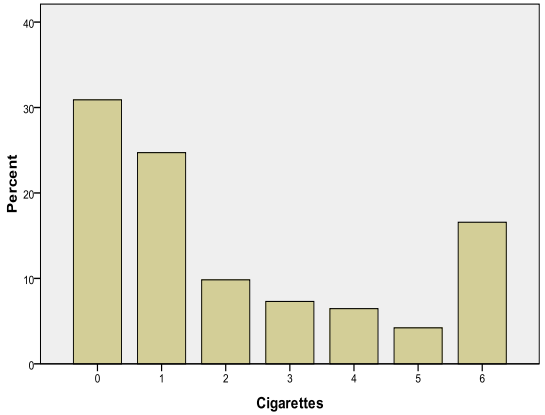
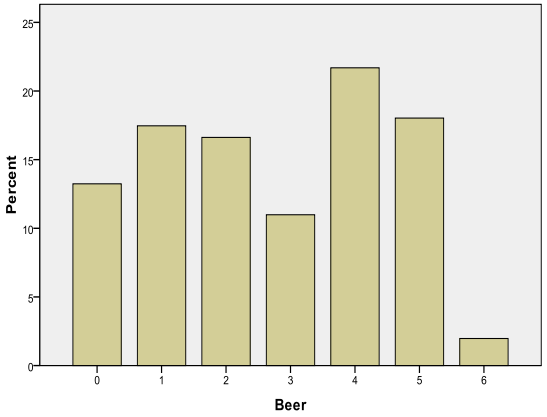
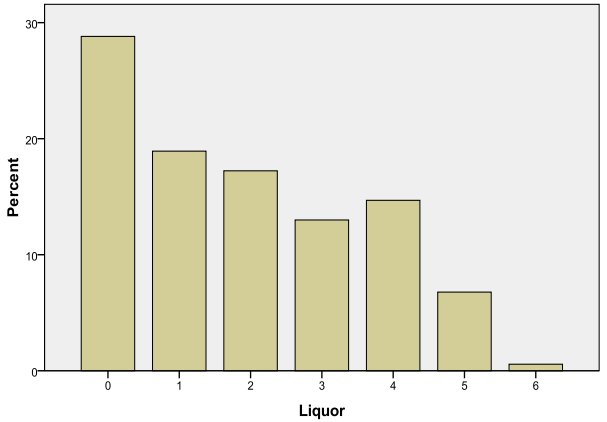
Measurement Models for Other Kinds of Continuous but Non-Normal Outcomes in Mplus version 8.1

This example examines alternative factor models for 6 outcomes that measure use of controlled substances on a scale of 0 to 6, where: 0 = Never used, 1 = Have used once or twice, 2 = Once or twice a year, 3 = Less than once a month, 4 = Once or twice a month, 5 = Once or twice a week, and 6 = Daily. Below are the distributions of the outcomes in a sample of 356 rural adolescents. It is admittedly not the best example because of the constrained 7-point ordinal scale rather than a true count, but it is what I have to illustrate these models…

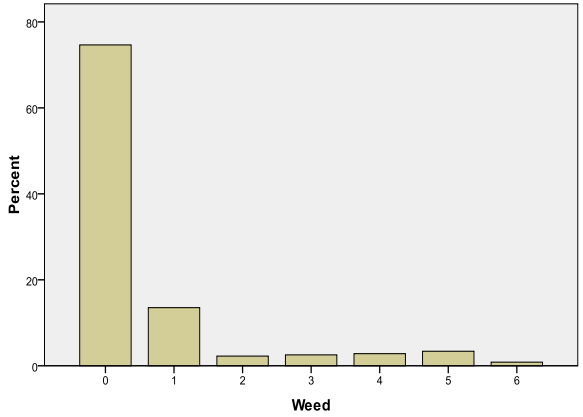
"Recreational Drugs": cigarettes, beer, and liquor

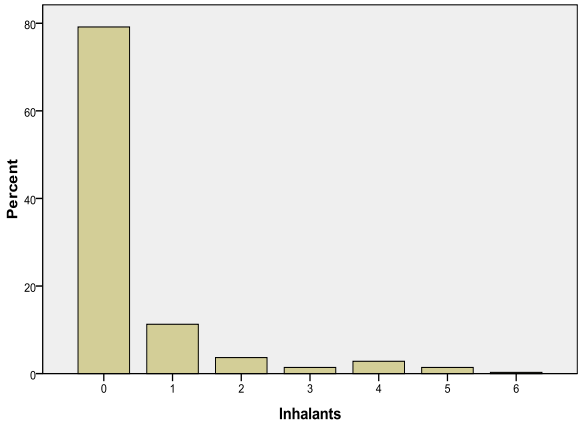


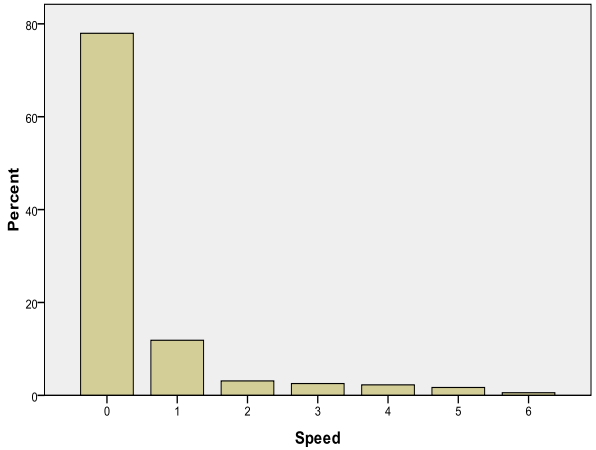




"Real Drugs": weed, inhalants, speed







Assuming we wish to model the distribution as some kind of continuum (i.e., not as graded response), there are several reasonable options described below for factor models that assume different conditional item response distributions. We will see examples of how to specify each of these in Mplus next, using MLR (robust ML) for all models. Model fit statistics will only be available for normal models that are easily summarized by a covariance matrix, though.

Normal (regular CFA) Model: We fit a linear model of the factor predicting the ORIGINAL item response and assume each item follows a conditionally normal distribution (i.e., the item residuals are normally distributed after controlling for the factor). The measurement model would thus include per item an intercept (the expected item response when factor = 0), a factor loading (change in item response per unit change in the factor), and a residual variance (amount of item variance not predicted by the factor). A normal model that assumes a linear relationship between the item response and the factor (i.e., an interval scaling of the response options) is not likely to be tenable for these kinds of data, but it's the most common approach. Although we can use MLR instead of ML for CFA models when item response distributions look non-normal to correct the fit statistics and standard errors accordingly, that doesn't solve the basic problem of whether it is reasonable to expect a linear relationship between the item response and the factor. The alternative models below address this latter problem.

Poisson and Negative Binomial Models: We fit a linear model of the factor predicting the LOG of the item response. We assume the items follow a **Poisson** distribution in which the mean is the same as the variance (a single parameter called "k"). The Poisson measurement model would thus include per item an intercept (the expected LOG of the item response when factor = 0) and a factor loading (change in the LOG of the item response per unit change in the factor), but no estimated residual variance (because it is determined by the conditional mean). In the closely related **Negative Binominal** model, we add to the Poisson model a scaling factor "α" that allows the residual variance to exceed the mean (called "over-dispersion"), such that the new variance = $k(1+k\alpha)$. In Mplus we can test if the scaling factor is different than 0 (because 0=Poisson), and thus we could do a nested model comparison as to whether a Negative Binominal fits better than a Poisson for each item response. These models works well for integer count data that can't be negative or data that are skewed, but they run into problems if the over-dispersion is caused by an excess of zeros. The alternative models below address this extra-zero problem.

Zero-Inflated Poisson (ZIP) or Zero-Inflated Negative Binomial (ZINB): These models specify two underlying distributions in the observed item responses: "structural zeros" and "non-structural zeros" (includes expected zeros based on regular Poisson or negative binomial distributions). A structural zero would never do any of the behaviors in question, whereas an expected zero (who belongs in the regular distribution) might do the general behavior, just not that particular item (e.g., zero for use of speed but non-zero for use of weed). We can potentially fit a factor model to each part of the distribution. The structural zero measurement model would have a linear model of the factor predicting the LOGIT of being a structural zero (so the "higher category" being predicted is the structural zero as 1). The structural zero factor model would thus estimate thresholds (expected LOGIT of being a non-structural zero if the factor = 0) and factor loadings (change in the LOGIT of being a structural zero per unit change in the factor). The non-structural-zero measurement model would have a linear model of its factor predicting the LOG of the item response, and the ZINB would again have an added scaling parameter for over-dispersion. Thus the non-structural-zero measurement model would estimate intercepts (expected LOG of item response if factor = 0) and factor loadings (change in LOG of item response per unit change in factor). Just as the Poisson is nested within the Negative Binomial (tests if the scaling parameter for extra residual variance is needed), the ZIP is nested within the ZINB. In addition, the AIC and BIC can be compared between the Poisson and ZIP, or between the Negative Binomial and ZINB, to see if the zero-inflation parameters are helpful. It is not required to have a factor for the inflation, but one can do so in Mplus (very hard to estimate). However, the interpretation of two kinds of zeros can be confusing, and so the alternative models below address the issue of excess zeros more directly.

Negative Binomial Hurdle and Two-Part Models: Rather than trying to distinguish "structural zeros" from "non-structural zeros", these models simply split each observed item response into two new variables: "0 vs. something", and "how much if not 0". The models differ in how they accomplish this same idea. The **negative binomial hurdle model** for "0 vs. something" uses "0" as what is predicted. Thus, the measurement model for the "not 0 vs. 0" part would have a linear model of its factor predicting the LOGIT of being a 0. It thus estimates a threshold (expected LOGIT of not being 0 if factor = 0) and a factor loading (expected change in the LOGIT of being a 0 per unit change in the factor). The negative binomial hurdle measurement model for the "not 0" part would have a linear model of its factor predicting the LOG of the item response past 0 (a zero-truncated distribution). It thus estimates an intercept (expected LOG of the non-zero item response if factor = 0), a factor loading (expected change in the LOG of the non-zero item response per unit change in the factor), and a scaling parameter for the over-dispersion of the residual variance. **The two-part model** for the "0 vs. something" uses "something" as what is predicted. Thus, the measurement model for the "0 vs. not 0" part would have a linear model of its factor predicting the LOGIT of being not 0. It thus estimates a threshold (expected LOGIT of being 0 if factor = 0) and a factor loading (expected change in the LOGIT of being not 0 per unit change in the factor). The two-part measurement model for the "not 0" part would have a linear model of its factor predicting the LOG of the item response past 0. It thus estimates an intercept (expected LOG of the non-zero item response if factor = 0), a factor loading (expected change in the LOG of the non-zero item response per unit change in the factor), and a residual variance. The "not 0" model uses a LOG transformation by default, but other transformations (including none) are available as well.

Here is one alternative: (1) Normal CFA model with Robust ML

```
TITLE:   Model 1: Normal Response Distribution
DATA:    FILE IS deviance.dat;

VARIABLE:    NAMES ARE        cig beer liquor weed inhale speed;
             USEVARIABLES ARE cig beer liquor weed inhale speed;
             MISSING ARE .;
! No extra code here means we assume each item response is normal


ANALYSIS:    ESTIMATOR IS MLR;
OUTPUT:      RESIDUAL STDYX;

MODEL:
! Factor loadings all estimated
   Rec  BY cig* beer* liquor*;
   Drug BY weed* inhale* speed*;
! Intercepts all estimated
   [cig* beer* liquor* weed* inhale* speed*];
! Residual variances all estimated
    cig* beer* liquor* weed* inhale* speed*;
! Factor mean=0 and variance=1 for identification, factors correlate
   [Rec@0 Drug@0]; Rec@1 Drug@1; Rec WITH Drug*;


Number of Free Parameters                       19
Loglikelihood
          H0 Value                       -3408.733
          H0 Scaling Correction Factor       2.0743
            for MLR
          H1 Value                       -3388.791
          H1 Scaling Correction Factor       1.8171
            for MLR

Information Criteria
          Akaike (AIC)                    6855.466
          Bayesian (BIC)                  6929.090
          Sample-Size Adjusted BIC        6868.813
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                             33.067*
          Degrees of Freedom                     8
          P-Value                           0.0001
          Scaling Correction Factor          1.206
            for MLR

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.094
          90 Percent C.I.                    0.062  0.128
          Probability RMSEA <= .05           0.014

CFI/TLI
          CFI                                0.947
          TLI                                0.900
```

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
FACTOR LOADINGS: CHANGE IN ACTUAL Y PER SD CHANGE IN FACTOR				
REC BY				
CIG	1.179	0.115	10.267	0.000
BEER	1.561	0.062	25.195	0.000
LIQUOR	1.359	0.066	20.667	0.000
DRUG BY				
WEED	1.037	0.121	8.582	0.000
INHALE	0.805	0.096	8.412	0.000
SPEED	0.857	0.096	8.930	0.000
CORRELATION BETWEEN KINDS OF DRUG USE				
REC WITH				
DRUG	0.613	0.051	12.110	0.000
EXPECTED ACTUAL Y WHEN FACTOR IS 0				
Intercepts				
CIG	2.126	0.116	18.257	0.000
BEER	2.726	0.093	29.221	0.000
LIQUOR	1.886	0.088	21.486	0.000
WEED	0.593	0.070	8.487	0.000
INHALE	0.431	0.056	7.670	0.000
SPEED	0.468	0.060	7.871	0.000
Residual Variances – AMOUNT OF ITEM VARIANCE THAT IS NOT THE FACTOR				
CIG	3.439	0.292	11.757	0.000
BEER	0.658	0.141	4.669	0.000
LIQUOR	0.894	0.108	8.282	0.000
WEED	0.636	0.175	3.628	0.000
INHALE	0.462	0.112	4.120	0.000
SPEED	0.510	0.118	4.332	0.000

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
RECAMT BY: **CORRELATION BETWEEN ACTUAL Y AND FACTOR**				
CIG	0.537	0.048	11.096	0.000
BEER	0.887	0.026	34.184	0.000
LIQUOR	0.821	0.026	31.516	0.000
DRUGAMT BY				
WEED	0.793	0.062	12.834	0.000
INHALE	0.764	0.053	14.322	0.000
SPEED	0.768	0.048	15.922	0.000
RECAMT WITH				
DRUGAMT	0.613	0.051	12.110	0.000

Here are two more alternatives: (2a) Poisson Factor Model and (2b) Negative Binomial/Poisson Factor Model

```
TITLE:  Model 2a: Poisson for all;
DATA:   FILE IS deviance.dat;
VARIABLE:   NAMES ARE        cig beer liquor weed inhale speed;
            USEVARIABLES ARE cig beer liquor weed inhale speed;
            MISSING ARE .;
! Tells Mplus which distribution each item response should get
COUNT ARE cig (p) beer (p) liquor (p) weed (p) inhale (p) speed (p);
ANALYSIS:   ESTIMATOR IS MLR;
OUTPUT:     RESIDUAL; ! STDYX ! standardized doesn't make any sense
MODEL:
! Factor loadings all estimated
   Rec  BY cig* beer* liquor*;
   Drug BY weed* inhale* speed*;
! Intercepts all estimated
   [cig* beer* liquor* weed* inhale* speed*];
! Factor mean=0 and variance=1 for identification, factors correlate
    [Rec@0 Drug@0]; Rec@1 Drug@1; Rec WITH Drug*;
```

```
Number of Free Parameters                       13
Loglikelihood
          H0 Value                      -2664.557
          H0 Scaling Correction Factor      0.8884
            for MLR
Information Criteria
          Akaike (AIC)                   5355.113
          Bayesian (BIC)                 5405.488
          Sample-Size Adjusted BIC       5364.246
            (n* = (n + 2) / 24)
```

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
FACTOR LOADINGS: CHANGE IN LOG(Y) PER SD CHANGE IN FACTOR				
REC BY				
CIG	0.879	0.065	13.562	0.000
BEER	0.538	0.042	12.892	0.000
LIQUOR	0.713	0.059	12.108	0.000
DRUG BY				
WEED	2.527	0.210	12.038	0.000
INHALE	2.476	0.259	9.565	0.000
SPEED	2.613	0.241	10.845	0.000
CORRELATION BETWEEN KINDS OF DRUG USE – MUCH LARGER NOW…				
REC WITH				
DRUG	0.952	0.032	29.753	0.000
EXPECTED LOG(Y) WHEN FACTOR IS 0				
Intercepts				
CIG	0.425	0.084	5.066	0.000
BEER	0.872	0.047	18.357	0.000
LIQUOR	0.413	0.069	5.994	0.000
WEED	-2.555	0.281	-9.107	0.000
INHALE	-2.809	0.328	-8.571	0.000
SPEED	-2.899	0.333	-8.711	0.000

NO RESIDUAL VARIANCES WERE ESTIMATED (ARE DETERMINED INSTEAD)

```
TITLE:  Model 2b: Poisson for all; Negative Binomial for CIG only
DATA:   FILE IS deviance.dat;
VARIABLE:   NAMES ARE        cig beer liquor weed inhale speed;
            USEVARIABLES ARE cig beer liquor weed inhale speed;
            MISSING ARE .;
! Tells Mplus which distribution each item response should get
COUNT ARE cig (nb) beer (p) liquor (p) weed (p) inhale (p) speed (p);
ANALYSIS:   ESTIMATOR IS MLR;
OUTPUT:     RESIDUAL;
MODEL:
! Factor loadings all estimated
   Rec  BY cig* beer* liquor*;
   Drug BY weed* inhale* speed*;
! Intercepts all estimated
   [cig* beer* liquor* weed* inhale* speed*];
! Factor mean=0 and variance=1 for identification, factors correlate
    [Rec@0 Drug@0]; Rec@1 Drug@1; Rec WITH Drug*;
```

NB was first estimated for all outcomes, but dispersion was only significant for cig (model not shown).

```
Number of Free Parameters                       14
Loglikelihood
          H0 Value                      -2657.992
          H0 Scaling Correction Factor      0.9035
            for MLR
Information Criteria
          Akaike (AIC)                   5343.984
          Bayesian (BIC)                 5398.233
          Sample-Size Adjusted BIC       5353.819
            (n* = (n + 2) / 24)
```

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
FACTOR LOADINGS: CHANGE IN LOG(Y) PER SD CHANGE IN FACTOR				
REC BY				
CIG	0.805	0.077	10.497	0.000
BEER	0.539	0.041	13.090	0.000
LIQUOR	0.719	0.058	12.326	0.000
DRUG BY				
WEED	2.578	0.207	12.432	0.000
INHALE	2.528	0.260	9.720	0.000
SPEED	2.663	0.239	11.123	0.000
CORRELATION BETWEEN KINDS OF DRUG USE – STILL MUCH LARGER NOW…				
REC WITH				
DRUG	0.989	0.032	31.109	0.000
EXPECTED LOG(Y) WHEN FACTOR IS 0				
Intercepts				
BEER	0.870	0.048	18.204	0.000
LIQUOR	0.410	0.070	5.866	0.000
WEED	-2.591	0.283	-9.141	0.000
INHALE	-2.848	0.336	-8.484	0.000
SPEED	-2.934	0.340	-8.639	0.000
CIG	0.482	0.082	5.888	0.000
Dispersion – ALPHA MULTIPLIER TO INCREASE VARIANCE RELATIVE TO MEAN				
CIG	0.229	0.088	2.589	0.010

Here is another alternative: (3) Zero-Inflated Negative Binomial or Poisson Factor Model

```
TITLE:   Model 3: Zero-Inflated Poisson and Negative Binomial (FOR CIG)
DATA:    FILE IS deviance.dat;

VARIABLE:    NAMES ARE        cig beer liquor weed inhale speed;
             USEVARIABLES ARE cig beer liquor weed inhale speed;
             MISSING ARE .;
! Tells Mplus which distribution each item response should get
COUNT ARE cig (nbi) beer (pi) liquor (pi) weed (pi) inhale (pi)
          speed (pi);

ANALYSIS:    ESTIMATOR IS MLR;
OUTPUT:      RESIDUAL;  ! STDYX ! standardized doesn't make any sense
MODEL:
! Factor loadings all estimated for AMOUNT if Structural Non-Zero
   RecAmt  BY cig* beer* liquor*;
   DrugAmt BY weed* inhale* speed*;
! Means all estimated for inflation variables (not predicted)
   [cig#1* beer#1* liquor#1* weed#1* inhale#1* speed#1*];
! Intercepts all estimated for AMOUNT factor
   [cig* beer* liquor* weed* inhale* speed*];
! Factor mean=0 and variance=1 for identification, factors correlate
    [RecAmt@0 DrugAmt@0]; RecAmt@1 DrugAmt@1; RecAmt WITH DrugAmt*;
```

```
MODEL FIT INFORMATION
Number of Free Parameters                       20

Loglikelihood
          H0 Value                      -2654.559
          H0 Scaling Correction Factor      0.9560
            for MLR

Information Criteria
          Akaike (AIC)                   5349.118
          Bayesian (BIC)                 5426.616
          Sample-Size Adjusted BIC       5363.167
            (n* = (n + 2) / 24)
```

ZIP AND ZINB Inflation factors: Although we could have fit factors for the zero-inflation part (the logit of being a structural zero is predicted by each factor), those models showed severe convergence problems, most likely because the probability of being a structural zero was so small in this particular sample. For instance, the largest probability is for the mean of CIG#1 (logit of -2.597 = prob of .07). So we proceed with a single factor for each item for now.

Further, the AIC and BIC are higher in this zero-inflated model, suggesting that most of the items do not need "structural zeros", or that including inflation parameters for the extra zeros does not help model fit.

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
FACTOR LOADINGS: CHANGE IN LOG(Y) PER SD CHANGE IN FACTOR APPLIES TO NON-STRUCTURAL ZEROS ONLY				
RECAMT BY				
CIG	0.787	0.075	10.538	0.000
BEER	0.542	0.041	13.094	0.000
LIQUOR	0.725	0.059	12.358	0.000
DRUGAMT BY				
WEED	2.618	0.219	11.946	0.000
INHALE	2.472	0.297	8.315	0.000
SPEED	2.707	0.245	11.041	0.000
CORRELATION BETWEEN KINDS OF DRUG USE IN NON-STRUCTURAL ZEROS				
REC WITH				
DRUG	0.983	0.034	28.730	0.000
EXPECTED LOGIT OF BEING A STRUCTURAL ZERO, -15 = "TOO SMALL TO FIND"				
Means				
RECAMT	0.000	0.000	999.000	999.000
DRUGAMT	0.000	0.000	999.000	999.000
BEER#1	-15.000	0.000	999.000	999.000
LIQUOR#1	-15.000	0.000	999.000	999.000
WEED#1	-2.835	0.848	-3.344	0.001
INHALE#1	-2.621	2.184	-1.200	0.230
SPEED#1	-4.123	5.086	-0.811	0.418
CIG#1	-2.597	0.598	-4.341	0.000
EXPECTED LOG(Y) WHEN FACTOR IS 0 IN NON-STRUCTURAL ZEROS				
Intercepts				
BEER	0.869	0.048	18.183	0.000
LIQUOR	0.407	0.070	5.820	0.000
WEED	-2.565	0.305	-8.414	0.000
INHALE	-2.715	0.457	-5.934	0.000
SPEED	-2.967	0.375	-7.905	0.000
CIG	0.555	0.094	5.892	0.000
Variances				
RECAMT	1.000	0.000	999.000	999.000
DRUGAMT	1.000	0.000	999.000	999.000
Dispersion – ALPHA MULTIPLIER TO INCREASE VARIANCE RELATIVE TO MEAN				
CIG	0.101	0.093	1.091	0.275

Here is another alternative: (4) Two-Part Factor Model (here, with a log transformation of the continuous part)

```
TITLE:  Model 4: Two-Part Distributions  (0 vs. log something)
DATA:   FILE IS deviance.dat;

DATA TWOPART: ! Instructs Mplus to cut up each into 0/log of amount
    NAMES ARE       cig  beer  liquor  weed  inhale  speed;
    BINARY ARE     Bcig Bbeer Bliquor Bweed Binhale Bspeed;
    CONTINUOUS ARE Ccig Cbeer Cliquor Cweed Cinhale Cspeed;
    CUTPOINT IS 0;
    TRANSFORM IS LOG;  ! Could also use "NONE" for no transformation

VARIABLE:   NAMES ARE         cig  beer  liquor  weed  inhale  speed;
            USEVARIABLES ARE Bcig Bbeer Bliquor Bweed Binhale Bspeed
                             Ccig Cbeer Cliquor Cweed Cinhale Cspeed;
            CATEGORICAL ARE  Bcig Bbeer Bliquor Bweed Binhale Bspeed;
            MISSING ARE .;

ANALYSIS:   ESTIMATOR IS MLR;
OUTPUT:     RESIDUAL STDYX TECH4; ! TECH4 gives factor correlation matrix
MODEL:
! Factor loadings all estimated for 2 separate factors (0/amount)
   RecNot0  BY Bcig* Bbeer* Bliquor*;
   DrugNot0 BY Bweed* Binhale* Bspeed*;

   RecAmt   BY Ccig* Cbeer* Cliquor*;
   DrugAmt  BY Cweed* Cinhale* Cspeed*;

! Thresholds all estimated for binary part
    [Bcig$1* Bbeer$1* Bliquor$1* Bweed$1* Binhale$1* Bspeed$1*];
! Intercepts all estimated for continuous part
    [Ccig* Cbeer* Cliquor* Cweed* Cinhale* Cspeed*];

! Residual variances all estimated for continuous part
    Ccig* Cbeer* Cliquor* Cweed* Cinhale* Cspeed*;

! Factor mean=0 and factor variance=1 for identification
   [RecNot0@0 RecAmt@0 DrugNot0@0 DrugAmt@0];
    RecNot0@1 RecAmt@1 DrugNot0@1 DrugAmt@1;

! All factors correlated by default
    RecNot0  WITH RecAmt* DrugNot0* DrugAmt*;
    RecAmt   WITH DrugNot0* DrugAmt*;
    DrugNot0 WITH DrugAmt*;
```

```
Number of Free Parameters                       36
Loglikelihood
          H0 Value                       -1727.508
          H0 Scaling Correction Factor       0.9497
            for MLR

Information Criteria
          Akaike (AIC)                    3527.016
          Bayesian (BIC)                  3666.513
          Sample-Size Adjusted BIC        3552.305
            (n* = (n + 2) / 24)
```

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
FACTOR LOADINGS FOR "NOT 0": CHANGE IN LOGIT(Y=SOMETHING INSTEAD OF 0) PER SD CHANGE IN FACTOR (APPLIES TO ALL 0 VALUES)				
RECNOT0 BY				
BCIG	1.350	0.210	6.415	0.000
BBEER	3.614	0.882	4.099	0.000
BLIQUOR	3.079	0.694	4.439	0.000
DRUGNOT0 BY				
BWEED	4.415	1.075	4.106	0.000
BINHALE	2.712	0.474	5.716	0.000
BSPEED	4.313	0.976	4.419	0.000
FACTOR LOADINGS FOR "AMT": CHANGE IN LOG(AMOUNT Y) PER SD CHANGE IN FACTOR (APPLIES TO ALL NON-ZEROS)				
RECAMT BY				
CCIG	0.385	0.052	7.365	0.000
CBEER	0.565	0.028	20.241	0.000
CLIQUOR	0.500	0.031	16.175	0.000
DRUGAMT BY				
CWEED	0.916	0.111	8.293	0.000
CINHALE	0.434	0.113	3.846	0.000
CSPEED	0.554	0.107	5.162	0.000
Thresholds – EXPECTED LOGIT(Y=0) FOR 0 VS SOMETHING WHEN FACTOR IS 0				
BCIG$1	-1.078	0.165	-6.523	0.000
BBEER$1	-4.545	0.921	-4.934	0.000
BLIQUOR$1	-2.012	0.420	-4.787	0.000
BWEED$1	3.215	0.733	4.386	0.000
BINHALE$1	2.636	0.403	6.542	0.000
BSPEED$1	3.643	0.768	4.745	0.000
Intercepts - EXPECTED LOG(AMOUNT Y) IF NON-ZERO WHEN FACTOR IS 0				
CCIG	0.789	0.049	16.256	0.000
CBEER	0.911	0.038	23.994	0.000
CLIQUOR	0.676	0.038	17.737	0.000
CWEED	-0.272	0.164	-1.657	0.097
CINHALE	0.116	0.139	0.840	0.401
CSPEED	-0.018	0.157	-0.116	0.908
Residual Variances – AMOUNT OF ITEM VARIANCE "NOT THE FACTOR"				
CCIG	0.413	0.036	11.384	0.000
CBEER	0.066	0.020	3.317	0.001
CLIQUOR	0.131	0.020	6.653	0.000
CWEED	0.074	0.084	0.882	0.378
CINHALE	0.260	0.060	4.345	0.000
CSPEED	0.252	0.054	4.656	0.000

TECH4 OUTPUT:

ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	RECNOT0	DRUGNOT0	RECAMT	DRUGAMT
RECNOT0	1.000			
DRUGNOT0	0.922	1.000		
RECAMT	0.659	0.707	1.000	
DRUGAMT	0.766	0.834	0.757	1.000

Unfortunately, absolute model fit statistics are not given for the non-normal models, and relative fit statistics (AIC and BIC) are not comparable across the normal, Poisson/NB/ZIP/ZINB, and two-part families. What we can do is examine the predicted item response across factor levels for each alternative model and see what seems reasonable. Here are the plots (made in excel) for cigarettes and for weed, with scale ends noted with the horizontal lines.

As we can see, the Negative Binomial (for cigarettes) and Poisson (for weed) dramatically overshoot the possible item response at higher levels of the factor. The same is true for the zero-inflated versions of these models. But the normal model extends below the possible scale for both items.

The two-part models seems to have the best fit – results are shown for models with either a log transformation (model 4) or no transformation of the "how much" part (those model results were not shown). They both "shut off" towards the 0 end of the scale as needed (because "0 vs. something" is covered by the other part not plotted), but the predicted "how much" doesn't have the dramatic upswing at higher factor levels like the other models. Plus they have a more straightforward interpretation than the inflated models: Here, this is the relationship between answering "how much if not 0" and the factor.

Not shown is the model for the other factor that predicts the probability of "0 vs. something" instead. Finally, we could have had the binary "0 vs. something" items and the "how much if not 0" items load onto the same factor (but fit got worse for that in these data).

STDYX Standardization – STANDARDIZED LOADINGS are available

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
RECNOT0 BY – CORRELATION BETWEEN LOGIT(SOMETHING) AND FACTOR				
BCIG	0.597	0.060	9.970	0.000
BBEER	0.894	0.044	20.369	0.000
BLIQUOR	0.862	0.050	17.227	0.000
DRUGNOT0 BY – CORRELATION BETWEEN LOGIT(SOMETHING) AND FACTOR				
BWEED	0.925	0.033	28.436	0.000
BINHALE	0.831	0.045	18.500	0.000
BSPEED	0.922	0.031	29.402	0.000
RECAMT BY – CORRELATION BETWEEN LOG(AMOUNT) AND FACTOR				
CCIG	0.514	0.066	7.820	0.000
CBEER	0.910	0.029	31.146	0.000
CLIQUOR	0.810	0.035	23.391	0.000
DRUGAMT BY – CORRELATION BETWEEN LOG(AMOUNT) AND FACTOR				
CWEED	0.959	0.050	19.117	0.000
CINHALE	0.649	0.133	4.888	0.000
CSPEED	0.741	0.093	7.937	0.000