Regression, Mediation, Moderation

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*Title*: The influence of cognitive and affective based job satisfaction measures on the relationship between satisfaction and organizational citizenship behavior

*Abstract*: One of the most widely believed maxims of management is that a happy worker is a productive worker. However, most research on the nature of the relationship between job satisfaction and job performance has not yielded convincing evidence that such a relationship exists to the degree most managers believe. One reason for this might lie in the way in which job performance is measured. Numerous studies have been published that showed that using Organizational Citizenship Behavior to supplant more traditional measures of job performance has resulted in a more robust relationship between job satisfaction and job performance. Yet, recent work has suggested that the relationship between job satisfaction and citizenship may be more complex than originally reported. This study investigated whether the relationship between job satisfaction and citizenship could depend upon the nature of the job satisfaction measure used. Specifically, it was hypothesized that job satisfaction measures which reflect a cognitive basis would be more strongly related to OCB than measures of job satisfaction, which reflect an affective basis. Results from data collected in two midwestern companies show support for the relative importance of cognition based satisfaction over affect based satisfaction. Implications for research on the causes of citizenship are discussed.

# Dataset:

- Dependent variable (Y): OCB - Organizational citizenship behavior measure  
- Independent variables (X)  
 - Affective - job satisfaction measures that measure emotion  
 - Cognitive - job satisfaction measures that measure cognitions (thinking)  
 - Years - years on the job  
 - Type\_work - type of employee measured (secretary, assistant, manager, boss)

# Data Screening:

Assume the data is accurate with no missing values. You will want to screen the dataset using all the predictor variables to predict the outcome in a simultaneous multiple regression (all the variables at once). This analysis will let you screen for outliers and assumptions across all subsequent analyses/steps. Be sure to factor type\_work.

library('foreign')  
data <- read.spss('08\_data.sav', to.data.frame=TRUE)  
data

## type\_work OCB cognitive affective years  
## 1 secretary 65.73282 10.031952 3.6737725 7.823567  
## 2 secretary 73.57188 5.989115 3.1143693 5.589168  
## 3 secretary 87.31026 16.858115 40.5288752 8.442037  
## 4 secretary 75.96581 8.785180 7.5941023 9.705736  
## 5 secretary 84.36135 13.576137 15.4575953 9.346494  
## 6 secretary 71.70728 3.205512 -2.4400237 7.386107  
## 7 secretary 78.50697 10.494487 23.7289796 8.341867  
## 8 secretary 66.41651 6.789686 -0.3782410 6.183052  
## 9 secretary 77.06418 0.944686 -24.7302535 8.718638  
## 10 secretary 77.89303 13.800519 28.9618769 8.424974  
## 11 secretary 66.60720 -3.917409 -50.8981977 7.755276  
## 12 secretary 69.15235 6.098408 30.1902772 9.917073  
## 13 secretary 74.82258 11.584355 23.6607656 8.193441  
## 14 secretary 77.31180 12.540490 34.7051388 9.629999  
## 15 secretary 64.34254 22.575809 59.5004245 4.795816  
## 16 secretary 68.51688 11.835825 24.7471653 7.096533  
## 17 secretary 76.20671 19.735826 15.8654246 8.397879  
## 18 secretary 68.04649 13.960763 27.2259219 9.939245  
## 19 secretary 67.52785 6.104015 -2.4073002 9.152878  
## 20 secretary 69.91643 6.644776 11.1574764 9.286578  
## 21 secretary 61.92135 5.970243 -25.0704333 7.783359  
## 22 secretary 65.12421 9.074955 16.5526379 9.640953  
## 23 secretary 71.83864 10.666591 39.8961925 7.153957  
## 24 secretary 58.07777 7.154107 -20.1775815 8.098407  
## 25 secretary 69.87890 3.432962 -15.5069268 9.143266  
## 26 secretary 75.44760 20.882961 45.8156243 5.987283  
## 27 secretary 67.15941 15.136830 22.7344834 6.763494  
## 28 secretary 76.60730 11.169652 1.7868876 7.473460  
## 29 secretary 73.85535 9.839855 16.5252787 8.906884  
## 30 secretary 69.07040 6.792761 -17.0382373 8.125175  
## 31 secretary 87.13484 10.482951 33.7750826 8.054646  
## 32 secretary 64.35413 3.178829 -16.5242845 8.167749  
## 33 secretary 84.85953 15.904819 33.7811176 9.346049  
## 34 secretary 78.63675 4.481995 26.2154938 9.996098  
## 35 secretary 71.17813 8.962652 2.7605173 6.094545  
## 36 secretary 78.65584 7.716436 13.4181997 6.826493  
## 37 secretary 68.17409 13.075306 41.5364359 7.293646  
## 38 secretary 88.52698 9.022996 19.3516230 8.893825  
## 39 secretary 71.08107 8.139749 -5.1341181 4.981891  
## 40 secretary 81.82522 4.441390 -12.7148059 9.609311  
## 41 assistant 87.07323 28.613221 -4.1530375 10.657031  
## 42 assistant 87.87760 38.149573 17.1827844 7.581111  
## 43 assistant 87.34751 17.349311 19.6376563 8.575829  
## 44 assistant 83.49134 13.474618 22.5078564 8.211847  
## 45 assistant 85.29723 21.426019 37.5700754 8.951231  
## 46 assistant 86.01292 26.163877 -6.6276695 4.067519  
## 47 assistant 82.67942 0.261969 13.4286966 7.270569  
## 48 assistant 81.80500 -9.648210 -8.0478127 9.379455  
## 49 assistant 83.28620 11.591223 47.5852012 8.949178  
## 50 assistant 81.88183 5.580157 -0.2417576 7.456227  
## 51 assistant 87.29892 24.729479 44.9760047 5.623285  
## 52 assistant 84.72574 22.195712 0.6625829 6.675261  
## 53 assistant 88.46158 32.450120 52.4759459 11.584173  
## 54 assistant 89.30209 27.531828 6.7558414 6.535849  
## 55 assistant 81.03323 6.905905 1.9379150 7.949863  
## 56 assistant 84.61758 5.010310 18.4369790 6.871577  
## 57 assistant 85.77899 19.434694 26.7342342 11.031158  
## 58 assistant 84.68337 39.212347 7.1096905 7.856148  
## 59 assistant 86.63655 42.970710 31.0892296 8.884471  
## 60 assistant 83.29020 18.377932 8.2415636 9.200174  
## 61 assistant 85.84667 9.526178 3.7267904 10.563123  
## 62 assistant 86.05043 23.335752 -11.0554822 7.605984  
## 63 assistant 86.02522 5.564733 17.0601001 7.604906  
## 64 assistant 82.72715 30.891287 25.8935495 7.733023  
## 65 assistant 82.92025 10.822570 9.2290563 11.815215  
## 66 assistant 83.63228 17.993545 15.9741688 9.039816  
## 67 assistant 86.23841 40.495619 53.1394894 8.502430  
## 68 assistant 87.02409 34.038333 18.2087527 7.689492  
## 69 assistant 84.64299 3.732857 12.5909664 6.692717  
## 70 assistant 86.32128 16.285676 31.7773148 9.002547  
## 71 assistant 87.09496 -5.525233 0.4216924 4.064593  
## 72 assistant 88.68739 41.056219 48.6955586 7.273414  
## 73 assistant 83.88403 31.081058 20.6511798 6.529628  
## 74 assistant 84.20634 7.388256 -13.4954545 7.472741  
## 75 assistant 87.31164 19.608657 14.3379006 5.840322  
## 76 assistant 87.71272 37.715699 -3.3313830 6.545806  
## 77 assistant 83.83625 5.781405 -29.2308548 10.404299  
## 78 assistant 83.97678 16.348781 11.4583591 6.256205  
## 79 assistant 82.75029 -2.631702 5.7775940 9.148792  
## 80 assistant 82.22146 -16.812207 7.4687821 6.019084  
## 81 manager 89.86232 19.414243 49.5831087 7.038898  
## 82 manager 89.58736 20.163208 38.1258236 8.760406  
## 83 manager 90.35620 22.484745 22.9567623 9.724461  
## 84 manager 89.33202 24.860030 1.7957168 6.936132  
## 85 manager 92.66208 29.838940 28.9541306 8.301706  
## 86 manager 91.94767 15.389686 29.9233773 5.827124  
## 87 manager 90.70651 13.163496 47.3134568 8.611517  
## 88 manager 89.11471 15.305707 22.3393182 7.903699  
## 89 manager 90.07389 22.496493 15.9360767 7.116358  
## 90 manager 86.08719 11.753903 10.6792483 6.880362  
## 91 manager 88.88241 19.345940 16.0977889 9.911540  
## 92 manager 90.73076 14.891832 19.1252593 10.172687  
## 93 manager 90.00686 31.095808 0.5557401 4.457348  
## 94 manager 88.98491 44.651604 22.3898772 8.383058  
## 95 manager 91.88476 26.613118 12.4962065 6.168019  
## 96 manager 92.63148 25.011385 36.0212768 9.037104  
## 97 manager 86.97365 23.481474 6.2979840 8.879450  
## 98 manager 89.68856 20.733659 -20.3856877 10.560822  
## 99 manager 88.23159 34.339937 -8.2294548 10.168698  
## 100 manager 91.79302 26.687225 35.5317788 7.022992  
## 101 manager 90.90204 11.287525 18.4141947 8.825340  
## 102 manager 91.08025 21.477256 25.7002455 9.154697  
## 103 manager 91.93264 18.003712 14.2470587 7.621096  
## 104 manager 89.37145 24.468117 19.5925470 9.995805  
## 105 manager 88.11857 16.694102 -9.1807525 8.594460  
## 106 manager 89.69392 14.687243 0.8720820 6.904683  
## 107 manager 87.64614 31.376591 21.3341503 4.247587  
## 108 manager 89.18646 28.803023 21.6079646 10.606374  
## 109 manager 90.40863 22.129213 -29.1448419 5.440184  
## 110 manager 89.61619 23.291011 41.2594149 7.341057  
## 111 manager 91.91118 16.589545 7.2830007 9.769110  
## 112 manager 92.55732 24.765698 30.3724600 8.318524  
## 113 manager 91.52936 11.554138 -8.1891745 7.579907  
## 114 manager 91.11378 24.681550 25.4999652 10.013256  
## 115 manager 92.66925 8.973601 44.1557899 12.233324  
## 116 manager 88.91031 23.713307 -2.1613456 9.698229  
## 117 manager 88.79486 28.998701 23.2445616 10.457328  
## 118 manager 90.01042 27.044986 5.5987006 9.125765  
## 119 manager 92.47339 14.954469 60.7569986 8.015518  
## 120 manager 88.69306 22.111671 30.3863909 7.488723  
## 121 boss 96.38877 29.523625 30.0619221 5.471090  
## 122 boss 95.39780 15.203400 50.7866395 8.634842  
## 123 boss 92.33210 27.835856 -33.5033123 5.485008  
## 124 boss 102.37126 47.437293 142.7864363 7.152880  
## 125 boss 95.88637 23.892930 53.1258109 6.832887  
## 126 boss 98.38402 29.172480 61.2152356 7.863111  
## 127 boss 92.88164 34.276663 1.9747841 8.134340  
## 128 boss 100.33987 20.302697 63.7288002 7.540896  
## 129 boss 97.76886 25.465004 43.6293454 6.974306  
## 130 boss 94.01718 9.816611 -49.3423949 9.177437  
## 131 boss 97.57555 28.694945 22.1910876 7.968978  
## 132 boss 104.72164 19.126840 87.9839803 8.222546  
## 133 boss 101.34201 29.750535 107.6341674 8.192807  
## 134 boss 96.38660 29.495530 35.2791723 8.347107  
## 135 boss 97.05261 24.801064 23.9323337 10.921364  
## 136 boss 102.90432 44.674742 126.6423673 7.212560  
## 137 boss 95.52200 28.577376 41.8230751 8.170556  
## 138 boss 96.90609 13.383785 5.8976228 6.823960  
## 139 boss 98.72546 27.657193 33.9805416 6.998726  
## 140 boss 102.98180 20.470809 75.5668626 8.408524  
## 141 boss 95.62155 20.505728 8.7844428 4.764341  
## 142 boss 101.58739 35.202539 150.3002812 9.424465  
## 143 boss 105.35721 32.590942 107.9876838 10.097664  
## 144 boss 91.73381 14.888676 -46.6497719 7.489380  
## 145 boss 99.23154 39.837164 87.3411990 5.543745  
## 146 boss 100.23791 21.123429 60.1745650 10.702814  
## 147 boss 93.95981 36.537022 26.5035050 7.706006  
## 148 boss 94.19580 23.747866 38.0789294 8.420183  
## 149 boss 98.67661 39.663101 64.0228767 7.576741  
## 150 boss 101.21881 23.921497 100.5390394 8.282735  
## 151 boss 93.76841 27.846122 -43.4702921 7.762297  
## 152 boss 94.20518 39.159789 38.1861821 8.387030  
## 153 boss 102.36676 19.974089 94.4689773 5.154534  
## 154 boss 98.23225 29.465117 84.9991074 10.362845  
## 155 boss 95.06027 26.427096 76.0134511 6.785828  
## 156 boss 95.90431 42.876677 47.5477885 5.898670  
## 157 boss 99.26346 32.067819 72.3244361 8.590852  
## 158 boss 96.99971 35.346470 43.5075667 7.220490  
## 159 boss 98.08387 22.741249 25.4551556 5.749586  
## 160 boss 93.01210 28.478394 -29.1731548 8.020111

summary(data)

## type\_work OCB cognitive affective   
## secretary:40 Min. : 58.08 Min. :-16.81 Min. :-50.898   
## assistant:40 1st Qu.: 82.72 1st Qu.: 10.62 1st Qu.: 3.026   
## manager :40 Median : 88.18 Median : 19.67 Median : 20.144   
## boss :40 Mean : 86.53 Mean : 19.38 Mean : 23.183   
## 3rd Qu.: 92.64 3rd Qu.: 27.70 3rd Qu.: 38.091   
## Max. :105.36 Max. : 47.44 Max. :150.300   
## years   
## Min. : 4.065   
## 1st Qu.: 7.017   
## Median : 8.077   
## Mean : 8.021   
## 3rd Qu.: 9.130   
## Max. :12.233

str(data)

## 'data.frame': 160 obs. of 5 variables:  
## $ type\_work: Factor w/ 4 levels "secretary","assistant",..: 1 1 1 1 1 1 1 1 1 1 ...  
## $ OCB : num 65.7 73.6 87.3 76 84.4 ...  
## $ cognitive: num 10.03 5.99 16.86 8.79 13.58 ...  
## $ affective: num 3.67 3.11 40.53 7.59 15.46 ...  
## $ years : num 7.82 5.59 8.44 9.71 9.35 ...  
## - attr(\*, "codepage")= int 65001

## Outliers

a. Leverage:  
 i. What is your leverage cut off score? 0.0875  
 ii. How many leverage outliers did you have? 7

screen = lm(OCB ~ cognitive + affective + years + type\_work, data = data)  
summary(screen)

##   
## Call:  
## lm(formula = OCB ~ cognitive + affective + years + type\_work,   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -13.142 -1.834 -0.102 1.659 14.793   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 70.26607 1.70941 41.105 < 2e-16 \*\*\*  
## cognitive 0.02314 0.03379 0.685 0.494   
## affective 0.05766 0.01086 5.309 3.82e-07 \*\*\*  
## years 0.24098 0.19295 1.249 0.214   
## type\_workassistant 11.70696 0.90430 12.946 < 2e-16 \*\*\*  
## type\_workmanager 16.32134 0.95267 17.132 < 2e-16 \*\*\*  
## type\_workboss 22.15615 1.06233 20.856 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.853 on 153 degrees of freedom  
## Multiple R-squared: 0.8548, Adjusted R-squared: 0.8491   
## F-statistic: 150.1 on 6 and 153 DF, p-value: < 2.2e-16

k = 4  
leverage = hatvalues(screen)   
cutlev = (2\*k+2)/nrow(data)   
cutlev

## [1] 0.0625

badlev = leverage > cutlev  
badlev

## 1 2 3 4 5 6 7 8 9 10 11 12 13   
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE   
## 14 15 16 17 18 19 20 21 22 23 24 25 26   
## FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE   
## 27 28 29 30 31 32 33 34 35 36 37 38 39   
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE   
## 40 41 42 43 44 45 46 47 48 49 50 51 52   
## FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE TRUE FALSE FALSE FALSE FALSE   
## 53 54 55 56 57 58 59 60 61 62 63 64 65   
## TRUE FALSE FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE FALSE FALSE TRUE   
## 66 67 68 69 70 71 72 73 74 75 76 77 78   
## FALSE TRUE FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE TRUE FALSE FALSE   
## 79 80 81 82 83 84 85 86 87 88 89 90 91   
## FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE   
## 92 93 94 95 96 97 98 99 100 101 102 103 104   
## FALSE TRUE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE   
## 105 106 107 108 109 110 111 112 113 114 115 116 117   
## FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE   
## 118 119 120 121 122 123 124 125 126 127 128 129 130   
## FALSE FALSE FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE FALSE FALSE TRUE   
## 131 132 133 134 135 136 137 138 139 140 141 142 143   
## FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE TRUE FALSE   
## 144 145 146 147 148 149 150 151 152 153 154 155 156   
## TRUE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE TRUE FALSE FALSE FALSE   
## 157 158 159 160   
## FALSE FALSE FALSE TRUE

table(badlev)

## badlev  
## FALSE TRUE   
## 135 25

b. Cook's:  
 i. What is your Cook's cut off score? 0.02614379  
 ii. How many Cook's outliers did you have? 9

cooks = cooks.distance(screen)   
cooks

## 1 2 3 4 5 6   
## 1.225463e-02 1.166497e-03 5.029703e-02 2.432021e-03 3.526288e-02 2.224594e-05   
## 7 8 9 10 11 12   
## 5.657965e-03 1.075741e-02 1.451653e-02 3.679633e-03 3.808685e-03 1.108634e-02   
## 13 14 15 16 17 18   
## 2.383730e-04 2.087451e-03 1.015271e-01 7.821574e-03 2.190021e-03 1.569656e-02   
## 19 20 21 22 23 24   
## 7.477856e-03 3.411134e-03 2.834872e-02 2.382987e-02 2.521813e-03 5.736358e-02   
## 25 26 27 28 29 30   
## 1.119790e-03 1.962344e-04 1.321278e-02 4.768519e-03 1.878018e-05 1.717982e-03   
## 31 32 33 34 35 36   
## 4.728308e-02 1.589656e-02 3.468501e-02 7.408768e-03 3.067413e-04 1.006719e-02   
## 37 38 39 40 41 42   
## 1.466282e-02 6.020171e-02 4.078343e-05 3.666385e-02 2.968427e-03 2.899177e-03   
## 43 44 45 46 47 48   
## 8.325249e-04 1.206827e-03 7.052560e-04 6.288149e-03 1.812768e-03 2.781822e-03   
## 49 50 51 52 53 54   
## 6.428733e-03 1.514343e-03 3.263894e-04 1.159565e-04 5.404602e-06 8.740159e-03   
## 55 56 57 58 59 60   
## 3.361605e-03 1.639213e-05 3.679759e-04 1.712181e-04 5.589364e-05 9.717750e-04   
## 61 62 63 64 65 66   
## 3.872924e-04 1.955789e-03 4.856833e-04 4.159976e-03 5.070174e-03 9.753605e-04   
## 67 68 69 70 71 72   
## 2.180808e-03 8.552855e-04 2.879505e-05 2.816074e-07 2.319204e-02 1.003960e-03   
## 73 74 75 76 77 78   
## 1.072163e-03 3.973248e-04 2.651575e-03 8.776459e-03 5.245844e-04 9.897209e-05   
## 79 80 81 82 83 84   
## 1.793862e-03 2.512477e-03 1.255739e-03 9.374483e-04 5.350593e-05 5.198153e-05   
## 85 86 87 88 89 90   
## 8.798403e-04 1.805256e-03 4.259586e-04 3.150925e-04 3.224682e-05 3.679934e-03   
## 91 92 93 94 95 96   
## 6.982304e-04 2.261427e-05 1.970526e-03 2.633095e-03 2.423750e-03 4.237528e-04   
## 97 98 99 100 101 102   
## 1.988423e-03 8.535168e-04 8.169176e-04 2.380524e-04 2.621894e-04 2.601983e-05   
## 103 104 105 106 107 108   
## 1.438641e-03 5.847500e-04 5.005864e-05 3.939524e-04 2.920782e-03 1.544568e-03   
## 109 110 111 112 113 114   
## 8.822816e-03 8.998678e-04 1.556370e-03 7.165705e-04 4.072215e-03 1.741565e-06   
## 115 116 117 118 119 120   
## 1.323986e-04 6.904978e-05 2.285537e-03 2.446359e-05 5.742435e-06 1.107295e-03   
## 121 122 123 124 125 126   
## 2.204356e-05 2.344250e-03 1.510050e-05 1.386751e-03 9.625104e-04 5.037013e-06   
## 127 128 129 130 131 132   
## 3.156633e-03 1.328781e-03 8.598928e-05 5.042326e-03 5.299519e-04 1.206849e-02   
## 133 134 135 136 137 138   
## 1.431418e-06 1.671889e-04 1.225968e-06 1.402319e-04 9.960470e-04 2.409215e-03   
## 139 140 141 142 143 144   
## 1.140525e-03 5.569706e-03 7.034017e-04 8.208036e-03 8.294206e-03 2.265426e-05   
## 145 146 147 148 149 150   
## 1.327122e-04 8.922793e-04 2.811674e-03 2.547087e-03 1.157167e-05 1.111219e-04   
## 151 152 153 154 155 156   
## 1.914712e-03 4.549986e-03 6.512249e-03 2.747594e-03 5.768585e-03 1.440814e-03   
## 157 158 159 160   
## 6.284060e-06 7.371967e-05 2.079802e-03 8.516285e-05

cutcooks = 4 / (nrow(data) - k - 1)   
cutcooks

## [1] 0.02580645

badcooks = cooks > cutcooks   
table(badcooks)

## badcooks  
## FALSE TRUE   
## 151 9

c. Mahalanobis:  
 i. What is your Mahalanobis df? OCB, cognitive, affective, years  
 ii. What is your Mahalanobis cut off score? 18.46683  
 iii. How many outliers did you have for Mahalanobis? None

mahal <- mahalanobis(data[ , -1],   
 colMeans(data[ , -1]),  
 cov(data[ , -1]))   
cutmahal = qchisq(1-.001, ncol(data[ , -5]))   
cutmahal

## [1] 18.46683

badmahal = mahal > cutmahal   
table(badmahal)

## badmahal  
## FALSE   
## 160

d. Overall:  
 i. How many total outliers did you have across all variables? None  
 ii. Delete them!

totalout = badlev + badcooks + badmahal  
table(totalout)

## totalout  
## 0 1 2   
## 127 32 1

# Assumptions:

## Additivity:

a. Include a correlation table of your independent variables.  
b. Do your correlations meet the assumption for additivity (i.e. do you have multicollinearity)?  
Yes the additivity has met and have the evidence of multicolinearity.

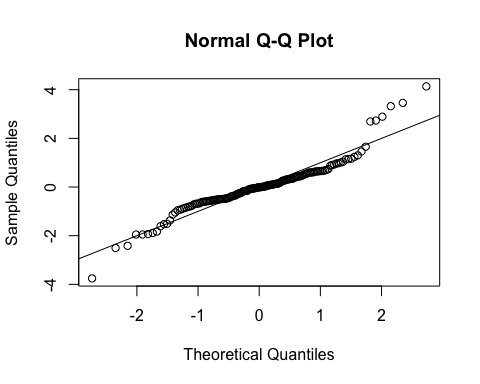
noout = subset(data, totalout < 2)  
screen1 = lm(OCB ~ cognitive + affective + years + type\_work, data = noout)   
standardized = rstudent(screen1)   
fitted = scale(screen1$fitted.values)  
summary(screen1, correlation = T)

##   
## Call:  
## lm(formula = OCB ~ cognitive + affective + years + type\_work,   
## data = noout)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -13.2999 -1.8774 -0.0393 1.6270 14.5532   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 71.27342 1.69699 42.000 < 2e-16 \*\*\*  
## cognitive 0.02905 0.03296 0.881 0.380   
## affective 0.06148 0.01065 5.772 4.25e-08 \*\*\*  
## years 0.14038 0.19076 0.736 0.463   
## type\_workassistant 11.34102 0.88873 12.761 < 2e-16 \*\*\*  
## type\_workmanager 15.95303 0.93553 17.052 < 2e-16 \*\*\*  
## type\_workboss 21.57443 1.05189 20.510 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.753 on 152 degrees of freedom  
## Multiple R-squared: 0.8587, Adjusted R-squared: 0.8531   
## F-statistic: 154 on 6 and 152 DF, p-value: < 2.2e-16  
##   
## Correlation of Coefficients:  
## (Intercept) cognitive affective years type\_workassistant  
## cognitive -0.22   
## affective 0.10 -0.32   
## years -0.92 0.07 -0.12   
## type\_workassistant -0.21 -0.31 0.05 0.02   
## type\_workmanager -0.10 -0.42 0.06 -0.06 0.57   
## type\_workboss -0.18 -0.46 -0.20 0.09 0.55   
## type\_workmanager  
## cognitive   
## affective   
## years   
## type\_workassistant   
## type\_workmanager   
## type\_workboss 0.59

## Linearity:

a. Include a picture that shows how you might assess multivariate linearity.  
b. Do you think you've met the assumption for linearity?   
 By looking at graph it looks like it amlost linear.

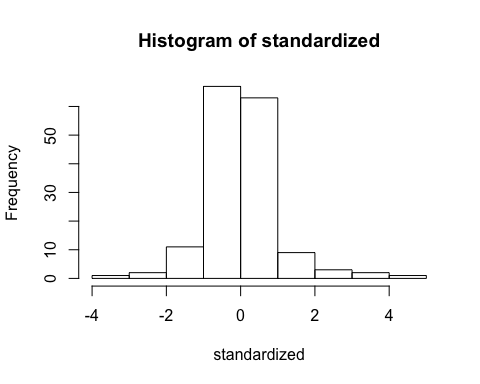
qqnorm(standardized)   
abline(0,1)



## Normality:

a. Include a picture that shows how you might assess multivariate normality.  
b. Do you think you've met the assumption for normality? Yes, almost looking similar

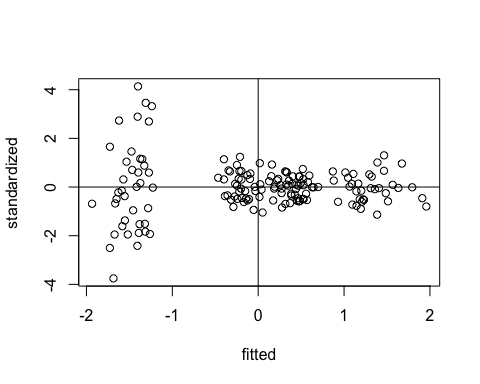
hist(standardized)



## Homogeneity and Homoscedasticity:

a. Include a picture that shows how you might assess multivariate homogeneity.  
b. Do you think you've met the assumption for homogeneity?  
 No homogeneity is not met  
c. Do you think you've met the assumption for homoscedasticity?  
 Yes the assumption for homoscedasticity is met.\, the value lies between -4 to 4.

plot(fitted, standardized)   
abline(0,0, v = 0)



# Hierarchical Regression:

a. First, control for years on the job in the first step of the regression analysis.  
b. Then use the factor coded type of job variable to determine if it has an effect on organizational citizenship behavior.  
c. Last, test if cognitive and affect measures of job satisfaction are predictors of organizational citizenship behavior.   
d. Include the summaries of each step, along with the ANOVA of the change between each step.

step1 = lm(OCB ~ years, data = noout)  
step2 = lm(OCB ~ years + type\_work, data = noout)   
step3 = lm(OCB ~ years + type\_work + cognitive + affective, data = noout)  
summary(step1)

##   
## Call:  
## lm(formula = OCB ~ years, data = noout)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -28.584 -3.878 1.846 6.061 18.962   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 87.7441 4.0174 21.841 <2e-16 \*\*\*  
## years -0.1336 0.4901 -0.273 0.786   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 9.82 on 157 degrees of freedom  
## Multiple R-squared: 0.0004731, Adjusted R-squared: -0.005893   
## F-statistic: 0.07431 on 1 and 157 DF, p-value: 0.7855

summary(step2)

##   
## Call:  
## lm(formula = OCB ~ years + type\_work, data = noout)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -15.2446 -2.1376 -0.1576 2.1524 14.9990   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 71.2290 1.8555 38.387 <2e-16 \*\*\*  
## years 0.2585 0.2122 1.218 0.225   
## type\_workassistant 11.8511 0.9477 12.505 <2e-16 \*\*\*  
## type\_workmanager 16.7711 0.9479 17.693 <2e-16 \*\*\*  
## type\_workboss 24.4926 0.9515 25.741 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 4.208 on 154 degrees of freedom  
## Multiple R-squared: 0.8199, Adjusted R-squared: 0.8153   
## F-statistic: 175.3 on 4 and 154 DF, p-value: < 2.2e-16

summary(step3)

##   
## Call:  
## lm(formula = OCB ~ years + type\_work + cognitive + affective,   
## data = noout)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -13.2999 -1.8774 -0.0393 1.6270 14.5532   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 71.27342 1.69699 42.000 < 2e-16 \*\*\*  
## years 0.14038 0.19076 0.736 0.463   
## type\_workassistant 11.34102 0.88873 12.761 < 2e-16 \*\*\*  
## type\_workmanager 15.95303 0.93553 17.052 < 2e-16 \*\*\*  
## type\_workboss 21.57443 1.05189 20.510 < 2e-16 \*\*\*  
## cognitive 0.02905 0.03296 0.881 0.380   
## affective 0.06148 0.01065 5.772 4.25e-08 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.753 on 152 degrees of freedom  
## Multiple R-squared: 0.8587, Adjusted R-squared: 0.8531   
## F-statistic: 154 on 6 and 152 DF, p-value: < 2.2e-16

anova(step1, step2, step3)

## Analysis of Variance Table  
##   
## Model 1: OCB ~ years  
## Model 2: OCB ~ years + type\_work  
## Model 3: OCB ~ years + type\_work + cognitive + affective  
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 157 15140.8   
## 2 154 2727.5 3 12413.3 293.841 < 2.2e-16 \*\*\*  
## 3 152 2140.4 2 587.1 20.847 9.98e-09 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Mediation

a. Calculate a mediation model wherein the number of years mediates the relationship between affective measurements and OCB.  
b. Include each path and summaries of those models.  
c. Include the Sobel test.  
d. Include the bootstrapped indirect effect.

model1 = lm(OCB ~ affective, data = data)   
summary(model1)

##   
## Call:  
## lm(formula = OCB ~ affective, data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -27.491 -2.587 1.779 5.507 18.078   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 83.14463 0.83531 99.537 < 2e-16 \*\*\*  
## affective 0.14604 0.02061 7.087 4.28e-11 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 8.668 on 158 degrees of freedom  
## Multiple R-squared: 0.2412, Adjusted R-squared: 0.2364   
## F-statistic: 50.23 on 1 and 158 DF, p-value: 4.285e-11

model2 = lm(years ~ affective, data = data)   
summary(model2)

##   
## Call:  
## lm(formula = years ~ affective, data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -3.9238 -1.0380 0.0626 1.1300 4.1824   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 7.987797 0.155542 51.355 <2e-16 \*\*\*  
## affective 0.001430 0.003837 0.373 0.71   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.614 on 158 degrees of freedom  
## Multiple R-squared: 0.0008779, Adjusted R-squared: -0.005446   
## F-statistic: 0.1388 on 1 and 158 DF, p-value: 0.7099

model3 = lm(OCB ~ affective + years, data = data)   
summary(model3)

##   
## Call:  
## lm(formula = OCB ~ affective + years, data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -27.639 -2.626 1.700 5.525 18.135   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 83.50504 3.52451 23.693 < 2e-16 \*\*\*  
## affective 0.14610 0.02068 7.065 4.93e-11 \*\*\*  
## years -0.04512 0.42858 -0.105 0.916   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 8.695 on 157 degrees of freedom  
## Multiple R-squared: 0.2413, Adjusted R-squared: 0.2316   
## F-statistic: 24.96 on 2 and 157 DF, p-value: 3.863e-10

a = coef(model2)[2]   
b = coef(model3)[3]   
SEa = summary(model2)$coefficients[2,2]  
SEb=summary(model3)$coefficients[3,2]   
zscore = (a \* b)/(sqrt((b^2 \* SEa^2)+(a^2 \* SEb^2)+(SEa \* SEb)))   
zscore

## affective   
## -0.00159046

pnorm(abs(zscore), lower.tail = F)\*2

## affective   
## 0.998731

total = coef(model1)[2]   
direct = coef(model3)[2]   
indirect = a\*b  
total; direct; indirect

## affective   
## 0.146038

## affective   
## 0.1461025

## affective   
## -6.450458e-05

indirectsaved = function(formula2, formula3, dataset, random)   
 { d = dataset[random, ] #randomize by row   
model2 = lm(formula2, data = d)   
model3 = lm(formula3, data = d)   
a = coef(model2)[2]   
b = coef(model3)[3]   
indirect = a\*b   
return(indirect) }  
library(boot)  
bootresults = boot(data = data, statistic = indirectsaved, formula2 = years ~ affective, formula3 = OCB ~ affective + years, R = 1000)  
bootresults

##   
## ORDINARY NONPARAMETRIC BOOTSTRAP  
##   
##   
## Call:  
## boot(data = data, statistic = indirectsaved, R = 1000, formula2 = years ~   
## affective, formula3 = OCB ~ affective + years)  
##   
##   
## Bootstrap Statistics :  
## original bias std. error  
## t1\* -6.450458e-05 -0.0002873066 0.001734983

boot.ci(bootresults, conf = .95, type = "norm")

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS  
## Based on 1000 bootstrap replicates  
##   
## CALL :   
## boot.ci(boot.out = bootresults, conf = 0.95, type = "norm")  
##   
## Intervals :   
## Level Normal   
## 95% (-0.0032, 0.0036 )   
## Calculations and Intervals on Original Scale

# Write up:

Hierarchical regression only!  
a. Include a brief description of the experiment, variables, and order entered into steps.  
b. Include a brief section on the data screening/assumptions.  
c. Include the all F-values for each step of the model - you can reference the above table.  
 Step 1  
 Residual standard error: 9.82 on 157 degrees of freedom  
 Multiple R-squared: 0.0004731, Adjusted R-squared: -0.005893   
 Step2  
 Residual standard error: 4.208 on 154 degrees of freedom  
 Multiple R-squared: 0.8199, Adjusted R-squared: 0.8153  
 Setp3  
 Residual standard error: 3.753 on 152 degrees of freedom  
 Multiple R-squared: 0.8587, Adjusted R-squared: 0.8531  
   
   
d. Include all the b or beta values for variables in the step they were entered. So, you will not have double b values for any predictor - you can reference the above table.  
  
years 0.14038   
type\_workassistant 11.34102  
type\_workmanager 15.95303  
type\_workboss 21.57443  
cognitive 0.02905   
affective 0.06148  
  
e. Include an interpretation of the results (dummy coding, do our results match the study results, etc.).

Answers for a adn b:

In step 1, Number of Years on the job was used to control previous experience. Here the model wasn’t significant and so this variable wasn’t a correct predictor of OCB. in the step 2, Type of Employee was entered as dummy variable sing secretary as a comparison group. From the models I saw that there was a significant increase in prediction confidence. Bosses, Assistants and Managers had significantly high OCBs than secretaries. In the step 3, I have added cognitive and affect measures of job satisfaction to test if they are predictors of OCB. While the addition was significant, cognition satisfaction was not a significant predictor, while affective satisfaction was positively correlated with OCB