### **Department of Economics**

University of Victoria

# **ECON 546: Themes in Econometrics**

### **Estimation of Simultaneous Equations Models in EViews**

In this handout we discuss the estimation of structural simultaneous equations models (SEM's) using various estimation techniques using the EViews econometrics package. In particular, we will use a simple well-known structural model to illustrate the results that are obtained when different "limited information" and "full information" estimators are used.

The idea SEM's for the economy came from Jan Tinbergen, who estimated a 24-eqatuion system for the Dutch economy in 1936. See Tinbergen (1959, pp.37-84) for an English translation. When the first Nobel Prize in Economic Science was awarded in 1969, Tinbergen shared the inaugural honour with Ragnar Frisch (a Norwegian econometrician) for their pioneering work that led to the development of econometrics as a recognized sub-discipline.

Klein's (1950) "Model I" for the U.S. economy was a 6-equation SEM, comprising 3 structural equations and 3 identities. The equations of Klein's model are given below, with the endogenous variables as the dependent variables:

$C_t = \alpha_0 + \alpha_1 P_t + \alpha_2 P_{t-1} + \alpha_3 (W_t^p + W_t^g) + \varepsilon_{1t}$	(Consumption)
$I_{t} = \beta_{0} + \beta_{1}P_{t} + \beta_{2}P_{t-1} + \beta_{3}K_{t-1} + \varepsilon_{2t}$	(Investment)
$W_t^{p} = \gamma_0 + \gamma_1 X_t + \gamma_2 X_{t-1} + \gamma_3 A_t + \varepsilon_{3t}$	(Private Wages)
$X_t \equiv C_t + I_t + G_t$	(Equilibrium Demand)
$P_t \equiv X_t - T_t - W_t^p$	(Private Profits)
$K_t \equiv K_{t-1} + I_t$	(Capital Stock)

The predetermined variables in the model are the intercept,  $G_t$  (government non-wage spending),  $T_t$  (indirect business taxes plus net exports),  $W_t^g$  (government wage bill),  $A_t$  (time trend, measured as years from 1931), and the lagged dependent variables,  $P_{t-1}$ ,  $X_{t-1}$  and  $K_{t-1}$ . Allowing for lags, the sample period for the estimation of the model was 1921 to 1941 inclusive.

- (1) Why, do you think, did the sample begin in 1921 and end in 1941, when the model was published in 1950?
- (2) The data for this exercise are on the server in the EViews file titled **Klein.wf1**. Note that the variable called "*K*1" is  $K_{t-1}$ , and "*W*" is  $(W_t^p + W_t^g)$ . Estimate each of the three structural equations using OLS. What can you say about the properties of this estimator in the present context? The results that you should obtain are as follows:

View Proc Object Print	Name Freeze	Estimate Forecas	t Stats Resid	s
Dependent Variable: C0 Method: Least Squares Date: 11/20/03 Time: 1 Sample(adjusted): 192 Included observations:	DNS   4:25   1 1941   21 after adjusti	ng endpoints		
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C P P(-1) W	16.23660 0.192934 0.089885 0.796219	1.302698 0.091210 0.090648 0.039944	12.46382 2.115273 0.991582 19.93342	0.0000 0.0495 0.3353 0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.981008 0.977657 1.025540 17.87945 -28.10857 1.367474	Mean depend S.D. depende Akaike info cri Schwarz criter F-statistic Prob(F-statist	ent var nt var terion tion	53.99524 6.860866 3.057959 3.256916 292.7076 0.000000

### View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: I Method: Least Squares Date: 03/14/02 Time: 11:39 Sample(adjusted): 1921 1941 Included observations: 21 after adjusting endpoints

Variable Coefficient Std. Error t-Statistic Prob. С 10.12579 5.465547 1.852658 0.0814 Ρ 4.938864 0.097115 0.0001 0.479636 P(-1) 0.333039 0.100859 3.302015 0.0042 -0.111795 K1 0.026728 -4.182749 0.0006 R-squared 0.931348 Mean dependent var 1.266667 Adjusted R-squared 0.919233 S.D. dependent var 3.551948 S.E. of regression 1.009447 Akaike info criterion 3.026325 Sum squared resid Schwarz criterion 17.32270 3.225282 Log likelihood -27.77641 F-statistic 76.87537 Durbin-Watson stat 1.810184 Prob(F-statistic) 0.000000

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: WP Method: Least Squares Date: 03/14/02 Time: 11:42 Sample(adjusted): 1921 1941 Included observations: 21 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C X X(-1) A	1.497044 0.439477 0.146090 0.130245	1.270032 0.032408 0.037423 0.031910	1.178745 13.56093 3.903734 4.081604	0.2547 0.0000 0.0011 0.0008
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.987414 0.985193 0.767147 10.00475 -22.01235 1.958434	Mean depend S.D. depende Akaike info cri Schwarz criter F-statistic Prob(F-statist	ent var nt var terion tion	36.36190 6.304401 2.477367 2.676324 444.5682 0.000000

(3) Now estimate by Two Stage Least Squares (2SLS) - this is just I.V. estimation with all of the predetermined variables in the model used as the instruments. What are we hoping to achieve by using 2SLS? The results that you should obtain are as follows:

iew Proc Object Print N	ame Freeze	Estimate Forecas	t Stats Resid	s
Dependent Variable: CO Method: Two-Stage Leas Date: 12/02/03 Time: 09 Sample(adjusted): 1921 Included observations: 2 Instrument list: C P(-1) W	NS st Squares 3:18 1941 1 after adjusti VG K1 X(-1) A	ng endpoints G T		
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C P P(-1) W	16.55476 0.017302 0.216234 0.810183	1.467979 0.131205 0.119222 0.044735	11.27725 0.131872 1.813714 18.11069	0.0000 0.8966 0.0874 0.0000
R-squared Adjusted R-squared S.E. of regression F-statistic Prob(F-statistic)	0.976711 0.972601 1.135659 225.9334 0.000000	Mean depend S.D. depende Sum squared Durbin-Watso Second-Stage	ent var nt var resid n stat e SSR	53.99524 6.860866 21.92525 1.485072 67.25682

View [Proc][Object] [Print][Name][Freeze] [Estimate][Forecast][Stats][Resids]

Dependent Variable: I Method: Two-Stage Least Squares Date: 12/02/03 Time: 09:19 Sample(adjusted): 1921 1941 Included observations: 21 after adjusting endpoints Instrument list: C P(-1) WG K1 X(-1) A G T

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.27821	8.383249	2.418896	0.0271
P	0.150222	0.192534	0.780237	0.4460
P(-1)	0.615944	0.180926	3.404398	0.0034
K1	-0.157788	0.040152	-3.929751	0.0011
R-squared	0.884884	Mean depend	dent var	1.266667
Adjusted R-squared	0.864569	S.D. depende	ent var	3.551948
S.E. of regression	1.307149	Sum squared	1 resid	29.04686
F-statistic	41.20019	Durbin-Watso	on stat	2.085334
Prob(F-statistic)	0.000000	Second-Stag	e SSR	41.13794

View Proc Object Print N	lame Freeze	Estimate Forecas	t Stats Resid	s
Dependent Variable: WF Method: Two-Stage Lea: Date: 12/02/03 Time: 0 Sample(adjusted): 1921 Included observations: 2 Instrument list: C P(-1) V	) st Squares 9:19 1941 ?1 after adjusti VG K1 X(-1) A	ing endpoints G T		
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C X X(-1) A	1.500297 0.438859 0.146674 0.130396	1.275686 0.039603 0.043164 0.032388	1.176070 11.08155 3.398063 4.026001	0.2558 0.0000 0.0034 0.0009
R-squared Adjusted R-squared S.E. of regression F-statistic Prob(F-statistic)	0.987414 0.985193 0.767155 424.1940 0.000000	Mean depend S.D. depende Sum squared Durbin-Watso Second-Stage	ent var nt var resid n stat e SSR	36.36190 6.304401 10.00496 1.963416 45.96024

\_

Compare the 2SLS and OLS estimates.

(4) We will now estimate the model by Three Stage Least Squares (3SLS) – a "full information" or "systems" estimator that has the same asymptotic efficiency as Full Information Maximum Likelihood (FIML). First, we need to create the system we are going to use. In the EViews workfile, select "Object", "New Object", "System". Name your system THREESTAGE. Then lay out the specification of the structural equations in the model as follows:



(To make things easy for you, the code for these equations is stored in the text-object called "Three\_Stage\_Spec" in the EViews workfile.)

Then select the "Estimate" tab and choose "Three-Stage Least Squares" as the estimation method:

timation method	Time series HAC specification
'hree-Stage Least Squares 🛛 👻	Prewhitening by VAR(1)
	Kernel options
timation settings	<ul> <li>Bartlett</li> </ul>
Add lagged regressors to instruments	🔘 Quadratic
for linear equations with AR terms	Bandwidth selection
	Fixed: Number or NW     Fixed: Nw     Fixed: Nw
(25LS coefs & GMM robust std,errors)	Andrews
,	🔿 Variable - Newey-West
	Sample
	1920 1941

Select "OK" to obtain the 3SLS estimates:

	ame Freeze	merge lext Estim	ate Spec Sta	ts Resids		
System: THREESTAGE						
Estimation Method: Thre	e-Stage Leas	t Squares				
Date: 10/14/09 Time: 1	4:48					
Sample: 1921 1941						
ncluded observations: 2	21					
Fotal system (balanced)	observations	63				
_inear estimation after c	ine-step weigt	nting matrix				
	Coefficient	Std. Error	t-Statistic	Prob.		
C(1)	16 44079	1 304549	12 60266	0 0000		
C(2)	0.124890	0 108129	1 1 5 5 0 1 3	0.2535		
C(3)	0.163144	0.100438	1.624323	0.1105		
C(4)	0.790081	0.037938	20.82563	0.0000		
C(5)	28.17785	6.793770	4.147601	0.0001		
C(6)	-0.013079	0.161896	-0.080787	0.9359		
C(7)	0.755724	0.152933	4.941532	0.0000		
C(8)	-0.194848	0.032531	-5.989674	0.0000		
C(9)	1.797218	1.115855	1.610619	0.1134		
C(10)	0.400492	0.031813	12.58877	0.0000		
C(11)	0.181291	0.034159	5.307304	0.0000		
C(12)	0.149674	0.027935	5.357897	0.0000		
Determinant residual co	variance	0 282997				
Determinant residual co	variance	0.282997				
Determinant residual co	variance	0.282997				
Determinant residual co	variance C(2)*P+C(3)*F	0.282997 ?(-1)+C(4)*(WP·	+WG)			
Equation: CONS=C(1)+(	variance C(2)*P+C(3)*F K1 X(-1) A G	0.282997 ?(-1)+C(4)*(WP- T	+WG)			
Equation: CONS=C(1)+( nstruments: C P(-1) WO	variance C(2)*P+C(3)*F K1 X(-1) A G	0.282997 ?(-1)+C(4)*(WP- T	+WG)			
Equation: CONS=C(1)+( nstruments: C P(-1) WG Deservations: 21 R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108	0.282997 P(-1)+C(4)*(WP- T Mean depend	+WG) lent var	53.99524		
Equation: CONS=C(1)+( nstruments: C P(-1) WG Dbservations: 21 R-squared Adjusted R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende	+WG) lent var int var	53.99524 6.860866		
Determinant residual co Equation: CONS=C(1)+( nstruments: C P(-1) WO Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watcon stat	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939	0.282997 ?(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared	+WG) lent var nt var I resid	53.99524 6.860866 18.72696		
Equation: CONS=C(1)+( nstruments: C P(-1) WC <u>Deservations: 21</u> R-squared Adjusted R-squared 3.E. of regression Durbin-Watson stat	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared	+WG) lent var nt var I resid	53.99524 6.860866 18.72696		
Determinant residual co Equation: CONS=C(1)+( nstruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+(	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1	+WG) lent var ınt var I resid	53.99524 6.860866 18.72696		
Determinant residual co Equation: CONS=C(1)+( nstruments: C P(-1) WG Dbservations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*P nstruments: C P(-1) WG	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T	+WG) lent var nt var I resid	53.99524 6.860866 18.72696		
Determinant residual co Equation: CONS=C(1)+( nstruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F nstruments: C P(-1) WG Observations: 21	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T	+WG) lent var nt var I resid	53.99524 6.860866 18.72696		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende Sum squared C(8)*K1 T Mean depend	+WG) lent var Int var I resid	53.99524 6.860866 18.72696 1.266667		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+G 0.825805 0.795065	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende	+WG) lent var nt var I resid lent var nt var	53.99524 6.860866 18.72696 1.266667 3.551948		
Determinant residual co Equation: CONS=C(1)+( nstruments: C P(-1) WO <u>Observations: 21</u> R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F nstruments: C P(-1) WO <u>Observations: 21</u> R-squared Adjusted R-squared S.E. of regression	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+G K1 X(-1) A G 0.825805 0.795065 1.607958	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared	+WG) Ient var Int var Iresid Ient var Int var	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared	+WG) lent var int var l resid lent var int var l resid	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*V	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende Sum squared C(8)*K1 T Mean depende S.D. depende Sum squared (-1)+C(12)*A	+WG) Ient var Int var I resid Ient var I resid	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: WP=C(9)+C(1)	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*X K1 X(-1) A G	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared (-1)+C(12)*A	+WG) Ient var Int var I resid Ient var I resid	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: WP=C(9)+C(1) Instruments: C P(-1) WG	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*X K1 X(-1) A G	0.282997 P(-1)+C(4)*(WP- T Mean depende S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared (-1)+C(12)*A T	+WG) Ient var Iresid Ient var Iresid	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WO Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WO Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: WP=C(9)+C(1) Instruments: C P(-1) WO Observations: 21 R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+G K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*X K1 X(-1) A G 0.986262	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared (-1)+C(12)*A T Mean depend	+WG) Ient var Int var Iresid Ient var Iresid	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared Equation: WP=C(9)+C(1 Instruments: C P(-1) WG Observations: 21 R-squared Adjusted R-squared	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*X K1 X(-1) A G 0.986262 0.983838	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared (-1)+C(12)*A T Mean depend S.D. depende	+WG) lent var int var l resid lent var l resid lent var nt var	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398 36.36190 6.304401		
Determinant residual co Equation: CONS=C(1)+( Instruments: C P(-1) WC Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: I=C(5)+C(6)*F Instruments: C P(-1) WC Observations: 21 R-squared Adjusted R-squared S.E. of regression Durbin-Watson stat Equation: WP=C(9)+C(1 Instruments: C P(-1) WC Observations: 21 R-squared Adjusted R-squared S.E. of regression	variance C(2)*P+C(3)*F K1 X(-1) A G 0.980108 0.976598 1.049565 1.424939 P+C(7)*P(-1)+( K1 X(-1) A G 0.825805 0.795065 1.607958 1.995884 0)*X+C(11)*X K1 X(-1) A G 0.986262 0.983838 0.801490	0.282997 P(-1)+C(4)*(WP- T Mean depend S.D. depende Sum squared C(8)*K1 T Mean depend S.D. depende Sum squared (-1)+C(12)*A T Mean depend S.D. depende Sum squared	+WG) lent var int var l resid lent var int var l resid lent var int var	53.99524 6.860866 18.72696 1.2666667 3.551948 43.95398 36.36190 6.304401 10.92056		

(5) Let's move ahead to FIML estimation of the model. *Now the identities have to be* "*solved out*" *in order for EViews to proceed*. With a larger model, this would be very tedious – some other econometrics packages allow you to include identities explicitly as part of the model specification, but EViews does not, unfortunately. So, in the EViews workfile, select "Object", "New Object", "System". Name your system FIML. Then lay out the specification of the structural equations in the model as follows:

🗖 System: FIML - Workfile: KLEIN::Klein\	
View Proc Object Print Name Freeze MergeText Estimate Spec Stats Resid	s
cons=c(1)+c(2)*(cons+i+g-t-wp)+c(3)*(cons(-1)+i(-1)+g(-1)-t(-1)-wp(-1))+c( (wp+wg)	4)*
i=c(5)+c(6)*(cons+i+g-t-wp)+c(7)*(cons(-1)+i(-1)+g(-1)-t(-1)-wp(-1))+c(8)*k1 wp=c(9)+c(10)*(cons+i+g)+c(11)*(cons(-1)+i(-1)+g(-1))+c(12)*a	I

(Again, to make things easy for you, these equations are stored in the text-object called "FIML\_Spec" in the EViews workfile.)

Now select the "Estimate" tab, choose "Full Information Maximum Likelihood" as the estimation method and then select the "Options" tab. Alter the settings as follows (including 1000 as the maximum number of iterations), and you should obtain the following estimation results and "Gradients Summary" (presented here in reverse order to save space):

Uiew Proc Object P	Workfile: KLL rint Name Freeze	IN::Klein\ e) (MergeText)	Estimate Spec	Sta	
Gradients of objective function at estimated parameters System: FIML Method: Full Information Maximum Likelihood Computed using analytic derivatives System specification is linear					
Coefficient	Sum	Mean	Newton Dir.		
C(1)	0.000428	2.04E-05	0.000113		
C(2)	0.007761	0.000370	0.000183		
C(3)	0.007698	0.000367	-0.000132		
C(4)	0.019870	0.000946	-9.60E-06		
C(5)	-0.000226	-1.07E-05	-0.000136		
C(6)	-0.004240	-0.000202	0.000353		
C(7)	-0.004248	-0.000202	-0.000253		
C(8)	-0.045926	-0.002187	-1.72E-06		
C(9)	0.000362	1.72E-05	0.000258		
C(10)	0.023867	0.001137	2.66E-07		
C(11)	0.023839	0.001135	5.43E-08		
C(12)	0.001288	6.14E-05	9.21E-06		

System: FIML Workfile: KLEIN::Klein\

View Proc Object Print Name Freeze MergeText Estimate Spec Stats Resids

-

System: FIML

Estimation Method: Full Information Maximum Likelihood (BHHH) Date: 10/14/09 Time: 14:59 Sample: 1921 1941 Included observations: 21 Total system (balanced) observations 63 Convergence achieved after 873 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	18.34295	12.87763	1.424404	0.1543
C(2)	-0.232347	1.930369	-0.120364	0.9042
C(3)	0.385657	1.083031	0.356090	0.7218
C(4)	0.801841	0.084178	9.525593	0.0000
C(5)	27.26372	21.47140	1.269769	0.2042
C(6)	-0.800945	2.334309	-0.343118	0.7315
C(7)	1.051836	1.403898	0.749225	0.4537
C(8)	-0.148102	0.099173	-1.493370	0.1353
C(9)	5.794027	4.645271	1.247296	0.2123
C(10)	0.234127	0.095283	2.457170	0.0140
C(11)	0.284672	0.061742	4.610703	0.0000
C(12)	0.234830	0.077642	3.024526	0.0025
Log likelihood	-83.32381	Schwarz crite	erion	9.675328
Avg. log likelihood	-1.322600	Hannan-Quir	nn criter.	9.207994
Akaike info criterion	9.078458			
Determinant residual co	ovariance	1.442705		

#### Equation: CONS=C(1)+C(2)\*(CONS+I+G-T-WP)+C(3)\*(CONS(-1)+I(-1)+G( -1)-T(-1)-WP(-1))+C(4)\*(WP+WG)

Observations: 21			
R-squared	0.953069	Mean dependent var	53.99524
Adjusted R-squared	0.944787	S.D. dependent var	6.860866
S.E. of regression	1.612123	Sum squared resid	44.18200
Durbin-Watson stat	1.367116		
Equation: I=C(5)+C(6)*(C(	DNS+I+G-T-V	VP)+C(7)*(CONS(-1)+I(-1)+(	∋(-1)-T(
-1)-WP(-1))+C(8)*K1			
Observations: 21			
R-squared	-0.062797	Mean dependent var	1.266667
Adjusted R-squared	-0.250349	S.D. dependent var	3.551948
S.E. of regression	3.971753	Sum squared resid	268.1720
Durbin-Watson stat	1.235548		
Equation: WP=C(9)+C(10)	*(CONS+I+G	))+C(11)*(CONS(-1)+I(-1)+G	(-1))
+C(12)*A			
Observations: 21			
R-squared	0.952421	Mean dependent var	36.36190
Adjusted R-squared	0.944025	S.D. dependent var	6.304401
S.E. of regression	1.491562	Sum squared resid	37.82089
Durbin-Watson stat	1.493348		

If you look on page 385 of Greene (2008) you will see a summary of the OLS, 2SLS, 3SLS and FIML results, together with some other estimates. His results agree closely with ours.

(6) The next thing is to see how we can "solve" the estimated structural form of the model for the restricted reduced form. In our case, the model is linear in both the endogenous variables and the parameters, so this is achieved by straightforward matrix manipulations. However, if the model were non-linear in the endogenous variables, this solution would have to be achieved iteratively as we would then have a system of non-linear equations to be solved. In that case techniques such as the Gauss-Seidel method or Newton's method would be used. Note that this "solution" process has nothing to do with estimation – that has been done already – what we are now doing is converting the structural form equations into the corresponding restricted reduced form equations so that we can either forecast, or else perform policy simulations.

First, select "Object", "New Object", "Model", and name your new model FIML\_CONTROL. There are various ways to get the estimated equations into this model. The easiest way at this stage is to copy and paste your FIML *system* into the blank window for the FIML\_CONTROL *model*. You should then see this:

Model: FIML_CONT	ROL Workfile:	: KLEIN::Klein\	
View Proc Object Print N	lame Freeze) Solv	ve Scenarios Equations	Variables Text
Equations: 3			Baseline
S FIML	Eq1	cons, i, wp = F( a, co	ns, g, i, k1, t, wg, wp )

Click on the blue "S" logo and you will see:

pertie	S							
uation	Endog	enous Add	Factors					
Equatio	n 1 —							
Endoge	eonus:	CONS		~	Linł	<: FIML		
System	n: FIML	estimated or	10/14/09 -	14:59				^
cons = i(-1) + @coe @coe @coe @coe @coe	= @coef g(-1) - ef(1) = ef(2) = - ef(3) = ef(4) = ef(5) = ef(6) = -	(1) + @coef( t(-1) - wp(-1 18.342947 0.2323471 0.3856568 0.8018414 27.263722 0.8009446	(2) * (cons + )) + @coef(4	i+g-t- ł)*(wp+	wp) + ( wg)	@coef(3) * (c	ons(-1) +	
Edit I	Equatior	n or Link Spec	tification	Equat Sto	ion type ochastic entity	with S.D.:	1.6121232	

You can then scroll the endogenous variables to see the specifications of the other two equations in the model.

To solve the model, select "Solve:

Basic Options Stochastic Options Tr	acked Variables Diagnostics Solver
Simulation type Deterministic Stochastic	Solution scenarios & output Active: Baseline Edit Scenario Options
Dynamics     Dynamic solution     Static solution     Fit (static - no eq interactions)	Solve for Alternate along with Active
Structural (ignore ARMA)	Edit Scenario Options
Solution sample	Edit Scenario Options

What is the difference between a "Deterministic" and "Stochastic" simulation?

What are the differences between "Dynamic Solution", "Static Solution" and "Fit" in the "Dynamics box?

Select "OK" and you will see:

🕮 Model: FIML_CONTROL 🛛 Workfile: KLEIN::Klein\ 📃 🗖 🔀
View Proc Object Print Name Freeze Solve Scenarios Equations Variables Text
Model: FIML_CONTROL Date: 10/14/09 Time: 15:11
Sample (adjusted): 1921 1941 Solve Options:
Solver: Broyden
Max iterations = 5000, Convergence = 1e-08
Parsing Analytic Jacobian: 9 derivatives kept, 0 derivatives discarded
Scenario: Baseline Solve begin 15:11:48 Solve complete 15:11:48

If you look at the main EViews workspace, you should also see that three new variables have been created. What are they?

Model variables	Graph series	
Select: All variable types	Solution series:	6
From:  All model variables Listed variables	Actuals	×
	Active: Baseline	~
		-
	Compare: Baseline	~
<u></u>	Compare: Baseline	Compare n Compari
Series grouping	Compare: Baseline Deviations: Active from C % Deviation: Active from Transform: Level	Compare n Compare
Series grouping C Each series in its own graph Group by Model Variable	Compare: Baseline Compare: Baseline Compare: Baseline Compare: Baseline Compare: Com	Compare n Compare

Now select "Proc", "Make Graph", and edit the window so that it looks like this:





Why are there two lines on some of the graphs and only one on others?

What does "Baseline" refer to in the legends?

(7) Finally, let's simulate the effect of a simple policy change. Specifically, we are going to see what the model predicts *would have happened* if Government Non-Wage Spending (G) had been 5 units larger in each of the years 1937 to 1941 inclusive. What follows shows how to conduct a dynamic/deterministic simulation and compare the "policy-on" results with both the "policy off" "(control", or "baseline") results and the actual data. You can experiment with other types of simulations.

In the Model window, select the "Scenarios" tab, and you will see:

t Scenario	Overrides	Excludes	Aliasing
-Select Acti	ive Scenario		
Actuals Baseline			Create New Scenario
Scenario (	1		Copy Scenario
			Apply Selected to Baseline
			Delete Selected
			Rename Selected
			Write protect active scenario

Highlight Scenario 1, as shown, and select "OK".

Then, in the Model window and select the "Variables" tab:

💷 Model: Fl	ML_CONTROL Workfile: KLEIN::Klein\	
View Proc Obje	ect) Print Name Freeze Solve Scenarios Equations	Variables Text
Filter/Sort	All Model Variables	Scenario 1
[Dependencies]	Variables: 8 (Endog = 3 , Exog = 5 , Adds = 0)	
🔀 a	Exog	
En cons	Eq1	
🔀 g	Exog	
En	Eq2	
🔀 k1	Exog	
🔀 t	Exog	
🔀 wg	Exog	
En Wp	Eq3	

Next, right mouse-click on the variable "g", and select "Properties". Check the "override" box as shown, and press "Select Override = Actual":

	Modify exogenous
Active Scenario: Scenario 1	Create (if necessary) an
Actual exogenous: G	override series and
Overridden exog: G_1	initialize with actuals.
Vuse override series in scenario	Set Override = Actual
Exogenous uncertainty in stochastic simulation —	
Exogenous uncertainty in stochastic simulation — Enter a number or series to be used as the exog forecast standard error in stochastic	Set exog to achieve a desired endog trajectory
Exogenous uncertainty in stochastic simulation — Enter a number or series to be used as the exog forecast standard error in stochastic NA	Set exog to achieve a desired endog trajectory Control =>Target

What new variable has been created in the Workfile? Note that "g" has changed colour to red in the Model box.

Now edit the series "G\_1" by increasing each of the last five values by 5 units. (*e.g.*, the 1941 value will now be 18.8.) Select the "Solve" tab in the Model window and you will now see:

sic Options Stochastic Opt	tions Tracked Variables Diagnostics Solver
Simulation type Deterministic Stochastic	Solution scenarios & output Active: Scenario 1 Edit Scenario Options
Dynamics     Dynamic solution     Static solution     Fit (static - no eq intera	Solve for Alternate along with Active
Structural (ignore ARM	A) Edit Scenario Options

Select "OK". Then select "Proc", "Make Graph" and edit the window as follows:

	Graphisenes	24	
ielect: All variable types	Solution series	ii Solutions	
rom:  All model variables Listed variables	Actuals		
£ 💦	Active:	Scenario 1	~
	Compare:	Baseline	~
	Deviations	Active from Cor	npare
<u>.</u>	🗌 % Deviatio	n: Active from C	ompare
eries grouping	Transform: Le	vel	~
	Sample for graph		
Each series in its own graph Group by Model Variable			

Select "OK", and interpret the graphs:



# **References:**

- Greene, W. H. (2008), *Econometric Analysis*, 6<sup>th</sup> ed., Pearson Prentice Hall, Upper Saddle River, NJ.
- Klein, L. R. (1950), Economic Fluctuations in the United States, 1921-1941, Wiley, New York.
- Tingbergen, J. (1959), *Selected Papers*, edited by L. H. Klaassen, L. M. Koyck and J. H. Witteveen, North-Holland, Amsterdam.