The SAS ROBREG9 Macro

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Abstract

The %ROBREG9 macro is a SAS version 9 macro that runs robust linear regression models showing both the model-based (assuming normality) and empirical standard errors, for situations where it is reasonable to use PROC REG (i.e. no repeated measures, continuous dependent variable). This macro can also calculate point and interval estimates of effect on the (unitless) percent change scale, which is often more widely interpretable.

Keywords: SAS, macro, PROC REG, empirical variance, robust variance

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1 Description

%ROBREG9 is a SAS version 9 macro that gives the empirical standard errors and *p*-values, equivalent to PROC MIXED empirical with TYPE=SIMPLE, when there are no repeated measures. Using this macro instead of PROC MIXED empirical with TYPE=SIMPLE will often result in a substantial reduction of CPU time.

2 a

nd DetailsInvocation

3 Invocation and Details

To call %ROBREG9, your program must know where to look for it. The most efficient way is to include the following line (or its equivalent) at the top of your program.

```
options mautosource sasautos='/usr/local/channing/sasautos';
```

After creating an analysis file, you call %ROBREG9 as follows:

%robreg9(data=	name of data set on which the regression is to be run REQUIRED
depend=	name of the dependent variable REQUIRED
independ=	list of the model variables REQUIRED

- "BY" variables, if any. byvar= OPTIONAL where= a subsetting statement OPTIONAL exp= whether you want to do the analysis on the log scale to compute percent difference in the dependent variable. default=F the name of a data set containing "observations" estdat= at which to compute predicted values. Each observation in the data set must have a value for every variable in the model. OPTIONAL test1= contrast that can be done. to make sure that SAS understands what you want, it is probably safest to put the test in %quote(). if we want to test whether a 1 gram decrease in fat intake is equivalent to a 2 gram increase in alcohol intake, we write test1=%quote(2*alco86n = tfat86n), test1=%quote(2*alco86n - tfat86n = 0),or or just test1=%quote(2*alco86n - tfat86n), (the '=0' is assumed) The tests are then shown with the labels test1, test2, etc. See Example 3 below. OPTIONAL . . . test5= contrast that can be done inc1= increment for a continuous variable so that the coefficient relates to an 'interesting' difference in the covariate. The form is inc1 = <variable name> <increment>. inc1=age86 5,
 - 3

```
means that the increment for age86 is 5 years.
See example 3 below.
The order of these parameters is not important
(i.e. they do not have to be in the same order
as the variables are listed in the model).
OPTIONAL
...
inc20= increment for a continuous variable...
```

4 Examples

Using a data set from HPFS, we examine the relationship between BMI and a number of possible correlates, cross-sectionally in 1986.

The basic data set is called ALL1X.

The trimmed data set ALL1 is a data set made from ALL1X by deleting observations with alcohol intake over 45 or fat intake over 125 or BMI outside the range of 18-45 or caloric intake outside the range of 1000-3200.

data all1; set all1x; where alco le 45 and fat le 125 and 18 le bmi86 le 45 and 1000 le calor le 3200; run;

Alcohol intake is highly skewed, and fat intake is also skewed, as shown by the stem-and-leaf plots below. Although highly skewed independent variables can lead to the presence of one or more underlying influential points, it should be noted that regression models never require normality assumptions on the *independent* variables.

Alcohol gm			Cum.		Cum.
Midpoint		Freq	Freq	Percent	Percent
	I				
0	*****	3371	3371	30.33	30.33
4	****	1957	5328	17.61	47.94
8	*****	1324	6652	11.91	59.85
12	*****	1236	7888	11.12	70.97
16	****	984	8872	8.85	79.83
20	**	499	9371	4.49	84.32
24	*	243	9614	2.19	86.50
28	*	196	9810	1.76	88.27
32	*	218	10028	1.96	90.23
36	**	326	10354	2.93	93.16
40	*	201	10555	1.81	94.97
44	*	121	10676	1.09	96.06
48	*	104	10780	0.94	96.99
52	I	40	10820	0.36	97.35
56	I	49	10869	0.44	97.80
60	l	37	10906	0.33	98.13
64		46	10952	0.41	98.54
68		52	11004	0.47	99.01
72		23	11027	0.21	99.22
76		27	11054	0.24	99.46
80		14	11068	0.13	99.59
84		17	11085	0.15	99.74
88		8	11093	0.07	99.81
92		3	11096	0.03	99.84
96		4	11100	0.04	99.87
100		8	11108	0.07	99.95
104		1	11109	0.01	99.96
108		1	11110	0.01	99.96
112		0	11110	0.00	99.96
116		2	11112	0.02	99.98
120		0	11112	0.00	99.98
124		0	11112	0.00	99.98
128		0	11112	0.00	99.98
132		1	11113	0.01	99.99
136		0	11113	0.00	99.99
140	I	1	11114	0.01	100.00

Ι

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1000 2000 3000

Frequency

Total Fat	gm		Cum.		Cum.
Midpoint	-	Freq	Freq	Percent	Percent
-		-	-		
16		14	14	0.13	0.13
24	* *	129	143	1.16	1.29
32	*****	416	559	3.74	5.03
40	******	837	1396	7.53	12.56
48	*****	1218	2614	10.96	23.52
56	*****	1354	3968	12.18	35.70
64	******	1413	5381	12.71	48.42
72	******	1338	6719	12.04	60.46
80	*****	1152	7871	10.37	70.82
88	 *********	872	8743	7.85	78.67
96	 ******	661	9404	5.95	84.61
104	*****	536	9940	4.82	89.44
112	****	384	10324	3.46	92.89
120	****	265	10589	2.38	95.28
128	**	175	10764	1.57	96.85
136	**	119	10883	1.07	97.92
144	*	78	10961	0.70	98.62
152	*	51	11012	0.46	99.08
160	*	42	11054	0.38	99.46
168		27	11081	0.24	99.70
176		10	11091	0.09	99.79
184		10	11101	0.09	99.88
192		4	11105	0.04	99.92
200		2	11107	0.02	99.94
208		3	11110	0.03	99.96
216		2	11112	0.02	99.98
224		0	11112	0.00	99.98
232		1	11113	0.01	99.99
240		0	11113	0.00	99.99
248		0	11113	0.00	99.99
256		0	11113	0.00	99.99
264		1	11114	0.01	100.00
	++				
	600 1200				

Frequency

NOTE also that we include the predictors as linear continuous variables. Unless linearity of the association is carefully investigated and verified, linear continuous variables should not be entered in models. We do this here only to illustrate.

Example 1. Basic macro call – untrimmed data

The basic macro call (using only the three required parameters) is

title2 '1986--untrimmed data';
%robreg9(data=all1x, depend=bmi86, independ=age86 tfat86n alco86n smk86);

The results are

/udd/stleh/helpme/pkb/robrbase.sas 14:16 Wednesday, April 14, 2010 57 1986--untrimmed data

Data set is all1x Dependent variable is bmi86

obs=8465 , R-squared=0.0093

						emp lower	emp upper
		Model-	Model-	Empirical	Empirical	95% conf	95% conf
varname	Estimate	based SE	based P	SE	Р	bound	bound
INTERCEPT	23.3589	0.19601	0.0000	0.20143	0.0000	22.9641	23.7537
AGE86	0.0169	0.00341	0.0000	0.00354	0.0000	0.0099	0.0238
TFAT86N	0.0080	0.00110	0.0000	0.00117	0.0000	0.0057	0.0103
ALCO86N	0.0037	0.00203	0.0682	0.00207	0.0737	-0.0004	0.0077
SMK86	-0.1361	0.11731	0.2462	0.12320	0.2694	-0.3775	0.1054

The macro tells you the number of observations and the value of R-squared. Then it gives the point estimates of the coefficients and both the modelbased and empirical standard errors and p-values.

Example 2. Untrimmed data with WHERE and BYVAR parameters

This is the same example, but restricting to men under 65 years old stratified by smoking status.

The macro call is

%robreg9(data=all1x, depend=bmi86, independ=age86 tfat86n alco86n , byvar=smk86, where=age86 lt 65);

The results are

/udd/stleh/helpme/pkb/robrbase.sas 14:16 Wednesday, April 14, 2010 58 1986--untrimmed data with WHERE parameter and BY variable

Data set is all1x Dependent variable is bmi86 where age86 lt 65

smk86=. # obs=91 , R-squared=0.0692

					emp lower	emp upper
	Model-	Model-	Empirical	Empirical	95% conf	95% conf
Estimate	based SE	based P	SE	Р	bound	bound
28.8442	2.03200	0.0000	1.72191	0.0000	25.4693	32.2192
-0.0472	0.03930	0.2326	0.03364	0.1602	-0.1132	0.0187
-0.0211	0.00962	0.0306	0.00790	0.0075	-0.0366	-0.0056
0.0100	0.01521	0.5114	0.01578	0.5253	-0.0209	0.0410
	Estimate 28.8442 -0.0472 -0.0211 0.0100	Model- Estimate based SE 28.8442 2.03200 -0.0472 0.03930 -0.0211 0.00962 0.0100 0.01521	Model-Model-Estimatebased SEbased P28.84422.032000.0000-0.04720.039300.2326-0.02110.009620.03060.01000.015210.5114	Model-Model-EmpiricalEstimatebased SEbased PSE28.84422.032000.00001.72191-0.04720.039300.23260.03364-0.02110.009620.03060.007900.01000.015210.51140.01578	Model-Model-EmpiricalEmpiricalEstimatebased SEbased PSEP28.84422.032000.00001.721910.0000-0.04720.039300.23260.033640.1602-0.02110.009620.03060.007900.00750.01000.015210.51140.015780.5253	emp lower Model- Model- Empirical Empirical Empirical 95% conf Estimate based SE based P SE P bound 28.8442 2.03200 0.0000 1.72191 0.0000 25.4693 -0.0472 0.03930 0.2326 0.03364 0.1602 -0.1132 -0.0211 0.00962 0.0306 0.00790 0.0075 -0.0366 0.0100 0.01521 0.5114 0.01578 0.5253 -0.0209

smk86=0 # obs=7153 , R-squared=0.0136

					emp lower	emp upper
	Model-	Model-	Empirical	Empirical	95% conf	95% conf
Estimate	based SE	based P	SE	Р	bound	bound
22.7953	0.24110	0.000	0.23907	0.0000	22.3267	23.2639
0.0268	0.00451	0.000	0.00448	0.0000	0.0180	0.0356
0.0092	0.00119	0.000	0.00126	0.0000	0.0068	0.0117
0.0040	0.00229	0.082	0.00226	0.0779	-0.0004	0.0084
	Estimate 22.7953 0.0268 0.0092 0.0040	Model- Estimate based SE 22.7953 0.24110 0.0268 0.00451 0.0092 0.00119 0.0040 0.00229	Model-Model-Estimatebased SEbased P22.79530.241100.0000.02680.004510.0000.00920.001190.0000.00400.002290.082	Model-Model-EmpiricalEstimatebased SEbased PSE22.79530.241100.0000.239070.02680.004510.0000.004480.00920.001190.0000.001260.00400.002290.0820.00226	Model-Model-EmpiricalEmpiricalEstimatebased SEbased PSEP22.79530.241100.0000.239070.00000.02680.004510.0000.004480.00000.00920.001190.0000.001260.00000.00400.002290.0820.002260.0779	emp lower Model- Model- Empirical Empirical 95% conf Estimate based SE based P SE P bound 22.7953 0.24110 0.000 0.23907 0.0000 22.3267 0.0268 0.00451 0.000 0.00448 0.0000 0.0180 0.0092 0.00119 0.000 0.00126 0.0000 0.0068 0.0040 0.00229 0.082 0.00226 0.0779 -0.0004

smk86=1 # obs=563 , R-squared=0.0005

					emp lower	emp upper
	Model-	Model-	Empirical	Empirical	95% conf	95% conf
Estimate	based SE	based P	SE	Р	bound	bound
24.8982	0.91156	0.0000	1.28098	0.0000	22.3874	27.4089
-0.0050	0.01673	0.7673	0.02421	0.8379	-0.0524	0.0425
0.0016	0.00436	0.7097	0.00468	0.7283	-0.0075	0.0108
-0.0014	0.00610	0.8170	0.00643	0.8262	-0.0140	0.0112
	Estimate 24.8982 -0.0050 0.0016 -0.0014	Model- Estimate based SE 24.8982 0.91156 -0.0050 0.01673 0.0016 0.00436 -0.0014 0.00610	Model- Model- Estimate based SE based P 24.8982 0.91156 0.0000 -0.0050 0.01673 0.7673 0.0016 0.00436 0.7097 -0.0014 0.00610 0.8170	Model-Model-EmpiricalEstimatebased SEbased PSE24.89820.911560.00001.28098-0.00500.016730.76730.024210.00160.004360.70970.00468-0.00140.006100.81700.00643	Model-Model-EmpiricalEmpiricalEstimatebased SEbased PSEP24.89820.911560.00001.280980.0000-0.00500.016730.76730.024210.83790.00160.004360.70970.004680.7283-0.00140.006100.81700.006430.8262	emp lower Model- Model- Empirical Empirical Empirical 95% conf Estimate based SE based P SE P bound 24.8982 0.91156 0.0000 1.28098 0.0000 22.3874 -0.0050 0.01673 0.7673 0.02421 0.8379 -0.0524 0.0016 0.00436 0.7097 0.00468 0.7283 -0.0075 -0.0014 0.00610 0.8170 0.00643 0.8262 -0.0140

NOTE that the macro has told you that the analysis data set was restricted using a WHERE parameter.

NOTE that there is a group of men for whom SMK86 is unknown. Since we are probably not interested in results in this small group, we could use the WHERE parameter to exclude them. In that case, the macro call would have

where = age86 lt 65 and smk86 ne .

Example 3. Trimmed data with increments and estimating points (ESTDAT) and a test

The data set ESTDAT was made using the following code.

/* data set of points at which want to estimate bmi */

```
data estdat;
age86=60; tfat86n=70;
                         alco86n=5;
                                     smk86=0;
                                                output;
           tfat86n=50;
age86=60;
                         alco86n=5;
                                     smk86=0;
                                                output;
                                                output;
age86=60;
           tfat86n=70;
                         alco86n=0;
                                     smk86=0;
           tfat86n=60;
age86=65;
                         alco86n=0;
                                     smk86=0;
                                                output;
age86=65;
           tfat86n=60;
                         alco86n=0;
                                      smk86=1;
                                                output;
run;
```

ESTDAT could also have been made by reading a file.

The macro call is

```
%robreg9(data=all1, depend=bmi86, independ=age86 tfat86n alco86n smk86,
inc1=age86 5, inc2=tfat86n 5, inc3=alco86n 10, estdat=estdat,
test1=%quote(tfat86n=2*alco86n));
```

The increments correspond to 'interesting' changes in the values of the variables, such as 5 years of age, 5 grams of fat, 10 grams of alcohol (1 drink).

In addition, we are interested in testing whether the effects of alcohol and fat are inversely proportional to their caloric contributions, so we do a test. Since fat is twice as energy-dense as alcohol, we multiply the coefficient of alcohol by 2 to test whether a 2 gram increase in alcohol is the same as a 1 gram increase in fat. Note that we used %quote on the test condition, because it contains an =. We could also have used %str. The results are

Data set is all1 Dependent variable is bmi86

obs=7775 , R-squared=0.0075

emp lower emp upper Model- Model- Empirical Empirical 95% conf 95% conf varname Estimate based SE based P SE P bound bound

INTERCEPT	23.3339	0.20660	0.0000	0.20401	0.0000	22.9340	23.7337
AGE86	0.0903	0.01751	0.0000	0.01758	0.0000	0.0558	0.1247
TFAT86N	0.0397	0.00675	0.0000	0.00664	0.0000	0.0267	0.0527
ALCO86N	-0.0058	0.02890	0.8414	0.02924	0.8433	-0.0631	0.0515
SMK86	-0.0662	0.12538	0.5974	0.12879	0.6071	-0.3187	0.1862

/udd/stleh/helpme/pkb/robrbase.sas 14:16 Wednesday, April 14, 2010 60 1986--trimmed data, with increments and estimating points testing whether fat effect is twice as large as alcohol effect

Data set is all1 Dependent variable is bmi86

estimates at specific data values

				Predicted	Lower Bound
	Total	Alcohol		Value of	of 95% C.I.
age86	Fat gm	gm	smk86	bmi86	for Mean
60	70	5	0	24.9699	24.8766
60	50	5	0	24.8111	24.7069
60	70	0	0	24.9728	24.8672
65	60	0	0	24.9837	24.8526
65	60	0	1	24.9174	24.6471

	Lower Bound of	Upper Bound of
Upper Bound	95%	95%
of 95% C.I.	C.I.(Individual	C.I.(Individual
for Mean	Pred)	Pred)
25.0632	19.6858	30.2540
24.9153	19.5268	30.0954
25.0784	19.6885	30.2571
25.1147	19.6988	30.2685
25.1878	19.6273	30.2076

/udd/stleh/helpme/pkb/robrbase.sas 14:16 Wednesday, April 14, 2010 61 1986--trimmed data, with increments and estimating points testing whether fat effect is twice as large as alcohol effect

Data set is all1 Dependent variable is bmi86

results of tests

			p for	p for
			ols std	empirical
Obs	Test	testing	err	std err
1	test1	tfat86n=2*alco86n	0.3804	0.3855

NOTE: Since the p-value for the test is not significant, we say that there is no evidence that alcohol and fat affect BMI through any mechanism other than their energy content.

Example 4. Trimmed data with a contrast and exponentiated coefficients

Sometimes the linear model for the conditional mean as a function of the model covariates fits better on the log scale (multiplicative model). Here our dependent variable is lbmi86=log(bmi86). Again using the trimmed data set ALL1, we demonstrate other features of ROBREG9.

Our model is now

log(bmi)=intercept + b1*age86 + b2*tfat86n + b3*alco86n + smk86

Because the model predicts the dependent variable on the log scale, but we are really interested in the original scale, we use

exp=T

to give the percent difference in BMI for each covariate. The increment parameters can be used here to get percent differences for 'interesting' changes in the continuous covariates.

The macro call is

```
%robreg9(data=all1, depend=lbmi86, exp=T, independ=age86 tfat86n alco86n smk86,
inc1=age86n 5, inc2=tfat86n 5, inc3=alco86n 10);
```

The results are

/udd/stleh/helpme/pkb/robrbase.sas 14:41 Wednesday, April 14, 2010 63
1986-trimmed data
outcome is log(bmi), so we use EXP=T
using test1 parameter
Data set is all1 Dependent variable is lbmi86

exponentiated

obs=7775 , R-squared=0.0077

	Percent	Model-	Empirical	Lower 95%	Upper 95%	
varname	difference	based P	Р	CL % diff	CL % diff	
	0006 0	0 0000	0.0000	0100 0	0062 0	
INTERCEPT	2226.2	0.0000	0.0000	2189.8	2263.2	
AGE86	0.4	0.0000	0.0000	0.2	0.5	
TFAT86N	0.2	0.0000	0.0000	0.1	0.2	
ALCO86N	0.0	0.9719	0.9722	-0.2	0.2	
SMK86	-0.3	0.5092	0.5286	-1.3	0.7	

5 References

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White H. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrics 1980; 48:817-838.

6 Credits

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7 See Also