## The SAS SUBTYPE Macro

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#### Abstract

The %SUBTYPE macro examines whether the effects of the exposure(s) vary by subtypes of a disease. It can be applied to data from the cohort studies, nested or matched case-control studies, unmatched case-control studies and case-case studies.

Keywords: SAS macro, etiologic heterogeneity, competing risk analysis, cohort study, case-control study, case-case study, subtypes

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### 1 Description

%SUBTYPE is a SAS macro that examines whether the effect of the exposure(s) vary by subtypes of a disease in the cohort studies, matched or unmatched case-control studies or case-case studies. Let  $\beta_j$  be the log relative risks of the exposure for subtype j, j = 1, 2, ..., J. It provides overall heterogeneity test ( $H_0: \beta_1 = \beta_2 =, ..., = \beta_J$ ) and pair-wise heterogeneity tests ( $H_{01}: \beta_1 = \beta_2, \beta_1 = \beta_3, ..., \beta_{J-1} = \beta_J$ ) performed by the likelihood ratio test or Wald test. It provides the constrained and unconstrained models for adjusting the potential confounders. In the constrained model, the effects of the covariates are assumed to be the same across the subtypes; in the unconstrained model, the effects of the subtypes.

For cohort study, the macro uses Cox proportional hazards model with a data augmentation method. It works with both an augmented data set created by the user and a standard data set, for which the macro creates the augmented data set. It allows the constrained and unconstrained models. The model-based variance-covariance matrix estimate is used, unless the user specifies COV=YES, which requests robust sandwich variance-covariance matrix estimates. The heterogeneity test is performed by the likelihood ratio test (by default). The Wald test is available with WALD=YES.

For nested or matched case-control study, the macro uses the conditional logistic regression model. It allows the constrained and unconstrained models. The model-based variance-covariance matrix estimate is used, unless the user specifies COV=YES, which requests robust sandwich variance-covariance

matrix estimates. The heterogeneity test is performed by the likelihood ratio test (by default). The Wald test is available with WALD=YES.

For unmatched case-control study, the macro provides two approaches. By default, it uses unconditional nominal polytomous logistic regression model. It provides the unconstrained analysis and Wald test for the heterogeneity test, using the model-based variance-covariance matrix estimate. The other approach is conducted by conditional logistic regression analysis with a data augmentation method. If the user chooses this approach by specifying conditional=YES, the macro creates the augmented data set. It allows the user to request the constrained model for some or all covariates, likelihood ratio test for the heterogeneity test and the robust sandwich variance-covariance matrix estimate, in addition to the analysis options available in the first approach.

For case-case study, the macro uses unconditional nominal polytomous logistic regression model. It provides the unconstrained analysis and Wald test for the heterogeneity test, using the model-based variance-covariance matrix estimate. Note that unlike the above three study designs, the casecase study provides the heterogeneity tests only, not estimating and testing the effects of exposures on the risk on each subtype.

## 2 Invocation and Details

In order to run this macro, your program must know where to look for it. You can tell SAS where to look for macros by using the options:

options mautosource sasautos=<directories macro is located>;

In the Channing servers, the option statements might be

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

In the rest of this section, we will list all the input parameters, some of which are required and some of which are optional.

%macro subtype(

data=, name of data set on which the analysis is conducted studydesign=COHORT, COHORT if cohort study, MCACO if matched or nested case-control study, CACO if case-control study, CACA if case-case study (the default value is COHORT)

- id=ID, subject IDs; each subject may have multiple
   entries; required when studydesign=COHORT
   (the default value is ID)
- augmented=YES/NO; YES if the input dataset is augmented for every outcome subtype; applicable only if studydesign=COHORT; the default value is NO
- the exposure variable(s); the heterogeneity exposure=, test is for comparing coefficient(s) of this/these variable(s); the macro can handle multiple exposure variables , which can be indicator variables for a categorical exposure, which should be put in curly brackets, or multiple exposures, for each of which the heterogeneity test is performed; for a cohort study, if augmented=YES, the variable names should have the suffix \_j indicating subtypes  $(j=1,2,\ldots,J \text{ total subtypes})$  and the variables should be sorted by subtypes in curly brackets. For example, if you have two exposures, a 3-level categorical exposure alcohol drinking, with indicators, alco2 and alco3, and another binary exposure bmi (body mass index), and J=3, for augmented=YES, this macro parameter should be defined as {alco2\_1 alco3\_1 alco2\_2 alco3\_2 alco2\_3 alco3\_3} {bmi\_1 bmi\_2 bmi\_3}; if the data set is no augmented, this macro parameter should be {alco2 alco3} bmi.

- time=, time-to-failure variable used in the model statement of PROC PHREG; a single failure-time variable, or t2 of at-risk intervals (t1,t2] for the counting process format; required if studydesign=COHORT; otherwise not applicable.
- entrytime=, entry time variable, t1, of the at-risk intervals
   (t1,t2], mentioned in the description above
   for macro parameter time; applicable if
   studydesign=COHORT; if the user
   specifies a single failure-time variable,
   this parameter should be empty.
- eventtype=, subtype variable, required for all designs; for a cohort study, if augmented=YES, the specified variable takes on the value j for all person-times for the outcome subtype j (j=1,2,...,J total subtypes) and censoring status will be specified in the parameter censoring; if augmented=NO, the variable specified has value j if the outcome subtype j has occurred by end of follow up or 0 if censored; for a case-control or case-case study, the variable has j for cases with outcome subtype j and 0 for controls (in case-control study)
- censoring=, censoring variable. The variable takes
   on value 0 if censored and 1 if the corresponding
   outcome subtype contained in eventtype occurs;
   applicable only if augmented=YES

 with the outcome are forced to be the same across subtypes of outcome

- conditional= YES/NO; YES if requesting conditional
   logistic regression analysis for unmatched
   case-control study; this allows the constrained
   analysis and heterogeneity test by likelihood ratio
   test; applicable only if studydesign=CACO;
   the default value is NO
- wald= YES/NO; YES if requesting Wald test for the heterogeneity test, in addition to the default likelihood ratio test; only applicable if studydesign=COHORT, MCACO, or CACO with conditional=YES; Wald test is the only heterogeneity test available (and is the default test) for studydesign=CACA and CACO with conditional=NO; the default value is NO

```
eventtypelabel (optional) = it can be used to define
              the coding of eventtype; please do not use ','
                    for example, note = 1=high; 2=low;
              here;
 paramest (optional) = name of the SAS dataset
              containing the parameter estimates
heterotest (optional) = name of the SAS dataset
              containing the results from the
              heterogeneity tests; if the Wald test is
              requested with
              studydesign=COHORT, MCACO, or CACO
              with conditional=YES, those results are
              contained in the dataset named heterotest_WT
covest (optional) = name of SAS dataset containing the estimated
                    covariance matrix of the parameter estimates
    );
```

```
,,
```

### 3 Examples

The examples below describe the macro calls for each study design, using data from a study of the alcohol effects on LINE-1 methylation subtypes of colon cancer in the Health Professional Follow-up study. The outcome is incidence colon cancer defined by LINE-1 methylation status; there are three subtypes: LINE-1 high, medium and low. The exposure of interest is alcohol intake and we'll focus on the trend test for median alcohol intake at the baseline (0g/day, 1.8g/day, 10.2g/day, 27.5g/day) divided by the standard alcohol serving unit of 12g/day. The potential confounders controlled for in the analysis include current aspirin use, body mass index, history of screening, physical activity, history of prior polyps, family history of colon cancer, pack year of smoking, red meat intake, multivitamin use, calcium intake and folate intake, which are all categorical variables.

All data sets used in the example include the following variables:

id	study subject's unique ID
cancer	outcome variable
	(1 for LINE-1 high, 2 for median, 3 for low,
	0 for non-cancer)
alcohol	exposure score for alcohol intake
	(0, 0.15, 0.85, 2.29)

The other design-specific variables will be described in each Example section

# 3.1 Example 1. Cohort study analysis with the standard counting process data format

The data set, cohort1, below is in the standard counting process data format, where period is questionnaire period, agemo is age in months at the beginning of each questionnaire period, time is the months from the start of the questionnaire cycle until date of colon cancer incidence, date of death, or date of the end of questionnaire period, whichever happens first.

Cohort1:

id	time	cancer	period	agemo	alcohol	OTHER COVARIATES
1	20	0	1	560	0.15	• • •
1	23	0	2	580	0.15	• • •
1	16	1	3	603	0.15	
•••						
2	23	0	1	606	0	
2	21	0	2	623	0	
2	19	0	3	644	0	
2	25	0	4	663	0	
•••						

The macro call to apply the unconstrained model for all covariates is:

```
%subtype(data=cohort1, studydesign=cohort, id=id,
exposure=alcohol, augmented=no, time=time, eventtype=cancer,
unconstrvar=ause_p2 screen2 polyps2 cafam2
```

```
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5, stratavar=agemo period,
eventtypelabel=1=high; 2=medium; 3=low,
heterotest=heterogeneity);
```

For using the constrained models for some or all covariates, those covariates can be placed in CONSTRVAR .

The output is

Running on data set Tie CANCER:	COHORT1, Read handling: BRES 1=high; 2=medi cases in each c	47363 LOW um; 3=1 utcome	observations ow	52
c	Frequer ancer Cour			
	1 99 2 102 3 67			
Running on data set	COHORT1, Read	47363	observations	53
С	onvergence Stat	us		
	Reason			
Convergence cr	iterion (GCONV=	1E-8) s	atisfied.	
Running on data set	COHORT1, Read	47363	observations	54
Мо	del Fit Statist	ics		
Criterion	Without Covariates	Wi Covar		
 -2 LOG L AIC SBC	2301.497 2301.497 2301.497	2350 2717	.860 .140	
 Running on data set				 55
Testing Glo	bal Null Hypoth	esis: B	ETA=0	
Test	Chi-Square	DF	Pr > Chi-Square	
Likelihood Ratio Score Wald		102 102 102	0.0006 0.0009 0.0056	

	Runnin	g on data set	COHORT1, Read	47363	observations			56
		Analysis of	Maximum Likeli	hood Esti	mates			
		Parameter	Standard	Hazard				
Label	DF	Estimate	Error	Ratio	lowerCL	upperCL	Pvalue	Parameter
exposure alcohol and cancer 1	1	-0.0007371	0.11743	0.99926	0.79382	1.2579	0.9950	_expND_1_1
exposure alcohol and cancer 2	1	0.44929	0.10814	1.56720	1.26787	1.9372	<.0001	_expND_1_2
exposure alcohol and cancer 3	1	0.30950	0.13467	1.36274	1.04660	1.7744	0.0215	_expND_1_3
ause_p2 and cancer 1	1	-0.11295	0.20992	0.89319	0.59191	1.3478	0.5905	_ucv_1_1
ause_p2 and cancer 2		-0.58319	0.21481	0.55811	0.36633	0.8503	0.0066	_ucv_1_2
ause_p2 and cancer 3	1	-0.24737	0.25845	0.78085	0.47051	1.2959	0.3385	_ucv_1_3
(The rest is omitted)								
	Runnin	g on data set	COHORT1, Read	47363	observations			58
		Heterogeneity	Tests (Likeli	hood rati	o test)			
		Label		DF P	value			
		All: alcohol		2 0.	01563			
		Pairwise 1 vs	2: alcohol	1 0.	00443			
		Pairwise 1 vs	3: alcohol	1 0.	08233			
		Pairwise 2 vs	3: alcohol	1 0.	41765			

The titles tell you the name of data set and the number of the observations on which the analysis is conducted. First, the macro tells you the number of events for each subtype and the method of handling ties. Then, you get the results of Cox proportional hazards model. The first table shows Convergence Status, which should be satisfied. The second and third tables show Model Fit Statistics and Testing Global Null Hypothesis, respectively. The table of Analysis of Maximum Likelihood Estimates shows the hazard ratios and confidence intervals of the exposures and covariates, which indicates here the HRs of alcohol for subtype 1, 2 and 3 are 0.999, 1.567 and 1.363, respectively. Note that since the unconstrained model are requested for all covariates, the HRs of covariates for each subtype are shown. Finally, you get the results of heterogeneity test. The rows starting with "All:" and "Pair-wise:" correspond to the results of the overall heterogeneity test across the three subtypes and the pair-wise heterogeneity tests, respectively. Pair-wise 1 vs 2, Pair-wise 1 vs 3, and Pair-wise 2 vs 3 correspond to the comparisons of the effects of alcohol intake between subtype 1 and subtype 2, between subtype 1 and subtype 3 and between subtype 2 and subtype 3, respectively. The data set, heterogeneity, which contains the results of heterogeneity tests is created with using the macro parameter heterotest.

## 3.2 Example 2. Cohort study analysis with the augmented data set

The data set, cohort2, is the augmented data set for id =1 in cohort1, where the variable censor is a censoring indicator for each subtype which is specified by variable type; it is 1 for censored and 0 if the specific type of cancer is diagnosed in the corresponding block of person-time. The variables alcohol\_1, alcohol\_2 and alcohol\_3 are the subtype-specific exposure variables, which are for subtype 1, 2 and 3, respectively. Note that the data set should have the subtype-specific variables of covariates for which you want to request the unconstrained model, in the same way as the exposure variables.

Cohort2:

id	time	cancer	period	agemo	alcohol	censor	type	alcohol_1	alcohol_2	alcohol_3	OTHER COVARIATES
1	20	0	1	560	0.15	1	1	0.15	0	0	
1	20	0	1	560	0.15	1	2	0	0.15	0	
1	20	0	1	560	0.15	1	3	0	0	0.15	
1	23	0	2	580	0.15	1	1	0.15	0	0	
1	23	0	2	580	0.15	1	2	0	0.15	0	
1	23	0	2	580	0.15	1	3	0	0	0.15	
1	16	1	3	603	0.15	0	1	0.15	0	0	
1	16	1	3	603	0.15	1	2	0	0.15	0	
1	16	1	3	603	0.15	1	3	0	0	0.15	

The macro call to apply the same model as that used in Example 1 is

```
%subtype(data=cohort2, studydesign=cohort, id=id,
exposure=alcohol_1 alcohol_2 alcohol_3, augmented=yes,
time=time, eventtype=type, censoring=censor,
unconstrvar=ause_p2_1 ause_p2_2 ause_p2_3
screen2_1 screen2_2 screen2_3
polyps2_1 polyps2_2 polyps2_3
cafam2_1 cafam2_2 cafam2_3
py30ct2_1 py30ct2_2 py30ct2_3
py30ct3_1 py30ct3_2 py30ct3_3
py30ct4_1 py30ct4_2 py30ct4_3
py30ct4_1 py30ct5_2 py30ct5_3
py30ct5_1 py30ct5_2 py30ct5_3
py30ctm_1 py30ctm_2 py30ctm_3
actct2_1 actct2_2 actct2_3
actct3_1 actct3_2 actct3_3
```

```
actct4_1 actct4_2 actct4_3
actct5_1 actct5_2 actct5_3
actctm_1 actctm_2 actctm_3
mvit2 1 mvit2 2 mvit2 3
mvitm_1 mvitm_2 mvitm_3
bmain2 1 bmain2 2 bmain2 3
bmain3_1 bmain3_2 bmain3_3
bmain4 1 bmain4 2 bmain4 3
bmi2_1 bmi2_2 bmi2_3
bmi3_1 bmi3_2 bmi3_3
bmi4_1 bmi4_2 bmi4_3
bmi5_1 bmi5_2 bmi5_3
bmim_1 bmim_2 bmim_3
calcq2_1 calcq2_2 calcq2_3
calcq3_1 calcq3_2 calcq3_3
calcq4_1 calcq4_2 calcq4_3
calcq5_1 calcq5_2 calcq5_3
calcqm_1 calcqm_2 calcqm_3
folq2_1 folq2_2 folq2_3
folq3_1 folq3_2 folq3_3
folq4_1 folq4_2 folq4_3
folq5_1 folq5_2 folq5_3,
stratavar=agemo period);
```

The results are the same as those in Example 1.

# 3.3 Example 3. Nested or matched case-control study analysis

Example 3 use a nested case-control data set, necaco, sampled from the original cohort data set by the risk set sampling with age (years) as time scale and matched on race/ethnicity. There are one cases and two controls in each matching set. The necaco includes the variables matched which indexes matched set ID.

The macro call is

%subtype(data=necaco, studydesign=mcaco, exposure=alcohol, eventtype=cancer, matchid=matchid,

```
constrvar=ause_p2 screen2 polyps2 cafam2
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm
bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5,
wald=yes
);
```

Note that this macro call requests the constrained models for all covariates and requests Wald test for the heterogeneity test. If you want the unconstrained models for some or all of covariates, those covariates can be placed in the macro parameter unconstruar.

The output is

Running on data set NECACO, Read 268 matched pairs	10
Number of controls and cases in each outcome type	
Frequency	
cancer Count	
0 536	
1 99 2 102	
3 67	
5 07	
Running on data set NECACO, Read 268 matched pairs	11
Convergence Status	
Reason	
Reason	
Convergence criterion (GCONV=1E-8) satisfied.	
Running on data set NECACO, Read 268 matched pairs	12
Model Fit Statistics	
Without With	
Criterion Covariates Covariates	
-2 LOG L 588.856 505.805	
AIC 588.856 577.805	
SBC 588.856 707.081	

Running on data set NECACO, Read 268 matched pairs

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Testing Global Null Hypothesis: BETA=0

	Test	Chi-Square	DF	Pr > Chi-Square			
	Likelihood Ratio Score Wald	83.0512 76.8894 65.2835	36 36 36	<.0001 <.0001 0.0020			
	Running on data set						14
	Analysis of	Maximum Likeli	hood Es	timates			
	Parameter	Standard	Hazar	d			
Label	DF Estimate	Error	Rati	o lowerCL	upperCL	Pvalue	Parameter
exposure alcohol and cancer 1 exposure alcohol and cancer 2 exposure alcohol and cancer 3	1 -0.02251 1 0.35664 1 0.32872 1 -0.38554	0.14774 0.14972 0.18305 0.17998	0.97 1.42 1.38 0.68	9 1.06524 9 0.97039	1.30613 1.91570 1.98872 0.96774	0.8789 0.0172 0.0725 0.0322	_expND_1_1 _expND_1_2 _expND_1_3 ause_p2
(The rest is omitted)							
	Label All: alcohol Pairwise 1 v Pairwise 1 v	y Tests (Likeli	DF 2 1 1	rio test) Pvalue 0.13649			15
	Running on data set Hetero	NECACO, Read		-			16
	Label		DF	Pvalue			
	Pairwise 1 v Pairwise 2 v	vs 2: alcohol vs 3: alcohol vs 3: alcohol	1 1 1	0.1390 0.0663 0.1310 0.9036			

The titles tell you the name of data set and the number of matched pairs on which the analysis is conducted. First, the macro tells you the number of controls and cases for each subtype. Then, you get the results of conditional polytomous logistic regression model. The results are shown in the same way as those in the cohort study analysis. The table of Analysis of Maximum Likelihood Estimates shows the hazard ratios and confidence intervals of the exposures and covariates, which indicates here the HRs of alcohol for subtype 1, 2 and 3 are 0.978, 1.429 and 1.389, respectively. Note that since the constrained model are requested for all covariates, the HRs of covariates for overall colon cancer are shown, assuming the effects of the covariates are the same across the subtypes. Since WALD=yes is specified, you get the results of the heterogeneity test by Wald test, following those by likelihood

ratio test.

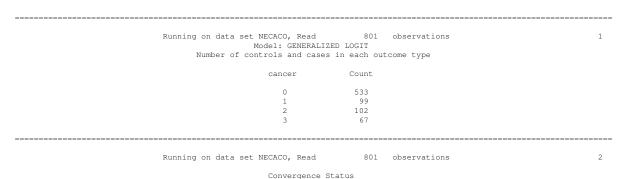
#### 3.4 Example 4. Unmatched case-control study analysis

Example 4 analyze the data set used in the Example 3, excluding 3 controls in that data set who were colon cancer cases but in the risk set sampling were sampled as matched controls for ages before the cancer were developed, with adjusting for the matching factors (age and race) by including them as covariates instead of stratified by matcheid. The unconstrained analysis is based on the unconditional nomial polytomous logistic regression model.

The macro call is

```
%subtype(data=necaco, studydesign=caco, exposure=alcohol,
eventtype=cancer,
unconstrvar=ause_p2 screen2 polyps2 cafam2
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm
bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5
);
```

The output is



Reason

			on data	set NECACO	O, Read					
				Mode	l Fit Statist:	ics				
						Model Wi	th			
						Intercep				
					Intercept	and				
			Cri	terion	Only Model	Covariat	es			
			AIC	2	1607.088	1687.27	8			
			SC		1621.146	2207.40				
				Log L	1601.088	1465.27				
		Running (					observations			
					l Null Hypoth					
				2			Pr >			
		Test	÷.	(	Chi-Square	DF C	hi-Square			
			elihood	Ratio	135.8103	108	0.0363			
		Sco: Wald			127.5854 113.0353	108 108	0.0961 0.3510			
		Walt			113.0555	100	0.3310			
		Rupping	on data	set NECAC	), Read	801	observations			
			Ju waid		Analysis of E:		SESCE VALIDIIS			
				TAbe 2 1	Wald	Pr				
			Effect	DF						
			alcoho							
			ause_p	2 3			238			
(Tho )	rost is omitor	41	<u>-</u> 1		9.457	7 0.0				
	rest is omitec	d) ====================================								
			on data	set NECACO		801	observations			
			on data Analy	set NECACO	O, Read ximum Likeliho Standard	801	observations tes	upperCL	Pvalue	
	Variable	Running o	on data Analy DF	set NECACC vsis of Ma: Estimate	D, Read ximum Likelihn Standard Error	801 Dod Estima Odds Ratio	observations tes lowerCL	upperCL	Pvalue	
	Variable Intercept	Running o outcometype 1	Dn data Analy DF 1	set NECACC vsis of Max Estimate -0.7457	D, Read ximum Likeliha Standard Error 1.1061	801 Odd Estima Odds Ratio 0.47439	observations tes lowerCL 0.05428	upperCL 4.1464	Pvalue 0.5002	
	Variable	Running o	on data Analy DF	set NECACC vsis of Ma: Estimate	C, Read ximum Likeliho Standard Error 1.1061 1.3155	801 Odd Estima Odds Ratio 0.47439 0.08159	observations tes lowerCL 0.05428 0.00619	upperCL	Pvalue	
	Variable Intercept Intercept Intercept alcohol	Running o outcometype 1 2 3 1	Dn data Analy DF 1 1	set NECACC vsis of Max Estimate -0.7457 -2.5060 -4.3589	D, Read ximum Likeliha Standard Error 1.1061 1.3155 1.8352	801 Odd Estima Odds Ratio 0.47439 0.08159 0.01279	observations tes lowerCL 0.05428 0.00619 0.00035	upperCL 4.1464 1.0750	Pvalue 0.5002 0.0568	
	Variable Intercept Intercept Intercept alcohol alcohol	Running o outcometype 1 2 3 1 2	on data Analy DF 1 1 1 1 1	set NECAC( vsis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278	801 Odd Estima Ratio 0.47439 0.08159 0.01279 0.95870 1.54988	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006	
	Variable Intercept Intercept Intercept alcohol alcohol	Running o outcometype 1 2 3 1 2 3 1 2 3	Dr data Analy DF 1 1 1 1 1 1	set NECAC( vsis of Max Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660	D, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1	Dr data Analy DF 1 1 1 1 1 1 1 1	set NECACC rsis of Max Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413	D, Read ximum Likeliha Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023	
	Variable Intercept Intercept alcohol alcohol ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2	Dn data Analy DF 1 1 1 1 1 1 1 1 1	set NECAC( sis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3	Dr data Analy DF 1 1 1 1 1 1 1 1	set NECACC rsis of Max Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3	Dn data Analy DF 1 1 1 1 1 1 1 1 1	set NECAC( sis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3 tted)	on data Analy DF 1 1 1 1 1 1 1 1 1	set NECACC vsis of Max Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110 -0.3766	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444	801 Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115 0.68617	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929 1.1947	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3 tted)	Dr data Analy DF 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0	set NECAC( vsis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110 -0.3766 	D, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444 0.2829	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115 0.68617 801	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422 0.39410	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929 1.1947	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3 tted)	on data Analy DF 1 1 1 1 1 1 1 1 1 0 n data Label	set NECACC vsis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110 -0.3766 set DATASI Heterogene	C, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444 0.2829 ET1, Read	801 Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115 0.68617 801 ald test) DF Pv	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422 0.39410 observation	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929 1.1947	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3 tted)	on data Analy DF 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	set NECACC vsis of Max Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110 -0.3766 -0.3766 set DATASI Heterogene	D, Read ximum Likeliho Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444 0.2829 ET1, Read eity Tests (W.	801 Odds Estima Odds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115 0.68617 801 ald test) DF Pv 2 0.	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422 0.39410 observatior alue 0139	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929 1.1947	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	
	Variable Intercept Intercept alcohol alcohol alcohol ause_p2 ause_p2 ause_p2	Running o outcometype 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 3 tted)	on data Analy DF 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	set NECACC vsis of Ma: Estimate -0.7457 -2.5060 -4.3589 -0.0422 0.4382 0.2660 -0.2413 -0.7110 -0.3766 set DATASI Heterogene	C), Read ximum Likelihu Standard Error 1.1061 1.3155 1.8352 0.1311 0.1278 0.1542 0.2339 0.2444 0.2829 ET1, Read eity Tests (Wather the second seco	801 00d Estima 00ds Ratio 0.47439 0.08159 0.01279 0.95870 1.54988 1.30471 0.78564 0.49115 0.68617 801 ald test) DF Pv 2 0. 1 0.	observations tes lowerCL 0.05428 0.00619 0.00035 0.74150 1.20641 0.96443 0.49673 0.30422 0.39410 observation	upperCL 4.1464 1.0750 0.4668 1.2395 1.9911 1.7650 1.2426 0.7929 1.1947	Pvalue 0.5002 0.0568 0.0175 0.7476 0.0006 0.0845 0.3023 0.0036	

The first table shows the number of common controls (533) and subtype specific cancer cases. The results for the association of alcohol intake with high, medium and low LINE-1 colon cancer risk are shown in the table Analysis of Maximum Likelihood Estimates, indicating that odds ratios in unconditional and conditional logistic regression model are 0.96, 1.55 and 1.30, and 0.94, 1.56 and 1.30, respectively. These results suggest that the association of alcohol with LINE-1 tumor risk varies with subtype (p values in unconditional and conditional logistic regression model are 0.014 and 0.023, respectively). Note that, by default, the heterogeneity test was performed using the Wald test in the unconditional nominal polytomous logistic regression model, while the likelihood ratio test was used in the conditional model.

As described above, this approach allow only the unconstrained models for the covariates. A constrained analysis is available with conditional logistic regression model through setting the macro parameter conditional to yes, and place the confounders in the macro parameter construar.

The macro call is

```
%subtype(data=necaco, studydesign=caco, exposure=alcohol,
eventtype=cancer, conditional=yes,
constrvar=ause_p2 screen2 polyps2 cafam2
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm
bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5,
eventtypelabel =1=high; 2=medium; 3=low
);
```

The main part of the output is

Running on data set NECACO, Read 801 observations Number of controls and cases in each outcome type CANCER: 1=high; 2=medium; 3=low Frequency cancer Count

104

		1 2 1	33 99 02 67				
	Running on data set	NECACO, Read	801	observations			105
		Convergence St.	atus				
		Reason					
	Convergence c	riterion (GCON	V=1E-8) s	atisfied.			
	Running on data set			observations			106
	M	odel Fit Stati	stics				
		Without	Wi	th			
	Criterion						
	-2 LOG L AIC SBC	1509.867 1509.867 1509.867	1399 1475 1612	.693			
	Running on data set	NECACO, Read	801	observations			107
	Testing Gl	obal Null Hypo	thesis: B	ETA=0			
	Test	Chi-Square	DF	Pr > Chi-Square			
	Likelihood Ratio Score Wald	110.1735 110.3896 100.0512	38 38 38	<.0001 <.0001 <.0001			
	Running on data set			observations			108
	Analysis of	Maximum Likel	ihood Est	imates			
Label	Parameter DF Estimate	Standard Error	Odds Ratio	lowerCL	upperCL	Pvalue	Parameter
exposure alcohol and cancer 1	1 -0.02658		0.97377		1.24859	0.8340	_expND_1_1
exposure alcohol and cancer 2 exposure alcohol and cancer 3	1 0.41225 1 0.22222	0.12011 0.14136	1.51021		1.91107 1.64754	0.0006 0.1160	_expND_1_2 _expND_1_3
(The rest is omitted)	1 -0.41489	0.14461	0.66041	0.49742	0.87682	0.0041	ause_p2
	Running on data set		801	observations			109
	Heterogeneit	y Tests (Likel	ihood rat	io test)			
	Label		DF	Pvalue			
	Pairwise 1	l vs 2: alcohol vs 3: alcohol vs 3: alcohol	1 1	0.03214 0.00883 0.17575 0.28964			

#### 3.5 Example 5. Case-case study analysis

The example data set consists of all 268 cases from the data set used in Example 1. Unlike the above three study designs, the case-case study allows for testing and estimating of heterogeneity in the exposure associations among subtypes, but cannot estimate the associations of exposures with the risk of each subtype. The Wald test is used for the heterogeneity test.

The data set, caonly is in the standard format, where id, cancer, alcohol and other variables are as described above, and agemo is age in months when the cancer was diagnosed.

```
caonly:
id cancer alcohol agemo Other variables
1
    2
             0.85
                       885
                              . . .
2
     3
             0.85
                       713
                              . . .
3
    1
                       953
             0
                              . . .
. . .
```

Let the reference level of LINE-1 be the high LINE-1, cancer=1. The macro code that allows the associations of all confounders to be different among subtypes is:

```
%subtype(data=caonly, studydesign=caca, exposure=alcohol,
eventtype=cancer, reftype=1,
unconstrvar=ause_p2 screen2 polyps2 cafam2
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm
bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5
ageyr,
eventtypelabel = 1 high; 2=medium; 3=low
);
```

The main part of the output is

	Run	CANCER:	CAONLY, Read el: GENERALIZEI 1=high; 2=mec cases in each	D LOGIT dium; 3=low		ations		35
			cancer (	Count				
			1	99				
			2 3	102 67				
	Run	ning on data set	CAONLY, Read	268	observa	ations		36
		с	onvergence Sta	atus				
			Reason					
		Convergence cr	iterion (GCON	V=1E-8) sati:	sfied.			
	Run	ning on data set	CAONLY, Read	268	observa	ations		37
		Мс	del Fit Statis	stics				
				Model Wit	th			
			Intercept	Intercept and				
		Criterion	Only Model	Covariate	es			
		AIC SC	584.012 591.194	671.70 <sup>°</sup> 930.25				
		-2 Log L	580.012	527.70	7			
		ning on data set						38
		ning on data set		268	observa			
	Run	ning on data set	CAONLY, Read bal Null Hypot	268 thesis: BETA=	observa =0 Pr >			
	Run: T	ning on data set Testing Glo est	CAONLY, Read obal Null Hypot Chi-Square	268 thesis: BETA- DF Cl	observa =0 Pr > ni-Square			
	Run: Tr L S	ning on data set Testing Glo est ikelihood Ratio core	CAONLY, Read Wobal Null Hypot Chi-Square 52.3046 48.5199	268 thesis: BETA DF Cl 70 70	observa =0 Pr > ni-Square 0.9437 0.9765			
	Run: Tr L S W	ning on data set Testing Glo est ikelihood Ratio core ald	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484	268 Chesis: BETA DF Cl 70 70 70 70	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970	ations		38
	Run: T, S W.	ning on data set Testing Glo est ikelihood Ratio core ald	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484	268 thesis: BETA DF Cl 70 70 70	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970	ations		38
	Run: T, S W.	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read	268 thesis: BETA DF Cl 70 70 70 268	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970	ations		38
	Run: T, S W.	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of	268 Chesis: BETA DF Cl 70 70 70 70 268 Effects	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations		38
	Run: T, S W.	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set Type	CAONLY, Read abal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald	268 Chesis: BETA DF Cl 70 70 70 70 268 Effects	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 observa	ations		38
	Run: T, S W.	ning on data set Testing Glo est ikelihood Ratio core ald  ning on data set Type Effect alcohol	CAONLY, Read abal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-square 2 8.48	268 thesis: BETA DF Cl 70 70 70 268 Effects Pr are Chi-So 864 0.03	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations		38
	Run. T L W. Run.	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set Type Effect alcohol ause_p2	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of DF Chi-squa 2 8.44 2 2.25	268 thesis: BETA DF Cl 70 70 70 268 Effects Pr are Chi-Sc 364 0.03 924 0.33	observa =0 Pr > ni-Square 0.9437 0.9705 0.9970 	ations		38
	Run. T. S. W.	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set Type Effect alcohol ause_p2	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-squa 2 8.44 2 2.29	268 thesis: BETA DF Cl 70 70 70 268 Effects effects Pr are Chi-So 864 0.03	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 observa > quare 144 178	ations		38
	Run. T. S. W.	ning on data set Testing Glo est ikelihood Ratio core ald 	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-squa 2 8.44 2 2.29 CAONLY, Read	268 thesis: BETA DF Cl 70 70 70 268 Effects Pr are Chi-So 364 0.03 924 0.33	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations		38
	Run. T. S. W.	ning on data set Testing Glo est ikelihood Ratio core ald 	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-squa 2 8.44 2 2.25 CAONLY, Read Maximum Likel:	268 thesis: BETA: DF Cl 70 70 70 268 Effects Pr are Chi-Sc 364 0.03 924 0.33 	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations		38
	Run. T. S. W.	ning on data set Testing Glo est ikelihood Ratio core ald 	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-squa 2 8.44 2 2.29 CAONLY, Read	268 thesis: BETA DF Cl 70 70 70 268 Effects Pr are Chi-So 364 0.03 924 0.33	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations		38
(The rest is omitted) Variable Intercept	Run T, S W Run Run Iinel 2	ning on data set Testing Glo est ikelihood Ratio core ald 	CAONLY, Read abal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-square 2 8.44 2 2.29 CAONLY, Read Maximum Likel: Standard Error 1.9294	268 DF Cl 70 70 70 268 Effects Pr are Chi-So 364 0.03 924 0.33 924 0.33 1000 Estimat Odds Ratio 0.2255	observa =0 Pr > ni-Square 0.9437 0.9765 0.9970 	ations ations vations upperCL 9.896	Pvalue 0.4401	38
(The rest is omitted)	Run. T L S W Run Run Iinel	ning on data set Testing Glo est ikelihood Ratio core ald ning on data set Type Effect alcohol ause_p2 ning on data set Analysis of DF Estimate	CAONLY, Read bbal Null Hypot Chi-Square 52.3046 48.5199 41.8484 CAONLY, Read 3 Analysis of Wald DF Chi-squa 2 8.44 2 2.25 CAONLY, Read Maximum Likel: Standard Error	268 thesis: BETA DF Cl 70 70 70 268 Effects Pr are Chi-54 864 0.03 924 0.33 1000 261 1000 Estimat Odds Ratio	observa =0 Pr > ni-Square 0.9437 0.9705 0.9970 	ations ations vations upperCL	Pvalue	38

	ause_p2 ause_p2	2 3		-0.4733 -0.0363			0.32131 0.47132		0.1611 0.9208	
(The rest	is omitted)									
Running on data set CAONLY, Read 268 observations										42
Heterogeneity Tests (Wald test)										
		Label				DF	Pvalue			
		All: alcohol				2	0.0144			
	Pairwise 1 vs 2: alcohol					1	0.0039			
	Pairwise 1 vs 3: alcohol					1	0.0947			
	Pairwise 2 vs 3: alcohol						0.3263			

The table Heterogeneity Tests (Wald test) shows the results of overall and pair-wise heterogeneity tests in the same way as the other study designs. Pair-wise heterogeneity tests comparing the association of exposure with high LINE-1 to that with medium LINE-1 and low LINE-1 are also provided in the table Analysis of Maximum Likelihood Estimates, since high LINE-1 is the reference group as declared by a macro parameter reftype=1. The respective p-values are p = 0.0039 and p = 0.0947. Additionally, the result of the overall heterogeneity test is displayed in the table Type 3 Analysis of Effects as p = 0.0144. It should be noted that the odds ratios given in this case-case analysis are the ratio of the odds ratio for the alcohol association with each subtype relative to the odds ratio for the alcohol association with reference subtype (i.e., high LINE-1).

Under the assumption of the associations of all confounders to be the same with all subtypes, the macro code ca be as follows.

```
%subtype(data=caonly, studydesign=caca, exposure=alcohol,
eventtype=cancer, reftype=1,
constrvar=ause_p2 screen2 polyps2 cafam2
py30ct2 py30ct3 py30ct4 py30ct5 py30ctm
actct2 actct3 actct4 actct5 actctm
mvit2 mvitm
bmain2 bmain3 bmain4
bmi2 bmi3 bmi4 bmi5 bmim
calcq2 calcq3 calcq4 calcq5 calcqm
folq2 folq3 folq4 folq5,
eventtypelabel =1=high; 2=medium; 3=low
);
```

### 4 Warnings

If the required input is incorrect, the macro will display warnings or errors. For example, if the user specifies STUDYDESIGN=COHORT and inputs no variable in ID parameter, the macro will display an error as follows.

ERROR in macro call: You did not give a variable name in ID, as required when you use studydesign=COHORT.

If the user specifies STUDYDESIGN=CACA and CONDITIONAL=NO and gives the variable age for a CONSTRVAR parameter, the macro will display a warning message as follows.

WARNING in macro call: Your SUBTYPE call have a value for a CONSTRVAR parameter, but this model does not accept the constrained analysis. You may consider using CONDITIONAL=YES option. The macro will continue, not adjusting for age.

If the data set for a matched case-control study includes the matched sets with only controls or only cases, the macro will display a warning message and exclude those matched sets from the analysis. For example, the warning message below was displayed when MATCHID=matchid was specified and the matched sets with matchid=1 and 16 included only cases.

```
WARNING in macro run: There are 2 matched sets with control
or case only
matchid = 1,16
will be excluded from a data set used in analysis.
```

## 5 How should I describe this in my Methods section?

Please refer to the following paper:

Wang M, Spiegelman D, Kuchiba A, Lochhead P, Kim S, Chan AT, Poole EM, Tamimi R, Tworoger SS, Giovannucci E, Rosner B, Ogino S. Statistical methods for studying disease subtype heterogeneity. Stat Med. 2016; 35(5): 782-800.

## 6 Correspondence

Questions should be addressed to Molin Wang via email stmow@channing.harvard.edu.

## 7 Other reference

Lunn M, McNeil D. Applying Cox regression to competing risks. Biometrics 1995;51(2):524-32.