

Supplementary Materials for Replication of ‘Instrumentally Inclusive: The Political Psychology of Homonationalism’ (Turnbull-Dugarte and López Ortega, 2024).

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Note on Computational Reproducibility

This appendix reports on computational reproducibility. The paper is almost perfectly computationally reproducible from the processed data provided. That is, the authors provide the code and data required to (almost exactly) reproduce all results in the paper and supplementary materials, and the code runs (largely) without error. However, the data have evidently been pre-processed (e.g. the creation of the weights which were likely not provided by Prolific), and neither the raw data nor this pre-processing code are provided. I note a few minor issues encountered below:

- The `modelsummary::modelsummary` function does not support the use of `robust = TRUE` as an argument for returning robust standard errors. Despite this, the standard errors in the paper are robust where this argument is used (perhaps a prior version supported this). The correct result should be achieved with `vcov = "HC3"` instead.
- The `ritest` package not available on CRAN, and must be downloaded using: `remotes::install_github("grantmcdermott/ritest")`. Ideally this would be noted in the materials.
- The `starbility` package not available on CRAN, and must be downloaded using: `remotes::install_github('https://github.com/AakaashRao/starbility')`. Ideally this would be noted in the materials.
- When using `ggsave()` it would be wise to hard-code the dimensions of the output figure. This function defaults to the current dimensions of the plot window in RStudio (or whatever graphics device is currently active), which will vary by user.
- In the script `study1_summarystats.R` the code erroneously asks for `UKdata_analysis.csv` which is not provided in the replication archive. The correct file is `study1_data.csv` – when correcting this the results are reproduced. There are also some slight inconsistencies in the tables produced by this code and the tables in the supplementary materials (e.g. there are rows returned by the code for Table A.3. that are not in the supplementary materials). There is a similar discrepancy in the code that produces Table A.5. in `study2_summarystats.R`. In this file there are two lines that seem to produce summary statistics tables (one that is weighted, one that is not), but only one is in the supplementary materials (the weighted one). This is not indicated in the table.
- For the power analyses, while I was able to reproduce the results in the supplementary information by running the provided code, I was not able to trace the input values myself. These values are hard-coded in the replication code, but it is unclear where the values come from (they do not appear to come directly from the replication data, based on my cursory explorations).
- It is worth noting that the replication materials do not include any data processing code. Though this is not generally required by journals at present and is very rare in the discipline, it would be particularly useful for understanding some of the issues with regards to the weights in the Spain experiment.

Regression Results and Additional Analyses

This SI includes a series of reproductions and analyses of the authors' data, with a primary focus on study 2.

Re-analyses of main specifications

In this subsection I report the primary re-analyses of study 2, varying both the weighting choices and the standard error estimation. In Table SM 1 I first reproduce the results from Table A9 in the published paper's supplementary materials. This table reports results for four different specifications – the base model, the interaction model, the pro-immigration only sample, and the anti-immigration only sample. Results from Table A9 are reproduced exactly.

	Base	Interaction model	Pro-immigration only	Anti-immigration only
Treatment	0.095*** (0.025)	0.211*** (0.062)	0.111*** (0.027)	0.103** (0.044)
Immigration	0.065*** (0.005)	0.075*** (0.007)		
Treatment x Immi- gration		-0.019** (0.009)		
Intercept	0.238*** (0.033)	0.180*** (0.044)	0.784*** (0.019)	0.484*** (0.030)
Num.Obs.	1196	1196	700	516
R2	0.154	0.157	0.023	0.011

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 1: Spain Experiment: Regression Results With Weights and Classical (Non-Robust) Standard Errors

In Table SM 2 I vary the weighting and standard error choices for the base model. I do the same for the interaction models in Table SM 3, for the pro-immigration sample in Table SM 4, and finally for the anti-immigration sample in Table SM 5. In each case I also reproduce the results from Table A9 as the first column ('replication').

	Replication	No Weights	Weighted Ro- bust SE	Unweighted Robust SE	Weighted Sur- vey-Robust SE
Treatment	0.095*** (0.025)	0.026 (0.023)	0.095** (0.042)	0.026 (0.023)	0.095** (0.042)
Immigration	0.065*** (0.005)	0.059*** (0.005)	0.065*** (0.008)	0.059*** (0.005)	0.065*** (0.008)
Intercept	0.238*** (0.033)	0.366*** (0.034)	0.238*** (0.057)	0.366*** (0.039)	0.238*** (0.057)
Num.Obs.	1196	1196	1196	1196	1196
R2	0.154	0.125	0.154	0.125	0.154
Weighted	Yes	No	Yes	No	Yes
HC3 Robust SEs	No	No	Yes	Yes	No
Survey Ro- bust SEs	No	No	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 2: Spain Experiment: Base Model (Table A9, Column 1) Sensitivity

	Replication	No Weights	Weighted Ro- bust SE	Unweighted Robust SE	Weighted Sur- vey-Robust SE
Treatment	0.211*** (0.062)	0.094 (0.065)	0.211* (0.112)	0.094 (0.075)	0.211* (0.110)
Immigration	0.075*** (0.007)	0.065*** (0.007)	0.075*** (0.011)	0.065*** (0.007)	0.075*** (0.011)
Treatment x Immigration	-0.019** (0.009)	-0.010 (0.009)	-0.019 (0.016)	-0.010 (0.010)	-0.019 (0.015)
Intercept	0.180*** (0.044)	0.331*** (0.047)	0.180** (0.071)	0.331*** (0.053)	0.180** (0.070)
Num.Obs.	1196	1196	1196	1196	1196
R2	0.157	0.125	0.157	0.125	0.157
Weighted	Yes	No	Yes	No	Yes
HC3 Robust SEs	No	No	Yes	Yes	No
Survey Ro- bust SEs	No	No	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 3: Study 2 (Spain): Interaction Model (Table A9, Column 2) Sensitivity

(a)

	Replication	No Weights	Weighted Ro- bust SE	Unweighted Robust SE	Weighted Sur- vey-Robust SE
Treatment	0.111*** (0.027)	0.037 (0.024)	0.111** (0.051)	0.037 (0.024)	0.111** (0.050)
Intercept	0.784*** (0.019)	0.871*** (0.017)	0.784*** (0.041)	0.871*** (0.018)	0.784*** (0.040)
Num.Obs.	700	700	700	700	700
R2	0.023	0.004	0.023	0.004	0.023
Weighted	Yes	No	Yes	No	Yes
HC3 Robust SEs	No	No	Yes	Yes	No
Survey Ro- bust SEs	No	No	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 4: Study 2 (Spain): Pro-Immigration Only Model (Table A9, Column 3) Sensitivity

	Replication	No Weights	Weighted Ro- bust SE	Unweighted Robust SE	Weighted Sur- vey-Robust SE
Treatment	0.103** (0.044)	0.034 (0.043)	0.103 (0.069)	0.034 (0.043)	0.103 (0.068)
Intercept	0.484*** (0.030)	0.601*** (0.031)	0.484*** (0.048)	0.601*** (0.031)	0.484*** (0.048)
Num.Obs.	516	516	516	516	516
R2	0.011	0.001	0.011	0.001	0.011
Weighted	Yes	No	Yes	No	Yes
HC3 Robust SEs	No	No	Yes	Yes	No
Survey Ro- bust SEs	No	No	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 5: Study 2 (Spain): Anti-Immigration Only Model (Table A9, Column 4) Sensitivity

Re-analyses of Western Values

In Table SM 6 I re-analyse the results from Table A11 in the supplementary materials, which reports results for the ancillary and placebo outcomes. The only change here is to remove the weights, given that the original version of Table A11 uses robust standard errors. As column 2 shows, the results for Western liberal values disappears once weights are removed.

	EU norms	Western liberal values	Green politics	Domestic violence protections	Spanish flag	Spanish military efforts
Treatment	0.508 (0.471)	0.493 (0.426)	-0.242 (0.455)	0.329 (0.472)	-0.245 (0.594)	0.432 (0.595)
Immigration	0.256*** (0.048)	0.005 (0.045)	0.143*** (0.049)	0.210*** (0.050)	-0.343*** (0.060)	-0.083 (0.062)
Treatment x Immigration	-0.088 (0.068)	-0.051 (0.062)	0.007 (0.066)	-0.061 (0.069)	0.009 (0.083)	-0.058 (0.084)
Intercept	4.312*** (0.335)	6.902*** (0.312)	4.932*** (0.343)	4.915*** (0.349)	5.899*** (0.423)	5.011*** (0.434)
Num.Obs.	1163	1171	1180	1179	1144	1113
R2	0.044	0.003	0.022	0.029	0.068	0.009
Weighted	No	No	No	No	No	No
HC3 Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey Robust SEs	No	No	No	No	No	No

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 6: Study 2 (Spain): Regression Results Without Weights for Ancillary and Placebo Outcomes (Re-Estimation of Table A11)

Interaction effects by weight bin

In Table SM 7 I present the results of the interaction model estimated on three sub-samples – those with low weights (under 0.01), those with high weights (over 3), and those mid weights (in-between).

	Low Weights	Mid Weights	High Weights
Treatment	–0.019 (0.103)	–0.159 (0.336)	0.233** (0.118)
Immigration	0.050*** (0.010)	0.049* (0.025)	0.075*** (0.011)
Treatment x Immigration	0.001 (0.013)	0.017 (0.045)	–0.019 (0.017)
Intercept	0.477*** (0.077)	0.487** (0.206)	0.161** (0.074)
Num.Obs.	755	76	365
R2	0.096	0.122	0.164
Weighted	No	No	No
HC3 Robust SEs	Yes	Yes	Yes
Survey Robust SEs	No	No	No

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 7: Study 2 (Spain): Heterogeneous Interaction Effects By Weight Bin

Heterogeneous effects by age group

As noted in the main body of the comment, age is one of the primary factors that appears to differ between weight bins. A more detailed visualisation of the distribution of age across weight bins is presented in Figure SM 1. Essentially, every respondent who is over the age of 52 receives a high weight, those over the age of 35 but under 53 are much more likely to receive high weights than low weights, and those under 35 are much more likely to receive a low weight.

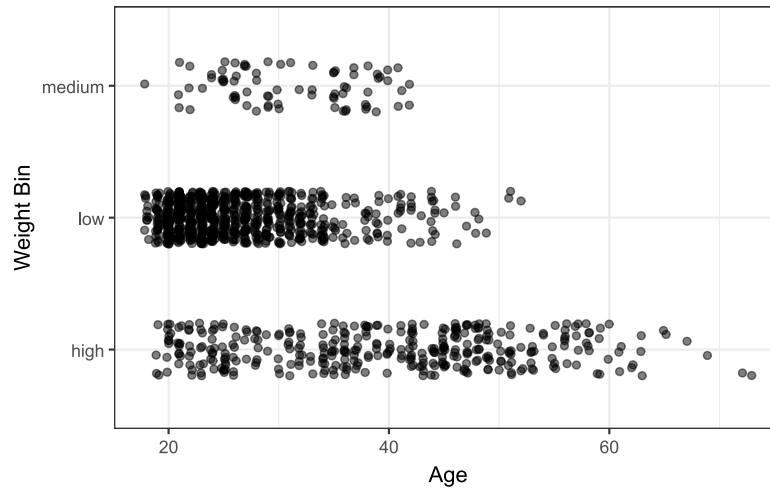


Figure SM 1: Study 2 (Spain): Age Distributions by Weight Bin

One might imagine that age is correlated with immigration sentiment, such that older people are more predisposed to be anti-immigrant than younger people. This is not the case in the study 2 data. As shown in Figure SM 2, there is no meaningful association between age and `imm_1`, and in fact the oldest respondents are often the most positively disposed toward immigration.

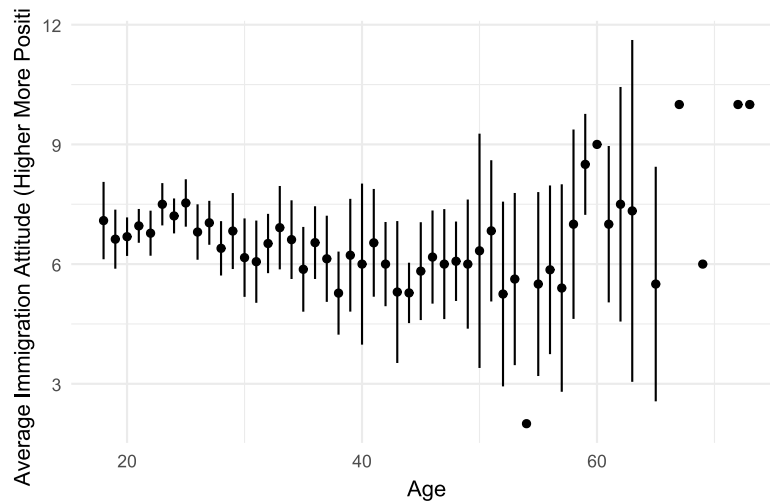


Figure SM 2: Study 2 (Spain): Age Is Unrelated to Immigration Sentiment

A closer analysis is offered in Table SM 8, which shows the results of a simple linear regression of the outcome variable on the treatment indicator, subset into six age categories that were provided in the replication data. The treatment effect is only non-zero in the oldest age categories (45 years and older). The only statistically significant result is for the 45-54 category, and the point estimate is very large. While the point estimates for those in the two oldest categories are also quite large (albeit half the size of the 45-54 category), there are too few observations in this categories to say much with confidence. Notably it appears from this analysis that a small number of observations (around 150) likely drive the overall result presented in the paper. When these individuals are not up-weighted (and those who do not respond to the treatment are not down-weighted), the results unsurprisingly mostly attenuate.

	Age < 25	Age 25-34	Age 35-44	Age 45-54	Age 55-64	Age >64
Treatment	-0.039 (0.034)	0.004 (0.039)	-0.035 (0.071)	0.367*** (0.090)	0.131 (0.147)	0.194 (0.231)
Intercept	0.859*** (0.024)	0.811*** (0.027)	0.673*** (0.047)	0.396*** (0.068)	0.682*** (0.104)	0.556*** (0.186)
Num.Obs.	459	406	184	108	38	21
R2	0.003	0.000	0.001	0.139	0.021	0.042

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 8: Study 2 (Spain): Heterogeneous Treatment Effects by Age Category

It appears that the results in study 2 are largely on account of a combination of the weighting scheme targeting a small segment of the sample that appears to respond strongly to the stimulus. While this may be attributable to those individuals' characteristics (for example, that older people are theoretically more likely to respond to homonationalist appeals), it may well be down to pure chance.

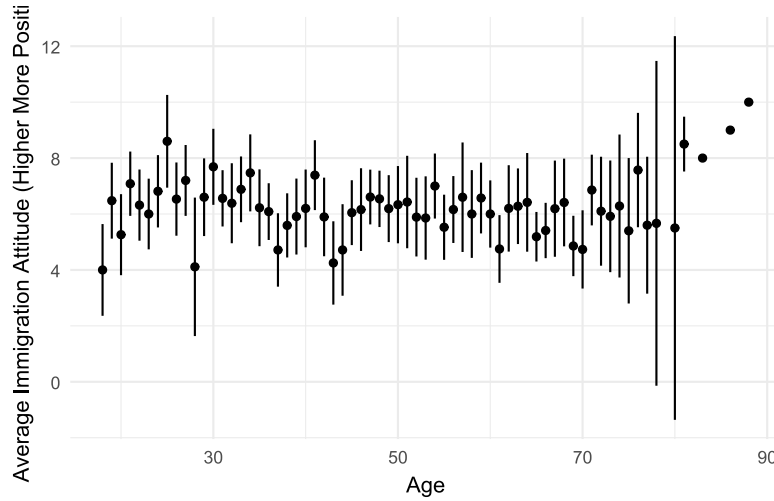


Figure SM 3: Study 1 (UK): Age Is Unrelated to Immigration Sentiment

Two things weigh against this deeper interpretation of these results. First, as was shown in Figure SM 2, it is not the case that older voters are more likely to be more anti-immigration in the study 2 data. Second, for the UK (study 1) there is likewise no association between age and immigration sentiment, nor are there any coherent age heterogeneities. The relationship between age and immigration sentiment in the UK is shown in Figure SM 3, and the results of the binned regression analysis are shown in Table SM 9. In this context, the youngest age category has a statistically significant positive treatment effect, while the second youngest has a statistically significant negative effect. The remaining categories are not statistically significant, and the point estimates bounce around between 0 and 0.1, with no clear pattern.

	Age < 25	Age 25-34	Age 35-44	Age 45-54	Age 55-64	Age >64
Treatment	0.189**	-0.149**	0.094	-0.038	0.073	-0.013
	(0.086)	(0.073)	(0.063)	(0.065)	(0.070)	(0.063)
Intercept	0.518***	0.797***	0.653***	0.699***	0.602***	0.597***
	(0.068)	(0.051)	(0.043)	(0.046)	(0.048)	(0.045)
Num.Obs.	131	152	215	212	194	244
R2	0.037	0.026	0.010	0.002	0.006	0.000

* p < 0.1, ** p < 0.05, *** p < 0.01

Table SM 9: Study 1 (UK): Heterogeneous Treatment Effects by Age Category

Corrected Figure 6 (No Weights)

In Figure SM 4 I present the corrected (linear regression, robust standard errors) version of Figure 6 from the published paper, but with weights removed.

Conditional average treatment effect: Study 2 (Spain)

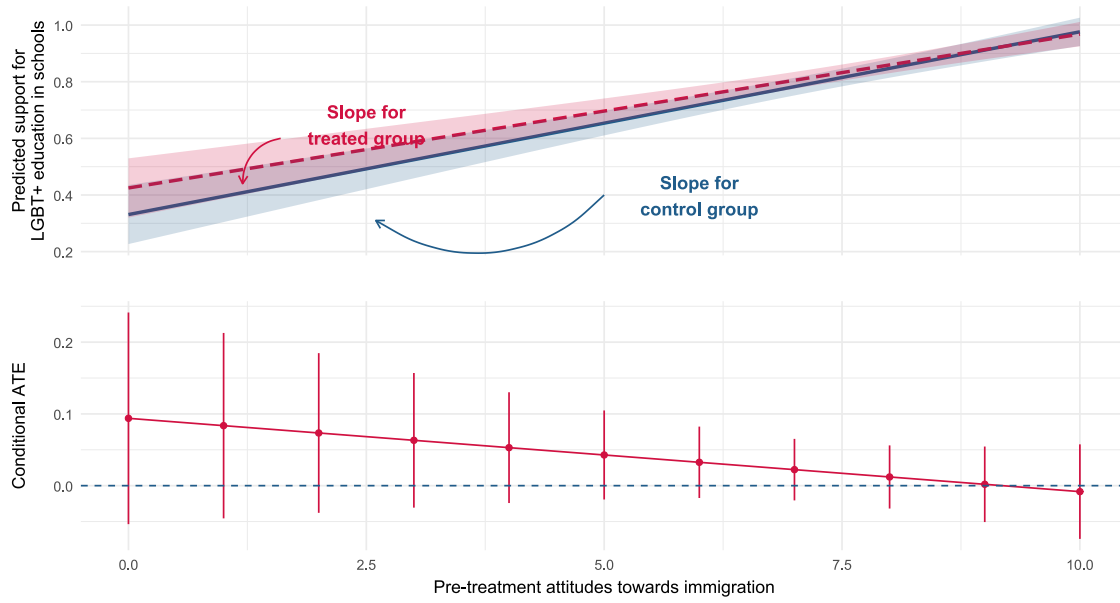


Figure SM 4: Study 2 (Spain): Corrected Reproduction of Figure 6 Without Weighting

All Code Used In This Comment

This supplementary material was produced as a dynamic document using Quarto. All code run is included below.

```
# Note to replicators from DdK: As much as possible, I have attempted
# throughout to avoid adjusting the original authors' code. Most changes are
# documented as comments. Please run this chunk once to install any missing
# packages using groundhog.
# load libraries
library(groundhog)

pkgs <- c("tidyverse", "jtools", "ggpubr", "ggrepel", "patchwork", "gt",
"modelsummary", "interactions", "margins", "skimr", "survey", "estimatr")
groundhog::groundhog.library(pkgs, "2024-06-01")

# modelsummary options
options(modelsummary_model_labels = "Computer Modern")

# set seed exactly as per replication materials
set.seed(1)
# load both datasets
uk <- read_csv("study1_data.csv")
load("study2_data.Rda")

# set color palette as per replication materials
colors<- c("#205C8A", "#d11141")

# cleaning per replication materials
uk <- uk%>%
  mutate(treat= as.factor(treatment),
         treatnum= as.numeric(treatment),
         gender= as.factor(gender),
         degree= as.factor(degree),
         nonwhite= as.factor(nonwhite),
         queer= as.factor(queer),
         relig= as.factor(relig),
         religion= as.factor(religion),
         race= as.factor(race),
         fourarm= as.factor(fourarm),
         immbelow= as.factor(immbelow),
         imm3= as.factor(imm3),
         region= as.factor(region),
         voterecall= as.factor(voterecall),
         brexit= as.factor(brexit),
         ideology= as.factor(ideology),
         agecat= as.factor(agecat))

# cleaning per replication materials
```

```

spain <- spain%>%
  mutate(treat= as.factor(treat),
         treatnum= as.numeric(treat),
         gender= as.factor(gender),
         supportcat= as.factor(support),
         agecat= as.factor(agecat),
         child= as.factor(child),
         immdum= as.factor(immdum),
         imm5= as.factor(imm5),
         imm3= as.factor(imm3),
         foreignborn= as.factor(foreignborn),
         CCAA= as.factor(CCAA),
         queer= as.factor(queer))
# subset uk data per replication materials
treat <- subset(uk, treatnum==1)
control <- subset(uk, treatnum==0)
proimm <- subset(uk, immbelow==0)
noproimm <- subset(uk, immbelow==1)

# analyse uk data per replication materials
modelsub1<- lm(support ~ treat, data=proimm)
proimm$predictedb <- predict(modelsub1, proimm)

modelsub2<- lm(support ~ treat, data=noproimm)
noproimm$predictedb <- predict(modelsub2, noproimm)

# subset again per replication materials
treatsub1 <- subset(proimm, treatnum==1)
controlsub1 <- subset(proimm, treatnum==0)
treatsub2 <- subset(noproimm, treatnum==1)
controlsub2 <- subset(noproimm, treatnum==0)
# subset spain data per replication materials
treatES <- subset(spain, treat==1)
controlES <- subset(spain, treat==0)
proimmES <- subset(spain, immdum==1)
noproimmES <- subset(spain, immdum==0)

# analyse spain data, but use lm() not glm() so that Spain and UK analyses are
exactly the same:
modelsub1ES <- lm(support ~ treat, weight=nationalweight, data=proimmES)
proimmES$predictedb <- predict(modelsub1ES, proimmES)

modelsub2ES <- lm(support ~ treat, weight=nationalweight, data=noproimmES)
noproimmES$predictedb <- predict(modelsub2ES, noproimmES)

# subset again per replication materials
treatsub1ES <- subset(proimmES, treat==1)
controlsub1ES <- subset(proimmES, treat==0)

```

```

treatsub2ES <- subset(noproimmES, treat==1)
controlsub2ES <- subset(noproimmES, treat==0)
# computational reproduction of Table A9:
models_rep <- list(
  'Base' = lm(support ~ treat + imm_1, data=spain, weight = nationalweight),
  'Interaction model' = lm(support ~ treat*imm_1, data=spain, weight =
nationalweight),
  'Pro-immigration only' = lm(support ~ treat, data=proimmES, weight =
nationalweight),
  'Anti-immigration only' = lm(support ~ treat, data=noproimmES, weight =
nationalweight)
)

# reproduction by analysis, with varying researcher choices:
models_base <- list(
  'Replication' = lm(support ~ treat + imm_1, data=spain, weight =
nationalweight),
  'No Weights' = lm(support ~ treat + imm_1, data=spain),
  'Weighted Robust SE' = estimatr::lm_robust(support ~ treat + imm_1,
data=spain, weight = nationalweight, se_type = "HC3"),
  'Unweighted Robust SE' = estimatr::lm_robust(support ~ treat + imm_1,
data=spain, se_type = "HC3"),
  'Weighted Survey-Robust SE' = survey::svyglm(support ~ treat + imm_1,
design=svydesign(ids=~1, weights=~nationalweight, data=spain))
)

models_int <- list(
  'Replication' = lm(support ~ treat*imm_1, data=spain, weight =
nationalweight),
  'No Weights' = lm(support ~ treat*imm_1, data=spain),
  'Weighted Robust SE' = estimatr::lm_robust(support ~ treat*imm_1,
data=spain, weight = nationalweight, se_type = "HC3"),
  'Unweighted Robust SE' = estimatr::lm_robust(support ~ treat*imm_1,
data=spain, se_type = "HC3"),
  'Weighted Survey-Robust SE' = survey::svyglm(support ~ treat*imm_1,
design=svydesign(ids=~1, weights=~nationalweight, data=spain))
)

models_proimmes <- list(
  'Replication' = lm(support ~ treat, data=proimmES, weight =
nationalweight),
  'No Weights' = lm(support ~ treat, data=proimmES),
  'Weighted Robust SE' = estimatr::lm_robust(support ~ treat, data=proimmES,
weight = nationalweight, se_type = "HC3"),
  'Unweighted Robust SE' = estimatr::lm_robust(support ~ treat, data=proimmES,
se_type = "HC3"),
  'Weighted Survey-Robust SE' = survey::svyglm(support ~ treat,
design=svydesign(ids=~1, weights=~nationalweight, data=proimmES))
)

```

```

)

models_noproimmES <- list(
  'Replication' = lm(support ~ treat, data=noproimmES, weight =
nationalweight),
  'No Weights' = lm(support ~ treat, data=noproimmES),
  'Weighted Robust SE' = estimatr::lm_robust(support ~ treat, data=noproimmES,
weight = nationalweight, se_type = "HC3"),
  'Unweighted Robust SE' = estimatr::lm_robust(support ~ treat,
data=noproimmES, se_type = "HC3"),
  'Weighted Survey-Robust SE' = survey::svyglm(support ~ treat,
design=svydesign(ids=~1, weights=~nationalweight, data=noproimmES))
)

# ancillary mechanism test (A11):
mech <- list(
  'EU norms' = estimatr::lm_robust(pride_valoresUE ~ treat*imm_1, data=spain,
se_type = "HC3"),
  'Western liberal values' = estimatr::lm_robust(pride_libertadOCC ~
treat*imm_1, data=spain, se_type = "HC3"),
  'Green politics' = estimatr::lm_robust(pride_verde ~ treat*imm_1,
data=spain, se_type = "HC3"),
  'Domestic violence protections' = estimatr::lm_robust(pride_viomach ~
treat*imm_1, data=spain, se_type = "HC3"),
  'Spanish flag' = estimatr::lm_robust(pride_bandera ~ treat*imm_1,
data=spain, se_type = "HC3"),
  'Spanish military efforts' = estimatr::lm_robust(pride_mili ~ treat*imm_1,
data=spain, se_type = "HC3")
)

# create bins of weights:
spain <- spain %>%
  mutate(weightbins = case_when(
    nationalweight >= 0 & nationalweight < 0.01 ~ "low",
    nationalweight >= 0.1 & nationalweight < 3 ~ "medium",
    nationalweight >= 3 ~ "high",
    TRUE ~ "other"
  ))

# re-subset
proimmES <- subset(spain, immdum==1)
noproimmES <- subset(spain, immdum==0)

# build tables - anti-immigration subsample
models_hetfx_anti <- list(
  'Low Weights' = estimatr::lm_robust(support ~ treat,
data=noproimmES[noproimmES$weightbins=="low",], se_type = "HC3"),
  'Mid Weights' = estimatr::lm_robust(support ~ treat,

```

```

data=noproimmES[noproimmES$weightbins=="medium",], se_type = "HC3"),
  'High Weights' = estimatr::lm_robust(support ~ treat,
data=noproimmES[noproimmES$weightbins=="high",], se_type = "HC3")
)

# build tables - pro-immigration subsample
models_hetfx_pro <- list(
  'Low Weights' = estimatr::lm_robust(support ~ treat,
data=proimmES[proimmES$weightbins=="low",], se_type = "HC3"),
  'Mid Weights' = estimatr::lm_robust(support ~ treat,
data=proimmES[proimmES$weightbins=="medium",], se_type = "HC3"),
  'High Weights' = estimatr::lm_robust(support ~ treat,
data=proimmES[proimmES$weightbins=="high",], se_type = "HC3")
)

# build tables - interaction hetfx
models_hetfx_int <- list(
  'Low Weights' = estimatr::lm_robust(support ~ treat*imm_1,
data=spain[spain$weightbins=="low",], se_type = "HC3"),
  'Mid Weights' = estimatr::lm_robust(support ~ treat*imm_1,
data=spain[spain$weightbins=="medium",], se_type = "HC3"),
  'High Weights' = estimatr::lm_robust(support ~ treat*imm_1,
data=spain[spain$weightbins=="high",], se_type = "HC3")
)

# correct the code to use a linear regression lm() and not logistic
regression.
modell <- lm(support ~ treat*imm_1, data=uk)
# use lm_robust for robust SEs that can be used by margins(). Set se_type =
"HC3" to be consistent with summ(.,robust=TRUE). Point estimates are of course
numerically identical bar rounding.
modell_robust <- estimatr::lm_robust(support ~ treat*imm_1, data=uk, se_type =
"HC3")

# correct the code to use a linear regression lm() and not logistic
regression.
modelES <- lm(support ~ treat*imm_1, data=spain, weight=nationalweight)
# use lm_robust for robust SEs that can be used by margins(). Set se_type =
"HC3" to be consistent with summ(.,robust=TRUE). Point estimates are of course
numerically identical bar rounding.
modelES_robust <- estimatr::lm_robust(support ~ treat*imm_1, data=spain,
weight=nationalweight, se_type = "HC3")

modelsummary(models_rep, output = "gt",
  coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
'treat1:imm_1' = 'Treatment x Immigration', '(Intercept)' = 'Intercept'),
  gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
  stars = c('*'=.1, "**"=.05, "***"=.01))

```

```

suppressWarnings(
  modelsummary(models_base, output = "gt",
    coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
  '(Intercept)' = 'Intercept'),
    gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
    stars = c('*'=.1, "**"=.05, "***"=.01),
    add_rows = tribble(~term, ~Base, ~Base, ~Base, ~Base, ~Base,
      "Weighted", "Yes", "No", "Yes", "No", "Yes",
      "HC3 Robust SEs", "No", "No", "Yes", "Yes", "No",
      "Survey Robust SEs", "No", "No", "No", "No", "Yes"
    ))
)

suppressWarnings(
  modelsummary(models_int, output = "gt",
    coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
  'treat1:imm_1' = 'Treatment x Immigration',
    '(Intercept)' = 'Intercept'),
    gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
    stars = c('*'=.1, "**"=.05, "***"=.01),
    add_rows = tribble(~term, ~Base, ~Base, ~Base, ~Base, ~Base,
      "Weighted", "Yes", "No", "Yes", "No", "Yes",
      "HC3 Robust SEs", "No", "No", "Yes", "Yes", "No",
      "Survey Robust SEs", "No", "No", "No", "No", "Yes"
    ))
)

suppressWarnings(
  modelsummary(models_proimmes, output = "gt",
    coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
    '(Intercept)' = 'Intercept'),
    gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
    stars = c('*'=.1, "**"=.05, "***"=.01),
    add_rows = tribble(~term, ~Base, ~Base, ~Base, ~Base, ~Base,
      "Weighted", "Yes", "No", "Yes", "No", "Yes",
      "HC3 Robust SEs", "No", "No", "Yes", "Yes", "No",
      "Survey Robust SEs", "No", "No", "No", "No", "Yes"
    ))
)

suppressWarnings(
  modelsummary(models_noproimmes, output = "gt",
    coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
    '(Intercept)' = 'Intercept'),
    gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
    stars = c('*'=.1, "**"=.05, "***"=.01),
    add_rows = tribble(~term, ~Base, ~Base, ~Base, ~Base, ~Base,
      "Weighted", "Yes", "No", "Yes", "No", "Yes",

```

```

      "HC3 Robust SEs", "No", "No", "Yes", "Yes", "No",
      "Survey Robust SEs", "No", "No", "No", "No", "Yes"
    ))
  )

suppressWarnings(
modelssummary(mech, output = "gt",
  coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
'treat1:imm_1' = 'Treatment x Immigration',
              '(Intercept)' = 'Intercept'),
  gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
  stars = c('*'=.1, "***"=.05, "****"=.01),
  add_rows = tribble(~term, ~Base, ~Base, ~Base, ~Base, ~Base,
~Base,
                    "Weighted", "No", "No", "No", "No", "No", "No",
                    "HC3 Robust SEs", "Yes", "Yes", "Yes", "Yes", "Yes", "Yes",
                    "Survey Robust SEs", "No", "No", "No", "No", "No", "No"
  ))
)

suppressWarnings(
modelssummary(models_hetfx_int, output = "gt",
  coef_map = c('treat1' = 'Treatment', 'imm_1' = 'Immigration',
'treat1:imm_1' = 'Treatment x Immigration',
              '(Intercept)' = 'Intercept'),
  gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
  stars = c('*'=.1, "***"=.05, "****"=.01),
  add_rows = tribble(~term, ~Base, ~Base, ~Base,
                    "Weighted", "No", "No", "No",
                    "HC3 Robust SEs", "Yes", "Yes", "Yes",
                    "Survey Robust SEs", "No", "No", "No",
  ))
)

ggplot(spain, aes(x=age, y=weightbins)) +
  geom_jitter(height=.2, width=.2, alpha = .5, na.rm=TRUE) +
  ylab("Weight Bin") +
  xlab("Age") +
  theme_bw()
# standard error function:
stderr <- function(x, na.rm=FALSE) {
  if (na.rm) x <- na.omit(x)
  sqrt(var(x)/length(x))
}

# aggregate up imm_1 by age, Spain:
age_imm_es <- spain %>%
  filter(!is.na(age)) %>%
  group_by(age) %>%

```

```

summarise(imm_1_mean = mean(imm_1, na.rm=TRUE),
          imm_1_se = stderr(imm_1, na.rm=TRUE),
          count = n()) %>%
ungroup()

# plot:
ggplot(age_imm_es, aes(x = age, y = imm_1_mean)) +
  geom_point() +
  geom_errorbar(aes(ymin = imm_1_mean - 1.96 * imm_1_se, ymax = imm_1_mean +
1.96 * imm_1_se), width = 0) +
  ylab("Average Immigration Attitude (Higher More Positive)") +
  xlab("Age") +
  theme_minimal()

# use the age categories already defined in the replication data:
models_hetfxage <- list(
  'Age < 25' = lm(support ~ treat, data=spain[spain$agecat==1,]),
  'Age 25-34' = lm(support ~ treat, data=spain[spain$agecat==2,]),
  'Age 35-44' = lm(support ~ treat, data=spain[spain$agecat==3,]),
  'Age 45-54' = lm(support ~ treat, data=spain[spain$agecat==4,]),
  'Age 55-64' = lm(support ~ treat, data=spain[spain$agecat==5,]),
  'Age >64' = lm(support ~ treat, data=spain[spain$agecat==6,])
)
modelssummary(models_hetfxage, output = "gt", robust = TRUE,
              coef_map = c('treat1' = 'Treatment', '(Intercept)' =
'Intercept'),
              gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
              stars = c('*'=.1, "***"=.05, "****"=.01))

# aggregate up imm_1 by age, UK:
age_imm_uk <- uk %>%
  filter(!is.na(age)) %>%
  group_by(age) %>%
  summarise(imm_1_mean = mean(imm_1, na.rm=TRUE),
            imm_1_se = stderr(imm_1, na.rm=TRUE),
            count = n()) %>%
  ungroup()

# plot:
ggplot(age_imm_uk, aes(x = age, y = imm_1_mean)) +
  geom_point() +
  geom_errorbar(aes(ymin = imm_1_mean - 1.96 * imm_1_se, ymax = imm_1_mean +
1.96 * imm_1_se), width = 0) +
  ylab("Average Immigration Attitude (Higher More Positive)") +
  xlab("Age") +
  theme_minimal()

# use the age categories already defined in the replication data:
models_hetfxage_uk <- list(
  'Age < 25' = lm(support ~ treat, data=uk[uk$agecat=="18-24",]),
  'Age 25-34' = lm(support ~ treat, data=uk[uk$agecat=="25-34",]),

```

```

'Age 35-44' = lm(support ~ treat, data=uk[uk$agecat=="35-44",]),
'Age 45-54' = lm(support ~ treat, data=uk[uk$agecat=="45-54",]),
'Age 55-64' = lm(support ~ treat, data=uk[uk$agecat=="55-64",]),
'Age >64' = lm(support ~ treat, data=uk[uk$agecat=="65+",])
)
modelsummary(models_hetfxage_uk, output = "gt", robust = TRUE,
  coef_map = c('treat1' = 'Treatment', '(Intercept)' =
'Intercept'),
  gof_omit = "BIC|AIC|R2 Adj.|F|RMSE|Log.Lik.",
  stars = c('*'=.1, "**"=.05, "***"=.01))
# run the linear model without weights
modelES_noweight <- lm(support ~ treat*imm_1, data=spain)
# use lm_robust for robust SEs that can be used by margins(). Set se_type =
"HC3" to be consistent with summ(., robust=TRUE). Point estimates are of course
numerically identical bar rounding.
modelES_noweight_robust <- estimatr::lm_robust(support ~ treat*imm_1,
data=spain, se_type = "HC3")

# generate code per replication materials, adding in the CI and making SE
robust
predES <- interact_plot(modelES_noweight, pred = imm_1, modx = treat, interval
= TRUE, robust = TRUE,
  colors = colors)+
  labs(title="",
    y="Predicted support for\nLGBT+ education in schools",
    x="")+
  theme_minimal()+
  theme(legend.position = "none",
    axis.text.x =element_blank())+
  annotate(
    geom="text", x = 2.5, y = .65, size = 4, color = "#d11141", fontface=2,
    label = "Slope for\ntreated group")+
  annotate(
    geom = "curve", x =1.6, y = .6, xend = 1.2, yend = .44,
    curvature = .4, arrow = arrow(length = unit(2, "mm")), colour="#d11141")+
  annotate(
    geom="text", x = 6, y = .4, size = 4, color = "#205C8A", fontface=2,
    label = "Slope for\ncontrol group")+
  annotate(
    geom = "curve", x =5, y = .4, xend = 2.6, yend =.31,
    curvature = -.4, arrow = arrow(length = unit(2, "mm")), colour="#205C8A")

gg_df <-
# move to robust object
modelES_noweight_robust %>%
margins(at = list(imm_1 = seq(0, 10, by = 1))) %>%
summary %>%
as.data.frame() %>%

```

```

filter(factor == "treat1")

ameES<- ggplot(gg_df, aes(imm_1, AME)) +
  geom_point(colour="#d11141") +
  geom_line(colour="#d11141") +
  coord_cartesian(xlim = c(0, 10)) +
  # change to 95% ci:
  geom_errorbar(aes(ymin = (AME-SE*1.96), ymax = (AME+SE*1.96)), width = 0,
  colour="#d11141") +
  geom_hline(yintercept = 0, linetype = "dashed", colour="#205C8A") +
  xlab("Pre-treatment attitudes towards immigration")+
  ylab("Conditional ATE") +
  theme_minimal()

predES/ameES+
  plot_annotation(title = 'Conditional average treatment effect: Study 2
  (Spain)',
  theme = theme(plot.title = element_text(size = 14,
  face="bold")))

```