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Supplement for "Partisan differences in risk taking in a simulated pandemic": Analysis Code and Additional Results (A)

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Abstract

Analysis Code and Additional Results (A)

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Part I
Data preparation

A1 Data preparation

This document was prepared in Overleaf, as an Rtex file implementing knitr. Any output is generated by R during compilation, and can thus be replicated by entering the same commands referencing the same dataset. Overleaf's R version and selection and versions of packages are not under the user's control. This section demonstrates the R version and the list of packages used for calculations and output generation. https://cran.r-project.org/web/packages/psych/psych.pdf

A1.1 R libraries

```
library(foreign)
library(formatR)
library(ggplot2)
#library(tidyr)
library("purrr")
library("tidyverse")

## Warning in system("timedatectl", intern = TRUE): running command
'timedatectl' had status 1
## - Attaching core tidyverse packages ------------ tidyverse 2.0.0 -
## v dplyr     1.1.2     v stringr   1.5.0
## v forcats   1.0.0     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v readr     2.1.4
## - Conflicts ---------------------- tidyverse_conflicts() -
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force
all conflicts to become errors

library("psych", verbose=TRUE)

##
## Attaching package:  'psych'
##
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

library("rmarkdown",verbose=TRUE)
library("viridis")
```

```
## Loading required package: viridisLite

library(viridisLite)
#library("GGally") ## not in Overleaf
library(afex)

## Loading required package: lme4
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
##
## ************
## Welcome to afex. For support visit: http://afex.singmann.science/
## - Functions for ANOVAs: aov_car(), aov_ez(), and aov_4()
## - Methods for calculating p-values with mixed(): 'S', 'KR', 'LRT', and
'PB'
## - 'afex_aov' and 'mixed' objects can be passed to emmeans() for
follow-up tests
## - Get and set global package options with: afex_options()
## - Set sum-to-zero contrasts globally: set_sum_contrasts()
## - For example analyses see: browseVignettes("afex")
## ************
##
## Attaching package: 'afex'
##
## The following object is masked from 'package:lme4':
##
##     lmer

library(car)

## Loading required package: carData
##
## Attaching package: 'car'
##
## The following object is masked from 'package:psych':
##
##     logit
##
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
##
## The following object is masked from 'package:purrr':
##
##     some
```

```
library(sjstats)
```

```
##
## Attaching package:  'sjstats'
##
## The following object is masked from 'package:psych':
##
##     phi
```

```
library(data.table)
```

```
##
## Attaching package:  'data.table'
##
## The following objects are masked from 'package:lubridate':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year
##
## The following objects are masked from 'package:dplyr':
##
##     between, first, last
##
## The following object is masked from 'package:purrr':
##
##     transpose
```

```
library(grid)
library(gridExtra)
```

```
##
## Attaching package:  'gridExtra'
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(ggthemes) ## not in Overleaf, but see below
```

```
## Error in library(ggthemes):  there is no package called 'ggthemes'
```

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(ggridges)
library(ggmosaic)  ## not in Overleaf, but see below

## Error in library(ggmosaic):  there is no package called 'ggmosaic'

library(kableExtra)

##
## Attaching package:  'kableExtra'
##
## The following object is masked from 'package:dplyr':
##
##     group_rows

library(effectsize)

##
## Attaching package:  'effectsize'
##
## The following objects are masked from 'package:sjstats':
##
##     cohens_f, phi
##
## The following object is masked from 'package:psych':
##
##     phi

#library(productplots) ## not in Overleaf
R.version

##                _
## platform       x86_64-pc-linux-gnu
## arch           x86_64
## os             linux-gnu
## system         x86_64, linux-gnu
## status
## major          4
## minor          1.2
## year           2021
## month          11
## day            01
## svn rev        81115
## language       R
## version.string R version 4.1.2 (2021-11-01)
## nickname       Bird Hippie

sessionInfo()
```

```
## R version 4.1.2 (2021-11-01)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 22.04.2 LTS
##
## Matrix products: default
## BLAS:   /usr/lib/x86_64-linux-gnu/openblas-pthread/libblas.so.3
## LAPACK: /usr/lib/x86_64-linux-gnu/openblas-pthread/libopenblasp-r0.3.20.so
##
## locale:
##  [1] LC_CTYPE=C.UTF-8       LC_NUMERIC=C           LC_TIME=C.UTF-8
##  [4] LC_COLLATE=C.UTF-8     LC_MONETARY=C.UTF-8    LC_MESSAGES=C.UTF-8
##  [7] LC_PAPER=C.UTF-8       LC_NAME=C              LC_ADDRESS=C
## [10] LC_TELEPHONE=C         LC_MEASUREMENT=C.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] grid      stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] effectsize_0.8.3  kableExtra_1.3.4  ggridges_0.5.4    corrplot_0.92
##  [5] gridExtra_2.3     data.table_1.14.8 sjstats_0.18.2    car_3.1-2
##  [9] carData_3.0-5     afex_1.3-0        lme4_1.1-34       Matrix_1.6-0
## [13] viridis_0.6.3     viridisLite_0.4.2 rmarkdown_2.23    psych_2.3.6
## [17] lubridate_1.9.2   forcats_1.0.0     stringr_1.5.0     dplyr_1.1.2
## [21] readr_2.1.4       tidyr_1.3.0       tibble_3.2.1      tidyverse_2.0.0
## [25] purrr_1.0.1       ggplot2_3.4.2     formatR_1.14      foreign_0.8-84
## [29] knitr_1.43
##
## loaded via a namespace (and not attached):
##  [1] nlme_3.1-162        insight_0.19.3      webshot_0.5.5
##  [4] httr_1.4.6          numDeriv_2016.8-1.1 tools_4.1.2
##  [7] backports_1.4.1     utf8_1.2.3          R6_2.5.1
## [10] sjlabelled_1.2.0    colorspace_2.1-0    withr_2.5.0
## [13] tidyselect_1.2.0    mnormt_2.1.1        emmeans_1.8.7
## [16] compiler_4.1.2      performance_0.10.4  cli_3.6.1
## [19] rvest_1.0.3         xml2_1.3.5          sandwich_3.0-2
## [22] bayestestR_0.13.1   scales_1.2.1        mvtnorm_1.2-2
## [25] systemfonts_1.0.4   digest_0.6.33       minqa_1.2.5
## [28] svglite_2.1.1       pkgconfig_2.0.3     htmltools_0.5.5
## [31] fastmap_1.1.1       rlang_1.1.1         rstudioapi_0.15.0
## [34] generics_0.1.3      zoo_1.8-12          magrittr_2.0.3
## [37] parameters_0.21.1   Rcpp_1.0.11         munsell_0.5.0
## [40] fansi_1.0.4         abind_1.4-5         lifecycle_1.0.3
## [43] stringi_1.7.12      multcomp_1.4-25     MASS_7.3-60
```

```
## [46] plyr_1.8.8          parallel_4.1.2      sjmisc_2.8.9
## [49] lattice_0.21-8      splines_4.1.2       hms_1.1.3
## [52] pillar_1.9.0        boot_1.3-28.1       estimability_1.4.1
## [55] reshape2_1.4.4      codetools_0.2-19    glue_1.6.2
## [58] evaluate_0.21       modelr_0.1.11       vctrs_0.6.3
## [61] nloptr_2.0.3        tzdb_0.4.0          gtable_0.3.3
## [64] datawizard_0.8.0    xfun_0.39           xtable_1.8-4
## [67] broom_1.0.5         coda_0.19-4         survival_3.5-5
## [70] lmerTest_3.1-3      timechange_0.2.0    TH.data_1.1-2
```

A1.1.1 ggthemes

Parts of The library ggthemes were inserted manually in this document by copying the code from https://github.com/jrnold/ggthemes for "economist" and "theme_foundation" on 06.09.2023 in version v4.2.4. The code is not echoed into this document, but it is executed at this point.

```
## NULL
## [1] ".data"
```

A1.1.2 ggmosaic

Due to complex dependencies of the package ggmosaic, it was not possible to include this package in Overleaf. Two figures were created using this package. For these figures, we give the source code (generating an expected error during compilation) and add the figure exported from RStudio as a png-file.

A1.2 Load dataset

```
data=read.spss("PartisanDifferencesDeidentifiedMay24.sav")
saveData<-data
df=data.frame(data)
```

A1.3 Calculate variables

The following parts are similar to the calculations in the Scales and Variables document. Diagnostic output has been suppressed in this version, though. See the other document (SV) for scale consistency, scale distributions, and item inter-correlation information.

A1.3.1 Game behavior

```
  scaleVarsTG <- c("TG_R01Choice", "TG_R02Choice", "TG_R03Choice",
                   "TG_R04Choice", "TG_R05Choice", "TG_R06Choice",
                   "TG_R07Choice", "TG_R08Choice", "TG_R09Choice",
                   "TG_R10Choice", "TG_R11Choice", "TG_R12Choice",
                   "TG_R13Choice", "TG_R14Choice", "TG_R15Choice",
                   "TG_R16Choice", "TG_R17Choice", "TG_R18Choice",
                   "TG_R19Choice", "TG_R20Choice", "TG_R21Choice",
                   "TG_R22Choice", "TG_R23Choice", "TG_R24Choice",
                   "TG_R25Choice"
  )

  scaleFrameTG <- df[scaleVarsTG]
  remove(scaleVarsTG)

  scaleFrameTG <- scaleFrameTG %>%
    dplyr::rename(
      R01=TG_R01Choice,R02=TG_R02Choice,R03=TG_R03Choice,
      R04=TG_R04Choice,R05=TG_R05Choice,R06=TG_R06Choice,
      R07=TG_R07Choice,R08=TG_R08Choice,R09=TG_R09Choice,
      R10=TG_R10Choice,R11=TG_R11Choice,R12=TG_R12Choice,
      R13=TG_R13Choice,R14=TG_R14Choice,R15=TG_R15Choice,
      R16=TG_R16Choice,R17=TG_R17Choice,R18=TG_R18Choice,
      R19=TG_R19Choice,R20=TG_R20Choice,R21=TG_R21Choice,
      R22=TG_R22Choice,R23=TG_R23Choice,R24=TG_R24Choice,
      R25=TG_R25Choice
    )

  scaleFrameTG[] <-data.matrix(scaleFrameTG)

  scaleTG=scoreItems(keys=c(1,1,1,1,1,1,1,1,1,1,
                            1,1,1,1,1,1,1,1,1,1,
                            1,1,1,1,1 ),
                     items =scaleFrameTG,totals=TRUE)

  #categories are scored 1 for 8 points and 2 for 40 points
  scoresTG<-data.frame(8*25+(scaleTG$scores-25)*32)

  summary(scoresTG)
```

```
##     Scale11
##  Min.   : 200
##  1st Qu.: 200
##  Median : 264
##  Mean   : 382
##  3rd Qu.: 488
```

```
##  Max.   :1000

  head(scoresTG)

##   Scale11
## 1     200
## 2     200
## 3     200
## 4     200
## 5     296
## 6     360

  scale_meanTG =summarise_all(scoresTG,mean)
  TGdf=data.frame(scale_mean=t(summarise_all(scoresTG,mean)),
                  key=names(scoresTG))

    roundwiseTG=pivot_longer(
      cols=starts_with("R"),
      data=scaleFrameTG,
      names_to="Round",
      names_prefix="R"
    )

  roundwiseTG <- roundwiseTG %>%
    mutate(partic=rep(seq(from=1,to=819),each=25),
           condition=rep(df$conditionShortName, each=25),
           label=rep(df$PID, each=25))

  roundwiseTG$Round <- as.numeric(roundwiseTG$Round)

  head(roundwiseTG)

## # A tibble: 6 x 3
##   Round value partic
##   <dbl> <int>  <int>
## 1     1     1      1
## 2     2     1      1
## 3     3     1      1
## 4     4     1      1
## 5     5     1      1
## 6     6     1      1

  plotdata= roundwiseTG %>%
    dplyr::group_by(Round) %>%
    dplyr::summarize(counted=(sum(value)-819)/8.19,
              CIlower=100*prop.test(sum(value)-819, 819)$conf.int[1],
```

```
              CIupper=100*prop.test(sum(value)-819, 819)$conf.int[2])


  plotdata
```

```
## # A tibble: 25 x 4
##    Round counted CIlower CIupper
##    <dbl>   <dbl>   <dbl>   <dbl>
##  1     1    36.6    33.3    40.0
##  2     2    33.1    29.9    36.4
##  3     3    31.1    28.0    34.5
##  4     4    28.2    25.2    31.4
##  5     5    27.1    24.1    30.3
##  6     6    22.8    20.0    25.9
##  7     7    24.4    21.5    27.5
##  8     8    22.3    19.6    25.4
##  9     9    23.2    20.4    26.3
## 10    10    23.0    20.1    26.0
## # i 15 more rows
```

A1.3.2 Postquestionnaire

```
 VarsPost <- c("PostTG_01", "PostTG_02", "PostTG_03",
                "PostTG_04", "PostTG_05","PostTG_06","PostTG_07",
                "PostTG_08","PostTG_09","PostTG_10","PostTG_11")

  FramePost <- df[VarsPost]

     remove(VarsPost)

  FramePost <- FramePost %>%
    dplyr::rename(
      Post01=PostTG_01,Post02=PostTG_02,Post03=PostTG_03,Post04=PostTG_04,
      Post05=PostTG_05,Post06=PostTG_06,Post07=PostTG_07,Post08=PostTG_08,
      Post09=PostTG_09,Post10=PostTG_10,Post11=PostTG_11
    )

  FramePost[] <-data.matrix(FramePost)


  sampleSize=NROW(df)

  round<-c()
  round[1:sampleSize]<-1
```

```
round[(sampleSize+1):(2*sampleSize)]<-5
round[(2*sampleSize+1):(3*sampleSize)]<-10
round[(3*sampleSize+1):(4*sampleSize)]<-15
round[(4*sampleSize+1):(5*sampleSize)]<-20
round[(5*sampleSize+1):(6*sampleSize)]<-25


participantID<-c()
participantID[1:sampleSize]<-1:sampleSize
participantID[(sampleSize+1):(2*sampleSize)]<-1:sampleSize
participantID[(2*sampleSize+1):(3*sampleSize)]<-1:sampleSize
participantID[(4*sampleSize+1):(5*sampleSize)]<-1:sampleSize
participantID[(5*sampleSize+1):(6*sampleSize)]<-1:sampleSize


estimateH<-c()
estimateH[1:sampleSize] <-df$playersH_R01
estimateH[(sampleSize+1):(2*sampleSize)] <-df$playersH_R05
estimateH[(2*sampleSize+1):(3*sampleSize)] <-df$playersH_R10
estimateH[(3*sampleSize+1):(4*sampleSize)] <-df$playersH_R15
estimateH[(4*sampleSize+1):(5*sampleSize)] <-df$playersH_R20
estimateH[(5*sampleSize+1):(6*sampleSize)] <-df$playersH_R25


condInterv<-c()
condInterv[1:sampleSize]<-as.numeric(as.factor(df$interventionCondition))-1
condInterv[(sampleSize+1):(2*sampleSize)]<-
    as.numeric(as.factor(df$interventionCondition))-1
condInterv[(2*sampleSize+1):(3*sampleSize)]<-
    as.numeric(as.factor(df$interventionCondition))-1
condInterv[(3*sampleSize+1):(4*sampleSize)]<-
    as.numeric(as.factor(df$interventionCondition))-1
condInterv[(4*sampleSize+1):(5*sampleSize)]<-
    as.numeric(as.factor(df$interventionCondition))-1
condInterv[(5*sampleSize+1):(6*sampleSize)]<-
    as.numeric(as.factor(df$interventionCondition))-1


condFrame<-c()
condFrame[1:sampleSize]<-
    as.numeric(as.factor(df$politicalFraming))-1
condFrame[(sampleSize+1):(2*sampleSize)]<-
    as.numeric(as.factor(df$politicalFraming))-1
condFrame[(2*sampleSize+1):(3*sampleSize)]<-
```

```
      as.numeric(as.factor(df$politicalFraming))-1
  condFrame[(3*sampleSize+1):(4*sampleSize)]<-
      as.numeric(as.factor(df$politicalFraming))-1
  condFrame[(4*sampleSize+1):(5*sampleSize)]<-
      as.numeric(as.factor(df$politicalFraming))-1
  condFrame[(5*sampleSize+1):(6*sampleSize)]<-
      as.numeric(as.factor(df$politicalFraming))-1


  condVoter<-c()
  condVoter[1:sampleSize]<-as.numeric(as.factor(df$DATAFILE))-1
  condVoter[(sampleSize+1):(2*sampleSize)]<-
      as.numeric(as.factor(df$DATAFILE))-1
  condVoter[(2*sampleSize+1):(3*sampleSize)]<-
      as.numeric(as.factor(df$DATAFILE))-1
  condVoter[(3*sampleSize+1):(4*sampleSize)]<-
      as.numeric(as.factor(df$DATAFILE))-1
  condVoter[(4*sampleSize+1):(5*sampleSize)]<-
      as.numeric(as.factor(df$DATAFILE))-1
  condVoter[(5*sampleSize+1):(6*sampleSize)]<-
      as.numeric(as.factor(df$DATAFILE))-1


  condCondition<-4*condVoter+2*condFrame+condInterv+1

# LINE FRAME H

  lineFrameH<-data.frame(
    round,
    estimateH,
    participantID,
    condInterv=as.factor(condInterv),
    condFrame=as.factor(condFrame),
    condVoter=as.factor(condVoter),
    condition=as.factor(condCondition)
  )


  levels( lineFrameH$condition)<-list("Trump|Masks|Inj"="1",
          "Trump|Masks|None"="2","Trump|Color|Inj"="3",
          "Trump|Color|None"="4","Clint|Masks|Inj"="5",
          "Clint|Masks|None"="6","Clint|Color|Inj"="7",
          "Clint|Color|None"="8")
```

```
  VarsPostIN <- c("AddPostInjunctive_1", "AddPostInjunctive_2",
                  "AddPostInjunctive_3", "AddPostInjunctive_4",
                  "AddPostInjunctive_5","AddPostInjunctive_6")

  FramePostIN <- df[VarsPostIN]

     remove(VarsPostIN)

  FramePostIN <- FramePostIN %>%
    dplyr::rename(
      PostIN1=AddPostInjunctive_1,PostIN2=AddPostInjunctive_2,
      PostIN3=AddPostInjunctive_3,PostIN4=AddPostInjunctive_4,
      PostIN5=AddPostInjunctive_5,PostIN6=AddPostInjunctive_6
    )

  FramePostIN[] <-data.matrix(FramePostIN)

  cctgVars <- c("CCtgi01", "CCtgi02", "CCtgi03",
                "CCtgi04","CCtgi05","CCtgi06","CCtgi07",
                "CCtgi08", "CCtgi09","CCtgi10","CCtgi11",
                "CCtgi12","CCtgi13", "CCtgi14","CCtgi15",
                "CCtgi16" )


  comprehensionTGframe <- df[cctgVars]
     remove(cctgVars)


  scaleComprehensionTG=scoreItems(keys=c(1,1,1,1,1,1,
                                         1,1,1,1,1,1,1,1,1,1),
                                  items=comprehensionTGframe,totals=TRUE)

## Number of categories should be increased  in order to count frequencies.
```

A1.3.3 Presidential candidates in 2020

```
  polVars <- c("polCandScale_Trump", "polCandScale_Biden")
  scoresCandidates <- df[polVars]

  scoresCandidates <- scoresCandidates %>%
    dplyr::rename(
      Trump=polCandScale_Trump,
      Biden=polCandScale_Biden
    )
```

A1.4 Scales

A1.4.1 Cognitive Reflection Test (CRT)

```
scaleVarsCRT <- c("CRT01", "CRT02", "CRT03",
                  "CRT04")
scaleFrameCRT <- df[scaleVarsCRT]

  remove(scaleVarsCRT)

scaleFrameCRT$CRT01num <-  as.numeric(scaleFrameCRT$CRT01)
scaleFrameCRT$CRT02num <-  as.numeric(scaleFrameCRT$CRT02)
scaleFrameCRT$CRT03num <-  as.numeric(scaleFrameCRT$CRT03)
scaleFrameCRT$CRT04num <-  as.numeric(scaleFrameCRT$CRT04)

scaleFrameCRT = subset(scaleFrameCRT,
                       select=-c(CRT01,CRT02,CRT03,CRT04))

scaleFrameCRT$CRT01cat <- dplyr::recode(scaleFrameCRT$CRT01num,
                                "7"="intuitive","8"="correct",
                                .default="other")
scaleFrameCRT$CRT02cat <- dplyr::recode(scaleFrameCRT$CRT02num,
                                "5"="intuitive","6"="correct",
                                .default="other")
scaleFrameCRT$CRT03cat <- dplyr::recode(scaleFrameCRT$CRT03num,
                                "4"="intuitive","7"="correct",
                                .default="other")
scaleFrameCRT$CRT04cat <- dplyr::recode(scaleFrameCRT$CRT04num,
                                "4"="intuitive","5"="correct",
                                .default="other")

scaleFrameCRT = subset(scaleFrameCRT,
                       select=-c(CRT01num,CRT02num,CRT03num,CRT04num))

scaleFrameCRT$CRT01int <- dplyr::recode(scaleFrameCRT$CRT01cat,
                                "intuitive"=1, .default=0)
scaleFrameCRT$CRT02int <- dplyr::recode(scaleFrameCRT$CRT02cat,
                                "intuitive"=1, .default=0)
scaleFrameCRT$CRT03int <- dplyr::recode(scaleFrameCRT$CRT03cat,
                                "intuitive"=1, .default=0)
scaleFrameCRT$CRT04int <- dplyr::recode(scaleFrameCRT$CRT04cat,
                                "intuitive"=1, .default=0)

scaleFrameCRT$CRT01correct <- dplyr::recode(scaleFrameCRT$CRT01cat,
                                    "correct"=1, .default=0)
```

```
scaleFrameCRT$CRT02correct <- dplyr::recode(scaleFrameCRT$CRT02cat,
                                      "correct"=1, .default=0)
scaleFrameCRT$CRT03correct <- dplyr::recode(scaleFrameCRT$CRT03cat,
                                      "correct"=1, .default=0)
scaleFrameCRT$CRT04correct <- dplyr::recode(scaleFrameCRT$CRT04cat,
                                      "correct"=1, .default=0)

scaleFrameCRT = subset(scaleFrameCRT,
                       select=-c(CRT01cat,CRT02cat,CRT03cat,CRT04cat))

weightsCRT <-list(CRTscore=c("CRT01correct","CRT02correct",
                             "CRT03correct","CRT04correct"),
                  CRTintuitive=c("CRT01int",
                                 "CRT02int","CRT03int","CRT04int"))

scaleCRT=scoreItems(keys=weightsCRT, items =scaleFrameCRT,totals=TRUE)
scoresCRT<-data.frame(scaleCRT$scores)
```

A1.4.2 Psychological Reactance

```
scaleReactanceVars <- c("PsyReact_01", "PsyReact_02", "PsyReact_03",
                        "PsyReact_04","PsyReact_05","PsyReact_06",
                        "PsyReact_07","PsyReact_08", "PsyReact_09",
                        "PsyReact_10", "PsyReact_11")

scaleReactanceFrame <- df[scaleReactanceVars]

remove(scaleReactanceVars)

scaleReactanceFrame[] <-data.matrix(scaleReactanceFrame)


weightsReactance <-list(psychReactance=c("PsyReact_01", "PsyReact_02",
                        "PsyReact_03", "PsyReact_04", "PsyReact_05",
                         "PsyReact_06", "PsyReact_07", "PsyReact_08",
                         "PsyReact_09", "PsyReact_10","PsyReact_11"))

scoresPR=scoreItems(items=scaleReactanceFrame,
                    keys=weightsReactance)

scalesPR=data.frame(scale_mean=mean(scoresPR$scores),
                    key="psychReactance")
```

```
scoresPRdf=data.frame(
  psychReactance=scoresPR$scores
)
```

A1.4.3 Social and Economic Conservatism Scale (SECS)

```
scaleVarsSECS <- c("SECScale_1", "SECScale_2", "SECScale_5",
                   "SECScale_6", "SECScale_7", "SECScale_8",
                   "SECScale_9", "SECScale_10", "SECScale_11",
                   "SECScale_12","SECScale_13", "SECScale_14")

scaleFrameSECS <- df[scaleVarsSECS]

remove(scaleVarsSECS)

scaleFrameSECS <- scaleFrameSECS %>%
dplyr::rename(
     SC01n=SECScale_1,EC01n=SECScale_2,
     EC02p=SECScale_5,SC02p=SECScale_6,
     SC03p=SECScale_7,EC03p=SECScale_8,
     SC04p=SECScale_9,SC05p=SECScale_10,
     EC04p=SECScale_11,EC05p=SECScale_12,
     SC06p=SECScale_13,SC07p=SECScale_14
   )

scaleFrameSECS[] <-data.matrix(scaleFrameSECS)

weightsSECS <-list(sclConsALL=c("-SC01n","-SC02p","EC02p","SC02p",
                                "SC03p","EC03p","SC04p","SC05p",
                                "EC04p","EC05p","SC06p","SC07p") ,
                   sclConsSoc=c("-SC01n","SC02p","SC03p","SC04p",
                                "SC05p","SC06p","SC07p"),
                   sclConsEcon=c("-EC01n","EC02p","EC03p","EC04p",
                                 "EC05p")
 )

scaleSECS=scoreItems(keys=weightsSECS, items =scaleFrameSECS,totals=FALSE)

## Number of categories should be increased  in order to count frequencies.

scoresSECS<-data.frame(scaleSECS$scores)
```

A1.4.4 Social value orientatioation (SVO)

```
scaleVarsSVO <- c("SVO1_1", "SVO2_1", "SVO3_1",
                  "SVO4_1", "SVO5_1","SVO6_1" )

scaleFrameSVO <- df[scaleVarsSVO]

remove(scaleVarsSVO)

scaleFrameSVO$SVO1_1 <-  as.numeric(scaleFrameSVO$SVO1_1)
scaleFrameSVO$SVO2_1 <-  as.numeric(scaleFrameSVO$SVO2_1)
scaleFrameSVO$SVO3_1 <-  as.numeric(scaleFrameSVO$SVO3_1)
scaleFrameSVO$SVO4_1 <-  as.numeric(scaleFrameSVO$SVO4_1)
scaleFrameSVO$SVO5_1 <-  as.numeric(scaleFrameSVO$SVO5_1)
scaleFrameSVO$SVO6_1 <-  as.numeric(scaleFrameSVO$SVO6_1)



scaleFrameSVO$SVO1self <- dplyr::recode(scaleFrameSVO$SVO1_1, .default=85)
scaleFrameSVO$SVO1other <- dplyr::recode(scaleFrameSVO$SVO1_1,
                                  "1"=85,"2"=76,"3"=68,"4"=59,
                                  "5"=50, "6"=41,"7"=33,
                                  "8"=24,"9"=15)

scaleFrameSVO$SVO2self <- dplyr::recode(scaleFrameSVO$SVO2_1,
                                 "1"=85,"2"=87,"3"=89,"4"=91,
                                 "5"=93,"6"=94,"7"=96,
                                 "8"=98,"9"=100)
scaleFrameSVO$SVO2other <- dplyr::recode(scaleFrameSVO$SVO2_1,
                                  "1"=15,"2"=19,"3"=24,"4"=28,
                                  "5"=33, "6"=37,"7"=41,
                                  "8"=46,"9"=50)

scaleFrameSVO$SVO3self <- dplyr::recode(scaleFrameSVO$SVO3_1,
                                 "1"=50,"2"=54,"3"=59,"4"=63,
                                 "5"=68,"6"=72,"7"=76,
                                 "8"=81,"9"=85)
scaleFrameSVO$SVO3other <- dplyr::recode(scaleFrameSVO$SVO3_1,
                                  "1"=100,"2"=98,"3"=96,"4"=94,
                                  "5"=93, "6"=91,"7"=89,
                                  "8"=87,"9"=85)

scaleFrameSVO$SVO4self <- dplyr::recode(scaleFrameSVO$SVO4_1,
                                 "1"=50,"2"=54,"3"=59,"4"=63,
                                 "5"=68,"6"=72,"7"=76,
                                 "8"=81,"9"=85)
```

```
scaleFrameSVO$SVO4other <- dplyr::recode(scaleFrameSVO$SVO4_1,
                                  "1"=100,"2"=89,"3"=79,"4"=68,
                                  "5"=58, "6"=47,"7"=36,
                                  "8"=26,"9"=15)

scaleFrameSVO$SVO5self <- dplyr::recode(scaleFrameSVO$SVO5_1,
                                 "1"=100,"2"=94,"3"=88,"4"=81,
                                 "5"=75,"6"=69,"7"=63,
                                 "8"=56,"9"=50)
scaleFrameSVO$SVO5other <- dplyr::recode(scaleFrameSVO$SVO5_1,
                                  "1"=50,"2"=56,"3"=63,"4"=69,
                                  "5"=75, "6"=81,"7"=88,
                                  "8"=94,"9"=100)

scaleFrameSVO$SVO6self <- dplyr::recode(scaleFrameSVO$SVO6_1,
                                 "1"=100,"2"=98,"3"=96,"4"=94,
                                 "5"=93,"6"=91,"7"=89,
                                 "8"=87,"9"=85)
scaleFrameSVO$SVO6other <- dplyr::recode(scaleFrameSVO$SVO6_1,
                                  "1"=50,"2"=54,"3"=59,"4"=63,
                                  "5"=68, "6"=72,"7"=76,
                                  "8"=81,"9"=85)

scaleFrameSVO = subset(scaleFrameSVO,
                 select=-c(SVO1_1,SVO2_1,SVO3_1,SVO4_1,SVO5_1,SVO6_1)
)

scaleFrameSVO[] <-data.matrix(scaleFrameSVO)

weightsSVO <-list(sclSVOself=c("SVO1self","SVO2self","SVO3self",
                               "SVO4self","SVO5self","SVO6self"),
                  sclSVOother=c("SVO1other","SVO2other","SVO3other",
                                "SVO4other","SVO5other","SVO6other")
)

#### NOTE: The below worked in previous implementation: SVO1self was
#### automatically removed
##### meanSVOinc=scoreItems(keys=weightsSVO, items =scaleFrameSVO,totals=FALSE)
#### This needs additional steps now

weightsSVO <-list(sclSVOself=c("SVO2self","SVO3self",
                               "SVO4self","SVO5self","SVO6self"),
                  sclSVOother=c("SVO1other","SVO2other","SVO3other","SVO4other",
                                "SVO5other","SVO6other")
```

```
  )

  var(scaleFrameSVO$SVO1self)

## [1] 0

  scaleFrameSVO <- subset(scaleFrameSVO, select = -SVO1self)

  ### Now the command below works fine
  meanSVOinc=scoreItems(keys=weightsSVO, items =scaleFrameSVO,totals=FALSE)

## Number of categories should be increased  in order to count frequencies.

  sumSVOscores=meanSVOinc$scores
  # 85 is deleted due to lack of variance
  meanSVOself=5/6*sumSVOscores[,1]+1/6*85
  meanSVOother=sumSVOscores[,2]
  angleSVO=
    atan(   (meanSVOother -50) / (meanSVOself-50) )* 90/ 1.57079632679

  scoresSVO<-data.frame(angleSVO)
```

A1.4.5 Behavioral Intentions

```
  behIntVars <- c("CVBehInt_01", "CVBehInt_02", "CVBehInt_03",
                          "CVBehInt_04", "CVBehInt_05", "CVBehInt_06",
                  "CVBehInt_07", "CVBehInt_08", "CVBehInt_09",
                  "CVBehInt_10", "CVBehInt_11", "CVBehInt_12")


  behIntentionsFrame <- df[behIntVars]
  remove(behIntVars)


  behIntentionsFrame <- behIntentionsFrame %>%
    dplyr::rename(
      behIntent01=CVBehInt_01,
      behIntent02=CVBehInt_02,
      behIntent03=CVBehInt_03,
      behIntent04=CVBehInt_04,
      behIntent05=CVBehInt_05,
      behIntent06=CVBehInt_06,
      behIntent07=CVBehInt_07,
      behIntent08=CVBehInt_08,
```

```
      behIntent09=CVBehInt_09,
      behIntent10=CVBehInt_10,
      behIntent11=CVBehInt_11,
      behIntent12=CVBehInt_12
    )

  behIntentionsFrame[] <-data.matrix(behIntentionsFrame)

  weightsBehInt <-list(behIntentionsAll=c("behIntent01", "behIntent02",
                                          "behIntent03", "behIntent04",
                  "behIntent05", "behIntent06",
                  "behIntent07", "behIntent08", "behIntent09",
                  "behIntent10", "behIntent11", "behIntent12"),
                  physicalDistancing=c("behIntent02","behIntent03",
                                       "behIntent09"),
                  movementRestriction=c("behIntent01","behIntent04",
                                        "behIntent08"),
                  handHygiene=c("behIntent05","behIntent06","behIntent07"),
                  faceCovering=c("behIntent10", "behIntent11",
                                 "behIntent12")
                  )

  behIntentionsScales=scoreItems(items=behIntentionsFrame,
                       keys=weightsBehInt)

## Number of categories should be increased  in order to count frequencies.

  scoresBehIntentions<-data.frame(behIntentionsScales$scores)
```

A1.4.6 Creating a dataframe with all variables

```
anovaFrame=data.frame(
   facTrumpClint=factor(df$DATAFILE),
   elecTrump=df$polCandScale_Trump,
   polPos=as.numeric(df$polPosition),
   riskTaking=as.numeric(df$RTGeneral)-1,
   gameScore=scoresTG$Scale1,
   SVO=scoresSVO,
   psychReact=scoresPR$scores,
   secsALL=scoresSECS$sclConsALL,
   secsEcon=scoresSECS$sclConsEcon,
   secsSoc=scoresSECS$sclConsSoc,
   bhintALL=scoresBehIntentions$behIntentionsAll,
   bhintPhysicalDistancing=scoresBehIntentions$physicalDistancing,
```

```
    bhintMovementRestriction=scoresBehIntentions$movementRestriction,
    bhintHandHygiene=scoresBehIntentions$handHygiene,
    bhintFaceCovering=scoresBehIntentions$faceCovering,
    CRT=scoresCRT$CRTscore
   )


anovaFrame$facSample=as.factor(df$DATAFILE)
anovaFrame$facInterv=as.factor(df$interventionCondition)
anovaFrame$facFraming=as.factor(df$politicalFraming)
anovaFrame$subj=1:819

anovaFrame$dummySample=as.numeric(anovaFrame$facSample)-1
anovaFrame$dummyInterv=2-as.numeric(anovaFrame$facInterv)
anovaFrame$dummyFrame=2-as.numeric(anovaFrame$facFraming)

anovaFrame$conservatism=as.numeric(anovaFrame$polPos)-
                      mean(as.numeric(anovaFrame$polPos))
anovaFrame$connectionCovidDrawn=as.factor(df$connectionCovidDrawn)


#NONNUMERIC
sampleDescriptionFrame=data.frame(
    TrumpVsClint=df$DATAFILE,
    gender=df$demo01Gender,
    age=df$demo01Age
)
```

Part II
Main analyses

A2 ANOVA and linear models

In this section, we explore the relationship between game behavior, experimental conditions, and several candidates for predictors.

A2.1 Prepare data for ANOVA and regressions

```
options(contrasts = c("contr.sum", "contr.poly"))

barFrame=data.frame(
    RiskyChoices=(anovaFrame$gameScore-200)/32,
```

```
    Framing= as.factor(anovaFrame$facFraming),
    Intervention= as.factor(anovaFrame$facInterv),
    Voter= as.factor(anovaFrame$facSample)
   )

barFrame$Framing<-factor(barFrame$Framing, levels =c("NEUTRAL   ","MASKS     "))
#barFrame$Framing<-factor(barFrame$Framing,labels=c("Neutral","Masks"))
barFrame$Framing<-factor(barFrame$Framing,labels=c("Neutral frame","Pandemic frame"))
barFrame$Intervention<-factor(barFrame$Intervention,
                              levels =c("NONE           ","INJUNCTIVE     "))
#barFrame$Intervention<-factor(barFrame$Intervention,labels=c("None","Norms"))
barFrame$Intervention<-factor(barFrame$Intervention,labels=c("None","Norms intervention"))

barFrame$Voter<-factor(barFrame$Voter,
                       levels =c("Conservatives","Liberals"))
barFrame$Voter<-factor(barFrame$Voter,labels=c("Trump","Clinton"))


modelFrame=data.frame(
    RiskyChoices=(anovaFrame$gameScore-200)/32,
    facFraming= as.factor(anovaFrame$facFraming),
    facInterv= as.factor(anovaFrame$facInterv),
    facSample= as.factor(anovaFrame$facSample),
    dummyMasks=2-as.numeric(anovaFrame$facFraming),
    dummyInjunctive=2-as.numeric(anovaFrame$facInterv),
    riskTaking=anovaFrame$riskTaking,
    CRT=anovaFrame$CRT,
    angleSVO=anovaFrame$angleSVO,
    gameScore=anovaFrame$gameScore,
    conservatism=anovaFrame$polPos,
    numericSample=as.numeric(anovaFrame$facSample)-1,
    SECS=anovaFrame$secsALL,
    SECSEcon=anovaFrame$secsEcon,
    SECSSoc=anovaFrame$secsSoc,
    trump=anovaFrame$elecTrump,
    binaryConnection=2-as.numeric(df$connectionCovidDrawn),
    psychReactance=anovaFrame$psychReactance,
    behIntMasks=anovaFrame$bhintFaceCovering,
    behIntDistancing=anovaFrame$bhintPhysicalDistancing,
    behIntHandHYgiene=anovaFrame$bhintHandHygiene,
    behIntMovement=anovaFrame$bhintMovementRestriction
 )

modelFrame$binaryConnection=dplyr::recode(modelFrame$binaryConnection,
```

```
                                        '1'=1,'0'=0,'-1'=0)
modelFrame$connectionCovidUncentered=modelFrame$binaryConnection

#MEAN CENTERING
modelFrame$riskTaking=modelFrame$riskTaking-mean(modelFrame$riskTaking)
modelFrame$CRT=modelFrame$CRT-mean(modelFrame$CRT)
modelFrame$angleSVO=modelFrame$angleSVO-mean(modelFrame$angleSVO)
modelFrame$psychReactance=modelFrame$psychReactance-mean(modelFrame$psychReactance)
modelFrame$conservatism=modelFrame$conservatism-
     mean(modelFrame$conservatism)
modelFrame$SECS=modelFrame$SECS-mean(modelFrame$SECS)
modelFrame$SECSEcon=modelFrame$SECSEcon-mean(modelFrame$SECSEcon)
modelFrame$SECSSoc=modelFrame$SECSSoc-mean(modelFrame$SECSSoc)
modelFrame$trump=modelFrame$trump-mean(modelFrame$trump)
modelFrame$binaryConnection=modelFrame$binaryConnection-
     mean(modelFrame$binaryConnection)

# INTERACTIONS

modelFrame$dummyMasksInj=modelFrame$dummyMasks*modelFrame$dummyInjunctive

modelFrame$mskRisk<-modelFrame$dummyMasks*modelFrame$riskTaking
modelFrame$injRisk<-modelFrame$dummyInjunctive*modelFrame$riskTaking
modelFrame$mskinjRisk<-modelFrame$dummyMasksInj*modelFrame$riskTaking

modelFrame$mskCRT<-modelFrame$dummyMasks*modelFrame$CRT
modelFrame$injCRT<-modelFrame$dummyInjunctive*modelFrame$CRT
modelFrame$mskinjCRT<-modelFrame$dummyMasksInj*modelFrame$CRT

modelFrame$mskSVO<-modelFrame$dummyMasks*modelFrame$angleSVO
modelFrame$injSVO<-modelFrame$dummyInjunctive*modelFrame$angleSVO
modelFrame$mskinjSVO<-modelFrame$dummyMasksInj*modelFrame$angleSVO

modelFrame$mskConservatism<-
   modelFrame$dummyMasks*modelFrame$conservatism
modelFrame$injConservatism<-
   modelFrame$dummyInjunctive*modelFrame$conservatism
modelFrame$mskinjConservatism<-
   modelFrame$dummyMasksInj*modelFrame$conservatism

modelFrame$mskTrump<-modelFrame$dummyMasks*modelFrame$trump
modelFrame$injTrump<-modelFrame$dummyInjunctive*modelFrame$trump
modelFrame$mskinjTrump<-modelFrame$dummyMasksInj*modelFrame$trump
```

```
modelFrame$mskSECS<-modelFrame$dummyMasks*modelFrame$SECS
modelFrame$injSECS<-modelFrame$dummyInjunctive*modelFrame$SECS
modelFrame$mskinjSECS<-modelFrame$dummyMasksInj*modelFrame$SECS

modelFrame$mskSECSEcon<-modelFrame$dummyMasks*modelFrame$SECSEcon
modelFrame$injSECSEcon<-modelFrame$dummyInjunctive*modelFrame$SECSEcon
modelFrame$mskinjSECSEcon<-modelFrame$dummyMasksInj*modelFrame$SECSEcon

modelFrame$mskSECSSoc<-modelFrame$dummyMasks*modelFrame$SECSSoc
modelFrame$injSECSSoc<-modelFrame$dummyInjunctive*modelFrame$SECSSoc
modelFrame$mskinjSECSSoc<-modelFrame$dummyMasksInj*modelFrame$SECSSoc

modelFrame$mskPsychReactance<-
   modelFrame$dummyMasks*modelFrame$psychReactance
modelFrame$injPsychReactance<-
   modelFrame$dummyInjunctive*modelFrame$psychReactance
modelFrame$mskinjPsychReactance<-
   modelFrame$dummyMasksInj*modelFrame$psychReactance

modelFrame$mskConnection<-
   modelFrame$dummyMasks*modelFrame$binaryConnection
modelFrame$injConnection<-
   modelFrame$dummyInjunctive*modelFrame$binaryConnection
modelFrame$mskinjConnection<-
   modelFrame$dummyMasksInj*modelFrame$binaryConnection

modelFrame$mskRiskyChoices<-
    modelFrame$dummyMasks*modelFrame$RiskyChoices
modelFrame$injRiskyChoices<-
    modelFrame$dummyInjunctive*modelFrame$RiskyChoices
modelFrame$mskinjRiskyChoices<-
   modelFrame$dummyMasksInj*modelFrame$RiskyChoices

modelFrame$dummySample=as.numeric(modelFrame$facSample)-1
```

A2.2 ANOVA models

The three-factorial ANOVA model with the factors framing, intervention, and voter type mirrors the structure of the experiment. The ANOVA shows clear main effects for all three factors with a two-way interaction between framing and intervention. Coefficients and the bar diagram in Figure A2 below demonstrate that the effect of the intervention is smaller in the mask version of the game than in the color version, while the direction of the effect remains the same.

```r
options(contrasts = c("contr.sum", "contr.poly"))

lmANOVA3<-lm(RiskyChoices~facFraming*facInterv*facSample,
             data = modelFrame)
modANOVA3<-Anova(lmANOVA3, type="III")
print(modANOVA3)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                                Sum Sq  Df  F value    Pr(>F)
## (Intercept)                     27138   1 577.5014 < 2.2e-16 ***
## facFraming                       8096   1 172.2844 < 2.2e-16 ***
## facInterv                        2538   1  54.0031 4.889e-13 ***
## facSample                         823   1  17.5110 3.169e-05 ***
## facFraming:facInterv             1324   1  28.1736 1.433e-07 ***
## facFraming:facSample                0   1   0.0067    0.9350
## facInterv:facSample                84   1   1.7912    0.1812
## facFraming:facInterv:facSample     17   1   0.3520    0.5532
## Residuals                       38110 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
lmANOVA3$coefficients
```

```
##                        (Intercept)                         facFraming1
##                         5.76208817                        -3.14721426
##                         facInterv1                          facSample1
##                        -1.76202825                         1.00336450
##            facFraming1:facInterv1             facFraming1:facSample1
##                         1.27269505                        -0.01955855
##             facInterv1:facSample1 facFraming1:facInterv1:facSample1
##                        -0.32090617                         0.14225258
```

```r
print(eta_squared(modANOVA3, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter                      | Eta2 (partial) |       95% CI
## ------------------------------------------------------------------
## facFraming                     |           0.18 | [0.14, 1.00]
## facInterv                      |           0.06 | [0.04, 1.00]
## facSample                      |           0.02 | [0.01, 1.00]
## facFraming:facInterv           |           0.03 | [0.02, 1.00]
```

```
## facFraming:facSample           |       8.20e-06 | [0.00, 1.00]
## facInterv:facSample            |       2.20e-03 | [0.00, 1.00]
## facFraming:facInterv:facSample |       4.34e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

The two-factorial model without the voter type factor fits the data significantly worse ($F(4, 811) = 4.88$, $p < .001$). The following series of models tries to achieve some insight into the nature of the differences between the two samples that can explain the differences in behavior.

```
lmANOVA2<-lm(RiskyChoices~facFraming*facInterv, data = modelFrame)
modANOVA2<-Anova(lmANOVA2, type="III")
print(modANOVA2)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                       Sum Sq  Df F value    Pr(>F)
## (Intercept)            26892   1 561.567 < 2.2e-16 ***
## facFraming              7942   1 165.840 < 2.2e-16 ***
## facInterv               2499   1  52.178 1.164e-12 ***
## facFraming:facInterv    1275   1  26.632 3.094e-07 ***
## Residuals              39028 815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

lmANOVA2$coefficients

##            (Intercept)             facFraming1              facInterv1
##               5.730818              -3.114302              -1.746874
## facFraming1:facInterv1
##               1.248005

print(eta_squared(modANOVA2, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter            | Eta2 (partial) |       95% CI
## -----------------------------------------------------
## facFraming           |           0.17 | [0.13, 1.00]
## facInterv            |           0.06 | [0.04, 1.00]
## facFraming:facInterv |           0.03 | [0.01, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
anova(lmANOVA2,lmANOVA3)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ facFraming * facInterv
## Model 2: RiskyChoices ~ facFraming * facInterv * facSample
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    815 39028
## 2    811 38110  4    917.54 4.8814 0.0006805 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A2.3 Bar diagram

Figure A2 shows the average number of H/no mask choices in the four experimental conditions split by voter type.

```
ggplot(data=barFrame, aes(x=Intervention, y=RiskyChoices, fill=Voter)) +
   stat_summary(geom="bar",fun=mean,position="dodge")+
   stat_summary(fun.data = mean_se, geom = "errorbar",
         position=position_dodge(width=0.9),width=0.2)+
   facet_wrap(~Framing)+ # geom_point(size=2)+
   theme_economist()+
   scale_color_manual(values=c("#661100","#6699CC"))+
   scale_fill_manual(values=c("#661100","#6699CC"))+
   scale_linetype_manual(values=c("solid","dotted"))+
   labs(title='Number of risky choices',
         subtitle="Split by framing, intervention and voter type")+
   theme(axis.title.y =element_text(vjust=3) ,
         axis.title.x =element_text(vjust=-2))+
   labs(y="Number of risky choices")
```

```
## Warning:  The ‘size‘ argument of ‘element_line()‘ is deprecated as of
ggplot2 3.4.0.
## i Please use the ‘linewidth‘ argument instead.
## This warning is displayed once every 8 hours.
## Call ‘lifecycle::last_lifecycle_warnings()‘ to see where this warning
was
## generated.
```

A2.4 Robustness check regarding ANOVA and previously established predictors

In our previous study, we found correlations of game scores and behavioral types with three covariates: social values orientation (Murphy et al., 2011), a CRT measure

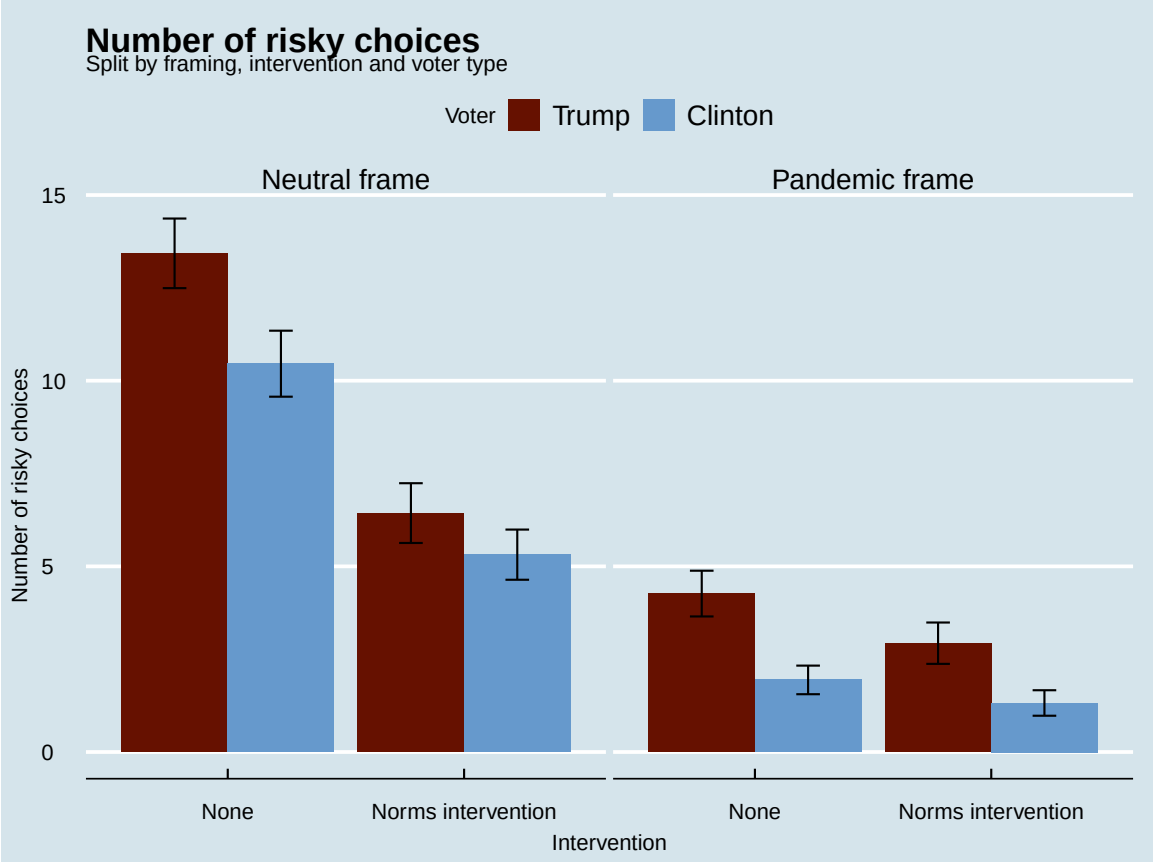


Figure A1
Game scores by framing, intervention and voter type

(Frederick, 2005; Woike, 2019), and a general risk item measure (Dohmen et al., 2011).

Two ANCOVA-models were estimated to test the robustness of the results when these three predictors were added as covariates.

```
    lmSC2<-lm(RiskyChoices~facFraming*facInterv+CRT+angleSVO+
                      riskTaking, data = modelFrame)
    modSC2<-Anova(lmSC2, type="III")
    print(modSC2)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                      Sum Sq  Df  F value    Pr(>F)
## (Intercept)           26885   1 594.0479 < 2.2e-16 ***
## facFraming             7482   1 165.3217 < 2.2e-16 ***
## facInterv              2426   1  53.5979 5.926e-13 ***
## CRT                      43   1   0.9592  0.327674
## angleSVO               1351   1  29.8535 6.200e-08 ***
```

```
## riskTaking              445   1   9.8373  0.001772 **
## facFraming:facInterv   1250   1  27.6122 1.896e-07 ***
## Residuals             36748 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmSC2$coefficients
```

```
##            (Intercept)             facFraming1             facInterv1
##             5.73007525             -3.03091566             -1.72316578
##                    CRT                angleSVO             riskTaking
##            -0.16261279             -0.09234619              0.30549930
## facFraming1:facInterv1
##             1.23705047
```

```
    print(eta_squared(modSC2, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter            | Eta2 (partial) |       95% CI
## -----------------------------------------------------
## facFraming           |           0.17 | [0.13, 1.00]
## facInterv            |           0.06 | [0.04, 1.00]
## CRT                  |       1.18e-03 | [0.00, 1.00]
## angleSVO             |           0.04 | [0.02, 1.00]
## riskTaking           |           0.01 | [0.00, 1.00]
## facFraming:facInterv |           0.03 | [0.02, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Results for the two-factorial ANCOVA model are in line with the results for the ANOVA model. Social value orientation and risk taking are significant predictors. The cognitive reflection test does not predict game choices in this model.

```
    lmSC3<-lm(RiskyChoices~facSample*facFraming*facInterv+CRT+angleSVO+
                      riskTaking, data = modelFrame)
    modSC3<-Anova(lmSC3, type="III")
    print(modSC3)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                                Sum Sq  Df  F value    Pr(>F)
## (Intercept)                     27024   1 601.6226 < 2.2e-16 ***
## facSample                         357   1   7.9522  0.004921 **
```

```
## facFraming                         7599   1 169.1829 < 2.2e-16 ***
## facInterv                          2468   1  54.9356 3.144e-13 ***
## CRT                                  33   1   0.7298  0.393188
## angleSVO                           1099   1  24.4606 9.228e-07 ***
## riskTaking                          375   1   8.3451  0.003971 **
## facSample:facFraming                  3   1   0.0646  0.799475
## facSample:facInterv                  73   1   1.6268  0.202506
## facFraming:facInterv               1292   1  28.7530 1.074e-07 ***
## facSample:facFraming:facInterv       23   1   0.5151  0.473166
## Residuals                         36294 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmSC3$coefficients
```

```
##                         (Intercept)                          facSample1
##                          5.75016417                          0.67751524
##                         facFraming1                          facInterv1
##                         -3.05868576                         -1.73948189
##                                 CRT                            angleSVO
##                         -0.14201166                         -0.08440139
##                          riskTaking              facSample1:facFraming1
##                          0.28210087                          0.05965861
##              facSample1:facInterv1              facFraming1:facInterv1
##                         -0.29957375                          1.25864692
## facSample1:facFraming1:facInterv1
##                          0.16857658
```

```
    print(eta_squared(modSC3, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter                        | Eta2 (partial) |       95% CI
## ------------------------------------------------------------------
## facSample                        |       9.75e-03 | [0.00, 1.00]
## facFraming                       |           0.17 | [0.14, 1.00]
## facInterv                        |           0.06 | [0.04, 1.00]
## CRT                              |       9.02e-04 | [0.00, 1.00]
## angleSVO                         |           0.03 | [0.01, 1.00]
## riskTaking                       |           0.01 | [0.00, 1.00]
## facSample:facFraming             |       7.99e-05 | [0.00, 1.00]
## facSample:facInterv              |       2.01e-03 | [0.00, 1.00]
## facFraming:facInterv             |           0.03 | [0.02, 1.00]
## facSample:facFraming:facInterv   |       6.37e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Results of the ANOVA and ANCOVA are generally comparable. Again, social value orientation and risk taking but not the CRT are significant predictors. The main effect of voter sample is attenuated in the ANCOVA model.

The comparison between the two groups demonstrates a higher social value orientation angle (indicating more prosocial choices), a higher cognitive reflection score, and a lower degree of general risk preference in the Clinton voter sample.

```
    lmRisk<-lm(riskTaking~dummySample, data = modelFrame)
    modRisk<-Anova(lmRisk, type="III")
    print(modRisk)

## Anova Table (Type III tests)
##
## Response: riskTaking
##             Sum Sq  Df F value    Pr(>F)
## (Intercept)   46.2   1   7.642 0.0058309 **
## dummySample   89.9   1  14.867 0.0001245 ***
## Residuals   4940.3 817
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmRisk$coefficients

## (Intercept) dummySample
##   0.3407422  -0.6628690

    print(eta_squared(lmRisk, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA
##
## Parameter   | Eta2 |       95% CI
## ---------------------------------
## dummySample | 0.02 | [0.01, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    lmSVO<-lm(angleSVO~dummySample, data = modelFrame)
    modSVO<-Anova(lmSVO, type="III")
    print(modSVO)

## Anova Table (Type III tests)
##
## Response: angleSVO
##             Sum Sq  Df F value    Pr(>F)
## (Intercept)   2581   1  13.219 0.0002944 ***
## dummySample   5021   1  25.716 4.896e-07 ***
```

```
## Residuals   159529 817
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmSVO$coefficients
```

```
## (Intercept) dummySample
##   -2.546657    4.954185
```

```
    print(eta_squared(modSVO, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA
##
## Parameter   | Eta2 |       95% CI
## ---------------------------------
## dummySample | 0.03 | [0.01, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    lmCRT<-lm(CRT~dummySample, data = modelFrame)
    modCRT<-Anova(lmCRT, type="III")
    print(modCRT)
```

```
## Anova Table (Type III tests)
##
## Response: CRT
##              Sum Sq  Df F value   Pr(>F)
## (Intercept)    8.62   1  4.2427 0.039735 *
## dummySample   16.76   1  8.2537 0.004172 **
## Residuals   1659.28 817
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmCRT$coefficients
```

```
## (Intercept) dummySample
##  -0.1471399   0.2862412
```

```
    print(eta_squared(modCRT, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA
##
## Parameter   | Eta2 |       95% CI
## ---------------------------------
## dummySample | 0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

The attenuation might thus be either due to the explanatory power of the three predictors or due to a spurious correlation with other differences between the two voter samples. To explore the relationship further, we estimated a series of regression model without the sample factor (see Section A4).

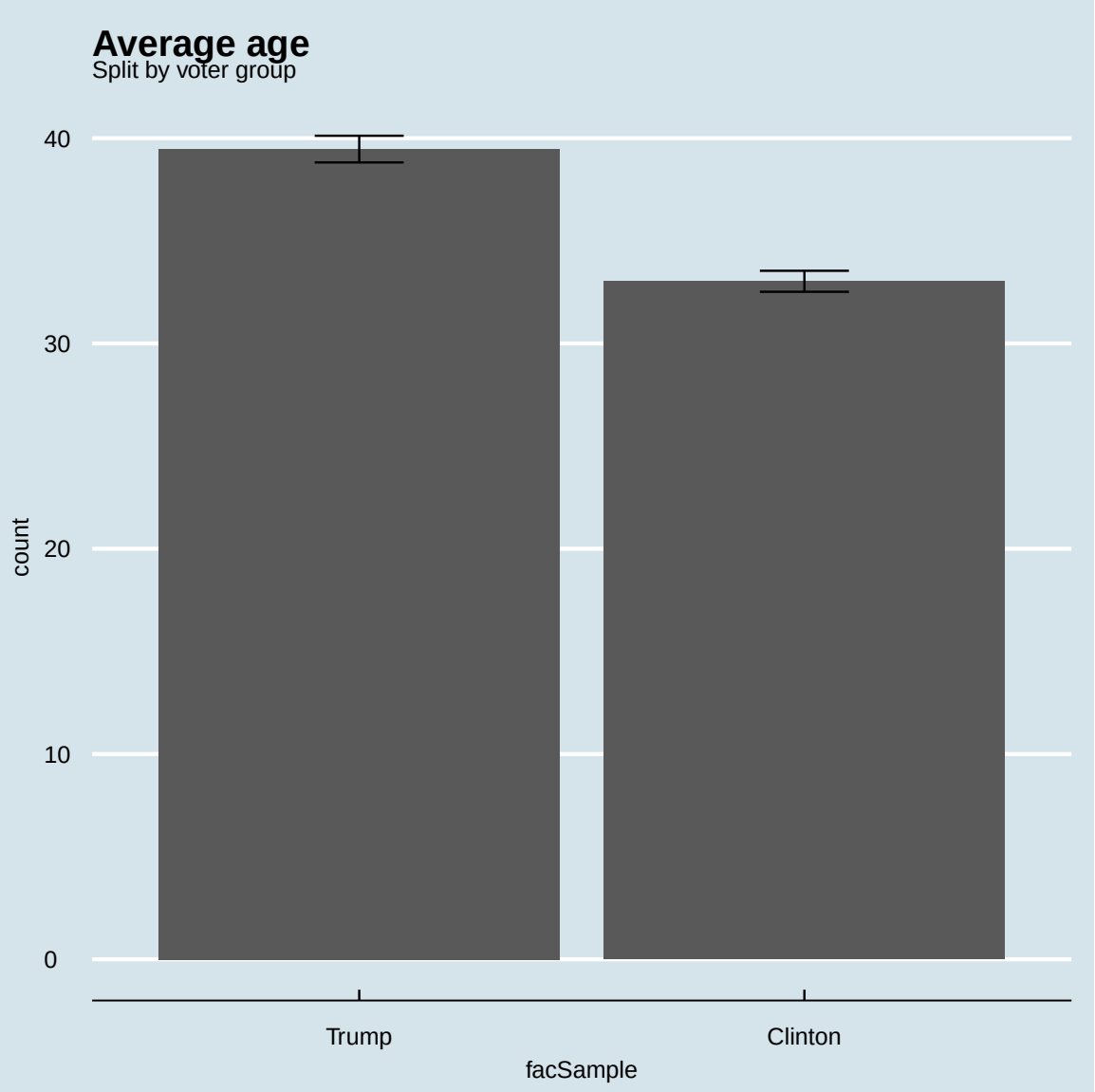
A2.5 Robustness check regarding demographic variables

A2.5.1 Demographic differences between voter samples

Republican and Democratic voters differ in demographic variables, and this is also true for our samples. We have collected information on age, gender, and education.

```
modelTestFrame=data.frame(
   RiskyChoices=(anovaFrame$gameScore-200)/32,
   facFraming= as.factor(anovaFrame$facFraming),
   facInterv= as.factor(anovaFrame$facInterv),
   facSample= as.factor(anovaFrame$facSample),
   gender=as.factor(df$demo01Gender),
   age=df$demo01Age,
   education=as.factor(df$demo02Education)

 )

modelTestFrame$facSample<-factor(modelTestFrame$facSample,
                                 labels=c("Trump","Clinton"))



table1 <- table(modelTestFrame$gender, modelTestFrame$facSample)
table1

##
##                            Trump Clinton
##   Prefer not to say            0       0
##   Male                       239     186
##   Female                     158     229
##   non-binary (open answer)     1       4
##   agender                      0       1
##   genderqueer woman            0       1
##   Alternative answer:          0       0

prop.table(table1,margin=2)

##
##                                  Trump     Clinton
##   Prefer not to say        0.000000000 0.000000000
```

```
##   Male                       0.600502513 0.441805226
##   Female                     0.396984925 0.543942993
##   non-binary (open answer) 0.002512563 0.009501188
##   agender                    0.000000000 0.002375297
##   genderqueer woman          0.000000000 0.002375297
##   Alternative answer:        0.000000000 0.000000000

table2 <- table(modelTestFrame$education, modelTestFrame$facSample)
table2

##
##                                Trump Clinton
##   Some High School                 3       1
##   High School                    115      91
##   Bachelor's degree              165     219
##   Master's degree                 90      79
##   PhD / MD / doctorate degree     10      16
##   Professional degree             15      15

prop.table(table2,margin=2)

##
##                                      Trump     Clinton
##   Some High School             0.007537688 0.002375297
##   High School                  0.288944724 0.216152019
##   Bachelor's degree            0.414572864 0.520190024
##   Master's degree              0.226130653 0.187648456
##   PhD / MD / doctorate degree 0.025125628 0.038004751
##   Professional degree          0.037688442 0.035629454

 modelTestFrame$education<-factor(modelTestFrame$education,
                                  labels=c("Some HS","HS", "BachD", "MastD", "PhD", "Prof. D

 ggplot(data=modelTestFrame, aes(x=facSample,  y=age)) +
    stat_summary(geom="bar",fun=mean,position="dodge")+
    stat_summary(fun.data = mean_se, geom = "errorbar",
          position=position_dodge(width=0.9),width=0.2)+
    theme_economist()+
    scale_color_manual(values=c("#661100","#6699CC"))+
    scale_fill_manual(values=c("#661100","#6699CC"))+
    scale_linetype_manual(values=c("solid","dotted"))+
    labs(title='Average age',
          subtitle="Split by voter group")+
    theme(axis.title.y =element_text(vjust=3) ,
          axis.title.x =element_text(vjust=-2))+
    labs(y="count")
```



There are differences in gender distribution and age, and smaller discrepancies regarding attained education levels.

A2.5.2 Addressing potential confounds

Our main analysis included the voter factor that is correlated with demographic variables as seen above. Our main model did not include demographic variables, as we had not observed a relationship between game decisions and age and gender in our previous study Woike et al., 2022. In this context, it is relevant to stress that we measure risk taking in the context of a social dilemma, not risk taking per se. We originally had no research hypotheses regarding gender and age, but some comments received on an earlier version of the manuscript motivated us to address possible concerns regarding these variables. To exclude the possibility that these variables could explain the observed effects, we present

additional models here that add these variables to the analysis.

In the first model, we add gender and age.

```
 options(contrasts = c("contr.sum", "contr.poly"))
   lmANOVAdem1<-lm(RiskyChoices~facFraming*facInterv*facSample+gender+age,
               data = modelTestFrame)

   modANOVAdem1<-Anova(lmANOVAdem1, type="III")

   print(modANOVAdem1)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)                        239   1   5.0728 0.0245727 *
## facFraming                        8022   1 170.1521 < 2.2e-16 ***
## facInterv                         2462   1  52.2090 1.158e-12 ***
## facSample                          673   1  14.2754 0.0001695 ***
## gender                             105   4   0.5578 0.6933597
## age                                  1   1   0.0272 0.8689295
## facFraming:facInterv              1327   1  28.1406 1.459e-07 ***
## facFraming:facSample                 1   1   0.0182 0.8928072
## facInterv:facSample                 88   1   1.8652 0.1724110
## facFraming:facInterv:facSample      16   1   0.3493 0.5546603
## Residuals                        38002 806
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

 lmANOVAdem1$coefficients

##                         (Intercept)                          facFraming1
##                         4.878246174                        -3.145399627
##                          facInterv1                           facSample1
##                        -1.744895749                         0.957038740
##                             gender1                              gender2
##                         1.307991524                         0.714763358
##                             gender3                              gender4
##                        -1.610776341                        -0.427251806
##                                 age              facFraming1:facInterv1
##                        -0.003409336                         1.276186494
##             facFraming1:facSample1               facInterv1:facSample1
##                        -0.032461549                        -0.328771871
## facFraming1:facInterv1:facSample1
##                         0.142209416
```

```
print(eta_squared(modANOVAdem1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter                      | Eta2 (partial) |       95% CI
## -----------------------------------------------------------------
## facFraming                     |           0.17 | [0.14, 1.00]
## facInterv                      |           0.06 | [0.04, 1.00]
## facSample                      |           0.02 | [0.01, 1.00]
## gender                         |       2.76e-03 | [0.00, 1.00]
## age                            |       3.38e-05 | [0.00, 1.00]
## facFraming:facInterv           |           0.03 | [0.02, 1.00]
## facFraming:facSample           |       2.25e-05 | [0.00, 1.00]
## facInterv:facSample            |       2.31e-03 | [0.00, 1.00]
## facFraming:facInterv:facSample |       4.33e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

The effects for neither gender nor age are significant in this model, and none of the previously observed effects changes to a substantial degree. In a second model, we add education.

```
options(contrasts = c("contr.sum", "contr.poly"))
  lmANOVAdem1b<-lm(RiskyChoices~facFraming*facInterv*facSample+gender+age+education,
              data = modelTestFrame)

  modANOVAdem1b<-Anova(lmANOVAdem1b, type="III")

  print(modANOVAdem1b)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                               Sum Sq  Df  F value    Pr(>F)
## (Intercept)                      296   1   6.3622 0.0118504 *
## facFraming                      7732   1 166.4698 < 2.2e-16 ***
## facInterv                       2406   1  51.7983 1.416e-12 ***
## facSample                        623   1  13.4212 0.0002652 ***
## gender                            99   4   0.5349 0.7101191
## age                               15   1   0.3135 0.5757088
## education                        798   5   3.4355 0.0044477 **
## facFraming:facInterv            1346   1  28.9832 9.598e-08 ***
## facFraming:facSample               2   1   0.0403 0.8410318
## facInterv:facSample               91   1   1.9646 0.1614107
## facFraming:facInterv:facSample    45   1   0.9720 0.3244721
```

```
## Residuals                       37204 801
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
 lmANOVAdem1b$coefficients
```

```
##                       (Intercept)                       facFraming1
##                        5.64375260                       -3.11606511
##                        facInterv1                        facSample1
##                       -1.72798136                        0.92455319
##                           gender1                           gender2
##                        1.29582031                        0.78420065
##                           gender3                           gender4
##                       -2.18570798                       -0.11812630
##                               age                        education1
##                       -0.01167388                        2.60430857
##                        education2                        education3
##                       -0.14483085                       -0.75761063
##                        education4                        education5
##                       -0.42464447                       -4.26336554
##           facFraming1:facInterv1           facFraming1:facSample1
##                        1.28760189                        0.04815079
##            facInterv1:facSample1 facFraming1:facInterv1:facSample1
##                       -0.33646092                        0.23678551
```

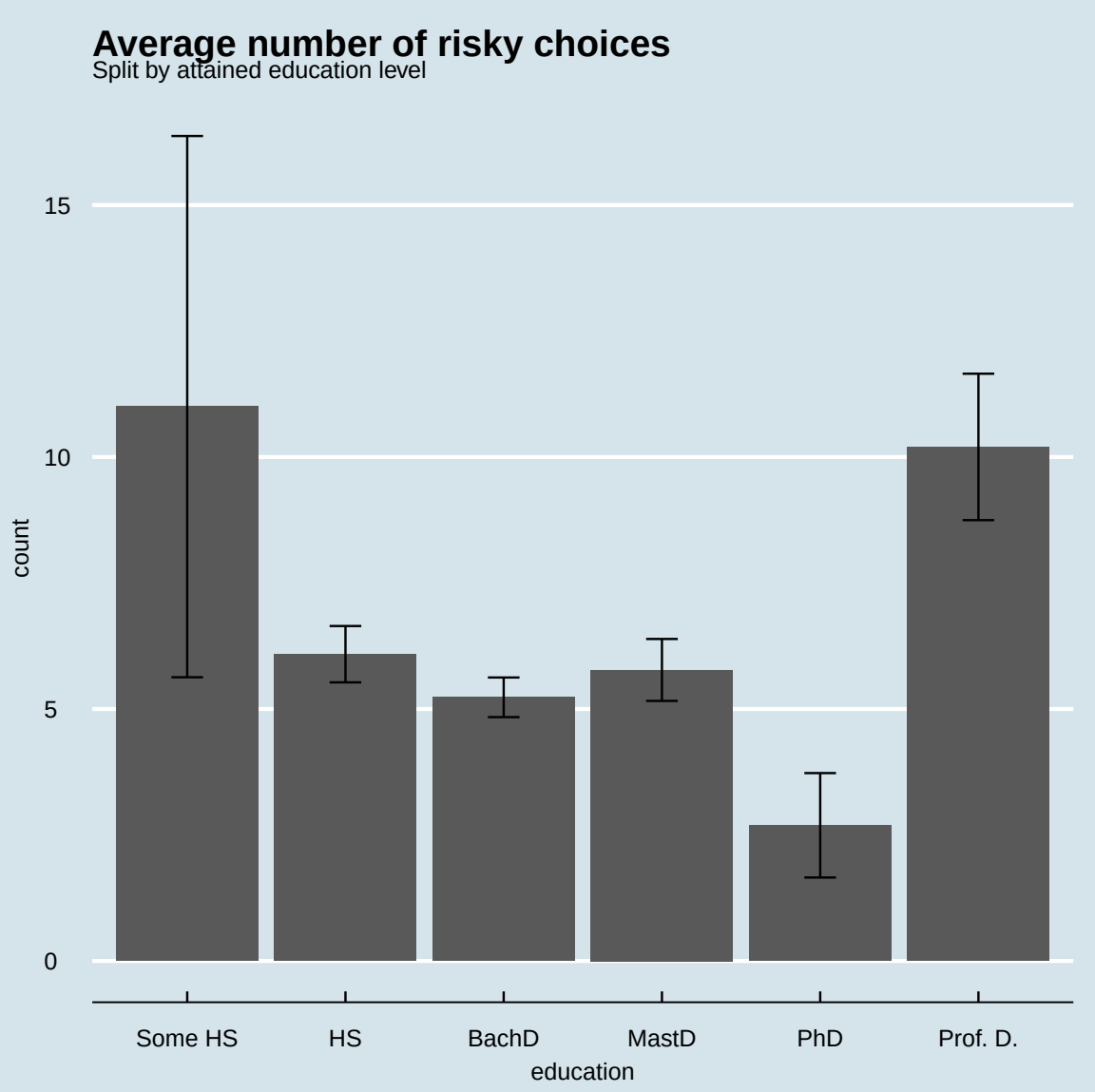
```
 print(eta_squared(modANOVAdem1b, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter                      | Eta2 (partial) |       95% CI
## ------------------------------------------------------------
## facFraming                     |           0.17 | [0.13, 1.00]
## facInterv                      |           0.06 | [0.04, 1.00]
## facSample                      |           0.02 | [0.01, 1.00]
## gender                         |       2.66e-03 | [0.00, 1.00]
## age                            |       3.91e-04 | [0.00, 1.00]
## education                      |           0.02 | [0.00, 1.00]
## facFraming:facInterv           |           0.03 | [0.02, 1.00]
## facFraming:facSample           |       5.03e-05 | [0.00, 1.00]
## facInterv:facSample            |       2.45e-03 | [0.00, 1.00]
## facFraming:facInterv:facSample |       1.21e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Education is a significant predictor of game behavior, but none of the previously

observed effects changes to a substantial degree. Isolating the education factor, the pattern of differences between subgroups is visualized below.

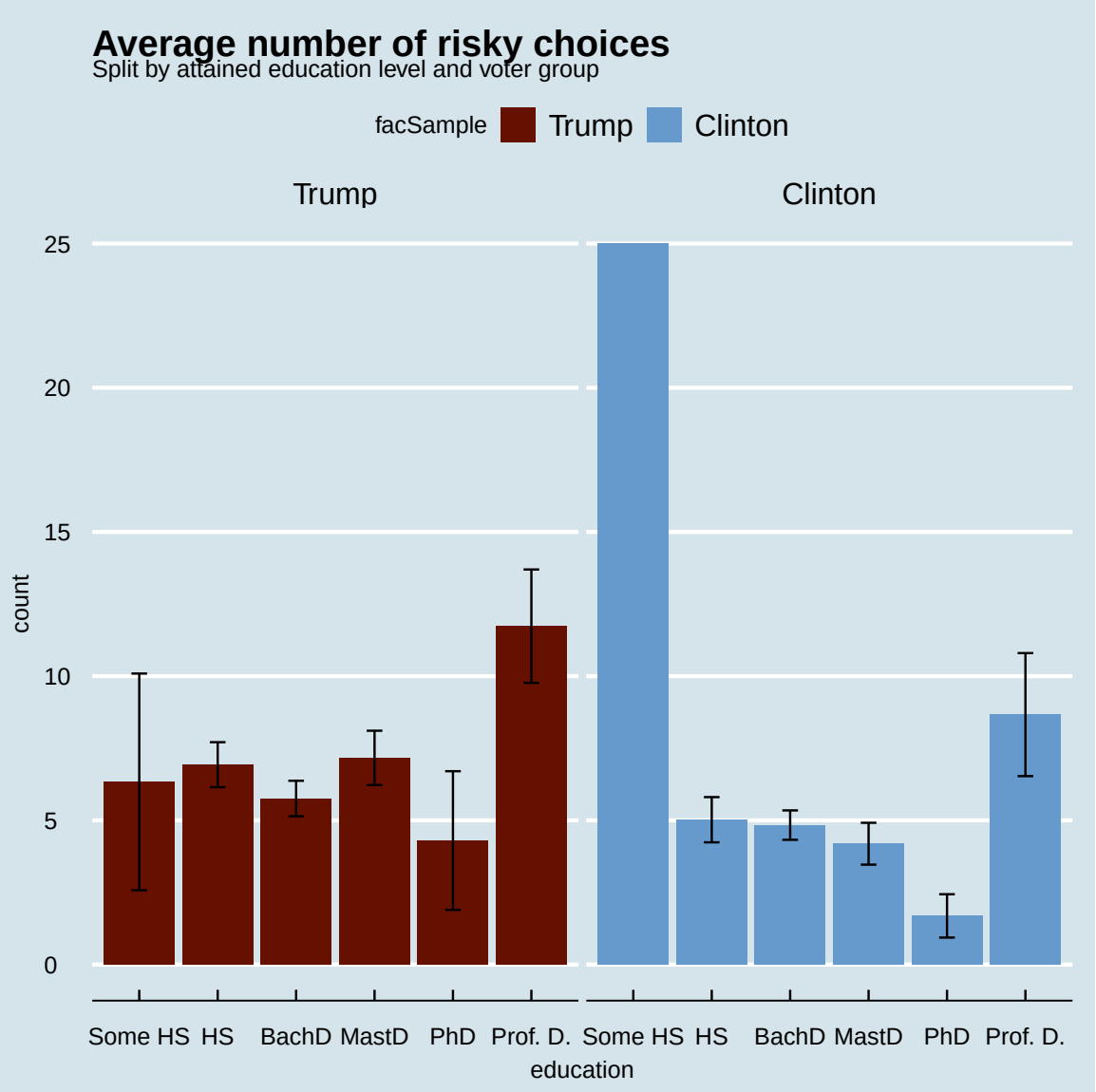
```
ggplot(data=modelTestFrame, aes(x=education,  y=RiskyChoices)) +
   stat_summary(geom="bar",fun=mean,position="dodge")+
   stat_summary(fun.data = mean_se, geom = "errorbar",
         position=position_dodge(width=0.9),width=0.2)+
   theme_economist()+
   scale_color_manual(values=c("#661100","#6699CC"))+
   scale_fill_manual(values=c("#661100","#6699CC"))+
   scale_linetype_manual(values=c("solid","dotted"))+
   labs(title='Average number of risky choices',
         subtitle="Split by attained education level")+
   theme(axis.title.y =element_text(vjust=3) ,
         axis.title.x =element_text(vjust=-2))+
   labs(y="count")
```



The larger deviations from the overall mean can be attributed to three groups that have the lowest number of members (about 60 participants in total). Splitting the analysis further by voting group again reveals no indication that education can help to explain the obtained findings:

```
ggplot(data=modelTestFrame, aes(x=education,  y=RiskyChoices, fill=facSample)) +
   stat_summary(geom="bar",fun=mean,position="dodge")+
   stat_summary(fun.data = mean_se, geom = "errorbar",
         position=position_dodge(width=0.9),width=0.2)+
   theme_economist()+
   scale_color_manual(values=c("#661100","#6699CC"))+
   scale_fill_manual(values=c("#661100","#6699CC"))+
```

```
    scale_linetype_manual(values=c("solid","dotted"))+
    labs(title='Average number of risky choices',
          subtitle="Split by attained education level and voter group")+
    theme(axis.title.y =element_text(vjust=3) ,
          axis.title.x =element_text(vjust=-2))+
    labs(y="count")+
    facet_wrap(~facSample)
```



With the exception of a single participant in the "some high school" category, the averages in all educational categories are lower (within the educational category) in the Clinton voter sample than in the Trump sample.

A2.5.3 Addressing binarized gender identity as a confound

Many analyses of risk-taking use binarized gender identities as a predictor. Without conceding the appropriateness of this simplified categorization Godman, 2018, we want to demonstrate that our results do not depend on the additional degrees of freedom in our gender factor. In a first step, we filter the total sample to exclude all participants no identifying as male or female, and then compare the average risk taking for male and female voters between voter samples.

```
modelFilteredTestFrame = subset(modelTestFrame, (gender == 'Male') |(gender == 'Female'))

 ggplot(data=modelFilteredTestFrame, aes(x=gender,  y=RiskyChoices, fill=facSample)) +
    stat_summary(geom="bar",fun=mean,position="dodge")+
    stat_summary(fun.data = mean_se, geom = "errorbar",
          position=position_dodge(width=0.9),width=0.2)+
    theme_economist()+
    scale_color_manual(values=c("#661100","#6699CC"))+
    scale_fill_manual(values=c("#661100","#6699CC"))+
    scale_linetype_manual(values=c("solid","dotted"))+
    labs(title='Average number of risky choices',
          subtitle="Split by gender (male/female) and voter group")+
    theme(axis.title.y =element_text(vjust=3) ,
          axis.title.x =element_text(vjust=-2))+
    labs(y="count")+
    facet_wrap(~facSample)
```

In each gender category, Clinton voters take less risk in the game than Trump voters, with Clinton voters identifying as male taking less risk than Trump voters identifying as female. Using the simplified gender variable in the ANOVA model tested earlier results in the same pattern of findings as before.

```
modelFilteredTestFrame = subset(modelTestFrame, (gender == 'Male') |(gender == 'Female'))

 options(contrasts = c("contr.sum", "contr.poly"))
   lmANOVAdem2<-lm(RiskyChoices~facFraming*facInterv*facSample+gender+age+education,
               data = modelFilteredTestFrame)

   modANOVAdem2<-Anova(lmANOVAdem2, type="III")

   print(modANOVAdem2)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                                Sum Sq  Df  F value    Pr(>F)
## (Intercept)                      1703   1  36.5040 2.337e-09 ***
```

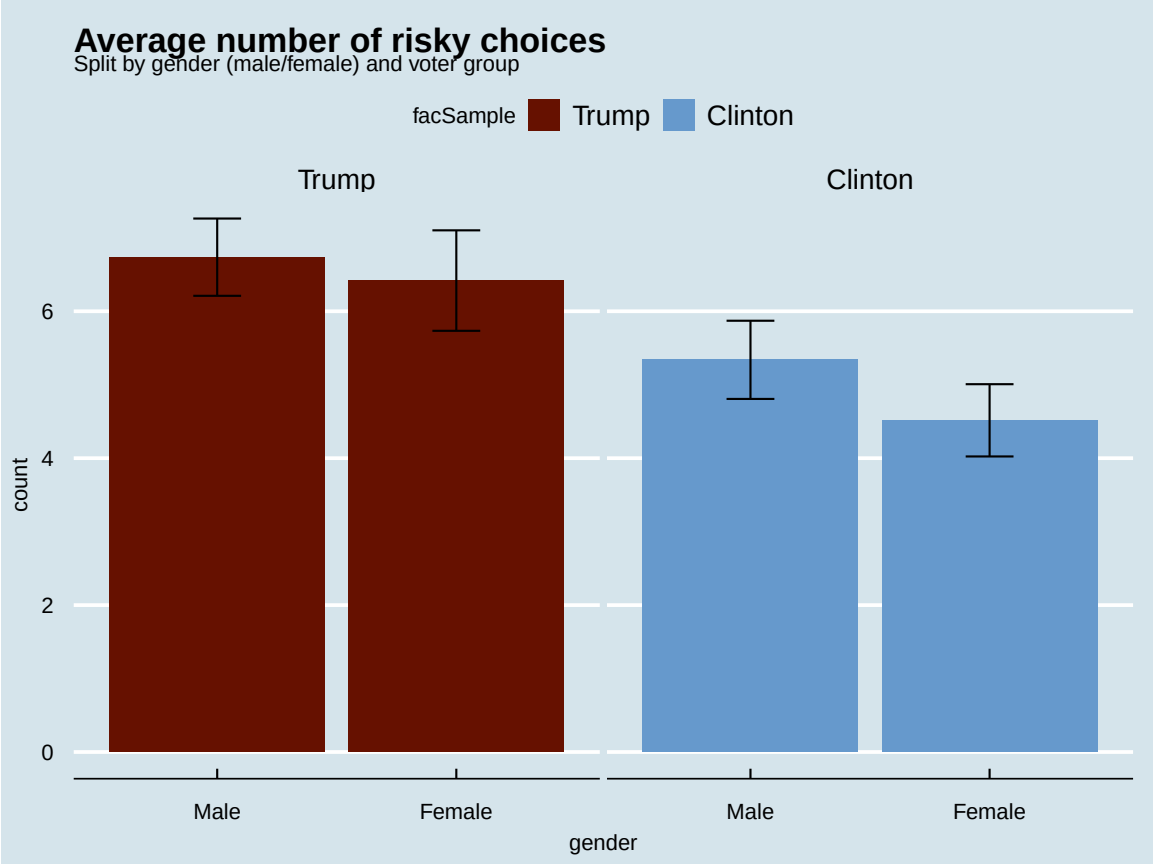


Figure A2
Game scores by framing, intervention and voter type

```
## facFraming                          7740   1 165.8687 < 2.2e-16 ***
## facInterv                           2406   1  51.5537 1.598e-12 ***
## facSample                            622   1  13.3219 0.0002794 ***
## gender                                50   1   1.0741 0.3003247
## age                                   14   1   0.3039 0.5816315
## education                            794   5   3.4025 0.0047633 **
## facFraming:facInterv                1319   1  28.2675 1.373e-07 ***
## facFraming:facSample                   3   1   0.0560 0.8130547
## facInterv:facSample                   91   1   1.9453 0.1634876
## facFraming:facInterv:facSample        48   1   1.0358 0.3091080
## Residuals                          37189 797
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

 lmANOVAdem2$coefficients

##                       (Intercept)                        facFraming1
##                        6.68103374                        -3.12530551
```

```
##                          facInterv1                          facSample1
##                         -1.72796028                          0.92431764
##                             gender1                                 age
##                          0.25558684                         -0.01152851
##                          education1                          education2
##                          2.62570628                         -0.14774249
##                          education3                          education4
##                         -0.76189169                         -0.42271959
##                          education5             facFraming1:facInterv1
##                         -4.27659867                          1.27847106
##             facFraming1:facSample1              facInterv1:facSample1
##                          0.05704527                         -0.33596976
## facFraming1:facInterv1:facSample1
##                          0.24560594
```

```
print(eta_squared(modANOVAdem2, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter                       | Eta2 (partial) |       95% CI
## ------------------------------------------------------------------
## facFraming                      |           0.17 | [0.13, 1.00]
## facInterv                       |           0.06 | [0.04, 1.00]
## facSample                       |           0.02 | [0.00, 1.00]
## gender                          |       1.35e-03 | [0.00, 1.00]
## age                             |       3.81e-04 | [0.00, 1.00]
## education                       |           0.02 | [0.00, 1.00]
## facFraming:facInterv            |           0.03 | [0.02, 1.00]
## facFraming:facSample            |       7.02e-05 | [0.00, 1.00]
## facInterv:facSample             |       2.43e-03 | [0.00, 1.00]
## facFraming:facInterv:facSample  |       1.30e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

In summary, the observed pattern of results cannot be explained by differences in demographic factors. As this series of models was computed after the completion of the manuscript, we opted to place it into the supplementary material and not into the main manuscript.

A3 Manipulation check for the framing factor

A3.1 Perceived connection to the pandemic

Here, we consider the threat posed by the ubiquitous nature of the pandemic in media reporting and also in online research at the time of the study, which might have pre-disposed participants to interpret the game as related to the pandemic irrespective of

Table A1
Percentage of participants stating to have drawn a connection between transmission game and pandemic during the simulation, split by framing condition, intervention condition, and voter group.

		Voter group	
Framing	Intervention	Clinton	Trump
Colors	no	15.9	12.9
	yes	14.8	15.2
Masks	no	98.1	90.5
	yes	100.0	91.1

framing condition. In the post-questionnaire, we asked participants irrespective of condition whether they had drawn a connection between the transmission game and the pandemic before being prompted to think about it by the question (see Tab. A1). In theory, framing should impact these perceptions, but not the presence of an intervention or the specific voter group. This is indeed what the results show with the vast majority (>90% in all conditions) seeing the connection in the pandemic framing, and the minority of participants drawing this connection in neutrally framed conditions (less than a sixth of participants in all cases). As a robustness check, we filtered out participants that had either drawn a connection with the pandemic in the neutrally framed conditions or not drawn a connection in the pandemic-framed conditions. The pattern of results found for the ANOVA in the main manuscript remained unchanged.

```
modelFilterFrame=modelFrame

modelFilterFrame$binaryConnection=2-as.numeric(df$connectionCovidDrawn)
modelFilterFrame$binaryConnection=dplyr::recode(modelFilterFrame$binaryConnection,
   '1'=1,'0'=0,'-1'=0)


attach(modelFilterFrame)

## The following object is masked _by_ .GlobalEnv:
##
##     angleSVO

connTable <- table(facFraming,binaryConnection)
connTable

##             binaryConnection
## facFraming     0   1
##   MASKS       21 391
##   NEUTRAL    347  60

prop.table(connTable, 1) # row percentages
```

```
##             binaryConnection
## facFraming             0          1
##   MASKS      0.05097087 0.94902913
##   NEUTRAL    0.85257985 0.14742015

secondtable<- table(facSample,facFraming,binaryConnection)
ftable(secondtable)

##                           binaryConnection   0   1
## facSample     facFraming
## Conservatives MASKS                        19 187
##               NEUTRAL                     165  27
## Liberals      MASKS                         2 204
##               NEUTRAL                     182  33

prop.table(secondtable, c(1:2))

## , , binaryConnection = 0
##
##                facFraming
## facSample        MASKS       NEUTRAL
##   Conservatives 0.092233010 0.859375000
##   Liberals      0.009708738 0.846511628
##
## , , binaryConnection = 1
##
##                facFraming
## facSample        MASKS       NEUTRAL
##   Conservatives 0.907766990 0.140625000
##   Liberals      0.990291262 0.153488372

thirdtable<- table(facSample,facFraming,facInterv,binaryConnection)
ftable(thirdtable)

##                                        binaryConnection   0   1
## facSample     facFraming facInterv
## Conservatives MASKS      INJUNCTIVE                      9  92
##                          NONE                           10  95
##               NEUTRAL    INJUNCTIVE                     84  15
##                          NONE                           81  12
## Liberals      MASKS      INJUNCTIVE                      0 103
##                          NONE                           2 101
##               NEUTRAL    INJUNCTIVE                     92  16
##                          NONE                           90  17

prop.table(thirdtable, c(1:3))
```

```
## , , facInterv = INJUNCTIVE     , binaryConnection = 0
##
##                facFraming
## facSample       MASKS      NEUTRAL
##   Conservatives 0.08910891 0.84848485
##   Liberals      0.00000000 0.85185185
##
## , , facInterv = NONE           , binaryConnection = 0
##
##                facFraming
## facSample       MASKS      NEUTRAL
##   Conservatives 0.09523810 0.87096774
##   Liberals      0.01941748 0.84112150
##
## , , facInterv = INJUNCTIVE     , binaryConnection = 1
##
##                facFraming
## facSample       MASKS      NEUTRAL
##   Conservatives 0.91089109 0.15151515
##   Liberals      1.00000000 0.14814815
##
## , , facInterv = NONE           , binaryConnection = 1
##
##                facFraming
## facSample       MASKS      NEUTRAL
##   Conservatives 0.90476190 0.12903226
##   Liberals      0.98058252 0.15887850
```

A3.2 ANOVA after filtering participants based on perceived connection to the pandemic

We included a manipulation check for the framing factor, in which we asked participants whether they had drawn a connection between the scenario and the pandemic. Given the prevalence of studies addressing pandemic-related topics at the time of data collection, there is a possible concern that the neutral scenario was not considered to be neutral. In the following analysis we excluded participants who stated to have seen a connection during the game in the neutrally-framed conditions (and also those participants who did not see the connection in the pandemic-framed conditions).

```
modelFilterFrame=modelFrame

modelFilterFrame$binaryConnection=2-as.numeric(df$connectionCovidDrawn)
modelFilterFrame$binaryConnection=dplyr::recode(modelFilterFrame$binaryConnection,
   '1'=1,'0'=0,'-1'=0)
```

```
modelFilteredFrame =modelFilterFrame[(modelFilterFrame$binaryConnection==1
    &as.numeric(modelFilterFrame$facFraming)==1)|(modelFilterFrame$binaryConnection==0&
      as.numeric(modelFilterFrame$facFraming)==2),]

 options(contrasts = c("contr.sum", "contr.poly"))

 lmANOVA3f<-lm(RiskyChoices~facFraming*facInterv*facSample,
               data = modelFilteredFrame)
 modANOVA3f<-Anova(lmANOVA3f, type="III")
 print(modANOVA3f)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                                Sum Sq  Df  F value    Pr(>F)
## (Intercept)                     25335   1 560.9270 < 2.2e-16 ***
## facFraming                       8551   1 189.3319 < 2.2e-16 ***
## facInterv                        2282   1  50.5237 2.807e-12 ***
## facSample                         529   1  11.7172 0.0006538 ***
## facFraming:facInterv             1532   1  33.9234 8.592e-09 ***
## facFraming:facSample                3   1   0.0723 0.7880833
## facInterv:facSample                61   1   1.3472 0.2461449
## facFraming:facInterv:facSample     28   1   0.6205 0.4311280
## Residuals                       32971 730
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

 lmANOVA3f$coefficients

##                        (Intercept)                         facFraming1
##                         5.87648213                         -3.41409949
##                         facInterv1                          facSample1
##                        -1.76364695                          0.84933023
##            facFraming1:facInterv1             facFraming1:facSample1
##                         1.44515414                          0.06671962
##             facInterv1:facSample1 facFraming1:facInterv1:facSample1
##                        -0.28799357                          0.19544520

 print(eta_squared(modANOVA3f, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter                      | Eta2 (partial) |       95% CI
## ------------------------------------------------------------
## facFraming                     |           0.21 | [0.16, 1.00]
```

```
## facInterv                       |           0.06 | [0.04, 1.00]
## facSample                       |           0.02 | [0.00, 1.00]
## facFraming:facInterv            |           0.04 | [0.02, 1.00]
## facFraming:facSample            |       9.90e-05 | [0.00, 1.00]
## facInterv:facSample             |       1.84e-03 | [0.00, 1.00]
## facFraming:facInterv:facSample |       8.49e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A comparison of ANOVA results shows the identical qualitative pattern of results with the same significant effects as before. A direct comparison of effect sizes shows an increase for the effect size of the framing factor (as to be expected) and also a slight increase of the interaction involving the framing factor. The changes do not rise to a level of concern, and we decided to report the unfiltered analysis in the main manuscript.

A4 Series of regression models

A4.1 The basic regression model

We start with a regression model that is virtually identical to the two-factorial ANOVA model. The intercept in this model represents the mean number of risky choices in the control condition. The three dummy variables adapt to the differences between conditions. The "mask" dummy is coded 1 for every observation in the pandemic frame conditions and 0 otherwise (the mean in the condition with pandemic frame and without an intervention must correspond to the sum of intercept and mask dummy). The "injunctive" dummy is coded 1 for every observation in the injunctive norms conditions and 0 otherwise (the mean in the condition with intervention and without pandemic frame corresponds to the sum of intercept and injunctive dummy). The final dummy "MasksInj" is coded 1 for observations in the condition with both pandemic frame and injunctive norms intervention (the mean in this condition corresponds to the sum of the intercept and all three dummy values).

```
lm0<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj,
        data = modelFrame)
mod0<-Anova(lm0, type="III")
print(mod0)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df F value    Pr(>F)
## (Intercept)      28037   1 585.489 < 2.2e-16 ***
## dummyMasks        7761   1 162.073 < 2.2e-16 ***
## dummyInjunctive   3649   1  76.210 < 2.2e-16 ***
## dummyMasksInj     1275   1  26.632 3.094e-07 ***
## Residuals        39028 815
```

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

   lm0$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj
##       11.840000       -8.724615       -5.989758        4.992021

   print(eta_squared(mod0, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## ------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.01, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

   anova(lm0,lmANOVA2)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj
## Model 2: RiskyChoices ~ facFraming * facInterv
##   Res.Df   RSS Df Sum of Sq F Pr(>F)
## 1    815 39028
## 2    815 39028  0         0
```

The residual sum of squares is (unsurprisingly) identical to the residual sum of squares in the two-factorial ANOVA above.

A4.2 Adding established covariates

A4.2.1 Differences between voter groups regarding covariates

```
testFrame=data.frame(
   facSample= as.factor(anovaFrame$facSample),
   riskTaking=as.numeric(df$RTGeneral)-1,
   CRT=scoresCRT$CRTscore,
   angleSVO=scoresSVO,
   SECS=scoresSECS$sclConsALL,
   trump=df$polCandScale_Trump
 )
```

```
 res.ftest <- var.test(angleSVO ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  angleSVO by facSample
## F = 1.2675, num df = 397, denom df = 420, p-value = 0.01667
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  1.043951 1.539722
## sample estimates:
## ratio of variances
##           1.267489

res <- t.test(angleSVO ~ facSample , data = testFrame, var.equal = FALSE)
res

##
##  Welch Two Sample t-test
##
## data:  angleSVO by facSample
## t = -5.0543, df = 793.05, p-value = 5.366e-07
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  -6.878251 -3.030119
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    25.21320                    30.16738

cohens_d(angleSVO ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |         95% CI
## -------------------------
## -0.35     | [-0.49, -0.22]
##
## - Estimated using pooled SD.

by(testFrame$angleSVO, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 25.2132
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 30.16738
```

```
by(testFrame$angleSVO, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 14.79945
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 13.14539

 res.ftest <- var.test(CRT ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  CRT by facSample
## F = 0.98189, num df = 397, denom df = 420, p-value = 0.8544
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.8087222 1.1927838
## sample estimates:
## ratio of variances
##          0.9818917

res <- t.test(CRT ~ facSample , data = testFrame, var.equal = TRUE)
res

##
##  Two Sample t-test
##
## data:  CRT by facSample
## t = -2.8729, df = 817, p-value = 0.004172
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  -0.48181045 -0.09067192
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    1.804020                    2.090261

cohens_d(CRT ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |         95% CI
## -------------------------
## -0.20     | [-0.34, -0.06]
##
## - Estimated using pooled SD.
```

```
by(testFrame$CRT, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 1.80402
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 2.090261

by(testFrame$CRT, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 1.418405
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 1.431425

 res.ftest <- var.test(SECS ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  SECS by facSample
## F = 0.77289, num df = 397, denom df = 420, p-value = 0.009511
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.6365842 0.9388977
## sample estimates:
## ratio of variances
##          0.7728944

res <- t.test(SECS ~ facSample , data = testFrame, var.equal = FALSE)
res

##
##  Welch Two Sample t-test
##
## data:  SECS by facSample
## t = 27.033, df = 812.76, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  57.02756 65.95775
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    48.00594                   -13.48672
```

```
cohens_d(SECS ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |       95% CI
## ------------------------
## 1.88      | [1.72, 2.05]
##
## - Estimated using pooled SD.

by(testFrame$SECS, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 48.00594
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] -13.48672

by(testFrame$SECS, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 30.43632
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 34.6204

res.ftest <- var.test(trump ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  trump by facSample
## F = 4.6552, num df = 397, denom df = 420, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  3.834157 5.654996
## sample estimates:
## ratio of variances
##           4.655155

res <- t.test(trump ~ facSample , data = testFrame, var.equal = FALSE)
res

##
##  Welch Two Sample t-test
##
## data:  trump by facSample
```

```
## t = 34.12, df = 553.06, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  117.4637 131.8144
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    36.65327                   -87.98575

cohens_d(trump ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |       95% CI
## -------------------------
## 2.43      | [2.25, 2.61]
##
## - Estimated using pooled SD.

by(testFrame$trump, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 36.65327
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] -87.98575

by(testFrame$trump, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 66.44124
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 30.79432

res.ftest <- var.test(riskTaking ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  riskTaking by facSample
## F = 1.1189, num df = 397, denom df = 420, p-value = 0.2562
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.9215598 1.3592079
## sample estimates:
## ratio of variances
##           1.118891
```

```r
res <- t.test(riskTaking ~ facSample , data = testFrame, var.equal = TRUE)
res

##
##  Two Sample t-test
##
## data:  riskTaking by facSample
## t = 3.8557, df = 817, p-value = 0.0001245
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  0.3254146 1.0003234
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    5.263819                    4.600950

cohens_d(riskTaking ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |       95% CI
## ------------------------
## 0.27      | [0.13, 0.41]
##
## - Estimated using pooled SD.

by(testFrame$riskTaking, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 5.263819
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 4.60095

by(testFrame$riskTaking, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 2.529075
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 2.390935

 res.ftest <- var.test(SECS ~ facSample , data = testFrame)
res.ftest

##
##  F test to compare two variances
##
## data:  SECS by facSample
```

```
## F = 0.77289, num df = 397, denom df = 420, p-value = 0.009511
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.6365842 0.9388977
## sample estimates:
## ratio of variances
##          0.7728944

res <- t.test(SECS ~ facSample , data = testFrame, var.equal = TRUE)
res

##
##  Two Sample t-test
##
## data:  SECS by facSample
## t = 26.935, df = 817, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Conservatives and group L
## 95 percent confidence interval:
##  57.01149 65.97383
## sample estimates:
## mean in group Conservatives      mean in group Liberals
##                    48.00594                   -13.48672

cohens_d(SECS ~ facSample, data = testFrame,paired = FALSE)

## Cohen's d |       95% CI
## -------------------------
## 1.88      | [1.72, 2.05]
##
## - Estimated using pooled SD.

by(testFrame$SECS, testFrame$facSample,mean)

## testFrame$facSample: Conservatives
## [1] 48.00594
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] -13.48672

by(testFrame$SECS, testFrame$facSample,sd)

## testFrame$facSample: Conservatives
## [1] 30.43632
## ------------------------------------------------------------
## testFrame$facSample: Liberals
## [1] 34.6204
```

A4.2.2 Adding SVO, CRT, and risk-taking

```
   lm1<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+
             angleSVO+CRT+riskTaking, data = modelFrame)
    mod1<-Anova(lm1, type="III")
    print(mod1)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27403   1 605.5037 < 2.2e-16 ***
## dummyMasks        7381   1 163.0895 < 2.2e-16 ***
## dummyInjunctive   3560   1  78.6517 < 2.2e-16 ***
## dummyMasksInj     1250   1  27.6122 1.896e-07 ***
## angleSVO          1351   1  29.8535 6.200e-08 ***
## CRT                 43   1   0.9592  0.327674
## riskTaking         445   1   9.8373  0.001772 **
## Residuals        36748 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm1$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.72120717     -8.53593227     -5.92043251      4.94820189     -0.09234619
##             CRT      riskTaking
##     -0.16261279      0.30549930

    print(eta_squared(mod1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.04 | [0.02, 1.00]
## CRT             |       1.18e-03 | [0.00, 1.00]
## riskTaking      |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm0,lm1)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    815 39028
## 2    812 36748  3    2279.3 16.788 1.374e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We replicate the results from the previous study for social value orientation and risk-taking. The relationship between the CRT and game behavior is further explored in the section dealing with behavioral types.

A4.2.3 Testing interactions with the framing factor

To test whether the relationship between game behavior and predictors might be condition-specific, we compare the model above (lm_1) with a model adding interactions between the framing factor and the covariates (calculated as products between condition dummy and each covariate).

```
    lm1I<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+
               angleSVO+mskSVO+CRT+mskCRT+riskTaking+mskRisk,
               data = modelFrame)
    mod1I<-Anova(lm1I, type="III")
    print(mod1I)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27164   1 600.5087 < 2.2e-16 ***
## dummyMasks        7343   1 162.3323 < 2.2e-16 ***
## dummyInjunctive   3515   1  77.6972 < 2.2e-16 ***
## dummyMasksInj     1226   1  27.1059 2.444e-07 ***
## angleSVO           931   1  20.5854 6.567e-06 ***
## mskSVO              42   1   0.9181  0.338265
## CRT                 59   1   1.3118  0.252414
## mskCRT              28   1   0.6247  0.429526
## riskTaking         363   1   8.0271  0.004723 **
## mskRisk             49   1   1.0732  0.300542
## Residuals        36595 809
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm1I$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.68618597     -8.51705870     -5.88794922      4.90663405     -0.10542167
##          mskSVO             CRT          mskCRT      riskTaking         mskRisk
##      0.03256086     -0.27780662      0.26381625      0.40483227     -0.20264031

    print(eta_squared(mod1I, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.02 | [0.01, 1.00]
## mskSVO          |       1.13e-03 | [0.00, 1.00]
## CRT             |       1.62e-03 | [0.00, 1.00]
## mskCRT          |       7.72e-04 | [0.00, 1.00]
## riskTaking      |       9.82e-03 | [0.00, 1.00]
## mskRisk         |       1.32e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm0,lm1I)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + CRT + mskCRT + riskTaking + mskRisk
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    815 39028
## 2    809 36595  6      2433 8.9644 1.698e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm1,lm1I)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + CRT + mskCRT + riskTaking + mskRisk
```

```
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    812 36748
## 2    809 36595  3    153.68 1.1325  0.335
```

The model with interactions does not significantly improve the model without interactions.

A4.2.4 Testing interactions with framing and intervention factor

Model *lm1Ib* adds interactions with the intervention factor and with both factors. This models allows for distinct slopes in all four experimental conditions.

```
    lm1Ib<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+
                angleSVO+mskSVO+injSVO+mskinjSVO+CRT+mskCRT+injCRT+
                mskinjCRT+riskTaking+mskRisk+injRisk+mskinjRisk,
              data = modelFrame)
    mod1Ib<-Anova(lm1Ib, type="III")
    print(mod1Ib)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27044   1 594.2700 < 2.2e-16 ***
## dummyMasks        7319   1 160.8214 < 2.2e-16 ***
## dummyInjunctive   3535   1  77.6749 < 2.2e-16 ***
## dummyMasksInj     1239   1  27.2266 2.305e-07 ***
## angleSVO           443   1   9.7312  0.001876 **
## mskSVO              12   1   0.2738  0.600940
## injSVO               0   1   0.0007  0.978768
## mskinjSVO            2   1   0.0544  0.815673
## CRT                 97   1   2.1366  0.144213
## mskCRT              59   1   1.2868  0.256969
## injCRT              39   1   0.8512  0.356498
## mskinjCRT           29   1   0.6278  0.428414
## riskTaking         114   1   2.5034  0.113991
## mskRisk             16   1   0.3513  0.553528
## injRisk             10   1   0.2290  0.632430
## mskinjRisk           1   1   0.0251  0.874198
## Residuals        36543 803
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm1I$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
```

```
##     11.68618597     -8.51705870     -5.88794922      4.90663405     -0.10542167
##          mskSVO             CRT          mskCRT      riskTaking         mskRisk
##      0.03256086     -0.27780662      0.26381625      0.40483227     -0.20264031
```

```
    print(eta_squared(mod1Ib, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## ------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.01 | [0.00, 1.00]
## mskSVO          |       3.41e-04 | [0.00, 1.00]
## injSVO          |       8.83e-07 | [0.00, 1.00]
## mskinjSVO       |       6.77e-05 | [0.00, 1.00]
## CRT             |       2.65e-03 | [0.00, 1.00]
## mskCRT          |       1.60e-03 | [0.00, 1.00]
## injCRT          |       1.06e-03 | [0.00, 1.00]
## mskinjCRT       |       7.81e-04 | [0.00, 1.00]
## riskTaking      |       3.11e-03 | [0.00, 1.00]
## mskRisk         |       4.37e-04 | [0.00, 1.00]
## injRisk         |       2.85e-04 | [0.00, 1.00]
## mskinjRisk      |       3.12e-05 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm0,lm1Ib)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + injSVO + mskinjSVO + CRT + mskCRT + injCRT +
##     mskinjCRT + riskTaking + mskRisk + injRisk + mskinjRisk
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    815 39028
## 2    803 36543 12    2484.9 4.5503 3.868e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm1,lm1Ib)
```

```
## Analysis of Variance Table
##
```

```
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + injSVO + mskinjSVO + CRT + mskCRT + injCRT +
##     mskinjCRT + riskTaking + mskRisk + injRisk + mskinjRisk
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    812 36748
## 2    803 36543  9    205.56 0.5019 0.8737

    anova(lm1I,lm1Ib)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + CRT + mskCRT + riskTaking + mskRisk
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + mskSVO + injSVO + mskinjSVO + CRT + mskCRT + injCRT +
##     mskinjCRT + riskTaking + mskRisk + injRisk + mskinjRisk
##   Res.Df   RSS Df Sum of Sq    F Pr(>F)
## 1    809 36595
## 2    803 36543  6    51.881 0.19 0.9796
```

Again, this model does not significantly improve the model without interactions nor the model with framing interactions. Thus, we keep the three predictors as simple covariates.

A4.3 Inter-correlations of conservatism variables

Three variables potentially capture the main differences between the two voter groups. As preregistered, we explore their potential for explaining behavioral differences in the transmission game. These three variables are a simple conservatism item asking for the political position on a scale from very liberal to very conservative. A second measure captures conservatism by asking for the evaluation of multiple partisan issues. The Social and Economic Conservatism Scale (SECS) has two correlated subscales, social conservatism and economic conservatism. As a third measure, we asked for the preference for presidential candidates in 2020. The Prolific samples were selected based on voting behavior in 2016. The preference for an electoral win for Donald Trump was thus a likely candidate for capturing the differences between samples, even if some voters might have changed their preference in the mean time.

```
conservatismMatrix=data.frame(
  conservatismItem=modelFrame$conservatism,
  SECSFull=modelFrame$SECS,
  SECSEcon=modelFrame$SECSEcon,
  SECSSocial=modelFrame$SECSSoc,
  trumpPref=modelFrame$trump
```

```
)
```

An analysis of the inter-correlations between these measures shows the expected pattern of high positive correlations between measures (see Fig. A3).

```
corMatrix<-cor(conservatismMatrix,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

Thus, it does not seem to be a good idea to simply add all three variables to the model. Instead, we enter variables on their own and in pairs to test whether predictions can be substantially improved.

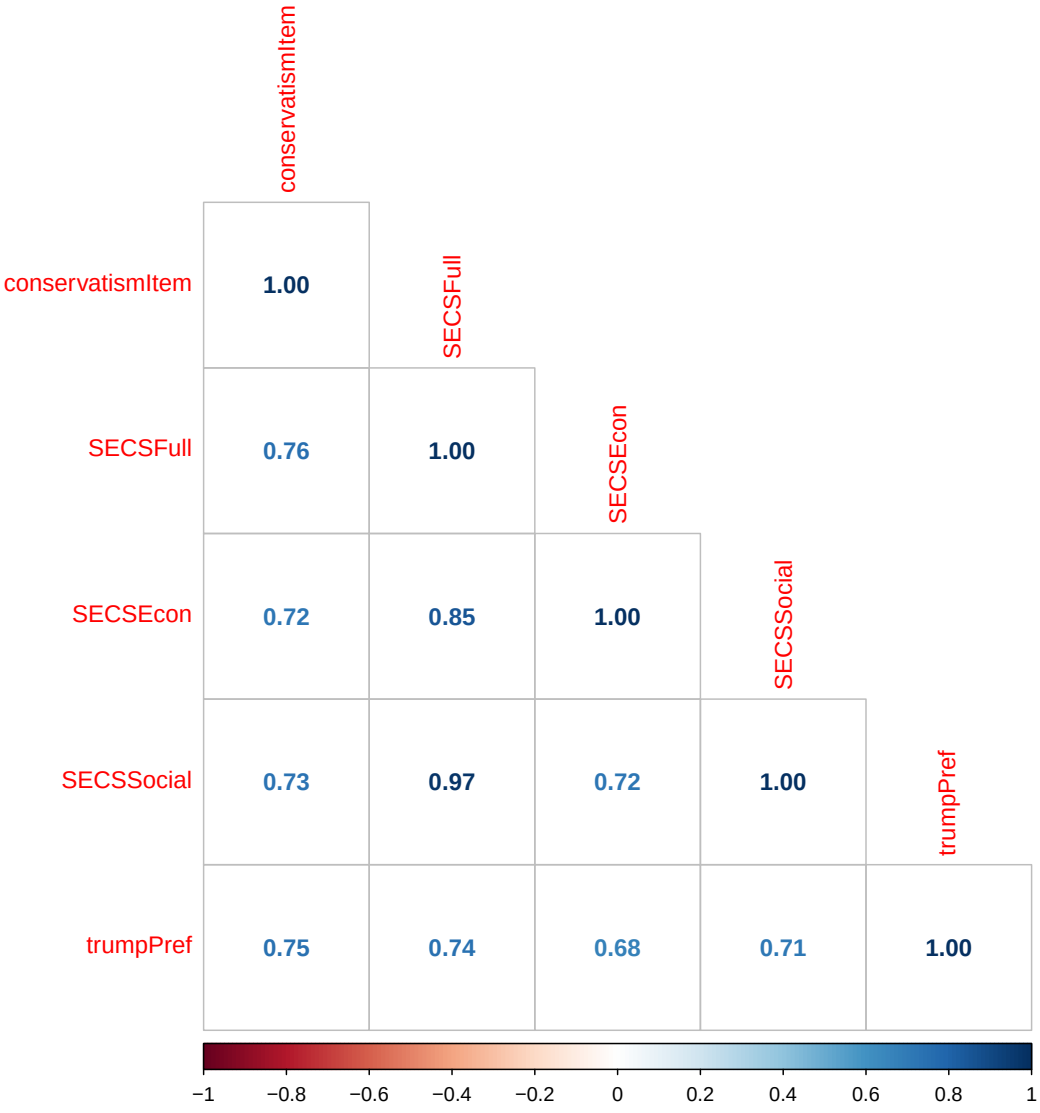


Figure A3
Intercorrelation between conservatism measures

A4.4 Adding a single conservatism measure

A4.4.1 Adding Trump preference as predictor

```
     lm2<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+trump, data = modelFrame)
    mod2<-Anova(lm2, type="III")
    print(mod2)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27509   1 612.2206 < 2.2e-16 ***
## dummyMasks        7424   1 165.2261 < 2.2e-16 ***
## dummyInjunctive   3573   1  79.5238 < 2.2e-16 ***
## dummyMasksInj     1237   1  27.5300 1.976e-07 ***
## angleSVO          1096   1  24.3881 9.565e-07 ***
## CRT                 15   1   0.3238  0.569467
## riskTaking         352   1   7.8248  0.005275 **
## trump              308   1   6.8465  0.009047 **
## Residuals        36441 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm2$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.746219286    -8.561846506    -5.931980161     4.923387309    -0.084481491
##             CRT      riskTaking           trump
##    -0.095277980     0.273619065     0.007942033

    print(eta_squared(mod2, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       3.99e-04 | [0.00, 1.00]
## riskTaking      |       9.56e-03 | [0.00, 1.00]
## trump           |       8.37e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm1,lm2)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    812 36748
## 2    811 36441  1    307.63 6.8465 0.009047 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Starting with the attitude towards an electoral win by Donald Trump in 2020 as a single predictor, the model is clearly improved without a qualitative change in other effects.

A4.4.2 Adding conservatism as predictor

```
    lm2a<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+conservatism, data = modelFrame)
    mod2a<-Anova(lm2a, type="III")
    print(mod2a)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27564   1 611.1279 < 2.2e-16 ***
## dummyMasks        7477   1 165.7726 < 2.2e-16 ***
## dummyInjunctive   3645   1  80.8151 < 2.2e-16 ***
## dummyMasksInj     1286   1  28.5112 1.210e-07 ***
## angleSVO          1145   1  25.3839 5.795e-07 ***
## CRT                 29   1   0.6508  0.420053
## riskTaking         427   1   9.4704  0.002158 **
## conservatism       169   1   3.7521  0.053088 .
## Residuals        36579 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm2a$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.77770364     -8.60280558     -6.00357326      5.02394722     -0.08640321
##             CRT      riskTaking    conservatism
##     -0.13424012      0.29939824      0.24291611
```

```
    print(eta_squared(mod2a, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       8.02e-04 | [0.00, 1.00]
## riskTaking      |           0.01 | [0.00, 1.00]
## conservatism    |       4.61e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm1,lm2a)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + conservatism
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    811 36579  1    169.23 3.7521 0.05309 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding the single conservatism item leads to an improvement, but not a significant improvement of the model. One should note that there is a relationship between conservatism and the other predictors in the model. A model without these predictor shows a coefficient for the conservatism factor that is significantly different from zero. These relationships are explored in section A8.

```
    lm2ar<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+conservatism, data = m
    mod2ar<-Anova(lm2ar, type="III")
    print(mod2ar)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                Sum Sq  Df F value    Pr(>F)
## (Intercept)     28362   1 599.165 < 2.2e-16 ***
```

```
## dummyMasks        7931   1 167.555 < 2.2e-16 ***
## dummyInjunctive   3798   1  80.239 < 2.2e-16 ***
## dummyMasksInj     1341   1  28.330 1.324e-07 ***
## conservatism       496   1  10.481  0.001255 **
## Residuals        38532 814
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm2ar$coefficients
```

```
##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj    conservatism
##       11.926268       -8.829821       -6.121498        5.123569        0.406138
```

```
    print(eta_squared(mod2ar, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## conservatism    |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm0,lm2ar)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     conservatism
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    815 39028
## 2    814 38532  1    496.13 10.481 0.001255 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A4.4.3 Adding SECS as predictor

```
     lm2b<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+SECS, data = modelFrame)
    mod2b<-Anova(lm2b, type="III")
```

```
    print(mod2b)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27550   1 612.1092 < 2.2e-16 ***
## dummyMasks        7456   1 165.6488 < 2.2e-16 ***
## dummyInjunctive   3606   1  80.1188 < 2.2e-16 ***
## dummyMasksInj     1261   1  28.0155 1.550e-07 ***
## angleSVO          1147   1  25.4759 5.533e-07 ***
## CRT                 23   1   0.5080  0.476196
## riskTaking         379   1   8.4299  0.003791 **
## SECS               247   1   5.4829  0.019444 *
## Residuals        36502 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm2b$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.75955257     -8.58287727     -5.96098378      4.97076576     -0.08612370
##             CRT      riskTaking            SECS
##     -0.11876941      0.28335869      0.01261756

    print(eta_squared(mod2b, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## ------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       6.26e-04 | [0.00, 1.00]
## riskTaking      |           0.01 | [0.00, 1.00]
## SECS            |       6.72e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm1,lm2b)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
```

```
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + SECS
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    811 36502  1    246.78 5.4829 0.01944 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding the SECS scale leads to an improvement of the model that is significant but with a smaller effect size than the electoral preference variable. In the next step, we explore interactions between the preference variable and design factors.

A4.4.4 Probing for interactions

Given the politicization of mask-wearing, we hypothesize an interaction between the effect of political preferences and the framing factor. Model $mode_{2c}$ adds the product between dummy and preference variable.

```
    lm2c<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+mskTrump, data = modelFrame)
    mod2c<-Anova(lm2c, type="III")
    print(mod2c)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27468   1 612.2762 < 2.2e-16 ***
## dummyMasks        7406   1 165.0850 < 2.2e-16 ***
## dummyInjunctive   3574   1  79.6699 < 2.2e-16 ***
## dummyMasksInj     1230   1  27.4129 2.096e-07 ***
## angleSVO          1133   1  25.2620 6.162e-07 ***
## CRT                 15   1   0.3345  0.563191
## riskTaking         361   1   8.0406  0.004688 **
## trump               28   1   0.6246  0.429564
## mskTrump           102   1   2.2798  0.131462
## Residuals        36338 810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm2c$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.738226577    -8.551866304    -5.932748908     4.909273528    -0.086078461
##             CRT      riskTaking           trump        mskTrump
##    -0.096756824     0.277230768     0.003382536     0.008788435
```

```
    print(eta_squared(mod2c, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       4.13e-04 | [0.00, 1.00]
## riskTaking      |       9.83e-03 | [0.00, 1.00]
## trump           |       7.71e-04 | [0.00, 1.00]
## mskTrump        |       2.81e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm1,lm2c)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    810 36338  2    409.91 4.5685 0.01064 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm2,lm2c)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    811 36441
## 2    810 36338  1    102.28 2.2798 0.1315
```

While there is a stronger relationship between preference and game behavior in the mask condition, the model is not significantly improved by the interaction.

```
    lm2d<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+mskTrump+injTrump+mskinjTrump, data = modelFrame)
    mod2d<-Anova(lm2d, type="III")
    print(mod2d)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27488   1 612.5833 < 2.2e-16 ***
## dummyMasks        7411   1 165.1639 < 2.2e-16 ***
## dummyInjunctive   3586   1  79.9095 < 2.2e-16 ***
## dummyMasksInj     1241   1  27.6466 1.866e-07 ***
## angleSVO          1108   1  24.6880 8.230e-07 ***
## CRT                 17   1   0.3734  0.541344
## riskTaking         368   1   8.2014  0.004294 **
## trump               65   1   1.4519  0.228580
## mskTrump            53   1   1.1853  0.276604
## injTrump            37   1   0.8237  0.364379
## mskinjTrump          0   1   0.0029  0.957351
## Residuals        36256 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm2d$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##   11.7429021029   -8.5548874288   -5.9431224830    4.9314306691   -0.0851710898
##             CRT      riskTaking           trump        mskTrump        injTrump
##   -0.1022835678    0.2806196085    0.0072468590    0.0090135064   -0.0075455986
##     mskinjTrump
##   -0.0006225593

    print(eta_squared(mod2d, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       4.62e-04 | [0.00, 1.00]
## riskTaking      |           0.01 | [0.00, 1.00]
```

```
## trump           |       1.79e-03 | [0.00, 1.00]
## mskTrump        |       1.46e-03 | [0.00, 1.00]
## injTrump        |       1.02e-03 | [0.00, 1.00]
## mskinjTrump     |       3.54e-06 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm1,lm2d)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump + injTrump +
##     mskinjTrump
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    808 36256  4    492.12 2.7418 0.02763 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm2,lm2d)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump + injTrump +
##     mskinjTrump
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    811 36441
## 2    808 36256  3    184.48 1.3705 0.2505
```

```
    anova(lm2c,lm2d)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + mskTrump + injTrump +
##     mskinjTrump
##   Res.Df   RSS Df Sum of Sq     F Pr(>F)
## 1    810 36338
## 2    808 36256  2    82.208 0.916 0.4005
```

Adding two more variables to include condition-specific slopes for all four groups does not significantly improve the model.

A4.5 Adding pairs of conservatism measures

As a next step, we add possible combinations of two of the three measures.

A4.5.1 Adding Trump preference and conservatism as predictors

```
        options(contrasts = c("contr.sum", "contr.poly"))
     lm3a<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+trump+conservatism, data = modelFrame)
    mod3a<-Anova(lm3a, type="III")
    print(mod3a)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27382   1 608.6378 < 2.2e-16 ***
## dummyMasks        7398   1 164.4479 < 2.2e-16 ***
## dummyInjunctive   3547   1  78.8386 < 2.2e-16 ***
## dummyMasksInj     1231   1  27.3639 2.148e-07 ***
## angleSVO          1089   1  24.2168 1.043e-06 ***
## CRT                 15   1   0.3237  0.569575
## riskTaking         349   1   7.7623  0.005459 **
## trump              138   1   3.0766  0.079805 .
## conservatism         0   1   0.0003  0.987264
## Residuals        36441 810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm3a$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.746741274    -8.562488992    -5.932916805     4.924476315    -0.084461490
##             CRT      riskTaking           trump    conservatism
##    -0.095381166     0.273757314     0.007889062     0.002961670

    print(eta_squared(mod3a, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
```

```
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       3.99e-04 | [0.00, 1.00]
## riskTaking      |       9.49e-03 | [0.00, 1.00]
## trump           |       3.78e-03 | [0.00, 1.00]
## conservatism    |       3.15e-07 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm1,lm3a)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + conservatism
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    810 36441  2    307.64 3.4191 0.03321 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm2,lm3a)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + conservatism
##   Res.Df   RSS Df Sum of Sq     F Pr(>F)
## 1    811 36441
## 2    810 36441  1  0.011471 3e-04 0.9873
```

The simple conservatism measure does not add predictive information beyond the preference variable.

A4.5.2 Adding Trump preference and SECS as predictors

```
     lm3b<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+trump+SECS, data = modelFrame)
    mod3b<-Anova(lm3b, type="III")
    print(mod3b)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27528   1 612.1939 < 2.2e-16 ***
## dummyMasks        7439   1 165.4432 < 2.2e-16 ***
## dummyInjunctive   3586   1  79.7464 < 2.2e-16 ***
## dummyMasksInj     1244   1  27.6657 1.847e-07 ***
## angleSVO          1083   1  24.0752 1.120e-06 ***
## CRT                 15   1   0.3234  0.569737
## riskTaking         350   1   7.7860  0.005389 **
## trump               80   1   1.7710  0.183635
## SECS                19   1   0.4175  0.518347
## Residuals        36422 810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm3b$coefficients
```

```
##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.755074520    -8.573914147    -5.945227849     4.938898251    -0.084036126
##             CRT      riskTaking           trump            SECS
##    -0.095245820     0.273049580     0.005872745     0.005058198
```

```
    print(eta_squared(mod3b, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       3.99e-04 | [0.00, 1.00]
## riskTaking      |       9.52e-03 | [0.00, 1.00]
## trump           |       2.18e-03 | [0.00, 1.00]
## SECS            |       5.15e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm1,lm3b)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
```

```
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    810 36422  2    326.41 3.6296 0.02696 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm2,lm3b)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    811 36441
## 2    810 36422  1    18.775 0.4175 0.5183
```

Adding the SECS scale does not improve the model significantly, but both variables contribute to the prediction.

A4.5.3 Adding conservatism and SECS as predictors

```
     lm3c<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+SECS+conservatism, data = modelFrame)
    mod3c<-Anova(lm3c, type="III")
    print(mod3c)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27504   1 610.4048 < 2.2e-16 ***
## dummyMasks        7455   1 165.4570 < 2.2e-16 ***
## dummyInjunctive   3605   1  80.0004 < 2.2e-16 ***
## dummyMasksInj     1264   1  28.0621 1.515e-07 ***
## angleSVO          1124   1  24.9536 7.196e-07 ***
## CRT                 23   1   0.5052  0.477414
## riskTaking         382   1   8.4881  0.003673 **
## SECS                81   1   1.7993  0.180168
## conservatism         4   1   0.0785  0.779464
## Residuals        36498 810
```

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

```
    lm3c$coefficients
```

```
##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.76668748     -8.59111219     -5.97363061      4.98423212     -0.08566914
##             CRT      riskTaking            SECS    conservatism
##     -0.11851074      0.28502208      0.01091144      0.05297150
```

```
    print(eta_squared(mod3c, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## ------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       6.23e-04 | [0.00, 1.00]
## riskTaking      |           0.01 | [0.00, 1.00]
## SECS            |       2.22e-03 | [0.00, 1.00]
## conservatism    |       9.69e-05 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm1,lm3c)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + SECS + conservatism
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    812 36748
## 2    810 36498  2    250.31 2.7776 0.06278 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm2,lm3c)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
```

```
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + SECS + conservatism
##   Res.Df   RSS Df Sum of Sq F Pr(>F)
## 1    811 36441
## 2    810 36498  1   -57.322
```

Adding SECS and the simple measure is the least successful combination (as seen by the highest residual sum of squares).

A4.5.4 Testing potential interactions

Again, we test for possible interaction with the framing factor alone, or with both factors at the same time for the strongest of the three models.

```
    lm3d<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+SECS+mskTrump+mskSECS,
             data = modelFrame)
    mod3d<-Anova(lm3d, type="III")
    print(mod3d)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27680   1 624.3198 < 2.2e-16 ***
## dummyMasks        7470   1 168.4835 < 2.2e-16 ***
## dummyInjunctive   3673   1  82.8365 < 2.2e-16 ***
## dummyMasksInj     1266   1  28.5550 1.185e-07 ***
## angleSVO          1129   1  25.4567 5.591e-07 ***
## CRT                  7   1   0.1585 0.6906612
## riskTaking         355   1   8.0121 0.0047618 **
## trump              111   1   2.4980 0.1143827
## SECS               364   1   8.2021 0.0042927 **
## mskTrump           545   1  12.2957 0.0004790 ***
## mskSECS            493   1  11.1228 0.0008916 ***
## Residuals        35824 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm3d$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.793289874    -8.592714576    -6.020159517     4.983533015    -0.085967606
##             CRT      riskTaking           trump            SECS        mskTrump
##    -0.066310221     0.275126792    -0.009972096     0.031796312     0.030340085
```

```
##         mskSECS
##    -0.051909621

    print(eta_squared(mod3d, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.14, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       1.96e-04 | [0.00, 1.00]
## riskTaking      |       9.82e-03 | [0.00, 1.00]
## trump           |       3.08e-03 | [0.00, 1.00]
## SECS            |           0.01 | [0.00, 1.00]
## mskTrump        |           0.01 | [0.00, 1.00]
## mskSECS         |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm1,lm3d)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    812 36748
## 2    808 35824  4    924.17 5.2111 0.0003791 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm2,lm3d)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    811 36441
```

```
## 2    808 35824  3    616.54 4.6353 0.003196 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm3b,lm3d)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    810 36422
## 2    808 35824  2    597.77 6.7412 0.001249 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This model shows a significant improvement over the strongest model with a single predictor and the model without interaction components.

```
    lm3e<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+SECS+mskTrump+mskSECS+
               injTrump+injSECS+mskinjTrump+mskinjSECS, data = modelFrame)
    mod3e<-Anova(lm3e, type="III")
    print(mod3e)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27852   1 630.9470 < 2.2e-16 ***
## dummyMasks        7539   1 170.7762 < 2.2e-16 ***
## dummyInjunctive   3694   1  83.6913 < 2.2e-16 ***
## dummyMasksInj     1279   1  28.9841 9.584e-08 ***
## angleSVO          1019   1  23.0779 1.856e-06 ***
## CRT                 13   1   0.3037 0.5816971
## riskTaking         368   1   8.3362 0.0039906 **
## trump              172   1   3.8918 0.0488633 *
## SECS               618   1  13.9906 0.0001968 ***
## mskTrump           542   1  12.2861 0.0004816 ***
## mskSECS            590   1  13.3630 0.0002733 ***
## injTrump            79   1   1.7902 0.1812841
## injSECS            265   1   6.0107 0.0144310 *
## mskinjTrump        102   1   2.3131 0.1286803
```

```
## mskinjSECS         160   1   3.6192 0.0574750 .
## Residuals        35491 804
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm3b$coefficients
```

```
##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##    11.755074520    -8.573914147    -5.945227849     4.938898251    -0.084036126
##             CRT      riskTaking           trump            SECS
##    -0.095245820     0.273049580     0.005872745     0.005058198
```

```
    print(eta_squared(mod3b, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks      |           0.17 | [0.13, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       3.99e-04 | [0.00, 1.00]
## riskTaking      |       9.52e-03 | [0.00, 1.00]
## trump           |       2.18e-03 | [0.00, 1.00]
## SECS            |       5.15e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm1,lm3e)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     injTrump + injSECS + mskinjTrump + mskinjSECS
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1    812 36748
## 2    804 35491  8      1257 3.5594 0.0004581 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm2,lm3e)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     injTrump + injSECS + mskinjTrump + mskinjSECS
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    811 36441
## 2    804 35491  7    949.36 3.0723 0.003365 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm3b,lm3e)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     injTrump + injSECS + mskinjTrump + mskinjSECS
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    810 36422
## 2    804 35491  6    930.58 3.5135 0.001943 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lm3d,lm3e)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     injTrump + injSECS + mskinjTrump + mskinjSECS
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    808 35824
## 2    804 35491  4    332.82 1.8849 0.1111
```

The full model still shows a significant improvement over the model with a single predictor or two predictors without interactions, but not over the model with solely the framing interaction.

A4.5.5 Robustness check: adding the sample factor

To test whether the added components capture the relevant information of the voter sample factor, we add this factor to the model to see whether it can still be improved by this addition. In the first model we just add a dummy for the sample, in the second we add the full model with interactions.

```
    lm3dS<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
              CRT+riskTaking+trump+SECS+mskTrump+mskSECS+facSample,
              data = modelFrame)
    mod3dS<-Anova(lm3dS, type="III")
    print(mod3dS)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df  F value    Pr(>F)
## (Intercept)      27729   1 625.5240 < 2.2e-16 ***
## dummyMasks        7502   1 169.2410 < 2.2e-16 ***
## dummyInjunctive   3678   1  82.9638 < 2.2e-16 ***
## dummyMasksInj     1279   1  28.8464 1.025e-07 ***
## angleSVO          1120   1  25.2693 6.144e-07 ***
## CRT                 10   1   0.2175 0.6410511
## riskTaking         354   1   7.9870 0.0048279 **
## trump              155   1   3.4937 0.0619630 .
## SECS               299   1   6.7474 0.0095594 **
## mskTrump           536   1  12.0914 0.0005336 ***
## mskSECS            488   1  11.0113 0.0009462 ***
## facSample           50   1   1.1246 0.2892433
## Residuals        35774 807
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm3dS$coefficients

##     (Intercept)      dummyMasks dummyInjunctive   dummyMasksInj        angleSVO
##     11.81194230     -8.61614044     -6.02442981      5.01036009     -0.08565669
##             CRT      riskTaking           trump            SECS        mskTrump
##     -0.07784709      0.27467600     -0.01280809      0.02941906      0.03009533
##         mskSECS      facSample1
##     -0.05165111      0.40399070

    print(eta_squared(mod3dS, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
```

```
## Parameter       | Eta2 (partial) |       95% CI
## ------------------------------------------------
## dummyMasks      |           0.17 | [0.14, 1.00]
## dummyInjunctive |           0.09 | [0.06, 1.00]
## dummyMasksInj   |           0.03 | [0.02, 1.00]
## angleSVO        |           0.03 | [0.01, 1.00]
## CRT             |       2.69e-04 | [0.00, 1.00]
## riskTaking      |       9.80e-03 | [0.00, 1.00]
## trump           |       4.31e-03 | [0.00, 1.00]
## SECS            |       8.29e-03 | [0.00, 1.00]
## mskTrump        |           0.01 | [0.00, 1.00]
## mskSECS         |           0.01 | [0.00, 1.00]
## facSample       |       1.39e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm3d,lm3dS)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     facSample
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    808 35824
## 2    807 35774  1    49.854 1.1246 0.2892
```

Adding the simple dummy variable in model mod_{3dS} does not significantly improve the model.

```
    lm3dF<-lm(RiskyChoices~facSample*facInterv*facFraming+angleSVO+
                CRT+riskTaking+trump+SECS+mskTrump+mskSECS,
                data = modelFrame)
    mod3dF<-Anova(lm3dF, type="III")
    print(mod3dF)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                               Sum Sq  Df  F value    Pr(>F)
## (Intercept)                    26975   1 608.2031 < 2.2e-16 ***
## facSample                         46   1   1.0367  0.308893
## facInterv                       2567   1  57.8729 7.820e-14 ***
```

```
## facFraming                          7627   1 171.9745 < 2.2e-16 ***
## angleSVO                            1091   1  24.5943 8.635e-07 ***
## CRT                                   13   1   0.3036  0.581782
## riskTaking                           361   1   8.1387  0.004444 **
## trump                                168   1   3.7916  0.051857 .
## SECS                                 269   1   6.0588  0.014046 *
## mskTrump                             468   1  10.5556  0.001206 **
## mskSECS                              415   1   9.3539  0.002299 **
## facSample:facInterv                   84   1   1.8923  0.169324
## facSample:facFraming                  16   1   0.3548  0.551562
## facInterv:facFraming                1298   1  29.2550 8.374e-08 ***
## facSample:facInterv:facFraming        18   1   0.3948  0.529962
## Residuals                          35659 804
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lm3dF$coefficients
```

```
##                          (Intercept)                           facSample1
##                           5.74870935                           0.38858265
##                           facInterv1                          facFraming1
##                          -1.77638233                          -3.06619391
##                             angleSVO                                  CRT
##                          -0.08459232                          -0.09214882
##                           riskTaking                                trump
##                           0.27773481                          -0.01424210
##                                 SECS                             mskTrump
##                           0.02837202                           0.03341032
##                              mskSECS                facSample1:facInterv1
##                          -0.04934791                          -0.32135800
##               facSample1:facFraming1               facInterv1:facFraming1
##                          -0.22683766                           1.26285289
## facSample1:facInterv1:facFraming1
##                           0.14686399
```

```
print(eta_squared(mod3dF, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter                     | Eta2 (partial) |       95% CI
## ------------------------------------------------------------
## facSample                     |       1.29e-03 | [0.00, 1.00]
## facInterv                     |           0.07 | [0.04, 1.00]
## facFraming                    |           0.18 | [0.14, 1.00]
## angleSVO                      |           0.03 | [0.01, 1.00]
```

```
## CRT                               |       3.77e-04 | [0.00, 1.00]
## riskTaking                        |           0.01 | [0.00, 1.00]
## trump                             |       4.69e-03 | [0.00, 1.00]
## SECS                              |       7.48e-03 | [0.00, 1.00]
## mskTrump                          |           0.01 | [0.00, 1.00]
## mskSECS                           |           0.01 | [0.00, 1.00]
## facSample:facInterv               |       2.35e-03 | [0.00, 1.00]
## facSample:facFraming              |       4.41e-04 | [0.00, 1.00]
## facInterv:facFraming              |           0.04 | [0.02, 1.00]
## facSample:facInterv:facFraming    |       4.91e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm3d,lm3dF)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ facSample * facInterv * facFraming + angleSVO +
##     CRT + riskTaking + trump + SECS + mskTrump + mskSECS
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    808 35824
## 2    804 35659  4    165.47 0.9327 0.4442
```

```
    anova(lm3dS,lm3dF)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     facSample
## Model 2: RiskyChoices ~ facSample * facInterv * facFraming + angleSVO +
##     CRT + riskTaking + trump + SECS + mskTrump + mskSECS
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    807 35774
## 2    804 35659  3    115.61 0.8689 0.4568
```

Adding the interaction components in model mod_{3dF} does not significantly improve model mod_{3dS}, and all four components together do not improve the original model. Thus, the chosen variables capture the relevant information contained in the sample components.

A4.6 Visualization of interaction components

An analysis of the coefficients in the model shows an interesting difference in the direction of the SECS and the preference items between framing conditions. To visualize

this pattern, we first isolate the additive components in the linear model.

```
lm3d<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
              CRT+riskTaking+trump+SECS+mskTrump+mskSECS,
            data = modelFrame)

interactionFrame=modelFrame

interactionFrame$facFraming<-factor(interactionFrame$facFraming,
                                    levels =c("NEUTRAL   ","MASKS     "))
interactionFrame$facFraming<-factor(interactionFrame$facFraming,
                                    labels=c("Neutral","Masks"))

interactionFrame$facInterv<-factor(interactionFrame$facInterv,
                         levels =c("NONE           ","INJUNCTIVE     "))
interactionFrame$facInterv<-factor(interactionFrame$facInterv,
                                   labels=c("None","Norms"))

interactionFrame$facSample<-factor(interactionFrame$facSample,
                                   levels =c("Conservatives","Liberals"))
interactionFrame$facSample<-factor(interactionFrame$facSample,
                                   labels=c("Trump","Clinton"))

interactionFrame$residualsMasks=lm3d$residuals
interactionFrame$predictionsMasks=lm3d$fitted.values

interactionFrame$InteractComp=lm3d$coefficients[8]*interactionFrame$trump+
  lm3d$coefficients[9]*interactionFrame$SECS+
  lm3d$coefficients[10]*interactionFrame$mskTrump+
  lm3d$coefficients[11]*interactionFrame$mskSECS
```

Figure A4 shows the value of the conservatism component (trump+SECS+mskTrump+mskSECS) for all combinations of the three experimental factors. For each condition, the scatterplot shows the distribution of the preference variable (for President Donald Trump) and the SECS scale with the color indicating the sum of the weighted components. In all conditions, higher values of the preference item are associated with a larger number of riskier decisions. Higher values of SECS are associated with higher numbers of H/no mask decisions in the neutral framing, but with lower numbers in the pandemic framing. The clear distributional differences between Trump and Clinton voters result in overall higher values for Trump than for Clinton voters, which recovers the differences that were observed between the samples.

```
ggplot(data=interactionFrame, aes(x=trump, y=SECS, col=InteractComp)) +
  geom_point()+geom_jitter()+facet_wrap(~facFraming~facInterv~facSample,
  ncol=4)+scale_color_viridis(option="magma")+theme_dark()+
```

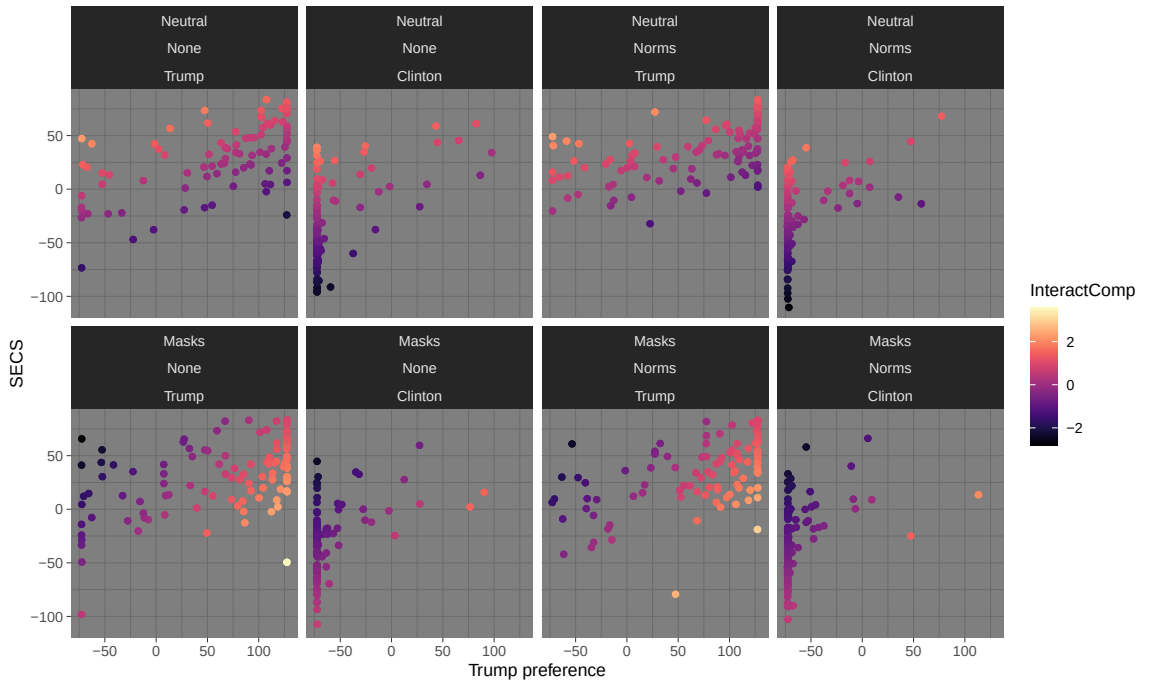


Figure A4

Visualization of the model prediction change induced by the SECS and Trump preference components of the model equation: The color of points in the scatterplots illustrates the additive change in the number of riskier choices predicted for each individual due to the conservatism components in the model (positive numbers correspond to a higher number predicted)

```
    xlab("Trump preference")
```

A4.7 Adding perceived connection between game and pandemic

In our preregistration, we discussed a potential role for the perceived connection between game scenario and the pandemic. Participants were asked after the game whether they drew this connection before seeing the question, after reading the question or not at all. To analyze the effect of the variable we binarize this variable: Only those participants who indicated seeing the connection during the game were categorized as positive cases (as only for these participants, the insight might have influenced their game decisions). This is represented by the variable "binaryConnection".

A4.7.1 Adding the binary connection variable

```
lm4a<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+SECS+mskTrump+mskSECS+binaryConnection,
             data = modelFrame)
```

```
    mod4a<-Anova(lm4a, type="III")
    print(mod4a)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                   Sum Sq  Df  F value    Pr(>F)
## (Intercept)       16182   1 367.4950 < 2.2e-16 ***
## dummyMasks         2524   1  57.3146 1.016e-13 ***
## dummyInjunctive    3660   1  83.1279 < 2.2e-16 ***
## dummyMasksInj      1275   1  28.9483 9.747e-08 ***
## angleSVO           1058   1  24.0211 1.152e-06 ***
## CRT                   1   1   0.0278  0.867596
## riskTaking          331   1   7.5220  0.006230 **
## trump                82   1   1.8542  0.173672
## SECS                304   1   6.9060  0.008754 **
## mskTrump            445   1  10.1117  0.001530 **
## mskSECS             421   1   9.5712  0.002045 **
## binaryConnection    290   1   6.5879  0.010447 *
## Residuals         35534 807
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lm4a$coefficients

##      (Intercept)       dummyMasks  dummyInjunctive    dummyMasksInj
##      10.95929219      -6.95280649      -6.01009783       5.00060307
##         angleSVO              CRT       riskTaking             trump
##      -0.08336888      -0.02779500       0.26584649      -0.00859321
##             SECS         mskTrump          mskSECS binaryConnection
##       0.02919733       0.02762485      -0.04819581      -2.05823392

    print(eta_squared(mod4a, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks       |           0.07 | [0.04, 1.00]
## dummyInjunctive  |           0.09 | [0.06, 1.00]
## dummyMasksInj    |           0.03 | [0.02, 1.00]
## angleSVO         |           0.03 | [0.01, 1.00]
## CRT              |       3.45e-05 | [0.00, 1.00]
## riskTaking       |       9.23e-03 | [0.00, 1.00]
## trump            |       2.29e-03 | [0.00, 1.00]
```

```
## SECS              |       8.49e-03 | [0.00, 1.00]
## mskTrump          |           0.01 | [0.00, 1.00]
## mskSECS           |           0.01 | [0.00, 1.00]
## binaryConnection |       8.10e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm3d,lm4a)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    808 35824
## 2    807 35534  1    290.08 6.5879 0.01045 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The addition of the component improves the model significantly: Participants who drew the connection are estimated to make 2 fewer H/no mask decisions.

A4.7.2 Testing for an interaction with the framing factor

```
 lm4b<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+trump+SECS+mskTrump+mskSECS+binaryConnection+
            mskConnection,
              data = modelFrame)
    mod4b<-Anova(lm4a, type="III")
    print(mod4b)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                  Sum Sq  Df  F value    Pr(>F)
## (Intercept)       16182   1 367.4950 < 2.2e-16 ***
## dummyMasks         2524   1  57.3146 1.016e-13 ***
## dummyInjunctive    3660   1  83.1279 < 2.2e-16 ***
## dummyMasksInj      1275   1  28.9483 9.747e-08 ***
## angleSVO           1058   1  24.0211 1.152e-06 ***
## CRT                   1   1   0.0278  0.867596
## riskTaking          331   1   7.5220  0.006230 **
```

```
## trump                82   1   1.8542  0.173672
## SECS                304   1   6.9060  0.008754 **
## mskTrump            445   1  10.1117  0.001530 **
## mskSECS             421   1   9.5712  0.002045 **
## binaryConnection    290   1   6.5879  0.010447 *
## Residuals         35534 807
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm4b$coefficients
```

```
##      (Intercept)       dummyMasks  dummyInjunctive    dummyMasksInj
##     10.896573105     -7.048309921     -6.008856834      4.992314103
##         angleSVO              CRT       riskTaking            trump
##     -0.083552515     -0.025200057      0.267733965     -0.008521246
##             SECS         mskTrump          mskSECS binaryConnection
##      0.028992518      0.027862587     -0.048229368     -2.210848616
##    mskConnection
##      0.559071886
```

```
    print(eta_squared(mod4b, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks       |           0.07 | [0.04, 1.00]
## dummyInjunctive  |           0.09 | [0.06, 1.00]
## dummyMasksInj    |           0.03 | [0.02, 1.00]
## angleSVO         |           0.03 | [0.01, 1.00]
## CRT              |       3.45e-05 | [0.00, 1.00]
## riskTaking       |       9.23e-03 | [0.00, 1.00]
## trump            |       2.29e-03 | [0.00, 1.00]
## SECS             |       8.49e-03 | [0.00, 1.00]
## mskTrump         |           0.01 | [0.00, 1.00]
## mskSECS          |           0.01 | [0.00, 1.00]
## binaryConnection |       8.10e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm3d,lm4b)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
```

```
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + mskConnection
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    808 35824
## 2    806 35530  2    294.36 3.3388 0.03597 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm4a,lm4b)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + mskConnection
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    807 35534
## 2    806 35530  1    4.2834 0.0972 0.7553
```

Adding an interaction with the framing factor does not significantly improve the model.

A4.7.3 Testing for an interactions with both framing and intervention factor

```
 lm4c<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
                CRT+riskTaking+trump+SECS+mskTrump+mskSECS+binaryConnection+
            injConnection+mskConnection+mskinjConnection,
              data = modelFrame)
    mod4c<-Anova(lm4c, type="III")
    print(mod4c)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                   Sum Sq  Df  F value    Pr(>F)
## (Intercept)         8927   1 203.5725 < 2.2e-16 ***
## dummyMasks           968   1  22.0632 3.102e-06 ***
## dummyInjunctive     1003   1  22.8749 2.056e-06 ***
## dummyMasksInj         35   1   0.8058  0.369631
## angleSVO            1081   1  24.6420 8.431e-07 ***
## CRT                    0   1   0.0070  0.933437
```

```
## riskTaking          338   1   7.6989  0.005654 **
## trump                73   1   1.6535  0.198856
## SECS                291   1   6.6374  0.010163 *
## mskTrump            415   1   9.4746  0.002154 **
## mskSECS             385   1   8.7815  0.003133 **
## binaryConnection    353   1   8.0475  0.004671 **
## injConnection       120   1   2.7260  0.099118 .
## mskConnection         1   1   0.0132  0.908427
## mskinjConnection     22   1   0.5080  0.476222
## Residuals         35258 804
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lm4c$coefficients
```

```
##      (Intercept)       dummyMasks  dummyInjunctive    dummyMasksInj
##     10.251387693     -5.452705846     -4.771266663      1.519982662
##         angleSVO              CRT       riskTaking             trump
##     -0.084481796     -0.013932309      0.269341049     -0.008109235
##             SECS         mskTrump          mskSECS binaryConnection
##      0.028622364      0.026819934     -0.046156382     -3.799916894
##    injConnection    mskConnection mskinjConnection
##      3.068683604     -0.277703023      2.526839767
```

```
    print(eta_squared(mod4c, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks       |           0.03 | [0.01, 1.00]
## dummyInjunctive  |           0.03 | [0.01, 1.00]
## dummyMasksInj    |       1.00e-03 | [0.00, 1.00]
## angleSVO         |           0.03 | [0.01, 1.00]
## CRT              |       8.68e-06 | [0.00, 1.00]
## riskTaking       |       9.48e-03 | [0.00, 1.00]
## trump            |       2.05e-03 | [0.00, 1.00]
## SECS             |       8.19e-03 | [0.00, 1.00]
## mskTrump         |           0.01 | [0.00, 1.00]
## mskSECS          |           0.01 | [0.00, 1.00]
## binaryConnection |       9.91e-03 | [0.00, 1.00]
## injConnection    |       3.38e-03 | [0.00, 1.00]
## mskConnection    |       1.65e-05 | [0.00, 1.00]
## mskinjConnection |       6.31e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lm3d,lm4c)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection + mskConnection + mskinjConnection
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    808 35824
## 2    804 35258  4    565.91 3.2261 0.0122 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm4a,lm4c)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection + mskConnection + mskinjConnection
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    807 35534
## 2    804 35258  3    275.83 2.0966 0.09922 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding all interaction components does not significantly improve the model. Nonetheless, the new components seem to be more predictive than the framing interaction. Exploring this further, we test for an interaction with the intervention factor alone.

A4.7.4 Testing for an interaction with the intervention factor

```
lm4d<-lm(RiskyChoices~dummyMasks+dummyInjunctive+dummyMasksInj+angleSVO+
               CRT+riskTaking+trump+SECS+mskTrump+mskSECS+binaryConnection+
           injConnection,
             data = modelFrame)
   mod4d<-Anova(lm4d, type="III")
   print(mod4d)

## Anova Table (Type III tests)
```

```
##
## Response: RiskyChoices
##                   Sum Sq  Df  F value    Pr(>F)
## (Intercept)       10771   1 245.9914 < 2.2e-16 ***
## dummyMasks         1082   1  24.7068 8.156e-07 ***
## dummyInjunctive    1069   1  24.4045 9.497e-07 ***
## dummyMasksInj        74   1   1.6806 0.1952124
## angleSVO           1092   1  24.9466 7.229e-07 ***
## CRT                   1   1   0.0207 0.8855243
## riskTaking          323   1   7.3839 0.0067222 **
## trump                73   1   1.6754 0.1959119
## SECS                297   1   6.7788 0.0093944 **
## mskTrump            411   1   9.3907 0.0022535 **
## mskSECS             393   1   8.9806 0.0028124 **
## binaryConnection    533   1  12.1677 0.0005126 ***
## injConnection       243   1   5.5535 0.0186824 *
## Residuals         35291 806
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lm4d$coefficients
```

```
##      (Intercept)       dummyMasks  dummyInjunctive    dummyMasksInj
##     10.216583369     -5.494228577     -4.514219970      2.028842955
##         angleSVO              CRT       riskTaking             trump
##     -0.084773365     -0.023936823      0.262680742     -0.008148947
##             SECS         mskTrump          mskSECS binaryConnection
##      0.028848459      0.026581651     -0.046598214     -3.889777604
##    injConnection
##      3.710006361
```

```
print(eta_squared(mod4d, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## dummyMasks       |           0.03 | [0.01, 1.00]
## dummyInjunctive  |           0.03 | [0.01, 1.00]
## dummyMasksInj    |       2.08e-03 | [0.00, 1.00]
## angleSVO         |           0.03 | [0.01, 1.00]
## CRT              |       2.57e-05 | [0.00, 1.00]
## riskTaking       |       9.08e-03 | [0.00, 1.00]
## trump            |       2.07e-03 | [0.00, 1.00]
## SECS             |       8.34e-03 | [0.00, 1.00]
```

```
## mskTrump          |           0.01 | [0.00, 1.00]
## mskSECS           |           0.01 | [0.00, 1.00]
## binaryConnection  |           0.01 | [0.00, 1.00]
## injConnection     |       6.84e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lm3d,lm4d)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1    808 35824
## 2    806 35291  2    533.24 6.0893 0.002373 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm4a,lm4d)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1    807 35534
## 2    806 35291  1    243.16 5.5535 0.01868 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lm4d,lm4c)

## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection
## Model 2: RiskyChoices ~ dummyMasks + dummyInjunctive + dummyMasksInj +
```

```
##     angleSVO + CRT + riskTaking + trump + SECS + mskTrump + mskSECS +
##     binaryConnection + injConnection + mskConnection + mskinjConnection
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1    806 35291
## 2    804 35258  2    32.671 0.3725 0.6891
```

Adding this interaction significantly improves the model. An analysis of the coefficients shows that the coefficient for the intervention condition nearly cancels out the coefficient in the non-intervention condition. A closer analysis reveals problems for a simple interpretation of this coefficient.

A4.7.5 Interpretation problems for the connection variable

Comparing the previous models with mod_{4D}, the two-factorial interaction between intervention and framing is no longer significant in the new model. The following code calculates means for risky choices and the proportion of participants that saw a connection in all four conditions split by sample.

```
interactionFrame$binaryConnection=
 as.numeric(as.factor(interactionFrame$binaryConnection))-1

tapply(interactionFrame$RiskyChoices,
      list(as.factor(interactionFrame$binaryConnection),
           interactionFrame$facFraming,interactionFrame$facInterv,
           interactionFrame$facSample), function(x) mean(x))

## , , None, Trump
##
##    Neutral    Masks
## 0 13.76543 8.800000
## 1 11.16667 3.789474
##
## , , Norms, Trump
##
##    Neutral    Masks
## 0 6.380952 2.555556
## 1 6.733333 2.967391
##
## , , None, Clinton
##
##     Neutral     Masks
## 0 11.233333 10.500000
## 1  6.352941  1.772277
##
## , , Norms, Clinton
##
```

```
##    Neutral    Masks
## 0 5.782609       NA
## 1 2.625000 1.320388

tapply(100*interactionFrame$binaryConnection,
      list(interactionFrame$facFraming,interactionFrame$facInterv,
           interactionFrame$facSample), function(x) mean(x))

## , , Trump
##
##             None    Norms
## Neutral 12.90323 15.15152
## Masks   90.47619 91.08911
##
## , , Clinton
##
##             None     Norms
## Neutral 15.88785  14.81481
## Masks   98.05825 100.00000
```

Non-surprisingly, the proportion of drawn connections is quite high in the pandemic framing (>90%; with even higher values in Clinton voter sample) and quite low in the neutral framing (<16%). In other words, there is a high overlap between framing factor and connection variable (see also Figure A5) .

```
##modelFrame$facSample<-factor(modelFrame$facSample,
##                             levels =c("Conservatives","Liberals"))

modelFrame$facSample<-factor(modelFrame$facSample,
                             labels=c("Trump","Clinton"))

modelBarFrame <- modelFrame


##levels (modelBarFrame$facFraming) <- list ("Neutral frame"="Neutral", "Pandemic frame"="M
##levels (modelBarFrame$facIntervention) <- list ("None"="None", "Norms intervention"="Norm

modelBarFrame$facFraming<-factor(modelBarFrame$facFraming, levels =c("NEUTRAL   ","MASKS
modelBarFrame$facFraming<-factor(modelBarFrame$facFraming,labels=c("Neutral frame","Pandemi

modelBarFrame$facInterv<-factor(modelBarFrame$facInterv, levels =c("NONE          ","INJUN
modelBarFrame$facInterv<-factor(modelBarFrame$facInterv,labels=c("None","Norms intervention


ggplot(data=modelBarFrame, aes(x=facInterv,
```

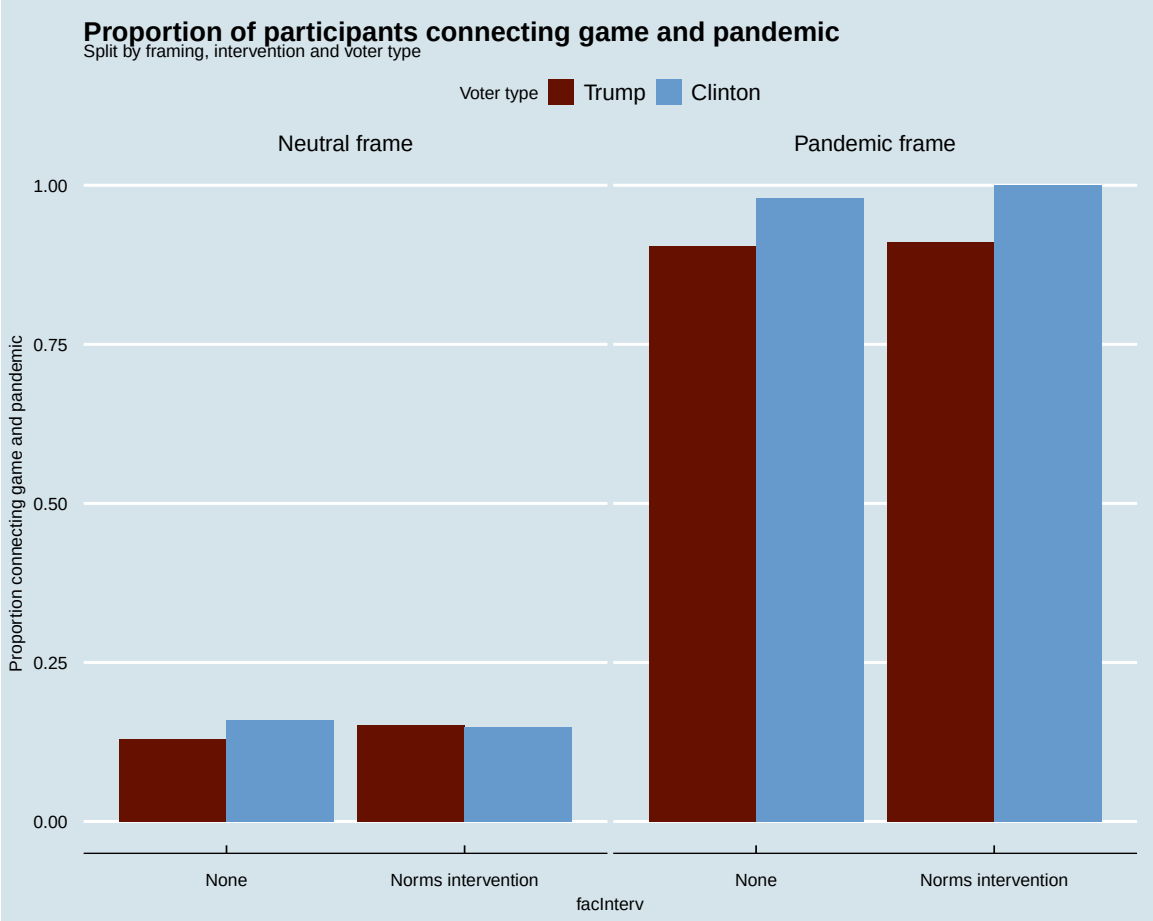


Figure A5

Proportion of participants connectiong game and pandemic split by framing, intervention, and voter type

```
                          y=connectionCovidUncentered, fill=facSample)) +
stat_summary(geom="bar",fun=mean,position="dodge")+
facet_wrap(~facFraming)+ # geom_point(size=2)+
theme_economist()+
scale_color_manual(values=c("#661100","#6699CC"))+
scale_fill_manual(values=c("#661100","#6699CC"))+
scale_linetype_manual(values=c("solid","dotted"))+
labs(title='Proportion of participants connecting game and pandemic',
     subtitle="Split by framing, intervention and voter type")+
theme(axis.title.y =element_text(vjust=3) ,
      axis.title.x =element_text(vjust=-2))+
labs(y="Proportion connecting game and pandemic")+
labs(fill="Voter type")
```

Based on this analysis, it is unclear what is really captured in the model. Visualizing

the interaction component in the fitted model demonstrates the components impact on predictions.

A4.7.6 Visualizing the interaction component

```
interactionFrame$ConnectionComp=
      lm4d$coefficients[12]*interactionFrame$binaryConnection+
      lm4d$coefficients[13]*interactionFrame$injConnection



ggplot(data=interactionFrame, aes(x=binaryConnection, y=ConnectionComp,
                                  col=ConnectionComp)) +
  geom_point()+geom_jitter()+
  facet_wrap(~facFraming~facInterv~facSample,ncol=4)+
  scale_color_viridis(option="magma")+
  theme_dark()+xlab("Connection drawn")
```

Figure A6 visualizes the impact of the term $binaryConnection + injConnection$ in the fitted model. There are small differences in prediction for those drawing and not drawing the connection in the normative intervention condition. There is a difference of about four choices between these two groups in the condition without intervention. It remains an open question, though, whether the predictions in the top left part and bottom left part are both warranted. Do those rejecting the seemingly obvious connection between masks inside and outside the game really make riskier choices than those who saw the connection? And is there really a relationship between seeing the connection and a lower number of riskier choices in the color condition? Based on the design of this study, it is impossible to address the question of direction of causality: There might after all even be a third variable explaining both caution in the game and likelihood to draw the connection.

A4.7.7 Condition-specific models

To explore the predictive usefulness of the connection variable, we fit four separate models in the four conditions of the experiment. These models obviously drop the interaction components but contain all other covariates.

```
  conditionFactorFour= (as.numeric(modelFrame$facFraming)-1)*2+
              as.numeric(modelFrame$facInterv)

  cond4=as.numeric(factor(conditionFactorFour,  labels =c('Mskr-Inj','Msk-No',
                                            'Clr-Inj','Clr-No')))

  modelFrame$cond4=cond4

  groupNoIntervNoFraming <- modelFrame[which(modelFrame$cond4==4),]
  groupIntervNoFraming <- modelFrame[which(modelFrame$cond4==3),]
```

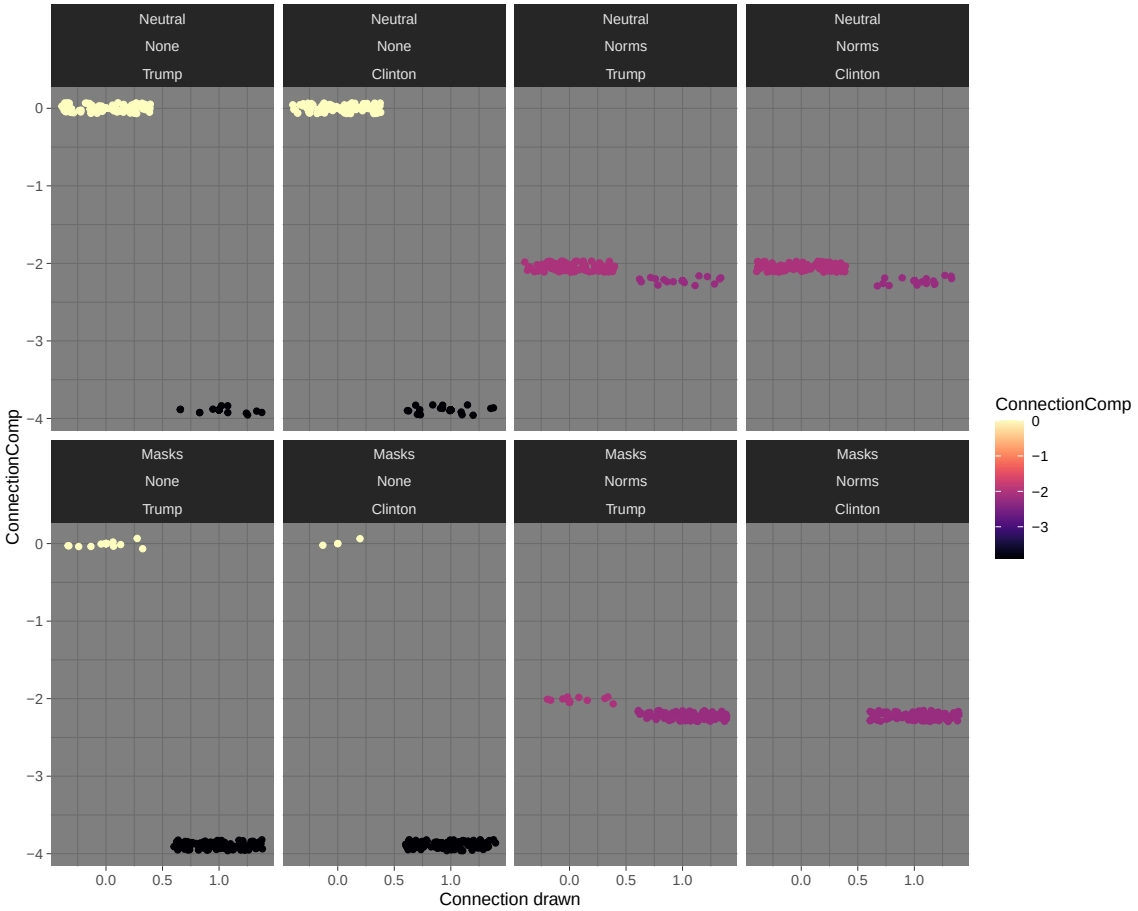


Figure A6

Value of the interaction components for drawn connection and the intervention factor in the model: Colors represent the value of the sum of terms in the fitted model for each participant.

```
  groupNoIntervFraming <- modelFrame[which(modelFrame$cond4==2),]
  groupIntervFraming <- modelFrame[which(modelFrame$cond4==1),]
```

We first split the sample into the four respective experimental groups. These analyses of course use sub-samples and suffer from a lower power to detect differences.

```
lmColControl<-lm(RiskyChoices~angleSVO+
              CRT+riskTaking+trump+SECS+binaryConnection,
              data = groupNoIntervNoFraming)
modColControl<-Anova(lmColControl, type="III")
print(modColControl)

## Anova Table (Type III tests)
##
```

```
## Response: RiskyChoices
##                    Sum Sq  Df  F value  Pr(>F)
## (Intercept)       9103.6   1 116.1859 < 2e-16 ***
## angleSVO           254.8   1   3.2524 0.07288 .
## CRT                 50.6   1   0.6452 0.42283
## riskTaking          96.9   1   1.2364 0.26756
## trump              132.8   1   1.6952 0.19447
## SECS               495.6   1   6.3252 0.01272 *
## binaryConnection   269.5   1   3.4397 0.06517 .
## Residuals        15122.2 193
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
 lmColControl$coefficients
```

```
##      (Intercept)         angleSVO              CRT       riskTaking
##      10.44516049      -0.08463619      -0.37360178       0.30454713
##            trump             SECS binaryConnection
##      -0.01573876       0.05149055      -3.36455750
```

```
 print(eta_squared(modColControl, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## angleSVO         |           0.02 | [0.00, 1.00]
## CRT              |       3.33e-03 | [0.00, 1.00]
## riskTaking       |       6.37e-03 | [0.00, 1.00]
## trump            |       8.71e-03 | [0.00, 1.00]
## SECS             |           0.03 | [0.00, 1.00]
## binaryConnection |           0.02 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

In the group with neutral framing and without intervention, only the SECS scale is a significant (positive predictor) or risky choices. The strongest non-significant predictors are the SVO measure (negative) and the drawn connection (negative).

```
 lmColInjunctive<-lm(RiskyChoices~angleSVO+
               CRT+riskTaking+trump+SECS+binaryConnection,
             data = groupIntervNoFraming)
 modColInjunctive<-Anova(lmColInjunctive, type="III")
 print(modColInjunctive)
```

```
## Anova Table (Type III tests)
```

```
##
## Response: RiskyChoices
##                    Sum Sq  Df F value    Pr(>F)
## (Intercept)       2575.9   1 48.8225 4.075e-11 ***
## angleSVO           489.3   1  9.2750  0.002636 **
## CRT                  0.9   1  0.0173  0.895483
## riskTaking         272.8   1  5.1700  0.024043 *
## trump                7.1   1  0.1351  0.713589
## SECS                 0.2   1  0.0042  0.948235
## binaryConnection    19.0   1  0.3606  0.548846
## Residuals        10552.0 200
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
 lmColInjunctive$coefficients
```

```
##      (Intercept)         angleSVO              CRT       riskTaking
##      5.413052431     -0.107625281     -0.049981770      0.497902697
##            trump             SECS binaryConnection
##     -0.003632923      0.001180259     -0.872725951
```

```
 print(eta_squared(modColInjunctive, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## angleSVO         |           0.04 | [0.01, 1.00]
## CRT              |       8.65e-05 | [0.00, 1.00]
## riskTaking       |           0.03 | [0.00, 1.00]
## trump            |       6.75e-04 | [0.00, 1.00]
## SECS             |       2.11e-05 | [0.00, 1.00]
## binaryConnection |       1.80e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

In the condition with neutral framing and intervention, SVO and general risk taking are the only significant predictors.

```
 lmMaskControl<-lm(RiskyChoices~angleSVO+
               CRT+riskTaking+trump+SECS+binaryConnection,
             data = groupNoIntervFraming)
 modMaskControl<-Anova(lmMaskControl, type="III")
 print(modMaskControl)
```

```
## Anova Table (Type III tests)
```

```
##
## Response: RiskyChoices
##                   Sum Sq  Df F value    Pr(>F)
## (Intercept)      1217.2   1 49.7828 2.719e-11 ***
## angleSVO          109.9   1  4.4952 0.0352160 *
## CRT                28.6   1  1.1678 0.2811548
## riskTaking          4.8   1  0.1980 0.6567839
## trump             333.2   1 13.6277 0.0002871 ***
## SECS               59.6   1  2.4385 0.1199658
## binaryConnection  200.8   1  8.2128 0.0046020 **
## Residuals        4914.5 201
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lmMaskControl$coefficients
```

```
##      (Intercept)         angleSVO              CRT       riskTaking
##       4.89547409      -0.05521768       0.25712667       0.06251689
##            trump             SECS binaryConnection
##       0.02379442      -0.01793845      -4.41023844
```

```
print(eta_squared(modMaskControl, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## angleSVO         |           0.02 | [0.00, 1.00]
## CRT              |       5.78e-03 | [0.00, 1.00]
## riskTaking       |       9.84e-04 | [0.00, 1.00]
## trump            |           0.06 | [0.02, 1.00]
## SECS             |           0.01 | [0.00, 1.00]
## binaryConnection |           0.04 | [0.01, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

In the condition with pandemic framing and no intervention, SVO and preference for Trump are significant predictors, with the connection variable a significant predictor as well.

```
lmMaskInjunctive<-lm(RiskyChoices~angleSVO+
              CRT+riskTaking+trump+SECS+binaryConnection,
            data = groupIntervFraming)
  modMaskInjunctive<-Anova(lmMaskInjunctive, type="III")
  print(modMaskInjunctive)
```

```
## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                   Sum Sq  Df F value   Pr(>F)
## (Intercept)        108.9   1  5.2431 0.023094 *
## angleSVO           141.9   1  6.8287 0.009663 **
## CRT                  1.5   1  0.0711 0.790076
## riskTaking          65.0   1  3.1274 0.078534 .
## trump              158.3   1  7.6191 0.006321 **
## SECS                49.8   1  2.3986 0.123052
## binaryConnection    11.2   1  0.5371 0.464498
## Residuals         4092.8 197
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lmMaskInjunctive$coefficients
```

```
##      (Intercept)         angleSVO              CRT       riskTaking
##       1.66777573      -0.06390259       0.06085487       0.23123963
##            trump             SECS binaryConnection
##       0.01660344      -0.01658583       1.18164963
```

```
print(eta_squared(modMaskInjunctive, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter        | Eta2 (partial) |       95% CI
## -------------------------------------------------
## angleSVO         |           0.03 | [0.00, 1.00]
## CRT              |       3.61e-04 | [0.00, 1.00]
## riskTaking       |           0.02 | [0.00, 1.00]
## trump            |           0.04 | [0.01, 1.00]
## SECS             |           0.01 | [0.00, 1.00]
## binaryConnection |       2.72e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Finally, in the pandemic framing with intervention, SVO and preference for Trump were the only significant predictors.

One possible explanation for this pattern of results is that the injunctive norms condition made the connection between game and pandemic irrelevant, as the social dilemma was clearly spelled out. Risk taking become a more pronounced predictor in the intervention conditions, potentially because these conditions stressed the risk of choosing option H/no mask. The single models also confirm the usefulness of including the interactions between conservatism variables and the framing factor. This effect is consistent with the idea that

masks have become politicized.

A5 Game behavior as predictor of pandemic behavioral intentions

A5.1 Pandemic behavioral intention measures

We used four scales measuring behavioral intentions. The face covering subscale (BI-FC) was adapted from Capraro and Barcelo (2021). The three item texts were copied verbatim, the first part of the sentence has been altered. Items BI-HH2+, BI-HH3+, and BI-MR3+ were adapted from Jordan et al. (2021). The remaining items were adapted from various government guidelines and public health webpages.

The items were introduced with the sentence "In light of the coronavirus outbreak, I intend to...". Items are categorized into four subscales and measured on a scale from -50 ("Strongly disagree") to 50 ("Strongly agree").

- **BI-MR1+**: ...leave my home only for essentials.
- **BI-PD1+**: ...avoid face-to-face interactions with friends.
- **BI-PD2+**: ...engage in physical contact with no one other than those I live with.
- **BI-MR2+**: ...self-quarantine if feeling sick for a minimum of 14 days.
- **BI-HH1+**: ...wash my hands regularly for 20 seconds.
- **BI-HH2+**: ...stop shaking other people's hands.
- **BI-HH3+**: ...try my hardest to avoid touching my face.
- **BI-MR3+**: ...try to stay home whenever possible, even if I am not sick.
- **BI-PD3+**: ...remain at least 6 feet away from other people.
- **BI-FC1+**: ...wear a face covering any time I leave home.
- **BI-FC2+**: ...wear a face covering any time I am engaged in essential activities and/or work, and there is no substitute for physical distancing and staying at home.
- **BI-FC3+**: ...wear a face covering any time I'm around people outside my household.

The four subsscales are intentions to 1) wear a face covering, 2) engage in physical distancing, 3) observe proper hand hygiene, and 4) restrict one's movement during the pandemic. One might note that the focus on hand hygiene was most pronounced in the beginning of the pandemic and at the time of the study, the focus had not yet fully shifted towards ventilation and aerosols.

Figure A7 hows the inter-correlation matrix between variables, showing medium to high correlations between all four scales. It still makes sense to study relationships between game behavior and each of these measures, as the game itself in the framing condition focuses on masks in particular and least on hand hygiene.

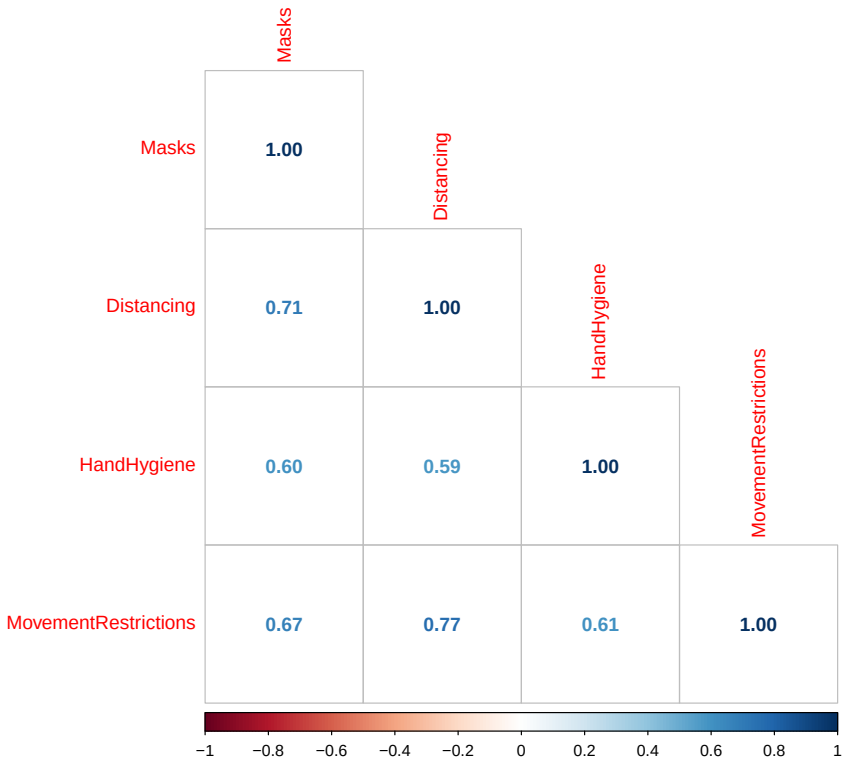


Figure A7
Inter-correlation matrix of pandemic behaivor measures.

```
behaviorFrame=data.frame(
  Masks=modelFrame$behIntMasks,
  Distancing=modelFrame$behIntDistancing,
  HandHygiene=modelFrame$behIntHandHYgiene,
  MovementRestrictions=modelFrame$behIntMovement
)

corMatrix<-cor(behaviorFrame,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

A5.2 Sequence of models

To avoid finding spurious correlations between game behavior and behavioral intentions, we add other potential predictors to the model first. For each of the scales, we add the cognitive reflection test (CRT), general risk taking (riskTaking) and the social value orientation (SVO) measure first. In a second step, we add the SECS scale and the preference

for a win by Trump in the 2020 presidential election. In the third step, we add psychological reactance, measured with the 11-item version of the Hong psychological reactance scale (Hong & Faedda, 1996). This is a potential predictor based on theory, but also has face validity based on items such as "Regulations trigger a sense of resistance in me".

We enter variables relating to game behavior only in the fourth and fifth step. In step four, we enter the number of H/no mask choices in the game. The variable "RiskyChoices" contains this value irrespective of condition. Step five adds predictors that allow to test for condition-specific prediction: The variable "mskRiskyChoices" codes the number of risky choices for participants in the pandemic framing and 0 for participants in the neutral framing. Similarly, "injRiskyChoices" codes the number of risky choices only for participants in the injunctive norm conditions, and "mskinjRiskyChoices" for participants in the condition with both pandemic framing and injunctive norms intervention. This results in four coefficients that can capture the relationship between risky choices and the criterion in each condition instead of a single parameter in Step four.

A5.3 Results for facial coverings

A5.3.1 Step 1

```
  lmM1<-lm(behIntMasks~ CRT+riskTaking+angleSVO, data = modelFrame)
    modM1<-Anova(lmM1, type="III")
    print(modM1)

## Anova Table (Type III tests)
##
## Response: behIntMasks
##              Sum Sq  Df   F value    Pr(>F)
## (Intercept) 1177373   1 3143.6997 < 2.2e-16 ***
## CRT               4   1    0.0101  0.920016
## riskTaking      340   1    0.9086  0.340773
## angleSVO       3718   1    9.9278  0.001687 **
## Residuals    305232 815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmM1$coefficients

## (Intercept)         CRT  riskTaking    angleSVO
## 37.91534392 -0.04790845 -0.26619303  0.15309990

    print(eta_squared(modM1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
```

```
## CRT        |       1.24e-05 | [0.00, 1.00]
## riskTaking |       1.11e-03 | [0.00, 1.00]
## angleSVO   |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Only SVO is a significant predictor in this model, with more prosocial values predicting a higher intention to use face coverings.

A5.3.2 Step 2

```
    lmM2<-lm(behIntMasks~ CRT+riskTaking+angleSVO+trump+SECS,
             data = modelFrame)
    modM2<-Anova(lmM2, type="III")
    print(modM2)

## Anova Table (Type III tests)
##
## Response: behIntMasks
##              Sum Sq  Df   F value    Pr(>F)
## (Intercept) 1177373   1 3533.2010 < 2.2e-16 ***
## CRT             923   1    2.7708   0.09639 .
## riskTaking       21   1    0.0620   0.80335
## angleSVO        783   1    2.3491   0.12575
## trump         17540   1   52.6369  9.37e-13 ***
## SECS             50   1    0.1491   0.69946
## Residuals    270917 813
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmM2$coefficients

##  (Intercept)          CRT   riskTaking     angleSVO        trump         SECS
## 37.915343915 -0.757911975  0.066125867  0.071402227 -0.087125206  0.008224591

    print(eta_squared(modM2, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       3.40e-03 | [0.00, 1.00]
## riskTaking |       7.63e-05 | [0.00, 1.00]
## angleSVO   |       2.88e-03 | [0.00, 1.00]
## trump      |           0.06 | [0.04, 1.00]
```

```
## SECS       |       1.83e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmM1,lmM2)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 305232
## 2    813 270917  2     34315 51.489 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

After adding the conservatism measures, the only significant predictor is the preference for Trump, predicting a lower intention to wear a mask. The addition of the two variables significantly improves the model.

A5.3.3 Step 3

```
    lmM3<-lm(behIntMasks~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance, data = modelFrame)
    modM3<-Anova(lmM3, type="III")
    print(modM3)

## Anova Table (Type III tests)
##
## Response: behIntMasks
##                 Sum Sq  Df   F value    Pr(>F)
## (Intercept)    1177373   1 3766.3548 < 2.2e-16 ***
## CRT                886   1    2.8328   0.09274 .
## riskTaking         294   1    0.9397   0.33263
## angleSVO            63   1    0.2025   0.65280
## trump            11480   1   36.7239 2.082e-09 ***
## SECS                 0   1    0.0011   0.97404
## psychReactance   17084   1   54.6494 3.588e-13 ***
## Residuals       253833 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmM3$coefficients

##    (Intercept)            CRT     riskTaking       angleSVO          trump
```

```
##  37.9153439153  -0.7422554943   0.2504220923   0.0205414071  -0.0716216216
##           SECS psychReactance
##  -0.0006727117  -6.2078825411

    print(eta_squared(modM3, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT            |       3.48e-03 | [0.00, 1.00]
## riskTaking     |       1.16e-03 | [0.00, 1.00]
## angleSVO       |       2.49e-04 | [0.00, 1.00]
## trump          |           0.04 | [0.02, 1.00]
## SECS           |       1.31e-06 | [0.00, 1.00]
## psychReactance |           0.06 | [0.04, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmM1,lmM3)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 305232
## 2    812 253833  3     51399 54.807 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM2,lmM3)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 270917
## 2    812 253833  1     17084 54.649 3.588e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The addition of the reactance variable significantly improves the model with reactance predicting a lower degree of face mask wearing intentions. The effect size is even larger than the effect size for the still significant preference variable.

A5.3.4 Step 4

```
    lmM4<-lm(behIntMasks~ CRT+riskTaking+angleSVO+trump+SECS+
                psychReactance+RiskyChoices, data = modelFrame)
    modM4<-Anova(lmM4, type="III")
    print(modM4)

## Anova Table (Type III tests)
##
## Response: behIntMasks
##                Sum Sq  Df   F value    Pr(>F)
## (Intercept)    809210   1 2611.9281 < 2.2e-16 ***
## CRT               943   1    3.0447  0.081380 .
## riskTaking        517   1    1.6679  0.196904
## angleSVO            0   1    0.0002  0.990025
## trump           11118   1   35.8857 3.144e-09 ***
## SECS                0   1    0.0001  0.993782
## psychReactance  16505   1   53.2729 6.928e-13 ***
## RiskyChoices     2575   1    8.3108  0.004045 **
## Residuals      251259 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmM4$coefficients

##    (Intercept)            CRT     riskTaking       angleSVO          trump
##  39.2403406019  -0.7662142920   0.3342471748   0.0005748197  -0.0705200358
##           SECS psychReactance   RiskyChoices
##  -0.0001603511  -6.1071237885  -0.2329195721

    print(eta_squared(modM4, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## ------------------------------------------------
## CRT            |       3.74e-03 | [0.00, 1.00]
## riskTaking     |       2.05e-03 | [0.00, 1.00]
## angleSVO       |       1.93e-07 | [0.00, 1.00]
## trump          |           0.04 | [0.02, 1.00]
## SECS           |       7.49e-08 | [0.00, 1.00]
## psychReactance |           0.06 | [0.04, 1.00]
## RiskyChoices   |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmM1,lmM4)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 305232
## 2    811 251259  4     53974 43.553 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM2,lmM4)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    813 270917
## 2    811 251259  2     19658 31.726 5.42e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM3,lmM4)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    812 253833
## 2    811 251259  1    2574.8 8.3108 0.004045 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The number of risky choices is a significant predictor in this model, and its inclusion leads to a significant model improvement.

A5.3.5 Step 5

```
   lmM5<-lm(behIntMasks~ CRT+riskTaking+angleSVO+trump+SECS+
              psychReactance+RiskyChoices+mskRiskyChoices+injRiskyChoices+
              mskinjRiskyChoices, data = modelFrame)
    modM5<-Anova(lmM5, type="III")
    print(modM5)

## Anova Table (Type III tests)
##
## Response: behIntMasks
##                     Sum Sq  Df   F value    Pr(>F)
## (Intercept)         815980   1 2715.1078 < 2.2e-16 ***
## CRT                    765   1    2.5448 0.1110464
## riskTaking             557   1    1.8522 0.1739045
## angleSVO                45   1    0.1513 0.6973662
## trump                 8543   1   28.4269 1.264e-07 ***
## SECS                    54   1    0.1799 0.6715578
## psychReactance       16248   1   54.0633 4.766e-13 ***
## RiskyChoices             7   1    0.0244 0.8759471
## mskRiskyChoices       4128   1   13.7361 0.0002247 ***
## injRiskyChoices       2662   1    8.8576 0.0030057 **
## mskinjRiskyChoices     182   1    0.6050 0.4368854
## Residuals           242831 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmM5$coefficients

##         (Intercept)                 CRT          riskTaking             angleSVO
##        39.809021227        -0.690326589         0.347344594        -0.017675750
##               trump                SECS      psychReactance        RiskyChoices
##        -0.062548667        -0.008625719        -6.064125283        -0.014399030
##     mskRiskyChoices    injRiskyChoices mskinjRiskyChoices
##        -0.793392082        -0.451331697         0.265196272

    print(eta_squared(modM4, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## ------------------------------------------------
## CRT            |       3.74e-03 | [0.00, 1.00]
## riskTaking     |       2.05e-03 | [0.00, 1.00]
## angleSVO       |       1.93e-07 | [0.00, 1.00]
## trump          |           0.04 | [0.02, 1.00]
## SECS           |       7.49e-08 | [0.00, 1.00]
```

```
## psychReactance |           0.06 | [0.04, 1.00]
## RiskyChoices   |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmM1,lmM5)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices + mskRiskyChoices + injRiskyChoices + mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 305232
## 2    808 242831  7     62401 29.662 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM2,lmM5)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices + mskRiskyChoices + injRiskyChoices + mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 270917
## 2    808 242831  5     28086 18.691 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM3,lmM5)

## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices + mskRiskyChoices + injRiskyChoices + mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    812 253833
## 2    808 242831  4     11002 9.1524 3.109e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmM4,lmM5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices
## Model 2: behIntMasks ~ CRT + riskTaking + angleSVO + trump + SECS + psychReactance +
##     RiskyChoices + mskRiskyChoices + injRiskyChoices + mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    811 251259
## 2    808 242831  3    8427.7 9.3475 4.441e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding the four game behavior variables significantly improves the model at the third step, but adding the three interaction coefficients in Step 5 also significantly improves the model at Step 4. The relationship between risky choices and the attitude towards facial masks is stronger with either pandemic framing or in the intervention condition (or in the pandemic framing with interventions. Note that in the latter condition all four coefficient values are added to determine the effect of risky choices (the sum is negative, even though it is smaller than the sum of the effects of framing and intervention). In all conditions, the number of H/no mask choices predicts a lower intention to wear actual masks during the pandemic.

A5.4 Results for physical distancing

A5.4.1 Step 1

```
  lmD1<-lm(behIntDistancing~ CRT+riskTaking+angleSVO, data = modelFrame)
    modD1<-Anova(lmD1, type="III")
    print(modD1)

## Anova Table (Type III tests)
##
## Response: behIntDistancing
##             Sum Sq  Df   F value  Pr(>F)
## (Intercept) 728227   1 1677.1716 < 2e-16 ***
## CRT             17   1    0.0383 0.84489
## riskTaking    1035   1    2.3848 0.12291
## angleSVO      2233   1    5.1439 0.02359 *
## Residuals   353872 815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmD1$coefficients

## (Intercept)         CRT  riskTaking    angleSVO
##  29.8188848   0.1005067  -0.4643525   0.1186599
```

```
    print(eta_squared(modD1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       4.70e-05 | [0.00, 1.00]
## riskTaking |       2.92e-03 | [0.00, 1.00]
## angleSVO   |       6.27e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

Similar to Step 1 for mask-wearing, SVO is the single significant predictor of intended social distancing.

A5.4.2 Step 2

```
    lmD2<-lm(behIntDistancing~ CRT+riskTaking+angleSVO+trump+SECS,
    data = modelFrame)
    modD2<-Anova(lmD2, type="III")
    print(modD2)

## Anova Table (Type III tests)
##
## Response: behIntDistancing
##             Sum Sq  Df   F value    Pr(>F)
## (Intercept) 728227   1 1781.2740 < 2.2e-16 ***
## CRT            342   1    0.8365    0.3607
## riskTaking     189   1    0.4632    0.4963
## angleSVO       427   1    1.0454    0.3069
## trump         9207   1   22.5213 2.455e-06 ***
## SECS            44   1    0.1067    0.7440
## Residuals   332374 813
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmD2$coefficients

## (Intercept)         CRT  riskTaking    angleSVO       trump        SECS
## 29.81888482 -0.46126764 -0.20012782  0.05275927 -0.06312343 -0.00770683

    print(eta_squared(modD2, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
```

```
## Parameter  | Eta2 (partial) |       95% CI
## ----------------------------------------
## CRT        |       1.03e-03 | [0.00, 1.00]
## riskTaking |       5.69e-04 | [0.00, 1.00]
## angleSVO   |       1.28e-03 | [0.00, 1.00]
## trump      |           0.03 | [0.01, 1.00]
## SECS       |       1.31e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmD1,lmD2)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 353872
## 2    813 332374  2     21499 26.294 8.609e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Again, the preference for Trump is the single significant predictor in step 2.

A5.4.3 Step 3

```
    lmD3<-lm(behIntDistancing~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance, data = modelFrame)
    modD3<-Anova(lmD3, type="III")
    print(modD3)

## Anova Table (Type III tests)
##
## Response: behIntDistancing
##                Sum Sq  Df   F value    Pr(>F)
## (Intercept)    728227   1 1868.4422 < 2.2e-16 ***
## CRT               320   1    0.8209  0.365179
## riskTaking          2   1    0.0060  0.938249
## angleSVO            2   1    0.0053  0.942172
## trump            5193   1   13.3227  0.000279 ***
## SECS              194   1    0.4985  0.480375
## psychReactance  15896   1   40.7848 2.858e-10 ***
## Residuals      316478 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmD3$coefficients
```

```
##    (Intercept)            CRT     riskTaking       angleSVO          trump
##    29.81888482    -0.44616517    -0.02235297     0.00369818    -0.04816844
##           SECS psychReactance
##    -0.01628930    -5.98821483
```

```
    print(eta_squared(modD3, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## ------------------------------------------------
## CRT            |       1.01e-03 | [0.00, 1.00]
## riskTaking     |       7.40e-06 | [0.00, 1.00]
## angleSVO       |       6.48e-06 | [0.00, 1.00]
## trump          |           0.02 | [0.00, 1.00]
## SECS           |       6.14e-04 | [0.00, 1.00]
## psychReactance |           0.05 | [0.03, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmD1,lmD3)
```

```
## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 353872
## 2    812 316478  3     37395 31.982 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmD2,lmD3)
```

```
## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 332374
## 2    812 316478  1     15896 40.785 2.858e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As before, reactance is a significant predictor at step 3.

A5.4.4 Step 4

```
    lmD4<-lm(behIntDistancing~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance+RiskyChoices, data = modelFrame)
    modD4<-Anova(lmD4, type="III")
    print(modD4)
```

```
## Anova Table (Type III tests)
##
## Response: behIntDistancing
##                Sum Sq  Df   F value    Pr(>F)
## (Intercept)    503663   1 1298.4861 < 2.2e-16 ***
## CRT               350   1    0.9025 0.3424041
## riskTaking         11   1    0.0295 0.8637500
## angleSVO           27   1    0.0686 0.7935084
## trump            4985   1   12.8520 0.0003573 ***
## SECS              184   1    0.4741 0.4912980
## psychReactance  15412   1   39.7345 4.773e-10 ***
## RiskyChoices     1903   1    4.9058 0.0270433 *
## Residuals      314575 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmD4$coefficients
```

```
##    (Intercept)            CRT     riskTaking       angleSVO          trump
##    30.95795813    -0.46676207     0.04970979    -0.01346670    -0.04722143
##           SECS psychReactance   RiskyChoices
##    -0.01584883    -5.90159454    -0.20023633
```

```
    print(eta_squared(modD4, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT            |       1.11e-03 | [0.00, 1.00]
## riskTaking     |       3.63e-05 | [0.00, 1.00]
## angleSVO       |       8.45e-05 | [0.00, 1.00]
## trump          |           0.02 | [0.00, 1.00]
## SECS           |       5.84e-04 | [0.00, 1.00]
## psychReactance |           0.05 | [0.03, 1.00]
## RiskyChoices   |       6.01e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmD1,lmD4)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 353872
## 2    811 314575  4     39298 25.328 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmD2,lmD4)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    813 332374
## 2    811 314575  2     17799 22.943 2.03e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmD3,lmD4)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1    812 316478
## 2    811 314575  1    1902.9 4.9058 0.02704 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding the game behavior, the model is improved with a higher number of risky choices predicting a more negative intentions regarding social distancing.

A5.4.5 Step 5

```
    lmD5<-lm(behIntDistancing~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance+RiskyChoices+mskRiskyChoices+
               injRiskyChoices+mskinjRiskyChoices, data = modelFrame)
    modD5<-Anova(lmD5, type="III")
    print(modD5)

## Anova Table (Type III tests)
##
## Response: behIntDistancing
##                     Sum Sq  Df   F value    Pr(>F)
## (Intercept)         511854   1 1351.9485 < 2.2e-16 ***
## CRT                    247   1    0.6534 0.4191409
## riskTaking              19   1    0.0501 0.8229196
## angleSVO               160   1    0.4230 0.5156334
## trump                 3414   1    9.0182 0.0027555 **
## SECS                   425   1    1.1227 0.2896503
## psychReactance       15291   1   40.3870 3.478e-10 ***
## RiskyChoices            41   1    0.1084 0.7420972
## mskRiskyChoices       4540   1   11.9923 0.0005623 ***
## injRiskyChoices       3710   1    9.7997 0.0018082 **
## mskinjRiskyChoices     637   1    1.6835 0.1948329
## Residuals           305912 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmD5$coefficients

##         (Intercept)                 CRT          riskTaking            angleSVO
##         31.52931829         -0.39260674          0.06412760         -0.03316816
##               trump                SECS      psychReactance        RiskyChoices
##         -0.03954203         -0.02418476         -5.88280177          0.03406915
##    mskRiskyChoices    injRiskyChoices mskinjRiskyChoices
##         -0.83205769         -0.53283047          0.49650363

    print(eta_squared(modD5, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter          | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT                |       8.08e-04 | [0.00, 1.00]
## riskTaking         |       6.20e-05 | [0.00, 1.00]
## angleSVO           |       5.23e-04 | [0.00, 1.00]
## trump              |           0.01 | [0.00, 1.00]
## SECS               |       1.39e-03 | [0.00, 1.00]
```

```
## psychReactance     |           0.05 | [0.03, 1.00]
## RiskyChoices       |       1.34e-04 | [0.00, 1.00]
## mskRiskyChoices    |           0.01 | [0.00, 1.00]
## injRiskyChoices    |           0.01 | [0.00, 1.00]
## mskinjRiskyChoices |       2.08e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmD1,lmD5)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 353872
## 2    808 305912  7     47960 18.097 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmD2,lmD5)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 332374
## 2    808 305912  5     26461 13.978 3.999e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmD3,lmD5)

## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
```

```
## 1    812 316478
## 2    808 305912  4     10565 6.9765 1.598e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmD4,lmD5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
## Model 2: behIntDistancing ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    811 314575
## 2    808 305912  3    8662.4 7.6266 4.95e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Adding the interactions leads to similar improvements to the model as in the case for face masks. In this case, the relationship between choices and intentions is insignificant, yet positive under neutral framing without intervention and negative and significant in all other conditions.

A5.5 Results for hand hygiene

A5.5.1 Step 1

```
  lmH1<-lm(behIntHandHYgiene~ CRT+riskTaking+angleSVO, data = modelFrame)
    modH1<-Anova(lmH1, type="III")
    print(modH1)
```

```
## Anova Table (Type III tests)
##
## Response: behIntHandHYgiene
##              Sum Sq  Df   F value    Pr(>F)
## (Intercept) 1081777   1 4282.7620 < 2.2e-16 ***
## CRT              98   1    0.3870  0.534051
## riskTaking       10   1    0.0400  0.841612
## angleSVO       2323   1    9.1958  0.002503 **
## Residuals    205860 815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmH1$coefficients
```

```
## (Intercept)         CRT  riskTaking    angleSVO
## 36.34350834 -0.24367757 -0.04584447  0.12100778

    print(eta_squared(modH1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       4.75e-04 | [0.00, 1.00]
## riskTaking |       4.90e-05 | [0.00, 1.00]
## angleSVO   |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

For hand hygiene, as for the other two variables before, SVO is the single significant predictor.

A5.5.2 Step 2

```
    lmH2<-lm(behIntHandHYgiene~ CRT+riskTaking+angleSVO+trump+SECS,
             data = modelFrame)
    modH2<-Anova(lmH2, type="III")
    print(modH2)

## Anova Table (Type III tests)
##
## Response: behIntHandHYgiene
##              Sum Sq  Df   F value    Pr(>F)
## (Intercept) 1081777   1 4440.2638 < 2.2e-16 ***
## CRT             484   1    1.9848   0.15927
## riskTaking       41   1    0.1682   0.68185
## angleSVO       1233   1    5.0592   0.02476 *
## trump          6816   1   27.9766  1.58e-07 ***
## SECS           1480   1    6.0737   0.01393 *
## Residuals    198070 813
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmH2$coefficients

## (Intercept)         CRT  riskTaking    angleSVO       trump        SECS
## 36.34350834 -0.54848456  0.09308393  0.08959734 -0.05431095  0.04487894

    print(eta_squared(modH2, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       2.44e-03 | [0.00, 1.00]
## riskTaking |       2.07e-04 | [0.00, 1.00]
## angleSVO   |       6.18e-03 | [0.00, 1.00]
## trump      |           0.03 | [0.02, 1.00]
## SECS       |       7.42e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmH1,lmH2)

## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    815 205860
## 2    813 198070  2    7789.4 15.986 1.55e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this model, preference for Trump is a negative predictor of hand hygiene, but the SECS value is a positive predictor.

A5.5.3 Step 3

```
     lmH3<-lm(behIntHandHYgiene~ CRT+riskTaking+angleSVO+trump+SECS+
                psychReactance, data = modelFrame)
    modH3<-Anova(lmH3, type="III")
    print(modH3)

## Anova Table (Type III tests)
##
## Response: behIntHandHYgiene
##                 Sum Sq  Df   F value    Pr(>F)
## (Intercept)    1081777   1 4738.5572 < 2.2e-16 ***
## CRT                460   1    2.0151   0.15613
## riskTaking         297   1    1.3027   0.25405
## angleSVO           314   1    1.3757   0.24117
## trump             3752   1   16.4350 5.519e-05 ***
## SECS              1014   1    4.4403   0.03541 *
## psychReactance   12697   1   55.6167 2.263e-13 ***
```

```
## Residuals       185373 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmH3$coefficients
```

```
##    (Intercept)            CRT     riskTaking       angleSVO          trump
##    36.34350834    -0.53498706     0.25196633     0.04575005    -0.04094526
##           SECS psychReactance
##     0.03720855    -5.35183653
```

```
    print(eta_squared(modH3, partial = TRUE,ci=.95,verbose=TRUE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT            |       2.48e-03 | [0.00, 1.00]
## riskTaking     |       1.60e-03 | [0.00, 1.00]
## angleSVO       |       1.69e-03 | [0.00, 1.00]
## trump          |           0.02 | [0.01, 1.00]
## SECS           |       5.44e-03 | [0.00, 1.00]
## psychReactance |           0.06 | [0.04, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmH1,lmH3)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 205860
## 2    812 185373  3     20486 29.912 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmH2,lmH3)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
```

```
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 198070
## 2    812 185373  1     12697 55.617 2.263e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Psychological reactance is an additional significant predictor.

A5.5.4 Step 4

```
    lmH4<-lm(behIntHandHYgiene~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance+RiskyChoices, data = modelFrame)
    modH4<-Anova(lmH4, type="III")
    print(modH4)

## Anova Table (Type III tests)
##
## Response: behIntHandHYgiene
##                Sum Sq  Df   F value    Pr(>F)
## (Intercept)    730672   1 3219.3523 < 2.2e-16 ***
## CRT               490   1    2.1575   0.14226
## riskTaking        449   1    1.9798   0.15979
## angleSVO          146   1    0.6421   0.42318
## trump            3606   1   15.8869  7.33e-05 ***
## SECS             1034   1    4.5541   0.03314 *
## psychReactance  12337   1   54.3569  4.13e-13 ***
## RiskyChoices     1307   1    5.7584   0.01663 *
## Residuals      184066 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmH4$coefficients

##    (Intercept)            CRT     riskTaking       angleSVO          trump
##    37.28750666    -0.55205659     0.31168779     0.03152479    -0.04016043
##           SECS psychReactance   RiskyChoices
##     0.03757358    -5.28005062    -0.16594433

    print(eta_squared(modH4, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## ------------------------------------------------
## CRT            |       2.65e-03 | [0.00, 1.00]
```

```
## riskTaking     |       2.44e-03 | [0.00, 1.00]
## angleSVO       |       7.91e-04 | [0.00, 1.00]
## trump          |           0.02 | [0.01, 1.00]
## SECS           |       5.58e-03 | [0.00, 1.00]
## psychReactance |           0.06 | [0.04, 1.00]
## RiskyChoices   |       7.05e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmH1,lmH4)

## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 205860
## 2    811 184066  4     21793 24.005 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmH2,lmH4)

## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 198070
## 2    811 184066  2     14004 30.851 1.222e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmH3,lmH4)

## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1    812 185373
## 2    811 184066  1    1306.9 5.7584 0.01663 *
```

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

The model is again significantly improved by adding the game behavior variable with riskier choices predicting less hand hygiene intentions.

A5.5.5 Step 5

```
    lmH5<-lm(behIntHandHYgiene~ CRT+riskTaking+angleSVO+trump+SECS+
                psychReactance+RiskyChoices+mskRiskyChoices+
                injRiskyChoices+mskinjRiskyChoices, data = modelFrame)
    modH5<-Anova(lmH5, type="III")
    print(modH5)

## Anova Table (Type III tests)
##
## Response: behIntHandHYgiene
##                     Sum Sq  Df   F value    Pr(>F)
## (Intercept)         723638   1 3208.9975 < 2.2e-16 ***
## CRT                    450   1    1.9963 0.1580732
## riskTaking             470   1    2.0823 0.1494028
## angleSVO                71   1    0.3171 0.5735325
## trump                 3160   1   14.0115 0.0001946 ***
## SECS                   887   1    3.9335 0.0476722 *
## psychReactance       12489   1   55.3840  2.54e-13 ***
## RiskyChoices           116   1    0.5129 0.4740844
## mskRiskyChoices        826   1    3.6637 0.0559622 .
## injRiskyChoices       1410   1    6.2548 0.0125829 *
## mskinjRiskyChoices     877   1    3.8878 0.0489793 *
## Residuals           182206 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmH5$coefficients

##         (Intercept)                 CRT          riskTaking             angleSVO
##         37.48887241         -0.52961799          0.31901828          0.02216226
##               trump                SECS      psychReactance        RiskyChoices
##         -0.03803871          0.03493635         -5.31666049         -0.05720347
##    mskRiskyChoices    injRiskyChoices mskinjRiskyChoices
##         -0.35493314         -0.32852795          0.58230788

    print(eta_squared(modH5, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
```

```
##
## Parameter          | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT                |       2.46e-03 | [0.00, 1.00]
## riskTaking         |       2.57e-03 | [0.00, 1.00]
## angleSVO           |       3.92e-04 | [0.00, 1.00]
## trump              |           0.02 | [0.01, 1.00]
## SECS               |       4.84e-03 | [0.00, 1.00]
## psychReactance     |           0.06 | [0.04, 1.00]
## RiskyChoices       |       6.34e-04 | [0.00, 1.00]
## mskRiskyChoices    |       4.51e-03 | [0.00, 1.00]
## injRiskyChoices    |       7.68e-03 | [0.00, 1.00]
## mskinjRiskyChoices |       4.79e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmH1,lmH5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 205860
## 2    808 182206  7     23653 14.985 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmH2,lmH5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq     F    Pr(>F)
## 1    813 198070
## 2    808 182206  5     15864 14.07 3.268e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmH3,lmH5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    812 185373
## 2    808 182206  4    3167.1 3.5112 0.007485 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmH4,lmH5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
## Model 2: behIntHandHYgiene ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1    811 184066
## 2    808 182206  3    1860.2 2.7497 0.04182 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Riskier choices predict less hand hygiene intentions in all conditions (with a weak relationship in the neutral condition without intervention). The relationship is weaker than for the previous two criterion variables.

A5.6 Results for movement restriction

A5.6.1 Step 1

```
  lmV1<-lm(behIntMovement~ CRT+riskTaking+angleSVO, data = modelFrame)
    modV1<-Anova(lmV1, type="III")
    print(modV1)
```

```
## Anova Table (Type III tests)
##
## Response: behIntMovement
##             Sum Sq  Df   F value    Pr(>F)
## (Intercept) 860795   1 2373.1079 < 2.2e-16 ***
```

```
## CRT            150   1    0.4138 0.5202127
## riskTaking    1238   1    3.4135 0.0650290 .
## angleSVO      4292   1   11.8336 0.0006113 ***
## Residuals   295624 815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmV1$coefficients

## (Intercept)         CRT  riskTaking    angleSVO
##  32.4196174  -0.3019616  -0.5077690   0.1644981
```

```
    print(eta_squared(modV1, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       5.08e-04 | [0.00, 1.00]
## riskTaking |       4.17e-03 | [0.00, 1.00]
## angleSVO   |           0.01 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

SVO is the only significant predictor in the model.

A5.6.2 Step 2

```
    lmV2<-lm(behIntMovement~ CRT+riskTaking+angleSVO+trump+SECS, data = modelFrame)
    modV2<-Anova(lmV2, type="III")
    print(modV2)

## Anova Table (Type III tests)
##
## Response: behIntMovement
##             Sum Sq  Df   F value    Pr(>F)
## (Intercept) 860795   1 2554.0362 < 2.2e-16 ***
## CRT           1199   1    3.5569   0.05966 .
## riskTaking     285   1    0.8470   0.35768
## angleSVO      1556   1    4.6167   0.03196 *
## trump        12178   1   36.1341  2.78e-09 ***
## SECS           176   1    0.5236   0.46951
## Residuals   274008 813
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmV2$coefficients

## (Intercept)         CRT  riskTaking    angleSVO       trump        SECS
## 32.41961742 -0.86360724 -0.24570218  0.10066803 -0.07259729  0.01549870

    print(eta_squared(modV2, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter  | Eta2 (partial) |       95% CI
## -----------------------------------------
## CRT        |       4.36e-03 | [0.00, 1.00]
## riskTaking |       1.04e-03 | [0.00, 1.00]
## angleSVO   |       5.65e-03 | [0.00, 1.00]
## trump      |           0.04 | [0.02, 1.00]
## SECS       |       6.44e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmV1,lmV2)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 295624
## 2    813 274008  2     21616 32.068 3.935e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this model, both SVO and the preference for Trump are significant predictors, with the preference variable being the stronger predictor.

A5.6.3 Step 3

```
    lmV3<-lm(behIntMovement~ CRT+riskTaking+angleSVO+trump+SECS+
                psychReactance, data = modelFrame)
    modV3<-Anova(lmV3, type="III")
    print(modV3)

## Anova Table (Type III tests)
##
## Response: behIntMovement
##                Sum Sq  Df   F value    Pr(>F)
```

```
## (Intercept)    860795   1 2693.1734 < 2.2e-16 ***
## CRT              1159   1    3.6264   0.05722 .
## riskTaking         27   1    0.0848   0.77100
## angleSVO          435   1    1.3614   0.24364
## trump            7613   1   23.8201 1.273e-06 ***
## SECS               39   1    0.1224   0.72657
## psychReactance  14476   1   45.2901 3.209e-11 ***
## Residuals      259532 812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    lmV3$coefficients
```

```
##    (Intercept)            CRT     riskTaking       angleSVO          trump
##   32.419617420   -0.849195239   -0.076054992    0.053849949   -0.058326030
##           SECS psychReactance
##    0.007308608   -5.714440490
```

```
    print(eta_squared(modV3, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## ------------------------------------------------
## CRT            |       4.45e-03 | [0.00, 1.00]
## riskTaking     |       1.04e-04 | [0.00, 1.00]
## angleSVO       |       1.67e-03 | [0.00, 1.00]
## trump          |           0.03 | [0.01, 1.00]
## SECS           |       1.51e-04 | [0.00, 1.00]
## psychReactance |           0.05 | [0.03, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmV1,lmV3)
```

```
## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
##   Res.Df    RSS Df Sum of Sq     F    Pr(>F)
## 1    815 295624
## 2    812 259532  3     36092 37.64 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmV2,lmV3)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
##   Res.Df    RSS Df Sum of Sq     F    Pr(>F)
## 1    813 274008
## 2    812 259532  1     14476 45.29 3.209e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Psychological reactance is a strong negative predictor in this mode, but SVO is no longer significant.

A5.6.4 Step 4

```
    lmV4<-lm(behIntMovement~ CRT+riskTaking+angleSVO+trump+SECS+
               psychReactance+RiskyChoices, data = modelFrame)
    modV4<-Anova(lmV4, type="III")
    print(modV4)

## Anova Table (Type III tests)
##
## Response: behIntMovement
##                Sum Sq  Df   F value    Pr(>F)
## (Intercept)    568602   1 1779.0512 < 2.2e-16 ***
## CRT              1182   1    3.6987    0.0548 .
## riskTaking         10   1    0.0307    0.8608
## angleSVO          320   1    1.0012    0.3173
## trump            7503   1   23.4756 1.516e-06 ***
## SECS               41   1    0.1286    0.7200
## psychReactance  14269   1   44.6446 4.389e-11 ***
## RiskyChoices      329   1    1.0292    0.3106
## Residuals      259203 811
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmV4$coefficients

##    (Intercept)            CRT     riskTaking       angleSVO          trump
##    32.89320926    -0.85775880    -0.04609350     0.04671332    -0.05793229
##           SECS psychReactance   RiskyChoices
##     0.00749174    -5.67842642    -0.08325214
```

```
    print(eta_squared(modV4, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter      | Eta2 (partial) |       95% CI
## -------------------------------------------------
## CRT            |       4.54e-03 | [0.00, 1.00]
## riskTaking     |       3.79e-05 | [0.00, 1.00]
## angleSVO       |       1.23e-03 | [0.00, 1.00]
## trump          |           0.03 | [0.01, 1.00]
## SECS           |       1.59e-04 | [0.00, 1.00]
## psychReactance |           0.05 | [0.03, 1.00]
## RiskyChoices   |       1.27e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].

    anova(lmV1,lmV4)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 295624
## 2    811 259203  4     36421 28.488 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmV2,lmV4)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq     F    Pr(>F)
## 1    813 274008
## 2    811 259203  2     14805 23.16 1.653e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmV3,lmV4)

## Analysis of Variance Table
##
```

```
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1    812 259532
## 2    811 259203  1    328.94 1.0292 0.3106
```

In this case, adding the number of risky choices does not significantly improve the model (the coefficient is not significantly different from zero).

A5.6.5 Step 5

```
    lmV5<-lm(behIntMovement~ CRT+riskTaking+angleSVO+trump+SECS+
                psychReactance+RiskyChoices+mskRiskyChoices+
                injRiskyChoices+mskinjRiskyChoices, data = modelFrame)
    modV5<-Anova(lmV5, type="III")
    print(modV5)

## Anova Table (Type III tests)
##
## Response: behIntMovement
##                     Sum Sq  Df   F value    Pr(>F)
## (Intercept)         570959   1 1809.9554 < 2.2e-16 ***
## CRT                   1039   1    3.2946  0.069879 .
## riskTaking               6   1    0.0201  0.887174
## angleSVO               159   1    0.5055  0.477287
## trump                 5980   1   18.9566 1.509e-05 ***
## SECS                     2   1    0.0051  0.943365
## psychReactance       14150   1   44.8545 3.974e-11 ***
## RiskyChoices           218   1    0.6907  0.406180
## mskRiskyChoices       2302   1    7.2961  0.007055 **
## injRiskyChoices       1621   1    5.1394  0.023652 *
## mskinjRiskyChoices     240   1    0.7617  0.383067
## Residuals           254888 808
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmV5$coefficients

##         (Intercept)                 CRT          riskTaking             angleSVO
##        33.299998200        -0.804726153        -0.037110499         0.033098170
##               trump                SECS      psychReactance        RiskyChoices
##        -0.052330597         0.001480572        -5.659031241         0.078510468
##     mskRiskyChoices    injRiskyChoices mskinjRiskyChoices
##        -0.592412128        -0.352221027         0.304842864
```

```
    print(eta_squared(modV5, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter          | Eta2 (partial) |       95% CI
## -----------------------------------------------------
## CRT                |       4.06e-03 | [0.00, 1.00]
## riskTaking         |       2.49e-05 | [0.00, 1.00]
## angleSVO           |       6.25e-04 | [0.00, 1.00]
## trump              |           0.02 | [0.01, 1.00]
## SECS               |       6.25e-06 | [0.00, 1.00]
## psychReactance     |           0.05 | [0.03, 1.00]
## RiskyChoices       |       8.54e-04 | [0.00, 1.00]
## mskRiskyChoices    |       8.95e-03 | [0.00, 1.00]
## injRiskyChoices    |       6.32e-03 | [0.00, 1.00]
## mskinjRiskyChoices |       9.42e-04 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmV1,lmV5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    815 295624
## 2    808 254888  7     40737 18.448 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmV2,lmV5)
```

```
## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1    813 274008
## 2    808 254888  5     19120 12.122 2.417e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    anova(lmV3,lmV5)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq     F   Pr(>F)
## 1    812 259532
## 2    808 254888  4    4644.8 3.681 0.005584 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    anova(lmV4,lmV5)

## Analysis of Variance Table
##
## Model 1: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices
## Model 2: behIntMovement ~ CRT + riskTaking + angleSVO + trump + SECS +
##     psychReactance + RiskyChoices + mskRiskyChoices + injRiskyChoices +
##     mskinjRiskyChoices
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    811 259203
## 2    808 254888  3    4315.8 4.5604 0.003544 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Condition-specific coefficients improve the model significantly. More risky choices predict stronger intentions to restrict one's movement.

A5.7 Most important predictors

We observed consistent findings across the four scales: the preference for a Trump win and psychological reactance are significant negative predictors of intentions to change behavior in response to the pandemic. Moreover, the game results predict these intentions as well, especially in the intervention and pandemic framing conditions. No other variable included in the models was a consistently strong predictor. Social value orientation was a significant predictor in models without the Trump preference variable, but it was not a significant predictor in any of the full models. The relationship between game behavior and criterion variables is strongest for masks and social distancing. These might capture the scenario in the transmission game more closely than others.

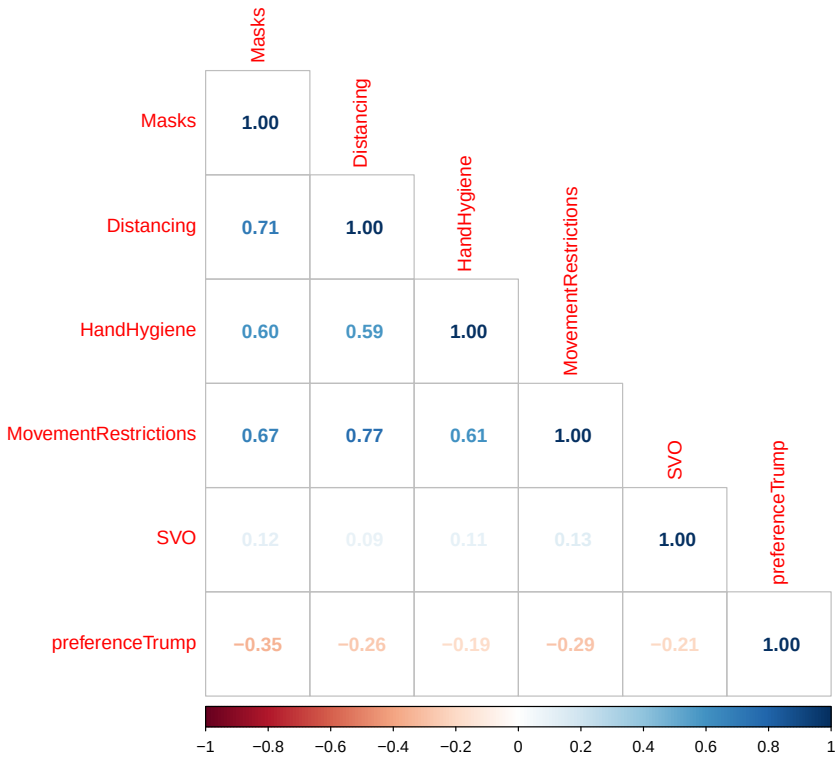


Figure A8
Inter-correlation matrix of pandemic behaivor measures, SVO and preference for Trump.

```
behaviorFrame$SVO=modelFrame$angleSVO
behaviorFrame$preferenceTrump=modelFrame$trump

corMatrix<-cor(behaviorFrame,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

Figure A8 shows the extended correlation matrix with the preference and SVO measure added to the intention measures. Bivariate correlations between Trump preference and intentions are all negative, correlations with SVO are all positive. At the same time, there is a negative correlation between SVO and preference for Trump. One might interpret the results as showing that the effect of SVO is mainly already covered by the preference variable, but this conclusion is speculative.

A5.8 Differences between conditions

Game behavior is less predictive of real-world intentions in the neutral framing without interventions. A reason for this difference might lie in the fact that the real-world

situation in August 2020 saw a variety of interventions in place. At this time, masks and social distancing were clearly established as means to combat the pandemic. Thus, the real-world situation was less comparable to the transmission game in its most neutral format without clear advice to protect others through choosing the safer action. Players who took more risky actions in the pandemic framing or when faced with the intervention advising not to take these actions were also less likely to endorse non-pharmaceutical interventions outside the game.

A6 Results for behavioral types

A6.1 Four behavioral types

The analysis for our previous study (Woike et al., 2022) focused on behavioral patterns. The current study offers the opportunity to test whether our previous findings replicate. We classified participants into four categories depending on the pattern of their responses across rounds. These patterns are:

1. *All G*: These are participants who choose option G/mask from round 1 to round 25.
2. *H-G*: These are participants who choose option H/no mask in round 1 and option G/mask in round 25 with a single switch between options.
3. *Switch*: These are participants who switch between the two options more than once.
4. *All H*: These are participants who choose option H/no mask from round 1 to round 25.

Simulation results showed that the H-G strategy played by all participants is collectively optimal if the number of H-choices is kept small. As the risk of meeting an infected other participant cannot become smaller over the rounds of the game, choosing the H/no mask-option at the beginning is associated with a lower risk of losing the bonus payments compared to later rounds of the game.

The following code classifies decision patterns into these four types.

```
patternSwitch <- data.frame(
  S02=abs(scaleFrameTG$R02-scaleFrameTG$R01),
  S03=abs(scaleFrameTG$R03-scaleFrameTG$R02),
  S04=abs(scaleFrameTG$R04-scaleFrameTG$R03),
  S05=abs(scaleFrameTG$R05-scaleFrameTG$R04),
  S06=abs(scaleFrameTG$R06-scaleFrameTG$R05),
  S07=abs(scaleFrameTG$R07-scaleFrameTG$R06),
  S08=abs(scaleFrameTG$R08-scaleFrameTG$R07),
  S09=abs(scaleFrameTG$R09-scaleFrameTG$R08),
  S10=abs(scaleFrameTG$R10-scaleFrameTG$R09),
  S11=abs(scaleFrameTG$R11-scaleFrameTG$R10),
  S12=abs(scaleFrameTG$R12-scaleFrameTG$R11),
  S13=abs(scaleFrameTG$R13-scaleFrameTG$R12),
```

```
  S14=abs(scaleFrameTG$R14-scaleFrameTG$R13),
  S15=abs(scaleFrameTG$R15-scaleFrameTG$R14),
  S16=abs(scaleFrameTG$R16-scaleFrameTG$R15),
  S17=abs(scaleFrameTG$R17-scaleFrameTG$R16),
  S18=abs(scaleFrameTG$R18-scaleFrameTG$R17),
  S19=abs(scaleFrameTG$R19-scaleFrameTG$R18),
  S20=abs(scaleFrameTG$R20-scaleFrameTG$R19),
  S21=abs(scaleFrameTG$R21-scaleFrameTG$R20),
  S22=abs(scaleFrameTG$R22-scaleFrameTG$R21),
  S23=abs(scaleFrameTG$R23-scaleFrameTG$R22),
  S24=abs(scaleFrameTG$R24-scaleFrameTG$R23),
  S25=abs(scaleFrameTG$R25-scaleFrameTG$R24)
)

scaleSwitch=scoreItems(keys=c(1,1,1,1,1,1,1,1,1,1,
                              1,1,1,1,1,1,1,1,1,1,
                              1,1,1,1 ),
                       items =patternSwitch,totals=TRUE)


####RStudio produces a variable called "Scale1" here,
####R package versions implemented in Overleaf create
### a variable "Scale11"


switchNumber<-data.frame(
scaleSwitch$scores,
score=scoresTG$Scale1,
R1=scaleFrameTG$R01,
pattern=0
) %>% dplyr::rename(
  switches=Scale11
)


head(switchNumber)


##   switches score R1 pattern
## 1        0   200  1       0
## 2        0   200  1       0
## 3        0   200  1       0
## 4        0   200  1       0
## 5        1   296  2       0
## 6        9   360  2       0
```

```
switchNumber <- switchNumber %>%
  mutate(pattern = case_when(
      (R1=="1") & (switches ==0) ~ "p1-All G",
      (R1=="2") & (switches ==0) ~ "p5-All H",
      (R1=="1") & (switches ==1) ~ "p6-G then H",
      (R1=="2") & (switches ==1)&score<500 ~ "p2-H then G",
      (R1=="2") & (switches ==1)&score>500 ~ "p4-H then G (late)",
      (R1=="2") & (switches ==1) ~ "p2-H then G",
      switches>1 ~"p3-Switching"
    )
  )


switchNumber <- switchNumber %>%
  mutate(pattern = case_when(
    (R1=="1") & (switches ==0) ~ "p1-All G",
    (R1=="2") & (switches ==0) ~ "p4-All H",
    (R1=="2") & (switches ==1) ~ "p2-H then G",
    ((R1=="1") & (switches ==1))|(switches>1) ~"p3-Switching"
  )
  )

patterncheck=data.frame(
  pattern=as.factor(switchNumber$pattern)
)
```

A6.2 Distribution of types across conditions

The differences in scores should correspond to a differential distribution of types across conditions. This distribution is shown in Figure A9.

```
patterncheck$conditions=4*(as.numeric(modelFrame$facSample)-1)+
  2*(as.numeric(modelFrame$facFraming)-1)+
  as.numeric(modelFrame$facInterv)


patterncheck$conditions=as.factor(patterncheck$conditions)

levels(patterncheck$conditions)<-list("Trump|Masks|Inj"="1",
          "Trump|Masks|None"="2","Trump|Color|Inj"="3",
          "Trump|Color|None"="4","Clint|Masks|Inj"="5",
          "Clint|Masks|None"="6","Clint|Color|Inj"="7",
          "Clint|Color|None"="8")
```

```
p<-ggplot(data = patterncheck) +
  geom_mosaic(aes(x = product(conditions), fill=pattern), na.rm=TRUE) +
  scale_fill_viridis_d(option="inferno",direction=-1)+
  labs(x="", y='Decision pattern',size=15) +
  theme_dark()+
  annotate("segment", x = 0, xend=1, y = 0.5, yend=0.5,color="gray")+
  annotate("text", x = 1.02,  y = 0.5, label = "50%", size = 6,
           color="gray",angle=-90)+
  annotate("text", x = -0.04,  y = 0.98, label = "All H", size = 6,
           color="black",angle=90)+
  annotate("text", x = -0.04,  y = 0.85, label = "Switch", size = 6,
           color="black",angle=90)+
  annotate("text", x = -0.04,  y = 0.67, label = "H-G", size = 6,
           color="black",angle=90)+
  annotate("text", x = -0.04,  y = 0.3, label = "All G", size = 6,
           color="black",angle=90)+
  annotate("text", x = 0.0625,  y = -0.05, label = "Tr/Pd/Norm",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.1875,  y = -0.05, label = "Tr/Pd/None",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.3125,  y = -0.05, label = "Tr/Nt/Norm",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.4375,  y = -0.05, label = "Tr/Nt/None",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.5625,  y = -0.05, label = "Cl/Pd/Norm",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.6875,  y = -0.05, label = "Cl/Pd/None",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.8125,  y = -0.05, label = "Cl/Nt/Norm",
           size = 5, color="black",angle=0)+
  annotate("text", x = 0.9375,  y = -0.05, label = "Cl/Nt/None",
           size = 5, color="black",angle=0)+
  theme(legend.position = "none")
```

```
## Error in geom_mosaic(aes(x = product(conditions), fill = pattern), na.rm
= TRUE): could not find function "geom_mosaic"
```

Note that the following code will generate an error, as "geom_mosaic()" is part of the ggmosaic package that is not available for the compilation in Overleaf. An exported image file from RStudio is shown below that was generated using the source code.

```
p
```

```
## Error in eval(expr, envir, enclos):  object 'p' not found
```

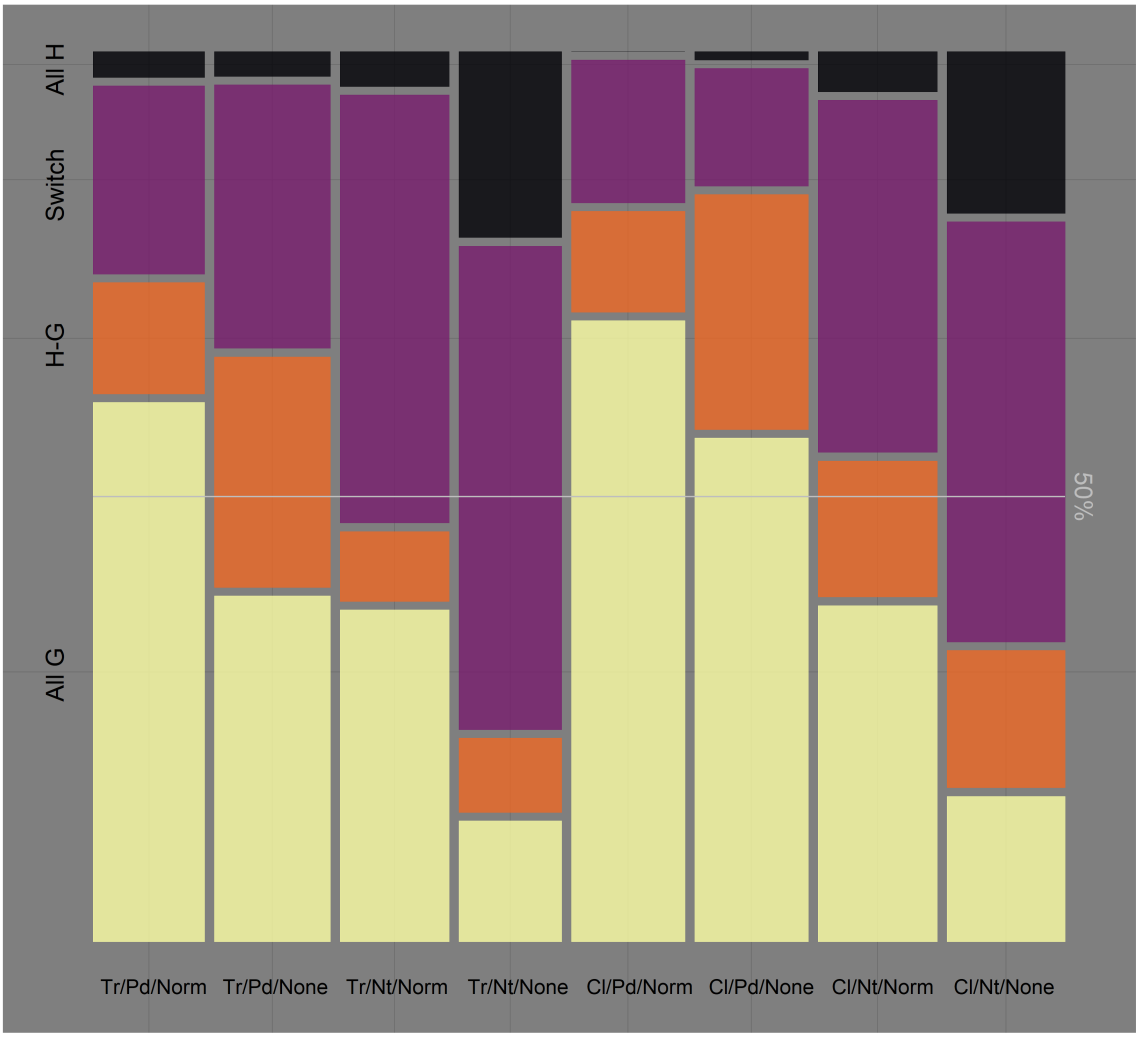


Figure A9

Mosaic plot of decision patterns by conditions [imported from an RStudio output.] The abbreviations used are "Tr": Trump voters, "Cl": Clinton voters, "Pd": Pandemic frame, "Nt": Neutral frame, "Norms": Norms intervention, "None": No intervention.

The distribution of types shows significant variation (see the χ^2 test below).

```
chiCondition<-chisq.test(table(patterncheck$conditions,patterncheck$pattern))
chiCondition

##
##  Pearson's Chi-squared test
##
## data:  table(patterncheck$conditions, patterncheck$pattern)
## X-squared = 219.85, df = 21, p-value < 2.2e-16
```

The distribution of types for Trump voters across conditions is similar to that of Clinton voters and follows comparable shifts between framings and interventions. There is a higher proportion of the *All G* type with Clinton voters and a slightly lower proportion of the *Switch* type.

The distribution shows a clear difference between the control condition and all other conditions. In the control condition, a relatively small minority of participants showed the *All G* strategy. This group also had the largest proportion of *All H* strategies. With the pandemic framing, fewer participants chose a *Switch* strategy.

Our previous study did not vary the framing, and the injunctive norms condition was one of five different interventions. The results for the two color conditions are comparable to the results in our previous study.

A6.3 Covariates and behavioral patterns

We found strong relationships between types and three covariates in our previous study: general risk preference, social value orientation and the cognitive reflection test.

A6.3.1 ANOVAs

```
 patterncheck$risk=as.numeric(df$RTGeneral)-1
 patterncheck$SVO=scoresSVO
 patterncheck$CRT=scoresCRT$CRTscore

a <-aov(risk~pattern, data=patterncheck)
summary(a)

##              Df Sum Sq Mean Sq F value   Pr(>F)
## pattern       3    193   64.45   10.86 5.32e-07 ***
## Residuals   815   4837    5.93
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

a <-aov(angleSVO~pattern, data=patterncheck)
summary(a)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## pattern       3   5458  1819.3    9.32 4.61e-06 ***
## Residuals   815 159092   195.2
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

a <-aov(CRT~pattern, data=patterncheck)
summary(a)

##              Df Sum Sq Mean Sq F value   Pr(>F)
## pattern       3   80.8  26.950   13.77 9.12e-09 ***
## Residuals   815 1595.2   1.957
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The three ANOVAs demonstrate that the previously found relationships hold in this study. A visualization of the relationship allows for a more informative comparison.

A6.3.2 Decision pattern and general risk preference

As in our previous study, higher risk preference values are observed for participants in the *All H* and *Switch* groups. In addition, low values of general risk preference are mainly observed in the *All G* group and in the *H-G* group (see Fig. A10).

```
p<-ggplot(patterncheck, aes(x = risk, y = factor(pattern),
                            fill = pattern)) +
  geom_density_ridges(alpha = 0.7, color = "white",
                      scale = 5, rel_min_height = 0.02,bandwidth=1) +
  labs(x = "General risk item", y = "") +
  theme_ridges()+
  xlim(0,10)+
  theme_gray()+
  scale_y_discrete(limits = rev(levels(factor(patterncheck$pattern))))+
  scale_fill_viridis_d(option="inferno",direction=-1)+
  theme(legend.position = "none", axis.text.y=element_blank())+
  annotate("text", x = 0.5,  y = 0.8, label = "All H", size = 6,
           color="black",angle=0)+
  annotate("text", x = 0.5,  y = 1.8, label = "Switch", size = 6,
           color="black",angle=0)+
  annotate("text", x = 0.5,  y = 2.8, label = "H-G", size = 6,
           color="black",angle=0)+
  annotate("text", x = 0.5,  y = 3.8, label = "All G", size = 6,
           color="black",angle=0)
p
```

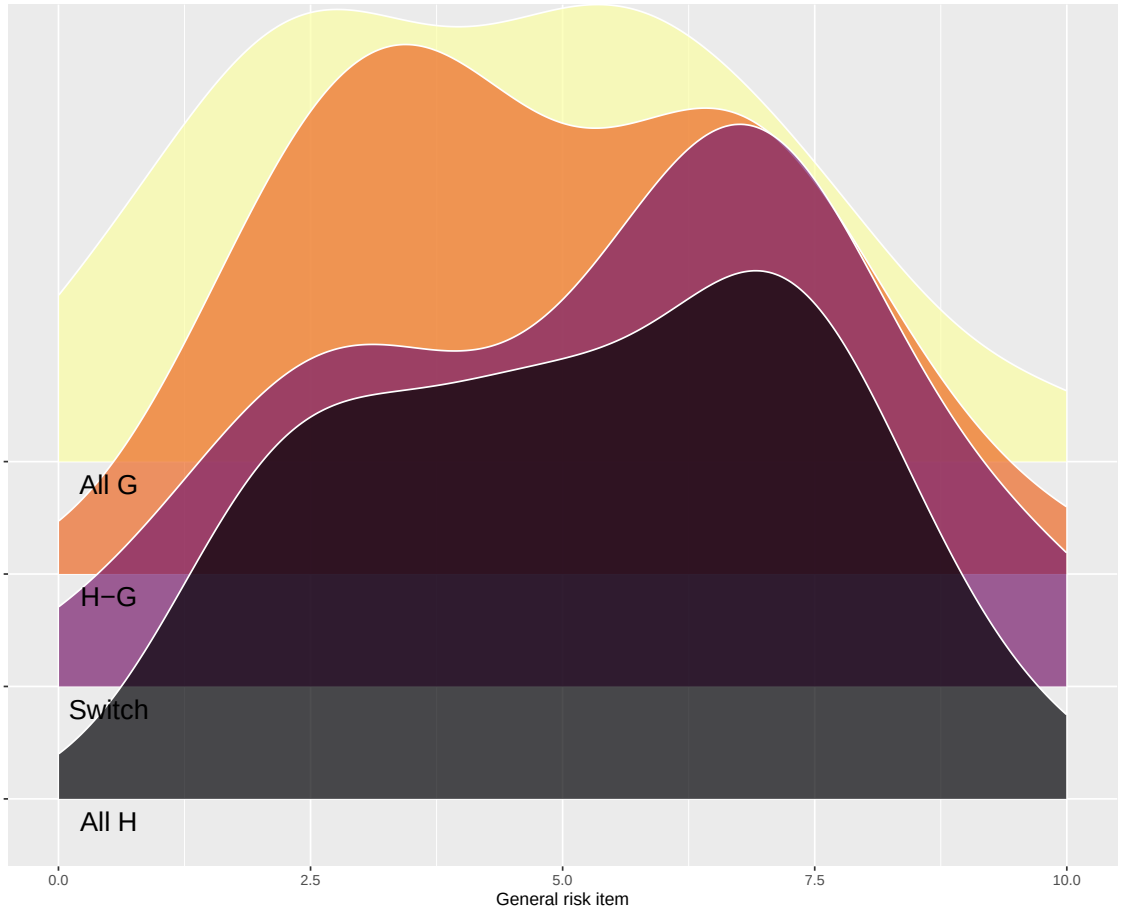


Figure A10
Ridge plot of risk preference distribution by decision pattern.

A6.3.3 Decision pattern and social value orientation

As in our previous study, the highest proportion of individualistic types and the lowest proportion of prosocial types was observed in the *All H* condition, and vice versa in the *All G* condition, with the other two groups showing intermediate distributions (see Fig. A11). It is not untypical to see few individuals classified as competitive or altruistic (Murphy et al., 2011).

```
p<-ggplot(patterncheck, aes(x = angleSVO, y = factor(pattern),
                            fill = pattern)) +
  geom_density_ridges(alpha = 0.7, color = "white",
                      scale = 5, rel_min_height = 0.02,bandwidth=3) +
  labs(x = "SVO (angle)", y = "") +
  theme_ridges()+
  theme_gray()+
  scale_y_discrete(limits = rev(levels(factor(patterncheck$pattern))))+
  scale_fill_viridis_d(option="inferno",direction=-1)+
```

```
  annotate("text", x = -5,  y = 0.8, label = "All H", size = 6,
           color="black",angle=0)+
  annotate("text", x = -5,  y = 1.8, label = "Switch", size = 6,
           color="black",angle=0)+
  annotate("text", x = -5,  y = 2.8, label = "H-G", size = 6,
           color="black",angle=0)+
  annotate("text", x = -5,  y = 3.8, label = "All G", size = 6,
           color="black",angle=0)+
  theme(legend.position = "none", axis.text.y=element_blank())+
  xlim(-25, 55)+
  annotate(geom = "text", x = -22.5, y = 9.5, label = "Competitive",
         color = "black") +
  annotate(geom = "text", x = 5, y = 9.5, label = "Individualistic",
           color = "black")  +
  annotate(geom = "text", x = 37.5, y = 9.5, label = "Prosocial",
           color = "black") +
  annotate("segment", x = 22.45, xend = 22.45, y = 0, yend = 10,
           colour = "red")           +
  annotate("segment", x = -12.04, xend = -12.04, y = 0, yend = 10,
           colour = "red")
p

## Warning:  Removed 10 rows containing non-finite values
(‘stat_density_ridges()‘).
```

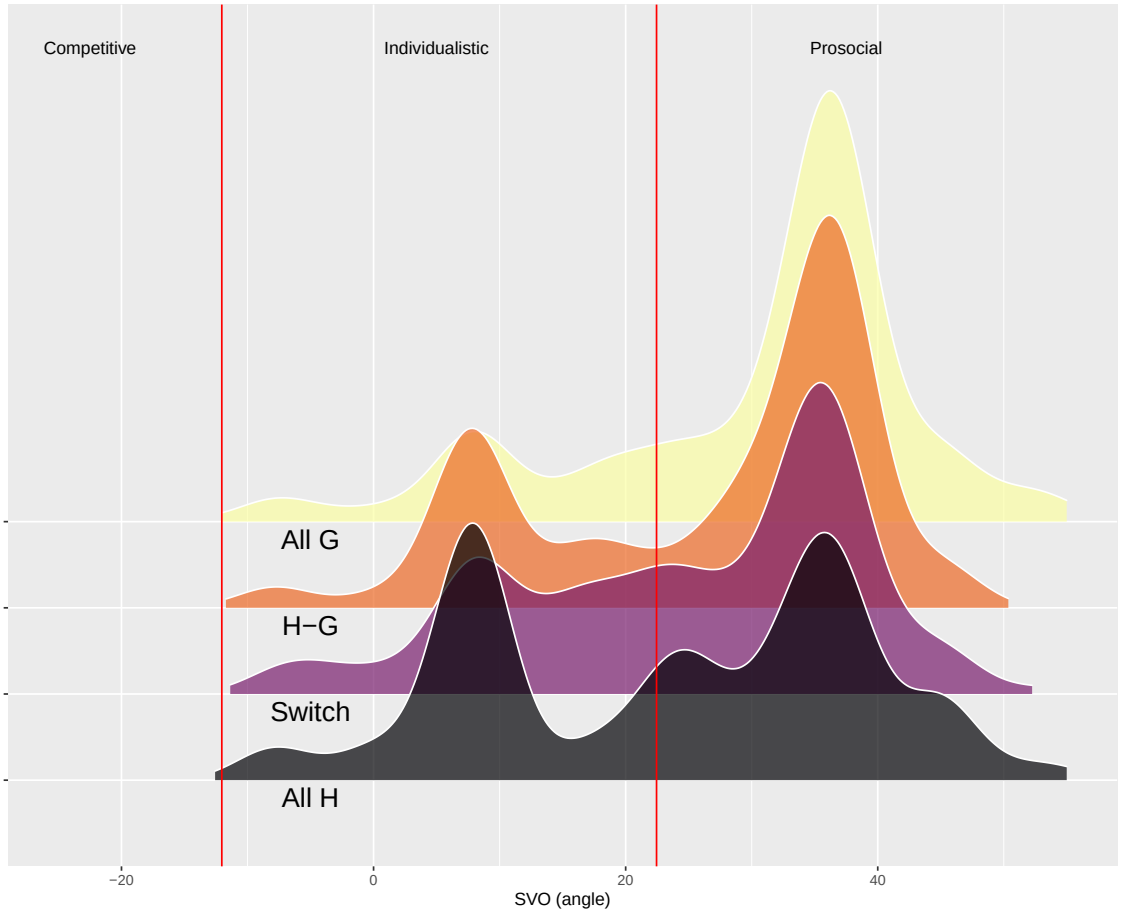


Figure A11
Ridge plot of the distribution of the social value orientation angle by decision pattern.

A6.3.4 Decision pattern and CRT

The visualization of results for the cognitive reflection test reveals the same striking differences between groups that was observed in our previous study. Participants using the H-G decision pattern are the only group with a median of 3 correct responses (2 correct responses for the other three groups). In contrast to the previous study, participants with the *All H* pattern have slightly higher values compared to *All G* and *Switch*, but again not at the level of the *H-G* group. As observed before, early H-choices carry a lower risk of incurring the loss of bonus funds than later H-choices while offering the same increase in game score. This pattern is far from obvious, though, as the large number of *Switch* patterns reveals.

```
p<-ggplot(data = patterncheck) +
geom_mosaic(aes(x =product(pattern), fill=CRT), na.rm=TRUE) +
scale_fill_viridis_d(option="plasma",direction=-1)+
labs(x="", y='CRT score',size=6) +
theme_dark()+
```

```
annotate("text", x = 0.205, y = -0.03, label = "All G", size = 6,
color="black",angle=0)+
annotate("text", x = 0.505, y = -0.03, label = "H-G", size = 6,
color="black",angle=0)+
annotate("text", x = 0.7505, y = -0.03, label = "Switch", size = 6,
color="black",angle=0)+
annotate("text", x = 0.9625, y = -0.03, label = "All H", size = 6,
color="black",angle=0)+
annotate("text", x = -0.05, y = 0.911, label = "4", size = 6,
color="black",angle=0)+
annotate("text", x = -0.05, y = 0.72, label = "3", size = 6,
color="black",angle=0)+
annotate("text", x = -0.05, y = 0.535, label = "2", size = 6,
color="black",angle=0)+
annotate("text", x = -0.05, y = 0.3225, label = "1", size = 6,
color="black",angle=0)+
annotate("text", x = -0.05, y = 0.107, label = "0", size = 6,
color="black",angle=0)+
annotate("segment", x = 0, xend=1, y = 0.5, yend=0.5,color="white")+
annotate("text", x = 1.02, y = 0.5, label = "Median", size = 5,
color="white",angle=-90)+
theme(legend.position = "none")+
    theme(axis.title.x=element_blank(),
        axis.text.x=element_blank(),
        axis.ticks.x=element_blank())+
  theme(axis.text.y=element_blank(),
        axis.ticks.y=element_blank())

## Error in geom_mosaic(aes(x = product(pattern), fill = CRT), na.rm =
TRUE): could not find function "geom_mosaic"

# p ggmosaic creates an error (this would just show the previous graph)
```

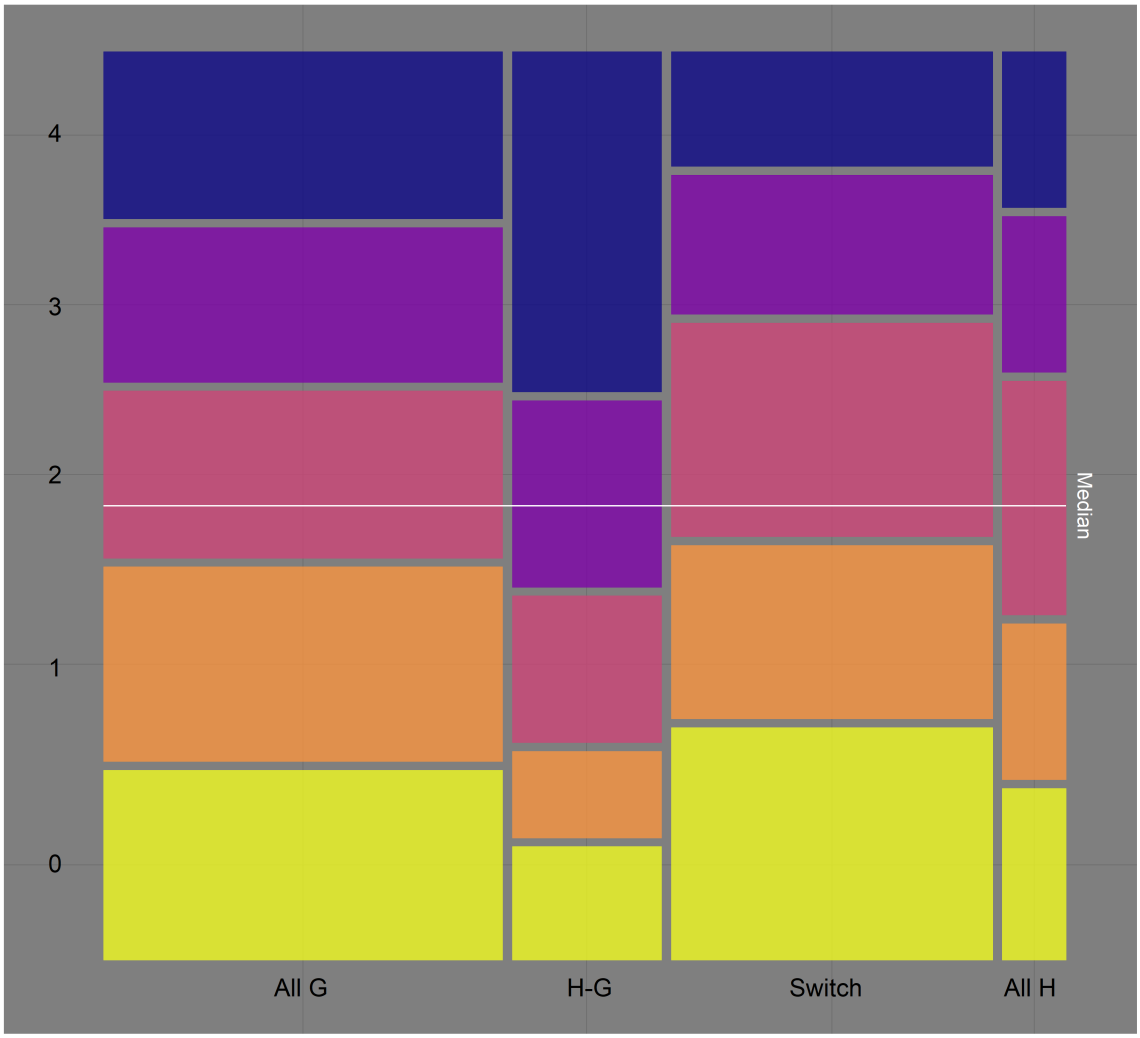


Figure A12
Mosaic plot of CRT scores by decision pattern [imported from an RStudio output.]

A7 Postquestionnaire: Game motivation and estimates

A7.1 Motivation for game behavior

A7.1.1 Questions

The postquestionnaire measured game motivation with eleven questions (answered on a five-point scale from strongly disagree to strongly agree). Below is the neutral frame version of this questionnaire.

- **Post01**: I wanted to make as much bonus money as possible.
- **Post02**: I wanted to make more bonus money than other players.
- **Post03**: I felt responsible for other players.

- **Post04**: I wanted to make other players switch color.
- **Post05**: I was afraid to switch color in this game.
- **Post06**: I tried to anticipate what others were doing in this game.
- **Post07**: I followed my gut in this game.
- **Post08**: I wanted to take some risk in this game.
- **Post09**: I wanted to protect others in this game.
- **Post10**: I did not care at all what happened in this game.
- **Post11**: I wanted that the entire group receives as much money as possible.

A7.1.2 Data frame preparation and subgroup definition

We add the number of H/no mask choices and SVO, the CRT and risk preference to the postquestionnaire item to analyze their inter-relationship. We also prepare subgroups of the dataset to study relations within the four experimental conditions.

```
  FramePost <- data.frame(
      MaxBonus=as.numeric(df$PostTG_01),
      MoreBonus=as.numeric(df$PostTG_02),
      Responsible=as.numeric(df$PostTG_03),
      MakeSwitch=as.numeric(df$PostTG_04),
      AfraidSwitch=as.numeric(df$PostTG_05),
      Anticipate=as.numeric(df$PostTG_06),
      FollowGut=as.numeric(df$PostTG_07),
      TakeRisk=as.numeric(df$PostTG_08),
      ProtectOthers=as.numeric(df$PostTG_09),
      DidNotCare=as.numeric(df$PostTG_10),
      AllReceive=as.numeric(df$PostTG_11),
      CRT=modelFrame$CRT,
      SVO=modelFrame$angleSVO,
      Risk=modelFrame$riskTaking,
      RiskyChoices=modelFrame$RiskyChoices
    )

conditionFactorFour= (as.numeric(modelFrame$facFraming)-1)*2+
      as.numeric(modelFrame$facInterv)

cond4=as.numeric(factor(conditionFactorFour,
                        labels =c('Mskr-Inj','Msk-No',
                                  'Clr-Inj','Clr-No')))

FramePost$cond4=cond4
```

```
postNoIntervNoFraming <- FramePost[which(FramePost$cond4==4),]
postIntervNoFraming <- FramePost[which(FramePost$cond4==3),]
postNoIntervFraming <- FramePost[which(FramePost$cond4==2),]
postIntervFraming <- FramePost[which(FramePost$cond4==1),]


FramePost<- FramePost[, !(colnames(FramePost) %in% c("cond4"))]
```

A7.1.3 Correlation matrix and regression model across all conditions

Figure A13 shows the inter-correlation matrix for the entire sample.

```
corMatrix<-cor(FramePost,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

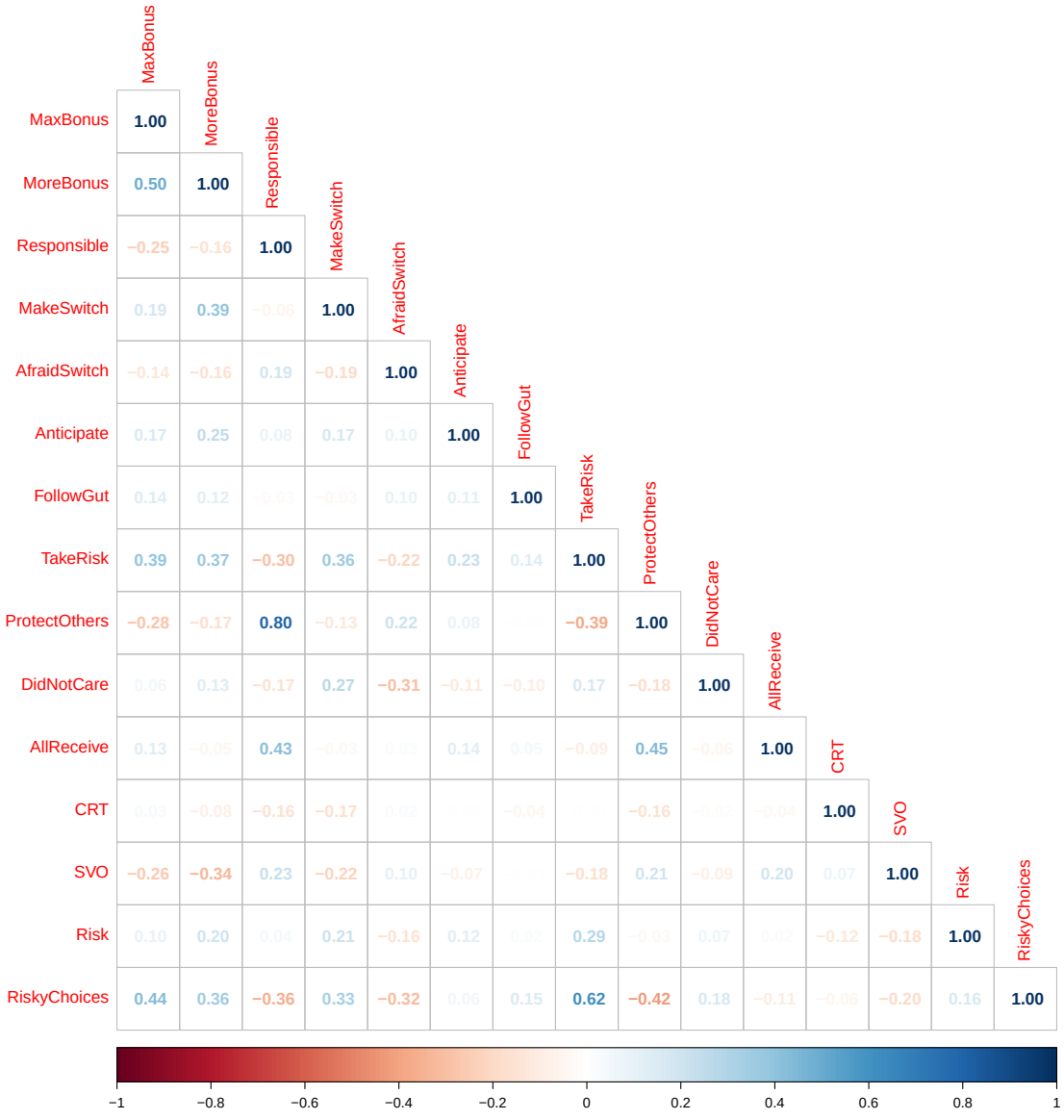


Figure A13
Inter-correlation matrix of postquestionnaire items, SVO, CRT, risk preference and game decisions: Entire sample.

```
lmPAll<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
             MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
             TakeRisk+ProtectOthers+DidNotCare+AllReceive,
             data = FramePost)
    modPAll<-Anova(lmPAll, type="III")
    print(modPAll)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                Sum Sq  Df  F value    Pr(>F)
## (Intercept)       3.0   1   0.0968 0.7558298
## MaxBonus        951.6   1  30.5839 4.320e-08 ***
## MoreBonus        29.0   1   0.9314 0.3347946
## Responsible      67.4   1   2.1668 0.1414106
## MakeSwitch      466.0   1  14.9769 0.0001176 ***
## AfraidSwitch    893.5   1  28.7162 1.094e-07 ***
## Anticipate      255.8   1   8.2205 0.0042498 **
## FollowGut       349.6   1  11.2352 0.0008400 ***
## TakeRisk       5622.0   1 180.6841 < 2.2e-16 ***
## ProtectOthers   157.3   1   5.0562 0.0248064 *
## DidNotCare        7.3   1   0.2357 0.6274264
## AllReceive        2.4   1   0.0772 0.7811702
## Residuals     25110.0 807
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmPAll$coefficients

##   (Intercept)      MaxBonus     MoreBonus   Responsible    MakeSwitch
##     0.4592732     1.0606604     0.1994059    -0.3685816     0.9518185
##  AfraidSwitch    Anticipate     FollowGut      TakeRisk ProtectOthers
##    -1.0109559    -0.4729039     0.6349447     2.2131621    -0.5867425
##    DidNotCare    AllReceive
##    -0.1166467    -0.0533535

    print(eta_squared(modPAll, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter     | Eta2 (partial) |       95% CI
## ------------------------------------------------
## MaxBonus      |           0.04 | [0.02, 1.00]
## MoreBonus     |       1.15e-03 | [0.00, 1.00]
## Responsible   |       2.68e-03 | [0.00, 1.00]
```

```
## MakeSwitch    |           0.02 | [0.01, 1.00]
## AfraidSwitch  |           0.03 | [0.02, 1.00]
## Anticipate    |           0.01 | [0.00, 1.00]
## FollowGut     |           0.01 | [0.00, 1.00]
## TakeRisk      |           0.18 | [0.15, 1.00]
## ProtectOthers |       6.23e-03 | [0.00, 1.00]
## DidNotCare    |       2.92e-04 | [0.00, 1.00]
## AllReceive    |       9.57e-05 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A multiple linear regression with all questions as predictors and game choices as criterion shows multiple predictors with coefficients significantly different from zero: Desiring the maximum bonus, wanting to make others switch, following one's gut, and taking risk are significant predictors of more H/no mask choices. Being afraid to switch and anticipating the behavior of others are negative predictors of riskier decisions.

A7.1.4 Correlation matrix and regression model in the control condition (neutral framing/no intervention)

Figure A14 shows inter-correlations in the neutral frame/no intervention condition.

```
postNoIntervNoFraming$cond4<-NULL
corMatrix<-cor(postNoIntervNoFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

Given the smaller sample size, the power of the coefficient tests is lower. Four predictor coefficients are significantly different from zero. Maximizing one's bonus and taking risk are positive predictors, being afraid to switch and anticipating the behavior of others are negative predictors.

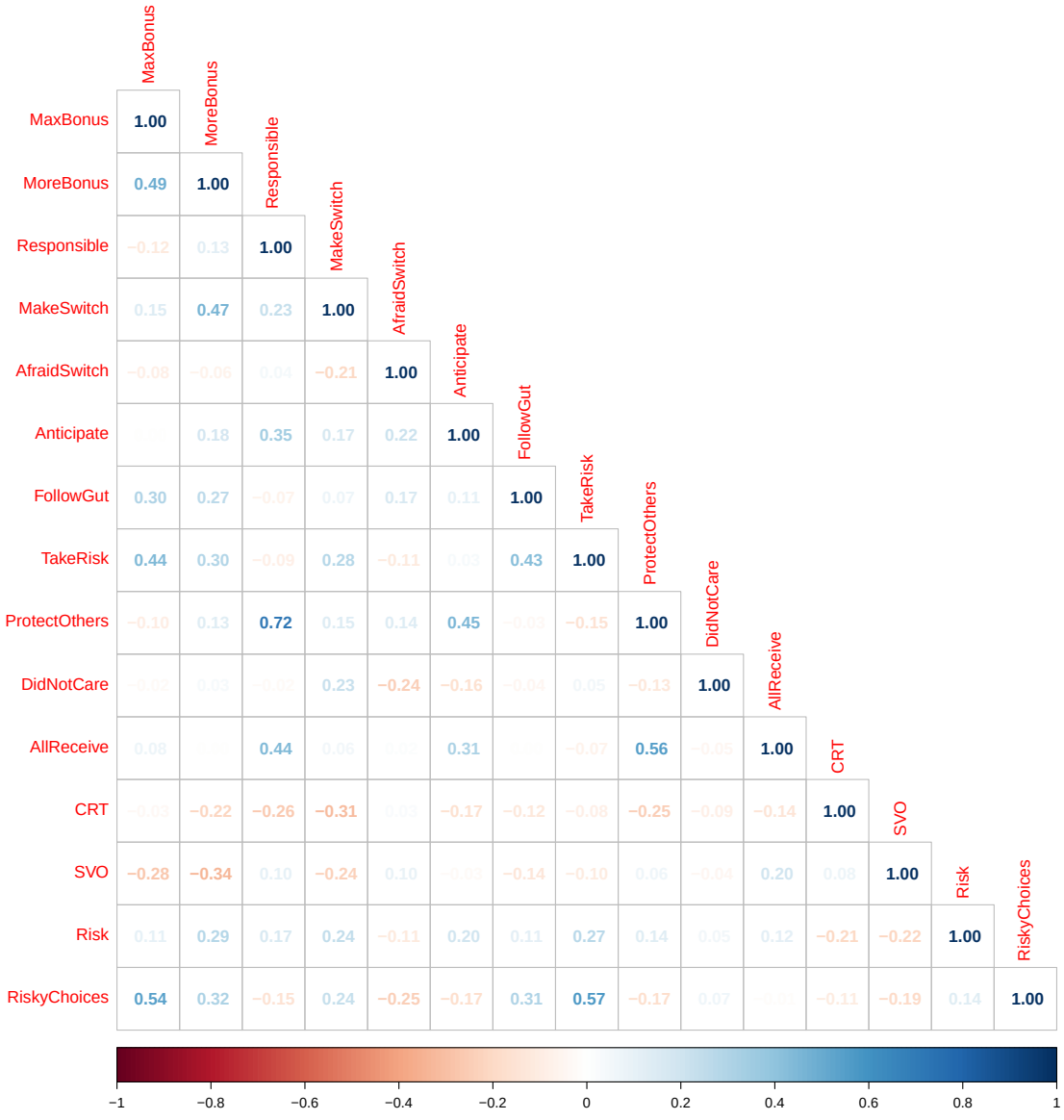


Figure A14
Inter-correlation matrix of postquestionnaire items, SVO, CRT, risk preference and game decisions: Neutral frame without intervention.

```
lmNoCol<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
              MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
              TakeRisk+ProtectOthers+DidNotCare+AllReceive,
              data = postNoIntervNoFraming)
    modNoCol<-Anova(lmNoCol, type="III")
    print(modNoCol)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##               Sum Sq  Df F value    Pr(>F)
## (Intercept)     30.7   1  0.6889  0.407583
## MaxBonus       942.2   1 21.1156 7.912e-06 ***
## MoreBonus        4.1   1  0.0917  0.762334
## Responsible     41.9   1  0.9391  0.333754
## MakeSwitch      98.6   1  2.2093  0.138856
## AfraidSwitch   283.5   1  6.3528  0.012552 *
## Anticipate     415.5   1  9.3109  0.002607 **
## FollowGut      100.9   1  2.2620  0.134261
## TakeRisk      1356.7   1 30.4049 1.147e-07 ***
## ProtectOthers    3.0   1  0.0665  0.796734
## DidNotCare       7.4   1  0.1668  0.683429
## AllReceive      36.3   1  0.8140  0.368098
## Residuals     8388.5 188
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmNoCol$coefficients

##   (Intercept)      MaxBonus     MoreBonus   Responsible    MakeSwitch
##    -2.7030717     2.3438729     0.1514925    -0.5215707     0.7527826
##  AfraidSwitch    Anticipate     FollowGut      TakeRisk ProtectOthers
##    -1.1091990    -1.3037871     0.8544122     2.3893232     0.1594609
##    DidNotCare    AllReceive
##    -0.2207873     0.4426662

    print(eta_squared(modNoCol, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter     | Eta2 (partial) |       95% CI
## ------------------------------------------------
## MaxBonus      |           0.10 | [0.04, 1.00]
## MoreBonus     |       4.88e-04 | [0.00, 1.00]
## Responsible   |       4.97e-03 | [0.00, 1.00]
```

```
## MakeSwitch    |           0.01 | [0.00, 1.00]
## AfraidSwitch  |           0.03 | [0.00, 1.00]
## Anticipate    |           0.05 | [0.01, 1.00]
## FollowGut     |           0.01 | [0.00, 1.00]
## TakeRisk      |           0.14 | [0.07, 1.00]
## ProtectOthers |       3.54e-04 | [0.00, 1.00]
## DidNotCare    |       8.86e-04 | [0.00, 1.00]
## AllReceive    |       4.31e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A7.1.5 Correlation matrix and regression model in the neutral framing/intervention condition

Figure A15 shows inter-correlation in the neutral frame condition with intervention.

```
postIntervNoFraming$cond4<-NULL
corMatrix<-cor(postIntervNoFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

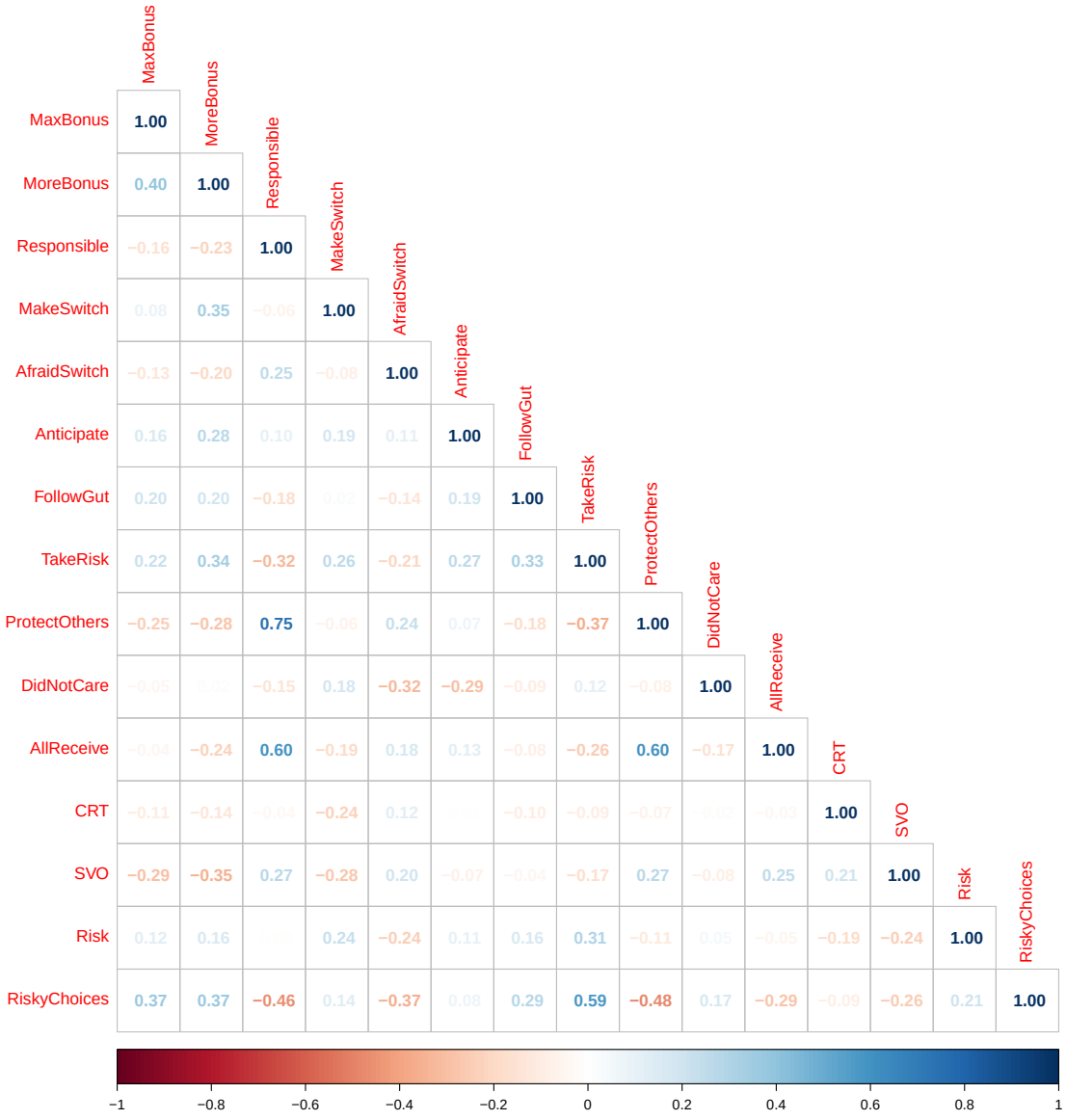


Figure A15
Inter-correlation matrix of postquestionnaire items, SVO, CRT, risk preference and game decisions: Neutral frame with intervention.

Again, four coefficients are significantly different from zero. These are maximizing one's bonus, taking risks and being afraid to switch, as before. This time, feeling responsible for others is a significant negative predictor.

```
lmInjCol<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
               MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
               TakeRisk+ProtectOthers+DidNotCare+AllReceive,
               data = postIntervNoFraming)
    modInjCol<-Anova(lmInjCol, type="III")
    print(modInjCol)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##               Sum Sq  Df F value    Pr(>F)
## (Intercept)     10.1   1  0.3574  0.550644
## MaxBonus       278.0   1  9.8526  0.001959 **
## MoreBonus       55.4   1  1.9618  0.162908
## Responsible    137.5   1  4.8748  0.028418 *
## MakeSwitch      12.7   1  0.4484  0.503906
## AfraidSwitch   227.1   1  8.0486  0.005035 **
## Anticipate       6.6   1  0.2337  0.629371
## FollowGut       21.3   1  0.7544  0.386167
## TakeRisk      1206.1   1 42.7467 5.329e-10 ***
## ProtectOthers   61.9   1  2.1946  0.140109
## DidNotCare      30.0   1  1.0641  0.303559
## AllReceive      20.7   1  0.7336  0.392755
## Residuals     5502.1 195
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmInjCol$coefficients

##   (Intercept)      MaxBonus     MoreBonus   Responsible    MakeSwitch
##     1.9079604     1.0984864     0.5344112    -1.0740784    -0.3021102
##  AfraidSwitch    Anticipate     FollowGut      TakeRisk ProtectOthers
##    -0.9862058    -0.1725319     0.3337150     2.0729228    -0.7410753
##    DidNotCare    AllReceive
##     0.4439069     0.3814035

    print(eta_squared(modInjCol, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter     | Eta2 (partial) |       95% CI
## ------------------------------------------------
```

```
## MaxBonus      |           0.05 | [0.01, 1.00]
## MoreBonus     |       9.96e-03 | [0.00, 1.00]
## Responsible   |           0.02 | [0.00, 1.00]
## MakeSwitch    |       2.29e-03 | [0.00, 1.00]
## AfraidSwitch  |           0.04 | [0.01, 1.00]
## Anticipate    |       1.20e-03 | [0.00, 1.00]
## FollowGut     |       3.85e-03 | [0.00, 1.00]
## TakeRisk      |           0.18 | [0.11, 1.00]
## ProtectOthers |           0.01 | [0.00, 1.00]
## DidNotCare    |       5.43e-03 | [0.00, 1.00]
## AllReceive    |       3.75e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A7.1.6 Correlation matrix and regression model in the pandemic framing/no intervention condition

Figure A16 shows inter-correlations for the pandemic frame condition without intervention.

Taking risks is the strongest predictor, followed by being afraid to switch. Finally, wanting the maximum bonus and not caring were positive predictors.

```
postNoIntervFraming$cond4<-NULL
corMatrix<-cor(postNoIntervFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

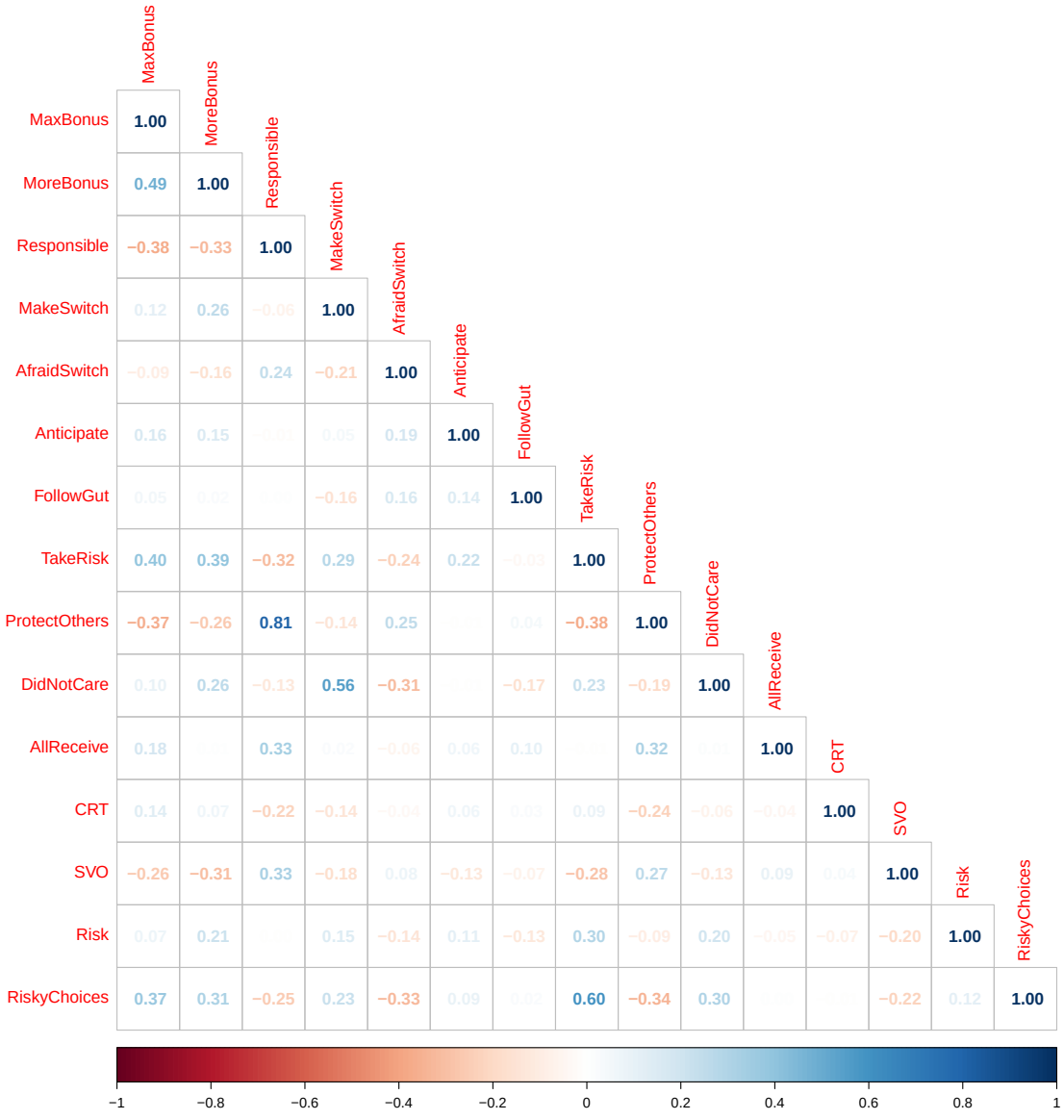


Figure A16
Inter-correlation matrix of postquestionnaire items, SVO, CRT, risk preference and game decisions: pandemic frame without intervention.

```
lmNoMask<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
               MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
               TakeRisk+ProtectOthers+DidNotCare+AllReceive,
               data = postNoIntervFraming)
    modNoMask<-Anova(lmNoMask, type="III")
    print(modNoMask)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##               Sum Sq  Df F value    Pr(>F)
## (Intercept)      8.7   1  0.5198  0.471805
## MaxBonus       104.1   1  6.2407  0.013307 *
## MoreBonus        0.0   1  0.0008  0.977807
## Responsible     40.9   1  2.4524  0.118957
## MakeSwitch      10.1   1  0.6082  0.436422
## AfraidSwitch   146.2   1  8.7621  0.003455 **
## Anticipate       0.4   1  0.0230  0.879611
## FollowGut       43.3   1  2.5964  0.108715
## TakeRisk       878.2   1 52.6514 9.072e-12 ***
## ProtectOthers   36.6   1  2.1929  0.140256
## DidNotCare      96.6   1  5.7895  0.017051 *
## AllReceive      11.6   1  0.6926  0.406303
## Residuals     3269.3 196
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmNoMask$coefficients

##   (Intercept)      MaxBonus     MoreBonus   Responsible    MakeSwitch
##   -1.63912722    0.71797939   -0.00946436    0.61416614   -0.48460138
##  AfraidSwitch    Anticipate     FollowGut      TakeRisk ProtectOthers
##   -0.94311581   -0.03573510    0.45218112    1.81820476   -0.56704784
##    DidNotCare    AllReceive
##    1.02488706   -0.23536161

    print(eta_squared(modNoMask, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter     | Eta2 (partial) |       95% CI
## ------------------------------------------------
## MaxBonus      |           0.03 | [0.00, 1.00]
## MoreBonus     |       3.96e-06 | [0.00, 1.00]
## Responsible   |           0.01 | [0.00, 1.00]
```

```
## MakeSwitch    |       3.09e-03 | [0.00, 1.00]
## AfraidSwitch  |           0.04 | [0.01, 1.00]
## Anticipate    |       1.17e-04 | [0.00, 1.00]
## FollowGut     |           0.01 | [0.00, 1.00]
## TakeRisk      |           0.21 | [0.13, 1.00]
## ProtectOthers |           0.01 | [0.00, 1.00]
## DidNotCare    |           0.03 | [0.00, 1.00]
## AllReceive    |       3.52e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A7.1.7 Correlation matrix in the pandemic framing/intervention condition

Figure A17 shows inter-correlation for the pandemic frame with intervention.

```
postIntervFraming$cond4<-NULL
corMatrix<-cor(postIntervFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

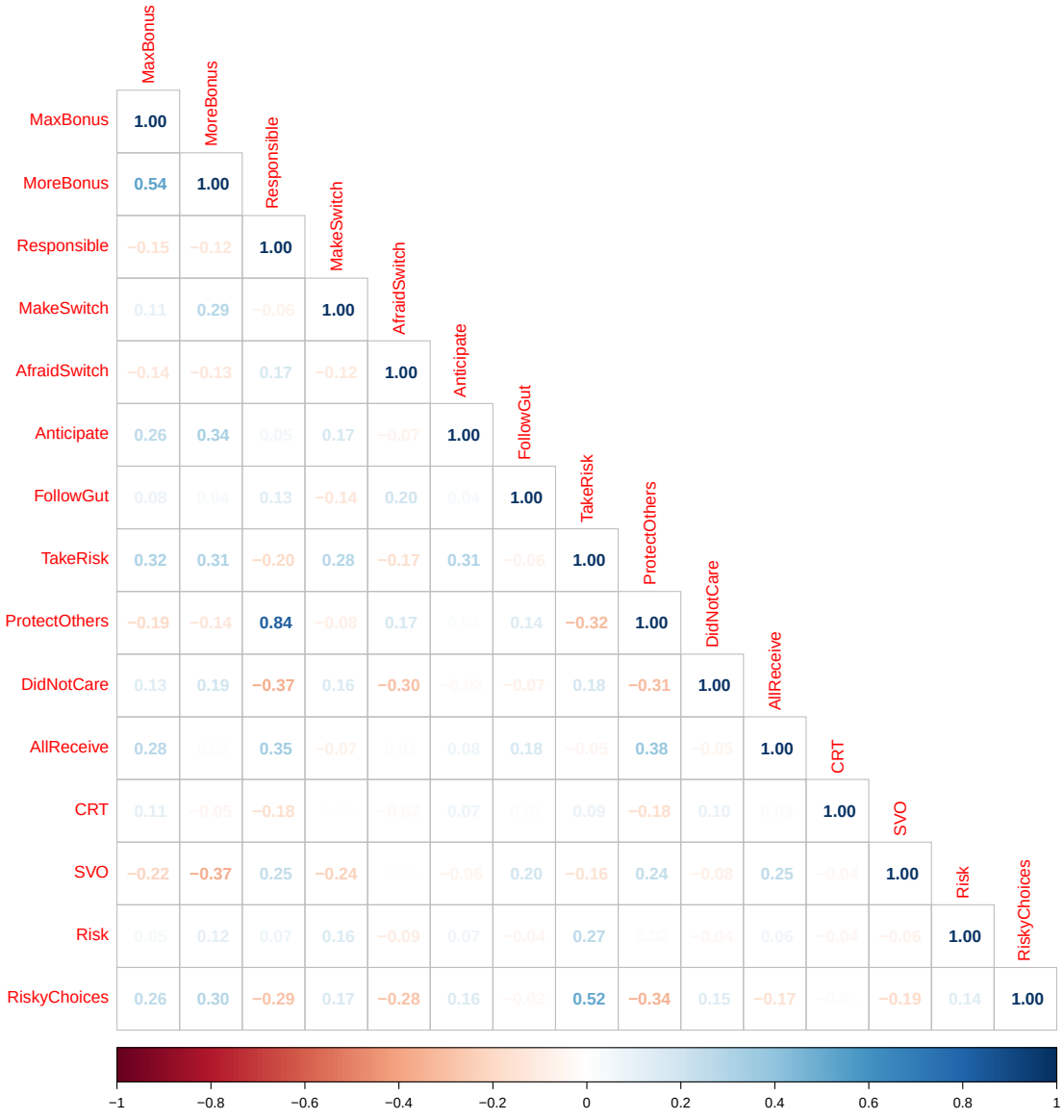


Figure A17

Inter-correlation matrix of postquestionnaire items, SVO, CRT, risk preference and game decisions: pandemic frame with intervention.

Only two predictors are significant in this condition: being afraid of switching and wanting to take risks.

```
lmInjMask<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
                MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
                TakeRisk+ProtectOthers+DidNotCare+AllReceive,
                data = postIntervFraming)
    modInjMask<-Anova(lmInjMask, type="III")
    print(modInjMask)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                Sum Sq  Df F value    Pr(>F)
## (Intercept)     71.42   1  4.7883  0.029860 *
## MaxBonus         8.34   1  0.5592  0.455497
## MoreBonus       33.16   1  2.2231  0.137599
## Responsible      7.24   1  0.4857  0.486709
## MakeSwitch       0.11   1  0.0074  0.931510
## AfraidSwitch   145.12   1  9.7288  0.002093 **
## Anticipate       1.58   1  0.1062  0.744840
## FollowGut       15.29   1  1.0250  0.312604
## TakeRisk       533.19   1 35.7451 1.077e-08 ***
## ProtectOthers    5.92   1  0.3969  0.529437
## DidNotCare      14.44   1  0.9679  0.326446
## AllReceive      46.33   1  3.1063  0.079581 .
## Residuals     2863.95 192
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmInjMask$coefficients

##   (Intercept)      MaxBonus     MoreBonus   Responsible    MakeSwitch
##    4.72626183    0.19848587    0.43273898   -0.29667192   -0.03928639
##  AfraidSwitch    Anticipate     FollowGut      TakeRisk ProtectOthers
##   -0.85206967   -0.07367655    0.24671560    1.41689058   -0.28555456
##    DidNotCare    AllReceive
##   -0.40267852   -0.44457090

    print(eta_squared(modInjMask, partial = TRUE,ci=.95,verbose=FALSE))

## # Effect Size for ANOVA (Type III)
##
## Parameter     | Eta2 (partial) |       95% CI
## ------------------------------------------------
## MaxBonus      |       2.90e-03 | [0.00, 1.00]
```

```
## MoreBonus     |           0.01 | [0.00, 1.00]
## Responsible   |       2.52e-03 | [0.00, 1.00]
## MakeSwitch    |       3.86e-05 | [0.00, 1.00]
## AfraidSwitch  |           0.05 | [0.01, 1.00]
## Anticipate    |       5.53e-04 | [0.00, 1.00]
## FollowGut     |       5.31e-03 | [0.00, 1.00]
## TakeRisk      |           0.16 | [0.09, 1.00]
## ProtectOthers |       2.06e-03 | [0.00, 1.00]
## DidNotCare    |       5.02e-03 | [0.00, 1.00]
## AllReceive    |           0.02 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

A7.1.8 Summary across conditions

The most consistent predictor of H/no mask decisions are the willingness to take risks and the fear of switching colors or becoming infected. The other predictors point in the expected directions, with maximizing one's bonus being a positive predictor and feelings of responsibility a negative predictor. Especially in the control condition, following one's gut is associated with riskier decisions.

A7.2 Specific motivation for game behavior in the intervention conditions

A7.2.1 Questions

Participants in the injunctive norms conditions responded to a separate set of items focusing on the intervention. The six questions were answered on a six-point Likert scale (from "Strongly disagree" to "Strongly agree").

- **PostIN1**: I liked the message.
- **PostIN2**: The message was easy to understand.
- **PostIN3**: The message influenced my decisions in the game.
- **PostIN4**: The message was a waste of my time.
- **PostIN5**: Without the message I would have tried to score more points (by choosing action H and 40 points more often).
- **PostIN6**: I would have chosen action H (40 points) less often, if I had not received this message.

A7.2.2 Data preparation

```
FrameInjPost <- data.frame(
     Liked=as.numeric(df$AddPostInjunctive_1),
     Understandable=as.numeric(df$AddPostInjunctive_2),
     Influenced=as.numeric(df$AddPostInjunctive_3),
     WasteTime=as.numeric(df$AddPostInjunctive_4),
     MoreRiskWithout=as.numeric(df$AddPostInjunctive_5),
     LessRiskWithout=as.numeric(df$AddPostInjunctive_6),
     CRT=modelFrame$CRT,
     SVO=modelFrame$angleSVO,
     Risk=modelFrame$riskTaking,
     RiskyChoices=modelFrame$RiskyChoices
   )

FrameInjPostFull<-data.frame(

MaxBonus=as.numeric(df$PostTG_01),
     MoreBonus=as.numeric(df$PostTG_02),
     Responsible=as.numeric(df$PostTG_03),
     MakeSwitch=as.numeric(df$PostTG_04),
     AfraidSwitch=as.numeric(df$PostTG_05),
     Anticipate=as.numeric(df$PostTG_06),
     FollowGut=as.numeric(df$PostTG_07),
     TakeRisk=as.numeric(df$PostTG_08),
     ProtectOthers=as.numeric(df$PostTG_09),
     DidNotCare=as.numeric(df$PostTG_10),
     AllReceive=as.numeric(df$PostTG_11),
     Liked=as.numeric(df$AddPostInjunctive_1),
     Understandable=as.numeric(df$AddPostInjunctive_2),
     Influenced=as.numeric(df$AddPostInjunctive_3),
     WasteTime=as.numeric(df$AddPostInjunctive_4),
     MoreRiskWithout=as.numeric(df$AddPostInjunctive_5),
     LessRiskWithout=as.numeric(df$AddPostInjunctive_6),
     CRT=modelFrame$CRT,
     SVO=modelFrame$angleSVO,
     Risk=modelFrame$riskTaking,
     RiskyChoices=modelFrame$RiskyChoices
 )


conditionFactorFour= (as.numeric(modelFrame$facFraming)-1)*2+
   as.numeric(modelFrame$facInterv)
cond4=as.numeric(factor(conditionFactorFour,
                        labels =c('Mskr-Inj','Msk-No',
                                  'Clr-Inj','Clr-No')))
```

```
FrameInjPost$cond4=cond4
FrameInjPostFull$cond4=cond4


postInjIntervNoFraming <- FrameInjPost[which(FrameInjPost$cond4==3),]
postInjIntervFraming <- FrameInjPost[which(FrameInjPost$cond4==1),]

postInjIntervNoFraming$cond4<-NULL
postInjIntervFraming$cond4<-NULL


postInjFullIntervNoFraming <-
   FrameInjPostFull[which(FrameInjPostFull$cond4==3),]
postInjFullIntervFraming <-
   FrameInjPostFull[which(FrameInjPostFull$cond4==1),]
postInjFullIntervNoFraming$cond4<-NULL
postInjFullIntervFraming$cond4<-NULL


FrameInjPost$cond4<-NULL
```

A7.2.3 Inter-correlation of intervention-specific items: Both frames

Figure A18 shows inter-correlation for the specific postquestionnaire items for both intervention groups. Riskier game choices are negatively correlated with liking the intervention, perceiving the intervention as understandable and admitting to be influenced by the intervention. They are positively correlated with regarding the intervention as a waste of one's time.

```
corMatrix<-cor(FrameInjPost,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

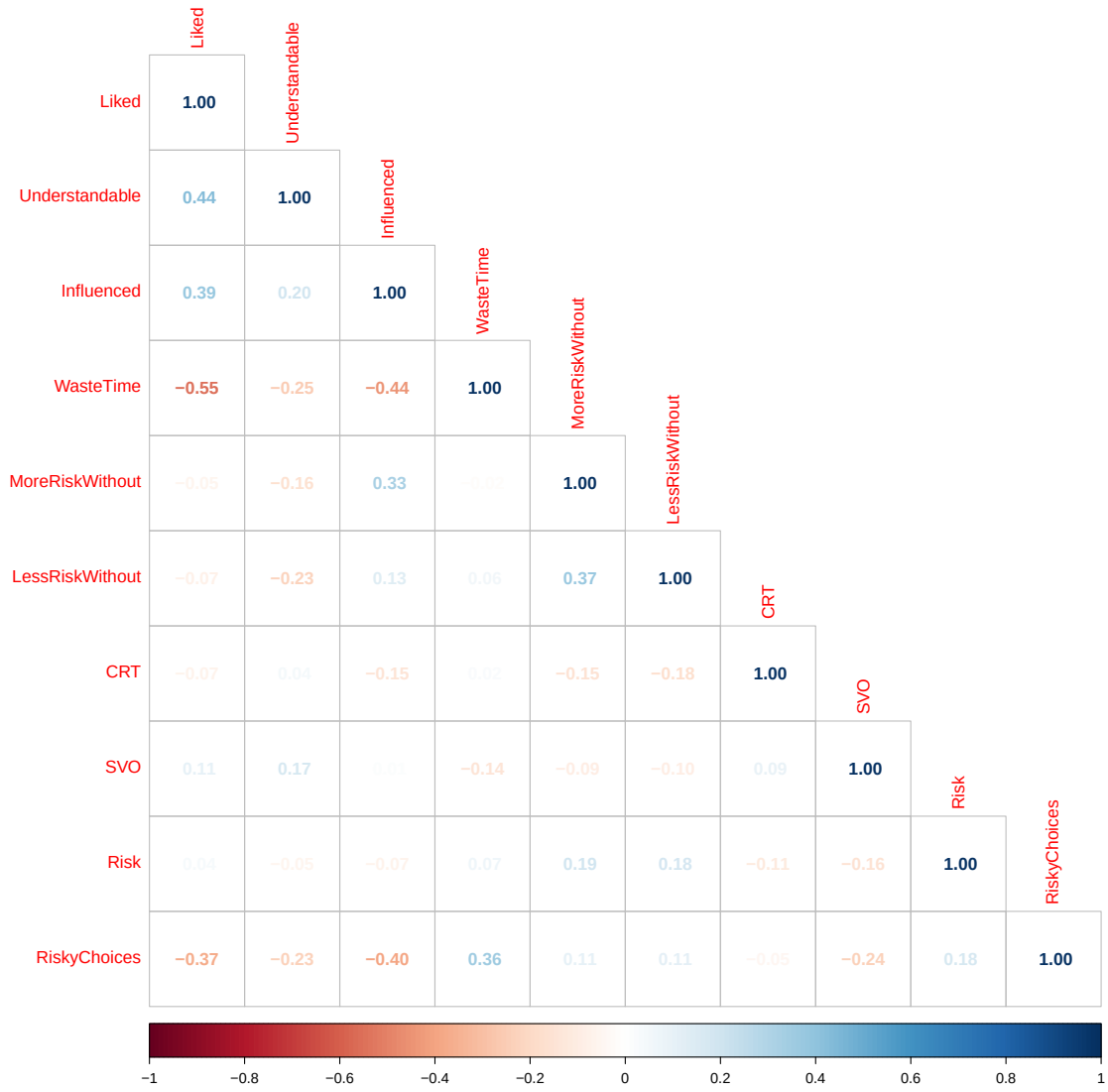


Figure A18
Inter-correlation matrix of specific postquestionnaire items, SVO, CRT, risk preference and game decisions: Both intervention groups.

A7.2.4 Inter-correlation of intervention-specific items: Neutral frame

Figure A19 shows inter-correlations for the specific postquestionnaire items for the intervention group with neutral framing. The qualitative pattern of correlations is the same as for both groups.

```
corMatrix<-cor(postInjIntervNoFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

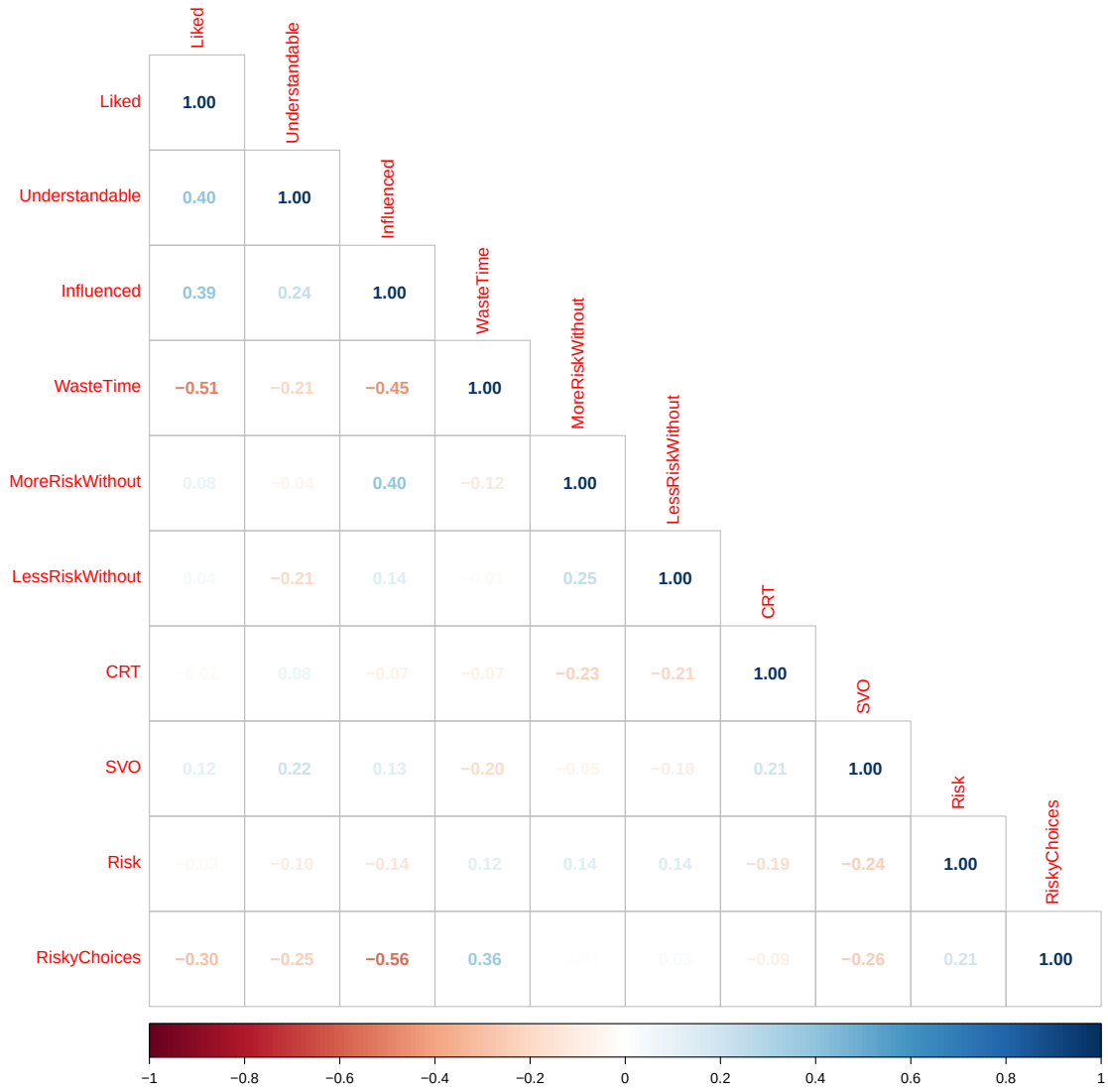


Figure A19

Inter-correlation matrix of specific postquestionnaire items, SVO, CRT, risk preference and game decisions: Intervention in neutral frame.

A7.2.5 Inter-correlation of intervention-specific items: Pandemic frame

Figure A20 shows inter-correlation for the specific postquestionnaire items for the intervention group with pandemic framing. Again, the qualitative pattern of correlations is the same as for both groups.

```
corMatrix<-cor(postInjIntervFraming,use="complete.obs")
corrplot(corMatrix,type="lower",method="number")
```

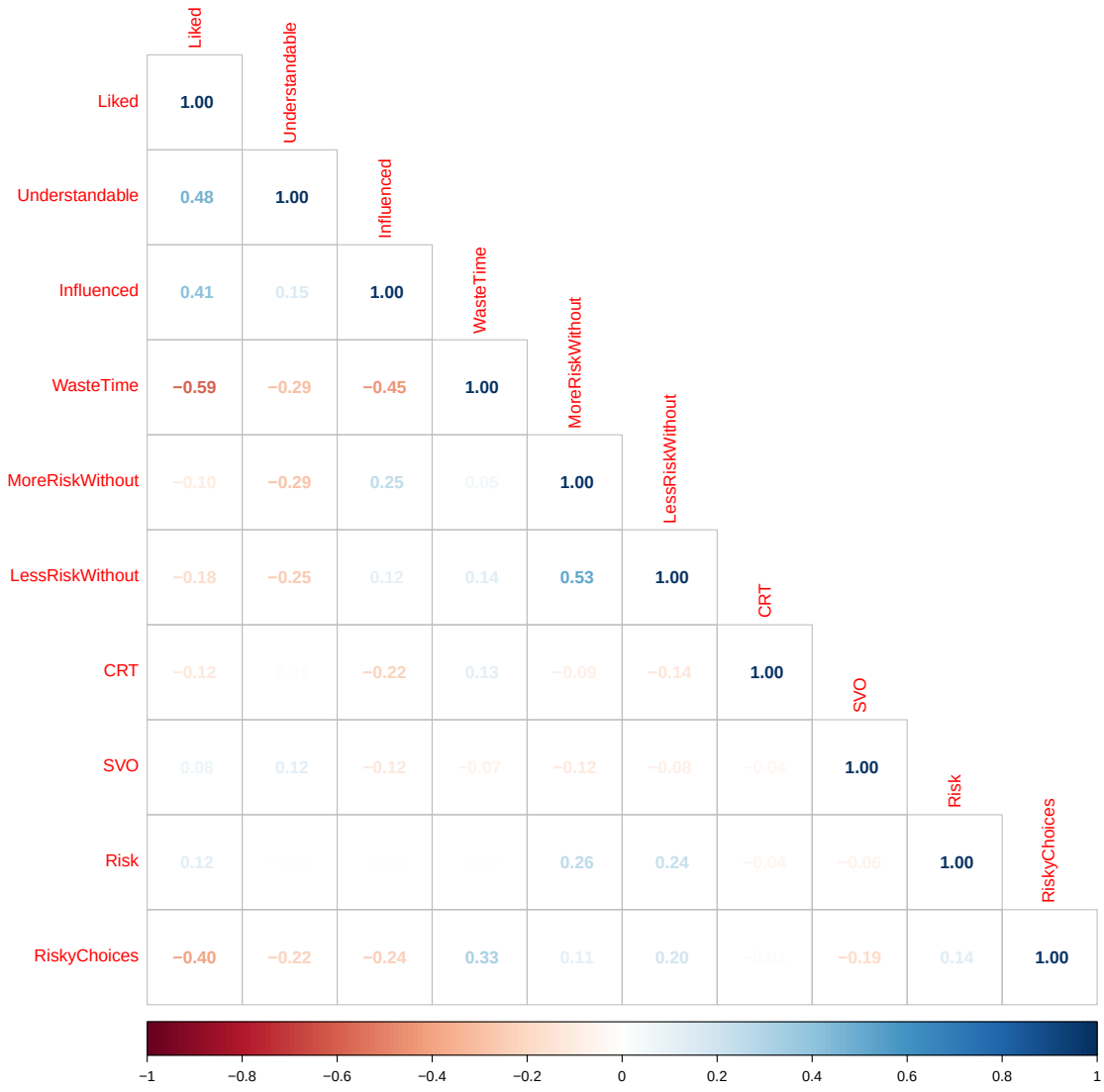


Figure A20

Inter-correlation matrix of specific postquestionnaire items, SVO, CRT, risk preference and game decisions: Intervention in pandemic frame.

A7.2.6 Regression model for all postquestionnaire items: Intervention group with neutral frame

Adding the specific postquestionnaire item to the model with all standard postquestionnaire item leads to a significant improvement of the model. Only the coefficient for the question about being influenced by the intervention is significantly different from zero.

```
   lmInjColorFull<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
                        MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
                        TakeRisk+ProtectOthers+DidNotCare+AllReceive+
                        Liked+Understandable+Influenced+WasteTime+
                        MoreRiskWithout+LessRiskWithout,
                        data = postInjFullIntervNoFraming)
    modInjColorFull<-Anova(lmInjColorFull, type="III")
    print(modInjColorFull)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                 Sum Sq  Df F value    Pr(>F)
## (Intercept)       87.9   1  3.5156 0.0623359 .
## MaxBonus         254.1   1 10.1626 0.0016775 **
## MoreBonus         81.2   1  3.2480 0.0731060 .
## Responsible       68.7   1  2.7458 0.0991715 .
## MakeSwitch        21.3   1  0.8536 0.3567213
## AfraidSwitch     104.5   1  4.1773 0.0423560 *
## Anticipate         4.8   1  0.1930 0.6609376
## FollowGut         22.4   1  0.8966 0.3449004
## TakeRisk         660.5   1 26.4146 6.839e-07 ***
## ProtectOthers      4.5   1  0.1806 0.6713490
## DidNotCare         2.1   1  0.0839 0.7723395
## AllReceive        24.3   1  0.9733 0.3251252
## Liked             19.2   1  0.7665 0.3824077
## Understandable    32.9   1  1.3158 0.2527950
## Influenced       308.1   1 12.3219 0.0005597 ***
## WasteTime         42.2   1  1.6874 0.1955216
## MoreRiskWithout   59.8   1  2.3925 0.1235879
## LessRiskWithout    0.2   1  0.0082 0.9281276
## Residuals       4726.1 189
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    lmInjColorFull$coefficients

##     (Intercept)        MaxBonus       MoreBonus     Responsible      MakeSwitch
##      7.96969044      1.05475006      0.65468720     -0.78684168     -0.41215445
```

```
##    AfraidSwitch      Anticipate       FollowGut        TakeRisk   ProtectOthers
##     -0.68882976     -0.14933416      0.34945537      1.65189111     -0.20875244
##      DidNotCare      AllReceive           Liked  Understandable      Influenced
##      0.12265968      0.41844028     -0.36171125     -0.59900498     -1.29222542
##       WasteTime MoreRiskWithout LessRiskWithout
##      0.47829249      0.38841358      0.02454662
```

```
    print(eta_squared(modInjColorFull, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## MaxBonus        |           0.05 | [0.01, 1.00]
## MoreBonus       |           0.02 | [0.00, 1.00]
## Responsible     |           0.01 | [0.00, 1.00]
## MakeSwitch      |       4.50e-03 | [0.00, 1.00]
## AfraidSwitch    |           0.02 | [0.00, 1.00]
## Anticipate      |       1.02e-03 | [0.00, 1.00]
## FollowGut       |       4.72e-03 | [0.00, 1.00]
## TakeRisk        |           0.12 | [0.06, 1.00]
## ProtectOthers   |       9.55e-04 | [0.00, 1.00]
## DidNotCare      |       4.44e-04 | [0.00, 1.00]
## AllReceive      |       5.12e-03 | [0.00, 1.00]
## Liked           |       4.04e-03 | [0.00, 1.00]
## Understandable  |       6.91e-03 | [0.00, 1.00]
## Influenced      |           0.06 | [0.02, 1.00]
## WasteTime       |       8.85e-03 | [0.00, 1.00]
## MoreRiskWithout |           0.01 | [0.00, 1.00]
## LessRiskWithout |       4.32e-05 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmInjCol,lmInjColorFull)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ MaxBonus + MoreBonus + Responsible + MakeSwitch +
##     AfraidSwitch + Anticipate + FollowGut + TakeRisk + ProtectOthers +
##     DidNotCare + AllReceive
## Model 2: RiskyChoices ~ MaxBonus + MoreBonus + Responsible + MakeSwitch +
##     AfraidSwitch + Anticipate + FollowGut + TakeRisk + ProtectOthers +
##     DidNotCare + AllReceive + Liked + Understandable + Influenced +
##     WasteTime + MoreRiskWithout + LessRiskWithout
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
```

```
## 1    195 5502.1
## 2    189 4726.1  6    776.06 5.1726 5.992e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A7.2.7 Regression model for all postquestionnaire item: Intervention group with pandemic frame

For the pandemic frame, adding the specific postquestionnaire item to the model with all standard postquestionnaire item leads again to a significant improvement of the model. In this model, only the coefficient for the question about liking the intervention is significantly different from zero.

```
    lmInjMaskFull<-lm(RiskyChoices~ MaxBonus+MoreBonus+Responsible+
                        MakeSwitch+AfraidSwitch+Anticipate+FollowGut+
                        TakeRisk+ProtectOthers+DidNotCare+AllReceive+
                        Liked+Understandable+Influenced+WasteTime+
                        MoreRiskWithout+LessRiskWithout,
                        data = postInjFullIntervFraming)
    modInjMaskFull<-Anova(lmInjMaskFull, type="III")
    print(modInjMaskFull)

## Anova Table (Type III tests)
##
## Response: RiskyChoices
##                   Sum Sq  Df F value    Pr(>F)
## (Intercept)        69.37   1  4.9520  0.027261 *
## MaxBonus            6.04   1  0.4313  0.512148
## MoreBonus          55.36   1  3.9521  0.048279 *
## Responsible         0.74   1  0.0527  0.818681
## MakeSwitch          0.45   1  0.0321  0.858032
## AfraidSwitch       55.04   1  3.9294  0.048921 *
## Anticipate          6.12   1  0.4368  0.509493
## FollowGut          29.26   1  2.0888  0.150063
## TakeRisk          424.11   1 30.2773 1.228e-07 ***
## ProtectOthers       4.00   1  0.2859  0.593499
## DidNotCare         38.85   1  2.7733  0.097531 .
## AllReceive         31.70   1  2.2628  0.134208
## Liked             111.95   1  7.9925  0.005211 **
## Understandable      0.74   1  0.0530  0.818236
## Influenced          9.21   1  0.6575  0.418469
## WasteTime           2.97   1  0.2122  0.645609
## MoreRiskWithout     0.21   1  0.0151  0.902338
## LessRiskWithout    11.11   1  0.7930  0.374332
## Residuals        2605.39 186
```

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

```
    lmInjMaskFull$coefficients
```

```
##     (Intercept)        MaxBonus       MoreBonus     Responsible      MakeSwitch
##      7.33983356      0.17119571      0.58878474      0.09866533     -0.08069764
##    AfraidSwitch      Anticipate       FollowGut        TakeRisk   ProtectOthers
##     -0.55293753     -0.14951507      0.34865963      1.30014821     -0.24290514
##      DidNotCare      AllReceive           Liked  Understandable      Influenced
##     -0.69235363     -0.38104868     -1.17487511      0.09141949     -0.18292340
##       WasteTime MoreRiskWithout LessRiskWithout
##      0.15687113     -0.02927921      0.26895673
```

```
    print(eta_squared(modInjMaskFull, partial = TRUE,ci=.95,verbose=FALSE))
```

```
## # Effect Size for ANOVA (Type III)
##
## Parameter       | Eta2 (partial) |       95% CI
## -------------------------------------------------
## MaxBonus        |       2.31e-03 | [0.00, 1.00]
## MoreBonus       |           0.02 | [0.00, 1.00]
## Responsible     |       2.83e-04 | [0.00, 1.00]
## MakeSwitch      |       1.72e-04 | [0.00, 1.00]
## AfraidSwitch    |           0.02 | [0.00, 1.00]
## Anticipate      |       2.34e-03 | [0.00, 1.00]
## FollowGut       |           0.01 | [0.00, 1.00]
## TakeRisk        |           0.14 | [0.07, 1.00]
## ProtectOthers   |       1.53e-03 | [0.00, 1.00]
## DidNotCare      |           0.01 | [0.00, 1.00]
## AllReceive      |           0.01 | [0.00, 1.00]
## Liked           |           0.04 | [0.01, 1.00]
## Understandable  |       2.85e-04 | [0.00, 1.00]
## Influenced      |       3.52e-03 | [0.00, 1.00]
## WasteTime       |       1.14e-03 | [0.00, 1.00]
## MoreRiskWithout |       8.12e-05 | [0.00, 1.00]
## LessRiskWithout |       4.25e-03 | [0.00, 1.00]
##
## - One-sided CIs: upper bound fixed at [1.00].
```

```
    anova(lmInjMask,lmInjMaskFull)
```

```
## Analysis of Variance Table
##
## Model 1: RiskyChoices ~ MaxBonus + MoreBonus + Responsible + MakeSwitch +
##     AfraidSwitch + Anticipate + FollowGut + TakeRisk + ProtectOthers +
```

```
##     DidNotCare + AllReceive
## Model 2: RiskyChoices ~ MaxBonus + MoreBonus + Responsible + MakeSwitch +
##     AfraidSwitch + Anticipate + FollowGut + TakeRisk + ProtectOthers +
##     DidNotCare + AllReceive + Liked + Understandable + Influenced +
##     WasteTime + MoreRiskWithout + LessRiskWithout
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1    192 2863.9
## 2    186 2605.4  6    258.56 3.0765 0.006788 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A7.2.8 Summary

The influence of the intervention that can be observed in the game behavior is reflected in responses to the postquestionnaire. At least in the color condition, participants seem to be aware of the influence (which does not make the intervention inefficient). The two contrafactual items seem to be problematic and ill-understood. In theory, there should be a strong negative correlation between those items, but there is a positive correlation. It seems that the contrafactual created confusion and the differences were not correctly perceived by participants. The simpler items all show the expected patterns.

A7.3 Estimated behavior

Participants estimated the number of people choosing option H/no masks in six specific rounds: Round 1, Round 5, Round 10, Round 15, Round 20, and Round 25. Here, we present the estimates visually and compare estimated and actual values.

A7.3.1 Data preparation

```
roundFrame=data.frame(
  R01=(scaleFrameTG$R01-1)*100,
  R05=(scaleFrameTG$R05-1)*100,
  R10=(scaleFrameTG$R10-1)*100,
  R15=(scaleFrameTG$R15-1)*100,
  R20=(scaleFrameTG$R20-1)*100,
  R25=(scaleFrameTG$R25-1)*100,
  cond=as.factor(condCondition[1:sampleSize])
)
roundFrameLong<- roundFrame %>% pivot_longer(cols=c(-cond))
levels( roundFrameLong$cond)<-list("Trump|Masks|Inj"="1",
          "Trump|Masks|None"="2","Trump|Color|Inj"="3",
          "Trump|Color|None"="4","Clint|Masks|Inj"="5",
          "Clint|Masks|None"="6","Clint|Color|Inj"="7",
          "Clint|Color|None"="8")
```

A7.3.2 Lineplot

Figure A21 shows the estimated rate of choosing riskier options in all four experimental conditions split by voter group.

```
  ggplot(lineFrameH, aes(x = round, y = estimateH, color = condition,
                         group=condition) ) +
  geom_point(position = "jitter") +
  geom_smooth(se = TRUE,size=2)+
  theme_dark()+
    scale_colour_viridis_d(option="plasma")
```

```
## Warning:  Using ‘size‘ aesthetic for lines was deprecated in ggplot2
3.4.0.
## i Please use ‘linewidth‘ instead.
## This warning is displayed once every 8 hours.
## Call ‘lifecycle::last_lifecycle_warnings()‘ to see where this warning
was
## generated.
## ‘geom_smooth()‘ using method = ’loess’ and formula = ’y ~ x’
```

Qualitatively, the estimates follow the pattern of the actual data. Estimates for Clinton voters are slightly lower than for Trump voters.The highest estimates are in the neutral frame without intervention, the lowest in the pandemic frame with intervention. In most group the expected number of riskier choices is lower for later groups than for earlier groups, whereas there are some groups that expect relatively stable rates.

A7.3.3 Comparison between estimates and true values

How do these estimates compare with the actual rates?
This below is a summary table of the mean estimates by round and group.

```
EstimatesH<-tapply(lineFrameH$estimateH, list(lineFrameH$condition,
                     lineFrameH$round), function(x) mean(x))
EstimatesH
```

```
##                          1        5       10       15       20       25
## Trump|Masks|Inj  39.48515 34.30693 29.87129 26.79208 25.79208 26.74257
## Trump|Masks|None 51.97143 41.92381 35.57143 30.61905 28.50476 29.11429
## Trump|Color|Inj  41.03030 41.13131 39.74747 38.71717 39.19192 44.74747
## Trump|Color|None 65.04301 59.37634 54.94624 52.87097 51.56989 54.90323
## Clint|Masks|Inj  44.49515 33.54369 26.77670 22.98058 21.51456 22.58252
## Clint|Masks|None 55.48544 43.36893 34.10680 27.38835 25.19417 25.64078
## Clint|Color|Inj  47.55556 43.85185 39.89815 35.50000 35.88889 40.00926
## Clint|Color|None 68.48598 58.17757 51.70093 46.80374 42.59813 41.71963
```

This is a summary table of actual values by round and group.

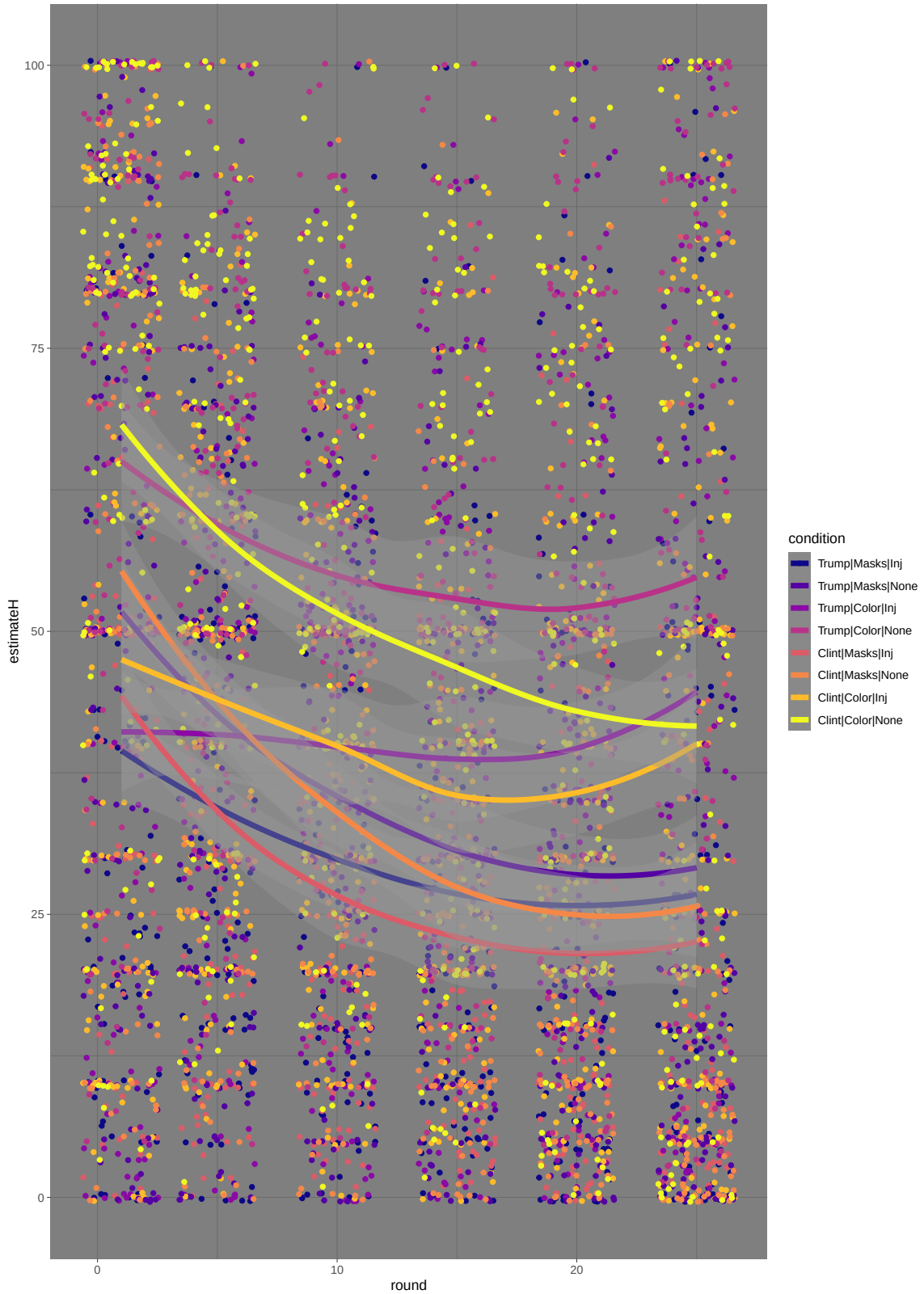


Figure A21

Estimated proportions of participants choosing the H/no mask option in each condition bsplit by voter sample.

```
ActualH<-tapply(roundFrameLong$value, list(roundFrameLong$cond,
                      roundFrameLong$name), function(x) mean(x))
ActualH
```

```
##                        R01       R05       R10       R15       R20       R25
## Trump|Masks|Inj  25.74257 13.861386 11.881188 10.891089 10.891089  7.920792
## Trump|Masks|None 42.85714 22.857143 18.095238 12.380952 12.380952 11.428571
## Trump|Color|Inj  25.25253 30.303030 26.262626 25.252525 23.232323 21.212121
## Trump|Color|None 58.06452 63.440860 60.215054 50.537634 50.537634 53.763441
## Clint|Masks|Inj  17.47573  9.708738  2.912621  3.883495  4.854369  4.854369
## Clint|Masks|None 33.00971  8.737864  5.825243  2.912621  5.825243  3.883495
## Clint|Color|Inj  35.18519 25.000000 22.222222 19.444444 17.592593 18.518519
## Clint|Color|None 56.07477 45.794393 39.252336 31.775701 42.056075 42.056075
```

The difference between these two tables shows the amount of overestimation (in case of positive values) or underestimation (in case of negative values).

```
EstimatesH-ActualH
```

```
##                           1         5        10        15         20         25
## Trump|Masks|Inj  13.742574 20.445545 17.990099 15.900990 14.9009901 18.8217822
## Trump|Masks|None  9.114286 19.066667 17.476190 18.238095 16.1238095 17.6857143
## Trump|Color|Inj  15.777778 10.828283 13.484848 13.464646 15.9595960 23.5353535
## Trump|Color|None  6.978495 -4.064516 -5.268817  2.333333  1.0322581  1.1397849
## Clint|Masks|Inj  27.019417 23.834951 23.864078 19.097087 16.6601942 17.7281553
## Clint|Masks|None 22.475728 34.631068 28.281553 24.475728 19.3689320 21.7572816
## Clint|Color|Inj  12.370370 18.851852 17.675926 16.055556 18.2962963 21.4907407
## Clint|Color|None 12.411215 12.383178 12.448598 15.028037  0.5420561 -0.3364486
```

In general, participants overestimate the average number of riskier choices by other participants. There are three (relatively small) negative values among all 48 estimates. Clinton voters tend to overestimate values to a larger degree. One should note, though, that the estimates of both groups are actually quite similar: The increased over-estimation should rather be regarded as an artifact of comparing each group of voters with other voters of the same group only. Clinton voters make fewer H/no mask choices on average, leading to seeming differences in bias. Nonetheless, both groups substantially over-estimate the prevalence of risky decisions.

A7.4 Self-other discrepancy in risk estimates

In our previous study, we found participants in all groups to estimate their own survival chances as higher than those of other members of their groups. Here, we want to see whether this finding replicates in the new study.

A7.4.1 Data preparation

```
ID=1:sampleSize;



riskEstimateData=data.frame(
  Id=as.factor(ID),
  self=df$PostTGcolorMe,
  everyone=df$PostTGcolorAll,
  cond=condCondition[1:sampleSize]
)


levels( riskEstimateData$cond)<-list("Trump|Masks|Inj"="1",
          "Trump|Masks|None"="2","Trump|Color|Inj"="3",
          "Trump|Color|None"="4","Clint|Masks|Inj"="5",
          "Clint|Masks|None"="6","Clint|Color|Inj"="7",
          "Clint|Color|None"="8")

riskEstimateDataLong<- riskEstimateData %>% pivot_longer(cols=c(-Id,-cond))

riskEstimateFactors <-data.frame(
 Id=riskEstimateDataLong$Id,
 cond=as.factor(riskEstimateDataLong$cond),
 target=as.factor(riskEstimateDataLong$name),
 value=riskEstimateDataLong$value
)

levels( riskEstimateFactors$cond)<-list("Trump|Masks|Inj"="1",
          "Trump|Masks|None"="2","Trump|Color|Inj"="3",
          "Trump|Color|None"="4","Clint|Masks|Inj"="5",
          "Clint|Masks|None"="6","Clint|Color|Inj"="7",
          "Clint|Color|None"="8")

SO_Estimate <-  aov_car(formula = value ~ cond+target+
                    Error(Id/target), data = riskEstimateFactors,
                    anova_table=list('pes'))

SO_Estimate

## Anova Table (Type 3 tests)
##
## Response: value
##        Effect     df     MSE          F  pes p.value
## 1        cond 7, 811 1067.39   7.68 *** .062   <.001
## 2      target 1, 811  243.74 168.86 *** .172   <.001
```

```
## 3 cond:target 7, 811  243.74   5.66 *** .047   <.001
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

A7.4.2 Comparison of groups

Figure A22 shows the estimated infection rate that participants estimated for the average participant compared with their estimated probability (expressed as a percentage) of ending the game infected themselves. If participants assumed to be a typical participant, these values should be the same.

```
riskEstimateFactors %>%ggplot(
  aes(y=value,color=target,x=cond, fill=target))+  scale_x_discrete() +
      geom_boxplot(outlier.colour = NA,
                   position = position_dodge(width=0.9),alpha=0.5)  +
  geom_point(position=position_jitterdodge(),alpha=0.3,aes(group=target)) +
  stat_summary(fun=mean, geom="point", shape=20, size=6,
               fill="black", aes(x=cond, group=target,color=target),
               position = position_dodge(width=0.9)) +
  scale_fill_manual("Estimate for ",values=c("white","black"))+
  scale_color_viridis_d("Estimate for ")+
  theme_dark()+
  xlab("Condition")+
  ylab("Estimated infection probability")+
  theme(axis.text.x = element_text(color = "grey20",
              size = 12, hjust = .5, vjust = .5, face = "plain"))+
  theme(axis.title.x = element_text(color = "grey20",
              size = 20, hjust = .5, vjust = .5, face = "plain"))+
  theme(axis.text.y = element_text(color = "grey20",
              size = 16, hjust = .5, vjust = .5, face = "plain"))+
  theme(axis.title.y = element_text(color = "grey20",
              size = 20, hjust = .5, vjust = .5, face = "plain"))+
  theme(legend.title = element_text(color = "grey20",
              size = 18, hjust = .5, vjust = .5, face = "plain"))+
  theme(legend.text = element_text(color = "grey20",
              size = 14, hjust = .5, vjust = .5, face = "plain"))
```

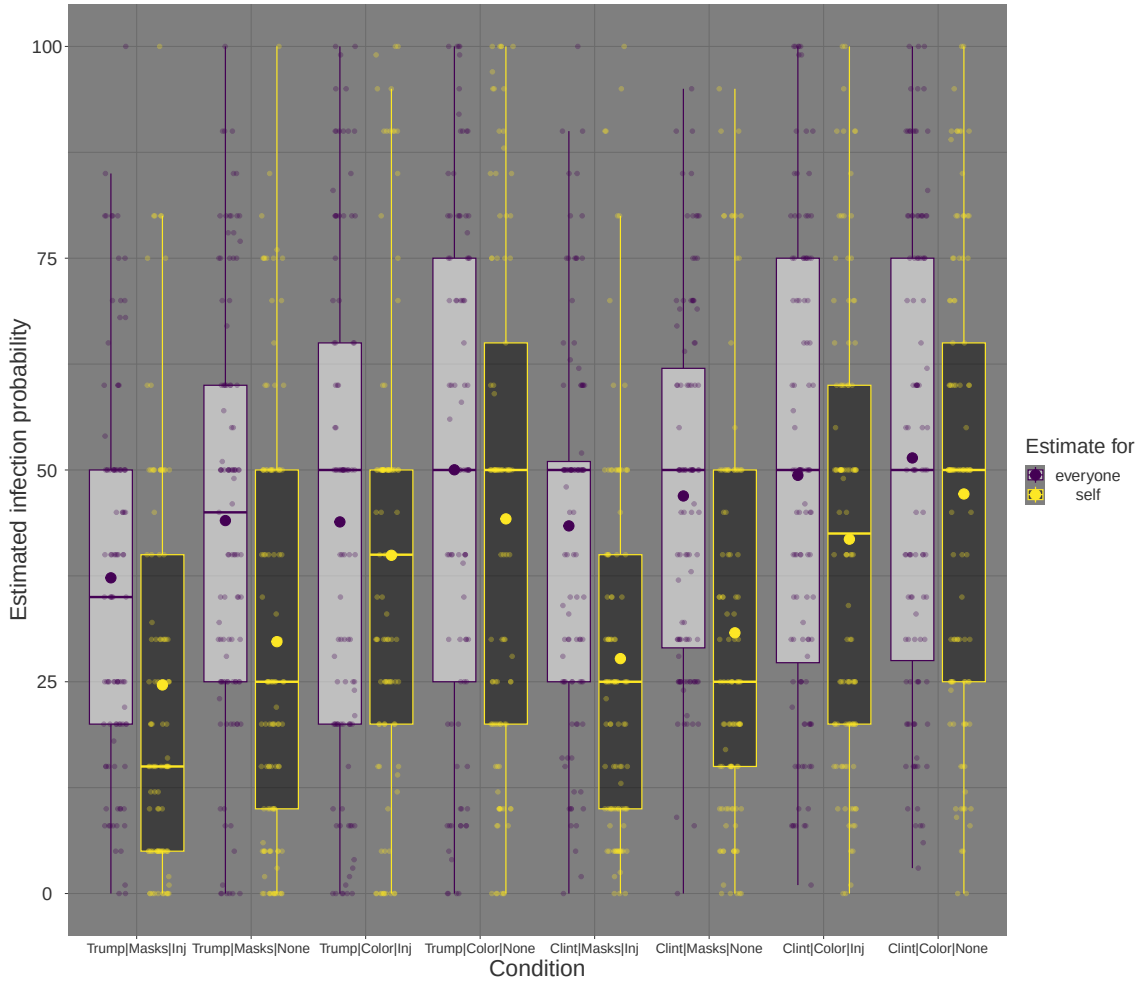


Figure A22
Boxplots of estimated proportions of participants ending the game in the purple/infected state in each condition split by voter sample.

First, it can be seen that infection rates are estimated the highest in the condition without intervention and neutral framing and the lowest in the condition with intervention and pandemic framing (corresponding to the actual behavior and its consequences, see the simulation appendix). Second, as in our previous study, the estimated for everyone in the group is higher than for the participants themselves. This is consistent with assuming that everyone else made riskier choices than oneself. An ANOVA shows that the effect size for this relative optimism is substantial.

```
    MixedAOV <- aov_car(value~ cond*target+ Error(Id/target), data=riskEstimateFactors)
    MixedAOV
```

```
## Anova Table (Type 3 tests)
##
## Response: value
```

```
##         Effect     df     MSE          F  ges p.value
## 1         cond 7, 811 1067.39   7.68 *** .051   <.001
## 2       target 1, 811  243.74 168.86 *** .037   <.001
## 3 cond:target 7, 811  243.74   5.66 *** .009   <.001
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

Thus, we can replicate and extend our previous findings respective the old and new conditions in this study.

Part III
Exploratory Analyses

As announced in our preregistration and detailed in our Materials and Variables supplements, our survey contained a number of additional variables and scales that were discussed as relevant a the time of our study. While there are many possible questions to address with this dataset, we found it more appropriate to report the scales and offer the data to other researchers to test existing well-defined hypotheses or confirm findings from other studies. Selecting out of the range of possible questions that were not well-developed at the start of our study carries the risk of false positive findings and statistical artifacts. At the same time, it would be wasteful to hide the additional variables and we decided to offer them with our study data to others. What we present here are some simple correlations that show that none of the additional variables raise questions that would impact our previous findings. The qualitative pattern of results seems unsurprising in the desired way. The dataset in its entirety might also serve as a good demonstration that it will be very difficult to isolate the effect of specific single factors, as many of the political variables are heavily intercorrelated. The presented correlation matrices could serve as a starting point for re-evaluating results found in other studies that used specific subsets of these variables.

A8 Relationship between political variables and other predictors

Analyses in the main manuscript focus on differences between voter groups in relation to game behavior and attitudes towards non-pharmaceutical interventions. Here, we present results on differences between voter groups in respect to other predictor variables, and the correlation of political and other measures.

A8.1 Differences in predictor variables between voter groups

A8.1.1 Data preparation

```
corrFrame<-data.frame(
  riskTaking=anovaFrame$riskTaking,
  CRT=anovaFrame$CRT,
  angleSVO=anovaFrame$angleSVO,
```

```
  psychReactance=anovaFrame$psychReactance
)

 corrFrame$trumpVoter=anovaFrame$facSample
 levels(corrFrame$trumpVoter)<-c("Trump","Clinton")
```

A8.1.2 Violin plots

The following Figures compare the two voter groups regarding the four non-political predictor variables in our models: general risk preference (Fig. A23), cognitive reflection (Fig. A24), social value orientation (Fig. A25), and psychological reactance (Fig. A27). All figures show

```
ggplot(corrFrame, aes(x=trumpVoter, y=riskTaking, fill = trumpVoter)) +
  geom_violin() +
  xlab("Voter group") + ylab("Risk Taking") +
  theme_dark()+scale_fill_manual(values=c("#BC211A","#4444BC"))+
  stat_summary(fun=mean,  geom="point", color="black")+
  theme(legend.position="none")+
  theme(aspect.ratio=1)
```

```
ggplot(corrFrame, aes(x=trumpVoter, y=CRT, fill = trumpVoter)) +
  geom_violin() +
  xlab("Voter group") + ylab("CRT") +
```

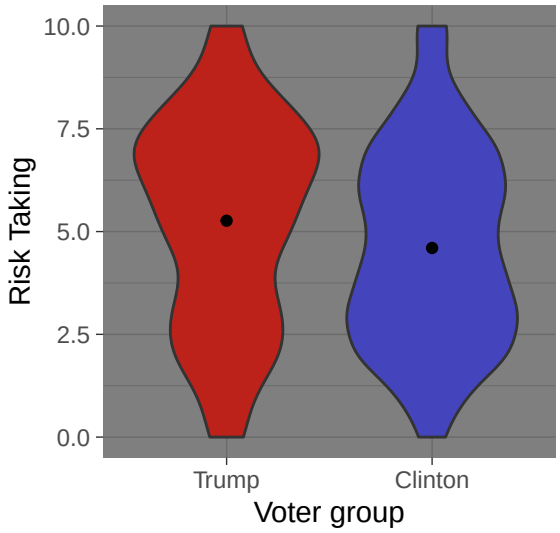


Figure A23
Violin plot comparing voter groups in general risk preference

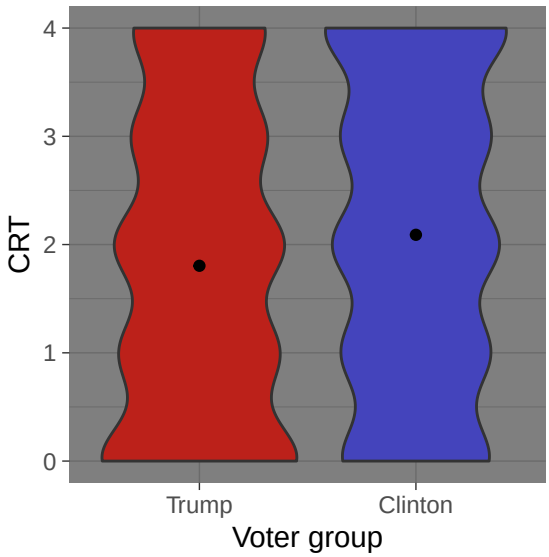


Figure A24
Violin plot comparing voter groups in cognitive reflection scores

```
  theme_dark()+scale_fill_manual(values=c("#BC211A","#4444BC"))+
  stat_summary(fun=mean,  geom="point", color="black")+
  theme(legend.position="none")+
  theme(aspect.ratio=1)
```

```
ggplot(corrFrame, aes(x=trumpVoter, y=angleSVO, fill = trumpVoter)) +
  geom_violin() +
  xlab("Voter groupr") + ylab("SVO (prosocial)") +
  theme_dark()+scale_fill_manual(values=c("#BC211A","#4444BC"))+
  stat_summary(fun=mean,  geom="point", color="black")+
  theme(legend.position="none")+
  theme(aspect.ratio=1)
```

```
ggplot(corrFrame, aes(x=trumpVoter, y=psychReactance, fill = trumpVoter)) +
  geom_violin() +
  xlab("Voter group") + ylab("Reactance") +
  theme_dark()+scale_fill_manual(values=c("#BC211A","#4444BC"))+
  stat_summary(fun=mean,  geom="point", color="black")+
  theme(legend.position="none")+
  theme(aspect.ratio=1)
```

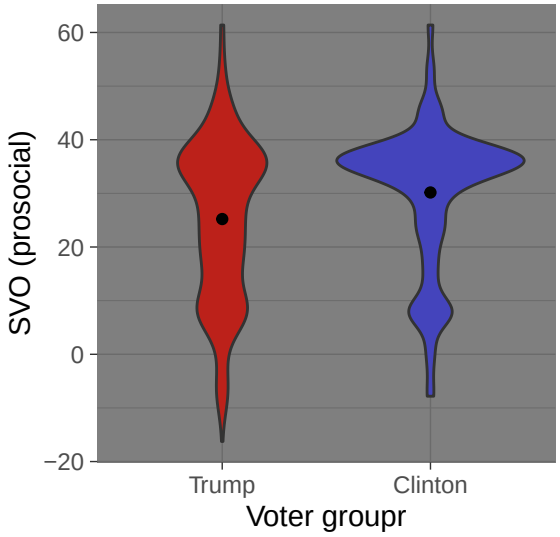


Figure A25
Violin plot comparing voter groups in social value orientation (prosociality)

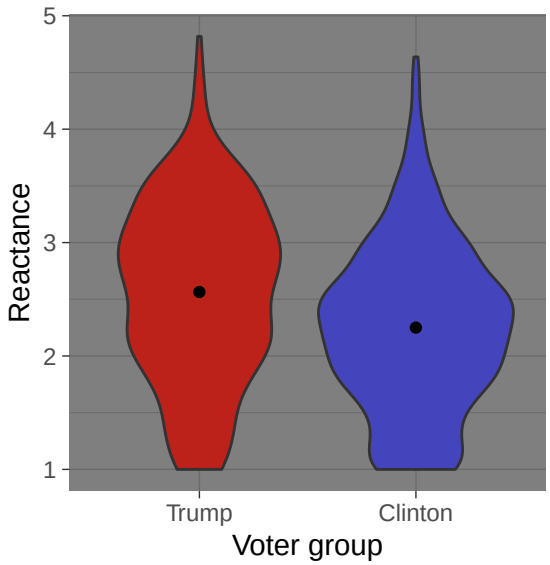


Figure A26
Violin plot comparing voter groups in psychlogical reactance

A8.1.3 T-tests

All four Plots show differences between the means for the two voter groups. Testing these differences for significance via t-tests reveals significant results in each case.

```
t.test(riskTaking ~ trumpVoter, data = corrFrame)

##
##  Welch Two Sample t-test
##
## data:  riskTaking by trumpVoter
## t = 3.8496, df = 806.83, p-value = 0.0001277
## alternative hypothesis: true difference in means between group Trump and group Clinton i
## 95 percent confidence interval:
##  0.3248754 1.0008625
## sample estimates:
##   mean in group Trump mean in group Clinton
##              5.263819              4.600950

t.test(CRT ~ trumpVoter, data = corrFrame)

##
##  Welch Two Sample t-test
##
## data:  CRT by trumpVoter
## t = -2.8737, df = 815.19, p-value = 0.004163
## alternative hypothesis: true difference in means between group Trump and group Clinton i
## 95 percent confidence interval:
##  -0.48176085 -0.09072151
## sample estimates:
##   mean in group Trump mean in group Clinton
##              1.804020              2.090261

t.test(angleSVO ~ trumpVoter, data = corrFrame)

##
##  Welch Two Sample t-test
##
## data:  angleSVO by trumpVoter
## t = -5.0543, df = 793.05, p-value = 5.366e-07
## alternative hypothesis: true difference in means between group Trump and group Clinton i
## 95 percent confidence interval:
##  -6.878251 -3.030119
## sample estimates:
##   mean in group Trump mean in group Clinton
##              25.21320              30.16738
```

```
t.test(psychReactance ~ trumpVoter, data = corrFrame)

##
##  Welch Two Sample t-test
##
## data:  psychReactance by trumpVoter
## t = 5.9075, df = 802.35, p-value = 5.129e-09
## alternative hypothesis: true difference in means between group Trump and group Clinton i
## 95 percent confidence interval:
##  0.2097610 0.4185251
## sample estimates:
##   mean in group Trump mean in group Clinton
##              2.564413              2.250270
```

Trump voters in comparison to Clinton voters are on average characterized by a higher general preference for risk, a more pro-self social value orientation, a lower cognitive reflection score (albeit with a small difference), and a higher score in psychological reactance. Social value orientation and risk preference have been shown to be predictive for risk-seeking game behavior. Adding both political variables and these predictors to a model will therefore reduce the added predictive value of the second variable as shown in section A4.4.2.

One should also point out that these differences should be considered part of the reason why voter groups differ in their game behavior, even though these variables do not capture the entire mechanism.

A8.2 Correlations of predictor variables and political variables

A8.2.1 Custom correlation function and data preparation

The following builds on a function used to create a matrix of significance values in parallel to a matrix of correlation coefficients. This variant takes into account that some variable pairs may not have any joint observations.

```
#http://www.sthda.com/english/wiki/visualize-correlation-matrix-using-correlogram
# mat : is a matrix of data
# ... : further arguments to pass to the native R cor.test function
cor.mtest <- function(mat, ...) {
    mat <- as.matrix(mat)
    n <- ncol(mat)
    p.mat<- matrix(NA, n, n)
    diag(p.mat) <- 0
    for (i in 1:(n - 1)) {
        for (j in (i + 1):n) {

            ####ADDED: CHECK IF NONZERO observations
             ###line below added to code
             if (sum(ifelse(!is.na(mat[, i])&!is.na(mat[, j]),1,0))>0){
```

```
            tmp <- cor.test(mat[, i], mat[, j], ...)
            p.mat[i, j] <- p.mat[j, i] <- tmp$p.value
            }else{                                    ### added
              p.mat[i, j] <- p.mat[j, i] <- 1         ### added
            }                                         ### added
        }
    }
  colnames(p.mat) <- rownames(p.mat) <- colnames(mat)
  p.mat
}
```

Here, the relvant variables are collected in a data frame.

```
corrFrame2<-data.frame(
  riskTaking=anovaFrame$riskTaking,
  CRT=anovaFrame$CRT,
  angleSVO=anovaFrame$angleSVO,
  conservatism=anovaFrame$polPos,
  SECS=anovaFrame$secsALL,
  trumpPref=anovaFrame$elecTrump,
  psychReactance=anovaFrame$psychReactance
)


cMat=cor(corrFrame2, use="pairwise.complete.obs")
pMat=cor.mtest(corrFrame2, use="pairwise.complete.obs")

sMat=cMat[c("riskTaking","CRT","angleSVO","psychReactance"),
          c("conservatism","SECS","trumpPref")]
spMat=pMat[c("riskTaking","CRT","angleSVO","psychReactance"),
           c("conservatism","SECS","trumpPref")]


 #corrFrame2$trumpVoter=anovaFrame$facSample
 #levels(corrFrame2$trumpVoter)<-c("Trump","Clinton")
```

Correlation matrix

Figure A27 presents correlations between the four predictor variables and the three political measures. All directions correspond to the mean differences observed in the previous analysis, and all coefficients are significantly different from zero ($p < 0.05$).

```
corrplot(sMat,   col = c('orange', 'lightblue'), cl.pos='n',  bg = 'white',p.mat=spMat, tl.
```

In summary, this confirms that there are clear differences between voter groups in relation to variables predicting game behavior.

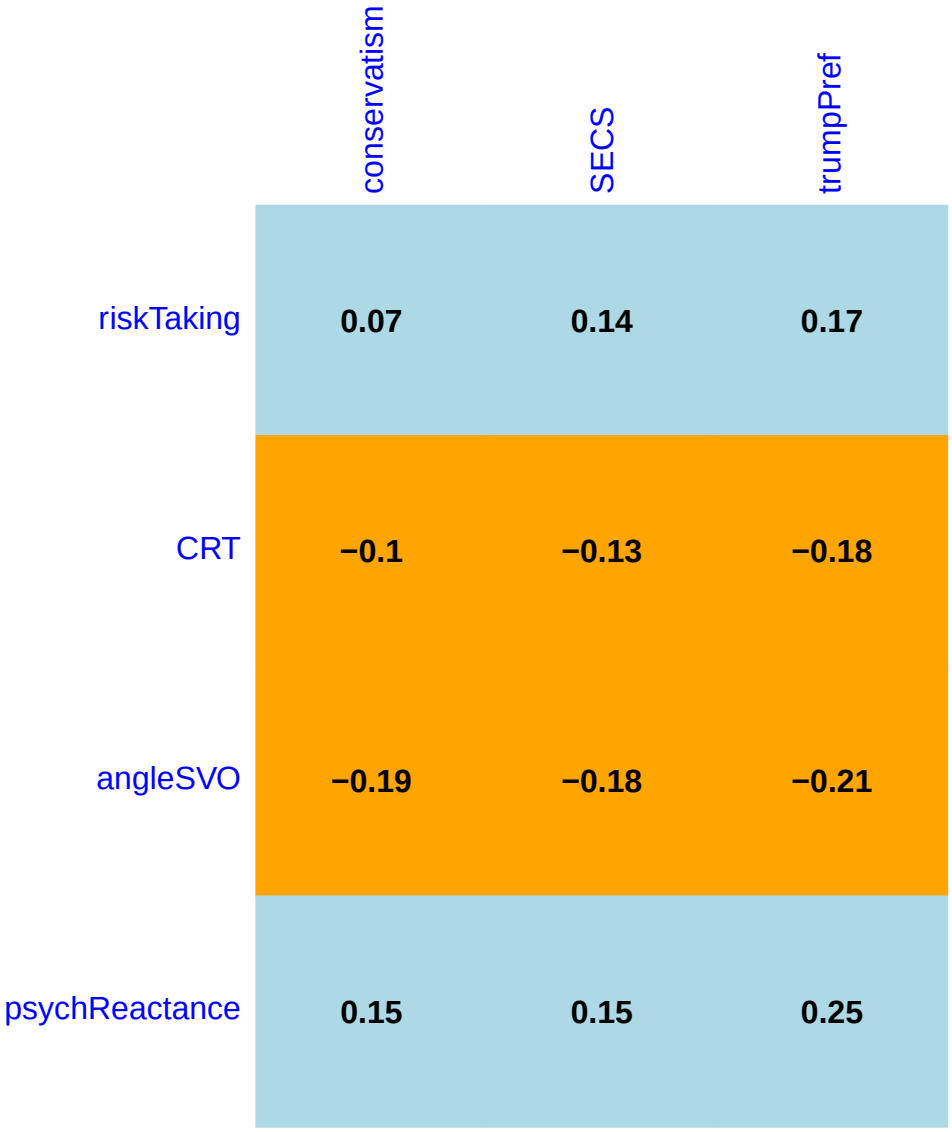


Figure A27
Correlation matrix for political and other predictor variables

A9 Correlations with exploratory variables

We decided to present asymmetric correlation matrices with the variables focused on in the main manuscript in columns and exploratory variables in rows. As column variables we chose the SECS score, endorsement of Trump (happiness with re-election), game behavior and behavioral intentions. Game behavior we split into the numbe of risky choices irrespective of condition as a single variable and four variables with risky choices for one of the four combinations of framing and intervention factors. For the latter four variables, the sample is reduced to about a fourth, reducing the power to detect significant correlations (but eliminating the non-independence of sets of observations in the full variable). We also added the four criterion variables used for behavioral intentions in the main manuscript.

We present two sets of exploratory variables mainly to keep the resulting matrices easier to read. In the first set, we present the results for the scale distrust of officialdom, and seven evaluations of the US government response to COVID (focusing on restrictions, punishment, reactance, research, stimulus decisions, possible informational contamination of government communication, and attitudes towards the need for tradeoffs between health and the economy). Three variables measure evaluations of the American national response: two focus on the president and the nation on the whole respectively, the third corresponds to the joint scale (americanResponse). Finally, we included five one-item evaluations of political figures (AOC, Barr) and organizations/movements (BLM, Antifa, QAnon) that were expected to divide the two voter samples.

In the second set, we present scale scores for collective narcissism, social distancing support, susceptibility to Covid misinformation, and climate change skepticism. Three further variables measure perceived risk, with the two subscales focusing on personal health risk and health risks on the society level and the joint scale (perceivesRiskAll). Three variables measure the perceived threat on the symbolic level (symbolicThreatCovid; e.g., a threat to American values) and the immediate physical level (realThreatCovid; e.g., personal health), and he joint scale (threatCovid). Finally the last two rows include intentions to vaccinate (vaccines were not yet available at the time of the study, so this was asked under the assumption that a safe vaccine would have been developed in the relative future) and the level of education.

A9.1 Data preparation

Here, the scales are calculated in parallel to the calculations done in the Variables supplement.

```
### Distrust of Officialdom

distrustVars <- c("DistOff1", "DistOff2", "DistOff3")
DistrustOfficialFrame <- df[distrustVars]
remove(distrustVars)
DistrustOfficialFrame[] <-data.matrix(DistrustOfficialFrame)
weightsDistOff <-list(distrOfficialdom=c("DistOff1", "DistOff2", "DistOff3"))
scoresDistrOff=scoreItems(items=DistrustOfficialFrame,
keys=weightsDistOff)
```

```
#head(DistrustOfficialFrame)
#head(scoresDistrOff$scores)



#### #CV-GRC: government response to corona

    GRCVars <-c("CV_GRC_1", "CV_GRC_2","CV_GRC_3", "CV_GRC_4","CV_GRC_5",
    "CV_GRC_6","CV_GRC_7", "CV_GRC_8","CV_GRC_9", "CV_GRC_10","CV_GRC_11",
    "CV_GRC_12","CV_GRC_15")

    grcframe <- df[GRCVars]
    remove(GRCVars)


grcframe[] <-data.matrix(grcframe)

  weightsGRC <-list(grcRestrictions=c("CV_GRC_1","CV_GRC_2"),
    grcPunishment=c("CV_GRC_3","CV_GRC_4"),
    grcReactance=c("CV_GRC_5","CV_GRC_6"),
    grcResearch=c("CV_GRC_7","CV_GRC_8"),
    grcStimulus=c("CV_GRC_9","CV_GRC_10"),
    grcContamination=c("CV_GRC_11","CV_GRC_12"),
    grcTradeoff=c("CV_GRC_15")
                  )


#head(grcframe)


     scalesGRC=scoreItems(items=grcframe,
                          keys=weightsGRC)


####     collective Narcissism
collNarcVars <- c("CollNarc01", "CollNarc02", "CollNarc03",
"CollNarc04", "CollNarc05")
collNarcFrame <- df[collNarcVars]
remove(collNarcVars)

collNarcFrame[] <-data.matrix(collNarcFrame)
```

```
weightsCollNarc <-list(collNarc=c("CollNarc01", "CollNarc02", "CollNarc03",
"CollNarc04", "CollNarc05"))
scaleCollNarc=scoreItems(items=collNarcFrame,
keys=weightsCollNarc)


### Social Distancing Support
socDistVars <-c("CV_SRPHB_1R", "CV_SRPHB_2R","CV_SRPHB_3", "CV_SRPHB_4")
socDistFrame <- df[socDistVars]
remove(socDistVars)


socDistFrame[] <-data.matrix(socDistFrame)

weightsSocDist <-list(socialDistancing=c("-CV_SRPHB_1R","-CV_SRPHB_2R",
        "CV_SRPHB_3", "CV_SRPHB_4"))
scoresSocDist=scoreItems(items=socDistFrame,
keys=weightsSocDist)



#### COVID Misinformation
scaleVarsCVMI <- c("Misinfo_01", "Misinfo_02", "Misinfo_03",
"Misinfo_04", "Misinfo_05","Misinfo_06",
"Misinfo_07R","Misinfo_08R","Misinfo_09","Misinfo_10")
scaleFrameCVMI <- df[scaleVarsCVMI]
scaleFrameCVMI <- scaleFrameCVMI %>%
dplyr::rename(
CVMI01p = Misinfo_01, CVMI02p = Misinfo_02, CVMI03p = Misinfo_03,
CVMI04p = Misinfo_04, CVMI05p = Misinfo_05, CVMI06p = Misinfo_06,
CVMI07n = Misinfo_07R, CVMI08n = Misinfo_08R, CVMI09p = Misinfo_09,
CVMI10p = Misinfo_10 )
scaleFrameCVMI[] <-data.matrix(scaleFrameCVMI)
weightsCVMI <-list(sclMisinform=c("CVMI01p",
"CVMI02p","CVMI03p","CVMI04p",
"CVMI05p", "CVMI06p","-CVMI07n",
"-CVMI08n", "CVMI09p", "CVMI10p" )
)
scaleCVMI=scoreItems(keys=weightsCVMI, items =scaleFrameCVMI,totals=FALSE)


###Conspiracy Mentality
cmqVars <- c("CMQ01", "CMQ02", "CMQ03",
"CMQ04","CMQ05")
```

```
conspiracyFrame <- df[cmqVars]
remove(cmqVars)

conspiracyFrame[] <-data.matrix(conspiracyFrame)

weightsConspiracy <-list(conspiracyMentality=c("CMQ01", "CMQ02", "CMQ03",
"CMQ04", "CMQ05"))
scoresCM=scoreItems(items=conspiracyFrame,
keys=weightsConspiracy)

## Number of categories should be increased  in order to count frequencies.

### Climate Change Skepticism
scaleVarsCC <- c("ClimCh1", "ClimCh2R", "ClimCh3R", "ClimCh4R", "ClimCh5",
"ClimCh6")
scaleFrameCC <- df[scaleVarsCC]

scaleFrameCC <- scaleFrameCC %>%
dplyr::rename(
CC1p=ClimCh1,CC2n=ClimCh2R,CC3n=ClimCh3R,CC4n=ClimCh4R,
CC5p=ClimCh5,CC6p=ClimCh6 )
scaleFrameCC[] <-data.matrix(scaleFrameCC)

weightsCC <-list(sclClimSkept=c("CC1p","-CC2n","-CC3n","-CC4n",
            "CC5p","CC6p")
)

scaleCC=scoreItems(keys=weightsCC, items =scaleFrameCC,totals=FALSE)


### COVID risk perception
scaleVarsCPR <- c("CV_Risk1_weeks", "CV_Risk1_months", "CV_Risk2_weeks",
"CV_Risk2_months", "CV_Risk3_community", "CV_Risk3_state","CV_Risk3_US" )
scaleFrameCPR <- df[scaleVarsCPR]

scaleFrameCPR <- scaleFrameCPR %>%
dplyr::rename(
PPR1=CV_Risk1_weeks,PPR2=CV_Risk1_months,POR1=CV_Risk2_weeks,
POR2=CV_Risk2_months,PSR1=CV_Risk3_community,
PSR2=CV_Risk3_state, PSR3=CV_Risk3_US )

scaleFrameCPR[] <-data.matrix(scaleFrameCPR)

weightsCPR <-list(perceivedRiskAll=c("PPR1","PPR2","POR1","POR2",
"PSR1","PSR2","PSR3"),
```

```
perceivedRiskPeople=c("PPR1","PPR2","POR1","POR2"),
perceivedRiskSociety=c("PSR1","PSR2","PSR3")
)


scaleCPR=scoreItems(keys=weightsCPR, items =scaleFrameCPR,totals=FALSE)


### Threat of COVID
threatVars <- c("ThreatReal01", "ThreatReal02", "ThreatReal03",
"ThreatReal04", "ThreatReal05","ThreatSymb01",
"ThreatSymb02", "ThreatSymb03",
"ThreatSymb04", "ThreatSymb05")
threatFrame <- df[threatVars]
remove(threatVars)
threatFrame[] <-data.matrix(threatFrame)
weightsThreat <-list(threatSymbolic=c("ThreatSymb01", "ThreatSymb02",
"ThreatSymb03", "ThreatSymb04", "ThreatSymb05"),
threatReal=c("ThreatReal01", "ThreatReal02", "ThreatReal03",
"ThreatReal04", "ThreatReal05"),
threatFull=c("ThreatSymb01", "ThreatSymb02", "ThreatSymb03",
"ThreatSymb04","ThreatSymb05","ThreatReal01",
"ThreatReal02","ThreatReal03","ThreatReal04", "ThreatReal05")
)
scoresThreat=scoreItems(items=threatFrame,
keys=weightsThreat)

### American response to Covid

respARCFrame=data.frame(
ARCPres01=as.numeric(df$ARCTrump01),
ARCPres02=as.numeric(df$ARCTrump02),
ARCPres03=as.numeric(df$ARCTrump03),
ARCPres04=as.numeric(df$ARCTrump04),
ARCPres05=as.numeric(df$ARCTrump05),
ARCPres06R=as.numeric(df$ARCTrump06),
ARCPres07R=as.numeric(df$ARCTrump07),
ARCPres08R=as.numeric(df$ARCTrump08),
ARCPres09R=as.numeric(df$ARCTrump09),
ARCPres10R=as.numeric(df$ARCTrump10),
ARCNational01=as.numeric(df$ACRNational01),
ARCNational02=as.numeric(df$ACRNational02),
ARCNational03=as.numeric(df$ACRNational03),
ARCNational04=as.numeric(df$ACRNational04)
```

```
)

respARCFrame[] <-data.matrix(respARCFrame)
weightsARC <-list(arcPresidential=c("ARCPres01", "ARCPres02", "ARCPres03",
"ARCPres04", "ARCPres05","-ARCPres06R","-ARCPres07R",
"-ARCPres08R","-ARCPres09R","-ARCPres10R"),
arcNational=c("ARCNational01", "ARCNational02",
"ARCNational03", "ARCNational04"),
arcFull=c("ARCPres01", "ARCPres02", "ARCPres03",
"ARCPres04", "ARCPres05","-ARCPres06R","-ARCPres07R",
"-ARCPres08R","-ARCPres09R","-ARCPres10R",
"ARCNational01", "ARCNational02", "ARCNational03",
"ARCNational04")
)

scoresARC=scoreItems(items=respARCFrame,
keys=weightsARC)
```

All variables are collected in the "exploreFrame" in the following code.

```
exploreFrame=data.frame(
  ### criterion-variables game
  gameRisk=modelFrame$RiskyChoices,
  gameRiskColNo=ifelse((1-modelFrame$dummyInjunctive)*
                (1-modelFrame$dummyMasks)==1,
                 modelFrame$RiskyChoices,NA),
  gameRiskPanNo=ifelse((1-modelFrame$dummyInjunctive)*
                modelFrame$dummyMasks==1,
                modelFrame$RiskyChoices,NA),
  gameRiskColInt=ifelse(modelFrame$dummyInjunctive*
                (1-modelFrame$dummyMasks)==1,
                modelFrame$RiskyChoices,NA),
  gameRiskPanInt=ifelse(modelFrame$dummyInjunctive*
                   modelFrame$dummyMasks==1,
                   modelFrame$RiskyChoices,NA),


  ### criterion-variables behavior
  behMasks=modelFrame$behIntMasks,
  behDist=modelFrame$behIntDistancing,
  behHand=modelFrame$behIntHandHYgiene,
  behRestr=modelFrame$behIntMovement,
  SECS=modelFrame$SECS,
  Trump=modelFrame$trump,
```

```
  ### exploratory variables
 distrOfficialdom=scoresDistrOff$scores,
 GovRespRestrictions=scalesGRC$scores[,1],
 GovRespPunishment=scalesGRC$scores[,2],
 GovRespReactance=scalesGRC$scores[,3],
 GovRespResearch=scalesGRC$scores[,4],
 GovRespStimulus=scalesGRC$scores[,5],
 GovRespContamination=scalesGRC$scores[,6],
 GovRespTradeoff=scalesGRC$scores[,7],
 collNarcissism=scaleCollNarc$scores[,1],

 socDistSupport=scoresSocDist$scores[,1],
 Misinformation=scaleCVMI$scores[,1],
 conspiracyMentality=scoresCM$scores[,1],
 climateChangeSkepticism=scaleCC$scores[,1],
 perceivedRiskAll=scaleCPR$scores[,1],
 perceivedRiskPeople=scaleCPR$scores[,2],
 perceivedRiskSociety=scaleCPR$scores[,3],
 symbolicThreatCovid=scoresThreat$scores[,1],
 realThreatCovid=scoresThreat$scores[,2],
 threatCovid=scoresThreat$scores[,3],

 presidentialResponse=scoresARC$scores[,1],
 nationalResponse=scoresARC$scores[,2],
 americanResponse=scoresARC$scores[,3],

  feelAOC=df$Feel_AOcasio_Cortez,
 feelBarr=df$Feel_BBarr,
  feelAntifa= df$Feel_Antifa,
  feelBLM=df$Feel_BLM,
  feelQAnon=df$Feel_QAnon,

 vaccination=as.numeric(df$Vaccination),
 education=as.numeric(df$demo02Education)


)


exploreFrameNames=exploreFrame


cMat=cor(exploreFrameNames, use="pairwise.complete.obs")
pMat=cor.mtest(exploreFrameNames, use="pairwise.complete.obs")
```

A9.2 Correlations (part 1)

Figure A28 presents the first of the two correlation matrices with exploratory variables. Disregarding the non-significant coefficients, there is a clear qualitative pattern that can be seen concerning the three groups of focus variables. Exploratory variables either correlate positively or negatively with both conservatism/Trump endorsement and risk-taking in the game, without exception. The direction of correlations with behavioral variables is opposed to that of the correlations with the previous groups (the only exception is the informational contamination variable).

In most rows, the correlation coefficients for game behavior in pandemic-framed conditions are higher than those in neutrally-framed conditions. There is a positive correlation between conservatism and risk-taking on the one hand and distrust in officialdom, reactance to government interventions, the perceived need for trading off health to benefit economics, positive evaluations of the American response to Covid, as well as positive feelings towards William Barr and QAnon. As explained above, these same variables also predict lower intentions to engage with non-pharmaceutical interventions to combat the virus. Conservatism and risk-taking are negatively correlated with evaluations of government restrictions and the use of punishment, research on Covid, stimulus interventions, as well as positive feelings towards AOC, BLM, and Antifa. In this case, these variables predict more willingness to adapt counter-measures against the virus.

The special status of informational contamination might be explained by a closer look at the two items of the subscale:

- **GR-Ico1+**: I distrust the information I receive about the Coronavirus (COVID-19) from my government.

- **GR-Ico2+**: I think the government has an agenda that's causing them not to give the whole story to the populace.

These two items are formulated in a way that expresses doubt about the Covid messaging while at the same time blaming the current government. This creates possible cognitive dissonance on both sides of the spectrum: On the right, there is a tendency to endorse the President, but at the same time disregard official government communication without blaming the President for that communication. On the left, the government is rejected but the messaging about Covid is regarded as helpful (at least at the time). Covid has created rally-around-the-flag effects in many countries (Yam et al., 2020), complicating matters further. Thus, this will be most strongly endorsed by those who reject health measures and do not favor the Republican government. This explanation stays speculative, but seems consistent with the data.

One other observation is striking: The correlation between variables and the conservatism/Trump endorsement are very high, demonstrating that some of the scales tap heavily into these more general political attitudes. We would readily admit that our study design does not allow for a causal ordering, but these findings still raise questions of uniqueness and dimensionality for this collection of scales.

```
sMat=cMat[c("distrOfficialdom","GovRespRestrictions",
  "GovRespPunishment","GovRespReactance",
  "GovRespResearch","GovRespStimulus",
  "GovRespContamination","GovRespTradeoff",
  "presidentialResponse","nationalResponse","americanResponse",
  "feelAOC","feelAntifa","feelBLM","feelBarr","feelQAnon"),
  c("SECS","gameRisk","gameRiskColNo","gameRiskColInt","gameRiskPanNo",
  "gameRiskPanInt","behMasks","behDist","behHand","behRestr")]

spMat=pMat[c("distrOfficialdom","GovRespRestrictions",
  "GovRespPunishment","GovRespReactance",
  "GovRespResearch","GovRespStimulus",
  "GovRespContamination","GovRespTradeoff",
  "presidentialResponse","nationalResponse","americanResponse",
  "feelAOC","feelAntifa","feelBLM","feelBarr","feelQAnon"),
  c("SECS","gameRisk","gameRiskColNo","gameRiskColInt","gameRiskPanNo",
  "gameRiskPanInt","behMasks","behDist","behHand","behRestr")]



corrplot(sMat,   col = c('orange', 'lightblue'), cl.pos='n',  bg = 'white',
 p.mat=spMat, tl.col="blue", sig.level = 0.05, insig="blank",
  addCoef.col = "black",method="color")
```

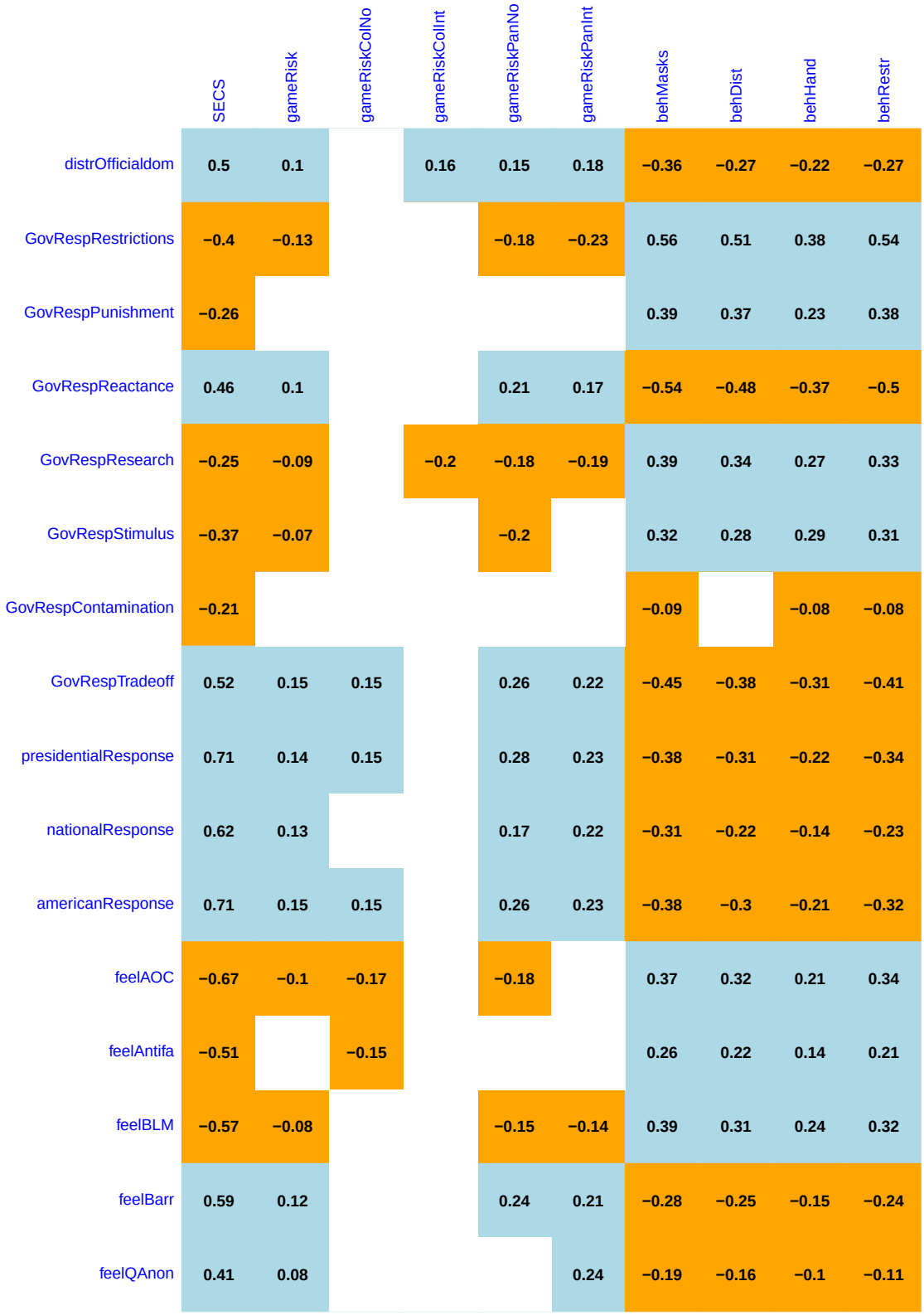


Figure A28

Correlations between exploratory variables (in rows) and Conservatism, Trump endorsement, game behavior, and behavioral intentions (Part 1): Game behavior is correlated for the whole group and the four framing and intervention combinations separately. The backgrounds for significant correlation coefficient cells ($p<.05$) are colored in blue (positive) and orange (negative).

A9.3 Correlations (part 2)

Figure A29 presents the second correlation matrix for exploratory variables, structure in the same way as the previous matrix. In this case, there is only one exception to the previously observed patterns for significant correlation coefficients: The directions of relationships with game variables and conservatism are always the same and opposed to those with behavioral intentions. The joint scale for Covid threat is the exception and it will be discussed below. Correlations with game behavior in pandemic-framed conditions are higher than those in neutrally-framed conditions.

Conservatives and risk-takers in the game tend to score higher in collective narcissism, the susceptibility to misinformation and in affirming the symbolic threat of Covid to political values. The same is true for those who have lower intentions to adapt health measures. Conspiracy mentality is positively associated with conservatism and negatively with health measures, but not strongly related to game behavior.

In contrast, conservatives and risk-takers score lower in terms of support for social distancing, the perceived risk for people and the perceived risk for society, the health threat the virus poses and the intention to vaccinate (again, these variables predict the opposite for health behaviors and are positively correlated with adaption). While not the focus of our manuscript, differences in vaccination should be pointed out as a major determinant of differential health outcomes during the pandemic. In contrast to 82.4% of Clinton voters willing to take the vaccine (and 14.7% potentially willing), only 54% of Trump voters indicate this willingness (with a respectable 30.7% undecided).

The threat scale is comprised of two subscales with opposite relationships to other variables (the subparts are relatively weakly correlated at r=.18). The complete scale thus confounds two different attitudes and the result predicts both conservatism and adaption of hand hygiene. Education does not substantially predict focus variables.

An interesting contrast can be observed between the symbolic threat of Covid and the threat of Covid for the American society that seem very related at first glance. The second variable focuses on health risks, and it is clear from the observed pattern that conservatives do not see the symbolic threat of Covid as produced by its health impact. Threats to society, democracy, and American values are more likely associated with the government response to the virus, not the virus itself. Again, this remains speculative.

Again, the high correlations make it difficult to judge the primacy of effects based on a single-time measurement. They are both consistent with study result that find a distinct role for misinformation in predicting health behavior (Hornik et al., 2021) and those that find relatively small impacts when studied along political variables (Van Stekelenburg et al., 2021). It is of course vital to study causal connections to estimate the usefulness of interventions focusing on false information about the virus. The pattern of conservatives' reduced support for interventions is consistent with results found in larger samples (Van Bavel et al., 2022).

```
sMat=cMat[c("collNarcissism","socDistSupport","Misinformation",
   "conspiracyMentality","climateChangeSkepticism","perceivedRiskAll",
   "perceivedRiskPeople","perceivedRiskSociety","symbolicThreatCovid",
   "realThreatCovid","threatCovid","vaccination",
```

```
   "education"),
  c("SECS","Trump","gameRisk","gameRiskColNo",
   "gameRiskColInt","gameRiskPanNo","gameRiskPanInt",
   "behMasks","behDist","behHand","behRestr")]

spMat=pMat[c("collNarcissism","socDistSupport","Misinformation",
   "conspiracyMentality","climateChangeSkepticism","perceivedRiskAll",
   "perceivedRiskPeople","perceivedRiskSociety","symbolicThreatCovid",
   "realThreatCovid","threatCovid","vaccination",
   "education"),
  c("SECS","Trump","gameRisk","gameRiskColNo",
   "gameRiskColInt","gameRiskPanNo","gameRiskPanInt",
   "behMasks","behDist","behHand","behRestr")]


corrplot(sMat,   col = c('orange', 'lightblue'), cl.pos='n',  bg = 'white',
    p.mat=spMat, tl.col="blue", sig.level = 0.05, insig="blank",
    addCoef.col = "black",method="color")
```

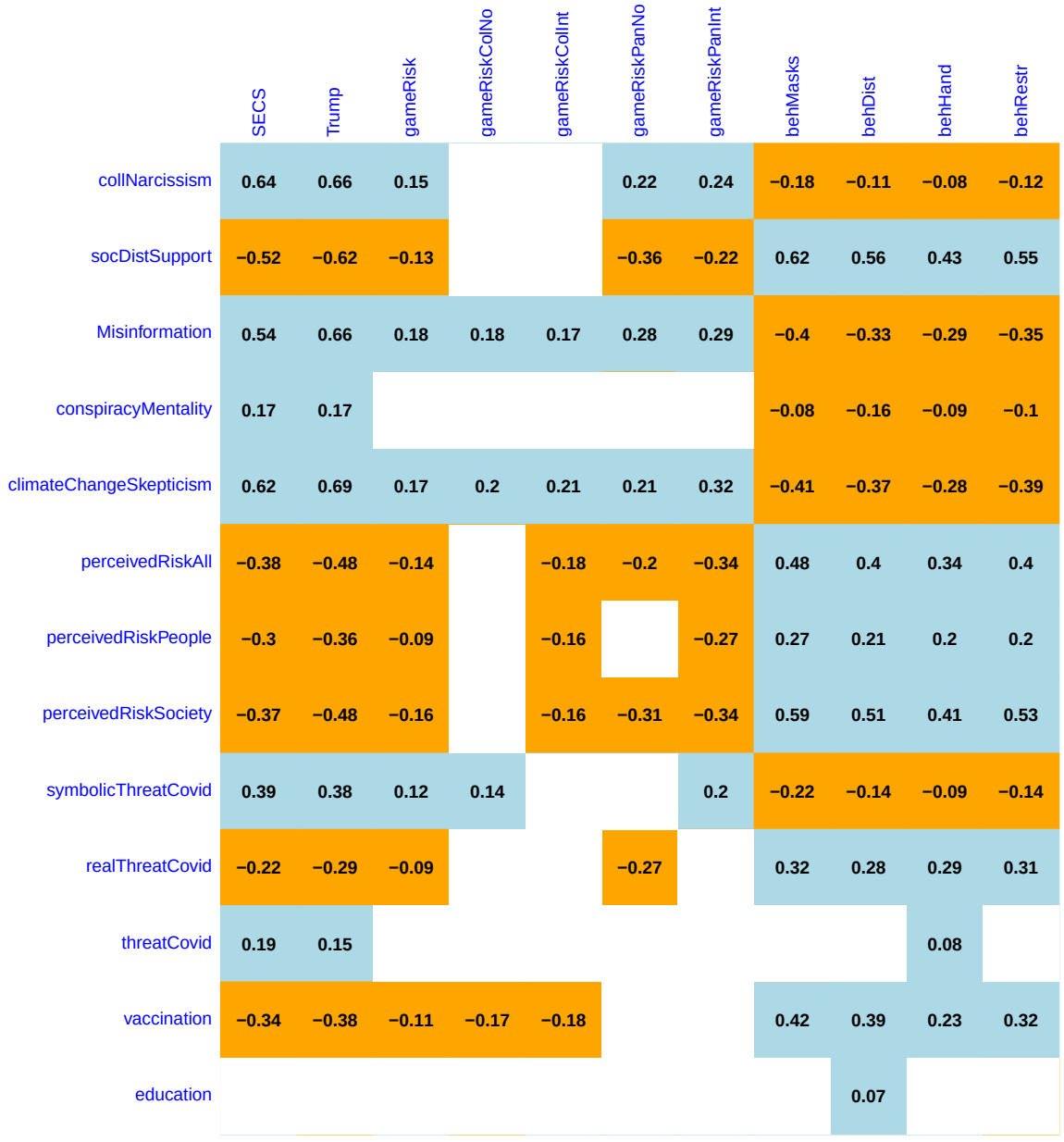


Figure A29

Correlations between exploratory variables (in rows) and Conservatism, Trump endorsement, game behavior, and behavioral intentions (Part 2): Game behavior is correlated for the whole group and the four framing and intervention combinations separately. The backgrounds for significant correlation coefficient cells ($p<.05$) are colored in blue (positive) and orange (negative).

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