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From Data Assignment 2.dta:
1. State reduce form model of these system models.

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$$\ln S_t = \beta_{10} + \beta_{11} \ln P_{Dt} + \beta_{12} \ln P_{X2_t} + \beta_{13} \ln P_{X3_t} + \beta_{14} \ln P_{X4_t} + \varepsilon_{1t}$$

$$\ln D_t = \beta_{20} + \beta_{21} \ln P_{D_t} + \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

Assume $\ln S_t = \ln D_t$

$$\beta_{10} + \beta_{11} \ln P_{D_t} + \beta_{12} \ln P_{X2_t} + \beta_{13} \ln P_{X3_t} + \beta_{14} \ln P_{X4_t} + \varepsilon_{1t} = \beta_{20} + \beta_{21} \ln P_{D_t} + \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

$$\beta_{11} \ln P_{D_t} - \beta_{21} \ln P_{D_t} = (\beta_{20} - \beta_{10}) - (\beta_{12} \ln P_{X2_t}) - (\beta_{13} \ln P_{X3_t}) - (\beta_{14} \ln P_{X4t}) + (\beta_{22} \ln GDP_t) + (\varepsilon_{2t} - \varepsilon_{1t})$$

$$\ln P_{D_t} = \frac{(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{(\beta_{12} \ln P_{X2_t})}{\beta_{11} - \beta_{21}} - \frac{(\beta_{13} \ln P_{X3_t})}{\beta_{11} - \beta_{21}} - \frac{\beta_{14} \ln P_{X4_t})}{\beta_{11} - \beta_{21}} + \frac{\beta_{22} \ln GDP_t)}{\beta_{11} - \beta_{21}} + \frac{\beta_{22} \ln GDP_t}{\beta_{11} - \beta_{21}} + \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}$$

$$\ln P_{D_t} = \left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}}\right) - \frac{(\beta_{12} \ln P_{X2_t})}{\beta_{11} - \beta_{21}} - \frac{(\beta_{13} \ln P_{X3_t})}{\beta_{11} - \beta_{21}} - \frac{(\beta_{14} \ln P_{X4_t})}{\beta_{11} - \beta_{21}} + \frac{(\beta_{22} \ln GDP_t)}{\beta_{11} - \beta_{21}} + \frac{(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}}$$

→ Plug in $\ln P_{D_t}$ in $\ln S_t$

$$\ln S_t = \beta_{10} + \beta_{11}\left(\frac{(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{(\beta_{12} \ln P_{X2t})}{\beta_{11} - \beta_{21}} - \frac{\beta_{13} \ln P_{X3_t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{14} \ln P_{X4_t}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22} \ln GDP_t}{\beta_{11} - \beta_{21}} + \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}\right) + \beta_{12} \ln P_{X2_t} + \beta_{13} \ln P_{X3_t} + \beta_{14} P_{X4_t} + \varepsilon_{1t}$$

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$$= \beta_{10} + \frac{\beta_{11}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{\beta_{11}\beta_{21} \ln P_{x2t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{11}\beta_{13} \ln P_{x3_t}}{\beta_{11} - \beta_{21}} -$$

$$\frac{\beta_{11}\beta_{14} \ln P_{x4_t}}{\beta_{11} - \beta_{21}} + \frac{\beta_{11}\beta_{22} \ln GDP}{\beta_{11} - \beta_{21}} + \frac{\beta_{11}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}}$$

$$+ \beta_{12} \ln P_{x2_t} + \beta_{13} \ln P_{x3_t} + \beta_{14} P_{x4_t} + \varepsilon_{1t}$$

where $\pi_{10} = \beta_{10} + \frac{\beta_{11}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}}$ $\quad \pi_{11} = \frac{-\beta_{11}\beta_{12}}{\beta_{11} - \beta_{21}} + \beta_{12}$

$\pi_{12} = \frac{-\beta_{11}\beta_{13}}{\beta_{11} - \beta_{21}} + \beta_{13}$ $\quad \pi_{13} = \frac{\beta_{11}\beta_{14}}{\beta_{11} - \beta_{21}} + \beta_{14}$

$\pi_{14} = \frac{\beta_{11}\beta_{22}}{\beta_{11} - \beta_{21}}$ $\quad W_{1t} = \frac{\beta_{11}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} + \varepsilon_{1t}$

$\rightarrow$ Plug in $\ln P_{2_t}$ in $\ln D_t$

$$\ln D_t = \beta_{20} + \beta_{21}\left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} - \frac{\beta_{12} \ln P_{x2_t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{13} \ln P_{x3_t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{14} \ln P_{x4_t}}{\beta_{11} - \beta_{21}} + \left(\frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}\right)\right) + \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

$$= \beta_{20} + \frac{\beta_{21}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{\beta_{21}\beta_{12}(\ln P_{x2_t})}{\beta_{11} - \beta_{21}} - \frac{\beta_{21}\beta_{13}(\ln P_{x3_t})}{\beta_{11} - \beta_{21}}$$

$$- \frac{\beta_{21}\beta_{14}(\ln P_{x4_t}) + \beta_{21}\beta_{22}(\ln GDP_t)}{\beta_{11} - \beta_{21}} + \frac{\beta_{21}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}}$$

$$+ \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

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where $\pi_{20} = \beta_{20} + \dfrac{\beta_{21}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}}$ $\quad \pi_{21} = \dfrac{-\beta_{21}\beta_{12}}{\beta_{11} - \beta_{21}}$

$\pi_{22} = \dfrac{-\beta_{21}\beta_{13}}{\beta_{11} - \beta_{21}}$ $\quad \pi_{23} = \dfrac{-\beta_{21}\beta_{14}}{\beta_{11} - \beta_{21}}$ $\quad \pi_{24} = \dfrac{\beta_{21}\beta_{22}}{\beta_{11} - \beta_{21}} + \beta_{20}$ $\quad W_{2t} = \dfrac{\beta_{21}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} +$

$\pi_{30} = \dfrac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}}$ $\quad \pi_{33} = \dfrac{-\beta_{12}}{\beta_{11} - \beta_{21}}$ $\quad \pi_{32} = \dfrac{-\beta_{13}}{\beta_{11} - \beta_{21}}$

$\pi_{33} = \dfrac{-\beta_{1t}}{\beta_{11} - \beta_{21}}$ $\quad \pi_{34} = \dfrac{\beta_{22}}{\beta_{11} - \beta_{21}}$ $\quad W_{3t} = \dfrac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}$

To reduce form model of these system model

$\ln S_t = \pi_{10} + \pi_{1}(\ln P_{x2_t}) + \pi_{12}(\ln P_{x3_t}) + \pi_{13}(\ln P_{x4t}) + \pi_{14}(\ln GDP) + w$

$\ln P_t = \pi_{20} + \pi_{21}(\ln P_{x2t}) + \pi_{22}(\ln P_{x3t}) + \pi_{23}(\ln P_{x4t}) + \pi_{24}(\ln GDP) + W_{2t}$

$\ln P_{Dt} = \pi_{30} + \pi_{31}(\ln P_{x2t}) + \pi_{32}(\ln P_{x3t}) + \pi_{33}(\ln P_{x4t}) + \pi_{34}(\ln GDP) + W_{3t}$

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2. Estimate reduce form model using OLS and prediction of the endogenous variables.

```
. g pd = pm+ t

. g lnst = ln(st)

. g lndt = ln(dt)

. g lnpd = ln(pd)

. g lnpx2 = ln(px2)

. g lnpx3 = ln(px3)

. g lnpx4 = ln(px4)

. g lngdp = ln(gdp)

. reg lnst lnpx2 lnpx3 lnpx4 lngdp
```

Source	SS	df	MS			
				Number of obs	=	22
				F(4, 17)	=	37.32
Model	4.64569724	4	1.16142431	Prob > F	=	0.0000
Residual	.529104674	17	.031123804	R-squared	=	0.8978
				Adj R-squared	=	0.8737
Total	5.17480192	21	.246419139	Root MSE	=	.17642

lnst	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnpx2	-.4503744	.1515961	-2.97	0.009	-.7702142	-.1305347
lnpx3	-.9242052	.2783356	-3.32	0.004	-1.511442	-.3369685
lnpx4	-.3883793	.4222332	-0.92	0.371	-1.279214	.5024549
lngdp	.3438812	.1913463	1.80	0.090	-.0598242	.7475865
_cons	24.65741	5.309757	4.64	0.000	13.4548	35.86002

```
. predict lnsthat
(option xb assumed; fitted values)
```

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```
. reg lndt lnpx2 lnpx3 lnpx4 lngdp
```

Source	SS	df	MS
Model	3.4026552	4	.850663799
Residual	.54721789	17	.032189288
Total	3.94987309	21	.188089195

Number of obs	=	22
F(4, 17)	=	26.43
Prob > F	=	0.0000
R-squared	=	0.8615
Adj R-squared	=	0.8289
Root MSE	=	.17941

lndt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnpx2	-.4887365	.1541691	-3.17	0.006	-.8140049	-.1634682
lnpx3	-.7243134	.2830597	-2.56	0.020	-1.321517	-.1271097
lnpx4	-.577921	.4293997	-1.35	0.196	-1.483875	.3280333
lngdp	.1265855	.194594	0.65	0.524	-.2839719	.5371429
_cons	27.18614	5.399879	5.03	0.000	15.79339	38.57889

```
. predict lndthat
(option xb assumed; fitted values)

. reg lnpd lnpx2 lnpx3 lnpx4 lngdp
```

Source	SS	df	MS
Model	.17707359	4	.044268398
Residual	.111247189	17	.006543952
Total	.288320779	21	.013729561

Number of obs	=	22
F(4, 17)	=	6.76
Prob > F	=	0.0019
R-squared	=	0.6142
Adj R-squared	=	0.5234
Root MSE	=	.08089

lnpd	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnpx2	.1318015	.0695123	1.90	0.075	-.0148567	.2784596
lnpx3	.0939842	.127627	0.74	0.472	-.1752851	.3632535
lnpx4	.4939641	.1936093	2.55	0.021	.0854842	.9024439
lngdp	.1632779	.0877392	1.86	0.080	-.0218357	.3483914
_cons	2.87652	2.434717	1.18	0.254	-2.260283	8.013322

```
. predict lnpdhat
(option xb assumed; fitted values)
```

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3. Estimate structural form using predicted endogenous variables as independent
variables in the structural form model.

```
. reg lnst lnpdhat lnpx2 lnpx3 lnpx4

      Source |       SS           df       MS      Number of obs   =        22
-------------+----------------------------------   F(4, 17)        =     37.32
       Model |  4.64569773         4  1.16142443   Prob > F        =    0.0000
    Residual |  .529104183        17  .031123775   R-squared       =    0.8978
-------------+----------------------------------   Adj R-squared   =    0.8737
       Total |  5.17480192        21  .246419139   Root MSE        =    .17642

------------------------------------------------------------------------------
        lnst |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnpdhat |   2.106112   1.171903     1.80   0.090    -.3663879    4.578612
       lnpx2 |   -.727963   .1840856    -3.95   0.001     -1.11635   -.3395762
       lnpx3 |  -1.122146   .2824139    -3.97   0.001    -1.717988   -.5263052
       lnpx4 |  -1.428722   .4751381    -3.01   0.008    -2.431176   -.4262679
       _cons |   18.59912   8.546622     2.18   0.044     .5673274    36.63092
------------------------------------------------------------------------------
```

```
. reg lndt lnpdhat lngdp

      Source |       SS           df       MS      Number of obs   =        22
-------------+----------------------------------   F(2, 19)        =     44.99
       Model |  3.26129847         2  1.63064924   Prob > F        =    0.0000
    Residual |  .688574614        19  .036240769   R-squared       =    0.8257
-------------+----------------------------------   Adj R-squared   =    0.8073
       Total |  3.94987309        21  .188089195   Root MSE        =    .19037

------------------------------------------------------------------------------
        lndt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnpdhat |  -2.574157   .5697943    -4.52   0.000     -3.76675   -1.381563
       lngdp |   .5212927   .1344816     3.88   0.001     .2398194     .802766
       _cons |   35.93498   7.189835     5.00   0.000     20.88648    50.98347
------------------------------------------------------------------------------
```

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4. Estimate the structural models of these system equations using OLS, 2SLS, 3SLS, and I3SLS. Concerning on the asymptotic property, which model is the most appropriated model? Why?

```
. reg3 (lnst lnpd lnpx2 lnpx3 lnpx4) (lndt lnpd lngdp), ols
```

Multivariate regression

Equation	Obs	Parms	RMSE	"R-sq"	F-Stat	P
lnst	22	4	.1652258	0.9103	43.14	0.0000
lndt	22	2	.1391259	0.9069	92.53	0.0000

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnst						
lnpd	-1.111835	.4515147	-2.46	0.019	-2.027549	-.1961207
lnpx2	-.4189546	.1431634	-2.93	0.006	-.7093034	-.1286059
lnpx3	-.9424196	.2585266	-3.65	0.001	-1.466736	-.4181034
lnpx4	-.521346	.3441643	-1.51	0.139	-1.219344	.1766516
_cons	41.4946	3.661911	11.33	0.000	34.0679	48.9213
lndt						
lnpd	-2.181329	.2946999	-7.40	0.000	-2.779008	-1.58365
lngdp	.5776586	.0887536	6.51	0.000	.397658	.7576593
_cons	31.03578	3.761201	8.25	0.000	23.40771	38.66385

```
. reg3 (lnst lnpd lnpx2 lnpx3 lnpx4) (lndt lnpd lngdp), 2sls nodfk inst(lnpx2 lnpx3 lnpx4 lngdp)
```

Two-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	F-Stat	P
lnst	22	4	.329951	0.6424	13.81	0.0000
lndt	22	2	.1454858	0.8982	89.20	0.0000

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnst						
lnpd	2.10611	1.926677	1.09	0.282	-1.801371	6.013591
lnpx2	-.7279628	.3026471	-2.41	0.021	-1.34176	-.114166
lnpx3	-1.122146	.464304	-2.42	0.021	-2.063798	-.180494
lnpx4	-1.428722	.7811544	-1.83	0.076	-3.012977	.1555325
_cons	18.59914	14.05113	1.32	0.194	-9.897873	47.09616
lndt						
lnpd	-2.574157	.4046743	-6.36	0.000	-3.394875	-1.75344
lngdp	.5212921	.0955104	5.46	0.000	.327588	.7149961
_cons	35.93499	5.106302	7.04	0.000	25.57893	46.29105

Endogenous variables: lnst lnpd lndt
Exogenous variables: lnpx2 lnpx3 lnpx4 lngdp

```
. reg3 (lnst lnpd lnpx2 lnpx3 lnpx4) (lndt lnpd lngdp), 3sls ireg3 nodfk inst(lnpx2 lnpx3 lnpx4 lngdp)

Iteration 1:   tolerance =   .1059484
Iteration 2:   tolerance =  .04569793
Iteration 3:   tolerance =  .01846611
Iteration 4:   tolerance =  .00725496
Iteration 5:   tolerance =  .00281814
Iteration 6:   tolerance =  .00108981
Iteration 7:   tolerance =  .00042072
Iteration 8:   tolerance =  .00016231
Iteration 9:   tolerance =   .0000626
Iteration 10:   tolerance =  .00002414
Iteration 11:   tolerance =  9.310e-06
Iteration 12:   tolerance =  3.590e-06
Iteration 13:   tolerance =  1.384e-06
Iteration 14:   tolerance =  5.339e-07

Three-stage least-squares regression, iterated
```

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lnst	22	4	.3022006	0.6117	54.83	0.0000
lndt	22	2	.135203	0.8982	178.41	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnst						
lnpd	2.212666	2.005956	1.10	0.270	-1.718936	6.144268
lnpx2	-.8435967	.3049354	-2.77	0.006	-1.441259	-.2459342
lnpx3	-1.460044	.4623671	-3.16	0.002	-2.366267	-.5538216
lnpx4	-1.009892	.7998393	-1.26	0.207	-2.577548	.557764
_cons	17.37893	14.61488	1.19	0.234	-11.26571	46.02357
lndt						
lnpd	-2.574157	.4046743	-6.36	0.000	-3.367304	-1.78101
lngdp	.5212921	.0955104	5.46	0.000	.3340951	.708489
_cons	35.93499	5.106302	7.04	0.000	25.92682	45.94316

```
Endogenous variables:  lnst lnpd lndt
Exogenous variables:   lnpx2 lnpx3 lnpx4 lngdp
```

According to the result, 2SLS is more appropriate model since OLS would give us bias, inconsistent, and inefficiency due to the endogeneity problem in the model. Since we don’t know whether there is specification error or not, 3SLS and I3SLS might give us inconsistent. We use the techniques of instrumental variable and reduce form to obtain consistent and efficiency by solving the endogeneity problem in 2SLS.

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5. What do β_{21} and β_{22} mean?

β_{21} represents the price elasticity of domestic demand where we capture the effect of price change. For example, when domestic price change by 1%, how much the demand will change holding other things constant.

β_{22} represents the income elasticity of demand where we capture the effect of income change holding other things constant.