

# 宏观与微观数据的混合回归及 Stata 应用: mixregress

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#### 内容

#### 混合回归

Stata 混合回归: mixregress

### 混频回归

低频时间序列 vs 高频时间序列 (midasreg)

宏观时间序列 vs 微观面板 (mixregress)

### 混合回归

混合回归模型:

$$y_t = z_t \beta + \alpha \sum_{i=1}^{n_t} w_{it} x_{it} + \epsilon_t.$$

其中, $(y_t, z_t)$  (t = 1, ..., T) 为宏观变量, $x_{it}$ 为微观变量,i表示第i个体(比如个人、企业等)。 $w_{it}$ 表示个体i的权重。即微观 $x_{it}$ 的加权和来解释和预测 $y_t$ 。

 $n_t$ : t期有 $n_t$ 个微观个体,微观面板数据可以是平衡或非平衡的。

设有m个微观指标,权重函数设为

$$w_{it} = \theta_1 w_{1,it} + \dots + \theta_m w_{m,it}.$$

### 混合回归

要识别 $\theta$ 、 $\alpha$ ,必须施加必要的约束。Gysel(2019)用企业收益预测季度 GDP 的模型

$$GDP_{t+1} = \alpha + \beta_{earn} \sum_{i=1}^{n_t} w_{it} \, earn_{it} + \sum \beta_k z_{k,t} + \epsilon_{t+1}.$$

$$w_{it} = (\theta_1 e w_{it} + \theta_2 v w_{it} + \tau \times smth_{it}.$$

Gysel (2019)约束 $\theta_1 + \theta_2 = 1$ , 即

$$w_{it} = (1 - \theta)ew_{it} + \theta vw_{it} + \tau \times smth_{it}$$
.

其中, $(1-\theta)ew_{it} + \theta vw_{it}$ 叫做基准成分(benchmark component),  $\tau \times smth_{it}$ 叫做调节成分(tilt component).

其它约束:  $\beta_{earn} = 1$ , 或者 $\tau = 1$ .

### 估计方法

非线性最小二乘法:  $y_t = x_t(\beta) + u_t$ , 最小化残差平方和:

$$SSR(\beta) = \sum_{t=1}^{T} (y_t - x_t(\beta))^2.$$

数值优化算法: Newton-Raphson, BHHH 等。

同方差条件下,NLS 估计量 $\hat{\beta}$ 的方差为

$$\widehat{Var}(\hat{\beta}) = s^2 (\widehat{X}'\widehat{X})^{-1}.$$

其中,  $X(\beta) = \partial x(\beta)/\partial \beta$ ,  $\hat{X} = \partial x(\hat{\beta})/\partial \hat{\beta}$ .

$$s^2 = \frac{1}{T - k} \sum_{t=1}^{T} \hat{u}_t^2.$$

## 估计方法

异方差稳健方差:

$$\widehat{Var}(\hat{\beta}) = (\hat{X}'\hat{X})^{-1} (\hat{X}'\hat{\Omega}\hat{X}) (\hat{X}'\hat{X})^{-1},$$

其中, $\hat{\Omega}$ 为对角矩阵,元素为 $\hat{u}_{i}^{2}$ ,

$$\hat{X}'\hat{\Omega}\hat{X} = \hat{X}'\hat{\Omega}_0\hat{X} = \frac{T}{T-k}\sum_{t=1}^T \hat{u}_t^2 x_t' x_t$$

Newey-West (1987)异方差自相关稳健方差

$$\hat{X}'\hat{\Omega}\hat{X} = \hat{X}'\hat{\Omega}_0\hat{X} + \frac{n}{n-k}\sum_{l=1}^m \left(1 - \frac{l}{m+1}\right)\sum_{t=l+1}^T \hat{u}_t\,\hat{u}_{t-l}(x_t'x_{t-l} + x_{t-l}'x_t).$$

#### **Stata**

model:  $y_t = z_t \beta + \alpha \sum_{i=1}^{n_t} w_{it} x_{it} + \epsilon_t$ .

mixregress depvar indeps [ if ] [ in ], xmicro(varname) wmicro(varlist) idtype(integer)
vce(string) maxlag(integer) [ options ]

xmicro(varname): 微观变量 $z_{it}$ 

wmicro(varlist): 微观变量wit

idtype(integer): 识别策略。idtype(0): 约束 $\theta_1 + \theta_2 = 1$ , idtype(1)约束 $\theta_2 = 1$ .

vce(string): vce(0)(同方差); vce(1): 异方差稳健; vce(2): 异方差自相关稳健

maxlag(integer): Newey-West (1987)标准差的滞后阶数。默认值为 $ceil(0.43T^{1/3})$  (Stock and Watson , 2011).

#### 例

. use "macro2.dta", clear

. tsset

Time variable: yearquarter, 2003q1 to 2019q4

Delta: 1 quarter

. des ppi m0

Variable Storage Display Value name type **format** label Variable label

ppi float %9.0g

m0 float %9.0g

. use "micro2.dta", clear

. xtset

Panel variable: stock (unbalanced)

Time variable: yearquarter, 2003q1 to 2019q4, but with gaps

Delta: 1 quarter

. des earn ew vw SA\_w

Variable name	Storage type	Display format	Value label	Variable label	
earn ew vw SA_w	float float float float	%9.0g %9.0g %9.0g %9.0g	_	季度盈余同比增长率	

# 例

- . use "micro2.dta", clear
- . qui merge m:1 yearquarter using macro2
- . mixregress ppi Lppi m0, xmicro(earn) wmicro(ew vw) vce(2) nolog

HÕTC	=	-350.4665 1.5174	Аај к-squarea Root MSE	=	0.8475 0.0167
HQIC	=	-350.4665	Adj R-squared	=	
BIC	=	-343.8051	R-squared	=	0.8591
AIC	=	-354.8285	Number <b>of</b> group	=	67
Log-likel	.ihood =	182.4143	Number of obs	=	10742

	ppi	Coefficient	HAC std. err.	Z	P> z	[95% conf.	interval]
macro							
	Lppi	.9004863	.0386545	23.30	0.000	.824725	.9762477
	m0	0003632	.0001122	-3.24	0.001	000583	0001433
	Wearn	.0987397	.0216344	4.56	0.000	.056337	.1411424
	_cons	0209212	.0050621	-4.13	0.000	0308428	0109997
micro							



ew	.8944858	.5411519	1.65	0.098	1661525	1.955124
Vw	.1055142	.5411519	0.19	0.845	9551241	1.166152
variance lnsigma	-4.141539	.0007202 -	5750.81	0.000	-4.142951	-4.140128

. est store mod

# 例

- . egen earnsum = total(earn), by(yearquarter)
- . reg ppi Lppi m0 earnsum if vw<=0.006

Source	SS	df	MS		er <b>of obs</b> 106450)	s = >	106,454 99999.00
Model Residual	157.013825 29.3202764	3 106,450	52.337941 .00027543	7 Prob 7 R-sc	> F  uared	=	0.0000 0.8426
Total	186.334102	106,453	.00175038	——— Adj R-square 50388 Root MSE		1 =	0.8426 .0166
ppi	Coefficient	Std. err.	t	P> t	[95% c	onf.	interval]
Lppi m0 earnsum _cons	.8885288 0005662 .0000459 0172298	.0012488 .0000112 2.06e-07 .0000954	711.50 -50.38 222.85 -180.59	0.000 0.000 0.000 0.000	.88608 00058 .00004 01741	382 155	.8909765 0005441 .0000463 0170428

# 例

. mixregress ppi Lppi m0 if vw<=0.006, xmicro(earn) wmicro(ew vw) vce(2) nolog

Log-likelihood	=	182.9834	Number of obs	=	106454
AIC	=	-355.9667	Number of group	=	67
BIC	=	-344.9433	R-squared	=	0.8614
HQIC	=	-351.6047	Adj R-squared	=	0.8501
DW	=	1.5601	Root MSE	=	0.0165
-			•		



	ppi	Coefficient	HAC std. err.	z	P> z	[95% conf.	interval]
macro							
	Lppi	.8923568	.0390872	22.83	0.000	.8157474	.9689663
	m0	0003377	.000119	-2.84	0.005	0005709	0001044
	Wearn	.1069264	.0198877	5.38	0.000	.0679473	.1459055
	_cons	0212474	.0047736	-4.45	0.000	0306035	0118913
micro							
	ew	.6010344	.3251257	1.85	0.065	0362004	1.238269
	VW	.3989656	.3251257	1.23	0.220	2382691	1.0362
varian	ce						
1	nsigma	-4.150034	.005244	-791.39	0.000	-4.160312	-4.139756

# 例

. mixregress ppi Lppi m0 if vw<=0.006, xmicro(earn) wmicro(ew vw) vce(2) idtype(1)
nolog</pre>

Log-likelihood AIC BIC HQIC DW	= -355 = -344 = -351	.9834 .9667 .9433 .6047		Number of Number of R-squared Adj R-squ Root MSE	f group d	= = = =	106454 67 0.8614 0.8501 0.0165
ppi	Coefficient	HAC std. err.	Z	P> z	[95%	conf.	interval]
macro Lppi m0 Wearn _cons	.8923568 0003377 .0642664 0212474	.0390872 .000119 .0408338 .0047736	22.83 -2.84 1.57 -4.45	0.000 0.005 0.116 0.000	.8157 0005 0157 0306	709 7664	.9689663 0001044 .1442993 0118913
micro ew vw	1 .6637991	.9436116	0.70	0.482	-1.185	5646	2.513244
variance lnsigma	-4.150034	.005244	-791.39	0.000	-4.160	312	-4.139756

# 例

. local r=1

```
. foreach v of varlist lnsale_w r_debtCF_w CashInEarn_w Tangibility_w {
2. qui mixregress ppi Lppi if vw<=0.006, xmicro(earn) wmicro(ew vw `v') vce(2)
3. est store mod`r'
4. local r=`r'+1
5. }</pre>
```

# 例

. est table mod1 mod2 mod3 mod4, star(.1 0.05 .01) stat(r2 r2a aic bic hqic)

Variable	mod1	mod2	mod3	mod4	
macro					
Lppi	.89819419***	.87999128***	.91469816***	.90153225***	
Wearn	.11262641***	.13102796***	.11936962***	.10771251***	
_cons	02090985***	02072773***	0278286***	02118514***	
micro					
ew	.56731637*	.5661791**	.56217911*	.59513198*	
VW	.43268363	.4338209	.43782089	.40486802	
lnsale_w	-1.593e-06				
r_debtCF_w		0008993**			
CashInEarn_w			9.178e-06		
Tangibilit~w				-3.332e-06	
variance					
lnsigma	-4.1441738***	-4.1559908***	-4.1477835***	-4.1436328***	
Statistics					
r2	.85981334	.86308766	.86082175	.85966156	
r2a	.84832263	.85186533	.84941369	.84815841	
aic	-353.18153	-354.76501	-353.66523	-353.10904	
bic	-295.72872	-297.3122	-296.21242	-295.65623	
hqic	-350.81952	-352.403	-351.30322	-350.74702	

Legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

### 贝叶斯估计

```
. use "micro2.dta", clear
. qui merge m:1 yearquarter using macro2
. bysort yearquarter: gen iflast = _n==_N

. bayesmh ppi Lppi, ///
    llevaluator(lnfmixregress, parameters({th} {tau} {alpha} {var}) extravars(earn e w vw Tangibility_w yearquarter iflast)) ///
    prior({ppi:Lppi}, beta(4,2)) prior({ppi:_cons}, normal(0, 10)) ///
    prior({th}, beta(4,2)) prior({tau}, normal(0,25)) ///
    prior({alpha}, normal(0,25)) prior({var}, igamma(0.01, 0.01)) ///
    initial({ppi:Lppi} 0.6 {ppi:_cons} 0 {th} 0.6 {tau} 0.5 {alpha} 0 {var} 100) //
    block({var}) ///
    mcmcsize(2000) thinning(5) burnin(2500)
```

#### 贝叶斯估计

```
Burn-in ...
Simulation ...
Model summary
Likelihood:
  ppi ~ lnfmixregress(xb_ppi,{th},{tau},{alpha},{var})
Priors:
   {ppi:Lppi} \sim beta(4,2)
                                                                             (1)
  {ppi:_cons} ~ normal(0,10)
                                                                             (1)
         \{th\} \sim beta(4,2)
        {tau} ~ exponential(10)
      {alpha} \sim normal(0,25)
        \{var\} \sim igamma(0.01,0.01)

    Parameters are elements of the linear form xb_ppi.

                                                  MCMC iterations =
Bayesian regression
                                                                          4,500
Random-walk Metropolis-Hastings sampling
                                                  Burn-in
                                                                          2,500
                                                  MCMC sample size =
                                                                         2,000
                                                  Number of obs =
                                                                        107,425
                                                  Acceptance rate =
                                                                         .3151
                                                  Efficiency: min =
                                                                       .005055
                                                                         .05403
                                                               avg =
```

Log marginal-likelihood = 125.09042

max = .2179

# 贝叶斯估计

		 				Equal-tailed		
		Mean	Std. dev.	MCSE	Median	[95% cred.	interval]	
ppi		+ 						
Lŗ	pi	.8907511	.0515945	.005436	.894502	.7761169	.967685	
_cc	ons	0180184	.0050149	.000659	0174062	0282563	0086244	
	th	.6730623	.1842118	.027673	.6957836	.2869377	.9616901	
t	au	.2215724	.1485909	.046731	.1642277	.0691477	.5964011	
alp	ha	.0007482	.000385	.00012	.000703	.0002096	.0015116	
\	/ar	.0006607	.0001173	5.6e-06	.0006407	.0004638	.0009249	

谢谢!