

From $Ln S_t = \beta_{10} + \beta_{11} Ln D_t + \beta_{12} Ln R_{st} + \beta_{13} Ln R_{st} + \beta_{14} Ln R_{st} + \epsilon_{1t}$ — (1)

$Ln D_t = \beta_{20} + \beta_{21} Ln R_{st} + \beta_{22} Ln GDP_t + \epsilon_{2t}$ — (2)

To make the Reduce Form Model, We need 3 equation for 3 unknown endogenous variables.

Thus we assume that the Market always clears.

$Ln D_t = Ln S_t$ — (3)

From (3): $\beta_{10} + \beta_{11} Ln D_t + \beta_{12} Ln R_{st} + \beta_{13} Ln R_{st} + \beta_{14} Ln R_{st} + \epsilon_{1t} = \beta_{20} + \beta_{21} Ln R_{st} + \beta_{22} Ln GDP_t + \epsilon_{2t}$

$\beta_{11} Ln D_t - \beta_{21} Ln R_{st} = \beta_{20} - \beta_{10} + \beta_{22} Ln GDP_t - \beta_{12} Ln R_{st} - \beta_{13} Ln R_{st} - \beta_{14} Ln R_{st} + \epsilon_{2t} - \epsilon_{1t}$

$(\beta_{11} - \beta_{21}) Ln D_t = \beta_{20} - \beta_{10} + \beta_{22} Ln GDP_t - \beta_{12} Ln R_{st} - \beta_{13} Ln R_{st} - \beta_{14} Ln R_{st} + \epsilon_{2t} - \epsilon_{1t}$

$Ln D_t = \frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22}}{\beta_{11} - \beta_{21}} Ln GDP_t - \frac{\beta_{12}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{13}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{14}}{\beta_{11} - \beta_{21}} Ln R_{st} + \frac{\epsilon_{2t} - \epsilon_{1t}}{\beta_{11} - \beta_{21}}$ — (4)

(4) in (2) $Ln D_t = \beta_{20} + \beta_{21} \left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22}}{\beta_{11} - \beta_{21}} Ln GDP_t - \frac{\beta_{12}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{13}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{14}}{\beta_{11} - \beta_{21}} Ln R_{st} + \frac{\epsilon_{2t} - \epsilon_{1t}}{\beta_{11} - \beta_{21}} \right) + \beta_{22} Ln GDP_t + \epsilon_{2t}$

(A). Let $W_0 = \beta_{20} + \beta_{21} \left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} \right) + \beta_{22} Ln GDP_t - \frac{\beta_{12}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{13}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{14}}{\beta_{11} - \beta_{21}} Ln R_{st} + \frac{\beta_{21}(\epsilon_{2t} - \epsilon_{1t})}{\beta_{11} - \beta_{21}}$ — (5)

B. Let $W_{20} = \beta_{20} - \beta_{10}$ $W_{21} = \frac{\beta_{22}}{\beta_{11} - \beta_{21}}$ $W_{22} = -\frac{\beta_{12}}{\beta_{11} - \beta_{21}}$ $W_{23} = -\frac{\beta_{13}}{\beta_{11} - \beta_{21}}$ $W_{24} = -\frac{\beta_{14}}{\beta_{11} - \beta_{21}}$ $W_{25} = \frac{\epsilon_{2t} - \epsilon_{1t}}{\beta_{11} - \beta_{21}}$

(4) in (1) $Ln S_t = \beta_{10} + \beta_{11} \left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} + \frac{\beta_{22}}{\beta_{11} - \beta_{21}} Ln GDP_t - \frac{\beta_{12}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{13}}{\beta_{11} - \beta_{21}} Ln R_{st} - \frac{\beta_{14}}{\beta_{11} - \beta_{21}} Ln R_{st} + \frac{\epsilon_{2t} - \epsilon_{1t}}{\beta_{11} - \beta_{21}} \right) + \beta_{12} Ln R_{st} + \beta_{13} Ln R_{st} + \beta_{14} Ln R_{st} + \epsilon_{1t}$

C. Let $W_{10} = \beta_{10} + \beta_{11} \left(\frac{\beta_{20} - \beta_{10}}{\beta_{11} - \beta_{21}} \right) + \beta_{12} Ln R_{st} + \beta_{13} Ln R_{st} + \beta_{14} Ln R_{st} + \epsilon_{1t}$ $W_{11} = \frac{\beta_{11} \beta_{22}}{\beta_{11} - \beta_{21}}$ $W_{12} = \frac{\beta_{11} \beta_{12}}{\beta_{11} - \beta_{21}}$ $W_{13} = \frac{\beta_{11} \beta_{13}}{\beta_{11} - \beta_{21}}$ $W_{14} = \frac{\beta_{11} \beta_{14}}{\beta_{11} - \beta_{21}}$ $W_{15} = \frac{\beta_{11}(\epsilon_{2t} - \epsilon_{1t})}{\beta_{11} - \beta_{21}}$

$$Ln D_t = \bar{\Pi}_{20} + \bar{\Pi}_{21} Ln GDP_t + \bar{\Pi}_{22} Ln Pr_{21} + \bar{\Pi}_{23} Ln Pr_{3t} + \bar{\Pi}_{24} Ln Pr_{4t} + W_{2t} \quad (7)$$

$$Ln S_t = \bar{\Pi}_{10} + \bar{\Pi}_{11} Ln GDP_t + \bar{\Pi}_{12} Ln Pr_{21} + \bar{\Pi}_{13} Ln Pr_{3t} + \bar{\Pi}_{14} Ln Pr_{4t} + W_{1t} \quad (8)$$

$$Ln Pr_t = \bar{\Pi}_{30} + \bar{\Pi}_{31} Ln GDP_t + \bar{\Pi}_{32} Ln Pr_{21} + \bar{\Pi}_{33} Ln Pr_{3t} + \bar{\Pi}_{34} Ln Pr_{4t} + W_{3t} \quad (9)$$

(7), (8) and (9) are reduced form of these system model.

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

```

. g lndt=ln(dt)

. g lnst=ln(st)

. g ln pdt =ln(pdt)
pdt not found
r(111);

. g pdt = pm+t

. g ln pdt=ln(pdt)

. g lngdp=ln(gdp)

. g lnpx2=ln(px2)

. g lnpx3=ln(px3)

. g lnpx4=ln(px4)

. reg lndt lngdp lnpx2 lnpx3 lnpx4

```

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
Total	3.94987309	21	.188089195	R-squared	=	0.8615
				Adj R-squared	=	0.8289
				Root MSE	=	.17941

lndt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lngdp	.1265855	.194594	0.65	0.524	-.2839719 .5371429
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
_cons	27.18614	5.399879	5.03	0.000	15.79339 38.57889

```

. predict lndthat, xb

```

```
. reg lnst lngdp lnpx2 lnpx3 lnpx4
```

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]
lngdp	.3438812	.1913463	1.80	0.090	-.0598242 .7475865
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
_cons	24.65741	5.309757	4.64	0.000	13.4548 35.86002

```
. predict lnsthat, xb
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```
. reg lnpgdt lngdp lnpx2 lnpx3 lnpx4
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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

lnpgdt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lngdp	.1632779	.0877392	1.86	0.080	-.0218357 .3483914
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
_cons	2.87652	2.434717	1.18	0.254	-2.260283 8.013322

```
.  
. predict lnpgdthat, xb
```

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

. reg lndt lnpdthat 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]	
lnpdthat	-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

. reg lnst lnpdthat 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]	
lnpdthat	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

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

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. reg3 (lnst lnpdt lnp2 lnp3 lnp4) (lndt lnpdt lngdp), ols
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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						
lnpdt	-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						
lnpdt	-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 lnpdt lnp2 lnp3 lnp4) (lndt lnpdt lngdp), 2sls nodfk inst(lnpx2 lnp3 lnp4 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						
lnpdt	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						
lnpdt	-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 lnpdt lndt
Exogenous variables: lnp2 lnp3 lnp4 lngdp

```
. reg3 (lnst lnprt lnpx2 lnpx3 lnpx4) (lnprt lnprt lngdp), 3sls 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
lnprt	22	2	.135203	0.8982	178.41	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lnst						
lnprt	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
lnprt						
lnprt	-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 lnprt lnprt

Exogenous variables: lnpx2 lnpx3 lnpx4 lngdp

```
. reg3 (lnst lnprt lnpx2 lnpx3 lnpx4) (lnprt lnprt lngdp), 3sls ireg3 inst(lnpx2 lnpx3 lnpx4 lngdp)
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```
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
lnprt	22	2	.135203	0.8982	178.41	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lnst						
lnprt	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	

lnprt						
lnprt	-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 lnprt lnprt

Exogenous variables: lnpx2 lnpx3 lnpx4 lngdp

Concerning on the asymptotic property, 2SLS is the most appropriated. 2SLS model ensures consistency since we estimated reduced form model using OLS to predict endogenous variable and use predict endogenous variable as instrumental variables (IV) for lagged endogenous variable instead of actual endogenous variable to predict betas. In 2SLS, We assume that endogeneity bias is solved therefore, The consistency will be the most strong. In OLS, there exists endogeneity problem so, coefficient of independent variables won't be consistent bias and inefficient. In 3SLS and I3SLS, there are a risk of specification error in one equation or any equations which might spread through all the equations in system and lead to inconsistency.

5. What do β_{21} and β_{22} mean?

β_{21} means the price elasticity of demand since it indicates how many percentage change in quantity of domestic demand will change from 1% change in price.

β_{22} means income elasticity of demand since it indicates how many percentage change in quantity of domestic demand will change from 1% change in GDP which represents income.