## 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:

byvar= "BY" variables, if any. 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

estdat= the name of a data set containing "observations" 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

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,

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.

```
BMI86 is the individual's BMI in 1986

age86 is the individual's age (in years) in 1986

tfat86n is the individual's daily intake of total fat
    in grams per day in 1986

alco86n is the individual's daily intake of alcohol
    in grams per day in 1986

smk86 is the individual's smoking status in 1986

(0=non-smoker, 1=smoker)
```

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 Midpoint		Freq	Cum. Freq	Percent	Cum. Percent
p	1	4	4	1 01 00110	1 01 00110
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	<b> </b> **	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	1	40	10820	0.36	97.35
56	1	49	10869	0.44	97.80
60		37	10906	0.33	98.13
64		46	10952	0.41	98.54
68	1	52	11004	0.47	99.01
72	1	23	11027	0.21	99.22
76		27	11054	0.24	99.46
80	1	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	1	0	11112	0.00	99.98
132	[	1	11113	0.01	99.99
136	1	0	11113	0.00	99.99
140	1	1	11114	0.01	100.00

1000 2000 3000

Frequency

Total Fat	gm		Cum.		Cum.
Midpoint		Freq	Freq	Percent	Percent
-	1	-	-		
16	I	14	14	0.13	0.13
24	<b> </b> **	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	1	2	11107	0.02	99.94
208	1	3	11110	0.03	99.96
216	1	2	11112	0.02	99.98
224	1	0	11112	0.00	99.98
232	1	1	11113	0.01	99.99
240	1	0	11113	0.00	99.99
248	1	0	11113	0.00	99.99
256	1	0	11113	0.00	99.99
264	1	1	11114	0.01	100.00
	1				

### 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 1986--untrimmed data

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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	P	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 model-based 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-	${\tt Empirical}$	Empirical	95% conf	95% conf
varname	Estimate	based SE	based P	SE	P	bound	bound
INTERCEPT	28.8442	2.03200	0.0000	1.72191	0.0000	25.4693	32.2192
AGE86	-0.0472	0.03930	0.2326	0.03364	0.1602	-0.1132	0.0187
TFAT86N	-0.0211	0.00962	0.0306	0.00790	0.0075	-0.0366	-0.0056
ALCO86N	0.0100	0.01521	0.5114	0.01578	0.5253	-0.0209	0.0410

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

						emp lower	emp upper
		Model-	Model-	Empirical	Empirical	95% conf	95% conf
varname	Estimate	based SE	based P	SE	P	bound	bound
INTERCEPT	22.7953	0.24110	0.000	0.23907	0.0000	22.3267	23.2639
AGE86	0.0268	0.00451	0.000	0.00448	0.0000	0.0180	0.0356
TFAT86N	0.0092	0.00119	0.000	0.00126	0.0000	0.0068	0.0117
ALCO86N	0.0040	0.00229	0.082	0.00226	0.0779	-0.0004	0.0084

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

						emp lower	emp upper
		Model-	Model-	Empirical	Empirical	95% conf	95% conf
varname	Estimate	based SE	based P	SE	P	bound	bound
INTERCEPT	24.8982	0.91156	0.0000	1.28098	0.0000	22.3874	27.4089
AGE86	-0.0050	0.01673	0.7673	0.02421	0.8379	-0.0524	0.0425
TFAT86N	0.0016	0.00436	0.7097	0.00468	0.7283	-0.0075	0.0108
ALCO86N	-0.0014	0.00610	0.8170	0.00643	0.8262	-0.0140	0.0112

### 

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

age86	Total Fat gm	Alcohol gm	smk86	Predicted Value of bmi86	Lower Bound of 95% C.I. 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
95%	95%
C.I.(Individual	C.I.(Individual
Pred)	Pred)
19.6858	30.2540
19.5268	30.0954
19.6885	30.2571
19.6988	30.2685
19.6273	30.2076
	95% C.I.(Individual Pred) 19.6858 19.5268 19.6885 19.6988

/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
0bs	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

varname	Percent difference	Model- based P	Empirical P	Lower 95% CL % diff	Upper 95% CL % diff
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
1111111111111	000000000000000000000000000000000000000	111111111111111111111111111111111111111	000000000000000000000000000000000000000	000000000000000000000000000000000000000	111111111111111111111111111111111111111

### 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