Supplement to 'How to reduce Item Nonresponse in Face-to-Face Surveys? A Review and Evidence from the European Social Survey'

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Version and Packages

This analysis was written for R version 4.2.0 (2022-04-22) on Linux. The following packages were used with the respective versions as comments.

```
library(tidyverse) # 1.3.1
library(haven) # 2.5.0
library(qqplotr) # 0.0.5
library(fixest) # 0.10.4
```

Data Manipulation

`ESS9e03_1.dta` is the main data file from the ESS 9 version 3.1 and `ESS9INTe03.dta` is the interviewer questionnaire. The data are available after registration here: https://www.europeansocialsurvey.org/data/download.html?r=9 *idno* is a respondent identifier and *cntry* is the country abbreviation.

It is necessary to change the encoding on Linux/Mac to *latin1*, remove the option if on Windows. See https://haven.tidyverse.org/reference/read_dta.html#character-encoding

```
ESS9 <- full_join(read_dta("ESS9e03_1.dta", encoding = "latin1"),
                  read_dta("ESS9INTe03.dta", encoding = "latin1"),
                  by = c("idno", "cntry"))
```

Dependent Variables

I use three dependent variables: the number of refusals by a respondent, the number of Don't know (DK) and their sum. I sum them over all questions applicable to all respondents. That means, all questions only asked a subset of respondents due to previous answers or survey experiments are left out.

As background information, refusal and DK are not read out to the respondents in the ESS or on the showcards. But interviewers have them as distinct options within their CAPI instrument. Interviewers are advised to accept them without probe. Whether the respondent refuses or says DK is therefore an interpretation of the interviewer.

`select(nwspol:impfun)` selects only the variables that are based on questions asked the respondent and gets rid of the interviewer questionnaire, weights etc. for the calculation of item nonresponse.

The ESS distinguishes different types of missings using labeled missings in Stata. Their codes are:

- .a - not applicable
- .b - respondent refused
- .c - Don't know
- .d - not available (should not exist: code for processing errors)

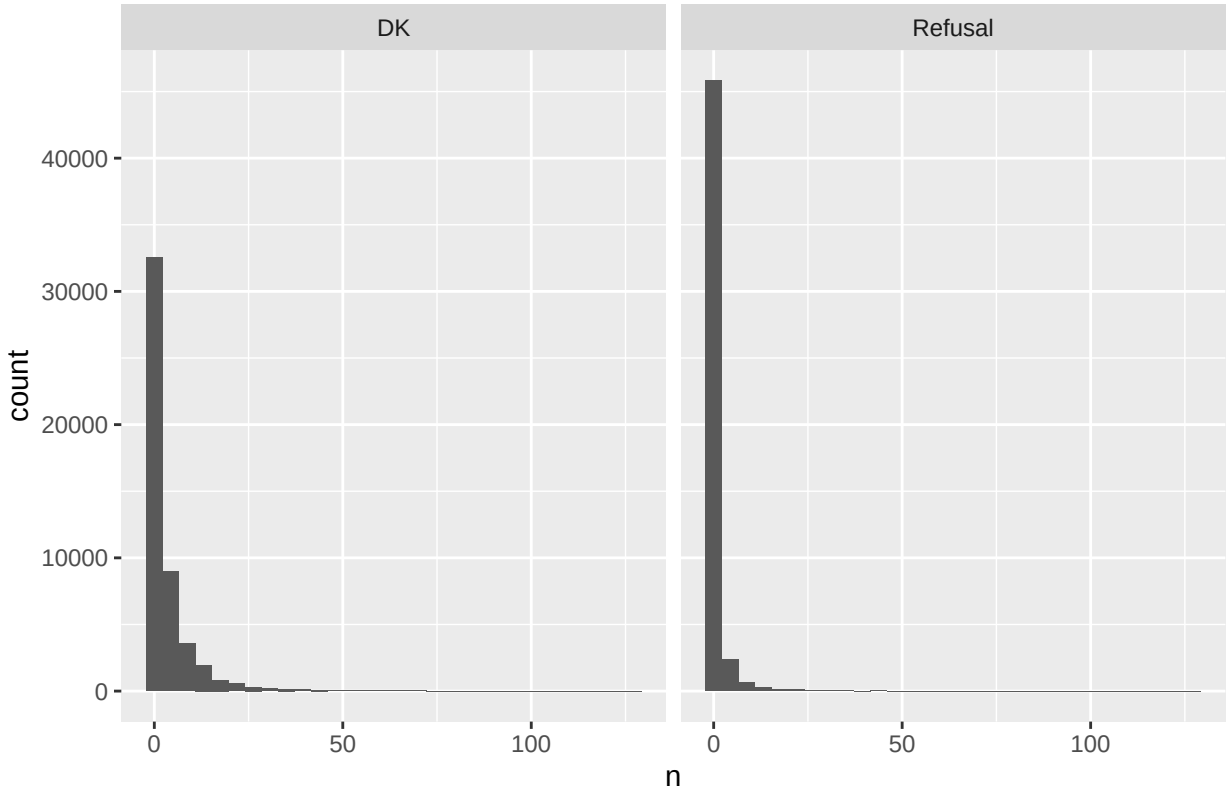
The package *haven* has a function to detect these tagged missings in a Stata dataset in R, see https://haven.tidyverse.org/articles/semantics.html#tagged-missing-values-1

To have a comparable set of items for all respondents, I only select the ones applicable to all: `select(where(~ any(is_tagged_na(.x, tag = "a")) == FALSE))`

Attention: the step to calculate the number of missings for each respondent takes some time.

```
count_refusals <- ESS9 %>%
  select(nwspol:impfun) %>%
  select(where(~ any(is_tagged_na(.x, tag = "a")) == FALSE)) %>%
  mutate(across(.fns = ~ is_tagged_na(.x, tag = "b"))) %>%
  rowwise() %>%
  transmute(n_refusals = sum(c_across()))

count_dk <- ESS9 %>%
  select(nwspol:impfun) %>%
  select(where(~ any(is_tagged_na(.x, tag = "a")) == FALSE)) %>%
  mutate(across(.fns = ~ is_tagged_na(.x, tag = "c"))) %>%
  rowwise() %>%
  transmute(n_dk = sum(c_across()))

rbind(tibble(n = count_refusals$n_refusals,
             type = "Refusal"),
      tibble(n = count_dk$n_dk,
             type = "DK")) %>%
  ggplot() +
  aes(n) +
  geom_histogram() +
  facet_wrap(~type) +
  labs(title = "Fig. S1: Histogram of INR by Type")
```

Fig. S1: Histogram of INR by Type



There are much more DKs than refusals. There are 176490 DKs, on average 3.564 per respondent. The number of refusals amounts to 41821, on average 0.845 per respondent. That totals 218311 cases of item nonresponse. There is a correlation of 0.226 between the number of DKs and refusals.

The standard deviation of DK is 7.194 and the of refusals is 3.317. Although for the regression the variance of the residuals matters, this is a first sign of overdispersion.

Independent Variables

Preparation for Analysis

The variables from the interviewer questionnaire still contain missing values as number codes 8 and 9. They are set to NA if their value is above 6. Bulgaria used the wrong format for interviewer age and therefore adds many missings to it and is resultantly excluded. The *other* category of ISCED (number code 55) is coded to NA as well. The length of the interviews are top coded to 3 hours because there were errors with the CAPI instruments time stamps in some occasions (see ESS 9 codebook).

```
analysis <- ESS9 %>%
  zap_label() %>% zap_missing() %>% zap_formats() %>% # getting rid of Stata formatting
  transmute(age = agea, # respondent
            age_sq = agea^2,
            educ = ifelse(eisced < 10, eisced, NA),
            duration = ifelse(inwtm < 180, inwtm / 30, 6),
            interference = ifelse(preintf < 6, preintf * -1 + 2, NA),
            notprimlang = as.integer(lnghom1 != intlnga),
            gndrmatch = ifelse(intgndr < 6, as.numeric(intgndr == gndr), NA),
            resolder = ifelse(intagea < 200, as.numeric(agea - intagea > 10), NA),
            intolder = ifelse(intagea < 200, as.numeric(intagea - agea > 10), NA),
```

```
            showcards = ifelse(resswcd < 6, -1*resswcd + 4, NA),
            clarif = ifelse(resclq < 6, resrelq, NA),
            bestab = ifelse(resbab < 6, resbab, NA),
            underst = ifelse(resundq < 6, resundq, NA),
            intver = paste0(intnum, cntry), # FE
            n_dk = count_dk$n_dk, # DV
            n_ref = count_refusals$n_refusals,
            n_tot = n_dk + n_ref)

# somehow, I had trouble recoding clarif in transmute
analysis$clarif[analysis$clarif > 6] <- NA

labels <- c(age = "Age",
            age_sq = "Age squared",
            educ = "Education (ISCED)",
            underst = "Understood Questions",
            bestab = "Answered to best Ability",
            duration = "Duration of Interview (30 Min)",
            interference = "Interference of Interview",
            notprimlang = "Int. not in primary Language",
            gndrmatch = "Gender Matching",
            resolder = "Respondent 10 years older",
            intolder = "Interviewer 10 years older",
            showcards = "Use of Showcards",
            clarif = "Amount of Clarifications",
            intver = "Interviewer",
            n_dk = "Don't know",
            n_ref = "Refusal",
            n_tot = "Total")
```

Descriptive Statistics

Variables of Interest

Except of the use of showcards and the duration of the interview, all variables of interest are dummys:

The proportion of interviews where the interviewer is more than 10 years older is 0.366 and the proportion where the respondent is more than 10 years older is 0.295. Both are based of the same original variables, age of the respondent and age of the interviewer and have therefore the same number of NAs: 4045. The large number of NAs is predominantly due to missings in interviewers age. It is missing very frequently. Romania used the wrong format for this item and therefore all interviews from Romania are excluded via missingness in these items.

The proportion of interviews where respondent and interviewer were of the same gender is 0.534 (4045 NAs).

In 8.032 percent of the interviews, someone besides the interviewer and respondent was present in the same room or interfered with the interview (65 NAs).

9.693 percent of the interviews were conducted in a language different from the one the respondent primarily speaks at home. There are no missings in this item.

The extent the respondent used showcards as perceived by the interviewer is measured on a three point scale: respondent used all the applicable showcards, respondent used only some applicable showcards, respondent refused/ was unable to use the showcards at all. This question is asked to the interviewer after the interview, see the ESS9 source questionnaire. I flipped the order to ease interpretation: higher number represents more frequent use. Most respondents used all the applicable showcards (0.792), 0.163 respondents used them only

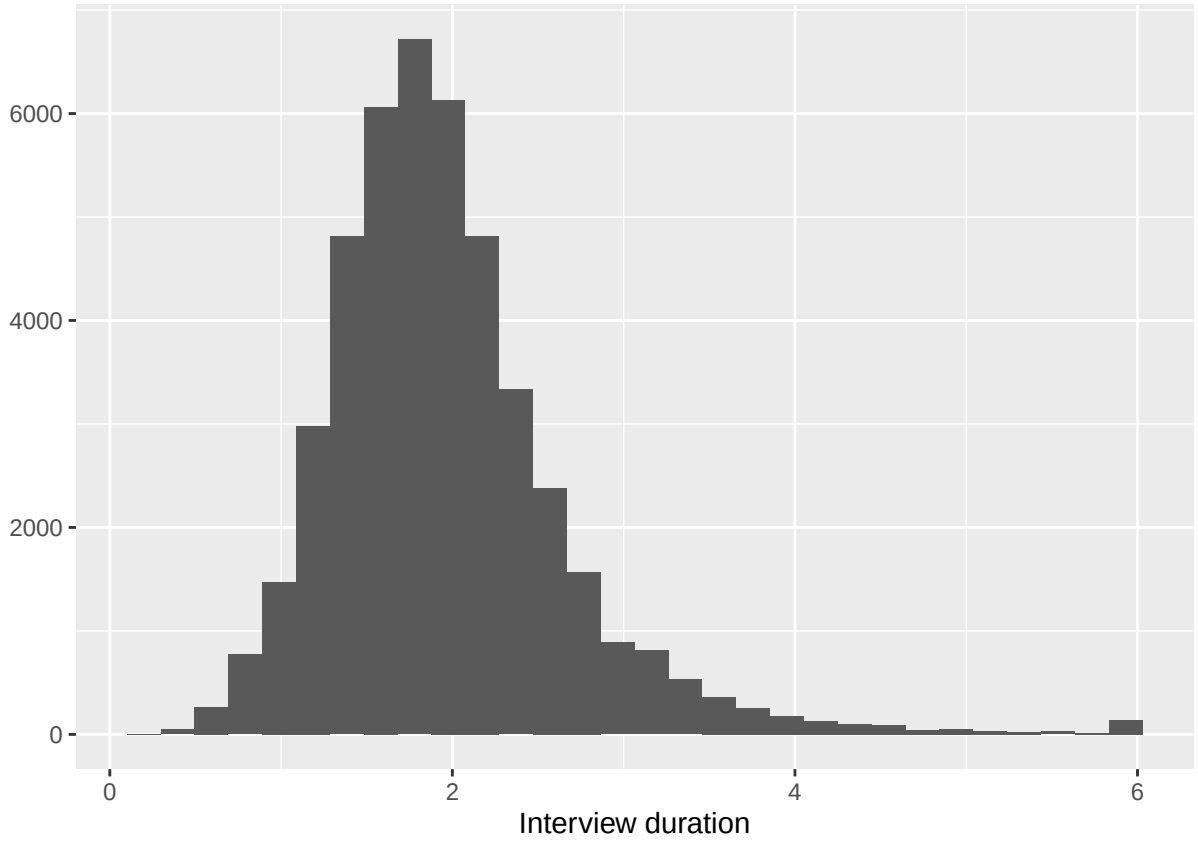
sometimes and 0.045 never used them. There are 129 NAs.

The duration of the interview is automatically computed by the CAPI instrument based on start and end time stamps. There have been some issues with the time stamps in some countries though, resulting in some unusually long durations. I top-coded them to 3 hours and rescaled the variables to 30 minutes.

```
summary(analysis$duration)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##       0       2       2       2       2       6    4485
```

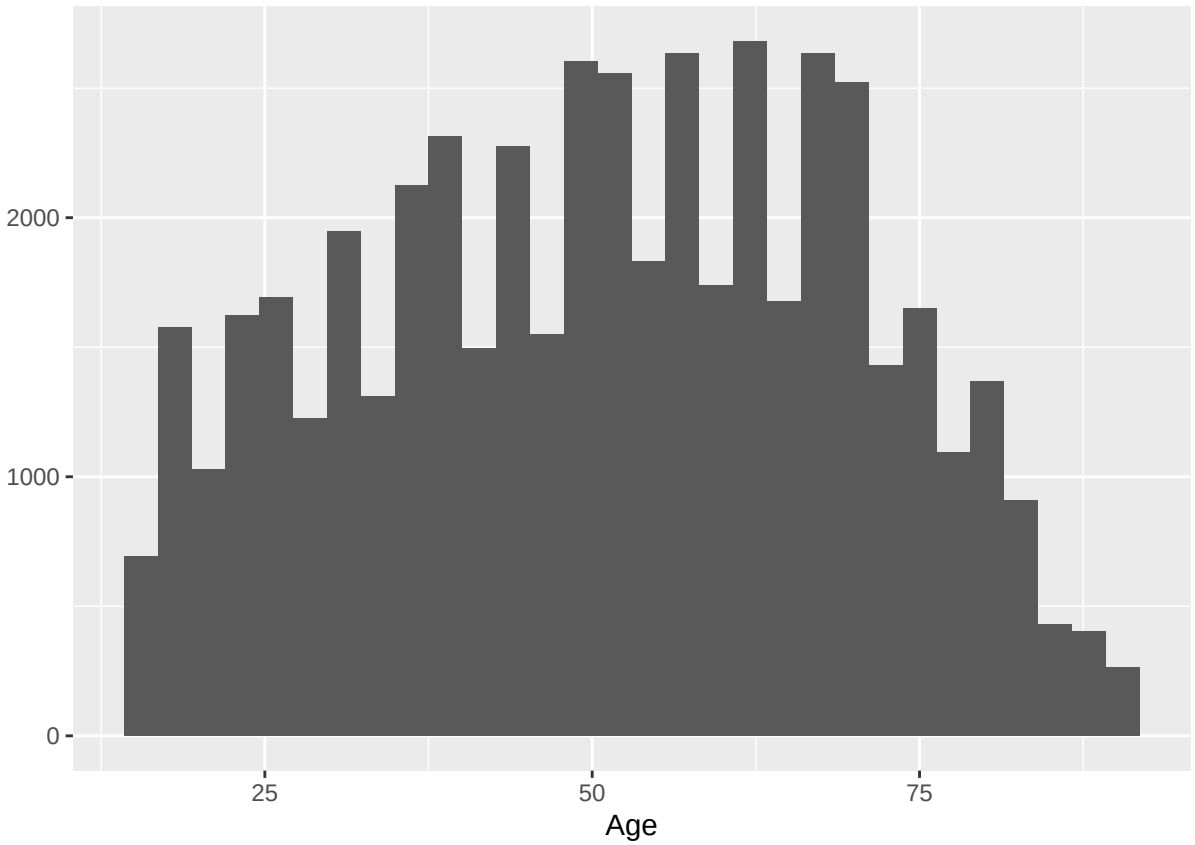
```
ggplot(analysis) +
        aes(x = duration) +
        geom_histogram() +
        labs(x = "Interview duration", y = "")
```



Control Variables

The ESS surveys European populations over the age of 15. This is therefore the minimum age in the sample. The maximum age is 90. The mean age is 51.066 with a standard deviation of 18.647. There are 222 NAs.

```
ggplot(analysis) +
        aes(x = as.numeric(age)) +
        geom_histogram() +
        labs(x = "Age", y = "")
```



Education is operationalised using the established ISCED scale that orders the latest educational degrees by level. The number codes and levels are:

- 1: ES-ISCED I , less than lower secondary
- 2: ES-ISCED II, lower secondary
- 3: ES-ISCED IIIb, lower tier upper secondary
- 4: ES-ISCED IIIa, upper tier upper secondary
- 5: ES-ISCED IV, advanced vocational, sub-degree
- 6: ES-ISCED V1, lower tertiary education, BA level
- 7: ES-ISCED V2, higher tertiary education, >= MA level

3800, 8329, 8027, 11212, 6079, 5517, 6281, 274

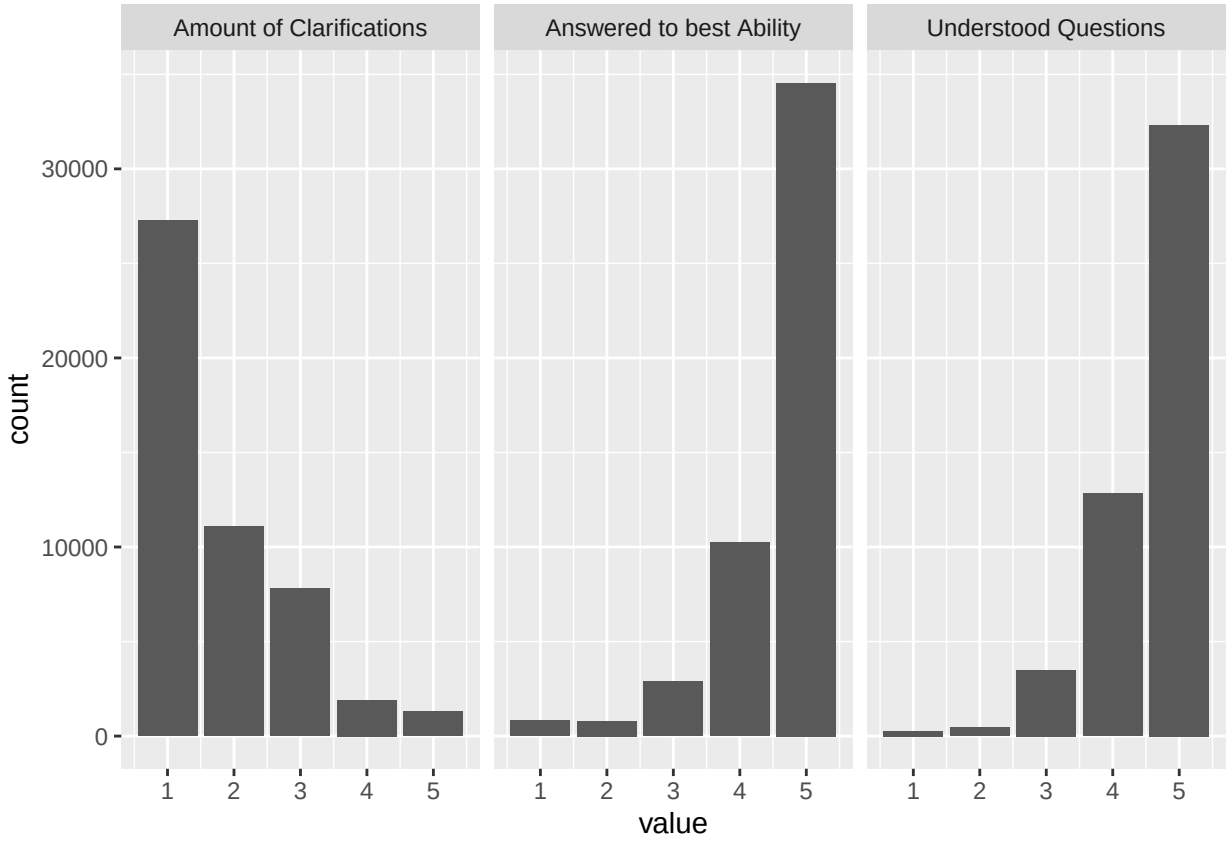
All control variables from the interviewer questionnaire are measured on a five point scale: Never, Almost never, Now and then, Often, Very often with number codes from 1 to 5.

I selected the assessment of the interviewer how often the respondent... - asked for clarifications, - answered to the best of their ability and - understood the question.

These items have two functions as controls. They are proxies of ability (and motivation) as well as the other controls. And they control for the interviewers' assessment of the interview which might influence the answer on showcard use. In multiple regression, only the effect of a variable *net of all others* is estimated, therefore dampening the endogeneity problem with the showcard use item.

```
rbind(tibble(value = analysis$clarif,
             var = "Amount of Clarifications"),
      tibble(value = analysis$bestab,
             var = "Answered to best Ability"),
      tibble(value = analysis$underst,
             var = "Understood Questions")) %>%
```

```
  ggplot() +
    aes(x = value) +
    geom_bar() +
    facet_wrap(~var)
```




```
rbind(tibble(value = analysis$clarif,
             var = "Amount of Clarifications"),
      tibble(value = analysis$bestab,
             var = "Answered to best Ability"),
      tibble(value = analysis$underst,
             var = "Understood Questions")) %>%
  group_by(var) %>%
  summarise(Mean = mean(value, na.rm = TRUE),
            SD = sd(value, na.rm = TRUE))
```

```
## # A tibble: 3 x 3
##   var                        Mean    SD
##   <chr>                     <dbl> <dbl>
## 1 Amount of Clarifications  1.76 1.02
## 2 Answered to best Ability  4.56 0.815
## 3 Understood Questions      4.55 0.715
```

Multivariate Analyses

I analyse the data using a negative binomial regression with interviewer fixed effects . Standard errors are clustered by interviewer. Since the population of interest in this case are interviews and not countries, no weighting is applied.

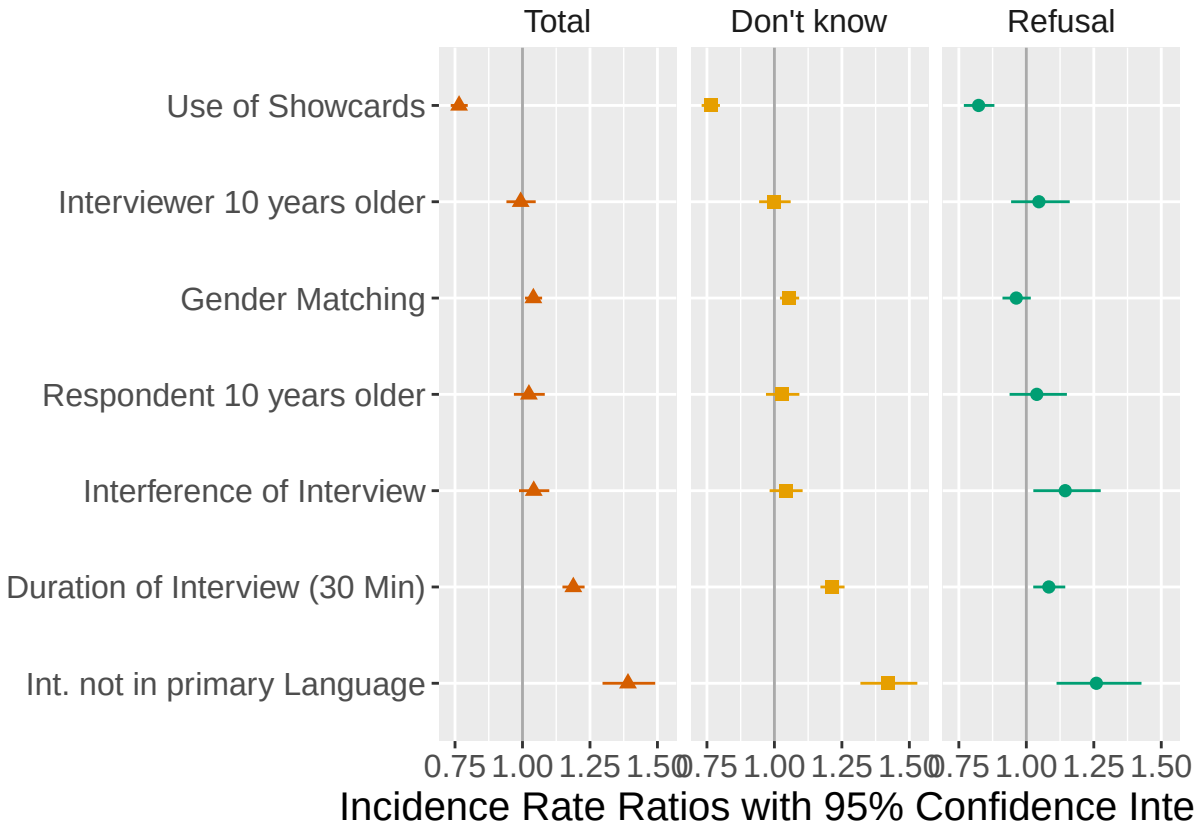
The missings are deleted listwise.

```
model <- fenegbin(data = analysis,
                  fml =  c(n_dk, n_ref, n_tot) ~
                    duration + interference + showcards + notprimlang +
                      gndrmatch + resolder + intolder +
                      educ + age + age_sq + underst + bestab +  clarif |
                      intver,
                  se = "cluster")

setFixest_dict(labels)
etable(model,
       file = "results_inr_ess9.tex", replace = TRUE, tex = TRUE,
       title = "Regression Results",
       digits = 3, se.below = TRUE,
       signifCode = c("***"=0.001, "**"=0.01, "*"=0.05),
       fitstat = c("n", "pr2", "wpr2", "bic", "theta", "f"))
etable(model,
       tex = FALSE,
       title = "Regression Results",
       digits = 3, se.below = TRUE,
       signifCode = c("***"=0.001, "**"=0.01, "*"=0.05),
       fitstat = c("n", "pr2", "wpr2", "bic", "theta", "f"))
```

```
##                                  model 1   model 2    model 3
## Dependent Var.:               Don't know   Refusal      Total
##
## Duration of Interview (30 Min)  0.194***   0.080**   0.173***
##                                (0.019)    (0.028)   (0.018)
## Interference of Interview       0.041      0.135*    0.041
##                                (0.030)    (0.056)   (0.028)
## Use of Showcards               -0.270***  -0.195*** -0.268***
##                                (0.023)    (0.035)   (0.021)
## Int. not in primary Language    0.351***   0.231***  0.330***
##                                (0.038)    (0.064)   (0.036)
## Gender Matching                 0.054**   -0.038     0.040*
##                                (0.017)    (0.028)   (0.016)
## Respondent 10 years older       0.028      0.038     0.024
##                                (0.031)    (0.052)   (0.029)
## Interviewer 10 years older      9.65e-5    0.045    -0.007
##                                (0.030)    (0.053)   (0.028)
## Education (ISCED)              -0.128***   0.065*** -0.097***
##                                (0.005)    (0.009)   (0.005)
## Age                            -0.050***   0.010*   -0.042***
##                                (0.003)    (0.005)   (0.002)
## Age squared                     0.0005*** -6.54e-5   0.0004***
##                                (2.43e-5)  (4.59e-5) (2.3e-5)
## Understood Questions           -0.337***  -0.046    -0.287***
##                                (0.017)    (0.028)   (0.016)
## Answered to best Ability       -0.035*    -0.177*** -0.062***
##                                (0.016)    (0.024)   (0.015)
## Amount of Clarifications        0.254***   0.598***  0.328***
##                                (0.011)    (0.021)   (0.011)
## Fixed-Effects:                 ---------- --------- ----------
## Interviewer                           Yes       Yes        Yes
```

```
## ---------------------------- ---------- --------- ----------
## S.E.: Clustered                by: intver by: int.. by: intver
## Observations                       41,512    34,632     41,795
## Pseudo R2                         0.11966   0.18119    0.12252
## Within Pseudo R2                  0.05809   0.08775    0.05937
## BIC                             189,641.8  86,863.5  204,151.4
## Over-dispersion                   0.89111   0.75064     1.0251
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
results <- bind_rows(bind_cols(var = rownames(model$n_dk$coeftable),
                               model$n_dk$coeftable,
                               y = "Don't know"),
                     bind_cols(var = rownames(model$n_ref$coeftable),
                               model$n_ref$coeftable,
                               y = "Refusal"),
                     bind_cols(var = rownames(model$n_tot$coeftable),
                               model$n_tot$coeftable,
                               y = "Total")) %>%
  rename(estimate = `Estimate`,
         se = `Std. Error`) %>%
  filter(var != ".theta") %>%
  filter(var %in% c("duration", "interference", "showcards", "notprimlang",
                    "gndrmatch", "resolder", "intolder")) %>%
  mutate(irr = exp(estimate),
         upper = exp(estimate + se * (-qnorm((1-0.95)/2))),
         lower = exp(estimate - se * (-qnorm((1-0.95)/2))))

ggplot(results) +
  aes(y = reorder(var, -irr),
      x = irr,
      colour = y,
      shape = y) +
  geom_vline(xintercept = 1,
             colour = "darkgrey") +
  geom_point(size = 2) +
  geom_linerange(aes(y = var,
                     xmin = lower,
                     xmax = upper),
                 lwd = .5) +
  facet_wrap(~factor(y, levels=c("Total", "Don't know", "Refusal"))) +
  scale_color_manual(values = c("#E69F00", "#009E73", "#D55E00")) +
  scale_shape_manual(values = 15:17) +
  scale_y_discrete(labels = labels) +
  theme(legend.position = "none",
        strip.background = element_blank(),
        text = element_text(size = 15)) +
  labs(y = "", x = "Incidence Rate Ratios with 95% Confidence Intervals")
```




```
ggsave(filename = "results_inr_ess9.pdf",
       width = 22, height = 10, units = "cm")
```

Although I removed all NAs before, there are different numbers of observations for each dependent variable. This is due to some interviewers having no within-variance (that have only respondents with not a single item nonresponse).

Regression Diagnostics and Model Justification

Fixed effects count data models are quite contested. Wooldridge (1999) claims that fixed effects negative binomial regression (FENB) is not a true fixed effects estimator and that overdispersion is not of much concern in these models. He therefore advises to always use FE Poisson regression (FEPois) over FENB.

Allison and Waterman (2002) agree that FENB in its previous form was not a true FE estimator but propose a modified version that they advise to always use over FEPois. This improved version is the one implemented in the fixest package.

I compare estimates and diagnostic plots for both regression models using the total sum of item nonresponse as the dependent variable to assess reliability of my results.

```
fepois <- fepois(data = analysis,
                 fml =  n_tot ~
                   duration + interference + showcards + notprimlang +
                     gndrmatch + resolder + intolder +
                     educ + age + age_sq + underst + bestab +  clarif |
                     intver,
                 se = "cluster")

setFixest_dict(labels)
etable(model$n_tot, fepois,
```

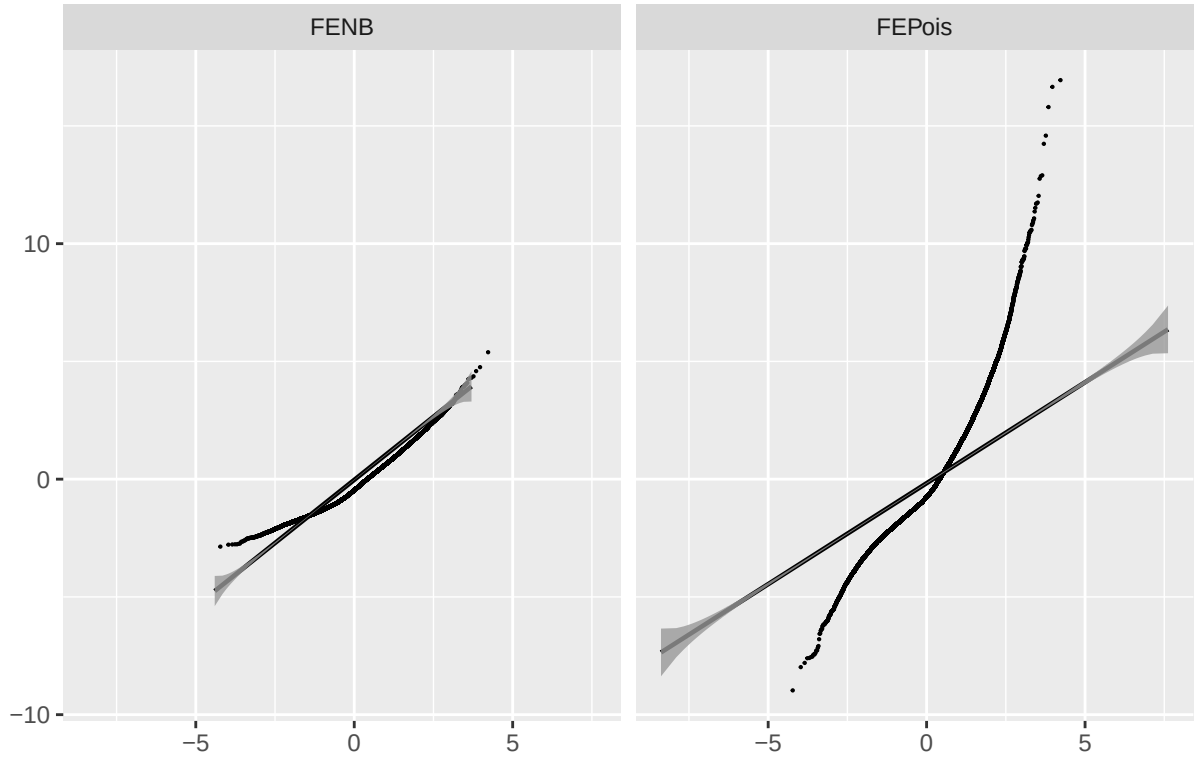
```
       tex = FALSE,
       title = "Tab. S2: FENB vs. FEPois",
       digits = 3, se.below = TRUE,
       signifCode = c("***"=0.001, "**"=0.01, "*"=0.05),
       fitstat = c("n", "pr2", "wpr2", "bic", "theta", "f"))
```

```
##                                model$n_..     fepois
## Dependent Var.:                     Total      Total
##
## Duration of Interview (30 Min)  0.173***   0.096***
##                                (0.018)    (0.017)
## Interference of Interview       0.041      0.064*
##                                (0.028)    (0.029)
## Use of Showcards               -0.268***  -0.256***
##                                (0.021)    (0.022)
## Int. not in primary Language    0.330***   0.370***
##                                (0.036)    (0.036)
## Gender Matching                 0.040*     0.040*
##                                (0.016)    (0.016)
## Respondent 10 years older       0.024      0.0003
##                                (0.029)    (0.029)
## Interviewer 10 years older     -0.007      0.022
##                                (0.028)    (0.028)
## Education (ISCED)              -0.097***  -0.086***
##                                (0.005)    (0.005)
## Age                            -0.042***  -0.037***
##                                (0.002)    (0.002)
## Age squared                     0.0004***  0.0004***
##                                (2.3e-5)   (2.22e-5)
## Understood Questions           -0.287***  -0.237***
##                                (0.016)    (0.016)
## Answered to best Ability       -0.062***  -0.077***
##                                (0.015)    (0.014)
## Amount of Clarifications        0.328***   0.271***
##                                (0.011)    (0.011)
## Fixed-Effects:                 ---------- ----------
## Interviewer                           Yes        Yes
## ------------------------------ ---------- ----------
## Family                          Neg. Bin.    Poisson
## S.E.: Clustered                by: intver by: intver
## Observations                       41,795     41,795
## Pseudo R2                         0.12252    0.42066
## Within Pseudo R2                  0.05937    0.15874
## BIC                             204,151.4  271,913.5
## Over-dispersion                    1.0251         --
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
diagnostics <- rbind(tibble(resid = resid(fepois,
                                          type = "deviance"),
                            fitval = fepois$fitted.values,
                            model = "FEPois"),
                     tibble(resid = resid(model$n_tot,
                                          type = "deviance"),
```

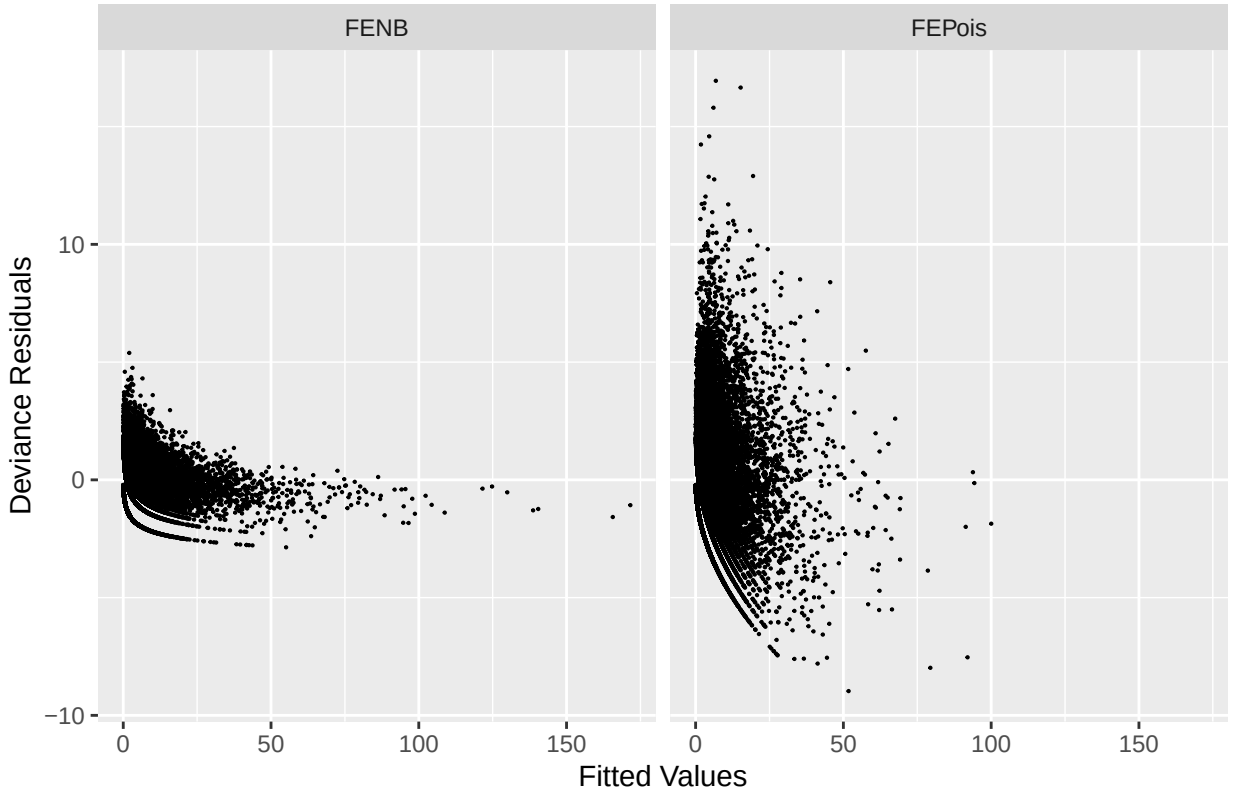
```
                          fitval = model$n_tot$fitted.values,
                          model = "FENB"))

ggplot(diagnostics) +
  aes(sample = resid) +
  stat_qq(size = 0.1) +
  stat_qq_line() +
  stat_qq_band() +
  facet_wrap(~model) +
  labs(title = "Fig. S2: QQ-Plot of Deviance Residuals",
       x = "", y = "")
```

Fig. S2: QQ−Plot of Deviance Residuals




```
ggplot(diagnostics) +
  aes(x = fitval,
      y = resid) +
  geom_point(size = 0.1) +
  facet_wrap(~model) +
  labs(title = "Fig. S3: Residuals vs Fitted: FENB",
       x = "Fitted Values",
       y = "Deviance Residuals")
```

Fig. S3: Residuals vs Fitted: FENB



As can be seen in the diagnostic plots, the Poisson Regression with fixed effects exhibits a much larger residual variance and the deviance residuals are much less normal than the negative binomial regression with fixed effects. The average deviance residual of the FEPois is -0.381 with a standard deviation of 1.894 compared to -0.351 with a standard deviation of 0.959 for FENB.

Although normality of the residuals is not such a strong criterion with count data models, Cameron and Trivedi (2013, chapter 9.4) expect normality in deviance residuals in correctly specified models. While not perfect, the deviance residuals of the FENB model are much closer to normally distributed than FEPois. And the unconditional FENB by Allison and Waterman (2002) implemented in the fixest package is a true fixed effects model unlike previous versions. It has an incidental parameter problem though, but it is usually very small. Wooldridge (1999) argued for Poisson regression when using fixed effects but this seems to be the worse option in this case. The overdispersion seems to be still consequential even with fixed effects.

On the other hand, the substantial results are very similar. Coefficients differ slightly between models but signs and significance are largely identical. I therefore settle on the FENB model in the paper.

Clustered standard errors are the default in the fixest package. Normal parametric standard errors tend to be way too large (Cameron and Trivedi 2013). I replicated the regressions in Stata using bootstrap standard errors (not shown) and only get marginally different results, likely from differences in the optimisation algorithm.

Literature

Allison, Paul D. and Richard P. Waterman (2002). “Fixed-Effects Negative Binomial Regression Models”. In: Sociological Methodology 32.1, pp. 247–265. doi: 10.1111/14679531.00117.

Cameron, A. Colin, and Pravin Trivedi. Regression Analysis of Count Data. 2nd ed. Cambridge: Cambridge University Press, 2013. https://doi.org/10.1017/CBO9781139013567.

Wooldridge, Jeffrey M. (1999). “Distribution-Free Estimation of Some Nonlinear Panel Data Models”. In: Journal of Econometrics 90.1, pp. 77–97. doi: 10.1016/S0304-4076(98)00033-5.