Final Project

Lendi Nicole Joy

5/3/2021

### Load the needed libraries.

library(tidyverse)  
library(psych)  
library(GPArotation)  
library(flextable)

### Load the dataset.

Motivation <- read\_csv(here::here("data", "Activities\_and\_Mood.csv"))

### Clean the data.

Next, clean up the data using variable Q166\_7, which indicates whether the survey was completed.

Motivation <-   
 Motivation %>%   
 drop\_na("Q166\_7")

There were 149 cases removed.

Now let’s select only the variables needed for the EFA (remove V4 and V5, which are attention check items).

Motivation\_EFA <-   
 Motivation %>%   
 select(VFI.U1:Int\_4,   
 -c(V4, V5))

##### Reverse code items.

After selecting the appropriate variables, I will reverse code the items so that higher scores indicate more positive attitudes. A few items are reverse coded, so exclude those variables from recoding.

Motivation\_EFA<-   
 8 - Motivation\_EFA[, -c(31, 33:35, 52, 57)]

### Save the dataset.

Save the resulting dataset.

write.csv(Motivation\_EFA,  
 here::here("data", "Motivation\_EFA.csv"))

### Run the EFA.

The original hypothesis is that there will be 7 belief factors, 3 factors indicating attitudes, subjective norms and perceived behavior control, then 1 factor to indicate intention or motivation to volunteer.

I start with extracting these 11 factors since this is the original hypothesis.

EFAresult1 = factanal(~ .,   
 data = Motivation\_EFA,   
 factors = 11,   
 fm = "pa",   
 rotation = "oblimin")  
EFAresult1

##   
## Call:  
## factanal(x = ~., factors = 11, data = Motivation\_EFA, rotation = "oblimin", fm = "pa")  
##   
## Uniquenesses:  
## VFI.U1 VFI.U2 VFI.U3 VFI.U4 VFI.U5 VFI.V1 VFI.V2 VFI.V3 VFI.V4 VFI.V5   
## 0.464 0.427 0.382 0.574 0.405 0.473 0.685 0.307 0.413 0.407   
## VFI.E1 VFI.E2 VFI.E3 VFI.E4 VFI.E5 VFI.P1 VFI.P2 VFI.P3 VFI.P4 VFI.P5   
## 0.530 0.397 0.356 0.246 0.515 0.447 0.520 0.662 0.315 0.261   
## VFI.C1 VFI.C2 VFI.C3 VFI.C4 VFI.C5 VFI.NB1 VFI.NB2 VFI.NB3 VFI.NB4 VFI.NB5   
## 0.535 0.311 0.502 0.284 0.404 0.545 0.288 0.242 0.413 0.330   
## Ctrl\_2 Att\_1 Att\_2 Att\_3 Att\_4 Att\_5 Att\_6 Att\_7 Att\_8 Att\_9   
## 0.660 0.221 0.251 0.246 0.174 0.245 0.264 0.235 0.284 0.266   
## SN\_1 SN\_2 SN\_3 SN\_4 SN\_5 PBC\_1 PBC\_2 PBC\_4 PBC\_5 Int\_1   
## 0.235 0.242 0.259 0.718 0.385 0.413 0.595 0.558 0.305 0.115   
## Int\_2 Int\_4   
## 0.069 0.115   
##   
## Loadings:  
## Factor1 Factor2 Factor3 Factor4 Factor5 Factor6 Factor7 Factor8 Factor9  
## VFI.U1 0.144 0.301 0.457   
## VFI.U2 0.136 0.313 0.370   
## VFI.U3 -0.113 0.180 0.195 0.122 0.159 0.474   
## VFI.U4 0.143 0.151 0.355   
## VFI.U5 0.141 0.152 0.531   
## VFI.V1 0.104 0.647   
## VFI.V2 0.203 -0.127 0.402 0.102   
## VFI.V3 0.107 0.713   
## VFI.V4 0.124 0.110 0.631   
## VFI.V5 0.112 0.120 0.217 0.491   
## VFI.E1 0.576   
## VFI.E2 0.102 0.569   
## VFI.E3 0.631 0.113   
## VFI.E4 0.745   
## VFI.E5 0.231 0.150 -0.157 0.348   
## VFI.P1 0.179 0.110 -0.150 0.121 0.189 0.154   
## VFI.P2 -0.120 0.336   
## VFI.P3 -0.113 0.198 0.394 0.172 -0.115   
## VFI.P4 0.183   
## VFI.P5 0.115 0.232   
## VFI.C1 0.115 0.671   
## VFI.C2 0.108 0.775   
## VFI.C3 0.481 0.263   
## VFI.C4 0.154 0.643 0.143 -0.126   
## VFI.C5 -0.104 0.712 0.190   
## VFI.NB1 0.227 0.485 -0.138 0.142   
## VFI.NB2 0.837   
## VFI.NB3 0.214 0.705   
## VFI.NB4 0.402 0.393   
## VFI.NB5 0.764   
## Ctrl\_2 -0.105 0.184 0.149 0.162 0.240 0.215   
## Att\_1 0.612 0.143   
## Att\_2 0.772   
## Att\_3 0.858   
## Att\_4 0.842   
## Att\_5 0.617 0.136   
## Att\_6 0.570 0.101 0.153   
## Att\_7 0.842   
## Att\_8 0.592 0.178   
## Att\_9 0.667 0.104 0.168   
## SN\_1 0.763 0.100   
## SN\_2 0.767   
## SN\_3 0.765 0.119   
## SN\_4 0.259 0.206   
## SN\_5 0.105 0.480 0.222   
## PBC\_1 0.767   
## PBC\_2 0.147 0.230 0.179 -0.242 0.330 0.135   
## PBC\_4 0.132 0.118 0.401 0.217   
## PBC\_5 0.853   
## Int\_1 0.938   
## Int\_2 0.977   
## Int\_4 0.902   
## Factor10 Factor11  
## VFI.U1   
## VFI.U2   
## VFI.U3   
## VFI.U4   
## VFI.U5 0.142   
## VFI.V1   
## VFI.V2   
## VFI.V3   
## VFI.V4   
## VFI.V5 0.221   
## VFI.E1 -0.129   
## VFI.E2 0.167   
## VFI.E3 0.164   
## VFI.E4 0.136   
## VFI.E5 0.235 -0.169   
## VFI.P1 0.360 -0.112   
## VFI.P2 0.335   
## VFI.P3 0.132   
## VFI.P4 0.631   
## VFI.P5 0.648   
## VFI.C1   
## VFI.C2 -0.119   
## VFI.C3 -0.209   
## VFI.C4 0.258 0.152   
## VFI.C5   
## VFI.NB1   
## VFI.NB2   
## VFI.NB3   
## VFI.NB4 -0.138   
## VFI.NB5 0.110   
## Ctrl\_2   
## Att\_1 -0.101 0.247   
## Att\_2   
## Att\_3 0.137   
## Att\_4 -0.101   
## Att\_5 0.202   
## Att\_6 -0.122 0.246   
## Att\_7 -0.142   
## Att\_8 0.199   
## Att\_9 0.167   
## SN\_1   
## SN\_2 0.100   
## SN\_3   
## SN\_4 0.178   
## SN\_5 0.219   
## PBC\_1   
## PBC\_2   
## PBC\_4 0.196   
## PBC\_5   
## Int\_1   
## Int\_2   
## Int\_4   
##   
## Factor1 Factor2 Factor3 Factor4 Factor5 Factor6 Factor7 Factor8  
## SS loadings 4.866 2.987 2.515 2.510 2.408 2.262 2.050 1.753  
## Proportion Var 0.094 0.057 0.048 0.048 0.046 0.043 0.039 0.034  
## Cumulative Var 0.094 0.151 0.199 0.248 0.294 0.337 0.377 0.411  
## Factor9 Factor10 Factor11  
## SS loadings 1.719 1.445 0.650  
## Proportion Var 0.033 0.028 0.012  
## Cumulative Var 0.444 0.471 0.484  
##   
## Factor Correlations:  
## Factor1 Factor2 Factor3 Factor4 Factor5 Factor6 Factor7 Factor8  
## Factor1 1.000 -0.3378 -0.1763 -0.1678 0.535 -0.2764 0.5068 -0.236  
## Factor2 -0.338 1.0000 0.1983 0.3481 -0.190 0.1636 -0.2436 0.450  
## Factor3 -0.176 0.1983 1.0000 0.1884 -0.321 0.1137 -0.2241 0.153  
## Factor4 -0.168 0.3481 0.1884 1.0000 -0.210 0.0127 -0.1256 0.204  
## Factor5 0.535 -0.1904 -0.3205 -0.2097 1.000 -0.2510 0.3208 -0.141  
## Factor6 -0.276 0.1636 0.1137 0.0127 -0.251 1.0000 -0.0915 0.023  
## Factor7 0.507 -0.2436 -0.2241 -0.1256 0.321 -0.0915 1.0000 -0.200  
## Factor8 -0.236 0.4501 0.1526 0.2043 -0.141 0.0230 -0.1997 1.000  
## Factor9 -0.337 0.2103 0.6507 0.1260 -0.452 0.1695 -0.3042 0.152  
## Factor10 -0.384 0.2947 0.1353 0.3842 -0.280 0.1978 -0.3794 0.267  
## Factor11 -0.240 0.0312 0.0452 0.0789 -0.267 0.0581 -0.0791 -0.115  
## Factor9 Factor10 Factor11  
## Factor1 -0.3368 -0.3844 -0.2398  
## Factor2 0.2103 0.2947 0.0312  
## Factor3 0.6507 0.1353 0.0452  
## Factor4 0.1260 0.3842 0.0789  
## Factor5 -0.4520 -0.2797 -0.2675  
## Factor6 0.1695 0.1978 0.0581  
## Factor7 -0.3042 -0.3794 -0.0791  
## Factor8 0.1516 0.2673 -0.1154  
## Factor9 1.0000 0.2249 0.0516  
## Factor10 0.2249 1.0000 0.0564  
## Factor11 0.0516 0.0564 1.0000  
##   
## Test of the hypothesis that 11 factors are sufficient.  
## The chi square statistic is 1271.76 on 809 degrees of freedom.  
## The p-value is 3.27e-23

##### Determine number of factors.

We look at the sum of squared loadings (SS loadings), which are the eigenvalues. The Kaiser Rule suggests that eigenvalues greater than 1 indicate meaningful factors. This rule, would suggest that there are *10 meaningful* factors.

We can look at the item loadings and see that even though ten factors have eigenvalues greater than 1, the items do not load very highly on some of the factors.

###### Use another method to determine number of factors.

Next, I will run a parallel analysis and examine the scree plot as another way of determining the number of factors to extract.

set.seed(13115)  
PA = fa.parallel(Motivation\_EFA,   
 fa = "fa",  
 quant = .95)

## Parallel analysis suggests that the number of factors = 8 and the number of components = NA

Instead of displaying the scree plot that is created, I will make a nicer plot of the parallel analysis.

First, create a data frame with the observed values.

obs = data.frame(PA$fa.values)  
obs$type = c('Observed Data')  
obs$num = c(row.names(obs))  
obs$num = as.numeric(obs$num)  
colnames(obs) =   
 c('eigenvalue',   
 'type',   
 'num')

Next, calculate and save the 95% quantiles for the eigenvalues for the observed data.

percent = apply(PA$values,  
 2,  
 function(x)   
 quantile(x,.95))  
min = as.numeric(nrow(obs))  
min = (4\*min) - (min-1)  
max = as.numeric(nrow(obs))  
max = 4\*max  
percentile = percent[min:max]

Now create a data frame for the simulated eigenvalues.

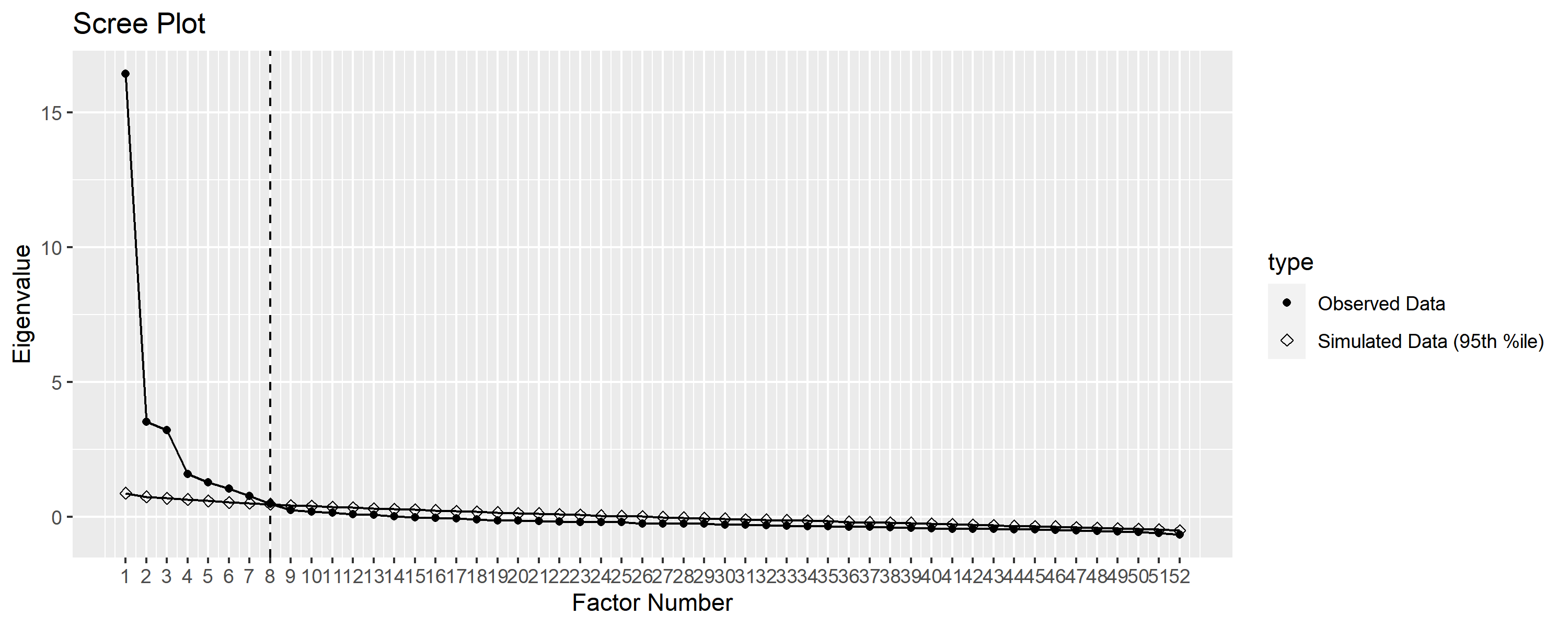
sim = data.frame(percentile)  
sim$type = c('Simulated Data (95th %ile)')  
sim$num = c(row.names(obs))  
sim$num = as.numeric(sim$num)  
colnames(sim) =   
 c('eigenvalue',   
 'type',   
 'num')

After creating the appropriate data frames, I will put them together into one data frame.

PAdata = rbind(obs,sim)

Create the plot.

ggplot(PAdata,   
 aes(x = num,   
 y = eigenvalue,   
 shape = type)) +  
geom\_line()+  
geom\_point(size = 1.5)+  
scale\_y\_continuous(name = 'Eigenvalue')+  
scale\_x\_continuous(name = 'Factor Number',   
 breaks = min(PAdata$num):max(PAdata$num))+  
scale\_shape\_manual(values =   
 c(16,5)) +  
geom\_vline(xintercept = PA$nfact, linetype = 'dashed') +  
 ggtitle("Scree Plot")



### Rerun EFA.

Now I will rerun the EFA with only 8 factors using the “fa” function from the psych package, but I will not print the results just yet.

EFAresult2 = fa(Motivation\_EFA,   
 nfactors = 8,   
 fm = "pa",   
 rotate = "oblimin")

Use the results from the EFA to create a table of the factor loadings.

table <- function(x, cut)   
 {loadings <- fa.sort(x)$loadings %>% round(3)  
 loadings[loadings < cut] <- ""  
 tableinfo <- cbind(x$communalities,   
 x$complexity) %>%  
 as.data.frame() %>%  
 rename("Communality" = V1,  
 "Complexity" = V2) %>%  
 rownames\_to\_column("Item")  
 loadings %>%  
 unclass() %>%  
 as.data.frame() %>%  
 rownames\_to\_column("Item") %>%  
 left\_join(tableinfo) %>%  
 mutate(across(where(is.numeric), round, 3))  
 }   
   
fa\_table <- flextable(table(EFAresult2, .30))

EFA Factor Loadings

| Item | PA1 | PA3 | PA2 | PA4 | PA7 | PA6 | PA5 | PA8 | Communality | Complexity |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Att\_3 | 0.898 |  |  |  |  |  |  |  | 30.786 | 1.060 |
| Att\_4 | 0.85 |  |  |  |  |  |  |  | 30.786 | 1.026 |
| Att\_7 | 0.822 |  |  |  |  |  |  |  | 30.786 | 1.073 |
| Att\_2 | 0.774 |  |  |  |  |  |  |  | 30.786 | 1.107 |
| Att\_9 | 0.766 |  |  |  |  |  |  |  | 30.786 | 1.053 |
| Att\_1 | 0.732 |  |  |  |  |  |  |  | 30.786 | 1.154 |
| Att\_5 | 0.715 |  |  |  |  |  |  |  | 30.786 | 1.171 |
| Att\_8 | 0.7 |  |  |  |  |  |  |  | 30.786 | 1.237 |
| Att\_6 | 0.688 |  |  |  |  |  |  |  | 30.786 | 1.346 |
| VFI.NB3 |  | 0.87 |  |  |  |  |  |  | 30.786 | 1.020 |
| VFI.NB2 |  | 0.774 |  |  |  |  |  |  | 30.786 | 1.079 |
| SN\_2 |  | 0.748 |  |  |  |  |  |  | 30.786 | 1.048 |
| VFI.NB4 |  | 0.739 |  |  |  |  |  |  | 30.786 | 1.069 |
| VFI.NB5 |  | 0.731 |  |  |  |  |  |  | 30.786 | 1.126 |
| SN\_1 |  | 0.724 |  |  |  |  |  |  | 30.786 | 1.161 |
| SN\_3 |  | 0.699 |  |  |  |  |  |  | 30.786 | 1.112 |
| VFI.NB1 |  | 0.693 |  |  |  |  |  |  | 30.786 | 1.148 |
| SN\_5 |  | 0.611 |  |  |  |  |  |  | 30.786 | 1.516 |
| SN\_4 |  |  |  |  |  |  |  |  | 30.786 | 3.654 |
| VFI.E4 |  |  | 0.83 |  |  |  |  |  | 30.786 | 1.107 |
| VFI.E3 |  |  | 0.713 |  |  |  |  |  | 30.786 | 1.096 |
| VFI.E2 |  |  | 0.67 |  |  |  |  |  | 30.786 | 1.119 |
| VFI.P5 |  |  | 0.635 |  |  |  |  | 0.311 | 30.786 | 1.651 |
| VFI.P4 |  |  | 0.598 |  |  |  |  | 0.301 | 30.786 | 1.630 |
| VFI.P2 |  |  | 0.583 |  |  |  |  |  | 30.786 | 1.281 |
| VFI.P3 |  |  | 0.504 |  |  |  |  |  | 30.786 | 1.503 |
| VFI.E1 |  |  | 0.483 |  |  |  |  |  | 30.786 | 1.698 |
| VFI.P1 |  |  | 0.367 |  |  |  |  |  | 30.786 | 4.088 |
| VFI.C2 |  |  |  | 0.767 |  |  |  |  | 30.786 | 1.024 |
| VFI.C5 |  |  |  | 0.718 |  |  |  |  | 30.786 | 1.348 |
| VFI.C1 |  |  |  | 0.657 |  |  |  |  | 30.786 | 1.081 |
| VFI.C4 |  |  |  | 0.629 |  |  |  |  | 30.786 | 1.344 |
| VFI.C3 |  |  |  | 0.538 |  |  |  |  | 30.786 | 1.567 |
| VFI.U3 |  |  |  | 0.395 |  | 0.333 |  |  | 30.786 | 2.970 |
| VFI.U5 |  |  |  | 0.374 |  |  |  | 0.303 | 30.786 | 3.136 |
| VFI.E5 |  |  |  | 0.367 |  |  |  | 0.355 | 30.786 | 3.129 |
| Int\_2 |  |  |  |  | 0.983 |  |  |  | 30.786 | 1.003 |
| Int\_1 |  |  |  |  | 0.918 |  |  |  | 30.786 | 1.004 |
| Int\_4 |  |  |  |  | 0.854 |  |  |  | 30.786 | 1.023 |
| VFI.V1 |  |  |  |  |  | 0.634 |  |  | 30.786 | 1.282 |
| VFI.V3 |  |  |  |  |  | 0.633 |  |  | 30.786 | 1.280 |
| VFI.V4 |  |  |  |  |  | 0.604 |  |  | 30.786 | 1.387 |
| VFI.U1 |  |  |  |  |  | 0.481 |  |  | 30.786 | 2.410 |
| VFI.V2 |  |  |  |  |  | 0.452 |  |  | 30.786 | 1.905 |
| VFI.U2 |  |  |  |  |  | 0.441 |  |  | 30.786 | 2.188 |
| VFI.V5 |  |  |  |  |  | 0.402 |  |  | 30.786 | 2.688 |
| VFI.U4 |  |  |  |  |  |  |  |  | 30.786 | 4.184 |
| PBC\_5 |  |  |  |  |  |  | 0.754 |  | 30.786 | 1.090 |
| PBC\_1 |  |  |  |  |  |  | 0.729 |  | 30.786 | 1.037 |
| PBC\_4 |  |  |  |  |  |  | 0.503 |  | 30.786 | 1.641 |
| PBC\_2 |  |  |  |  |  |  | 0.447 |  | 30.786 | 2.604 |
| Ctrl\_2 |  |  |  |  |  |  | 0.317 |  | 30.786 | 3.860 |