

1.

Richaya H.

6004640188

$$\ln S_t = \beta_{10} + \beta_{11} \ln P_{Dt} + \beta_{12} \ln P_{X2t} + \beta_{13} \ln P_{X3t} + \beta_{14} \ln P_{X4t} + \varepsilon_{1t} \quad - (1)$$

$$\ln D_t = \beta_{20} + \beta_{21} \ln P_{Dt} + \beta_{22} \ln GDP_t + \varepsilon_{2t} \quad - (2)$$

assume $D = S$, the market is competitive

$$\beta_{10} + \beta_{11} \ln P_{Dt} + \beta_{12} \ln P_{X2t} + \beta_{13} \ln P_{X3t} + \beta_{14} \ln P_{X4t} + \varepsilon_{1t} = \beta_{20} + \beta_{21} \ln P_{Dt} + \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

$$\beta_{11} \ln P_{Dt} - \beta_{21} \ln P_{Dt} = \beta_{20} - \beta_{10} + \beta_{22} \ln GDP_t - \beta_{12} \ln P_{X2t} - \beta_{13} \ln P_{X3t} - \beta_{14} \ln P_{X4t} + \varepsilon_{2t} - \varepsilon_{1t}$$

$$(\beta_{11} - \beta_{21}) \ln P_{Dt} = \beta_{20} - \beta_{10} - \beta_{12} \ln P_{X2t} - \beta_{13} \ln P_{X3t} - \beta_{14} \ln P_{X4t} + \beta_{22} \ln GDP_t + \varepsilon_{2t} - \varepsilon_{1t}$$

$$\ln P_{Dt} = \frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} - \frac{\beta_{12} \ln P_{X2t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{13} \ln P_{X3t}}{\beta_{11} - \beta_{21}} - \frac{\beta_{14} \ln P_{X4t}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22} \ln GDP_t}{\beta_{11} - \beta_{21}} + \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}} \quad - (3)$$

(A) plug $\ln P_{Dt}$ in $\ln D_t$

$$\ln D_t = \beta_{20} + \frac{\beta_{21}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{\beta_{21}\beta_{12}}{\beta_{11} - \beta_{21}} (\ln P_{X2t}) - \frac{\beta_{21}\beta_{13}}{\beta_{11} - \beta_{21}} (\ln P_{X3t}) - \frac{\beta_{21}\beta_{14}}{\beta_{11} - \beta_{21}} (\ln P_{X4t}) + \frac{\beta_{21}\beta_{22}}{\beta_{11} - \beta_{21}} (\ln GDP_t) + \frac{\beta_{21}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} + \beta_{22} \ln GDP_t + \varepsilon_{2t}$$

$$\text{where: } \pi_{20} = \beta_{20} + \frac{\beta_{21}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} \quad \pi_{21} = \frac{-\beta_{21}\beta_{12}}{\beta_{11} - \beta_{21}} \quad \pi_{22} = \frac{-\beta_{21}\beta_{13}}{\beta_{11} - \beta_{21}} \quad \pi_{23} = \frac{-\beta_{21}\beta_{14}}{\beta_{11} - \beta_{21}}$$

$$\pi_{24} = \frac{\beta_{21}\beta_{22}}{\beta_{11} - \beta_{21}} + \beta_{22} \quad w_{2t} = \frac{\beta_{21}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} + \varepsilon_{2t}$$

$$\pi_{30} = \frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} \quad \pi_{31} = \frac{-\beta_{12}}{\beta_{11} - \beta_{21}} \quad \pi_{32} = \frac{-\beta_{13}}{\beta_{11} - \beta_{21}} \quad \pi_{33} = \frac{-\beta_{14}}{\beta_{11} - \beta_{21}} \quad \pi_{34} = \frac{\beta_{22}}{\beta_{11} - \beta_{21}}$$

$$w_{3t} = \frac{\varepsilon_{2t} - \varepsilon_{1t}}{\beta_{11} - \beta_{21}}$$

(B) plug $\ln P_{Dt}$ in $\ln S_t$

$$\ln S_t = \beta_{10} + \frac{\beta_{11}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} - \frac{\beta_{11}\beta_{12}}{\beta_{11} - \beta_{21}} (\ln P_{X2t}) - \frac{\beta_{11}\beta_{13}}{\beta_{11} - \beta_{21}} (\ln P_{X3t}) - \frac{\beta_{11}\beta_{14}}{\beta_{11} - \beta_{21}} (\ln P_{X4t}) + \frac{\beta_{11}\beta_{22}}{\beta_{11} - \beta_{21}} (\ln GDP_t) + \frac{\beta_{11}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} + \varepsilon_{1t}$$

$$\text{where: } \pi_{10} = \beta_{10} + \frac{\beta_{11}(\beta_{20} - \beta_{10})}{\beta_{11} - \beta_{21}} \quad \pi_{11} = \frac{-\beta_{11}\beta_{12}}{\beta_{11} - \beta_{21}} + \beta_{12} \quad \pi_{12} = \frac{-\beta_{11}\beta_{13}}{\beta_{11} - \beta_{21}} + \beta_{13}$$

$$\pi_{13} = \frac{-\beta_{11}\beta_{14}}{\beta_{11} - \beta_{21}} + \beta_{14} \quad \pi_{14} = \frac{\beta_{11}\beta_{22}}{\beta_{11} - \beta_{21}} \quad w_{1t} = \frac{\beta_{11}(\varepsilon_{2t} - \varepsilon_{1t})}{\beta_{11} - \beta_{21}} + \varepsilon_{1t}$$

Reduced Form

$$\ln S_t = \pi_{10} + \pi_{11} (\ln P_{X2t}) + \pi_{12} (\ln P_{X3t}) + \pi_{13} (\ln P_{X4t}) + \pi_{14} (\ln GDP_t) + w_{1t}$$

$$\ln D_t = \pi_{20} + \pi_{21} (\ln P_{X2t}) + \pi_{22} (\ln P_{X3t}) + \pi_{23} (\ln P_{X4t}) + \pi_{24} (\ln GDP_t) + w_{2t}$$

$$\ln P_{Dt} = \pi_{30} + \pi_{31} (\ln P_{X2t}) + \pi_{32} (\ln P_{X3t}) + \pi_{33} (\ln P_{X4t}) + \pi_{34} (\ln GDP_t) + w_{3t}$$

2.

```
. g pd = pm+t
. g lnst = ln(st)
. g lndt = ln(dt)
. 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
Model	4.64569724	4	1.16142431	F(4, 17)	=	37.32
Residual	.529104674	17	.031123804	Prob > F	=	0.0000
				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)
```

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

Source	SS	df	MS	Number of obs	=	22
Model	3.4026552	4	.850663799	F(4, 17)	=	26.43
Residual	.54721789	17	.032189288	Prob > F	=	0.0000
				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 lndthat
(option xb assumed; fitted values)
```

```
. reg lnpd lnp2 lnp3 lnp4 lngdp
```

Source	SS	df	MS	Number of obs	=	22
Model	.17707359	4	.044268398	F(4, 17)	=	6.76
Residual	.111247189	17	.006543952	Prob > F	=	0.0019
				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

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

3.

```
. reg lnst lnpdhat lnp2 lnp3 lnp4
```

Source	SS	df	MS	Number of obs	=	22
Model	4.64569773	4	1.16142443	F(4, 17)	=	37.32
Residual	.529104183	17	.031123775	Prob > F	=	0.0000
				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
Model	3.26129847	2	1.63064924	F(2, 19)	=	44.99
Residual	.688574614	19	.036240769	Prob > F	=	0.0000
				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 lnpg lnpx2 lnpx3 lnpx4) (lndt lnpg 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						
lnpg	-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						
lnpg	-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 lnpg lnpx2 lnpx3 lnpx4) (lndt lnpg 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						
lnpg	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						
lnpg	-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 lnpg lndt

Exogenous variables: lnpx2 lnpx3 lnpx4 lngdp

. reg3 (lnst lnpd lnp2 lnp3 lnp4) (lndt lnpd lngdp), 3sls inst(lnpx2 lnp3 lnp4 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: lnp2 lnp3 lnp4 lngdp

. reg3 (lnst lnpd lnp2 lnp3 lnp4) (lndt lnpd lngdp), 3sls ireg3 inst(lnpx2 lnp3 lnp4 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: lnp2 lnp3 lnp4 lngdp

Concerning asymptotic property, 2SLS model would be the most appropriate in this case since there is an endogeneity bias in the model, so the OLS model can not be used and since we do not know whether there are any specification errors, the 3SLS model is not preferred. Using the 2SLS, reduced form and instrumental variables (IV) are performed to solve endogeneity problems, and it gives consistency and efficiency to the model.

5.

β_{21} represents the relationship between domestic price at time t and domestic demand at time t , in other words, quantity of domestic demand at time t will change by how many when there is an increase in domestic price by 1%.

β_{22} represents the relationship between GDP at time t and domestic demand at time t . GDP at time t increases by 1% affects quantity of domestic demand by how many.