

Psychometrics Using Stata

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Humor involves two risks

- May not be funny
- May offend

Disclaimer

The use of clinical depression and its diagnosis in this talk is not meant to make light of this very serious condition. The examples use a depression index and the examples are silly (and fictitious!). This is not meant to imply that depression is silly.

- Given the current state of the world economy, the staff at StataCorp began to worry about the emotional well-being of our users.
- In early 2010, the marketing department hired a consultant to design a depression index to assess our users.
- The index was pilot-tested on StataCorp employees to determine its psychometric properties.
- The index was then sent to 1000 randomly selected Stata users.
- **(All data are simulated and this is completely fictitious!)**

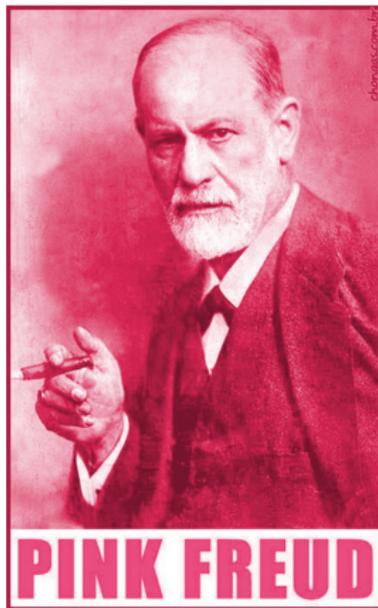
An Inventory for Measuring Depression

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M. MENDELSON, M.D.
J. MOCK, M.D.
AND
J. ERBAUGH, M.D.
PHILADELPHIA

The symptom-attitude categories are as follows:

- a. Mood
- b. Pessimism
- c. Sense of Failure
- d. Lack of Satisfaction
- e. Guilty Feeling
- f. Sense of Punishment
- g. Self-Hate
- h. Self Accusations
- i. Self Punitive Wishes
- j. Crying Spells
- k. Irritability
- l. Social Withdrawal
- m. Indecisiveness
- n. Body Image
- o. Work Inhibition
- p. Sleep Disturbance
- q. Fatigability
- r. Loss of Appetite
- s. Weight Loss
- t. Somatic Pre-occupation
- u. Loss of Libido

My statistical software makes me...



- Q1 ...feel sad
- Q2 ...feel pessimistic about the future
- Q3 ...feel like a failure
- Q4 ...feel dissatisfied
- Q5 ...feel guilty or unworthy
- Q6 ...feel that I am being punished
- Q7 ...feel disappointed in myself
- Q8 ...feel am very critical of myself
- Q9 ...feel like harming myself
- Q10 ...feel like crying more than usual
- Q11 ...become annoyed or irritated easily
- Q12 ...lose interest in other people
- Q13 ...have trouble making decisions
- Q14 ...feel unattractive
- Q15 ...feel like not working
- Q16 ...have trouble sleeping
- Q17 ...feel tired or fatigued
- Q18 ...makes my appetite lower than usual
- Q19 ...concerned about my health
- Q20 ...experience decreased libido

My statistical software makes me....

Question 1: ...feel sad.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

- Administered to all StataCorp employees
- Explore the psychometric properties of the index
 - Descriptive Statistics
 - Item Response Characteristics
 - Reliability
 - Validity
 - Dimensionality and Exploratory Factor Analysis

```
. describe id qu1_t1-qu20_t1
```

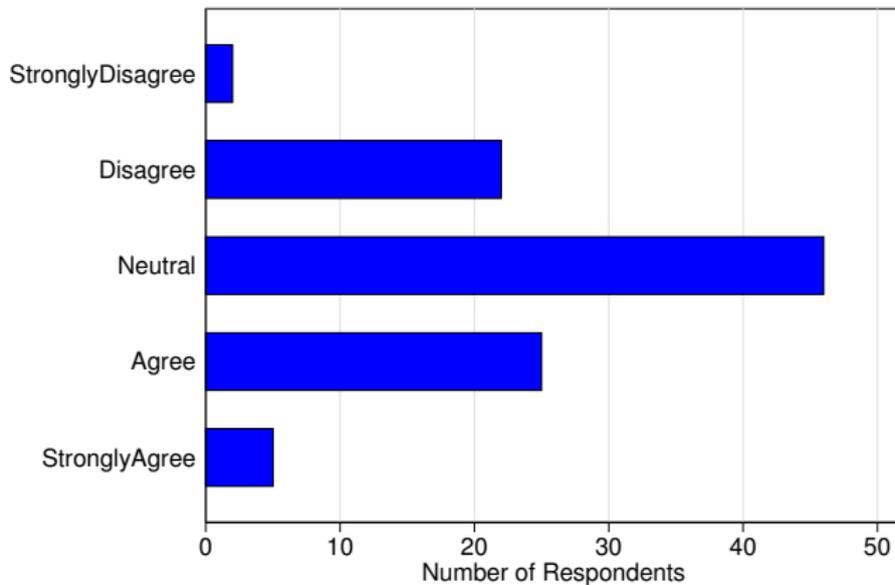
variable name	storage type	display format	value label	variable label
id	byte	%9.0g		Identification Number
qu1_t1	byte	%16.0g	qu1_t1	...feel sad
qu2_t1	byte	%16.0g	qu2_t1	...feel pessimistic about the future
qu3_t1	byte	%16.0g	qu3_t1	...feel like a failure
qu4_t1	byte	%16.0g	qu4_t1	...feel dissatisfied
qu5_t1	byte	%16.0g	qu5_t1	...feel guilty or unworthy
qu6_t1	byte	%16.0g	qu6_t1	...feel that I am being punished
qu7_t1	byte	%16.0g	qu7_t1	...feel disappointed in myself
qu8_t1	byte	%16.0g	qu8_t1	...feel am very critical of myself
qu9_t1	byte	%16.0g	qu9_t1	...feel like harming myself
qu10_t1	byte	%16.0g	qu10_t1	...feel like crying more than usual
qu11_t1	byte	%16.0g	qu11_t1	...become annoyed or irritated easily
qu12_t1	byte	%16.0g	qu12_t1	...have lost interest in other people
qu13_t1	byte	%16.0g	qu13_t1	...have trouble making decisions
qu14_t1	byte	%16.0g	qu14_t1	...feel unattractive
qu15_t1	byte	%16.0g	qu15_t1	...feel like not working
qu16_t1	byte	%16.0g	qu16_t1	...have trouble sleeping
qu17_t1	byte	%16.0g	qu17_t1	...feel tired or fatigued
qu18_t1	byte	%16.0g	qu18_t1	...makes my appetite lower than usual
qu19_t1	byte	%16.0g	qu19_t1	...concerned about my health
qu20_t1	byte	%16.0g	qu20_t1	...experience decreased libido

```
. summ qu1_t1-qu20_t1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
qu1_t1	100	3.09	.8656754	1	5
qu2_t1	100	2.7	.9265991	1	5
qu3_t1	100	3.1	.8819171	1	5
qu4_t1	100	3.07	.8905225	1	5
qu5_t1	100	3.04	.9419516	1	5
qu6_t1	100	3.1	.8932971	1	5
qu7_t1	100	3.09	.8052229	1	5
qu8_t1	100	3.11	.8633386	1	5
qu9_t1	100	3.12	.832181	1	5
qu10_t1	100	3.13	.8836906	1	5
qu11_t1	100	3.07	.8072275	1	5
qu12_t1	100	3.14	.7656779	1	5
qu13_t1	100	3.16	.7877855	1	5
qu14_t1	100	2.49	.8586459	1	5
qu15_t1	100	2.89	.8274947	1	5
qu16_t1	100	3.05	.8087276	1	5
qu17_t1	100	3.04	.7774603	1	5
qu18_t1	100	3.11	.7371115	1	5
qu19_t1	100	3.11	.8515583	1	5
qu20_t1	100	2.29	.8909761	1	5

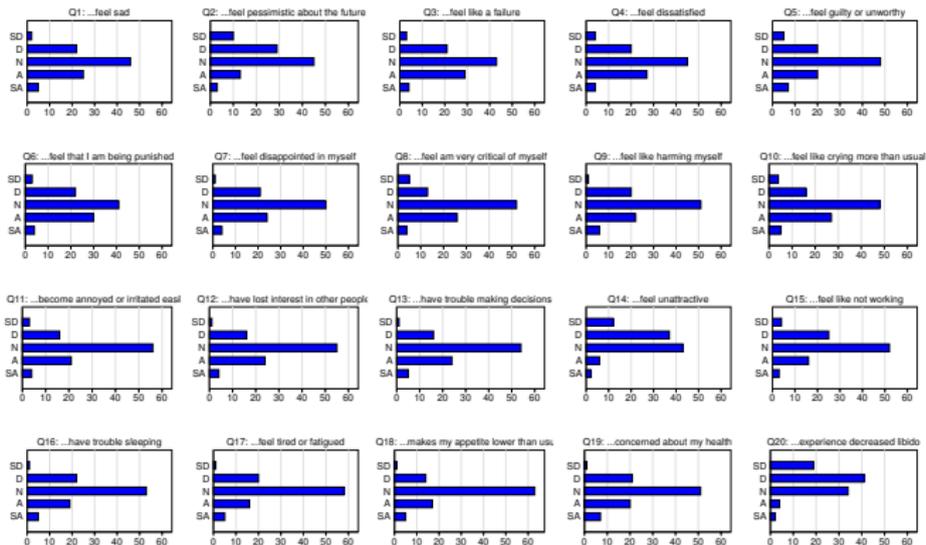
```
. tab qu1_t1
```

...feel sad	Freq.	Percent	Cum.
StronglyDisagree	2	2.00	2.00
Disagree	22	22.00	24.00
Neutral	46	46.00	70.00
Agree	25	25.00	95.00
StronglyAgree	5	5.00	100.00
Total	100	100.00	

Q1: My statistical software makes me...
...feel sad

My statistical software makes me...

SD="Stongly Disagree", D="Disagree", N="Neutral", A="Agree", SA="Strongly Agree"



...how did I make that graph?!?

```
// CREATE A TEMPORARY VARIABLE CALLED "one" FOR USE IN THE GRAPHS BELOW
gen one = 1

// GRAPH EACH OF QUESTIONS 1-20 FOR THE COMBO GRAPH
forvalues i = 1(1)20 {
  local GraphTitle : variable label qu`i'_t1
  graph hbar (count) one, over(qu`i'_t1, relabel(1 SD 2 D 3 N 4 A 5 SA)) ///
  bar(1, fcolor(blue) lcolor(black)) ///
  title("Q`i': 'GraphTitle'", size(medsmall) color(black)) ///
  ytitle(" ") ylabel(0(10)60) ymtick(0(10)60) ///
  scheme(sicolor) ///
  name(qu`i'_t1, replace)
}

// COMBINE THE GRAPHS OF EACH QUESTION INTO A SINGLE GRAPH
graph combine qui_t1 qu2_t1 qu3_t1 qu4_t1 qu5_t1 qu6_t1 qu7_t1 qu8_t1 qu9_t1 qui0_t1 ///
qui1_t1 qui2_t1 qui3_t1 qui4_t1 qui5_t1 qui6_t1 qui7_t1 qui8_t1 qui9_t1 qu20_t1, ///
rows(4) cols(5) ///
title("My statistical software makes me...") ///
subtitle('`SD="Stongly Disagree", D="Disagree", N="Neutral", A="Agree", SA="Strongly Agree"', ///
size(vsmall) color(black)) ///
btitle(Number of Respondents) ///
scheme(sicolor)
graph export .\graphs\Figure1.png, as(png) replace
graph export .\graphs\Figure1.ps, as(ps) mag(160) logo(off) orientation(landscape) replace

// REMOVE THE "one" VARIABLE
drop one
```

The Pilot Study

- Descriptive Statistics
- **Item Response Characteristics**
- Reliability
- Validity
- Dimensionality and Exploratory Factor Analysis

Item Response Theory

- What are the characteristics of each item?
- How do they relate to the overall test score?
- Are some items more predictive than others?

The Latent Trait: Depression

- The Idea
 - We **observe** the responses to the 20 questions
 - We would like to use these responses to **infer** something about a **latent trait** which we will call depression.
- The Mechanics
 - Dichotomize each question as Yes/No based on their ordinal response
 - Sum the dichotomized responses to create a total score
 - The total score is our **latent variable** (θ)

My statistical software makes me....

Question 1: ...feel sad.

**These responses suggest
no depression and
are coded as 0 (No)**

**These responses suggest
the presence of depression
and are coded as 1 (Yes)**



Strongly Disagree



Disagree



Neutral



Agree



Strongly Agree

Create A Dichotomous Variable For Each Question

```
// CREATE A DICHOTOMOUS VARIABLE FOR EACH QUESTION (1,2,3 = 0 & 4,5 = 1)
forvalues i = 1(1)20 {
  recode qu'i'_t1 (1/3=0 "No") (4/5=1 "Yes"), gen(qu'i'_t1_bin)
  local TempLabel : variable label qu'i'_t1
  label var qu'i'_t1_bin "'TempLabel' (binary)"
}
```

```
. tab qu1_t1 qu1_t1_bin
```

...feel sad	...feel sad (binary)		Total
	No	Yes	
StronglyDisagree	2	0	2
Disagree	22	0	22
Neutral	46	0	46
Agree	0	25	25
StronglyAgree	0	5	5
Total	70	30	100

Create The Latent Variable (theta)

```
// SUM THE 20 BINARY QUESTIONS
egen TotalBinary = rowtotal(qu1_t1_bin - qu20_t1_bin)
label var TotalBinary "Sum of all 20 binary question scores"
```

Responses for Participant #1

...feel sad (binary) =	0
...feel pessimistic about the future (binary) =	0
...feel like a failure (binary) =	0
...feel dissatisfied (binary) =	0
...feel guilty or unworthy (binary) =	0
...feel that I am being punished (binary) =	0
...feel disappointed in myself (binary) =	0
...feel am very critical of myself (binary) =	0
...feel like harming myself (binary) =	0
...feel like crying more than usual (binary) =	0
...become annoyed or irritated easily (binary) =	0
...have lost interest in other people (binary) =	0
...have trouble making decisions (binary) =	1
...feel unattractive (binary) =	0
...feel like not working (binary) =	0
...have trouble sleeping (binary) =	1
...feel tired or fatigued (binary) =	0
...makes my appetite lower than usual (binary) =	0
...concerned about my health (binary) =	1
...experience decreased libido (binary) =	0
<hr/>	
Sum of all 20 binary question scores =	3

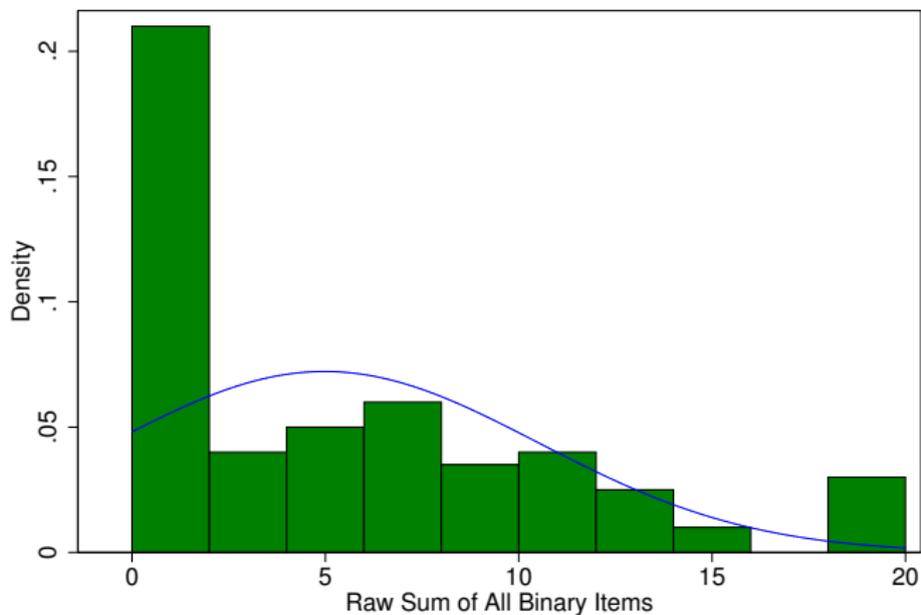
Create The Latent Variable (theta)

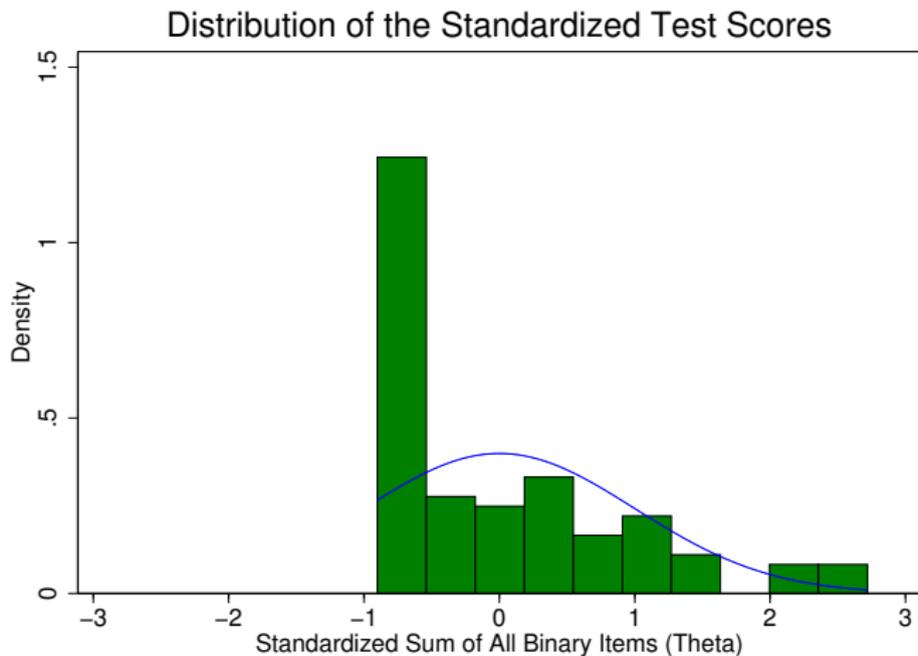
```
// SUM THE 20 BINARY QUESTIONS
egen TotalBinary = rowtotal(qu1_t1_bin - qu20_t1_bin)
label var TotalBinary "Sum of all 20 binary question scores"
```

Responses for Participant #1

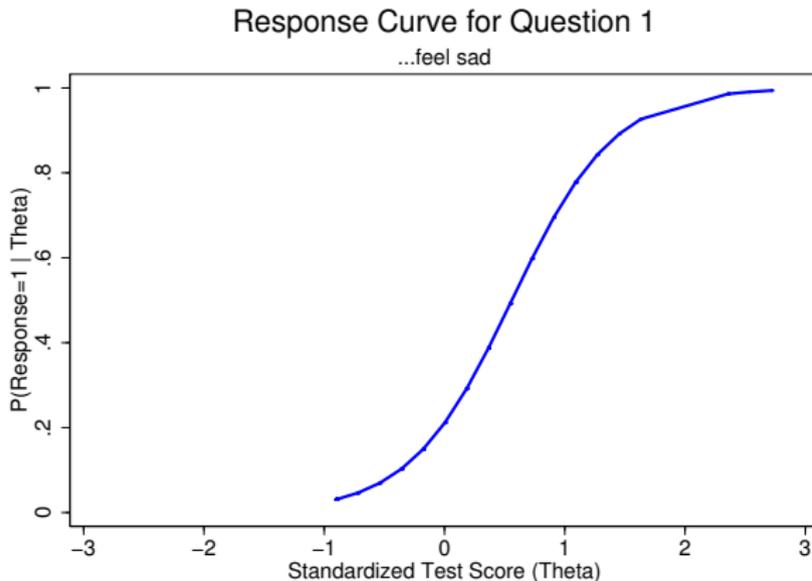
...feel sad (binary) =	0
...feel pessimistic about the future (binary) =	0
...feel like a failure (binary) =	0
...feel dissatisfied (binary) =	0
...feel guilty or unworthy (binary) =	0
...feel that I am being punished (binary) =	0
...feel disappointed in myself (binary) =	0
...feel am very critical of myself (binary) =	0
...feel like harming myself (binary) =	0
...feel like crying more than usual (binary) =	0
...become annoyed or irritated easily (binary) =	0
...have lost interest in other people (binary) =	0
...have trouble making decisions (binary) =	1
...feel unattractive (binary) =	0
...feel like not working (binary) =	0
...have trouble sleeping (binary) =	1
...feel tired or fatigued (binary) =	0
...makes my appetite lower than usual (binary) =	0
...concerned about my health (binary) =	1
...experience decreased libido (binary) =	0
<hr/>	
Sum of all 20 binary question scores =	3

Distribution of the Total Test Scores



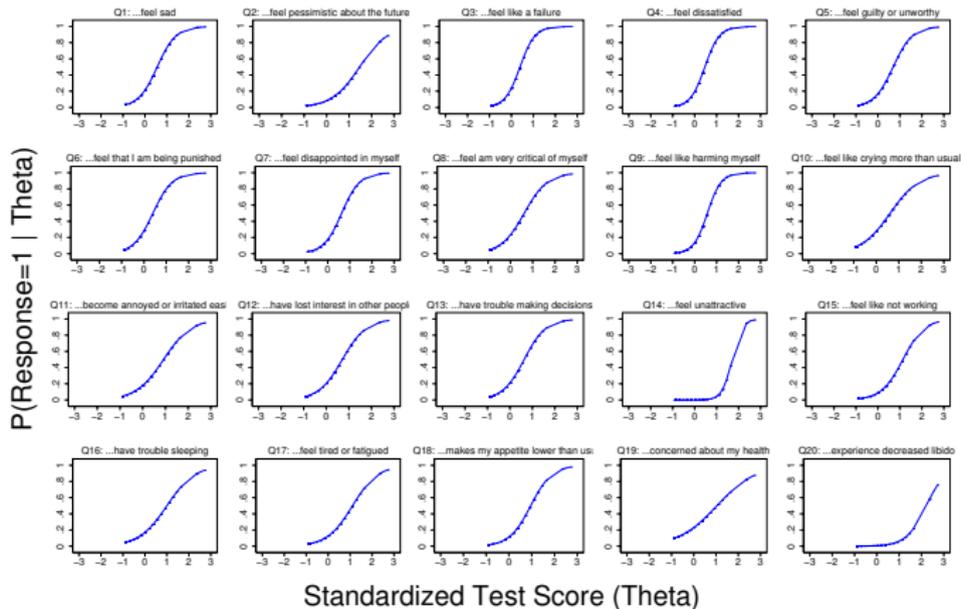


We can then fit a logistic regression model for each binary outcome using the latent variable (standardized test score) as a continuous predictor variable:



Response Curves

My statistical software makes me...



The Rasch Model

- Since each individual responds to all 20 questions, we could conceptualize this as a multilevel model.
- Could fit a mixed-effects logistic regression model with a coefficient for each question.
- The simplest form of this kind of model is known as The Rasch Model.

Reshape the Data From Wide to Long Format

```
list id qu1_t1_bin-qu10_t1_bin if id==1, nolabel
```

	id	qu1_t1-n	qu2_t1-n	qu3_t1-n	qu4_t1-n	qu5_t1-n	qu6_t1-n	qu7_t1-n	qu8_t1-n	qu9_t1-n	qu10_t-n
1.	1	0	0	0	0	0	0	0	0	0	0

```
. reshape long qu@_t1_bin, i(id) j(question)
. list id question qu_t1_bin if id==1, nolab
```

	id	question	qu_t1-n
1.	1	1	0
2.	1	2	0
3.	1	3	0
4.	1	4	0
5.	1	5	0
6.	1	6	0
7.	1	7	0
8.	1	8	0
9.	1	9	0
10.	1	10	0
11.	1	11	0
12.	1	12	0
13.	1	13	1
14.	1	14	0
15.	1	15	0
16.	1	16	1
17.	1	17	0
18.	1	18	0
19.	1	19	1
20.	1	20	0

Create Indicator Variables for Each Question

```
forvalues num =1/20{
  gen Delta`num' = -(question==`num')
}

. list id qu_t1_bin question Delta1-Delta10 if id==1, nodisplay noobs nolabel
```

id	qu_t1_n	question	Delta1	Delta2	Delta3	Delta4	Delta5	Delta6	Delta7	Delta8	Delta9	Delta10
1	0	1	-1	0	0	0	0	0	0	0	0	0
1	0	2	0	-1	0	0	0	0	0	0	0	0
1	0	3	0	0	-1	0	0	0	0	0	0	0
1	0	4	0	0	0	-1	0	0	0	0	0	0
1	0	5	0	0	0	0	-1	0	0	0	0	0
1	0	6	0	0	0	0	0	-1	0	0	0	0
1	0	7	0	0	0	0	0	0	-1	0	0	0
1	0	8	0	0	0	0	0	0	0	-1	0	0
1	0	9	0	0	0	0	0	0	0	0	-1	0
1	0	10	0	0	0	0	0	0	0	0	0	-1
1	0	11	0	0	0	0	0	0	0	0	0	0
1	0	12	0	0	0	0	0	0	0	0	0	0
1	1	13	0	0	0	0	0	0	0	0	0	0
1	0	14	0	0	0	0	0	0	0	0	0	0
1	0	15	0	0	0	0	0	0	0	0	0	0
1	1	16	0	0	0	0	0	0	0	0	0	0
1	0	17	0	0	0	0	0	0	0	0	0	0
1	0	18	0	0	0	0	0	0	0	0	0	0
1	1	19	0	0	0	0	0	0	0	0	0	0
1	0	20	0	0	0	0	0	0	0	0	0	0

Fit the Rasch Model with -xtmelogit-

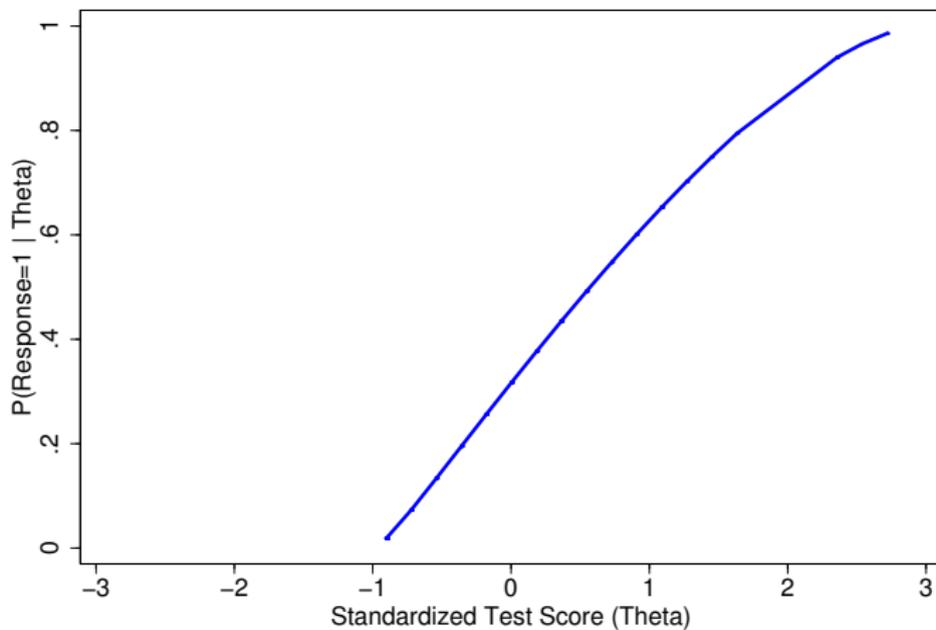
```
xtmelogit qu_t1_bin Delta1-Delta20, noconstant || id:, covariance(identity) nolog
Mixed-effects logistic regression      Number of obs   =    2000
Group variable: id                   Number of groups =    100
                                      Obs per group: min =     20
                                      avg           =    20.0
                                      max           =     20
Integration points = 7                Wald chi2(20)   =   117.44
Log likelihood = -765.69974           Prob > chi2     =    0.0000
```

qu_t1_bin	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Delta1	1.805149	.4280238	4.22	0.000	.9662381	2.644061
Delta2	3.171066	.4758495	6.66	0.000	2.238418	4.103714
Delta3	1.555716	.4238328	3.67	0.000	.7250189	2.386413
Delta4	1.72126	.4264998	4.04	0.000	.885336	2.557185
Delta5	2.062939	.4335186	4.76	0.000	1.213258	2.91262
Delta6	1.47382	.4226682	3.49	0.000	.6454058	2.302235
Delta7	1.975836	.4315174	4.58	0.000	1.130078	2.821595
Delta8	1.805149	.4280238	4.22	0.000	.9662382	2.644061
Delta9	1.975836	.4315174	4.58	0.000	1.130077	2.821595
Delta10	1.638157	.4251067	3.85	0.000	.8049635	2.471351
Delta11	2.241544	.4381266	5.12	0.000	1.382832	3.100256
Delta12	1.975836	.4315174	4.58	0.000	1.130077	2.821595
Delta13	1.889959	.4296914	4.40	0.000	1.04778	2.732139
Delta14	4.444528	.5805036	7.66	0.000	3.306762	5.582295
Delta15	2.829789	.4589574	6.17	0.000	1.930249	3.729329
Delta16	2.333454	.4407813	5.29	0.000	1.469538	3.197369
Delta17	2.622612	.4505291	5.82	0.000	1.739592	3.505633
Delta18	2.523699	.4469441	5.65	0.000	1.647705	3.399694
Delta19	2.062939	.4335186	4.76	0.000	1.213258	2.91262
Delta20	4.946324	.6431941	7.69	0.000	3.685686	6.206961

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Identity				
sd(_cons)	2.777908	.3097652	2.232545	3.456492

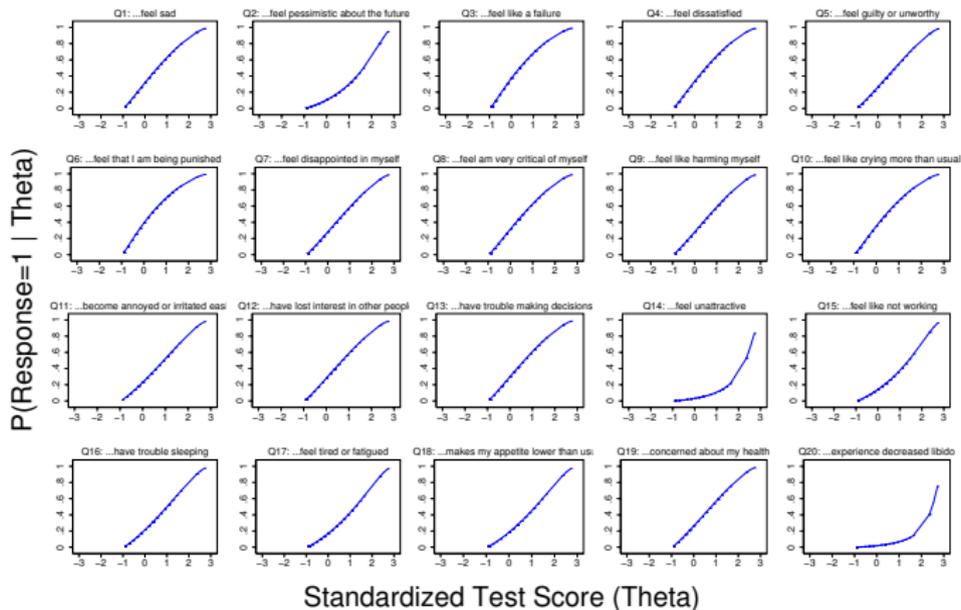
LR test vs. logistic regression: chibar2(01) = 643.87 Prob>=chibar2 = 0.0000

Item Characteristic Curve for Question 1



Item Characteristic Curves

My statistical software makes me...



Extensions of the Rasch Model

- The Rasch Model
 - One parameter logistic or 1PL model
 - Parameter quantifies the difficulty of the item
- Two parameter logistic (2PL) model
 - A second parameter accounts for guessing
- Three parameter logistic (3PL) model
 - A third parameter accounts for the ability of the question to discriminate between people with high and low values of the latent trait

User Written IRT Commands

- -raschtest- by Jean-Benoit Hardouin
 - Fixed and random effects Rasch Models
 - Stata Journal (2007) Volume 7, Number 1, pp. 22-44
- Nonparametric IRT models by Jean-Benoit Hardouin, Angèlique Bonnaud-Antignac and Vèronique Sèbille
 - Trace lines, Mokken scales, Loevinger coefficients, Guttman errors
 - Stata Journal (2011) Volume 11, Number 1, pp. 30-51
- -openirt- by Tristan Zajonc
 - Fits 1PL, 2PL and 3PL models
 - Maximum Likelihood (ML)
 - Bayesian Expected a Posterior (EAP)
 - Plausible Values (Multiple Imputation)

The Pilot Study

- Descriptive Statistics
- Item Response Characteristics
- **Reliability**
- Validity
- Dimensionality and Exploratory Factor Analysis

Reliability

We would like for our depression index to be **reliable** in the sense that repeated administration of the instrument would yield similar results.

- Test-Retest Reliability
 - Could be quantified using canonical correlation
 - Quantified by the intraclass correlation coefficient (ICC)
- Split-half reliability
 - Quantified by the Spearman-Brown prophecy formula
- Internal Consistency
 - Quantified by Cronbach's alpha

Test-Retest Reliability

- Perhaps the most obvious way to assess the reliability of a psychometric instrument is to administer it twice to the same group of people and examine the degree of agreement
- Could quantify reliability as the canonical correlation between the two sets of repeated questions
- Could consider repeated responses within a participant as longitudinal data and compute the intraclass correlation coefficient (ICC) based on a mixed-effects linear model

Canonical Correlation

- Each participant was given the Stata Depression Index twice with a 6-month interval between tests.
- The canonical correlation between the two sets of questions was then estimated:

```
canon (qu1_t1-qu20_t1) (qu1_t2-qu20_t2), lc(1)
```

Canonical correlations:

```
0.9907 0.7895 0.7468 0.6918 0.6207 0.5908 0.5407 0.4998 0.4755 0.4131
```

Tests of significance of all canonical correlations

	Statistic	df1	df2	F	Prob>F
Wilks' lambda	.000128345	400	914.629	2.0138	0.0000 a
Pillai's trace	4.82041	400	1580	1.2544	0.0016 a
Lawley-Hotelling trace	60.0375	400	1162	8.7204	0.0000 a
Roy's largest root	53.2379	20	79	210.2896	0.0000 u

e = exact, a = approximate, u = upper bound on F

Intraclass Correlation Coefficient (ICC)

- But it would be more convenient to simply use Stata's built-in `-icc-` command:

```
. icc qui_t id time
```

```
Intraclass correlations
Two-way random-effects model
Absolute agreement
```

```
Random effects: id           Number of targets =    100
Random effects: time        Number of raters   =     2
```

qui_t	ICC	[95% Conf. Interval]	
Individual	.4587313	.2890881	.6004393
Average	.6289456	.4485157	.7503431

```
F test that ICC=0.00: F(99.0, 99.0) = 2.69      Prob > F = 0.000
```

```
Note: ICCs estimate correlations between individual measurements
and between average measurements made on the same target.
```

Intraclass Correlation Coefficient (ICC)

- We could even loop through all 20 questions quickly:

```
forvalues i = 1(1)20 {  
    quietly icc qu'i'_t id time  
    disp as text "The ICC for Question 'i' = " _col(30) as result %5.4f r(icc_i)  
}
```

```
The ICC for Question 1 =    0.4587  
The ICC for Question 2 =    0.4367  
The ICC for Question 3 =    0.5210  
The ICC for Question 4 =    0.5450  
The ICC for Question 5 =    0.5847  
The ICC for Question 6 =    0.5299  
The ICC for Question 7 =    0.4914  
The ICC for Question 8 =    0.4329  
The ICC for Question 9 =    0.5044  
The ICC for Question 10 =   0.4634  
The ICC for Question 11 =   0.4848  
The ICC for Question 12 =   0.3827  
The ICC for Question 13 =   0.4706  
The ICC for Question 14 =   0.3806  
The ICC for Question 15 =   0.3376  
The ICC for Question 16 =   0.4766  
The ICC for Question 17 =   0.4859  
The ICC for Question 18 =   0.3879  
The ICC for Question 19 =   0.4704  
The ICC for Question 20 =   0.2491
```

Split-Half Reliability

- If we could assume that we have two equivalent forms of the instrument, we could simply calculate the correlation between those two "halves" of the test.
- For example, we could examine the correlation between the **even numbered questions** and the **odd numbered questions**.

```
egen TotalEven = rowtotal(qu2_t1 qu4_t1 qu6_t1 qu8_t1 qu10_t1 qu12_t1 qu14_t1 qu16_t1 qu18_t1 qu20_t1)
```

```
egen TotalOdd = rowtotal(qui_t1 qu3_t1 qu5_t1 qu7_t1 qu9_t1 qu11_t1 qu13_t1 qu15_t1 qu17_t1 qu19_t1)
```

```
corr TotalEven TotalOdd  
(obs=100)
```

	TotalE-n	TotalOdd
TotalEven	1.0000	
TotalOdd	0.9586	1.0000

Split-Half Reliability

Because we have correlated half of our test with the other half, it is common to use the Spearman-Brown Prophecy Formula to assess split-half reliability:

$$R_{sb} = \frac{2r_{sh}}{(1 + r_{sh})}$$

```
local sbpf = 2*r(rho) / (1+r(rho))  
disp "The Spearman-Brown Prophecy Reliability Estimate = " as result \%.4f `sbpf'  
The Spearman-Brown Prophecy Reliability Estimate = 0.9788
```

Split-Half Reliability

- Unfortunately, there is nothing sacred about odd and even numbered questions.
- If the questions were numbered differently, the estimate of the Spearman-Brown Prophecy Formula would change.
- It would be nice to get the same estimate regardless of the way the questions are numbered.

Cronbach's Alpha

Cronbach's Alpha is a function of the average covariance (or correlation) among all possible combinations of the variables.

```
alpha qu1_t1-qu20_t1
```

```
Test scale = mean(unstandardized items)
```

```
Average interitem covariance:      .3402467  
Number of items in the scale:      20  
Scale reliability coefficient:      0.9476
```

The Pilot Study

- Descriptive Statistics
- Item Response Characteristics
- Reliability
- **Validity**
- Dimensionality and Exploratory Factor Analysis

Validity

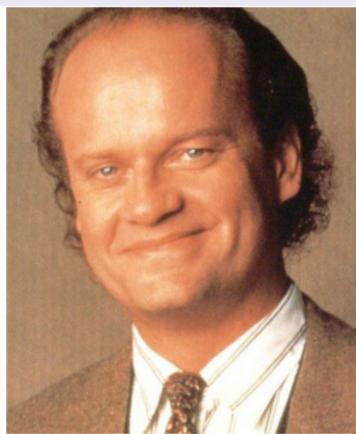
- While there are different kinds of validity, essentially we would like to be able to say that our instrument measures what we think we are measuring.
- One way to assess the validity of our instrument is to examine the correlation between our index and other known indices.
- For example, we might compare the results of the Stata Depression Index with the ratings of trained psychiatric professionals.

Validity

- To assess the validity of the Stata Depression Index, we wanted to compare our results to the rating of a psychiatrist.
- However, since psychiatrists are much like economists (no explanation necessary), we decided to hire two psychiatrists and compare their inter-rater reliability before comparing their ratings to our instrument.

Inter-Rater Reliability

Dr. Hannibal Lector and Dr. Frasier Crane were hired to interview each employee at StataCorp and rate them in terms of none, mild, moderate or severe depression.



Cohen's Kappa Statistic

We can tabulate the diagnoses of Dr Lector and Dr Crane and the first thing we notice is that their diagnoses tend to fall on the main diagonal of the table.

```
. tab DrLector DrCrane
```

Dr Lector's Diagnosis	Dr Crane's Diagnosis				Total
	None	Mild	Moderate	Severe	
None	2	5	0	0	7
Mild	20	45	0	0	65
Moderate	0	8	14	0	22
Severe	0	0	3	2	5
Total	22	58	17	2	99

The second thing we notice is that our sample size dropped from $n=100$ to $n=99$.

Cohen's Kappa Statistic

It appears that one of Dr. Lector's ratings is missing. This matter is still under investigation.

```
. tab DrLector DrCrane, missing
```

Dr Lector's Diagnosis	Dr Crane's Diagnosis				Total
	None	Mild	Moderate	Severe	
None	2	5	0	0	7
Mild	20	45	0	0	65
Moderate	0	8	14	0	22
Severe	0	0	3	2	5
.	1	0	0	0	1
Total	23	58	17	2	100

Cohen's Kappa Statistic

Because two raters can agree with each simply due to chance, we compute Cohen's Kappa statistic to assess the chance-corrected measure of inter-rater agreement:

```
. kap DrLector DrCrane
```

Agreement	Expected Agreement	Kappa	Std. Err.	Z	Prob>Z
63.64%	43.95%	0.3512	0.0659	5.33	0.0000

A Kappa of 0.3512 is generally considered poor agreement among raters. We are disappointed but not surprised.

Cohen's Kappa Statistic

However, we notice that very few ratings fall on the off-diagonals of the table. So we down-weight those cells in the table and compute a weighted kappa statistic:

```
. kapwgt MyWeight 1 \ .8 1 \ 0 0 1 \ 0 0 .8 1          // (define matrix)
. kapwgt MyWeight
1.0000
0.8000 1.0000
0.0000 0.0000 1.0000
0.0000 0.0000 0.8000 1.0000
. kap DrLector DrCrane, wgt(MyWeight)
Ratings weighted by:
1.0000 0.8000 0.0000 0.0000
0.8000 1.0000 0.0000 0.0000
0.0000 0.0000 1.0000 0.8000
0.0000 0.0000 0.8000 1.0000
```

Agreement	Expected Agreement	Kappa	Std. Err.	Z	Prob>Z
86.26%	59.99%	0.6566	0.0842	7.80	0.0000

Combine ratings into a "Diagnosis" variable

We elected to combine the ratings of Dr Lector and Dr Crane by creating new variable called "diagnosis":

```
. tab DrLector DrCrane
```

Dr Lector's Diagnosis	Dr Crane's Diagnosis				Total
	None	Mild	Moderate	Severe	
None	2	5	0	0	7
Mild	20	45	0	0	65
Moderate	0	8	14	0	22
Severe	0	0	3	2	5
Total	22	58	17	2	99

```
. gen diagnosis = 0
```

```
. replace diagnosis = 1 if DrLector>=3 | DrCrane>=3  
(28 real changes made)
```

Association Between Our Index and Diagnosis

Next we wanted to examine the association between the Stata Depression Index and the diagnosis based on Drs. Lector and Crane.

```
. tab qu1_t1 diagnosis, all exact
```

...feel sad	Diagnosis based on Drs Lector and Crane		Total
	NotDepres	Depressed	
StronglyDisagree	2	0	2
Disagree	22	0	22
Neutral	37	9	46
Agree	11	14	25
StronglyAgree	0	5	5
Total	72	28	100

```

Pearson chi2(4) = 33.5361 Pr = 0.000
likelihood-ratio chi2(4) = 38.8171 Pr = 0.000
Cramer's V = 0.5791
gamma = 0.8705 ASE = 0.057
Kendall's tau-b = 0.5104 ASE = 0.060
Fisher's exact = 0.000

```

Point-Biserial Correlation

- When one variable is continuous and the other is binary, a popular measure of association frequently used in psychometrics is the point-biserial correlation coefficient.
- This is easily calculated in one of two ways:
 - Student's t-test
 - Linear Regression

Point-Biserial Correlation Using Student's t-test

```
. ttest qui_t1, by(diagnosis)
```

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
NotDepre	72	2.791667	.0860758	.7303771	2.620036	2.963297
Depresse	28	3.857143	.1332766	.7052336	3.583682	4.130604
combined	100	3.09	.0865675	.8656754	2.918231	3.261769
diff		-1.065476	.1611445		-1.385262	-.7456902

```
diff = mean(NotDepre) - mean(Depresse)          t = -6.6119
Ho: diff = 0                                     degrees of freedom = 98
```

```
Ha: diff < 0          Ha: diff != 0          Ha: diff > 0
Pr(T < t) = 0.0000    Pr(|T| > |t|) = 0.0000    Pr(T > t) = 1.0000
```

```
. local rsquared = (r(t)^2) / ((r(t)^2)+r(df_t))
```

```
. disp as text "The Point-Biserial Correlation based on the t-test = " as result %5.4f sqrt('rsquared')
```

```
The Point-Biserial Correlation based on the t-test = 0.5554
```

Point-Biserial Correlation Using Linear Regression

```
. regress qui_t1 diagnosis
```

Source	SS	df	MS			
Model	22.8864286	1	22.8864286	Number of obs =	100	
Residual	51.3035714	98	.523505831	F(1, 98) =	43.72	
				Prob > F =	0.0000	
				R-squared =	0.3085	
				Adj R-squared =	0.3014	
Total	74.19	99	.749393939	Root MSE =	.72354	
qui_t1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
diagnosis	1.065476	.1611445	6.61	0.000	.7456902	1.385262
_cons	2.791667	.0852697	32.74	0.000	2.622452	2.960882

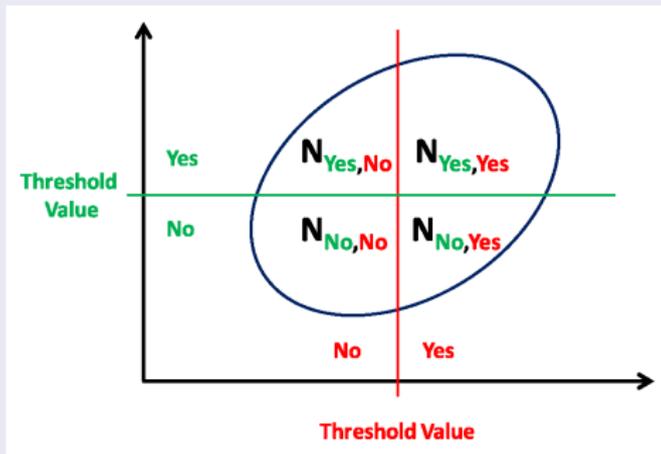
```
. local pointbs = sqrt(e(r2))
```

```
. disp as text "The Point-Biserial Correlation coefficient = " as result %5.4f `pointbs'
```

The Point-Biserial Correlation coefficient = 0.5554

Tetrachoric Correlation

When two dichotomous variables are conceptualized as having an underlying bivariate normal distribution, the association between them can be estimated using the tetrachoric correlation coefficient.



First, Dichotomize the Questions

My statistical software makes me....

Question 1: ...feel sad.

**These responses suggest
no depression and
are coded as 0 (No)**

**These responses suggest
the presence of depression
and are coded as 1 (Yes)**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

Tetrachoric Correlation Using -tetrachoric-

```
. tab qu1_t1_bin diagnosis
```

Question 1, Time 1 Coded as Binary	Diagnosis based on Drs Lector and Crane		Total
	NotDepres	Depressed	
NotDepressed	61	9	70
Depressed	11	19	30
Total	72	28	100

```
. tetrachoric qu1_t1_bin diagnosis
```

```
Number of obs =      100
Tetrachoric rho =      0.7415
Std error =          0.0971
```

```
Test of Ho: qu1_t1_bin and diagnosis are independent
2-sided exact P =      0.0000
```

Tetrachoric Correlation Using -biprobit-

```
. biprobit qu1_t1_bin diagnosis
```

```
Bivariate probit regression      Number of obs   =      100
Log likelihood = -107.6575      Wald chi2(0)    =      .
                                Prob > chi2       =      .
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
qu1_t1_bin _cons	-.5244005	.1317996	-3.98	0.000	-.782723	-.266078
diagnosis _cons	-.5828415	.1333832	-4.37	0.000	-.8442677	-.3214153
/athrho	.9538723	.2157823	4.42	0.000	.5309467	1.376798
rho	.7415311	.0971304			.4861044	.8802322

```
Likelihood-ratio test of rho=0:      chi2(1) = 25.4485      Prob > chi2 = 0.0000
```

Correlation Between Each Item and Diagnosis

Question	Pearson	Biserial	Tetrachoric
Question 1	0.5554	0.5554	0.7415
Question 2	0.5894	0.5894	0.8568
Question 3	0.5635	0.5635	0.8286
Question 4	0.6043	0.6043	0.8936
Question 5	0.5912	0.5912	0.8009
Question 6	0.5563	0.5563	0.7684
Question 7	0.5971	0.5971	0.8260
Question 8	0.4905	0.4905	0.7415
Question 9	0.5552	0.5552	0.8260
Question 10	0.4904	0.4904	0.7029
Question 11	0.4448	0.4448	0.6910
Question 12	0.4993	0.4993	0.7310
Question 13	0.5262	0.5262	0.7611
Question 14	0.5287	0.5287	1.0000
Question 15	0.5161	0.5161	0.7451
Question 16	0.4871	0.4871	0.5935
Question 17	0.4860	0.4860	0.6809
Question 18	0.4834	0.4834	0.7128
Question 19	0.4710	0.4710	0.5133
Question 20	0.5497	0.5497	1.0000

The Pilot Study

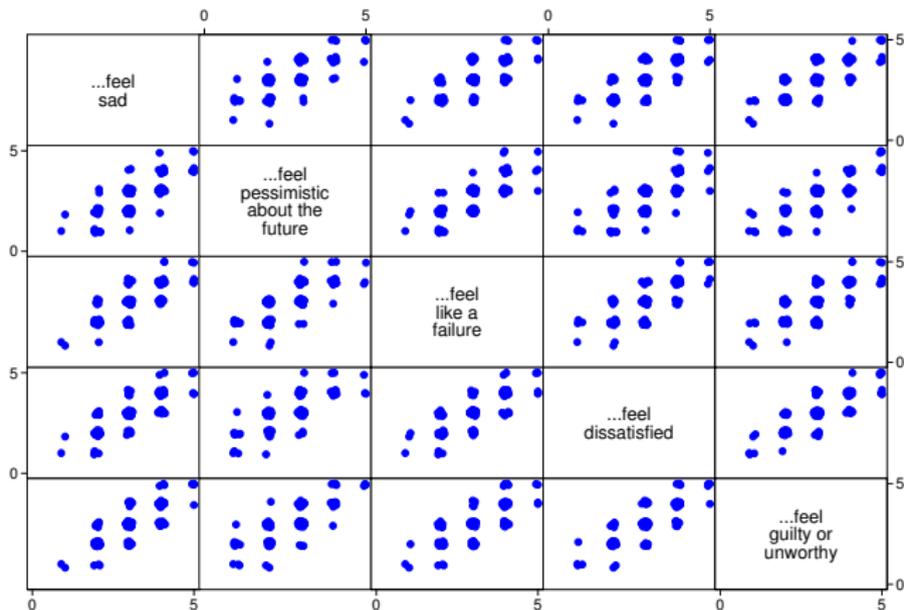
- Descriptive Statistics
- Item Response Characteristics
- Reliability
- Validity
- **Dimensionality and Exploratory Factor Analysis**

Dimensionality and Exploratory Factor Analysis

- The Cronbach's Alpha estimated earlier suggests a high degree of correlation among the questions
- It might be useful to look for patterns among these correlations
- There might be groups of questions that measure some underlying latent attribute
- We could treat the questions as ordinal or as continuous variables

Since all correlation coefficients measure the degree of linear relationship between variables, it might be wise to visually inspect scatterplots of the variables before calculating various correlation matrices...

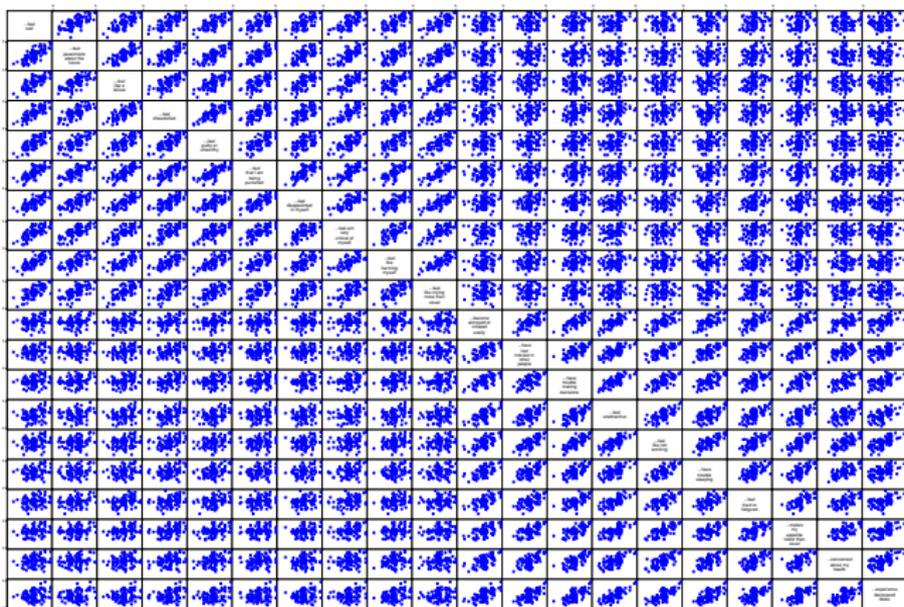
My statistical software makes me...



My statistical software makes me...



My statistical software makes me...



Kendall's Tau-a Rank Correlation Matrix

```
. quietly ktau qu1_t1-qu20_t1, stats(taua)
. matrix list r(Tau_a), format(%4.2f) nonames noheader

0.68
0.47 0.69
0.47 0.49 0.69
0.49 0.48 0.50 0.69
0.48 0.48 0.45 0.49 0.69
0.48 0.50 0.51 0.52 0.49 0.70
0.45 0.44 0.48 0.44 0.41 0.49 0.65
0.45 0.46 0.48 0.48 0.43 0.48 0.43 0.65
0.49 0.45 0.48 0.47 0.47 0.49 0.45 0.46 0.65
0.48 0.46 0.47 0.46 0.49 0.51 0.43 0.47 0.48 0.67
0.15 0.11 0.17 0.20 0.17 0.13 0.14 0.12 0.16 0.10 0.62
0.11 0.05 0.16 0.19 0.17 0.08 0.16 0.13 0.17 0.07 0.41 0.62
0.12 0.10 0.16 0.22 0.17 0.11 0.14 0.13 0.16 0.08 0.46 0.42 0.63
0.17 0.10 0.17 0.23 0.19 0.17 0.17 0.17 0.19 0.12 0.43 0.42 0.45 0.67
0.12 0.07 0.15 0.20 0.15 0.12 0.16 0.11 0.16 0.09 0.43 0.46 0.45 0.46 0.65
0.15 0.11 0.16 0.17 0.22 0.15 0.19 0.14 0.17 0.11 0.40 0.41 0.39 0.37 0.45 0.64
0.11 0.11 0.20 0.18 0.17 0.11 0.16 0.13 0.14 0.08 0.38 0.37 0.41 0.42 0.41 0.36 0.60
0.13 0.08 0.14 0.19 0.17 0.08 0.13 0.12 0.14 0.07 0.38 0.40 0.39 0.37 0.42 0.38 0.37 0.56
0.07 0.03 0.11 0.15 0.14 0.13 0.14 0.08 0.12 0.05 0.37 0.37 0.42 0.38 0.44 0.40 0.37 0.38 0.66
0.11 0.08 0.12 0.18 0.15 0.14 0.14 0.14 0.19 0.08 0.39 0.39 0.45 0.46 0.45 0.41 0.37 0.37 0.42 0.69
```


Simple Covariance Matrix

```

. quietly corr q1_t1-qu20_t1, cov means
. matrix list r(C), format(%4.2f) nonames noheader
0.75
0.60 0.86
0.58 0.62 0.78
0.59 0.62 0.61 0.79
0.63 0.68 0.60 0.65 0.89
0.59 0.65 0.61 0.62 0.62 0.80
0.51 0.54 0.54 0.51 0.52 0.56 0.65
0.54 0.60 0.57 0.59 0.58 0.58 0.51 0.75
0.54 0.55 0.54 0.56 0.59 0.55 0.48 0.53 0.69
0.58 0.59 0.59 0.58 0.65 0.61 0.51 0.58 0.56 0.78
0.16 0.15 0.19 0.24 0.23 0.16 0.17 0.16 0.18 0.11 0.65
0.13 0.08 0.18 0.22 0.23 0.08 0.17 0.16 0.19 0.07 0.45 0.59
0.14 0.14 0.18 0.26 0.22 0.14 0.17 0.15 0.18 0.09 0.49 0.45 0.62
0.22 0.16 0.22 0.28 0.28 0.21 0.22 0.22 0.23 0.16 0.51 0.49 0.53 0.74
0.14 0.12 0.18 0.24 0.23 0.12 0.18 0.15 0.19 0.12 0.49 0.50 0.50 0.55 0.68
0.18 0.16 0.19 0.23 0.29 0.18 0.22 0.20 0.19 0.13 0.46 0.46 0.45 0.47 0.52 0.65
0.14 0.18 0.22 0.22 0.24 0.14 0.19 0.18 0.17 0.10 0.43 0.41 0.44 0.50 0.47 0.41 0.60
0.15 0.13 0.15 0.22 0.24 0.09 0.15 0.15 0.15 0.09 0.42 0.42 0.43 0.43 0.48 0.43 0.41 0.54
0.11 0.08 0.14 0.20 0.21 0.16 0.17 0.14 0.14 0.07 0.47 0.45 0.49 0.49 0.53 0.50 0.44 0.44 0.73
0.16 0.15 0.16 0.23 0.23 0.18 0.20 0.19 0.24 0.09 0.47 0.46 0.52 0.57 0.56 0.50 0.46 0.45 0.54 0.79

```


Test of Univariate Normality For Each Question

```
. sktest qu1_t1-qu20_t1
```

Variable	Obs	Skewness/Kurtosis tests for Normality				joint Prob>chi2
		Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)		
qu1_t1	100	0.6399	0.8266	0.27	0.8751	
qu2_t1	100	0.6902	0.8652	0.19	0.9104	
qu3_t1	100	0.6441	0.6682	0.40	0.8179	
qu4_t1	100	0.5535	0.9643	0.36	0.8366	
qu5_t1	100	0.7737	0.7742	0.16	0.9208	
qu6_t1	100	0.6302	0.4610	0.79	0.6738	
qu7_t1	100	0.4207	0.9779	0.66	0.7189	
qu8_t1	100	0.1897	0.2654	3.04	0.2186	
qu9_t1	100	0.1973	0.7911	1.77	0.4117	
qu10_t1	100	0.4698	0.5995	0.81	0.6659	
qu11_t1	100	0.9611	0.1937	1.73	0.4205	
qu12_t1	100	0.4726	0.4254	1.18	0.5554	
qu13_t1	100	0.3664	0.4896	1.32	0.5162	
qu14_t1	100	0.3362	0.3805	1.74	0.4199	
qu15_t1	100	0.6689	0.3861	0.95	0.6210	
qu16_t1	100	0.1174	0.5234	2.94	0.2303	
qu17_t1	100	0.0599	0.1748	5.27	0.0717	
qu18_t1	100	0.0688	0.0573	6.47	0.0393	
qu19_t1	100	0.1073	0.7823	2.74	0.2539	
qu20_t1	100	0.0691	0.3650	4.24	0.1199	

Tests of Multivariate Normality and Sphericity

```
. mvtest normality qu1_t1-qu20_t1, all
```

```
Test for multivariate normality
```

Mardia mSkewness	=	92.7382	chi2(1540)	=	1596.522	Prob>chi2	=	0.1543
Mardia mKurtosis	=	437.7267	chi2(1)	=	0.147	Prob>chi2	=	0.7016
Henze-Zirkler	=	1.006083	chi2(1)	=	121.119	Prob>chi2	=	0.0000
Doornik-Hansen			chi2(40)	=	33.101	Prob>chi2	=	0.7719

```
. mvtest covariances qu1_t1-qu20_t1, spherical
```

```
Test that covariance matrix is spherical
```

Adjusted LR	chi2(209)	=	2035.12
Prob >	chi2	=	0.0000

Remove Correlations < 0.20

```

1.00
0.75 1.00
0.76 0.75 1.00
0.76 0.75 0.78 1.00
0.78 0.78 0.72 0.78 1.00
0.76 0.78 0.77 0.78 0.74 1.00
0.73 0.73 0.76 0.71 0.69 0.77 1.00
0.72 0.75 0.75 0.77 0.71 0.76 0.73 1.00
0.76 0.72 0.74 0.75 0.75 0.74 0.72 0.74 1.00
0.76 0.73 0.76 0.73 0.78 0.78 0.72 0.76 0.76 1.00
0.22 0.20 0.27 0.33 0.30 0.23 0.25 0.24 0.27 . 1.00
. . 0.26 0.33 0.31 . 0.27 0.24 0.29 . 0.74 1.00
0.20 . 0.25 0.37 0.29 . 0.26 0.23 0.28 . 0.78 0.75 1.00
0.29 . 0.29 0.36 0.35 0.28 0.32 0.29 0.33 0.21 0.74 0.74 0.78 1.00
. . 0.25 0.33 0.29 . 0.27 0.22 0.27 . 0.74 0.79 0.77 0.77 1.00
0.25 0.21 0.26 0.32 0.38 0.24 0.33 0.28 0.28 . 0.71 0.74 0.70 0.68 0.78 1.00
0.20 0.26 0.32 0.32 0.33 . 0.30 0.26 0.26 . 0.69 0.69 0.72 0.74 0.73 0.66 1.00
0.24 . 0.23 0.34 0.34 . 0.26 0.23 0.24 . 0.70 0.74 0.73 0.68 0.78 0.72 0.71 1.00
. . 0.27 0.26 0.21 0.25 . . . 0.68 0.69 0.73 0.67 0.75 0.73 0.66 0.70 1.00
0.20 . 0.21 0.29 0.27 0.23 0.27 0.25 0.32 . 0.66 0.68 0.74 0.75 0.76 0.69 0.67 0.69 0.72 1.00

```

Remove Correlations < 0.30

```

1.00
0.75 1.00
0.76 0.75 1.00
0.76 0.75 0.78 1.00
0.78 0.78 0.72 0.78 1.00
0.76 0.78 0.77 0.78 0.74 1.00
0.73 0.73 0.76 0.71 0.69 0.77 1.00
0.72 0.75 0.75 0.77 0.71 0.76 0.73 1.00
0.76 0.72 0.74 0.75 0.75 0.74 0.72 0.74 1.00
0.76 0.73 0.76 0.73 0.78 0.78 0.72 0.76 0.76 1.00
. . . 0.33 0.30 . . . 1.00
. . . 0.33 0.31 . . . 0.74 1.00
. . . 0.37 . . . 0.78 0.75 1.00
. . . 0.36 0.35 . 0.32 . 0.33 . 0.74 0.74 0.78 1.00
. . . 0.33 . . . 0.74 0.79 0.77 0.77 1.00
. . . 0.32 0.38 . 0.33 . . . 0.71 0.74 0.70 0.68 0.78 1.00
. . 0.32 0.32 0.33 . 0.30 . . . 0.69 0.69 0.72 0.74 0.73 0.66 1.00
. . . 0.34 0.34 . . . . . . 0.70 0.74 0.73 0.68 0.78 0.72 0.71 1.00
. . . . . . . . . . . . 0.68 0.69 0.73 0.67 0.75 0.73 0.66 0.70 1.00
. . . . . . . . . . . 0.32 . 0.66 0.68 0.74 0.75 0.76 0.69 0.67 0.69 0.72 1.00

```

Remove Correlations < 0.40

```

1.00
0.75 1.00
0.76 0.75 1.00
0.76 0.75 0.78 1.00
0.78 0.78 0.72 0.78 1.00
0.76 0.78 0.77 0.78 0.74 1.00
0.73 0.73 0.76 0.71 0.69 0.77 1.00
0.72 0.75 0.75 0.77 0.71 0.76 0.73 1.00
0.76 0.72 0.74 0.75 0.75 0.74 0.72 0.74 1.00
0.76 0.73 0.76 0.73 0.78 0.78 0.72 0.76 0.76 1.00
. . . . . 1.00
. . . . . 0.74 1.00
. . . . . 0.78 0.75 1.00
. . . . . 0.74 0.74 0.78 1.00
. . . . . 0.74 0.79 0.77 0.77 1.00
. . . . . 0.71 0.74 0.70 0.68 0.78 1.00
. . . . . 0.69 0.69 0.72 0.74 0.73 0.66 1.00
. . . . . 0.70 0.74 0.73 0.68 0.78 0.72 0.71 1.00
. . . . . 0.68 0.69 0.73 0.67 0.75 0.73 0.66 0.70 1.00
. . . . . 0.66 0.68 0.74 0.75 0.76 0.69 0.67 0.69 0.72 1.00

```

Remove Correlations < 0.50

```

1.00
0.75 1.00
0.76 0.75 1.00
0.76 0.75 0.78 1.00
0.78 0.78 0.72 0.78 1.00
0.76 0.78 0.77 0.78 0.74 1.00
0.73 0.73 0.76 0.71 0.69 0.77 1.00
0.72 0.75 0.75 0.77 0.71 0.76 0.73 1.00
0.76 0.72 0.74 0.75 0.75 0.74 0.72 0.74 1.00
0.76 0.73 0.76 0.73 0.78 0.78 0.72 0.76 0.76 1.00
. . . . . 1.00
. . . . . 0.74 1.00
. . . . . 0.78 0.75 1.00
. . . . . 0.74 0.74 0.78 1.00
. . . . . 0.74 0.79 0.77 0.77 1.00
. . . . . 0.71 0.74 0.70 0.68 0.78 1.00
. . . . . 0.69 0.69 0.72 0.74 0.73 0.66 1.00
. . . . . 0.70 0.74 0.73 0.68 0.78 0.72 0.71 1.00
. . . . . 0.68 0.69 0.73 0.67 0.75 0.73 0.66 0.70 1.00
. . . . . 0.66 0.68 0.74 0.75 0.76 0.69 0.67 0.69 0.72 1.00

```

Two Related Groups of Questions

My statistical software makes me...

**Questions 1-10 appear
to be highly correlated
with each other**

**Questions 11-20 appear
to be highly correlated
with each other**

- Q1 ...feel sad
- Q2 ...feel pessimistic about the future
- Q3 ...feel like a failure
- Q4 ...feel dissatisfied
- Q5 ...feel guilty or unworthy
- Q6 ...feel that I am being punished
- Q7 ...feel disappointed in myself
- Q8 ...feel am very critical of myself
- Q9 ...feel like harming myself
- Q10 ...feel like crying more than usual
- Q11 ...become annoyed or irritated easily
- Q12 ...lose interest in other people
- Q13 ...have trouble making decisions
- Q14 ...feel unattractive
- Q15 ...feel like not working
- Q16 ...have trouble sleeping
- Q17 ...feel tired or fatigued
- Q18 ...makes my appetite lower than usual
- Q19 ...concerned about my health
- Q20 ...experience decreased libido

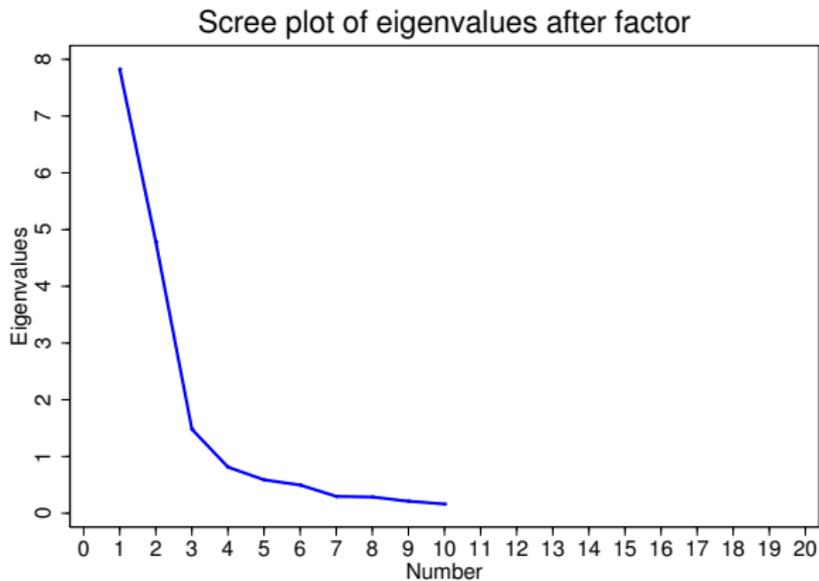
Exploratory Factor Analysis Retaining The First 10 Factors

```
. factor qui_t1-qu20_t1, factors(10) ml nolog
(obs=100)
```

```
Factor analysis/correlation
Method: maximum likelihood
Rotation: (unrotated)
Log likelihood = -9.110648
Beware: solution is a Heywood case
        (i.e., invalid or boundary values of uniqueness)
Number of obs   =   100
Retained factors =   10
Number of params =  155
Schwarz's BIC   =  732.023
(Akaike's) AIC  =  328.221
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.82891	3.04542	0.4618	0.4618
Factor2	4.78349	3.97049	0.2822	0.7439
Factor3	0.81301	0.52641	0.0480	0.7919
Factor4	0.28660	-1.19510	0.0169	0.8088
Factor5	1.48170	0.89269	0.0874	0.8962
Factor6	0.58901	0.09171	0.0347	0.9309
Factor7	0.49730	0.19950	0.0293	0.9603
Factor8	0.29781	0.08585	0.0176	0.9778
Factor9	0.21196	0.04826	0.0125	0.9903
Factor10	0.16370	.	0.0097	1.0000

```
LR test: independent vs. saturated: chi2(190) = 2028.01 Prob>chi2 = 0.0000
LR test: 10 factors vs. saturated:  chi2(35) = 15.64 Prob>chi2 = 0.9981
(tests formally not valid because a Heywood case was encountered)
```



Exploratory Factor Analysis Retaining Different Numbers of Factors

```
. estat factors
```

Factor analysis with different numbers of factors (maximum likelihood)

#factors	loglik	df_m	df_r	AIC	BIC
1	-522.9283	20	170	1085.857	1137.96
2	-77.7302	39	151	233.4604	335.062
3	-61.32184	57	133	236.6437	385.1384
4	-51.61906	74	116	251.2381	444.0207
5	-42.08895	90	100	264.1779	498.6432
6	-33.42972	105	85	276.8594	550.4023
7	-26.04991	119	71	290.0998	600.1151
8	-19.45802	132	58	302.916	646.7985
9	-14.17239	144	46	316.3448	691.4893
10	-9.110648	155	35	328.2213	732.0227
11	-5.691323	165	25	341.3826	771.2357
12	-3.663927	174	16	355.3279	808.6275
13	-1.444548	182	8	366.8891	841.0301
14	-.3439963	189	1	378.688	871.0652

How Many Factors?

- The "Guttman" (1954) or "K1" rule that only factors with eigenvalues greater than one should be retained suggests that there are 3 factors (factors 1,2 and 5)
- The "bend in the scree plot" rule also suggests that there are three factors
- The model with the smallest AIC and BIC is the model with two factors.

Exploratory Factor Analysis Retaining Two Factors

```

Factor analysis/correlation
Method: maximum likelihood
Rotation: (unrotated)
Log likelihood = -77.7302
Number of obs = 100
Retained factors = 2
Number of params = 39
Schwarz's BIC = 335.062
(Akaike's) AIC = 233.46

```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	9.78438	4.79069	0.6621	0.6621
Factor2	4.99369	.	0.3379	1.0000

```

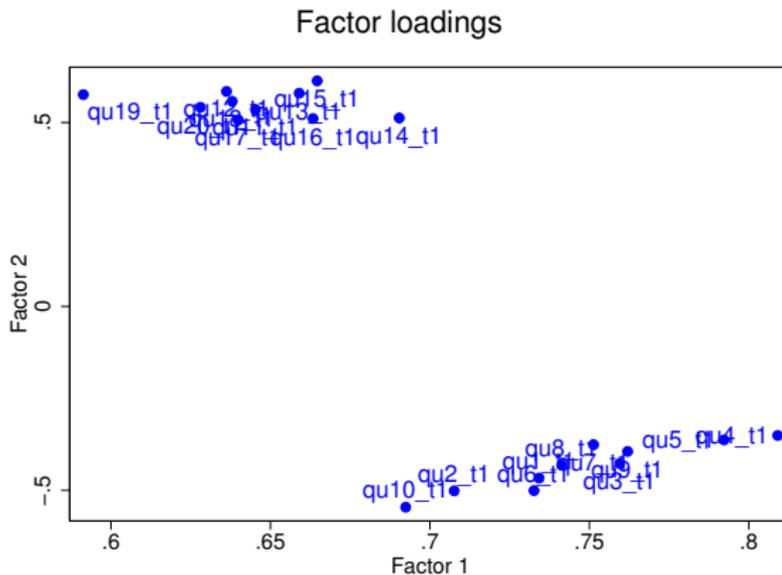
LR test: independent vs. saturated: chi2(190) = 2028.01 Prob>chi2 = 0.0000
LR test: 2 factors vs. saturated: chi2(151) = 141.73 Prob>chi2 = 0.6937

```

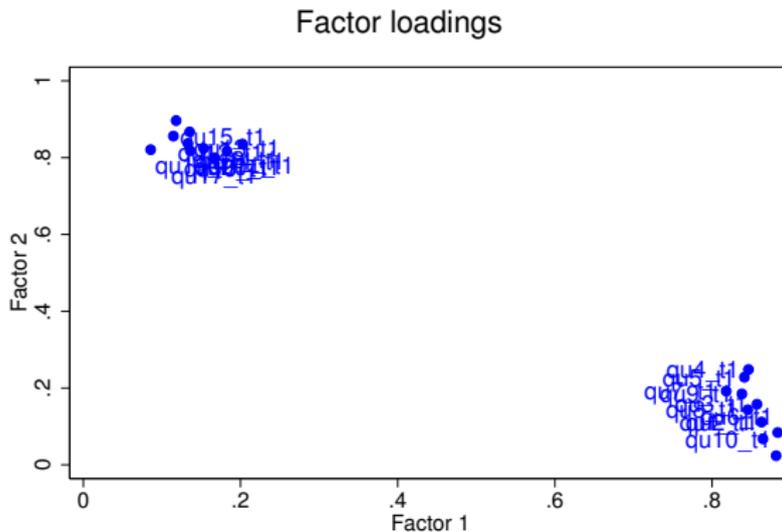
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
qu1_t1	0.7342	-0.4668	0.2430
qu2_t1	0.7076	-0.5015	0.2478
qu3_t1	0.7595	-0.4273	0.2405
qu4_t1	0.8090	-0.3510	0.2223
qu5_t1	0.7922	-0.3631	0.2405
qu6_t1	0.7326	-0.5008	0.2124
qu7_t1	0.7513	-0.3762	0.2940
qu8_t1	0.7413	-0.4310	0.2647
qu9_t1	0.7620	-0.3944	0.2638
qu10_t1	0.6924	-0.5459	0.2225
qu11_t1	0.6453	0.5352	0.2972
qu12_t1	0.6362	0.5844	0.2536
qu13_t1	0.6590	0.5794	0.2300
qu14_t1	0.6904	0.5122	0.2611
qu15_t1	0.6647	0.6131	0.1823
qu16_t1	0.6634	0.5106	0.2992
qu17_t1	0.6399	0.5071	0.3334
qu18_t1	0.6380	0.5576	0.2820
qu19_t1	0.5913	0.5757	0.3189
qu20_t1	0.6280	0.5412	0.3127

Factor Loadings (No Rotation)

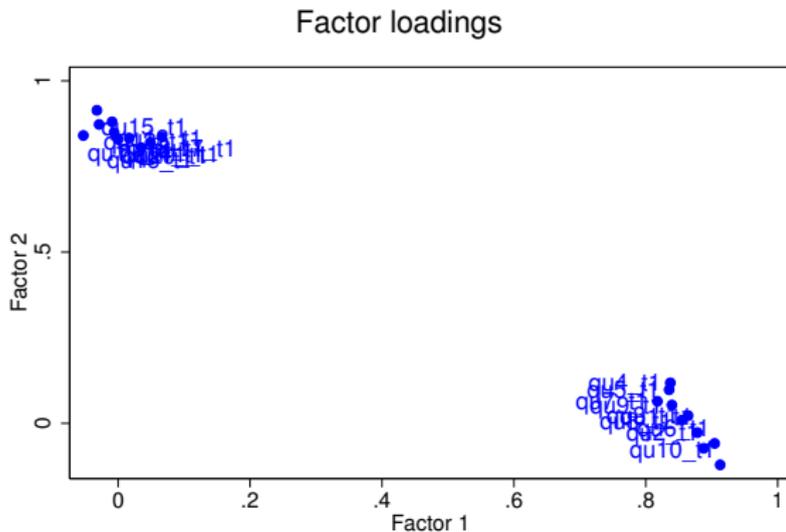


Factor Loadings (VariMax Rotation)



Rotation: orthogonal varimax
Method: maximum likelihood

Factor Loadings (ProMax Rotation)



Rotation: oblique promax(3)
Method: maximum likelihood

Predicted Latent Variables Based On Factor Loadings

```
. predict Factor1 Factor2, regression
```

Scoring coefficients (method = regression; based on promax(3) rotated factors)

Variable	Factor1	Factor2
qu1_t1	0.11303	-0.00313
qu2_t1	0.11213	-0.00955
qu3_t1	0.11234	0.00398
qu4_t1	0.11802	0.01949
qu5_t1	0.10858	0.01504
qu6_t1	0.13304	-0.00884
qu7_t1	0.08701	0.00826
qu8_t1	0.10091	0.00189
qu9_t1	0.09957	0.00777
qu10_t1	0.12832	-0.01825
qu11_t1	0.00234	0.09845
qu12_t1	-0.00280	0.12079
qu13_t1	-0.00047	0.13446
qu14_t1	0.00861	0.11252
qu15_t1	-0.00452	0.17602
qu16_t1	0.00569	0.09628
qu17_t1	0.00385	0.08478
qu18_t1	-0.00009	0.10568
qu19_t1	-0.00460	0.09250
qu20_t1	0.00057	0.09312

```
. corr Factor1 Factor2
(obs=100)
```

	Factor1	Factor2
Factor1	1.0000	
Factor2	0.3279	1.0000

My statistical software makes me...

Latent Factor 1 (Affective)

- Q1 ...feel sad
- Q2 ...feel pessimistic about the future
- Q3 ...feel like a failure
- Q4 ...feel dissatisfied
- Q5 ...feel guilty or unworthy
- Q6 ...feel that I am being punished
- Q7 ...feel disappointed in myself
- Q8 ...feel am very critical of myself
- Q9 ...feel like harming myself
- Q10 ...feel like crying more than usual
- Q11 ...become annoyed or irritated easily
- Q12 ...lose interest in other people
- Q13 ...have trouble making decisions
- Q14 ...feel unattractive
- Q15 ...feel like not working
- Q16 ...have trouble sleeping
- Q17 ...feel tired or fatigued
- Q18 ...makes my appetite lower than usual
- Q19 ...concerned about my health
- Q20 ...experience decreased libido

Latent Factor 2 (Physical)

The Pilot Study

- Descriptive Statistics
- Item Response Characteristics
- Reliability
- Validity
- Dimensionality and Exploratory Factor Analysis

The Full Study

- The Stata Depression Index was then administered to 1000 Stata users
- Analysis of the data included
 - Confirmatory Factor Analysis
 - Classical Univariate and Multivariate Models
 - Structural Equation Models

Description of the Stata User Data

```
. describe
```

```
Contains data from BDI2_Data.dta
```

```
obs:      1,000
vars:      27                               11 Jul 2012 08:54
size:      28,000
```

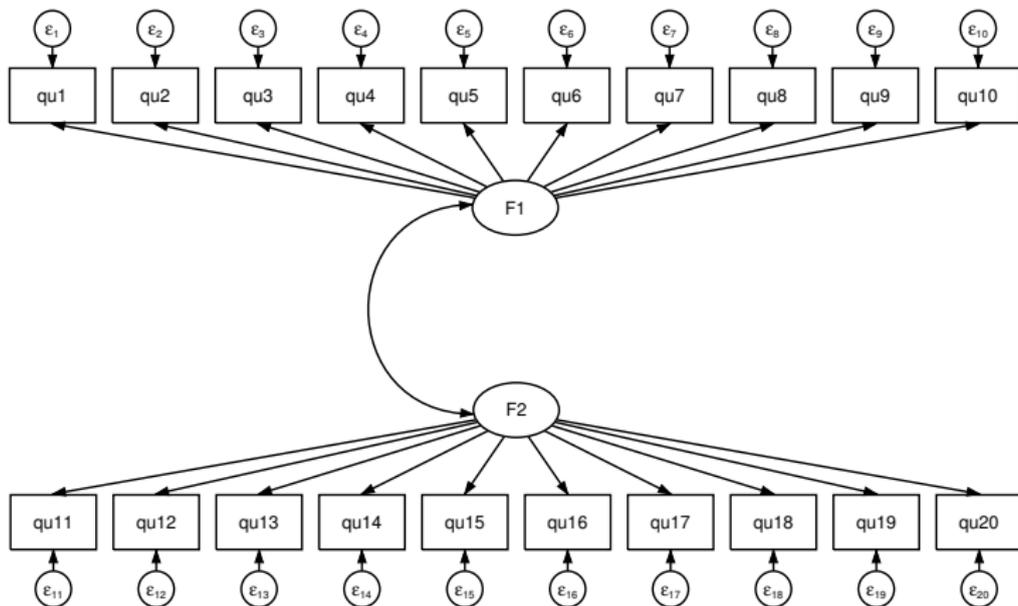
variable name	storage type	display format	value label	variable label
id	int	%9.0g		Identification Number
age	byte	%9.0g		Age (years)
sex	byte	%9.0g	sex	Sex
race	byte	%9.0g	race	Race
qu1	byte	%16.0g	qu1_t1	...feel sad
qu2	byte	%16.0g	qu2_t1	...feel pessimistic about the future
qu3	byte	%16.0g	qu3_t1	...feel like a failure
qu4	byte	%16.0g	qu4_t1	...feel dissatisfied
qu5	byte	%16.0g	qu5_t1	...feel guilty or unworthy
qu6	byte	%16.0g	qu6_t1	...feel that I am being punished
qu7	byte	%16.0g	qu7_t1	...feel disappointed in myself
qu8	byte	%16.0g	qu8_t1	...feel am very critical of myself
qu9	byte	%16.0g	qu9_t1	...feel like harming myself
qu10	byte	%16.0g	qu10_t1	...feel like crying more than usual
qu11	byte	%16.0g	qu11_t1	...become annoyed or irritated easily
qu12	byte	%16.0g	qu12_t1	...have lost interest in other people
qu13	byte	%16.0g	qu13_t1	...have trouble making decisions
qu14	byte	%16.0g	qu14_t1	...feel unattractive
qu15	byte	%16.0g	qu15_t1	...feel like not working
qu16	byte	%16.0g	qu16_t1	...have trouble sleeping
qu17	byte	%16.0g	qu17_t1	...feel tired or fatigued
qu18	byte	%16.0g	qu18_t1	...makes my appetite lower than usual
qu19	byte	%16.0g	qu19_t1	...concerned about my health
qu20	byte	%16.0g	qu20_t1	...experience decreased libido

Summary of the Stata User Data

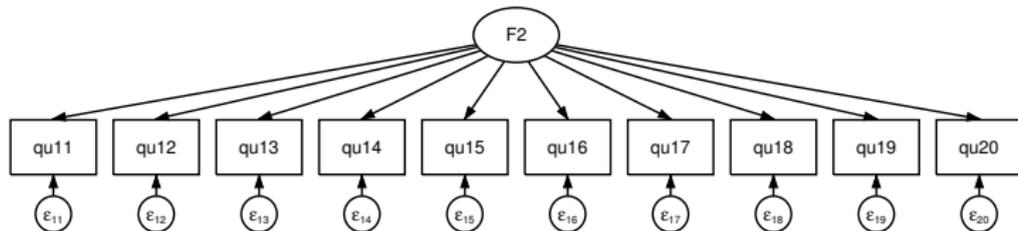
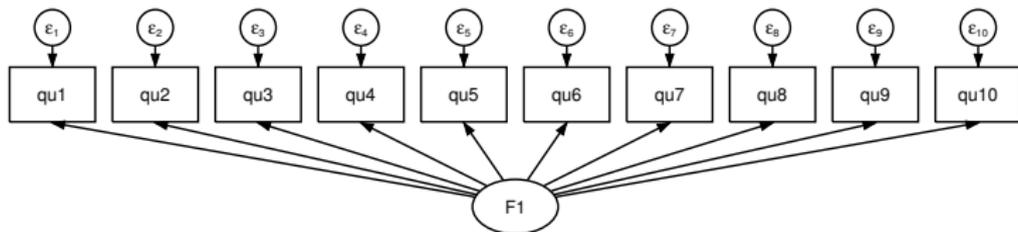
. summ

Variable	Obs	Mean	Std. Dev.	Min	Max
id	1000	500.5	288.8194	1	1000
age	1000	36.542	9.48009	22	60
sex	1000	.288	.4530577	0	1
race	1000	2.38	.7085916	1	3
qu1	1000	2.986	.859385	1	5
qu2	1000	2.637	.8461365	1	5
qu3	1000	2.978	.856884	1	5
qu4	1000	2.955	.8292543	1	5
qu5	1000	2.944	.8506395	1	5
qu6	1000	2.955	.8693277	1	5
qu7	1000	2.96	.8503665	1	5
qu8	1000	2.955	.8553986	1	5
qu9	1000	2.964	.8481883	1	5
qu10	1000	2.954	.85476	1	5
qu11	1000	2.999	.8060078	1	5
qu12	1000	2.984	.7977345	1	5
qu13	1000	2.985	.8008848	1	5
qu14	1000	2.421	.8200192	1	5
qu15	1000	2.793	.8466805	1	5
qu16	1000	3	.7953821	1	5
qu17	1000	2.988	.7965491	1	5
qu18	1000	2.969	.8116019	1	5
qu19	1000	3.002	.8041409	1	5
qu20	1000	1.982	.8308829	1	4

Confirmatory Factor Analysis



Confirmatory Factor Analysis



Likelihood Ratio Test For the Constrained vs Unconstrained Covariance Between Latent Factors

```
// STRUCTURAL EQUATION MODEL WITH UNCONSTRAINED COVARIANCE BETWEEN LATENT FACTORS
sem (F1 -> qu1-qu10) ///
    (F2 -> qu11-qu20), stand
est store full

// STRUCTURAL EQUATION MODEL WITH COVARIANCE BETWEEN LATENT FACTORS CONSTRAINED TO ZERO
sem (F1 -> qu1-qu10) ///
    (F2 -> qu11-qu20), ///
    cov(F1*F2@0) stand
est store reduced
lrtest full reduced

. lrtest full reduced

Likelihood-ratio test
(Assumption: reduced nested in full)                LR chi2(1) =    153.33
                                                    Prob > chi2 =    0.0000
```

Score Test For the Constrained vs Unconstrained Covariance Between Latent Factors

```
// STRUCTURAL EQUATION MODEL WITH COVARIANCE BETWEEN FACTORS CONSTRAINED TO ZERO
sem (F1 -> qu1-qu10) ///
    (F2 -> qu11-qu20), ///
    cov(Affective*Physical@0) stand
```

```
. estat scoretests
```

Score tests for linear constraints

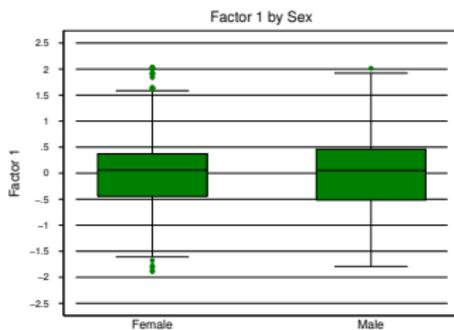
```
(3) [cov(F1,F2)]_cons = 0
```

	chi2	df	P>chi2
(3)	142.127	1	0.00

Create Predicted Variables from the Latent Variables

```
sem (F1 -> qu1-qu10) ///  
    (F2 -> qu11-qu20), stand  
  
// CREATE PREDICTED VARIABLES FOR THE LATENT VARIABLES  
predict F1 F2, latent(Affective Physical)  
label var F1 "Factor 1 (Affective)"  
label var F2 "Factor 2 (Physical)"
```

Student's t-test for Latent Variable F1 by Sex



```
. ttest F1, by(sex)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Female	712	.0018819	.0271581	.7246673	-.0514377	.0552014
Male	288	-.0046524	.04334	.7355044	-.089957	.0806522
combined	1000	-1.44e-10	.0230037	.727442	-.0451412	.0451412
diff		.0065343	.0508248		-.0932016	.1062701

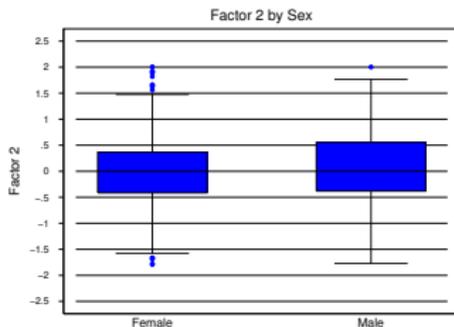
```
diff = mean(Female) - mean(Male)          t = 0.1286
Ho: diff = 0                             degrees of freedom = 998
```

```
Ha: diff < 0
Pr(T < t) = 0.5511
```

```
Ha: diff != 0
Pr(|T| > |t|) = 0.8977
```

```
Ha: diff > 0
Pr(T > t) = 0.4489
```

Student's t-test for Latent Variable F2 by Sex



```
. ttest F2, by(sex)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Female	712	-.0187195	.0247589	.6606498	-.0673288	.0298897
Male	288	.0462789	.0407991	.6923839	-.0340246	.1265823
combined	1000	-6.30e-10	.0211949	.6702416	-.0415916	.0415916
diff		-.0649984	.0467835		-.1568038	.026807

```
diff = mean(Female) - mean(Male)
Ho: diff = 0
```

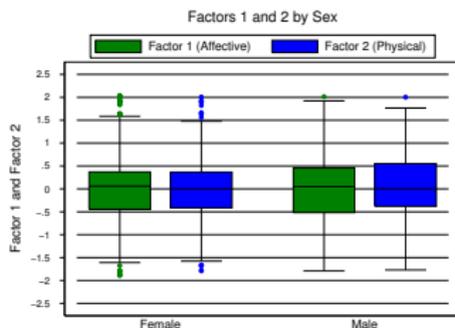
```
t = -1.3893
degrees of freedom = 998
```

```
Ha: diff < 0
Pr(T < t) = 0.0825
```

```
Ha: diff != 0
Pr(|T| > |t|) = 0.1650
```

```
Ha: diff > 0
Pr(T > t) = 0.9175
```

Hotelling's T-Squared for Latent Variables F1 and F2 by Sex



```
. hotelling F1 F2, by(sex)
```

-> sex = Female						
Variable	Obs	Mean	Std. Dev.	Min	Max	
F1	712	.0018819	.7246673	-1.891131	2.031987	
F2	712	-.0187195	.6606498	-1.78537	2.00687	

-> sex = Male						
Variable	Obs	Mean	Std. Dev.	Min	Max	
F1	288	-.0046524	.7355044	-1.790884	2.014114	
F2	288	.0462789	.6923839	-1.7694	2.002456	

2-group Hotelling's T-squared = 2.5043409

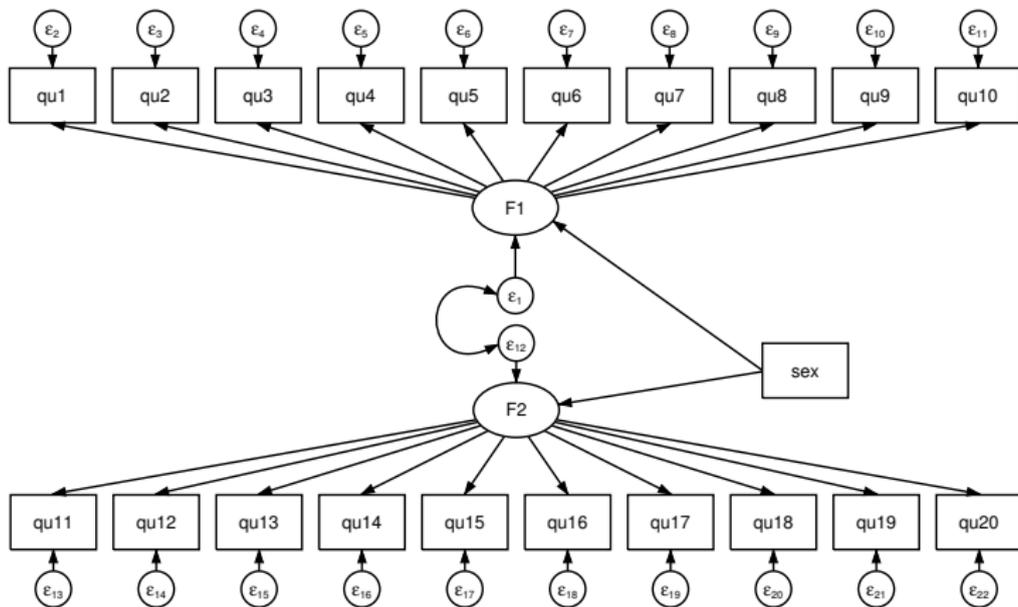
F test statistic: $((1000-2-1)/(1000-2)(2)) \times 2.5043409 = 1.2509158$

H0: Vectors of means are equal for the two groups

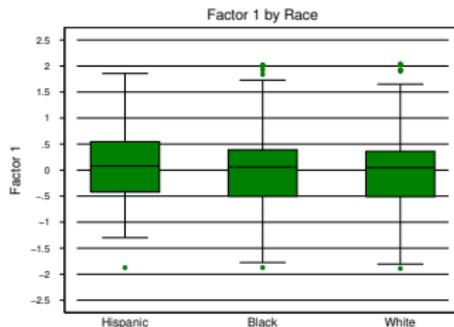
F(2,997) = 1.2509

Prob > F(2,997) = 0.2867

Structural Equation Model Including Sex



Oneway ANOVA for Latent Variable F1 by Race

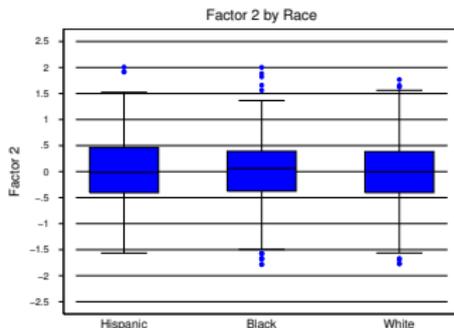


```
. anova F1 race
```

```
Number of obs = 1000      R-squared      = 0.0012
Root MSE      = .727742   Adj R-squared  = -0.0008
```

Source	Partial SS	df	MS	F	Prob > F
Model	.622465698	2	.311232849	0.59	0.5558
race	.622465698	2	.311232849	0.59	0.5558
Residual	528.020207	997	.529609034		
Total	528.642673	999	.529171845		

Oneway ANOVA for Latent Variable F2 by Race

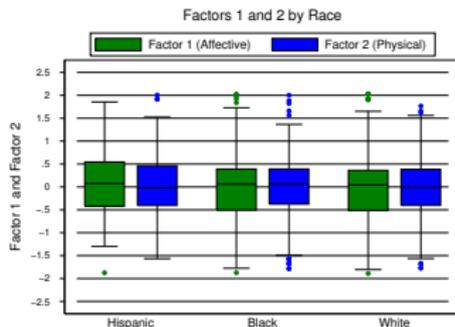


```
. anova F2 race
```

```
Number of obs = 1000      R-squared      = 0.0005
Root MSE      = .670744   Adj R-squared = -0.0015
```

Source	Partial SS	df	MS	F	Prob > F
Model	.2265257	2	.11326285	0.25	0.7775
race	.2265257	2	.11326285	0.25	0.7775
Residual	448.548027	997	.449897721		
Total	448.774553	999	.449223777		

Multivariate ANOVA for Latent Variables F1 and F2 by Race



```
. manova F1 F2 = race
```

```
Number of obs = 1000
```

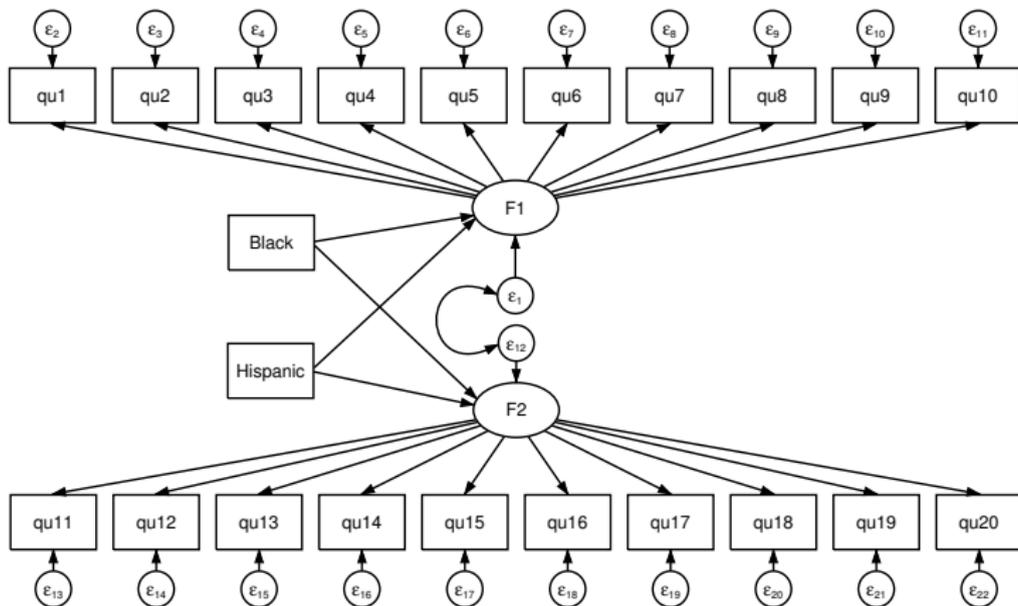
```
W = Wilks' lambda L = Lawley-Hotelling trace
```

```
P = Pillai's trace R = Roy's largest root
```

Source	Statistic	df	F(df1, df2) =	F	Prob>F	
race	W	0.9986	2	4.0	1992.0	0.36 0.8406 e
	P	0.0014		4.0	1994.0	0.36 0.8404 a
	L	0.0014		4.0	1990.0	0.35 0.8408 a
	R	0.0012		2.0	997.0	0.60 0.5501 u
Residual		997				
Total		999				

```
e = exact, a = approximate, u = upper bound on F
```

Structural Equation Model Including Race



Reference Level Contrasts for Race

```
// r. differences from a reference (base) level; the default
. contrast r.race
```

Contrasts of marginal linear predictions

Margins : asbalanced

	df	F	P>F
F1			
race			
(2 vs 1)	1	0.67	0.4133
(3 vs 1)	1	1.18	0.2786
Joint	2	0.59	0.5558
Residual	997		

	Contrast	Std. Err.	[95% Conf. Interval]	
F1				
race				
(2 vs 1)	-.0605743	.0740141	-.2058157	.0846671
(3 vs 1)	-.0767675	.0708124	-.215726	.062191

```
// THIS IS EQUIVALENT TO:
contrast {race -1 1 0} ///
          {race -1 0 1}, equation(F1)
```

Adjacent Categories Contrasts for Race

```
// a. differences from the next level (adjacent contrasts)
. contrast a.race
```

Contrasts of marginal linear predictions

Margins : asbalanced

	df	F	P>F
F1			
race			
(1 vs 2)	1	0.67	0.4133
(2 vs 3)	1	0.10	0.7475
Joint	2	0.59	0.5558
Residual	997		

	Contrast	Std. Err.	[95% Conf. Interval]	
F1				
race				
(1 vs 2)	.0605743	.0740141	-.0846671	.2058157
(2 vs 3)	.0161932	.0502837	-.0824807	.1148672

```
// THIS IS EQUIVALENT TO:
contrast {race 1 -1 0} ///
          {race 0 1 -1}, equation(F1)
```

Grand Means Contrasts for Race

```
// g. differences from the balanced grand mean
. contrast g.race
```

Contrasts of marginal linear predictions

Margins : asbalanced

	df	F	P>F
F1			
race			
(1 vs mean)	1	1.02	0.3123
(2 vs mean)	1	0.18	0.6723
(3 vs mean)	1	0.90	0.3432
Joint	2	0.59	0.5558
Residual	997		

	Contrast	Std. Err.	[95% Conf. Interval]	
F1				
race				
(1 vs mean)	.0457806	.0452849	-.0430841	.1346453
(2 vs mean)	-.0147937	.0349582	-.0833938	.0538064
(3 vs mean)	-.0309869	.0326728	-.0951022	.0331284

```
// THIS IS EQUIVALENT TO:
contrast {race -0.6666 0.3333 0.3333} ///
          {race 0.3333 -0.6666 0.3333} ///
          {race 0.3333 0.3333 -0.6666}, equation(F1)
```

Pairwise Comparisons for Race Using The Tukey Adjustment

```
. pwcompare race, equation(F1) effects mcompare(tukey)
```

Pairwise comparisons of marginal linear predictions

Margins : asbalanced

		Number of Comparisons
F1	race	3

		Contrast	Std. Err.	Tukey t	P> t	Tukey [95% Conf. Interval]
F1	race					
	2 vs 1	-.0605743	.0740141	-0.82	0.692	-.2343012 .1131526
	3 vs 1	-.0767675	.0708124	-1.08	0.524	-.2429793 .0894443
	3 vs 2	-.0161932	.0502837	-0.32	0.944	-.1342197 .1018332

Note: The tukey method requires balanced data for proper level coverage. A factor was found to be unbalanced.

Pairwise Comparisons for Race Using The Bonferroni Adjustment

```
. pwcompare race, equation(F1) effects mcompare(bonf)
```

Pairwise comparisons of marginal linear predictions

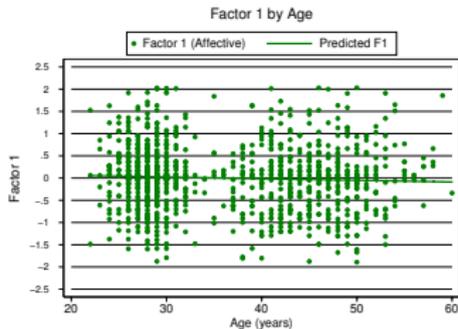
Margins : asbalanced

		Number of Comparisons
F1	race	3

		Contrast	Std. Err.	Bonferroni t	P> t	Bonferroni [95% Conf. Interval]
F1	race					
	2 vs 1	-.0605743	.0740141	-0.82	1.000	-.2380622 .1169136
	3 vs 1	-.0767675	.0708124	-1.08	0.836	-.2465776 .0930426
	3 vs 2	-.0161932	.0502837	-0.32	1.000	-.1367748 .1043884

- Built-In Contrasts (as-balanced and as-observed)
 - Reference Level Contrasts
 - Adjacent Levels Contrasts
 - Differences From The Grand Mean
 - Orthogonal Polynomials
 - Helmert and Reverse-Helmert
- Pairwise Comparison Adjustments
 - Bonferroni
 - Tukey
 - Scheffe
 - Duncan
 - Dunnett
 - Student-Newman-Keuls

Linear Regression for Latent Variable F1 by Age

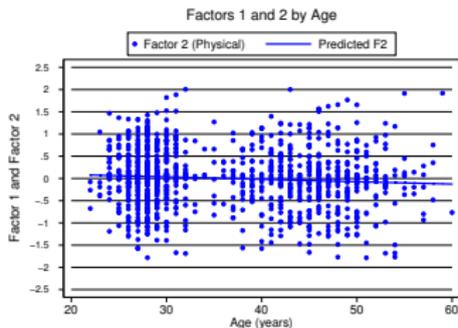


```
. regress F1 age
```

Source	SS	df	MS			
Model	1.27353577	1	1.27353577	Number of obs =	1000	
Residual	527.369137	998	.528425989	F(1, 998) =	2.41	
				Prob > F =	0.1209	
				R-squared =	0.0024	
				Adj R-squared =	0.0014	
Total	528.642673	999	.529171845	Root MSE =	.72693	

F1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
age	-.0037663	.002426	-1.55	0.121	-.008527 .0009945
_cons	.1376267	.091584	1.50	0.133	-.0420926 .317346

Linear Regression for Latent Variable F2 by Age

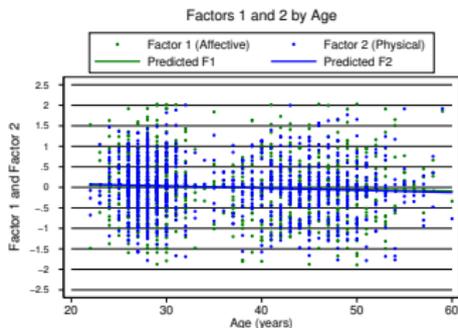


```
. regress F2 age
```

Source	SS	df	MS		
Model	2.62133472	1	2.62133472	Number of obs =	1000
Residual	446.153218	998	.447047313	F(1, 998) =	5.86
				Prob > F =	0.0156
				R-squared =	0.0058
				Adj R-squared =	0.0048
Total	448.774553	999	.449223777	Root MSE =	.66862

F2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	-.0054034	.0022314	-2.42	0.016	-.0097822	-.0010246
_cons	.1974505	.0842373	2.34	0.019	.0321481	.362753

Multivariate Regression for Latent Variables F1 and F2 by Age

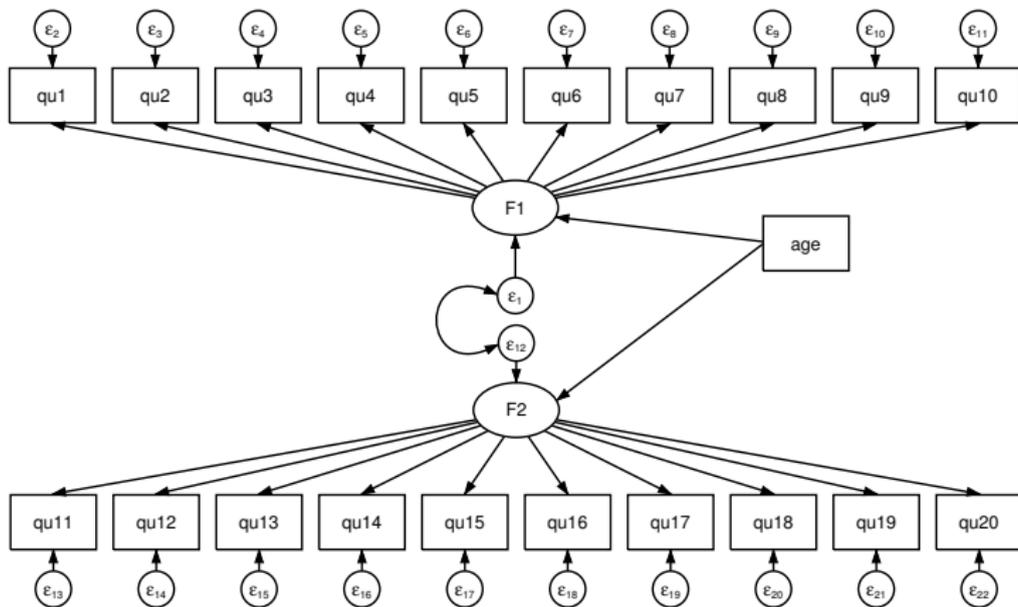


```
. mvreg F1 F2 = age
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
F1	1000	2	.7269291	0.0024	2.410055	0.1209
F2	1000	2	.668616	0.0058	5.863663	0.0156

		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
F1	age	-.0037663	.002426	-1.55	0.121	-.008527 .0009945
	_cons	.1376267	.091584	1.50	0.133	-.0420926 .317346
F2	age	-.0054034	.0022314	-2.42	0.016	-.0097822 -.0010246
	_cons	.1974505	.0842373	2.34	0.019	.0321481 .362753

Structural Equation Model Including Age



Multivariate Regression Model Including Sex, Race and Age

```
. mvreg F1 F2 = age i.sex##i.race
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P
F1	1000	7	.72724	0.0066	1.092484	0.3648
F2	1000	7	.6687077	0.0106	1.764698	0.1032

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
F1					
age	-.0036923	.002429	-1.52	0.129	-.0084588 .0010743
1.sex	.1130077	.1333148	0.85	0.397	-.1486033 .3746188
race					
2	-.040209	.0897508	-0.45	0.654	-.216332 .1359139
3	-.0114758	.0863719	-0.13	0.894	-.1809682 .1580165
sex#race					
1 2	-.0427163	.1593227	-0.27	0.789	-.3553641 .2699314
1 3	-.2035214	.1509514	-1.35	0.178	-.4997418 .0926989
_cons	.156677	.1166336	1.34	0.179	-.0721996 .3855537
F2					
age	-.0055679	.0022335	-2.49	0.013	-.0099509 -.001185
1.sex	.2013137	.1225849	1.64	0.101	-.0392415 .4418689
race					
2	.062532	.0825271	0.76	0.449	-.0994155 .2244796
3	.0100582	.0794202	0.13	0.899	-.1457925 .1659089
sex#race					
1 2	-.208859	.1464995	-1.43	0.154	-.4963432 .0786251
1 3	-.1206021	.138802	-0.87	0.385	-.392981 .1517767
_cons	.1558802	.1072463	1.45	0.146	-.0545752 .3663356

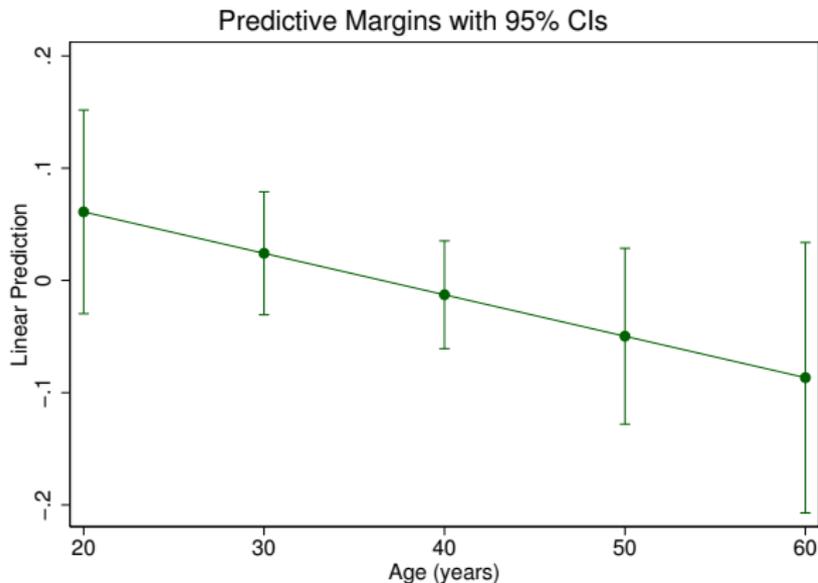
Linear Predictions of F1 at Ages 20,30,40,50 and 60

```
. margins , at(age=(20(10)60)) predict(equation(F1)) vsquish
Predictive margins                                Number of obs   =       1000
Expression   : Linear prediction, predict(equation(F1))
1._at       : age = 20
2._at       : age = 30
3._at       : age = 40
4._at       : age = 50
5._at       : age = 60
```

	Margin	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
_at						
1	.0610775	.0462963	1.32	0.187	-.0296615	.1518166
2	.0241548	.0279533	0.86	0.388	-.0306326	.0789423
3	-.0127679	.0244832	-0.52	0.602	-.0607541	.0352184
4	-.0496906	.0399684	-1.24	0.214	-.1280273	.0286461
5	-.0866133	.0614453	-1.41	0.159	-.2070439	.0338174

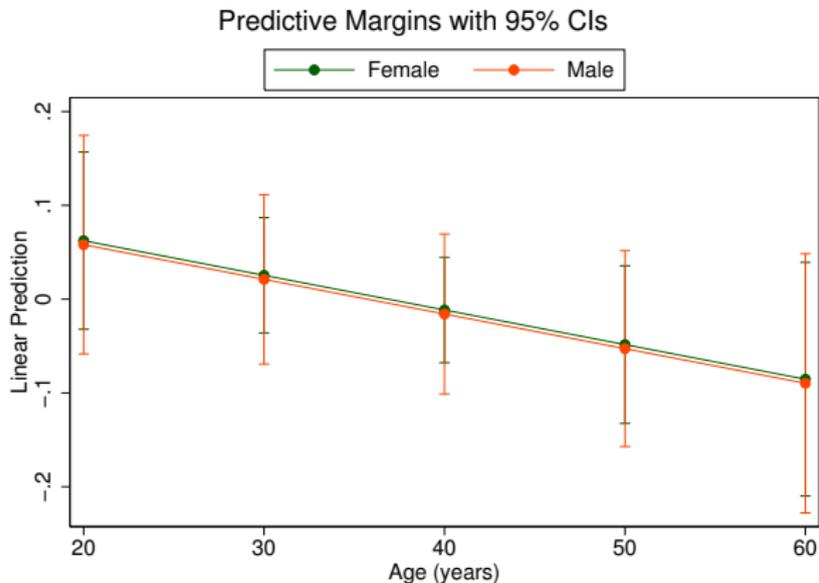
Margins Plot of Latent Variable F1 at Ages 20,30,40,50 and 60

```
margins , at(age=(20(10)60)) predict(equation(F1)) vsquish  
marginplot, scheme(sicolor)
```



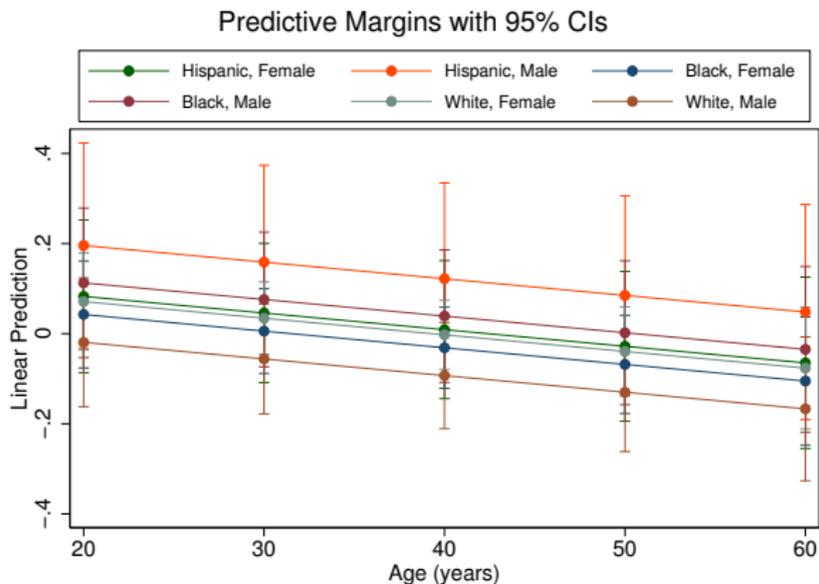
Margins Plot of Latent Variable F1 at By Sex at Ages 20-60

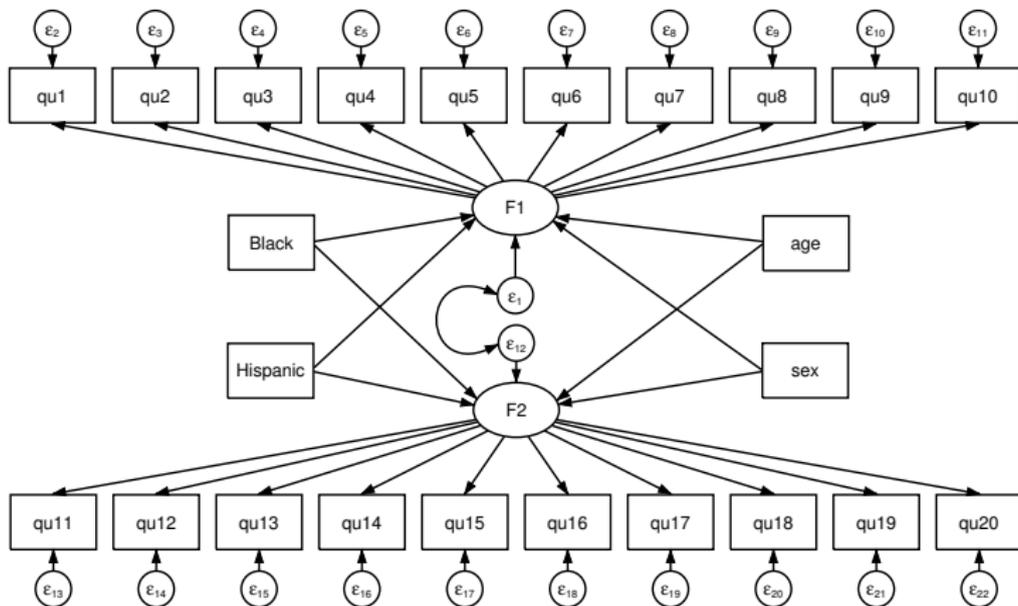
```
margins , over(sex) at(age=(20(10)60)) predict(equation(F1))  
marginsplot, scheme(sicolor)
```

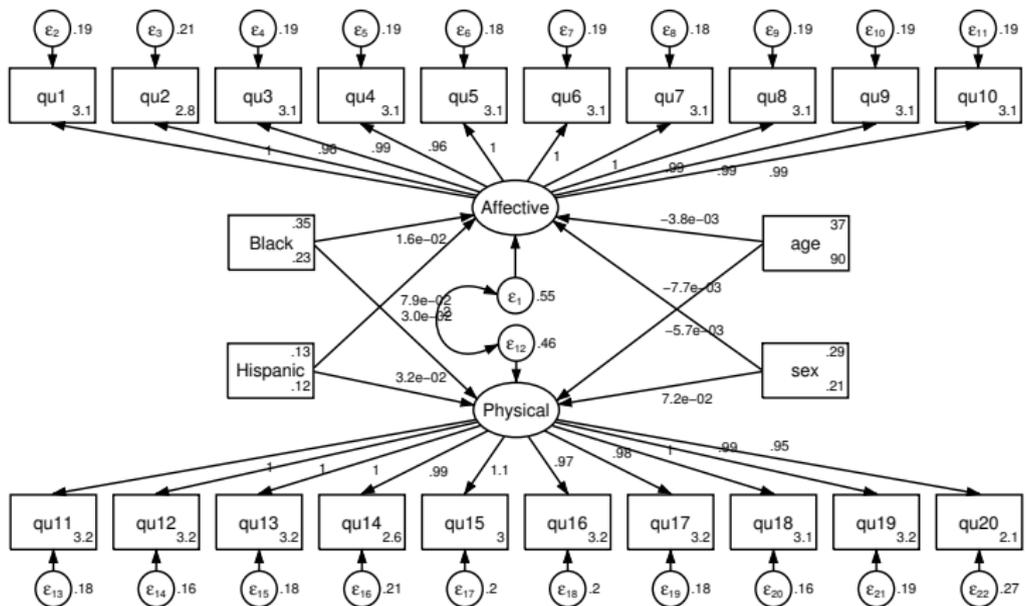


Margins Plot of F1 at By Sex and Race at Ages 20-60

```
margins , over(race sex) at(age=(20(10)60)) predict(equation(F1))  
marginplot, scheme(sicolor)
```







Conclusions

- For privacy reasons, we cannot reveal all the details of our analysis
- We are happy to report that Stata users are doing just fine
- Stata is very well equipped for both Classical and Modern psychometric analyses
- There were too many slides in this presentation!!!

References

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