A Monte Carlo Program for Multiple Linear Regression

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The primary purpose of this presentation is to demonstrate a new computer program that statistics instructors can use to help teach certain regression topics in their courses. In particular, a computer program was written in Borland Delphi 2007 and will run under most recent versions of the Microsoft Windows operating system, including XP and Vista. The program may be downloaded free of charge.

The MCMR: Monte Carlo for Multiple Regression program performs Monte Carlo simulations of ordinary least squares multiple linear regression with up to 6 predictors. The program runs single sample analyses in addition to Monte Carlo simulations. For single samples, data can be saved and imported in comma-delimited text format. For Monte Carlo analyses, sampling distribution data can be saved for several regression statistics for further analyses elsewhere. The on-screen results from any analysis can be saved to a file and printed. The summary results provided from the Monte Carlo simulations include R-squared statistics, shrinkage statistics, regression coefficients, standard errors, and other relevant statistical results. Suggestions for use will be provided to help users understand how the program can be used effectively in intermediate statistics courses.

MCMR: Monte Carlo for Mulitple Regression (version	2008j)			
File Reset (F4) Run Analysis (F9) Options Help				This is the Opening Screen
Population ParametersActual	Monte Carlo Parameters			that appears when the program
# of <u>M_SD_M_SD</u>	Sample Size: 32	Get N from PEAR Method		that appears when the program
C 1 V1:00 10	Alpha (2-tailed):0.05	Set alpha=0.01 Set a=0.05	Set a=0.10	is started (or after the "Reset
	Monte Carlo Simulations: 10000	Set to 1 simulation Set 1000	Set 10000	(F4)" menu option is chosen).
• 3 X3 [•] 0.0 1.0	The pseudorandom generator needs an IN	TEGER value to get started:		
04	Random Generator Seed:	Set a Random Seed		
05	Automatically set new set	ed for successive simulations		
06	Regression Coefficient Information			
Population Correlations (Rho)	<u>B SEB Beta t</u>	<u>Sig Zero- Part</u>	VIE	
Get Matrix for a given R ²	B0			
X1 X1 Blank all correlations	X1			
X2 X2 Set all Blank to 0	x2			
X3	X3			
			_	
	# (-then SIC models		
	# samples w/at least 1 significant X:	alter SIG mouel.		
Model Summary Information				
<u>R</u> <u>R</u> ² <u>Adjusted R</u> ² <u>Std. Er</u> (Ra ²) the Fet	<u>ror of Source of Sum of dt</u> imate Variation Squares	<u>Mean</u> <u>F</u> Souare	SIG	
	Besidual			
<u>Cross-validity R² (Rc²)</u> Precision Efficacy (R		Expected R	² if Null true	
MCMR		√ F	Run (F9)	

The MCMR Program is available at: http://oak.cats.ohiou.edu/~brooksg/software.htm

3 sections require user input

This is where we describe the population from which samples will be drawn in the Monte Carlo process. That is, the Monte Carlo process randomly generates samples of data that could come from the particular population described (using means, standard deviations, and correlations).

Click "Run" (bottom right) or press F9 to begin the Monte Carlo analysis.



Set sample size, alpha, number of simulations, and maybe a seed for the random number generator (if you use the same seed, you get the same results).

0.510	10 E E E	00		
# of	<u>_M</u>		<u>M</u>	<u>_SD</u>
Predictors:	Y: 0.0	1.0		
O 1	X1: 0.0	1.0		
O 2	X2: 0.0	1.0		
3	X3: 0.0	1.0		
O 4				
05				
O 6				

Choose the number of predictors and Set the population means and standard deviations (Y is the dependent variable, X1 is predictor 1, etc.)

	Ge	Get Matrix for a given R ²					
<u>_X1</u>		Blar	nk all correlations				
	<u>X2</u>		Set all Blank to 0				
	<u></u>		<u>Cet Mat</u> <u>Blar</u> <u>X2</u>				

Set the population correlations (rho). You can get a random matrix that meets certain criteria (described later). Some matrices will not work as proper CORRELATION MATRICES. If one is entered, and error message will pop up, saying that the matrix is not Positive Definite (see Get Matrix section below).

After an analysis

MCMR: Monte Carlo for Mulitple Regression (version 2008j)													19			• X
File Reset (F4) R	lun Ana	lysis (F9)	Options	6 Help											
Populatio	n Pai	ramete	ers	Ac	tual	Mor	Monte Carlo Parameters									
# of Predictors:	Y.	<u>M</u>	<u>SD</u>	<u>M</u> 0.000	<u>_SD</u> 0.994		:	Sample S	ize: <mark>37</mark>		Ge	et N from P	EAR Me	thod		
0.1	¥1.	0.0	10	0.004	0.994		Alp	ha (2-tail	ed): <mark>0.05</mark>		Se	et alpha=0.	.01 S	et a=0.0)5 S	et a=0.10
02	X2:	0.0	1.0	0.001	0.995	Mo	nte Carlo	Simulatio	ons: 10000	1	Set	to 1 simula	ation	Set 1000) S	Set 10000
03	X3:	0.0	1.0	0.000	0.994	The	pseudoran	dom gene	erator needs	s an IN	TEG	ER value to	o get star	ted:		
0.4	X4:	0.0	1.0	0.001	0.995	Ra	ndom Gen	erator Se	ed: 1932		Set	: a Randon	n Seed			
€ 5	X5:	0.0	1.0	0.000	0.992		Γ	Automa	tically set	new s	eed f	or succes	sive sim	ulations	5	
0 6						Reg	ression	Coefficio	ent Inform	ation	ı (Av	erages a	nd Cour	its)		
Populatio	n Co	rrelati	ons (R	ho) —			<u> </u>	<u>SEB</u>	<u>Beta</u>	Reje	ected	Pro-	Zero-	Pa	irt	VIE
DV		G	et Matr	ix for a q	iven R²	В0	-0.0008	0.1760	-	492		0.0492	uruer	<u>u</u>	<u>nr</u>	
X10.0	<u></u> X1	. —	Blan	k all corre	elations	X1	0.0002	0.1797	-0.0001	494		0.0494	-0.000	8 0.00	00	1.1334
X20.0	0.0	_ <u>X2</u>		Set all BI	ank to 0	x2	0.0005	0.1794	0.0005	500	_	0.0500	0.0017	0.00	06	1.1323
X30.0	0.0	0.0	_X3	<u>i</u>		X3	-0.0005	0.1798	-0.0008	524		0.0524	-0.001	3 -0.0	007	1.1350
X40.0	0.0	0.0	0.0	X4		XA	0.000	0 1795	0.0008	490		0.0490	0.0006	0.00	07	1 1345
X50.0	0.0	0.0	0.0	0.0	-	X5	0.0029	0 1801	0.0030	542		0.0542	0.0020		27	1 1339
1 1		1		,		7.0	0.0020	0.1001	10.0000	072		0.0042	0.0020	10.00	~ *	1.1005
Charles Aast		14		ha? - 0	000					× [6 010		-	
Snow Act	uarci	orrelati	ions r	nu v.	000	# sa	mples w/a	at least 1	significant	X: 2	2154	(0.215) a	fter SIG	model	508	(0.051)
Model Su	mma	ry Info	rmatio	n (Avera	ages and	Coun	its)	roo of	Cum of		¢	Maan	Daia	otiono	De	
<u>_R</u>		<u> </u>	_ <u>A</u>	<u>djusted F</u> (Ra²)	the Est	<u>ror of</u> timate	Va	riation	<u>Squares</u>			<u>Mean</u> Square	neje	cuons	Sig	uportion Inificant
0.3564	0.	1385	0.	0365	0.993	1	Regr	ession 5	.01	5		1.001	<mark>524</mark>		0.0	<mark>524</mark>
Cross-vali	dity R	² (Rc ²)	Pr	ecision F	fficacy (R	c^{2}/R^{2}	Re	sidual 3	1.06	31		1.002		vneete	4 D2 :	f Null true
0.0044			0.	0120		_ /	Г	OTAL 3	6.07	36			Ī	/(n-1)	= 0 .	1389
MC -													1	,		
MR						Fini	shed 1	0000							/ Ru	ın (F9)

4 boxes contain results after an analysis, but not all are immediately obvious. Each section is described in greater detail below. This analysis was done with a seed of 1932. All population correlations were 0.0.

Predic Predic C C C C C C C C C C C C C C C C C C C	Iation Paof ctors:Y:1X12X23X34X45X56erage AC d in aqua	<u>M</u> 0.0 0.0 0.0 0.0 0.0 0.0	SD 1.0	<u>M</u> 0.000 0.004 0.001 0.000 0.001 0.000	SD 0.994 0.995 0.995 0.995 0.992	ations are I	AVERAGE Sar DV (1-0.001 X1 (20.002 0.001 (3-0.001 -0.001 (40.001 0.002 (50.002 0.002 (50.002 (50.002 0.002 (50.002 0.002 (50.002 (50.002 (50.002	X2 0.000 X3 0.000 -0.002 -0.001 0.002 rrelations rho Show Actual C ACTUAL con rrelations" to	$\frac{X4}{0.004}$ $b^2 = 0.000$ Correlations" brrelations. (Yo run another c	putton, you can u must hit unalysis)	
- <u>Reg</u> B0	<u>ressio</u> 	<u>on C</u> - 08	<u>SEB</u>	ient lı E	nforma <u>Seta</u>	ation (Av Rejected <mark>492</mark>	erages al Pro- portion 0.0492	nd Counts Zero- order	<u>s)</u> Part Corr	<u>VIF</u>	
X1	0.000	2	0.1797	7 -0.	0001	494	0.0494	-0.0008	0.0000	1.1334	
x 2	0.000	5	0.1794	1 0.0	0005	500	0.0500	0.0017	0.0006	1.1323	
хз	-0.00	05	0.1798	3 -0.	8000	524	0.0524	-0.0013	-0.0007	1.1350	
X4	0.000	9	0.1795	5 0.0	8000	490	0.0490	0.0006	0.0007	1.1345	
X5	0.002	9	0.180 1	I 0.0	030	542	0.0542	0.0020	0.0027	1.1339	
#sa	X5 0.0029 0.1801 0.0030 542 0.0542 0.0020 0.0027 1.1339 # samples w/at least 1 significant X: 2154 (0.215) after SIG model 508 (0.051)										

The average ACTUAL regression coefficient information is reported in this box — except for the "Rejected" and "Proportion" columns, which report the number (and proportion) of samples in which the particular regression coefficient (represented by X1, X2, etc.) was statistically significant.

"# samples w/at least 1 significant X" reports how many samples had at least one significant predictor.

"after SIG model" reports how many samples had at least one significant predictor following a significant overall regression model (the idea being that we don't usually examine the statistical significance of regression coefficients unless the model was first significant—but that doesn't mean that some predictors weren't significant anyway).

B0 represents the CONSTANT in the regression equation. By default, B0 is not included in the 2 counts (above), but there is a menu option that will allow it to be included.

Model Summary Informa	tion (Averag	es and Count Std. Error of	ts) Source of	Sum of	df	Mean	Rejectio	ns Proportion
	<u>(Ra²)</u>	the Estimate	Variation	<u>Squares</u>		<u>Square</u>		Significant
0.3564 0.1385	0.0365	0.9931	Regression	5.01	5	1.001	<mark>524</mark>	0.0524
Cross-validity R ² (Rc ²)	Precision Eff	icacy (Rc²/R²)	Residual	31.06	31	1.002	Experi	cted R ² if Null true
0.0044	0.0120		TOTAL	36.07	36	4,00	<mark>k/(n-</mark>	1) = 0.1389
Model summary informa "Proportion Significant" significant overall regres	ation is provi columns, w ssion models	ided here. Ag hich report h	ain, these are ow many (and	AVERAGE the propor	E results tion of)	except for samples that	the "Reject at had stati	ctions" and istically
0	12%		100000	🗙 Stop Ru	inning			√ Run (F9)
While the Monte Carlo s Carlo analyses if you ne	simulations a ed to by clicl	re running, the store the the the the the the the the the th	he bottom pan p Running" bu	el (progres itton.	s bar) loo	oks like this	s. You car	n stop the Monte
		Finished	10000					✓ Run (F9)
After the analysis is fini Running" button, the nu	shed, the bot	tom panel wi y finished wi	Il look like thi Il appear in the	s. If you ha e panel.	ave abort	ted the proc	ess by pre	essing the "Stop
		Finished	10000			Click "Show RUN another	Pop. Correl analysis	ations" button to
If you review the ACTU continue with additional the same button as the "	AL correlati Monte Carlo Show Actual	ons by clicki o analyses un Correlations	ng on the "Sho til you press the s" button.	ow Actual he "Show I	Correlati Pop. Cor	ions" buttor relations" b	n, you will outton (wh	l not be able to ich is actually
		Finished	1			Back L	Jp	✓ Run (F9)
Although not done in th going backwards by one a sample with interesting	s example, v sample. Oft g results. Thi	vhen you run en, you get to s "Back Up"	multiple SIN clicking the ' button will al	GLE SAM 'Run'' butt low you to	PLE ana on too qu go back	lyses, you v uickly and y 1 sample (l	will have t you aren't but only 1	he option of able to stop on).
ACTUAL Single Samp	le Correlati	ons						
LV X1 -0.267 _X1_ X2 0.050 0.147 _X2_ X3 -0.093 0.35 * -0.41* X4 -0.31 * -0.197 -0.050 X5 -0.145 -0.004 0.024	<mark></mark> 0.011 0.055 0.24	16	Another d statistically asterisks w	ifference significa hen you cl	for SIN nt pairw ick "Sho	IGLE SAN vise correla w Actual C	MPLE an ations are correlation	alyses is that e marked with s."
Show Pop. Correlation	s *p<.05, '	**p<.01						

	<u>_B_</u>	<u>SEB</u>	<u>Beta</u>	t	Sig	<u>Zero-</u> order	<u>Part</u> <u>Corr</u>	VIF
B0	0.0300	0.1699		<mark>0.1766</mark>	0.8610			
K1	-0.3296	0.1523	-0.3974	-2.1649	0.0382	-0.2665	-0.3422	1.3480
K2	0.1560	0.2108	0.1366	0.7400	0.4649	0.0499	0.1170	1.3634
(3	0.1075	0.1918	0.1097	0.5607	0.5790	-0.0928	0.0886	1.5318
(4	-0.3338	0.1524	-0.3659	<mark>-2.1908</mark>	0.0361	-0.3094	-0.3463	1.1159
(5	-0.0686	0.1708	-0.0658	-0.4017	0.6907	-0.1449	-0.0635	1.0721

For SINGLE SAMPLE analyses, the "Rejected" and "Proportion" columns change to the actual *t* statistics and *p* values ("Sig") for each regression coefficient.

By the way, "B" is the unstandardized regression coefficient, "SEB" is the standard error for the unstandardized regression coefficient, "Zero-order" is the Pearson correlation between each predictor and Y, "Part Corr" is the part (or semi-partial) correlation between each predictor and Y GIVEN the other predictors in the model, and "VIF" is the variance inflation factor (1/Tolerance) used for diagnosing multicollinearity.

The "At least 1 significant predictor (X) ?" box shows whether any of the regression coefficients was statistically significant (but not which one).

Both bottom boxes turn from white to GREEN if "YES"

- <u>Model Sum</u> R	mary Inform 	ation (Single Adjusted R ²	Sample) Std. Error of	Source of	Sum of	df	Mean		_Sig_
0.4746	0.2253	(<u>Ra²)</u> 0.1003	the Estimate	<u>Variation</u> Regression	Squares 8.60	5	<u>Square</u> 1.719	1.8029	0.1414
Cross-validit	<u>y R² (Rc²)</u>	Precision Effi	cacy (Rc²/R²)	Residual TOTAL	29.57 38.16	31 36	0.954	Expected	d R ² if Null true

For SINGLE SAMPLE analyses, the "Rejections" and "Proportion Significant" columns change to the actual *F* statistic and the actual *p* value significance of the regression model ("Sig").

If the model is statistically significant, the "F" and "Sig" boxes turn from yellow to GREEN. If Adjusted R^2 or Cross-validity R^2 are negative they are set to 0.0 (theoretically, neither they nor R^2 can be negative).

By the way, the "Expected R² if Null True" box uses the calculation presented by Herzberg (1969), k/(n-1), to show the bias of the R² statistic. The "Options" menu allows you to change the information reported here to a few other things.

File F	Reset (F	4) Run A	nalysis (F9) Option	s Help				
Popu # Predi	ulation of ictors: 1	Param M Y: 0.0 X1: 0.0	eters SD 1.0 1.0	<u></u> 0.001 _0.001	tual <u>SD</u> 0.993 0.989	- <u>Monte C</u>			
File," "Optic ven action. " alysis, just 1	ons," and "H "Reset (F4) like clicking	(elp" show sub- " will return the g the "Run (F9)	menus (below), program to the "button or press	but "Reset (F4)" main opening sc sing the F9 key.	' and ''Run Analy creen and ''Run A	vsis (F9)" just perform the nalysis (F9)" will run the			
View an	d Save An	alysis							
View & View &	Save Simu Save Simu	ation Data for ation Data for	Models (a li Predictors (rea	ttle SLOW for maily SLOW for mail	aximum 10000 s aximum 10000 s	saved) imulations)			
Import Comma Delimited Data (no missing cases, no case ID, no variable names, DV is first)									
Exit						Ctrl+F4			
View and Sa save and pr View & Sav stimate) from cepts Comm	ve Analysis int the resu e Simulatic n all the Mo na-Delimite	" will show a te ts of the analys n Data for Mod onte Carlo simu d text files. Var	ext version of th is. lels" will save th lated samples (u riable names AR	e results in anoth ne Model Summa up to a maximum RE included on th	ner window (belown ary statistics (e.g. of 10,000) for an are first line of the	w), which will also allow y , R ² , Standard Error of the nalysis in any program that file.			
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you are run e current sir	ning a SINO Igle sample	GLE SAMPLE analysis is save	analysis, there is d WITHOUT v	s also an option t ariable names or	o save SINGLE S the first line.	SAMPLE data. The data from			
Import Com	ma Delimit mport data	ed Data" will al saved in approp	llow you to read riate format fro	in data that you m any other prog	have previously gram (e.g., a sprea	saved with MCMR, or will adsheet or statistics program			

K View Information	
Save Print Exit	
MCMR AnalysisInformation as it appears on Screen	
(note that the term AVERAGE has been used in this) (output even for individual single sample results)	
	-
Number of Predictors = 5 Number of Cases = 32 Alpha level = 0.05 Number of Simulations = 10000 Seed Showing Now = 1932	
Means and Standard Deviations:	
Dependent V: Pop_M=0.0 Pop_SD=1.0 Avg_M=0.001 Avg_SD=0.991 Predictor 1: Pop_M=0.0 Pop_SD=1.0 Avg_M=0.000 Avg_SD=0.993 Predictor 2: Pop_M=0.0 Pop_SD=1.0 Avg_M=0.003 Avg_SD=0.992 Predictor 3: Pop_M=0.0 Pop_SD=1.0 Avg_M=-0.001 Avg_SD=0.991	
Predictor 4: Pop_M=0.0 Pop_SD=1.0 Avg_M=0.000 Avg_SD=0.995	
Fredrecor 5. rop_m=0.0 rop_sn=1.0 Avg_m=0.001 Avg_sn=0.993	
Population Correlations:	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	
r5y=0.0 r51=0.0 r52=0.0 r53=0.0 r54=0.0	-

All "View and Save" options will open this window. From here, you can "Save" or "Print" the information in the window (using the appropriate menu option).

12	ALL OPTIONS START WITH NEXT ANALYSIS	Currently, only analyses with the Constant
•	CONSTANT Include Constant in Equation Do Not Include Constant	There are 4 types of information that can be reported in the box that by default is labeled
•	EXPECTED R ² info (starts with next analysis) Always use Expected R ² for true Null Hypothesis Use Expected R ² for given rho ² {rho ² +[k/(n-1)](1-rho ²)} (Herzberg, 1969) Show average shrinkage based on Adjusted R ² (R ² - Ra ²) Show average shrinkage based on Cross-Validity R ² (R ² - Rc ²)	"Expected R ² if Null true" — 2 for expected R ² and 2 for shrinkage. Precision Efficacy (Brooks, 1998) is calculated
•	PRECISION EFFICACY Calculation Use Cross-Validity R ² in Precision Efficacy Formula Use Adjusted ² in Precision Efficacy Formula	using Cross-Validity R ² by default, but could be calculated using Adjusted R ² . (see help menu for additional information about Precision Efficacy)
•	CROSS-VALIDITY R ² (Shrinkage) FORMULA TO USE: Stein (1960)-Darlington (1968) Random-model formula Lord (1950) from Uhl & Eisenberg (1970) Random-model formula Browne (1975) Random-model formula Lord (1950)-Nicholson (1960) Fixed-model formula Rozeboom (1978) Fixed-model formula Olkin-Pratt from Herzberg (1969) Adjusted R ² formula (note: Adjusted R ² is from Wherry (1931)-Ezekiel (1930)	Validity $R^2 - 6$ are available here. You can choose to have significant B0 included in the counts reported (by default it is not).
	"AT LEAST 1" COUNTS Include B0 in "At Least 1" counts	

Multiple Linear Regression Viewpoints, 2008, Vol. 34(2)

Precision Efficacy (PEAR) Information

Show Population Regression Equation

User Agreement

About

The "Precision Efficacy (PEAR) Information" option will open a window that contains an except from a paper written in 1998 (see below).

"Show Population Regression Equation" will show the STANDARDIZED regression model based on the Population Correlation matrix used to generate data for the analysis.

"User Agreement" opens a window with LICENSE information (important).

"About" provides some basic information about the MCMR program.

Precision Efficacy Information							
EXCERPTED AND ADAPTED FROM:							
Brooks, G. P. (1998, October). Precision efficacy analysis for regression. Paper presented at the meeting of the Mid-Western Educational Research Association, Chicago, IL. (ERIC Document Reproduction Service No. ED 428 083)							
FUNDAMENTALS OF PRECISION EFFICACY ANALYSIS FOR REGRESSION (PEAR)							
The primary goal of precision efficacy analysis is to reduce the upward bias of R ² , thereby better estimating both RHO ² and RHOc ² so that results are less likely to be sample specific. The PEAR method provides researchers with a means to determine the optimum minimum sample size for prediction studies. Provided that the researcher can make a reasonable estimate of the population RHO ² , the PEAR method has been shown to provide very consistent precision efficacy rates.							
PRECISION EFFICACY							
The term precision efficacy (PE) is proposed to indicate how well a regression model is expected to perform when applied to future subjects relative to its effectiveness in the derivation sample. It should be noted that Brooks and Barcikowski (1994, 1995, 1996) have used the terms "predictive power" and "precision power" for this expectation. However, it is believed that the use of the word "power" may mislead researchers into thinking that precision power is directly related to statistical power. Therefore, for the present study, the term precision efficacy will be used, recognizing that efficacy is the "the power to produce an effect" (Woolf, 1975, p.362).							
Precision efficacy provides a measure of the relative efficiency of a regression equation, but does not indicate the value of a model in any absolute sense for either prediction or explanation. The formal definition of precision efficacy is							
$PE = Rc^2 / R^2,$							
where R^2 is the sample coefficient of determination and Rc^2 is the sample cross-validity estimate. For example, if 48% cross-validity shrinkage from sample R^2 =.50 to Rc^2 =.26 occurs, the precision efficacy is PE=.26/.50=.52. Larger precision efficacy values imply that a regression model is expected to generalize better in future samples.							
Cross-validity estimates describe how well a multiple linear regression equation will generalize to other samples. Several							
Print ✓ Done							



Secondary Window: Get a Population Matrix	with certain Given Characteri	istics					
Population Correlations (Rho) If DV Get Matrix for a given R ² Wi X1 0.170 X1 Blank all correlations Cr X2 0.329 0.725 X2 Set all Blank to 0 Cr X3 0.107 0.631 0.810 X3 X3 X4 0.318 0.413 0.849 0.476	you click the "Get Matrix for a ill open — allowing you to get iteria.	a Given R2" button, the foll a correlation matrix that m	owing window eets certain				
Set R ²							
What R ² would you like for your data?	0.25 Set to .10	Set to .25 Set to .50	Set to .75				
(please note that because this will serve as a	POPULATION matrix, the sample	e data may not produce this n	natrix exactly)				
How close do you want to approximate	this R ² value? 0.01	Set to .005 Set to .01	Set to .02				
(please note that the closer you wish to appr	oximte R ² , the longer this proces	s may take 0.01 works rela	atively well)				
What VIF value do you consider proble	matic? 10	Set to 5 Set to 10	Set to 20				
(many scholars consider it problematic when	VIF is over 10, but some conside	er it troublesome even when V	/IF > 5)				
Approximately how many NEGATIVE co NONE C Some (please note that this is based on probability,	rrelations do you want in yo C About HALF C , so you may not get exactly the r	ur population matrix? Most C ALL right numberyou can always	s try again)				
How much MULTICOLLINEARITY would you like built into your population correlation matrix? Absolutely None (all correlations among predictor = 0) No worrisome Collinearity (no VIF values for any predictor above the "problematic" value set above) 1 or 2 predictor with VIF over the "problematic" value set above 2 or 3 predictors with VIF over the "problematic" value set above 4 or more predictors with VIF over the "problematic" value set above Set one predictor correlation with DV to be 0.0 (please note that some options may not work well with some numbers of predictors)							
	× Cancel	√ОК					
Each section is described more below. When (if possible) AND that correlation matrix will Correlations (rho)" section.	you click "OK" a correlation r l be transferred to the main MC	matrix will be found with th CMR program screen into th	e given criteria ne "Population				

What R ² would you like for your data? 0.25 Set to .10 Set to .25 Set to .50 Set to .75 (please note that because this will serve as a POPULATION matrix, the sample data may not produce this matrix exactly) You can choose any R ² for your POPULATION correlation matrix (so really this is a rho ² or ρ^2 value), but buttons are provided for some common values (these are based on tables from Park & Dudycha, 1974). Remember, however, that this will derive a POPULATION correlation matrix, from which samples will be drawn during the Monte Carlo process. This value says nothing specific about any of the R ² values calculated in the samples (other than they should be from the population with the derived population correlation matrix).						
How close do you want to approximate this R ² value? 0.01 Set to .005 Set to .01 Set to .02 (please note that the closer you wish to approximte R ² , the longer this process may take 0.01 works relatively well) You can choose how close you want to approximate the population R ² set in the previous box. While it is indeed possible to approximate some matrices very closely, anything smaller than 0.001 will likely take a good deal of time. The values 0.01, or even 0.005, seem to work pretty well if you really want to get exact. Remember, however, that this is how closely you approximate the desired population R ² in the POPULATION correlation matrix, and says nothing about the samples drawn during the Monte Carlo process.						
What VIF value do you consider problematic?10Set to 5Set to 10Set to 20(many scholars consider it problematic when VIF is over 10, but some consider it troublesome even when VIF > 5)You can set any value above 1.0 for the critical VIF threshold value. Most scholars choose 5.0 or 10.0, depending on how much MULTICOLLINEARITY(also called COLLINEARITY) you're willing to tolerate.Recall that VIF = 1/Tolerance, where Tolerance = $1 - R_j^2$, where R_j^2 is the squared correlation when the j^{th} predictor acts as a temporary dependent variable being predicted by all the other predictors.						
Approximately how many NEGATIVE correlations do you want in your population matrix? • NONE • Some • About HALF • Most • All (please note that this is based on probability, so you may not get exactly the right numberyou can always try again) This option will allow you to create a population correlation matrix with some (or many) negative correlations.						

\$

How much MULTICOLLINEARITY would you like built into your population correlation matrix?

- Absolutely None (all correlations among predictor = 0)
- No worrisome Collinearity (no VIF values for any predictor above the "problematic" value set above)
- 1 or 2 predictor with VIF over the "problematic" value set above
- 2 or 3 predictors with VIF over the "problematic" value set above
- 4 or more predictors with VIF over the "problematic" value set above
- Set one predictor correlation with DV to be 0.0

(please note that some options may not work well with some numbers of predictors)

- This box will allow you to request a certain level of multicollinearity in your population correlation matrix.
 - "Absolutely None" requires that all intercorrelations among predictors are 0.0, but the correlations between the predictors and Y will be set randomly to provide the R^2 given above.
- * "No Worrisome Collinearity" will produce a population correlation matrix where all predictor intercorrelations will be non-zero, but will be probably smaller than the critical VIF set above.
- * "1 or 2 predictors with VIF" will produce a population correlation matrix such that predictor intercorrelations will probably result in at least 1, but not more than 2, VIF values over the critical value
- \$ "2 or 3 predictors with VIF" will produce a population correlation matrix such that predictor intercorrelations will probably result in at least 2, but not more than 3, VIF values over the critical value
- \$ "4 or more predictors with VIF" will produce a population correlation matrix such that predictor intercorrelations will probably result in at least 4 VIF values over the critical value

Note that "probably" was included in these descriptions. There are rare occasions, given certain starting correlations used in the algorithm, where the resulting correlation matrix does not match the criteria exactly. You can either go ahead and use the derived matrix, or simply try another. Different seeds used in each run of this sub-program result in different matrices being created.



This matrix is not Positive	Definite, as correlation mat	rices are assumed to b	e. We need a goo
correlation matrix in orde	r to generate data. Please t	ry another matrix.	_
	-	•	
	[
	· · · · · · · · · · · · · · · · · · ·		

This error message will be shown whenever the "Stop" button is pushed (above), whenever the user has entered an inappropriate matrix, or on very rare occasions where rounding the derived correlations to 3 decimal places impacts the matrix enough to make it unusable.



Precision Efficacy would therefore be PE = 1 - PS, or

$\mathbf{PE} = \mathbf{R_C}^2 / \mathbf{R}^2$

Solving $PE = 1 - \epsilon/R^2$ for ϵ , and replacing R^2 with an expected, a priori Re^2 , results in the formula

$\varepsilon = R_{\rm E}^2 - (PE)(R_{\rm E}^2)$

where R_E^2 is often just set at the expected population ρ^2 . Because Precision Efficacy (PE) is usually set at .75 or .80, shrinkage would usually be $.25\rho^2$ or $.2\rho^2$, respectively. Note that shrinkage may also be set absolutely as something like $\epsilon = .05$ or $\epsilon = .10$.

Once parameters are set, "Calculate" will determine the required sample size. The recommended sample size will appear in the YELLOW box underneath the "Calculate" button.

"Close and Record N" will move this sample size to the main screen.

"Cancel" (on the menu bar) will close the dialog window without making any changes to the main screen.

The user can change the parameters of the PEAR method (Brooks, 1998). By default, this window will provide the information for the analysis in the main window, if possible. For example, once the number of predictors is determined, it will be filled in here. Note that any number of predictors can be inserted.

More information about Precision Efficacy (PE) and the Precision Efficacy Analysis for Regression (PEAR) sample size method can be found by clicking the "Click here for more information" button (see below).

Briefly, however, Precision Efficacy is a complement to Proportional Shrinkage based on an appropriate Cross-validity $R^2 (R_C^2)$ formula. Shrinkage itself (ε , or epsilon) can be written as

$$\varepsilon = \mathbf{R}^2 - \mathbf{R}_{\mathrm{C}}^{2}$$

whereas Proportional Shrinkage (PS) might be written as $PS = (R^2 - R_C^2) / R^2$

Although the PEAR method was derived using Cross-Validity R^2 (Brooks, 1998), it is theoretically reasonable to apply the same idea to Precision Efficacy calculated using Adjusted R^2 instead. Algina and Olejnik (2000) have discussed a similar idea, but different approach, to sample sizes for Adjusted R^2 .

In this case, sample sizes would be determined such that the SHRINKAGE from R^2 to Adjusted R^2 would be maintained within a certain range. For example, if R^2 is .25, then Adjusted R^2 would be at least .20 when Precision Efficacy of .80 was used as the criterion. The formula for sample sizes to be used with such an approach would be

$$N = (k+1)(1 - R_E^2 + \varepsilon) / \varepsilon$$

Where

 R_E^2 = expected population ρ^2 k = number of predictors $\varepsilon = (R^2 - R_A^2)$

as compared to

 $N = (k+1)(2-2R_E^2+\varepsilon) / \varepsilon$

where $\varepsilon = (\mathbf{R}^2 - \mathbf{R}_C^2)$

for Cross-Validity (see Brooks, 1998). Shrinkage tolerance can also be calculated as

 $\varepsilon = (1 - PE) R^2$

where, for PE = .80, it would simplify to (just like it would also for the Cross-Validity approach)

 $\varepsilon = .2R^2$

Recall that one of the options on the "Options" menu is to use Adjusted R^2 in the Precision Efficacy formula instead of Cross-Validity R^2 .

The key difference is that for Cross-validity Precision Efficacy, the idea is to INCREASE Cross-validity R^2 ; however, for Adjusted R^2 , the idea is more to DECREASE R^2 , making it closer to the true population parameter (since Adjusted R^2 is usually a good estimate of rho²).

Either method helps make the model more generalizable by decreasing the standard errors for the regression coefficients. The Corss-validity approach is more stringent because it accounts for error not only in the regression model derivation sample, but also for the error in future samples to which the regression model is applied.



	- <u>Reg</u>	ression B	<u>Coefficie</u> <u>SEB</u>	<u>nt Inform:</u> Beta	<u>ation (Av</u> Rejected	erages a Pro- portion	ind Coun Zero- order	<u>ts)</u> Part <u>Corr</u>	VIF		
	B0	-0.0011	0.1500		<mark>484</mark>	0.0484					
	X1	0.1706	0.1531	0.1692	<mark>1938</mark>	0.1938	0.1687	0.1620	1.0965		
	X2	0.3272	0.1532	0.3247	<mark>5506</mark>	0.5506	0.3231	0.3107	1.0964		
	Х3	0.1072	0.1527	0.1071	1070	0.1070	0.1075	0.1025	1.0963		
	X4	0.3160	0.1532	0.3135	5177	0.5177	0.3127	0.2998	1.0970		
# samples w/at least 1 significant X: 8297 (0.830) after SIG model 6991 (0.699) n this case, the standard errors for the regression coefficients ("SEB") are each approximately 0.153. Note that the /ariance Inflation Factors ("VIF") are all roughly 1.096—since there is no correlation among the predictors we would expect this to be near 1.0, but since each of the 10,000 samples drawn probably ad some minor correlation among the predictors, it will not be exactly 1.0.											
If we arbitraril LEAVE THE AND Y THE S Note that in th is arbitrary, bu In particular, in here), you wou the Sum of Squ things as well) different popul	y add CORI SAMI is mat t will f you ild see uares . This lation	some corr RELATIO E, we intro trix, the rh have some examine the e some min due to the s is not a R condition	NS BETW duce mult o^2 is not end e minor in the model so nor different regression EAL different s set by the	ticollinearity icollinearity xactly .250 summary re ences — esp (which im grence, but n e slightly la	edictors, E PREDICT y. any more. r results. sults (we v pecially in pacts othe rather due urger rho ² .	TORS This won't R^2 and r to the	Populat DV X10.170 X20.329 X30.107 X40.318 Show A	0.725 0.631 0 0.413 0	Get Matrix Blank a X2 Se .810 X3 .849 0.476	for a given R ² all correlations et all Blank to 0	
	- <u>F</u>	Regressio	n Coeffic	ient Inform	ation (Av	eraqes a	nd Counts	;) ——			
		<u> </u>	<u>SEB</u>	<u>Beta</u>	Rejected	Pro-	<u>Zero-</u> order	Part Corr	VIE		
	E	30 0.0004	0.1491		<mark>483</mark>	0.0483					
)	K1 -0.451	8 0.2976	0.4494	<mark>3220</mark>	0.3220	0.1687	-0.2192	4.3880		
)	(2 2.238	0.8839	2.2230	<mark>6905</mark>	0.6905	0.3242	0.3658	39.2285		
)	(3 -0.975	1 0.3966	-0.9700	6668	0.6668	0.1063	-0.3550	7.8630		
	X4 -0.9337 0.5275 -0.9274 4125 0.4125 0.3119 -0.2562 13.8991										
The most imp	tont	difference	wat least		THIS EVA		a tha "SEI	2" and "V	+ (0.004)	Note that all	
SEB values (ex	xcept	for B0) ha	ve increas	suits FOR	he multico	llinearity.	as have th	e VIF val	ues.	note that all	

Other important results, of course, include the regression coefficients ("B" and "Beta") themselves, along with the number of times they were significant. Indeed, different predictors are significant more frequently before (X2 and X4) and after (X2 and X3) due to the multicollinearity introduced into the population, even though the pairwise relationships (zero-order correlations) between the predictors and the dependent variable have not changed.

An Example: Shrinkage and Sample Size										
MCMR: Monte Carlo for Mulitple Regression (version	on 2008j)	1.1	Versee							
le Reset (F4) Run Analysis (F9) Options Help										
Population Parameters Actual	Monte Carlo Paramete	rs_								
# of <u>M_SD</u> <u>M_SD</u> Predictors: Y: 0.0 1.0 0.000 0.994	Sample Size	e: <mark>42</mark>	Get N from PEAF	R Method						
0 1 X1.0.0 1.0 0.000 0.992	Alpha (2-tailed	Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10								
C 2 X2:0.0 1.0 0.000 0.993	Monte Carlo Simulations	Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000								
C 3 X3:0.0 1.0 -0.001 0.994	The pseudorandom genera	The pseudorandom generator needs an INTEGER value to get started:								
• 4 X4:0.0 1.0 0.001 0.994	Random Generator Seed	7368179	Set a Random Se	ed						
05	🔽 Automatic	ally set new se	ed for successive	simulations						
© 6										
Conulation Correlations (Bbo)	<u>B</u> <u>SEB</u> <u>Beta</u> <u>Rejected</u> Pro- <u>Zero-</u> Part <u>VIF</u>									
	B0 -0.0005 0.1390	515	0.0515	<u>rder Corr</u>						
10.239 X1 Blank all correlations	X1 0.0960 0.1489	0.0052 002	0.0992 0.2	347 0.0873	1 2000					
20.085 0.052 X2 Set all Blank to 0	X2 0.6542 0.3571	0.6409 4321	0.4221 0.0	975 0 2490	7 1754					
30.389 0.207 0.227 X3	X2 -0.0342 0.3371		0.7400 0.0		1 0015					
	X3 0.4071 0.1505 0	0.4044 /433	0.7433 0.3		1.2310					
	X4 0.7067 0.3536 0	0.7025 <mark> 4953</mark>	0.4953 0.1	1878 0.2706	7.0478					
Show Actual Correlations rho ² = 0.257	# samples w/at least 1 sig	gnificant X: 87	'48 (0.875) after	SIG model 77	46 (0.775)					
Aodel Summary Information (Averages and	l Counts)									
<u> </u>	rror of Source of Source of Source of Source of Variation Source of Source o	<u>um of df</u> j <u>uares</u>	<u>Mean</u> <u>Square</u>	Rejections P S	roportion ignificant					
0.5579 0.3223 0.2495 0.855	4 Regression 13.	54 4	3.384 7	<mark>/997 0</mark> .	.7997					
Cross-validity B ² (Bc ²) Precision Efficacy (I	Residual 27.	44 37	0.742		9 16 M P .					
0.1564 0.3973	TOTAL 40.	97 41		$rac{Expected R}{k/(n-1)} = 0$	<u>• IT Null true</u>					
		1		14(11) 0						
CMR Finished 10000 ✓ Run (F9)										

Note that in this example, with a sample size of N = 42 (which provided statistical power for the model of approximately .80), shrinkage occurs from $R^2 = .32$ down to Adjusted $R^2 = .25$ or down to Cross-Validity $R^2 = .16$.

Recall that Adjusted R^2 represents the proportion of variance expected to be accounted for (explained) in the population if this particular regression model is used to predict scores in the population. It is generally considered a better SHRINKAGE estimate when <u>explanation</u> is the key purpose for the regression analysis.

Cross-validity R^2 represents the proportion of variance expected to be accounted for if this particular regression model is used in another sample of cases from the same population. It is generally considered a better SHRINKAGE estimate when **prediction** is the key purpose for the regression analysis.

If we use N = 60 (based on 15 cases per predictor), shrinkage is less, but perhaps still too much.	 0.5411 <u>Cross-validit</u> 0.1830	<u>R</u> 2 0.3009 y R ² (Rc ²)	Adjusted R ² (Ra ²) 0.2501 Precision Effi 0.5433	Std. Error of the Estimate 0.8578 cacy (Rc ² / R ²)
If we use, N = 70, which gives us some comfort that Precision Efficacy (using Adjusted R2) will be at least .80, shrinkage is even less.	<u>R</u> 0.5361 <u>Cross-validit</u> 0.1937	<u>R²</u> 0.2946 y R² (Rc²)	Adjusted R ² (Ra ²) 0.2512 Precision Effi 0.8273	<u>Std. Error of</u> <u>the Estimate</u> 0.8588 cacy (AdjR²/R²)
If we use $N = 150$, which gives us comfort that Precision Efficacy (using Cross-validity R2) will be at least .80, reduces shrinkage even further.	 0.5205 <u>Cross-validit</u> 0.2285	 0.2744 y R ² (Rc ²)	Adjusted R ² (Ra ²) 0.2544 Precision Effi 0.8198	Std. Error of the Estimate 0.8612 cacy (Rc²/R²)

While there is no agreed-upon criterion for SHRINKAGE, several authors have recommended CROSS-VALIDATION as more appropriate methods for determining sample sizes than using statistical power (e.g., Algina & Keselman, 2000; Brooks & Barcikowski, 1999; Park & Dudycha, 1974; Stevens, 1996).

Note that there are also other methods that exist for calculating sample sizes in regression, including statistical power for the *t* tests of the regression coefficients and size of the confidence intervals for the regression coefficients (and therefore size of the standard errors of the regression coefficients).

There are many conventional rules ("rules of thumb") that scholars have recommended over the years as well. These can all be tested and compared using the Monte Carlo method with the MCMR program.

Much more on the topic can be found in Brooks (1998).

An Example: Type I errors (and/or Statistics	al Power analyses)					
MCMR: Monte Carlo for Mulitple Regression (versio	n 2008j)		1.10				
File Reset (F4) Run Analysis (F9) Options Help							
Population Parameters	Monte Carlo Para	ameters					
# of <u>M</u> <u>SD</u> <u>M</u> <u>SD</u> Predictore: V:0.000 1.000 0.054 1.067	Samp	ole Size: <mark>37</mark>	Ge	t N from Pl	EAR Me	ethod	
1 X1:0.000 1.000 0.095 1.044	Alpha (2	-tailed): 0.05	Se	t alpha=0.0	01 S	et a=0.05	Set a=0.10
C 2 X2:0.000 1.000 0.181 0.987	Monte Carlo Simu	ulations: 1	Set	to 1 simula	tion S	Set 1000	Set 10000
© 3 X3:0.000 1.000 0.145 0.852	The pseudorandom	generator needs	an INTEG	ER value to	get star	ted:	
C 4	Random Generato	or Seed: <mark>92624</mark>	57 Set	a Random	Seed		
0.5	🗹 Aut	omatically set r	new seed f	or success	sive sim	ulations	
<u> </u>	Regression Coef	ficient Inform	<u>ation (Sir</u>	igle Samp	<u>le)</u>		Var
Population Correlations (Rho)	<u> </u>	<u>EB</u> Beta	t	Sig	<u>Zero-</u> order	<u>Part</u> Corr	
Get Matrix for a given R ²	B0 -0.0333 0.17	736	<mark>-0.1921</mark>	0.8489			
X1 0.00 X1 Blank all correlations	X1 0.0789 0.10	623 0.0772	0.4860	0.6302	0.0657	0.0771	1.0031
X2 0.00 0.00 <u>X2</u> Set all Blank to 0	X2 0.0317 0.17	729 0.0294	0.1836	0.8554	-0.016	6 0.0291	1.0172
X3 <mark>0.00</mark> 0.00 0.00	X3 0.5120 0.20	002 0.4090	2.5580	0.0153	0.4030	0.4058	1.0157
Show Actual Correlations rho² = 0.000	At least 1 significa	nt predictor (X)	? YES	af	ter SIG	model? No	,
Model Summary Information (Single Sample	e) — — — — — — — — — — — — — — — — — — —						
<u> </u>	rror of <u>Source</u> timate Variatio	of <u>Sum of</u> on <u>Squares</u>	df	<u>Mean</u> Square	_	<u>F</u>	<u>Sig</u>
0.4116 0.1694 0.0939 1.015	4 Regressio	on 6.94	3	2.313	2.243	35 0.	<mark>1016</mark>
Cross-validity R ² (Rc ²) Precision Efficacy (F	Rc ² /R ²) Residu	al 34.02	33	1.031	Б	vnected R	² if Null true
0.0000 0.0000	тоти	L 40.96	36		Ī	c/(n-1) = 0	.0833
MC.				Deel	, , , ,	1 4	
	Finished 1			Bac	к Ор	√ F	(un (F9)
Regression Coefficient Information (Single Sample)		We can run	SINGLI	E SAMPI	LE ana	lyses to s	how all the
<u>B SEB Beta</u> t Sig <u>Zerc</u> <u>orde</u>	<u>p- Part VIF</u> er <u>Corr</u>	possible con	mbinatio	ns of Typ	e I err	ors that o	ccur in
B0 -0.0333 0.1736 -0.1921 0.8489		multiple reg	gression.				
	7 0.0771 1.0031		1	whara al	l corre	lations ar	a 0 0 on a
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0217 0.1720 0.0204 0.1926 0.8554 0.01	66 0.0201 1.0172	In this first	ovomnlo	VAV I II II ZII		iations ai	<i>.</i>
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.403	66 0.0291 1.0172 0 0.4058 1.0157	In this first predictor ()	example (3) is sta	tistically	signifi	cant. but	the model
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.4033	66 0.0291 1.0172 60 0.4058 1.0157	In this first predictor (X is NOT stat	example (3) is statistically	tistically significar	signifi nt. The	cant, but refore, th	the model e count
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.403	66 0.0291 1.0172 0 0.4058 1.0157	In this first predictor (X is NOT stat boxes show	example (X3) is statistically a GREE	tistically significar	signifi nt. The for "At	cant, but refore, th least 1 si	the model e count gnificant
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.403	66 0.0291 1.0172 0 0.4058 1.0157	In this first predictor (X is NOT stat boxes show predictor (X	example (X3) is statistically (x a GREE (X)?" but a	tistically significar N YES f a white N	signifi nt. The or "At O for '	cant, but refore, th least 1 si "after SIC	the model e count gnificant 3 model?"
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.403 At least 1 significant predictor (X) ? YES after SIC	66 0.0291 1.0172 0 0.4058 1.0157 2 model? No	In this first predictor (X is NOT stat boxes show predictor (X	example (3) is sta istically a GREE ()?" but a	tistically significar N YES f a white N	signifi nt. The or "At O for '	cant, but refore, th least 1 si "after SIC	the model e count gnificant 6 model?"
X1 0.0789 0.1623 0.0772 0.4860 0.6302 0.065 X2 0.0317 0.1729 0.0294 0.1836 0.8554 -0.01 X3 0.5120 0.2002 0.4090 2.5580 0.0153 0.403 At least 1 significant predictor (X) ? YES after SIC J	66 0.0291 1.0172 60 0.4058 1.0157 6 model? No FSig_	In this first predictor (2 is NOT stat boxes show predictor (2	example (3) is sta istically a GREE ()?" but a	tistically significar N YES f a white N	signifi nt. The or "At O for '	cant, but refore, th least 1 si "after SIC	the model e count gnificant 5 model?"

33

36

1.031

Expected R² if Null true k/(n-1) = 0.0833

Residual 34.02

TOTAL 40.96

c²/R²)

Dog	roccion	Cooffic	iont Inform	ation (Si	ala Sami	da)							
កខម្ម	B	<u>SEB</u>	<u>Beta</u>	t	Sig	<u>Zero-</u> <u>order</u>	<u>Part</u> <u>Corr</u>	VIE					
B0	-0.0766	0.2134	l I	<mark>-0.3589</mark>	<mark>0.7219</mark>								
X1	0.0122	0.2299	0.0089	0.0530	0.9581	0.0236	8800.0	1.0212					
X2	-0.2341	0.1992	-0.2031	-1.1751	0.2484	-0.1393	-0.1953	1.0810					
Х3	-0.4642	0.2941	-0.2703	-1.5781	0.1241	-0.2209	-0.2623	1.0620					
At le	east 1 sigr	nificant p	oredictor (X	At least 1 significant predictor (X) ? No after SIG model? No									
_													
<u>or of</u> nate	<u>Sou</u> Va	irce of riation	<u>Sum of</u> Squares	df	<u>Mean</u> Square	Ē		_Sig_					
or of nate	<u>Sou</u> Va Regre	i <u>rce of</u> riation ession	Sum of Squares 4.57		Mean Square 1.524	F	0.3	_ <u>Sig_</u> 775					
or of nate 2 / R ²	<u>Sou</u> Va Regro	urce of riation ession sidual	Sum of Squares 4.57 47.24	df 3 33	<u>Mean</u> <u>Square</u> 1.524 1.432	F 	0.3	_Sig_ 775					

In this second example where all correlations are 0.0, nothing was statistically significant. This is what we would expect most frequently when the Null Hypothesis is true.

Reg	ression	Coeffic	ient Inform	nation (Si	ngle Samp	le)		
-	<u>_B</u>	SEB	<u>Beta</u>	t	Sig	Zero-	Part P	VIE
						order	<u>Corr</u>	
BO	0.1836	0.1607	7	1.1425	0.2615			
X1	-0.1045	0.143	7 -0.1131	- <mark>0.7278</mark>	0.4719	-0.1698	-0.1110	1.0375
X2	-0.4200	0.1456	6 -0.4452	<mark>-2.8841</mark>	0.0069	-0.4331	-0.4400	1.0235
X3	-0.1483	0.1449	9 -0.1598	-1.0229	0.3138	-0.1242	-0.1561	1.0486
At le	east 1 sigr	nificant	predictor (X)? <mark>YES</mark>	af	ter SIG m	odel? <mark>YE</mark> S	3
) rer of	Sou	irce of	Sum of	df	Mean			Sia
imate	Va	riation	<u>Squares</u>		Square			
ł.	Regr	ession	7.77	3	2.591	3.3201	0.0	316
c²/R ²) Re	sidual	25.75	33	0.780	Ex	pected R ²	if Null true
	T	OTAL	33.53	36		k/((n-1) = 0.	0833

In this third example where all correlations are 0.0, the overall regression model was statistically significant and at least one (here, exactly one, X2) predictor was statistically significant.

Note that different predictors are usually significant in different samples for Robustness (Type I error rate) analyses.

- <u>Regr</u>	ession (B	<u>Coefficie</u>	nt Inform Beta	ation (Si t	ngle Sam Sig	<u>ple)</u> Zero-	Part	VI	E.	NO with	TE: This s	creen comes from an analysis correlations, and therefore not a
BU [0 0263	0 1631		-0 1610	0.8730	<u>order</u>	<u>Corr</u>			Тур	e I error ra	ate analysis.
X1 0	1.2982	0.2164	0.2960	1.3777	0.1776	0.3670	0.2092	2.00	26	.		
x2 0	.6706	0.3353	0.6802	1.9997	0.0538	0.3328	0.3036	5.02	03	In t	his fourth e	example, the overall regression
X3 -	0.6156	0.3052	-0.6354	-2.0174	0.0518	0.1506	-0.306	3 4.30	40	oft	he predicto	rs was statistically significant
		J	1	1			1		<u></u> ,	Wh	ile this app	ears to be very rare when all
										cor	relations ar	e 0.0 (a Type I error rate
										ana	lysis), it oc	curs occasionally when the null
At lea	st 1 sigr	ificant pre	edictor (X)	? No	a	fter SIG m	odel? N	o	_	hyp	othesis is r	not true.
	j.											
ror of	Sou	rce of	Sum of	df	Mean	F		Sig	_			
<u>imate</u>	imate Variation Squares Square											
	Regro	ssion 9.	22	3	3.074	3.4615	U	0.0272				
<u>c² / R²)</u>	Re T	sidual 29	9.30	33	0.888	Exp	ected F	R ² if Null	true			
			5.53	30		k/(n-1) = I	0.0833				
Finis	hed 1				Bac	:k Up	 Image: A second s	Run (F	9)			
Rea	Regression Coefficient Information (Averages and Counts) Finally, after running through											
1109	B	S	EB	<u>Beta</u>	Rejected	Pro-	Z	ero-	- <u>Pa</u>	art	VIE	several samples to show
						portio	n <u>o</u>	<u>rder</u>	Co	orr		students what a Type I error
B0	-0.001	12 0.17	/05		485	0.0485	5					analysis is like, we can tell
X1	0.000	5 0.17	47 0.	0001	524	0.0524	-0.	0002	0.00	000	1.0627	them that instead of us going
X2	-0.003	8 0.17	39 -0	0032	549	0.0549	0-0	0031	-0.0	032	1.0617	single samples and keeping
Va	0.000	0.17	29 0	0007	492	0.0499		0009	0.0	002	1.0626	track, we can just have the
~3	-0.000	0 0.11	30 -U	.0007	400	0.040) -0.	0000	-0.0	000	1.0020	computer do it for us and run
												10,000 samples all at once.
												This screen shows the Monte
												Carlo results for 10 000
#sa	mples	w/at lea	st 1 sigr	ificant >	(: 1432	(0.143)	after	SIG m	odel	494	(0.049)	simulated samples. One can
Coun	ts)											05 Type I error rate expected
ror of	5	ource	of <u>Su</u>	<u>n of</u>	df	Mea	n E	Reject	ions	Pr	oportion	for all tests.
<u>imate</u>		Variatio	in <u>Squ</u>	<u>ares</u>		<u>Squa</u>	<u>re</u>			<u>Si</u>	<u>gnificant</u>	
	Re	gressio	n 3.01	:	3	1.004	5	18		0.0	<mark>518</mark>	
c ² /R ²	2)	Residu	al 33.0	5	33	1.001		Eve	ecte	d R2	if Null true	We can also discuss the idea
		TOTA	L 36.0	6	36			k/(n-1)	= 0	0833	of a "Protected F" test by
			1			4		141				reviewing the count boxes.
Here,	the pro	portion	of simu	lated sa	mples tha	at had at	least c	one stat	istica	ally s	ignificant p	predictor FOLLOWING a
statist	ically s	ignifica	nt overa	Il regres	ssion mo	del is ab	out .04	19 (5%). Ho	weve	er, the prop	ortion of samples that had any
numb	er of pi	edictors	s that we	ere statis	sucally si	gnifican	i was a	idout.	14 (1	4%).		

An Example: Suppressor Variables													
MCMR: Mo	onte Carlo fo	r Mulitple	e Regressi	ion (versio	n 2008	j)					11		
File Reset (F4	4) Run Anal	ysis (F9)	Options	Help									
Population	Paramete	ers	Act	tual	Mo	nte Carlo	Parame	ters					
# of	M	<u>SD</u>	<u>M</u>	<u>SD</u>		\$	Sample S	ize: <mark>32</mark>		Get N from F	PEAR I	Viethod	
Predictors:	Y: 0.0	1.0	-0.007	0.989		Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.1					Set a=0.10		
01	X1: 0.0	1.0	-0.005	0.996						Set 10000			
0 2	X2: 0.0	1.0	-0.004	0.992	Monte Carlo Simulations: 1000 Set to 1 simulation Set 1000 Set 10000				Set 10000				
03	X3: 0.0	1.0	-0.005	0.989	The pseudorandom generator needs an INTEGER value to get started:								
04	X4: 0.0	1.0	-0.003	0.995	Ra	ndom Gen	erator Se	ea: 53675	09 (Set a Randon	n Seec	1	
© 5	X5: 0.0	1.0	-0.005	0.991		~	Automa	tically set	new see	d for succes	sive si	imulations	
0 6	C 6 Regression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro- Zero- Part VIE												
Population	Correlation	ons (Rh	<u>lo)</u>			_ <u>D</u>	<u>SED</u>	Deta	Reject	portion	ord	<u>u- Part</u> er Corr	
DV	G	et Matri:	x for a gi	ven R²	B0	-0.0096	0.1624	_	<mark>58</mark>	0.0580			8
X10.365	<u></u>	Blank	all corre	elations	X 1	0.3932	0.2108	0.3888	456	0.4560	0.36	31 0.2859	1.9281
X20.063 0	.409 🔀	S	et all Bla	ank to 0	x2	-0.3904	0.4545	-0.3890	124	0.1240	0.06	33 -0.131	8 9.2201
X30.177 0	.566 0.88	0 <u>X3</u>	-		X3	0.6683	0 6844	0.6646	141	0 1410	0.17	56 0 1496	20.8620
X40.2850	.132 0.15	1 0.366	5 X4		VA	0.1505	0.2151	0.1406	06	0.0060	0.29	27 0 1070	2 0072
X50.000 0	502 0 59	5 0.800	0 188		A4	0.1303	0.2151	0.1490	30	0.0300	0.20		
10000 0		0 0.000	, 0.100		Х5	-0.5254	0.3263	-0.5237	363	0.3630	0.00	27 -0.246	6 4.6957
Show Actu	al Correlati	ons rh	10 ² = 0.2	279	#sa	amples w/a	at least 1	significant	X: 700	(0.700) a	fter SI	G model 5	78 (0.578)
Model Sur	nmary Info	rmatior	(Avera	iges and	Cour	nts)							
<u>_R</u>	R ²	Ad	justed R	12 Std. E	rror of	Sou	rce of	Sum of	df	<u>Mean</u>	Re	jections	Proportion
			<u>(Ra²)</u>	the Est	timate		riation 3	<u>Squares</u>		<u>Square</u>	<u> </u>		<u>Significant</u>
0.6108	0.3849	0.2	2691	0.8389	9	Regre	ession 1	2.22	5	2.444	661	B O	.6680
Cross-validi	ity R ² (Rc ²)	Pre	cision E	fficacy (R	c ² /R	2) Re	sidual 1	8.67	26	0.718		Expected F	3 ² if Null true
0.1312		0.2	659			Т	OTAL 3	0.89	31			k/(n-1) =	0.1613
MC _{MR}					Fini	shed 1	000					~	Run (F9)

If we arbitrarily set a population correlation matrix in which one predictor has zero (0.0) correlation with the dependent variable (DV) but has non-zero correlation with the other predictors, we can examine suppressor relationships.

Population Co	rrelatio	ons (Rho)	You can see a little better the correlations here.
DV	Ge	et Matrix for a given R ²	Note the nonulation multiple rhc^2 for this correlation matrix is
X1 0.365 <u>X1</u>	-	Blank all correlations	.279
X2 0.063 0.409	<u>X2</u>	Set all Blank to 0	
X30.177 0.560	6 0.880	D <u>X3</u>	
X40.285 0.13	0.151	1 0.366 <u>X4</u>	
X5 0.000 0.502	0.595	5 0.800 0.188	
Show Actual C	orrelatic	ons rho ² = 0.279	

-Model Sum	mary Inform	ation (Averag	es and Counts	5)					
<u>_R</u> _	<u></u> <u>R</u> ²	Adjusted R ² (Ra ²)	<u>Std. Error of</u> <u>the Estimate</u>	<u>Source of</u> <u>Variation</u>	<u>Sum of</u> Squares	<u>df</u>	<u>Mean</u> Square	<u>Rejections</u>	Proportion Significant
0.6108	0.3849	0.2691	0.8389	Regression	12.22	5	2.444	<mark>668</mark>	0.6680
Cross-validi	ty R ² (Rc ²)	Precision Effi	cacy (Rc ² /R ²)	Residual	18.67	26	0.718	Expected	R ² if Null true
0.1312		0.2659		TOTAL	30.89	31		k/(n-1)	= 0.1613
			15			23	τ.		

We have an R2 value of .38 for this analysis.

	<u> </u>	<u>SEB</u>	<u>Beta</u>	Rejected	Pro- portion	<u>Zero-</u> order	<u>Part</u> <u>Corr</u>	VIF
B0	-0.0096	0.1624		<mark>58</mark>	0.0580			
X1	0.3932	0.2108	0.3888	456	0.4560	0.3631	0.2859	1.9281
x 2	-0.3904	0.4545	-0.3890	124	0.1240	0.0633	-0.1318	9.2201
хз	0.6683	0.6844	0.6646	141	0.1410	0.1756	0.1496	20.8620
X4	0.1505	0.2151	0.1496	96	0.0960	0.2827	0.1079	2.0072
X5	-0.5254	0.3263	-0.5237	363	0.3630	0.0027	-0.2466	4.6957

Note the VIF is high for X3, not the variable with 0.0 correlation with the dependent variable (which is X5). However, there is a strong correlation between X3 and X5.

Population Correl	lations (Rho)	If we remove X5 from the analysis in an effort to remove the
	Get Matrix for a given R ²	multicollinearity (because among the predictors, it has very little correlation with Y) we would have this correlation
X1 0.365 <u>X1</u>	Blank all correlations	matrix.
X20.063 0.409	X2 Set all Blank to 0	Note that rho ² is lower without X5 EVEN THOUGH it had no
X30.177 0.566 0	.917 <u>X3</u>	correlation with the Dependent Variable !!
X4 0.285 0.132 0	0.151 0.366	
Show Actual Corre	elations rho ² = 0.207	

	_ <u>B_</u>	<u>SEB</u>	<u>Beta</u>	Rejected	Pro- portion	<u>Zero-</u> order	Part Corr	VIF
B0	0.0009	0.1680		<mark>482</mark>	0.0482			
X1	0.4181	0.2190	0.4116	4625	0.4625	0.3588	0.3068	1.8586
X2	-0.0250	0.4111	-0.0244	<mark>525</mark>	0.0525	0.0637	-0.0099	6.7221
Х3	-0.1438	0.4838	-0.1409	605	0.0605	0.1751	-0.0475	9.3599
	0.0000	0.0051	0.2838	2760	0.2760	0.2829	0.2258	1.6217
Х4	0.2882	0.2051	0.2000			1	,	1
X4 # sa	amples w/a	at least 1 s	ignificant	X: 6035 (evidenced by	0.604) व all VIF < 10	after SIG n).	nodel 449	3 (0.449)
X4 # sa Note th	u.2882 amples w/a nat multicollin	at least 1 s earity has bee	n removed (as	X: 6035 (evidenced by	0.604) all VIF < 10	after SIG n).	nodel 449	3 (0.449)
X4 # sa Note th <u>Model</u>	amples w/a nat multicollin Summary Info	at least 1 s earity has bee <u>rmation (Aver</u> _ <u>Adjusted F</u> (<u>Ra²)</u>	n removed (as significant 2 n removed (as significant 2 n removed (as significant 2 n removed (as	X: 6035 (evidenced by ts) Source o Variation	0.604) द all VIF < 10 f <u>Sum of</u> squares	after SIG n). df <u>Me</u>	nodel 449 an <u>Rejection</u>	3 (0.449)
X4 # sa Note th R 0.5353	amples w/a nat multicollin <u>Summary Info</u> <u>R</u> 3 0.3011	t least 1 s earity has bee <u>rmation (Aver</u> <u>Adjusted F (Ra²)</u> 0.2012	ignificant n removed (as ages and Cour 2 ² Std. Error of the Estimate 0.8857	X: 6035 (evidenced by tts) Source o Variation Regression	0.604) a all VIF < 10 <u>f Sum of</u> Squares 9.70 4	after SIG n). Me Squ 42.425	nodel 449 an Rejection are 5225	3 (0.449) Significant 0.5225

.30 now).

An Example: Impact of Means and S	andard Deviations on Regression Results	
MCMR: Monte Carlo for Mulitple Regression (version	1 2008i)	
File Reset (F4) Run Analysis (F9) Options Help	y,	
Population Parameters <u>Actual</u>	Monte Carlo Parameters	
# of <u>M_SD_M_SD</u> Predictors: V:0 1 0.000 0.994	Sample Size: 37 Get N from PEAR Metho	od 🛛
0 1 X1:0 1 0.002 0.991	Alpha (2-tailed): 0.05 Set alpha=0.01 Set a	1=0.05 Set a=0.10
C 2 X2:0 1 0.001 0.993	Monte Carlo Simulations: 10000 Set to 1 simulation Set	1000 Set 10000
• 3 X3:0 1 0.001 0.996	The pseudorandom generator needs an INTEGER value to get started	;
04	Random Generator Seed: 1932 Set a Random Seed	
05	Automatically set new seed for successive simula	tions
<u> </u>	Regression Coefficient Information (Averages and Counts)	Part VIE
Population Correlations (Rho)	portion order	Corr
Get Matrix for a given R ²	B0 -0.0019 0.1470 494 0.0494	
X10.315 XI Blank all correlations	X1 0.4448 0.1892 0.4396 6276 0.6276 0.3117	0.3395 1.7156
X20.131 0.397 XZ Set all Blank to 0	X2 -0.3041 0.2039 -0.3013 3123 0.3123 0.1270	-0.2155 2.0076
X3 0.366 0.125 0.393	X3 0.4270 0.1648 0.4240 7090 0.7090 0.3592	0.3742 1.2993
Show Actual Correlations rho ² = 0.257	# samples w/at least 1 significant X: 8730 (0.873) after SIG mo	del 7705 (0.771)
-Model Summary Information (Averages and	<u>Counts)</u>	and Branartian
<u> </u>	imate Variation Squares Square	Significant
0.5444 0.3095 0.2473 0.8563	Regression 11.50 3 3.834 7890	0.7890
Cross-validity R ² (Rc ²) Precision Efficacy (R	(² /R ²) Residual 24.56 33 0.744	acted P ² if Null true
0.1640 0.4311	TOTAL 36.06 36 k/(r	n-1) = 0.0833
MC		
MR	Finished 10000	✓ Run (F9)
MCMP: Monto Carlo for Mulitola Pagrarsian (varsion 2009)		The important thing to notice as
File Reset (F4) Run Analysis (F9) Options Help		we change from all standardized
Population ParametersActual Monte t	Carlo Parameters	data (above) to a Dependent
# of	Sample Size: 37 Get N from PEAR Method	Variable Mean of 50 (while
C 1 X1:0 1 0.002 0.991	Alpha (2-tailed):0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Code Simulations 10000 Code Simulations 10000 Code Simulations 10000 Code Simulations 10000 Code Simulations 10000	standard deviation remains 1 0)
C 2 X2:0 1 0.001 0.993 Monte	dorandom generator needs an INTEGEB value to get started:	is that only the CONSTANT B0
C 4	n Generator Seed: 1932 Set a Random Seed	and its statistical significance
C 5	Automatically set new seed for successive simulations	changed.
<u> </u>	sion Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro- Zero- Part VIE	B
Population Correlations (Rho)	poper o 1470 toppo t pope	NOTHING ELSE changed !!
X10.315 X1 Blank all correlations V1 0.4	SS61 U.1470 IUUUU 1.0000 448 0.1802 0.4306 6276 0.6276 0.9117 0.9305 1.7156	
X2 0.131 0.597 X2 Set all Blank to 0 X2 -0.5	3041 0.2039 -0.3013 3123 0.3123 0.1270 -0.2155 2.0076	
X3 0.366 0.125 0.393 X3 0.4	270 0.1648 0.4240 7090 0.7090 0.3592 0.3742 1.2993	
Show Actual Correlations rbs2 = 0.257		
Model Summary Information (Averages and Counter)	es w/at least 1 significant A. $ 8730 (0.873)$ after Sitz model $ 7705 (0.771)$	
<u>R</u> <u>R</u> ² <u>Adjusted R</u> ² <u>Std. Error of</u>	Source of Sum of df Mean Rejections Proportion	
(<u>Ra²)</u> the Estimate 0.5444 0.3095 0.2473 0.8563	variation square square significant Regression 11.50 3 3.834 7890 0.7890	
Cross-validity R ² (Rc ²) Precision Efficacy (Rc ² /R ²)	Residual 24.56 33 0.744 Expected D2 if Multimere	
0.1640 0.4311	TOTAL 36.06 36 k/(n-1) = 0.0833	
MC Finishe	d 10000 ✓ Run (F9)	

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MCMR: Monte Carlo for Mulitple Regression (version	in 2008j)	However, when the
File Reset (F4) Run Analysis (F9) Options Help		Dependent Variable
Population ParametersActual	Monte Carlo Parameters	Mean is 0.0, but the
# of <u>M_SD_M_SD</u> Predictore: V:0 10 0.001 9.940	Sample Size: 37 Get N from PEAR Method	Standard Deviation
$(1 \times 1)^{-1}$	Alpha (2-tailed):0.05 Set alpha=0.01 Set a=0.05 Set a=0.10	changes to 10.0
(2×2) $(1 \times$	Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000	several things change
• 3 X3:0 1 0.001 0.996	The pseudorandom generator needs an INTEGER value to get started:	most notably the
	Random Generator Seed: 1932 Set a Random Seed	most notably the
0.5	Automatically set new seed for successive simulations	regression coefficients
0.6	Regression Coefficient Information (Averages and Counts)	and their significance
Population Correlations (Rho)	<u>B</u> <u>SEB</u> <u>Beta</u> Rejected Pro- <u>Zero-Part</u> <u>VIF</u>	and the SUMS OF
Get Matrix for a given R ²	B0 -0.0195 1.4700 494 0.0494	SQUARES.
X10.315 X1 Blank all correlations	X1 4 4481 1 8922 0 4396 6276 0 6276 0 3117 0 3395 1 7156	
X20.131 0.597 X2 Set all Blank to 0	X2 3 0413 2 0386 -0 3013 2123 0 3123 0 1270 -0 2155 2 0076	But none of the other
X30.366 0.125 0.393	X2 0.0410 2.0000 -0.010 0120 0.0120 0.1270 -0.2130 2.0070	important model
	X3 4.2703 1.0481 0.4240 7090 0.7090 0.3592 0.3742 1.2993	information changed
		$(e \sigma R^2 F rejections)$
		Reta VIE)
		Deta, VII).
Show Actual Correlations rho ² = 0.257	# samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771)	
Model Summary Information (Averages and	Counts)	
<u>R</u> <u>R</u> ² <u>Adjusted R</u> ² <u>Std. E</u>	rror of <u>Source of Sum of df Mean Rejections Proportion</u>	
0.5444 0.3095 0.2473 8.502	9 Regression 1150.21 3 383.404 7890 0.7890	
Cross-validity R ² (Rc ²) Precision Efficacy (F	Residual 2455.65 33 74.414 Expected R ² if Null true	
0.1640 0.4311	TOTAL 3605.86 36 k/(n-1) = 0.0833	
MCMP	Finished 10000	
IALL X		J
MCMR: Monte Carlo for Mulitole Regression (version	n 2008i)	Changing both the
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help	n 2008j)	Changing both the Mean and the
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual	n 2008j)	Changing both the Mean and the Standard Deviation
File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD	n 2008j) Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method	Changing both the Mean and the Standard Deviation
File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of Y: 50 10 9.940	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set a=0.01 Set a=0.05 Set a=0.10	Changing both the Mean and the Standard Deviation combines these
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD M SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations (10000 Saturation Set 1000 Set 10000	Changing both the Mean and the Standard Deviation combines these previous two results.
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual M SD # of M SD M SD Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.933	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual M SD M SD # of Y: 50 10 50.001 9.940 0.991 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 @ 3 X3: 0 1 0.001 0.996	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Dandem Generator Send: 1022	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters # of M SD M SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 2 X2: 0 1 0.001 0.993 @ 3 X3: 0 1 0.001 0.993	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 @ 3 X3: 0 1 0.001 0.996	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 10000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD M SD # of Y: 50 10 50.001 9.940 C 1 X1:0 1 0.002 0.991 C 2 X2:0 1 0.001 0.993 © 3 X3:0 1 0.001 0.996 C 6	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro- Zero- Part VIE	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 © 3 X3: 0 1 0.001 0.996 C 4 5 6 Population Correlations (Rho) D D	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B. SEB Beta Rejected Pro-Zero-Part VIE portion order Corr	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50.
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD SD SD # of Y: 50 10 50.001 9.940 1 X1: 0 1 0.002 0.991 2 X2: 0 1 0.001 0.993 3 X3: 0 1 0.001 0.996 4 5 6 Population Correlations (Rho) DV Get Matrix for a given R ²	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Begression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro-Zero-Part VIF portion order Corr B0 49.9805 1.4700 10000 1.0000	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD SD SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 5 6 Population Correlations (Rho) Get Matrix for a given R ² Blank all correlations	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations B. SEB Beta Rejected Pro-Zero-Part VIE portion order Corr B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant
MCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual M SD SD SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 5 6	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro-Zero-Part VIE portion order Corr B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 -0.2155 2.0076	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often)
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MCMR: Monte Carlo for Mulitple Regression (version file File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD M SD # of Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 © 3 X3: 0 1 0.001 0.996 C 4 5 6	Monte Carlo Parameters Sample Size: Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set control Set 1000 Set alpha=0.01 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual M SD M SD # of Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 © 3 X3: 0 1 0.001 0.996 C 4 5 6	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Image: Set a Random Seed Image: Set a Random Seed Image: Set a Rejected Pro-Zero: Part VIE VIE Portion order Corr Part VIE Set 3.44481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 5 - 6 Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 Set all Blank to 0	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations B SEB Beta Rejected Pro-Zero-Part VIF portion order Corr B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771)	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 C 5 6 Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 Show Actual Correlations rho ² = 0.257	Monte Carlo Parameters. Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro- Zero- Part VIE B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 3.0413 2.0386 -0.3013 3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771)	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 C 5 6 Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 Show Actual Correlations rho ² = 0.257	Monte Carlo Parameters. Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B. SEB Beta Rejected Pro-Zero-Part VIE portion order Corr B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771) Counts] rror of Source of Sum of df Mean Rejections Proportion	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50 B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual H of Predictors: Y: 50 10 50.001 9.940 \bigcirc 1 X1: 0 1 0.002 0.991 \bigcirc 2 X2: 0 1 0.001 0.993 \bigcirc 3 X3: 0 1 0.001 0.993 \bigcirc 3 X3: 0 1 0.001 0.993 \bigcirc 3 X3: 0 1 0.001 0.996 \bigcirc 4 \bigcirc 5 \bigcirc 6 Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 Show Actual Correlations rho ² = 0.257 Model Summary Information (Averages and Ra ² X1 Ra ² Ra ² Adjusted R ² Std. E (Ra ²) the Estimate of the set of	Monte Carlo Parameters. Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B. SEB Beta Rejected Pro-Zero-Part VIE portion order Corr B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771) Counts) rror of Source of Sum of df Mean Rejections Proportion timate Variation Squares Square Significant	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50 10 50.001 9.940	Monte Carlo Parameters. Sample Size: Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B. SEB Beta Rejected Pro- Zero- Part VIE B0 49.9805 1.4700 10000 1.0000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771)	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50 10 50.001 9.940 \bigcirc 1 X1: 0 1 0.002 0.991 \bigcirc 2 X2: 0 1 0.001 0.993 \bigcirc 3 X3: 0 1 0.001 0.993 \bigcirc 3 X3: 0 1 0.001 0.996 \bigcirc 4 \bigcirc 5 \bigcirc 6 \bigcirc Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 \bigcirc Show Actual Correlations rho ² = 0.257 \bigcirc Model Summary Information (Averages and R R R ² Adjusted R ² Std. E (Ra ²) the Es 0.5444 0.3095 0.2473 8.562 Cross-validity R ² (Rc ²) Precision Efficacy (F	Monte Carlo Parameters. Sample Size: Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B SEB Beta Rejected Pro- Zero- Part VIE B0 49.9805 1.4700 10000 1.0000 0.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -3.0413 2.0386 -0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 If counts If more for the second squares Square Significant <tr< td=""><td>Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).</td></tr<>	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD 90 M SD 90 1 $1:0$ 0.002 0.991 C 2 $2:0$ 1 0.001 0.993 G 3 $X3:0$ 1 0.001 0.996 C 4 5 6 7 7 DV Get Matrix for a given R ² $X1$ 0.315 $X1$ M $Blank all correlations$ $X2_0.131$ 0.597 $X2$ Set all Blank to 0 $X3$ 3.366 0.125 0.393 Show Actual Correlations $rho^2 = 0.257$ $Hodel Summary Information (Averages and Ra2) He Es (Ra2) He Es 0.5444 0.3095 0.2473 8.562 Cross-va$	Monte Carlo Parameters. Sample Size: Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) Portion Part VIE B0 49.9805 1.4700 10000 1.0000 .03395 1.7156 X2 -3.0413 2.0386 0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 If counts If counts If counts If counts Significant If counts If counts If counts Significant Significant 9 Regression 1150.21 3 383.404	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).
MCMR: Monte Carlo for Mulitple Regression (version file Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50 10 50.001 9.940 C 1 X1: 0 1 0.002 0.991 C 2 X2: 0 1 0.001 0.993 C 3 X3: 0 1 0.001 0.996 C 4 5 - 6 Population Correlations (Rho)	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10 Monte Carlo Simulations: 10000 Set to 1 simulation Set 10000 Set to 1 simulation The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Automatically set new seed for successive simulations B SEB Beta Rejected Pro- Zero. Part VIE B0 49.9805 1.4700 10000 1.0000 X1 4.4481 1.8922 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 3.0413 2.0386 -0.3013 3123 0.1270 0.2155 2.0076 X3 4.2703 1.6481 0.4240 7090 0.7090 0.3592 0.3742 1.2993 Irror of timate Sum of df Mean Rejections Proportion Significant 9 Regression 1150.21 3 383.404 7890 0.7890 Regression	Changing both the Mean and the Standard Deviation combines these previous two results. That is, all the information EXCEPT B0 remains the same as the previous example. But now with the Y mean at 50, B0 changed to match (and is significant more often).

MCMR: Monte Carlo for Mulitple Regression (version)	on 2008j)	If we change the
File Reset (F4) Run Analysis (F9) Options Help		predictor Means and
Population Parameters Actual	Monte Carlo Parameters	Standard Deviations,
# of	Sample Size: 37 Get N from PEAR Method	but leave the
0 1 X1.10 2 10.005 1.982	Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10	Dependent Variable Y
$\bigcirc 2$ X2 20 5 20.004 4.964	Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 10000	standardized you can
© 3 X3:100 15 100.01 14.933	The pseudorandom generator needs an INTEGER value to get started:	saa savaral diffarances
	Random Generator Seed: 1932 Set a Random Seed	see several differences
0.5	Automatically set new seed for successive simulations	— most notably in the
0.5	Regression Coefficient Information (Averages and Counts)	regression
	<u>B</u> <u>SEB</u> <u>Beta</u> Rejected Pro- <u>Zero-</u> Part <u>VIF</u>	coefficients.
Population Correlations (Rho)	portion <u>order</u> <u>Corr</u>	
Get Matrix for a given R ²	B0 -3.8563 1.2067 8593 0.8593	- The "Sum of Squares"
Blank all correlations	X1 0.2224 0.0946 0.4396 6276 0.6276 0.3117 0.3395 1.7156	values have returned
X2 0.131 0.597 X2 Set all Blank to 0	X2 -0.0608 0.0408 -0.3013 3123 0.3123 0.1270 -0.2155 2.0076	to what they were in
X30.366 0.125 0.393	X3 0.0285 0.0110 0.4240 7090 0.7090 0.3592 0.3742 1.2993	to what they were in
		the first example.
Show Actual Correlations rbs ² = 0.257	#	1
Show Actual Correlations Thio 0.237	# samples w/at least 1 significant X: 8/30 (0.8/3) after SIG model 7/05 (0.7/1)	
Model Summary Information (Averages and	<u>d Counts)</u>	
<u>R</u> <u><u>R</u>²<u>Adjusted R</u>²<u>Std. E</u> (Ra²) the Fe</u>	<u>rror of Source of Sum of of Mean Rejections Proportion</u>	
	Begrassian 11 50 3 3 834 7800 0 7800	
0.5444 0.5055 0.2475 0.550	Desidual 04.55 02 0.744	•
Cross-validity R ² (Rc ²) Precision Efficacy (I	Rc ² /R ²) Residual 24.56 33 0.744 Expected R ² if Null true	2
0.1640 0.4311	TOTAL 36.06 36 k/(n-1) = 0.0833	
MC	Einished 10000	1
MIN	Finished 10000	
MC MCMP: Monte Carlo for Mulitale Degracion (version	a 20080	Finally if everything
MCMR: Monte Carlo for Mulitple Regression (version	n 2008j)	Finally, if everything
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help	n 2008j)	Finally, if everything changes, the regression
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters <u>Actual</u> # of <u>M_SD_M_SD</u>	Monte Carlo Parameters Sample Size 37 Get N from PEAP Method	Finally, if everything changes, the regression coefficients all change,
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Population Parameters # of M SD M SD Predictors: Y: 50.0 10.0 9.940	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method	Finally, if everything changes, the regression coefficients all change, but note that all the
WCMR: Monte Carlo for Mulitple Regression (version) File Reset (F4) Run Analysis (F9) Options Help Population Parameters # of M SD Actual # of Y: 50.0 10.0 50.001 9.940 C 1 X1: 10 2 10.005 1.982	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Set a=0.10	Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary
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MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual SD M SD # of M SD M SD Predictors: Y: 50.0 10.0 50.001 9.940	Monte Carlo Parameters. Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Regression Coefficient Information (Averages and Counts) B SEB B SEB B0 11.4368 12.2241 0.9461 0.4396 6276 0.6276 0.3117 0.3995 1.7156 X2 0.6083 0.4077 0.3013 3123 0.1270 0.2155 X3 0.2847 0.1099 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771) Counts) Counts) Source of Sum of df Mean Rejections Proportion Yariation Square Significant Significant	 Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50.0 10.0 50.001 9.940 C 1 X1: 10 2 10.005 1.982 C 2 X2: 20 5 20.004 4.964 © 3 X3: 100 15 100.01 14.933 C 4 5 6 Population Correlations (Rho)	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Automatically set new seed for successive simulations Begression Coefficient Information (Averages and Counts) B SEB B SEB Beta Rejected Pro- Zero- Part VIF B0 11.4368 12.0673 1528 0.1528 X1 2.2241 0.9461 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 -0.6083 0.4077 -0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 0.2847 0.1099 0.4240 7090 0.7090 0.3592 0.3742 1.2993 ## samples w/at least 1 significant X: 8730 (0.873) <t< td=""><td>Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.</td></t<>	Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50.0 10.0 50.001 9.940 C 1 X1: 10 2 10.005 1.982 C 2 X2: 20 5 20.004 4.964 © 3 X3: 100 15 100.01 14.933 C 4 5 6 Population Correlations (Rho) DV Get Matrix for a given R ² X1 0.315 X1 Blank all correlations X2 0.131 0.597 X2 Set all Blank to 0 X3 0.366 0.125 0.393 Show Actual Correlations rho ² = 0.257 Model Summary Information (Averages and Re ²) the Es 0.5444 0.3095 0.2473 8.5623 Cross-validity R ² (Re ²) Precision Efficacy (Re ²) Precision Efficacy (Re ²)	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Monte Carlo Simulations: 10000 Set to 1 simulation Set 10000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations B SEB Beta Rejected Pro- Zero- Part VIF portion order Corr Source or B0 11.4368 12.0673 1528 0.1528 X1 2.2241 0.9461 0.4396 6276 0.6276 0.3117 0.3395 1.7156 X2 0.6083 0.4077 -0.3013 3123 0.3123 0.1270 -0.2155 2.0076 X3 0.2847 0.1099 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771) Counts Surce of Sum of df Mean Rejections Proportion Significant	Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.
MCMR: Monte Carlo for Mulitple Regression (version File Reset (F4) Run Analysis (F9) Options Help Population Parameters Actual # of M SD M SD Predictors: Y: 50.0 10.0 50.001 9.940 C 1 X1: 10 2 10.005 1.982 C 2 X2: 20 5 20.004 4.964 © 3 X3: 100 15 100.01 14.933 C 4 5 6	Monte Carlo Parameters Sample Size: 37 Get N from PEAR Method Alpha (2-tailed): 0.05 Set alpha=0.01 Set a=0.05 Monte Carlo Simulations: 10000 Set to 1 simulation Set 1000 The pseudorandom generator needs an INTEGER value to get started: Random Generator Seed: 1932 Set a Random Seed Automatically set new seed for successive simulations Begression Coefficient Information (Averages and Counts) B SEB B SEB Bo 11.4368 12.0673 12.2241 0.9461 0.4396 6276 0.6276 0.3117 X2 0.6083 0.4077 0.3013 3123 0.3123 0.2170 0.2155 2.0076 X3 0.2847 0.1099 0.4240 7090 0.7090 0.3592 0.3742 1.2993 # samples w/at least 1 significant X: 8730 (0.873) after SIG model 7705 (0.771) Counts) Sequeres Regression 1150.21 <tr< td=""><td>Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.</td></tr<>	Finally, if everything changes, the regression coefficients all change, but note that all the MODEL summary information and the CORRELATION information remains the same. Means and Standard Deviations have not impact on the decisions regarding the Null Hypotheses for either coefficients or the model, nor on the interpretations of the value of the predictors or the model.

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