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.

```r
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:

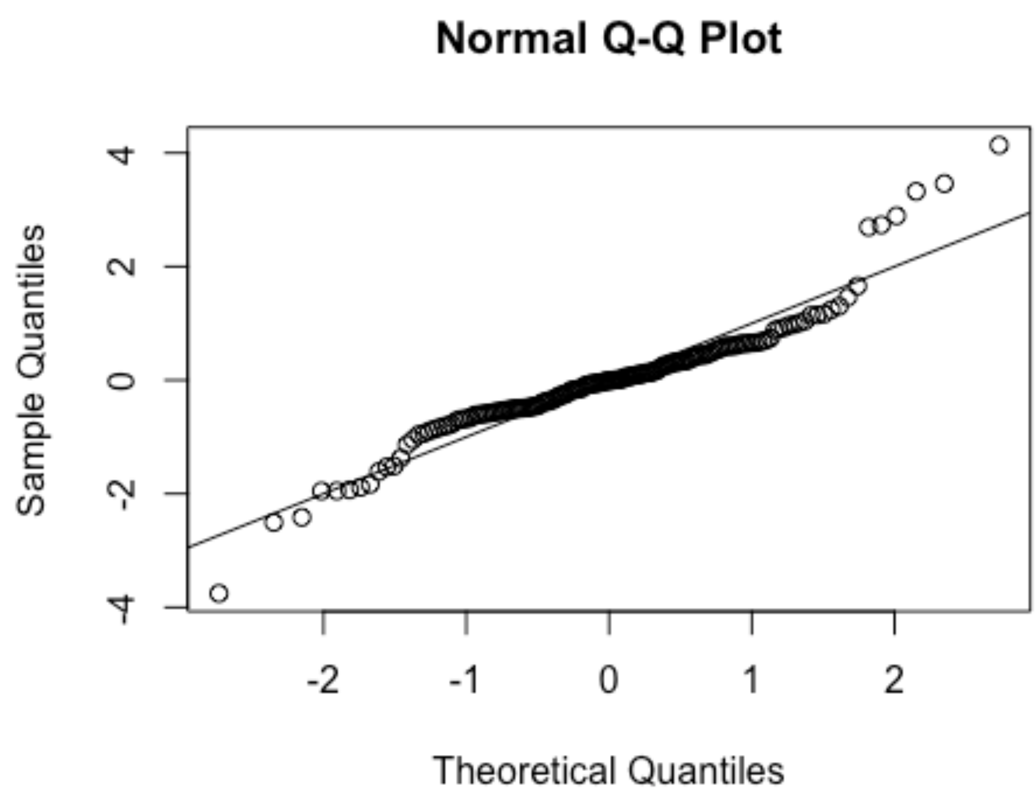
Additivity:

```
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
```

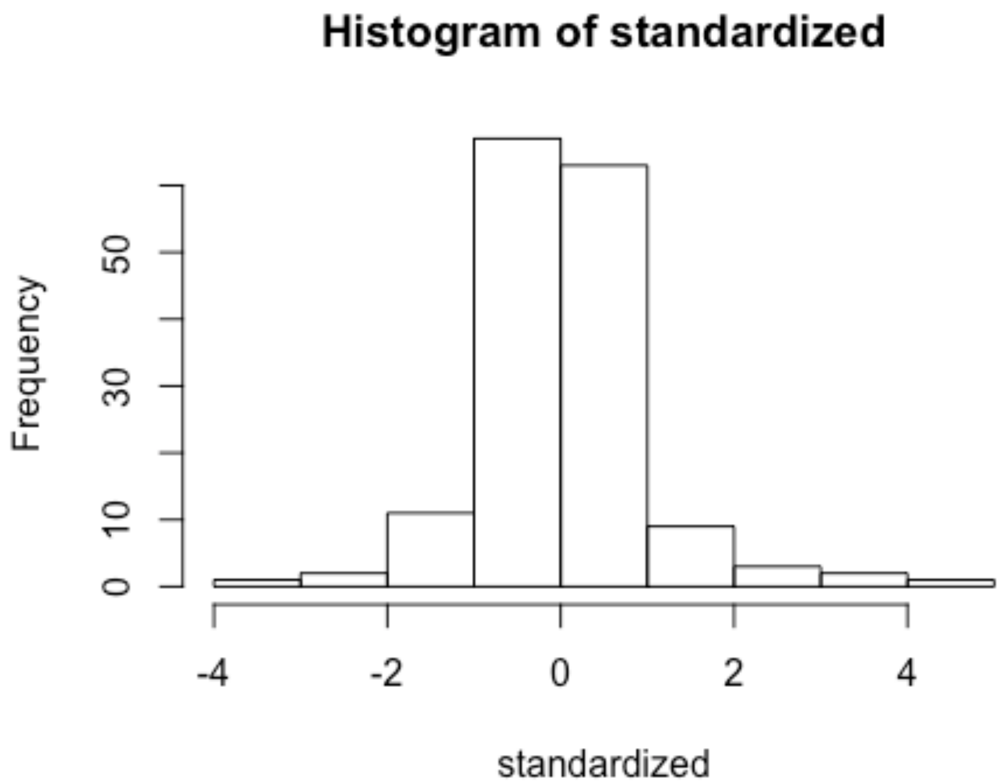
Linearity:

```
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)
```



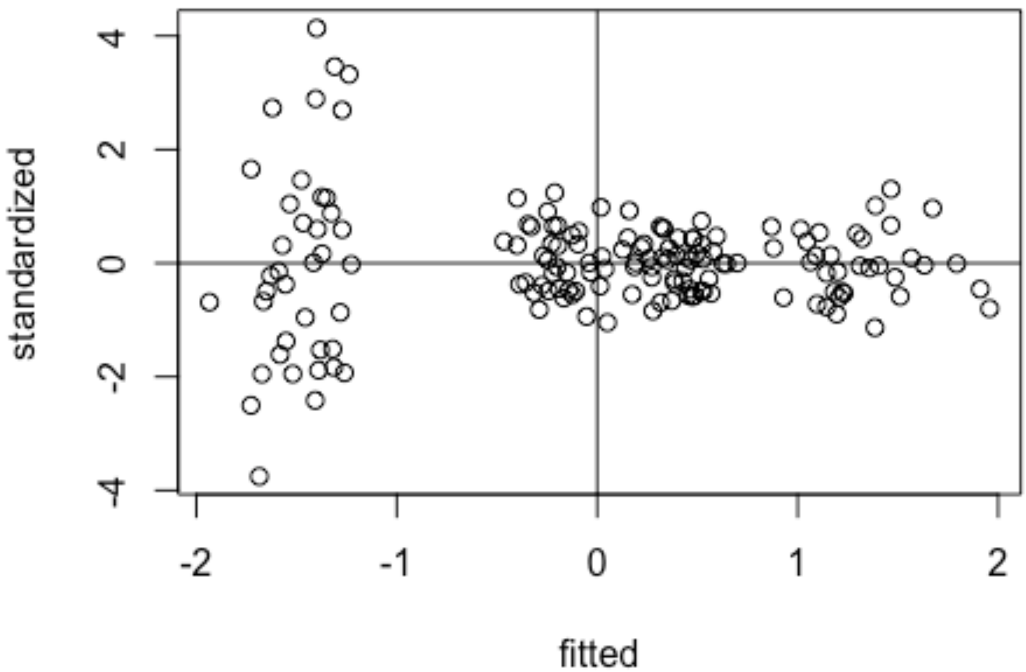
Normality:

```
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
```

```r
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.
```

```r
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
```

```r
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
```

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

```
## affective
##  0.998731
```

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

```
## affective
##  0.146038
```

```
## affective
## 0.1461025
```

```
##     affective
## -6.450458e-05
```

```r
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