var trajectory
  - Example: Control money supply so that GNP grows at 0.8 percent per quarter on average between 1987Q4 and 1989Q4.

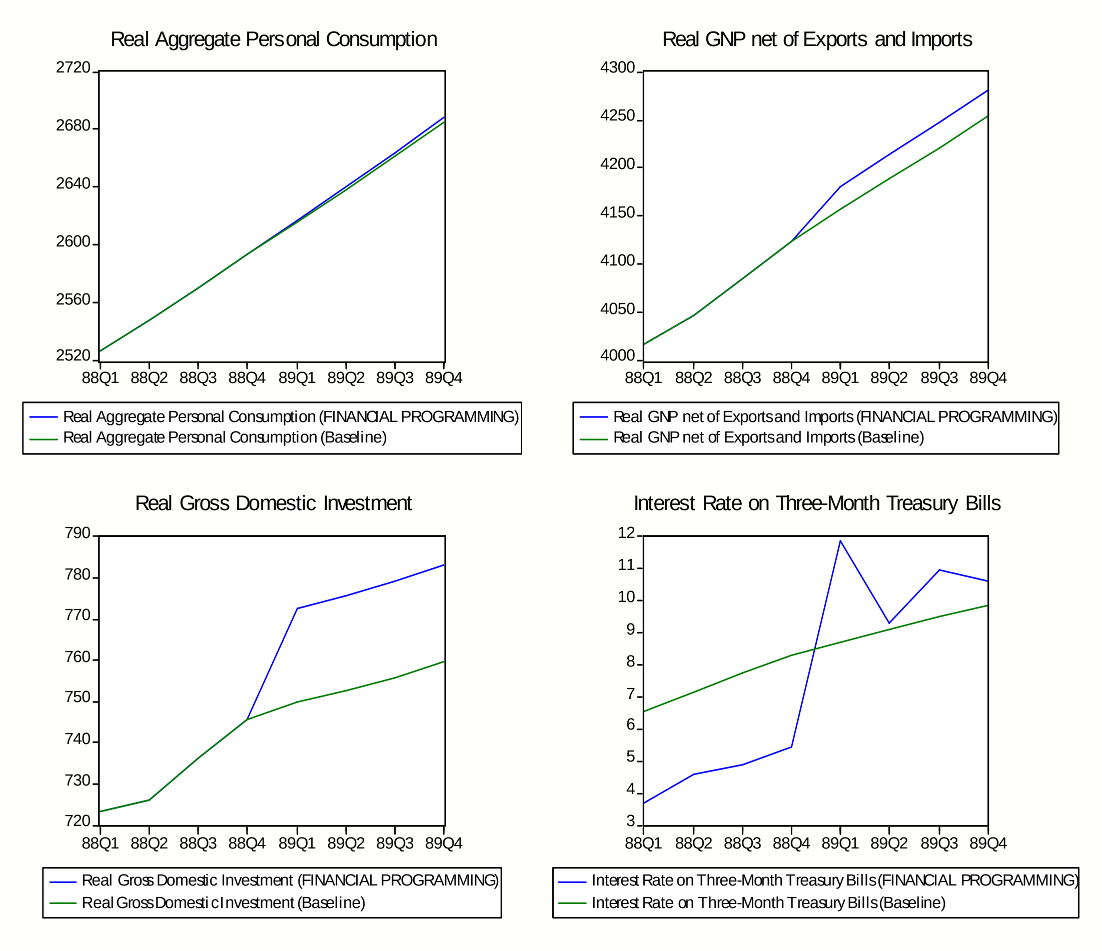
Scenario Implementation

```
SMPL 1987Q4 1987Q4
GNPTRAJ=GNP
SMPL 1987Q4+1 @LAST
        GNPTRAJ=(1+ (0.032/4))*GNPTRAJ(-1)
SMPL  1988Q1  @LAST
ISLMD.SCENARIO(n, a=fpr) FINANCIAL PROGRAMMING
ISLMD.OVERRIDE RMNY
ISLMD.CONTROL RMNY GNP GNPTRAJ
ISLMD.SOLVE(s=d, d=d, c=1e-15)
GROUP MSTOCK RMNY RMNY_fpr
FREEZE(MPROG) MSTOCK.LINE
ISLMD.MAKEGRAPH(c) FINANCIAL  @ENDOG
```

Financial Programming



Financial Programming



Upshot

- The computation of the consequences of a policy choice is of vital importance in policy analysis.
- The model object in EViews provides a convenient tool for the job.
- Model specification relies on the MERGE or APPEND procedure depending on whether the equation is linked or inline.
- There are two basic solvers: Gauss-Seidel and Newton.
- The SCENARIO procedure greatly facilitates the implementation of various types of simulations:
  - Historical (validation)
  - Ex post forecast
  - Ex ante forecast and policy simulations
  - Solving the model in programming mode.

Exercise

- Klein's Model I
  - Structure
  - Estimation
  - Simulation

Exercise

- Structure of the Klein Interwar Model
  - A small dynamic macro-econometric model developed by Lawrence R. Lawrence to analyze the U.S. economy during the period between World War I and World War II (1921-1941).
  - Three behavioral equations: Consumption, Investment, and Private wages.
  - An equilibrium condition depicting the national income identity.
  - Two identities: total profits and end year capital stock.

Exercise

- Structure of the Klein Interwar Model
  - Consumption

$$C_t = \alpha_1 + \alpha_2 P_t + \alpha_3 P_{t-1} + \alpha_4 (W_t^p + W_t^g) + \varepsilon_{1t}$$

  - Net Investment

$$I_t = \beta_1 + \beta_2 P_t + \beta_3 P_{t-1} + \beta_4 K_{t-1} + \varepsilon_{2t}$$

  - Private Wages

$$W_t^p = \gamma_1 + \gamma_2 X_t + \gamma_3 X_{t-1} + \gamma_4 Time + \varepsilon_{3t}$$

Exercise

- Structure of the Klein Interwar Model
  - Goods Market Equilibrium

$$X_t = C_t + I_t + G_t$$

  - Profits

$$P_t = X_t - T_t - W_t^p$$

  - Capital Stock

$$K_t = K_{t-1} + I_t$$

Exercise

- Limited and Full Information Estimation of Klein's Model I.
  - Two-Stage Least Squares
    - Use equation object to find 2SLSE
    - Use equation object and GMM command to 2SLSE
    - Use system object to find 2SLSE
    - Recall Syntax:
    - EQ_NAME.TSLS(OPTIONS) Y X1 [X2 X3 …] @Z1 [Z2 Z3 …]
    - SYSTEM_NAME.TSLS(OPTIONS)
    - EQ_NAME.GMM(OPTIONS) Y X1 [X2 X3 …] @Z1 [Z2 Z3 …]
    - SYSTEM_NAME.GMM(OPTIONS)

Exercise

- Limited and Full Information Estimation of Klein's Model I.
  - GMM under Heteroskedasticity
    - Use equation object and GMM command to produce estimates that are robust to unknown form of heteroskedasticity.
  - Three-Stage Least Squares
    - Use the system object to find 3SLSE
    - Syntax: SYSTEM_NAME.3SLS(OPTIONS)

Exercise

System: KLEIN2SLS

Estimation Method: **Two-Stage Least Squares**

Date: 10/10/05 Time: 15:54

Sample: 1921 1941

Included observations: 21

Total system (balanced) observations 63

Estimation settings: tol=0.00010, derivs=analytic (linear)

Initial Values: ALPHA(1)=15.8295, ALPHA(2)=0.29304,
ALPHA(3)=0.04782, ALPHA(4)=0.78180, BETA(1)=16.1710,
BETA(2)=0.37981, BETA(3)=0.41245, BETA(4)=-0.14001,
GAMMA(1)=2.08808, GAMMA(2)=0.37473, GAMMA(3)=0.20299,
GAMMA(4)=0.18229

Exercise

	Coefficient	Std. Error	t-Statistic	Prob.
ALPHA(1)	16.55476	1.467979	11.27725	0.0000
ALPHA(2)	0.017302	0.131205	0.131872	0.8956
ALPHA(3)	0.216234	0.119222	1.813714	0.0756
ALPHA(4)	0.810183	0.044735	18.11069	0.0000
BETA(1)	20.27821	8.383249	2.418896	0.0192
BETA(2)	0.150222	0.192534	0.780237	0.4389
BETA(3)	0.615944	0.180926	3.404398	0.0013
BETA(4)	-0.157788	0.040152	-3.929751	0.0003
GAMMA(1)	1.500297	1.275686	1.176070	0.2450
GAMMA(2)	0.438859	0.039603	11.08155	0.0000
GAMMA(3)	0.146674	0.043164	3.398063	0.0013
GAMMA(4)	0.130396	0.032388	4.026001	0.0002
Determinant residual covariance		0.287714		

Exercise

Equation: CS=ALPHA(1) +ALPHA(2)*P +ALPHA(3)*P(-1)+ALPHA(4)*(WP+WG)

Instruments: G T WG TIME K1 P(-1) X(-1) C

Observations: 21

R-squared	0.976711	Mean dependent var	53.99524
Adjusted R-squared	0.972601	S.D. dependent var	6.860866
S.E. of regression	1.135659	Sum squared resid	21.92525
Durbin-Watson stat	1.485072		

Equation: I=BETA(1) +BETA(2)*P+BETA(3)*P(-1) +BETA(4)*K1

Instruments: G T WG TIME K1 P(-1) X(-1) C

Observations: 21

R-squared	0.884884	Mean dependent var	1.266667
Adjusted R-squared	0.864569	S.D. dependent var	3.551948
S.E. of regression	1.307149	Sum squared resid	29.04686
Durbin-Watson stat	2.085334		

Equation: WP=GAMMA(1) +GAMMA(2)*X +GAMMA(3)*X(-1) +GAMMA(4)*TIME

Instruments: G T WG TIME K1 P(-1) X(-1) C

Observations: 21

R-squared	0.987414	Mean dependent var	36.36190
Adjusted R-squared	0.985193	S.D. dependent var	6.304401
S.E. of regression	0.767155	Sum squared resid	10.00496
Durbin-Watson stat	1.963416		

Exercise

System: KLEIN3SLS

Estimation Method: Three-Stage Least Squares

Date: 10/10/05 Time: 12:01

Sample: 1921 1941

Included observations: 21

Total system (balanced) observations 63

Estimation settings: tol=0.00010, derivs=analytic (linear)

Initial Values: ALPHA(1)=0.00000, ALPHA(2)=0.00000,
ALPHA(3)=0.00000, ALPHA(4)=0.00000, BETA(1)=0.00000,
BETA(2)=0.00000, BETA(3)=0.00000, BETA(4)=0.00000,
GAMMA(1)=0.00000, GAMMA(2)=0.00000, GAMMA(3)=0.00000,
GAMMA(4)=0.00000

Linear estimation after one-step weighting matrix

Exercise

	Coefficient	Std. Error	t-Statistic	Prob.
ALPHA(1)	16.44079	1.304549	12.60266	0.0000
ALPHA(2)	0.124890	0.108129	1.155013	0.2535
ALPHA(3)	0.163144	0.100438	1.624323	0.1105
ALPHA(4)	0.790081	0.037938	20.82563	0.0000
BETA(1)	28.17785	6.793770	4.147601	0.0001
BETA(2)	-0.013079	0.161896	-0.080787	0.9359
BETA(3)	0.755724	0.152933	4.941532	0.0000
BETA(4)	-0.194848	0.032531	-5.989674	0.0000
GAMMA(1)	1.797218	1.115855	1.610619	0.1134
GAMMA(2)	0.400492	0.031813	12.58877	0.0000
GAMMA(3)	0.181291	0.034159	5.307304	0.0000
GAMMA(4)	0.149674	0.027935	5.357897	0.0000
Determinant residual covariance		0.282997		

Exercise

Equation: CS=ALPHA(1) +ALPHA(2)*P +ALPHA(3)*P(-1)+ALPHA(4) *(WP+WG)

Observations: 21

R-squared	0.980108	Mean dependent var	53.99524
Adjusted R-squared	0.976598	S.D. dependent var	6.860866
S.E. of regression	1.049564	Sum squared resid	18.72696
Durbin-Watson stat	1.424939		

Equation: I=BETA(1) +BETA(2)*P+BETA(3)*P(-1) +BETA(4)*K1

Observations: 21

R-squared	0.825805	Mean dependent var	1.266667
Adjusted R-squared	0.795065	S.D. dependent var	3.551948
S.E. of regression	1.607958	Sum squared resid	43.95398
Durbin-Watson stat	1.995884		

Equation: WP=GAMMA(1) +GAMMA(2)*X +GAMMA(3)*X(-1) +GAMMA(4)*TIME

Observations: 21

R-squared	0.986262	Mean dependent var	36.36190
Adjusted R-squared	0.983837	S.D. dependent var	6.304401
S.E. of regression	0.801490	Sum squared resid	10.92056
Durbin-Watson stat	2.155046		

Exercise

- Simulation
  - Create a simulation model on the basis of the full information estimates.
  - How well does it track history?

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The End.