

# Replication Paper - Niall Carty

Are Irish Voters Moving to the Left? Irish Political Studies  
(*Stefan Müller, Aidan Regan, 2021*)

Due: March 31, 2024

## Introduction

The abstract to this paper notes that the Irish party system has been an outlier in comparative politics. Ireland never had a left-right divide in parliament, and for decades, the dominant centrist political parties competed around a centre-right policy agenda. Müller and Regan note that the absence of an explicit left-right divide in party competition suggested that Irish voters, on average, occupy centre-right policy preferences.

Combining survey data since 1973 and all Irish election studies between 2002 and 2020, the authors aim to show that the average Irish voter now leans to the centre-left. They also state that income has recently emerged as a predictor of left-right self-placement, and that left-right positions increasingly structure vote choice. Müller and Regan find that these patterns hold when using policy preferences on taxes, spending, and government interventions to reduce inequality as alternative indicators. They outline potential explanations for this leftward shift, and conclude that these developments might be anchored in economic inequalities and the left populist strategies of Sinn Féin.

The replication of the data behind this paper is presented below, as well as an additional contribution to the work.

# Figure 1

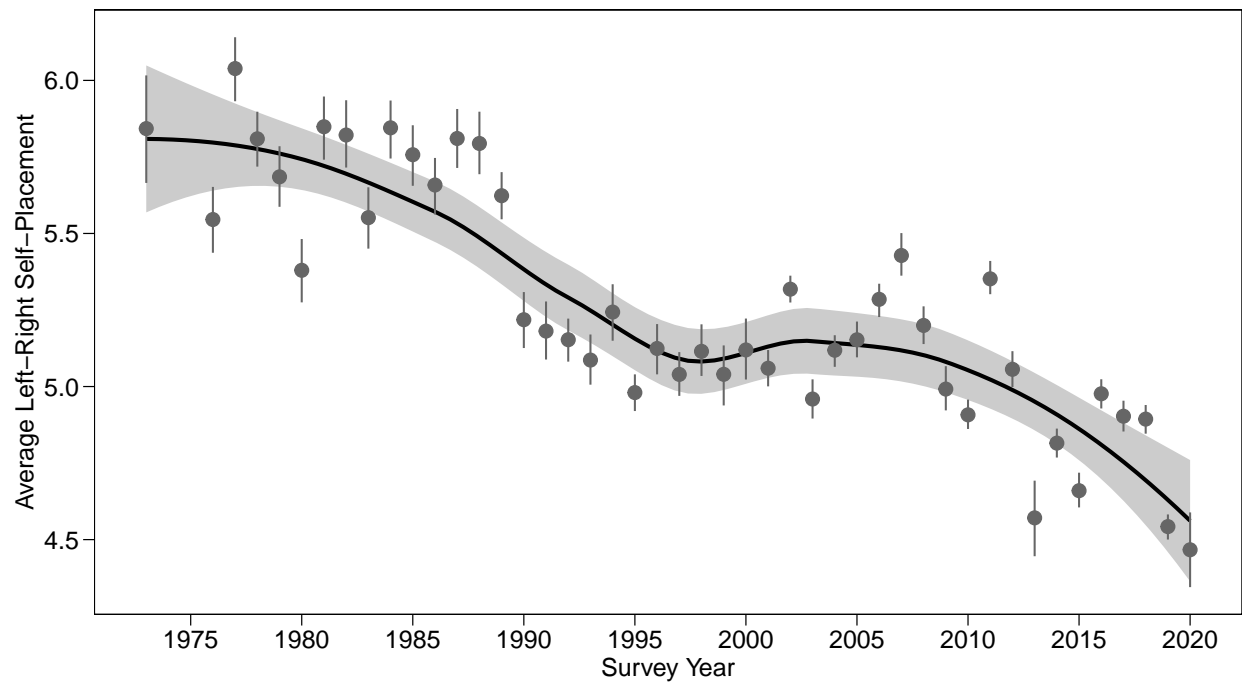
Average left-right self-placements of Irish voters, 1973–2020, based on various surveys.

```
1
2 # load harmonised survey dataset (created in 00a_filter_and_harmonise_lr_
  surveys.R)
3
4 data_surveys_1973_2020 <- readRDS("data_surveys_1973_2020.rds")
5
6
7 # load dataset with harmonised election studies
8
9 dat_electionstudies <- readRDS("data_election_studies_ireland.rds")
10
11 table(dat_electionstudies$left_right_self,
12 dat_electionstudies$year)
13
14 # descriptive statistics of surveys with Irish respondents, 1973–2020
15
16 # filter only Irish respondents
17 dat_ire <- filter(data_surveys_1973_2020,
18 country == "Ireland")
19
20
21 # number of years
22 length(unique(dat_ire$year))
23 # 47 years
24
25 # number of valid responses from Irish citizens
26 dat_ire %>%
27 filter(!is.na(left_right0to10)) %>%
28 filter(!is.na(year)) %>%
29 nrow()
30 # 152344 valid responses
31
32
33 # Sources: CSES, ESS, Eurobarometer
34 table(dat_ire$dataset)
35
36
37 set.seed(14)
38 dat_ire_sum <- dat_ire %>%
39 group_by(year) %>%
40 do(data.frame(rbind(Hmisc::smean.cl.boot(. $left_right0to10))))
41
42
43 ## Figure 1 —
44 ggplot(dat_ire_sum, aes(x = year, y = Mean,
45 ymin = Lower, ymax = Upper)) +
46 geom_smooth(fill = "grey80", colour = "black", alpha = 1) +
```

```

47 geom_point(size = 3, fill = "grey40", colour = "grey40") +
48 geom_linerange(colour = "grey40") +
49 scale_x_continuous(breaks = c(seq(1975, 2020, 5))) +
50 labs(x = "Survey Year", y = "Average Left-Right Self-Placement")
51 ggsave("fig_01.pdf",
52 width = 9, height = 5)
53
54

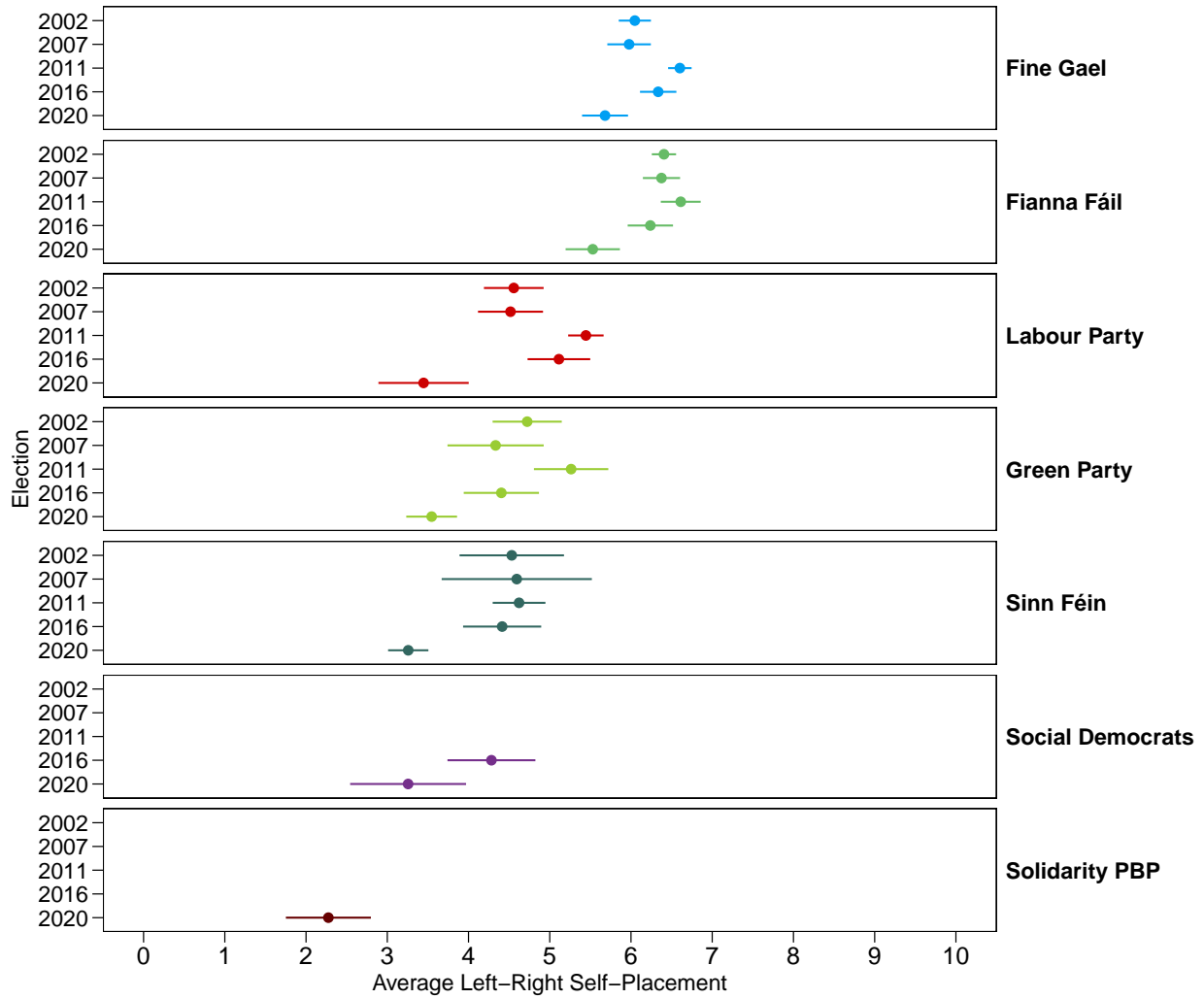
```



## Figure 2

Average-left right self-placements by first-preference vote choice.

```
1 ## Figure 2 ———
2
3 table(dat_electionstudies$party_vote_recoded_precise ,
4 dat_electionstudies$year)
5
6 # select only a subset of parties for Figure 2
7 dat_all_elections_subset <- dat_electionstudies %>%
8 filter(party_vote_recoded_precise %in% c(
9 "Solidarity PBP",
10 "Social Democrats", "Sinn Fein",
11 "Green Party", "Labour Party",
12 "Fianna Fail", "Fine Gael"
13 ))
14
15
16 left_right_self_partymeans <- dat_all_elections_subset %>%
17 srvyr::as_survey_design() %>%
18 group_by(year, party_vote_recoded_precise) %>%
19 summarise(lr_mean = srvyr::survey_mean(left_right_self,
20 na.rm = TRUE)) %>%
21 mutate(lr_ci_95_lower = lr_mean - 1.96 * lr_mean_se) %>%
22 mutate(lr_ci_95_upper = lr_mean + 1.96 * lr_mean_se) %>%
23 mutate(lr_ci_90_lower = lr_mean - 1.645 * lr_mean_se) %>%
24 mutate(lr_ci_90_upper = lr_mean + 1.645 * lr_mean_se)
25
26 # reorder parties
27 left_right_self_partymeans$party_vote_recoded_precise <- factor(
28 left_right_self_partymeans$party_vote_recoded_precise ,
29 levels = c("Fine Gael",
30 "Fianna Fail",
31 "Labour Party",
32 "Green Party",
33 "Sinn Fein",
34 "Social Democrats",
35 "Solidarity PBP"))
36
37 ggplot(left_right_self_partymeans ,
38 aes(x = forcats::fct_rev(as.factor(year)),
39 y = lr_mean,
40 colour = party_vote_recoded_precise)) +
41 geom_point(size = 2) +
42 # geom_linerange(aes(ymin = lr_ci_90_lower ,
43 #                    ymax = lr_ci_90_upper) ,
44 #               size = 1.05) +
45 geom_linerange(aes(ymin = lr_ci_95_lower ,
46 ymax = lr_ci_95_upper)) +
47 coord_flip() +
```



```

48 scale_y_continuous(limits = c(0, 10),
49 breaks = c(seq(0, 10, 1))) +
50 scale_colour_manual(values = colours_party) +
51 facet_grid(party_vote_recoded_precise ~.) +
52 theme(legend.position = "none",
53 axis.text.y = element_text(size = 12),
54 axis.title = element_text(size = 12),
55 strip.text.y = element_text(angle = 0, hjust = 0, size = 12)) +
56 labs(x = "Election",
57 y = "Average Left-Right Self-Placement")

```

## Table 1: Linear Regression Models

```
1
2 ## Linear regression models ———
3
4
5 dat_reg <- dat_electionstudies
6
7 summary(dat_reg)
8
9 # adjust factor variables
10 dat_reg$income_harmonised <- as.factor(dat_reg$income_harmonised)
11
12
13 dat_reg$gender <- relevel(as.factor(dat_reg$gender),
14 ref = "Male")
15 dat_reg$urban <- relevel(as.factor(dat_reg$urban),
16 ref = "0")
17
18 dat_reg$university_degree <- relevel(as.factor(dat_reg$university_degree),
19 ref = "0")
20
21 dat_reg$income_harmonised <- relevel(as.factor(dat_reg$income_harmonised),
22 ref = "1")
23
24 dat_reg$party_vote <- relevel(as.factor(dat_reg$party_vote),
25 ref = "Fianna Fail")
26
27 dat_reg$age_cat <- factor(dat_reg$age_cat)
28
29
30 # models with left-right self-placements as DV
31
32 # 2002
33 lm_lr_02 <- lm(left_right_self ~
34 income_harmonised +
35 age_cat +
36 gender + urban +
37 university_degree,
38 weight = weights,
39 data = filter(dat_reg,
40 year == "2002"))
41
42 # 2007
43 lm_lr_07 <- update(lm_lr_02,
44 data = filter(dat_reg,
45 year == "2007"))
46
47 # 2011
48 lm_lr_11 <- update(lm_lr_02,
```

```

49 data = filter(dat_reg,
50 year == "2011"))
51
52 # 2011
53 lm_lr_16 <- update(lm_lr_02,
54 data = filter(dat_reg,
55 year == "2016"))
56
57
58 # 2020
59 lm_lr_20 <- update(lm_lr_02,
60 data = filter(dat_reg,
61 year == "2020"))
62
63 ## Table 1 —
64 screenreg(list(
65 lm_lr_02,
66 lm_lr_07,
67 lm_lr_11,
68 lm_lr_16,
69 lm_lr_20
70 ))
71
72 wordreg(list(lm_lr_02,
73 lm_lr_07,
74 lm_lr_11,
75 lm_lr_16,
76 lm_lr_20),
77 single.row = FALSE,
78 custom.coef.names = c(
79 "(Intercept)",
80 "Income category: 2 (ref.: 1)",
81 "Income category: 3",
82 "Income category: 4",
83 "Income category: 5",
84 "Age: 25–34 (ref.: 18–24)",
85 "Age: 35–44",
86 "Age: 45–54",
87 "Age: 55–64",
88 "Age: 65+",
89 "Female",
90 "Urban constituency",
91 "University degree"),
92 size = "footnotesize",
93 custom.model.names = c("2002", "2007", "2011", "2016", "2020"),
94 file = "tab_01.doc")

```

	<b>2002</b>	<b>2007</b>	<b>2011</b>	<b>2016</b>	<b>2020</b>
(Intercept)	4.91 *** (0.20)	6.08 *** (0.34)	5.82 *** (0.21)	5.15 *** (0.31)	4.30 *** (0.30)
Income category: 2 (ref.: 1)	-0.19 (0.17)	0.26 (0.31)	0.33 (0.17)	-0.04 (0.23)	0.17 (0.20)
Income category: 3	0.25 (0.16)	0.08 (0.29)	0.47 ** (0.17)	-0.05 (0.25)	0.73 ** (0.24)
Income category: 4	-0.01 (0.16)	0.60 * (0.30)	0.49 * (0.21)	-0.12 (0.24)	0.62 * (0.29)
Income category: 5	0.32 (0.18)	0.50 (0.31)	0.46 * (0.19)	0.42 (0.23)	1.33 *** (0.38)
Age: 25-34 (ref.: 18-24)	0.69 *** (0.19)	-0.75 ** (0.27)	-0.26 (0.21)	0.21 (0.30)	0.02 (0.35)
Age: 35-44	0.74 *** (0.19)	-0.33 (0.27)	0.13 (0.22)	0.40 (0.30)	0.19 (0.36)
Age: 45-54	0.88 *** (0.19)	-0.05 (0.29)	0.11 (0.22)	0.60 (0.31)	0.10 (0.34)
Age: 55-64	0.98 *** (0.21)	-0.09 (0.29)	0.13 (0.24)	0.79 * (0.31)	0.81 * (0.33)
Age: 65+	1.69 *** (0.21)	0.79 ** (0.30)	0.54 * (0.23)	1.36 *** (0.31)	0.74 * (0.33)
Female	0.07 (0.10)	-0.24 (0.15)	-0.22 (0.11)	-0.34 * (0.15)	-0.10 (0.16)
Urban constituency	-0.34 ** (0.11)	-0.87 *** (0.16)	-0.32 ** (0.12)	-0.20 (0.15)	-0.20 (0.17)
University degree	-0.53 *** (0.16)	-0.66 ** (0.20)	-0.15 (0.14)	-0.13 (0.16)	-0.43 * (0.17)
R <sup>2</sup>	0.06	0.11	0.04	0.05	0.05
Adj. R <sup>2</sup>	0.06	0.09	0.03	0.04	0.04
Num. obs.	1643	797	1095	816	921



## Figure 3

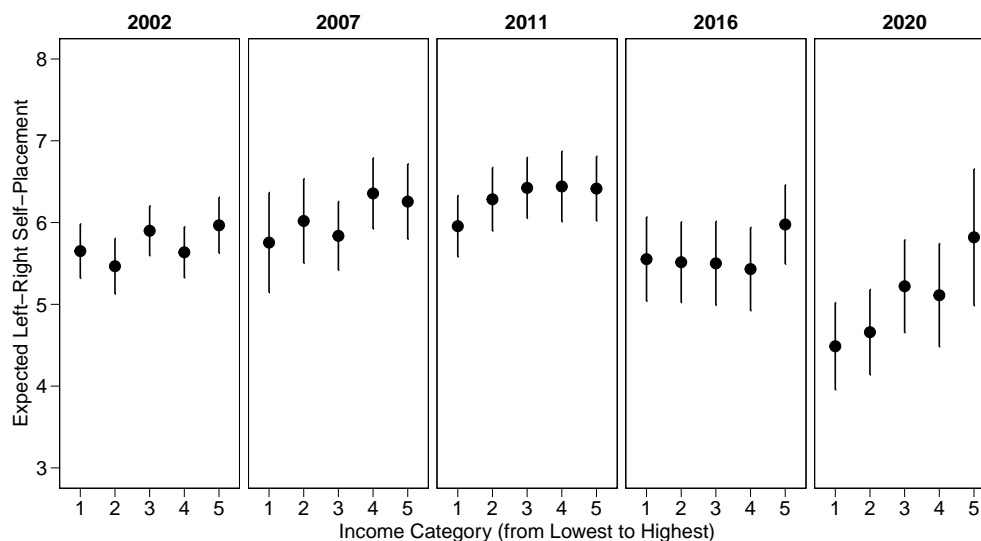
Predicting left-right self-placement conditional on income

```
1
2 ## Figure 3 ———
3 ## get expected values of income levels for each election
4
5 # 2002
6 pred_income_02 <- ggpredict(lm_lr_02, terms = c("income_harmonised"),
7 condition = c(
8 age_cat = "35-44",
9 gender = "Male",
10 urban = "0",
11 university_degree = "0")) %>% mutate(model = "2002")
12 pred_income_02
13
14
15 # 2007
16 pred_income_07 <- ggpredict(lm_lr_07, terms = c("income_harmonised"),
17 condition = c(
18 age_cat = "35-44",
19 gender = "Male",
20 urban = "0",
21 university_degree = "0")) %>% mutate(model = "2007")
22
23 pred_income_07
24
25 # 2011
26 pred_income_11 <- ggpredict(lm_lr_11, terms = c("income_harmonised"),
27 condition = c(
28 age_cat = "35-44",
29 gender = "Male",
30 urban = "0",
31 university_degree = "0")) %>% mutate(model = "2011")
32 pred_income_11
33
34
35 # 2016
36 pred_income_16 <- ggpredict(lm_lr_16, terms = c("income_harmonised"),
37 condition = c(
38 age_cat = "35-44",
39 gender = "Male",
40 urban = "0",
41 university_degree = "0")) %>% mutate(model = "2016")
42 pred_income_16
43
44 # 2020
45 pred_income_20 <- ggpredict(lm_lr_20, terms = c("income_harmonised"),
46 condition = c(
47 age_cat = "35-44",
```

```

48 gender = "Male",
49 urban = "0",
50 university_degree = "0")) %>% mutate(model = "2020")
51 pred_income_20
52
53 # bind expected values from all models
54 pred_income <- bind_rows(pred_income_02,
55 pred_income_07,
56 pred_income_11,
57 pred_income_16,
58 pred_income_20)
59
60 pred_income <- pred_income %>%
61 filter(!is.na(x))
62
63 # Change labels of income categories
64 #pred_income <- pred_income %>%
65 #mutate(income_cat = dplyr::recode(
66 # x, "1" = "1: Lowest", "5" = "5: Highest"
67 # ))
68
69 ggplot(pred_income, aes(x = predicted, y = x)) +
70 geom_point(size = 3) +
71 geom_errorbarh(aes(xmin = predicted - 1.96 * std.error,
72 xmax = predicted + 1.96 * std.error),
73 size = 0.5, height = 0) +
74 # geom_errorbarh(aes(xmin = predicted - 1.645 * std.error,
75 #                      xmax = predicted + 1.645 * std.error),
76 # size = 1.3, height = 0) +
77 coord_flip() +
78 facet_wrap(~model, nrow = 1) +
79 scale_x_continuous(limits = c(3, 8)) +
80 labs(x = "Expected Left-Right Self-Placement",
81 y = "Income Category (from Lowest to Highest)")
82 ggsave("fig_03.pdf",
83 width = 9, height = 5)

```



**Figure 4**

Predicting vote choice conditional on left-right self-placements

```

1  ## Multinomial regression models ———
2  ## predict party choice conditional on left-right self-placement
3
4  # get years
5  years <- unique(dat_reg$year)
6
7  # empty dataframe to store predicted probabilities
8  dat_multinom_merged <- data.frame()
9
10 for (i in years) {
11   dat_year <- filter(dat_reg, year == i)
12
13   lm_multinom <- multinom(party_vote ~ left_right_self + income_harmonised +
14     age_cat +
15     gender +
16     urban + university_degree,
17     weight = weights,
18     data = dat_year)
19
20   aic_election <- lm_multinom$AIC
21   dat_effect_lr <- as.data.frame(
22     Effect(c("left_right_self"),
23       lm_multinom, xlevels = 20))
24
25   dat_effect_lr_prob <- dat_effect_lr %>%

```

```

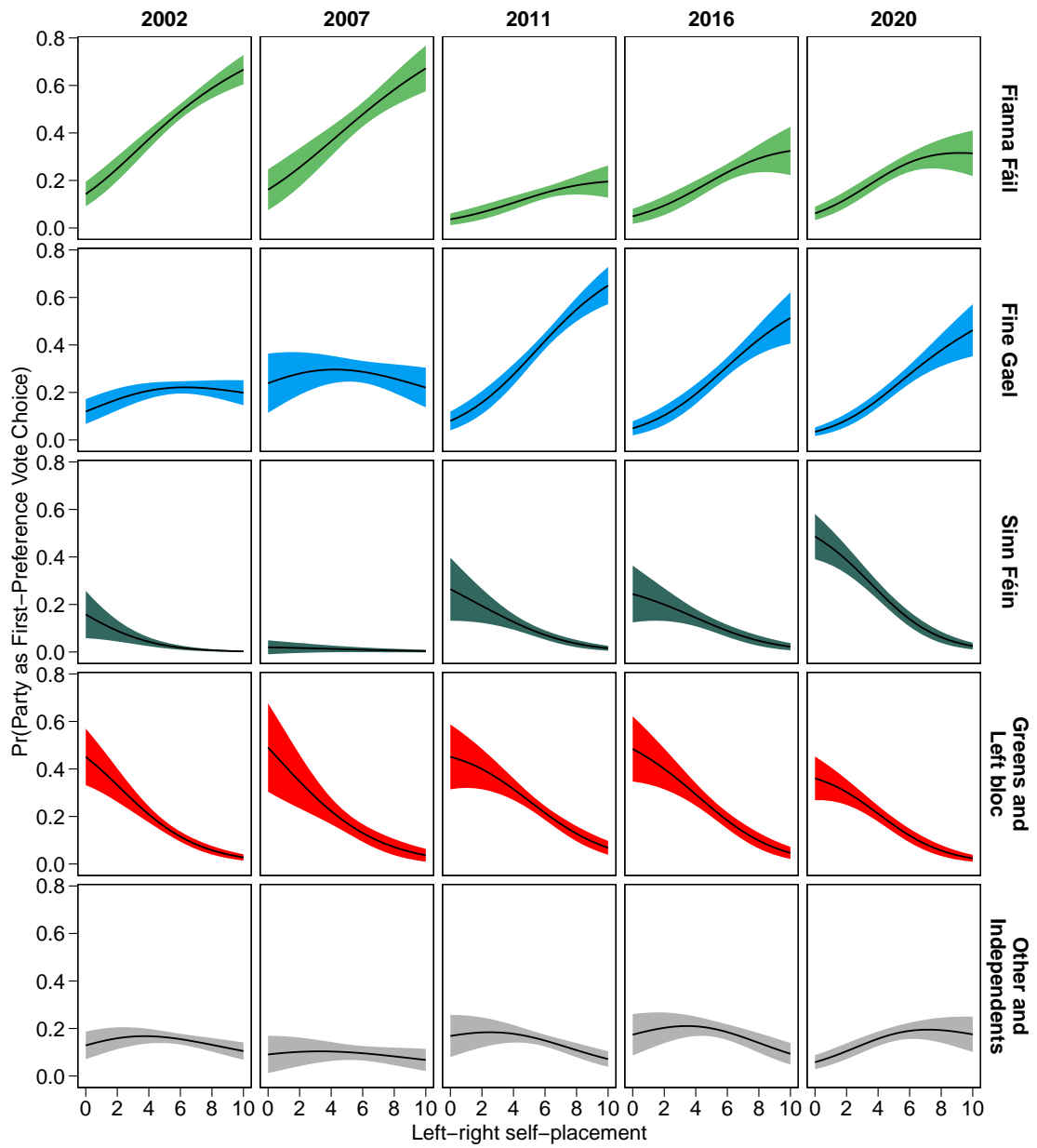
28 select(c(left_right_self, starts_with("prob.")))
29
30 dat_effect_lr_prob_long <- dat_effect_lr_prob %>%
31 gather(party_vote_aggregated, predicted, -c(left_right_self)) %>%
32 mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "prob.",
33   ", "))
34
35 dat_effect_lr_se <- dat_effect_lr %>%
36 select(c(left_right_self, starts_with("se.prob.")))
37
38 dat_effect_lr_se_long <- dat_effect_lr_se %>%
39 gather(party_vote_aggregated, std.error, -c(left_right_self)) %>%
40 mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "se.
41   prob.", ""))
42
43 dat_effect_lr_se_long <- left_join(dat_effect_lr_prob_long,
44   dat_effect_lr_se_long,
45   by = c("party_vote_aggregated", "left_right_self")) %>%
46   mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "\\.",
47     ""))
48
49 dat_effect_lr_se_long$year <- i
50 dat_effect_lr_se_long$aic_election <- aic_election
51
52 dat_multinom_merged <- bind_rows(dat_effect_lr_se_long,
53   dat_multinom_merged)
54 }
55
56 # colours for parties and levels for factors
57 colours_party <- c("#66BB66", "#009FF3", "#326760",
58   "red",
59   "grey70")
60
61 factors_party <- c("Fianna Fail", "Fine Gael",
62   "Sinn Fein",
63   "Greens and Left bloc",
64   "Other and Independents")
65
66 dat_multinom_merged$party_vote_aggregated <- factor(dat_multinom_merged$party_
67   vote_aggregated,
68   levels = factors_party)
69
70 # determine confidence intervals
71 ci_90 <- 1.645
72 ci_95 <- 1.96
73
74 ## Figure 4 —
75 ggplot(dat_multinom_merged, aes(x = left_right_self,
76   y = predicted)) +
77 # geom_ribbon(aes(ymin = predicted - ci_90 * std.error,

```

```

75 #               ymax = predicted + ci_90 * std.error ,
76 #               fill = party_vote_aggregated)) +
77 geom_ribbon(aes(ymin = predicted - ci_95 * std.error ,
78 ymax = predicted + ci_95 * std.error ,
79 fill = party_vote_aggregated)) +
80 geom_line() +
81 scale_fill_manual(values = colours_party) +
82 scale_x_continuous(breaks = c(seq(0, 10, 2))) +
83 scale_colour_grey(name = "Income", start = 0.7, end = 0) +
84 facet_grid(party_vote_aggregated ~ year, scales = "free_x",
85 labeller = label_wrap_gen(width = 15)) +
86 labs(x = "Left-right self-placement", y = "Pr(Party as First-Preference Vote
      Choice)") +
87 theme(legend.position = "none",
88 legend.title = element_blank())
89 ggsave("fig_04.pdf",
90 width = 9, height = 10)
91
92

```



## Figure 5

Predicting vote choice in the 2020 general election conditional on attitudes towards reducing differences in income and wealth.

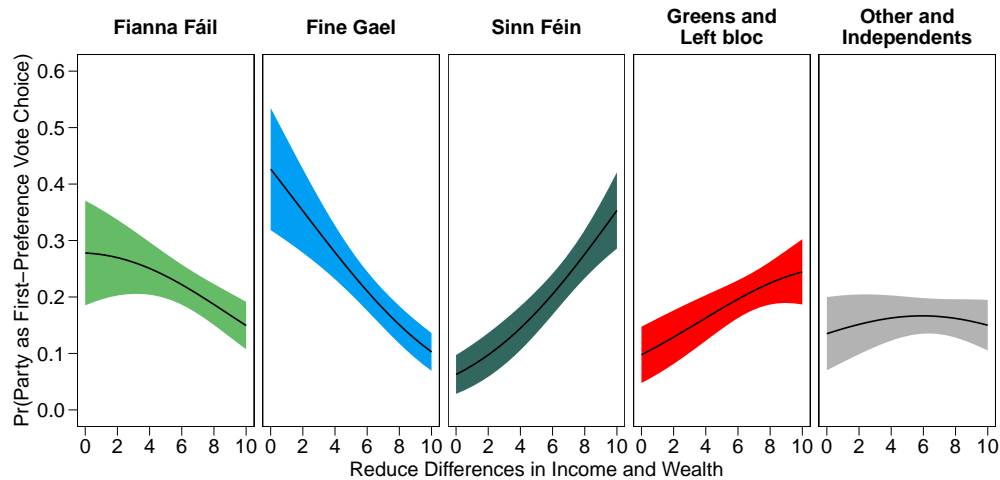
```
1 ## Repeat multinomial logistic regression models for 2020 with different set
  of independent variables
2
3 dat_reg_multinom <- dat_reg
4 head(dat_reg_multinom)
5
6 multinom_20_incomediff <- multinom(party_vote ~ income_differences + income_
  harmonised +
7 age_cat +
8 gender +
9 urban + university_degree,
10 weight = weights,
11 data = filter(dat_reg_multinom,
12 year == "2020"))
13
14 multinom_20_incomediff
15
16 multinom_20_taxespend <- multinom(party_vote ~ taxes_spending +
17 income_harmonised +
18 age_cat +
19 gender +
20 urban + university_degree,
21 weight = weights,
22 data = filter(dat_reg_multinom,
23 year == "2020"))
24
25 # get predicted probabilities for income differences
26 dat_effect_incomediff_2020 <- as.data.frame(
27 Effect(c("income_differences"),
28 multinom_20_incomediff, xlevels = 20))
29
30 dat_effect_incomediff_2020_prob <- dat_effect_incomediff_2020 %>%
31 select(c(income_differences, starts_with("prob.")))
32
33 dat_effect_incomediff_prob_2020_long <- dat_effect_incomediff_2020_prob %>%
34 gather(party_vote_aggregated, predicted, -c(income_differences)) %>%
35 mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "prob.",
  ""))
36
37 dat_effect_incomediff_2020_se <- dat_effect_incomediff_2020 %>%
38 select(c(income_differences, starts_with("se.prob.")))
39
40 dat_effect_incomediff_se_2020_long <- dat_effect_incomediff_2020_se %>%
41 gather(party_vote_aggregated, std.error, -c(income_differences)) %>%
42 mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "se.prob
  .", ""))
```

```

43
44 dat_effect_incomediff_2020_se_long <- left_join(dat_effect_incomediff_prob_
    2020_long ,
45 dat_effect_incomediff_se_2020_long ,
46 by = c("party_vote_aggregated", "income_differences")) %>%
47 mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "\\.", "
    "))
48
49 dat_effect_incomediff_2020_se_long$party_vote_aggregated <-
50 factor(dat_effect_incomediff_2020_se_long$party_vote_aggregated ,
51 levels = factors_party)
52
53 # colours for parties and levels for factors
54 colours_party <- c("#66BB66", "#009FF3", "#326760", "red", "grey70")
55
56 ## Figure 5 —
57 ggplot(dat_effect_incomediff_2020_se_long, aes(x = income_differences ,
58 y = predicted)) +
59 # geom_ribbon(aes(ymin = predicted - ci_90 * std.error ,
60 #               ymax = predicted + ci_90 * std.error ,
61 #               fill = party_vote_aggregated)) +
62 geom_ribbon(aes(ymin = predicted - ci_95 * std.error ,
63 ymax = predicted + ci_95 * std.error ,
64 fill = party_vote_aggregated)) +
65 geom_line() +
66 scale_fill_manual(values = colours_party) +
67 scale_x_continuous(breaks = c(seq(0, 10, 2))) +
68 scale_colour_grey(name = "Income", start = 0.7, end = 0) +
69 facet_wrap(~party_vote_aggregated ,
70 labeller = label_wrap_gen(width = 15) ,
71 nrow = 1) +
72 scale_y_continuous(limits = c(0, 0.6) ,
73 breaks = c(seq(0, 0.6, 0.1))) +
74 labs(x = "Reduce Differences in Income and Wealth", y = "Pr(Party as First-
    Preference Vote Choice)") +
75 theme(legend.position = "none" ,
76 legend.title = element_blank())
77 ggsave("fig_05.pdf" ,
78 width = 9, height = 4.5)

```





**Figure 6**

Figure 6. Predicting vote choice in the 2020 general election conditional on attitudes towards taxes and spending.

```

1 # get predicted values for taxes and spending
2 dat_effect_tax_2020 <- as.data.frame(
3   Effect(c("taxes_spending"),
4   multinom_20_taxespend, xlevels = 20))
5
6 dat_effect_tax_2020_prob <- dat_effect_tax_2020 %>%
7   select(c(taxes_spending, starts_with("prob.")))
8
9 dat_effect_tax_prob_2020_long <- dat_effect_tax_2020_prob %>%
10  gather(party_vote_aggregated, predicted, -c(taxes_spending)) %>%
11  mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "prob.",
12  ""))
13
14 dat_effect_tax_2020_se <- dat_effect_tax_2020 %>%
15   select(c(taxes_spending, starts_with("se.prob.")))
16
17 dat_effect_tax_se_2020_long <- dat_effect_tax_2020_se %>%
18   gather(party_vote_aggregated, std.error, -c(taxes_spending)) %>%
19   mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "se.prob.",
20   ". , ""))
21
22 dat_effect_tax_2020_se_long <- left_join(dat_effect_tax_prob_2020_long,
23   dat_effect_tax_se_2020_long,
24   by = c("party_vote_aggregated", "taxes_spending")) %>%
25   mutate(party_vote_aggregated = str_replace_all(party_vote_aggregated, "\\.", ""))
26

```



```

27 dat_effect_tax_2020_se_long$party_vote_aggregated <-
28 factor(dat_effect_tax_2020_se_long$party_vote_aggregated,
29 levels = factors_party)
30
31 library(shades)
32
33 ## Figure 6 —
34 ggplot(dat_effect_tax_2020_se_long, aes(x = taxes_spending,
35 y = predicted)) +
36 # geom_ribbon(aes(ymin = predicted - ci_90 * std.error,
37 #               ymax = predicted + ci_90 * std.error,
38 #               fill = party_vote_aggregated)) +
39 geom_ribbon(aes(ymin = predicted - ci_95 * std.error,
40 ymax = predicted + ci_95 * std.error,
41 fill = party_vote_aggregated)) +
42 geom_line() +
43 scale_fill_manual(values = colours_party) +
44 scale_x_continuous(breaks = c(seq(0, 10, 2))) +
45 scale_colour_grey(name = "Income", start = 0.7, end = 0) +
46 facet_wrap(~ party_vote_aggregated,
47 labeller = label_wrap_gen(width = 15),
48 nrow = 1) +
49 scale_y_continuous(limits = c(0, 0.6),
50 breaks = c(seq(0, 0.6, 0.1))) +
51 labs(x = "More Taxes and Spending", y = "Pr(Party as First-Preference Vote
    Choice)") +
52 theme(legend.position = "none",
53 legend.title = element_blank())
54 ggsave("fig_06.pdf",
55 width = 9, height = 4.5)

```

## Twist

Added “Urban” as an interaction term to each of the linear regression models for 2020.

Why? The authors note that “Urban cities with a concentration of high-growth multinationals tend to have rapidly growing house prices, high levels of market income inequalities, and very unequal access to housing wealth”, so appears to be a variable of particular interest.

```
1
2 # Model with interaction term for taxes and spending
3 lm_taxesspend_Int_20 <- lm(taxes_spending ~ urban * age_cat +
4   gender + university_degree + urban * income_harmonised,
5   weight = weights,
6   data = filter(dat_reg, year == "2020"))
7
8 lm_taxesspend_Int_20
9
10 # Model with interaction term for income differences
11 lm_incomediff_Int_20 <- lm(income_differences ~ urban * age_cat +
12   gender + university_degree + urban * income_harmonised,
13   weight = weights,
14   data = filter(dat_reg, year == "2020"))
15
16 lm_incomediff_Int_20
17
18 lm_lr_02 <- lm(left_right_self ~
19   income_harmonised +
20   age_cat +
21   gender + urban +
22   university_degree,
23   weight = weights,
24   data = filter(dat_reg,
25     year == "2002"))
26
27 lm_lr_20 <- update(lm_lr_02,
28   data = filter(dat_reg,
29     year == "2020"))
30
31 lm_lr_urban_INT <- lm(left_right_self ~
32   urban * income_harmonised +
33   urban * age_cat +
34   gender + university_degree,
35   weight = weights,
36   data = filter(dat_reg, year == "2020"))
37
38 lm_lr_urban_INT
39
```

	<b>M1: Left-right_INT</b>	<b>M2: Income Diff_INT.</b>	<b>M3: Taxes and Spending_INT</b>
(Intercept)	4.13 *** (0.35)	6.43 *** (0.42)	6.32 *** (0.38)
urban1	0.37 (0.60)	-0.25 (0.71)	-0.42 (0.62)
income_harmonised2	0.40 (0.22)	-1.07 *** (0.27)	-0.73 ** (0.25)
income_harmonised3	1.12 *** (0.29)	-0.49 (0.38)	-0.87 ** (0.33)
income_harmonised4	1.09 ** (0.36)	-1.79 *** (0.46)	-1.13 ** (0.44)
income_harmonised5	1.77 *** (0.51)	-1.72 ** (0.65)	-1.21 (0.63)
age_cat25-34	0.35 (0.43)	0.46 (0.53)	-0.78 (0.47)
age_cat35-44	0.23 (0.43)	1.20 * (0.51)	-0.54 (0.47)
age_cat45-54	-0.03 (0.40)	1.45 ** (0.49)	-0.64 (0.43)
age_cat55-64	0.52 (0.40)	0.57 (0.48)	-0.05 (0.43)
age_cat65+	0.91 * (0.39)	0.62 (0.48)	0.25 (0.42)
genderFemale	-0.15 (0.16)	0.45 * (0.20)	0.53 ** (0.18)
university_degree1	-0.42 * (0.17)	-0.21 (0.21)	0.04 (0.20)
urban1:income_harmonised2	-1.20 ** (0.46)	1.00 (0.56)	0.63 (0.52)
urban1:income_harmonised3	-1.52 ** (0.49)	0.05 (0.62)	1.13 * (0.55)
urban1:income_harmonised4	-1.70 ** (0.59)	0.90 (0.74)	0.85 (0.70)
urban1:income_harmonised5	-1.48 * (0.73)	1.09 (0.90)	0.52 (0.87)
urban1:age_cat25-34	-0.27 (0.75)	0.15 (0.89)	0.19 (0.82)
urban1:age_cat35-44	0.34 (0.76)	-0.50 (0.94)	0.50 (0.84)
urban1:age_cat45-54	0.93 (0.75)	-0.72 (0.90)	0.63 (0.80)
urban1:age_cat55-64	1.43 * (0.72)	-1.25 (0.86)	-0.62 (0.77)
urban1:age_cat65+	-0.46 (0.70)	-0.58 (0.83)	0.10 (0.74)
R^2	0.08	0.08	0.08
Adj. R^2	0.06	0.06	0.05
Num. obs.	921	816	770

Figure 1:

The results show that the interactions between urban and each of the income categories are significant, as is the interaction of urban and the age category 55-64.

To further explore this relationship, an Anova test was run for each model. Only the addition of the interaction term in the first model appears to have a significant on average affect.

```

1
2 > anova(lm_lr_20, lm_lr_urban_INT)
3 Analysis of Variance Table
4
5 Model 1: left_right_self ~ income_harmonised + age_cat + gender + urban +
6 university_degree
7 Model 2: left_right_self ~ urban * income_harmonised + urban * age_cat +
8 gender + university_degree
9 Res.Df    RSS Df Sum of Sq      F    Pr(>F)
10 1      908 4714.9
11 2      899 4564.5   9    150.37 3.2907 0.0005876 ***
12 ———
13
14 > anova(lm_taxesspend_20, lm_taxesspend_Int_20)
15 Analysis of Variance Table
16
17 Model 1: taxes_spending ~ gender + urban + university_degree + age_cat +
18 income_harmonised
19 Model 2: taxes_spending ~ urban * age_cat + gender + university_degree +
20 urban * income_harmonised
21 Res.Df    RSS Df Sum of Sq      F Pr(>F)
22 1      757 4124.1
23 2      748 4058.6   9    65.537 1.3421 0.2112
24 > anova(lm_incomediff_20, lm_incomediff_Int_20)
25 Analysis of Variance Table
26
27 Model 1: income_differences ~ +age_cat + income_harmonised + gender +
28 urban + university_degree
29 Model 2: income_differences ~ urban * age_cat + gender + university_degree +
30 urban * income_harmonised
31 Res.Df    RSS Df Sum of Sq      F Pr(>F)
32 1      803 5481.9
33 2      794 5414.3   9    67.558 1.1008 0.3595

```

**Conclusion:** In the case of Left-Right preferences, the addition of the 'Urban' interaction term for the first model appears to have a significant effect with regard to left wing preferences across all income categories, and also for the 55-64 year old age category, with Urban voters more inclined to vote Left.