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The present dataset “klausur.dta” is based on German Longitudinal Election Study, that investigates determinants for the election decisions of the electorates. Overall, this panel-dataset contains 135.234 observations of 22.539 respondents over 6 waves. The panel is “strongly balanced”. Therefore, a multilevel structure of the dataset can be assumed, whereby observations are nested in respondents that are nested in waves.

Task 1

Assume you can model the variable internet (the number of day in the last week that the respondent used the internet to inform her or himself about politics) as a linear multilevel model. Estimate such a model with the explanatory variables of your choice. Interpret that model (the model coefficients and the error components). If you add a square term (e.g. for year of birth) you can either interpret the coefficients or use a graph (marginsplot).

Preparation: While investigating the probable linear relationship between the dependent variable “internet” and the independent variable “age” (recode based on “birthyear”), it seems obvious that we cannot assume such a relationship (Fig. 1).

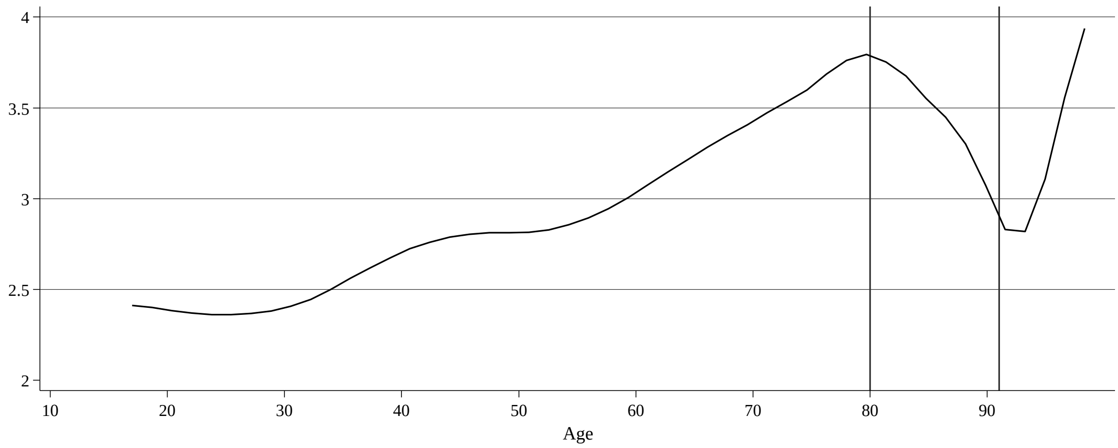

Fig. 1 – Local polynomial smoothing of days in last week informed about politics on the internet and age

Therefore, I added a spline for this variable at the age of 80 and excluded some presumably influential observations of respondents over 91 years old from the analysis, that would unnecessarily bias the effect of age as outliers (17 observations over 3 respondents, whereby only one respondent answered the internet related question).

Analysis (Tab. A): The random-effects GLS regression-model contains 76.952 observations over 21.084 unique respondents. On average, every respondent participated on 3.6 of 6 waves. The within-variance is explained by 6%, the between-variance by 40% and the overall-variance by 34% by this model. The “prob > chi2”-test tells us, that we can reject the null-hypothesis that every coefficient equals zero ($p < 0.000$).

The constant represents male respondents that are 80 years old, perceive themselves in the underclass, come from West-Germany, do not talk about politics with someone and have no educational tertiary degree amounts to 2.04. Thus, respondents with these characteristics inform themselves on the internet about political topics about 2 days in the previous week.

Respondents under the age of 80 years spend marginal more time (0.005) on the internet to inform themselves about politics with every year they age. Yet, this effect is statistically significant ($p < 0.000$), so we can reject the null-hypothesis that the effect equals zero. Furthermore, respondents that are 80-90 years old spend less time (-0.09) on the internet about political topics with every year that they age. Also, we would not reject the null-hypothesis ($p > 0.05$) in this case and therefore this effect could equal zero.[1] Thus, we can assume that younger and middle-aged respondents inform themselves more on the internet about political topics.

In comparison to respondents that see themselves as part of the underclass, respondents that perceive themselves as working-class spend a little bit less time (-0.15) on the internet to inform themselves about political topics. On the contrary, respondents that experience themselves as lower (0.18) or as average middleclass (0.20) consume more political topics on the internet than respondents at the underclass. Respondents that see themselves as upper middleclass also spend even a bit more time (0.37) on the internet on political topics than, that even mentioned, underclass. The biggest difference (0.77) in comparison to the reference-category can be observed from respondents that perceive themselves as upperclass. All these differences are also statistically significant ($p < 0.006$) and therefore, we can reject the null-hypothesis that these differences do not differ from the reference-category. Despite the difference between the underclass and the working-class, we got the expected results, that usually persons from higher classes are more into political subjects.

Female respondents spend nearly one day less (-0.82) on the internet to inform themselves about political topics than male respondents. This difference is statistically significant ($p < 0.000$).

[1] But we would not assume that the null-hypothesis is true, since the p-value is rather small (see Greenland et al., 2016).

Reasonably, respondents that talk about political topics also spend about half a day more (0.50) on the internet to inform themselves about political topics with every additional day that they spend discussing these topics with somebody else. This effect is statistically significant ($p < 0.000$) and therefore the null-hypothesis that this effect equals zero, can be rejected.

Respondents from East-Germany spend only a bit more time (0.16) on the internet to inform themselves about political topics than respondents from West-Germany. Nevertheless, this difference is statistical significant ($p < 0.000$), so that we can reject the null-hypothesis that the effect does not differ between these groups.

Respondents that have an educational tertiary degree, spend more time (0.70) on the internet to inform themselves about political topics, than respondents without such a degree. This effect is also statistical significant ($p < 0.000$) and therefore, we can reject the null-hypothesis that there is no difference between such respondents. This result is not unexpected, since higher educated people are usually more in political subjects.

σ_u shows the standard deviation of the residuals between groups (macro-level error term), in this case respondents, and amounts to 1.48, while the standard deviation of the individual-level error term σ_e has a value of 1.43. Furthermore, 52% of the variance is due to the difference across the respondents. It is the fraction of the variance of “Internet” that can be explained by the variation across the macro-level.

```
Random-effects GLS regression                   Number of obs     =     76,952
Group variable: lfdn                            Number of groups  =     21,084

R-sq:                                           Obs per group:
     within  = 0.0598                                         min =          1
     between = 0.4027                                         avg =        3.6
     overall = 0.3380                                         max =          6

                                                Wald chi2(11)     =   16393.09
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

internet	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age0	.0052149	.0008232	6.33	0.000	.0036015	.0068284
age1	-.0944356	.0537245	-1.76	0.079	-.1997336	.0108625
subjclass						
Unterschicht	0	(base)				
Arbeiterschicht	-.1468416	.0521216	-2.82	0.005	-.248998	-.0446852
untere Mittelschicht	.1827537	.0492568	3.71	0.000	.0862122	.2792953
mittlere Mittelschicht	.2039856	.0484178	4.21	0.000	.1090885	.2988827
obere Mittelschicht	.3713989	.0660758	5.62	0.000	.2418926	.5009051
Oberschicht	.7712931	.1884057	4.09	0.000	.4020247	1.140561
female						
male	0	(base)				
female	-.8210575	.024801	-33.11	0.000	-.8696665	-.7724484
talk	.5005306	.0045113	110.95	0.000	.4916886	.5093726
east						
no	0	(base)				
yes	.1602769	.0294881	5.44	0.000	.1024814	.2180724
uni						
no	0	(base)				
yes	.7018895	.0314231	22.34	0.000	.6403014	.7634777
_cons	2.039554	.0548538	37.18	0.000	1.932043	2.147066
sigma_u	1.4778417					
sigma_e	1.4292514					
rho	.51670971	(fraction of variance due to u_i)				

Tab. A – Random-effects GLS regression-model of internet, age, subjective class, sex, talk about politics, East- or West-Germany and tertiary degree

Task 2

Write the equation for that model as an error components model and as a random intercept model.

The default random intercept model (see “Random slope – Slide 2”):

$$y_{ij} = \beta_{0j} + \beta_1 x_1 + \beta_2 x_2 + \varepsilon_{ij}$$

That can also be written as default error component model:

$$y_{ij} = \gamma_{00} + \beta_1 x_1 + \beta_2 x_2 + \upsilon_{0j} + \varepsilon_{ij}$$

Therefore, the present model can be written down as random intercept model:

$$\begin{aligned} y_{ij} = \beta_{0j} &+ .005 \times age0 + (-.09) \times age1 + (-.15) \times subjclass_1 + .18 \times subjclass_2 \\ &+ .20 \times subjclass_3 + .37 \times subjclass_4 + .77 \times subjclass_5 \\ &+ (-.82) \times female + .50 \times talk + .16 \times east + .70 \times uni + \varepsilon_{ij} \end{aligned}$$

where “$subjclass_x$” shows the according dummy variables for the subjective class categories, in which $x(1, 2, 3, 4, 5)$ display the several categories. The dummy variables refer to the respective reference category “$subjclass_0$”, where respondents perceive themselves as being part of the underclass. Additionally, every respondent can only refer to one $subjclass_x$ or $subjclass_0$ but not for several perceived classes.

The corresponding error component model contains:

$$\begin{aligned} y_{ij} = 2.04 &+ .005 \times age0 + (-.09) \times age1 + (-.15) \times subjclass_1 + .18 \times subjclass_2 \\ &+ .20 \times subjclass_3 + .37 \times subjclass_4 + .77 \times subjclass_5 \\ &+ (-.82) \times female + .50 \times talk + .16 \times east + .70 \times uni + \upsilon_{0j} + \varepsilon_{ij} \end{aligned}$$

where υ_{0j} refers to the random error component for the deviation of the intercept of a respondent from the overall intercept and is a normal distribution with a mean of 0 and a standard deviation of 1.48. ε_{ij} refers to the individual error term that contains a standard deviation of 1.43.

Task 3

Allow one of your explanatory variables to have a random effect (remember the covariance between error terms). Interpret the model.

We allow the variable “talk”, the amount of days in the last week that the respondents talked about politics with someone, to have a random effect.

Concerning the covariance-structure between the error terms I would usually follow the example on “Random Slope – Slide 12-14”, where we can see that by adding the option “cov(unstructured)” the second “BLUP” (Slide 14) seems to follow a linear pattern. In this current model, a similar pattern cannot be achieved by the options “cov(independent/unstructured/identity)” but with the option “cov(exchangeable)” (Fig. 2).

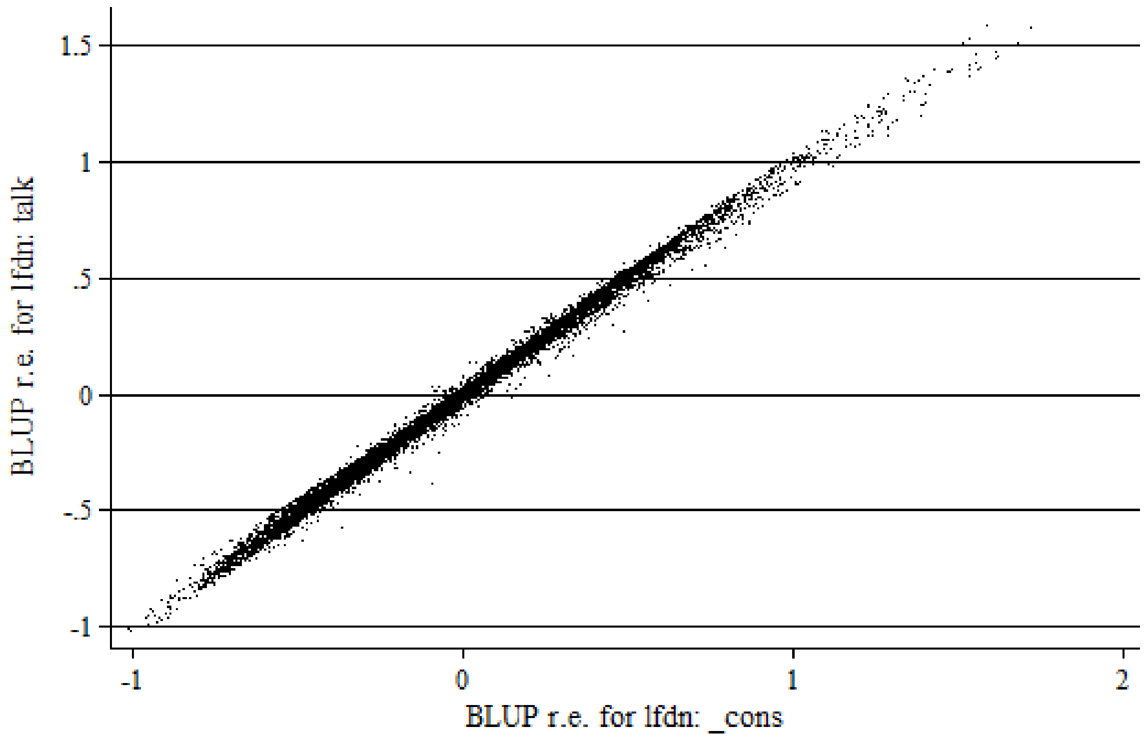

Fig. 2 – BLUP – Covariance of the error terms with option “cov(exchangeable)”

According to Rising (2013, p. 17) an exchangeable covariance between the error terms is useful for “nested intercept-only models”, wherefore despite the observed structure of figure 1 an unstructured covariance will be assumed, that is apparently “typical for slope models”.[2]

[2] I am well aware of the fact, that not everything that is published on the internet is true or should be taken seriously. But in this case, it is a presentation by the StataCorp LP, wherefore I assume a certain level of trustworthiness.

Analysis (Tab. B): To include a random effect of an explanatory variable a mixed-effects ML regression-model is used, which contains 76.952 observations over 21.084 unique respondents. On average, every respondent participated on 3.6 of 6 waves. The “prob > chi2”-test tells us, that we can reject the null-hypothesis that every coefficient equals zero.

```
Mixed-effects ML regression                     Number of obs     =     76,952
Group variable: lfdn                            Number of groups  =     21,084

                                                Obs per group:
                                                              min =          1
                                                              avg =        3.6
                                                              max =          6

                                                Wald chi2(11)     =   14036.64
Log likelihood = -154767.27                     Prob > chi2       =     0.0000
```

internet	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age0	.0054847	.0008209	6.68	0.000	.0038757	.0070937
age1	-.0938595	.0539843	-1.74	0.082	-.1996668	.0119478
subjclass						
Arbeiterschicht	-.1450313	.0521269	-2.78	0.005	-.2471981	-.0428644
untere Mittelschicht	.176165	.0492801	3.57	0.000	.0795779	.2727522
mittlere Mittelschicht	.1979582	.0484398	4.09	0.000	.1030179	.2928986
obere Mittelschicht	.3580584	.0662968	5.40	0.000	.2281192	.4879976
Oberschicht	.7455577	.1921764	3.88	0.000	.3688989	1.122216
female						
female	-.8203235	.0248044	-33.07	0.000	-.8689392	-.7717079
talk	.5290666	.0052184	101.38	0.000	.5188387	.5392945
east						
yes	.1567557	.0295462	5.31	0.000	.0988463	.2146651
uni						
yes	.6994012	.0314955	22.21	0.000	.6376711	.7611313
_cons	2.016466	.0549429	36.70	0.000	1.90878	2.124152

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
lfdn: Unstructured				
sd(talk)	.2817855	.0070782	.2682485	.2960056
sd(_cons)	1.5943	.0158599	1.563516	1.62569
corr(talk,_cons)	-.3617733	.0185019	-.3974768	-.3249762
sd(Residual)	1.446926	.0046269	1.437886	1.456023

```
LR test vs. linear model: chi2(3) = 24132.84          Prob > chi2 = 0.0000
```

Tab. B – Mixed-effects ML regression model of internet, age, subjective class, sex, talk about politics as random slope, East- or West-Germany and tertiary degree

The constant represents male respondents that are 80 years old, see themselves in the underclass, come from West-Germany, do not talk about political issues and have no educational tertiary degree amounts to 2.02. Thus, respondents with these characteristics inform themselves on the internet about political topics about 2 days in the previous week.

As we see, neither the constant nor the coefficients actually differ from the previous model (Tab. A). Some of the differences are due to the alternative estimation procedure, which was in this case a maximum likelihood estimation. Therefore, I will pass the interpretation of the coefficients and focus on the interesting part, the random-effect parameters.

The random-effects parameters show that there is indeed some variation over the respondents concerning the amount of days talking about political topics with someone. The standard deviation of this random slope amounts to .28 and thus, the various slopes differ from each other. The standard deviation of the macro-level error term enhances a bit to 1.59. The micro-level error-term amounts to 1.45 and remains accordingly at a similar value. The correlation between talk and the constant amounts to -0.36 and thus, the random slope seems to be worthy.

The likelihood-ratio vs. linear model test confirms that not all respondents have the same constant, since the according null-hypothesis, that all have the same constant, can be rejected (Prob > chi^2 = 0.0000). Thus, a random-intercept model was reasonable.

Task 4

Write the equation for that model as an error components model and as a random intercept model.

The default random intercept model with a random slope (see “Random slope – Slide 4”):

$$y_{ij} = \beta_{0j} + \beta_{1j}x_1 + \beta_2 x_2 + \varepsilon_{ij}$$

That can also be written as default error component model:

$$y_{ij} = \gamma_{00} + \gamma_{10}x_1 + \beta_2 x_2 + \upsilon_{0j} + \upsilon_{1j}x_1 + \varepsilon_{ij}$$

The present model can be written down as random intercept model:

$$
\begin{aligned}
y_{ij} = \ & \beta_{0j} + .006 \times age0 + (-.09) \times age1 + (-.15) \times subjclass_1 + .18 \times subjclass_2 \\
& + .20 \times subjclass_3 + .36 \times subjclass_4 + .75 \times subjclass_5 \\
& + (-.82) \times female + \beta_{9j} \times talk + .16 \times east + .70 \times uni + \ \varepsilon_{ij}
\end{aligned}
$$

The corresponding error component model contains:

$$
\begin{aligned}
y_{ij} = \ & 2.02 + .006 \times age0 + (-.09) \times age1 + (-.15) \times subjclass_1 + .18 \times subjclass_2 \\
& + .20 \times subjclass_3 + .36 \times subjclass_4 + .75 \times subjclass_5 \\
& + (-.82) \times female + .53_0 \times talk + .16 \times east + .70 \times uni + \upsilon_{0j} \\
& + \upsilon_{9j} \times talk + \ \varepsilon_{ij}
\end{aligned}
$$

where υ_{0j} refers to the random error component for the deviation of the intercept of a respondent from the overall intercept and is a normal distribution with a mean of 0 and a standard deviation of 1.59. υ_{9j} refers to the random error component for the deviation of the random slope from the variable "talk" and is a normal distribution with a mean of 0 and a standard deviation of .28. ε_{ij} refers to the individual error term that contains a standard deviation of 1.45.

Task 5

Within a person the errors may be auto-correlated. Investigate that and report your decision.

The auto-correlation within a person can be investigated by specifying the structure of the residual errors within the lowest-level groups (see help-file "mixed"). Since we can observe unequally spaced and noninteger time values, a generalization of an auto-regressive covariance as exponential structure seems reasonable.

The coefficients do not really differ from a mixed-effects ML regression-model with the same variables without the exponential covariance structure. Just the constant seems to increase from 2.04 to 2.07. $\rho = \ .15$ indicates that 85% of the correlation between the error terms of the previous observations within a respondent with the current one disappears (Tab. C).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
lfdn: Identity				
sd(_cons)	1.475456	.0110017	1.454049	1.497177
Residual: Exponential				
rho	.1473776	.006419	.1352354	.1604077
sd(e)	1.537481	.0055584	1.526625	1.548414

Tab. C – Random-effects parameters of a mixed-effects ML regression model of internet, age, subjective class, sex, talk, East- and West-Germany and tertiary degree, where the structure of the residual errors within the lowest-level group is assumed exponential

Task 6

Make a multilevel model explaining whether or not you know what you are going to vote (you'll need to make a new variable based on the variable intention). Interpret that model.

<u>Preparation</u>: While investigating the relationship between the dependent variable voting intention and the independent variable age, it catch one's eye that there is a probable influential observation at the age of 88 (Fig. 3). To avoid a too pronounced influence of the respondents with the ID ("lfdn") 1357 and 17924, they are both excluded from the model.

<u>Analysis (Tab. D)</u>: The mixed-effects logistic regression model contains 67.868 observations over 19.948 unique respondents. On average, every respondent participated on 3.4 of 6 waves. The chi²-test shows that none of the coefficients, in this case odds ratios, are equal zero ($p < 0.000$). Furthermore, the model was estimated with 34 Integration points, since the coefficients were still varying until this amount of integration points ("quadchk").

Among male respondents from West-Germany, that are 40 years old, perceive themselves in the underclass, have no tertiary degree, talk about politics 3 days a week, inform themselves about politics on the internet, paper or[3] tv 3 days a week and were questioned one year before the federal election we can expect 15.99 respondents, that know what to vote, for every respondent that does not.

[3] "or" as including or.

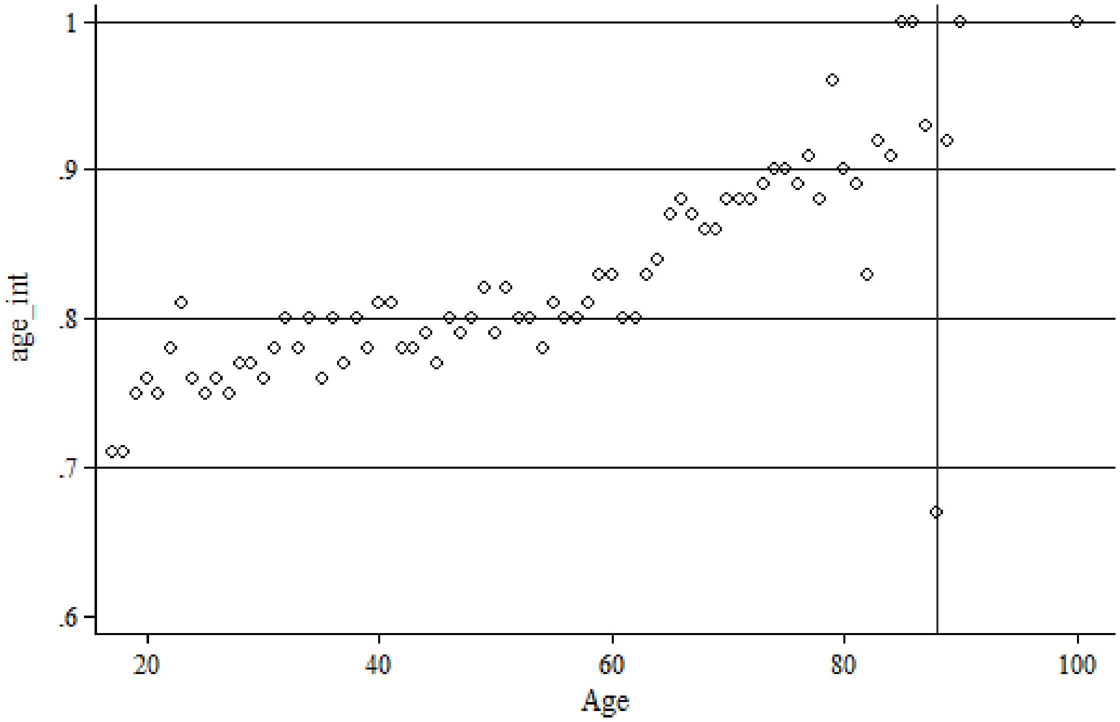

Fig. 3 – Equities of voting intention per age

These odds increase by almost 1% with every additional year that the respondents age and is statistically significant ($p < 0.000$), which means, that the null-hypothesis, that the odds equals zero, can be rejected. Therefore, we can assume that older respondents rather know what to vote.

The odds increase by 17% with every additional day in a previous week that the respondents talked to someone about political topics. These odds are also statistically significant ($p < 0.000$), wherefore we can reject the null-hypothesis, that the odds equal zero. Thus, talking about politics seems to have a relationship with the odds of knowing what to vote.

The odds increase by 12% with every additional day in a previous week that the respondents informed themselves about politics on the internet. These odds are also statistically significant ($p < 0.000$), wherefore we can reject the null-hypothesis, that the odds equal zero. Thus, informing themselves about politics on the internet seems to have a relationship with the odds of knowing what to vote.

The odds increase by 4% with every additional day in a previous week that the respondents informed themselves about politics on paper. These odds are also statistically significant ($p < 0.000$), wherefore we can reject the null-hypothesis, that the odds equal zero. Thus, informing themselves about politics on paper seems to have a weak relationship with the odds of knowing what to vote.

The odds increase by 9% with every additional day in a previous week that the respondents informed themselves about politics over the tv. These odds are also statistically significant ($p < 0.000$), wherefore we can reject the null-hypothesis, that the odds equal zero. Thus, informing themselves about politics on tv seems to have a relationship with the odds of knowing what to vote.

In comparison to respondents that perceive themselves as part of the underclass, the odds to know what to vote for increases by 2% for respondents that see themselves as part of the working-class. But this difference is not statistically significant ($p = 0.87$) and thus the null-hypothesis, that there is no difference between these subjective classes, cannot be rejected. The odds increase by 23% for respondents that see themselves as part of the under middleclass in comparison to the reference-category. This effect is not statistically significant ($p = 0.9$) and therefore we cannot reject the null-hypothesis that there is no difference. The odds to know what to vote for increase by 26% if the respondents perceive themselves as part of the average middleclass in comparison to the reference-category. This effect is not statistically significant ($p = 0.06$) and therefore we cannot reject the null-hypothesis that there is no difference. For Respondents of the upper middleclass the odds increase even by 69% to know what to vote for in comparison to the reference-category. This difference is even statistically significant ($p < 0.003$) and thus, we can reject the null-hypothesis, that the effects do not differ from the reference-category. The odds increase by 40% if the respondent perceive themselves as part of the upperclass in comparison to respondents that see themselves as part of the underclass, but this difference is not statistically significant ($p = 0.51$) and therefore, we cannot reject the null-hypothesis that these odds do not differs from the reference-category.

The odds of knowing what to vote decrease by 69% if the respondents are female in comparison to male respondents. This difference is statistically significant ($p < 0.000$), wherefore we can reject the null-hypothesis that the odds equal zero.

The odds of knowing what to vote increase by 14% for respondents from East-Germany in comparison to respondents from West-Germany. This difference is not statistically significant ($p = 0.08$) and thus, we cannot reject the null-hypothesis.

The odds of knowing what to vote decrease by 5% for respondents that obtain a tertiary degree in comparison to respondents without such an educational degree. But this difference is not statistically significant ($p = 0.50$) and therefore we cannot assume that people without tertiary degree rather know what to vote than people with a tertiary degree.

In comparison to the first wave, one year before the federal election, the odds increase by 99% that the respondents in the second wave, four months before the federal election, know what to vote. Two months before the federal election the odds increase by 134% that the respondents know what to vote, in comparison to the reference category. One month before the federal election the odds increase by 161% that the respondents know what to vote, in comparison to the reference category. Three weeks and one week before the federal election the odds increase even by 253% and 472% that the respondents know what to vote in comparison to the reference category. All these odds in comparison to the reference category are statistically significant ($p < 0.000$), wherefore we can reject the null-hypotheses that any of these mentioned differences equals zero. Therefore, these results match the expectations that the closer the federal elections are, the more increases the odds that respondents know what to vote. In this case almost exponential.

${\sigma^2}_u$ shows the variance of the residuals between groups, in this case respondents, and amounts to 9.48, which seems rather high. Accordingly, there seems to be a lot of variance of knowing what to vote between the respondents.

The likelihood-ratio vs. logistic model test confirms that not all respondents have the same constant, since the according null-hypothesis, that all have the same constant, can be rejected ($Prob > chi^2 = 0.0000$). Thus, a random-intercept model was reasonable.

```
Mixed-effects logistic regression               Number of obs     =     67,868
Group variable:            lfdn                 Number of groups  =     19,948

                                                Obs per group:
                                                              min =          1
                                                              avg =        3.4
                                                              max =          6

Integration method: mvaghermite                 Integration pts.  =         34

                                                Wald chi2(18)     =    1926.64
Log likelihood = -24654.677                     Prob > chi2       =     0.0000
------------------------------------------------------------------------------------------------
                                   intent | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------------------+-----------------------------------------------------
                                   age_cc |   1.008087   .0021256     3.82   0.000     1.003929    1.012261
                                   talk_c |   1.171741   .0160512    11.57   0.000     1.140699    1.203627
                               internet_c |   1.116734   .0116517    10.58   0.000     1.094129    1.139806
                                  paper_c |   1.037204    .009701     3.91   0.000     1.018364    1.056393
                                     tv_c |   1.093315   .0107201     9.10   0.000     1.072505    1.114529
                                          |
                                subjclass |
                              Unterschicht |          1  (base)
                          Arbeiterschicht |   1.021995    .132021     0.17   0.866     .7933971    1.316457
                     untere Mittelschicht |   1.233993    .150971     1.72   0.086     .9708983    1.568381
                   mittlere Mittelschicht |   1.257447   .1516614     1.90   0.058     .9927174    1.592771
                      obere Mittelschicht |   1.690856   .2813412     3.16   0.002     1.220325    2.342814
                              Oberschicht |   1.399399   .7036045     0.67   0.504     .5223549    3.749018
                                          |
                                   female |
                                     male |          1  (base)
                                   female |   .3098505   .0196876   -18.44   0.000     .2735695    .3509432
                                          |
                                     east |
                                       no |          1  (base)
                                      yes |   1.135592   .0827475     1.75   0.081     .9844587    1.309927
                                          |
                                      uni |
                                       no |          1  (base)
                                      yes |   .9485751   .0737494    -0.68   0.497     .8145033    1.104716
                                          |
                                   n_wave |
             Wave 1 - 2016 - 1 Jahr vor BtW |          1  (base)
          Wave 2 - 2017 - 4 Monate vor BtW |   1.988128   .0984959    13.87   0.000     1.804156     2.19086
          Wave 3 - 2017 - 2 Monate vor BtW |   2.333841   .1197792    16.51   0.000     2.110499    2.580817
           Wave 4 - 2017 - 1 Monat vor BtW |   2.612187    .132138    18.98   0.000     2.365626    2.884447
          Wave 5 - 2017 - 3. Woche vor BtW |   3.525429   .1901512    23.36   0.000     3.171762    3.918531
          Wave 6 - 2017 - 1. Woche vor BtW |   5.718058   .3520276    28.32   0.000     5.068098    6.451372
                                          |
                                    _cons |   15.98682   1.986131    22.31   0.000     12.53177    20.39443
------------------------------------------+-----------------------------------------------------
lfdn                                      |
                                var(_cons)|   9.479481   .3037829                       8.902391    10.09398
------------------------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 12577.48    Prob >= chibar2 = 0.0000
```

Tab. D – Mixed-effects logistic regression model of voting intention, centred age, centred talk, centred internet, centred paper, centred tv, subjective class, sex, East- or West-Germany and tertiary degree

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