

Quantitative Methods in Finance

Tutorial, Part 9: *Distributed-lag models.*

Example 1: Write down the infinite distributed-lag model and explain the terms impact, intermediate, cumulative, and long-term multiplier.

Infinite distributed-lag model and types of multipliers

In empirical estimation we often encounter lagged variables. These are very important, since they allow not only static, but also dynamic evaluation of the relations between economic and financial categories. Thus, we can e.g. distinguish between the short-term and the long-term propensity to consume, between the expected (desired) and the actual stock of capital, or between the expected and the actual amount of money in circulation.

A model that includes not only current, but also lagged values of explanatory variables (for the sake of simplicity, we will take into account only one explanatory variable, denoted by x) is called the distributed-lag model. This means that the effect of changes in the explanatory variable on the dependent variable is distributed over a longer period of time. If we do not determine its length, meaning that we do not define how far in the past we want to go, we get the infinite distributed-lag model, which can in its general form be written as follows:

$$y_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \dots + u_t.$$

We distinguish the following types of effects:

- a) Regression coefficient β_0 – *short-term or impact multiplier*: If the value of the explanatory variable in a given unit of time increases by one unit of measurement, the dependent variable changes in the same time unit on average by β_0 units of measurement.
- b) Regression coefficients β_1, β_2, \dots – *intermediate multipliers*: If the value of the explanatory variable in a given unit of time increases by one unit of measurement, the dependent variable changes e.g. for example in two time units on average by β_2 units of measurement.
- c) Subtotals of regression coefficients – *cumulative multipliers* (let us take a period of three consecutive time units): If the value of the explanatory variable in a given unit of time increases by one unit of measurement, the dependent variable changes in all three time units together on average by $\beta_0 + \beta_1 + \beta_2$ units of measurement (by β_0 in a given time unit, by β_1 in the next time unit, and by β_2 in the last time unit).

- d) Sum of all regression coefficients – *long-term or total multiplier*: If the value of the explanatory variable in a given unit of time increases by one unit of measurement, the value of the dependent variable changes in the long-run on average by $\sum_{k=0}^{\infty} \beta_k$ units of measurement.

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Example 2: Based on data for 20 years on imports (I) and gross domestic product (GDP), we estimated the following (autoregressive) function of imports for a given country:

$$\hat{I}_t = 2.45 + 0.70GDP_t + 0.25I_{t-1}$$

$t: \quad (17.0) \quad (3.2) \quad \quad (2.5)$

while taking into account the so-called Koyck transformation (the values are in billion EUR).

- Write down and explain the Koyck assumption.
- Based on the above estimates of the import function, calculate and interpret the impact multiplier, the second intermediate multiplier, and the equilibrium (total) multiplier. How is the latter parameter called in this case from the economics point of view?
- Calculate and interpret the median lag.

Koyck model (geometric scheme of distributed lags)

The infinite distributed-lag model can in its general form be written as:

$$y_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \dots + u_t.$$

When estimating such a model, we can help ourselves with a variety of assumptions about the distribution of the effects of the explanatory variable on the dependent variable. Koyck assumed that all the effects of the lagged explanatory variable have the same sign and are in time decreasing in a geometric sequence. This means that the values of the regression coefficients of the lagged explanatory variable are geometrically decreasing by moving into the past (i.e. by increasing the lag length). This assumption can be written as follows:

$$\beta_k = \beta_0 \lambda^k; \quad k = 0, 1, 2, \dots,$$

where the parameter λ , also referred to as the rate of decline (decay), takes the values between 0 and 1. The values of the regression coefficients for lags are dependent on the regression coefficient β_0 , which represents the effect of the explanatory variable on the dependent variable contemporaneously, and the rate of decline λ . The closer the value of λ is to one (zero), the slower (faster) is the decline of the effects of a lagged explanatory variable on the dependent variable.

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Example 3: The data file `moneydemand2.dta` contains the following data for the U.S. for the period 1960–1993: the quantity of money in circulation (MI ; in billion USD at 1987 prices), gross domestic product (GDP ; in billion USD at 1987 prices), and the reference interest rate (IR ; in percent). Estimate the following regression model:

$$MI_t^* = \beta_1 + \beta_2 GDP_t + \beta_3 IR_t + u_t ,$$

where MI_t^* represents the desired or long-term amount of money in circulation. Explain the model that you have just taken into account and interpret the results. Check for the presence of first- and higher-order autocorrelation and, if necessary, correct for it.

Partial adjustment (stock adjustment) model

Based on the above regression model we can observe that the equilibrium (desired) amount of money in circulation is a linear function of gross domestic product and the interest rate. As the long-term quantity of money in circulation MI^* is not directly observed (known), we can help ourselves with the partial adjustment process:

$$MI_t - MI_{t-1} = \delta(MI_t^* - MI_{t-1}) ; \quad 0 < \delta \leq 1 .$$

Actual change in the quantity of money in circulation in time unit t equals a share δ (called the adjustment coefficient) of the desired change in the quantity of money during this time unit. If we insert the initial regression model into the previous expression, we obtain:

$$MI_t - MI_{t-1} = \delta(\beta_1 + \beta_2 GDP_t + \beta_3 IR_t + u_t - MI_{t-1}) ,$$

which we can properly rearrange as:

$$MI_t = \delta\beta_1 + \delta\beta_2 GDP_t + \delta\beta_3 IR_t + (1-\delta)MI_{t-1} + \delta u_t .$$

In a completely general form, we can write the previous equation as:

$$MI_t = \gamma_1 + \gamma_2 GDP_t + \gamma_3 IR_t + \gamma_4 MI_{t-1} + v_t ,$$

where the following holds:

$$\gamma_1 = \delta\beta_1 ; \quad \gamma_2 = \delta\beta_2 ; \quad \gamma_3 = \delta\beta_3 ; \quad \gamma_4 = (1-\delta) ; \quad v_t = \delta u_t .$$

The initial model represents the long-term or equilibrium money-demand function, while the final autoregressive model represents the short-term money-demand function. The regression coefficient β_2 represents the long-term effect of the gross domestic product on the amount of money in circulation, whereas the regression coefficient γ_2 represents the short-term effect. The same reasoning applies for the regression coefficient β_3 , which represents the long-term

effect of the interest rate on the amount of money in circulation, whereas the regression coefficient γ_3 represents the interest rates short-term effect.

It also follows from the restrictions based on our autoregressive model that the coefficients of the long-term function are calculated by dividing the regression coefficients γ_1 , γ_2 and γ_3 from the autoregressive function by the adjustment coefficient δ . The latter tells us what share of the gap between the desired and the actual amount of money in circulation is eliminated in each time unit.

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Computer printout of the results in Stata:

```
. tsset year
      time variable:  year, 1960 to 1993
              delta:  1 unit
```

```
. regress ml gdp ir
```

Source	SS	df	MS	Number of obs = 34		
Model	240672.24	2	120336.12	F(2, 31)	=	141.67
Residual	26331.0384	31	849.388335	Prob > F	=	0.0000
Total	267003.278	33	8091.00842	R-squared	=	0.9014
				Adj R-squared	=	0.8950
				Root MSE	=	29.144

ml	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
gdp	.1192877	.0071285	16.73	0.000	.104749	.1338264
ir	-23.30547	2.438946	-9.56	0.000	-28.27973	-18.33121
_cons	425.344	19.92984	21.34	0.000	384.6968	465.9912


```
. regress ml gdp ir l.ml
```

Source	SS	df	MS	Number of obs = 33		
Model	240881.011	3	80293.6704	F(3, 29)	=	142.25
Residual	16369.56	29	564.467588	Prob > F	=	0.0000
Total	257250.571	32	8039.08035	R-squared	=	0.9364
				Adj R-squared	=	0.9298
				Root MSE	=	23.759

ml	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
gdp	.0566796	.0160087	3.54	0.001	.023938	.0894211
ir	-11.64861	3.421357	-3.40	0.002	-18.64607	-4.651148
ml						
L1.	.6254733	.1489465	4.20	0.000	.3208434	.9301032
_cons	148.0334	68.39056	2.16	0.039	8.159004	287.9078


```
. predict em1, resid
(1 missing value generated)
```

```
. regress eml l.eml, nocons
```

Source	SS	df	MS	Number of obs =	32
Model	4721.54612	1	4721.54612	F(1, 31) =	12.65
Residual	11569.7725	31	373.218469	Prob > F =	0.0012
				R-squared =	0.2898
				Adj R-squared =	0.2669
Total	16291.3187	32	509.103708	Root MSE =	19.319

eml	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
eml					
L1.	.5563226	.1564106	3.56	0.001	.2373211 .8753241

```
. scalar rho=_b[l.eml]
```

```
. regress eml gdp ir l.ml l.eml
```

Source	SS	df	MS	Number of obs =	32
Model	5470.19205	4	1367.54801	F(4, 27) =	3.41
Residual	10818.6816	27	400.69191	Prob > F =	0.0221
				R-squared =	0.3358
				Adj R-squared =	0.2374
Total	16288.8736	31	525.447536	Root MSE =	20.017

eml	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gdp	.0174963	.0142944	1.22	0.232	-.0118334 .0468261
ir	-2.603332	2.996615	-0.87	0.393	-8.751878 3.545215
ml					
L1.	-.1725952	.134589	-1.28	0.211	-.4487489 .1035585
eml					
L1.	.6440759	.1744669	3.69	0.001	.2860995 1.002052
_cons	71.01483	61.81335	1.15	0.261	-55.8157 197.8454

```
. scalar lm=e(N)*e(r2)
```

```
. display lm, invchi2tail(1,0.05), chi2tail(1,lm)
```

```
10.746363 3.8414588 .00104484
```

```
. qui regress ml gdp ir l.ml
```

```
. estat bgodfrey, nomiss0
```

```
Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
1	10.746	1	0.0010

```
H0: no serial correlation
```

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	11.030	1	0.0009

H0: no serial correlation

. estat bgodfrey, lag(1/28)

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	11.030	1	0.0009
2	11.994	2	0.0025
3	13.825	3	0.0032
4	13.888	4	0.0077
5	14.466	5	0.0129
6	14.555	6	0.0240
7	19.916	7	0.0058
8	20.909	8	0.0074
9	20.933	9	0.0130
10	22.895	10	0.0111
11	24.361	11	0.0113
12	24.745	12	0.0161
13	24.751	13	0.0249
14	24.751	14	0.0371
15	25.032	15	0.0495
16	25.033	16	0.0693
17	25.549	17	0.0831
18	25.552	18	0.1104
.			
.			
.			
26	32.713	26	0.1706
27	32.713	27	0.2067
28	32.714	28	0.2464

H0: no serial correlation

. newey ml gdp ir l.ml, lag(17)

Regression with Newey-West standard errors
maximum lag: 17

Number of obs = 33
F(3, 29) = 376.56
Prob > F = 0.0000

ml	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
gdp	.0566796	.0153896	3.68	0.001	.0252044	.0881547
ir	-11.64861	2.656746	-4.38	0.000	-17.08226	-6.214952
ml						
L1.	.6254733	.1481754	4.22	0.000	.3224206	.928526
_cons	148.0334	63.55881	2.33	0.027	18.04103	278.0258

