

Structural Equation Models

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Outline

- 1 Get the affect data
- 2 Path Diagrams
 - Linear Regression
 - Moderators
 - Mediation
- 3 Structural Equation Modeling
 - Remember Regression?
- 4 SEM in R
 - Plots
 - Estimate the Moderation Model
 - More Elaborate Path Model
- 5 Full Latent Variable Regression Model
 - Confirmatory Factor Analysis
 - Structural Regressions among Latent Constructs
 - Supplementary Hypothesis Test
- 6 Conclusion

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Use affect.rds from summeR-3-2-lm

```
file.copy(from =
  "../summeR-3-2-lm/workingdata/affect.rds", to
  = "workingdata/affect.rds", overwrite = TRUE)
```

```
[1] TRUE
```

```
dat <- readRDS("workingdata/affect.rds")
```

```
head(dat)
```

	Agency1	Agency2	Agency3	Intrin1	Intrin2	Intrin3	Extrin1
1	3.5000	4.0000	4.0000	4.0000	4.0	4	1.0000
2	2.5000	3.1667	3.0000	3.2123	2.0	3	1.8333
3	1.8333	2.0000	1.5000	3.0000	3.0	2	1.0000
4	2.7714	3.0602	2.3639	3.1337	4.0	3	1.0774
5	3.1667	3.3333	2.8333	3.5000	4.0	4	1.8333
6	2.3333	2.8333	2.3333	3.0000	2.5	3	3.0588
	Extrin2	Extrin3	PosAFF1	PosAFF2	PosAFF3	NegAFF1	NegAFF2
1	1.0000	1.5000	4.0000	4.0	4.0	1.0	1.0000
2	2.6667	1.8333	3.0000	3.5	2.5	1.5	1.6858
3	1.0000	1.0000	3.0184	2.5	3.0	1.0	1.0000
4	1.1667	1.0000	3.0000	2.5	3.0	2.5	2.5000
5	2.0000	1.8333	3.7804	3.5	3.0	2.5	2.0000
6	2.4125	2.6667	4.0000	3.0	3.0	2.0	1.5000

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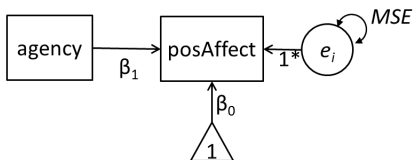
Path: This goes into that

- The regression equation

$$posAffect_i = \beta_0 + \beta_1 agency_i + \epsilon_i, \epsilon \sim N(0, \sigma_\epsilon^2)$$

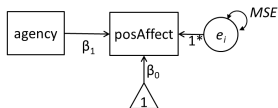
The parameters to be estimated are β_0 , β_1 , and σ_ϵ^2 .

- Some people understand this more readily in a path diagram:



MSE = “mean squared error” is an estimate of σ_ϵ^2

Symbols



Rectangles: Observed variables

Triangle: a constant value

Circle: unobserved variable (error term, in this case)

Double arrowed-loop: modern way of saying there's random variance in this thing.

1^* : a coefficient is fixed at 1, the error is assumed additive.

β : path coefficients

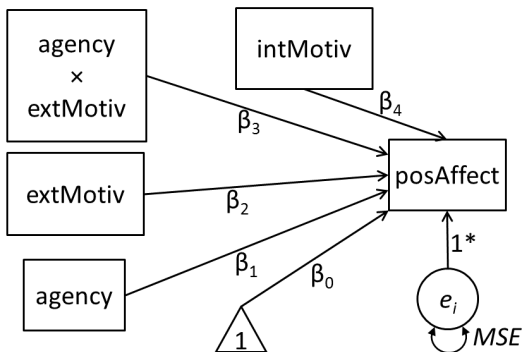
Throw in More Variables

- I think of this:

$$\begin{aligned} posAffect_i &= \beta_0 + \beta_1 agency_i + \beta_2 extMotiv_i \\ &\quad \beta_3 agency_i \times extMotiv_i + \beta_4 intMotiv_i + \\ &\quad \epsilon_i, \epsilon \sim N(0, \sigma_\epsilon^2) \end{aligned}$$

Path Diagram of posAffect Regression

- A Path diagram oriented person thinks of this (might want to quibble about how to draw interaction)



Moderator effects

When we ran the regression model

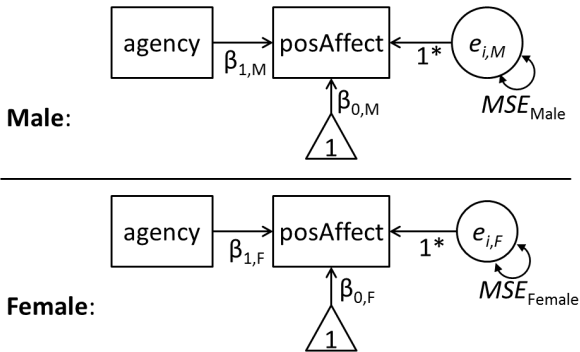
$$posAffect_i = \beta_0 + \beta_1 agency + \beta_2 female_i + \beta_3 agency_i \cdot female_i, \epsilon_i \sim N(0, \sigma_\epsilon^2) \quad (1)$$

we allowed the genders to differ in intercept and slope

- Gender is a “**moderator**” of the agency effect
- But we assumed that the error variance is the same in the 2 groups.
 - That’s a testable assumption

In Psychology, they would rather look at the problem in this way

- In the usual path diagram, interactions don't fit well, especially to fully represent the interaction of gender.
- An alternative sketch segregates the 2 genders entirely.



Assume β_j and σ_ϵ^2 differ between groups

If the 2 groups have all different parameters, we might as well think of them as completely separate data exercises.

- Could run one model for males, one for females, or
- fit both within some larger structure that allows us to see if the intercepts, slopes, and error variances are truly different.
- We are (probably) hoping to “simplify” our analysis to a more “parsimonious” model.
- In econometrics, they’d call this a “pooling test”
- In psychology, they call it “measurement invariance testing”

Write out 2 equations

- agency affects intrinsic motivation

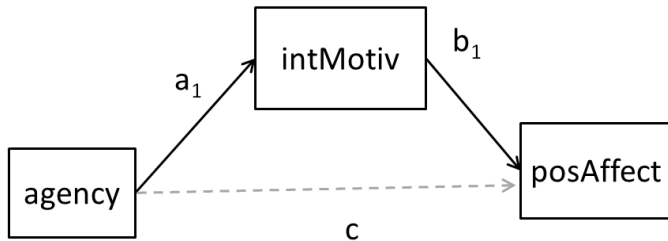
$$intMotiv_i = const1 + a_1 agency_i + \epsilon1_i \quad (2)$$

- agency affects positiveAffect, but positiveAffect is also affected by intrinsic motivation

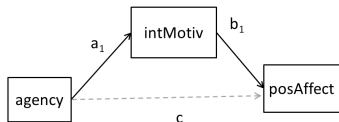
$$posAffect = const2 + b_1 intMotiv + c agency_i + \epsilon2_i \quad (3)$$

- The coefficient “c” represents the direct effect of agency on positive affect

Some people like a picture



Some people like a picture



- The product “ $a_1 \cdot b_1$ ” is the indirect effect of agency. To see that, substitute

$$\begin{aligned}
 posAffect &= const1 + b_1\{const1 + a_1agency_i + error_i\} + cagency_i + \epsilon2_i \quad (4) \\
 &= \{const2 + b_1const1\} + \{b_1 \cdot a_1\}agency_i + cagency_i + \{\epsilon1_i + \epsilon2_i
 \end{aligned}$$

Some people like a picture ...

- As a result, a regression model of *posAffect* on *agency* might be wrong, in the sense that if we estimate

$$posAffect_i = \beta_0 + \beta_1 agency_i + \epsilon_i \quad (5)$$

then the coefficient we estimate, β_1 includes both the “direct” effect b_1 and the indirect effect $a_1 b_1$

- The age old question is, “does *agency*’s *direct* effect outweigh the *indirect* effect”?
- In the olden days (maybe even today),
 - students will fit 2 separate regression models, and
 - try to test the hypothesis that the product $a_1 b_1$ is different from 0.
- As long as ϵ_{1i} and ϵ_{2i} are uncorrelated, that should be sufficient.
- If they are correlated, then some sort of simultaneous regression is needed
 - in economics, they might use “Seemingly Unrelated Regression” (3SLS)
 - in psychology, they would see this as a structural equation model (SEM)

There is a horrible detail waiting around the corner

- The indirect effect is a_1b_1 , a *product*
- It will be zero (really small) if either a_1 or b_1 is zero (really small).
- Thus, the null hypothesis we would like to test,

$$H_0 : a_1b_1 = 0$$

- is a gnarly, horrible thing that amounts to a null statement that “either a_1 or b_1 (or both), is (are) 0.”
- After chasing approximations for 20 years, it appears the best answer we can get is 'bootstrapped standard errors'.

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We created scales

$$agency = (Agency1 + Agency2 + Agency3)/3$$

$$intMotiv = (Intrin1 + Intrin2 + Intrin3)/3$$

$$extMotiv = (Extrin1 + Extrin2 + Extrin3)/3$$

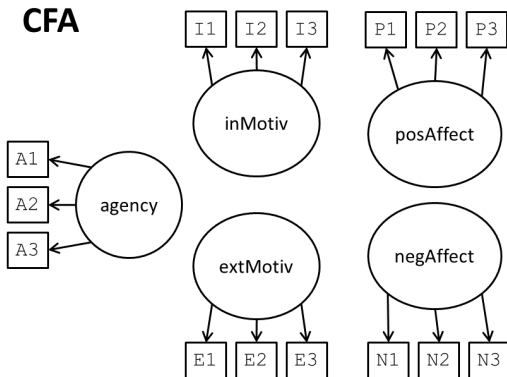
$$posAffect = (PosAFF1 + PosAFF2 + PosAFF3)/3$$

$$negAffect = (NegAFF1 + NegAFF2 + NegAFF3)/3$$

- And then we ran regressions *as if* those were “real measurements”.

We were Careless about Measurement

- A structural equation modeler sees a need to build a measurement model
- A “Confirmatory Factor Analysis” simultaneously
 - 1 Checks how the individual variables load on the unmeasured latent “constructs”
 - 2 Investigates relationships between the latent “constructs”



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Competing packages

- The `sem()` function in the “car” package was the first SEM fitter for R (R Core Team, 2017)
- `lavaan` is a complete framework for SEM modeling in the style of Mplus
- `OpenMX` is a large package recently introduced in CRAN that can estimate SEM and many other matrix-based models
- Various other R packages exist, either as wholesale replacements (`lava`) or as supplementary tools (`semPlot`).

SEM software can fit single equation models

- The linear regression estimated with `lm()`, for example

```
lm1 <- lm(posAffect ~ agency + intMotiv +
  extMotiv*agency, data = dat)
coef(lm1)
```

(Intercept)	agency	intMotiv
2.7505404	-0.1104093	0.2526032
extMotiv	agency:extMotiv	
-0.6521769	0.2150615	

- SEM software seems to want us to manually create the interaction variable. I manually calculate that interaction:

```
dat$agency.X.extMotiv <- dat$agency * dat$extMotiv
```

then specify a model formula and fit with lavaan's function `sem()`

SEM software can fit single equation models ...

```
library(lavaan)
sem.fmla <- 'posAffect ~ agency + intMotiv +
  extMotiv + agency.X.extMotiv'
sem1 <- sem(sem.fmla, data = dat, meanstructure =
  TRUE)
```

“meanstructure” = “I want to see the intercept in the output”

SEM output

- The default print output is a little uninspiring

```
sem1
```

```
lavaan (0.5-23.1097) converged normally after 22 iterations
```

Number of observations	380
Estimator	ML
Minimum Function Test Statistic	0.000
Degrees of freedom	0
Minimum Function Value	0.00000000000000

- The lavaan summary method more helpful

```
summary(sem1)
```

SEM output ...

```
lavaan (0.5-23.1097) converged normally after 22 iterations
```

```
Number of observations                380
```

```
Estimator                            ML
```

```
Minimum Function Test Statistic      0.000
```

```
Degrees of freedom                   0
```

```
Minimum Function Value                0.000000000000000
```

```
Parameter Estimates:
```

```
Information                            Expected
Standard Errors                        Standard
```

```
Regressions:
```

	Estimate	Std.Err	z-value	P(> z)
posAffect ~				
agency	-0.110	0.192	-0.576	0.565
intMotiv	0.253	0.051	4.992	0.000
extMotiv	-0.652	0.314	-2.074	0.038
agency.X.xtMtv	0.215	0.114	1.878	0.060

```
Intercepts:
```

	Estimate	Std.Err	z-value	P(> z)
.posAffect	2.751	0.512	5.371	0.000

SEM output ...

Variances:

	Estimate	Std.Err	z-value	P(> z)
.posAffect	0.339	0.025	13.784	0.000

- The lavaan summary method allows customization. If you want the R-square, for example

```
lavaan (0.5-23.1097) converged normally after 22 iterations
```

```
Number of observations                380
```

```
Estimator                             ML
```

```
Minimum Function Test Statistic        0.000
```

```
Degrees of freedom                     0
```

```
Minimum Function Value                  0.000000000000000
```

```
Parameter Estimates:
```

```
Information                             Expected
```

```
Standard Errors                         Standard
```

```
Regressions:
```

	Estimate	Std.Err	z-value	P(> z)
--	----------	---------	---------	---------

SEM output ...

```

posAffect ~
  agency          -0.110    0.192    -0.576    0.565
  intMotiv        0.253    0.051     4.992    0.000
  extMotiv       -0.652    0.314    -2.074    0.038
  agency.X.xtMtv  0.215    0.114     1.878    0.060
Std.lv  Std.all

```

```

-0.110  -0.088
 0.253   0.264
-0.652  -0.492
 0.215   0.571

```

Intercepts:

```

                Estimate  Std.Err  z-value  P(>|z|)
.posAffect      2.751     0.512    5.371    0.000
Std.lv  Std.all
2.751   4.361

```

Variances:

```

                Estimate  Std.Err  z-value  P(>|z|)
.posAffect      0.339     0.025   13.784    0.000
Std.lv  Std.all
0.339   0.851

```

R-Square:

```

                Estimate

```

SEM output ...

```
posAffect          0.149
```

- I don't know anything about this, but I thought `parTable()` and `parameterEstimates()` were super informative

```
options(width=60)
parameterEstimates(sem1)
```

	lhs	op	rhs	est	se
1	posAffect	~	agency	-0.110	0.192
2	posAffect	~	intMotiv	0.253	0.051
3	posAffect	~	extMotiv	-0.652	0.314
4	posAffect	~	agency.X.extMotiv	0.215	0.114
5	posAffect	~~	posAffect	0.339	0.025
6	agency	~~	agency	0.250	0.000
7	agency	~~	intMotiv	0.140	0.000
8	agency	~~	extMotiv	0.058	0.000
9	agency	~~	agency.X.extMotiv	0.548	0.000
10	intMotiv	~~	intMotiv	0.435	0.000
11	intMotiv	~~	extMotiv	-0.012	0.000
12	intMotiv	~~	agency.X.extMotiv	0.184	0.000

SEM output ...

```

13          extMotiv ~          extMotiv    0.226 0.000
14          extMotiv ~ agency.X.extMotiv    0.698 0.000
15 agency.X.extMotiv ~ agency.X.extMotiv    2.800 0.000
16          posAffect ~1
17          agency ~1
18          intMotiv ~1
19          extMotiv ~1
20 agency.X.extMotiv ~1
           4.190 0.000
      z pvalue ci.lower ci.upper
1 -0.576 0.565 -0.486 0.265
2  4.992 0.000 0.153 0.352
3 -2.074 0.038 -1.268 -0.036
4  1.878 0.060 -0.009 0.439
5 13.784 0.000 0.290 0.387
6      NA      NA 0.250 0.250
7      NA      NA 0.140 0.140
8      NA      NA 0.058 0.058
9      NA      NA 0.548 0.548
10     NA      NA 0.435 0.435
11     NA      NA -0.012 -0.012
12     NA      NA 0.184 0.184
13     NA      NA 0.226 0.226
14     NA      NA 0.698 0.698
15     NA      NA 2.800 2.800
16  5.371 0.000 1.747 3.754
17     NA      NA 2.512 2.512

```

SEM output ...

```
18    NA    NA    3.023    3.023
19    NA    NA    1.645    1.645
20    NA    NA    4.190    4.190
```

```
options(options.orig)
```

I want a nice output table

```
library(kutils)
semtable10 <- semTable(sem1, fits = c("cfi",
  "rmsea"), longtable=TRUE, type = "latex",
  print.results = FALSE)
cat(semtable10)
```


		Model			
		Estimate	Std. Err.	z	p
		<u>Regression Slopes</u>			
<u>posAffect</u>	agency	-0.11	0.19	-0.58	.565
	intMotiv	0.25	0.05	4.99	.000
	extMotiv	-0.65	0.31	-2.07	.038
	agency.X.extMotiv	0.22	0.11	1.88	.060
		<u>Intercepts</u>			
	posAffect	2.75	0.51	5.37	.000
	agency	2.51 ⁺			
	intMotiv	3.02 ⁺			
	extMotiv	1.64 ⁺			
	agency.X.extMotiv	4.19 ⁺			
		<u>Residual Variances</u>			
	posAffect	0.34	0.02	13.78	.000
	agency	0.25 ⁺			
	intMotiv	0.44 ⁺			
	extMotiv	0.23 ⁺			
	agency.X.extMotiv	2.80 ⁺			

Residual Covariances

agency w/intMotiv	0.14 ⁺
agency w/extMotiv	0.06 ⁺
agency w/agency.X.extMotiv	0.55 ⁺
intMotiv w/extMotiv	-0.01 ⁺
intMotiv w/agency.X.extMotiv	0.18 ⁺
extMotiv w/agency.X.extMotiv	0.70 ⁺

Fit Indices

CFI	1.00
RMSEA	0.00

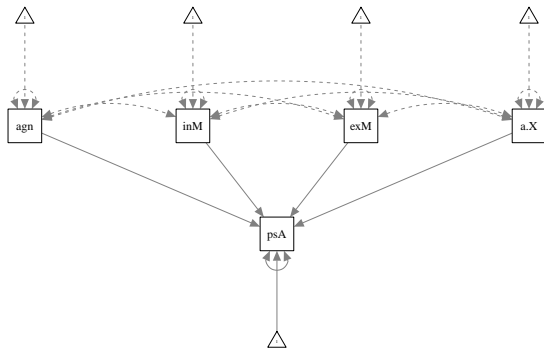
⁺Fixed parameter

Plots

- There is no plot method for a lavaan object.
- But there are other packages devoted to creating graphics for models that involve path diagrams (e.g., SEM and neural networks).
- The path diagram is visualized here with the `semPaths()` function in `semPlot`.

```
library(semPlot)
semPaths(sem1)
```

Plots ...



Other follow-up functions

- R-style accessor functions for lavaan

```
coef(sem1)
fitted(sem1)
resid(sem1)
anova(sem1)
```

- If you run those things, you will notice some wrinkles.
 - Notice that predicted observations (and residuals) are not 1-per-person
 - `anova()` returns a chi-squared test indicates there are 0 degrees of freedom (that's an SEM concept).

2 fits

- Moderation analysis focuses on the differences between groups. In this case, males and females.
- When one of the predictors in an interaction is categorical (e.g., gender), the sem “measurement invariance” approach would lead us to compare
 - a model in which the coefficients for the two groups are assumed to be entirely different, against
 - a simpler model in which some coefficients might be the same
- Estimate separately

```
group.mod.1 <- 'posAffect ~ c(A, B)*agency'  
group.out.1 <- sem(group.mod.1, data = dat,  
  meanstructure = TRUE, group = "gender")  
summary(group.out.1)
```

2 fits ...

```
lavaan (0.5-23.1097) converged normally after 19 iterations
```

```
Number of observations per group
```

```
male 195
```

```
female 185
```

```
Estimator ML
```

```
Minimum Function Test Statistic 0.000
```

```
Degrees of freedom 0
```

```
Minimum Function Value 0.000000000000000
```

```
Chi-square for each group:
```

```
male 0.000
```

```
female 0.000
```

```
Parameter Estimates:
```

```
Information Expected
```

```
Standard Errors Standard
```

```
Group 1 [male]:
```

```
Regressions:
```

2 fits ...

	Estimate	Std.Err	z-value	P(> z)
posAffect ~ agency (A)	0.452	0.079	5.704	0.000
Intercepts:				
.posAffect	1.890	0.203	9.329	0.000
Variances:				
.posAffect	0.309	0.031	9.874	0.000
Group 2 [female]:				
Regressions:				
posAffect ~ agency (B)	0.237	0.096	2.477	0.013
Intercepts:				
.posAffect	2.514	0.245	10.241	0.000
Variances:				
	Estimate	Std.Err	z-value	P(> z)

2 fits ...

.posAffect	0.419	0.044	9.618	0.000
------------	-------	-------	-------	-------

- Now fit same, with the exception that agency coefficient is same in both.

```
group.mod.0 <- 'posAffect ~ c(B, B)*agency'
group.out.0 <- sem(group.mod.0, data = dat,
  meanstructure = TRUE, group = "gender")
summary(group.out.0)
```

```
lavaan (0.5-23.1097) converged normally after 16 iterations
```

```
Number of observations per group
```

male	195
female	185

Estimator	ML
-----------	----

Minimum Function Test Statistic	2.978
---------------------------------	-------

Degrees of freedom	1
--------------------	---

P-value (Chi-square)	0.084
----------------------	-------

```
Chi-square for each group:
```

2 fits ...

```

15   male                1.207
    female              1.771

```

Parameter Estimates:

```

20   Information                Expected
    Standard Errors          Standard

```

Group 1 [male]:

25 Regressions:

	Estimate	Std.Err	z-value	P(> z)
posAffect ~ agency (B)	0.365	0.061	5.954	0.000

30 Intercepts:

	Estimate	Std.Err	z-value	P(> z)
.posAffect	2.108	0.159	13.285	0.000

Variances:

```

35   Estimate Std.Err z-value P(>|z|)
    .posAffect    0.311   0.032   9.874   0.000

```

2 fits ...

```

40 Group 2 [female]:
Regressions:
      Estimate  Std.Err  z-value  P(>|z|)
  posAffect ~
45   agency      (B)    0.365    0.061    5.954    0.000
Intercepts:
      Estimate  Std.Err  z-value  P(>|z|)
  .posAffect      2.192    0.161   13.587    0.000
50 Variances:
      Estimate  Std.Err  z-value  P(>|z|)
  .posAffect      0.423    0.044    9.618    0.000

```

- The fit of the more complex model is similar to the less complex model, so there is no evidence of an interaction.

```
anova(group.out.0, group.out.1)
```

2 fits ...

Chi Square Difference Test

```

      Df      AIC      BIC  Chisq  Chisq diff  Df  diff  Pr(>Chisq)
group.out.1  0 1252.4 1276.0 0.0000
group.out.0  1 1253.4 1273.1 2.9781      2.9781      1      0.0844 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

2 fits ...

- The slopes “appear to differ” in the two models.

```
parameterEstimates(group.out.1, ci = FALSE)[ ,
  c(1,2, 3, 4, 5, 6, 7)]
```

	lhs	op	rhs	block	group	label	est
1	posAffect	~	agency	1	1	A	0.452
2	posAffect	~	posAffect	1	1		0.309
3	agency	~	agency	1	1		0.253
4	posAffect	~1		1	1		1.890
5	agency	~1		1	1		2.508
6	posAffect	~	agency	2	2	B	0.237
7	posAffect	~	posAffect	2	2		0.419
8	agency	~	agency	2	2		0.247
9	posAffect	~1		2	2		2.514
10	agency	~1		2	2		2.516

- The agency effect difference between male and female seems to be $0.452 - 0.237 = 0.215$, but that's not “statistically significant”
- The effect of agency is .365 if the effects are assumed the same

I want a nice output table

```
library(kutils)
cfaTable10 <- compareLavaan(list("Restricted" =
  group.out.0, "Unrestricted" = group.out.1),
  fitmeas = c("chisq", "df", "rmsea", "cfi"),
  nesting = NULL, type = "latex", file =
  "output/cfaTable10.tex", print.results =
  FALSE)
cat(cfaTable10)
```

	χ^2	df	rmsea	cfi	$\Delta\chi^2$	Δdf	p
Unrestricted	0.00	0.00	0.00	1.00	-	-	-
Restricted	2.98	1.00	0.10	0.94	2.978a	1	0.084

a = Restricted vs Unrestricted

linear regression is equivalent

- If outcome is a single measure like posAffect, we can double-check the SEM result with a linear model.
- I'll assume the variances of the error terms are the same in the 2 groups (otherwise I'd have to go on a weighted least squares adventure)
- This allows both slopes and intercepts to differ among groups

```
modlm1 <- lm(posAffect ~ -1 + gender/agency, data
  = dat)
summary(modlm1, signif.stars = FALSE)
```


linear regression is equivalent ...

```

Call:
lm(formula = posAffect ~ -1 + gender/agency, data = dat)

Residuals:
    Min       1Q   Median       3Q      Max
-2.10608 -0.40401  0.02606  0.44460  1.32508

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
gendermale      1.88976     0.22056   8.568 2.75e-16 ***
genderfemale    2.51356     0.22955  10.950 < 2e-16 ***
gendermale:agency 0.45182     0.08624   5.239 2.69e-07 ***
genderfemale:agency 0.23701     0.08950   2.648 0.00843 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6054 on 376 degrees of freedom
Multiple R-squared:  0.963, Adjusted R-squared:  0.9626
F-statistic: 2444 on 4 and 376 DF,  p-value: < 2.2e-16

```

- Keep the same slope, but different intercepts

linear regression is equivalent ...

```
modlm2 <- lm(posAffect ~ -1 + gender + agency,
             data = dat)
summary(modlm2, signif.stars = FALSE)
```

```
Call:
lm(formula = posAffect ~ -1 + gender + agency, data = dat)

Residuals:
    Min       1Q   Median       3Q      Max
-2.10427 -0.39890  0.05395  0.44156  1.35513

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
gendermale    2.14912     0.16207   13.260 < 2e-16 ***
genderfemale  2.23329     0.16290   13.710 < 2e-16 ***
agency        0.34839     0.06226    5.596 4.24e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.607 on 377 degrees of freedom
Multiple R-squared:  0.9627, Adjusted R-squared:  0.9624
F-statistic: 3241 on 3 and 377 DF,  p-value: < 2.2e-16
```

linear regression is equivalent ...

- Test the difference between the models

```
anova(modlm1 , modlm2)
```

```
Analysis of Variance Table
```

```
Model 1: posAffect ~ -1 + gender/agency
```

```
Model 2: posAffect ~ -1 + gender + agency
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	376	137.82				
2	377	138.92	-1	-1.095	2.9873	0.08474 .

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

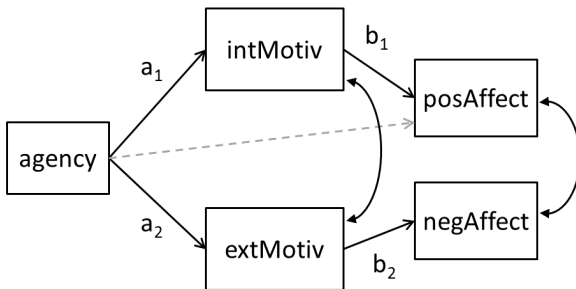
- Note anova defaults to a χ^2 test, and the p-value is identical to SEM output

Use SEM to represent several endogenous variables

- Suppose you had a more complex theory about the association among variables:
 - Positive Affect is affected by Intrinsic Motivation
 - Negative Affect is affected by Extrinsic Motivation
 - Intrinsic and Extrinsic Motivation are both affected by sense of Agency

Path Analysis: Mediation

We are still using the “scale” variables we created as averages



lavaan implementation of mediation model

- We'll need to get a psychologist to explain why the positive and negative affects are modeled separately in this way

```
mediat.mod.0 <- '  
  posAffect ~ intMotiv  
  negAffect ~ extMotiv  
  intMotiv + extMotiv ~ agency  
  intMotiv ~ extMotiv  
'  
  
mediat.out.0 <- sem(mediat.mod.0, data = dat)  
summary(mediat.out.0, rsquare = TRUE, fit = TRUE)
```

lavaan implementation of mediation model ...

```
lavaan (0.5-23.1097) converged normally after 23 iterations
```

```
Number of observations                380
```

```
Estimator                            ML
```

```
Minimum Function Test Statistic      11.604
```

```
Degrees of freedom                   4
```

```
P-value (Chi-square)                 0.021
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic      182.877
```

```
Degrees of freedom                   10
```

```
P-value                               0.000
```

```
User model versus baseline model:
```

```
Comparative Fit Index (CFI)         0.956
```

```
Tucker-Lewis Index (TLI)            0.890
```

```
Loglikelihood and Information Criteria:
```

```
Loglikelihood user model (H0)        -1555.935
```

```
Loglikelihood unrestricted model (H1) -1550.133
```

lavaan implementation of mediation model ...

```

Number of free parameters          10
Akaike (AIC)                      3131.870
Bayesian (BIC)                    3171.271
Sample-size adjusted Bayesian (BIC) 3139.543

```

Root Mean Square Error of Approximation:

```

RMSEA                             0.071
90 Percent Confidence Interval      0.025  0.120
P-value RMSEA <= 0.05              0.192

```

Standardized Root Mean Square Residual:

```

SRMR                               0.036

```

Parameter Estimates:

```

Information                        Expected
Standard Errors                    Standard

```

Regressions:

	Estimate	Std.Err	z-value	P(> z)
posAffect ~				
intMotiv	0.329	0.046	7.153	0.000
negAffect ~				
extMotiv	0.245	0.067	3.683	0.000

lavaan implementation of mediation model ...

```

intMotiv ~
  agency          0.558    0.061    9.102    0.000
extMotiv ~
  agency          0.233    0.047    4.938    0.000
55
Covariances:
      Estimate  Std.Err  z-value  P(>|z|)
50
.intMotiv ~
.extMotiv      -0.045    0.014   -3.130    0.002
.posAffect ~
.negAffect     -0.026    0.019   -1.401    0.161

Variances:
      Estimate  Std.Err  z-value  P(>|z|)
55
.posAffect     0.351    0.025   13.784    0.000
.negAffect     0.383    0.028   13.784    0.000
.intMotiv      0.357    0.026   13.784    0.000
.extMotiv      0.212    0.015   13.784    0.000
70

R-Square:
      Estimate
75
posAffect      0.118
negAffect      0.034
intMotiv       0.179
extMotiv       0.060

```

lavaan implementation of mediation model ...

```
mediat.mod.0 <- '  
  posAffect ~ intMotiv  
  negAffect ~ extMotiv  
  intMotiv + extMotiv ~ agency  
  intMotiv ~ extMotiv  
'  
  
mediat.out.0 <- sem(mediat.mod.0, data = dat)  
summary(mediat.out.0, rsquare = TRUE, fit = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 23 iterations
```

Number of observations	380
Estimator	ML
Minimum Function Test Statistic	11.604
Degrees of freedom	4
P-value (Chi-square)	0.021

```
Model test baseline model:
```

lavaan implementation of mediation model ...

```

Minimum Function Test Statistic      182.877
Degrees of freedom                    10
P-value                              0.000

User model versus baseline model:

Comparative Fit Index (CFI)          0.956
Tucker-Lewis Index (TLI)            0.890

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)        -1555.935
Loglikelihood unrestricted model (H1) -1550.133

Number of free parameters            10
Akaike (AIC)                        3131.870
Bayesian (BIC)                      3171.271
Sample-size adjusted Bayesian (BIC)  3139.543

Root Mean Square Error of Approximation:

RMSEA                                0.071
90 Percent Confidence Interval       0.025  0.120
P-value RMSEA <= 0.05              0.192

Standardized Root Mean Square Residual:

```

lavaan implementation of mediation model ...

SRMR					0.036
Parameter Estimates:					
Information					Expected
Standard Errors					Standard
Regressions:					
	Estimate	Std.Err	z-value	P(> z)	
posAffect ~					
intMotiv	0.329	0.046	7.153	0.000	
negAffect ~					
extMotiv	0.245	0.067	3.683	0.000	
intMotiv ~					
agency	0.558	0.061	9.102	0.000	
extMotiv ~					
agency	0.233	0.047	4.938	0.000	
Covariances:					
	Estimate	Std.Err	z-value	P(> z)	
.intMotiv ~					
.extMotiv	-0.045	0.014	-3.130	0.002	
.posAffect ~					
.negAffect	-0.026	0.019	-1.401	0.161	

lavaan implementation of mediation model ...

Variances:

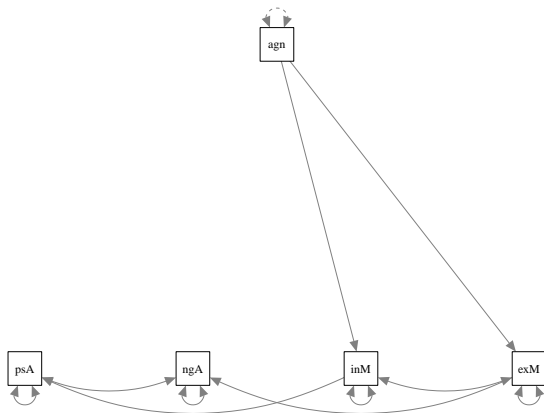
	Estimate	Std.Err	z-value	P(> z)
.posAffect	0.351	0.025	13.784	0.000
.negAffect	0.383	0.028	13.784	0.000
.intMotiv	0.357	0.026	13.784	0.000
.extMotiv	0.212	0.015	13.784	0.000

R-Square:

	Estimate
posAffect	0.118
negAffect	0.034
intMotiv	0.179
extMotiv	0.060

Trouble with semPaths

```
semPaths(mediat.out.0)
```



Should Agency have a direct effect on positive affect?

- The regression paths are significant, but so is our model fit statistic.
 - in SEM, a significant fit statistic is a “bad thing”, it means our model is not doing well as the “saturated” model.
- Perhaps a sense of Agency still has a direct effect on Positive Affect. Note we insert “+ agency” in the posAffect equation.

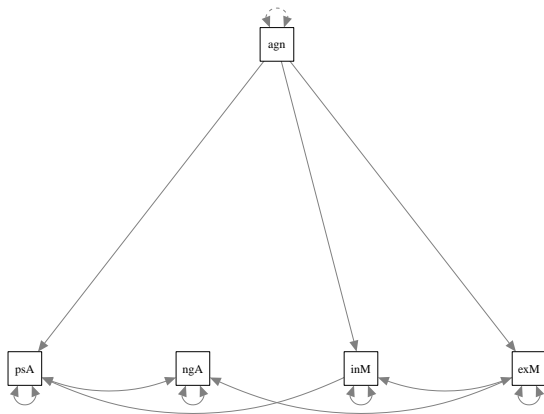
```
mediat.mod.1 <- '  
  posAffect ~ intMotiv + agency  
  negAffect ~ extMotiv  
  intMotiv + extMotiv ~ agency  
  intMotiv ~ extMotiv  
'  
mediat.out.1 <- sem(mediat.mod.1, data = dat)
```

Should Agency have a direct effect on positive affect? ...

```
mediat.mod.1 <- '  
  posAffect ~ intMotiv + agency  
  negAffect ~ extMotiv  
  intMotiv + extMotiv ~ agency  
  intMotiv ~ extMotiv  
'  
mediat.out.1 <- sem(mediat.mod.1, data = dat)
```


Visualize Whirled Peas II

```
semPaths(mediat.out.1)
```



Compare the fit of the models with and without the direct effect

- Are we wise to include the direct effect?
- It appears there is a statistically significant difference between the models in the `anova()` output.

```
anova(mediat.out.0 , mediat.out.1)
```

```
Chi Square Difference Test
```

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
mediat.out.1	3	3124.9	3168.3	2.6647			
mediat.out.0	4	3131.9	3171.3	11.6040	8.9393	1	0.002791 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
anova(mediat.out.0 , mediat.out.1)
```

Compare the fit of the models with and without the direct effect ...

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)				
mediat.out.1	3	3124.9	3168.3	2.6647							
mediat.out.0	4	3131.9	3171.3	11.6040	8.9393	1	0.002791	**			

Signif. codes:	0	'***'	0.001	'**'	0.01	'*'	0.05	','	0.1	' '	1

The small p value indicates there is probably a difference

Review the summary of the output

- The fit improvement may be reflected in the R^2 for Positive Affect (increased by 2%).

```
summary(mediat.out.1, rsquare = TRUE, fit = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 26 iterations
```

```
Number of observations                380
```

```
Estimator                             ML
```

```
Minimum Function Test Statistic       2.665
```

```
Degrees of freedom                    3
```

```
P-value (Chi-square)                  0.446
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic       182.877
```

```
Degrees of freedom                    10
```

```
P-value                                0.000
```

```
User model versus baseline model:
```

```
Comparative Fit Index (CFI)           1.000
```

Review the summary of the output ...

```

Tucker-Lewis Index (TLI)                                1.006

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)                            -1551.465
Loglikelihood unrestricted model (H1)                    -1550.133

Number of free parameters                                11
Akaike (AIC)                                             3124.930
Bayesian (BIC)                                           3168.272
Sample-size adjusted Bayesian (BIC)                     3133.371

Root Mean Square Error of Approximation:

RMSEA                                                    0.000
90 Percent Confidence Interval                          0.000  0.083
P-value RMSEA <= 0.05                                   0.758

Standardized Root Mean Square Residual:

SRMR                                                    0.017

Parameter Estimates:

Information                                             Expected
Standard Errors                                         Standard

```

Review the summary of the output ...

Regressions:

	Estimate	Std.Err	z-value	P(> z)
posAffect ~				
intMotiv	0.265	0.050	5.280	0.000
agency	0.199	0.066	3.011	0.003
negAffect ~				
extMotiv	0.242	0.067	3.624	0.000
intMotiv ~				
agency	0.558	0.061	9.102	0.000
extMotiv ~				
agency	0.233	0.047	4.938	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
.intMotiv ~				
.extMotiv	-0.045	0.014	-3.130	0.002
.posAffect ~				
.negAffect	-0.024	0.019	-1.277	0.202

Variances:

	Estimate	Std.Err	z-value	P(> z)
.posAffect	0.343	0.025	13.784	0.000
.negAffect	0.383	0.028	13.784	0.000
.intMotiv	0.357	0.026	13.784	0.000
.extMotiv	0.212	0.015	13.784	0.000

Review the summary of the output ...

R-Square:

	Estimate
posAffect	0.139
negAffect	0.033
intMotiv	0.179
extMotiv	0.060

```
summary(mediat.out.1, rsquare = TRUE, fit = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 26 iterations
```

Number of observations	380
Estimator	ML
Minimum Function Test Statistic	2.665
Degrees of freedom	3
P-value (Chi-square)	0.446

```
Model test baseline model:
```

Minimum Function Test Statistic	182.877
Degrees of freedom	10
P-value	0.000

Review the summary of the output ...

15 User model versus baseline model:

Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.006

20 Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-1551.465
Loglikelihood unrestricted model (H1)	-1550.133

Number of free parameters	11
Akaike (AIC)	3124.930
Bayesian (BIC)	3168.272
Sample-size adjusted Bayesian (BIC)	3133.371

30 Root Mean Square Error of Approximation:

RMSEA	0.000
90 Percent Confidence Interval	0.000 0.083
P-value RMSEA <= 0.05	0.758

35 Standardized Root Mean Square Residual:

SRMR	0.017
------	-------

Review the summary of the output ...

Parameter Estimates:

Information
Standard Errors

Expected
Standard

Regressions:

	Estimate	Std.Err	z-value	P(> z)
posAffect ~				
intMotiv	0.265	0.050	5.280	0.000
agency	0.199	0.066	3.011	0.003
negAffect ~				
extMotiv	0.242	0.067	3.624	0.000
intMotiv ~				
agency	0.558	0.061	9.102	0.000
extMotiv ~				
agency	0.233	0.047	4.938	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
.intMotiv ~				
.extMotiv	-0.045	0.014	-3.130	0.002
.posAffect ~				
.negAffect	-0.024	0.019	-1.277	0.202

Variances:

	Estimate	Std.Err	z-value	P(> z)
--	----------	---------	---------	---------

Review the summary of the output ...

```

.posAffect      0.343    0.025    13.784    0.000
.negAffect      0.383    0.028    13.784    0.000
.intMotiv       0.357    0.026    13.784    0.000
.extMotiv       0.212    0.015    13.784    0.000

```

R-Square :

Estimate

```

posAffect      0.139
negAffect      0.033
intMotiv       0.179
extMotiv       0.060

```

Hypothesis test for the indirect effect

- For testing the significance of indirect paths in mediation models, the major advantage of SEM over OLS regression is that all parameters can be estimated in a single model.
- Most SEM software packages include bootstrapping options, which is the preferred method for testing indirect paths because products of parameters are not normally distributed.

```
Nboot <- 500
mediat.mod.1 <- '
  posAffect ~ b1*intMotiv + agency
  negAffect ~ b2*extMotiv
  intMotiv ~ a1*agency
  extMotiv ~ a2*agency
  intMotiv ~ extMotiv
## define mediation parameters (indirect effects)
ind1 := a1 * b1
ind2 := a2 * b2
```

Hypothesis test for the indirect effect ...

```
,  
mediat.out.1 <- sem(mediat.mod.1, data = dat,  
                    se = "boot", bootstrap =  
                    Nboot)
```

```
Nboot <- 500  
mediat.mod.1 <- '  
  posAffect ~ b1*intMotiv + agency  
  negAffect ~ b2*extMotiv  
  intMotiv ~ a1*agency  
  extMotiv ~ a2*agency  
  intMotiv ~ extMotiv  
  ## define mediation parameters (indirect effects)  
  ind1 := a1 * b1  
  ind2 := a2 * b2  
,  
mediat.out.1 <- sem(mediat.mod.1, data = dat,
```

Hypothesis test for the indirect effect ...

```
se = "boot", bootstrap =  
  Nboot)
```

- This takes a couple of minutes. We can adjust the “Nboot” parameter for testing. In analysis for a report, Nboot should be a large value, such as 1000. Here, the bootstrap estimates are requested, with 500 iterations

```
parameterEstimates(mediat.out.1, boot.ci.type =  
  "bca.simple")
```

Hypothesis test for the indirect effect ...

	lhs	op	rhs	label	est	se	z	pvalue	ci.lower
			ci.upper						
1	posAffect	~	intMotiv	b1	0.265	0.051	5.219	0.000	0.150
	0.360								
2	posAffect	~	agency		0.199	0.073	2.738	0.006	0.059
	0.338								
3	negAffect	~	extMotiv	b2	0.242	0.079	3.060	0.002	0.097
	0.397								
4	intMotiv	~	agency	a1	0.558	0.067	8.277	0.000	0.443
	0.713								
5	extMotiv	~	agency	a2	0.233	0.051	4.534	0.000	0.139
	0.334								
6	intMotiv	~~	extMotiv		-0.045	0.013	-3.523	0.000	-0.071
	-0.019								
7	posAffect	~~	posAffect		0.343	0.026	13.128	0.000	0.295
	0.395								
8	negAffect	~~	negAffect		0.383	0.039	9.722	0.000	0.313
	0.464								
9	intMotiv	~~	intMotiv		0.357	0.024	14.781	0.000	0.310
	0.404								
10	extMotiv	~~	extMotiv		0.212	0.018	11.854	0.000	0.181
	0.249								
11	posAffect	~~	negAffect		-0.024	0.022	-1.091	0.275	-0.068
	0.019								

Hypothesis test for the indirect effect ...

```

12  agency ~      agency      0.250 0.000      NA      NA      0.250
    0.250
13  ind1 :=      a1*b1  ind1  0.148 0.029  5.062  0.000  0.097
    0.216
14  ind2 :=      a2*b2  ind2  0.056 0.023  2.493  0.013  0.021
    0.110

```

```
parameterEstimates(mediat.out.1, boot.ci.type =
  "bca.simple")
```

```

      lhs op      rhs label      est      se      z pvalue ci.lower
1  posAffect ~  intMotiv  b1  0.265 0.051  5.219  0.000  0.150
  0.360
2  posAffect ~      agency      0.199 0.073  2.738  0.006  0.059
  0.338
3  negAffect ~  extMotiv  b2  0.242 0.079  3.060  0.002  0.097
  0.397
4  intMotiv ~      agency  a1  0.558 0.067  8.277  0.000  0.443
  0.713
5  extMotiv ~      agency  a2  0.233 0.051  4.534  0.000  0.139
  0.334

```

Hypothesis test for the indirect effect ...

6	intMotiv	~	extMotiv		-0.045	0.013	-3.523	0.000	-0.071
	-0.019								
7	posAffect	~	posAffect		0.343	0.026	13.128	0.000	0.295
	0.395								
8	negAffect	~	negAffect		0.383	0.039	9.722	0.000	0.313
	0.464								
9	intMotiv	~	intMotiv		0.357	0.024	14.781	0.000	0.310
	0.404								
10	extMotiv	~	extMotiv		0.212	0.018	11.854	0.000	0.181
	0.249								
11	posAffect	~	negAffect		-0.024	0.022	-1.091	0.275	-0.068
	0.019								
12	agency	~	agency		0.250	0.000	NA	NA	0.250
	0.250								
13	ind1	:=	a1*b1	ind1	0.148	0.029	5.062	0.000	0.097
	0.216								
14	ind2	:=	a2*b2	ind2	0.056	0.023	2.493	0.013	0.021
	0.110								

Outline

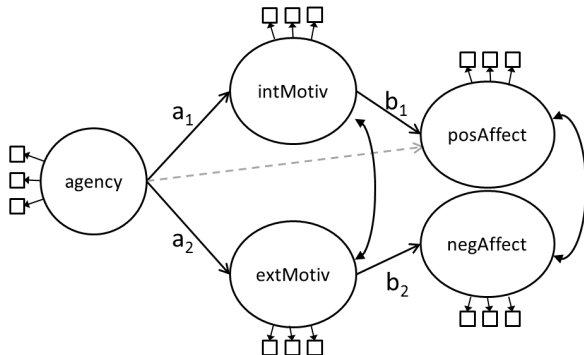
- 1 Get the affect data
- 2 Path Diagrams
 - Linear Regression
 - Moderators
 - Mediation
- 3 Structural Equation Modeling
 - Remember Regression?
- 4 SEM in R
 - Plots
 - Estimate the Moderation Model
 - More Elaborate Path Model
- 5 Full Latent Variable Regression Model
 - Confirmatory Factor Analysis
 - Structural Regressions among Latent Constructs
 - Supplementary Hypothesis Test
- 6 Conclusion

Regression relationships among latent variables

- This is the SEM in its full glory.
- Assume
 - 1 there are “latent variables” (unmeasured personal traits)
 - 2 assume that there is a multivariate normal relationship among those traits
 - 3 the observed scores are a reflection of each individual's latent variables.
- Instead of blinding you with mathematical wizardry, I better show a picture.

The Big Picture

The circles are unmeasured variables.



- The SEM integrates
 - “measurement error” analysis with
 - analysis of the underlying relationships.

The Big Picture ...

- Regression models that we used before assume predictors are measured without error.
 - If there is random error in predictors, slope coefficients are “attenuated”—underestimated.
 - Hence, we miss relationships because of measurement error.
 - However, to be honest, the mean-scale score regressions we have discussed so far are quite good in comparison to the usual regression in the social science literature, where just a single indicator is typically available for each construct.

Quick Jargon review

Indicators: The observed scale items

Latent variables: (aka “factors”, “latent constructs” or “common factors”): unobserved variables thought to be the things we are truly interested in. We’d really like to study the relationship among them, but we are unable to do so.

factor loadings: the coefficients which indicate how tightly an indicator is linked to the latent variable.

Confirmatory Factor Analysis

- We are focused on the measurement properties
- We estimate loadings for all of the indicators.
- We don't worry about the relationship among the latent variables yet.
 - But we don't ignore them.
 - The opposite is true. CFA models freely estimate all correlations among latent variables, without imposing any further constraints on their relationships.
- These are also called "measurement models" because they provide details about how strongly each item is related to the latent construct.

Confirmatory Factor Analysis

- The lavaan model has the style
latent_construct =~ indicator1 + indicator2 + indicator3
- The function “cfa()” is used.
 - The only argument worth mentioning is “std.lv = TRUE”.
 - The underlying unmeasured constructs are to be scaled so that the variance of each one is equal to 1.0. (standardized)

```
cfa.mod <- '  
## factor loadings  
Agency =~ Agency1 + Agency2 + Agency3  
Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
,  
cfa.out <- cfa(cfa.mod, data = dat, std.lv = TRUE)
```

Confirmatory Factor Analysis ...

```
cfa.mod <- '  
## factor loadings  
Agency =~ Agency1 + Agency2 + Agency3  
Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
,  
cfa.out <- cfa(cfa.mod, data = dat, std.lv = TRUE)
```

- So far, it does not seem dangerous. Wait till the output vectors start flying on the next slide.

CFA Output

```
summary(cfa.out, standardized = TRUE, fit = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 59 iterations
```

```
Number of observations                380
```

```
Estimator                            ML
```

```
Minimum Function Test Statistic      106.847
```

```
Degrees of freedom                   80
```

```
P-value (Chi-square)                 0.024
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic      3749.411
```

```
Degrees of freedom                   105
```

```
P-value                               0.000
```

```
User model versus baseline model:
```

```
Comparative Fit Index (CFI)         0.993
```

```
Tucker-Lewis Index (TLI)            0.990
```

```
Loglikelihood and Information Criteria:
```

CFA Output ...

```

Loglikelihood user model (H0)                -3699.110
Loglikelihood unrestricted model (H1)        -3645.686

```

```

Number of free parameters                    40
Akaike (AIC)                                7478.219
Bayesian (BIC)                              7635.826
Sample-size adjusted Bayesian (BIC)         7508.914

```

Root Mean Square Error of Approximation:

```

RMSEA                                        0.030
90 Percent Confidence Interval              0.011  0.044
P-value RMSEA <= 0.05                      0.994

```

Standardized Root Mean Square Residual:

```

SRMR                                        0.031

```

Parameter Estimates:

```

Information                                Expected
Standard Errors                            Standard

```

Latent Variables:

```

          Estimate   Std.Err   z-value   P(>|z|)   Std.lv   Std.all
Agency =~

```

CFA Output ...

Agency1	0.466	0.021	22.560	0.000	0.466	0.905
Agency2	0.492	0.021	23.774	0.000	0.492	0.934
Agency3	0.497	0.022	22.815	0.000	0.497	0.911
Intrinsic =~						
Intrin1	0.541	0.039	13.960	0.000	0.541	0.704
Intrin2	0.581	0.043	13.489	0.000	0.581	0.683
Intrin3	0.615	0.038	16.201	0.000	0.615	0.799
Extrinsic =~						
Extrin1	0.388	0.022	17.606	0.000	0.388	0.808
Extrin2	0.456	0.027	17.168	0.000	0.456	0.792
Extrin3	0.471	0.026	18.100	0.000	0.471	0.826
Positive =~						
PosAFF1	0.569	0.028	20.132	0.000	0.569	0.853
PosAFF2	0.603	0.029	21.150	0.000	0.603	0.882
PosAFF3	0.632	0.029	21.648	0.000	0.632	0.895
Negative =~						
NegAFF1	0.634	0.029	21.670	0.000	0.634	0.889
NegAFF2	0.585	0.027	21.457	0.000	0.585	0.883
NegAFF3	0.598	0.026	22.805	0.000	0.598	0.918
Covariances:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency ~						
Intrinsic	0.507	0.047	10.782	0.000	0.507	0.507
Extrinsic	0.270	0.054	5.028	0.000	0.270	0.270
Positive	0.302	0.051	5.950	0.000	0.302	0.302

CFA Output ...

75	Negative	0.017	0.055	0.312	0.755	0.017	0.017
	Intrinsic ~						
	Extrinsic	-0.028	0.063	-0.441	0.659	-0.028	-0.028
	Positive	0.414	0.052	7.918	0.000	0.414	0.414
	Negative	0.021	0.060	0.341	0.733	0.021	0.021
80	Extrinsic ~						
	Positive	-0.029	0.058	-0.503	0.615	-0.029	-0.029
	Negative	0.209	0.056	3.764	0.000	0.209	0.209
	Positive ~						
	Negative	-0.071	0.056	-1.274	0.203	-0.071	-0.071
85	Variances:						
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
	.Agency1	0.048	0.005	9.649	0.000	0.048	0.181
	.Agency2	0.036	0.005	7.604	0.000	0.036	0.129
90	.Agency3	0.051	0.005	9.278	0.000	0.051	0.170
	.Intrin1	0.298	0.029	10.204	0.000	0.298	0.505
	.Intrin2	0.386	0.036	10.620	0.000	0.386	0.533
	.Intrin3	0.214	0.029	7.474	0.000	0.214	0.361
	.Extrin1	0.080	0.009	8.924	0.000	0.080	0.347
95	.Extrin2	0.123	0.013	9.465	0.000	0.123	0.372
	.Extrin3	0.103	0.012	8.264	0.000	0.103	0.318
	.PosAFF1	0.121	0.012	9.921	0.000	0.121	0.272
	.PosAFF2	0.104	0.012	8.615	0.000	0.104	0.222
	.PosAFF3	0.099	0.013	7.870	0.000	0.099	0.198
00	.NegAFF1	0.107	0.012	9.202	0.000	0.107	0.210

CFA Output ...

.NegAFF2	0.096	0.010	9.498	0.000	0.096	0.220
.NegAFF3	0.067	0.009	7.369	0.000	0.067	0.158
Agency	1.000				1.000	1.000
Intrinsic	1.000				1.000	1.000
Extrinsic	1.000				1.000	1.000
Positive	1.000				1.000	1.000
Negative	1.000				1.000	1.000

```
summary(cfa.out, standardized = TRUE, fit = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 59 iterations
```

```
Number of observations                380
```

```
Estimator                             ML
```

```
Minimum Function Test Statistic       106.847
```

```
Degrees of freedom                    80
```

```
P-value (Chi-square)                  0.024
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic       3749.411
```

```
Degrees of freedom                    105
```

```
P-value                               0.000
```

CFA Output ...

15 User model versus baseline model:

Comparative Fit Index (CFI)	0.993
Tucker-Lewis Index (TLI)	0.990

20 Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-3699.110
Loglikelihood unrestricted model (H1)	-3645.686

Number of free parameters	40
Akaike (AIC)	7478.219
Bayesian (BIC)	7635.826
Sample-size adjusted Bayesian (BIC)	7508.914

25
30 Root Mean Square Error of Approximation:

RMSEA	0.030
90 Percent Confidence Interval	0.011 0.044
P-value RMSEA \leq 0.05	0.994

35 Standardized Root Mean Square Residual:

SRMR	0.031
------	-------

CFA Output ...

Parameter Estimates:

Information	Expected					
Standard Errors	Standard					
Latent Variables:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.560	0.000	0.466	0.905
Agency2	0.492	0.021	23.774	0.000	0.492	0.934
Agency3	0.497	0.022	22.815	0.000	0.497	0.911
Intrinsic =~						
Intrin1	0.541	0.039	13.960	0.000	0.541	0.704
Intrin2	0.581	0.043	13.489	0.000	0.581	0.683
Intrin3	0.615	0.038	16.201	0.000	0.615	0.799
Extrinsic =~						
Extrin1	0.388	0.022	17.606	0.000	0.388	0.808
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Extrin3	0.471	0.026	18.100	0.000	0.471	0.826
Positive =~						
PosAFF1	0.569	0.028	20.132	0.000	0.569	0.853
PosAFF2	0.603	0.029	21.150	0.000	0.603	0.882
PosAFF3	0.632	0.029	21.648	0.000	0.632	0.895
Negative =~						
NegAFF1	0.634	0.029	21.670	0.000	0.634	0.889
NegAFF2	0.585	0.027	21.457	0.000	0.585	0.883

CFA Output ...

	NegAFF3	0.598	0.026	22.805	0.000	0.598	0.918
Covariances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
	Agency ~						
	Intrinsic	0.507	0.047	10.782	0.000	0.507	0.507
	Extrinsic	0.270	0.054	5.028	0.000	0.270	0.270
	Positive	0.302	0.051	5.950	0.000	0.302	0.302
	Negative	0.017	0.055	0.312	0.755	0.017	0.017
	Intrinsic ~						
	Extrinsic	-0.028	0.063	-0.441	0.659	-0.028	-0.028
	Positive	0.414	0.052	7.918	0.000	0.414	0.414
	Negative	0.021	0.060	0.341	0.733	0.021	0.021
	Extrinsic ~						
	Positive	-0.029	0.058	-0.503	0.615	-0.029	-0.029
	Negative	0.209	0.056	3.764	0.000	0.209	0.209
	Positive ~						
	Negative	-0.071	0.056	-1.274	0.203	-0.071	-0.071
Variances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
	.Agency1	0.048	0.005	9.649	0.000	0.048	0.181
	.Agency2	0.036	0.005	7.604	0.000	0.036	0.129
	.Agency3	0.051	0.005	9.278	0.000	0.051	0.170
	.Intrin1	0.298	0.029	10.204	0.000	0.298	0.505
	.Intrin2	0.386	0.036	10.620	0.000	0.386	0.533

CFA Output ...

.Intrin3	0.214	0.029	7.474	0.000	0.214	0.361
.Extrin1	0.080	0.009	8.924	0.000	0.080	0.347
.Extrin2	0.123	0.013	9.465	0.000	0.123	0.372
.Extrin3	0.103	0.012	8.264	0.000	0.103	0.318
.PosAFF1	0.121	0.012	9.921	0.000	0.121	0.272
.PosAFF2	0.104	0.012	8.615	0.000	0.104	0.222
.PosAFF3	0.099	0.013	7.870	0.000	0.099	0.198
.NegAFF1	0.107	0.012	9.202	0.000	0.107	0.210
.NegAFF2	0.096	0.010	9.498	0.000	0.096	0.220
.NegAFF3	0.067	0.009	7.369	0.000	0.067	0.158
Agency	1.000				1.000	1.000
Intrinsic	1.000				1.000	1.000
Extrinsic	1.000				1.000	1.000
Positive	1.000				1.000	1.000
Negative	1.000				1.000	1.000

CFA Commentary

- The model appears to fit well,
 - all factor loadings are significant, and the
 - standardized factor loadings indicate strong correlations between indicators and constructs.
- However, we did not take into account the relationships among the latent variables.
 - We don't have "Agency" as predictor of "Positive" affect.

Structural Regressions among Latent Constructs

- Now that we have a strong measurement model, we can specify a structure among the latent variables (instead of free correlations).
- Because the CFA was freely allowed to estimate correlations among the latent variables, this step can be viewed as a “restriction” of allowed paths.

```
mediat.mod.2 <- '  
  ## measurement model declares the latent  
  constructs  
  Agency =~ Agency1 + Agency2 + Agency3  
  Intrinsic =~ Intrin1 + Intrin2 + Intrin3  
  Extrinsic =~ Extrin1 + Extrin2 + Extrin3  
  Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
  Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
  ## structural model represents relationships  
  Positive ~ b1*Intrinsic + Agency  
  Negative ~ b2*Extrinsic
```

Structural Regressions among Latent Constructs ...

```

Intrinsic ~ a1*Agency
Extrinsic ~ a2*Agency
Intrinsic ~ Extrinsic
## define mediation parameters (indirect effects)
ind1 := a1 * b1
ind2 := a2 * b2
'

```

```

mediat.mod.2 <- '
## measurement model declares the latent
  constructs
Agency =~ Agency1 + Agency2 + Agency3
Intrinsic =~ Intrin1 + Intrin2 + Intrin3
Extrinsic =~ Extrin1 + Extrin2 + Extrin3
Positive =~ PosAFF1 + PosAFF2 + PosAFF3
Negative =~ NegAFF1 + NegAFF2 + NegAFF3
## structural model represents relationships

```

Structural Regressions among Latent Constructs ...

```
Positive ~ b1*Intrinsic + Agency
Negative ~ b2*Extrinsic
Intrinsic ~ a1*Agency
Extrinsic ~ a2*Agency
Intrinsic ~ Extrinsic
## define mediation parameters (indirect effects)
ind1 := a1 * b1
ind2 := a2 * b2
,
```

```
mediat.out.2 <- sem(mediat.mod.2, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.2, standardized = TRUE, fit =
        TRUE)
```

Structural Regressions among Latent Constructs ...

lavaan (0.5-23.1097) converged normally after 62 iterations

Number of observations 380

Estimator ML

Minimum Function Test Statistic 109.152

Degrees of freedom 83

P-value (Chi-square) 0.029

Model test baseline model:

Minimum Function Test Statistic 3749.411

Degrees of freedom 105

P-value 0.000

User model versus baseline model:

Comparative Fit Index (CFI) 0.993

Tucker-Lewis Index (TLI) 0.991

Loglikelihood and Information Criteria:

Loglikelihood user model (H0) -3700.262

Loglikelihood unrestricted model (H1) -3645.686

Structural Regressions among Latent Constructs ...

Number of free parameters	37
Akaike (AIC)	7474.524
Bayesian (BIC)	7620.310
Sample-size adjusted Bayesian (BIC)	7502.917

Root Mean Square Error of Approximation:

RMSEA	0.029
90 Percent Confidence Interval	0.010 0.043
P-value RMSEA <= 0.05	0.996

Standardized Root Mean Square Residual:

SRMR	0.034
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Bootstrap
Number of requested bootstrap draws	500
Number of successful bootstrap draws	500

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.302	0.000	0.466	0.905

Structural Regressions among Latent Constructs ...

Agency2	0.492	0.021	23.227	0.000	0.492	0.933
Agency3	0.497	0.024	20.574	0.000	0.497	0.912
Intrinsic ≈						
Intrin1	0.466	0.035	13.489	0.000	0.540	0.703
Intrin2	0.500	0.037	13.502	0.000	0.580	0.682
Intrin3	0.531	0.032	16.397	0.000	0.616	0.800
Extrinsic ≈						
Extrin1	0.373	0.022	16.779	0.000	0.388	0.808
Extrin2	0.440	0.028	15.945	0.000	0.457	0.793
Extrin3	0.454	0.029	15.466	0.000	0.471	0.827
Positive ≈						
PosAFF1	0.514	0.025	20.161	0.000	0.569	0.854
PosAFF2	0.545	0.029	18.693	0.000	0.604	0.882
PosAFF3	0.570	0.027	21.232	0.000	0.632	0.895
Negative ≈						
NegAFF1	0.620	0.038	16.174	0.000	0.633	0.889
NegAFF2	0.573	0.042	13.579	0.000	0.585	0.883
NegAFF3	0.586	0.035	16.865	0.000	0.598	0.918
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.343	0.075	4.557	0.000	0.359	0.359
Agency	0.129	0.071	1.824	0.068	0.116	0.116
Negative ~						
Extrinsic (b2)	0.199	0.069	2.902	0.004	0.202	0.202

Structural Regressions among Latent Constructs ...

Intrinsic ~							
Agency	(a1)	0.588	0.080	7.315	0.000	0.507	0.507
Extrinsic ~							
Agency	(a2)	0.278	0.064	4.328	0.000	0.268	0.268
Covariances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intrinsic ~							
.Extrinsic		-0.202	0.062	-3.235	0.001	-0.202	-0.202
.Positive ~							
.Negative		-0.076	0.070	-1.091	0.275	-0.076	-0.076
Variances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Agency1		0.048	0.006	8.464	0.000	0.048	0.181
.Agency2		0.036	0.005	7.928	0.000	0.036	0.129
.Agency3		0.050	0.006	8.976	0.000	0.050	0.169
.Intrin1		0.299	0.032	9.299	0.000	0.299	0.506
.Intrin2		0.387	0.038	10.217	0.000	0.387	0.535
.Intrin3		0.213	0.035	6.099	0.000	0.213	0.359
.Extrin1		0.080	0.011	7.217	0.000	0.080	0.348
.Extrin2		0.123	0.016	7.492	0.000	0.123	0.372
.Extrin3		0.103	0.017	5.948	0.000	0.103	0.317
.PosAFF1		0.121	0.016	7.750	0.000	0.121	0.271
.PosAFF2		0.104	0.015	6.798	0.000	0.104	0.222
.PosAFF3		0.099	0.014	6.879	0.000	0.099	0.199

Structural Regressions among Latent Constructs ...

.NegAFF1	0.107	0.016	6.789	0.000	0.107	0.210
.NegAFF2	0.096	0.013	7.540	0.000	0.096	0.219
.NegAFF3	0.067	0.012	5.555	0.000	0.067	0.158
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.743	0.743
.Extrinsic	1.000				0.928	0.928
.Positive	1.000				0.815	0.815
.Negative	1.000				0.959	0.959

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.202	0.046	4.348	0.000	0.182	0.182
ind2	0.055	0.023	2.436	0.015	0.054	0.054

```
mediat.out.2 <- sem(mediat.mod.2, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.2, standardized = TRUE, fit =
        TRUE)
```

Structural Regressions among Latent Constructs ...

lavaan (0.5-23.1097) converged normally after 62 iterations

Number of observations 380

Estimator ML

Minimum Function Test Statistic 109.152

Degrees of freedom 83

P-value (Chi-square) 0.029

Model test baseline model:

Minimum Function Test Statistic 3749.411

Degrees of freedom 105

P-value 0.000

User model versus baseline model:

Comparative Fit Index (CFI) 0.993

Tucker-Lewis Index (TLI) 0.991

Loglikelihood and Information Criteria:

Loglikelihood user model (H0) -3700.262

Loglikelihood unrestricted model (H1) -3645.686

Structural Regressions among Latent Constructs ...

Number of free parameters	37
Akaike (AIC)	7474.524
Bayesian (BIC)	7620.310
Sample-size adjusted Bayesian (BIC)	7502.917

Root Mean Square Error of Approximation:

RMSEA	0.029
90 Percent Confidence Interval	0.010 0.043
P-value RMSEA \leq 0.05	0.996

Standardized Root Mean Square Residual:

SRMR	0.034
------	-------

Parameter Estimates:

Information	Observed
Standard Errors	Bootstrap
Number of requested bootstrap draws	500
Number of successful bootstrap draws	500

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.302	0.000	0.466	0.905

Structural Regressions among Latent Constructs ...

Agency2	0.492	0.021	23.227	0.000	0.492	0.933
Agency3	0.497	0.024	20.574	0.000	0.497	0.912
Intrinsic =~						
Intrin1	0.466	0.035	13.489	0.000	0.540	0.703
Intrin2	0.500	0.037	13.502	0.000	0.580	0.682
Intrin3	0.531	0.032	16.397	0.000	0.616	0.800
Extrinsic =~						
Extrin1	0.373	0.022	16.779	0.000	0.388	0.808
Extrin2	0.440	0.028	15.945	0.000	0.457	0.793
Extrin3	0.454	0.029	15.466	0.000	0.471	0.827
Positive =~						
PosAFF1	0.514	0.025	20.161	0.000	0.569	0.854
PosAFF2	0.545	0.029	18.693	0.000	0.604	0.882
PosAFF3	0.570	0.027	21.232	0.000	0.632	0.895
Negative =~						
NegAFF1	0.620	0.038	16.174	0.000	0.633	0.889
NegAFF2	0.573	0.042	13.579	0.000	0.585	0.883
NegAFF3	0.586	0.035	16.865	0.000	0.598	0.918
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.343	0.075	4.557	0.000	0.359	0.359
Agency	0.129	0.071	1.824	0.068	0.116	0.116
Negative ~						
Extrinsic (b2)	0.199	0.069	2.902	0.004	0.202	0.202

Structural Regressions among Latent Constructs ...

Intrinsic ~							
Agency	(a1)	0.588	0.080	7.315	0.000	0.507	0.507
Extrinsic ~							
Agency	(a2)	0.278	0.064	4.328	0.000	0.268	0.268
Covariances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intrinsic ~							
.Extrinsic		-0.202	0.062	-3.235	0.001	-0.202	-0.202
.Positive ~							
.Negative		-0.076	0.070	-1.091	0.275	-0.076	-0.076
Variances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Agency1		0.048	0.006	8.464	0.000	0.048	0.181
.Agency2		0.036	0.005	7.928	0.000	0.036	0.129
.Agency3		0.050	0.006	8.976	0.000	0.050	0.169
.Intrin1		0.299	0.032	9.299	0.000	0.299	0.506
.Intrin2		0.387	0.038	10.217	0.000	0.387	0.535
.Intrin3		0.213	0.035	6.099	0.000	0.213	0.359
.Extrin1		0.080	0.011	7.217	0.000	0.080	0.348
.Extrin2		0.123	0.016	7.492	0.000	0.123	0.372
.Extrin3		0.103	0.017	5.948	0.000	0.103	0.317
.PosAFF1		0.121	0.016	7.750	0.000	0.121	0.271
.PosAFF2		0.104	0.015	6.798	0.000	0.104	0.222
.PosAFF3		0.099	0.014	6.879	0.000	0.099	0.199

Structural Regressions among Latent Constructs ...

.NegAFF1	0.107	0.016	6.789	0.000	0.107	0.210
.NegAFF2	0.096	0.013	7.540	0.000	0.096	0.219
.NegAFF3	0.067	0.012	5.555	0.000	0.067	0.158
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.743	0.743
.Extrinsic	1.000				0.928	0.928
.Positive	1.000				0.815	0.815
.Negative	1.000				0.959	0.959

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.202	0.046	4.348	0.000	0.182	0.182
ind2	0.055	0.023	2.436	0.015	0.054	0.054

- The mediation model with latent variables estimates fewer parameters than the CFA, but it fits just as well as the CFA.

```
anova(cfa.out, mediat.out.2)
```

Structural Regressions among Latent Constructs ...

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
cfa.out	80	7478.2	7635.8	106.85			
mediat.out.2	83	7474.5	7620.3	109.15	2.3051	3	0.5116

```
anova(cfa.out , mediat.out.2)
```

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
cfa.out	80	7478.2	7635.8	106.85			
mediat.out.2	83	7474.5	7620.3	109.15	2.3051	3	0.5116

- Compared to the model with observed scale means, the model with latent variables has greater effect size for the indirect effect of Agency on Positive Affect via Internal Motivation. Internal Motivation indicators have the most measurement error (lowest standardized factor loadings), so it is not surprising that this indirect path was attenuated most by measurement error.

Structural Regressions among Latent Constructs ...

```
summary(mediat.out.2, standardized = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 62 iterations
```

```

Number of observations                380

Estimator                             ML
Minimum Function Test Statistic      109.152
Degrees of freedom                    83
P-value (Chi-square)                 0.029

```

```
Parameter Estimates:
```

```

Information                          Observed
Standard Errors                       Bootstrap
Number of requested bootstrap draws   500
Number of successful bootstrap draws   500

```

```
Latent Variables:
```

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.302	0.000	0.466	0.905
Agency2	0.492	0.021	23.227	0.000	0.492	0.933
Agency3	0.497	0.024	20.574	0.000	0.497	0.912

Structural Regressions among Latent Constructs ...

Intrinsic =~						
Intrin1	0.466	0.035	13.489	0.000	0.540	0.703
Intrin2	0.500	0.037	13.502	0.000	0.580	0.682
Intrin3	0.531	0.032	16.397	0.000	0.616	0.800
Extrinsic =~						
Extrin1	0.373	0.022	16.779	0.000	0.388	0.808
Extrin2	0.440	0.028	15.945	0.000	0.457	0.793
Extrin3	0.454	0.029	15.466	0.000	0.471	0.827
Positive =~						
PosAFF1	0.514	0.025	20.161	0.000	0.569	0.854
PosAFF2	0.545	0.029	18.693	0.000	0.604	0.882
PosAFF3	0.570	0.027	21.232	0.000	0.632	0.895
Negative =~						
NegAFF1	0.620	0.038	16.174	0.000	0.633	0.889
NegAFF2	0.573	0.042	13.579	0.000	0.585	0.883
NegAFF3	0.586	0.035	16.865	0.000	0.598	0.918
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.343	0.075	4.557	0.000	0.359	0.359
Agency	0.129	0.071	1.824	0.068	0.116	0.116
Negative ~						
Extrinsic (b2)	0.199	0.069	2.902	0.004	0.202	0.202
Intrinsic ~						
Agency (a1)	0.588	0.080	7.315	0.000	0.507	0.507

Structural Regressions among Latent Constructs ...

50	Extrinsic ~ Agency (a2)	0.278	0.064	4.328	0.000	0.268	0.268
	Covariances:						
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
55	.Intrinsic ~ .Extrinsic	-0.202	0.062	-3.235	0.001	-0.202	-0.202
	.Positive ~ .Negative	-0.076	0.070	-1.091	0.275	-0.076	-0.076
	Variances:						
50		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
	.Agency1	0.048	0.006	8.464	0.000	0.048	0.181
	.Agency2	0.036	0.005	7.928	0.000	0.036	0.129
	.Agency3	0.050	0.006	8.976	0.000	0.050	0.169
	.Intrin1	0.299	0.032	9.299	0.000	0.299	0.506
55	.Intrin2	0.387	0.038	10.217	0.000	0.387	0.535
	.Intrin3	0.213	0.035	6.099	0.000	0.213	0.359
	.Extrin1	0.080	0.011	7.217	0.000	0.080	0.348
	.Extrin2	0.123	0.016	7.492	0.000	0.123	0.372
	.Extrin3	0.103	0.017	5.948	0.000	0.103	0.317
70	.PosAFF1	0.121	0.016	7.750	0.000	0.121	0.271
	.PosAFF2	0.104	0.015	6.798	0.000	0.104	0.222
	.PosAFF3	0.099	0.014	6.879	0.000	0.099	0.199
	.NegAFF1	0.107	0.016	6.789	0.000	0.107	0.210
	.NegAFF2	0.096	0.013	7.540	0.000	0.096	0.219

Structural Regressions among Latent Constructs ...

.NegAFF3	0.067	0.012	5.555	0.000	0.067	0.158
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.743	0.743
.Extrinsic	1.000				0.928	0.928
.Positive	1.000				0.815	0.815
.Negative	1.000				0.959	0.959

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.202	0.046	4.348	0.000	0.182	0.182
ind2	0.055	0.023	2.436	0.015	0.054	0.054

```
parameterEstimates(mediat.out.1, standardized =
  TRUE, ci =
  FALSE)[which(parameterEstimates(mediat.out.1)[, "lhs"
  %in% c("ind1", "ind2")), ]
```

	lhs	op	rhs	label	est	se	z	pvalue	std.lv	std.all	std.nox
13	ind1	:=	a1*b1	ind1	0.148	0.029	5.062	0.000	0.148	0.117	0.234
14	ind2	:=	a2*b2	ind2	0.056	0.023	2.493	0.013	0.056	0.045	0.090

Structural Regressions among Latent Constructs ...

```
summary(mediat.out.2, standardized = TRUE)
```

```
lavaan (0.5-23.1097) converged normally after 62 iterations
```

```

Number of observations                380

Estimator                             ML
Minimum Function Test Statistic       109.152
Degrees of freedom                     83
P-value (Chi-square)                  0.029

```

```
Parameter Estimates:
```

```

Information                          Observed
Standard Errors                       Bootstrap
Number of requested bootstrap draws   500
Number of successful bootstrap draws   500

```

```
Latent Variables:
```

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.466	0.021	22.302	0.000	0.466	0.905
Agency2	0.492	0.021	23.227	0.000	0.492	0.933
Agency3	0.497	0.024	20.574	0.000	0.497	0.912

Structural Regressions among Latent Constructs ...

Intrinsic =~						
Intrin1	0.466	0.035	13.489	0.000	0.540	0.703
Intrin2	0.500	0.037	13.502	0.000	0.580	0.682
Intrin3	0.531	0.032	16.397	0.000	0.616	0.800
Extrinsic =~						
Extrin1	0.373	0.022	16.779	0.000	0.388	0.808
Extrin2	0.440	0.028	15.945	0.000	0.457	0.793
Extrin3	0.454	0.029	15.466	0.000	0.471	0.827
Positive =~						
PosAFF1	0.514	0.025	20.161	0.000	0.569	0.854
PosAFF2	0.545	0.029	18.693	0.000	0.604	0.882
PosAFF3	0.570	0.027	21.232	0.000	0.632	0.895
Negative =~						
NegAFF1	0.620	0.038	16.174	0.000	0.633	0.889
NegAFF2	0.573	0.042	13.579	0.000	0.585	0.883
NegAFF3	0.586	0.035	16.865	0.000	0.598	0.918
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.343	0.075	4.557	0.000	0.359	0.359
Agency	0.129	0.071	1.824	0.068	0.116	0.116
Negative ~						
Extrinsic (b2)	0.199	0.069	2.902	0.004	0.202	0.202
Intrinsic ~						
Agency (a1)	0.588	0.080	7.315	0.000	0.507	0.507

Structural Regressions among Latent Constructs ...

50	Extrinsic ~ Agency (a2)	0.278	0.064	4.328	0.000	0.268	0.268
Covariances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
55	.Intrinsic ~ .Extrinsic	-0.202	0.062	-3.235	0.001	-0.202	-0.202
	.Positive ~ .Negative	-0.076	0.070	-1.091	0.275	-0.076	-0.076
Variances:							
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
50	.Agency1	0.048	0.006	8.464	0.000	0.048	0.181
	.Agency2	0.036	0.005	7.928	0.000	0.036	0.129
	.Agency3	0.050	0.006	8.976	0.000	0.050	0.169
	.Intrin1	0.299	0.032	9.299	0.000	0.299	0.506
55	.Intrin2	0.387	0.038	10.217	0.000	0.387	0.535
	.Intrin3	0.213	0.035	6.099	0.000	0.213	0.359
	.Extrin1	0.080	0.011	7.217	0.000	0.080	0.348
	.Extrin2	0.123	0.016	7.492	0.000	0.123	0.372
	.Extrin3	0.103	0.017	5.948	0.000	0.103	0.317
70	.PosAFF1	0.121	0.016	7.750	0.000	0.121	0.271
	.PosAFF2	0.104	0.015	6.798	0.000	0.104	0.222
	.PosAFF3	0.099	0.014	6.879	0.000	0.099	0.199
	.NegAFF1	0.107	0.016	6.789	0.000	0.107	0.210
	.NegAFF2	0.096	0.013	7.540	0.000	0.096	0.219

Structural Regressions among Latent Constructs ...

.NegAFF3	0.067	0.012	5.555	0.000	0.067	0.158
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.743	0.743
.Extrinsic	1.000				0.928	0.928
.Positive	1.000				0.815	0.815
.Negative	1.000				0.959	0.959

Defined Parameters:

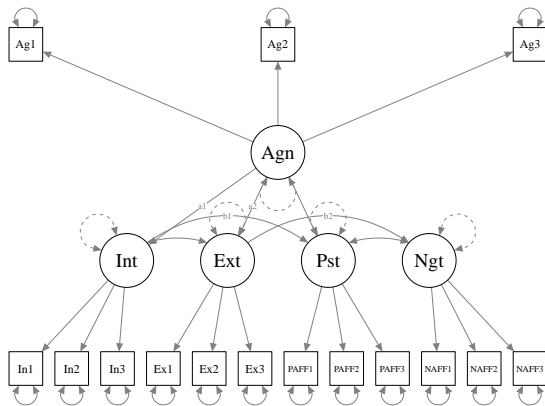
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.202	0.046	4.348	0.000	0.182	0.182
ind2	0.055	0.023	2.436	0.015	0.054	0.054

```
parameterEstimates(mediat.out.1, standardized =
  TRUE, ci =
  FALSE)[which(parameterEstimates(mediat.out.1)[, "lhs"
  %in% c("ind1", "ind2")), ]
```

	lhs	op	rhs	label	est	se	z	pvalue	std.lv	std.all	std.nox
13	ind1	:=	a1*b1	ind1	0.148	0.029	5.062	0.000	0.148	0.117	0.234
14	ind2	:=	a2*b2	ind2	0.056	0.023	2.493	0.013	0.056	0.045	0.090

I was afraid to see what the plotter would do

```
semPaths(mediat.out.2)
```



Check if ind1 and ind2 are significantly different

- Did you wonder if ind1 is significantly different from ind2?
- The assumption that they are the same is another restriction we can put on the model.
- We re-fit, and then run the anova test.

```
mediat.mod.3 <- '  
## measurement model  
Agency =~ Agency1 + Agency2 + Agency3  
Intrinsic =~ Intrinsic1 + Intrinsic2 + Intrinsic3  
Extrinsic =~ Extrinsic1 + Extrinsic2 + Extrinsic3  
Positive =~ PosAFF1 + PosAFF2 + PosAFF3  
Negative =~ NegAFF1 + NegAFF2 + NegAFF3  
## structural model  
Positive ~ b1*Intrinsic + Agency  
Negative ~ b2*Extrinsic  
Intrinsic ~ a1*Agency
```

Check if ind1 and ind2 are significantly different ...

```

Extrinsic ~ a2*Agency
Intrinsic ~ Extrinsic
## define mediation parameters (indirect effects)
ind1 := a1 * b1
ind2 := a2 * b2
ind1 == ind2
'

```

```

mediat.mod.3 <- '
## measurement model
Agency =~ Agency1 + Agency2 + Agency3
Intrinsic =~ Intrin1 + Intrin2 + Intrin3
Extrinsic =~ Extrin1 + Extrin2 + Extrin3
Positive =~ PosAFF1 + PosAFF2 + PosAFF3
Negative =~ NegAFF1 + NegAFF2 + NegAFF3
## structural model
Positive ~ b1*Intrinsic + Agency

```

Check if ind1 and ind2 are significantly different ...

```
10 Negative ~ b2*Extrinsic
    Intrinsic ~ a1*Agency
    Extrinsic ~ a2*Agency
    Intrinsic ~ Extrinsic
15 ## define mediation parameters (indirect effects)
    ind1 := a1 * b1
    ind2 := a2 * b2
    ind1 == ind2
    ,
```

```
mediat.out.3 <- sem(mediat.mod.3, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.3, standardized = TRUE, fit =
        TRUE)
```

Check if ind1 and ind2 are significantly different ...

```
lavaan (0.5-23.1097) converged normally after 480 iterations
```

```
Number of observations                380
```

```
Estimator                             ML
```

```
Minimum Function Test Statistic       118.955
```

```
Degrees of freedom                    84
```

```
P-value (Chi-square)                  0.007
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic       3749.411
```

```
Degrees of freedom                    105
```

```
P-value                                0.000
```

```
User model versus baseline model:
```

```
Comparative Fit Index (CFI)           0.990
```

```
Tucker-Lewis Index (TLI)              0.988
```

```
Loglikelihood and Information Criteria:
```

```
Loglikelihood user model (H0)          -3705.163
```

```
Loglikelihood unrestricted model (H1)   -3645.686
```

Check if ind1 and ind2 are significantly different ...

```

Number of free parameters          36
Akaike (AIC)                      7482.326
Bayesian (BIC)                    7624.172
Sample-size adjusted Bayesian (BIC) 7509.951

```

Root Mean Square Error of Approximation:

```

RMSEA                             0.033
90 Percent Confidence Interval      0.018 0.046
P-value RMSEA <= 0.05             0.986

```

Standardized Root Mean Square Residual:

```

SRMR                               0.051

```

Parameter Estimates:

```

Information                        Observed
Standard Errors                    Bootstrap
Number of requested bootstrap draws 500
Number of successful bootstrap draws 500

```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.467	0.021	22.738	0.000	0.467	0.905

Check if ind1 and ind2 are significantly different ...

Agency2	0.491	0.020	24.518	0.000	0.491	0.933
Agency3	0.497	0.022	22.271	0.000	0.497	0.911
Intrinsic ~						
Intrin1	0.468	0.041	11.435	0.000	0.528	0.693
Intrin2	0.508	0.036	14.071	0.000	0.573	0.679
Intrin3	0.540	0.032	16.825	0.000	0.609	0.801
Extrinsic ~						
Extrin1	0.373	0.023	15.931	0.000	0.395	0.813
Extrin2	0.439	0.029	15.095	0.000	0.465	0.798
Extrin3	0.452	0.029	15.606	0.000	0.478	0.829
Positive ~						
PosAFF1	0.530	0.024	21.669	0.000	0.564	0.853
PosAFF2	0.562	0.028	19.847	0.000	0.598	0.881
PosAFF3	0.587	0.028	21.244	0.000	0.624	0.892
Negative ~						
NegAFF1	0.614	0.038	15.994	0.000	0.639	0.890
NegAFF2	0.567	0.039	14.484	0.000	0.590	0.885
NegAFF3	0.579	0.037	15.774	0.000	0.603	0.919
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.183	0.078	2.347	0.019	0.194	0.194
Agency	0.218	0.077	2.831	0.005	0.205	0.205
Negative ~						
Extrinsic (b2)	0.275	0.056	4.961	0.000	0.280	0.280

Check if ind1 and ind2 are significantly different ...

Intrinsic ~							
Agency (a1)	0.523	0.104	5.041	0.000	0.463	0.463	
Extrinsic ~							
Agency (a2)	0.348	0.064	5.462	0.000	0.328	0.328	
Covariances:							
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all	
.Intrinsic ~							
.Extrinsic	-0.202	0.064	-3.163	0.002	-0.202	-0.202	
.Positive ~							
.Negative	-0.063	0.070	-0.909	0.363	-0.063	-0.063	
Variances:							
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all	
.Agency1	0.048	0.006	8.495	0.000	0.048	0.181	
.Agency2	0.036	0.005	7.550	0.000	0.036	0.129	
.Agency3	0.050	0.006	8.839	0.000	0.050	0.170	
.Intrin1	0.301	0.033	9.066	0.000	0.301	0.519	
.Intrin2	0.383	0.039	9.800	0.000	0.383	0.539	
.Intrin3	0.208	0.039	5.373	0.000	0.208	0.359	
.Extrin1	0.080	0.010	7.633	0.000	0.080	0.339	
.Extrin2	0.123	0.016	7.500	0.000	0.123	0.363	
.Extrin3	0.104	0.017	6.180	0.000	0.104	0.312	
.PosAFF1	0.120	0.016	7.510	0.000	0.120	0.273	
.PosAFF2	0.103	0.016	6.352	0.000	0.103	0.224	
.PosAFF3	0.100	0.014	7.035	0.000	0.100	0.205	

Check if ind1 and ind2 are significantly different ...

.NegAFF1	0.107	0.016	6.657	0.000	0.107	0.207
.NegAFF2	0.096	0.013	7.209	0.000	0.096	0.216
.NegAFF3	0.067	0.011	6.245	0.000	0.067	0.156
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.785	0.785
.Extrinsic	1.000				0.892	0.892
.Positive	1.000				0.883	0.883
.Negative	1.000				0.922	0.922

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.096	0.026	3.708	0.000	0.090	0.090
ind2	0.096	0.026	3.708	0.000	0.092	0.092

Constraints:

	Slack
ind1 - (ind2)	0.000

```

mediat.out.3 <- sem(mediat.mod.3, data = dat,
                    std.lv = TRUE, se = "boot",
                    bootstrap = Nboot)
summary(mediat.out.3, standardized = TRUE, fit =
        TRUE)

```

Check if ind1 and ind2 are significantly different ...

```
lavaan (0.5-23.1097) converged normally after 480 iterations
```

```
Number of observations                380
```

```
Estimator                            ML
```

```
Minimum Function Test Statistic      118.955
```

```
Degrees of freedom                   84
```

```
P-value (Chi-square)                 0.007
```

```
Model test baseline model:
```

```
Minimum Function Test Statistic      3749.411
```

```
Degrees of freedom                   105
```

```
P-value                              0.000
```

```
User model versus baseline model:
```

```
Comparative Fit Index (CFI)         0.990
```

```
Tucker-Lewis Index (TLI)            0.988
```

```
Loglikelihood and Information Criteria:
```

```
Loglikelihood user model (H0)        -3705.163
```

```
Loglikelihood unrestricted model (H1) -3645.686
```

Check if ind1 and ind2 are significantly different ...

```

Number of free parameters          36
Akaike (AIC)                      7482.326
Bayesian (BIC)                    7624.172
Sample-size adjusted Bayesian (BIC) 7509.951

```

Root Mean Square Error of Approximation:

```

RMSEA                             0.033
90 Percent Confidence Interval      0.018 0.046
P-value RMSEA <= 0.05             0.986

```

Standardized Root Mean Square Residual:

```

SRMR                             0.051

```

Parameter Estimates:

```

Information                       Observed
Standard Errors                   Bootstrap
Number of requested bootstrap draws 500
Number of successful bootstrap draws 500

```

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Agency =~						
Agency1	0.467	0.021	22.738	0.000	0.467	0.905

Check if ind1 and ind2 are significantly different ...

Agency2	0.491	0.020	24.518	0.000	0.491	0.933
Agency3	0.497	0.022	22.271	0.000	0.497	0.911
Intrinsic ~						
Intrin1	0.468	0.041	11.435	0.000	0.528	0.693
Intrin2	0.508	0.036	14.071	0.000	0.573	0.679
Intrin3	0.540	0.032	16.825	0.000	0.609	0.801
Extrinsic ~						
Extrin1	0.373	0.023	15.931	0.000	0.395	0.813
Extrin2	0.439	0.029	15.095	0.000	0.465	0.798
Extrin3	0.452	0.029	15.606	0.000	0.478	0.829
Positive ~						
PosAFF1	0.530	0.024	21.669	0.000	0.564	0.853
PosAFF2	0.562	0.028	19.847	0.000	0.598	0.881
PosAFF3	0.587	0.028	21.244	0.000	0.624	0.892
Negative ~						
NegAFF1	0.614	0.038	15.994	0.000	0.639	0.890
NegAFF2	0.567	0.039	14.484	0.000	0.590	0.885
NegAFF3	0.579	0.037	15.774	0.000	0.603	0.919
Regressions:						
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Positive ~						
Intrinsic (b1)	0.183	0.078	2.347	0.019	0.194	0.194
Agency	0.218	0.077	2.831	0.005	0.205	0.205
Negative ~						
Extrinsic (b2)	0.275	0.056	4.961	0.000	0.280	0.280

Check if ind1 and ind2 are significantly different ...

Intrinsic ~							
Agency (a1)	0.523	0.104	5.041	0.000	0.463	0.463	
Extrinsic ~							
Agency (a2)	0.348	0.064	5.462	0.000	0.328	0.328	
Covariances:							
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all	
.Intrinsic ~							
.Extrinsic	-0.202	0.064	-3.163	0.002	-0.202	-0.202	
.Positive ~							
.Negative	-0.063	0.070	-0.909	0.363	-0.063	-0.063	
Variances:							
	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all	
.Agency1	0.048	0.006	8.495	0.000	0.048	0.181	
.Agency2	0.036	0.005	7.550	0.000	0.036	0.129	
.Agency3	0.050	0.006	8.839	0.000	0.050	0.170	
.Intrin1	0.301	0.033	9.066	0.000	0.301	0.519	
.Intrin2	0.383	0.039	9.800	0.000	0.383	0.539	
.Intrin3	0.208	0.039	5.373	0.000	0.208	0.359	
.Extrin1	0.080	0.010	7.633	0.000	0.080	0.339	
.Extrin2	0.123	0.016	7.500	0.000	0.123	0.363	
.Extrin3	0.104	0.017	6.180	0.000	0.104	0.312	
.PosAFF1	0.120	0.016	7.510	0.000	0.120	0.273	
.PosAFF2	0.103	0.016	6.352	0.000	0.103	0.224	
.PosAFF3	0.100	0.014	7.035	0.000	0.100	0.205	

Check if ind1 and ind2 are significantly different ...

.NegAFF1	0.107	0.016	6.657	0.000	0.107	0.207
.NegAFF2	0.096	0.013	7.209	0.000	0.096	0.216
.NegAFF3	0.067	0.011	6.245	0.000	0.067	0.156
Agency	1.000				1.000	1.000
.Intrinsic	1.000				0.785	0.785
.Extrinsic	1.000				0.892	0.892
.Positive	1.000				0.883	0.883
.Negative	1.000				0.922	0.922

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
ind1	0.096	0.026	3.708	0.000	0.090	0.090
ind2	0.096	0.026	3.708	0.000	0.092	0.092

Constraints:

ind1 - (ind2)	Slack
	0.000

```
anova(mediat.out.3 , mediat.out.2)
```

Check if ind1 and ind2 are significantly different ...

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
mediat.out.2	83	7474.5	7620.3	109.15			
mediat.out.3	84	7482.3	7624.2	118.95	9.8021	1	0.001743 **

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
anova(mediat.out.3 , mediat.out.2)
```

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
mediat.out.2	83	7474.5	7620.3	109.15			
mediat.out.3	84	7482.3	7624.2	118.95	9.8021	1	0.001743 **

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Outline

- 1 Get the affect data
- 2 Path Diagrams
 - Linear Regression
 - Moderators
 - Mediation
- 3 Structural Equation Modeling
 - Remember Regression?
- 4 SEM in R
 - Plots
 - Estimate the Moderation Model
 - More Elaborate Path Model
- 5 Full Latent Variable Regression Model
 - Confirmatory Factor Analysis
 - Structural Regressions among Latent Constructs
 - Supplementary Hypothesis Test
- 6 Conclusion

Structural Equation Modeling

- In Psychology, SEM has been an area of tremendous growth since 1980.
- SEM is being absorbed slowly into other fields
- The “gold standard” software for SEM modeling is Mplus, although lavaan has succeeded in “matching” side-by-side many of the calculations.

References

R Core Team (2017). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Session

```
sessionInfo()
```

```
R version 3.4.4 (2018-03-15)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 18.04 LTS

Matrix products: default
BLAS: /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.7.1
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.7.1

locale:
 [1] LC_CTYPE=en_US.UTF-8          LC_NUMERIC=C
     LC_TIME=en_US.UTF-8
 [4] LC_COLLATE=en_US.UTF-8      LC_MONETARY=en_US.UTF-8
     LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8        LC_NAME=C              LC_ADDRESS=C
[10] LC_TELEPHONE=C              LC_MEASUREMENT=en_US.UTF-8
     LC_IDENTIFICATION=C

attached base packages:
 [1] stats      graphics  grDevices  utils      datasets  base

other attached packages:
 [1] semPlot_1.1          kutils_1.44          lavaan_0.5-23.1097
```

Session ...

loaded via a namespace (and not attached):

```

[1] splines_3.4.4           ellipse_0.4.1           gtools_3.5.0
     network_1.13.0
[5] Formula_1.2-2          semTools_0.4-14        BDgraph_2.44
     stats4_3.4.4
[9] latticeExtra_0.6-28    d3Network_0.5.2.1      lisrelToR_0.1.4
     pbivnorm_0.6.0
[13] pillar_1.1.0           backports_1.1.2        lattice_0.20-35
     quantreg_5.35
[17] quadprog_1.5-5         digest_0.6.15          RColorBrewer_1.1-2
     checkmate_1.8.5
[21] ggm_2.3                minqa_1.2.4            colorspace_1.3-2
     htmltools_0.3.6
[25] Matrix_1.2-14          plyr_1.8.4             psych_1.7.8
     XML_3.98-1.9
[29] pkgconfig_2.0.1        SparseM_1.77           xtable_1.8-2
     corpcor_1.6.9
[33] scales_0.5.0           whisker_0.3-2          glasso_1.8
     sna_2.4
[37] jpeg_0.1-8             openxlsx_4.0.17        fdrtool_1.2.15
     lme4_1.1-17
[41] MatrixModels_0.4-1     hugin_1.2.7            arm_1.9-3
     htmlTable_1.11.2
[45] tibble_1.4.2           rockchalk_1.8.111      mgcv_1.8-23
     car_2.1-6

```

Session ...

[49]	ggplot2_2.2.1 pbkrtest_0.4-7	nnet_7.3-12	lazyeval_0.2.1
[53]	mnormt_1.5-5 magrittr_1.5	statnet.common_4.0.0	survival_2.41-3
[57]	methods_3.4.4 foreign_0.8-69	nlme_3.1-137	MASS_7.3-49
[61]	OpenMx_2.8.3 stringr_1.2.0	tools_3.4.4	data.table_1.10.4-3
[65]	munsell_0.4.3 sem_3.1-9	cluster_2.0.6	compiler_3.4.4
[69]	rlang_0.1.6 rstudioapi_0.7	grid_3.4.4	nloptr_1.0.4
[73]	rjson_0.2.15 base64enc_0.1-3	htmlwidgets_1.0	igraph_1.1.2
[77]	boot_1.3-20 abind_1.4-5	mi_1.0	gtable_0.2.0
[81]	reshape2_1.4.3 knitr_1.19	qgraph_1.4.4	gridExtra_2.3
[85]	Hmisc_4.1-1 parallel_3.4.4	stringi_1.2.2	matrixcalc_1.0-3
[89]	Rcpp_0.12.15 png_0.1-7	rpart_4.1-13	acepack_1.4.1
[93]	coda_0.19-1		