Mittitat 6096491657

Reduce form, Set $\ln S_t = \ln D_t$

$$\beta_{10} + \beta_{11}\ln P_{Dt} + \beta_{12}\ln P_{x2t} + \beta_{13}\ln P_{x3t} + \beta_{14}\ln P_{x4t} + \varepsilon_{1t} = \beta_{20} + \beta_{21}\ln P_{Dt} + \beta_{22}\ln GDP_t + \varepsilon_{2t}$$

$$\beta_{11}\ln P_{Dt} - \beta_{21}\ln P_{Dt} = (\beta_{20} - \beta_{10}) - (\beta_{12}\ln P_{x2t}) - (\beta_{13}\ln P_{x3t} - \beta_{14}\ln P_{x4t}) + (\beta_{22}\ln GDP_t)$$

$$(\beta_{11} - \beta_{21})\ln P_{Dt} \quad + (\varepsilon_{2t} - \varepsilon_{1t})$$

$$\ln P_{Dt} = \underbrace{\frac{(\beta_{20} - \beta_{10})}{(\beta_{11} - \beta_{21})}}_{\pi_{10}} - \underbrace{\frac{\beta_{12}\ln P_{x2t}}{\beta_{11} - \beta_{21}}}_{\pi_{11}} - \underbrace{\frac{\beta_{13}\ln P_{x3t}}{\beta_{11} - \beta_{21}}}_{\pi_{12}} - \underbrace{\frac{\beta_{14}\ln P_{x4t}}{\beta_{11} - \beta_{21}}}_{\pi_{13}} + \underbrace{\frac{\beta_{22}\ln GDP_t}{\beta_{11} - \beta_{21}}}_{\pi_{14}} + \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}} = w_{1t}$$

Plugging in $\ln P_{Dt}$ to find demand

$$\ln_{St} = \beta_{10} + \beta_{21}\left(\frac{\beta_{10} - \beta_{10}}{\beta_{11} - \beta_{21}} - \frac{\beta_{12}\ln P_{x2t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{13}\ln P_{x3t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{14}\ln P_{x4t}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22}\ln GDP_t}{\beta_{11} - \beta_{21}} + \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}\right) + \beta_{22}\ln GDP_t + \varepsilon_{2t}$$

$$= \underbrace{\beta_{20} + \beta_{21}\frac{(\beta_{10} - \beta_{10})}{\beta_{11} - \beta_{21}}}_{\pi_0} - \underbrace{\frac{\beta_{21}\beta_{12}}{\beta_{11} - \beta_{21}}}_{\pi_1}\ln P_{x2t} - \underbrace{\frac{\beta_{21}\beta_{13}}{\beta_{11} - \beta_{21}}}_{\pi_2}\ln P_{x3t} - \underbrace{\frac{\beta_{21}\beta_{14}}{\beta_{11} - \beta_{21}}}_{\pi_3}\ln P_{x4t}$$

$$+ \underbrace{\frac{\beta_{21}\beta_{22}}{\beta_{11} - \beta_{21}}}_{\pi_4}\ln GDP_t + \underbrace{\frac{\beta_{21}}{\beta_{11} - \beta_{21}}}_{w_{1t}}(\varepsilon_{2t} - \varepsilon_{1t}) + \underbrace{\beta_{22}}_{\pi_4}\ln GDP_t + \varepsilon_{2t}$$

Reduce form of demand

$$\ln_{Dt} = \pi_0 - \pi_1\ln P_{x2t} - \pi_2\ln P_{x3t} - \pi_3\ln P_{x4t} + \pi_4\ln GDP_t + w_{1t}$$

Plugging in $\ln P_{xt}$ to find Supply

$$\ln q_t = \beta_{10} + \beta_{11}\left(\frac{\beta_{20}-\beta_{10}}{\beta_{11}-\beta_{21}} - \frac{\beta_{12}\ln P_{x2t}}{\beta_{11}-\beta_{21}} - \frac{\beta_{13}\ln P_{x3t}}{\beta_{11}-\beta_{21}} - \frac{\beta_{14}\ln P_{x4t}}{\beta_{11}-\beta_{21}} + \frac{\beta_{15}\ln GDP_t}{\beta_{11}-\beta_{21}} + \frac{\varepsilon_{2t}-\varepsilon_{1t}}{\beta_{11}-\beta_{21}}\right) + \beta_{12}\ln P_{x2t} + \beta_{13}\ln P_{x3t} + \beta_{14}\ln P_{x4t} + \varepsilon_{1t}$$

$= \pi_5$ $= \pi_6$ $= \pi_7$

$$= \left(\beta_{10} + \beta_{11}\frac{(\beta_{20}-\beta_{10})}{\beta_{11}-\beta_{21}}\right) - \left(\frac{\beta_{11}\beta_{12}}{\beta_{11}-\beta_{21}} + \beta_{12}\right)\ln P_{x2t} - \left(\frac{\beta_{11}\beta_{13}}{\beta_{11}-\beta_{21}} + \beta_{13}\right)\ln P_{x3t} - \left(\frac{\beta_{11}\beta_{14}}{\beta_{11}-\beta_{21}} + \beta_{14}\right)\ln P_{x4t} + \left(\frac{\beta_{11}\beta_{15}}{\beta_{11}-\beta_{21}}\right)\ln GDP_t + \frac{\beta_{11}(\varepsilon_{2t}-\varepsilon_{1t})+\varepsilon_{1t}}{\beta_{11}-\beta_{21}}$$

π_8 π_9 π_{10} π_{11} w_{1t}

Reduce form of Supply

$$\ln q_t = \pi_5 - \pi_6\ln P_{x2t} - \pi_7\ln P_{x3t} - \pi_8\ln P_{x4t} + \pi_9\ln GDP_t + w_{1t}$$

Reduce form of Price

$$\ln P_{1t} = \pi_{10} - \pi_{11}\ln P_{x2t} - \pi_{12}\ln P_{x3t} - \pi_{13}\ln P_{x4t} + \pi_{14}\ln GDP_t + (w_{2t}$$

2.

```
. use "C:\Users\Kittitat Thubtong\Downloads\Assignment 2.dta"

. generate pd=pm+t

. generate lnst=ln(st)

. generate lnpd=ln(pd)

. generate lndt=ln(dt)

. generate lnpx2=ln(px2)

. generate lnpx3=ln(px3)

. generate lnpx4=ln(px4)

. generate lngdp=ln(gdp)

. regress 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 insthat
(option xb assumed; fitted values)

. regress lndt lnpx2 lnpx3 lnpx4 lngdp
```

Source	SS	df	MS	Number of obs	=	22
				F(4, 17)	=	26.43
Model	3.4026552	4	.850663799	Prob > F	=	0.0000
Residual	.54721789	17	.032189288	R-squared	=	0.8615
				Adj R-squared	=	0.8289
Total	3.94987309	21	.188089195	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 lndhat
(option xb assumed; fitted values)

. regress lnpd lnpx2 lnpx3 lnpx4 lngdp
```

Source	SS	df	MS	Number of obs	=	22
				F(4, 17)	=	6.76
Model	.17707359	4	.044268398	Prob > F	=	0.0019
Residual	.111247189	17	.006543952	R-squared	=	0.6142
				Adj R-squared	=	0.5234
Total	.288320779	21	.013729561	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

3.

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

. regress 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

```
. regress 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

4.

```
. 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 nodfk inst(lnpx2 lnpx3 lnpx4 lngdp)

Three-stage least-squares regression
```

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lnst	**22**	**4**	**.2963642**	**0.6266**	**57.47**	**0.0000**
lndt	**22**	**2**	**.135203**	**0.8982**	**178.41**	**0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnst						
lnpd	**2.171576**	**1.926095**	**1.13**	**0.260**	**-1.603501**	**5.946652**
lnpx2	**-.7990055**	**.2985983**	**-2.68**	**0.007**	**-1.384247**	**-.2137635**
lnpx3	**-1.329743**	**.4560002**	**-2.92**	**0.004**	**-2.223487**	**-.4359989**
lnpx4	**-1.171403**	**.775654**	**-1.51**	**0.131**	**-2.691657**	**.348851**
_cons	**17.84948**	**14.04122**	**1.27**	**0.204**	**-9.670808**	**45.36976**
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
```

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

With 3SLS, we would achieve more asymptotically efficient than ILS and 2SLS. However, it's not preferable since there might be specification error exist which could make our model to be inconsistent. So, 2SLS may be more preferred since it surely gives us consistent and asymptotically efficient model.

5. Beta 21 is the price elasticity of demand (percentage change in price over percentage change in quantity) and Beta 22 is the income elasticity of demand (percentage change in GDP over the percentage change in quantity)