Sample size solutions for $N = 1$ intensive longitudinal designs

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Settings things up

Before we proceed, we need to ensure we have several packages installed and loaded into our `R` session. For the scripts below, we will use the following packages:

- `data.table`

- psych
- tidyverse
- MASS

Which we can install in one go as follows:

```r
# Prepare the package list.
packages = c("data.table", "psych", "tidyverse", "MASS")

# Install packages.
install.packages(packages)
```

> **Tip**
>
> You may consider first checking if the packages are installed before actually installing them. Nevertheless, the code above will not reinstall packages that are already installed and up-to-date.

Now that we have all packages installed, we continue by loading them.

```r
# To create lagged outcome variables.
library(data.table)

# To compute descriptive statistics.
library(psych)

# A useful package.
library(tidyverse)

# Handy functions for data analysis.
library(MASS)

# Set a seed for reproducibility.
set.seed(123)
```

Description

In this tutorial, we use data from Heininga et al. (2019). In this study, the authors applied the ESM methodology to study emotion dynamics in people with *Major Depressive Disorder* (MDD). The study consist of an ESM testing period of seven days in which participants had to fill out questions about mood and social context on their daily lives ten times a day (i.e., 70 measurement occasions). The data set contains 38 participants diagnosed with MDD and 40 control subjects. Participants filled out the ESM questionnaires in a stratified random interval scheme between 9:30 AM and 9:30 PM.

First, we are going to load the data set:

```
# Load the data set.
load(file = "assets/data/clinical-dataset.RData")
```

Tip

Make sure you load the data from the location where you downloaded it. If your analysis script (i.e., the `.R` file) and the dataset are in the same location, than you can simply load the data as follows:

```
load(file = "clinical-dataset.RData")
```

Data exploration

In this section we will explore briefly the variables in the data set.

Data structure

Now, that we have the data ready, we can start by exploring it to get a better understanding of the variable measured.

```
# Select the first participant diagnosed with MDD.
i.ID <- unique(data$PID[data$MDD == 1])[1]

# Select data from participant with person identification number `101`.
data <- data[data$PID == 101, ]
```

Note

From now on we will work with data from participant `101` only. In other words, `data` is now a subset of the original data set, containing only the responses from participant `101`.

```
# Find the dimensions.
dim(data)
```

```
[1] 70  8
```

```r
# Find the structure.
str(data)
```

```
'data.frame':   70 obs. of  8 variables:
 $ PID      : num  101 101 101 101 101 101 101 101 101 101 ...
 $ day      : num  1 1 1 1 1 1 1 1 1 1 ...
 $ daybeep  : num  1 2 3 4 5 6 7 8 9 10 ...
 $ PA       : num  NA 27.3 49.7 43 43 ...
 $ NA.      : num  NA 30.4 23.8 24.2 32.8 19.6 18.4 21.2 23 21.8 ...
 $ anhedonia: num  NA 26 25 25 50 21 42 30 22 30 ...
 $ MDD      : num  1 1 1 1 1 1 1 1 1 1 ...
 $ QIDS     : num  12 12 12 12 12 12 12 12 12 12 ...
```

```r
# See the first 6 rows.
head(data)
```

```
  PID day daybeep       PA  NA. anhedonia MDD QIDS
1 101   1       1       NA   NA        NA   1   12
2 101   1       2 27.33333 30.4        26   1   12
3 101   1       3 49.66667 23.8        25   1   12
4 101   1       4 43.00000 24.2        25   1   12
5 101   1       5 43.00000 32.8        50   1   12
6 101   1       6 18.00000 19.6        21   1   12
```

```r
# See the last 6 rows.
tail(data)
```

```
   PID day daybeep       PA  NA. anhedonia MDD QIDS
65 101   7       5 24.33333 31.8        52   1   12
66 101   7       6 28.66667 20.6        53   1   12
67 101   7       7 23.33333 23.8        51   1   12
68 101   7       8 33.66667 36.2        46   1   12
69 101   7       9 41.66667 21.0        29   1   12
70 101   7      10 34.00000 18.4        47   1   12
```

```r
# Find the column names.
names(data)
```

```
[1] "PID"       "day"       "daybeep"   "PA"        "NA."       "anhedonia"
[7] "MDD"       "QIDS"
```

```r
# Summary of the data.
summary(data)
```

```
      PID           day          daybeep            PA               NA.       
 Min.   :101   Min.   :1   Min.   : 1.0   Min.   :14.67   Min.   :14.40  
 1st Qu.:101   1st Qu.:2   1st Qu.: 3.0   1st Qu.:26.08   1st Qu.:21.40  
 Median :101   Median :4   Median : 5.5   Median :33.33   Median :25.90  
 Mean   :101   Mean   :4   Mean   : 5.5   Mean   :33.51   Mean   :29.62  
 3rd Qu.:101   3rd Qu.:6   3rd Qu.: 8.0   3rd Qu.:41.67   3rd Qu.:36.25  
 Max.   :101   Max.   :7   Max.   :10.0   Max.   :57.33   Max.   :65.60  
                                          NA's   :6       NA's   :6      
   anhedonia          MDD          QIDS   
 Min.   :14.00   Min.   :1   Min.   :12  
 1st Qu.:24.75   1st Qu.:1   1st Qu.:12  
 Median :41.50   Median :1   Median :12  
 Mean   :39.34   Mean   :1   Mean   :12  
 3rd Qu.:52.00   3rd Qu.:1   3rd Qu.:12  
 Max.   :83.00   Max.   :1   Max.   :12  
 NA's   :6                               
```

```r
# Number of participants.
length(unique(data$PID))
```

```
[1] 1
```

The data set contains the following variables:

- `PID` that denotes the individual identification number
- `day` is a variable that ranges from 1 to 7 and identifies the day of ESM testing
- `daybeep` is a variable that ranges from 1 to 10 and identifies the number of the prompt or beep within a day
- `PA` is the *Positive Affect* computed as the mean of items:
    - *How happy do you feel at the moment?*

  - *How relaxed do you feel at the moment?*
  - *How euphoric do you feel at the moment?*
- `NA.` is the *Negative Affect* computed as the mean of items:
  - *How depressed do you feel at the moment?*
  - *How stressed do you feel at the moment?*
  - *How anxious do you feel at the moment?*
  - *How angry do you feel at the moment?*
  - *How restless do you feel at the moment?*
- `anhedonia` corresponds to the ESM item:
  - *To what degree do you find it difficult to experience pleasure in activities at the moment?*
- `MDD` is a dummy variable equal to one when the individual has been diagnosed with MDD and 0 otherwise
- `QIDS` denotes the sum of the items of the *Quick Inventory of Depressive Symptomatology* (QIDS; Rush et al., 2003). QIDS was measured before the ESM testing period.

> **Note**
>
> Time-varying variables (PA, NA, and anhedonia) have been lagged within days to account for the night breaks.

Descriptive statistics and visualizations

We first obtain some descriptive statistics including number of observations per day, and compliance.

```r
# Get the number of assessment per day.
table(data$PID)
```

```
101
 70
```

```r
# Compute a binary variable indicating if a participant answered a beep. We take
# the ESM item PA as reference because in this ESM design participants were not
# allowed to skip items.
data$Compliance <- ifelse(is.na(data$PA) == FALSE, 1, 0)

# Mean, median of the compliance for the participant PID=101
```

```r
describe(data$Compliance)
```

```
   vars  n mean   sd median trimmed mad min max range skew kurtosis   se
X1    1 70 0.91 0.28      1       1   0   0   1     1 -2.9     6.48 0.03
```

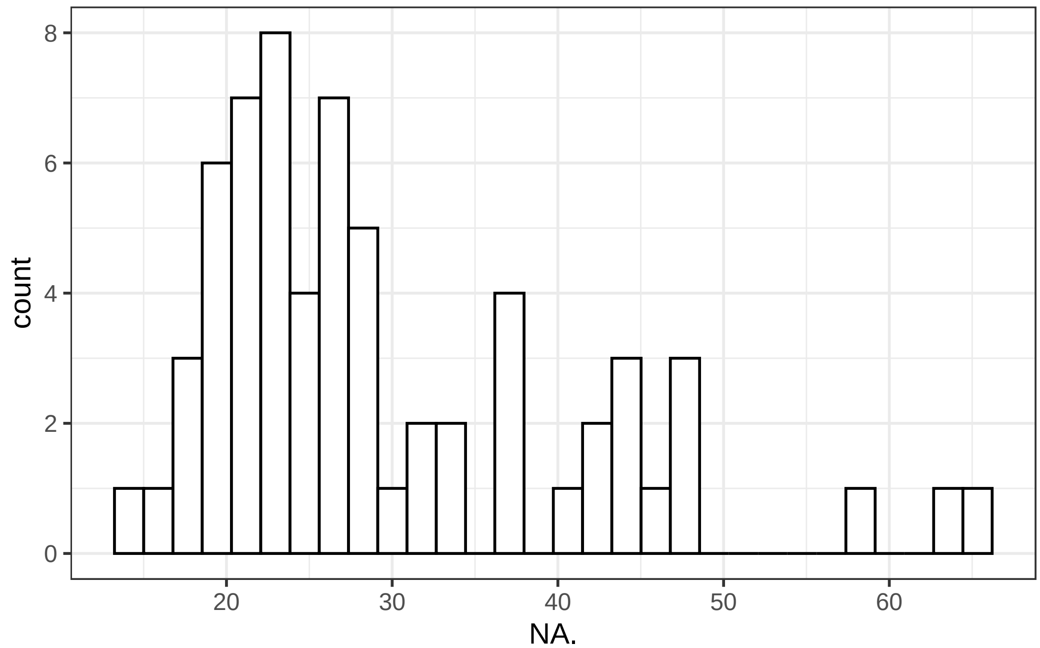
Next, we can obtain visualizations and statistics of the distribution of the person-level or time-invariant variables variables.

```r
# We create a data set that will aggregate the data by the time invariant
# variables, i.e., the MDD diagnosis and QIDS depression score.
dt.person = aggregate(
    cbind(data$MDD, data$QIDS),
    by = list(data$PID),
    mean,
    na.rm = TRUE
)

# Add column names to the aggregated data set.
colnames(dt.person) = c("Group.1", "MDD", "QIDS")

# Print the aggregated data set.
dt.person
```

```
  Group.1 MDD QIDS
1     101   1   12
```

We now focus on time-varying variables NA, PA, and anhedonia and we obtain visualization and descriptive statistics

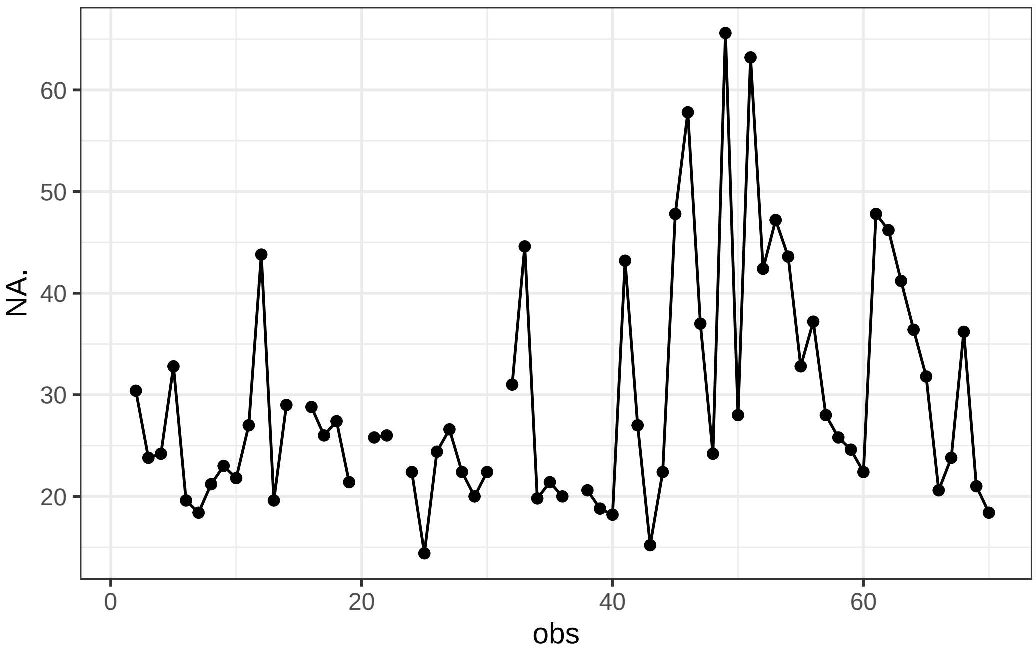
```r
# Histogram for the time-varying variable negative affect (NA.).
ggplot(data, aes(NA.)) +
    geom_histogram(
        color = "black",
        fill = "white",
        bins = 30
    ) +
    theme_bw()
```



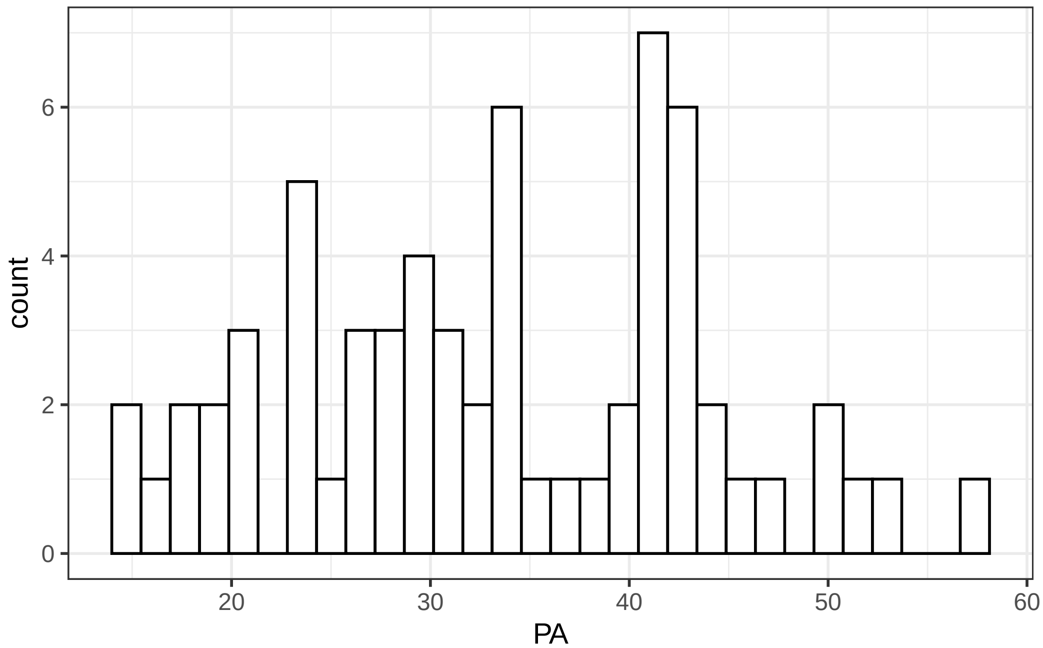

```r
# Descriptive statistics for NA.
describe(data$NA.)
```

```
   vars  n  mean    sd median trimmed  mad  min  max range skew kurtosis   se
X1    1 64 29.62 11.47   25.9   28.13 7.86 14.4 65.6  51.2 1.25     1.01 1.43
```

```r
# Create obs order variable.
data$obs = 1:nrow(data)

# Plot the trajectories of the time-varying variable NA by person.
data %>%
    ggplot(aes(x = obs, y = NA.)) +
    geom_point() +
    geom_line() +
    theme_bw()
```



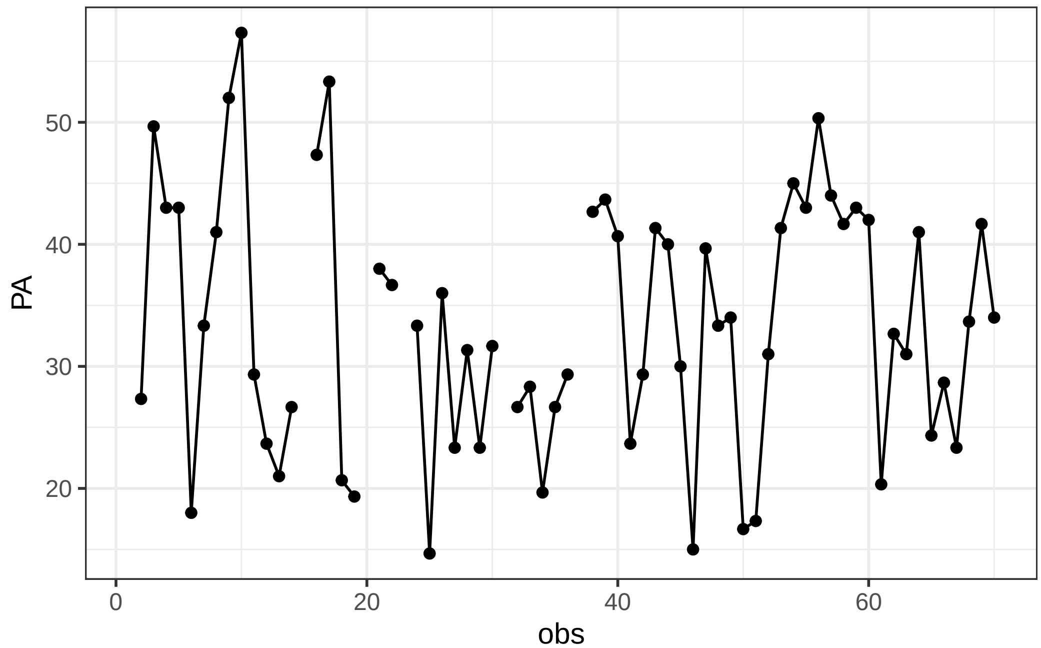

```r
# Histogram for the time-varying variable negative affect (PA).
ggplot(data, aes(PA)) +
    geom_histogram(
        color = "black",
        fill = "white",
        bins = 30
    ) +
    theme_bw()
```



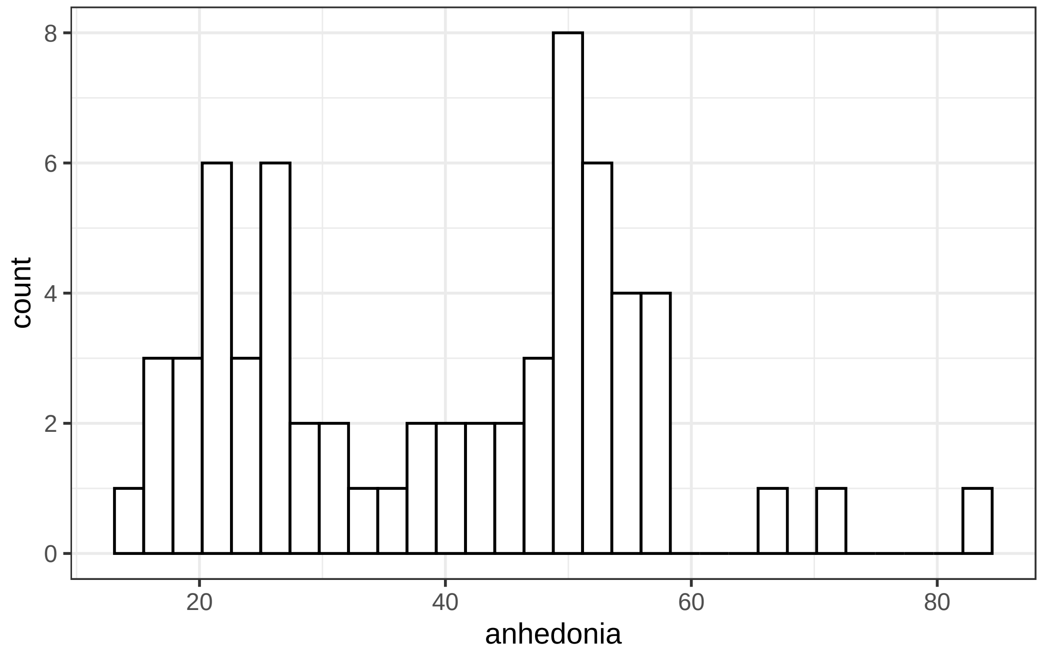

```
# Descriptive statistics for PA.
describe(data$PA)
```

```
   vars  n  mean    sd median trimmed   mad   min   max range skew kurtosis
X1    1 64 33.51 10.32  33.33   33.33 12.35 14.67 57.33 42.67 0.09    -0.84
     se
X1 1.29
```

```
# Plot the trajectories of the time-varying variable PA by person.
data %>%
    ggplot(aes(x = obs, y = PA)) +
    geom_point() +
    geom_line() +
    theme_bw()
```



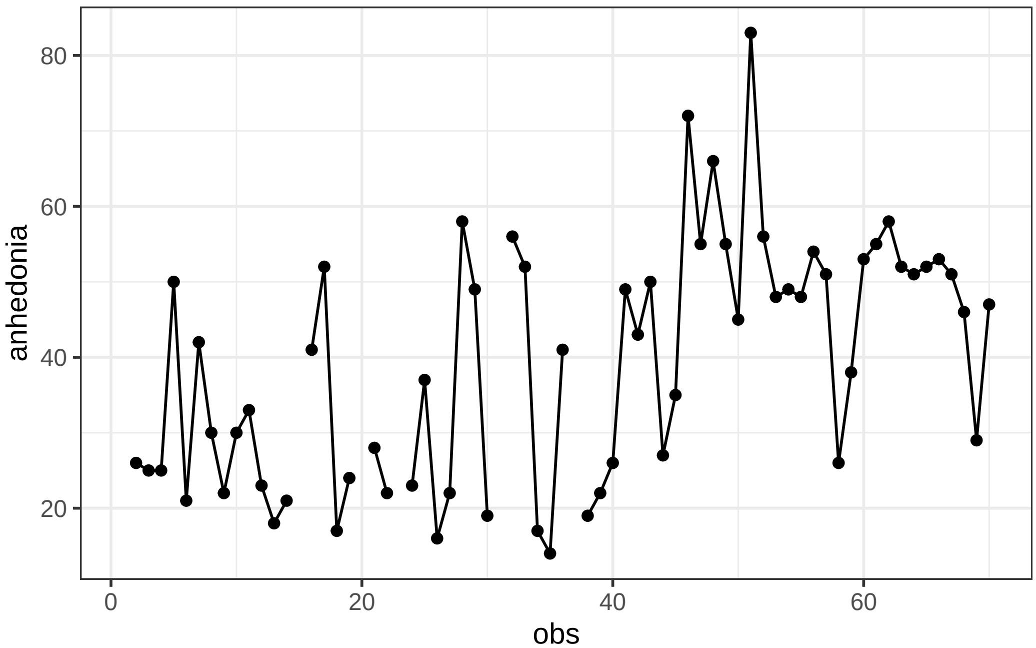

```
# Histogram for the time-varying variable anhedonia.
ggplot(data, aes(anhedonia)) +
    geom_histogram(
        color = "black",
        fill = "white",
        bins = 30
    ) +
    theme_bw()
```




```
# Descriptive statistics for anhedonia.
describe(data$anhedonia)
```

```
   vars  n  mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 64 39.34 15.84   41.5   38.92 20.02  14  83    69 0.22    -0.77 1.98
```

```
# Plot the trajectories of the time-varying variable anhedonia by person.
data %>%
    ggplot(aes(x = obs, y = anhedonia)) +
    geom_point() +
    geom_line() +
    theme_bw()
```



Data preparation

At this point, we are almost ready to start estimating our models. The last step before doing that, is creating the lagged version of the variables `PA` and `NA`.. They will be used on the subsequent AR(1) and VAR(1) models we fit below.

```
# Create lagged variables.
# Lagged within days to take into account night breaks.
data$PA.lag <- rep(NA, nrow(data))
data$NA.lag <- rep(NA, nrow(data))
data$anhedonia.lag <- rep(NA, nrow(data))
day.id <- unique(data$day)

for (t in day.id) {
    data$PA.lag[which(data$day == t)] <- shift(data$PA[which(data$day == t)], 1)
    data$NA.lag[which(data$day == t)] <- shift(data$NA.[which(data$day == t)], 1)
    data$anhedonia.lag[which(data$day == t)] <- shift(data$anhedonia[which(data$day == t)]
}
```

Estimating AR(1) for PA

We estimate an AR(1) model for PA using a linear regression model (ordinary least squares, OLS). You can extract the estimates with the `summary()` function. Finally, you can compute the estimate of the standard deviation of the errors of the AR(1) model computing the standard deviation using the function `sd()` on the residuals of the fitted model.

```
# Fit AR(1) model for PA.
fit.AR.PA <- lm(PA ~ 1 + PA.lag, data = data)

# Show fit summary.
summary(fit.AR.PA)
```

```
Call:
lm(formula = PA ~ 1 + PA.lag, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.486  -5.866   2.070   5.820  18.155 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  20.3258     4.5755   4.442 4.68e-05 ***
PA.lag        0.4092     0.1308   3.130  0.00287 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.658 on 52 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.1585,    Adjusted R-squared:  0.1423 
F-statistic: 9.796 on 1 and 52 DF,  p-value: 0.002866
```

```
# Estimate the standard deviation of the errors.
sd(residuals(fit.AR.PA))
```

```
[1] 9.566865
```

Estimating VAR(1) for PA and NA

We estimate a VAR(1) model for PA and NA using two separate linear regression models. You can extract the estimates with the `summary()` function. Finally, you can compute the estimate of the variance-covariance matrix of the errors of the VAR(1) model computing the covariance matrix using the function `cov()` on the residuals of each of the fitted models.

```r
# Linear regression model for PA.
fit.VAR.PA = lm(PA ~ 1 + PA.lag + NA.lag, data = data)

# Linear regression model for NA.
fit.VAR.NA = lm(NA. ~ 1 + PA.lag + NA.lag, data = data)

# Show fit summary for PA.
summary(fit.VAR.PA)
```

```

Call:
lm(formula = PA ~ 1 + PA.lag + NA.lag, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.551  -6.480   1.262   5.859  18.008 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 23.45530    6.27640   3.737 0.000471 ***
PA.lag       0.39213    0.13341   2.939 0.004930 ** 
NA.lag      -0.08273    0.11299  -0.732 0.467416    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.702 on 51 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.1673,    Adjusted R-squared:  0.1346 
F-statistic: 5.123 on 2 and 51 DF,  p-value: 0.009391
```

```r
# Show fit summary for NA.
summary(fit.VAR.NA)
```

```

Call:
lm(formula = NA. ~ 1 + PA.lag + NA.lag, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-14.260  -5.933  -2.073   3.104  39.302 
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  17.8818     6.6337   2.696  0.00949 **
PA.lag       -0.0202     0.1410  -0.143  0.88664
NA.lag        0.3756     0.1194   3.145  0.00277 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 10.25 on 51 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.1692,    Adjusted R-squared:  0.1366
F-statistic: 5.194 on 2 and 51 DF,  p-value: 0.008851
```

```r
# Estimate variance-covariance matrix of the errors.
res = cbind(residuals(fit.VAR.PA),residuals(fit.VAR.NA))

# Print the covariance matrix.
cov(res)
```

```
          [,1]       [,2]
[1,] 90.572865   4.295723
[2,]  4.295723 101.177796
```

Estimating VAR(1) model for NA, PA and anhedonia

We estimate a VAR(1) model for PA, NA and anhedonia using three separate linear regression models. You can extract the estimates with the `summary()` function. Finally, you can compute the estimate of the variance-covariance matrix of the errors of the VAR(1) model by computing the covariance matrix using the function `cov()` on the residuals of each of the fitted models.

```r
# Linear regression model for PA.
fit.VAR.PA = lm(PA ~ 1 + PA.lag + NA.lag + anhedonia.lag, data = data)

# Linear regression model for NA.
fit.VAR.NA = lm(NA. ~ 1 + PA.lag + NA.lag + anhedonia.lag, data = data)

# Linear regression model for anhedonia.
fit.VAR.anhedonia = lm(anhedonia ~ 1 + PA.lag + NA.lag + anhedonia.lag, data = data)

# Show fit summary for PA.
```

```r
summary(fit.VAR.PA)
```

```

Call:
lm(formula = PA ~ 1 + PA.lag + NA.lag + anhedonia.lag, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-22.374  -5.907   1.342   5.856  18.787 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)   
(Intercept)   22.60373    6.50921   3.473  0.00107 **
PA.lag         0.39067    0.13436   2.908  0.00542 **
NA.lag        -0.12662    0.13926  -0.909  0.36759   
anhedonia.lag  0.05564    0.10179   0.547  0.58711   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.769 on 50 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.1722,    Adjusted R-squared:  0.1226 
F-statistic: 3.468 on 3 and 50 DF,  p-value: 0.02288
```

```r
# Show fit summary for NA.
summary(fit.VAR.NA)
```

```

Call:
lm(formula = NA. ~ 1 + PA.lag + NA.lag + anhedonia.lag, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-14.413  -5.302  -2.096   3.864  33.201 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)   14.84269    6.66252   2.228   0.0304 *
PA.lag        -0.02541    0.13752  -0.185   0.8542  
NA.lag         0.21894    0.14254   1.536   0.1309  
anhedonia.lag  0.19856    0.10419   1.906   0.0624 .
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.999 on 50 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.2255,    Adjusted R-squared:  0.179
F-statistic: 4.852 on 3 and 50 DF,  p-value: 0.00486
```

```
# Show fit summary for anhedonia.
summary(fit.VAR.anhedonia)
```

```
Call:
lm(formula = anhedonia ~ 1 + PA.lag + NA.lag + anhedonia.lag,
    data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-29.750  -9.599   1.195  10.194  29.364

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   14.94851    8.92402   1.675   0.1002
PA.lag         0.04386    0.18420   0.238   0.8128
NA.lag         0.32640    0.19093   1.710   0.0936 .
anhedonia.lag  0.30771    0.13955   2.205   0.0321 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.39 on 50 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.268, Adjusted R-squared:  0.2241
F-statistic: 6.102 on 3 and 50 DF,  p-value: 0.001276
```

```
# Estimate variance-covariance matrix of the errors.
res = cbind(residuals(fit.VAR.PA),residuals(fit.VAR.NA),residuals(fit.VAR.anhedonia))

# Print the covariance matrix.
cov(res)
```

```
          [,1]      [,2]      [,3]
[1,] 90.034929  2.375884  16.02124
```

```
[2,]  2.375884 94.326082  37.21901
[3,] 16.021244 37.219012 169.22933
```

Running the `Shiny` application

The `Shiny` application is associated to a package that is stored at gitlab.kuleuven.be/ppw-okpiv/researchers/u0148925/shinyapp-paa_var_n1. To install the package and run the `Shiny` app, you can use the following `R` code:

```r
# Install the package containing the application.
remotes::install_gitlab(
    "ppw-okpiv/researchers/u0148925/shinyapp-paa_var_n1",
    host = "https://gitlab.kuleuven.be",
    force = TRUE
)

# Import the package containing the application.
library(paavar1)

# Run the shiny app.
run_paa_var1()
```

Power analysis for VAR(1) with three variables

> Exercise
>
> Try on your own and compare your results to the ones presented below!

Power analysis result

Running the simulation with the application, you should end up with a similar plot as the one below.

Sensitivity analysis for power: varying parameters

We slightly changed the values of three coefficients to investigate how they change either the sample size recommendation or the precision of estimates:

- $\beta_{11} = .39$ to $\beta_{11} = .8$

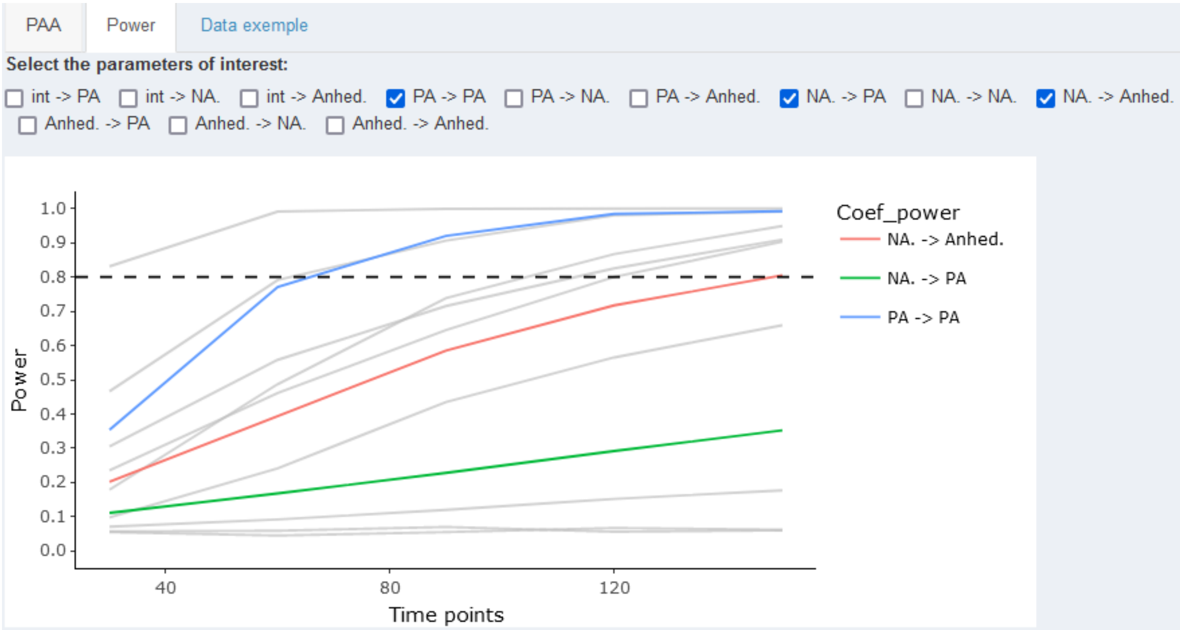


Figure 1: Power analysis VAR(1) with three variables

- $\sigma_{00} = 90$ to $\sigma_{00} = 180$
- $R = 1000$ to $R = 100$

> **Exercise**
>
> What conclusions can you draw based on the following power curves?

Sensitivity analysis for power: using CI

Following Lafit, Revol et al. (under review), we run a sensitivity analysis using the upper and lower boundaries of the estimated coefficients of interest. First, we extract the 95% confidence interval of the estimated values of each parameter.

```
# Linear regression model for PA.
confint(fit.VAR.PA, level = 0.95)

# Linear regression model for NA.
confint(fit.VAR.NA, level = 0.95)

# Linear regression model for anhedonia.
```

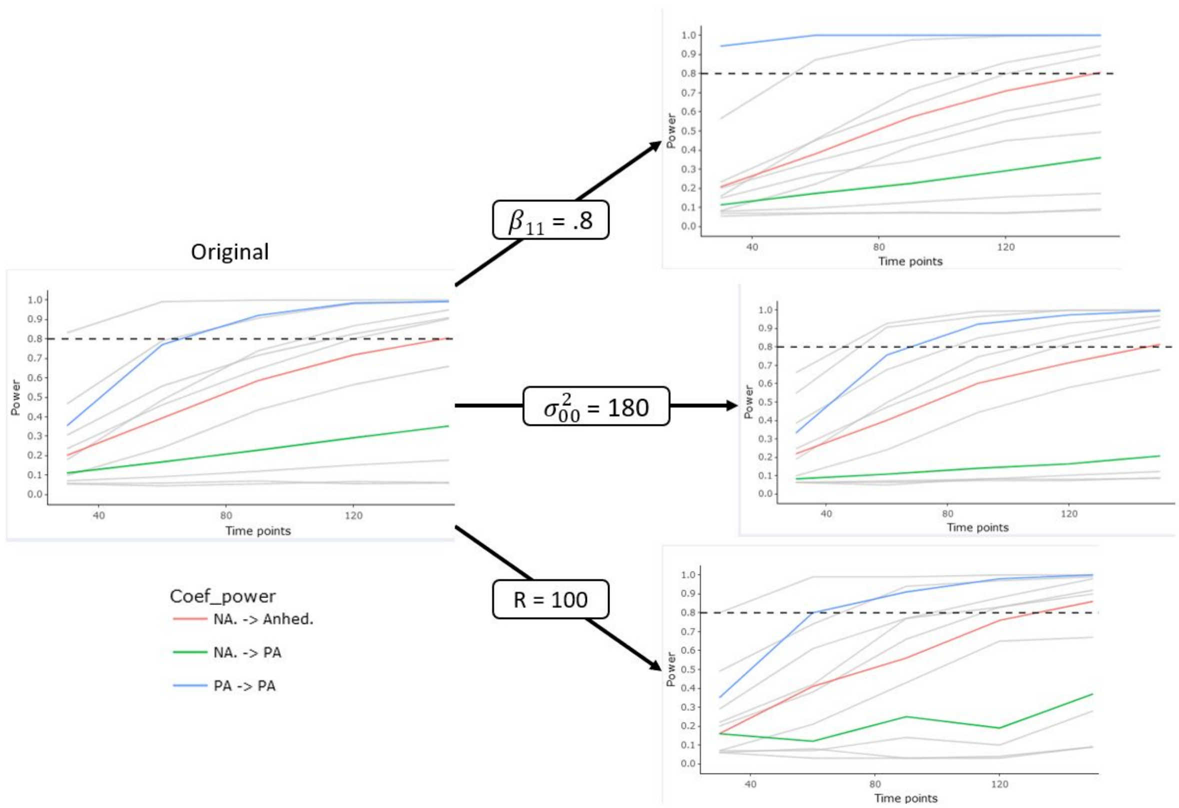


Figure 2: Sensitivity analysis for power

```r
confint(fit.VAR.anhedonia, level = 0.95)
```

We only varied the parameter values for the auto-regressive effect of PA (β_{11}) following the confidence interval. We run two new power analyses. The results are displayed below.

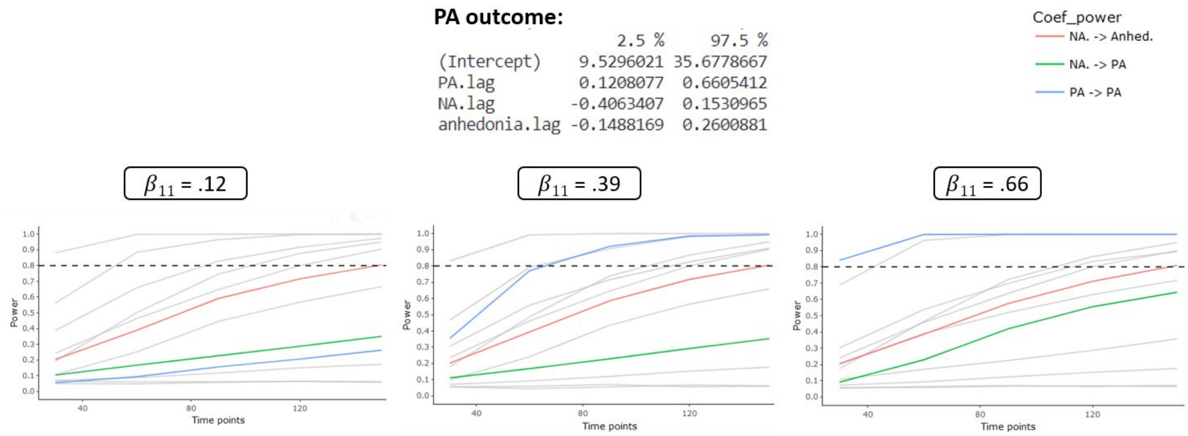


Figure 3: Sensitivity analysis for power

> **Exercise**
>
> What conclusions can you draw based on the following power curves?

PAA for VAR(1) with three variables

> **Exercise**
>
> Try on your own and compare your results to the ones presented below!

PAA result

Running the simulation with the application, you should end up with a similar plot as the one below.

Sensitivity analysis for power: varying parameters

We changed the values of the transition matrix to investigate how it changes the sample size recommendation.

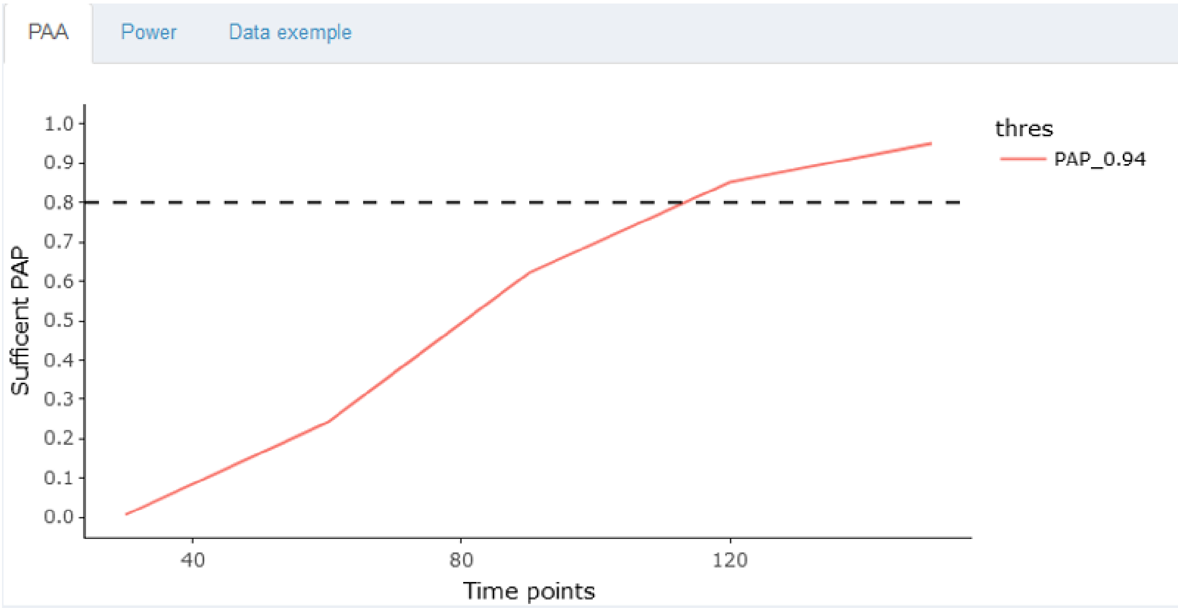
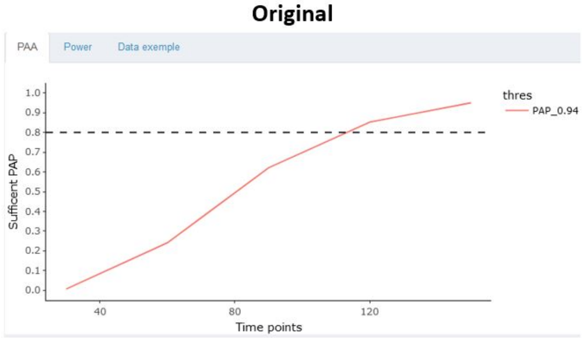


Figure 4: PAA for VAR(1) with three variables

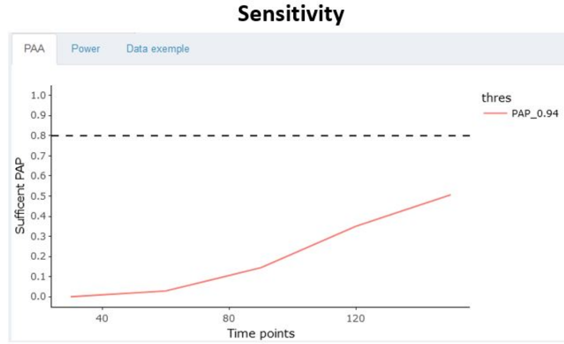
Original



	PA	NA	Anhed.
PA	.39	-.13	.06
NA	-.03	.22	.2
Anhed.	.04	.33	.31

Transition

Sensitivity



	PA	NA	Anhed.
PA	.5	-.4	.2
NA	-.3	.51	.4
Anhed.	.4	.6	.5

Transition

Figure 5: Sensitive PAA for VAR(1)

Exercise

What conclusions can you draw based on the following power curves?

Note

Despite the raising of the coefficients, the new transition matrix still fulfills the stationary assumption. Higher coefficients could lead to a violation of this assumption.

Session information

Using the command below, we can print the `session` information (i.e., operating system, details about the `R` installation, and so on) for reproducibility purposes.

```r
# Session information.
sessionInfo()
```

```
R version 4.3.0 (2023-04-21)
Platform: aarch64-apple-darwin20 (64-bit)
Running under: macOS Ventura 13.4

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/lib/libRlapack.dylib;  

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: Europe/Amsterdam
tzcode source: internal

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] MASS_7.3-58.4     lubridate_1.9.2   forcats_1.0.0     stringr_1.5.0
 [5] dplyr_1.1.2       purrr_1.0.1       readr_2.1.4       tidyr_1.3.0
 [9] tibble_3.2.1      ggplot2_3.4.2     tidyverse_2.0.0   psych_2.3.3
[13] data.table_1.14.8

loaded via a namespace (and not attached):
```

```
 [1] gtable_0.3.3     jsonlite_1.8.5   compiler_4.3.0   tidyselect_1.2.0
 [5] parallel_4.3.0   scales_1.2.1     yaml_2.3.7       fastmap_1.1.1
 [9] lattice_0.21-8   R6_2.5.1         labeling_0.4.2   generics_0.1.3
[13] knitr_1.43       munsell_0.5.0    pillar_1.9.0     tzdb_0.4.0
[17] rlang_1.1.1      utf8_1.2.3       stringi_1.7.12   xfun_0.39
[21] timechange_0.2.0 cli_3.6.1        withr_2.5.0      magrittr_2.0.3
[25] digest_0.6.31    grid_4.3.0       rstudioapi_0.14  hms_1.1.3
[29] lifecycle_1.0.3  nlme_3.1-162     vctrs_0.6.2      mnormt_2.1.1
[33] evaluate_0.21    glue_1.6.2       farver_2.1.1     fansi_1.0.4
[37] colorspace_2.1-0 rmarkdown_2.22   tools_4.3.0      pkgconfig_2.0.3
[41] htmltools_0.5.5
```

References

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Rush, A. J., Trivedi, M. H., Ibrahim, H. M., Carmody, T. J., Arnow, B., Klein, D. N., Markowitz, J. C., Ninan, P. T., Kornstein, S., Manber, R., et al. (2003). The 16-item quick inventory of depressive symptomatology (QIDS), clinician rating (QIDS-c), and self-report (QIDS-SR): A psychometric evaluation in patients with chronic major depression. *Biological Psychiatry*, *54*(5), 573–583.