Psychological Capital and Social Norms in Times of Uncertainty: Restructuring J2K4L8 Corp.

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Answer 1A:

```
rm(list = ls())
set.seed(1234)

setwd('/Users/R/clarke_lisi')

library(rio)
library(tidyverse)
library(psych)
library(effects)
library(performance)

  ## The corrplot package had to be installed as it could not be found.
install.packages('corrplot', dependencies = T)

library(corrplot)
```

Answer 2A:

```
my.data <- rio::import('J2K4L8Corp.xlsx')
```

Answer 2B:

```
head(my.data)
##   id sex age branch norms hope neuroticism trust brs openness
## 1  1   1  51      1     0   24          30     8  17       24
## 2  2   1  44      1     0   28          38    13  21       17
## 3  3   0  41      1     0   29          27    21  17       25
## 4  4   0  49      1     0   19          32    12  13       31
## 5  5   1  54      1     0   30          28    15  20       26
## 6  6   0  41      1     0   29          32    17  24       22

dim(my.data) # It shows the elements per dimension (n_rows, n_columns)
## [1] 611  10

str(my.data)
## 'data.frame':    611 obs. of  10 variables:
##  $ id         : num  1 2 3 4 5 6 7 8 9 10 ...
##  $ sex        : num  1 1 0 0 1 0 0 0 1 0 ...
##  $ age        : num  51 44 41 49 54 41 42 40 42 46 ...
##  $ branch     : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ norms      : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ hope       : num  24 28 29 19 30 29 25 21 23 28 ...
```

```
## $ neuroticism: num  30 38 27 32 28 32 37 31 32 33 ...
## $ trust      : num  8 13 21 12 15 17 17 9 13 12 ...
## $ brs        : num  17 21 17 13 20 24 15 14 20 18 ...
## $ openness   : num  24 17 25 31 26 22 26 16 21 29 ...

names(my.data)
## [1] "id"          "sex"         "age"         "branch"      "norms"
## [6] "hope"        "neuroticism" "trust"       "brs"         "openness"
```

The R object named `my.data` is a data frame with 611 rows (cases, observations, participants) and 10 columns (variables). All of the variables are numeric (real or decimal), with some variables being numeric vectors and others being vectors representing categorical data (i.e., factors). The latter are variables such as `sex`, `branch`, or `norms` that need to be transformed into factors.

Answer 2C:

```
my.data$sex <- factor(my.data$sex)
my.data$branch <- factor(my.data$branch)
my.data$norms <- factor(my.data$norms)
```

We can use the pipes (`%>%`) to concatenate operations aimed at importing the dataset and tidying it, and store this dataset in the R object `my.data`. A close inspection of the R object using the `str()` function shows that we have imported and transformed the variables as needed in a very compact way.

```
my.data <- rio::import('J2K4L8Corp.xlsx') %>%
  mutate(
    branch = factor(branch, levels = c(1, 2, 3),
                     labels = c('Mexico', 'Singapore', 'The Netherlands'),
                     ordered = F),
    norms = factor(norms, levels = c(0, 1),
                     labels = c('Tight', 'Loose'), ordered = F),
    sex = factor(sex, levels = c(0, 1),
                     labels = c('Female', 'Male'), ordered = F))

str(my.data)
## 'data.frame':    611 obs. of  10 variables:
## $ id         : num  1 2 3 4 5 6 7 8 9 10 ...
## $ sex        : Factor w/ 2 levels "Female","Male": 2 2 1 1 2 1 1 1 2 1
...
## $ age        : num  51 44 41 49 54 41 42 40 42 46 ...
## $ branch     : Factor w/ 3 levels "Mexico","Singapore",..: 1 1 1 1 1 1
1 1 1 1 ...
## $ norms      : Factor w/ 2 levels "Tight","Loose": 1 1 1 1 1 1 1 1 1 1
...
## $ hope       : num  24 28 29 19 30 29 25 21 23 28 ...
## $ neuroticism: num  30 38 27 32 28 32 37 31 32 33 ...
## $ trust      : num  8 13 21 12 15 17 17 9 13 12 ...
## $ brs        : num  17 21 17 13 20 24 15 14 20 18 ...
## $ openness   : num  24 17 25 31 26 22 26 16 21 29 ...
```

Answer 3A:

```
summary(my.data)
##          id              sex              age                          branch         n
orms
##  Min.   :  1.0   Female:266   Min.   :18.00   Mexico         :247   Tig
ht:419
##  1st Qu.:153.5   Male  :345   1st Qu.:34.00   Singapore      :172   Loo
se:192
##  Median :306.0                Median :39.00   The Netherlands:192
##  Mean   :306.0                Mean   :39.04
##  3rd Qu.:458.5                3rd Qu.:44.00
##  Max.   :611.0                Max.   :60.00
##       hope          neuroticism        trust             brs            openn
ess
##  Min.   :14.00   Min.   :10.0   Min.   : 4.00   Min.   : 6.0   Min.   :
6.00
##  1st Qu.:24.00   1st Qu.:21.0   1st Qu.:13.00   1st Qu.:13.0   1st Qu.:
18.00
##  Median :28.00   Median :27.0   Median :17.00   Median :17.0   Median :
22.00
##  Mean   :28.48   Mean   :26.1   Mean   :17.84   Mean   :17.1   Mean   :
22.64
##  3rd Qu.:33.00   3rd Qu.:31.0   3rd Qu.:22.00   3rd Qu.:22.0   3rd Qu.:
27.00
##  Max.   :46.00   Max.   :40.0   Max.   :28.00   Max.   :30.0   Max.   :
42.00
```

Answer 3B:

```
my.data %>%
  psych::describe()
##             vars   n   mean     sd median trimmed    mad min max range
skew
## id             1 611 306.00 176.52    306  306.00 226.84   1 611   610
0.00
## sex*           2 611   1.56   0.50      2    1.58   0.00   1   2     1
-0.26
## age            3 611  39.04   7.85     39   38.94   7.41  18  60    42
0.10
## branch*        4 611   1.91   0.84      2    1.89   1.48   1   3     2
0.17
## norms*         5 611   1.31   0.46      1    1.27   0.00   1   2     1
0.80
## hope           6 611  28.48   6.00     28   28.30   5.93  14  46    32
0.27
## neuroticism    7 611  26.10   6.44     27   26.31   7.41  10  40    30
-0.28
## trust          8 611  17.84   5.49     17   17.80   7.41   4  28    24
0.04
## brs            9 611  17.10   5.82     17   17.00   7.41   6  30    24
0.17
```

```
## openness      10 611  22.64   6.15     22   22.59   5.93   6  42    36
0.07
##              kurtosis   se
## id              -1.21 7.14
## sex*            -1.94 0.02
## age             -0.17 0.32
## branch*         -1.58 0.03
## norms*          -1.36 0.02
## hope            -0.48 0.24
## neuroticism     -0.59 0.26
## trust           -1.02 0.22
## brs             -0.86 0.24
## openness        -0.28 0.25
```

The function `describeBy()` provides summary statistics by the group selected within of the parenthesis of the function. For example, we might be interested in looking at the different scores on the `hope` and `brs` scales as a function of the `branch` of the corporation: Mexico, Singapore, and The Netherlands.

```
  psych::describeBy(hope + brs ~ branch, data = my.data)
##
##  Descriptive statistics by group
## branch: Mexico
##      vars   n  mean   sd median trimmed  mad min max range  skew kurtos
is   se
## hope    1 247 25.81 4.12     26   25.86 4.45  14  37    23 -0.11    -0.
23 0.26
## brs     2 247 15.98 2.93     16   15.97 2.97   9  24    15  0.08    -0.
39 0.19
## ------------------------------------------------------------
## branch: Singapore
##      vars   n  mean   sd median trimmed  mad min max range skew kurtosi
s   se
## hope    1 172 24.99 4.02     25   24.98 4.45  14  37    23 0.11     0.2
0 0.31
## brs     2 172 11.07 2.98     11   11.00 2.97   6  19    13 0.23    -0.5
3 0.23
## ------------------------------------------------------------
## branch: The Netherlands
##      vars   n  mean   sd median trimmed  mad min max range  skew kurtos
is   se
## hope    1 192 35.04 3.89     35   35.05 4.45  26  46    20 -0.01    -0.
10 0.28
## brs     2 192 23.93 2.79     24   23.92 2.97  15  30    15  0.00     0.
02 0.20
```

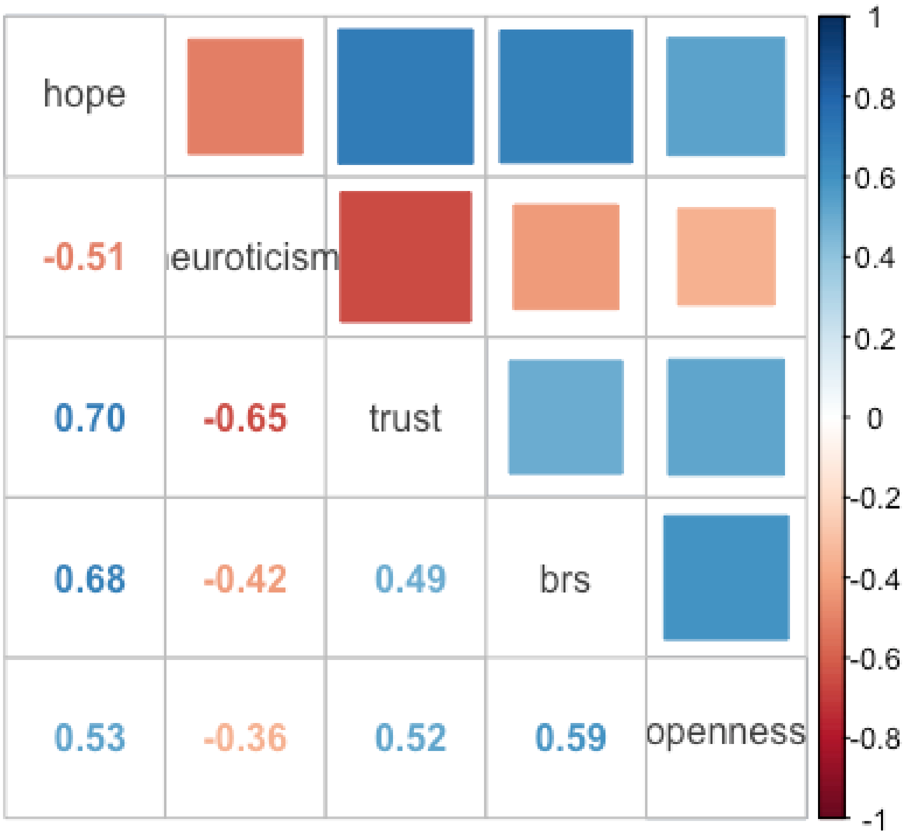
Answer 4A:

```
my.cor <- cor(na.omit(
  my.data[ , c('hope', 'neuroticism', 'trust',
               'brs', 'openness')]
  ))
```

```r
my.cor
##                   hope neuroticism      trust        brs   openness
## hope         1.0000000  -0.5065073  0.6996479  0.6751944  0.5307463
## neuroticism -0.5065073   1.0000000 -0.6526227 -0.4222283 -0.3583231
## trust        0.6996479  -0.6526227  1.0000000  0.4935643  0.5207221
## brs          0.6751944  -0.4222283  0.4935643  1.0000000  0.5935202
## openness     0.5307463  -0.3583231  0.5207221  0.5935202  1.0000000
```

Answer 4B:

```r
corrplot.mixed(my.cor, upper = 'square', tl.col = 'gray25')
```



Answer 4C:

```r
cor.test(my.data$openness, my.data$brs)
##
##  Pearson's product-moment correlation
##
## data:  my.data$openness and my.data$brs
## t = 18.199, df = 609, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.5396037 0.6425885
## sample estimates:
```

```
##       cor
## 0.5935202
```

We tested whether Openness to Experience scores were independent of Resilience scores, rejecting the null hypothesis of independence, $r = .59$, $95\% CI[.54, .64]$, $p < .001$, $R^2 = .35$. Overall, employees who reported being more creative, open-minded and open to change also reported being more resilient.

Answer 5A:

```
var.test(brs ~ sex, data = my.data)
##
##  F test to compare two variances
##
## data:  brs by sex
## F = 1.005, num df = 265, denom df = 344, p-value = 0.9614
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.8022976 1.2632712
## sample estimates:
## ratio of variances
##           1.005034

t.test(brs ~ sex, data = my.data, var.equal = T)
##
##  Two Sample t-test
##
## data:  brs by sex
## t = 6.5075, df = 609, p-value = 1.597e-10
## alternative hypothesis: true difference in means between group Female a
nd group Male is not equal to 0
## 95 percent confidence interval:
##  2.086691 3.890535
## sample estimates:
## mean in group Female   mean in group Male
##             18.78571             15.79710
```

Since we could not conclude that the variances of the two groups were different [$F(265, 344) = 1.01, p = .961$], we estimated a t-test assuming equal variances between the female and male resilience scores.

We rejected the null hypothesis of equal means between the two groups, finding that female employees ($M = 18.79$) were significantly more resilient on average than male employees ($M = 15.80$), $t(609) = 6.51, p < .001$.

```
resil.model1 <- lm(brs ~ sex, data = my.data)

summary(resil.model1)
##
## Call:
## lm(formula = brs ~ sex, data = my.data)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.7857  -4.7857  -0.7857   4.2143  14.2029
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  18.7857     0.3451  54.435  < 2e-16 ***
## sexMale      -2.9886     0.4593  -6.507  1.6e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.628 on 609 degrees of freedom
## Multiple R-squared:  0.06501,    Adjusted R-squared:  0.06348
## F-statistic: 42.35 on 1 and 609 DF,  p-value: 1.597e-10
```

The linear model estimated with the resilience scores regressed on the categorical predictor sex showed a significant effect of the predictor, $B = -2.99, SE = .50, p < .001$. The intercept estimate is the average resilience score of the reference group (i.e., female employees; $M = 18.79$), while the slope shows the predicted resilience scores when we move from the female to the male employee estimate ($18.79 - 2.99 = 15.80$). In sum, there is a significant decrease in the predicted resilience score for male employees compared to their female counterparts.

Answer 5B:

```
ggplot2::ggplot(data = my.data, aes(x = sex, y = brs)) +
  geom_boxplot() + stat_summary(fun.y = mean, geom = "point",
                                shape = 19, size = 4, color = "red3",
                                fill = "blue") +
  labs(title = 'Resilience of J2K4L8 Corp. employees as a function of Sex'
,
       x = "Sex", y = "Resilience")
```

Answer 5C:

```
my.data %>%
group_by(sex, branch) %>%
  summarise(
    mean = round(mean(brs, na.rm = TRUE), 2),
    sd = round(sd(brs, na.rm = TRUE), 2)
  )
## # A tibble: 6 × 4
## # Groups:   sex [2]
##   sex    branch           mean    sd
##   <fct>  <fct>           <dbl> <dbl>
## 1 Female Mexico           16.6  3.05
## 2 Female Singapore        12.6  2.59
## 3 Female The Netherlands  24.3  2.97
## 4 Male   Mexico           15.6  2.79
## 5 Male   Singapore        10.1  2.82
## 6 Male   The Netherlands  23.5  2.47
```

Although it appears that female employees tend to score higher on the resilience scale in each branch, the difference is 2.5 points in Mexico, but less than 1 point in the Netherlands.

The following code provides evidence for a main effect of sex [$F(1, 605) = 170.17, p < .001$], a main effect of branch [$F(2, 605) = 916.75, p < .001$], and an interaction effect [$F(2, 605) = 4.38, p < .001$].

```
resil.model2 <- aov(brs ~ sex * branch, data = my.data)
summary(resil.model2)
##                Df Sum Sq Mean Sq F value Pr(>F)
## sex             1   1342    1342  170.17 <2e-16 ***
## branch          2  14454    7227  916.75 <2e-16 ***
## sex:branch      2     69      35    4.38 0.0129 *
## Residuals     605   4769       8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Using the function `TukeyHSD()` (i.e., Tukey's Honest Significant Differences), we can estimate the differences in all 3 by 2 levels while controlling for Type I error across all pairwise comparisons.

As expected, we found that females were significantly more resilient than male overall. We also found that the Dutch branch was the most resilient of the three international offices. Finally, we found that all the simple effects were significant (all $ps < .001$), with the difference in resilience scores between females and males in the Mexico branch still marginally significant ($p = .047$), and the difference in resilience scores between female and male Dutch employees not significant ($p = .379$).

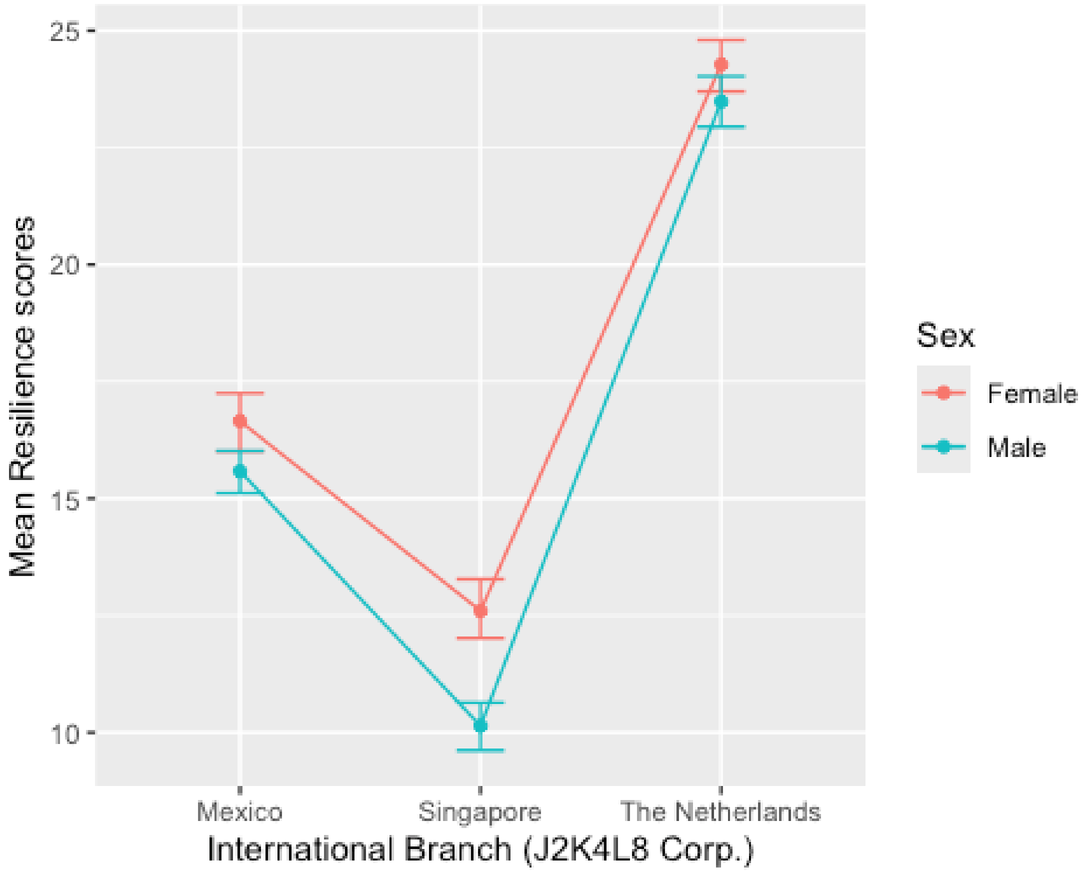
```
TukeyHSD(resil.model2)
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = brs ~ sex * branch, data = my.data)
##
## $sex
##                  diff      lwr       upr p adj
## Male-Female -2.988613 -3.43854 -2.538685     0
##
## $branch
##                                diff       lwr       upr p adj
## Singapore-Mexico          -4.930288 -5.585411 -4.275165     0
## The Netherlands-Mexico     7.364993  6.730303  7.999683     0
## The Netherlands-Singapore 12.295281 11.602710 12.987853     0
##
## $`sex:branch`
##                                                      diff       lwr        
upr
## Male:Mexico-Female:Mexico                      -1.0650771 -2.121502 -0.008
652425
## Female:Singapore-Female:Mexico                 -4.0521739 -5.352790 -2.751
557972
## Male:Singapore-Female:Mexico                   -6.5119870 -7.653263 -5.370
711287
## Female:The Netherlands-Female:Mexico            7.6230554  6.486631  8.759
480250
## Male:The Netherlands-Female:Mexico              6.8297538  5.614587  8.044
920619
## Female:Singapore-Male:Mexico                   -2.9870968 -4.173244 -1.800
```

```
949401
## Male:Singapore-Male:Mexico                       -5.4469099 -6.455797 -4.438
022347
## Female:The Netherlands-Male:Mexico                8.6881326  7.684736  9.691
529366
## Male:The Netherlands-Male:Mexico                  7.8948309  6.803055  8.986
606631
## Male:Singapore-Female:Singapore                  -2.4598131 -3.722122 -1.197
504619
## Female:The Netherlands-Female:Singapore          11.6752294 10.417305 12.933
153741
## Male:The Netherlands-Female:Singapore            10.8819277  9.552438 12.211
417394
## Female:The Netherlands-Male:Singapore            14.1350424 13.042668 15.227
416999
## Male:The Netherlands-Male:Singapore              13.3417408 12.167666 14.515
815426
## Male:The Netherlands-Female:The Netherlands -0.7933016 -1.962661  0.376
058148
##                                                      p adj
## Male:Mexico-Female:Mexico                        0.0468247
## Female:Singapore-Female:Mexico                   0.0000000
## Male:Singapore-Female:Mexico                     0.0000000
## Female:The Netherlands-Female:Mexico             0.0000000
## Male:The Netherlands-Female:Mexico               0.0000000
## Female:Singapore-Male:Mexico                     0.0000000
## Male:Singapore-Male:Mexico                       0.0000000
## Female:The Netherlands-Male:Mexico               0.0000000
## Male:The Netherlands-Male:Mexico                 0.0000000
## Male:Singapore-Female:Singapore                  0.0000006
## Female:The Netherlands-Female:Singapore          0.0000000
## Male:The Netherlands-Female:Singapore            0.0000000
## Female:The Netherlands-Male:Singapore            0.0000000
## Male:The Netherlands-Male:Singapore              0.0000000
## Male:The Netherlands-Female:The Netherlands 0.3790282
```

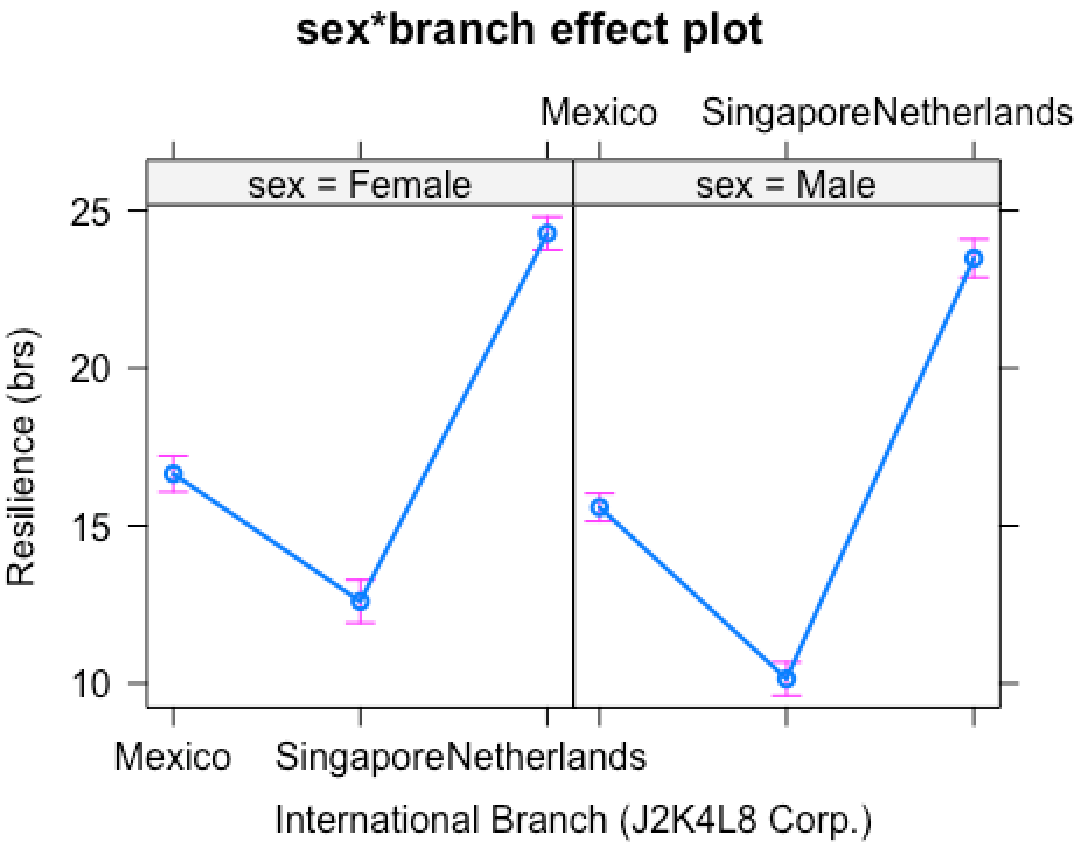
Answer 5D:

```
my.plot <- ggplot(my.data, aes(branch, brs, colour = sex))

my.plot + stat_summary(fun.y = mean, geom = "point") +
    stat_summary(fun.y = mean, geom = "line", aes(group= sex)) +
    stat_summary(fun.data = mean_cl_boot, geom = 'errorbar', width = 0.2)
+
    labs(x = 'International Branch (J2K4L8 Corp.)',
         y = 'Mean Resilience scores', colour = 'Sex')
```




```
plot(effects::allEffects(resil.model2))
```



Answer 6A:

```
hope.model1 <- lm(hope ~ norms + trust + neuroticism + brs + openness,
                  data = my.data)
summary(hope.model1)
##
## Call:
## lm(formula = hope ~ norms + trust + neuroticism + brs + openness,
##     data = my.data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.8083  -2.3229  -0.0326   2.4839  10.7468
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.88971    1.37643   8.638  < 2e-16 ***
## normsLoose   2.84169    0.89963   3.159  0.00166 **
## trust        0.44959    0.04326  10.393  < 2e-16 ***
## neuroticism  0.06249    0.03843   1.626  0.10441
## brs          0.31913    0.04860   6.567 1.11e-10 ***
## openness     0.02603    0.03138   0.829  0.40718
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.614 on 605 degrees of freedom
```

```
## Multiple R-squared:  0.6401, Adjusted R-squared:  0.6371
## F-statistic: 215.2 on 5 and 605 DF,  p-value: < 2.2e-16
```

Model 1 explains 64 per cent of the variation in hope scores ($R^2 = .64$), with the NEO-PI-R Openness to Experience and Neuroticism subscales providing no evidence of a substantial contribution to the model ($ps > .103$).

Answer 6B:

```
hope.model2 <- lm(hope ~ norms + trust + brs, data = my.data)
summary(hope.model2)
##
## Call:
## lm(formula = hope ~ norms + trust + brs, data = my.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.107  -2.319  -0.022   2.437  10.812
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.64777    0.99534  13.712  < 2e-16 ***
## normsLoose   1.96832    0.71163   2.766  0.00585 **
## trust        0.45035    0.04190  10.747  < 2e-16 ***
## brs          0.36144    0.04313   8.380 3.68e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.619 on 607 degrees of freedom
## Multiple R-squared:  0.6379, Adjusted R-squared:  0.6361
## F-statistic: 356.5 on 3 and 607 DF,  p-value: < 2.2e-16
```

Despite dropping the NEO-PI-R Openness to Experience and Neuroticism subscales from the model, Model 2 explains 64 per cent of the variation in hope scores ($R^2 = .64$) as did Model 1.

Holding the other predictors constant, an increase of 1.97 units in Hope scores is predicted for employees working in company branches with **loose cultures** (i.e., The Netherlands), $B = 1.97$, $SE = .71$, $p = .006$. Similarly, holding the other predictors constant, an increase of 0.45 units in Hope scores is predicted for each increase of one unit in organizational trust scores, $B = 0.45$, $SE = .04$, $p < .001$, and an increase of 0.36 units for each increment of one unit in resilience scores, $B = 0.36$, $SE = .04$, $p < .001$.

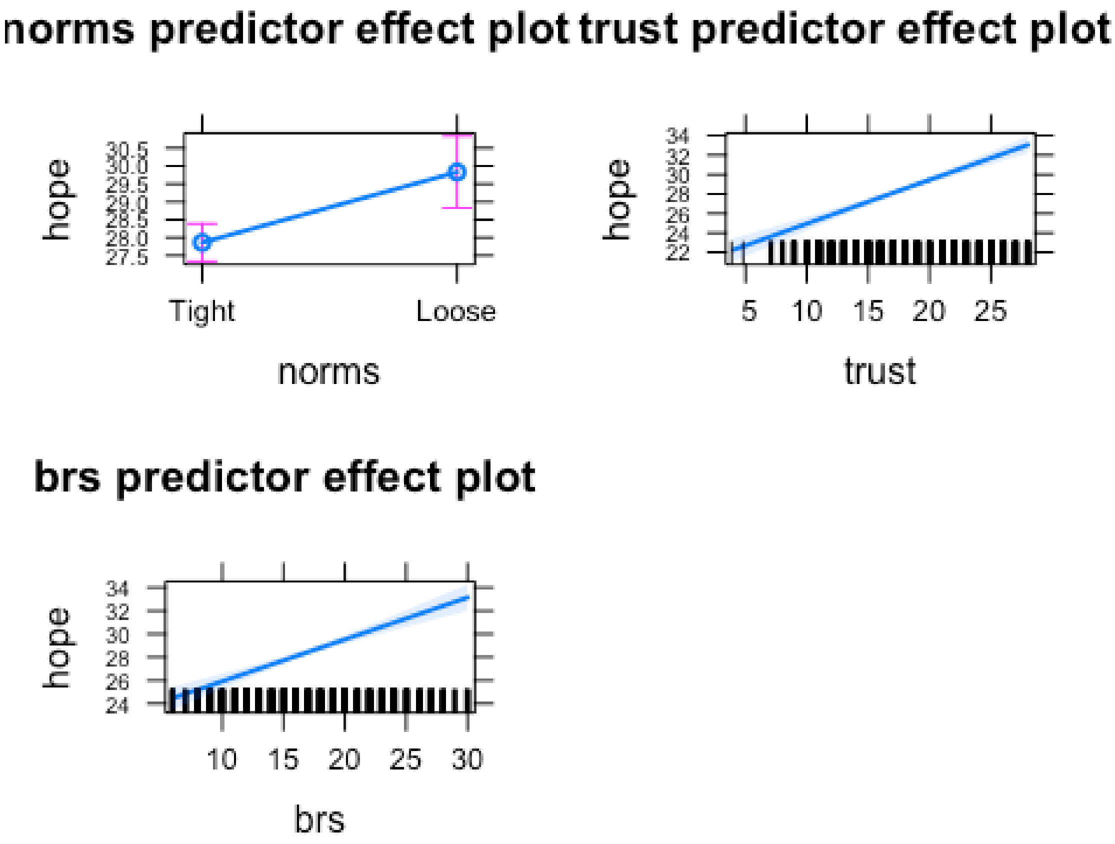
Answer 6C:

```
performance::check_heteroscedasticity(hope.model2)
## OK: Error variance appears to be homoscedastic (p = 0.242).
performance::check_outliers(hope.model2)
## OK: No outliers detected.
## - Based on the following method and threshold: cook (0.8).
## - For variable: (Whole model)
performance::check_collinearity(hope.model2)
```

```
## # Check for Multicollinearity
##
## Low Correlation
##
##   Term  VIF   VIF 95% CI Increased SE Tolerance Tolerance 95% CI
##  trust 2.47 [2.19, 2.81]         1.57      0.41     [0.36, 0.46]
##    brs 2.93 [2.59, 3.35]         1.71      0.34     [0.30, 0.39]
##
## Moderate Correlation
##
##   Term  VIF   VIF 95% CI Increased SE Tolerance Tolerance 95% CI
##  norms 5.09 [4.43, 5.88]         2.26      0.20     [0.17, 0.23]
performance::check_normality(hope.model2)
## OK: residuals appear as normally distributed (p = 0.891).
```

Answer 6D:

```
plot(effects::predictorEffects(hope.model2,
                      predictors = ~ norms + trust + brs))
```



The predictor effect plots show that the more organizational trust employees have in the corporation's decisions, the more hope the employees will have in these restructuring business plans.

Similarly, the more resilient that the employees are, the more hope that they will report having.

Finally, branches in **loose cultures** (e.g., The Netherlands) have weak social norms that foster an organizational culture that is more dynamic, creative, open and resilient when in times of crisis and restructuring. On the other hand, branches located in countries with **tight cultures** (e.g., Singapore, Mexico) tend to be less tolerant, with a higher degree of social and self-control, and a tendency to maintain the status quo.