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Emotional Attachment to Germany and its Effect on the Support for Redistribution in Germany

(A Replication of Johnston et al. Study "National Identity and Support for the Welfare State)

DESCRIPTION OF STUDY AND CONSIDERATION ON ADAPTION

Description of Richard Johnston's, Keith Banting's, Will Kymlicka's and Stuart Soroka's study: "National Identity and Support for the Welfare State"

In this paper I will try to replicate Johnston et al. (2010) study on nationality and the welfare state. In detail Johnston's study is focused on how national identity influences the support for a welfare state system. In the 2010 study Johnston and his colleagues researched this effect at the national level in Canada using data stemming from fieldwork conducted between 2002 and 2003 by the second wave of the Equality, Security and Community survey (Johnston et al. 2010: 357) . Their driving motivation for the study was the growing in equality in the world while at the same time the welfare state got weaker. Their goal for the study is to test if a shared national identity is beneficial for positive attitudes towards the welfare state (Johnston et al. 2010: 349).

The existing research, as states by Johnston and his colleagues, between which the study is situated, tries to explain the welfare state using economic interests and the implications of ethnic diversity. They draw heavily on works by David Miller who argued that people with different economic situations will have different attitudes towards the welfare state as the welfare state usually redistributes the resources vertically and that a national identity could help in sustaining the welfare state despite this well tested mechanism (Johnston et al. 2010: 351-353). Miller, as presented by Johnston et al., argues that sympathy and trust towards other conationals especially facilitates this effect and helps to sustain the national identity (Johnston et al. 2010: 352). If a strong sense of nationhood exists within a country then economic discrepancies should matter less, because the people within the nation should feel a stronger obligation towards one another. This is especially true if there is interpersonal trust between the people as well as when the people trust in the government. However, nationhood can also be an excluding force, and this can lead to the national identity facilitating anti-immigration tendencies within the nation

(Johnston et al. 2010: 354). Johnston and his colleagues therefore conduct a regression analysis in which they test if the support for the welfare state is higher the higher the national identity is. Then they introduce economic factors, as these are well researched causes for lower support of the welfare state, and then control the regression using indicators for trust and anti-immigration tendencies (Johnston et al. 2010: Table 1).

Thoughts and challenges for the adaption to Germany

Germany is quite different from Canada. We do have a comparatively strong welfare state for example universal healthcare; however, it is split into essentially two classes, unconditional unemployment support and basically free education. National identity is relatively low in Germany. The past made it for some people difficult to express their national support as right wing extremism is still a problem and persons often do not want to be associated with them. As well as the divide between east and west Germany.

East and West Germany even after over 30 years of being united still have vast structural differences and a mutual feeling is not a given. Infrastructure as well as wages are better in West Germany. The GDP per capita is also higher and the unemployment rate is lower than in East Germany. This could lead to a less extensive national identity between the two parts and further local identities as East Germany could feel disadvantaged and sour towards the West. For example, local identities sometimes supersede the national identity as in the case of Bavaria who still have their own version of the CDU. This divide is not captured in the dataset I will be working with but has to be considered.

The national identity in Germany could also be held back by the efforts of the EU to create a EU transnational identity. This double attempt could lead to Germans feeling more pulled towards the EU than Germany. The double layered problematic only gets more complicated if we look at one of the concepts mentioned by Johnston et al. to further national identity: Trust.

In particular the trust in one's government, interpersonal trust won't be affected by this. Because Germany is under EU jurisdiction the individual must put trust into 2 governments to fully feel comfortable with them instead of one in Canada. Local governments can be excluded from this equation as they are also present in Germany.

Germany has more than double the citizens and has therefore directly a higher challenge of sustaining a national identity. Furthermore, about 20 million people in Germany either are immigrants or the children of immigrants. This equates to about 12% of German citizens being immigrants and including their children to about 25% of the population (Tatsachen über Deutschland 2021). This is a lower figure of people born outside the country than the 20% of Canada (Johnston et al. 2010: 356) and historically speaking was Germany not a destination of immigration and the national identity was not constructed around a heterogeneous set of people. These two factors could severely dampen the positive attitudes towards immigration.

Immigration is an interesting topic compared to Canada, as Canada was built by immigrants and a national identity of diversity reflects that. Germany was not built by immigrants. Germans have a different view on different types of immigration. Immigration from Non-EU countries is less accepted as immigration from EU member countries. The EU has tried to construct a EU-Identity and people in Germany feel more and more like EU-citizens. Which would also make EU immigration less of a dividing factor and rather provide a different type of social glue. Furthermore, Germans have more in common with e.g., the French in contrast to someone who enters the country from the middle east.

Germans in 2018 (year of the ESS9) felt mistreated or overwhelmed by the immigration crisis starting in 2015 and still not being resolved in 2018. This could trigger more extreme anti-immigration sentiments than would have been found before the crisis, especially against immigrants from outside the EU who come from middle eastern countries. These sentiments will be present in the dataset.

Research Agenda

The goal of this study is to test the hypothesis of Johnston and his colleagues for a different country. As they stated: "If national identity and the welfare state are mutually supportive in Canada [...], the obvious question is wether this experience is distinctive or whether similar patterns should emerge elswhere." (Johnston et al. 2010: 368). My aim it to go after this call for action. I will follow their steps as closely as possible. Some obvious limitations in terms of data are present as will be discussed in detail further below. My dataset does not include suitable variables for the healthcare and pensions argument advanced in their study. I will instead focus on the redistribution aspect of their study. An interesting difference between Canada and Germany which will influence the study is the fact that Germany is a member of the EU. Therefore, my paper will differentiate between trust in local government and EU government as well as immigration from within the EU and outside of the EU.

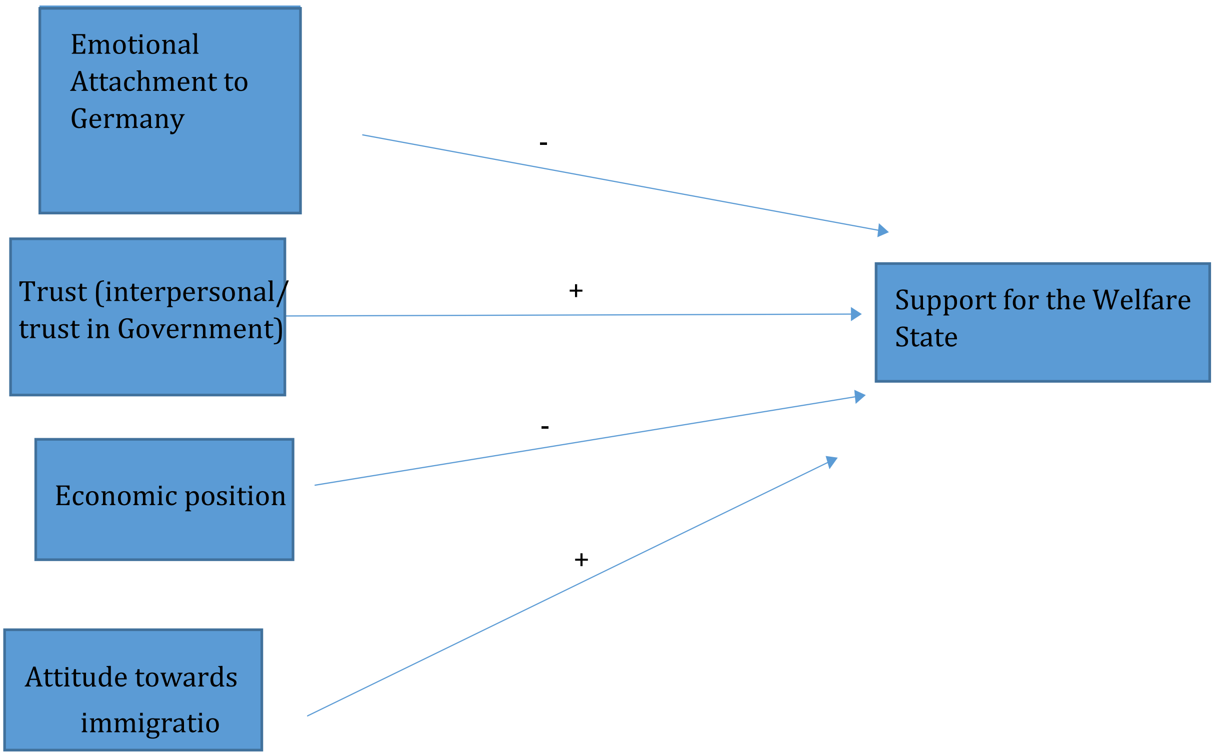
The biggest differentiating factor will be my dependent variable as mine does not capture national identity and therefore my research question will be:

Does emotional attachment to Germany undermine support for redistribution?

H0: Emotional attachment to Germany does not undermine support for redistribution.

H1: Emotional attachment to Germany does undermine support for redistribution.

Causal links



DATA AND METHOD

Description of dataset

For this replication and adoption, I will be using the 9th Round of the European Social Survey which was conducted in 2018. In detail I will be using the Version 3.1 of the dataset as well as the codebook linked to this version. The dataset was released on the 17 of February 2021 and the codebook 2 days later. I do not use the full dataset with every country in which the survey was conducted, instead I will be using the subset for Germany as I will solely focus on Germany in this replication. In the German subset of the ESS9 are in total 2358 observations across 572 variables. Many of those are not usable as they correspond to other Countries and are filled in with NA in the German subset. After cleaning and managing the data I am left with 1967 total observations. The method I used for cleaning the data was listwise deletion. I only dropped 391 observations (about 16.58% of the original observations) which does not call for measures like data interpolation like Johnston and his colleagues used to fill their income variable.

Description and evaluation of variables used/omitted

The summary table (Table 1) has across all the different variables the same number of observations because I used list wise deletion for data cleaning and the summary table is based on the listwise deleted data.

Table 1

Variable	Variable label	Obs	Mean	SD	Min	Max
gincdif_reversed	Support for redistribution	1967	3.850	0.994	1	5
atchctr_m	Emotional Attachment to Germany	1967	7.515	2.167	0	10
inter_trust	Interpersonal Trust	1967	5.713	1.649	0	10
gov_trust	Trust in Government	1967	4.546	2.182	0	10
trust_EU_gov	Trust in EU Government	1967	4.575	2.377	0	10
hinctnta_m	Total Household Income	1967	6.123	2.804	1	10
AGE	Age	1967	50.010	18.387	15	90
female	Female	1967	0.470	0.499	0	1
trade_dummy	Member of Trade Union	1967	0.129	0.335	0	1
unemployed_dummy	Work Status: Unemployed	1967	0.034	0.180	0	1
work_status_other	Worl Status: Other	1967	0.400	0.490	0	1
imueclt_m	Immigrants enrich Culture	1967	6.015	2.509	0	10
allow_immigrants	Anti-Immigration	1967	1.866	0.643	1	4
allow_immigrants_out_EU	Anti-Immigration, Non European	1967	2.161	0.807	1	4
education_dummy	Completed Secondary Education	1967	0.311	0.463	0	1

Dependent variable.

The effect to measure is the attitudes towards redistribution and how different effects influence this attitude, namely national identity. In the ESS9 there is only one suitable variable for the question of redistribution: gincdif. The question posed to the individual reads: “Government should reduce differences in income levels.” The variable used is not an index derived from a set of questions as Johnston et. al. was able to generate but still the best fit within the dataset and the question clearly reflects one key aspect of redistribution. Furthermore, the variable corresponds to the 6th question used by Johnston et al. to generate their index. Even though they only provided as answers "Agree" or "Disagree", but more precision on the variable that I will be using is not an issue. The one dividing factor is that the wording of their question asks whether the government "must do MORE". This is clearly a difference from the question of the ESS9 which only asks if the respondent thinks that the government should do anything at all about income differences. Both the wording of the question to generate my variable and Johnston et. al.'s is neutral.

The variable I use is scaled from 1 to 5, one being "Agree Strongly" and 5 "Disagree strongly" with 3 setting the neutral. The direction of the variable is counterintuitive for the analysis. If the direction stays like this a negative coefficient would be a positive relations ship towards redistribution. I reversed the variable for ease of interpretation later and in the summary table (Table 1) the reversed gincdif is displayed.

The mean of 3.85 indicates that on average the people are more of the opinion that the government should reduce the differences in income in Germany as 3 is the neutral point and 3+ the positive one. Even when considering the standard deviation of 0.994 the lower bound is only just below 3.0 and reassures that most of the people are positive towards redistribution organized by the government. The variable is of ordinal level and will be treated as a quasi-continuous variable as the point increase does represent a measurable increase in positive attitude towards redistribution.

Identity.

The concept used by Johnston et al. to explain the support for redistribution is national identity. Again, they derive a summary indicator based on multiple questions. I am not able to mimic this as the ESS9 only provides one suitable variable for the task. Furthermore, the variable that

I will be using does not directly ask the respondent about his national identity but asks how emotionally attached he/she/them are to Germany. This is different from Johnston et al.'s index but emotional attachment as well as national identity are both a form of link to the country the respondent is living in. Therefore, the effects of mentioned concepts should be similar and comparable. No normative claim about what it means to be emotionally attached to Germany is made in the wording of the posed question like the questions used by Johnston et al.

The variable (atchctr) is scaled from 0 to 10 with 10 being the most emotionally attached and 0 the least. Level of measurement is ordinal but as the dependent variable will be treated as a quasi-continuous variable. The mean of 7.515 tells us that on average the German respondent is quite emotionally attached to Germany (the average respondent is also 50 years old which could influence the result). Standard deviation is not too special and about the same as the dependent variable.

Trust indicators.

Johnston et al. use to different indexes for trust. First the interpersonal trust index and second the trust in government. The variables used to generate the indexes I am using are different in wording but represent the same concepts. One key difference is that I will be differentiating between trust in the national government and the trust in the EU government because Germany is within the jurisdiction of the EU and therefore this must be considered.

The questions used by Johnston et al. to create the trust index are different than mine. However, the same concept of trust is captured within the ones as I am using as well as the ones used by them. The variables used by me to create the interpersonal trust index (ppltrst, pplfair, pplhlp) all do represent a slightly different aspect of the concept of trust. The question about trust is directly asked plus whether the respondent thinks that most people try to be fair/most people try to be helpful. Every one of these variables is scaled 0 to 10 (10 being the fairest etc.), have the same direction, similar wording and are quasi-continuous variables (ordinal scaled) and therefore are suitable to put into one index without any adjustments. The derived index inter_trust has a mean of over 5 meaning that on average the Germans do trust each other more than they distrust each other, even though the effect is marginal with 0.7 over neutral (5).

Johnston et al. use a "thermometer" or feeling of warmth towards the government and a question that asks whether the government does what is "right". None of these criteria can be filled by the variables I will be using, but mine do not carry any subjective connotations like "right" and directly ask whether the respondent has trust in the parliament, politicians, or EU-parliament. Furthermore, the sub concept of how the person relates to the government is still the same.

The variables capturing trust in the national parliament and politicians will be put into one index (gov_trust). Both these are scaled 0 to 10, have the same direction (10 being the most trust), and are quasi continuous variables. Trust in the EU Parliament will be left in a separate variable but has the same properties as the two other variables. Both of the items have a mean slightly below the neutral point (5) which means Germans distrust the governments under which they live slightly.

Economic position indicators.

I can only partially satisfy the "workhorse model" employed by Johnston et al. and will be dropping "Likelihood of Job loss" and "Economic Evaluations (worse)" because in the ESS9 no suitable or similar in concept variable exists. Every other variable will be kept; however, I do not use dummy variables for the respondents age group as a measure of age. Instead, I use age as a pure number because the interpretation is easier.

Household income is not measured by a number instead deciles are used in the ESS9. The variable is scaled from 1 to 10 and the level of measurement is interval. 1 corresponds to the first decile (lowest earning households) and 10 to the 10^{th} decile (highest earning households). Each number therefore represents 10% of respondents. A measure of household income does not significantly differ from individual income, used by Johnston et al., because individuals living in a wealth household and having low income themselves, e.g. spouse has a high income, will still have similar attitudes to other high income earners but respond with a low value on individual income.

Whether the respondent is part of a labor union, unemployed, not part of the workforce (home makers, students, disabled, retired) or female are all represented by dummy variables and are an exact replication of the variables deployed by Johnston et al. Education is mentioned in the appendix of the study by Johnston and his colleagues but not included in the regression table. I will include education as a dummy variable which captures whether the respondent has completed at least secondary education (Abitur) or not. This is inline with the text in the appendix. There are no anomalies in the mean or standard deviation of these dummy variables except for the mean on household income being 6.123 which indicates that this subsample has slightly more people who belong to the upper 50% of households. Age is scaled from 15 to 90 (min/max of the sample) and is ratio scaled in my analysis as opposed to dummy variables for the reasons noted above. (One thing to note is that my "unemployment_dummy" and "work_status_other" are derived from variables which only ask the respondent about the last 7 days as opposed to the typical 12 months questions in Johnston et al.'s dataset.)

The major difference between my model and Johnston and colleagues is that I do not derive a summary indicator for the "workhorse model" and rather put the variables directly into the full and partial models. I do this as I want to investigate the relation between each item and attitudes towards redistribution in detail.

Immigration indicators.

Johnston and his colleagues use anti-immigration sentiments to control the identity/economic position model. As they also do with trust. They use two indicators for their analysis. First an item which captures whether people think "recent immigrants" want to "fit in" and whether the country is accepting to many or too few immigrants. Johnston and colleagues admit that "recent" might have a racial subtext. Both concepts can't be identically fulfilled by the data I am using. For the "fit in" question I use a variable (imueclt) which asks the respondent if "County's cultural life undermined or enriched by immigrants.". The wording of the variable makes it in essence similar because "undermining" could also be seen as not participating in the cultural life and therefore not trying to "fit in". The variable is scaled 0 to 10 and will be treated as a quasi-continuous variable throughout the analysis.

The two variables (imsmetn, imdfetn) used to create an index about the respondent opinion whether Germany allows too many or too few immigrants from the same or different group as the majority are both scaled 1 to 4 and do not have a neutral point. The wording is identical and an index can be created without any hurdles.

One deviation form the study of Johnston et al. has to be made here. In the ESS9 one variable (impcntr) is provided which represents the attitudes towards immigrants from poorer countries outside Europe. This variable is relevant to include because since the refugee crisis staring in 2015 the non-European immigration is seen differently by many citizens of the EU and this question directly aims at this problem. The variable is coded the same way as the other two anti-immigration variables and has the same direction.

In general Germans think immigration enriches the cultural life because the mean of imueclt_m is above 5 (the neutral point of the variable). As expected Germans are not opposed to immigration as a whole, seen by the 1.866 average on anti-immigration, however they are slightly opposed to immigration from poorer countries outside Europe, as represented by the 2.161 average on non-European anti-immigration.

Method used

The analysis was conducted in R (R Core Team 2021, Version 4.1.0) and different packages listed in the bibliography below. For data cleaning, as stated above, I have used listwise deletion. Not many observations were dropped, and it is not necessary to resort to data interpolation like Johnston and his colleagues used on their income variable.

For the analysis I will use an OLS-Regression. The dependent variable does not need a logistic regression and the variables used all conform to the standard needed to use an OLS-Regression. At first, I will do a bivariate regression focusing on the emotional attachment to Germany and how only this variable affects redistribution. Afterwards I am going to emulate the exact same regression as used by Johnston and his colleagues in their study. I will, contrary to the original study, include a full model with all independent and control variables included, as this should give the most accurate results and is an attempt to explain as much of the variation of the dependent variable as possible.

ANALYSIS

To note before reading the analysis is that because the dependent variable is only scaled from 1 to 5 means that even small values such as these in the regression table below represent quite telling jumps in the support for redistribution. This must be kept in mind while reading the analysis of the regression output.

The bivariate model tells us that there is a significant correlation between the emotional attachment and the idea that the government should reduce income differences (redistribution) as the p-value is under 0.01. On average for each point gained on the emotional attachment variable the respondent scores 0.031 lower on the redistribution variable. The intercept (y-axis point) tells us that if the respondent has no emotional attachment to Germany the respondent scores 4.082 on redistribution variable. Emotional attachment to Germany has a persistent negative effect per point gained across all models and the effect keeps its statistical significance throughout the models. In the full model the effect is reduced to -0.029.

When the economic indicators are introduced to the regression the significance of the emotional attachment persists and essentially stays the same. Household income has a similar negative effect meaning for each higher decile the respondent scores 0.033 (or 0.034 in the trust model) points lower on the dependent variable. This effect is expected and significant in all models.

For each year of age the respondent gains they are more supportive of redistribution. Each year does not increase the attitude by a lot but when considered that the average age of the respondents is 50 the effect suddenly pushed the dependent variable 0.1 points towards more support for redistribution in the strictly economic position model or even 0.15 points all the other models. In the full model and the model which controls for anti-immigration tendencies the effect gains statistical significance.

If the respondent is female they are more likely to support redistribution. In every model the female variable has statistical significance and increases the support between 0.130 (in the full model) to 0.159 (economic indicator model). About the same can be said for the trade union variable. Between 0.161 and 0.155 point will be gained on average if the respondent is part of a trade union. The employment status as well as whether the respondent is not part of the workforce do not gain any statistical significance in any of the models in table 2. Whether the respondent has completed secondary education has a significant effect on the model, with the exception being the economic model controlled by trust (model 3). On average the respondent is between 0.1 and 0.124 less supportive of redistribution if they have completed secondary education. This is not unlikely as higher education usually means higher pay.

In the model which controls for trust every trust indicator has statistical significance, however interpersonal trust loses its significance in the full model. The other two indicators retain their significance levels. It is very interesting that the interpersonal trust losses all its significance in the full model. The trust in the national government reduces the support for redistribution between 0.046 points and 0.051 for every point gained on the the 0 to 10 index. Interestingly has the trust in the EU-parliament the reversed effect. For every point more trust in the EU parliament the respondent gains on average 0.038 or 0.033 points. Therefore, people who are more supportive of the EU are in fact also more supportive of redistribution as opposed to people who trust their national government in Germany.

If the respondent is of the opinion that immigrants enrich the cultural life in Germany, they are more supportive of redistribution. Interestingly at the same time people who think Germany should allow less immigrants into Germany are also more likely to support redistribution. Both effects are significant. As expected, the effect is different if the question concerns immigrants from outside the European continent. If the respondent is opposed to immigrants from poorer countries coming to Europe, then the respondent scores on average less likely to support redistribution.

All intercepts are above 3 (neutral point of the dependent variable) which indicates that the if all the independent and control variables would equal 0 the average respondent would still be in support of redistribution. Furthermore, even though every model returns good results in terms of significance for the individual variables the variance of the dependent variable maxed out at 4.9%. In the bivariate model the explained variance is even as low as 0.5%.

The null hypotheses can be rejected as the effect of emotional attachment to Germany on the attitudes towards redistribution is clearly negative and statistically significant in all models. H1 will therefore be accepted and my research hypotheses that emotional attachment to Germany undermines support for redistribution is confirmed.

Table 2

Johnston et. al. models plus full model

	Dependent variable:				
	Redistribution				
	(1)	(2)	(3)	(4)	(5)
Emotional Attachment to Germany	-0.031***	-0.032***	-0.032***	-0.032***	-0.029***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Total Household Income		-0.033***	-0.034***	-0.033***	-0.033***
		(0.009)	(0.009)	(0.009)	(0.009)
Age		0.002*	0.003*	0.003**	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
Female		0.159***	0.144***	0.143***	0.130***
		(0.045)	(0.045)	(0.045)	(0.045)
Member of Trade Union		0.159**	0.161**	0.155**	0.155**
		(0.066)	(0.066)	(0.066)	(0.066)
Work Status: Unemployed		-0.008	-0.006	-0.014	-0.018
		(0.126)	(0.126)	(0.126)	(0.126)
Work Status: Other		0.082	0.076	0.081	0.079
		(0.051)	(0.051)	(0.051)	(0.051)
Completed Secondary Education		-0.100**	-0.096*	-0.124**	-0.110**
		(0.049)	(0.051)	(0.051)	(0.051)
Interpersonal Trust			0.030**		0.021
			(0.015)		(0.015)
Trust in Government			-0.046***		-0.051***
			(0.015)		(0.015)
Trust in EU Government			0.038***		0.033**
			(0.013)		(0.013)
Immigrants enrich Culture				0.025**	0.027**
				(0.011)	(0.011)
Anti-Immigration				0.107**	0.101**
				(0.050)	(0.050)
Anti-Immigration, Non European				-0.104***	-0.096**
				(0.039)	(0.039)
Intercept	4.082***	4.081***	3.937***	3.940***	3.852***
	(0.081)	(0.109)	(0.125)	(0.167)	(0.178)
Observations	1,967	1,967	1,967	1,967	1,967
R^2	0.005	0.035	0.042	0.043	0.049

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Source data: ESS Round 9 (2018), own calculations

DICUSSION AND SUMMARY OF RESULTS

Some obvious limitation of the study come directly to mind. I could not investigate the support for universal health care nor pensions in Germany. Furthermore, my dependent variable and independent variable did not exactly represent the same wording as the ones used by Johnston et al. However, I think I have argued that the concepts behind those variables are still about the same and therefore the replication can be considered a success. A custom dataset just for this replication would be too expansive.

As I have shown that the effect observed by Johnston and his colleagues in their study does not neatly translate to other countries. Their results suggested that the welfare state and national identity are mutually supportive. This effect cannot be observed in Germany rather the opposite is true. If the respondent is highly emotionally attached, they are less likely to support redistribution by the state. This is only one of the three aspects investigated by Johnston and colleagues therefore I can't conclude if this effect persists across other parts of the welfare state. One interesting lesson learned by is that the trust in the national government does have the opposite effect of trust in the EU parliament (government). This gives rise to the question if other policies experience the same oppositional effect as redistribution. Even other questions like acceptance of gay rights, liberal policies or attitudes towards immigration should be examined for this effect.

BIBLIOGRAPY

Johnston, R., Banting, K., Kymlicka, W., Soroka, S. 2010. "National Identity and Support for the Welfare State." *Canadian Journal of Political Science / Revue Canadienne de sciences politique* 43(2): 349-377.

Tatsachen über Deutschland. 2021. "Offene Gesellschaft". Retrieved Aug. 15, 2021 (https://www.tatsachen-ueber-deutschland.de/de/deutschland-auf-einen-blick/offene-gesellschaft).

Software used:

R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Packages for R used:

Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.1. https://CRAN.R-project.org/package=stargazer

Hadley Wickham, Romain François, Lionel Henry and Kirill Müller (2021). dplyr: A Grammar of Data Manipulation. R package version 1.0.7. https://CRAN.R-project.org/package=dplyr

Chung-hong Chan, Geoffrey CH Chan, Thomas J. Leeper, and Jason Becker (2021). rio: A Swiss-army knife for data file I/O. R package version 0.5.27.

Leifeld, Philip (2013). texreg: Conversion of Statistical Model Output in R to LaTeX and HTML Tables. Journal of Statistical Software, 55(8), 1-24. URL http://dx.doi.org/10.18637/jss.v055.i08.

Hao Zhu (2021). kableExtra: Construct Complex Table with 'kable' and Pipe Syntax. R package version 1.3.4. https://CRAN.R-project.org/package=kableExtra

APPENDIX

Log of analysis

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15 8 2021

```
View(my.df)
```

Missing Values and rescaling

GINCDIF (Redistribution)

```
table(my.df$gincdif)
```

```
##
##    1    2    3    4    5
##  610 1107  309  264   48
```

```
attributes(my.df$gincdif)
```

```
## $label
## [1] "Government should reduce differences in income levels"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 9
##
## $labels
##             Agree strongly                      Agree
##                          1                          2
## Neither agree nor disagree                   Disagree
##                          3                          4
##          Disagree strongly                    Refusal
##                          5                          7
##                 Don't know                  No answer
##                          8                          9
```

```
attributes(my.df$atchctr)
```

```
## $label
## [1] "How emotionally attached to [country]"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 9
##
## $labels
## Not at all emotionally attached                               1
##                               0                               1
##                               2                               3
##                               2                               3
##                               4                               5
##                               4                               5
##                               6                               7
##                               6                               7
##                               8                               9
##                               8                               9
##       Very emotionally attached                         Refusal
##                              10                              77
##                      Don't know                       No answer
##                              88                              99
```

```
my.df <- my.df %>% mutate(atchctr_m = ifelse(atchctr == 77 | atchctr == 88 | atchctr == 99, NA, atchctr
table(my.df$atchctr_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##   25   18   45   72   78  172  189  350  588  333  480    8
```

```
class(my.df$atchctr_m)
```

```
## [1] "numeric"
```

PPLTRST, PPLFAIR, PPLHLP (Interpersonal trust)

```
table(my.df$ppltrst)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
##  85  43 120 238 228 462 314 458 311  53  46
```

```
attributes(my.df$ppltrst)
```

```
## $label
## [1] "Most people can be trusted or you can't be too careful"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 9
##
## $labels
##   You can't be too careful                          1
##                          0                          1
##                          2                          3
##                          2                          3
##                          4                          5
##                          4                          5
##                          6                          7
##                          6                          7
##                          8                          9
##                          8                          9
## Most people can be trusted                    Refusal
##                         10                         77
##                 Don't know                  No answer
##                         88                         99
```

```r
my.df <- my.df %>% mutate(ppltrst_m = ifelse(ppltrst == 77 | ppltrst == 88 | ppltrst == 99, NA, ppltrst)
table(my.df$ppltrst_m, useNA = "ifany")
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
##  85  43 120 238 228 462 314 458 311  53  46
```

```r
class(my.df$ppltrst_m)
```

```
## [1] "numeric"
```

```r
table(my.df$pplfair)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
##  31  20  60 153 165 459 274 504 454 150  87
```

```r
attributes(my.df$pplfair)
```

```
## $label
## [1] "Most people try to take advantage of you, or try to be fair"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
```

```
## [1] 9
##
## $labels
## Most people try to take advantage of me                                        1
##                                       0                                        1
##                                       2                                        3
##                                       2                                        3
##                                       4                                        5
##                                       4                                        5
##                                       6                                        7
##                                       6                                        7
##                                       8                                        9
##                                       8                                        9
##                Most people try to be fair                                  Refusal
##                                      10                                       77
##                               Don't know                                 No answer
##                                      88                                       99
```

```
my.df <- my.df %>% mutate(pplfair_m = ifelse(pplfair == 77 | pplfair == 88 | pplfair == 99, NA, pplfair)
table(my.df$pplfair_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##   31   20   60  153  165  459  274  504  454  150   87    1
```

```
class(my.df$pplfair_m)
```

```
## [1] "numeric"
```

```
table(my.df$pplhlp)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
##  37  25 111 245 264 566 329 403 268  57  50
```

```
attributes(my.df$pplhlp)
```

```
## $label
## [1] "Most of the time people helpful or mostly looking out for themselves"
##
## $format.spss
## [1] "F2.0"
##
## $labels
## People mostly look out for themselves                                     1
##                                     0                                     1
##                                     2                                     3
##                                     2                                     3
##                                     4                                     5
##                                     4                                     5
##                                     6                                     7
```

```
##                                   6                                      7
##                                   8                                      9
##                                   8                                      9
##       People mostly try to be helpful                              Refusal
##                                  10                                     77
##                          Don't know                              No answer
##                                  88                                     99
```

```r
my.df <- my.df %>% mutate(pplhlp_m = ifelse(pplhlp == 77 | pplhlp == 88 | pplhlp == 99, NA, pplhlp))
table(my.df$pplhlp_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##   37   25  111  245  264  566  329  403  268   57   50    3
```

```r
class(my.df$pplhlp_m)
```

```
## [1] "numeric"
```

```r
my.df <- my.df %>% mutate(inter_trust = (ppltrst_m + pplfair_m + pplhlp_m) / 3)
table(my.df$inter_trust, useNA = "ifany")
```

```
##
##                 0 0.666666666666667                 1  1.33333333333333
##                 9                 6                 8                 4
##  1.66666666666667                 2  2.33333333333333  2.66666666666667
##                15                16                28                47
##                 3  3.33333333333333  3.66666666666667                 4
##                48                68                88               102
##  4.33333333333333  4.66666666666667                 5  5.33333333333333
##               118               114               194               133
##  5.66666666666667                 6  6.33333333333333  6.66666666666667
##               168               186               188               205
##                 7  7.33333333333333  7.66666666666667                 8
##               159               170               104                71
##  8.33333333333333  8.66666666666667                 9  9.33333333333333
##                48                19                15                10
##  9.66666666666667                10              <NA>
##                 2                11                 4
```

TRSTPRL, TRSTPLT, TRSTEP (Trust in government)

```r
table(my.df$trstprl)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
## 134  73 161 254 258 396 301 320 281  88  61
```

```r
attributes(my.df$trstprl)
```

```
## $label
## [1] "Trust in country's parliament"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 9
##
## $labels
## No trust at all               1               2               3               4
##               0               1               2               3               4
##               5               6               7               8               9
##               5               6               7               8               9
##  Complete trust         Refusal      Don't know       No answer
##              10              77              88              99
```

```r
my.df <- my.df %>% mutate(trstprl_m = ifelse(trstprl == 77 | trstprl == 88 | trstprl == 99, NA, trstprl)
table(my.df$trstprl_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##  134   73  161  254  258  396  301  320  281   88   61   31
```

```r
class(my.df$trstprl_m)
```

```
## [1] "numeric"
```

```r
table(my.df$trstplt)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
## 239 129 244 362 345 431 255 218  84  14  18
```

```r
attributes(my.df$trstplt)
```

```
## $label
## [1] "Trust in politicians"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 9
##
## $labels
## No trust at all               1               2               3               4
##               0               1               2               3               4
```

```
##               5               6               7               8               9
##               5               6               7               8               9
##   Complete trust         Refusal      Don't know       No answer
##              10              77              88              99
```

```r
my.df <- my.df %>% mutate(trstplt_m = ifelse(trstplt == 77 | trstplt == 88 | trstplt == 99, NA, trstplt
table(my.df$trstplt_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##  239  129  244  362  345  431  255  218   84   14   18   19
```

```r
class(my.df$trstplt_m)
```

```
## [1] "numeric"
```

```r
table(my.df$trstep)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
## 186 101 158 296 283 440 296 267 171  52  27
```

```r
attributes(my.df$trstep)
```

```
## $label
## [1] "Trust in the European Parliament"
##
## $format.spss
## [1] "F2.0"
##
## $labels
## No trust at all               1               2               3               4
##               0               1               2               3               4
##               5               6               7               8               9
##               5               6               7               8               9
##   Complete trust         Refusal      Don't know       No answer
##              10              77              88              99
```

```r
my.df <- my.df %>% mutate(trust_EU_gov = ifelse(trstep == 77 | trstep == 88 | trstep == 99, NA, trstep)
table(my.df$trust_EU_gov, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##  186  101  158  296  283  440  296  267  171   52   27   81
```

```r
class(my.df$trust_EU_gov)
```

```
## [1] "numeric"
```

```r
my.df <- my.df %>% mutate(gov_trust = (trstprl_m + trstplt_m) / 2)
table(my.df$gov_trust, useNA = "ifany")
```

```
##
##    0  0.5    1  1.5    2  2.5    3  3.5    4  4.5    5  5.5    6  6.5    7  7.5
##  105   35   68   73  100  111  173  149  169  180  241  171  185  171  155  107
##    8  8.5    9  9.5   10 <NA>
##   65   32   16    5    9   38
```

HINCTNTA (Household income)

```r
table(my.df$hinctnta)
```

```
##
##   1   2   3   4   5   6   7   8   9  10
## 139 163 160 207 200 218 223 256 231 291
```

```r
attributes(my.df$hinctnta)
```

```
## $label
## [1] "Household's total net income, all sources"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 10
##
## $labels
##  J - 1st decile  R - 2nd decile  C - 3rd decile  M - 4th decile  F - 5th decile
##               1               2               3               4               5
##  S - 6th decile  K - 7th decile  P - 8th decile  D - 9th decile H - 10th decile
##               6               7               8               9              10
##         Refusal      Don't know       No answer
##              77              88              99
```

```r
my.df <- my.df %>% mutate(hinctnta_m = ifelse(hinctnta == 77 | hinctnta == 88 | hinctnta == 99, NA, hinc
table(my.df$hinctnta_m, useNA = "ifany")
```

```
##
##    1    2    3    4    5    6    7    8    9   10 <NA>
##  139  163  160  207  200  218  223  256  231  291  270
```

```r
class(my.df$hinctnta_m)
```

```
## [1] "numeric"
```

```
## has to be refactored as this is a categorial variable
```

YRBRN (year of birht, age)

```
table(my.df$yrbrn)
```

```
##
## 1928 1929 1930 1931 1932 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943
##    9    4    5    6   15   10    6   13   14   15   13   27   35   22   25   22
## 1944 1945 1946 1947 1948 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959
##   20   23   30   26   26   35   45   51   37   42   38   64   45   39   48   39
## 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975
##   40   42   38   51   46   48   42   41   44   35   38   44   32   37   31   38
## 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991
##   24   28   24   32   29   29   30   30   36   28   37   26   34   37   37   21
## 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003
##   25   36   24   36   41   30   27   39   29   32   40   17
```

```
attributes(my.df$yrbrn)
```

```
## $label
## [1] "Year of birth"
##
## $format.spss
## [1] "F4.0"
##
## $display_width
## [1] 7
##
## $labels
##    Refusal Don't know  No answer
##       7777       8888       9999
```

```
my.df <- my.df %>% mutate(yrbrn_m = ifelse(yrbrn == 7777 | yrbrn == 8888 | yrbrn == 9999, NA, yrbrn))
table(my.df$yrbrn_m, useNA = "ifany")
```

```
##
## 1928 1929 1930 1931 1932 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943
##    9    4    5    6   15   10    6   13   14   15   13   27   35   22   25   22
## 1944 1945 1946 1947 1948 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959
##   20   23   30   26   26   35   45   51   37   42   38   64   45   39   48   39
## 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975
##   40   42   38   51   46   48   42   41   44   35   38   44   32   37   31   38
## 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991
##   24   28   24   32   29   29   30   30   36   28   37   26   34   37   37   21
## 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 <NA>
##   25   36   24   36   41   30   27   39   29   32   40   17    4
```

```r
class(my.df$yrbrn_m)
```

```
## [1] "numeric"
```

```r
# has to be recoded into 4 seperate dummy variables: 30-39, 50-65, 66 over, 30 under

my.df <- my.df %>% mutate(AGE = 2018 - yrbrn_m)
table(my.df$AGE, useNA = "ifany")
```

```
##
##   15   16   17   18   19   20   21   22   23   24   25   26   27   28   29   30
##   17   40   32   29   39   27   30   41   36   24   36   25   21   37   37   34
##   31   32   33   34   35   36   37   38   39   40   41   42   43   44   45   46
##   26   37   28   36   30   30   29   29   32   24   28   24   38   31   37   32
##   47   48   49   50   51   52   53   54   55   56   57   58   59   60   61   62
##   44   38   35   44   41   42   48   46   51   38   42   40   39   48   39   45
##   63   64   65   66   67   68   69   70   71   72   73   74   75   76   77   78
##   64   38   42   37   51   45   35   26   26   30   23   20   22   25   22   35
##   79   80   81   82   83   84   85   86   87   88   89   90 <NA>
##   27   13   15   14   13    6   10   15    6    5    4    9    4
```

```r
class(my.df$AGE)
```

```
## [1] "numeric"
```

GNDR (Gender)

```r
table(my.df$gndr)
```

```
##
##    1    2
## 1212 1146
```

```r
attributes(my.df$gndr)
```

```
## $label
## [1] "Gender"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 6
##
## $labels
##      Male    Female No answer
##         1         2         9
```

```r
my.df <- my.df %>% mutate(gndr_m = ifelse(gndr == 9, NA, gndr))
table(my.df$gndr_m, useNA = "ifany")
```

```
##
##    1    2
## 1212 1146
```

```r
class(my.df$gndr_m)
```

```
## [1] "numeric"
```

```r
## gender recoding, female as 1 male as 0

my.df$female[my.df$gndr_m == 2] <- 1
my.df$female[my.df$gndr_m != 2] <- 0

table(my.df$female, useNA = "ifany")
```

```
##
##    0    1
## 1212 1146
```

MBTRU (member of trade union)

```r
table(my.df$mbtru)
```

```
##
##    1    2    3
##  285  475 1593
```

```r
attributes(my.df$mbtru)
```

```
## $label
## [1] "Member of trade union or similar organisation"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 7
##
## $labels
##  Yes, currently Yes, previously              No         Refusal      Don't know
##               1               2               3               7               8
##       No answer
##               9
```

```
my.df <- my.df %>% mutate(mbtru_m = ifelse(mbtru == 7 | mbtru == 8 | mbtru == 9, NA, mbtru))
table(my.df$mbtru_m, useNA = "ifany")
```

```
##
##    1    2    3 <NA>
##  285  475 1593    5
```

```
## dummy variable if currently member of trade union

my.df$trade_dummy[my.df$mbtru_m == 1] <- 1
my.df$trade_dummy[my.df$mbtru_m != 1] <- 0

table(my.df$trade_dummy, useNA = "ifany")
```

```
##
##    0    1 <NA>
## 2068  285    5
```

Workstatus (unemployment and workforce filter)

```
table(my.df$edctn, useNA = "ifany")
```

```
##
##    0    1
## 2091  267
```

```
attributes(my.df$edctn)
```

```
## $label
## [1] "Doing last 7 days: education"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 7
##
## $labels
## Not marked     Marked
##          0          1
```

```
table(my.df$dsbld, useNA = "ifany")
```

```
##
##    0    1
## 2234  124
```

```r
attributes(my.df$dsbld)
```

```
## $label
## [1] "Doing last 7 days: permanently sick or disabled"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 7
##
## $labels
## Not marked     Marked
##          0          1
```

```r
table(my.df$rtrd, useNA = "ifany")
```

```
##
##    0    1
## 1725  633
```

```r
attributes(my.df$rtrd)
```

```
## $label
## [1] "Doing last 7 days: retired"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 6
##
## $labels
## Not marked     Marked
##          0          1
```

```r
table(my.df$hswrk, useNA = "ifany")
```

```
##
##    0    1
## 1717  641
```

```r
attributes(my.df$hswrk)
```

```
## $label
## [1] "Doing last 7 days: housework, looking after children, others"
##
## $format.spss
## [1] "F1.0"
##
```

```
## $display_width
## [1] 7
##
## $labels
## Not marked     Marked
##          0          1
```

```r
my.df <- my.df %>% mutate(work_status_other = case_when(edctn == 1 ~ 1,
                                                        dsbld == 1 ~ 1,
                                                        rtrd == 1 ~ 1,
                                                        edctn == 0 ~ 0,
                                                        edctn == 0 ~ 0,
                                                        edctn == 0 ~ 0,))
table(my.df$work_status_other, useNA = "ifany")
```

```
##
##    0    1
## 1385  973
```

```r
table(my.df$uempla, useNA = "ifany")
```

```
##
##    0    1
## 2308   50
```

```r
attributes(my.df$uempla)
```

```
## $label
## [1] "Doing last 7 days: unemployed, actively looking for job"
##
## $format.spss
## [1] "F1.0"
##
## $labels
## Not marked     Marked
##          0          1
```

```r
table(my.df$uempli, useNA = "ifany")
```

```
##
##    0    1
## 2324   34
```

```r
attributes(my.df$uempli)
```

```
## $label
## [1] "Doing last 7 days: unemployed, not actively looking for job"
##
## $format.spss
## [1] "F1.0"
```

```
##
## $labels
## Not marked     Marked
##          0          1
```

```
my.df <- my.df %>% mutate(unemployed_dummy = case_when(uempla == 0 & uempli == 0 ~ 0,
                                                       uempla == 1 & uempli == 0 ~ 1,
                                                       uempla == 0 & uempli == 1 ~ 1))

table(my.df$unemployed_dummy, useNA = "ifany")
```

```
##
##    0    1 <NA>
## 2276   80    2
```

Immigration: want to fit in [imueclt]

```
table(my.df$imueclt)
```

```
##
##   0   1   2   3   4   5   6   7   8   9  10
##  71  57 118 159 163 391 254 385 366 186 189
```

```
attributes(my.df$imueclt)
```

```
## $label
## [1] "Country's cultural life undermined or enriched by immigrants"
##
## $format.spss
## [1] "F2.0"
##
## $display_width
## [1] 9
##
## $labels
## Cultural life undermined                        1                        2
##                        0                        1                        2
##                        3                        4                        5
##                        3                        4                        5
##                        6                        7                        8
##                        6                        7                        8
##                        9    Cultural life enriched                  Refusal
##                        9                       10                       77
##               Don't know                No answer
##                       88                       99
```

```
my.df <- my.df %>% mutate(imueclt_m = ifelse(imueclt == 77 | imueclt == 88 | imueclt == 99, NA, imueclt
table(my.df$imueclt_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##   71   57  118  159  163  391  254  385  366  186  189   19
```

Immigration: too many or too few immigrants

```
table(my.df$imsmetn)
```

```
##
##    1    2    3    4
## 1028 1083  192   28
```

```
attributes(my.df$imsmetn)
```

```
## $label
## [1] "Allow many/few immigrants of same race/ethnic group as majority"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 9
##
## $labels
## Allow many to come and live here                       Allow some
##                                1                                2
##                      Allow a few                       Allow none
##                                3                                4
##                          Refusal                       Don’t know
##                                7                                8
##                        No answer
##                                9
```

```
table(my.df$imdfetn)
```

```
##
##    1    2    3    4
##  522 1176  546   84
```

```
attributes(my.df$imdfetn)
```

```
## $label
## [1] "Allow many/few immigrants of different race/ethnic group from majority"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 9
##
## $labels
## Allow many to come and live here                       Allow some
##                                1                                2
##                      Allow a few                       Allow none
```

```
##                                 3                                 4
##                           Refusal                        Don't know
##                                 7                                 8
##                         No answer
##                                 9
```

```
table(my.df$impcntr)
```

```
##
##    1    2    3    4
##  487 1098  616  127
```

```
attributes(my.df$impcntr)
```

```
## $label
## [1] "Allow many/few immigrants from poorer countries outside Europe"
##
## $format.spss
## [1] "F1.0"
##
## $display_width
## [1] 9
##
## $labels
## Allow many to come and live here                        Allow some
##                                 1                                 2
##                       Allow a few                        Allow none
##                                 3                                 4
##                           Refusal                        Don't know
##                                 7                                 8
##                         No answer
##                                 9
```

```
my.df <- my.df %>% mutate(imsmetn_m = ifelse(imsmetn == 7 | imsmetn == 8 | imsmetn == 9, NA, imsmetn),
                          imdfetn_m = ifelse(imdfetn == 7 | imdfetn == 8 | imdfetn == 9, NA, imdfetn),
                          allow_immigrants_out_EU = ifelse(impcntr == 7 | impcntr == 8 | impcntr == 9, N

table(my.df$imsmetn_m, useNA = "ifany")
```

```
##
##    1    2    3    4 <NA>
## 1028 1083  192   28   27
```

```
table(my.df$imdfetn_m, useNA = "ifany")
```

```
##
##    1    2    3    4 <NA>
##  522 1176  546   84   30
```

```
table(my.df$impcntr_m, useNA = "ifany")
```

```
## < table of extent 0 >
```

```
my.df <- my.df %>% mutate(allow_immigrants = (imsmetn_m + imdfetn_m) / 2 )
table(my.df$allow_immigrants, useNA = "ifany")
```

```
##
##    1  1.5    2  2.5    3  3.5    4 <NA>
##  503  430  827  330  177   26   24   41
```

```
table(my.df$allow_immigrants_out_EU, useNA = "ifany")
```

```
##
##    1    2    3    4 <NA>
##  487 1098  616  127   30
```

Education: Dummy variable for at least high school

```
table(my.df$edubde1, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6 5555 <NA>
##    6   69    8  535  765  242  724    3    6
```

```
attributes(my.df$edubde1)
```

```
## $label
## [1] "Highest level of education, Germany: höchster allgemeinbildender Schulabschluss"
##
## $format.spss
## [1] "F4.0"
##
## $display_width
## [1] 9
##
## $labels
##                                                      Grundschule nicht beendet
##                                                                              0
##                           (Noch) kein Schulabschluss, aber Grundschule beendet
##                                                                              1
##                           Abschluss einer Förderschule (Sonderschule, Hilfsschule)
##                                                                              2
##              Volks- oder Hauptschule / Polytechn. Oberschule (8./9. Klasse)
##                                                                              3
##       Mittlere Reife, Realschule / MSA / Polytechn. Oberschule (10. Klasse)
##                                                                              4
##                                                            Fachhochschulreife
```

```
##                                                                              5
## Abitur, fachgebundene Hochschulreife / Erweiterte Oberschule (12. Klasse)
##                                                                              6
##                                                                          Other
##                                                                           5555
##                                                                        Refusal
##                                                                           7777
##                                                                     Don't know
##                                                                           8888
##                                                                      No answer
##                                                                           9999
```

```
my.df <- my.df %>% mutate(education_m = ifelse(edubde1 == 5555 |
                                                edubde1 == 7777 |
                                                edubde1 == 8888 |
                                                edubde1 == 9999, NA, edubde1))

table(my.df$education_m, useNA = "ifany")
```

```
##
##    0    1    2    3    4    5    6 <NA>
##    6   69    8  535  765  242  724    9
```

```
my.df$education_dummy[my.df$education_m == 6] <- 1
my.df$education_dummy[my.df$education_m != 6] <- 0

table(my.df$education_dummy, useNA = "ifany")
```

```
##
##    0    1 <NA>
## 1625  724    9
```

Listwise deleted model

```
varsinmodel.vc <- c("gincdif_reversed",
                    "atchctr_m",
                    "inter_trust",
                    "gov_trust",
                    "trust_EU_gov",
                    "hinctnta_m",
                    "AGE",
                    "female",
                    "trade_dummy",
                    "unemployed_dummy",
                    "work_status_other",
                    "imueclt_m",
                    "allow_immigrants",
                    "allow_immigrants_out_EU",
                    "education_dummy")
```

```r
my.df.filt <- my.df[varsinmodel.vc]
View(my.df.filt)
nrow(my.df.filt)
```

```
## [1] 2358
```

```r
names(my.df.filt)
```

```
##  [1] "gincdif_reversed"        "atchctr_m"
##  [3] "inter_trust"             "gov_trust"
##  [5] "trust_EU_gov"            "hinctnta_m"
##  [7] "AGE"                     "female"
##  [9] "trade_dummy"             "unemployed_dummy"
## [11] "work_status_other"       "imueclt_m"
## [13] "allow_immigrants"        "allow_immigrants_out_EU"
## [15] "education_dummy"
```

```r
#Listwise deletion
my.df.lw <- na.omit(my.df.filt)
View(my.df.lw)
nrow(my.df.lw)
```

```
## [1] 1967
```

Summary statistics

Variable	Variable label	Obs	Mean	SD	Min	Max
gincdif_reversed	Support for redistribution	1967	3.850	0.994	1	5
atchctr_m	Emotional Attachment to Germany	1967	7.515	2.167	0	10
inter_trust	Interpersonal Trust	1967	5.713	1.649	0	10
gov_trust	Trust in Government	1967	4.546	2.182	0	10
trust_EU_gov	Trust in EU Government	1967	4.575	2.377	0	10
hinctnta_m	Total Household Income	1967	6.123	2.804	1	10
AGE	Age	1967	50.010	18.387	15	90
female	Female	1967	0.470	0.499	0	1
trade_dummy	Member of Trade Union	1967	0.129	0.335	0	1
unemployed_dummy	Work Status: Unemployed	1967	0.034	0.180	0	1
work_status_other	Worl Status: Other	1967	0.400	0.490	0	1
imueclt_m	Immigrants enrich Culture	1967	6.015	2.509	0	10
allow_immigrants	Anti-Immigration	1967	1.866	0.643	1	4
allow_immigrants_out_EU	Anti-Immigration, Non European	1967	2.161	0.807	1	4
education_dummy	Completed Secondary Education	1967	0.311	0.463	0	1

Bivariate Regressions

```r
bi_m1.lw <- lm(gincdif_reversed ~ atchctr_m, data = my.df.lw)

multi_econ_m1.lw <- lm(gincdif_reversed ~ atchctr_m +
```

Variable	Variable label	Obs	Mean	SD	Min	Max
gincdif_reversed	Support for redistribution	1967	3.850	0.994	1	5
atchctr_m	Emotional Attachment to Germany	1967	7.515	2.167	0	10
inter_trust	Interpersonal Trust	1967	5.713	1.649	0	10
gov_trust	Trust in Government	1967	4.546	2.182	0	10
trust_EU_gov	Trust in EU Government	1967	4.575	2.377	0	10
hinctnta_m	Total Household Income	1967	6.123	2.804	1	10
AGE	Age	1967	50.010	18.387	15	90
female	Female	1967	0.470	0.499	0	1
trade_dummy	Member of Trade Union	1967	0.129	0.335	0	1
unemployed_dummy	Work Status: Unemployed	1967	0.034	0.180	0	1
work_status_other	Worl Status: Other	1967	0.400	0.490	0	1
imueclt_m	Immigrants enrich Culture	1967	6.015	2.509	0	10
allow_immigrants	Anti-Immigration	1967	1.866	0.643	1	4
allow_immigrants_out_EU	Anti-Immigration, Non European	1967	2.161	0.807	1	4
education_dummy	Completed Secondary Education	1967	0.311	0.463	0	1

```
                    hinctnta_m +
                    AGE +
                    female +
                    trade_dummy +
                    unemployed_dummy +
                    work_status_other +
                    education_dummy, data = my.df.lw)

multi_econ_trust_m2.lw <- lm(gincdif_reversed ~ atchctr_m +
                    hinctnta_m +
                    AGE +
                    female +
                    trade_dummy +
                    unemployed_dummy +
                    work_status_other +
                    education_dummy +
                    inter_trust +
                    gov_trust +
                    trust_EU_gov, data = my.df.lw)

multi_econ_immigration_m3.lw <- lm(gincdif_reversed ~ atchctr_m +
                    hinctnta_m +
                    AGE +
                    female +
                    trade_dummy +
                    unemployed_dummy +
                    work_status_other +
                    education_dummy +
                    imueclt_m +
                    allow_immigrants +
                    allow_immigrants_out_EU, data = my.df.lw)
```

Multivariate Regression

```
multi_full_model.lw <- lm(gincdif_reversed ~ atchctr_m +
                    hinctnta_m +
                    AGE +
                    female +
                    trade_dummy +
                    unemployed_dummy +
                    work_status_other +
                    education_dummy +
                    inter_trust +
                    gov_trust +
                    trust_EU_gov +
                    imueclt_m +
                    allow_immigrants +
                    allow_immigrants_out_EU, data = my.df.lw)
multi_full_model.lw
```

```
##
## Call:
## lm(formula = gincdif_reversed ~ atchctr_m + hinctnta_m + AGE +
##     female + trade_dummy + unemployed_dummy + work_status_other +
##     education_dummy + inter_trust + gov_trust + trust_EU_gov +
##     imueclt_m + allow_immigrants + allow_immigrants_out_EU, data = my.df.lw)
##
## Coefficients:
##             (Intercept)                atchctr_m               hinctnta_m
##                3.852119                -0.028857                -0.032657
##                     AGE                   female              trade_dummy
##                0.003142                 0.130369                 0.155139
##        unemployed_dummy        work_status_other          education_dummy
##               -0.017585                 0.078984                -0.109797
##             inter_trust                gov_trust             trust_EU_gov
##                0.020811                -0.051036                 0.033023
##               imueclt_m         allow_immigrants  allow_immigrants_out_EU
##                0.026827                 0.100700                -0.096427
```

Printing the regression table

```
setwd(results.dir)
library(stargazer)
stargazer(bi_m1.lw, multi_econ_m1.lw, multi_econ_trust_m2.lw, multi_econ_immigration_m3.lw, multi_full_m
          dep.var.labels = c("Redistribution"),
          title="Johnston et. al. models plus full model",
          notes = "Source data: ESS Round 9 (2018) published 17.02.2021, own calculations",
          covariate.labels = c("Emotional Attachment to Germany",
                               "Total Household Income",
                               "Age",
                               "Female",
                               "Member of Trade Union",
```

```
                              "Work Status: Unemployed",
                              "Work Status: Other",
                              "Completed Secondary Education",
                              "Interpersonal Trust",
                              "Trust in Government",
                              "Trust in EU Government",
                              "Immigrants enrich Culture",
                              "Anti-Immigration",
                              "Anti-Immigration, Non European",
                              "Intercept"),
          keep.stat = c("n", "rsq"))
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: So, Aug 15, 2021 - 19:29:38

```
stargazer(bi_m1.lw, multi_econ_m1.lw, multi_econ_trust_m2.lw, multi_econ_immigration_m3.lw, multi_full_m
          dep.var.labels = c("Redistribution"),
          title = "Johnston et. al. models plus full model",
          notes = "Source data: ESS Round 9 (2018), own calculations",
          covariate.labels = c("Emotional Attachment to Germany",
                              "Total Household Income",
                              "Age",
                              "Female",
                              "Member of Trade Union",
                              "Work Status: Unemployed",
                              "Work Status: Other",
                              "Completed Secondary Education",
                              "Interpersonal Trust",
                              "Trust in Government",
                              "Trust in EU Government",
                              "Immigrants enrich Culture",
                              "Anti-Immigration",
                              "Anti-Immigration, Non European",
                              "Intercept"),
          keep.stat = c("n", "rsq"),
          out = "johnston_models_plus_full_model.htm")
```

Johnston et. al. models plus full model

Dependent variable:

Redistribution

(1)

(2)

(3)

(4)

(5)

Emotional Attachment to Germany

-0.031***

-0.032***

Table 1: Johnston et. al. models plus full model

	Dependent variable:				
	Redistribution				
	(1)	(2)	(3)	(4)	(5)
Emotional Attachment to Germany	−0.031***	−0.032***	−0.032***	−0.032***	−0.029***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Total Household Income		−0.033***	−0.034***	−0.033***	−0.033***
		(0.009)	(0.009)	(0.009)	(0.009)
Age		0.002*	0.003*	0.003**	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
Female		0.159***	0.144***	0.143***	0.130***
		(0.045)	(0.045)	(0.045)	(0.045)
Member of Trade Union		0.159**	0.161**	0.155**	0.155**
		(0.066)	(0.066)	(0.066)	(0.066)
Work Status: Unemployed		−0.008	−0.006	−0.014	−0.018
		(0.126)	(0.126)	(0.126)	(0.126)
Work Status: Other		0.082	0.076	0.081	0.079
		(0.051)	(0.051)	(0.051)	(0.051)
Completed Secondary Education		−0.100**	−0.096*	−0.124**	−0.110**
		(0.049)	(0.051)	(0.051)	(0.051)
Interpersonal Trust			0.030**		0.021
			(0.015)		(0.015)
Trust in Government			−0.046***		−0.051***
			(0.015)		(0.015)
Trust in EU Government			0.038***		0.033**
			(0.013)		(0.013)
Immigrants enrich Culture				0.025**	0.027**
				(0.011)	(0.011)
Anti-Immigration				0.107**	0.101**
				(0.050)	(0.050)
Anti-Immigration, Non European				−0.104***	−0.096**
				(0.039)	(0.039)
Intercept	4.082***	4.081***	3.937***	3.940***	3.852***
	(0.081)	(0.109)	(0.125)	(0.167)	(0.178)
Observations	1,967	1,967	1,967	1,967	1,967
R^2	0.005	0.035	0.042	0.043	0.049

Note: *p<0.1; **p<0.05; ***p<0.01

Source data: ESS Round 9 (2018) published 17.02.2021, own calculations

-0.032***

-0.032***

-0.029***

(0.010)

(0.011)

(0.011)

(0.011)

(0.011)

Total Household Income

-0.033***

-0.034***

-0.033***

-0.033***

(0.009)

(0.009)

(0.009)

(0.009)

Age

0.002*

0.003*

0.003**

0.003**

(0.001)

(0.001)

(0.001)

(0.001)

Female

0.159***

0.144***

0.143***

0.130***

(0.045)

(0.045)

(0.045)

(0.045)

Member of Trade Union

0.159**

0.161**

0.155**

0.155**

(0.066)

(0.066)

(0.066)

(0.066)

Work Status: Unemployed

-0.008

-0.006

-0.014

-0.018

(0.126)

(0.126)

(0.126)

(0.126)

Work Status: Other

0.082

0.076

0.081

0.079

(0.051)

(0.051)

(0.051)

(0.051)

Completed Secondary Education

-0.100**

-0.096*

-0.124**

-0.110**

(0.049)

(0.051)

(0.051)

(0.051)

Interpersonal Trust

0.030**

0.021

(0.015)

(0.015)

Trust in Government

-0.046***

-0.051***

(0.015)

(0.015)

Trust in EU Government

0.038***

0.033**

(0.013)

(0.013)

Immigrants enrich Culture

0.025**

0.027**

(0.011)

(0.011)

Anti-Immigration

0.107**

0.101**

(0.050)

(0.050)

Anti-Immigration, Non European

-0.104***

-0.096**

(0.039)

(0.039)

Intercept

4.082***

4.081***

3.937***

3.940***

3.852***

(0.081)

(0.109)

(0.125)

(0.167)

(0.178)

Observations

1,967

1,967

1,967

1,967

1,967

R2

0.005

0.035

0.042

0.043

0.049

Note:

p<0.1; ***p<0.05;*** p<0.01

Source data: ESS Round 9 (2018), own calculations

Exporting Model

```
library(texreg)
setwd(results.dir)
htmlreg(list(bi_m1.lw, multi_econ_m1.lw, multi_econ_trust_m2.lw, multi_econ_immigration_m3.lw, multi_ful
        file = "johnston_replication_regression.doc",
        caption = "Johnston et. al. models plus full model",
        custom.note = "Source data: ESS Round 9 (2018), own calculations",
        custom.coef.names = c("Emotional Attachment to Germany",
                              "Total Household Income",
                              "Age",
                              "Female",
                              "Member of Trade Union",
                              "Work Status: Unemployed",
                              "Work Status: Other",
                              "Completed Secondary Education",
                              "Interpersonal Trust",
                              "Trust in Government",
                              "Trust in EU Government",
                              "Immigrants enrich Culture",
                              "Anti-Immigration",
                              "Anti-Immigration, Non European",
                              "Intercept"),
```

```
        include.rmse = F,
        include.adjrs = F)
```

Erklärung zur Prüfungsleistung

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Die am FB03 gültige Definition von Plagiaten ist mir vertraut und verständlich:

„Eine am FB03 eingereichte Arbeit wird als Plagiat identifiziert, wenn in ihr nachweislich fremdes geistiges Eigentum ohne Kennzeichnung verwendet wird und dadurch dessen Urheberschaft suggeriert oder behauptet wird. Das geistige Eigentum kann ganze Texte, Textteile, Formulierungen, Ideen, Argumente, Abbildungen, Tabellen oder Daten umfassen und muss als geistiges Eigentum der Urheberin/des Urhebers gekennzeichnet sein. Sofern eingereichte Arbeiten die Kennzeichnung vorsätzlich unterlassen, provozieren sie einen Irrtum bei denjenigen, welche die Arbeit bewerten und erfüllen somit den Tatbestand der Täuschung."

Ich versichere hiermit, dass ich die eingereichte Arbeit mit dem Titel
Emotional Attachment to Germany and its Effect on the Support for Redistribution in Germany

nach den Regeln guter wissenschaftlicher Praxis angefertigt habe. Alle Stellen, die wörtlich oder sinngemäß aus Veröffentlichungen oder aus anderen fremden Mitteilungen entnommen wurden, sind als solche kenntlich gemacht. Die vorliegende Arbeit ist von mir selbständig und ohne Benutzung anderer als der angegebenen Quellen und Hilfsmittel verfasst worden. Ebenfalls versichere ich, dass diese Arbeit noch in keinem anderen Modul oder Studiengang als Prüfungsleistung vorgelegt wurde.

Mir ist bekannt, dass Plagiate auf Grundlage der Studien- und Prüfungsordnung im Prüfungsamt dokumentiert und vom Prüfungsausschuss sanktioniert werden. Diese Sanktionen können neben dem Nichtbestehen der Prüfungsleistung weitreichende Folgen bis hin zum Ausschluss von der Erbringung weiterer Prüfungsleistungen für mich haben.

Franfkury, 15.08.2021 M. Scharmann

Ort, Datum, Unterschrift

Diese Erklärung ist der Prüfungsleistung als Anhang beizufügen.
Prüfungsleistungen ohne diese Erklärung werden nicht zur Bewertung angenommen.