Moderation and Mediation with Process

Materials prepared by A. Hernández and I.Tomás for the course on Multivariate Research Methods in the WOP-P master (2016-2017)

Proyecto "Evaluación de modelos de mediación y modulación con Process en la formación del Máster Erasmus Mundus WOP-P" (SFPIE_GER16_418612). Con el apoyo de la Universitat de València dentro de la Convocatoria de Proyectos de Innovación Educativa (01/09/ 2016 hasta 01/09/ 2017)

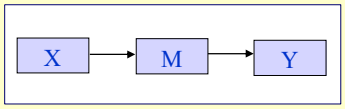
1

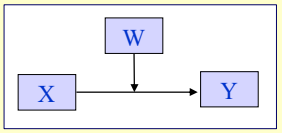
Multiple Regression Analysis

1. Introduction:
   - 1.1. Simple linear correlation
   - 1.2. Simple linear regression
2. The Multiple Linear Regression Model
3. Goodness of fit
4. Interpretation of results
5. Assumptions of the model
6. Hierarchical Regression
7. Mediation and Moderation in Multiple Regression
   - 7.1. Moderation with Multiple Regression
   - 7.2. Mediation with Multiple Regression

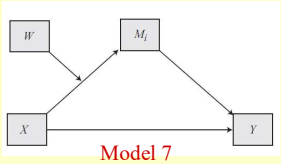
2

7. Mediation & Moderation in Multiple Regression

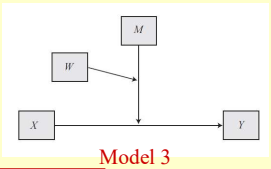




How to run those and other more complex regression models with **Process**?

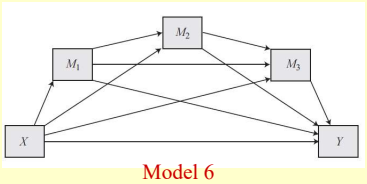


Model 7

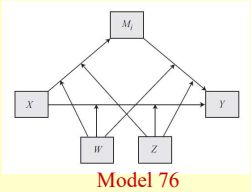


Model 3

Model Templates for PROCESS for SPSS and SAS
©2013 Andrew F. Hayes, http://www.afhayes.com/



Model 6



Model 76

3

3

Multiple Regression Analysis with PROCESS

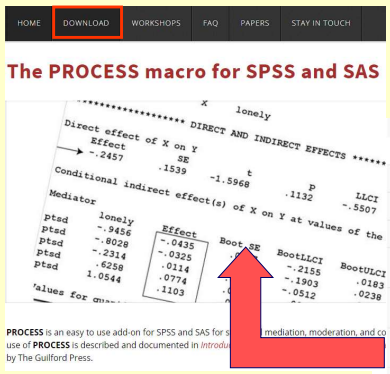
1. How to install Process in SPSS for Windows
2. How to run a model
3. How to interpret the results
4. And what if we want to test for the model assumptions?

4

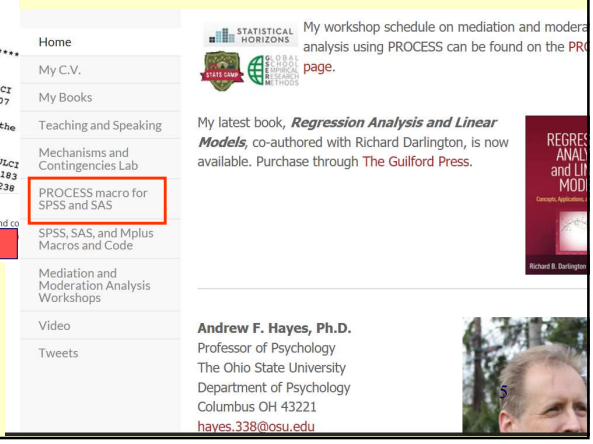
1. How to install Process in SPSS for Windows

1st Go to http://www.afhayes.com/

3rd Download the materials



2nd Click here



5

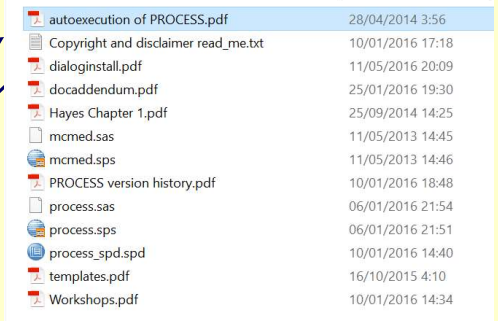
Download a zip archive containing the latest release of PROCESS for SPSS and SAS (version 2.16, released 5 July 2016) by clicking the button below. The archive will download in accordance with your browser settings.

4th Click here

PROCESS operates on both Windows and Mac versions of SPSS and SAS. PROCESS for SPSS requires SPSS version 18 or later.

5th Follow the instructions in "autoexecution of PROCESS.pdf"
(more detailed instructions in the following slides)

6th Follow the instructions in "dialoginstall"
(more detailed instructions in the following slides)



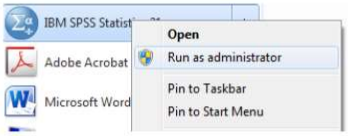
6

5th Follow the instructions in "autoexecution of PROCESS.pdf"

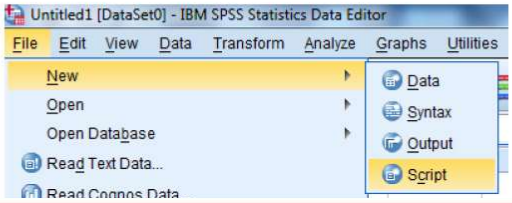
Automatic Execution of the PROCESS Macro Definition File
(Windows only)

The instructions below will set SPSS for Windows up to automatically execute process.sps every time that SPSS is opened. This will eliminate the need for you to execute PROCESS yourself each time you want to use the PROCESS command during an SPSS session.

(1) Open SPSS as an administrator (right click the SPSS icon and select "Run as administrator")



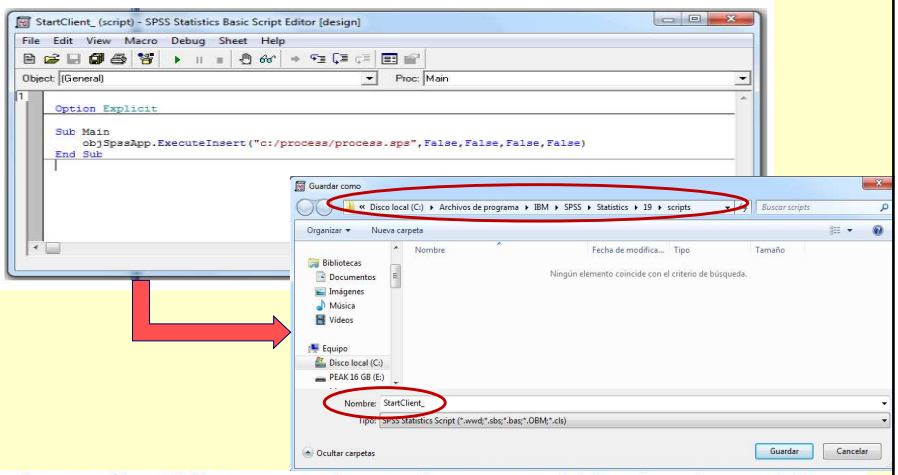
(2) In SPSS, open a new SPSS script (File→New→Script)



7

(3) Delete anything in the script window that opens and then type the following:

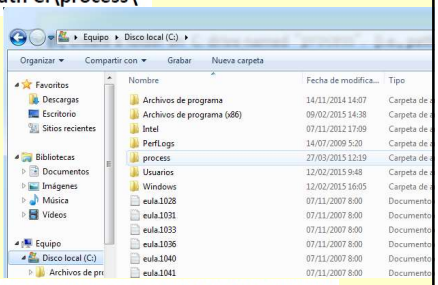
```
Option Explicit

Sub Main
   objSPSSApp.ExecuteInsert("c:/process/process.sps",False,False,False,False)
End Sub
```



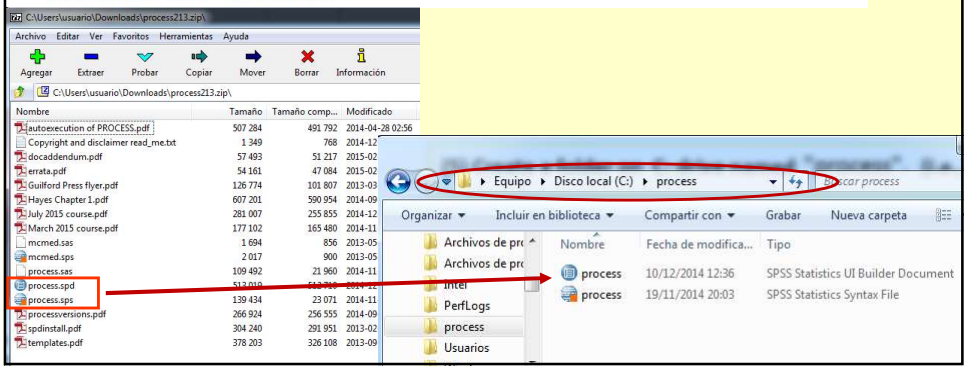
(4) Save this script file with file name StartClient_ in the SPSS scripts folder. The underscore following "StartClient" is important. This may be hard to locate, but you'll find it somewhere on your hard disk where SPSS is located. It will be buried in many layers of folders and subfolders. On my machine, it was located at C:\ Archivos de programa / IBM / SPSS / Statistics / 19 / scripts

8

(5) Create a folder on C: drive named "process". (i.e., path C:\process\

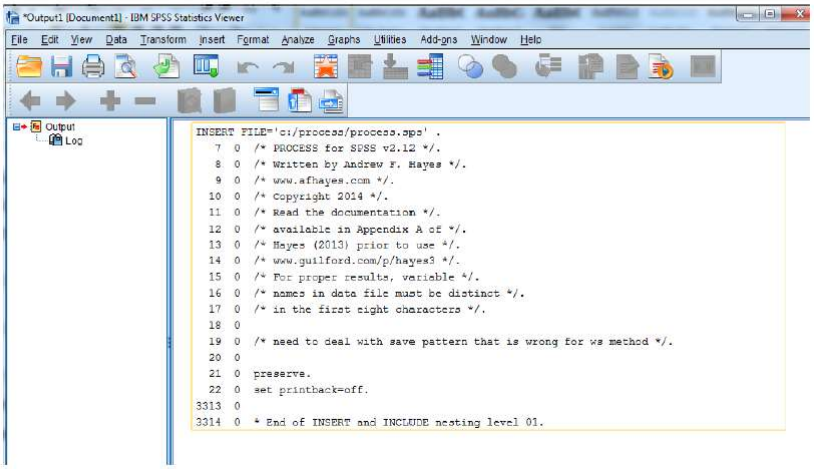


(6) Place into this PROCESS folder the following files that appeared in the zip folder downloaded:
"process.sps" and "process.spd"



9

(7) **Close SPSS and then restart SPSS.** If all steps were followed without error, SPSS will automatically run PROCESS.sps, so you can now execute a PROCESS command without first executing the PROCESS macro yourself. If you were successful, you will probably see an output window that looks something like this when SPSS opens:



10

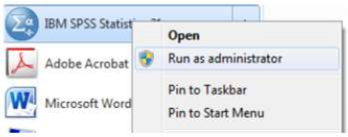
10

6th Follow the instructions in "dialoginstall.pdf" (**SPSS version 23 and earlier)**

Installing Custom Dialogs

Macros (the .sps files) are command based and can be tedious for people not used to working with syntax. Scripts (the .sbs files) are easier to use but must be run each time you want to call up the dialog box. And neither macros nor scripts live permanently in SPSS. They disappear once you close SPSS. Custom Dialog files are permanently installed in SPSS, integrating the procedure into SPSS menus. Either double click on the .spd file to install, or use the procedure below. Installation requires administrative access to your machine. You may have to open SPSS as an administrator as well. If your computer is owned by someone else (such as a university or your place of work), you probably don't have administrative access and will have to contact a local technical support person.

(1) Open SPSS as an administrator (right click the SPSS icon and select "Run as administrator")

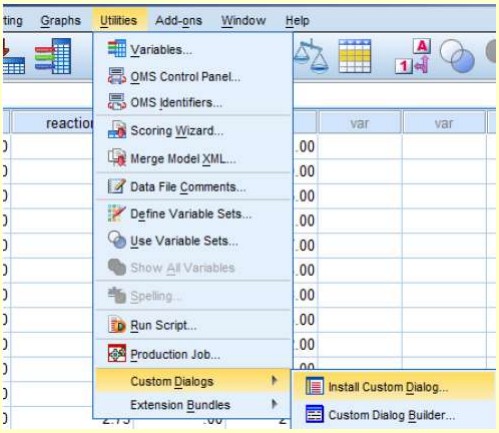


11

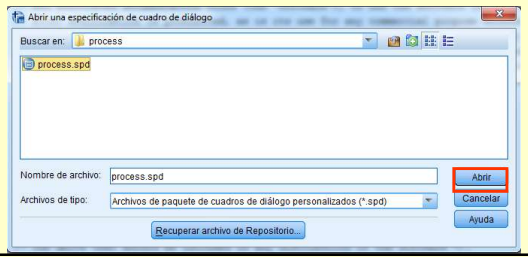
11

(2) In SPSS, install Custom Dialog

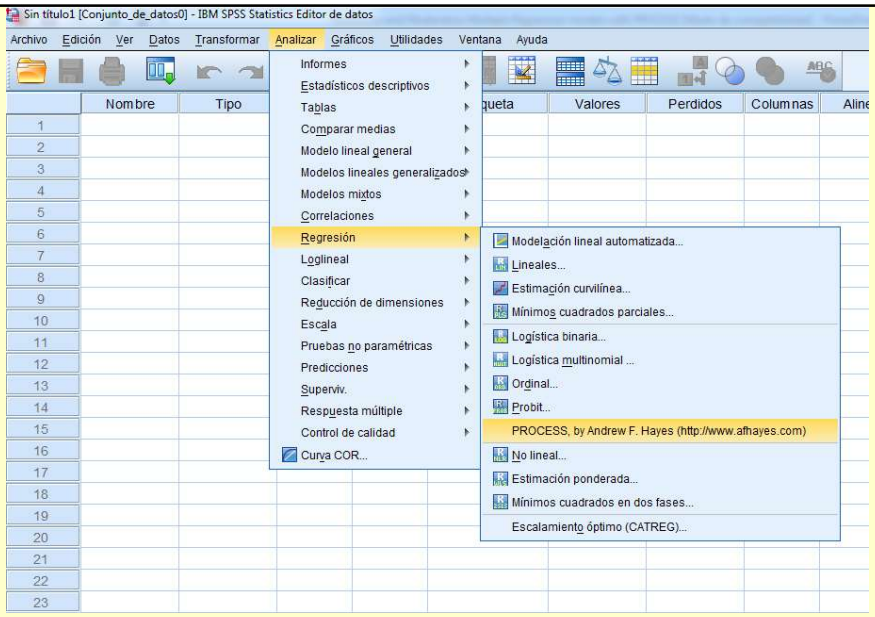
SPSS version 24 (it is in EXTENSIONS: utilities)



(3) In SPSS, open the "process.spd" file



12



Now, if you find the PROCESS option in the Regression menu, then you succeeded in installing the macro!!

13

13

Multiple Regression Analysis with **PROCESS**

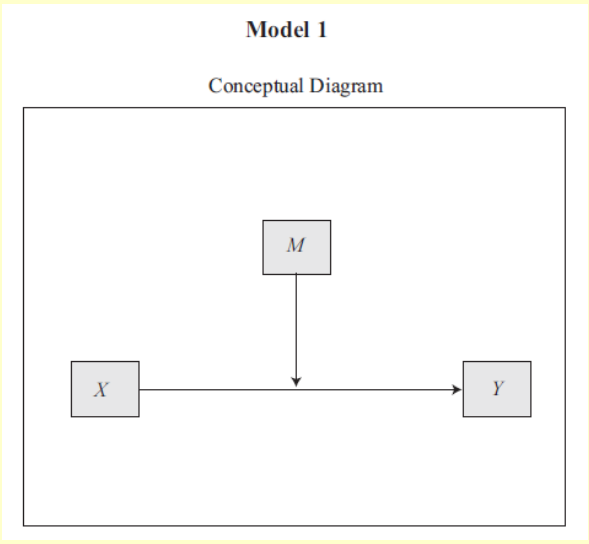
1. How to install Process in SPSS for Windows
2. How to run a model
3. How to interpret the results
4. And what if we want to test for the model assumptions?

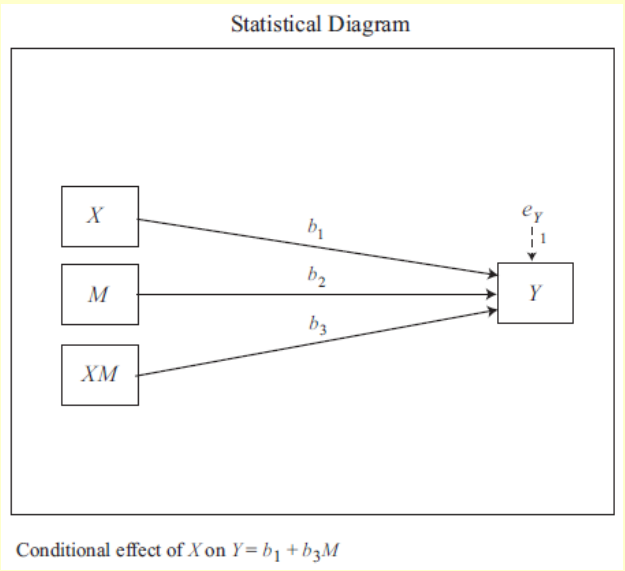
14

Multiple Regression Analysis with PROCESS

1. How to install Process in SPSS for Windows
2. How to run a MODERATION model
3. How to interpret the results
4. And what if we want to check for the assumptions?

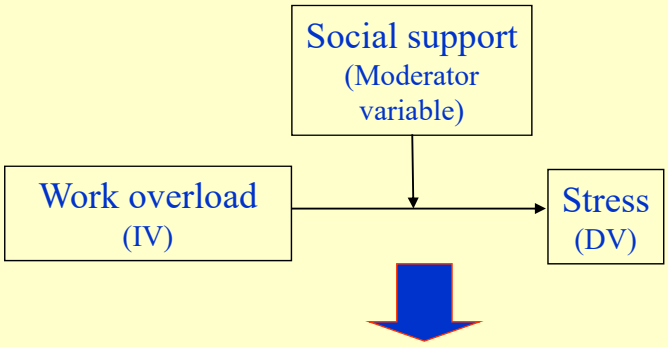
Moderation in Multiple Regression with PROCESS





Model Templates for PROCESS for SPSS and SAS

7.1. Moderation with Multiple Regression



Model to test for a moderation effect: Equation

$$Y' = a + b_1X_1 + b_2X_2 + b_3X_1X_2$$

Moderation & collinearity!!

$$\text{Stress} = a + b_1\,\text{Overload} + b_2\,\text{support} + b_3\,\text{overload*support}$$

If the interaction (product) term is significant → There is a moderation effect: the effect of overload on stress depends on the level of social support

Moderation with Multiple Regression

1st step: Mean-centering of the moderator and the predictor variables (when variables are continuous).
Even though it is not necessary, it has been recommended to generate more meaningful and substantively interpretable coefficients (eg. Hayes, 2013).

2nd step: Creating product terms.

3rd step: Structuring the equation.

Process will do all that for us!!

4th step: Specifying routine options.

5th step: Interpreting results.

6th step: Visualizing and probing the interaction (if statistically significant).

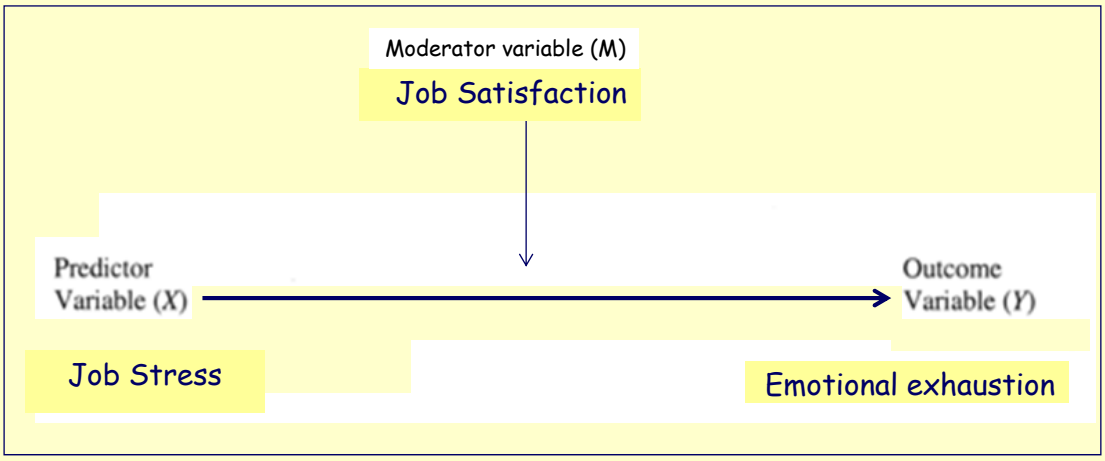
Moderation with Multiple Regression

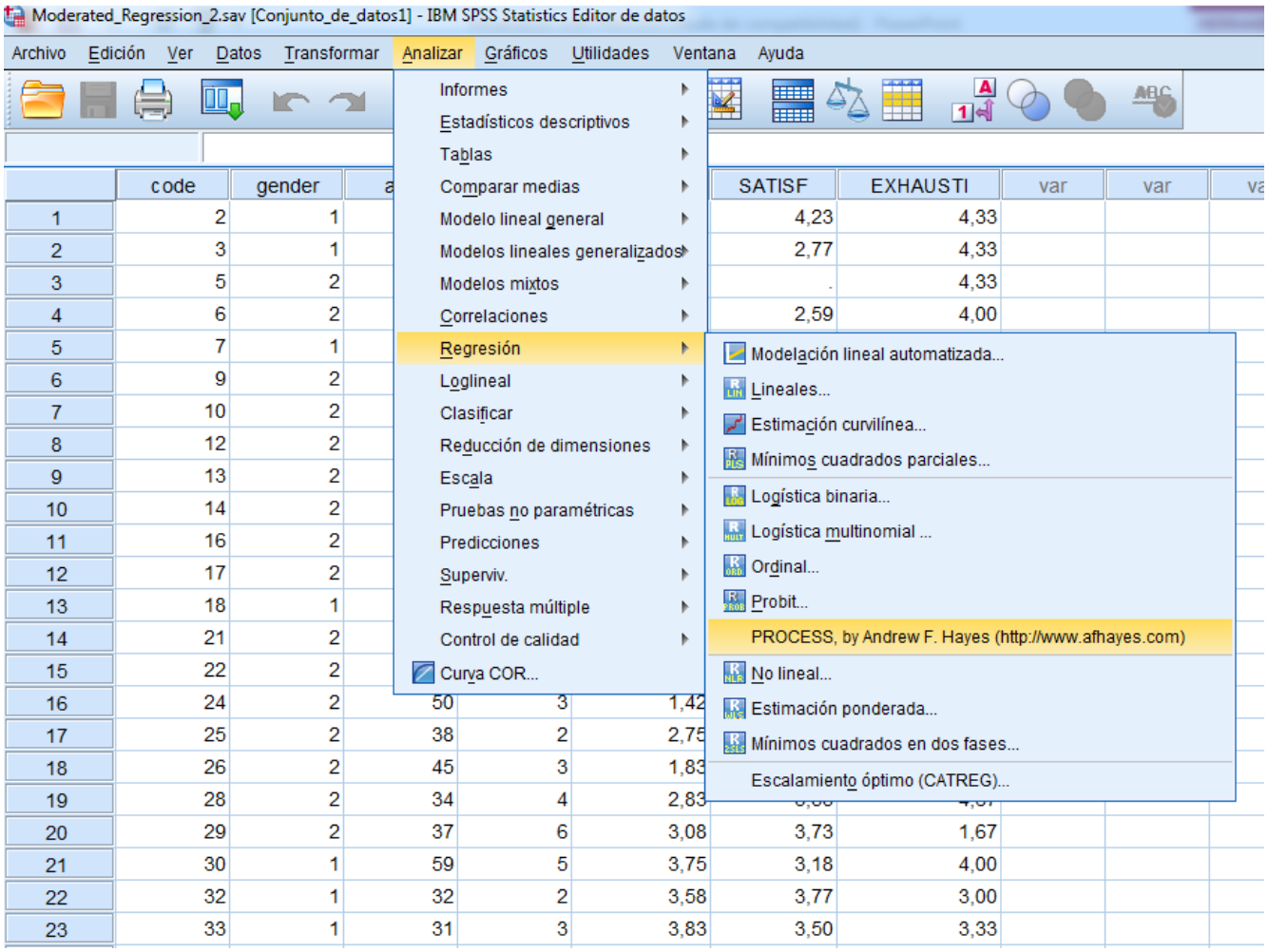
Hierarchical regression as a way of testing moderator effects

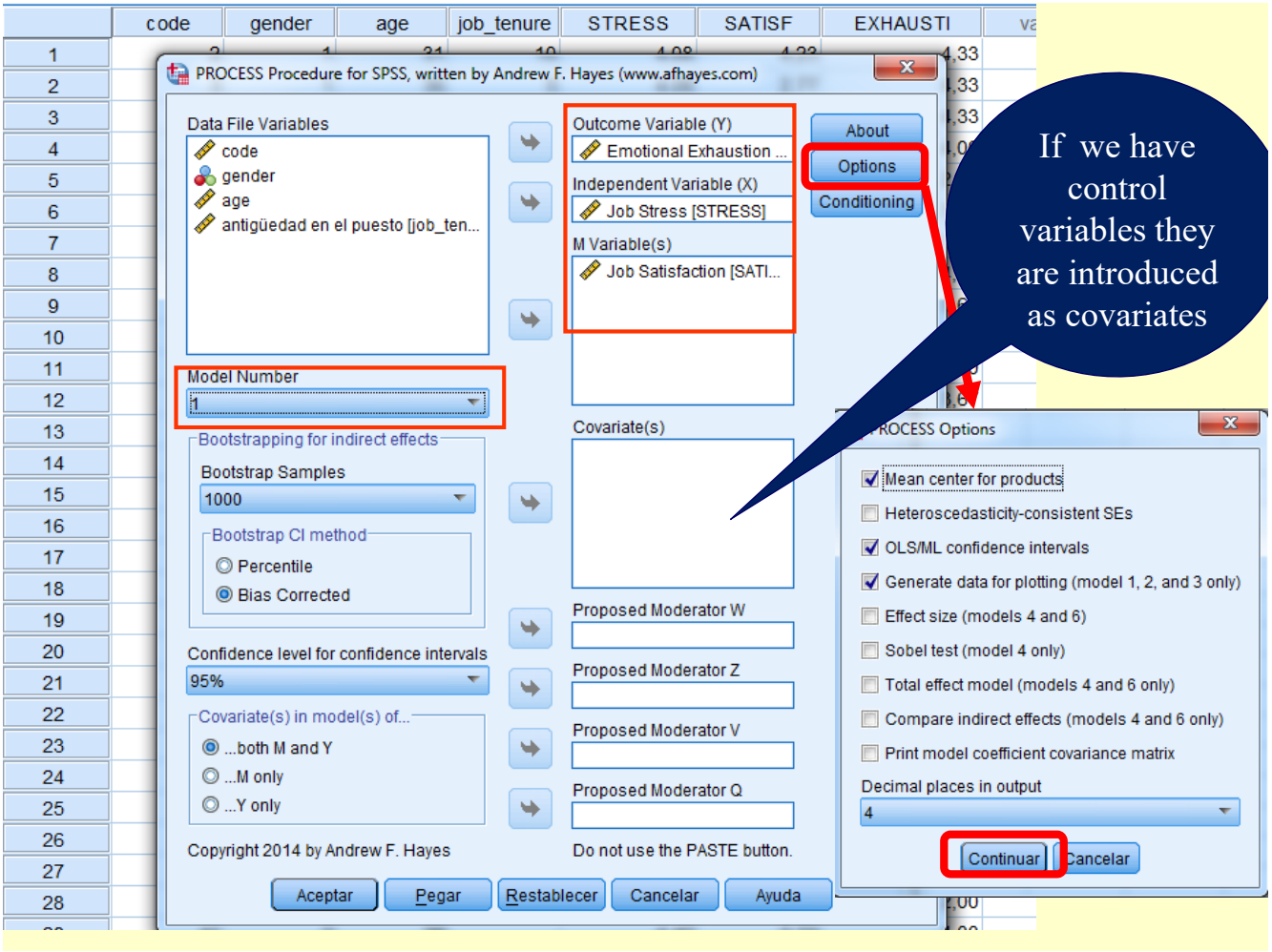
DATA FILE: Moderated_Regression_2

Research question:

- Does **Job Satisfaction** moderate the relationship between **Job Stress** and **Emotional exhaustion**?







Multiple Regression Analysis with PROCESS

1. How to install Process in SPSS for Windows
2. How to run a MODERATION model
3. How to interpret the results
4. And what if we want to check for the assumptions?

PROCESS

```
**************************************************
Model = 1
    Y = EXHAUSTI
    X = STRESS
    M = SATISF

Sample size
        600

**************************************************************************
Outcome: EXHAUSTI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
       ,501       ,251       ,678     66,421      3,000    596,000       ,000

Model
             coeff         se          t          p       LLCI       ULCI
constant     3,001       ,038     79,202       ,000      2,926      3,075
SATISF        ,011       ,069       ,162       ,871       -,125       ,147
STRESS        ,596       ,051     11,682       ,000       ,496       ,697
int_1         -,134      ,065     -2,061       ,040       -,262      -,006

Interactions:

 int_1    STRESS      X     SATISF

R-square increase due to interaction(s):
        R2-chng          F        df1        df2          p
int_1       ,005     4,246      1,000    596,000       ,040

**************************************************************************
```

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,495[a]	,245	,243	,82582	,245	96,981	2	597	,000	
2	,501[b]	,251	,247	,82358	,005	4,246	1	596	,040	1,832

a. Variables predictoras: (Constante), satisfaction_meancentered, stress_meancentered
b. Variables predictoras: (Constante), satisfaction_meancentered, stress_meancentered, Product_meancentered
c. Variable dependiente: emotional_exhaustion

Traditional SPSS analysis

PROCESS

```
**************************************************
Model = 1
    Y = EXHAUSTI
    X = STRESS
    M = SATISF

Sample size
        600

**************************************************
Outcome: EXHAUSTI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
       ,501       ,251       ,678     66,421      3,000    596,000       ,000

Model
             coeff         se          t          p       LLCI       ULCI
constant     3,001       ,038     79,202       ,000      2,926      3,075
SATISF        ,011       ,069       ,162       ,871       -,125       ,147
STRESS        ,596       ,051     11,682       ,000       ,496       ,697
int_1         -,134      ,065     -2,061       ,040       -,262      -,006

Interactions:

 int_1    STRESS      X     SATISF

R-square increase due to interaction(s):
        R2-chng          F        df1        df2          p
int_1       ,005     4,246      1,000    596,000       ,040

**************************************************************************
```

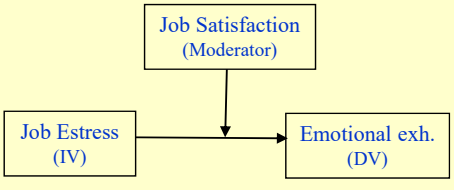
Coeficientes[a]

Modelo		Coeficientes no estandarizados		Coeficientes tipificados	t	Sig.
		B	Error típ.	Beta		
1	(Constante)	3,037	,034		90,073	,000
	stress_meancentered	,580	,051	,493	11,470	,000
	satisfaction_ meancentered	-,007	,069	-,004	-,096	,924
2	(Constante)	3,001	,038		79,203	,000
	stress_meancentered	,596	,051	,507	11,682	,000
	satisfaction_ meancentered	,011	,069	,007	,162	,871
	Product_meancentered	-,134	,065	-,074	-2,061	,040

a. Variable dependiente: emotional_exhaustion

Traditional SPSS analysis

The moderation effect is confirmed



How to interpret the significant interaction effect?

PROCESS

```
Conditional effect of X on Y at values of the moderator(s):
    SATISF     Effect         se          t          p       LLCI       ULCI
     -,593      ,676       ,069      9,832       ,000       ,541       ,811
      ,000      ,596       ,051     11,682       ,000       ,496       ,697
      ,593      ,517       ,059      8,781       ,000       ,401       ,632

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

Data for visualizing conditional effect of X on Y
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/STRESS SATISF EXHAUSTI.
BEGIN DATA.
    -,807      -,593     2,449
     ,000      -,593     2,994
     ,807      -,593     3,540
    -,807       ,000     2,519
     ,000       ,000     3,001
     ,807       ,000     3,482
    -,807       ,593     2,590
     ,000       ,593     3,007
     ,807       ,593     3,424
END DATA.
GRAPH/SCATTERPLOT=STRESS WITH EXHAUSTI BY SATISF.
```

Low Satisfaction

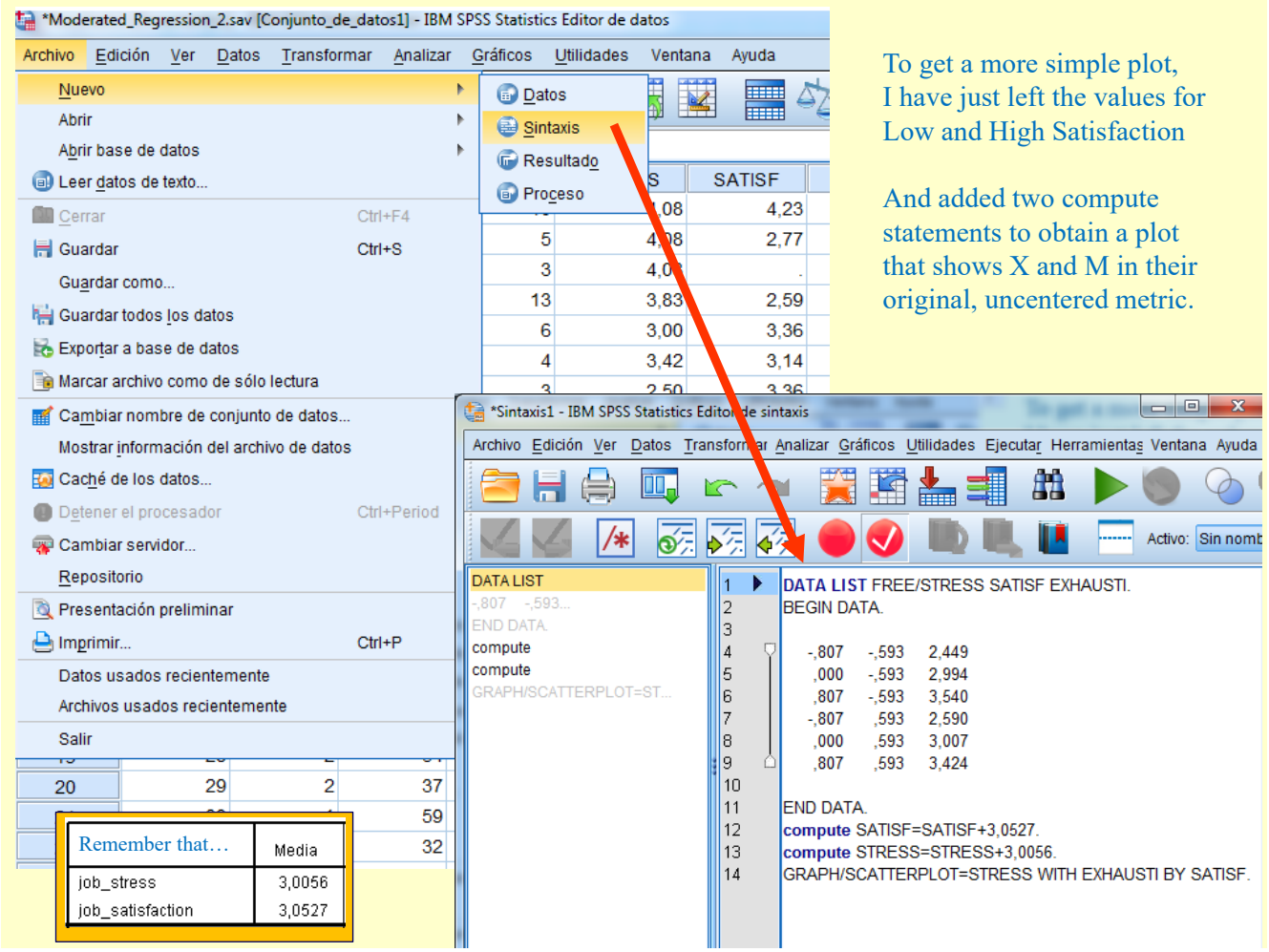
High Satisfaction

Estadísticos descriptivos

	Media	Desviación típica	N
emotional_exhaustion	3,0367	,94896	600
job_stress	3,0056	,80701	600
job_satisfaction	3,0527	,59258	600

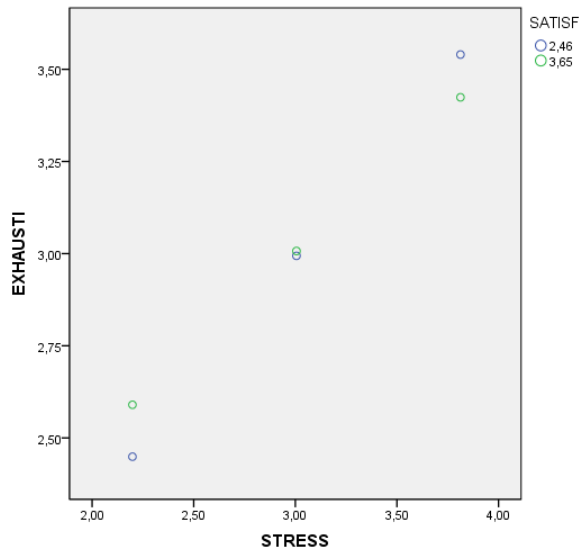
Excel values used with Traditional SPSS analysis

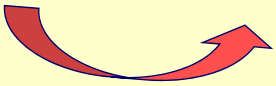
1st Column IV values		Low Satisfaction	High Satisfaction
mean minus 1,5 sd	-1,21	2,177	2,382
mean minus 1 sd	-0,81	2,449	2,591
mean minus 0,5 sd	-0,40	2,722	2,799
Mean IV	0,00	2,994	3,008
mean plus 0,5 sd	0,40	3,267	3,216
mean plus 1 sd	0,81	3,540	3,424
mean plus 1,5 sd	1,21	3,812	3,633



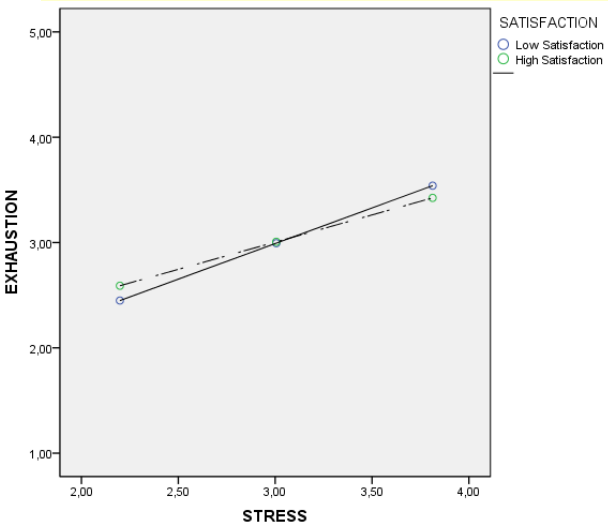
To get a more simple plot, I have just left the values for Low and High Satisfaction

And added two compute statements to obtain a plot that shows X and M in their original, uncentered metric.



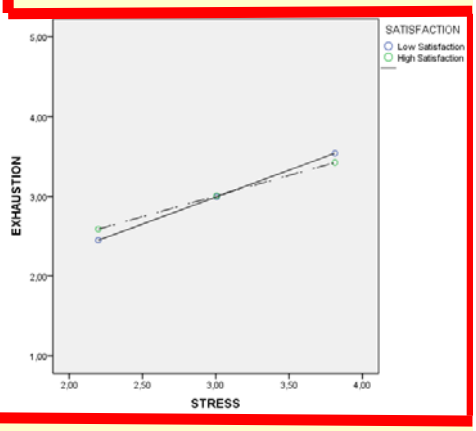


Double click to edit the plot:
Elementos → Linea de interpolacion
And some other SPSS's graphics editing features.



PROCESS

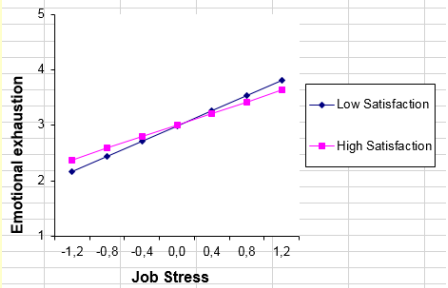
```
Conditional effect of X on Y at values of the moderator(s):
     SATISF     Effect         se          t          p       LLCI       ULCI
Low  -,593      ,676      ,069      9,832      ,000      ,541      ,811
      ,000      ,596      ,051     11,682      ,000      ,496      ,697
High  ,593      ,517      ,059      8,781      ,000      ,401      ,632

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.
```



We could conclude that Job Satisfaction moderates the relationship between Job Stress and Emotional Exhaustion (b=-.134, p<.05).
The slope linking job stress to emotional exhaustion is more steep among those lower in satisfaction.
Results also suggest that the conditional effect is statistically significant for low, medium and high values of the moderator.

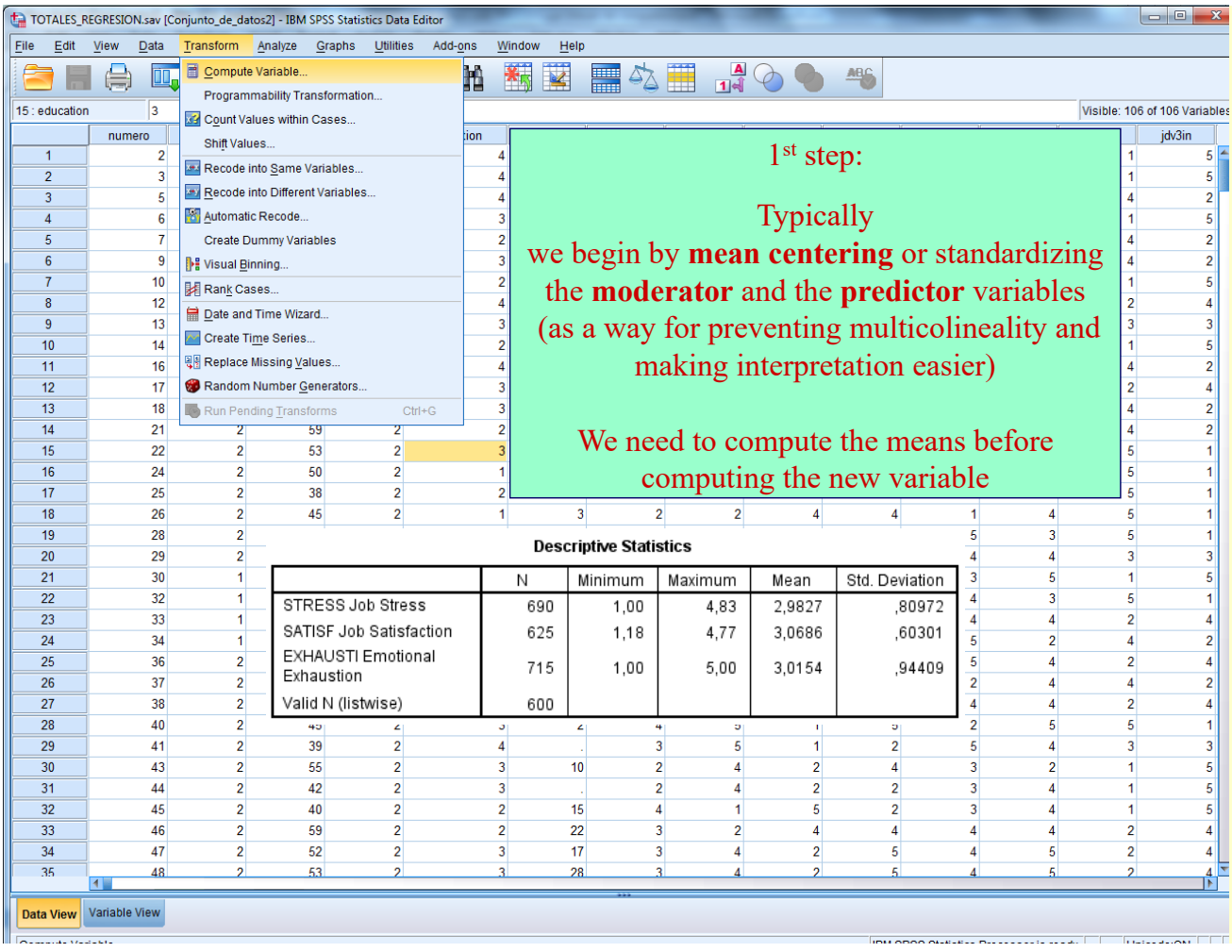
Excel values obtained for Traditional SPSS analysis

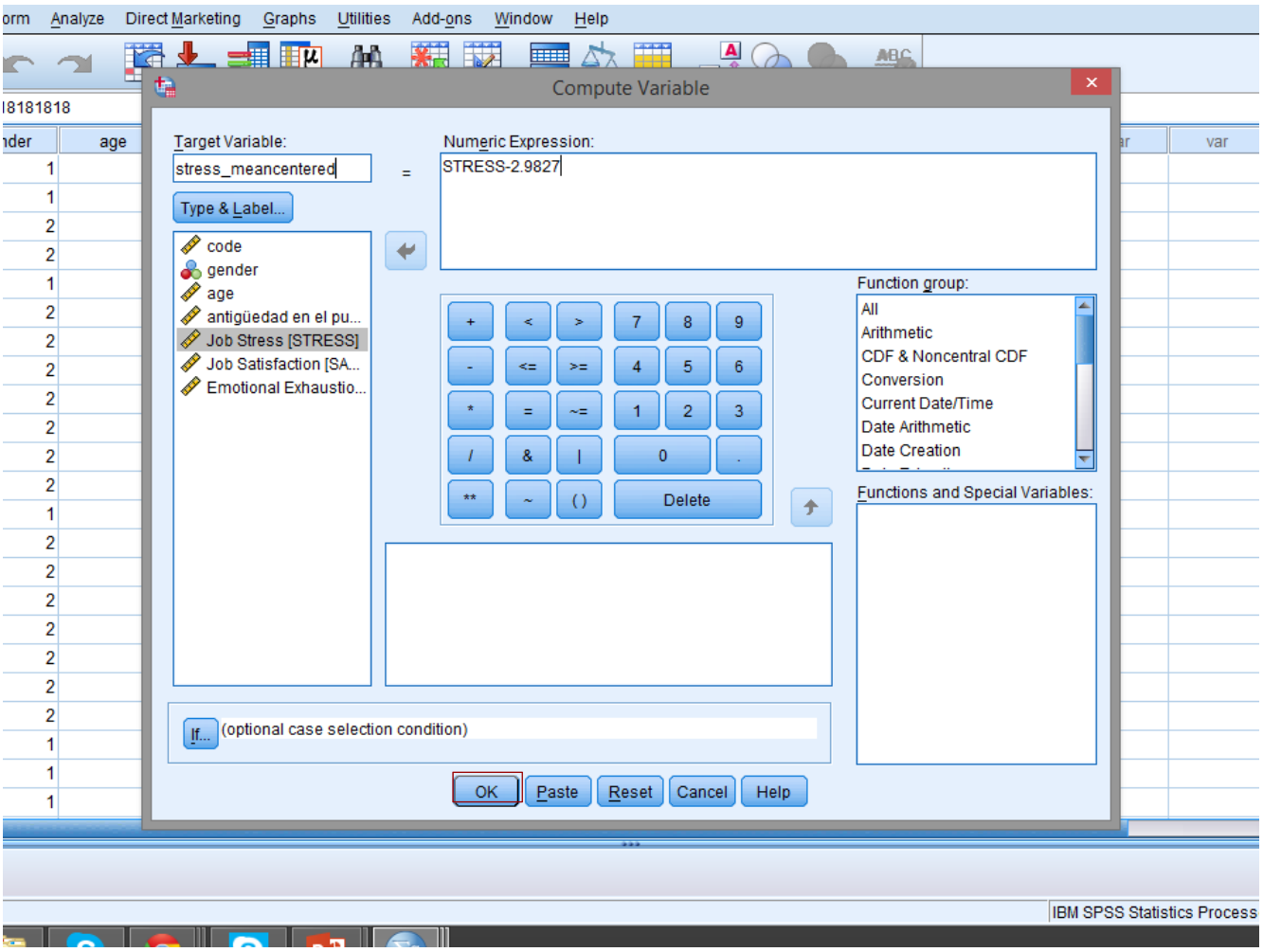
				stand error	t
Zlow	-0,593	simple slope low	0,675	0,07476473	9,03374837
Zhigh	0,593	simple slope high	0,517	0,05674015	9,10456373
Mean Modulator		simple slope average	0,596		

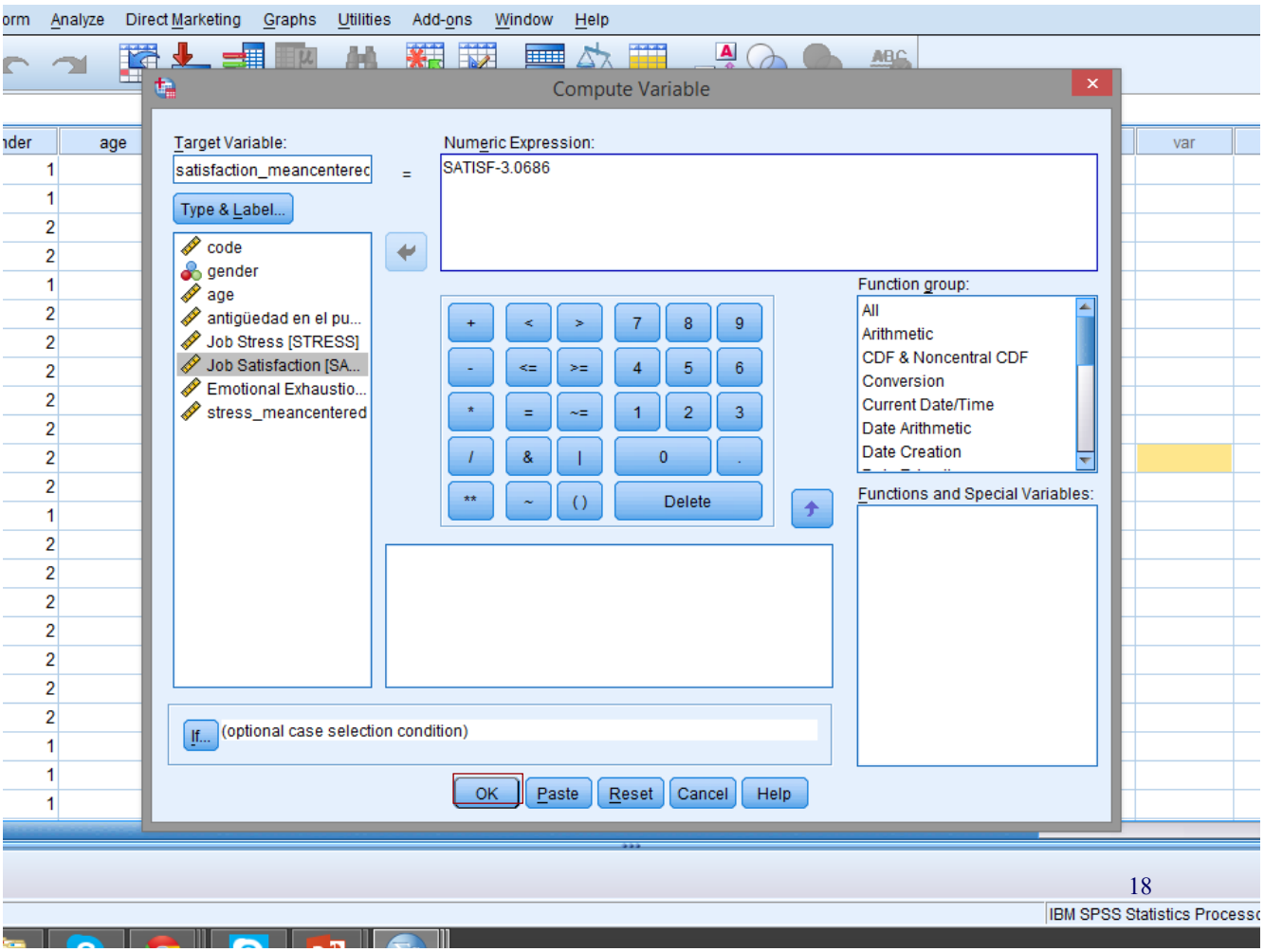


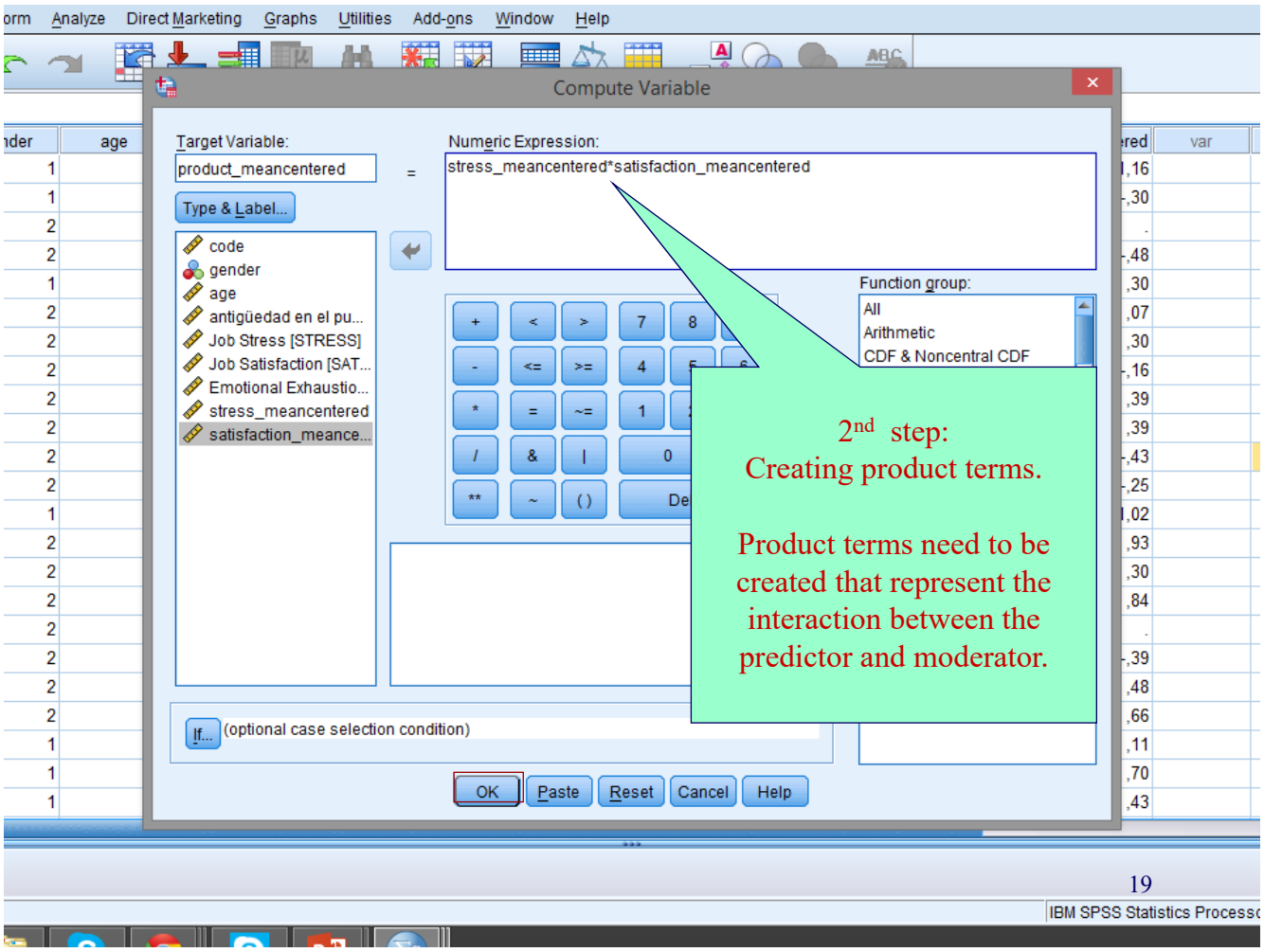
Multiple Regression Analysis with PROCESS

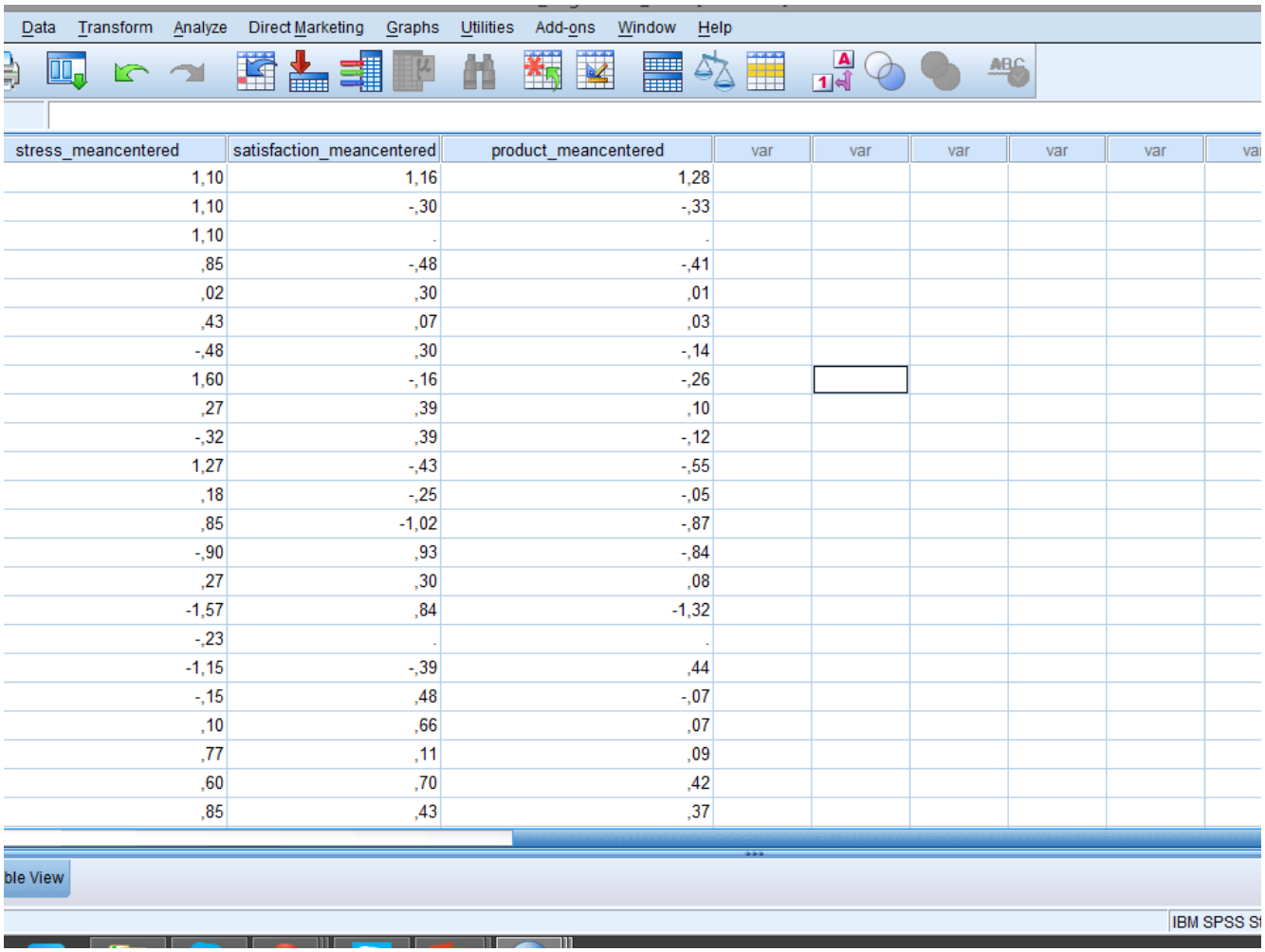
1. How to install Process in SPSS for Windows
2. How to run a MODERATION model
3. How to interpret the results
4. And what if we want to check for the assumptions?



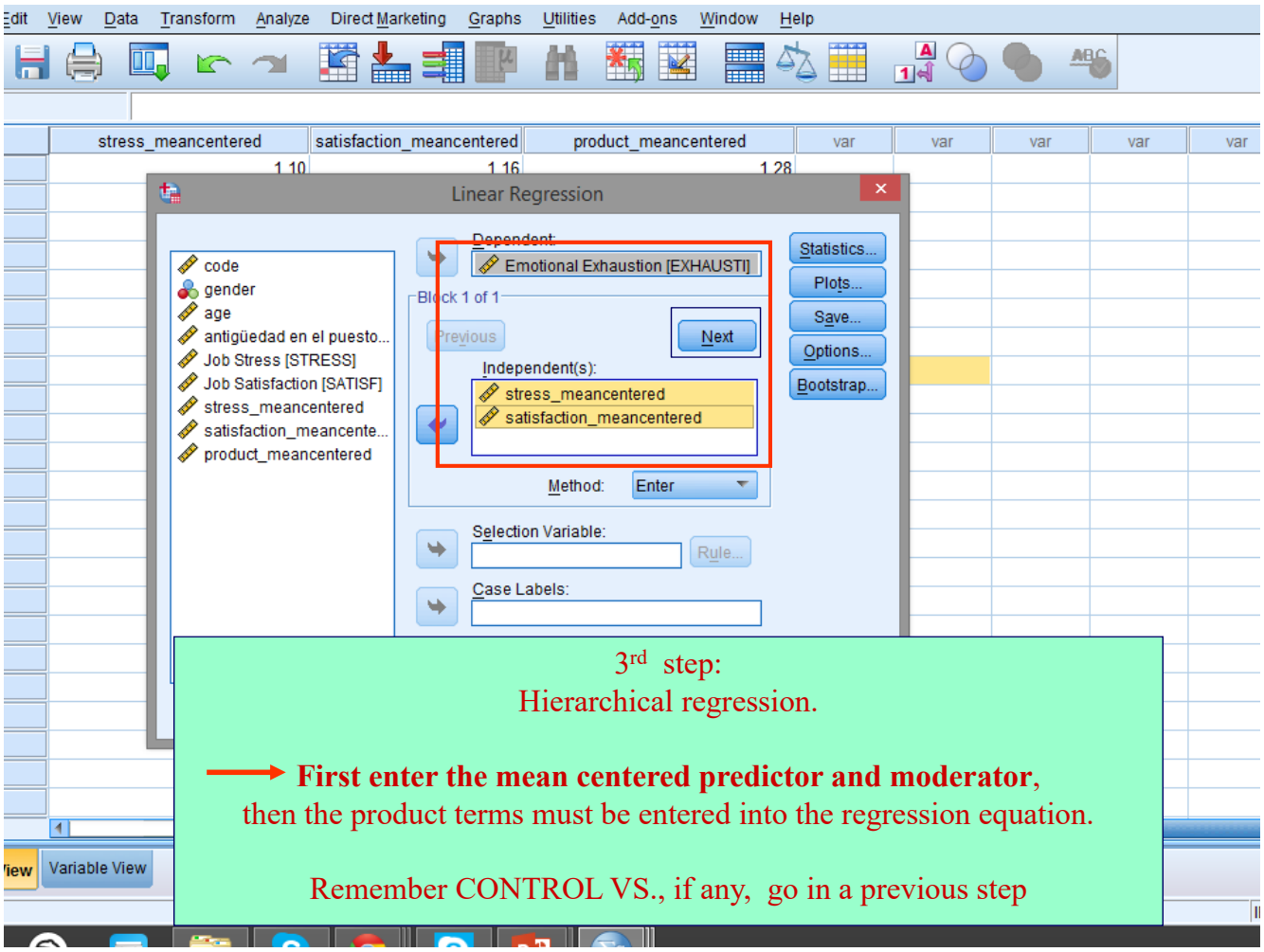

Analyze
Direct Marketing
Graphs
Utilities
Add-ons
Window
Help
Compute Variable
Target Variable:
stress_meancentered
Numeric Expression:
STRESS-2.9827
Type & Label...
code
gender
age
antigüedad en el pu...
Job Stress [STRESS]
Job Satisfaction [SA...
Emotional Exhaustio...
Function group:
All
Arithmetic
CDF & Noncentral CDF
Conversion
Current Date/Time
Date Arithmetic
Date Creation
Functions and Special Variables:
Delete
If...
(optional case selection condition)
OK
Paste
Reset
Cancel
Help
IBM SPSS Statistics Process


Analyze
Direct Marketing
Graphs
Utilities
Add-ons
Window
Help
Compute Variable
Target Variable:
satisfaction_meancenterec
Numeric Expression:
SATISF-3.0686
Type & Label...
code
gender
age
antigüedad en el pu...
Job Stress [STRESS]
Job Satisfaction [SA...
Emotional Exhaustio...
stress_meancentered
Function group:
All
Arithmetic
CDF & Noncentral CDF
Conversion
Current Date/Time
Date Arithmetic
Date Creation
Functions and Special Variables:
Delete
If...
(optional case selection condition)
OK
Paste
Reset
Cancel
Help
IBM SPSS Statistics Processc





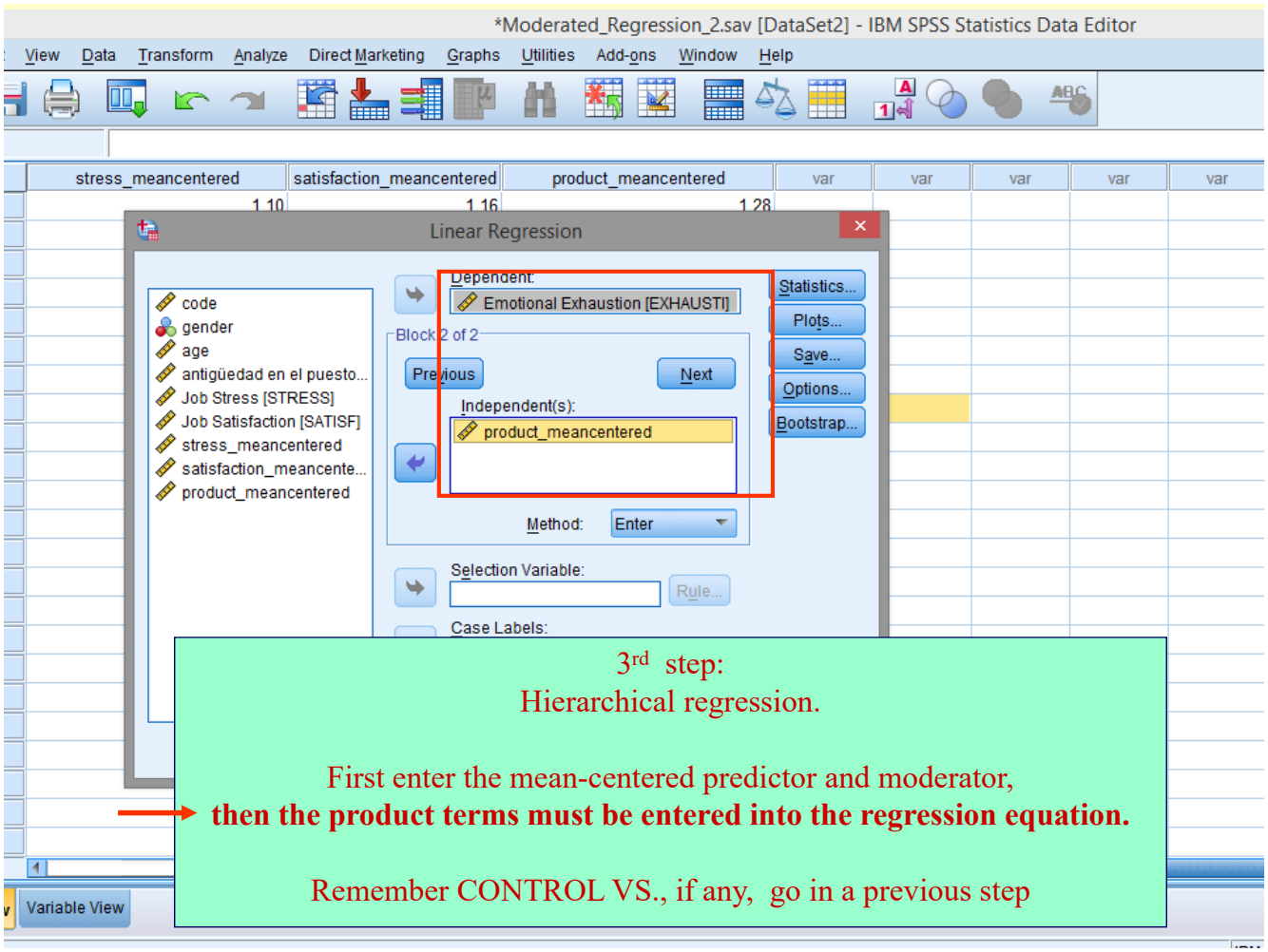
stress_meancentered	satisfaction_meancentered	product_meancentered
1,10	1,16	1,28
1,10	-,30	-,33
1,10	.	.
,85	-,48	-,41
,02	,30	,01
,43	,07	,03
-,48	,30	-,14
1,60	-,16	-,26
,27	,39	,10
-,32	,39	-,12
1,27	-,43	-,55
,18	-,25	-,05
,85	-1,02	-,87
-,90	,93	-,84
,27	,30	,08
-1,57	,84	-1,32
-,23	.	.
-1,15	-,39	,44
-,15	,48	-,07
,10	,66	,07
,77	,11	,09
,60	,70	,42
,85	,43	,37



3rd step:
Hierarchical regression.

→ **First enter the mean centered predictor and moderator,**
then the product terms must be entered into the regression equation.

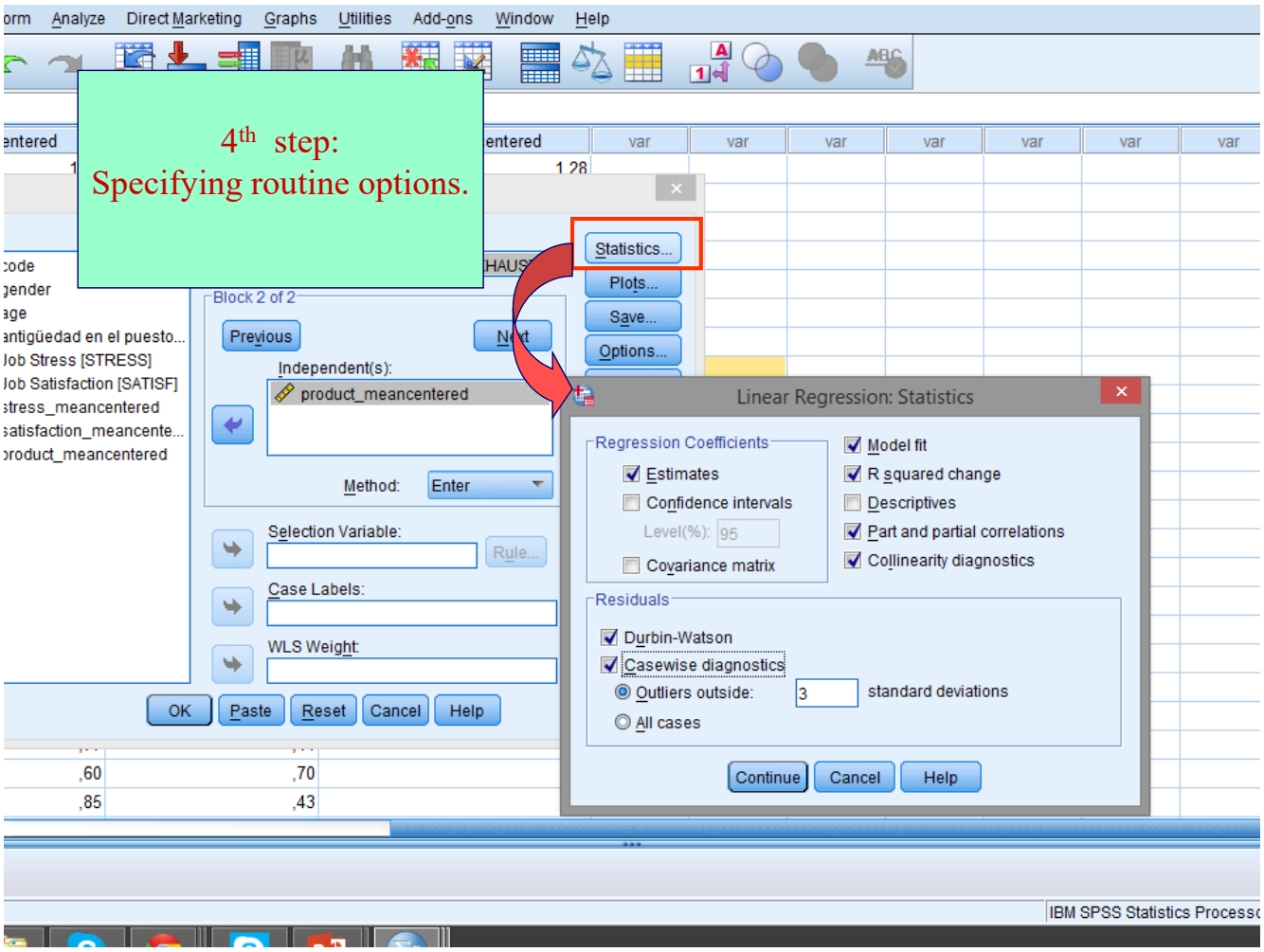
Remember CONTROL VS., if any, go in a previous step

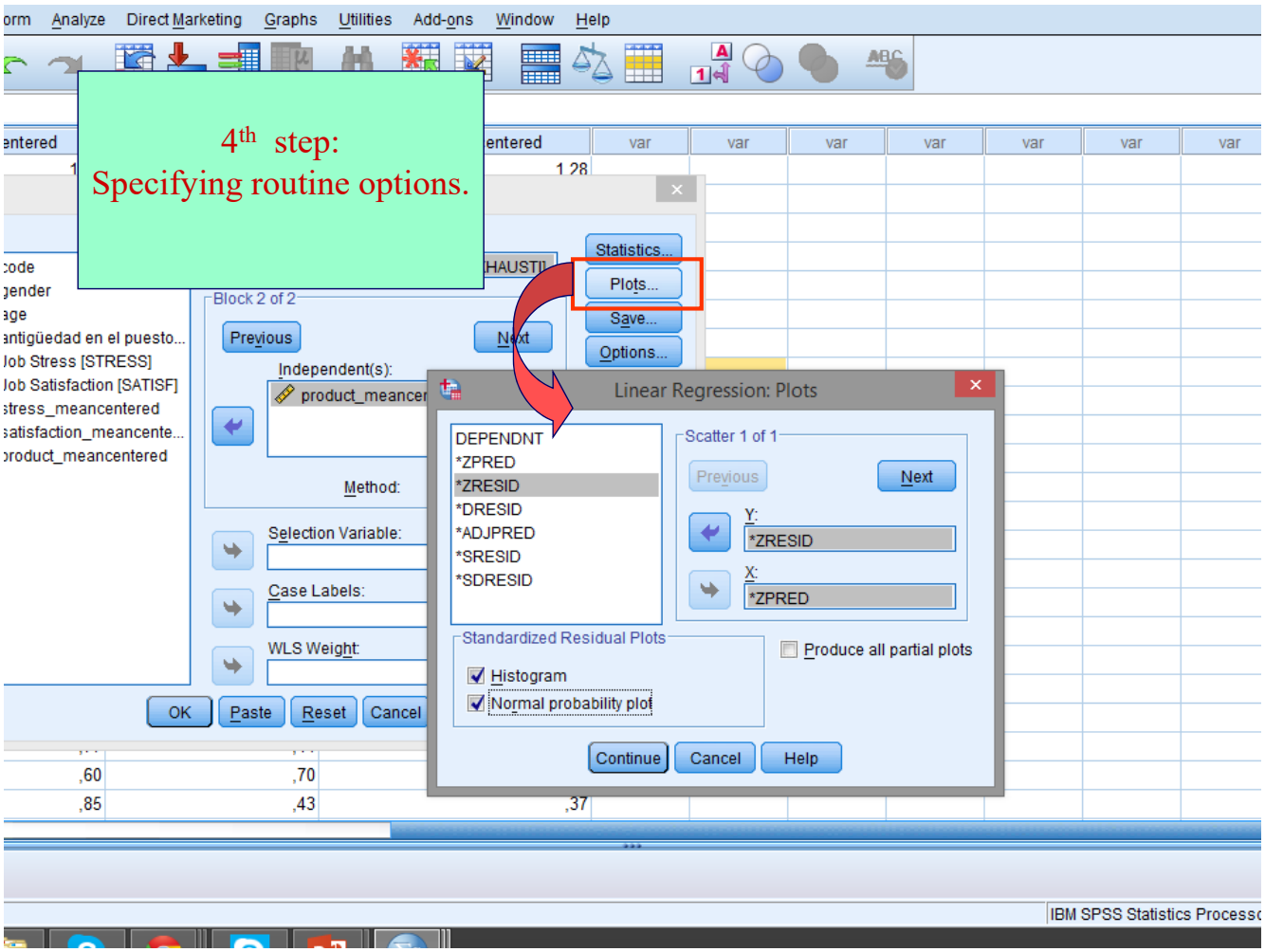


3rd step:
Hierarchical regression.

First enter the mean-centered predictor and moderator,
→ **then the product terms must be entered into the regression equation.**

Remember CONTROL VS., if any, go in a previous step


4th step:
Specifying routine options.
Statistics...
Plots...
Save...
Options...
Block 2 of 2
Previous
Next
Independent(s):
product_meancentered
Method: Enter
Selection Variable:
Rule...
Case Labels:
WLS Weight:
OK
Paste
Reset
Cancel
Help
Linear Regression: Statistics
Regression Coefficients
Estimates
Confidence intervals
Level(%): 95
Covariance matrix
Model fit
R squared change
Descriptives
Part and partial correlations
Collinearity diagnostics
Residuals
Durbin-Watson
Casewise diagnostics
Outliers outside: 3 standard deviations
All cases
Continue
Cancel
Help


4th step:
Specifying routine options.
Statistics...
Plots...
Save...
Options...
Block 2 of 2
Previous
Next
Independent(s):
Method:
Selection Variable:
Case Labels:
WLS Weight:
OK
Paste
Reset
Cancel
Linear Regression: Plots
DEPENDNT
*ZPRED
*ZRESID
*DRESID
*ADJPRED
*SRESID
*SDRESID
Scatter 1 of 1
Previous
Next
Y:
*ZRESID
X:
*ZPRED
Standardized Residual Plots
Histogram
Normal probability plot
Produce all partial plots
Continue
Cancel
Help

5th step: Interpreting results.

And... Checking the assumptions

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,495[a]	,245	,243	,82582	,245	96,981	2	597	,000	
2	,501[b]	,251	,247	,82358	,005	4,246	1	596	,040	1,832

a. Predictors: (Constant), satisfaction_meancentered, stress_meancentered

b. Predictors: (Constant), satisfaction_meancentered, stress_meancentered, product_meancentered

c. Dependent Variable: EXHAUSTI Emotional Exhaustion

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	132,277	2	66,138	96,981	,000[b]
	Residual	407,139	597	,682		
	Total	539,416	599			
2	Regression	135,157	3	45,052	66,421	,000[c]
	Residual	404,259	596	,678		
	Total	539,416	599			

a. Dependent Variable: EXHAUSTI Emotional Exhaustion

b. Predictors: (Constant), satisfaction_meancentered, stress_meancentered

c. Predictors: (Constant), satisfaction_meancentered, stress_meancentered, product_meancentered

Independence of residuals (between 1,5 and 2,5)

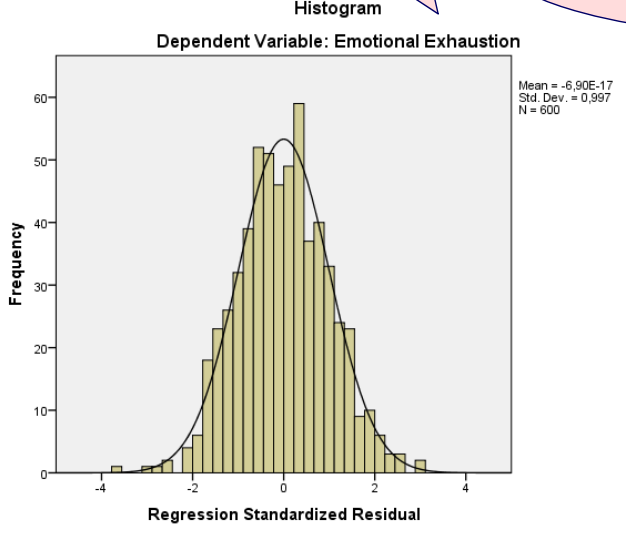
Coefficients[a]

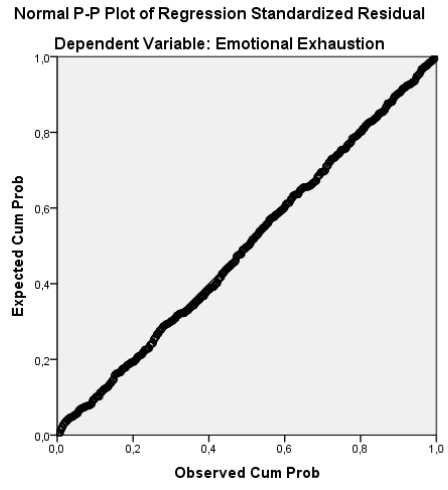
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,023	,034		89,632	,000					
	stress_meancentered	,580	,051	,493	11,470	,000	,495	,425	,408	,685	1,461
	satisfaction_meancentered		,069	-,004	-,096	,924	-,281	-,004	-,003	,685	1,461
2					78,793	,000					
				505	11,676	,000	,495	,431		,671	1,490
				,009	,206	,837	-,281		,007	,670	1,492
	product_me		,065						073	,974	1,027

a. Dependent Variable: EXHAUSTI Emot tion

Checking for normality of residuals (in this case OK)

Checking for lack of multicollinearity (in this case no problem)





Importance of plotting the effects to understand interactions

Psicothema 2009. Vol. 21, nº 4, pp. 515-520
www.psicothema.com

ISSN 0214 - 9915 CODEN PSOTEG

Leader charisma and affective team climate: The moderating role of the leader's influence and interaction

Ana Hernández Baeza*, Cristina Araya Lao, Juliana García Meneses and Vicente González Romá*
Universitat València * e Idocal

In this study, we evaluate the role of leader charisma in fostering positive affective team climate and preventing negative affective climate. The analysis of a longitudinal database of 137 bank branches by means of hierarchical moderated regression shows that leader charisma has a stronger effect on team optimism than on team tension. In addition, the leader's influence and the frequency of leader-team interaction moderate the relationship between charisma and affective climate. However, whereas the leader's influence enhances the relationship between leader charisma and positive affective climate, the frequency of interaction has counterproductive effects.

Table 1
Moderated hierarchical regressions for team optimism

Step		B	SE.	p	Tolerance	Change in R^2
1	Team tenure	.001	.001	.611	.96	.031 (p>.05)
	Team size	-.054	.026	.042	.96	
2	Team Optimism Time 1	.687	.066	<.001	.98	.442 (p<.001)
3	Leaders' charisma	.121	.054	.027	.68	.020 (p= .027)
4	Leaders' influence	.168	.094	.075	.73	.024 (p= .047)
	Leaders' interaction	-.249	.108	.023	.36	
5	Charisma*influence	.281	.104	.008	.63	.032 (p= .014)
	Charisma*interaction	-.177	.071	.014	.48	

Table 2
Moderated hierarchical regressions for team tension

Step		B	SE.	p	Tolerance	Change in R^2
1	Team tenure	.001	.001	.966	.96	.036 (p>.05)
	Team size	.058	.027	.033	.96	
2	Team Tension Time 1	.624	.065	<.001	.95	.402 (p<.001)
3	Leaders' charisma	-.033	.050	.508	.89	.002 (p>.05)
4	Leaders' influence	-.119	.101	.244	.73	.014 (p>.05)
	Leaders' interaction	.202	.117	.087	.35	
5	Charisma*influence	-.250	.113	.029	.63	.027 (p= .043)
	Charisma*interaction	.175	.078	.027	.47	

Importance of plotting the effects to understand interactions

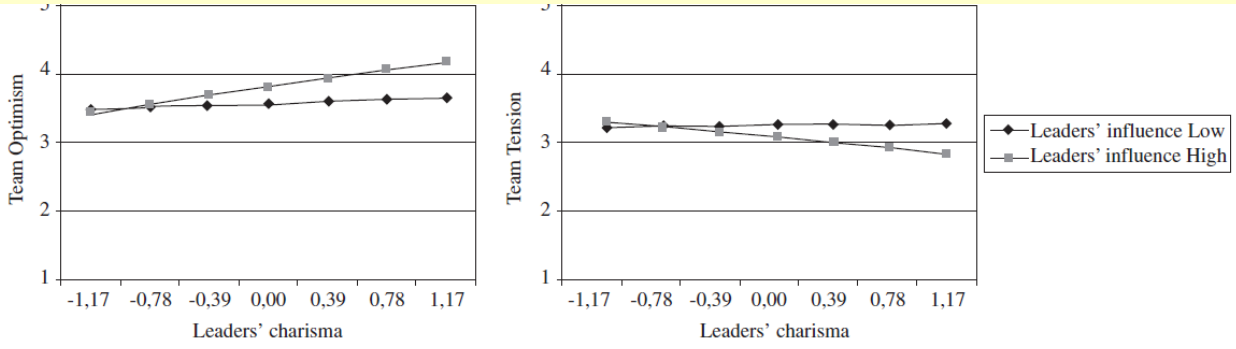


Figure 1. Interaction effects between leaders' charisma and leaders' influence

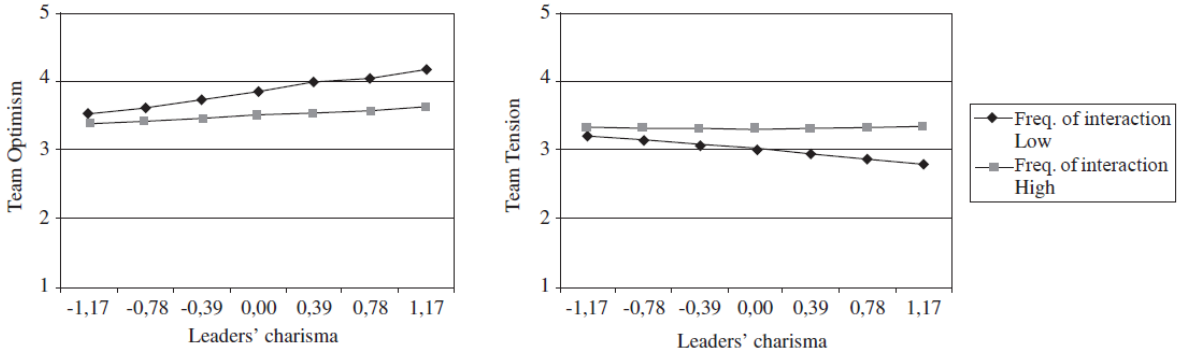
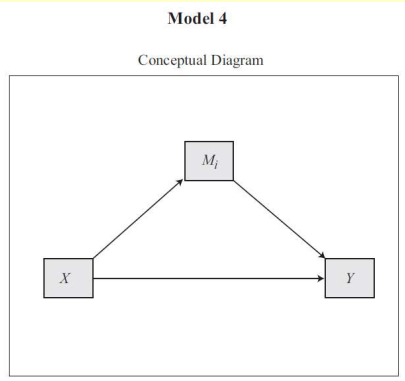


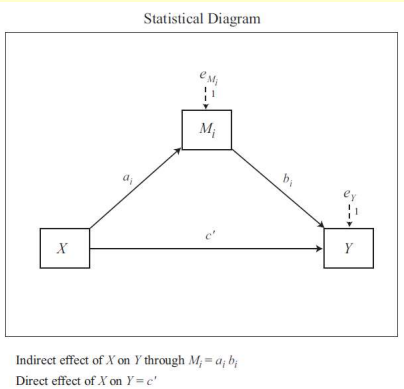
Figure 2. Interaction effects between leaders' charisma and frequency of leaders' interaction with the team

Multiple Regression Analysis with **PROCESS**

1. How to install Process in SPSS for Windows
2. How to run a **MEDIATION** model
3. How to interpret the results
4. And what if we complicate the model?

Mediation in Multiple Regression with PROCESS





Model Templates for PROCESS for SPSS and SAS
©2013 Andrew F. Hayes, http://www.afhayes.com/

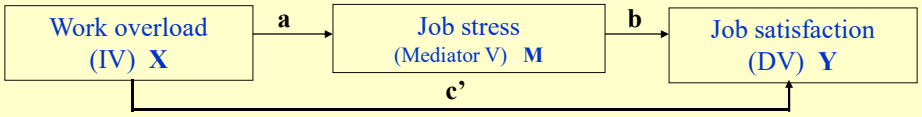
Same model in Process v3 (2017)

$$M = a_m + b_{mx} X + e_m \qquad Y = a_y + b_{yx.m} X + b_{ym.x} M + e_y$$

Path a → ¿Is *ab* significant? ← Path b

Mediation with Multiple Regression

Example



1st step: Regression equation (estimate a)

2nd step: Regression equation (estimate b and c')

3rd step: Determine if the product (ab) is statistically significant

Process will do all that for us!!

4th step: Determine if the mediation is total or partial.

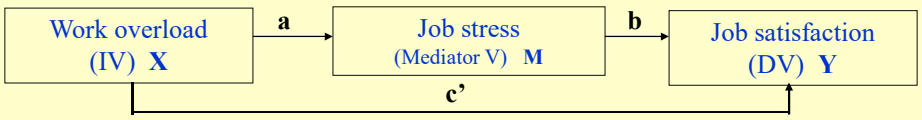
3

Mediation with Multiple Regression

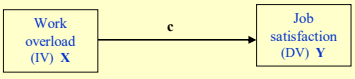
DATA FILE: Mediated_Regression

Research question:

- Does **Job Stress** mediate the relationship between **Work overload** and **Job Satisfaction**?



c = Total effect of X on Y



c = c' + a*b

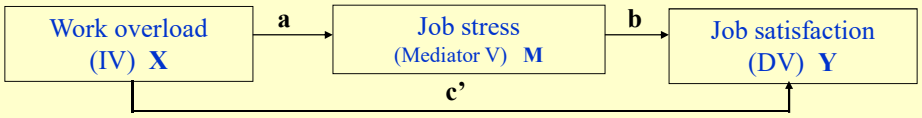
c' = Direct effect of X on Y (after controling for the effect of M)

a*b = Indirect effect of X on Y

a=0.5; b=0.3
X ↑ one unit,...
Y ↑ 0.15, vía M

Mediation with Multiple Regression

DATA FILE: Mediated_Regression



How can we check if there is mediation?

- Baron & Kenny (1986)
- Joint significance test for a and b
- Sobel test (Sobel, 1982)

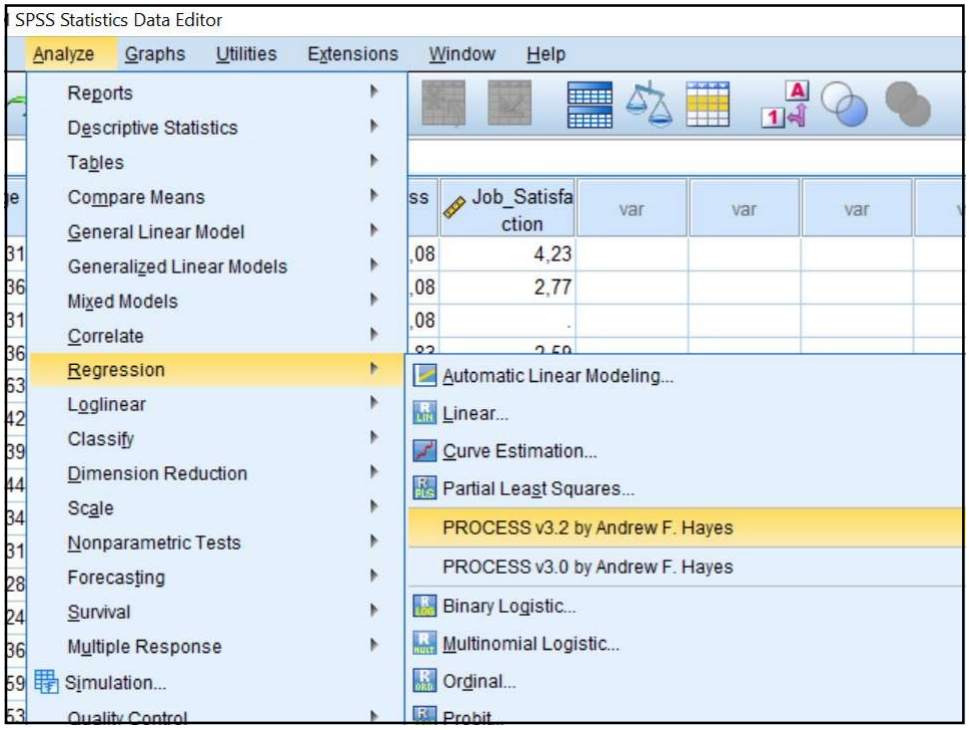
Problems!

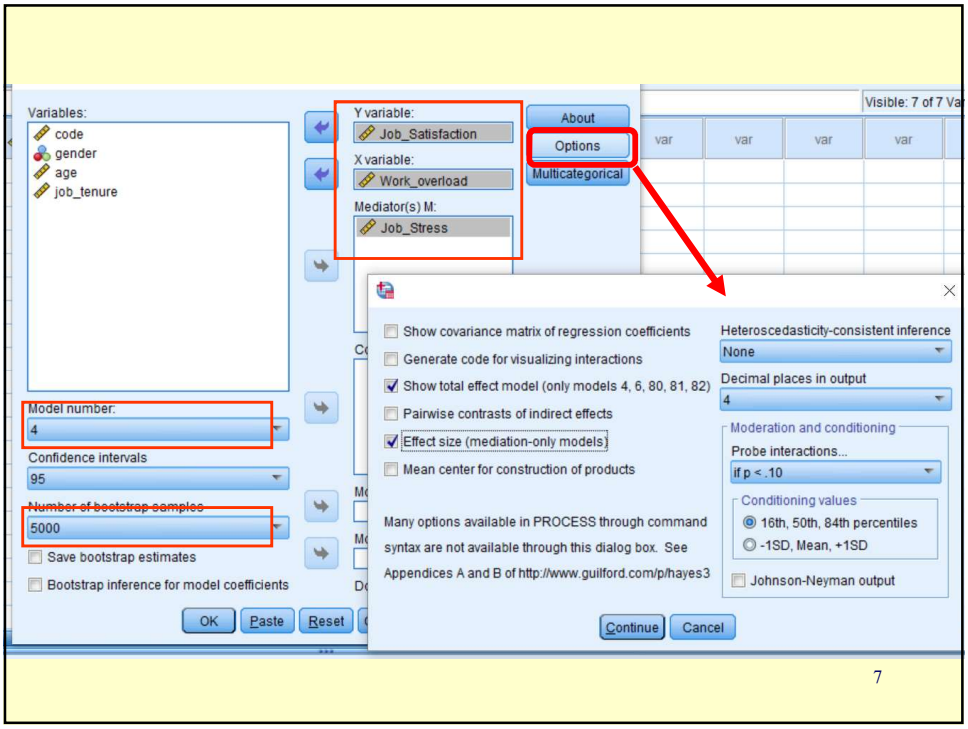
- The product of coefficients distribution method (MacKinnon, et al. 1998)
- Bootstrapping
- Monte Carlo (Rmediation)

Better options: Explicitly focus on indirect effect ab, without assuming a normal distribution of the product

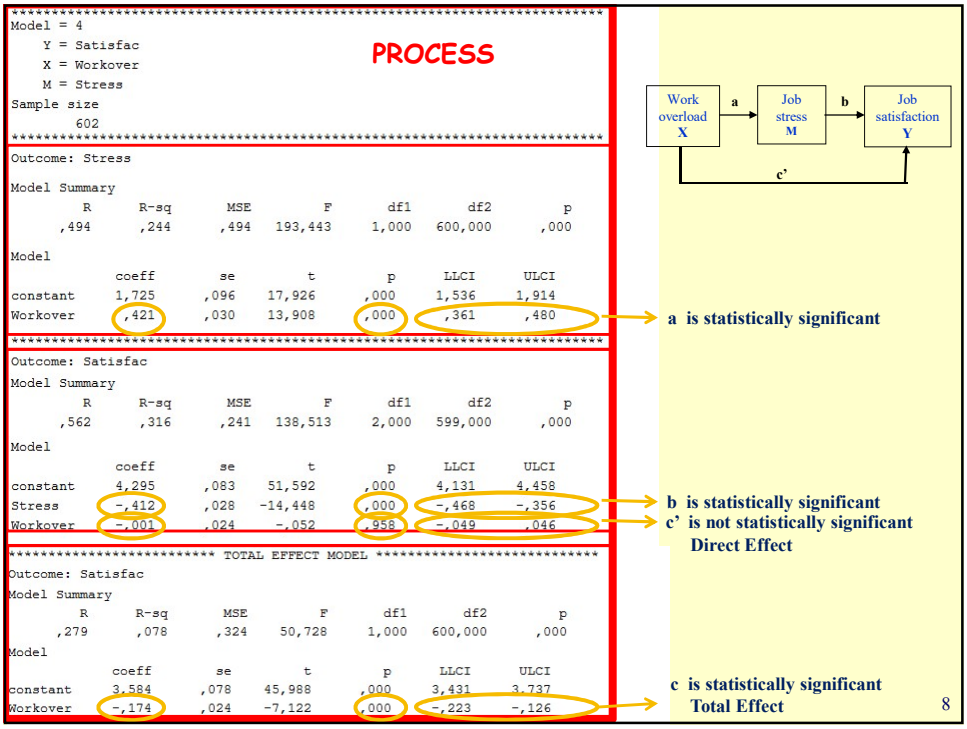
Best balance between power and type I error (see MacKinnon et al., 2002)
It is implemented by default in Process

5

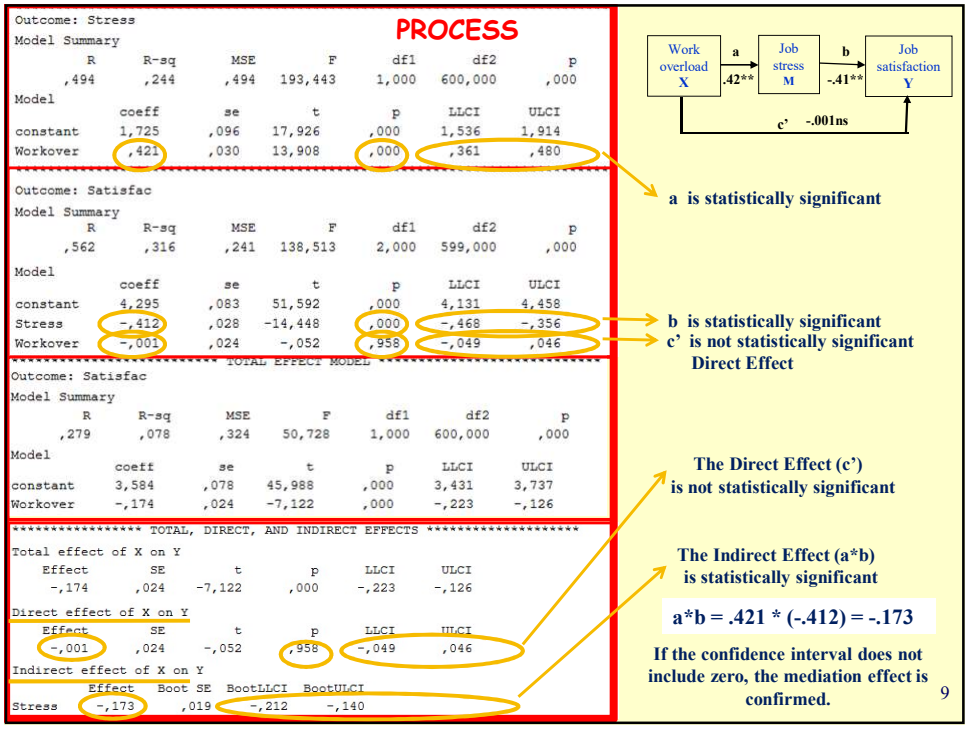



Variables:
code
gender
age
job_tenure
Y variable:
Job_Satisfaction
X variable:
Work_overload
Mediator(s) M:
Job_Stress
About
Options
Multicategorical
Model number:
4
Confidence intervals
95
Number of bootstrap samples
5000
Save bootstrap estimates
Bootstrap inference for model coefficients
OK
Paste
Reset
Show covariance matrix of regression coefficients
Generate code for visualizing interactions
Show total effect model (only models 4, 6, 80, 81, 82)
Pairwise contrasts of indirect effects
Effect size (mediation-only models)
Mean center for construction of products
Many options available in PROCESS through command syntax are not available through this dialog box. See Appendices A and B of http://www.guilford.com/p/hayes3
Heteroscedasticity-consistent inference
None
Decimal places in output
4
Moderation and conditioning
Probe interactions...
if p < .10
Conditioning values
16th, 50th, 84th percentiles
-1SD, Mean, +1SD
Johnson-Neyman output
Continue
Cancel
Visible: 7 of 7
var

7


Model = 4
Y = Satisfac
X = Workover
M = Stress
Sample size
602
PROCESS
Outcome: Stress
Model Summary
R R-sq MSE F df1 df2 p
,494 ,244 ,494 193,443 1,000 600,000 ,000
Model
coeff se t p LLCI ULCI
constant 1,725 ,096 17,926 ,000 1,536 1,914
Workover ,421 ,030 13,908 ,000 ,361 ,480
Outcome: Satisfac
Model Summary
R R-sq MSE F df1 df2 p
,562 ,316 ,241 138,513 2,000 599,000 ,000
Model
coeff se t p LLCI ULCI
constant 4,295 ,083 51,592 ,000 4,131 4,458
Stress -,412 ,028 -14,448 ,000 -,468 -,356
Workover -,001 ,024 -,052 ,958 -,049 ,046
TOTAL EFFECT MODEL
Outcome: Satisfac
Model Summary
R R-sq MSE F df1 df2 p
,279 ,078 ,324 50,728 1,000 600,000 ,000
Model
coeff se t p LLCI ULCI
constant 3,584 ,078 45,988 ,000 3,431 3,737
Workover -,174 ,024 -7,122 ,000 -,223 -,126
Work overload X
a
Job stress M
b
Job satisfaction Y
c'
a is statistically significant
b is statistically significant
c' is not statistically significant
Direct Effect
c is statistically significant
Total Effect

8



9

About effect sizes in mediation...

Preacher y Kelly (2011) Effect Size Measures for Mediation Models: Quantitative Strategies for Communicating Indirect Effects. Psychological Methods, 16, 93-115

Process:

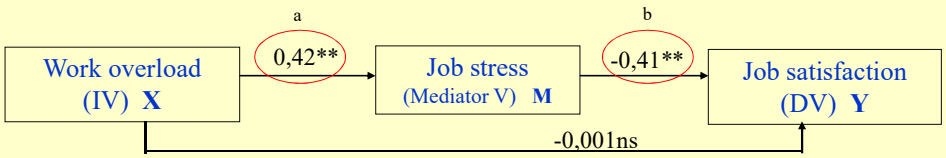
```
Partially standardized indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
Job_Stre    -,2923      ,0271     -,3464     -,2407

Completely standardized indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
Job_Stre    -,2772      ,0262     -,3307     -,2270
```

The closer to 1, the stronger

Another way: **Ratio between indirect effect and total effect**
Pm= ab/c

Only if ab and c have the same sign

Pm= .173/.174=.99 → 99% of the effect is indirect



We could say that a relationship is mediated if:

1) X is significantly related to M (a statistically significant) ✓

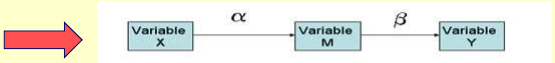
2) M is significantly related to Y after controlling for X (b statistically significant) ✓

3) The mediated effect is statistically significant (the product a*b is significant) ✓

(a*b = -.17; IC 95% = [-.21, -.14])

Total mediation or Partial mediation?

The Direct or non-mediated effect is not statistically significant (c‘ = -.001, p>.05)



Total Mediation model

We could conclude that Job Stress is an important mechanism that links Work overload to Job Satisfaction.

11

Assumptions?

- Again standard regression:
  DV: Job stress; IV: Work overload
  DV: Job Satisfaction; IVs: Work overload
  Job stress

12

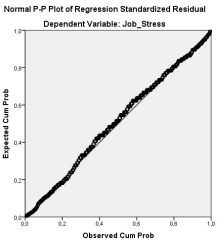
Assumptions

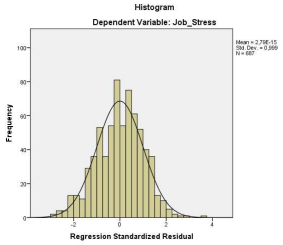
Model Summary[b]

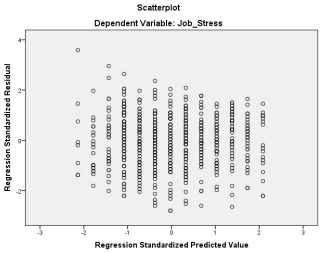
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,490[a]	,240	,239	,70489	1,752

a. Predictors: (Constant), Work_overload

b. Dependent Variable: Job_Stress

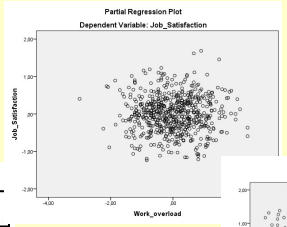


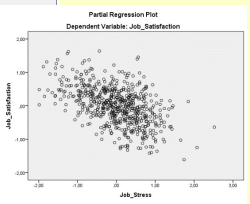




Need to check for collinearity?

13





Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,562[a]	,316	,314	,49065	1,751

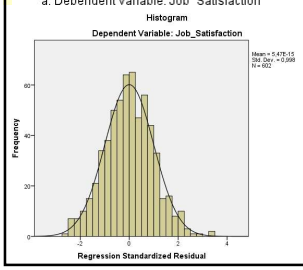
a. Predictors: (Constant), Job_Stress, Work_overload

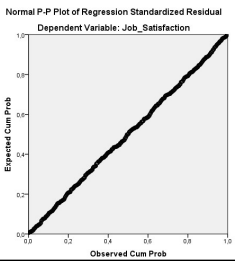
b. Dependent Variable: Job_Satisfaction

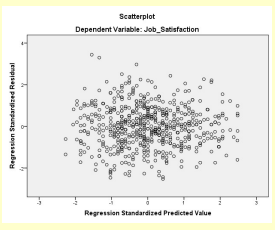
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,295	,083		51,592	,000		
	Work_overload	-,001	,024	-,002	-,052	,958	,756	1,322
	Job_Stress	-,412	,028	-,561	-14,448	,000	,756	1,322

a. Dependent Variable: Job_Satisfaction

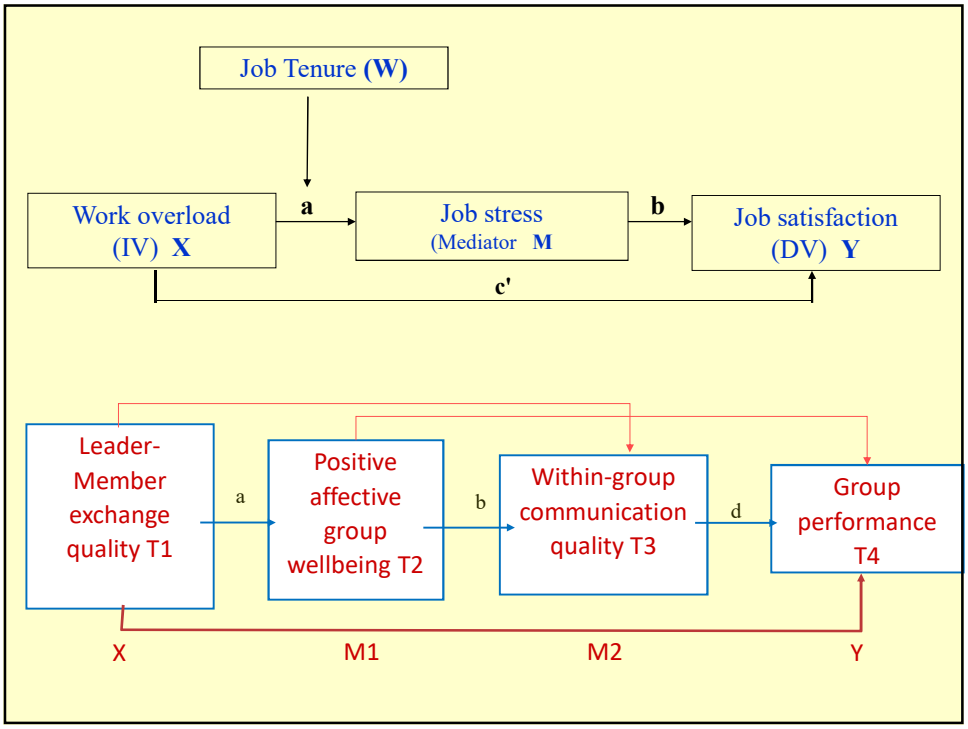


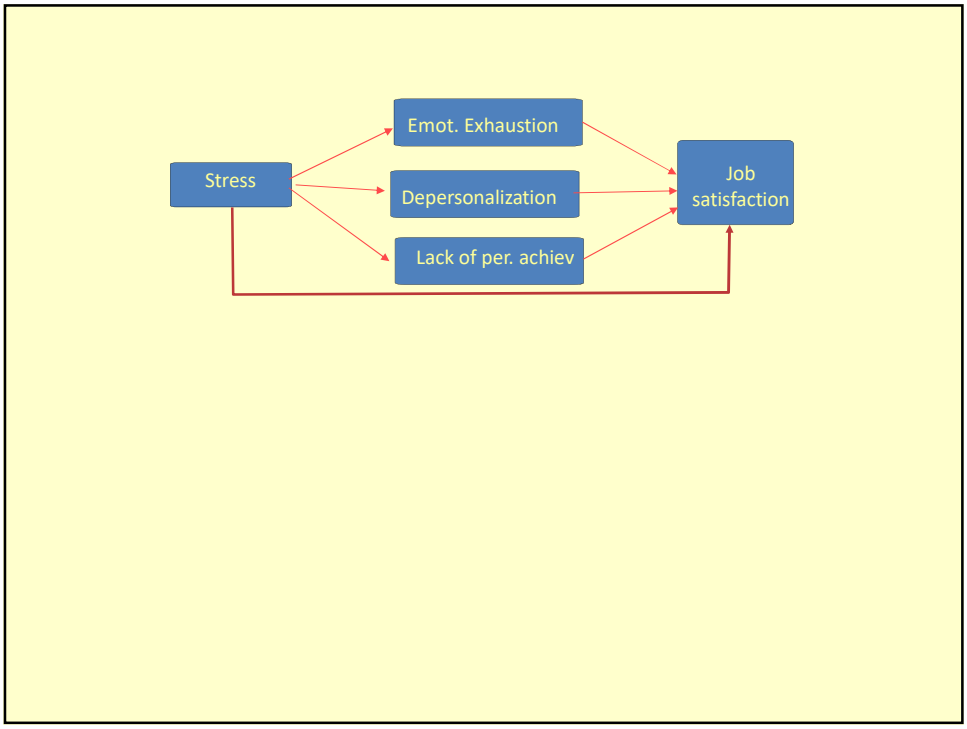


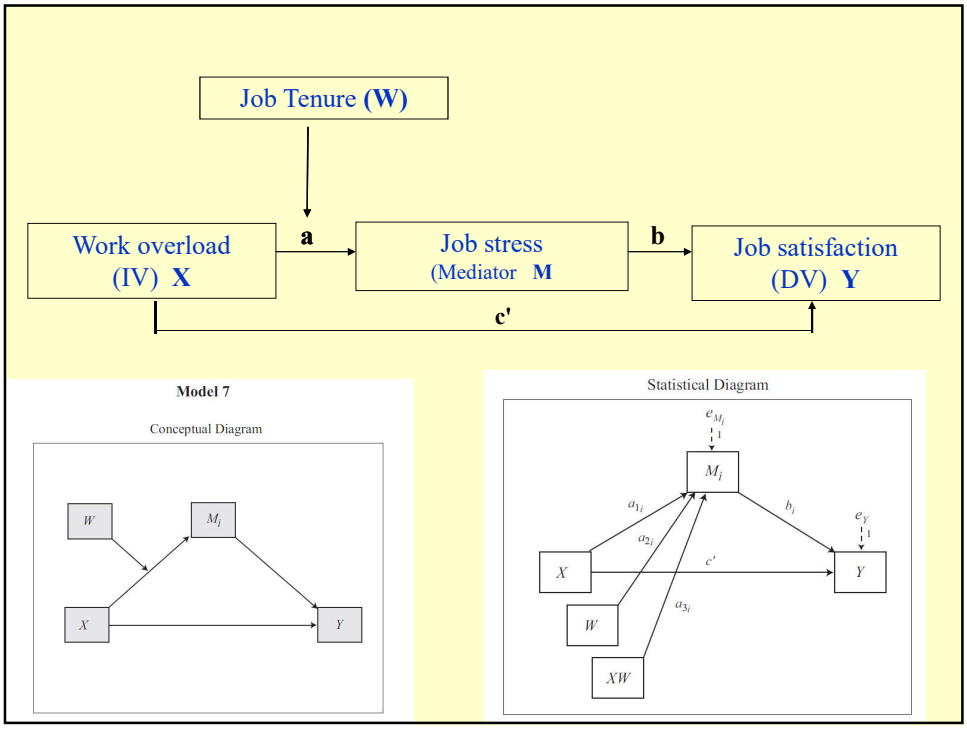


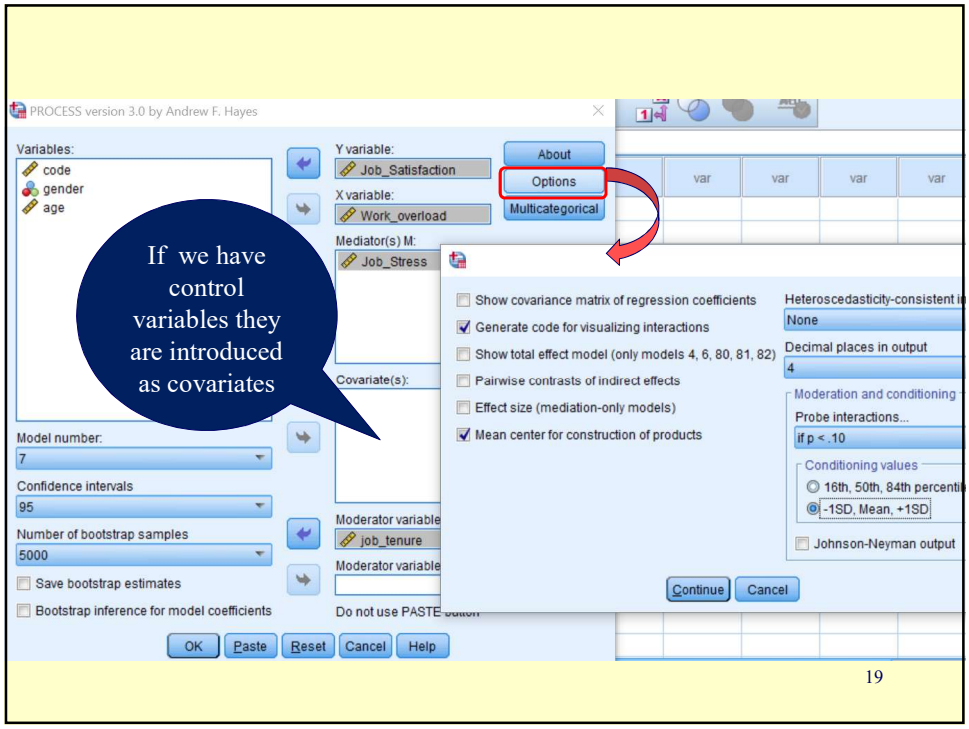
Multiple Regression Analysis with **PROCESS**

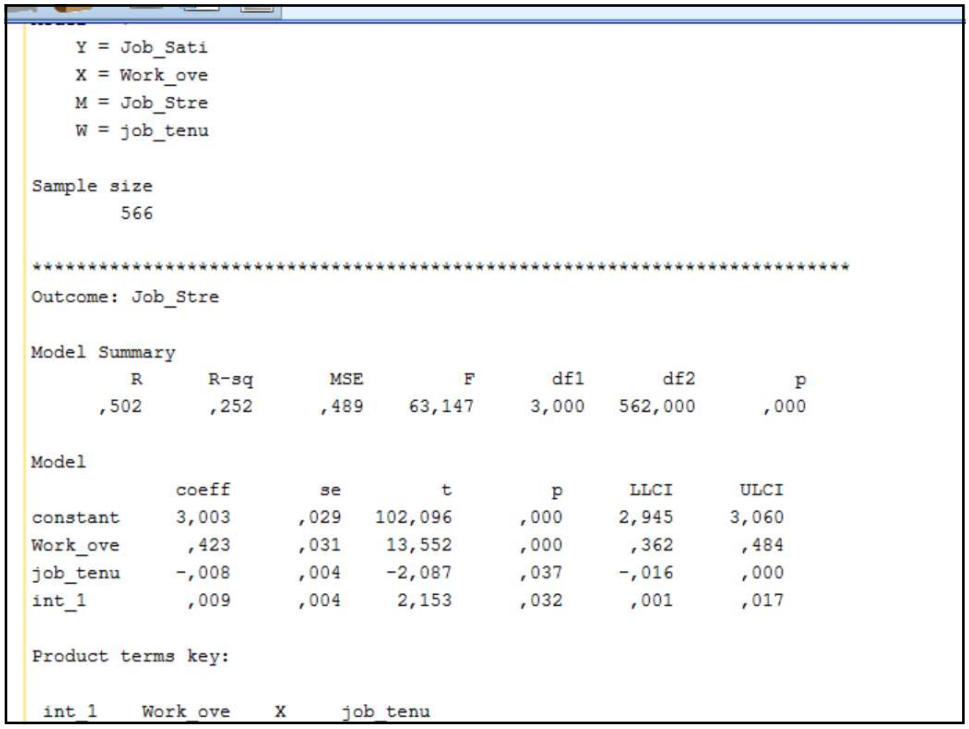
1. How to install Process in SPSS for Windows
2. How to run a **MEDIATION** model
3. How to interpret the results
4. And what if we complicate the model?




Stress
Emot. Exhaustion
Depersonalization
Lack of per. achiev
Job satisfaction


Job Tenure (W)
Work overload (IV) X
a
Job stress (Mediator M
b
Job satisfaction (DV) Y
c'
Model 7
Conceptual Diagram
W
Mi
X
Y
Statistical Diagram
eMi
1
Mi
a1i
a2i
bi
eY
1
X
c'
Y
W
a3i
XW



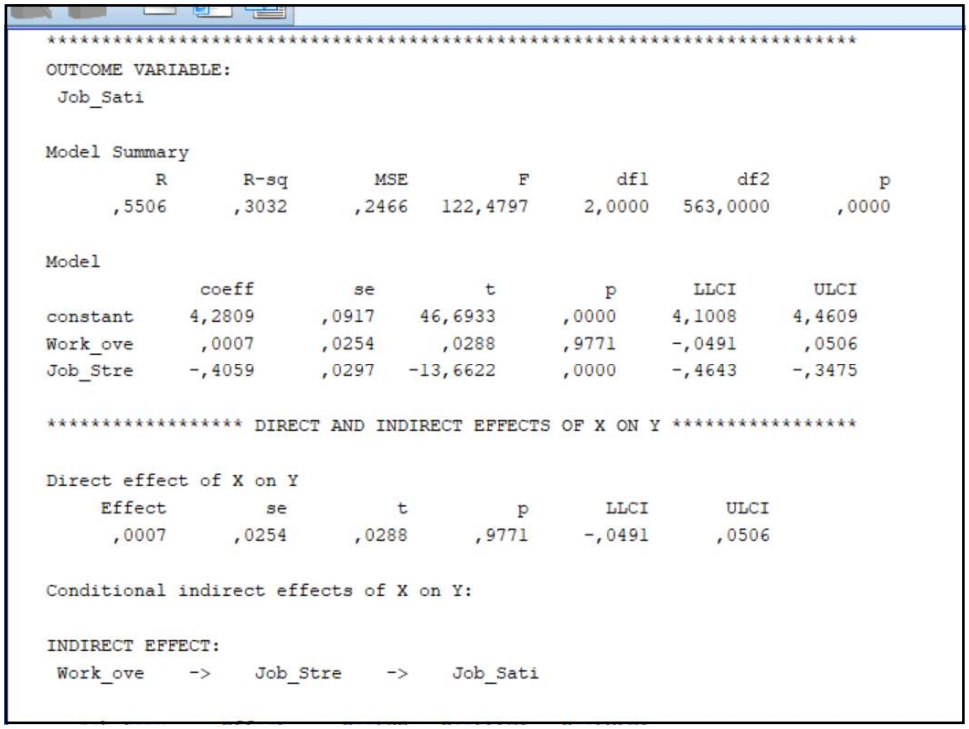


```
    Y = Job_Sati
    X = Work_ove
    M = Job_Stre
    W = job_tenu

Sample size
        566

**************************************************************************
Outcome: Job_Stre

Model Summary
         R       R-sq        MSE          F        df1        df2          p
      ,502       ,252       ,489     63,147      3,000    562,000       ,000

Model
             coeff         se          t          p       LLCI       ULCI
constant     3,003       ,029    102,096       ,000      2,945      3,060
Work_ove      ,423       ,031     13,552       ,000       ,362       ,484
job_tenu     -,008       ,004     -2,087       ,037      -,016       ,000
int_1         ,009       ,004      2,153       ,032       ,001       ,017

Product terms key:

 int_1    Work_ove     X      job_tenu
```

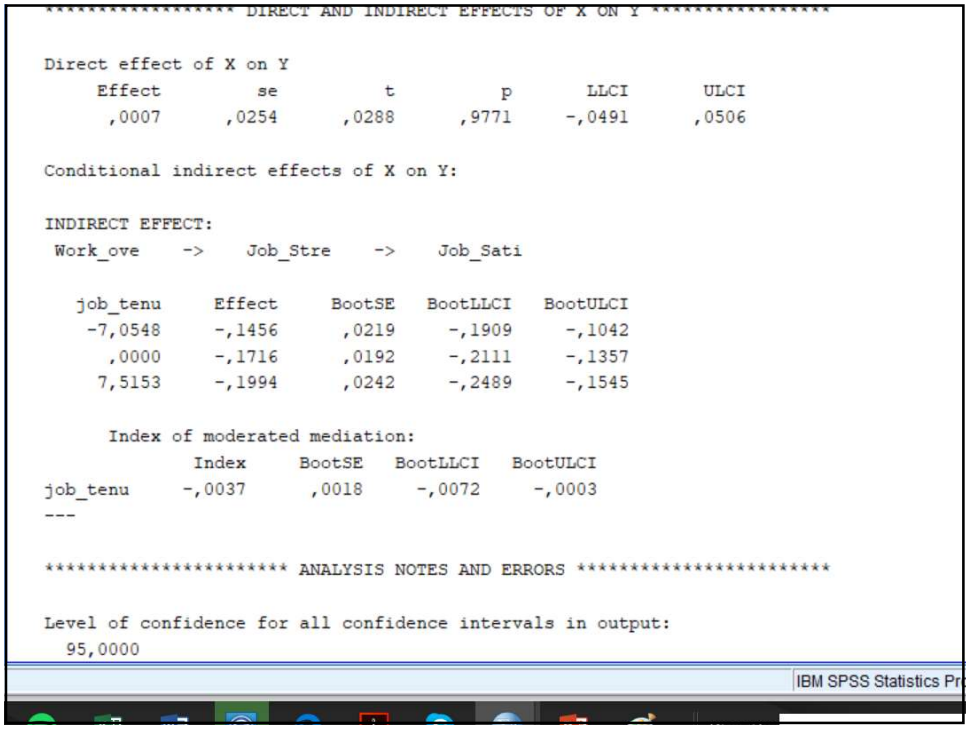
```
Product terms key:
 Int_1    :        Work_ove x        job_tenu

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0062     4,6369     1,0000   562,0000      ,0317
----------
    Focal predict: Work_ove (X)
          Mod var: job_tenu (W)

Conditional effects of the focal predictor at values of the moderator(s):

   job_tenu     Effect         se          t          p       LLCI       ULCI
   -7,0548      ,3586      ,0424     8,4545      ,0000      ,2753      ,4419
     ,0000      ,4229      ,0312    13,5518      ,0000      ,3616      ,4841
    7,5153      ,4913      ,0453    10,8468      ,0000      ,4023      ,5802

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Work_ove   job_tenu   Job_Stre   .
BEGIN DATA.
     -,9439    -7,0548     2,7218
      ,0000    -7,0548     3,0603
```

IBM SPSS Statistics Pr

```
DATA LIST FREE/
   Work_ove   job_tenu   Job_Stre   .
BEGIN DATA.
     -,9439    -7,0548     2,7218
      ,0000    -7,0548     3,0603
      ,9439    -7,0548     3,3988
     -,9439      ,0000     2,6035
      ,0000      ,0000     3,0026
      ,9439      ,0000     3,4017
     -,9439     7,5153     2,4774
      ,0000     7,5153     2,9411
      ,9439     7,5153     3,4048
END DATA.
GRAPH/SCATTERPLOT=
 Work_ove WITH     Job_Stre BY       job_tenu .

*************************************************************************
OUTCOME VARIABLE:
 Job_Sati

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5506      ,3032      ,2466   122,4797     2,0000   563,0000      ,0000

Model
```



```
**************************************************************************
OUTCOME VARIABLE:
 Job_Sati

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5506      ,3032      ,2466   122,4797     2,0000   563,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,2809      ,0917    46,6933      ,0000     4,1008     4,4609
Work_ove      ,0007      ,0254      ,0288      ,9771     -,0491      ,0506
Job_Stre     -,4059      ,0297   -13,6622      ,0000     -,4643     -,3475

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0007      ,0254      ,0288      ,9771     -,0491      ,0506

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Work_ove    ->    Job_Stre    ->    Job_Sati
```



```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0007      ,0254      ,0288      ,9771     -,0491      ,0506

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Work_ove    ->    Job_Stre    ->    Job_Sati

   job_tenu     Effect     BootSE   BootLLCI   BootULCI
    -7,0548     -,1456      ,0219     -,1909     -,1042
      ,0000     -,1716      ,0192     -,2111     -,1357
     7,5153     -,1994      ,0242     -,2489     -,1545

      Index of moderated mediation:
              Index     BootSE   BootLLCI   BootULCI
job_tenu     -,0037      ,0018     -,0072     -,0003
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000
```

Relevant references

- James, L.R.; Mulaik, S. A. & Brett, J.M. (2006) A tale of two methods. Organizational Research Methods, 9, 233-244.
- LeBreton, J.M., Wu, J., & Bing, M.N. (2009). The truth(s) on testing for mediation in the social and organizational sciences. In C.E. Lance & R.J. Vandenberg (Eds.), Statistical and methodological myths and urban legends (pp. 109-144). New York: Routledge.
- MacKinnon, D.P., Lockwood, C.M., Hoffman, J.M., West, S.G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. Psychological Methods, 7, 83-104.
- Zhao, X., Lynch, J. G. Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. Journal of Consumer Research, 37, 197- 206.