The Emergence of *Die Grünen* and the Chernobyl Disaster

Evidence from the 1987 West-German federal election

Abstract

By implementing a Difference in Differences (DiD) design, this study answers the research question: Did the Chernobyl Disaster affect the electoral success of *Die Grünen* in constituencies close to nuclear power plants in the 1987 West-German federal election?

This study argues that the Disaster made voters living close to nuclear power plants aware of the massive risks of nuclear energy. An immediate nuclear phase-out was therefore a primary interest of these people and since the Greens were the only party that offered such a rigid anti-nuclear policy at that time, they were more successful in constituencies close to nuclear power plants.

The results of this analysis prove the assumed causal relationship. The Chernobyl Disaster increased the share of green votes in constituencies close to nuclear power plants by on average 0.9 percentage points. This effect is statistically significant. However, the validity of these results is negatively affected by some violations of the Parallel Trends Assumption and the lack of covariates in this study.

1. Introduction

The 1980s anti-nuclear movement in West Germany was a major reason for the emergence of Green parties in Europe. One pivotal event of these years was the Chernobyl Disaster in 1986 (Richardson and Rootes 2006). Suddenly, the dangers of nuclear energy became visible for everyone. By using a DiD-design, I assess the effect of the Chernobyl Disaster on the electoral success of *Die Grünen* in the 1987 West-German federal election in constituencies close to nuclear power plants.

The main argument of this study is that the Disaster made voters living close to nuclear power plants aware that their lives and properties were massively endangered by possible nuclear accidents. Therefore, an immediate shut-down of all nuclear power plants was a primary interest of people living close to them. As a result, the young environmental party *Die Grünen* (The Greens), the only party to offer such a strong anti-nuclear policy proposal at that time, was the most appealing one for people living close to nuclear power plants and therefore more successful in constituencies close to such plants.

In the first part of this study I briefly summarize the literature on the emergence of D*ie Grünen* and on the role the Chernobyl Disaster played during this process. I then describe the data and methods used in this analysis. Afterwards, I present the results of the statistical analysis and conclude with a discussion of these findings with respect to validity and limitations.

2. The emergence of Die Grünen

Until the beginning of the 1980s West Germany was a stable four-party system. Besides the two mass parties CDU and SPD, only the liberal democrats FDP were able to fulfill the necessary threshold on a national level. In addition, the conservative Bavarian regional party CSU competed successfully in federal elections (Alemann et al. 2000). This equilibrium began changing in 1979 when an alliance of environmental activists got 3.2 per cent of the votes in the 1979 election of the European Parliament in Germany (Frankland 2006). Because of this success a bigger group of Green activists officially founded *Die Grünen* as a national party in 1980.

However, the first years of the Green party were dominated by several setbacks. The ‘pivotal point’ in its emergence was the Chernobyl Disaster in 1986. After the explosion of the Ukrainian nuclear power plant a radioactive fallout cloud affected large parts of Europe. Contaminated crop had to be destroyed and people were afraid of becoming sick by radioactive particles. Suddenly, environmental protection and the proposal to shut-down all nuclear power plants appealed to many voters (ibid.). The Greens profited immediately from these events and won 8.3 per cent of the votes in the 1987 federal election.

3. Data and Method

3.1 The Dependent Variable

The dependent variable under analysis in this study is the share of second votes of *Die Grünen* in the federal elections in 1980, 1983 (pre-treatment period) and 1987 (post-treatment period). In Germany, citizens elect their members of parliament with two votes. While the first vote is for the candidate only, the second vote is used to support a certain party list. Because unestablished parties in Germany rarely have enough candidates for all constituencies, this study focuses on the share of second votes. This study does not use individual voter-level panel data but instead cross-sectional data from the level of 248 constituencies from the *German Federal Returning Officer*.

3.2 The treatment indicator and the treatment periods

In the first stage of this study, the treatment indicator is binary. It takes the value 1 if a nuclear power plant in the 1980s was either located in or directly at the border of a given constituency and 0 otherwise. In the second stage of this study the treatment indicator is a continuous variable, measuring the distance between the population center of the given constituency and the closest nuclear power plant. These variables were created manually by using a map and are based on data of the *International Atomic Energy Agency*. One weakness of this study is that, despite precise work the treatment variables are slightly error-prone and not fully reproducible.

The activation of the treatment is the Chernobyl Disaster in April 1986. The post-treatment period of this study is the 11th German federal election which took place on the 25th of January 1987, only nine months after the disaster in Chernobyl. Even though the post-treatment period in this study is short, an extension is undesirable and could distort the results because the German Reunification in 1990 changed the political landscape in Germany immensely and removed issues such as the nuclear phase-out from the agenda.

3.3 Research Design

The causal relationship of interest in this study is the effect of having a nuclear power plant in a certain constituency on the electoral success of *Die Grünen.* I develop the research design along Angrist's and Pischke's "FAQs", published in Mostly Harmless Econometrics (2008).

3.3.1 What is the ideal experimental design that could capture this causal effect?

One basic approach for assessing the relationship would be a naïve comparison of the Difference in Group Means. For instance, I could compare the results of the Green Party in constituencies close to a nuclear power plant after the Chernobyl Disaster with the results of the Green Party in constituencies far apart. However, this approach will not produce valid estimators for understanding the causal relationship because of the selection bias. It is possible that voters living close to a nuclear power plant differ from voters living far apart from one in several ways. It seems logical for instance that people who work in such a power plant as engineers also live close to their workplace. These people are probably supporters and profiteers of nuclear energy and therefore less likely to vote for a Green party. This mechanism also works vice versa: Some people who are deeply concerned about negative effects of nuclear energy might move away once a nuclear power plant is constructed in their neighborhood.

One solution to the selection bias problem is to design an experiment in which people are randomly assigned to either live close to nuclear power plant or far apart and then observe the evolution of their political views over time. Obviously, such an experiment would be expensive and unethical. However, even such an experimental design could not solve the *fundamental problem of causal inference*. In an ideal situation I could observe the share of Green votes in both types of constituencies, the ones close to a nuclear power point and the ones far apart, for each unit at the same time. Unfortunately, this is logically impossible. Each constituency either had a nuclear power plant at that time or not. I will never find out how many votes the Greens would have received in a constituency without a nuclear power point, if this constituency had had a power plant – and vice versa.

3.3.2 What is the identification strategy of this study?[1]

To estimate the causal relationship of interest, a research strategy that is able to solve the selection bias problem and cope with the fundamental problem of causal inference is necessary. A third prerequisite is that the identification strategy requires data on an aggregate level only, since data for the individual level is not available for the phenomenon of interest. Having these conditions in mind, this study follows the quasi-experimental Difference in Differences approach in the broader Potential Outcomes Framework to estimate the causal effect of interest. The emergence of the Green party is also well suited for the DiD-approach, because the specific intervention and its timing is clear. In addition, big exchanges between units of the control and the treatment group that could affect the validity of the results negatively are highly unlikely.

The necessary statistical definitions for the DiD-design are:

D_i is an indicator of whether the unit i (a specific constituency) received the treatment (had a nuclear power plant nearby or not at the time of the Chernobyl Disaster).

$$D_i = \begin{cases} 0 \; if \; unit \; i \; was \; not \; treated \\ 1 \; if \; unit \; i \; was \; treated \end{cases}$$

[1] In these paragraphs I draw back upon the material on the course website, especially on the sample essay.

In addition, T_i is an indicator of whether unit i is observed in the pre- (before the Chernobyl Disaster in 1986) and post-treatment period (after 1986).

$$T_i = \begin{cases} 0 \;\; if\ unit\ i\ is\ observed\ in\ the\ pre-treatment\ period \\ 1\ if\ unit\ i\ is\ observed\ in\ the\ post-treatment\ period \end{cases}$$

Thirdly, $Y_{di}(t)$ is the potential outcome for unit *i* (when $T_i = 1$).

$$Y_{d0}(t) = \ outcome\ of\ unit\ i\ in\ period\ t\ when\ unit\ i\ was\ not\ treated$$
$$Y_{d1}(t) = \ outcome\ of\ unit\ i\ in\ period\ t\ when\ unit\ i\ was\ treated$$

The causal effect of interest τ for unit *i* at time *t* is therefore:

$$\tau_i(t) = \ Y_{1i}(t) - \ Y_{0i}(t)$$

With the afore mentioned *fundamental problem of causal inference* in mind, it is obvious that estimating this equation directly fails because of the impossibility to observe both potential outcomes for unit *i,* which is either treated or not - but never both.

The solution of the DiD-Design for this problem is a focus on *the Average Effect of the Treatment on the Treated* (ATET). The estimation in a DiD-Design "consists of identifying a specific intervention or treatment […]."(Bertrand, Duflo and Mullainathan 2004: 2) One then compares "the difference in outcomes after and before the intervention for groups affected by the intervention to the same difference for unaffected groups" (ibid.). The key assumption for making this method valid is that constituencies without a nuclear power plant would have had the same trend in the share of votes for the Green party as constituencies without a nuclear power plant if they had not been treated. Only the treatment "induces a deviation from this common trend" (Angrist and Pischke 2008: 171). The parallel trends assumption is defined as:

$$E[Y_{0i}(1) - \ Y_{0i}(0) |\ D_i = 1] = E[Y_{0i}(1) - Y_{0i}(0) | D_i = 0]$$

Only under this condition can I estimate the causal effect of interest by calculating the ATET, which is the difference between the differences in means in the post-treatment period and in the pre-treatment period of both, control and treatment units:

$$E[Y_{1i}(1) - Y_{0i}(1) | D = 1] = \ \{E[Y_i(1)\ | D_i = 1] - E[Y_i(1) | D_i = 0]\} - \ \{E[Y_i(0)\ | D_i = 1] - E[Y_i(0) | D_i = 0]\}$$

4. Testing the Parallel Trends Assumption

Even though the Parallel Trends Assumption is crucial for the DiD-design, it is directly untestable because of the fundamental problem of causal inference. I will never observe how the units of the treatment group would have had reacted in the post-treatment group in the absence of the treatment. Nonetheless, I can compare the trends in the pre-treatment period. During this period the trends for the Share of green votes among constituencies close to a nuclear power point and far apart should be similar.

Testing the Parallel Trends Assumption in this study is difficult because the Green Party took part in the general elections for the first time in 1980. Since the Chernobyl Disaster (the treatment) occurred in 1986, the pre-treatment period is short and consists of the election results of 1980 and 1983 only. By looking at these two election results of the Green party some minor violations of the Parallel Trends Assumption become visible (Figure 1.1).

However, because of the short pre-treatment period these findings are not sufficient. I therefore extend the pre-treatment period back to 1965 to test the assumption further. Since I cannot observe the trends for the Green Party for these years, I am relying my test on the election results of the other parties. I thereby exclude the Bavarian Party CSU since its regional concentration and its strong results in some constituencies would affect the validity of this study negatively. In particular, the results of the conservative CDU in the 1969 and the 1972 elections show that the Parallel Trends Assumption is violated (Fig. 1.3). This affects the validity of this study negatively because it indicates that besides the causal relationship of interest, other causal relationships may influence the results.

Fig 1.1 Parallel trends - Greens?

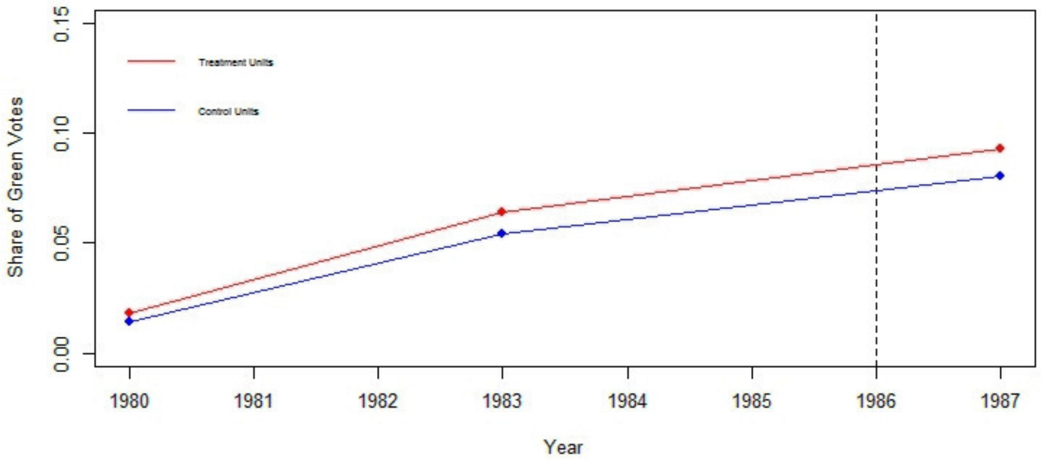


Fig. 1.2 Parallel trends - SPD?

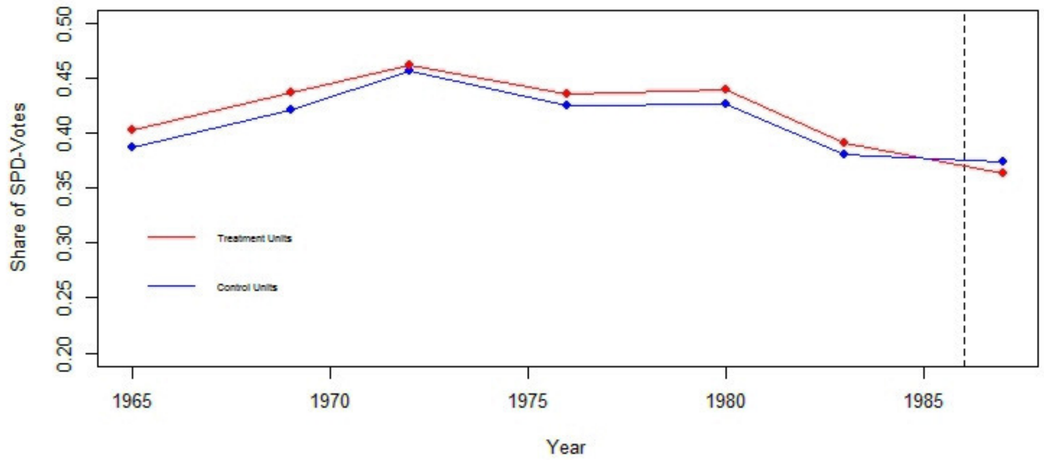


Fig. 1.3 Parallel trends - CDU?

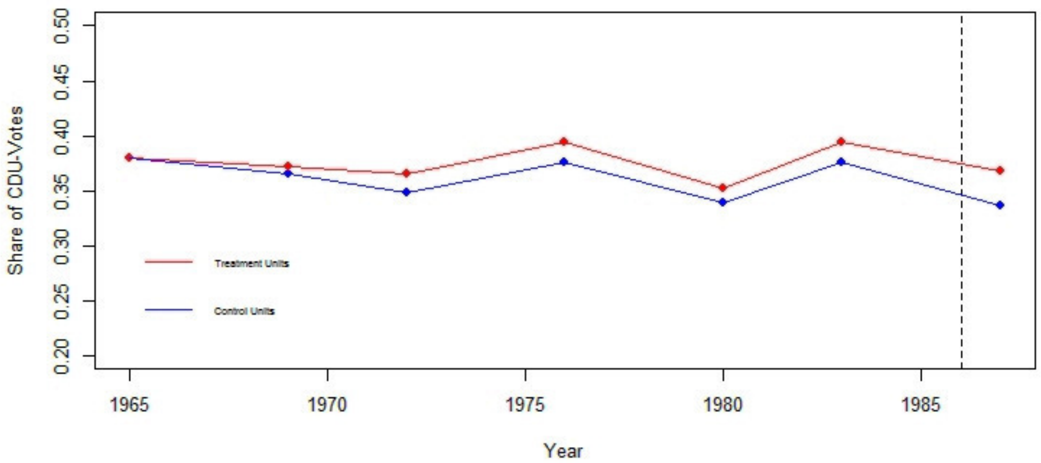
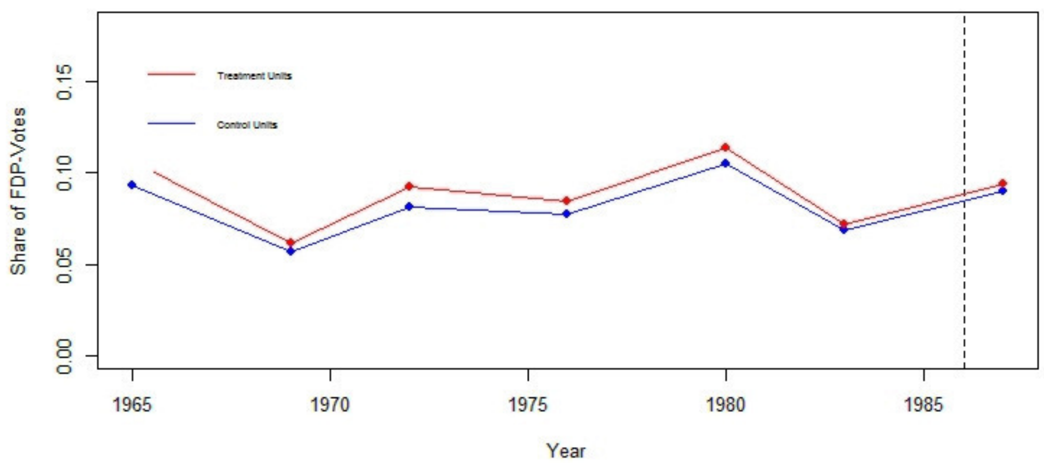


Fig. 1.4 Parallel trends - FDP?



5. Results and Robustness Checks

In the first part of this analysis, I estimate the ATET and the selection bias manually. Secondly, I control these results using a linear regression model and thirdly, implement a fixed-effect regression model to abolish specific variable biases and, in this case more importantly, to reduce the effect of changes in the outcome variable that affect all treatment and control units at the same time. In the second part I recode the treatment variable into a continuous variable and rerun the regression models.

The manually calculated difference between the differences in means in the post-treatment period and the pre-treatment period is 0.009 which means, that the Chernobyl Disaster on average caused an increase in the share of votes of the Green Party by 0.9 percentage points in constituencies close to a nuclear power plant (Fig. 2). Since the calculated effect is positive it can be assumed that voters living in a constituency close to a nuclear power plant were more in favor of the Green Party after the Chernobyl Disaster. This finding is supported by the calculated p-value of the DiD-regression, which is 0.035 and shows that the result is statistically significant on the 95 percent significance interval.

Fig. 2 DiD-regression model

	Dependent variable:
	Share of Green Votes
Distance to a Nuclear Power Plant (binary)	0.004 (0.003)
Year as factor 1983	0.040^{***} (0.002)
Year as factor 1987	0.066^{***} (0.002)
Interaction Power Plant (binary) and 1983	0.006 (0.004)
Interaction Power Plant (binary) and 1987	0.009^{**} (0.004)
Constant	0.014^{***} (0.001)
Observations	744
R^2	0.727
Adjusted R^2	0.725
Residual Std. Error	0.017 (df = 738)
F Statistic	392.177^{***} (df = 5; 738)
Note:	*p **p ***p<0.01

I can therefore reject the Null-Hypothesis and assume that there is a causal relationship between the distance to a nuclear power plant and the electoral success of the Green Party in the 1987 general election after the Chernobyl Disaster. The fixed-effect regression (Fig. 3), which I run to check the robustness and wash out latent variable biases principally confirms the direction of the effect as well as the statistical significance (p = 0.016).

Fig. 3 Fixed effect model with binary treatment

	Dependent variable:
	Share of Green Votes
Year as factor 1983	0.041^{***} (0.001)
Year as factor 1987	0.067^{***} (0.001)
Power Plant (binary)	0.006^{**} (0.002)
Observations	744
R^2	0.921
Adjusted R^2	0.881
Residual Std. Error	0.011 (df = 493)
F Statistic	22.992^{***} (df = 250; 493)
Note:	$^{*}p^{**}p^{***}p<0.01$

However, when the treatment variable is recoded from a binary to a continuous one, the explanatory variable is no longer significant (Fig. 4, Appendix). This may be a result of some influential statistical outliers, so constituencies in which the Green Party is successful even though they are located far apart from nuclear power plants, for instance constituency number 185. Here the Green party got 18.4 percent of the votes even though the distance to the nearest nuclear power plant is 144 kilometers. In case of a binary treatment such constituencies are weighted like all other control units, but once the distance is considered such constituencies influence the result more than others. Nonetheless, when including the continuous treatment variable in a fixed-effect-regression the results are again significant and therefore provide some evidence for the afore mentioned findings, even though the measured effect is weak (Fig. 5).

6. Discussion

The biggest threat to the validity of these results comes from the violations of the parallel trends assumption. The unparallel trends in the voting results of the other parties indicate that in constituencies close to nuclear power plants voters generally have different political opinions than voters living far apart from power plants. Therefore, it is possible that the measured above-average results of the Green party in these constituencies are a consequence of a different causal relationship than the one investigated in this study.

One potential way to deal with this problem would be the introduction of covariates into the regression models. Such variables could control for hidden differences between the control and treatment units that affect the results of this study (e.g. economic strength, urbanity). Another possibility would be changing the units of this study from the constituency level to the polling station level to look at the voting behaviour of people that live in direct proximity to nuclear power plants. However, in this case both attempts require archival research since the data for that time is not digitised. A third strategy would be the exclusion of some outliers that deviate strongly from the mean and therefore skew the results. Normally an extension of the pre- and the post-treatment period could increase the validity of the results, but because of the comprehensive reform of the constituency landscape in West Germany in 1965 and the German reunification in 1990, this would not be a promising strategy for this study.

Another significant point which is discussed in the literature on DiD-designs is the role of standard errors. In the majority of published DiD-papers, and similarly in this study, "DD estimates and their standard errors […] derive from using Ordinary Least Squares (OLS) in repeated cross-sections (or a panel) of data on individuals in treatment and control groups […]" (Bertrand, Duflo and Mullainathan 2004: 2). However, "because of serial correlation, conventional DD standard errors may grossly understate the standard deviation of the estimated treatment effects, leading to serious over-estimation of t-statistics and significance levels" (ibid. 18). It is therefore possible that the null hypothesis is rejected too often in DiD-studies. Several authors recommend clustering the standard errors to increase the validity of the DiD-results (Abadie et al. 2017, Bertrand, Duflo and Mullainathan 2004, McKenzie 2017). This could also be done for example by implementing block bootstrap or "allowing for an arbitrary auto-correlation process when computing the standard errors", if the number of observed groups is sufficiently large (Bertrand, Duflo and Mullainathan 2004: 18-19).

7. Conclusion

Bearing the limitations in mind, this study has shown a tentative causal relationship between the Chernobyl Disaster and the electoral success of the Green Party in West German constituencies close to a nuclear power plant in the 1987 general election. By calculating the DiD between the means of the pre- and the post-treatment period the study has shown that the Disaster increased the share of green votes in constituencies close to a nuclear power plant by on average 0.9 percentage points. The results of several regression models prove that this effect is statistically significant. However, this study has also made the limitations of these findings clear – these being that the essential Parallel Trends assumption might be violated, the lack of covariates included in the regression models, and the usage of unclustered, conventional standard errors.

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Appendix:

The Appendix includes information regarding the Results, the used Data and the original R-Code for this project.

Fig. 4 DiD-regression model with continuous treatment

	Dependent variable:
	Share of Green Votes
Distance to a Nuclear Power Plant (continous)	-0.00001 (0.00003)
Year as factor 1983	0.043^{***} (0.003)
Year as factor 1987	0.072^{***} (0.003)
Interaction Power Plant (continous) and 1983	-0.00003 (0.00004)
Interaction Power Plant (binary) and 1987	-0.0001 (0.00004)
Constant	0.016^{***} (0.002)
Observations	744
R^2	0.718
Adjusted R^2	0.716
Residual Std. Error	0.018 (df = 738)
F Statistic	375.171^{***} (df = 5; 738)
Note:	*p**p***p<0.01

Fig. 5 Fixed effect model with continous treatment

	Dependent variable:
	Share of Green Votes
Year as factor 1983	0.041^{***} (0.001)
Year as factor 1987	0.066^{***} (0.001)
Power Plant (continous)	0.0003^{***} (0.0001)
Observations	744
R^2	0.922
Adjusted R^2	0.882
Residual Std. Error	0.011 (df = 493)
F Statistic	23.309^{***} (df = 250; 493)
Note:	*p**p***p<0.01

The results of all federal German elections since 1949 [German only] can be retrieved from: https://www.bundeswahlleiter.de/bundestagswahlen/2017/ergebnisse.html

An immediate download starts by using this URL: https://www.bundeswahlleiter.de/dam/jcr/ce2d2b6a-f211-4355-8eea-355c98cd4e47/btw_kerg.zip

The data for the coding of the independent variable is based on information provided by the German Federal Ministry for Environment and Nuclear Safety. The best overview in English is thereby available at the International Atomic Energy Agency (IAEA) and can be retrieved from: https://www-pub.iaea.org/mtcd/publications/pdf/cnpp2003/cnpp_webpage/countryprofiles/Germany/Germany2003.htm

The data for the continuous treatment was generated by using GoogleMaps and measuring the direct distance between the nearest nuclear power plant and the respective constituency.

A merged dataset based on these sources was separately uploaded to Moodle.

```
## Start of Term Project for Advanced Quantitative Methods

## First step: Create Working Space
rm(list = ls())
setwd("C:/Users/Markus Kollberg/Desktop/Advanced Quant Methods")
nuc <-read.csv2("CGFF1_data.csv")
View(nuc)
library(foreign)
set.seed(12345)
summary(nuc)

## Second step: Calculate Means for the Greens before and After Treatment

## Untreated, post_treatment
y_control_1987_Greens <- mean(nuc$Greens_relative[nuc$power_plant == 0 & nuc$year == 1987])
## Treated, post_treatment
y_treat_1987_Greens <- mean(nuc$Greens_relative[nuc$power_plant == 1 & nuc$year == 1987])
## untreated, pre_treatment
y_control_8083_Greens <- mean(nuc$Greens_relative[nuc$power_plant == 0 & nuc$year == 1980 & 1983])
## treated, pre_treatment
y_treat_8083_Greens <- mean(nuc$Greens_relative[nuc$power_plant == 1 & nuc$year == 1980 & 1983])

## Third step: Parallel trend calculation

parallel_trends_value <- (y_treat_1987_Greens - y_treat_8083_Greens) - (y_control_1987_Greens -
y_control_8083_Greens)
parallel_trends_value

## Fourth step: Stable Selection Bias calculation

selection_bias_value <- (y_treat_1987_Greens - y_control_1987_Greens) - (y_treat_8083_Greens - y_control_8083_Greens)
selection_bias_value

##Interpretation: The "activation" of the treatment caused an increase in the support for the Green Party by 0.87
percentage points among treatment units.

## Fifth step: Proving the calculation by using regression

DiD_mod <- lm(Greens_relative ~ power_plant * as.factor(year),
             data = nuc)
summary(DiD_mod)

## Interpretation: The regression proves the manual calculation and it also shows that the relation we are looking
for is statistically significant.
## NOTE: At this stage I could either control for covariables or try to reschuffle my treatment in a continous
variable. After consulting the module teacher I decide for the latter.


## Sixth step: Fixed-effect model.
## here I need a new variable for treatet only in 1987

treated_1987 <- c(nuc$power_plant == 1 & nuc$year == 1987)

treated_1987

nuc$treated_1987 <- treated_1987
fixed_effect_model <- lm(Greens_relative ~ as.factor(district) + as.factor(year) + treated_1987,
                         data  = nuc)
options(max.print = 999999)

summary(fixed_effect_model)

##Interpretation: The results of the fixed effect model prove the significance I have seen in the standard regression
model.

##Seventh step: Regression wiht continous treatment

binary_model <- lm(Greens_relative ~ treat_continous * as.factor(year), data = nuc)

summary(binary_model)

new_continous <- treated_1987 * nuc$treat_continous

new_continous

fixed_effect_model_cont <- lm(Greens_relative ~ as.factor(district) + as.factor(year) + new_continous,
                           data  = nuc)

summary(fixed_effect_model_cont)


## From this point on it's all about proving the general trends asumption.

## make sure your margins are wide enough, otherwise it produces errors
```

```
par(mfrow = c(2, 2))

group_period_averages_Greens <- aggregate(x = nuc$Greens_relative,
                                          by = list(nuc$year, nuc$power_plant),
                                          FUN = mean)

names(group_period_averages_Greens) <- c("year", "power_plant", "Greens_relative")

group_period_averages_Greens

plot_Greens <- plot(x = group_period_averages_Greens$year,
     y  = group_period_averages_Greens$Greens_relative,
     col = ifelse(group_period_averages_Greens$power_plant, "red", "blue"),
     pch = 19,
     xlab = "Year",
     ylab = "Share of Green Votes",
     main = "Fig 1.1 Parallel trends - Greens?",
     xlim = c(1980, 1987),
     ylim = c(.0,.15),
     abline(v= 1986, col="black", lty ="dashed"))

lines(x = group_period_averages_Greens$year[group_period_averages_Greens$power_plant == T],
      y = group_period_averages_Greens$Greens_relative[group_period_averages_Greens$power_plant == T],
      col = "red")
lines(x = group_period_averages_Greens$year[group_period_averages_Greens$power_plant ==  F],
      y = group_period_averages_Greens$Greens_relative[group_period_averages_Greens$power_plant == F],
      col = "blue")
legend(x = 1979.8, y = .155, legend=c("Treatment Units", "Control Units"),
       col= c("red", "blue"), lty=1:1, cex = .53, box.lty = 0)

## plots for the SPD

group_period_averages_SPD <- aggregate(x = nuc$SPD_relative,
                                          by = list(nuc$year, nuc$power_plant),
                                          FUN = mean)

names(group_period_averages_SPD) <- c("year", "power_plant", "SPD_relative")

group_period_averages_SPD

plot_SPD <- plot(x = group_period_averages_SPD$year,
                    y  = group_period_averages_SPD$SPD_relative,
                    col = ifelse(group_period_averages_SPD$power_plant, "red", "blue"),
                    pch = 19,
                    xlab = "Year",
                    ylab = "Share of SPD-Votes",
                    main = "Fig. 1.2 Parallel trends - SPD?",
                    xlim = c(1965, 1987),
                    ylim = c(.2,.5),
                    abline(v= 1986, col="black", lty ="dashed"))

lines(x = group_period_averages_SPD$year[group_period_averages_SPD$power_plant == T],
      y = group_period_averages_SPD$SPD_relative[group_period_averages_SPD$power_plant == T],
      col = "red")
lines(x = group_period_averages_SPD$year[group_period_averages_SPD$power_plant ==  F],
      y = group_period_averages_SPD$SPD_relative[group_period_averages_SPD$power_plant == F],
      col = "blue")
legend(x = 1964.8, y = .35, legend=c("Treatment Units", "Control Units"),
       col= c("red", "blue"), lty=1:1, cex = .53, box.lty = 0)

## for the CDU

group_period_averages_CDU <- aggregate(x = nuc$CDU_relative,
                                          by = list(nuc$year, nuc$power_plant),
                                          FUN = mean)

names(group_period_averages_CDU) <- c("year", "power_plant", "CDU_relative")

group_period_averages_CDU

plot_CDU <- plot(x = group_period_averages_CDU$year,
                 y  = group_period_averages_CDU$CDU_relative,
                 col = ifelse(group_period_averages_CDU$power_plant, "red", "blue"),
                 pch = 19,
                 xlab = "Year",
                 ylab = "Share of CDU-Votes",
                 main = "Fig. 1.3 Parallel trends - CDU?",
                 xlim = c(1965, 1987),
                 ylim = c(.2,.5),
                 abline(v= 1986, col="black", lty ="dashed"))

lines(x = group_period_averages_CDU$year[group_period_averages_CDU$power_plant == T],
      y = group_period_averages_CDU$CDU_relative[group_period_averages_CDU$power_plant == T],
      col = "red")
lines(x = group_period_averages_CDU$year[group_period_averages_CDU$power_plant ==  F],
```

```
      y = group_period_averages_CDU$CDU_relative[group_period_averages_CDU$power_plant == F],
      col = "blue")
legend(x = 1964.8, y = .33, legend=c("Treatment Units", "Control Units"),
       col= c("red", "blue"), lty=1:1, cex = .53, box.lty = 0)

## for the FDP

group_period_averages_FDP <- aggregate(x = nuc$FDP_relative,
                                       by = list(nuc$year, nuc$power_plant),
                                       FUN = mean)

names(group_period_averages_FDP) <- c("year", "power_plant", "FDP_relative")

group_period_averages_FDP

plot_FDP <- plot(x = group_period_averages_FDP$year,
                 y  = group_period_averages_FDP$FDP_relative,
                 col = ifelse(group_period_averages_FDP$power_plant, "red", "blue"),
                 pch = 19,
                 xlab = "Year",
                 ylab = "Share of FDP-Votes",
                 main = "Fig. 1.4 Parallel trends - FDP?",
                 xlim = c(1965, 1987),
                 ylim = c(.0,.18),
                 abline(v= 1986, col="black", lty ="dashed"))

lines(x = group_period_averages_FDP$year[group_period_averages_FDP$power_plant == T],
      y = group_period_averages_FDP$FDP_relative[group_period_averages_FDP$power_plant == T],
      col = "red")
lines(x = group_period_averages_FDP$year[group_period_averages_FDP$power_plant ==  F],
      y = group_period_averages_FDP$FDP_relative[group_period_averages_FDP$power_plant == F],
      col = "blue")
legend(x = 1964.8, y = .18, legend=c("Treatment Units", "Control Units"),
       col= c("red", "blue"), lty=1:1, cex = .53, box.lty = 0)


## From here on it is only about exporting the results to word files

library(stargazer)

stargazer(DiD_mod, type="html",
          model.numbers = FALSE,
          title = "Fig. 2 DiD-regression model",
          dep.var.labels=c("Share of Green Votes"),
          covariate.labels=c("Distance to a Nuclear Power Plant (binary)", "Year as factor 1983", "Year as factor
1987", "Interaction Power Plant (binary) and 1983", "Interaction Power Plant (binary) and 1987"),
          out="DiD_regression.htm",
          single.row = TRUE,
          digits = 3)

stargazer(binary_model, type= "html",
          model.numbers = FALSE,
          title = "Fig. 4 DiD-regression model with continuous treatment",
          dep.var.labels = c("Share of Green Votes"),
          covariate.labels = c("Distance to a Nuclear Power Plant (continous)", "Year as factor 1983","Year as factor
1987", "Interaction Power Plant (continous) and 1983", "Interaction Power Plant (binary) and 1987"),
          out="DiD_regression_cont.htm",
          single.row = TRUE,
          digits = 3)

stargazer(fixed_effect_model, type = "html",
          model.numbers = FALSE,
          title = "Fig. 3 Fixed effect model with binary treatment",
          dep.var.labels = c("Share of Green Votes"),
          out = "FEM_binary.htm",
          single.row = TRUE,
          keep = c("1983", "1987", "TRUE"),
          digits = 3,
          covariate.labels = c("Year as factor 1983", "Year as factor 1987", "Power Plant (binary)"))

stargazer(fixed_effect_model_cont, type = "html",
          model.numbers = FALSE,
          title = "Fig. 5 Fixed effect model with continous treatment",
          dep.var.labels = c("Share of Green Votes"),
          out = "Fixed_continous.htm",
          single.row = TRUE,
          keep = c("1983", "1987", "continous"),
          digits = 3,
          covariate.labels = c("Year as factor 1983", "Year as factor 1987", "Power Plant (continous)"))
```