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Relationship Between Political Parties and CO2 Emissions

Are emissions from Norwegian municipalities influenced by political parties?

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NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

In this thesis, we investigate the relationship between political parties and carbon dioxide emissions in Norwegian municipalities from 2009 to 2021. We initially use a panel data approach to analyse Norway's eight largest political parties. Afterwards, we use regression discontinuity design (RDD), where we focus on the Labour Party and the Conservative Party, which represent the opposite sides of the political spectrum. To account for the different characteristics of the municipalities, we divide them into three clusters using k-means clustering. Our results reveal that the Labour Party is associated with an increase in total emissions, while the Conservative Party has no statistically significant effect. Robustness checks confirm these results, indicating an average 11,6% increase in emissions when the Labour Party is in charge. In conclusion, our findings show that there is a relationship between political parties and emissions.

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1. Introduction

Norway responded to the urgent need for measures to combat climate change highlighted by the United Nations' Intergovernmental Panel on Climate Change (IPCC) in 2007 by adopting an ambitious climate strategy aimed at reducing carbon dioxide emissions (Ministry of Agriculture and Food, 2009). Atya and Abdou (2013) validate the significant role of institutions in creating effective policies and regulations to decrease emissions. Additionally, recent studies indicate that left-wing parties tend to prioritise environmental concerns, while right-wing parties focus more on economic growth (Hu, Chen, Chang, & Chu, 2020). Neumayer (2004) supports these findings, as it highlights the strong correlation between left-wing political ideology and a more substantial commitment to address environmental concerns in election manifestos, as well as holding more environmentally friendly beliefs.

In this paper, we will investigate the relationship between individual political parties and emissions. We will concentrate on eight political parties and examine over 300 municipalities for the years 2009 – 2021. Initially, we will use the panel data approach as a benchmark for the regression discontinuity design (RDD) that we will perform afterwards. The panel data approach will consider all eight parties, while the RDD will concentrate on two of the largest political parties, which are on opposite sides of the political spectrum, the Labour Party, and the Conservative Party.

To account for the significant variation among the municipalities, it is necessary to adjust for these variations. To adjust for that, we collect several variables representing each municipality's characteristics. To ensure that the comparison is fair, we divide the municipalities into three clusters using k-means clustering. This enables us to investigate similar municipalities together. However, we will also investigate all the municipalities to observe differences between them pooled together and divided into clusters.

The lack of a clear distinctive cut-off differentiates the RDD analysis from some of the other papers which investigate the relationship between political parties and a specific subject. Instead of assuming that the party that receives the most votes is the winner and in charge, we assume that the party that obtains the mayor chair is the one truly in charge, regardless of their vote count. In practice, municipal councils often comprise more than one political party. However, to isolate the impact of a specific party, the analysis will focus on the party holding the mayor's chair to isolate the effect of the party in power.

Our findings indicate that the Labour Party is associated with an increase in total emissions. These results remain consistent after conducting several robustness checks for the full data and Cluster 1, which contains the smallest municipalities. When the Labour Party is in charge, there is on average an 11,6% increase in emissions across all municipalities and a 9,9% increase specifically in the smallest municipalities. For the Conservative Party, all estimates show statistical insignificance results, meaning they have no effect on total emissions.

In conclusion, we find a relationship between political parties and emissions in Norwegian municipalities, as evidenced by the results associated with the Labour Party.

2. Background

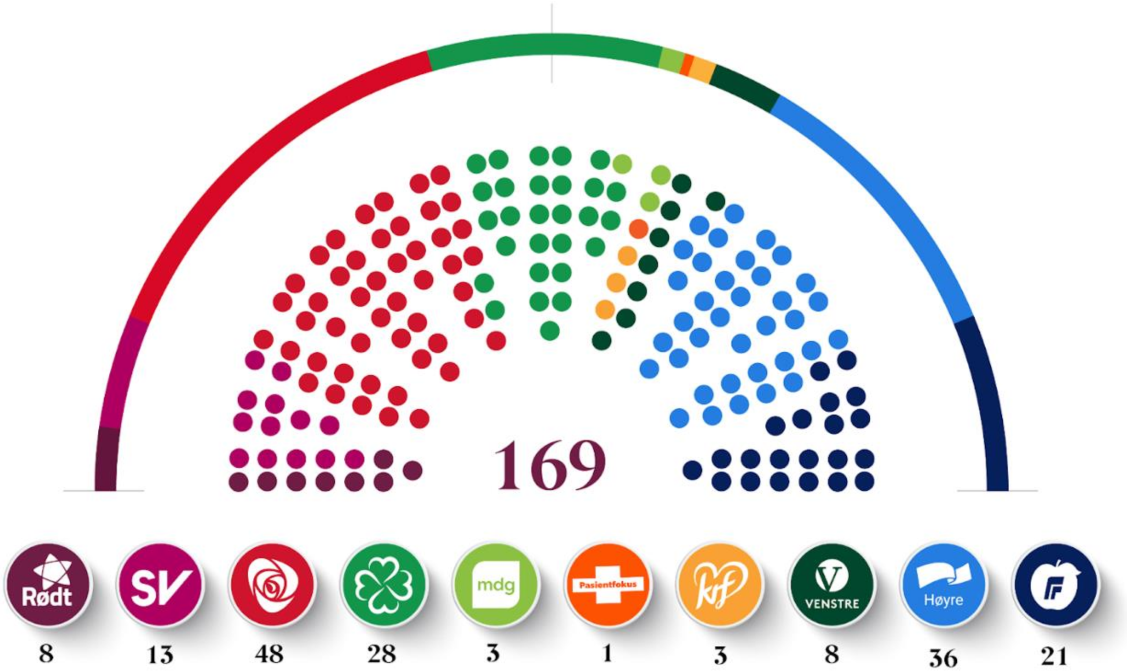
2.1 Political Parties and Elections

The municipal election is held every four years, and the last election took place in 2019. In Norway, there are currently 356 municipalities, divided into 11 counties, and each municipality has its unique council (KBN, 2023). There have been multiple mergers of municipalities in recent years, where some municipalities have merged under the name of an existing municipality or a new name. For the analysis of this paper, the collected data is aggregated for the merged municipality. For example, the data collected for Drammen from 2009 until 2021 is data for Drammen includes the aggregated values of the merged municipality, which has been calculated backwards to 2009. This data will, therefore, not include municipalities that have been merged under a new name or with an existing municipality.

The election process is the same for all municipalities in Norway. However, the size of the municipal councils is reflected in the size of the municipality. Once all the votes have been added up, the results are reflected in the number of seats each party has won on the council for that municipality. The results also depend on the number of municipal councils in that specific municipality. For example, if a municipality has 20 representatives on the municipal council, the total number of a party is summed up and multiplied by the number of representatives, in this case, 20. Once the list has been completed, the number of representatives for each party is calculated (Valg, 2021).

Figure 1 shows the political spectrum and the positioning of the political parties, which gives us an insight into their ideology. Each circle represents a political party, and the number below the circle says how many members of that party are currently in the parliament. This figure shows the political environment in the Norwegian parliament and enables us to understand if the political party is associated with a left or right-wing ideology. The location of the political parties in Figure 1 is later used to group the parties into central parties as well as right- and left-wing parties.

Figure 1. Political parties in the Norwegian parliament location on the political spectrum.



Note. The political parties in the current parliament in Norway where the parties are positioned on a political spectrum from left to right. The spectrum is coloured based on the party and the number of members from that party. The positioning of the political parties enables us to classify them under central, left-wing and right-wing (Stortinget, 2023).

Some political parties run only for the municipal council. However, the largest parties which run in the municipality elections also run for the parliament (Stortinget, 2023). In Norwegian politics, the Red Party, the Socialist Left Party, and the Labour Party are on the left wing of the spectrum. The Conservative Party, the Progress Party, and the Liberal Party are on the right wing of the spectrum. In the middle, there are the Centre Party, the Christian Democratic Party, and the Green Party (Stortinget, 2023).

2.2 Carbon Dioxide (CO_2) Emissions

CO_2 is the most detrimental greenhouse gas, significantly contributing to the escalation of global climate change. CO_2 is essential for the average global temperature since without it, the average temperature would be at a freezing point (Lindsey, 2022). As a result of climate change, there have been record amounts of heat waves and weather-related disasters in recent years (NASA, 2023). The recent events of heat waves and weather-related disasters resulting from climate change show the imminent danger that the world currently faces.

Norway entered into an agreement with the European Union to participate in their climate legislation for 2021 – 2030. Norway aims to be carbon neutral by 2030. Therefore, they need to lower their CO2 emissions to achieve their goal. To do so, the municipalities must do their part (IEA, 2021). The municipalities in Norway have set ambitious emission targets. For example, Oslo intends to reduce emissions by 95%, and Trondheim and Stavanger intend to reduce emissions by 80% before 2023 compared to 1990. Bergen aims to be fossil-free by 2030 (Norwegian Ministry of Climate and Environment, 2021). Therefore, investigating the relationship between the emissions and the political parties can reveal if the parties are truly working towards their emission targets.

2.3 Mechanisms

Numerous factors, like policy instruments, regulations, and government incentives, can influence municipalities' prioritization of climate change initiatives.

A study by Hovelsrud, Husabø, and Dannevig (2013) investigates the drivers behind climate change adaption in Norwegian municipalities, mainly due to lack of national regulations. The study finds that the municipalities depend heavily on national government funding tied to legally binding obligations. Since their services are heavily regulated and their budget is earmarked, there are few incentives for the municipalities to undertake tasks that are not regulated, including climate change adaptation. Based on their findings, the authors conclude that without a clear direction and incentives from the national government, initiatives concerning climate change will not be prioritized.

However, since the publication, there have been developments that demonstrate that the prioritization has changed. One example is the municipality of Bergen, which released a climate action plan in 2016. The plan listed policy instruments available to them with the aim of decreasing emissions. The instruments listed included strategies to increase public transport demand, promote cycling, impose parking restrictions, introduce fossil-free public transport, and establish low-emission zones that restrict access to fossil-fuel cars. The plan also mentioned the possibility of granting zero-emission cars access to bus and taxi lanes, free parking and free access to charging stations (Bergen Kommune, 2016).

Furthermore, in 2021, the Norwegian Ministry of Climate and Environment released a climate action plan for 2021 – 2030. The plan outlined the responsibilities of municipalities concerning climate change. The municipalities were required to prioritize climate-related measures and set ambitious targets. The main instruments mentioned in the plan are similar to what was mentioned in the report issued by Bergen in 2016. The government would, in addition, increase the carbon tax and tax on waste incineration (Norwegian Ministry of Climate and Environment, 2021).

While the study conducted in 2013 shed light on the lack of incentives for the municipalities when it comes to prioritizing climate change adaptation, recent developments indicate a growing commitment towards this issue. Furthermore, the available policy instruments enable us to understand in what sense political parties can influence emissions on a municipal level. Therefore, our analysis will focus on examining the relationship between the parties in charge and the emissions, which shows if the parties are using the tools at their disposal to address the problem.

2.4 Literature

Many papers have been written where the relationship between politics and emission, or impact on climate change, has been explored using various methods.

Atya and Abdou (2013) find that institutions have a significant role in setting effective policies and regulations to decrease emissions. Many recent papers view left-wing parties as more focused on environmental issues, while right-wing parties focus more on economic growth (Hu, Chen, Chang, & Chu, 2020). One of those papers, written by Neumayer (2004), claims that left-wing political ideology is highly correlated with a greater willingness to embrace environmental issues in election manifestos and more environmentally friendly beliefs.

A study conducted in 2016, investigates the relationship between government ideology and environmental performance for 85 countries during the years 2002 to 2012. Like many papers, the authors find that left-wing governments prefer environmental quality to economic performance, while it is the opposite for right-wing governments. However, under pressure for better economic performance, both left- and right-wing governments tend to forgo environmental goals for higher economic growth (Wen, Hao, Feng, & Chang, 2016). The method used in the paper is the panel data approach, which we will use as well. Our analysis will, however, be broader since we will examine individual political parties rather than solely political parties in coalition governments.

McKitrick (2006) investigates the relationship between party regimes and air quality in Canada. He evaluates the influence of the party in power on urban air pollution in 13 Canadian cities. His findings indicate that provincial parties on both the right- and left-wing are associated with elevated levels of some emission into the atmosphere. He concludes that a change in government is unlikely to be a reliable predictor of changes in air pollution. Instead of focusing on the air quality like McKitrick, we will focus on the total emission released into the atmosphere and investigate over 300 municipalities instead of focusing on a few cities.

Finally, David S. Lee (2008) performs a regression discontinuity design (RDD) analysis of the incumbency advantage in the United States (U.S.) House of Representatives. He measures the electoral advantage of incumbency in the U.S. House of Representatives. In the RDD estimates, the plots show the estimated probability of a Democrat running and winning election $t + 1$ as a function of the Democratic vote share margin of victory in election t. The running variable chosen is the Democratic Vote Share Margin of Victory. Lee finds a clear discontinuous jump at the cut-off point zero. Since the running variable is the vote share margin of a Democratic versus a Republican, the design is sharp. That means is that if you are under the cut-off, you lose and win if you are above. The RDD analysis of this thesis aims to take the paper written by Lee even further and perform an RDD for individual political parties and see how they affect the total emission of the municipalities. What is different is that the winner is not determined by who gets the most votes which was the case in the paper by Lee since there were only two political parties, the Democratic Party and the Republican Party. Finally, we will divide the data into clusters of municipalities that share similar characteristics instead of solely investigating all the municipalities together.

3. Data

3.1 Data Source

The CO_2 emission data from the Norwegian Environment Agency only contains figures from 2009 until 2021. The agency reasons this is due to the absence of a proper database and data collection (Norwegian Environment Agency, 2023b). Therefore, as a result, our analysis will be restricted to 2009 until 2021. Another aspect that should be noted is that the agency only updated its emissions figures every second year until 2015. In the variable section below, we explain in more detail how we address this issue.

Most of the data needed to describe the characteristics of the municipalities is obtained from Statistics Norway. However, due to various mergers of municipalities between 2009 and 2021, the data from Statistics Norway contains the values for the aggregated municipalities. When the data is not available in an aggregated form, we combine the data of individual municipalities to form a single synthetic municipality. This approach ensures that the data used for the analysis was consistent and based on aggregated information. The municipalities merged into bigger municipalities or under a new name are therefore not included in this analysis. The variables can be found in Table A.1. in the appendix.

3.2 Variables

3.2.1 Dependant and Independent Variable

The dependent variable for this empirical research is the logarithm of the total emission of CO_2. The data is available for every second year from 2009 to 2015 and yearly after that until 2021. To adjust for the missing years, we interpolate the missing data using a linear model to estimate the trend of the missing values (Junninen, Niska, Tuppurainen, Ruuskanen, & Kolehmainen, 2004).

The main independent variable is the political party. To determine one political party in charge of each municipality, the focus will be on the party which holds the mayor’s chair even though the party might be in a coalition with other parties. The data does not account for frequent changes in the municipality council and assumes that the majority is in charge for four years until the next elections. The data from Statistics Norway has some missing values, which we obtain and insert manually into the data frame. The municipality elections take place in November every four years, so for the analysis, the political party which obtains the mayor chair, is assumed to be in power from the year after.

3.2.2 Control Variables

Municipality characteristics are important determinants for the variation of CO2 emissions. Therefore, different control variables are included as proxies for municipality characteristics such as population, assets, average age, total energy consumption, and median household income.

The Paris Agreement was signed in November 2016; therefore, the dummy variable takes the value one from 2017 – 2021 since the countries most likely did not implement any measures this late into the year 2016 (United Nations, 2023a). The data for total energy consumption only goes back to 2010, while the others go back to 2009. To address this, we extrapolate the missing value for 2009, using a linear model to estimate the trend that comes after (Armstrong, 2000).

The manifesto analysis data comes from a dataset called Manifesto Research and Political Representation (MARPOR) which includes various analyses of political parties' manifestos. The dataset covers over 1.000 parties from 1945 until today for various countries. The data used for the regression is limited from 2009 to 2017 for political parties in Norway (Lehmann, et al., 2022). The variable used from the dataset is called per501, but from now on will be called "Manifesto". Manifesto covers general policies in favour of protecting the environment and various aspects related to fighting climate change. The manifestos of the political parties are analysed in relation to these aspects and a percentage is calculated, which means how much of the manifesto is related to this topic (Manifesto Project, 2023). It is necessary to keep in mind that the manifestos that were analysed are for a national election and do not include every political party.

The data collected for the variable "political party – Mayor" is used to determine which political party held the mayor chair for the municipality during the time period of the analysis since the assumption is that the party which holds the mayor chair is likely the most influential party of the ruling parties in the municipality.

The data for the total electricity consumption covers both the households and the companies for that specific municipality.

The total assets of the municipality are not available in one table on the website of Statistics Norway. Therefore, three different data frames have to be merged to obtain the full data for 2009 – 2021. Total assets are assets owned by the municipality and does not contain the habitant's assets. The data available does not include aggregated values for the merged municipalities, so the values are summed up manually.

Finally, for the median household income variable, it is not possible to obtain the aggregated value. To obtain a representative value from the median, we weigh each value with the pre-merger population before taking the mean of the weighted values. By using the weighted values, we correct for the different sizes of municipalities before they were merged.

3.3 Summary of Data

The following table provides an overview of the summary statistics for central political parties as well as left- and right-wing parties. We observe that the right-wing parties, on average, have a higher level of emissions, followed by the left-wing parties and the central parties. This is likely due to the population since both left- and right-wing parties have a higher population on average than the central parties. We also observe that the municipalities where the right-wing parties hold the mayor's chair are wealthier, and their habitants have a higher household income compared to the others. Lastly, the manifesto variable indicates that right-wing parties prioritize their environmental policy less than left-wing parties.

Table 1. Summary statistics for right-wing, left-wing, and central parties

Mean	**Left-wing**	**Central**	**Right-wing**
Log (Total Emission tons)	11.46	10.55	11.70
Population	14,654	5,256	24,886
Assets in Millions (NOK)	3,418	1,350	5,130
Average Age	41.87	42.15	40.61
Total Electricity Consumption (GWh)	433	140	482
Median - Household income (NOK)	597,519	614,019	626,194
Manifesto (in %)	7.26	6.91	6.01

Note. The table shows summary statistics for three groups for 2009 - 2021. The left-wing parties include the Labour Party and the Socialist Left Party. The right-wing parties include the Conservative Party, the Progress Party, and the Liberal Party. Finally, the central parties include the Christian Democratic Party, the Centre Party, and the Green Party.

Observing the different groups makes it clear that the municipalities governed by these parties have distinct characteristics. Notably, right-wing parties tend to be in charge of the larger municipalities, which have wealthier individuals. This highlights the differences between the municipalities under different political parties.

3.4 Limitations and Modifications to the Data

The total emission variable limits all the other variables since it only includes the current municipalities and not those merged into another municipality during the time period of the analysis. Therefore, the data from Statistics Norway has to be limited to the municipalities available in the total emission data. The total emission variable also controls the time period of the analysis since it does not go further back than 2009, while the majority of the other variables go much further back in time.

After examining the summaries of the variables, we observe that some variables have significant outliers. We address this issue by winsorizing the variables with large outliers at the $0{,}5^{th}$ percentile of both sides. This method involves adjusting the weights of the outliers or substituting their values with anticipated values. Consequently, the outliers are not discarded but altered by substituting their values with those at the 0,5th percentile level on each side (Kwak & Kim, 2017).

In addition to the outliers, some of the variables have a skewed distribution. To deal with that, some of the variables need to be logarithmically transformed (Feng, et al., 2014).

3.5 K-Means Clustering

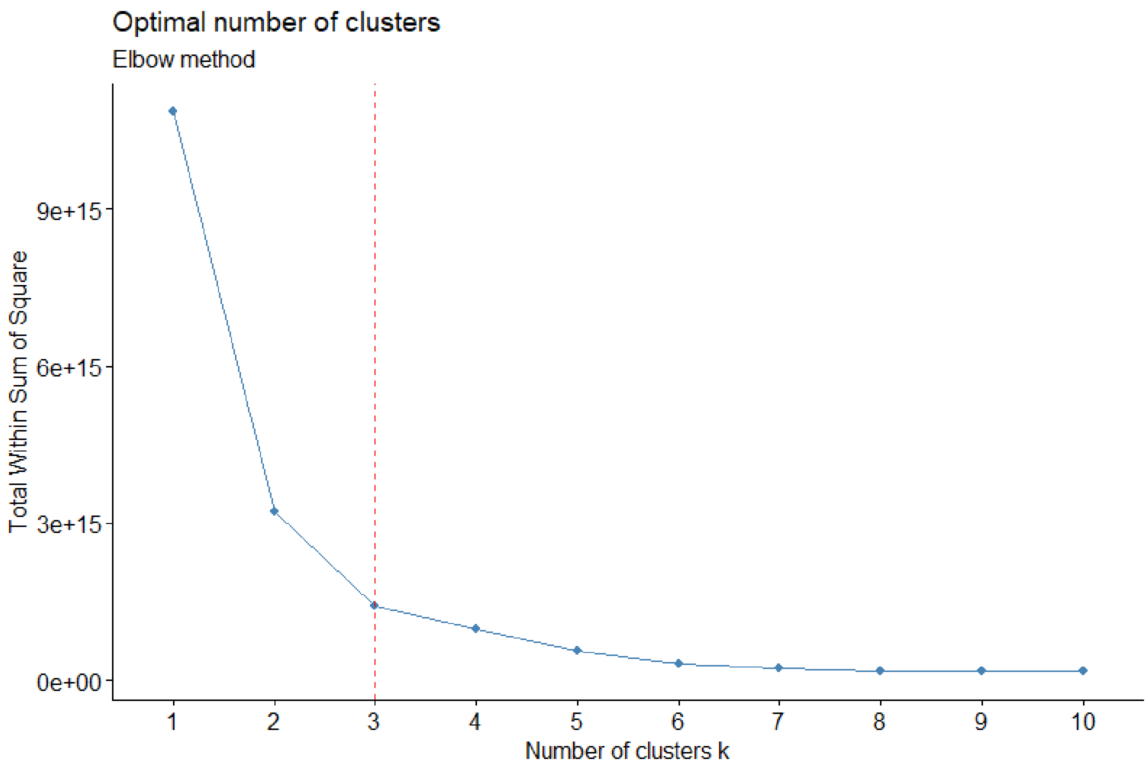
In order to perform regression discontinuity design (RDD) on municipalities that share similar characteristics, such as similar populations and assets, it is necessary to split the dataset into clusters where each cluster includes similar municipalities. The method used for the clustering is K-means.

K-means is a clustering algorithm that partitions the observations in a dataset into a predefined number of clusters, denoted as *k*. Each cluster is characterized by a centroid, and the observation objects that belong to it. The primary goal of k-means is to reduce the total distance between all data points and their respective cluster centres to the minimum possible value. By doing so, the algorithm aims to create clusters where the observations are as separated as possible from one another, to cluster together similar data points (Lletí, Ortiz, Sarabia, & Sánchez, 2004).

The variables used for the K-means are population, average household income, electricity consumption, average age, and assets of the municipalities. To simplify the classification, we take the average for 2009 – 2021, so there is only one value for each municipality,

Before performing the K-means clustering, the *k*, which is the number of clusters the dataset should be divided into, must be determined. The first method used is the elbow method.

Figure 2. Elbow method for different k.



Note. The plot shows the optimal number of clusters. When k = 3, an elbow is formed and is therefore the optimal point. That means it is optimal to split the dataset into three separate clusters.

Figure 2 displays the results of the elbow method applied to clusters ranging from one to ten. The elbow method assesses the total within-sum-of-squares (WSS) for each number of clusters considered. An elbow is formed in the plot when the decrease in WSS reduction becomes less significant by adding an extra cluster. In such a case, the optimal number of clusters is at the elbow point. Figure 2 illustrates that at $k = 3$, there is a noticeable point where the slope of the plot decreases and levels of (Zhang, Moges, & Block, 2016).

We can perform a sum of squared error (SSE) analysis to confirm that dividing the data into three clusters is effective. This involves calculating the within-sum-of-squares (WSS), between-sum-of-squares (BSS), and total-sum-of-squares (TSS). If the BSS is greater than the WSS, the objects in the clusters are close to each other, while the distance between clusters is large. In other words, the closer the BSS/TSS ratio is to 100%, the better the separation among zones is. In our analysis with $k = 3$ clusters, the BSS/TSS ratio is 99,7%, suggesting that the clustering is effective in separating the data into distinct clusters (Borge, Jung, Lejarraga, de la Paz, & Cordero, 2022).

Once we have obtained the WSS, BSS, and TSS values for the clustering analysis, we can, in addition, perform a one-way ANOVA test to compute an F-statistic and obtain a p-value. To conduct this test, we must determine the degrees of freedom for the WSS, BSS, and TSS components. The degrees of freedom for WSS is equal to $k - 1$, while for BSS, it is equal to the number of variables multiplied by $k - 1$. The degrees of freedom for TSS are determined by subtracting k from the total number of observations in the dataset (Elliott, 2013).

Once the degrees of freedom and the sum of squared errors have been calculated, they can be used to obtain an F-statistic. The null hypothesis is that the average values of the clusters are identical. The F-test is calculated as follows (Elliott, 2013):

$$F = \frac{\frac{BSS}{degrees\ of\ freedom\ for\ BSS}}{\frac{WSS}{degrees\ of\ freedom\ for\ WSS}} = \frac{BMS}{WMS} \tag{3.1}$$

After conducting a one-way ANOVA and F-test for $k = 3$ using the data in this thesis, the calculated F-statistic is 78,31 and the associated p-value is 0,0126. The F-statistic is significant and the corresponding p-value is below the conventional threshold of 0,05. This leads to rejecting the null hypothesis, which assumes that the cluster means are equal. Based on these results, we can conclude that dividing the dataset into three clusters effectively captures meaningful differences in the data (Elliott, 2013).

Table 2 summarizes the variables of three different clusters, which helps us identify the differences between them. Cluster 1 includes the smaller municipalities with lower populations and fewer assets. Cluster 3 includes the five largest municipalities in Norway, with a high population and the highest emissions. The average age decreases, and median household income increases across the clusters. The importance of environmental policies decreases as we move from Cluster 1 to Cluster 3. The significant differences between the clusters confirm the importance of using clusters in this analysis.

Table 2. Summary statistics for all clusters

Mean	**Cluster 1**	**Cluster 2**	**Cluster 3**
Log (Total Emission tons)	10.89	12.47	13.29
Population	6,656	51,812	197,417
Assets in Millions (NOK)	1,564	11,316	42,060
Average Age	42.01	40.06	38.28
Total Electricity Consumption (GWh)	225	1081	3027
Median - Household income (NOK)	604,281	614,497	656,523
Manifesto (in %)	6.93	6.35	5.94
Number of municipalities	272	26	5

Note. The table shows the summary statistics for all three clusters for the years 2009 – 2021. Cluster 1 is the largest cluster, followed by Cluster 2. Cluster 3 includes only five municipalities; however, they are the largest in Norway.

4. Methodology

4.1 Panel Data Regression

The collected data for the panel data regression is for the years 2009 to 2021 for different municipalities in Norway. Since the total emission is for different municipalities over time, it is essential to perform a panel data regression instead of a normal regression.

The models proposed for estimating the effect of political parties on total emissions are as follows:

$$
\begin{aligned}
log(Total\_emissions)_{it} \\
&= \beta_0 + \beta_1 Party_{i,t} + \beta_2 log(Population)_{i,t} + \beta_3 log(Assets)_{i,t} + \beta_4 Age_{i,t} \\
&+ \beta_5 log(Energy\_consumption)_{i,t} + \beta_6 log(Household\_income)_{i,t} \\
&+ \beta_7 Manifesto_{p,t} + \beta_8 \sum_{i=1}^{N} \delta_i + \beta_9 \sum_{t=2009}^{t} \gamma_t + \mu_{i,t}
\end{aligned}
$$

$$
\begin{cases} i = 1,\ldots,N \\ t = 2009,\ldots,2021 \\ p = 1,\ldots,8 \end{cases} \tag{4.1}
$$

where the subscript i denotes the municipality observed, subscript t refers to which year is observed, and p refers to the political party.

The rationale behind the choice of the model is that this type of regression allows for the elimination of other unobserved effects compared to a simple regression model. This enables us to obtain more accurate estimates while mitigating potential biases resulting from omitted variables through the application of fixed effects.

The biggest advantage of including the fixed effects is that it can allow the individual and time-specific effects to be correlated with the explanatory variable (Hsiao, 2006). By including fixed effects estimator in the models, the entity and time-variant heterogeneity will be eliminated. This mitigates the risk of omitted variable bias. By incorporating both time-fixed and entity-fixed effects in our models, we can obtain more accurate estimates of the effects of political parties on the total emissions within municipalities.

4.2 Regression Discontinuity Design (RDD)

RDD is the second method used for determining whether the political parties at the municipality level affect the total emissions. This method allows for comparisons of municipalities with similar characteristics, with the vote margin difference used to determine randomized elections. This way, it becomes possible to obtain a causal estimate of the relationship between political parties and total emissions.

RDD allows for the identification of a causal relationship and can only be used when there is a clear and distinct separation between the two groups compared. Furthermore, to mitigate potential biases, values near the cut-off are comparable since they are assumed to be similar (Zhu, 2021).

RDD has two distinctive designs, which are used for different scenarios depending on the probability of receiving treatment. The first one is called sharp design, where the probability of receiving a treatment goes from zero to one at the cut-off. The second design is called the fuzzy design, where the probability of receiving treatment or the likelihood increases at the cut-off instead of being zero and one (Cunningham, 2021).

4.2.1 Fuzzy Regression

The fuzzy design involves an increase in the probability of receiving a treatment based on whether an observation is above or below the cut-off. In contrast, the sharp design is suitable when all observations above the cut-off receive the treatment, while all values below the cut-off do not.

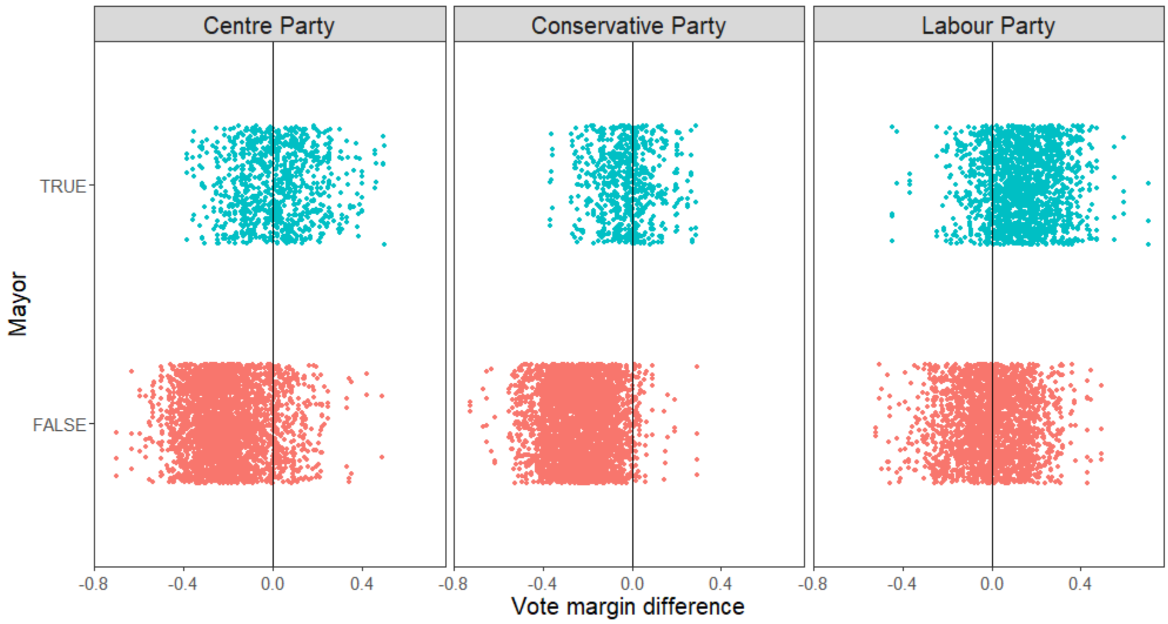
The fuzzy design approach allows for a smaller jump in the probability of assignment, and therefore it only requires the following:

$$\lim_{\varepsilon \downarrow 0} Pr(D = 1 \mid X = c + \varepsilon) \neq \lim_{\varepsilon \uparrow 0} Pr(D = 1 \mid X = c + \varepsilon) \tag{4.2}$$

As discussed in the literature section, the outcome of municipal elections in Norway are not always determined by the highest margin of votes for a particular party but instead often depends on political parties forming a combined majority. What makes the cut-off trickier in this analysis compared to the one performed by Lee (2008) is that you can have the highest votes and not get the mayor's chair, which means they are on the right side of the cut-off but not the winner. Therefore, the regression design is a fuzzy design, given that obtaining the highest number of votes only increases the likelihood of obtaining the mayor position.

To verify this claim, the correlation between the highest margin of votes and the political party holding the mayor's chair, alongside the vote margin difference for the entire dataset, is displayed in Figure 3 below.

Figure 3. Fuzzy design



Note. The plot displays the three largest political parties in the municipalities. The cut-off is at 0% vote margin difference. There is not a clear cut-off for when the party has the mayor chair or not. Therefore, the design is fuzzy.

There is no clear cut-off at zero. Therefore, the RDD design for this analysis is determined to be fuzzy.

Since the probability of treatment changes by less than one at cut-off, the change in the relationship between Y and X cannot be interpreted as an average treatment effect anymore (Lee & Lemieux, 2010). However, this treatment effect can be recovered using an instrument variable approach. Since the running variable is continuous and there is no clear cut-off between the margin of votes and the mayor in charge, we recover the treatment effect by applying a two-stage least squares estimation (2SLS), where the margin of votes bigger than zero is used as an instrument.

The rule of thumb suggests that the instrument is relevant if the F-statistic exceeds a value of ten (Burgess, Small, & Thompson, 2017). The second argument for an instrument to be valid is the exogeneity condition. This implies that the instrument percentage of the margin of votes won cannot be directly related to emissions, except that it only affects emissions through the party holding the mayor chair. The percentage of the margin of votes won in an election does not necessarily have a direct correlation with emissions, and any impact on emissions would be mediated through the political party holding the mayor chair that is determined by the margin of votes. Thus, it can be concluded that the instrument is relevant and exogenous.

The following two equations are applied for the implementation of 2SLS (Lee & Lemieux, 2010):

$$Y = \alpha + \tau D + f(X - c) + \varepsilon$$

$$D = \gamma + \delta T + g(X - c) + v$$

(4.3)

The fuzzy regression will therefore be as follows:

<u>1st stage equation:</u>

$$Party = \gamma_l + \delta T + \gamma_l(X - c) + D_{Diff>0}[(\gamma_r - \gamma_l)(X - c)] + \gamma_i W_i + v$$

(4.4)

First, we calculate the fitted values of $\widehat{D}$. The instrument T should be uncorrelated with v, so by assumption, $E[v|\delta] = 0$.

<u>2nd stage equation:</u>

$$Total\_Emission = \alpha_l + \tau\widehat{Party} + \alpha_l(X - c) + \widehat{D}[(\alpha_r - \alpha_l)(X - c)] + \alpha_i W_i + \varepsilon$$

(4.5)

Here the τ of $\widehat{Party}$ is the estimated treatment effect of change of political party, given by the margin of votes on total emission. The $\widehat{Party}$ are the fitted values from the first stage estimation, where the margin of votes is used as an instrument variable. From the first stage regression, an F-statistic of 450,24 is obtained, which is higher than ten. Therefore, we can conclude that the instrument is relevant and exogenous.

Imbens and Kalaynaraman (2012) investigated a choice of bandwidth for the RDD estimator. They developed a fully data-driven algorithm that calculates the optimal bandwidth. The algorithm minimizes the mean squared error at the cut-off. The algorithm suggests that the optimal bandwidth for our analysis is ±14%.

4.2.2 McCrary Density Test

In order to check if units are sorted on the running variable, we use the McCrary density test. The test checks if the density is continuous at the cut-off point. The test depends on many observations, so the full data set is used instead of each cluster (Cunningham, 2021).

The obtained p-value from the McCrary density test is 0,0059, which is lower than the conventional threshold of 0,05, so we can reject the null hypothesis that there is no continuity at the cutoff. By looking at Figure A.1. in the appendix, it can also be seen at the cut-off that there is a continuation.

5. Analysis

5.1 Panel Data Regression

The results from the panel data regressions are presented in the following section. The objective is to see if there is a relationship between different political parties in charge and the effect it has on total emissions. To achieve that, it is necessary to run different panel regressions, including both time-fixed and municipality-fixed effects. This method helps to control for omitted variables of the analysis. The first part of this section presents the results for the eight largest political parties and their effect on total emissions. The second part presents the difference between the right-wing parties and left-wing parties to provide better insight into the role of political ideology on environmental policy.

5.1.1 Regression Results of Individual Parties

Table 3 represents the first regression results for the eight largest political parties, with Labour Party being the residual category. The results show some level of significance for the political parties holding the mayor's chair. For the full data, we only observe a significant effect for the Green Party at a 1% level, which is associated with an average decrease in total emissions of 23,3% compared to the Labour Party, holding every other variable constant. This is also true when comparing Cluster 1. The Green Party is associated with a decrease in total emissions when they hold the mayor chair, at a 5% significance level. In Cluster 2, we observe that the Progress Party has a positive point estimate with a 1% level of significance, suggesting that they have, on average, 19,9% higher total emissions compared to the Labour Party. In Cluster 3, we only obtain a level of significance for the Socialist Left Party with a positive point estimate compared to the Labour Party.

Table 3. Political party effect on CO2 emissions

	Dependent variable:			
	Total Emission output (log)			
	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Progress Party	0.037 (0.041)	0.087 (0.105)	0.199*** (0.061)	0.005 (0.042)
Conservative Party	0.006 (0.012)	0.144*** (0.045)	-0.013 (0.027)	-0.033 (0.023)
Socialist Left Party	-0.014 (0.030)	0.053 (0.133)		0.089** (0.036)
Green Party	-0.233*** (0.020)	-0.276** (0.124)		
Centre Party	0.017 (0.011)	0.018 (0.038)	0.014 (0.035)	
Christian Democratic Party	-0.011 (0.019)	0.032 (0.077)	-0.078*** (0.029)	
Liberal Party	0.009 (0.021)	0.067 (0.054)		
(Log) Population	-0.341*** (0.132)	0.022 (0.133)	0.075 (0.419)	-0.737* (0.379)
Paris Agreement		-0.088*** (0.031)		
(Log) Assets	0.021 (0.040)	-0.154 (0.122)	-0.083 (0.096)	0.270*** (0.044)
Average Age	-0.022** (0.010)	0.001 (0.024)	-0.034 (0.059)	-0.026 (0.068)
(Log) Electricity Consumption (GWh)	0.218*** (0.073)	0.792*** (0.058)	0.818*** (0.182)	0.213 (0.278)
(Log) Household Income	0.033 (0.132)	0.084 (0.280)	0.452 (0.579)	-0.878** (0.391)
Manifesto	0.001 (0.002)	-0.002 (0.004)	0.015** (0.007)	0.001 (0.008)
Time FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Observations	3,729	3,335	329	65
Adjusted R^2	-0.029	0.621	0.180	-0.306

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

Note. The table shows the coefficients from the panel data regression for the eight largest political parties in Norway with respect to total emissions. The Labour Party is considered the residual category. The table shows four separate regressions for the full data and the three clusters. The time-fixed and municipality-fixed effects are also included in the estimators. All emissions are measured in the natural logarithm and include control variables. The standard errors are clustered for the municipalities and are displayed in parentheses.

The coefficients with a significant point estimate align with our expectations since the left-wing parties have been associated with prioritizing environmental policies. The table suggests that Progress Party, a right-wing party, has significantly higher emissions compared to the Labour Party. This also applies to the Green Party, as their political ideology is mostly focused on environmental issues. Therefore, we expect them to have a significantly lower emission when they hold the mayor's chair. Another takeaway from this table which is not expected is that the Christian Democratic Party, a central party, is associated with lower emission output compared to the Labour Party, with an average decrease of 7,8% in Cluster 2.

Since we obtain few significant point estimates for the parties, we cannot make conclusions regarding the political party's effect on total emissions. However, the table does support the use of a cluster approach. There are several explanations for why the level of significance differs between the cluster. For example, the characteristics of the clusters may affect the emissions level, policy implementations only showed results in certain kinds of municipalities, and the sample size of each cluster may also affect the significance levels.

5.1.2 Regression Results for Right-Wing, Left-Wing and Center Parties

For further analysis we estimate the effect of left-wing, right-wing, and center parties on total emissions. Table 4 displays the results of the analysis for the full data and the three clusters. Again, both time-fixed and municipality-fixed effects are included to mitigate the impact of unobserved variables that may introduce endogeneity issues.

From the results, we obtain only one level of significance, for the right-wing parties at a 1% level of significance. The coefficient indicates that in the larger municipalities, the right-wing parties have, on average, 5,3% lower emissions compared to the left-wing parties. However, this does not correspond with the expected stance of the left-wing parties, as they claim to prioritize environmental concerns more highly than the right-wing parties (Hu, Chen, Chang, & Chu, 2020). At the same time, we observe that for the smaller municipalities at Cluster 1, the right-wing parties have a significant positive effect on total emission, where on average, they have 13,2% higher emissions compared to the left-wing parties. The inconsistencies between the point estimates suggests that there are still biases that need to be addressed.

Again, we can see differences in the point estimates and the significance level between the full data and the different clusters.

Table 4. Effect of left-wing, right-wing, and center parties on CO2 emissions.

	Dependent variable:			
	Total Emission output (log)			
	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Center Parties	0.013	0.018	-0.027	
	(0.010)	(0.036)	(0.031)	
Right-Wing Parties	0.010	0.132^{***}	0.0003	-0.053^{***}
	(0.011)	(0.040)	(0.028)	(0.018)
(Log) Population	-0.331^{**}	0.019	-0.367	-0.533
	(0.134)	(0.133)	(0.466)	(0.533)
(Log) Assets	0.022	-0.155	-0.063	0.175^{***}
	(0.040)	(0.122)	(0.108)	(0.059)
Paris Agreement		-0.089^{***}		
		(0.032)		
Average Age	-0.021^{**}	-0.0001	-0.024	-0.029
	(0.010)	(0.024)	(0.061)	(0.064)
(Log) Electricity Consumption	0.219^{***}	0.794^{***}	0.879^{***}	-0.039
(GWh)	(0.073)	(0.058)	(0.182)	(0.331)
(Log) Household Income	0.028	0.090	0.243	-0.459
	(0.132)	(0.279)	(0.625)	(0.311)
Manifesto	0.001	-0.003	0.002	-0.007
	(0.002)	(0.004)	(0.009)	(0.006)
Time FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Observations	3,729	3,335	329	65
Adjusted R^2	-0.033	0.621	0.109	-0.309
				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note. For the left-wing parties, Socialist Left and Labour Party are included. For the right-wing parties, the Conservative, the Progress, and the Liberal Party are included. The center parties include the Centre Party, the Green Party, and the Christian Democratic Party. Left-wing parties is the residual category. Emissions on all models are measured using the natural logarithm. The regressors include time-fixed and municipality-fixed effects, and the standard errors are clustered for the municipalities.

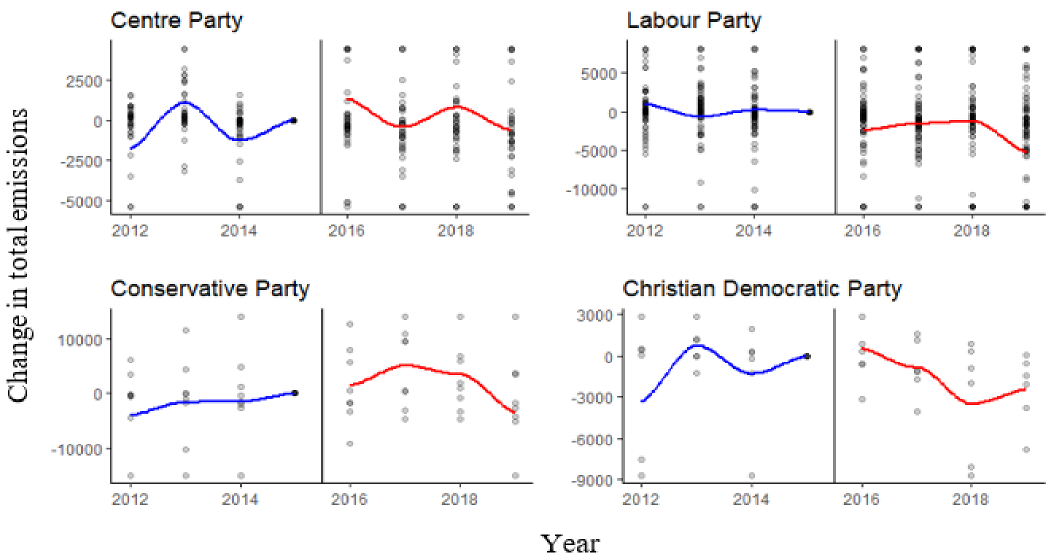
The results from the panel data approach show no clear evidence of political parties influencing total emissions. We do obtain significant point estimates. However, there are threats to validity. One concern is the randomness of the data, as many of the election results could be predicted. Another concern is that policies implemented in one term, might show results in the term after, which could lead us to estimate wrong emissions for the political parties.

Figure 4 shows the changes in total emissions from 2012 to 2019, covering two election terms for four political parties. The emissions for 2015 are used as a benchmark to calculate the change. Each party shown in the figure is responsible for the second term, while a different party is responsible for the first term. The data reveals that when the Labour Party took over in 2016, there was an immediate average decrease in emissions compared to 2015. By the end of their term, there was an even higher decrease, suggesting potential accomplishments in emission reduction.

On the other hand, the trend differs between the first and second terms when the Conservative Party takes over. Emissions show a consistent increase during the first term, which continues into the second term. However, towards the end of the second term, there is a decrease in emissions for the first time in the entire period. This indicates that the initial part of the second term might be influenced by policies implemented in the previous term, which is a potential bias that needs to be considered.

We conclude that there are biases that panel data does not capture. Therefore, we cannot make conclusions about the causal effect of political parties on total emissions.

Figure 4. Emission trend for four political parties before and after they were elected to take over in 2016.



Note. The figure shows the emission trend for four political parties where we fit a polynomial regression for each party before and after the 2015 elections. The red lines show the change in *emissions for each municipality where the party was in charge. Therefore, the blue lines show the emission trend for the party that was previously in charge. The year of the election, 2015, is used as a benchmark to calculate the change.*

5.2 Regression Discontinuity Design

In the previous section, we use panel data regression to examine the relationship between political parties and total emissions. While the analysis provides some insights, it also makes us question the validity of the findings because of potential biases. To enhance the depth of our analysis, this section will address the potential biases from the previous section.

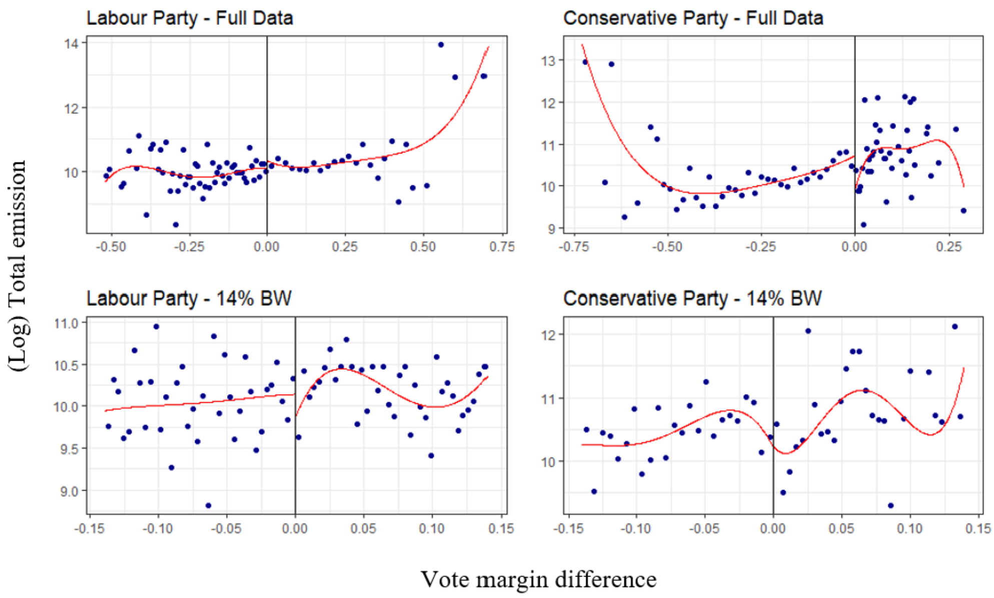
Another method is needed for addressing these problems. One of the concerns relates to the randomness of the data. In certain municipalities, there are occurrences where a specific political party wins an election with a substantial margin of votes. This indicates that some election outcomes could have been predicted. The RDD can overcome these issues under certain assumptions and be interpreted as a quasi-experiment, enabling the estimation of causal effects (Lee & Lemieux, 2010). This design involves comparing groups of clustered municipalities and examining the specific vote margin difference between the winning party and the other parties, creating a randomized experiment. The RDD method is convenient because it enables us to capture the immediate impact a political party in charge has on emissions by examining any "jumps" around the cut-off, which can be interpreted as the local treatment effect of a political party taking over (Lee & Lemieux, 2010).

5.2.1 Regression Results

Figure 5 displays the RDD plots for Norway's two biggest political parties, the Labour Party and the Conservative Party. The logarithm of total emissions has been averaged into bins alongside the running variable. It can be observed that there are no noticeable discontinuities around the cut-off. This is expected since there is no clear threshold between the political party holding the mayor's chair and their margin of votes. Since there seems to be no clear discontinuity around the cut-off, it might indicate that the political parties have a minor impact on total emissions.

However, further analysis is needed before making any conclusions, where we use the margin of votes as an instrument for the political party, as described earlier. Tables 5 and 6 present the results of the fitting of Equation (4.4) and Equation (4.5) for both the Labour Party and the Conservative Party.

Figure 5. RDD plots for the Labour Party and Conservative Party for Cluster 1



Note. The figure shows the RDD plots for full data with a bandwidth of ±14%. The cut-off is at zero, so the left-side means the party did not receive the most votes, and the right-side means the party received the most votes.

Table 5 presents the impact of the Labour Party when they hold the mayor chair on total emission for the full data and the three clusters. The analysis uses ±14% bandwidth, which is the optimal bandwidth, obtained by Imbens and Kalaynaraman (2012) algorithm.

The results for the Labour Party show a significant positive effect between the party and total emission for the full data, Cluster 1 and Cluster 3. For Cluster 3, the point estimate of the coefficient is significant at a 1% level. The coefficient indicates that, on average, when the Labour Party is in charge, the emission increases by 13,4% compared to when they are not. Again, we see differences between the full data and the different clusters, where Cluster 2 is the only group of municipalities which is statistically insignificant at conventional significance levels.

Table 6, however, shows no significant effects, which means we find no significant effect between the Conservative Party being in charge and emissions. This applies to the full data and all three clusters.

Table 5. RDD results for the Labour Party for the full dataset and three clusters with ±14% bandwidth.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Labour Party	0.116^{**}	0.099^{*}	0.406	0.134^{***}
	(0.054)	(0.059)	(0.635)	(0.048)
Observations	2,190	1,941	212	37
Adjusted R^2	0.994	0.991	0.945	0.988
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality Clustered SE	Yes	Yes	Yes	Yes
				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note. This table shows the RDD results for the Labour Party on total emissions, where the emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses. All models are estimated with a bandwidth of ± 14%.

Table 6. RDD results for the Conservative Party for the full dataset and three clusters with ±14% bandwidth.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Conservative Party	0.018	0.039	-0.606	0.003
	(0.061)	(0.066)	(1.483)	(0.062)
Observations	1,300	1,076	187	37
Adjusted R^2	0.993	0.989	0.883	0.993
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality Clustered SE	Yes	Yes	Yes	Yes
				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note. This table shows the RDD results for the Conservative Party on total emissions, where the emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses. All models are estimated with a bandwidth of ± 14%.

These results are not aligned with our expectations. Since the Labour Party is the largest left-wing political party in Norway, we expect them to have a negative effect on emissions, which would also be in line with Neumayer's (2004) findings.

There are still concerns regarding the validity of the results. As discussed in the mechanism chapter, it is well-known that municipalities in Norway are heavily dependent on funding from the national government. These fundings are earmarked for certain purposes. Therefore, one potential bias may arise from the fact that the government did not incentivise the governing parties in municipalities during the first years of our analysis since a clear direction needed to be provided (Amundsen, Berglund, & Westskog, 2013).

Another bias is that once the instruments were made available to the municipalities, the governing parties did not use them effectively. Furthermore, it is possible that the implemented policies lacked strength in incentivizing habitants or were not being implemented efficiently.

In the following section, we examine the validity of our main results through several robustness checks by modifying the underlying assumptions of RDD.

5.3 Robustness Check and Threats to Validity

5.3.1 Left-Wing and Right-Wing Parties

One potential concern about the underlying assumption is the sample size limitations, since RDD requires a lot of data around the discontinuities (Cunningham, 2021). Therefore, performing the RDD regression on the grouped political parties is essential. Furthermore, it enables us to use more observations and investigate political parties that share similar ideologies with the Labour Party on one hand, and the Conservative Party on the other hand.

Table A.2. and Table A.3. in the appendix display the estimates for left-wing and right-wing parties across the three clusters. The results indicate that there is still no significant relationship between right-wing parties and total emissions. However, the results for the left-wing parties have a significant positive effect on emissions for the full dataset and Cluster 1. Specifically, the point estimate for all municipalities suggests that when the left-wing parties hold the mayor chair, there is an increase in total emissions of 11,4%.

To summarize, this analysis supports the findings from the main analysis, that there is no relationship between the right-wing parties and total emissions when considering a larger number of observations. However, in the main RDD model, when examining the relationship between the Labour Party and total emissions, we observe that the Labour Party has a significant effect on total emissions in Cluster 3 at a 1% level. However, this significance level disappears for Cluster 3 for the left-wing parties when including more observations.

Looking further into this, we can see that Socialist Left Party only holds the mayor chair for one term in Oslo, which is a large outlier compared to the other municipalities in this cluster. Therefore, we should be more careful making conclusions from this, as a big outlier can lead to incorrect estimates and level of significance. In conclusion, these findings validate our main results.

5.3.2 Sensitivity of Bandwidths Choice

Our choice of bandwidth of ±14% is determined by a data-driven algorithm that minimizes the mean-squared error at the cut-off point (Imbens & Kalaynaraman, 2012). However, it is important to see how sensitive our results are when using other bandwidths. Therefore, in this section, we examine how sensitive the regressions are when compared to bandwidths of ±20% and ±10% for both the Labour Party and the Conservative Party.

Table A.4. in the appendix illustrates the results for the Labour Party. From this table, it is evident that the model exhibits slight sensitivity to the choice of bandwidth. The only significance level observed for ±10% bandwidth is in Cluster 3, at a 1% level, which aligns with the findings from the main analysis. On the other hand, at ±20% bandwidth, the point estimate shows a significant effect for full data and for Cluster 1, however, we no longer obtain a significant point estimate for Cluster 3.

The results for the Conservative Party, as shown in Table A.5. in the appendix, illustrate that we obtain no significance for both ±10% and ±20% bandwidth. This suggests that the choice of bandwidth does not impact the main results for the Conservative Party.

Comparing the results with the optimal bandwidth, we can see that ±10% bandwidth eliminates the majority of our significance for the Labour Party. However, when using ±20% bandwidth, we only lose the significance for Cluster 3. Since there is a bias-variance trade-off, it is important to be careful when interpreting the results from narrow bandwidths. That means narrow bandwidths are subject to small sample size bias, resulting in reduced statistical power and potentially unreliable results (Schwab, Pauly, & Konietschke, 2021). The optimal bandwidth's main purpose is to find the right balance between precisions and bias. Therefore, the differences between the bandwidths can be explained by the fact that a ±10% bandwidth limits the data too much compared to when the bandwidth is expanded to ±20%.

5.3.3 Robust Standard Errors

In the main analysis, we use clustered standard errors to account for the within-municipality correlation of observations. This is done to improve the accuracy of the standard error of the coefficients. However, using clustered standard error can be problematic when cluster sample is small. When there are few clusters, the assumption of uncorrelated standard errors within the cluster may not be valid. This can result in biased standard errors, as there may be a higher degree of within-cluster correlation (Imbens & Kolesár, 2016). In our example, Cluster 2 and Cluster 3 exhibit vulnerability to biased standard error as Cluster 2 contains 26 unique municipalities and Cluster 3 contains five unique municipalities.

Therefore, in this section, we examine our results' sensitivity to using robust standard errors instead of the clustered standard error. We do this to see if there are big differences in the point estimates' significance level. The results for robust standard errors for the Labour Party and the Conservative Party are presented in Table A.6. and Table A.7. in the appendix.

When comparing the main results for the Labour Party, we can see that the biggest change is the point estimate for Cluster 3, where the standard error has increased, and the coefficient is now insignificant. This suggest that using clustered standard error when we only have five municipalities is not optimal as the assumption of error terms to be constant across municipalities might be violated. On the other hand, for the full data and Cluster 1, we can see that the standard error has decreased, where the coefficients still have a high significance level, meaning that the results for the full data and Cluster 1 remain positive. Finally, for the Conservative Party, the conclusions remain the same after incorporating robust standard errors, as there were no changes in the level of significance at all point estimates.

In conclusion, using clustered standard errors has an effect when the cluster is small, but the results for the full data and Cluster 1 remain the same.

5.3.4 Delayed Effects

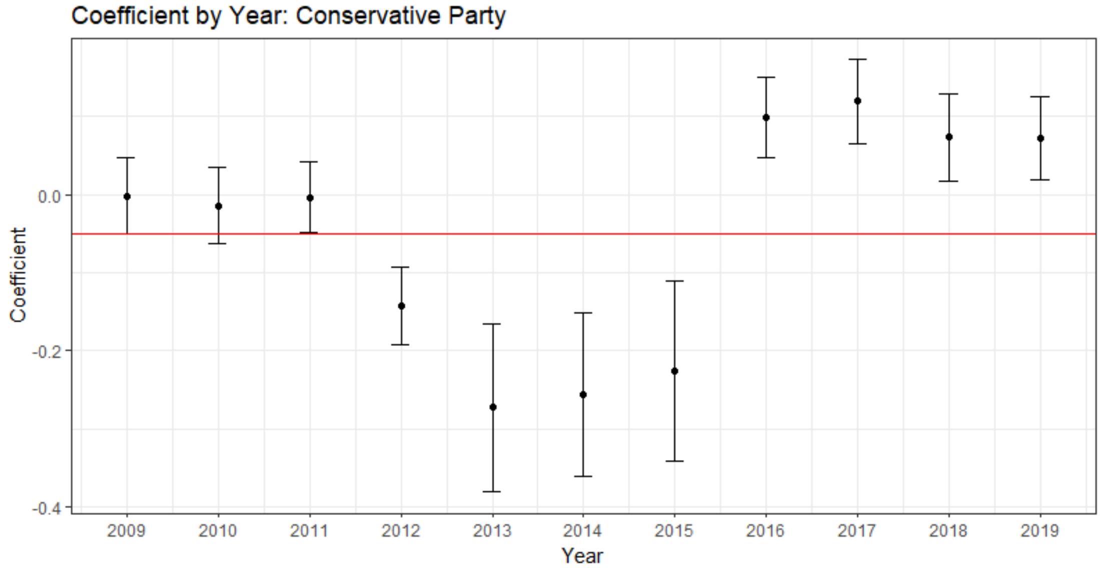
When an environmental policy is implemented, it often takes time for any visible changes to occur. This is because people in the municipality may need time to adjust to the new policies, which can cause a delay before any effects are noticed (Sapna & Gupta, 2019). To examine this potential bias further, we take the total emissions $t+1$ and $t+2$ to capture any delays.

Table A.8. in the appendix presents the results for the Labour Party, where we examine one-year and two-year delays in total emissions. The estimates showed no statistically significant relationship between the two variables in the full dataset and all clusters, which differs from the main analysis. When we examine the two-year delay in total emissions, we also get different results than the main analysis, where the only significance level is shown for Cluster 2. For the Conservative party, the results are presented in Table A.9. in the appendix. We do not find any significant relationship between the party and emissions, which is consistent with the main analysis.

Our analysis shows no significance relationship between the Conservative Party and emissions. However, there could be a broad issue here why we do not obtain significant effects. As we previously mentioned, emissions are a slow process. Therefore, a municipality may receive treatment early and late in the sample period, leading to zero effect. Therefore, it is important to see whether the main RDD specification is consistent over time by estimating the coefficients of political parties by year.

Therefore, we examine the yearly coefficients of the Conservative Party with the RDD specifications. In this robustness check, we use $t+2$ estimates of the yearly coefficients to control for the delays of total emissions. In Figure 6, we find some inconsistencies in the trend of the coefficients where we have a negative effect in the middle of the sample and positive effect late in the sample. Therefore, when performing the RDD on the entire time period, these two trends could even out the effect, leading to a close to zero effect, as the red line shows, representing the average of the yearly coefficients.

Figure 6. Yearly estimates of the Conservative Party on emissions for a ±14% bandwidth.



Note. The figure shows the yearly coefficients of the RDD specification for the Conservative Party. The regression analysis uses emissions from two years ahead (t+2) to capture delayed effects. The regression, like the main analysis, uses ±14% bandwidth. *The red line represents the average coefficients of all years. Notably, there is a negative trend in the middle of the time period and a positive trend towards the end. These opposing trends could offset each other, resulting in an estimated zero effect.*

6. Conclusion

This thesis investigates the relationship between the political party in control of the mayor's office and the total CO_2 emissions at a municipal level. We mainly build on previous studies that investigate the relationship between political parties and emissions. We look into Norway's eight largest political parties, focusing on the Labour Party and the Conservative Party.

We use panel data regression first as a benchmark model to identify any hints of significance. Afterwards, a regression discontinuity design (RDD) is used to analyse elections where the winner won by, at most a, 14% vote margin difference, which helps reduce potential biases and identify any causal effects of political party affiliation on total emissions. The RDD analysis builds on an analysis by Lee (2008), which performed an RDD analysis of the incumbency advantage in the United States House of Representatives.

The findings from the panel data regression show that when the Conservative Party is in charge, they have, on average, 14,4% higher emissions compared to the Labour Party in the small municipalities. However, since the coefficients are compared to the Labour Party, we cannot make conclusions regarding the relationship between individual parties and emissions. There is also plenty of biases that panel data regression does not capture. Therefore, we perform RDD.

The results from RDD show that the Conservative Party has no significant effect on total emissions. However, when conducting a robustness check, the yearly coefficients of the lead variables indicate that we estimate a zero effect. For the Labour Party, we find a positive effect on emissions for the full data, Cluster 1, and Cluster 3. By performing robustness checks, we find that the Labour Party has only significant effect on the full data and Cluster 1, which includes the small municipalities. This means that when the Labour Party holds the mayor chair, it is associated with an average increase of 11,6% in total emissions when looking at all municipalities. For the smallest municipalities, the presence of the Labour Party is associated with a 9,9% increase in emissions. In conclusion, we find a relationship between political parties and emissions on a municipal level. However, our results do not align with our expectations since left-wing parties have been associated with a greater willingness to embrace environmental issues and have more environmentally friendly beliefs (Neumayer, 2004).

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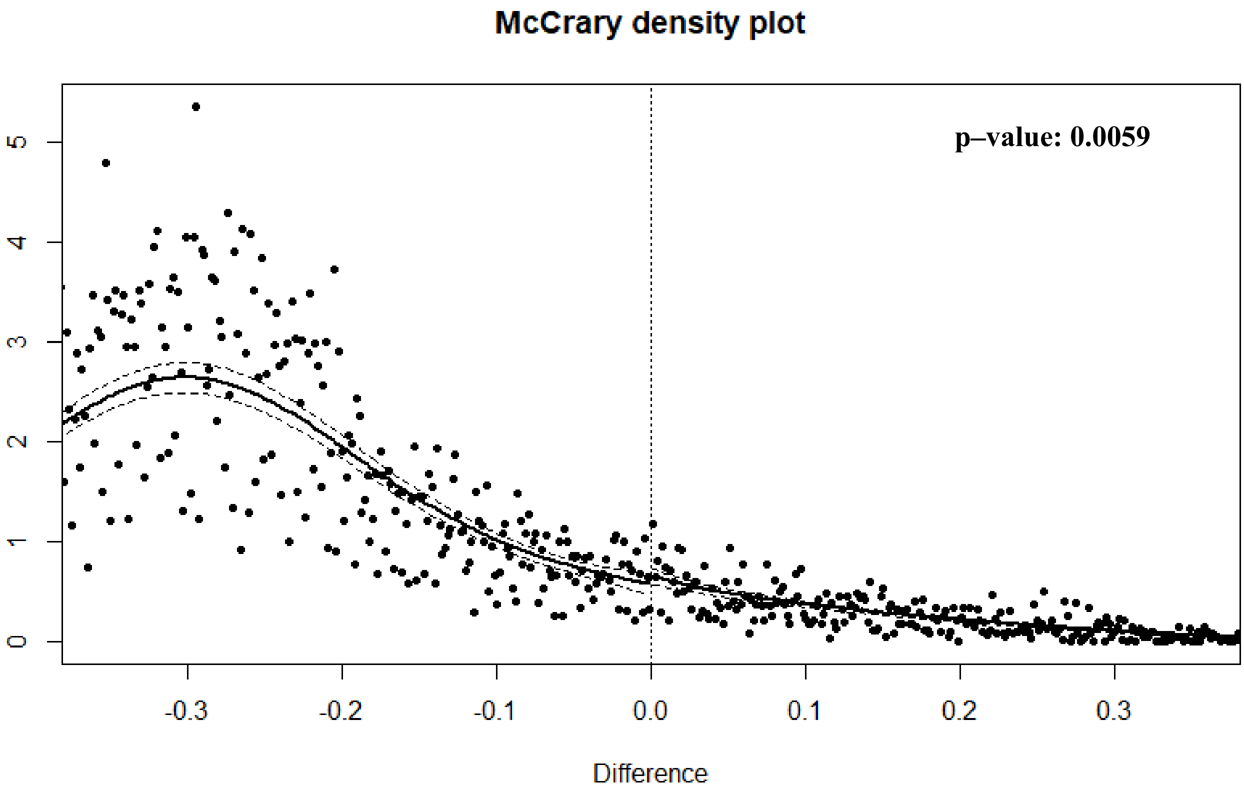
Appendix

Table A.1. Overview of the variables

Collected data	Year	Level	Source
Total emission of CO2	2009 – 2021	Municipal	(Norwegian Environment Agency, 2023a)
Vote margin difference	2009 – 2021	Municipal	(Statistics Norway, 2020a)
Population	2009 – 2021	Municipal	(Statistics Norway, 2023c)
Political party – Mayor	2009 – 2021	Municipal	(Statistics Norway, 2020b)
Total assets in million (NOK)	2009 – 2021	Municipal	(Statistics Norway, 2023b)
Average age	2009 – 2021	Municipal	(Statistics Norway, 2023c)
Total electricity consumption (GWh)	2010 – 2021	Municipal	(Statistics Norway, 2023a)
Median household income (NOK)	2009 – 2021	Municipal	(Statistics Norway, 2022)
Paris agreement	2017 – 2021	National	(United Nations, 2023b)
Manifesto	2009 – 2017	National	(Lehmann, et al., 2022)

Note. The table shows all the variables used in the analyses. All the variables show for which years they are collected. It can also be seen at what level the variables are for and the relevant source. The total emission of CO2 had missing values for every second year until 2015. We extrapolate the missing values using a linear model.

Figure A.1. McCrary density plot with a p-value



Note. The plot shows the density for ±30% vote margin difference. At the cut-off of 0%, it is clear that the density is continuous. The p-value of 0.0059 confirms that there is no discontinuity at the cut-off.

Table A.2. RDD pooled for the left-wing political parties for three clusters and ±14% bandwidth.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Left-wing parties	0.114**	0.098*	0.390	0.046
	(0.052)	(0.057)	(0.632)	(0.027)
Observations	2,246	1,993	214	39
Adjusted R^2	0.994	0.991	0.948	0.991
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality Clustered SE	Yes	Yes	Yes	Yes

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

Note. This table presents the RDD (Regression Discontinuity Design) results for the Left-wing parties, including The Socialist Left Party and The Labour Party, regarding the effect on total emissions. The emissions are measured using the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses. All models are estimated with a bandwidth of ± 14%.

Table A.3. RDD pooled for the right-wing political parties for three clusters and ±14% bandwidth.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Right-wing parties	-0.078	-0.036	-41.845	0.002
	(0.081)	(0.083)	(5144.183)	(0.045)
Observations	2,158	1,825	280	43
Adjusted R^2	0.992	0.989	-478.101	0.994
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality Clustered SE	Yes	Yes	Yes	Yes

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note. This table presents the RDD (Regression Discontinuity Design) results for the Right-wing parties, including The Conservative Party, The Liberal Party, and The Progress Party, regarding the effect on total emissions. The emissions are measured using the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses. All models are estimated with a bandwidth of ± 14%.

Table A.4. RDD Robustness with different bandwidths for the Labour Party.

	Dependent variable: Total Emission output (log)			
	±10% Bandwidth			
	Full Data (1)	Cluster 1 (2)	Cluster 2 (3)	Cluster 3 (4)
Labour Party	0.108	0.090	-5.309	0.134***
	(0.084)	(0.092)	(101.678)	(0.048)
Observations	1,652	1,470	145	37
Adjusted R^2	0.994	0.991	-6.145	0.988
	±20% Bandwidth			
Labour Party	0.117***	0.114**	0.271	0.067
	(0.045)	(0.051)	(0.333)	(0.054)
Observations	2,779	2,467	267	45
Adjusted R^2	0.993	0.991	0.970	0.991
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality clustered SE	Yes	Yes	Yes	Yes
				*p<0.1; **p<0.05; ***p<0.01

Note. This table shows the RDD results for the Labour Party on total emissions, with a bandwidth of ±10% and ±20%. The total emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses.

Table A.5. RDD Robustness with different bandwidths for the Conservative Party.

	Dependent variable: Total Emission output (log)			
	±10% Bandwidth			
	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Conservative Party	0.022	0.029	0.190	0.003
	(0.058)	(0.061)	(0.336)	(0.062)
Observations	915	753	125	37
Adjusted R^2	0.993	0.989	0.967	0.993
	±20% Bandwidth			
Conservative Party	0.037	0.057	-0.236	-0.012
	(0.056)	(0.063)	(0.282)	(0.038)
Observations	1,833	1,544	244	45
Adjusted R^2	0.994	0.991	0.974	0.992
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality clustered SE	Yes	Yes	Yes	Yes

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note. This table shows the RDD results for Conservative Party on total emissions using a bandwidth of ±10% and ±20%. The total emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality. The standard errors are clustered for the municipalities and are displayed in parentheses.

Table A.6. RDD results for the Labour Party for three clusters with ±14% bandwidth with robust standard error.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Labour Party	0.116***	0.099***	0.406	0.134
	(0.33)	(0.036)	(0.331)	(0.131)
Observations	2,190	1,941	212	37
Adjusted R^2	0.994	0.991	0.945	0.988
Municipality fixed effects	Yes	Yes	Yes	Yes
Robust standard error	Yes	Yes	Yes	Yes
				*p<0.1; **p<0.05; ***p<0.01

Note. This table shows the RDD results for the Labour Party on total emissions using a bandwidth of ±14% with robust standard errors instead of clustered standard errors. The total emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality.

Table A.7. RDD results for the Conservative Party for three clusters with ±14% bandwidth with robust standard error.

	Dependent variable:			
	Total Emission output (log)			
±14% bandwidth	Full Data	Cluster 1	Cluster 2	Cluster 3
	(1)	(2)	(3)	(4)
Conservative Party	0.018	0.039	-0.606	0.003
	(0.038)	(0.041)	(0.878)	(0.031)
Observations	1,300	1,076	187	37
Adjusted R^2	0.993	0.989	0.883	0.993
Municipality fixed effects	Yes	Yes	Yes	Yes
Robust standard error	Yes	Yes	Yes	Yes
				*p<0.1; **p<0.05; ***p<0.01

Note. This table shows the RDD results for the Conservative Party on total emissions using a bandwidth of ±14% with robust standard errors instead of clustered standard errors. The total emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality.

Table A.8. RDD for the Labour Party with the dependent variable *t+1* and *t+2* and ±14% bandwidth.

	Dependent variable: Total Emission output (log) (t+1)			
	Full Data	Cluster 1	Cluster 2	Cluster 3
±14% bandwidth	(1)	(2)	(3)	(4)
Labour Party	0.052	0.017	0.411	0.304
	(0.045)	(0.046)	(0.459)	(0.301)
Observations	1,991	1,765	193	33
Adjusted R^2	0.995	0.993	0.952	0.986
	Dependent variable: Total Emission output (log) (t+2)			
Labour Party	0.033	-0.013	0.295**	-0.010
	(0.046)	(0.050)	(0.135)	(0.049)
Observations	1,792	1,589	174	33
Adjusted R^2	0.995	0.993	0.979	0.996
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality clustered SE	Yes	Yes	Yes	Yes

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

Note. This table shows RDD results for the Labour Party on lead values of total emissions of one and two years (t+1) and (t+2). The emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality.

Table A.9. RDD for the Conservative Party with the dependent variable *t+1* and *t+2* and ±14% bandwidth.

	Dependent variable: Total Emission output (log) (t+1)			
	Full Data	Cluster 1	Cluster 2	Cluster 3
±14% bandwidth	(1)	(2)	(3)	(4)
Conservative Party	0.042	0.075	-0.569	-0.008
	(0.055)	(0.058)	(1.106)	(0.038)
Observations	1,199	996	170	33
Adjusted R^2	0.992	0.988	0.906	0.996
	Dependent variable: Total Emission output (log) (t+2)			
Conservative Party	0.034	0.070	-0.380	0.004
	(0.059)	(0.069)	(0.393)	(0.021)
Observations	1,098	916	153	33
Adjusted R^2	0.993	0.988	0.966	0.995
Municipality fixed effects	Yes	Yes	Yes	Yes
Municipality clustered SE	Yes	Yes	Yes	Yes

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

Note. Note. This table shows RDD results for the Conservative Party on lead values of total emissions of one and two years (t+1) and (t+2). The emissions are measured with the natural logarithm. All models include control variables to adjust for characteristics of municipalities, which are not displayed. Additionally, fixed effects are incorporated to control for unobserved variables specific to each municipality.