

Mixed Models for Clustered Binary Outcomes

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Multilevel models for categorical outcomes

- dichotomous outcomes
 - mixed-effects logistic regression
- ordinal outcomes
 - mixed-effects ordinal logistic regression
 - * proportional odds model
 - * partial or non-proportional odds model
- discrete or grouped time-to-event data
 - mixed-effects dichotomous or ordinal regression
 - replace logistic link with complementary log-log link to yield proportional (and non-proportional) hazards models

Logistic Regression Model

$$\log \left[\frac{P(Y_i = 1)}{1 - P(Y_i = 1)} \right] = \mathbf{x}'_i \boldsymbol{\beta}$$

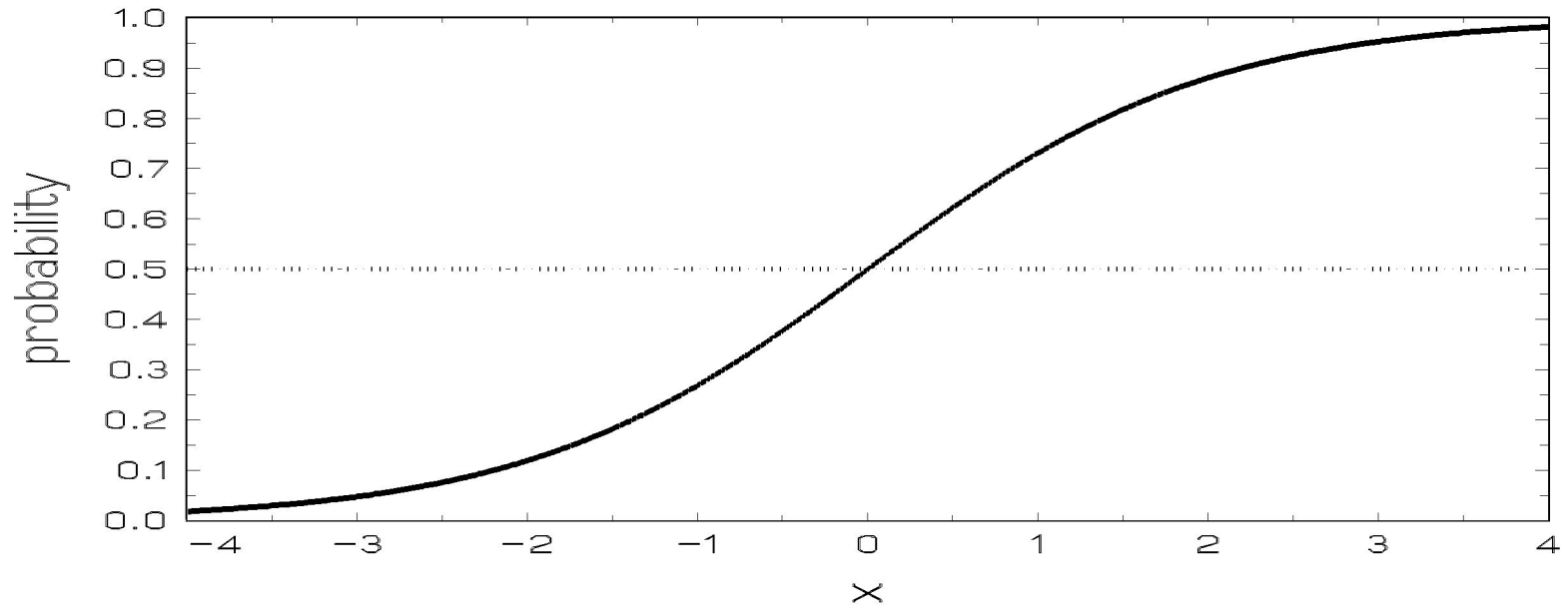
- Dichotomous outcome ($Y = 0$ absence, $Y = 1$ presence).
- Function that links probabilities to regressors is the logit (or log odds) function $\log [P/(1 - P)]$. Logit is called the link function.

The model can be written in terms of probabilities:

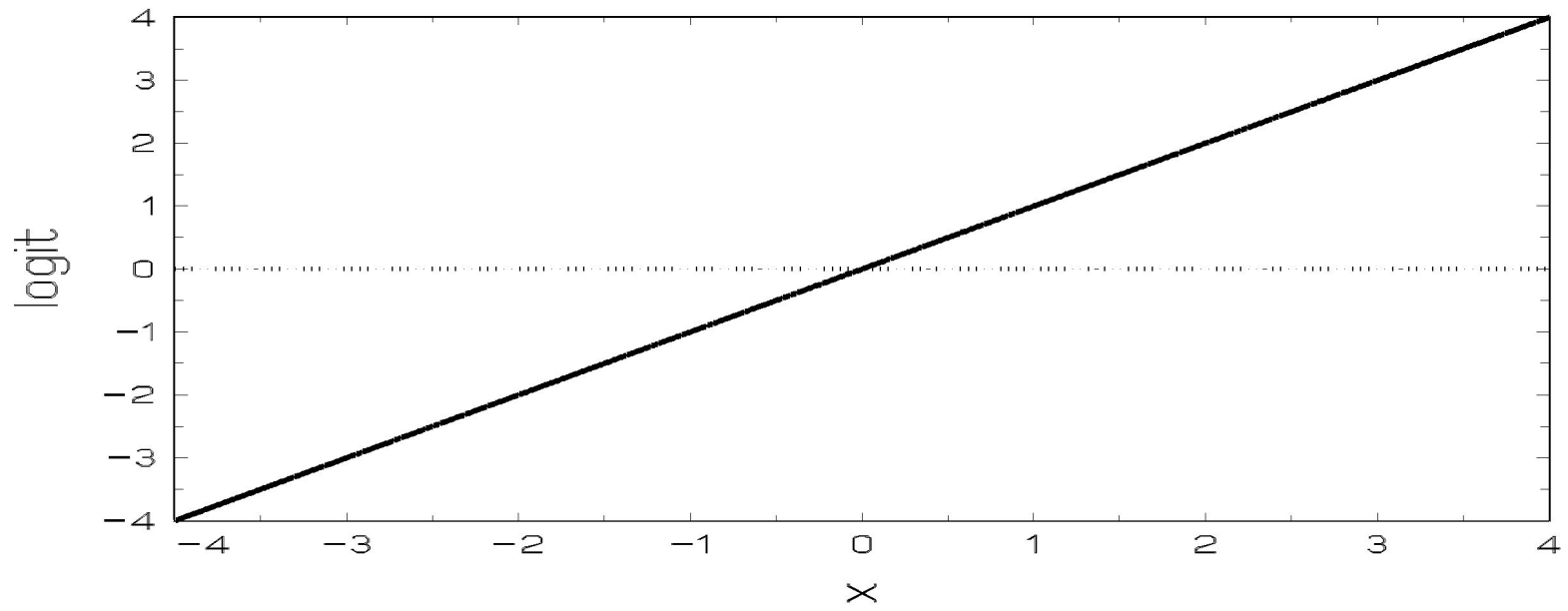
$$P(Y_i = 1) = \frac{1}{1 + \exp(-\mathbf{x}'_i \boldsymbol{\beta})}$$

- Model is a linear model for the logits, not for the probabilities. Logits can take on any values between negative and positive infinity, probabilities can only take on values between 0 and 1.

Logistic Regression Model [slope=1]



Logistic Regression Model [slope=1]



The model can also be written in terms of the odds:

$$\frac{P(Y_i = 1)}{1 - P(Y_i = 1)} = \exp(\mathbf{x}'_i \boldsymbol{\beta})$$

$\exp \beta$ = change in odds for Y per unit change of x

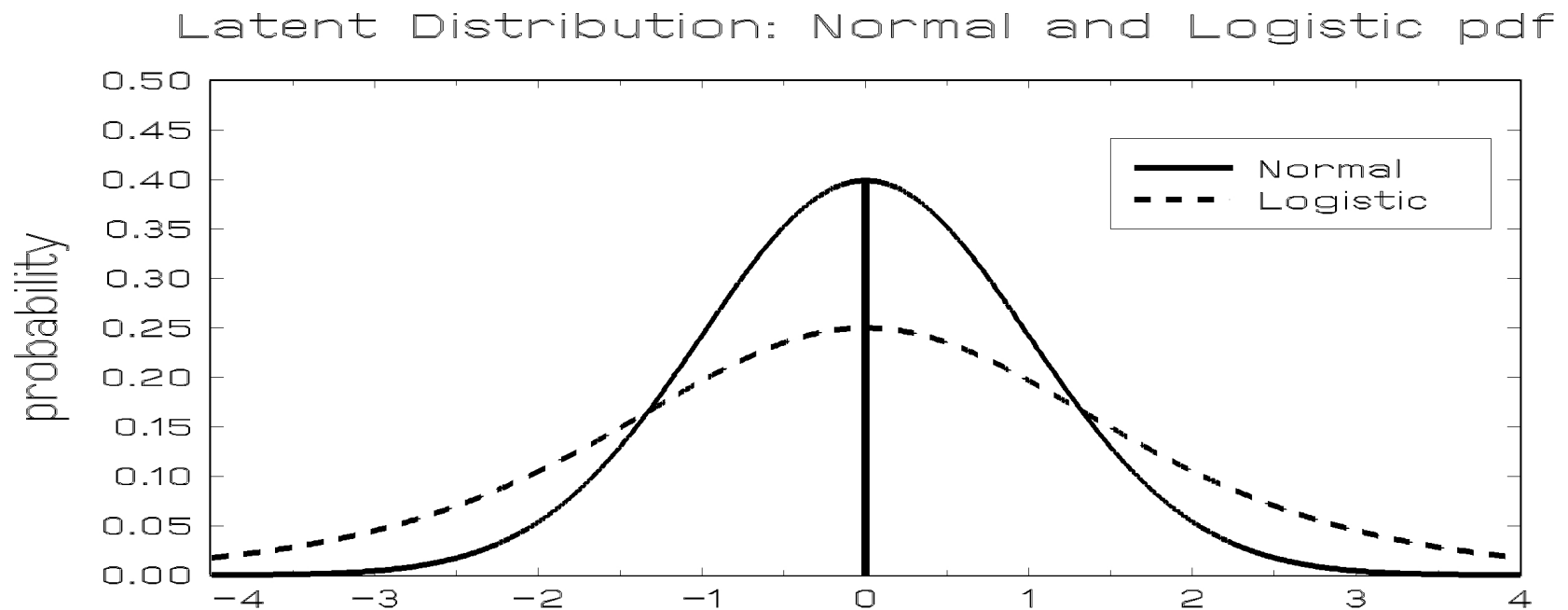
- $\beta = 0$ yields no effect on the odds
- $\beta > 0$ increases odds Y is present with increasing x
- $\beta < 0$ decreases odds Y is present with increasing x

Dichotomous Response and Threshold Concept

Continuous y_i - an unobservable latent variable - related to dichotomous response Y_i via “threshold concept”

Response occurs ($Y_i = 1$) if $\gamma < y_i$

otherwise, a response does not occur ($Y_i = 0$)



The Threshold Concept in Practice

“How was your day?” (what is your satisfaction level today?)

- Satisfaction may be continuous, but we usually emit a dichotomous response:



Great Day!



a day ...

Model for Latent Continuous Responses

Consider the model with p covariates for the latent response strength y_i ($i = 1, 2, \dots, N$):

$$y_i = \mathbf{x}'_i \boldsymbol{\beta} + \varepsilon_i$$

- probit: $\varepsilon_i \sim$ standard normal (mean=0, variance=1)
- logistic: $\varepsilon_i \sim$ standard logistic (mean=0, variance= $\pi^2/3$)

\Rightarrow $\boldsymbol{\beta}$ estimates from logistic regression are larger (in abs. value) than from probit regression by approximately $\sqrt{\pi^2/3} = 1.8$

Underlying latent variable

- useful way of thinking of the problem
- not an essential assumption of the model

Random-intercept Logistic Regression Model

Consider the model with p covariates for the response Y_{ij} for subject j ($j = 1, 2, \dots, n_i$) in cluster i ($i = 1, 2, \dots, N$):

$$\log \left[\frac{P(Y_{ij} = 1 \mid v_{0i})}{1 - P(Y_{ij} = 1 \mid v_{0i})} \right] = \mathbf{x}'_{ij} \boldsymbol{\beta} + v_{0i}$$

where

Y_{ij} = dichotomous response for subject j in cluster i

\mathbf{x}_{ij} = $(p + 1) \times 1$ covariate vector (includes 1 for intercept)

$\boldsymbol{\beta}$ = $(p + 1) \times 1$ vector of unknown parameters

v_{0i} = cluster effects distributed $\mathcal{NID}(0, \sigma_v^2)$

Characteristics of $v_{0i} \sim \mathcal{NID}(0, \sigma_v^2)$

- separates model from usual (fixed-effects) multiple logistic regression model
- takes on $i = 1, 2, \dots, N$ values
- assess impact of cluster i on individual outcome logit_{ij} , represents effect of subject clustering
- common for each cluster member, but changes for each cluster
- if $v_{0i} = 0$, then cluster has no effect for cluster i
- if $v_{0i} = 0$ for all clusters, cluster structure has no impact on individual data ($\sigma_v^2 = 0$)
 - no need for multilevel approach
 - ordinary logistic regression is OK
- if subject clustering has strong effect, estimates of $v_{0i} \neq 0$ and σ_v^2 will increase from 0

Model for Latent Continuous Responses

Consider the model with p covariates for the $n_i \times 1$ latent response strength y_{ij} :

$$y_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta} + v_{0i} + \varepsilon_{ij}$$

where assuming

- $\varepsilon_{ij} \sim$ standard normal (mean 0 and $\sigma^2 = 1$) leads to multilevel probit regression
- $\varepsilon_{ij} \sim$ standard logistic (mean 0 and $\sigma^2 = \pi^2/3$) leads to multilevel logistic regression

Underlying latent variable

- not an essential assumption of the model
- useful for obtaining intra-class correlation (r)

$$r = \frac{\sigma_v^2}{\sigma_v^2 + \sigma^2}$$

and for design effect (d)

$$d = \frac{\sigma_v^2 + \sigma^2}{\sigma^2} = 1/(1 - r)$$

ratio of actual variance to the variance that would be obtained by simple random sampling (holding sample size constant)

Scaling of regression coefficients

Fixed-effects model

β estimates from logistic regression are larger (in abs. value) than from probit regression by approximately

$$\sqrt{\frac{\pi^2/3}{1}} = 1.8$$

because

- $V(y) = \sigma^2 = \pi^2/3$ for logistic
- $V(y) = \sigma^2 = 1$ for probit

Mixed-effects model

β estimates from mixed-effects model are larger (in abs. value) than from fixed-effects model by approximately

$$\sqrt{d} = \sqrt{\frac{\sigma_v^2 + \sigma^2}{\sigma^2}}$$

because

- $V(y) = \sigma_v^2 + \sigma^2$ in mixed-effects model
- $V(y) = \sigma^2$ in fixed-effects model

difference depends on size of random-effects variance σ_v^2

Within-Clusters / Between-Clusters models

Within-clusters model - level 1 ($j = 1, \dots, n_i$)

$$\frac{\text{observed response}}{\log \left[\frac{P(Y_{ij} = 1 \mid v_{0i})}{1 - P(Y_{ij} = 1 \mid v_{0i})} \right]} = b_{0i} + b_{1i} Sex_{ij}$$

latent response

$$y_{ij} = b_{0i} + b_{1i} Sex_{ij} + \varepsilon_{ij}$$

Between-clusters model - level 2 ($i = 1, \dots, N$)

$$b_{0i} = \beta_0 + \beta_2 Grp_i + v_{0i}$$

$$b_{1i} = \beta_1 + \beta_3 Grp_i$$

$$v_{0i} \sim \mathcal{NID}(0, \sigma_v^2) \quad \text{and} \quad \varepsilon_{ij} \sim \mathcal{LID}(0, \pi^2/3)$$

Effects of a School-based Intervention

The Television School and Family Smoking Prevention and Cessation Project (Flay, *et al.*, 1988); a subsample:

- *sample* - 1600 7th-graders - 135 classes - 28 schools
 - 1 to 13 classes per school, 2 to 28 students per class
- *outcome* - knowledge of the effects of tobacco use
- *timing* - students tested at pre and post-intervention
- *design* - schools exposed to
 - a social-resistance classroom curriculum (CC)
 - a media (television) intervention (TV)
 - CC combined with TV
 - a no-treatment control group

Main question of interest:

- Influence of the intervention on the tobacco health knowledge scores (THKS) ?

Challenges in the analysis:

- outcome variable (THKS) is number correct of 7 items
- controlling for intra-school and intra-class variability
- potential explanatory variables are at different levels

Tobacco and Health Knowledge Scale
 Post-Intervention Scores ≥ 3 (out of 7)
 Subgroup Descriptive Statistics

	CC = no		CC = yes	
	TV=no	TV=yes	TV=no	TV=yes
<i>n</i>	421	416	380	383
proportions	.416	.483	.632	.603
odds	.711	.935	1.714	1.520
logits	-.341	-.067	.539	.419

Within-Clusters / Between-Clusters components

Within-clusters model - level 1 ($j = 1, \dots, n_i$ subjects)

$$\text{logit}_{ij} = b_{0i}$$

Between-clusters model - level 2 ($i = 1, \dots, N$ clusters)

$$b_{0i} = \beta_0 + \beta_1 CC_i + \beta_2 TV_i + \beta_3(CC_i \times TV_i) + v_{0i}$$

$$v_{0i} \sim \mathcal{NID}(0, \sigma_v^2)$$

β_0 = THKS logit for CC=no TV=no subgroup

β_1 = logit diff. between CC=yes vs CC=no (for TV=no)

$$b_{0i} = \beta_0 + (\beta_1 + \beta_3 TV_i) CC_i + \beta_2 TV_i + v_{0i}$$

β_2 = logit diff. between TV=yes vs TV=no (for CC=no)

$$b_{0i} = \beta_0 + (\beta_2 + \beta_3 CC_i) TV_i + \beta_1 CC_i + v_{0i}$$

β_3 = difference in logit attributable to interaction

v_{0i} = random cluster deviation

note: interpretation depends on coding of variables, and β s are adjusted for the cluster effects (cluster-specific effects)

3-level model

Within-classrooms (and schools) model - level 1
($k = 1, \dots, n_{ij}$ students)

$$\text{logit}_{ijk} = b_{0ij}$$

Between-classrooms (within-schools) model - level 2
($j = 1, \dots, n_i$ classrooms)

$$b_{0ij} = b_{0i} + v_{0ij}$$

Between-schools model - level 3 ($i = 1, \dots, N$ schools)

$$b_{0i} = \beta_0 + \beta_1 CC_i + \beta_2 TV_i + \beta_3(CC_i \times TV_i) + v_{0i}$$

$$v_{0ij} \sim \mathcal{NID}(0, \sigma_{v(2)}^2) \quad \text{and} \quad v_{0i} \sim \mathcal{NID}(0, \sigma_{v(3)}^2)$$

β_0 = THKS logit for CC=no TV=no subgroup

β_1 = logit diff. between CC=yes vs CC=no (for TV=no)

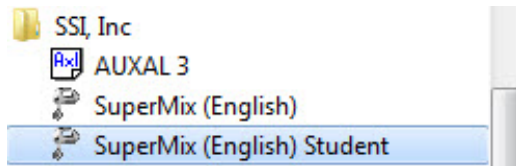
β_2 = logit diff. between TV=yes vs TV=no (for CC=no)

β_3 = difference in logit attributable to interaction

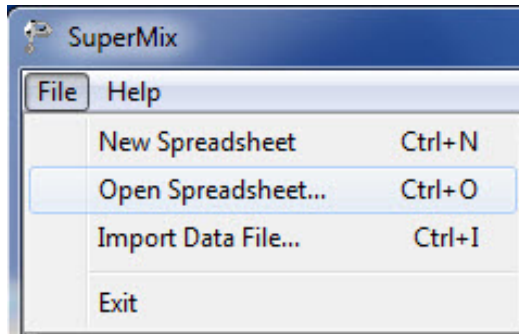
v_{0ij} = random classroom deviation

v_{0i} = random school deviation

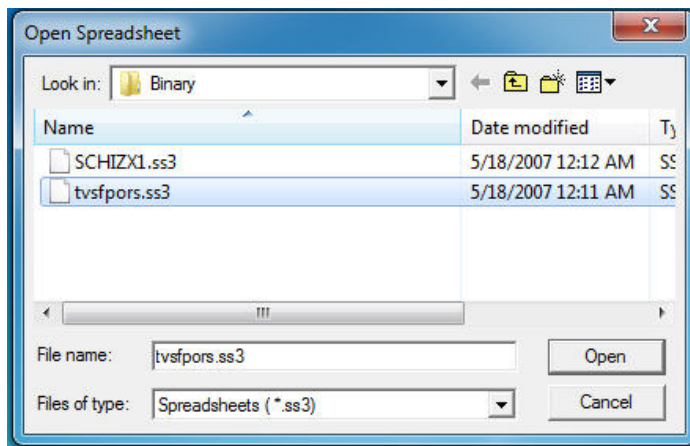
- Under SSI, Inc > “SuperMix (English)” or “SuperMix (English) Student”



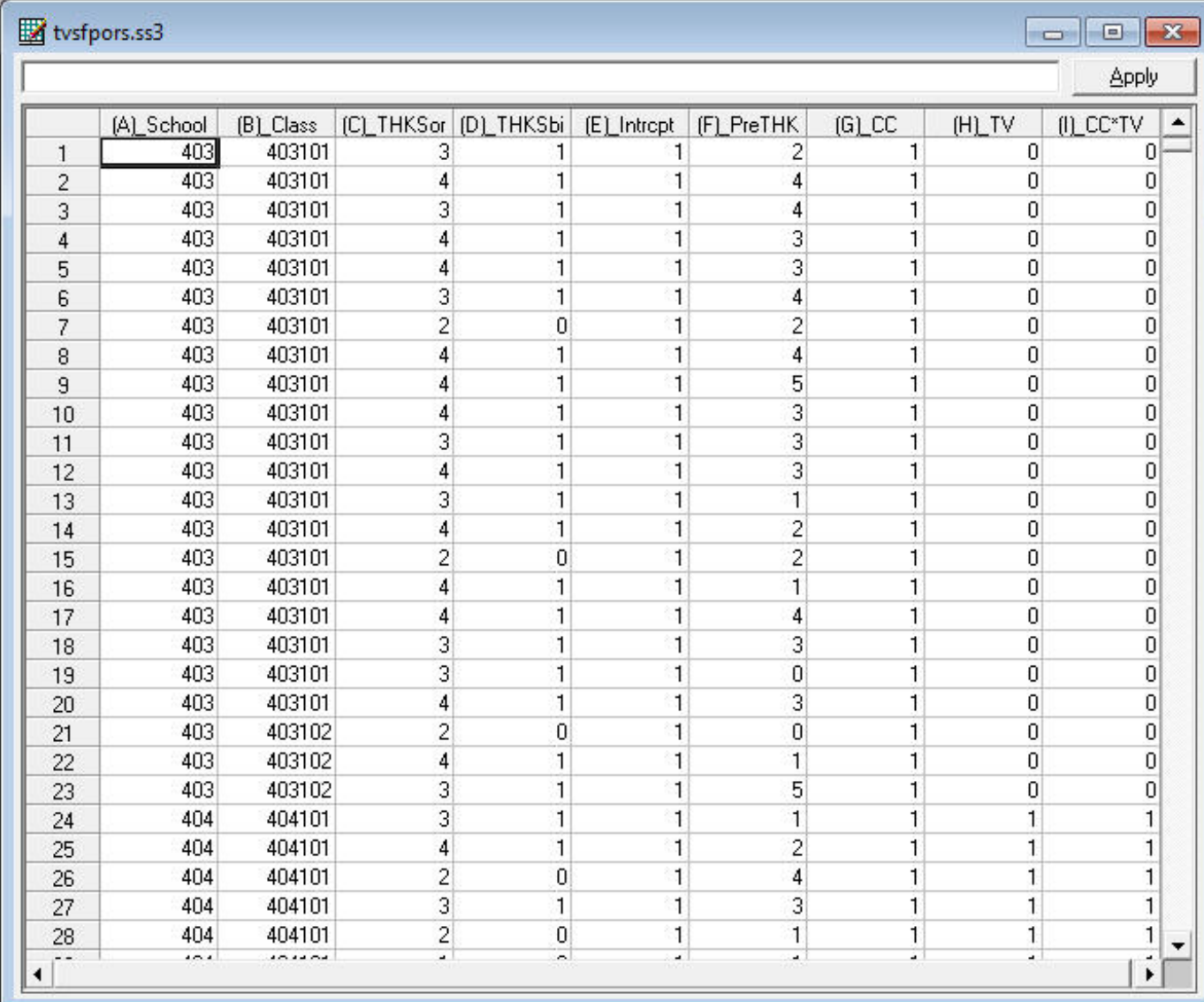
- Under “File” click on “Open Spreadsheet”



- Open C:\SuperMixEn Examples\Workshop\Binary\tvsfpors.ss3
(or C:\SuperMixEn Student Examples\Workshop\Binary\tvsfpors.ss3)



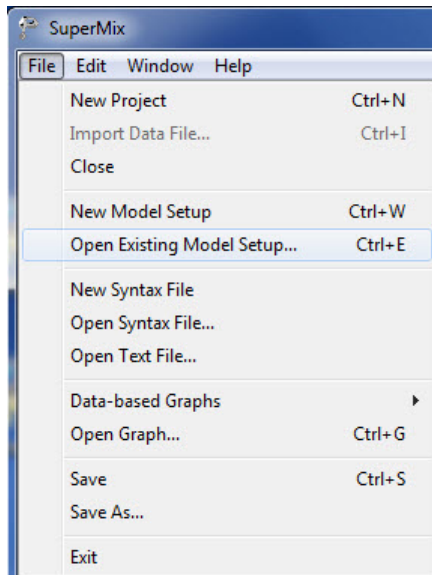
C:\SuperMixEn Examples\Workshop\Binary\tvsfpors.ss3



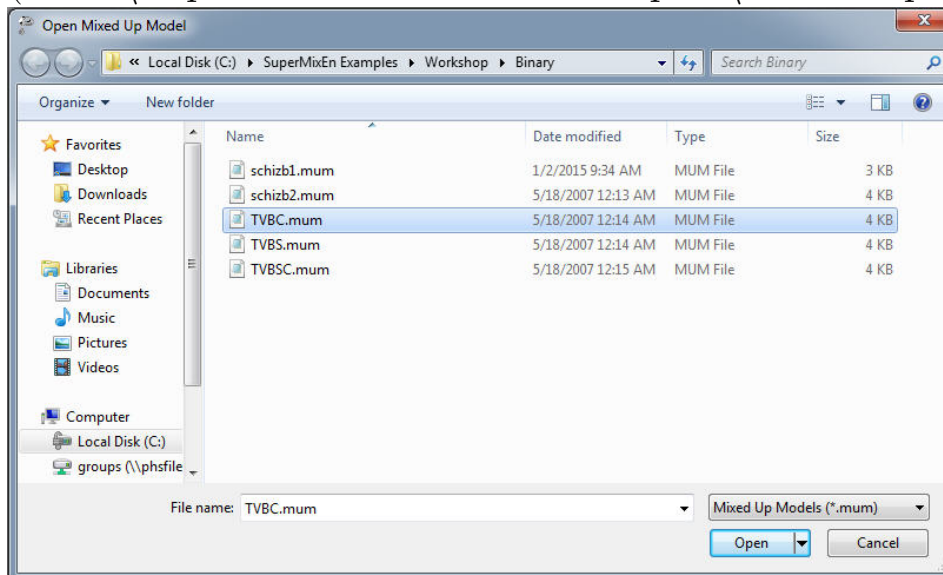
The screenshot shows a window titled "tvsfpors.ss3" with a table of data. The table has 9 columns and 28 rows. The columns are labeled (A)_School, (B)_Class, (C)_THKSor, (D)_THKSbi, (E)_Intrcpt, (F)_PreTHK, (G)_CC, (H)_TV, and (I)_CC*TV. The data is as follows:

	(A)_School	(B)_Class	(C)_THKSor	(D)_THKSbi	(E)_Intrcpt	(F)_PreTHK	(G)_CC	(H)_TV	(I)_CC*TV
1	403	403101	3	1	1	2	1	0	0
2	403	403101	4	1	1	4	1	0	0
3	403	403101	3	1	1	4	1	0	0
4	403	403101	4	1	1	3	1	0	0
5	403	403101	4	1	1	3	1	0	0
6	403	403101	3	1	1	4	1	0	0
7	403	403101	2	0	1	2	1	0	0
8	403	403101	4	1	1	4	1	0	0
9	403	403101	4	1	1	5	1	0	0
10	403	403101	4	1	1	3	1	0	0
11	403	403101	3	1	1	3	1	0	0
12	403	403101	4	1	1	3	1	0	0
13	403	403101	3	1	1	1	1	0	0
14	403	403101	4	1	1	2	1	0	0
15	403	403101	2	0	1	2	1	0	0
16	403	403101	4	1	1	1	1	0	0
17	403	403101	4	1	1	4	1	0	0
18	403	403101	3	1	1	3	1	0	0
19	403	403101	3	1	1	0	1	0	0
20	403	403101	4	1	1	3	1	0	0
21	403	403102	2	0	1	0	1	0	0
22	403	403102	4	1	1	1	1	0	0
23	403	403102	3	1	1	5	1	0	0
24	404	404101	3	1	1	1	1	1	1
25	404	404101	4	1	1	2	1	1	1
26	404	404101	2	0	1	4	1	1	1
27	404	404101	3	1	1	3	1	1	1
28	404	404101	2	0	1	1	1	1	1

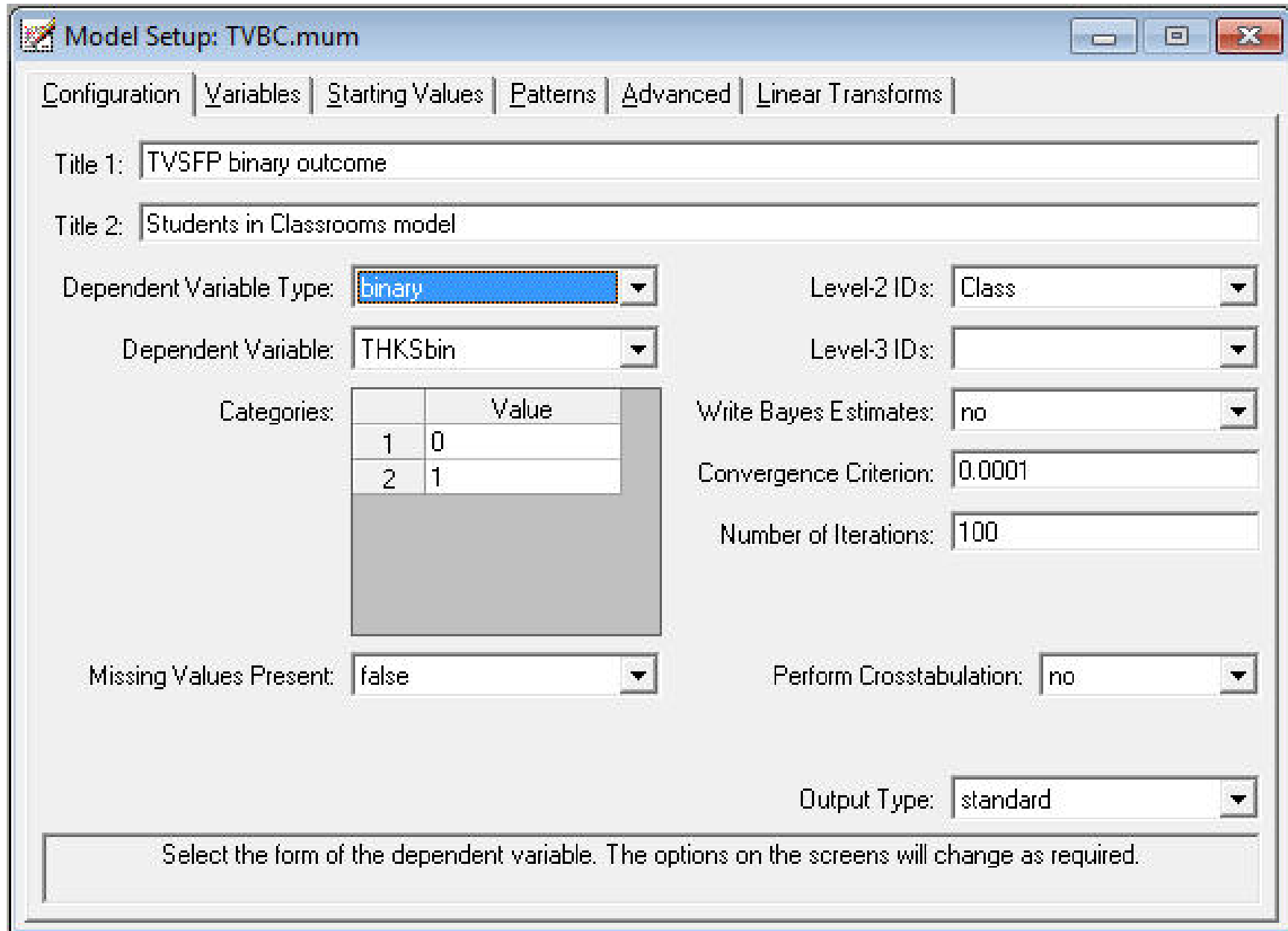
Under “File” click on “Open Existing Model Setup”



Open C:\SuperMixEn Examples\Workshop\Binary\tvbc.mum
(or C:\SuperMixEn Student Examples\Workshop\Binary\tvbc.mum)



Note “Dependent Variable Type” should be “binary”



Model Setup: TVBC.mum

Configuration | Variables | Starting Values | Patterns | Advanced | Linear Transforms

Title 1: TVSFP binary outcome

Title 2: Students in Classrooms model

Dependent Variable Type: binary

Dependent Variable: THKSbin

Level-2 ID: Class

Level-3 ID:

Write Bayes Estimates: no

Convergence Criterion: 0.0001

Number of Iterations: 100

Missing Values Present: false

Perform Crosstabulation: no

Output Type: standard

Select the form of the dependent variable. The options on the screens will change as required.

	Value
1	0
2	1

For the moment, unselect **PreTHKS** as an explanatory variable

Model Setup: TVBC.mum

Configuration | Variables | Starting Values | Patterns | Advanced | Linear Transforms

Available	E	2
School	<input type="checkbox"/>	<input type="checkbox"/>
Class	<input type="checkbox"/>	<input type="checkbox"/>
THKSord	<input type="checkbox"/>	<input type="checkbox"/>
THKSbin	<input type="checkbox"/>	<input type="checkbox"/>
Intcpt	<input type="checkbox"/>	<input type="checkbox"/>
PreTHKS	<input type="checkbox"/>	<input type="checkbox"/>
CC	<input checked="" type="checkbox"/>	<input type="checkbox"/>
TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>

Explanatory Variables	E
CC	<input checked="" type="checkbox"/>
TV	<input checked="" type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>

L-2 Random Effects 2

Include Intercept

Include Intercept

Select the columns of the spreadsheet to be used as explanatory variables and random effects.

Note “Optimization Method” should be “adaptive quadrature”

The image shows a software window titled "Model Setup: TVBC.mum" with several tabs: Configuration, Variables, Starting Values, Patterns, Advanced, and Linear Transforms. The "Advanced" tab is selected. The window is divided into two main sections: "General Settings" and "Dependent (Binary) Variable Settings".

General Settings:

- Unit Weighting: equal
- Optimization Method: adaptive quadrature
- Number of Quadrature Points: 25

Dependent (Binary) Variable Settings:

- Distribution Model: Bernoulli
- Function Model: logistic
- Estimate Scale: none

At the bottom of the window, there is a text box containing the instruction: "Select the optimization method. The default is adaptive quadrature."

```

=====
| TVSFP binary outcome      |
| Students in Classrooms model |
=====

```

Model and Data Descriptions

```

Sampling Distribution      = Bernoulli
Link Function              = Logistic
PROB(Success)= 1.0/[1.0+EXP(-ETA)]

```

```

Number of Level-2 Units      135
Number of Level-1 Units     1600
Number of Level-1 Units per Level-2 Unit =
20  3  11  9  5  26  11  10  15  12  12  10
21  10  17  19  2  4  21  16  15  13  2  14
13  1  12  18  21  17  16  15  16  21  21  27
17  3  2  15  7  24  22  15  19  7  12  8
6  11  7  7  8  3  5  8  3  8  9  8
2  11  9  21  13  12  12  14  9  6  11  10
12  11  6  6  14  10  14  2  3  2  4  3
6  10  14  11  6  22  4  7  22  18  23  19
14  5  14  28  15  15  11  12  11  11  15  17
24  20  15  6  8  14  5  11  9  17  14  11
17  15  6  7  14  10  14  18  4  9  7  12
15  11  10

```

```

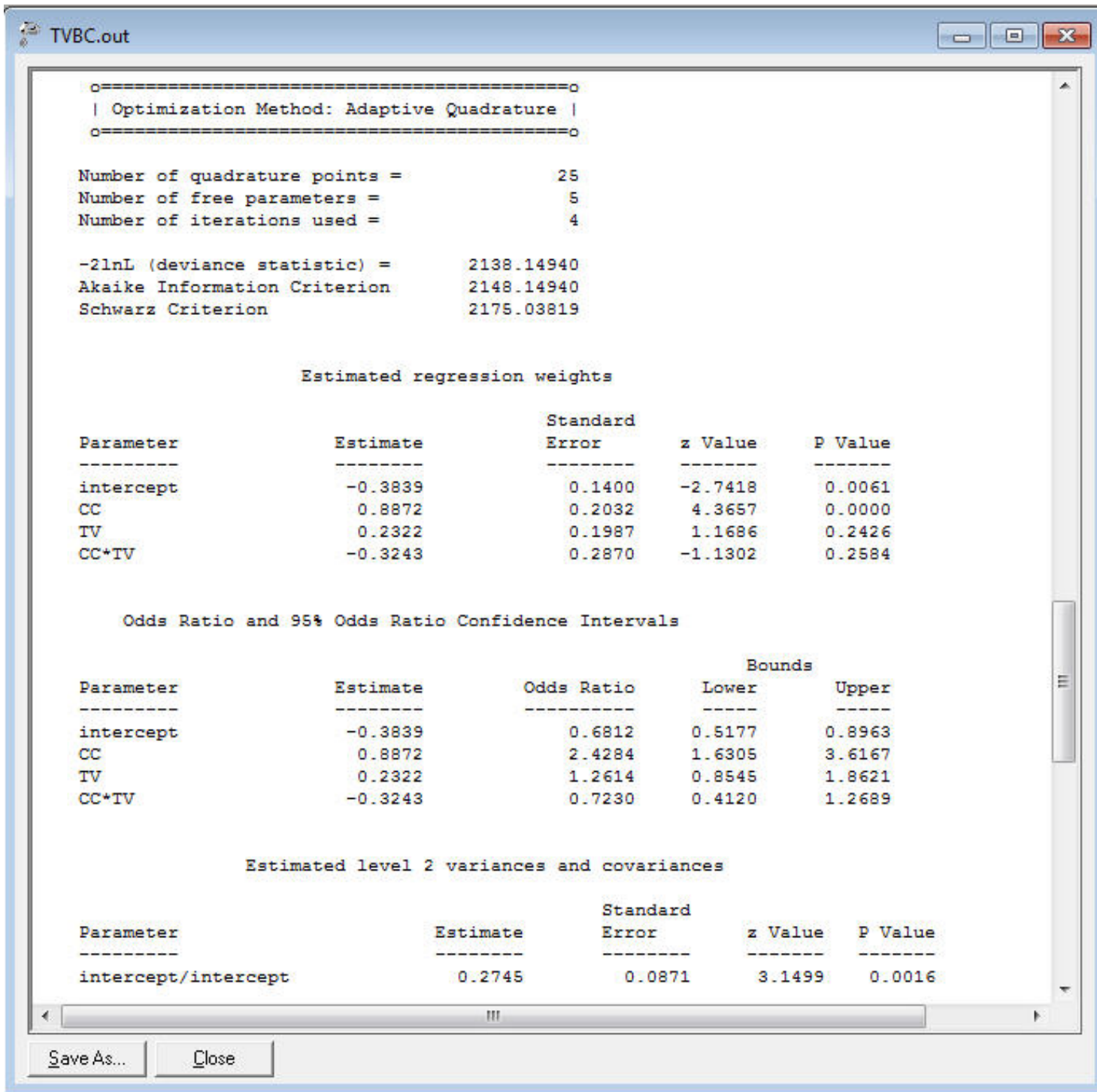
=====
| Descriptive statistics for all the variables in the model |
=====

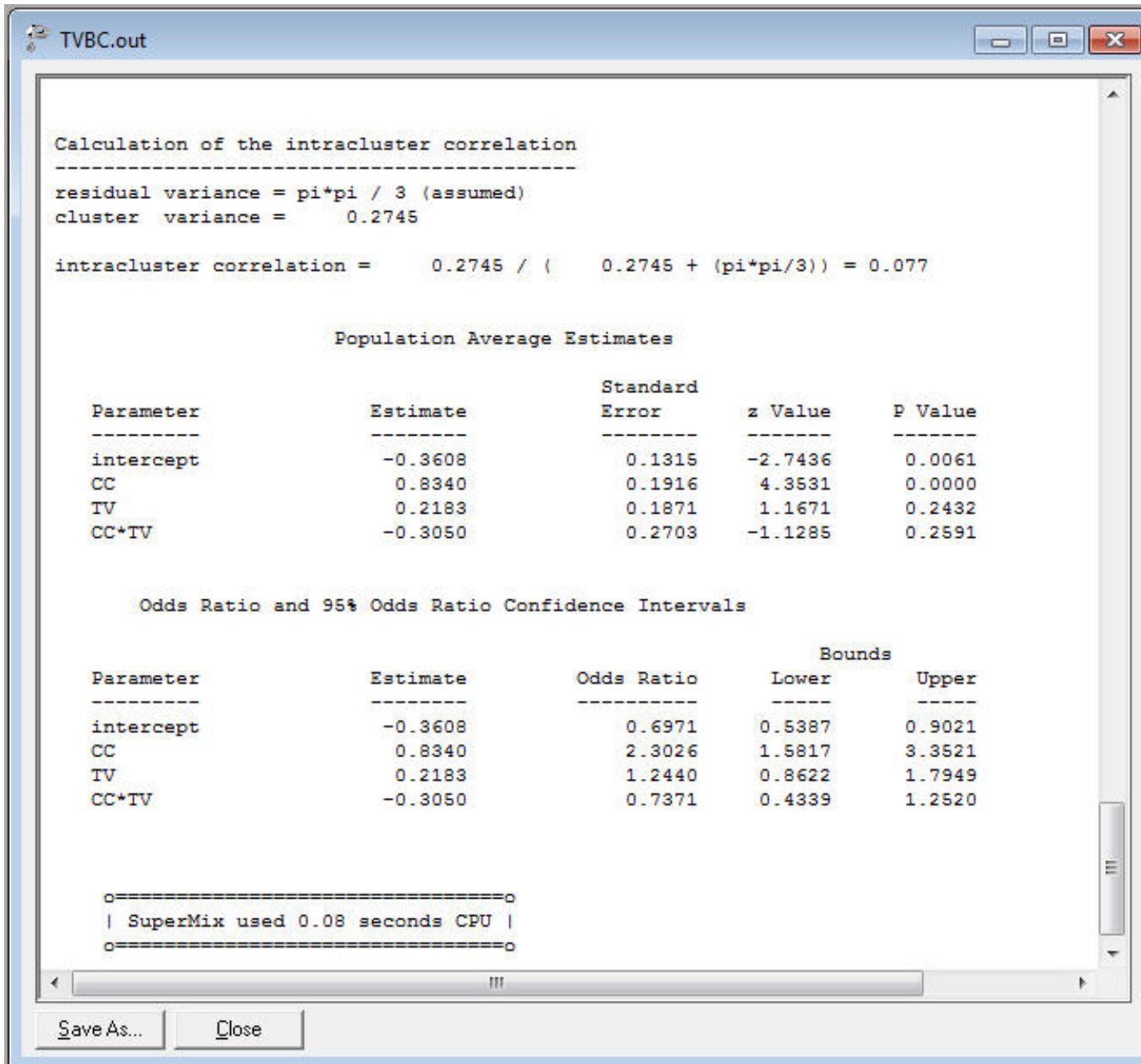
```

Variable	Minimum	Maximum	Mean	Standard Deviation
THKSbin1	0.0000	1.0000	0.4706	0.4993
THKSbin2	0.0000	1.0000	0.5294	0.4993
intercept	1.0000	1.0000	1.0000	0.0000
CC	0.0000	1.0000	0.4769	0.4996
TV	0.0000	1.0000	0.4994	0.5002
CC*TV	0.0000	1.0000	0.2394	0.4268

Save As...

Close





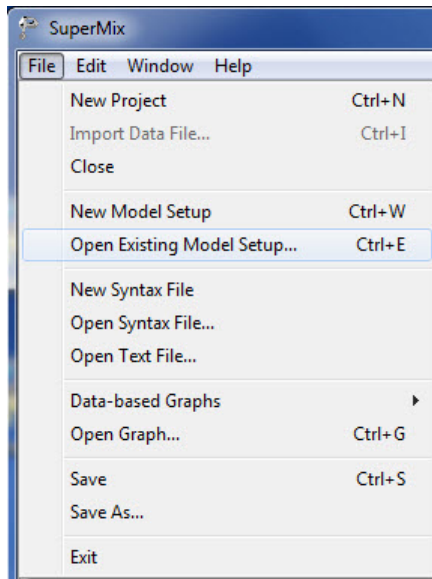
Empirical Bayes Estimates of Random Effects

Select “Analysis” > “View Level-2 Bayes Results”

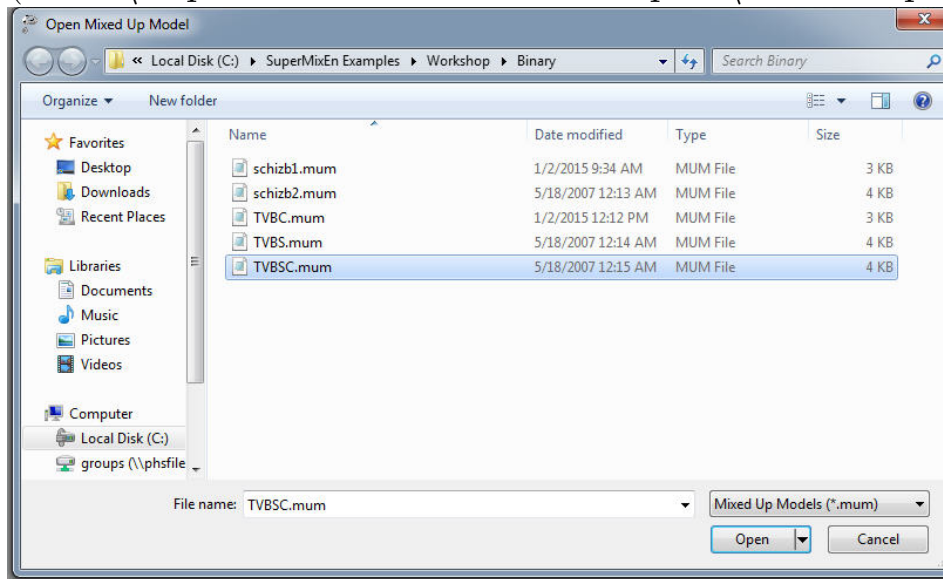
Class ID	random effect number	estimate	variance	name
403101.00	1	0.7275523	0.1409369	intercept
403102.00	1	0.0344524	0.2319444	intercept
404101.00	1	0.0689288	0.1625049	intercept
404102.00	1	0.1093860	0.1762543	intercept
404103.00	1	0.0034297	0.2087811	intercept
193101.00	1	0.1430232	0.1010267	intercept
194101.00	1	-0.0800558	0.1622734	intercept
194102.00	1	0.3179628	0.1654354	intercept
194103.00	1	-0.4486374	0.1484604	intercept
194104.00	1	0.3228970	0.1530624	intercept
194105.00	1	-0.1409860	0.1573158	intercept
194106.00	1	0.4833708	0.1655199	intercept
196101.00	1	0.3632567	0.1261172	intercept
196102.00	1	0.4889583	0.1794476	intercept
197101.00	1	0.0083327	0.1310989	intercept
197102.00	1	-0.2188577	0.1269543	intercept
197103.00	1	0.2870198	0.2429920	intercept
197104.00	1	0.0790041	0.2185922	intercept
198101.00	1	0.1688825	0.1196497	intercept
198102.00	1	-0.4779542	0.1330960	intercept
198103.00	1	-0.4114383	0.1375209	intercept
199101.00	1	-0.1520310	0.1489538	intercept
199102.00	1	-0.2259525	0.2437823	intercept
199103.00	1	-0.0696985	0.1431212	intercept
199104.00	1	-0.1520310	0.1489538	intercept
199105.00	1	-0.1197606	0.2580259	intercept
199106.00	1	-0.0863297	0.1539014	intercept

Class ID, random effect number, estimate, variance, name

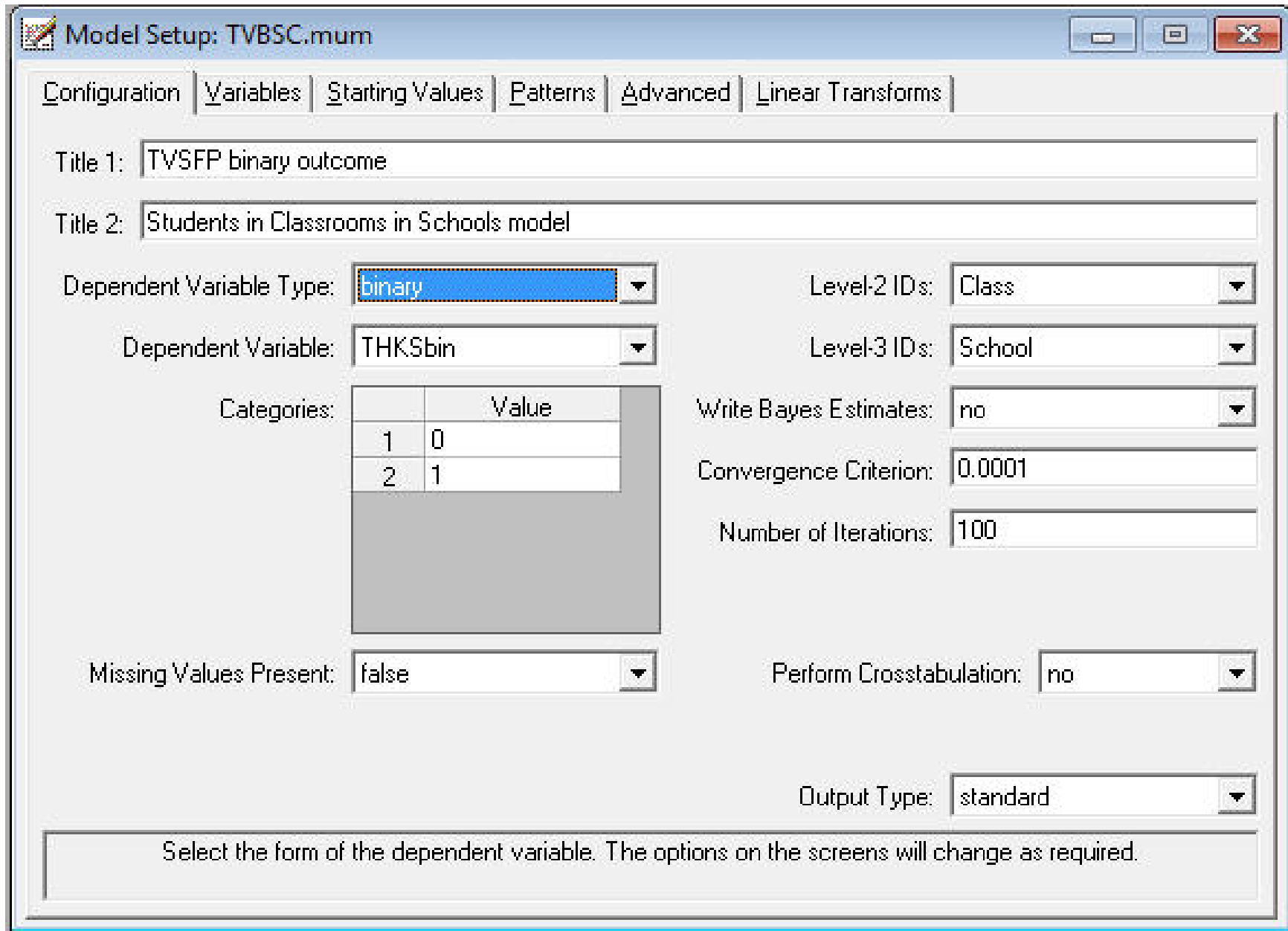
Under “File” click on “Open Existing Model Setup”



Open C:\SuperMixEn Examples\Workshop\Binary\tvbsc.mum
(or C:\SuperMixEn Student Examples\Workshop\Binary\tvbsc.mum)



Note “Dependent Variable Type” should be “binary”



Model Setup: TVBSC.mum

Configuration | Variables | Starting Values | Patterns | **Advanced** | Linear Transforms

Title 1: TVSFP binary outcome

Title 2: Students in Classrooms in Schools model

Dependent Variable Type: **binary**

Dependent Variable: THKSbin

Level-2 IDs: Class

Level-3 IDs: School

Write Bayes Estimates: no

Convergence Criterion: 0.0001

Number of Iterations: 100

Missing Values Present: false

Perform Crosstabulation: no

Output Type: standard

Select the form of the dependent variable. The options on the screens will change as required.

Categories:	
	Value
1	0
2	1

For the moment, unselect PreTHKS as an explanatory variable

Model Setup: TVBSC.mum

Configuration | Variables | Starting Values | Patterns | Advanced | Linear Transforms

Available	E	2	3
School	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Class	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
THKSord	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
THKSbin	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Intcpt	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
PreTHKS	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
CC	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Explanatory Variables	E
CC	<input checked="" type="checkbox"/>
TV	<input checked="" type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>

L-2 Random Effects 2

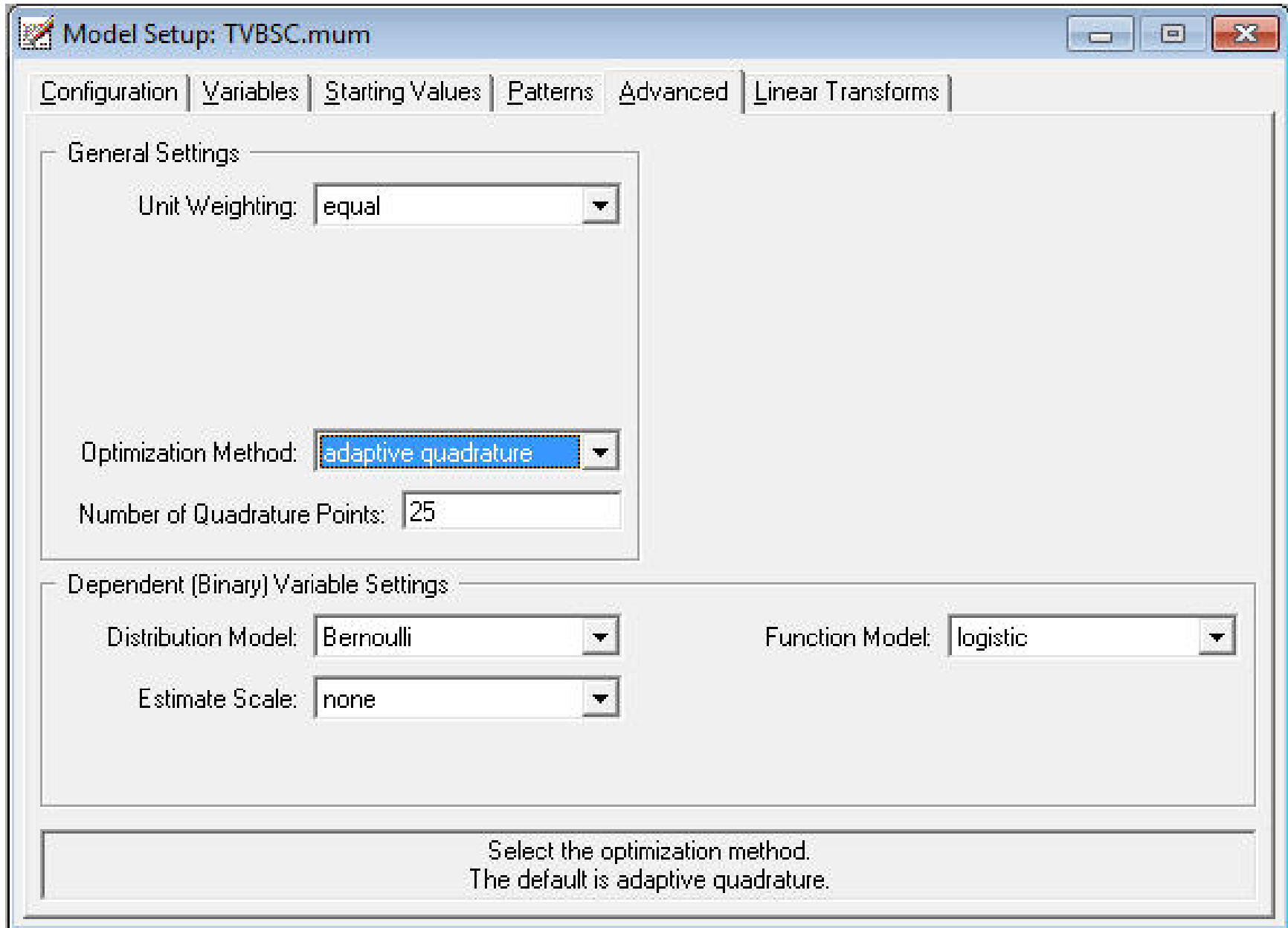
Include Intercept

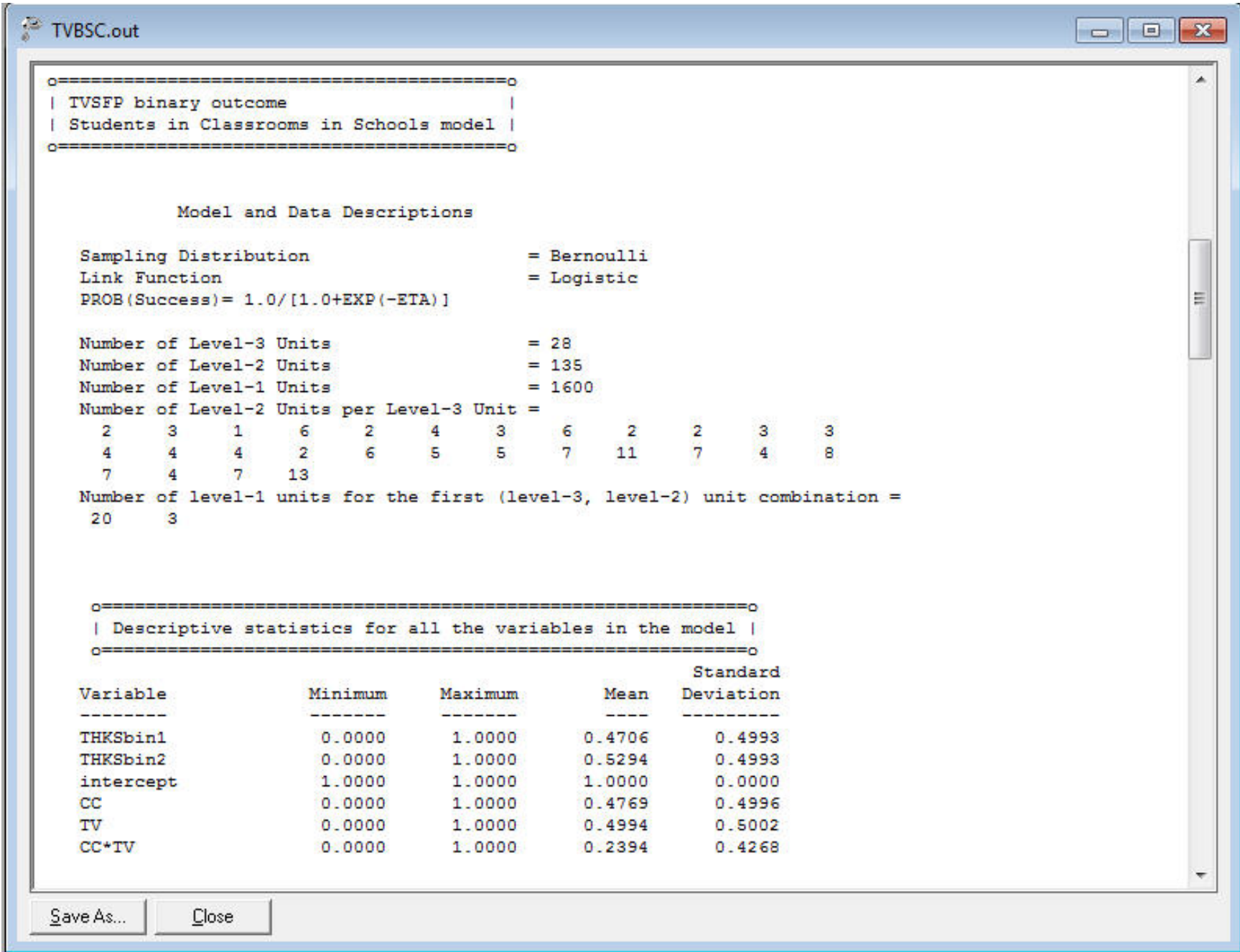
L-3 Random Effects 3

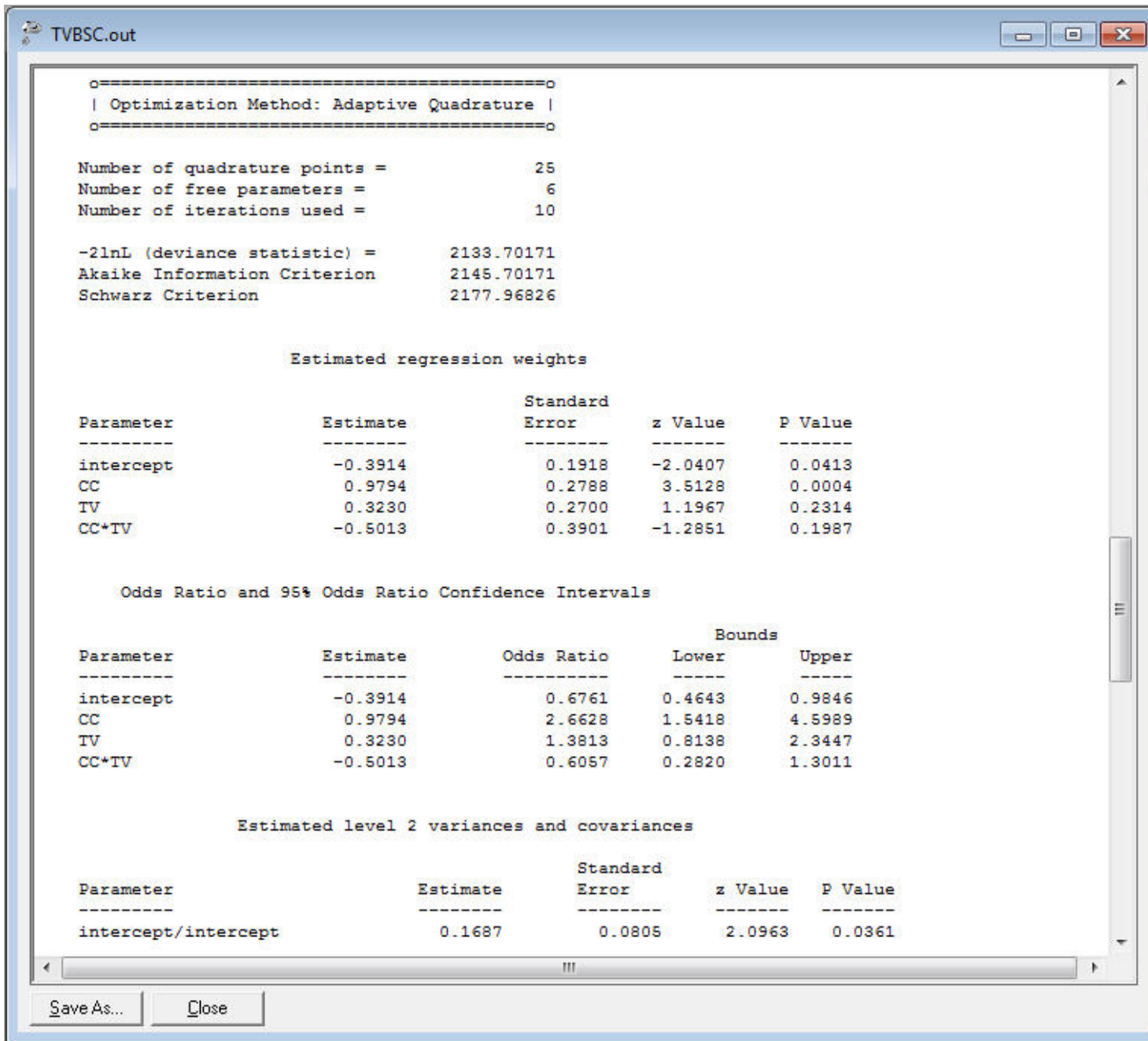
Include Intercept

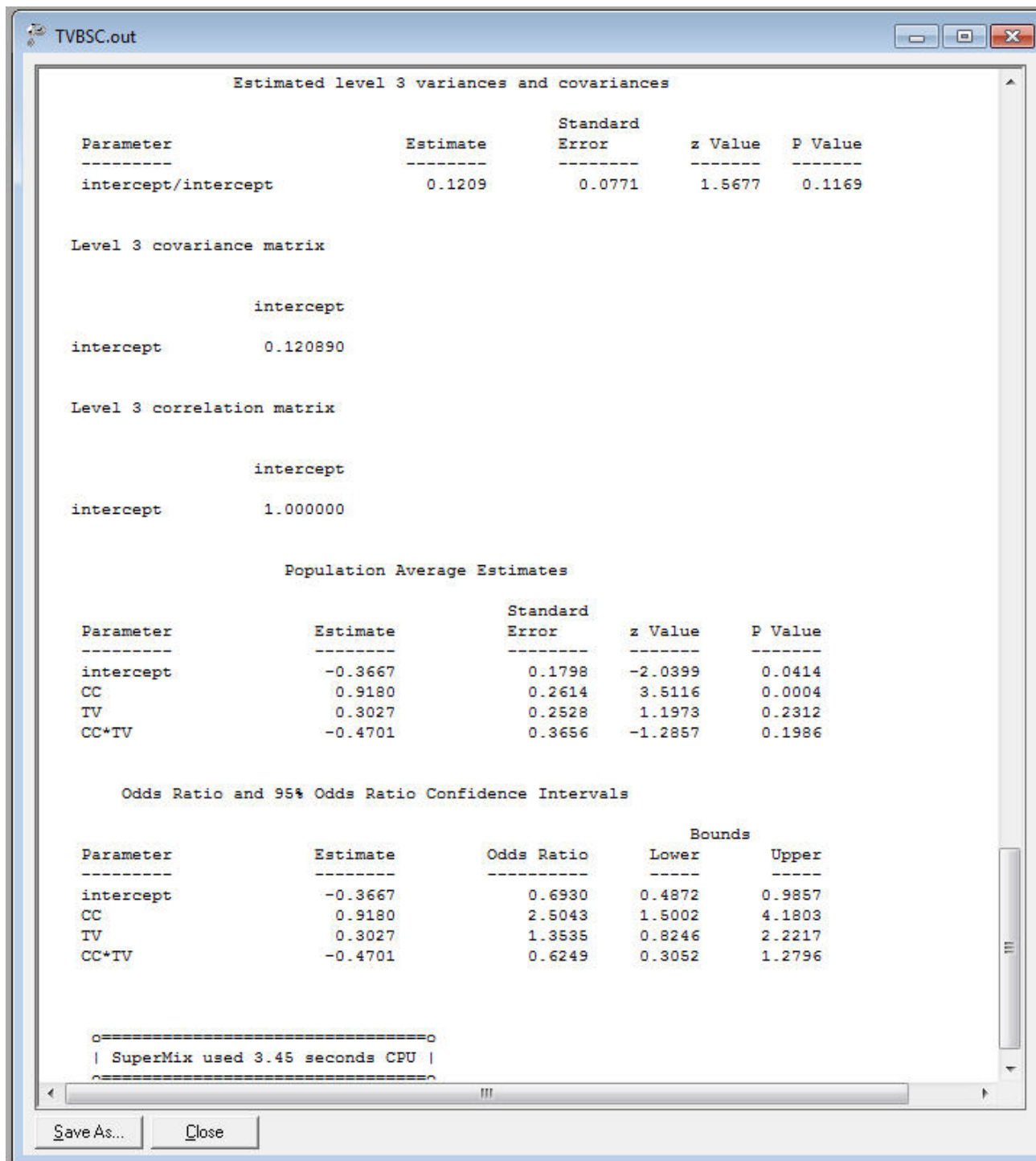
Select the columns of the spreadsheet to be used as explanatory variables and random effects.

Note “Optimization Method” should be “adaptive quadrature”









Empirical Bayes Estimates of Random Class Effects

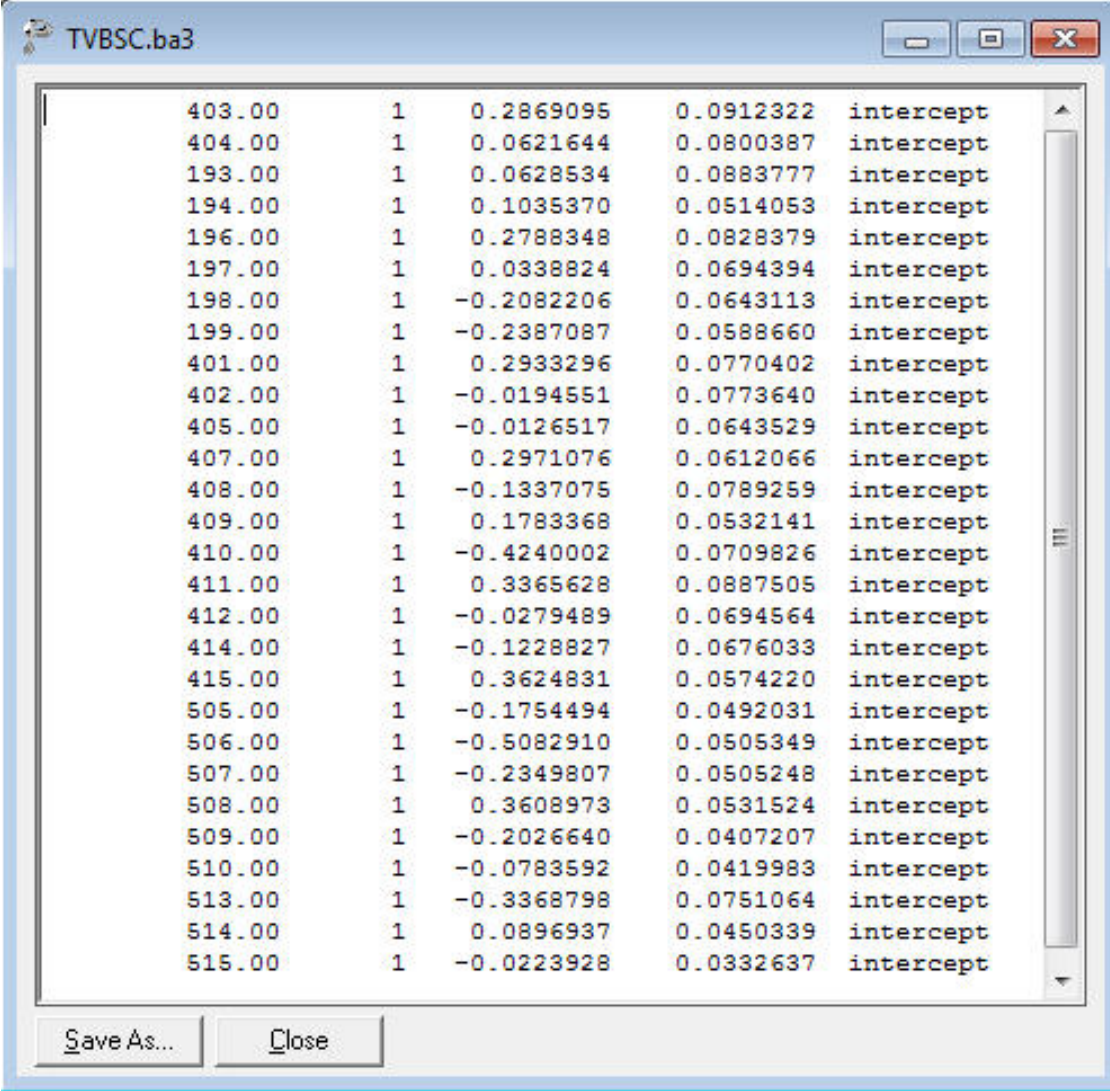
Select “Analysis” > “View Level-2 Bayes Results”

School ID	Class ID	random effect number	estimate	variance	name
403.00	403101.00	1	0.4140825	0.1196861	intercept
403.00	403102.00	1	-0.0138060	0.1537718	intercept
404.00	404101.00	1	0.0320752	0.1256837	intercept
404.00	404102.00	1	0.0623109	0.1308931	intercept
404.00	404103.00	1	-0.0076571	0.1435780	intercept
193.00	193101.00	1	0.0876924	0.1053751	intercept
194.00	194101.00	1	-0.0868046	0.1223228	intercept
194.00	194102.00	1	0.2031341	0.1242055	intercept
194.00	194103.00	1	-0.3690000	0.1150080	intercept
194.00	194104.00	1	0.2078250	0.1188163	intercept
194.00	194105.00	1	-0.1337117	0.1200018	intercept
194.00	194106.00	1	0.3230023	0.1241661	intercept
196.00	196101.00	1	0.1308682	0.1137998	intercept
196.00	196102.00	1	0.2581431	0.1336295	intercept
197.00	197101.00	1	-0.0040352	0.1119884	intercept
197.00	197102.00	1	-0.1806288	0.1099575	intercept
197.00	197103.00	1	0.1826475	0.1565903	intercept
197.00	197104.00	1	0.0492875	0.1469742	intercept
198.00	198101.00	1	0.2265312	0.1055450	intercept
198.00	198102.00	1	-0.2836035	0.1120466	intercept
198.00	198103.00	1	-0.2334184	0.1138528	intercept
199.00	199101.00	1	-0.0601714	0.1181782	intercept
199.00	199102.00	1	-0.1337333	0.1568976	intercept
199.00	199103.00	1	0.0036399	0.1157150	intercept
199.00	199104.00	1	-0.0601714	0.1181782	intercept
199.00	199105.00	1	-0.0693896	0.1624270	intercept
199.00	199106.00	1	-0.0132031	0.1202872	intercept

School ID, Class ID, random effect number, estimate, variance, name

Empirical Bayes Estimates of Random School Effects

Select “Analysis” > “View Level-3 Bayes Results”



School ID	random effect number	estimate	variance	name
403.00	1	0.2869095	0.0912322	intercept
404.00	1	0.0621644	0.0800387	intercept
193.00	1	0.0628534	0.0883777	intercept
194.00	1	0.1035370	0.0514053	intercept
196.00	1	0.2788348	0.0828379	intercept
197.00	1	0.0338824	0.0694394	intercept
198.00	1	-0.2082206	0.0643113	intercept
199.00	1	-0.2387087	0.0588660	intercept
401.00	1	0.2933296	0.0770402	intercept
402.00	1	-0.0194551	0.0773640	intercept
405.00	1	-0.0126517	0.0643529	intercept
407.00	1	0.2971076	0.0612066	intercept
408.00	1	-0.1337075	0.0789259	intercept
409.00	1	0.1783368	0.0532141	intercept
410.00	1	-0.4240002	0.0709826	intercept
411.00	1	0.3365628	0.0887505	intercept
412.00	1	-0.0279489	0.0694564	intercept
414.00	1	-0.1228827	0.0676033	intercept
415.00	1	0.3624831	0.0574220	intercept
505.00	1	-0.1754494	0.0492031	intercept
506.00	1	-0.5082910	0.0505349	intercept
507.00	1	-0.2349807	0.0505248	intercept
508.00	1	0.3608973	0.0531524	intercept
509.00	1	-0.2026640	0.0407207	intercept
510.00	1	-0.0783592	0.0419983	intercept
513.00	1	-0.3368798	0.0751064	intercept
514.00	1	0.0896937	0.0450339	intercept
515.00	1	-0.0223928	0.0332637	intercept

School ID, random effect number, estimate, variance, name

THKS Post-Int (dichotomized) Scores - LR Estimates (std errs)

	<i>Multilevel</i>		
	<i>Fixed</i>	<i>2-level</i>	<i>3-level</i>
intercept	-.341 *** (.099)	-.384 *** (.140)	-.391 *** (.192)
CC	.880 *** (.145)	.887 *** (.203)	.979 ** (.278)
TV	.273 ** (.139)	.232 (.199)	.323 (.270)
CC × TV	-.394 * (.204)	-.324 (.287)	-.501 (.390)
class var		.275 (.087)	.170 (.081)
school var			.120 (.077)
-2 log L	2162.53	2138.15	2133.70

*** $p < .01$ ** $p < .05$ * $p < .10$ (Wald tests not done for vars)

Calculation of ICC - 2 level model

$$r = \frac{\sigma_v^2}{\sigma_v^2 + \sigma^2}$$

Random classrooms model ($\pi^2/3 = 3.2897$)

$$r = \frac{.275}{.275 + \pi^2/3} = .077$$

\Rightarrow 7.7% of the unexplained variation is at the classroom level

Calculation of ICC - 3 level model

Level-3 (likeness of students in the same school)

$$r = \frac{\sigma_{v(3)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2} = \frac{.121}{.121 + .169 + \pi^2/3} = .034$$

Level-2 (likeness of students in same classroom & school)

$$r = \frac{\sigma_{v(3)}^2 + \sigma_{v(2)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2} = \frac{.121 + .169}{.121 + .169 + \pi^2/3} = .081$$

Level-2 (likeness of classes in the same school)

$$r = \frac{\sigma_{v(3)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2} = \frac{.121}{.121 + .169} = .415$$

- $r < .5$: the school level contributes slightly less to variability than the class level
- average classroom post THKS scores are moderately similar within schools

CC	TV	logistic $\Psi(z) = [1 + \exp(-z)]^{-1}$	estimate
<i>Fixed-effects model</i>			
0	0	$\Psi(-.341)$.416
0	1	$\Psi(-.341 + .273)$.483
1	0	$\Psi(-.341 + .880)$.632
1	1	$\Psi(-.341 + .273 + .880 - .394)$.603
<i>Random-classrooms model $\hat{d} = (.2745 + \pi^2/3)/(\pi^2/3)$</i>			
0	0	$\Psi((-0.384)/\sqrt{\hat{d}})$.409
0	1	$\Psi((-0.384 + 0.232)/\sqrt{\hat{d}})$.464
1	0	$\Psi((-0.384 + 0.887)/\sqrt{\hat{d}})$.619
1	1	$\Psi((-0.384 + 0.232 + 0.887 - 0.324)/\sqrt{\hat{d}})$.597
<i>Random-classrooms model using Population Average Estimates</i>			
0	0	$\Psi(-.361)$.411
0	1	$\Psi(-.361 + .218)$.464
1	0	$\Psi(-.361 + .834)$.616
1	1	$\Psi(-.361 + .218 + .834 - .305)$.595

$d = \text{design effect} = (\sigma_v^2 + \sigma^2)/\sigma^2$

CC	TV	logistic $\Psi(z) = [1 + \exp(-z)]^{-1}$	estimate
<i>3-level model</i>		$\hat{d} = (.121 + .169 + \pi^2/3)/(\pi^2/3)$	
0	0	$\Psi((-0.391)/\sqrt{\hat{d}})$.407
0	1	$\Psi((-0.391 + .323)/\sqrt{\hat{d}})$.484
1	0	$\Psi((-0.391 + .979)/\sqrt{\hat{d}})$.638
1	1	$\Psi((-0.391 + .323 + .979 - .501)/\sqrt{\hat{d}})$.597

3-level model using Population Average Estimates

0	0	$\Psi(-.367)$.409
0	1	$\Psi(-.367 + .303)$.484
1	0	$\Psi(-.367 + .918)$.634
1	1	$\Psi(-.367 + .303 + .918 - .470)$.595

$$d = \text{design effect} = (\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2)/\sigma^2$$

Within-Clusters / Between-Clusters components

Within-clusters model - level 1 ($j = 1, \dots, n_i$ subjects)

$$\text{logit}_{ij} = b_{0i} + b_{1i}PRETHKS_{ij}$$

Between-clusters model - level 2 ($i = 1, \dots, N$ clusters)

$$b_{0i} = \beta_0 + \beta_2CC_i + \beta_3TV_i + \beta_4(CC_i \times TV_i) + v_{0i}$$

$$b_{1i} = \beta_1$$

$$v_{0i} \sim \mathcal{NID}(0, \sigma_v^2)$$

β_0 = (PRETHKS adjusted) logit for CC=no TV=no subgroup

β_1 = effect of PRETHKS on POSTTHKS

β_2 = (PRETHKS adjusted) logit diff. between CC=yes vs CC=no (for TV=no)

β_3 = (PRETHKS adjusted) logit diff. between TV=yes vs TV=no (for CC=no)

β_4 = (PRETHKS adjusted) difference in logit attributable to interaction

v_{0i} = random cluster deviation

3-level model

Within-classrooms (and schools) model - level 1
($k = 1, \dots, n_{ij}$ students)

$$\text{logit}_{ijk} = b_{0ij} + b_{1ij}PRETHKS_{ijk}$$

Between-classrooms (within-schools) model - level 2
($j = 1, \dots, n_i$ classrooms)

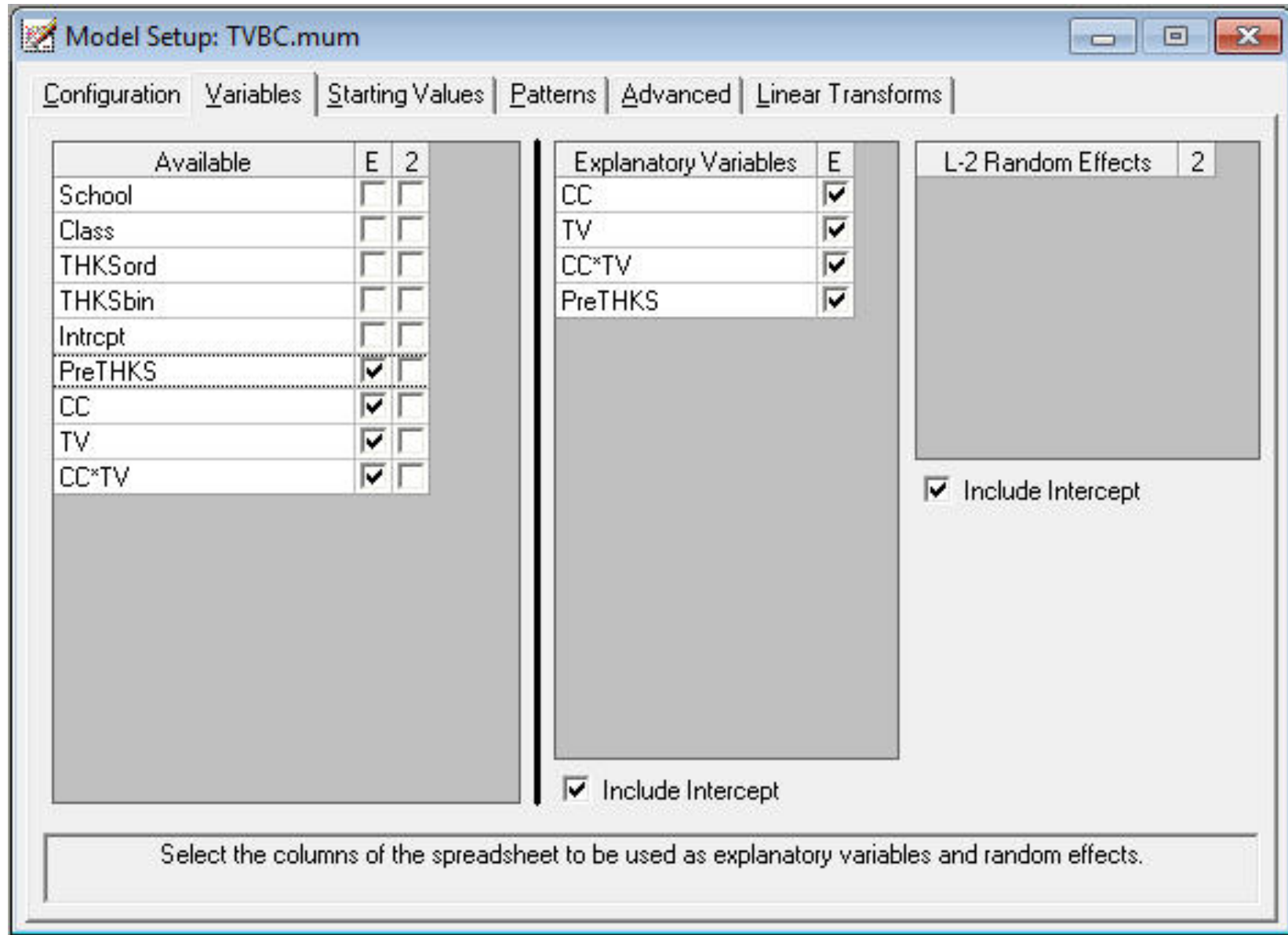
$$b_{0ij} = b_{0i} + v_{0ij}$$
$$b_{1ij} = b_{1i}$$

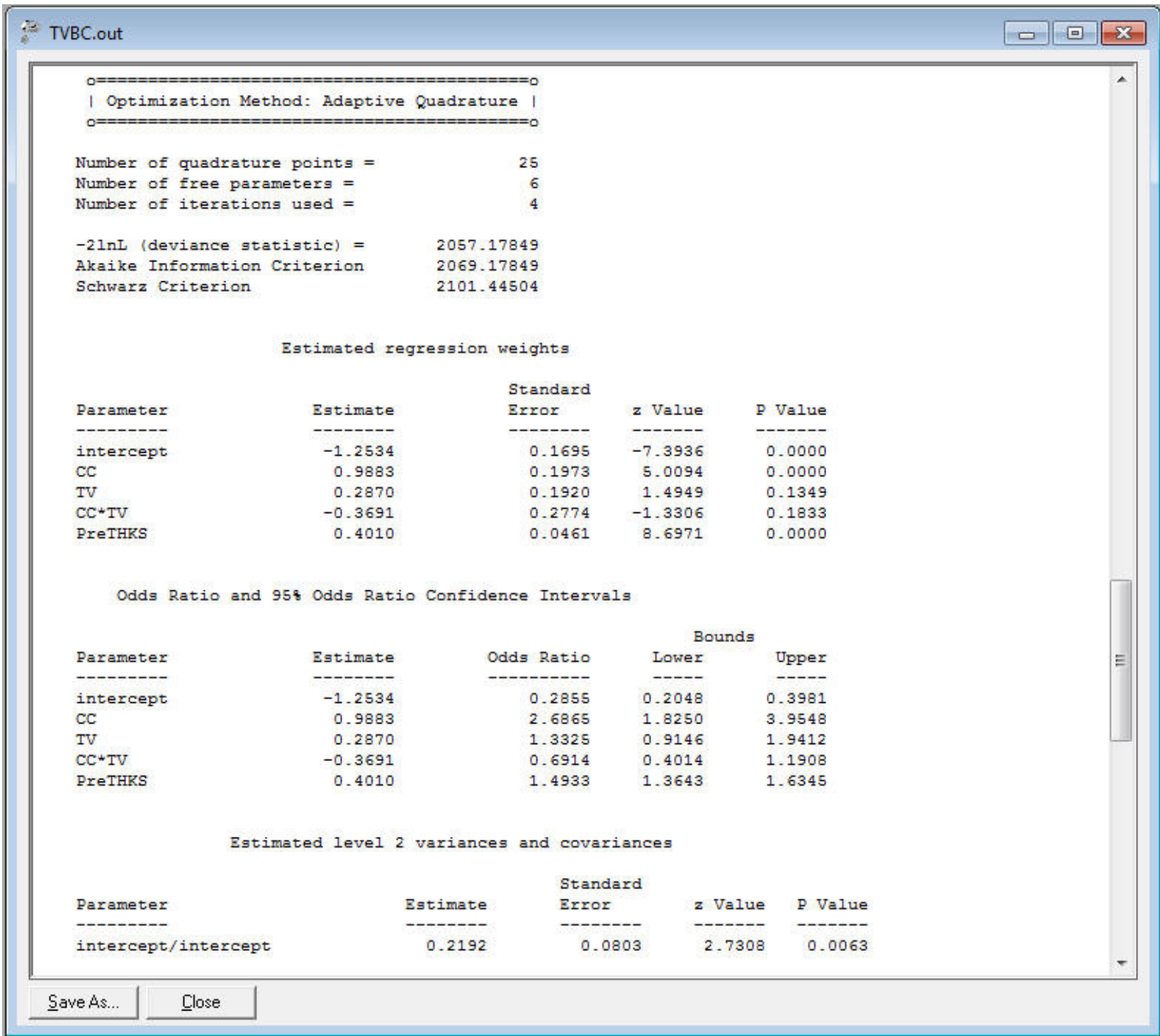
Between-schools model - level 3 ($i = 1, \dots, N$ schools)

$$b_{0i} = \beta_0 + \beta_2CC_i + \beta_3TV_i + \beta_4(CC_i \times TV_i) + v_{0i}$$
$$b_{1i} = \beta_1$$

$$v_{0ij} \sim \mathcal{NID}(0, \sigma_{v(2)}^2) \quad \text{and} \quad v_{0i} \sim \mathcal{NID}(0, \sigma_{v(3)}^2)$$

Reopening TVBC.mum and selecting PreTHKS as an explanatory variable





Calculation of the intraclass correlation

residual variance = $\pi^2 / 3$ (assumed)

cluster variance = 0.2192

intraclass correlation = $0.2192 / (0.2192 + (\pi^2/3)) = 0.062$

Population Average Estimates

Parameter	Estimate	Standard Error	z Value	P Value
intercept	-1.1953	0.1621	-7.3754	0.0000
CC	0.9421	0.1885	4.9981	0.0000
TV	0.2736	0.1833	1.4928	0.1355
CC*TV	-0.3518	0.2649	-1.3283	0.1841
PreTHKS	0.3825	0.0444	8.6121	0.0000

Odds Ratio and 95% Odds Ratio Confidence Intervals

Parameter	Estimate	Odds Ratio	Bounds	
			Lower	Upper
intercept	-1.1953	0.3026	0.2203	0.4158
CC	0.9421	2.5654	1.7730	3.7119
TV	0.2736	1.3147	0.9179	1.8829
CC*TV	-0.3518	0.7034	0.4185	1.1821
PreTHKS	0.3825	1.4660	1.3438	1.5994

```

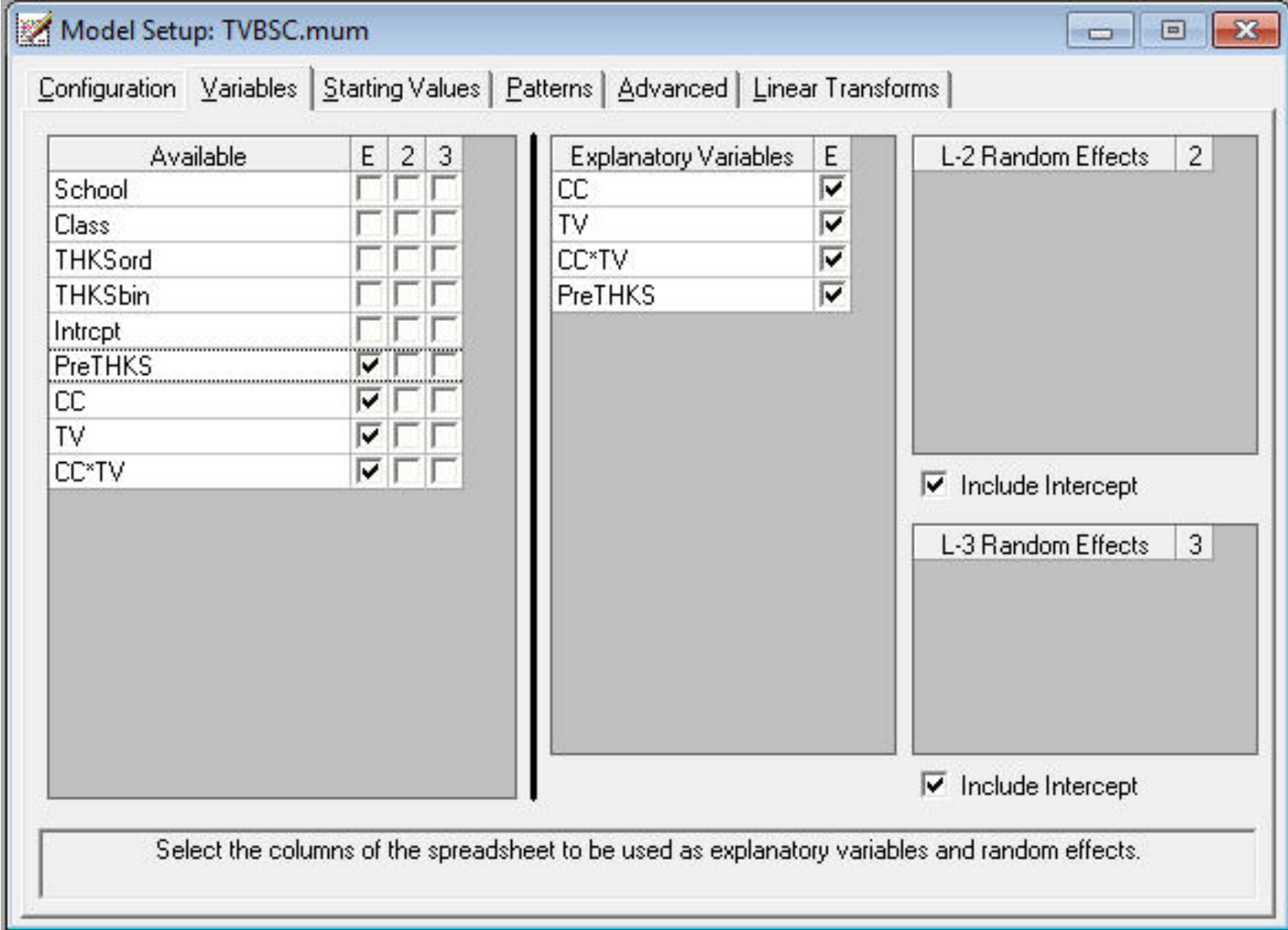
=====
| SuperMix used 0.09 seconds CPU |
=====

```

Save As...

Close

Reopening TVBSC.mum and selecting PreTHKS as an explanatory variable



Model Setup: TVBSC.mum

Configuration | Variables | Starting Values | Patterns | Advanced | Linear Transforms

Available	E	2	3
School	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Class	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
THKSord	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
THKSbin	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Intrcpt	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
PreTHKS	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
CC	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Explanatory Variables	E
CC	<input checked="" type="checkbox"/>
TV	<input checked="" type="checkbox"/>
CC*TV	<input checked="" type="checkbox"/>
PreTHKS	<input checked="" type="checkbox"/>

L-2 Random Effects 2

Include Intercept

L-3 Random Effects 3

Include Intercept

Select the columns of the spreadsheet to be used as explanatory variables and random effects.

TVBSC.out

| Optimization Method: Adaptive Quadrature |

Number of quadrature points = 25
 Number of free parameters = 7
 Number of iterations used = 11

-2lnL (deviance statistic) = 2055.70206
 Akaike Information Criterion = 2069.70206
 Schwarz Criterion = 2107.34637

Estimated regression weights

Parameter	Estimate	Standard Error	z Value	P Value
intercept	-1.2465	0.1957	-6.3687	0.0000
CC	1.0383	0.2448	4.2416	0.0000
TV	0.3325	0.2358	1.4104	0.1584
CC*TV	-0.4644	0.3427	-1.3552	0.1754
PreTHKS	0.3954	0.0463	8.5332	0.0000

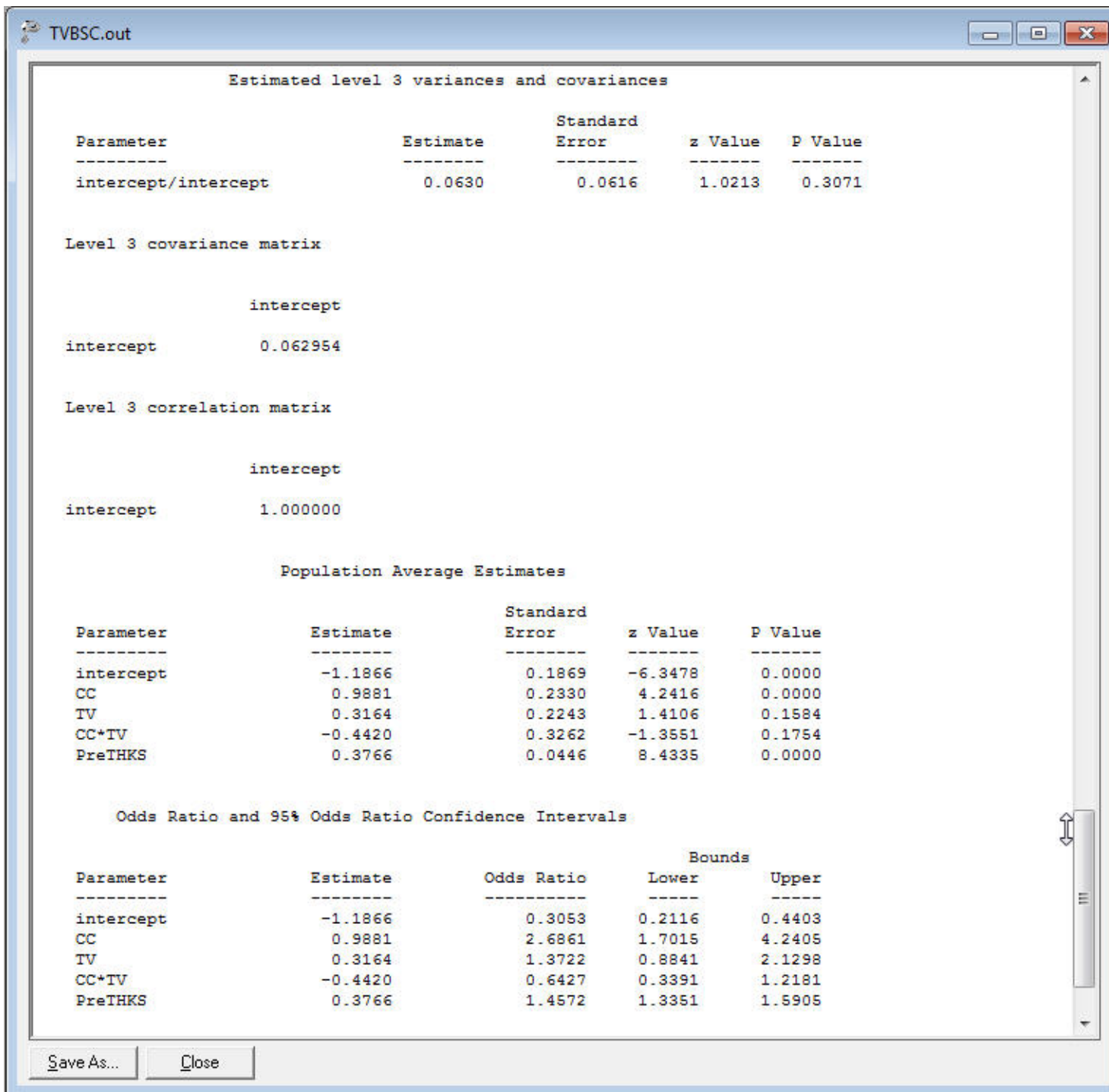
Odds Ratio and 95% Odds Ratio Confidence Intervals

Parameter	Estimate	Odds Ratio	Bounds	
			Lower	Upper
intercept	-1.2465	0.2875	0.1959	0.4220
CC	1.0383	2.8245	1.7481	4.5636
TV	0.3325	1.3945	0.8785	2.2137
CC*TV	-0.4644	0.6285	0.3211	1.2303
PreTHKS	0.3954	1.4849	1.3560	1.6261

Estimated level 2 variances and covariances

Parameter	Estimate	Standard Error	z Value	P Value
intercept/intercept	0.1649	0.0813	2.0277	0.0426

Save As... Close



THKS Post-Int (dichotomized) Scores - LR Estimates (std err)

	<i>Multilevel</i>					
	<i>Fixed</i>		<i>2-level</i>		<i>3-level</i>	
intercept	-1.217	***	-1.253	***	-1.246	***
	(.141)		(.170)		(.196)	
PRETHKS	.400	***	.401	***	.395	***
	(.044)		(.046)		(.046)	
CC	.973	***	.988	***	1.038	***
	(.150)		(.197)		(.245)	
TV	.316	**	.287		.333	
	(.143)		(.192)		(.236)	
CC × TV	-.413	**	-.369		-.464	
	(.210)		(.277)		(.343)	
class var			.219		.165	
			(.080)		(.081)	
school var					.063	
					(.062)	
-2 log L	2073.3		2057.18		2055.70	

*** $p < .01$ ** $p < .05$ * $p < .10$ (Wald-tests not done for vars)

Calculation of ICC - 2 level models

$$r = \frac{\sigma_v^2}{\sigma_v^2 + \sigma^2}$$

Random classrooms model

$$r = \frac{.219}{.219 + \pi^2/3} = .062$$

⇒ 6.2% of the unexplained variation is at the classroom level

Calculation of ICC - 3 level model

Level-3 (likeness of students in the same school)

$$r = \frac{\sigma_{v(3)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2} = \frac{.063}{.063 + .165 + \pi^2/3} = .018$$

Level-2 (likeness of students in same classroom & school)

$$r = \frac{\sigma_{v(3)}^2 + \sigma_{v(2)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2} = \frac{.063 + .165}{.063 + .165 + \pi^2/3} = .063$$

Level-2 (likeness of classes in the same school)

$$r = \frac{\sigma_{v(3)}^2}{\sigma_{v(3)}^2 + \sigma_{v(2)}^2} = \frac{.063}{.063 + .165} = .276$$

- $r < .5$: the school level contributes less to variability than the class level
- average classroom post THKS scores are moderately similar within schools

CC	TV	logistic $\Psi(z) = [1 + \exp(-z)]^{-1}$	estimate
<i>Fixed-effects model</i>			
0	0	$\Psi(-1.217 + 2.152 \times .400)$.412
0	1	$\Psi(-1.217 + .316 + 2.087 \times .400)$.483
1	0	$\Psi(-1.217 + .973 + 2.050 \times .400)$.640
1	1	$\Psi(-1.217 + .316 + .973 - .413 + 1.979 \times .400)$.610
<i>Random-classrooms model $\hat{d} = (.219 + \pi^2/3)/(\pi^2/3)$</i>			
0	0	$\Psi((-1.253 + 2.152 \times .401)/\sqrt{\hat{d}})$.407
0	1	$\Psi((-1.253 + .287 + 2.087 \times .401)/\sqrt{\hat{d}})$.469
1	0	$\Psi((-1.253 + .988 + 2.050 \times .401)/\sqrt{\hat{d}})$.632
1	1	$\Psi((-1.253 + .287 + .988 - .369 + 1.979 \times .401)/\sqrt{\hat{d}})$.606
<i>Random-classrooms model using Population Average Estimates</i>			
0	0	$\Psi(-1.195 + 2.152 \times .383)$.408
0	1	$\Psi(-1.195 + .287 + 2.087 \times .383)$.469
1	0	$\Psi(-1.195 + .988 + 2.050 \times .383)$.630
1	1	$\Psi(-1.195 + .287 + .988 - .369 + 1.979 \times .383)$.605

$$d = \text{design effect} = (\sigma_v^2 + \sigma^2)/\sigma^2$$

CC	TV	logistic $\Psi(z) = [1 + \exp(-z)]^{-1}$	estimate
<i>3-level model</i>		$\hat{d} = (.063 + .165 + \pi^2/3)/(\pi^2/3)$	
0	0	$\Psi((-1.246 + 2.152 \times .395)/\sqrt{\hat{d}})$.405
0	1	$\Psi((-1.246 + .333 + 2.087 \times .395)/\sqrt{\hat{d}})$.479
1	0	$\Psi((-1.246 + 1.038 + 2.050 \times .395)/\sqrt{\hat{d}})$.642
1	1	$\Psi((-1.246 + .333 + 1.038 - .464 + 1.979 \times .395)/\sqrt{\hat{d}})$.605

3-level model using Population Average Estimates

0	0	$\Psi(-1.187 + 2.152 \times .377)$.407
0	1	$\Psi(-1.187 + .316 + 2.087 \times .377)$.479
1	0	$\Psi(-1.187 + .988 + 2.050 \times .377)$.640
1	1	$\Psi(-1.187 + .316 + .988 - .442 + 1.979 \times .377)$.604

$$d = \text{design effect} = (\sigma_{v(3)}^2 + \sigma_{v(2)}^2 + \sigma^2)/\sigma^2$$

Summary

- Mixed logistic regression model is direct extension of ordinary logistic regression
- Useful approach for multilevel data
- Software is available in Supermix (and other programs)
- (Extended) methods are available for ordinal, nominal, count outcomes
- Similar models can be used for longitudinal, albeit more issues
 - more random effects are typically necessary
 - missing data and attrition