The Effects of Perceived Closeness on Voter Turnout:

A Look at US Presidential Elections

By

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Abstract

In this paper, we investigate the relationship between the closeness of a US presidential election and voter turnout, in the 2012, 2016, and 2020 election years. We use state-level panel data that includes voter turnout, statewide polling data before the elections (for closeness measures), as well as controls for demographic variables. We run OLS cross sectional regressions for each election year, an OLS regression across all years, and a Difference-in-Differences regression that controls for state and year fixed effects. Though we identify a strong correlation, we find no statistically significant effect of closeness of an election on voter turnout.

1) Introduction

In our paper, we look at the connection between election closeness and voter turnout in the United States. The presence of such a connection was first suggested by Anthony Downs in his 1957 paper "An Economic Theory of Political Action in a Democracy" in which he described what is now referred to as the Downsian Closeness Hypothesis (DCH). Simply put, the hypothesis states that individuals will only vote if they believe their vote will be decisive and make an impact on the election at hand. From this, we investigate whether such a connection exists through the lens of perceived election closeness and voter turnout. The current literature's stance on the effect of the closeness of an election on voter turnout is conflicted.

As we begin our evaluation of the DCH, we hypothesize a negative relationship with what we call the "Closeness Gap" and voter turnout, measured as the percentage of eligible voters who vote in the election. The independent variable of interest, Closeness Gap, is measured as the spread in polls between the two primary candidates prior to the election. We are interested in perceived closeness of an election because that is what we believe has an effect on voter turnout; that is if people perceive the election to be close then they will vote. Thus, we look at polls occurring before the election versus the actual closeness of an election given by the result. In the context of our independent variable, this means that a more one sided electorate would see a larger Closeness Gap. As the gap increases, we expect people's actions to follow Downs' prediction such that a larger gap signifies to voters that their vote is less influential and thus discourages voters from turning out to the polls.

As the US presidential election is one of the most important elections in the US and voter turnout throughout the US is low compared to other developed countries, it is paramount to understand the factors that affect turnout. Due to the two party system within the US, the concept of closeness could easily sway the views of voters as to whether it is worth their time and effort to go to the polls. Though other, older papers have studied this topic, there is little research on the US Presidential election, with the closest paper to ours being Cann and Cole, 2009 (see Section 2.3). In addition, a number of the papers do not isolate more recent elections to understand the present effects of perceived closeness in an era with easily accessible information/disinformation. As it stands, there is no paper that considers our research question and focuses on the US presidential election in the post-2000 era. Thus our work looks to add to and update the literature by observing the effects of pre-election polls on turnout for the US Presidential elections from the years 2012 to 2020.

In the following section, we examine specific papers that test the DCH as well as other relevant hypotheses and report their methods and findings. We compare their methods, investigating how they differ, and elaborate on how our paper adds to this literature. Section 3 provides our theoretical framework as well as describes regressions we run in order to determine the causal relationship between perceived closeness and voter turnout. In Section 4, we describe the sources, format, and various attributes of the data used in these regressions. Sections 5 and 6 provide the results of our various regressions and robustness checks, followed by a discussion about the implications of these results. Section 7 concludes.

2) Literature Review

2.1) Measures in the Literature

It is important to note that most of the papers in this review measure closeness through polling prior to when the election takes place or ex-post measures of closeness which are determined by the actual outcome of a specific election. In contrast, some papers in the field use indexes like the Cook Partisan Voting Index (CPV), which takes into account the general party competitiveness in the region, using past election results and the current split between parties on different legislative levels. Studies that use measures like the CPV index label tend to label their independent variables as “competitiveness” versus “closeness”. We are more interested in the closeness of specific elections, thus the papers cited here use the polling approach or ex-post results.

When evaluating the Downsian Closeness Hypothesis, it is important to recognize how scholars have historically defined both closeness and turnout. For example, Geys’ 2006 paper “Explaining voter turnout: A review of aggregate-level research” looks at 83 studies on voter turnout, and finds three different key metrics for turnout. These include the ratio of people who voted to the entire voting age population, the ratio of the number of people who voted to the number of eligible voters, and, in places where registration is not required, the ratio of people who voted to the number of registered voters. Depending on the location and type of election, all of these measures provide different levels of validity and give different answers. For example, in some nations, individuals who commit crimes may lose their eligibility to vote while others may simply abstain from registering altogether.

There also exists intra-paper variation in metrics as seen in Matsusaka (1993). Using 885 California Ballot Propositions from 1912 to 1990 as the elections of interest, Matsusaka’s 1993 paper “Election Closeness and Voter Turnout: Evidence from California Ballot Propositions" calculated four different metrics for closeness using ex-post results. First, a percentage of the difference between votes for and against relative to the number of total votes. Second was a measure that divided the same difference in votes by the count of cast ballots (thus including individuals who voted but may not have voted on propositions). Third was a similar metric deflated by the number of registered voters (to include individuals who did not go to the polls). The final metric took a different approach using an absolute measure of the difference between votes for and against a proposition. Similar adjustments were made for measures of turnout, with the percentage-based proportion of votes cast to ballots cast as the first metric and the proportion of total votes cast to the number of registered voters as the second. Ultimately, the paper contradicts the Downsian Closeness Hypothesis and concludes that effects found throughout the literature are more likely to be due to the effect of parties addressing tight races with various forms of support in order to get more people to vote. Other common measures for closeness in the literature include polling before the election, and exploiting election designs, particularly in other countries where they have rounds of voting.

2.2) Overview

Cancela and Geys' 2015 paper, "Explaining voter turnout: A meta-analysis of national and subnational elections" compiles 185 studies on voter turnout to summarize its key determinants. The general finding is that the closeness of an election, primarily measured by difference in the share of the winning versus losing votes after the election, has a study success rate of about 69%. This means that 69% of the studies in the sample found that closer elections increase turnout. What is not clear in the study is the relationship of the closeness of an election to campaign expenditures and other political "supply side" effects such as the elite mobilization hypothesis described by Matsusaka and Palda (1991) below. The meta-analysis, and many observational studies within, do not clearly isolate the effect of the closeness of the elections themselves in relation to these other variables.

Matsusaka and Palda in their 1991 paper "The Downsian voter meets the ecological fallacy" explore the literature to explain the variation in empirical findings confirming or denying the Downsian Closeness Hypothesis. They ultimately find that studies utilizing micro-level regressions that directly analyze a citizen's likelihood to vote find no relationship between closeness and the individual's decision to vote. In contrast, they found macro-level regressions that use aggregated measures such as district or state level turnout tend to find an effect of closeness on turnout. They conclude saying these macro-level findings are likely due to aggregation bias. This is to say that the same attributes that may affect an individual's decision to turn out to vote may not affect turnout on an aggregated level, such as the state or district level, and vice-versa. Finally, they explain the potential for spurious correlation arising from movement of party resources towards regions with closer races, conflating the effect of closeness with that of party spending and mobilization. Romero and Romero in their 2021 paper "National Presidential Election Turnout: 1952 to 2020" further support the connection between these variables. Considering the effect of presidential campaign advertisements on turnout, Romero and Romero (2021) find that there is a significant effect such that increasing the prevalence of negative campaign advertisements leads to greater turnout. This demonstrates the positive effects of party mobilization on the voter turnout of an area, supporting Matsusaka and Palda's explanation for the possible correlation between the effects of party mobilization and increased election closeness in a region.

While this meta-analysis gives us a hint as to the validity of the DCH we are interested primarily in closeness as measured by perceived closeness before the election takes place. This is due to concerns about endogeneity bias when using ex-post measures of closeness. Thus, we move onto individual and more recent research results that try to isolate the effect of perceived closeness on turnout for a clearer picture of the conflict within the literature.

2.3) Specific Papers

Bursztyn et al.'s 2020 paper "Identifying the Effect of Election Closeness on Voter Turnout: Evidence from Swiss Referenda" finds evidence in favor of anticipated election closeness increasing voter turnout. The authors exploit a quasi-experiment involving the timing of the release of polls in Switzerland allowing them to use an event study design that fixes the issue type seen in other observational studies. The authors find that when a closer poll is released voter turnout sharply rises in the days after. Specifically, they find that "A one-standard deviation closer poll increases voter turnout by a statistically significant 0.4 percentage points in each of three days immediately following the poll's release". The authors argue that their results control for many supply side political effects due to effects on increasing turnout occurring before increases in voter mobilization taking place.

Similarly, Paola and Scoppa in their 2012 paper "The impact of closeness on electoral participation exploiting the Italian double ballot system" find a significant positive causal relationship between closeness and turnout, and they contribute largely to the literature on why using ex-post-election closeness results lead to bias. As previously mentioned, many of the observational studies included in the meta-analysis use ex-post measures of closeness. The authors explain how using such an approach will create endogeneity problems. If there is an unobservable factor that positively affects the votes given to one candidate then it will affect both turnout and the vote possibly "creating a correlation between the error term and the variable of interest". Given this correlation, the authors conclude ex-post approaches will lead to biased coefficient estimates. Thus, the authors exploit the double ballot system in Italy where they can apply an instrumental variable technique where they use the closeness of results in the first round between the top two candidates as an instrument for closeness during the second round of voting. The authors find that after adding controls for candidate campaign traits and municipal fixed effects that expected closeness significantly increases turnout. They also find that when using ex-post electoral results, the effect is much smaller, which suggests significant endogeneity bias in other studies that use such an approach.

However, not all of these recent empirical research papers come to the same conclusions. Cann and Cole in their 2009 paper "Strategic campaigning, closeness, and voter mobilization in U.S. Presidential elections" find that the DCH does not hold and "closeness has no direct effect on turnout". The authors in this paper specifically test the hypothesis that individuals do not go out to vote even in close elections because they believe that their individual vote will not sway a close election. Instead, following from the Matsusaka and Palda and Romero papers discussed earlier, they believe that in many observational studies, like the ones in the Cancela and Gey paper, the increase in turnout due to closeness is driven by elite mobilization and extended resources in close races. They test this hypothesis using data from all 50 states for the five US presidential elections from 1988-2004. The utilize their own index for campaign activity and an expert rating of competitiveness to determine closeness in each state. Using their data and an integrated model of voter turnout and campaign resource allocation, the authors find that "elites indeed target campaign activities in close states and the asymmetric distribution of resources across states results in higher turnout in battleground states."

Similarly in Gerber et al's 2020 paper "One in a Million: Field Experiments on Perceived Closeness of the Election and Voter Turnout", the researchers also find little relationship between poll closeness and turnout. The authors utilize a RCT conducted in the 2010 and 2014 gubernatorial elections, with over 100,000 individuals included in the study overall. The authors elicit voter beliefs on the closeness of the election before and after they have been exposed to either a “close” poll and a poll that indicates a not-close race. They find that individuals update their beliefs in accordance with the poll they see, but tend to overestimate the closeness of the election. Despite this, when tracking the voting habits of individuals, they do not find evidence that election closeness affects turnout.

2.4) Lab Experiments

Even in lab experiments, designed to idealize the voting experience and emulate the various costs and benefits to voting without the numerous real world variables that may affect turnout, there are diverse conclusions. Duffy and Tavits in their 2008 paper “Beliefs and Voting Decisions: A Test of the Pivotal Voter Model” use a lab experiment performing twelve sessions of twenty-four subjects. Using monetary incentives to measure the benefit of having your candidate elected and the cost of voting, they create an experimental scheme that emulates the decisions made by a voter when they go to the polls. Though they did not present information on closeness, they had one group as a control in which they simply observed the voting strategies of the individual voters, and a treatment group where prior to voting, they prompted participants with questions about their likelihood of being a decisive vote. Utilizing neutral language, the researchers get rid of any bias related to social-norms or societal responsibilities with voting. Overall, they found that an individual’s views of their votes decisiveness does not affect their likelihood to vote.

Dissimilarly, Großer and Schram in their 2010 paper "Public opinion polls, voter turnout, and welfare: An experimental study" do find an effect of closeness on turnout. They use a different approach, considering the effect of polls and information on other voters' preferences in a study of 288 undergraduate students. Putting these groups in electorates of 12 each, they test two different variables: the amount of information the groups are given on the vote distribution and the distribution of voter alliances. Ultimately, they find that the presence of these polls not only boost turnout, but lead to turnout being greater than the socially optimal level. Both of these papers question two real world aspects of voters' decision making. First, the presence of polling data, and second, the belief of participants, based on past voting results, that their votes will be decisive, and through these two ex-ante measures of closeness, they, much like the literature at large, find conflicting results.

2.5) Summary

In summary there have been many observational studies that have found a positive effect of closeness on voter turnout. However, many of these studies use ex-post measures of closeness and do not specifically isolate the effect of closeness to other variables that may affect the relationship. Recent experimental studies, and lab experiments, that do try and isolate the effect are still relatively mixed with some finding the same positive results in support of DCH, while others find that factors like elite mobilization and campaign activities that stem from close elections drive increasing turnout.

Given this survey of the current literature, it is surprising that there have not been many recent papers that tackle the question of the closeness of an election's effect on turnout on a large scale in the US. Our paper will examine the effect of turnout and closeness using panel data for

US presidential elections, with controls at the state level. Our measure of closeness will be based on the latest state polls before the election as provided by poll aggregators. From our research there are few observational papers that take this approach, especially with updated data, including the 2020 election. Though a number of papers look into the effects of elite mobilization and campaign expenditure, suggesting they increase turnout in closer elections, we exclude these variables as we believe them to be one of the channels through which closeness affects turnout. Thus our paper is answering a modified version of the DCH that considers multiple channels through which closeness affects turnout. We don't just check the effects of the presence of closeness on the perceived importance of one's own vote, but also on how this closeness affects the decisions of party elites in increasing media presence and monetary contributions for campaign visibility. In order to accomplish this, we will be using Census turnout data, as measured as a percentage of eligible voters, provided by Statista and the American Community Survey for demographic data at the State level. For perceived closeness we use polling data right before the election from poll aggregators Real Clear Politics and FiveThirtyEight. If polls for a state are unavailable, we use the latest measure of electorate allegiances for estimations of ex-ante closeness: previous election results.

3) Theoretical Framework

In order to determine a causal relationship between perceived election closeness and voter turnout, we run three primary regression models. Our data is state level panel data looking at the presidential elections between the years 2012 and 2020. The primary composition of the dataset includes voter turnout as a percent of the population of eligible voters, closeness gap on the state level, whether the difference in closeness leans Republican or Democrat, and various

State level demographic data points to allow us to control for other factors that have been shown to affect voter turnout. Below, we describe our three sets of regressions. Our first set is a basic OLS regression which is performed on each election year, taking a cross section of these features and looking at the effects of closeness within a single election across various states. Our second is the same functional form as the cross sections, but it is run on the entire dataset. Our third is a Difference-in-Differences model in which we control for the state fixed effects and election years. The combination of these models will provide both a look into the causality of closeness on turnout as well as provide a robustness check for this relationship both within and between states.

Given our state level panel data, the first model we will run is a cross sectional, OLS regression for each presidential election year, that is for the three elections: 2012, 2016 and 2020. The following model is what we plan to run:

$$VoterTurnout_{i,t} = \beta_0 + \beta_1 ClosenessGap_{i,t} + \beta_2 (ClosenessGap_{i,t})^2 + \beta_3 LeaningDem_{i,t} + \beta_n StateControls_{i,t} + u_{i,t} \quad (1)$$

The above regression includes our key variables, with subscripts i and t, where i corresponds to a specific state, and t indicates the election year. First, our dependent variable of interest, voter turnout, is measured by the total number of voters in each election over the number of eligible voters. Voter turnout data is available on the state level through the Census Bureau.

Our independent variable is perceived election closeness gap for a given state as measured by the spread in polls between the Republican and Democratic party nominees. It is our belief that voters are more influenced by state polls, versus national polls, due to how electoral college votes are awarded to candidates who win the popular vote of a state. Perceived election closeness, as measured by polling data before the election is an ex-ante measure of closeness to avoid endogeneity bias discussed in the literature review. We use poll aggregators, such as RealClearPolitics and FiveThirtyEight, for polling data before the election. To implement these polls into our data set, we take the difference in polling between candidates. For example, polls conducted in the state of Pennsylvania in the 2012 election, had Obama at about 51 percent and Romney at 47 percent, the total difference is 4 percentage points. We then map that 4 percentage points to the state Pennsylvania for 2012 as what we call the Closeness Gap. Using this calculation, we expect the coefficient $\boldsymbol{\beta}_1$ to be negative given the DCH, as larger values for state closeness correspond to increasingly uncompetitive races and thus reduce turnout, due to our belief that individuals will see their vote as less impactful. We include a squared Closeness Gap term in the model because we believe there is a positive baseline level of turnout such that the relationship between Closeness Gap and turnout is non-linear. In addition, we believe the marginal change to turnout will decrease as Closeness Gap increases. For example, an increase in the Closeness Gap of 5 points from 5 to 10 can be seen as a close election becoming a not close election, while an increase in Closeness Gap from 30 to 35 will still seem like a sure-win either way. Thus the effect of the Closeness Gap increasing on turnout levels falling will be greater in the 5 to 10 case versus the 30 to 35 case, indicating a non-linear relationship, and prompting us to use a squared term.

LeaningDem will be a dummy variable where 1 = Democrat and 0 = Republican. This controls who the poll is in favor of. Referencing the last example for districts in Pennsylvania for 2012, this would take the value of 1 since Obama led in the polls. It is unclear what the coefficient of this term will be, but it helps isolate the effect of just the closeness of the race between the candidates regardless of which party is in the lead. As there are systematic differences between Republicans and Democrats, individuals from each party may react to the closeness of an election differently, depending on which party is leading in the polls.

Lastly, we have various demographic metrics of each state we plan to control for that have been found to influence turnout in other studies in the literature. The expanded model with these specific controls can be seen below:

$$VoterTurnout_{i,t} = \beta_0 + \beta_1 ClosenessGap_{i,t} + \beta_2 (ClosenessGap_{i,t})^2 + \beta_3 LeaningDem_{i,t} + \beta_4 Gini_{i,t} + \beta_5 log(MedianHouseholdIncome)_{i,t} + \beta_6 MedianAge_{i,t} + \beta_7 PercentBach_{i,t} + \beta_8 PercentMale_{i,t} + \beta_9 PercentMinority_{i,t} + \beta_{10} PercentPoverty_{i,t} + \beta_{11} UnempRate_{i,t} + \beta_{12} PercentMarriedMale_{i,t} + \beta_{13} PercentMarriedFemale_{i,t} + \beta_{14} AverageHouseHoldSize_{i,t} + \beta_{15} PercentChildren_{i,t} + \beta_{16} PercentElderly_{i,t} + u_{i,t} \quad (2)$$

All the control variables will be on the state level and can be obtained using census data through the American Community Survey (ACS) 5-Year Estimates. The ACS 5-Year estimates utilize data from four years prior to the year of interest, and data from the year of interest itself to come up with more reliable estimates. For example the 2016 5-Year Estimates by state include data from 2012-2016 to estimate the actual values of demographic variables of interest for 2016. We utilize the 5-Year estimates since they are more reliable than the 1-Year estimates, which tend to be less reliable due to the lack of substantial data collection on a year by year basis and their use of smaller sample sizes.

The first control variable will be the Gini coefficient of each district. The Gini coefficient measures the amount of income inequality in an area. There are several studies that have shown inequality influences voter turnout (Galbrith and Hale, 2008), (Solt, 2010). However, the effects that these studies find are conflicted and thus we are uncertain of the sign of the coefficient. There are two main economic arguments, the first being that higher income inequality can lead to lower voter turnout due to the working-class losing faith in the electoral system. The second is that higher income inequality in an area can incite a call to action for the working class to come out to vote in higher numbers. Regardless of the effect, we include this control variable to remove a possible factor influencing voter turnout.

In Cancela and Geys (2015) meta-analysis on the determinants of voter turnout, mentioned in the literature review (Section 2.2), they find several key variables that can influence turnout in a given area, which we now control for. Income in several studies cited by Cancela and Geys has a significant positive effect on voter turnout. We expect the coefficient in our study to thus be positive as the intuition follows that lower wage earners tend to work hourly jobs and have a harder time getting off work to vote/ need to work to support themselves and their family. We use the median value for household income to capture this effect. We take log of this value as it is our belief that the marginal effect of increases in income on turnout decreases as we move to wealthier and wealthier communities.

Moreover, age and education are also found to have substantial effects on voter turnout. It has been well documented that older and more educated communities have higher rates of turnout. We control for this by including the median age of a state and the percent of people who have graduated with a bachelor's degree in the regression and we expect both coefficients to be positive. The rationale behind age is that older people tend to have more time to vote, are more involved in policy decisions such as Medicare and Medicate and are less mobile. The rationale behind education is that people who are better educated tend to be more interested in politics and more aware of the consequences of the election at hand.

We also control for gender and race. There is a breadth of research that shows that historically women turnout in higher numbers then men and white individuals' turnout to vote more than minorities. To control for the gender effect, we include the total percentage of male individuals in a state, which we expect to have a negative coefficient. To control for the effect of race on turnout, we include the percent minority population in each state. Note that we don't include a percent female variable or a percent white variable to avoid perfect collinearity. Thus, the coefficients of the race and gender are in comparison to the missing category. We thus expect a negative coefficient on the race and male term.

Next, we include variables to control for family attributes of a community. Wolfinger and Wolfinger (2008) find that individuals who are married are more likely to vote while families with young children are less likely to vote. Thus, we include variables for percent married for each gender, percent of households with children (18 and under) and elderly people (65 and over), and average family size. We expect the coefficient of Percent Married controls to be positive, as the intuition is that it is administratively easier for married couples to register to vote since one partner can remember and help register for the other. We expect the coefficients of average family size, percent children and percent elderly to be negative since individuals with larger families, more young children, and older people may have more responsibilities and thus have less time to vote.

A control for unemployment is also included in the regression. The evidence in the field is relatively conflicted regarding unemployment's effect on turnout. We include the absolute percent unemployed of the civilian labor force in a given state. One explanation for this effect is that places with large unemployment feel the need to enact change and thus voter turnout increases. An alternative explanation is that unemployment can discourage voter turnout due to individuals feeling hopeless and having little faith in the electoral process, a similar argument to the effect of income inequality. Thus, the sign of the coefficient we can expect is unknown, but we control for this variable in case of its effect on turnout.

The last variable we control for is the amount of poverty, as measured by the percentage of people below the poverty line. We previously discussed that richer communities tend to vote in higher numbers however in that measure we are taking the median household income; we include the percentage of individuals below the poverty line to capture the effect of income on turnout at the tail of the income distribution. Similarly, we expect the coefficient for percent in poverty to be negative.

Along with a simple regression, we run this control inclusive regression four times. We run it once on the entire dataset and an additional time on each election. These results will allow us to determine if there is a significant correlative relationship between closeness and turnout as well as check for consistency among the various election years.

Our second model is a Difference-in-Difference model. The model is of the following form:

$$VoterTurnout_{i,t} = \beta_0 + \beta_1 ClosenessGap_{i,t} + \beta_2 (ClosenesGap_{i,t})^2 + \beta_3 LeaningDem_{i,y} + \beta_4 State_i + \beta_5 Year_t + \beta_n StateControls_{i,t} + u_{i,t} \ (3)$$

This form allows us to control for state level attributes as well as use the panel data to its fullest extent. This is because each state from each year is represented within a single regression. Each state is also given its own dummy variable such that each state can be compared to itself across time. In addition to the inclusion of various dummy variables, we maintain the importance of the political leaning of poll results as well as the various state controls previously mentioned.

Looking more into the effect of including these state and year dummy variables, we see that state dummies allow us to separate the effects of closeness from other state level attributes that may not be represented in the state controls. This means the immutable attributes of a state that may not be covered within the state controls are accounted for within the inherent presence of the dummy variable identifying that state.

That said, unchanging state attributes are not the only thing we need to control for in the new model. Using the panel data, we also want to control for candidates and major events between elections. As the US presidential election takes place every four years, a number of technological, economic or other large-scale changes could have occurred within that time frame or during the election itself. These national level differences could lead to an effect on that particular election. By adding a set of dummy variables for the years, we can control for these nationwide events and differences between candidates in the elections. This Difference-in-Differences methodology will add robustness to any claims of causality between closeness and turnout independent of unchanged state level attributes that would otherwise be omitted.

4) Data

We use turnout data, as a percentage of eligible voters, by state from the Census Bureau, summarized by Statista, and use perceived election closeness through polling data from RealClearPolitics and FiveThirtyEight. We utilize the Wayback Machine to gather averaged polling data by state in the weeks leading up to the election. This polling data provides us with the percentage spread between the polling numbers of the two candidates as well as which party the polls in a state are leaning toward. This provides us with our measure of Closeness Gap as well as Leaning Dem. For our other demographic controls, we utilize the American Community Survey (ACS) 5-Year Estimates. Due to limitations in the closeness data and the ACS only having data from 2010-2020, we have decided to focus our study to presidential election years

2012, 2016, and 2020. In addition, some states do not have available polls, often due to a lack of polling in the state for that election and year. As the perceived closeness in the state cannot be determined by polls, we suggest the use of a proxy: the results of the previous election. We believe this acts as an appropriate proxy because it is the latest data constituents can use to get an understanding of the distribution of constituents affiliations in the current election. Scatterplots showing the relationship between these measures of closeness and turnout for each year can be seen in Appendix F.

We merge these cross-sections across our three years of interest to create panel data that will allow us to compare states across time given the three election periods. Each entry is thus identified by a unique ID code and associated election year. For each year, there are fifty-one entries- for the fifty states and DC. In this section, we will look at various attributes of the data within each of these years.

Looking at Table 2, depicting the 2012 election, we see that turnout is within the range of 47.8 to 75.9 percent, with a mean of 62.9 percent. Closeness Gap ranges from 0.5 percent to 80 percent with a mean gap of 16.2 percent. In Table 3, depicting 2016, we see that turnout ranges from 42.52 percent to 74.16 percent, averaging at 59.9 percent. Closeness Gap on the other hand ranges from .5 to 70.5 percent with an average 14.3 percent. In 2020, Table 4, there is a turnout range from 55 to 80 percent, averaging highest at 67.9 percent. Closeness Gap has a larger range than prior elections ranging from .1 to 85 percent with a mean of 16.1. Table 1 includes the aggregated summary statistics on the whole data set, regardless of year. For the whole data set turnout ranges from 42.5 to 80 percent, with a mean of 63.5 percent, while Closeness Gap ranges from 0.1 to 85 percent with an average gap of 15.5. These tables also include the summary statistics for the state level controls for each year. Regardless of year though, Figures 1, 2, and 3, depict the relationship between these variables (without controls) and show in each election, there is a negative correlation between Closeness Gap and turnout, such that elections with a larger gap have lower turnout. Let us move onto the results of the regressions we run.

5) Results

Before we discuss the specific results, we run six main regressions in each sub-section. First is a simple regression that just regresses Closeness Gap on Turnout. The next four regressions we run are represented by equation (2) where we add controls and run the linear regression once for all election years together, and once for each election year individually, 2012, 2016 and 2020. The last regression we run is represented by equation (3) where we implement a Difference-in-Difference model on equation (2), utilizing all three election years in our data set. All these regressions are run with robust standard errors, and the Difference-in-Difference model is appropriately clustered, to account for heteroskedasticity. Lastly, the R-squared terms in the regression tables are adjusted R-squared values.

5.1) Initial Regressions

The first regression we run, as seen in Table 5, includes just our main variables of interest. We simply regress voter turnout against the closeness gap, using our 153 data points, 51 for each election. This regression is simply finding the line of best fit for the aggregated scatter plot of Figures 1, 2, and 3. In this regression we find a negative coefficient for closeness gap with a value of -0.076. We find that this coefficient is weakly significant, as its p-value is 0.07. We can interpret this result as the closeness gap increases in a state by 1 percentage point, then voter turnout decreases by 0.076 percentage points. This evidence supports the DCH, however the regression has a very low R-squared value of 0.022, and we have not yet included any controls. We run this regression to build intuition and see the baseline effect of our two main variables before controlling for demographic attributes, and adding the squared closeness variable. We now move onto these results.

The next regression we run is represented by equation (2), where we include all the control variables and run it across the whole data set, while still adding year controls. The results can be seen in Table 6. While we do observe a negative coefficient on Closeness Gap, we find that neither of our closeness gap variables has a statistically significant effect on turnout. We do observe a positive, statistically significant effect of our LeaningDem variable and our PercentBachelors control on voter turnout. We also observe a statistically significant negative effect for Gini coefficient and a positive statistically significant effect of our 2020 election year control on voter turnout. We now move onto the results on a per year breakdown.

The next three tables, Table 7, Table 8, and Table 9 display our results after running equation (2) for each election year of interest, 2012, 2016 and 2020, separately. In Table 7, the results for the 2012 election including controls, we find that closeness gap and squared closeness have no statistically significant effect on voter turnout. We also find no significant controls for this election. Moving on to the 2016 election, Table 8 yields similar results. We find that both our Closeness Gap measures have no statistically significant effect on turnout and no statistically significant controls. Moving on to Table 9, we again find no statistically significant impact of our Closeness Gap variables on voter turnout in the 2020 election. In this regression LeaningDem has a positive, statistically significant effect at the 5 percent level, while PercentBachelor is weakly significant and also has a positive effect on turnout. We now move onto the results of our Difference-in-Differences model.

Table 10 displays the results of our fixed effect Difference-in-Differences model, equation (3), where we are effectively studying the impact of changing levels of closeness and controls within a state over the election years and how that affects resulting turnout. Like the cross-sectional results, we again find no statistically significant effect of closeness gap on voter turnout. The statistically significant variables at the 5 percent level include PercentElderly, and PercentMinority, both of which have positive effects on voter turnout. Our PercentMale variable is weakly significant with a positive coefficient. Lastly, our controls for the election years, 2016 and 2020, are strongly significant.

In summary, we found a weakly significant effect of closeness gap on voter turnout, in line with the DCH, in our first regression, before including control variables. However, when running the cross sectional regressions that includes demographic controls, and the Difference-in-Differences model that adds fixed effects controls, we find no statistically significant relationship between closeness gap and voter turnout. Note that in all the regression the coefficient on closeness gap is negative, seemingly in line with the DCH, yet none are statistically significant. We now move onto a robustness check, followed by a discussion of these results.

5.2) Robustness Check 1: Proxy Efficacy

To test the robustness of our Closeness Gap proxy, we delete six data points from the dataset, giving us 147 total data points. These data points are all within the year 2012. The differences in the statistics for this dataset can be seen in Tables 11 and 12 of Appendix B. Table 11 shows the changes to the entire dataset, while Table 12 shows the changes to 2012 alone. Stats for 2016 and 2020 remain the same as in Appendix A as the polling data for these years can be found for every state, so we did not use the prior election proxy for these years. In Table 13, we once again perform a simple regression of Closeness Gap on Turnout, while Table 14 shows the results of a stacked OLS regression across all the years. Table 15 does a yearly regression for 2012, due to the loss of 2012 data in the new dataset, and Table 16 shows results from the Difference-in-Differences regression with state fixed effects on the proxy-less dataset.

Contrary to the simple regression with the proxy closeness measures, we find that the impact of closeness on turnout becomes strongly statistically significant with a coefficient of -.127. This implies that for every unit increase in the spread of polling data between the two candidates, the voter turnout decreases by .127 percentage points, an economically significant amount given the large range of possible Closeness Gaps. That said, this regression also presents a low R-squared value of .052. This initial result suggests that the effects of the proxy used may have weakened the effect of closeness on turnout.

In our stacked OLS, equation (2), we find more statistically significant variables than we did with our prior-election proxy. Though the same four variables remained significant, we additionally found the percent of married males to be significant. The linear effect of the Closeness Gap also became weakly statistically significant, maintaining an economically significant coefficient of -.147. In addition, the percent of married females also gains weak statistical significance. As seen in Table 15, this trend is only discernible given the entire dataset, since the 2012 regression fails to show statistical significance in the independent variable. Though the coefficient of the linear effect of Closeness Gap on an election has increased, Closeness Gap, along with all other variables, demonstrate no statistically significant effect on turnout.

Finally Table 16 shows our Diff-in-Diff regression for the polling-only dataset. The only variable that maintains statistical significance is the 2016 dummy variable. Besides this, only education measured as the percent of the population with a bachelor's degree is statistically significant at the 5 percent level. Differing from all prior regressions, the coefficient of Closeness Gap does become positive in this Diff-in-Diff. That said, it still lacks statistical significance at any level. We think it is important to note the large differences between all of the regressions that were rerun without the proxy data. The large shift in significance between regressions could signify that prior-elections are not a good proxy for polling. In addition, we still conclude no causal relationship between closeness and turnout, though we do find increased correlation. Finally, we fail to observe any changes to our squared Closeness Gap term which maintains a lack of statistical and economic significance in this robustness check, leading us to further investigate the functional form of the relationship between Closeness Gap and turnout in the following section.

5.3) Robustness Check 2: Removing Squared Closeness

For our second robustness check, we remove the squared Closeness Gap term from regression and continue to leave out the prior election results proxies. We suspect that the inclusion of two variables representing Closeness Gap may be highly correlated and thus limiting each other's significance. The squared Closeness Gap term is also never statistically significant with coefficients virtually equal to zero in both our initial set of regressions and our proxy exclusive set of regressions (see Sections 5.1 and 5.2). To test this, we remove the squared Closeness Gap, and only consider the linear effect of Closeness Gap on voter turnout. The results in Appendix C include five new regressions. We do not rerun a simple linear regression for this robustness check as it would be the same as the simple regression found in Appendix B.

Looking at Table 17, we see large significance changes to the control inclusive regression that covers all three years. The Closeness Gap variable is now strongly significant, along with the leaning democrat variable. We also see the increase in Closeness Gap significance across the years, as the 2012 regression (Table 18) demonstrates weak statistical significance, the 2016 regression (Table 19) demonstrates a standard 0.05 level of statistical significance, and the 2020 regression (Table 20) demonstrates a strong statistical significance at the 0.01 level. These shifts indicate a strong linear correlation between closeness and turnout. The coefficients for the linear Closeness Gap variable have a greater magnitude than those found in our previous regressions from Appendices A and B. We also note that these regressions all have negative coefficients with a magnitude greater than 0.2, which is economically significant, given that it can be the difference between up to a 17% decrease in turnout considering our maximum Closeness Gap is 85.

That said, we fail to find the same increase in significance when we look at the Difference-in-Differences results (Table 21). The linear Closeness Gap variable remains statistically insignificant as well as economically insignificant in this model with a coefficient of -0.003. This is in comparison to the other regression which all have negative coefficients with a magnitude greater than 0.2. As a result of these changes, we no longer consider the relationship between closeness and turnout to be non-linear, and believe there is a stronger correlation than we previously identified between our Closeness Gap variable and turnout. The following sections explain the results of other robustness checks with this high linear correlation in mind.

In the following two robustness checks, we continue to leave out the proxies for turnout as well as maintain the new functional form without a squared Closeness Gap.

5.4) Robustness Check 3: Removing 2016 and 2020 outlier

The next robustness check we conduct is removing outliers from our data set. There are three clear outliers, one for each year, which can be seen when looking at the scatter plots in Appendix F. These three points all belong to the District of Columbia electorate, where Closeness Gap is consistently around or above 70 points. We remove the District of Columbia data points in this robustness check to make sure its naturally high Closeness Gap is not leading to bias in the regressions. Since we saw significant changes to our results when removing the proxies and the squared closeness term, we implemented these changes as well when removing the outliers for this robustness checks. The outlier for our 2012 data, was actually a proxy where we used the closeness results of the 2008 election, so we have already removed that data point in the proxy robustness check. Thus, for this robustness check, the only difference from the results in section 5.3 is the removal of the 2016 and 2020 District of Columbia data points.

The results of this robustness check can be seen in Appendix D. Table 22 is a simple regression with just Closeness Gap and Turnout. Table 23 displays the result of our linear regression with controls on all the years. Table 24 and 25 include the results of the linear regression with controls for 2016, and 2020, respectively. Table 26 shows the result of our Difference-in-Difference model. Notice we do not include a regression for just 2012 since our regression on 2012 alone would just be yield the same results as Table 18 in Appendix C. To be clear the only difference between Appendix C and D is the removal of our outliers, thus we compare our results for this robustness check with Appendix C.

When looking at the simple regression, Table 22, we still find a strongly significant coefficient on closeness gap, which we also saw in Table 13 where we removed the proxies. The coefficient here actually increased in magnitude from -0.127, from Table 13, to -0.171, and our p-value decreased from 0.006 to 0.003, which suggests that the outliers did have an effect in weakening the coefficient of our estimators. However, we don't see any real significant results in the other regressions that include controls. Our stacked regression, Table 23, still relays a strongly significant estimate for Closeness Gap, with a slightly lower value of -0.198 when compared to the results in Appendix C, Table 17. Moreover, most of the other control variables remain at the same significance level. A similar trend arises when examining the results for just 2016 and 2020 and comparing them to the same regressions. Our 2016 estimate for Closeness Gap is still significant at the 5 percent level, and has barely any change in the estimated value of the coefficient when compared to Appendix C, Table 19. Moreover the control variables are also very similar in terms of significance level. The same can be said for our 2020 regression, Table 25, we see that the coefficient is still strongly significant and around the same magnitude in its coefficient when compared to Table 20, with little change to the controls. Lastly, our Difference and Difference model, Table 26, again finds no significance in the Closeness Gap term, and is still very close to zero for its coefficient.

In summary, when removing these outliers we see little change in the tables when compared to Appendix C, which ran the same regressions but with the outliers. There was no change in significance of our Closeness Gap variable and no notable changes in the control variables. The only noteworthy change was in the simple regression without the controls where the coefficient increased in magnitude and p-value halved. However, when considering the other models with controls, and their results, this robustness check does not add much insight on top of what was already seen in Appendix C.

5.5) Robustness Check 4: Population Weighting

Our last robustness check involves weighting our regression based on the population of each state. We conduct this robustness check since not all states have the same effect on the election as others. Broadly speaking, in the US the candidate that wins a state's popular vote gets its electoral votes. States with larger populations have more electoral votes and thus have a greater impact on the election. We weight our observations in the regression by population to try and capture this effect, that is a state like California will be more heavily weighted than Delaware; in our previous regressions, all states had the same weighting. Since we saw significant changes to our results when we removed our proxies and squared closeness term we also carry those changes on to this robustness check. However, because we saw little change when excluding the District of Columbia in our data set we still include those "outliers" here.

The results of this robustness check can be seen in Appendix E. Table 27 displays the simple regression, regressing Closeness Gap on Turnout alone. Table 28 shows the results from our linear regression with controls on the entire data set. Table 29, 30 and 31, are the individual regressions for each election year 2012, 2016, and 2020, respectively. Finally, Table 32 displays our results of the difference in difference model. The only difference between Appendix C and Appendix E is the addition of the population weighting, thus we compare our results for this robustness check to those in Appendix C.

When looking at the simple regression results in Table 27, there are significant changes when compared to the results in Table 13. Our estimate for the coefficient of Closeness Gap is now -0.108 and is only significant at the 10 percent level. This is a significant drop in both magnitude and significance as in Table 13, we saw a coefficient of -0.127 which was significant at the 1 percent level. This suggests that weighting our observations by population decreases the effect of closeness on turnout. When examining the other tables, a similar trend emerges. Looking at Table 28, our linear regression on all the years with controls, we see that our Closeness Gap coefficient is -0.13 and is weakly significant, this is again a drop in both magnitude and statistical significance, though it still remains economically significant. In Table 17, our coefficient was -0.213 and was strongly significant; significance of control variables also dropped in Table 28 such as Leaning Dem, Percent Bachelor's and Percent Married Male. A similar analysis can be made when examining the individual year regressions. Only our 2012 regression, Table 29, maintained its weakly significant level, which was the same as the comparable Table 18 in Appendix C. Our results for 2016, Table 30, and 2020, Table 31, yield no significance in the coefficient of Closeness Gap. This was a drastic drop off since in Appendix C we saw a Closeness Gap coefficient that was significant at the 5 percent level for 2016 and significant at the 1 percent level for 2020. Moreover, the Closeness Gap coefficients are all still negative for each year but dropped in magnitude when compared to the results in Appendix C. There was also very little change in the control variables for these regressions. Finally, when examining our Difference-in-Differences regression, Table 32, we again find no sigfigance for our Closeness Gap coefficient, and here it is in fact positive as compared to the negative coefficient in the comparable Table 21. We do find some significant changes in our controls in Table 32, seeing our Leaning Dem and Percent Male variables becoming much more significant.

In summary, we find that when weighting our observations by population, we see a drop in both the magnitude of coefficient of Closeness Gap and its significance level. All the coefficients, besides the Difference-in-Differences result remained negative, but were smaller in magnitude than the comparable tables in Appendix C. The only significant results in this robustness check were in the simple regression, stacked regression and 2012 regression, all of which were only significant at the 10 percent level. Thus it appears that when weighting our observations by population, the effect of closeness on turnout diminishes considerably.

6. Discussion

In this section, we look to explain and understand the results presented in Section 5 and the corresponding tables. Though our coefficients on Closeness Gap are negative, they are never statistically significant at the 5 percent level in our original regression (Section 5.1, Appendix A). These results suggest that there is no discernible change in turnout due to an increase in closeness. This goes against the DCH and contrasts previous findings that indicate that aggregated macro-level studies indicate an effect of closeness on turnout (Matsusaka & Palda, 1991). Given the simple regression in Table 5 shows a weakly significant change, we ultimately find that there is little explanative value in this as seen in the low R-squared, leading us to believe the overall effect of Closeness on US presidential elections would be small and have little impact overall. This trend of low R-squared values remains apparent in the simple regressions of all of the robustness checks. That said, our robustness checks contradict our initial findings of a lack of a relationship between closeness and turnout. Removing our erroneous proxy measures for Closeness Gap and considering only a linear relationship between Closeness Gap and turnout, we discover a strong correlation. This correlation is also empirically meaningful as it is based on economically significant coefficients, as discussed in the results section. That said, our Difference-in-Differences models continue to show no statistically significant relationship between closeness and turnout. Thus, our results fail to prove the DCH is applicable to the US presidential elections, and we do not find a causal relationship between closeness and turnout. However, we cannot extrapolate these findings to all US presidential elections, simply the ones in our dataset.

It is important to note that some papers do consider things such as campaign resource allocation which we purposefully omitted, arguing it to be a channel through which closeness affects turnout, though it is highly correlated with closeness (Cann and Cole, 2009). Our paper has no control for elite mobilization and increased expenditure, implying that the effect of closeness alone would be overestimated by our regressions given the positive effect of spending on turnout (Romero and Romero, 2021). This suggests a less significant effect of closeness (excluding its secondary effects) on elections than the one we found. Although our primary regressions do find a negative relationship between Closeness Gap and turnout, which suggests closer elections will lead to increased turnout, we cannot conclude closer elections have any effect on state level turnout in the US presidential elections. This lack of a causal relationship is upheld by the insignificant results in the Difference-in-Difference regressions from our robustness check. Nevertheless, we conclude the strong correlation between the two (as seen in Appendix C) could simply be a result of omitting these channels through which closeness affects turnout.

Putting the population weighted robustness check into the context of the Downsian Closeness Hypothesis, we find that there is a smaller correlation between closeness and turnout. Though this seems to conflict with the DCH, we argue that this finding actually highlights the underlying principle of the DCH. The rationale Downs proposes for closer elections leading to higher turnout stems from the idea that people are more likely to vote if they believe their individual vote matters. Given that the states we are applying a higher weight to are the ones that have larger populations, one may feel their vote is less significant among the large electorate. This could be amplified by the winner-take-all set up of the electoral college system which means an individual's vote only truly counts in determining the winner within their own state. Thus, the states we attribute a higher weight to in our regression are ultimately the states in which individuals are more likely to feel their votes are less relevant because they make up a smaller fraction of the electorate that determines who takes their states electoral college votes, so they may exhibit an underlying bias to believe their vote won't make a significant difference in election results.

Analyzing these results, we find that there are a number of other variables in our regression that show (or lack) significance in a manner that is inconsistent with the literature. In our Difference-in-Differences model, Table 10, our control of PercentMinority is statistically significant and positive, which contradicts what the literature would expect, indicating that increases of minorities in a state increases turnout relative to higher percentages of White individuals. In addition, we find PercentElderly is not statistically significant in our robustness checks, which conflicts with the statistics that point to older individuals being more likely to vote. Given these differences, we believe it is important to consider both the limitations and historical explanations that may have led to discrepancies from older works.

First, we look at the limitations of our data. The first issues are the relatively small sample size of 153 observations. Due to availability of data, we were only able to get data on three elections. Even in this regard, we had to estimate several Closeness Gaps based on the results of the previous presidential election when polls were not taken within a region. The analysis is also at the state level rather than the district level, leading to a loss of the effects of closeness within smaller communities and a larger dataset that provides greater variation in the features of each region. In addition, we miss some controls that would have provided some more context to the predictability of closeness and turnout, such as urbanization, voter suppression metrics, and prior voter party registration within a state. Variables such as these would clearly have an effect on voting habits and closeness within the state, as well as people's decisions prior to the election.

Considering historical explanations, we may consider major changes or events from older elections to these ones. Within these three elections there were also several historical events, including COVID-19 in the 2020 election and Hillary Clinton's run as the first female presidential candidate in a general election in 2016. In addition, two of the three elections feature the incumbent in the general election whose favorability could easily fluctuate during the election due to real time events and policy changes. The increased presence of social media platforms as a means for information and disinformation may also affect each of these elections and turnout in such a way that these results would be less likely to match those of older papers. Though individuals have more information at their fingertips, they may be watching TV or reading newspapers less and thus not get a standardized view of polls and tight races. Finally, societal change and historical events could also explain some of the variation in our control variables from the literature. For example, minority populations may have increased voter turnout because of movements such as the Black Lives Matter movement which began in 2013, which encourage voter registration and political activism among minority populations. The effects of these events could lead to larger systemic changes such that more recent elections are unlikely to mirror previous ones in terms of what variables are more correlated with turnout. Though we cannot confirm these changes due to aggregation in the turnout data, we present these as possible explanations for the discrepancies between our work and works that study older elections.

Ultimately, the differences from our conclusions to the previous literature can be attributed to one or more of three things: limitations of the data, systemic changes due to societal progress, or the novelty of the elections of study. Again, though the DCH has been previously tested and explored, our paper brings the novel contribution of looking at the US presidential election within a modernized election space. This area has no precedent, and thus different results are likely to occur as the societal norms that facilitate this major election change, and the election itself has seen little prior research. All things given, we find that there is no causal relationship such that closer elections on the state-level are likely to encourage increased voter turnout, though strong correlation between the two variables is present.

7) Conclusion

In this paper, we look at the effects of election closeness, measured as a Closeness Gap between pre-election polls, on voter turnout for the US presidential election for the post-2010 era. We considered a variant of the Downsian Closeness Hypothesis, which suggests that greater perceived closeness within an election would encourage the electorate to vote because voters are more likely to believe their vote will have an effect on the outcome of the election. Using independent yearly regressions, a panel data regression, and a Difference-in-Differences model to control for state-level fixed effects, we cannot confirm a causal relationship between the pre-election closeness of a US Presidential election and voter turnout. That said, we do find a strong correlation between Closeness Gap and turnout.

Moving forward, we believe it would be important to test a number of assumptions we exerted going into the paper. First, it would be advantageous to check the validity of polls as a means for perceived closeness. This would include a more in-depth look at how and when people react to polls, and if there were a better metric by which one could measure perceived closeness, such as local party composition. In addition, we make claims as to the importance of the proliferation of the internet and user-generated content on social media platforms. This could be tested using a regression discontinuity design, testing for changes to turnout as a result of the invention and adoption of various platforms and technologies. On a large scale, this could mean checking discontinuity in 2004, with the advent of web-2.0, or in 2012 with the increased adoption of smartphones. On a smaller scale, this could be asking individuals about how their activity on social media may have affected their political involvement. Given the clarification of these assumptions, we believe it would be paramount to increase the timeline of observation to 2000-2020, and we suggest considering midterm elections/US House of Representative races to keep the national importance of the race but allow for district level analysis. Finally, we believe all of these regressions could benefit from a demographic breakdown of turnout data such that we could get a better understanding about who is voting differently based on increases or decreases in perceived election closeness. Re-evaluation of our prior assumptions and larger, more granular datasets will not only increase our understanding of the findings we presented here, but will allow for more robust explorations into the DCH.

Appendix A:

TABLE 1: Descriptive Statistics (All Years)

Variable	Obs	Mean	Std. Dev.	Min	Max
year	153	2016	3.277	2012	2020
closeness gap	153	15.529	13.308	.1	85
leaning dem	153	.516	.501	0	1
percent children	153	31.125	3.222	20.3	42.8
percent elderly	153	27.333	3.545	15.9	37.8
avg hh size	153	2.555	.164	2.17	3.16
percent married male	153	50.57	3.705	28.3	57.6
percent married fe~e	153	47.706	4.521	23.7	56.3
percent hs	153	88.65	3.165	80.8	94
percent bach	153	30.271	6.353	17.9	59.8
unemp rate	153	6.837	2.057	2.8	12.6
median hh income	153	58133.098	10936.377	38882	90842
mean hh income	153	78431.752	15127.046	54072	133587
percent poverty	153	13.827	3.091	7.4	22.3
percent male	153	49.359	.819	47.3	52.3
percent female	153	50.641	.819	47.7	52.7
median age	153	38.016	2.398	29.3	44.8
percent latinx	153	11.327	10.054	1.2	49.2
percent white	153	69.137	16.089	21.6	94.4
percent black	153	10.912	10.66	.4	50.4
percent indigenous	153	1.426	2.718	.1	14.1
percent asian	153	3.957	5.362	.6	37.8
percent pi	153	.305	1.317	0	9.7
percent other	153	.207	.146	0	.8
percent two more r~e	153	2.715	2.627	1	19.3
percent minority	153	30.849	16.088	5.4	78.5
gini	153	.461	.021	.413	.533
turnout	153	63.549	6.904	42.52	80
squared closeness	153	417.086	900.327	.01	7225
log median hh income	153	10.954	.183	10.568	11.417
Iyear 2016	153	.333	.473	0	1
Iyear 2020	153	.333	.473	0	1

TABLE 2: Descriptive Statistics (2012)

Variable	Obs	Mean	Std. Dev.	Min	Max
year	51	2012	0	2012	2012
closeness gap	51	16.175	13.616	.5	80
leaning dem	51	.49	.505	0	1
percent children	51	32.331	3.266	20.4	42.8
percent elderly	51	24.659	2.576	15.9	31.5
avg hh size	51	2.551	.16	2.17	3.09
percent married male	51	51.52	4.015	28.3	57.6
percent married fe~e	51	48.351	4.738	23.7	56.3
percent hs	51	87.302	3.283	80.8	92.1
percent bach	51	28.229	5.788	17.9	51.2
unemp rate	51	8.514	1.92	3.4	12.6
median hh income	51	53323.059	8726.283	38882	72999
mean hh income	51	71049.255	11724.997	54072	99511
percent poverty	51	14.353	3.097	8.4	22.3
percent male	51	49.312	.796	47.3	52
percent female	51	50.688	.796	48	52.7
median age	51	37.508	2.302	29.3	42.8
percent latinx	51	10.58	9.886	1.2	46.3
percent white	51	70.629	16.144	22.8	94.4
percent black	51	10.857	10.981	.4	50.4
percent indigenous	51	1.431	2.713	.1	13.6
percent asian	51	3.671	5.429	.6	37.8
percent pi	51	.292	1.305	0	9.3
percent other	51	.169	.132	0	.7
percent two more r~e	51	2.347	2.668	1	19.3
percent minority	51	29.347	16.15	5.4	77.1
gini	51	.455	.022	.413	.531
turnout	51	62.914	6.059	47.8	75.9
squared closeness	51	443.368	925.484	.25	6400
log median hh income	51	10.871	.16	10.568	11.198
Iyear 2016	51	0	0	0	0
Iyear 2020	51	0	0	0	0

TABLE 3: Descriptive Statistics (2016)

Variable	Obs	Mean	Std. Dev.	Min	Max
year	51	2016	0	2016	2016
closeness gap	51	14.308	12.101	.5	70.5
leaning dem	51	.51	.505	0	1
percent children	51	31.124	3.022	22	42.2
percent elderly	51	27.249	2.785	19.3	34.5
avg hh size	51	2.576	.17	2.24	3.16
percent married male	51	50.171	3.578	30.8	56.2
percent married fe~e	51	47.316	4.44	25.9	55.6
percent hs	51	88.575	2.985	82.1	92.9
percent bach	51	30.037	6.121	19.6	55.4
unemp rate	51	6.859	1.514	2.8	9.6
median hh income	51	56031.059	9406.037	40528	76067
mean hh income	51	75885.392	12769.366	56358	110614
percent poverty	51	14.529	3.117	8.5	22.3
percent male	51	49.373	.835	47.4	52.3
percent female	51	50.627	.835	47.7	52.6
median age	51	37.98	2.426	30.3	44
percent latinx	51	11.345	10.118	1.4	47.8
percent white	51	69.222	16.157	22.4	93.7
percent black	51	10.933	10.732	.4	47.4
percent indigenous	51	1.437	2.738	.1	13.7
percent asian	51	3.959	5.364	.7	37
percent pi	51	.298	1.307	0	9.3
percent other	51	.167	.138	0	.7
percent two more r~e	51	2.629	2.635	1	19.3
percent minority	51	30.769	16.149	6.4	77.5
gini	51	.464	.021	.417	.533
turnout	51	59.861	6.304	42.52	74.16
squared closeness	51	348.277	723.966	.25	4970.25
log median hh income	51	10.92	.164	10.61	11.239
Iyear 2016	51	1	0	1	1
Iyear 2020	51	0	0	0	0

TABLE 4: Descriptive Statistics (2020)

Variable	Obs	Mean	Std. Dev.	Min	Max
year	51	2020	0	2020	2020
closeness gap	51	16.104	14.293	.1	85
leaning dem	51	.549	.503	0	1
percent children	51	29.92	2.966	20.3	40.2
percent elderly	51	30.09	2.959	22.2	37.8
avg hh size	51	2.539	.163	2.28	3.09
percent married male	51	50.02	3.379	32.1	56.1
percent married fe~e	51	47.451	4.396	26.5	55.4
percent hs	51	90.073	2.614	83.9	94
percent bach	51	32.545	6.492	21.3	59.8
unemp rate	51	5.139	1.04	3.1	7.2
median hh income	51	65045.176	11051.568	46511	90842
mean hh income	51	88360.608	15242.855	65156	133587
percent poverty	51	12.598	2.722	7.4	19.6
percent male	51	49.394	.839	47.5	52.2
percent female	51	50.606	.839	47.8	52.5
median age	51	38.559	2.394	31.1	44.8
percent latinx	51	12.055	10.299	1.6	49.2
percent white	51	67.559	16.139	21.6	92.6
percent black	51	10.947	10.473	.5	44.5
percent indigenous	51	1.41	2.756	.1	14.1
percent asian	51	4.241	5.385	.8	36.8
percent pi	51	.325	1.363	0	9.7
percent other	51	.284	.138	.1	.8
percent two more r~e	51	3.169	2.561	1.3	19.2
percent minority	51	32.431	16.136	7.3	78.5
gini	51	.465	.02	.423	.521
turnout	51	67.873	5.924	55	80
squared closeness	51	459.614	1037.383	.01	7225
log median hh income	51	11.069	.167	10.747	11.417
Iyear 2016	51	0	0	0	0
Iyear 2020	51	1	0	1	1

TABLE 5: Simple Linear Regression on Turnout (All Years)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.076	.042	-1.82	.07	-.159	.006	*
Constant	64.73	.853	75.90	0	63.045	66.415	***

Mean dependent var	63.549	SD dependent var	6.904
R-squared	0.022	Number of obs	153
F-test	3.318	Prob > F	0.070
Akaike crit. (AIC)	1025.071	Bayesian crit. (BIC)	1031.132

**** p<.01, ** p<.05, * p<.1*

TABLE 6: Controlled Linear regression on Turnout (All Years)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.183	.132	-1.38	.17	-.445	.079	
squared_closeness	0	.004	-0.05	.959	-.007	.007	
leaning_dem	2.619	1.075	2.44	.016	.493	4.746	**
percent_children	.006	.929	0.01	.995	-1.831	1.843	
percent_elderly	-.081	.525	-0.15	.878	-1.12	.959	
avg_hh_size	-13.727	14.126	-0.97	.333	-41.666	14.211	
percent_married_ male	1.662	2.003	0.83	.408	-2.3	5.624	
percent_married_f e~e	-1.779	1.956	-0.91	.365	-5.647	2.089	
percent_bach	.675	.225	3.01	.003	.231	1.12	***
unemp_rate	.307	.473	0.65	.517	-.628	1.242	
log_median_hh_in come	-2.925	15.141	-0.19	.847	-32.871	27.021	
percent_poverty	.281	.904	0.31	.756	-1.506	2.068	
percent_male	2.817	3.928	0.72	.474	-4.951	10.586	
median_age	-.148	.452	-0.33	.744	-1.042	.746	
percent_minority	-.085	.077	-1.10	.273	-.238	.068	
gini	-108.686	52.691	-2.06	.041	-212.9	-4.471	**
_Iyear_2016	-2.163	1.909	-1.13	.259	-5.94	1.613	
_Iyear_2020	6.422	3.17	2.03	.045	.153	12.691	**
Constant	26.547	262.664	0.10	.92	-492.956	546.05	

Mean dependent var	63.549	SD dependent var	6.904
R-squared	0.662	Number of obs	153
F-test	15.232	Prob > F	0.000
Akaike crit. (AIC)	896.584	Bayesian crit. (BIC)	954.162

**** p<.01, ** p<.05, * p<.1*

TABLE 7: Linear regression on Turnout (2012)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.242	.168	-1.44	.159	-.585	.1	
squared_closeness	.001	.004	0.28	.779	-.008	.01	
leaning_dem	1.928	2.374	0.81	.422	-2.896	6.752	
percent_children	1.203	2.145	0.56	.578	-3.155	5.561	
percent_elderly	.254	1.307	0.19	.847	-2.401	2.91	
avg_hh_size	-31.496	29.064	-1.08	.286	-90.561	27.569	
percent_married_ male	.553	4.477	0.12	.902	-8.547	9.652	
percent_married_f e~e	-1.27	4.707	-0.27	.789	-10.835	8.296	
percent_bach	.881	.564	1.56	.128	-.266	2.027	
unemp_rate	-.058	.838	-0.07	.945	-1.762	1.645	
log_median_hh_in come	-9.051	44.016	-0.21	.838	-98.502	80.4	
percent_poverty	.596	2.34	0.25	.8	-4.16	5.353	
percent_male	-.203	10.519	-0.02	.985	-21.58	21.173	
median_age	-.525	1.116	-0.47	.641	-2.793	1.743	
percent_minority	-.034	.163	-0.21	.837	-.366	.298	
gini	-216.539	139.022	-1.56	.129	-499.066	65.988	
Constant	328.201	667.362	0.49	.626	-1028.042	1684.444	

Mean dependent var	62.914	SD dependent var	6.059
R-squared	0.658	Number of obs	51
F-test	3.188	Prob > F	0.002
Akaike crit. (AIC)	306.679	Bayesian crit. (BIC)	339.520

**** p<.01, ** p<.05, * p<.1*

TABLE 8: Linear regression on Turnout (2016)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.203	.484	-0.42	.678	-1.186	.781	
squared_closeness	-.001	.015	-0.10	.924	-.032	.029	
leaning_dem	.697	3.066	0.23	.821	-5.533	6.927	
percent_children	-.683	1.763	-0.39	.701	-4.266	2.899	
percent_elderly	-.669	.872	-0.77	.448	-2.441	1.102	
avg_hh_size	-19.573	30.468	-0.64	.525	-81.493	42.346	
percent_married_male	1.403	3.708	0.38	.707	-6.133	8.939	
percent_married_fe~e	-.876	4.105	-0.21	.832	-9.219	7.467	
percent_bach	.406	.455	0.89	.378	-.519	1.332	
unemp_rate	.806	1.277	0.63	.532	-1.788	3.4	
log_median_hh_income	9.479	33.532	0.28	.779	-58.666	77.625	
percent_poverty	.366	1.476	0.25	.806	-2.633	3.365	
percent_male	.682	9.249	0.07	.942	-18.113	19.477	
median_age	.224	.942	0.24	.813	-1.69	2.139	
percent_minority	.012	.201	0.06	.952	-.396	.42	
gini	-108.606	84.168	-1.29	.206	-279.657	62.444	
Constant	5.135	327.902	0.02	.988	-661.241	671.512	

Mean dependent var	59.861	SD dependent var	6.304
R-squared	0.723	Number of obs	51
F-test	5.217	Prob > F	0.000
Akaike crit. (AIC)	299.973	Bayesian crit. (BIC)	332.814

**** p<.01, ** p<.05, * p<.1*

TABLE 9: Linear regression on Turnout (2020)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.139	.176	-0.79	.435	-.497	.219	
squared_closeness	-.002	.004	-0.46	.646	-.011	.007	
leaning_dem	4.56	1.689	2.70	.011	1.128	7.992	**
percent_children	-1.316	.956	-1.38	.178	-3.258	.627	
percent_elderly	-.8	.657	-1.22	.232	-2.134	.535	
avg_hh_size	14.689	15.689	0.94	.356	-17.195	46.574	
percent_married_male	1.214	1.597	0.76	.452	-2.032	4.461	
percent_married_fe~e	-.539	1.958	-0.28	.785	-4.519	3.441	
percent_bach	.575	.338	1.70	.098	-.113	1.262	*
unemp_rate	.203	1.373	0.15	.884	-2.588	2.993	
log_median_hh_income	13.983	23.126	0.60	.549	-33.014	60.981	
percent_poverty	1.281	1.279	1.00	.324	-1.319	3.881	
percent_male	.942	3.917	0.24	.811	-7.019	8.903	
median_age	.407	.913	0.45	.658	-1.448	2.262	
percent_minority	-.149	.119	-1.25	.221	-.391	.094	
gini	-72.122	54.446	-1.32	.194	-182.77	38.526	
Constant	-155.083	281.052	-0.55	.585	-726.249	416.082	

Mean dependent var	67.873	SD dependent var	5.924
R-squared	0.800	Number of obs	51
F-test	6.073	Prob > F	0.000
Akaike crit. (AIC)	277.087	Bayesian crit. (BIC)	309.928

**** p<.01, ** p<.05, * p<.1*

TABLE 10: Difference-in-Differences Regression on Turnout, absorbing indicators

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.158	.101	-1.56	.124	-.361	.045	
squared_closeness	.003	.002	1.37	.177	-.001	.007	
leaning_dem	-1.263	.986	-1.28	.206	-3.244	.718	
percent_children	.471	1.29	0.37	.717	-2.121	3.063	
percent_elderly	1.851	.745	2.48	.016	.355	3.347	**
avg_hh_size	-32.206	22.455	-1.43	.158	-77.309	12.897	
percent_married_ male	1.94	1.778	1.09	.28	-1.631	5.51	
percent_married_f e~e	-4.515	2.699	-1.67	.101	-9.935	.906	
percent_bach	1.905	1.55	1.23	.225	-1.209	5.019	
unemp_rate	-.307	.855	-0.36	.721	-2.024	1.411	
log_median_hh_in come	6.41	42.679	0.15	.881	-79.314	92.134	
percent_poverty	-.567	1.266	-0.45	.656	-3.109	1.976	
percent_male	13.946	7.175	1.94	.058	-.466	28.358	*
median_age	.475	1.743	0.27	.786	-3.027	3.977	
percent_minority	1.561	.597	2.62	.012	.362	2.76	**
gini	-11.738	153.561	-0.08	.939	-320.176	296.699	
_Iyear_2016	-15.86	4.986	-3.18	.003	-25.875	-5.845	***
_Iyear_2020	-23.354	8.363	-2.79	.007	-40.151	-6.556	***
Constant	-654.309	420.683	-1.56	.126	-1499.276	190.658	

Mean dependent var	63.549	SD dependent var	6.904
R-squared	0.918	Number of obs	153
F-test	18.702	Prob > F	0.000
Akaike crit. (AIC)	677.832	Bayesian crit. (BIC)	732.380

*** *p<.01*, ** *p<.05*, * *p<.1*

Appendix B:

TABLE 11: Descriptive Statistics (All Years) – Without Proxy Closeness

Variable	Obs	Mean	Std. Dev.	Min	Max
year	147	2016.163	3.239	2012	2020
closeness gap	147	15.039	12.405	.1	85
leaning dem	147	.524	.501	0	1
percent children	147	31.13	3.12	20.3	42.8
percent elderly	147	27.497	3.428	19.3	37.8
avg hh size	147	2.557	.164	2.24	3.16
percent married male	147	50.702	3.286	30.8	57.6
percent married female	147	47.849	4.131	25.9	56.3
percent hs	147	88.707	3.152	80.8	94
percent bach	147	30.281	6.178	17.9	59.8
unemp rate	147	6.752	2.01	2.8	12.6
median hh income	147	58252.973	10950.963	38882	90842
mean hh income	147	78596.898	15115.089	54072	133587
percent poverty	147	13.785	3.068	7.4	22.3
percent male	147	49.367	.776	47.4	52.3
percent female	147	50.633	.776	47.7	52.6
median age	147	38.076	2.395	29.3	44.8
percent latinx	147	11.553	10.184	1.2	49.2
percent white	147	69.378	16.097	21.6	94.4
percent black	147	10.476	10.108	.4	47.4
percent indigenous	147	1.324	2.508	.1	14.1
percent asian	147	4.014	5.454	.6	37.8
percent pi	147	.31	1.341	0	9.7
percent other	147	.21	.148	0	.8
percent two more r~e	147	2.72	2.647	1	19.3
percent minority	147	30.607	16.095	5.4	78.5
gini	147	.461	.02	.417	.533
turnout	147	63.495	6.944	42.52	80
squared closeness	147	379.016	771.566	.01	7225
log median hh income	147	10.956	.183	10.568	11.417
Iyear 2016	147	.347	.478	0	1
Iyear 2020	147	.347	.478	0	1

TABLE 12: Descriptive Statistics (2012) – Without Proxy Closeness

Variable	Obs	Mean	Std. Dev.	Min	Max
year	45	2012	0	2012	2012
closeness gap	45	14.662	10.487	.5	37
leaning dem	45	.511	.506	0	1
percent children	45	32.509	2.878	27.7	42.8
percent elderly	45	24.838	2.268	19.8	31.5
avg hh size	45	2.557	.158	2.3	3.09
percent married male	45	52.078	2.346	47.9	57.6
percent married female	45	48.904	3.26	42.9	56.3
percent hs	45	87.309	3.3	80.8	92.1
percent bach	45	27.991	4.98	17.9	39
unemp rate	45	8.458	1.89	3.4	12.6
median hh income	45	53073.311	8483.127	38882	72999
mean hh income	45	70604.4	11154.45	54072	97051
percent poverty	45	14.287	3.039	8.4	22.3
percent male	45	49.329	.636	48.3	50.9
percent female	45	50.671	.636	49.1	51.7
median age	45	37.638	2.314	29.3	42.8
percent latinx	45	11.22	10.335	1.2	46.3
percent white	45	71.618	16.068	22.8	94.4
percent black	45	9.424	9.047	.4	37
percent indigenous	45	1.1	1.909	.1	8.6
percent asian	45	3.82	5.741	.6	37.8
percent pi	45	.307	1.384	0	9.3
percent other	45	.173	.139	0	.7
percent two more r~e	45	2.313	2.738	1	19.3
percent minority	45	28.358	16.071	5.4	77.1
gini	45	.455	.018	.42	.501
turnout	45	62.653	6.061	47.8	74.5
squared closeness	45	322.51	380.733	.25	1369
log median hh income	45	10.867	.156	10.568	11.198
Iyear 2016	45	0	0	0	0
Iyear 2020	45	0	0	0	0

**** p<.01, ** p<.05, * p<.1*

TABLE 13: Simple linear regression on Turnout (All Years)

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.127	.045	-2.81	.006	-.217	-.038	***
Constant	65.406	.881	74.20	0	63.664	67.148	***
Mean dependent var		63.495	SD dependent var			6.944	
R-squared		0.052	Number of obs			147	
F-test		7.875	Prob > F			0.006	
Akaike crit. (AIC)		982.131	Bayesian crit. (BIC)			988.111	

**** p<.01, ** p<.05, * p<.1*

TABLE 14: Linear regression on Turnout (All years) – Without Proxy Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.147	.077	-1.91	.059	-.3	.005	*
squared_closeness	-.002	.002	-1.04	.302	-.005	.002	
leaning_dem	2.587	1.06	2.44	.016	.49	4.683	**
percent_children	-.224	.794	-0.28	.778	-1.796	1.348	
percent_elderly	-.285	.455	-0.63	.533	-1.185	.616	
avg_hh_size	-9.767	12.553	-0.78	.438	-34.606	15.072	
percent_married_ male	2.866	1.187	2.42	.017	.518	5.214	**
percent_married_f e~e	-2.827	1.462	-1.93	.055	-5.72	.065	*
percent_bach	.741	.222	3.33	.001	.301	1.181	***
unemp_rate	.102	.507	0.20	.841	-.901	1.105	
log_median_hh_i ncome	2.86	13.236	0.22	.829	-23.33	29.051	
percent_poverty	.828	.693	1.19	.235	-.544	2.199	
percent_male	5.075	3.207	1.58	.116	-1.271	11.421	
median_age	.099	.428	0.23	.818	-.748	.945	
percent_minority	-.105	.079	-1.33	.185	-.261	.051	
gini	-128.341	43.598	-2.94	.004	-214.608	-42.075	***
_Iyear_2016	-1.788	1.944	-0.92	.36	-5.635	2.059	
_Iyear_2020	7.225	3.02	2.39	.018	1.25	13.2	**
Constant	-164.856	165.176	-1.00	.32	-491.685	161.972	

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.707	Number of obs	147
F-test	20.067	Prob > F	0.000
Akaike crit. (AIC)	843.231	Bayesian crit. (BIC)	900.049

**** p<.01, ** p<.05, * p<.1*

TABLE 15: Linear regression on Turnout (2012) – Without Proxy Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.359	.359	-1.00	.326	-1.095	.376	
squared_closeness	.004	.011	0.32	.75	-.02	.027	
leaning_dem	1.429	3.288	0.43	.667	-5.306	8.165	
percent_children	1.862	2.661	0.70	.49	-3.588	7.313	
percent_elderly	.508	1.56	0.33	.747	-2.687	3.703	
avg_hh_size	-37.134	36.119	-1.03	.313	-111.121	36.853	
percent_married_male	.341	5.616	0.06	.952	-11.163	11.846	
percent_married_fe~e	-1.475	5.971	-0.25	.807	-13.707	10.756	
percent_bach	.99	.681	1.45	.157	-.405	2.385	
unemp_rate	-.338	1.034	-0.33	.746	-2.455	1.779	
log_median_hh_income	-7.326	59.902	-0.12	.904	-130.03	115.377	
percent_poverty	.82	3.075	0.27	.792	-5.479	7.118	
percent_male	1.892	13.759	0.14	.892	-26.292	30.076	
median_age	-.256	1.54	-0.17	.869	-3.411	2.899	
percent_minority	-.088	.223	-0.40	.695	-.546	.369	
gini	-208.903	164.11	-1.27	.214	-545.066	127.261	
Constant	199.054	835.083	0.24	.813	-1511.535	1909.643	

Mean dependent var	62.653	SD dependent var	6.061
R-squared	0.644	Number of obs	45
F-test	2.706	Prob > F	0.010
Akaike crit. (AIC)	276.371	Bayesian crit. (BIC)	307.084

**** p<.01, ** p<.05, * p<.1*

TABLE 16: Difference-in-Differences Regression on Turnout, absorbing indicators – Without Proxy Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	.023	.126	0.18	.857	-.23	.275	
squared_closeness	-.001	.002	-0.24	.815	-.006	.004	
leaning_dem	-1.623	1.216	-1.34	.188	-4.065	.819	
percent_children	1.232	1.403	0.88	.384	-1.587	4.051	
percent_elderly	.863	.865	1.00	.323	-.874	2.601	
avg_hh_size	-31.649	26.185	-1.21	.232	-84.243	20.946	
percent_married_ male	2.742	1.726	1.59	.118	-.725	6.208	
percent_married_f e~e	-4.89	2.604	-1.88	.066	-10.121	.341	*
percent_bach	3.396	1.679	2.02	.048	.024	6.768	**
unemp_rate	-.242	.927	-0.26	.795	-2.104	1.621	
log_median_hh_i ncome	-.982	47.01	-0.02	.983	-95.405	93.44	
percent_poverty	-.551	1.359	-0.41	.687	-3.281	2.179	
percent_male	10.487	7.768	1.35	.183	-5.116	26.09	
median_age	1.601	1.736	0.92	.361	-1.885	5.087	
percent_minority	.81	.64	1.27	.212	-.476	2.095	
gini	-15.085	162.351	-0.09	.926	-341.177	311.007	
_Iyear_2016	-12.959	5.765	-2.25	.029	-24.539	-1.379	**
_Iyear_2020	-18.276	9.286	-1.97	.055	-36.927	.375	*
Constant	-490.463	456.758	-1.07	.288	-1407.89	426.963	

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.932	Number of obs	147
F-test	19.278	Prob > F	0.000
Akaike crit. (AIC)	629.616	Bayesian crit. (BIC)	686.434

**** p<.01, ** p<.05, * p<.1*

Appendix C:

TABLE 17: Linear Regression on Turnout (All Years) - Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.213	.045	-4.76	0	-.302	-.125	***
leaning_dem	2.803	1.046	2.68	.008	.734	4.872	***
percent_children	.121	.753	0.16	.872	-1.369	1.612	
percent_elderly	-.155	.447	-0.35	.729	-1.04	.729	
avg_hh_size	-13.211	12.229	-1.08	.282	-37.407	10.986	
percent_married_ male	2.818	1.186	2.38	.019	.471	5.165	**
percent_married_f e~e	-2.773	1.449	-1.91	.058	-5.64	.094	*
percent_bach	.708	.225	3.15	.002	.263	1.154	***
unemp_rate	.07	.509	0.14	.89	-.938	1.078	
log_median_hh_in come	2.137	12.988	0.16	.87	-23.56	27.835	
percent_poverty	.748	.688	1.09	.279	-.613	2.109	
percent_male	5.327	3.175	1.68	.096	-.955	11.609	*
median_age	.208	.424	0.49	.625	-.631	1.047	
percent_minority	-.104	.079	-1.32	.188	-.261	.052	
gini	-116.44	43.807	-2.66	.009	-203.114	-29.767	***
_Iyear_2016	-1.714	1.949	-0.88	.381	-5.572	2.143	
_Iyear_2020	7.017	3.061	2.29	.023	.962	13.073	**
Constant	-182.141	166.104	-1.10	.275	-510.783	146.5	

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.705	Number of obs	147
F-test	20.464	Prob > F	0.000
Akaike crit. (AIC)	842.396	Bayesian crit. (BIC)	896.224

**** p<.01, ** p<.05, * p<.1*

TABLE 18: Linear regression on Turnout (2012) - Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.233	.136	-1.72	.097	-.51	.045	*
leaning_dem	1.56	3.072	0.51	.615	-4.724	7.844	
percent_children	1.789	2.504	0.71	.481	-3.332	6.91	
percent_elderly	.515	1.519	0.34	.737	-2.592	3.621	
avg_hh_size	-34.327	32.328	-1.06	.297	-100.444	31.791	
percent_married_ male	.864	5.668	0.15	.88	-10.727	12.456	
percent_married_f e~e	-2.009	6.078	-0.33	.743	-14.44	10.423	
percent_bach	1.058	.664	1.59	.122	-.301	2.417	
unemp_rate	-.276	1.056	-0.26	.796	-2.435	1.884	
log_median_hh_in come	-11.621	55.086	-0.21	.834	-124.284	101.042	
percent_poverty	.675	2.877	0.23	.816	-5.209	6.559	
percent_male	3.199	14.188	0.23	.823	-25.818	32.217	
median_age	-.251	1.307	-0.19	.849	-2.923	2.422	
percent_minority	-.099	.221	-0.45	.659	-.551	.354	
gini	-215.823	162.527	-1.33	.195	-548.229	116.582	
Constant	177.247	833.777	0.21	.833	-1528.018	1882.512	

Mean dependent var	62.653	SD dependent var	6.061
R-squared	0.641	Number of obs	45
F-test	2.995	Prob > F	0.005
Akaike crit. (AIC)	274.703	Bayesian crit. (BIC)	303.610

**** p<.01, ** p<.05, * p<.1*

TABLE 19: Linear regression on Turnout (2016) - Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.25	.098	-2.55	.015	-.449	-.051	**
leaning_dem	.994	3.449	0.29	.775	-6.008	7.995	
percent_children	-.469	1.945	-0.24	.811	-4.418	3.48	
percent_elderly	-.584	.814	-0.72	.478	-2.237	1.069	
avg_hh_size	-21.07	30.411	-0.69	.493	-82.807	40.668	
percent_married_ male	1.551	3.264	0.48	.638	-5.074	8.177	
percent_married_f e~e	-1.033	3.643	-0.28	.778	-8.428	6.362	
percent_bach	.384	.484	0.79	.433	-.599	1.367	
unemp_rate	.782	1.27	0.62	.542	-1.796	3.361	
log_median_hh_in come	8.038	30.002	0.27	.79	-52.87	68.946	
percent_poverty	.283	1.309	0.22	.83	-2.375	2.94	
percent_male	1.261	7.919	0.16	.874	-14.816	17.338	
median_age	.292	.977	0.30	.767	-1.69	2.275	
percent_minority	.006	.191	0.03	.974	-.381	.393	
gini	-99.661	72.818	-1.37	.18	-247.49	48.168	
Constant	-17.372	306.316	-0.06	.955	-639.226	604.481	

Mean dependent var	59.861	SD dependent var	6.304
R-squared	0.722	Number of obs	51
F-test	5.297	Prob > F	0.000
Akaike crit. (AIC)	298.144	Bayesian crit. (BIC)	329.053

**** p<.01, ** p<.05, * p<.1*

TABLE 20: Linear regression on Turnout (2020) - Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.216	.068	-3.19	.003	-.354	-.078	***
leaning_dem	4.987	1.867	2.67	.011	1.197	8.777	**
percent_children	-.885	1.021	-0.87	.392	-2.959	1.188	
percent_elderly	-.631	.675	-0.94	.356	-2.002	.739	
avg_hh_size	10.049	15.355	0.65	.517	-21.122	41.22	
percent_married_ male	1.13	1.591	0.71	.482	-2.1	4.361	
percent_married_f e~e	-.378	1.884	-0.20	.842	-4.202	3.446	
percent_bach	.523	.317	1.65	.108	-.121	1.167	
unemp_rate	.307	1.334	0.23	.819	-2.401	3.015	
log_median_hh_in come	13.755	22.754	0.60	.549	-32.439	59.949	
percent_poverty	1.175	1.286	0.91	.367	-1.437	3.786	
percent_male	.969	3.957	0.25	.808	-7.063	9.002	
median_age	.483	.923	0.52	.604	-1.39	2.356	
percent_minority	-.149	.124	-1.20	.237	-.4	.102	
gini	-58.362	59.17	-0.99	.331	-178.484	61.759	
Constant	-170.203	276.859	-0.61	.543	-732.256	391.851	

Mean dependent var	67.873	SD dependent var	5.924
R-squared	0.795	Number of obs	51
F-test	5.570	Prob > F	0.000
Akaike crit. (AIC)	276.334	Bayesian crit. (BIC)	307.244

**** p<.01, ** p<.05, * p<.1*

TABLE 21: Difference-in-Differences Regression on Turnout, absorbing indicators – Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.003	.067	-0.04	.968	-.136	.131	
leaning_dem	-1.601	1.151	-1.39	.17	-3.914	.711	
percent_children	1.267	1.335	0.95	.347	-1.414	3.948	
percent_elderly	.914	.775	1.18	.244	-.643	2.472	
avg_hh_size	-32.055	26.465	-1.21	.232	-85.211	21.102	
percent_married_male	2.666	1.55	1.72	.092	-.447	5.779	*
percent_married_fe~e	-4.807	2.452	-1.96	.056	-9.733	.118	*
percent_bach	3.348	1.622	2.06	.044	.091	6.606	**
unemp_rate	-.255	.913	-0.28	.781	-2.088	1.578	
log_median_hh_income	-.952	46.605	-0.02	.984	-94.561	92.656	
percent_poverty	-.569	1.365	-0.42	.678	-3.311	2.172	
percent_male	10.701	7.675	1.39	.169	-4.715	26.117	
median_age	1.634	1.677	0.97	.335	-1.735	5.003	
percent_minority	.853	.577	1.48	.146	-.307	2.013	
gini	-6.726	152.577	-0.04	.965	-313.186	299.734	
_Iyear_2016	-13.159	5.549	-2.37	.022	-24.305	-2.013	**
_Iyear_2020	-18.685	8.895	-2.10	.041	-36.551	-.818	**
Constant	-507.232	425.865	-1.19	.239	-1362.606	348.143	

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.932	Number of obs	147
F-test	20.418	Prob > F	0.000
Akaike crit. (AIC)	625.723	Bayesian crit. (BIC)	676.561

**** p<.01, ** p<.05, * p<.1*

Appendix D:

TABLE 22: Simple Linear Regression on Turnout (All Years) – Without Outliers, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.171	.056	-3.03	.003	-.283	-.059	***
Constant	65.968	.978	67.44	0	64.035	67.902	***

Mean dependent var	63.545	SD dependent var	6.962
R-squared	0.060	Number of obs	145
F-test	9.169	Prob > F	0.003
Akaike crit. (AIC)	968.203	Bayesian crit. (BIC)	974.157

**** p<.01, ** p<.05, * p<.1*

TABLE 23: Linear regression on Turnout (All Years) – Without Outliers, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.198	.046	-4.31	0	-.288	-.107	***
leaning_dem	2.264	1.062	2.13	.035	.162	4.365	**
percent_children	-.605	.847	-0.71	.477	-2.281	1.072	
percent_elderly	-.423	.472	-0.90	.372	-1.358	.511	
avg_hh_size	-6.778	12.604	-0.54	.592	-31.719	18.164	
percent_married_ male	2.736	1.219	2.24	.027	.324	5.147	**
percent_married_f e~e	-2.672	1.49	-1.79	.075	-5.621	.277	*
percent_bach	.748	.221	3.39	.001	.312	1.185	***
unemp_rate	.116	.506	0.23	.819	-.886	1.118	
log_median_hh_in come	6.05	13.253	0.46	.649	-20.176	32.275	
percent_poverty	1.003	.684	1.47	.145	-.351	2.357	
percent_male	4.331	3.273	1.32	.188	-2.145	10.807	
median_age	-.053	.441	-0.12	.904	-.925	.818	
percent_minority	-.105	.078	-1.35	.179	-.258	.049	
gini	-133.991	42.459	-3.16	.002	-218.009	-49.973	***
_Iyear_2016	-1.931	1.928	-1.00	.318	-5.747	1.885	
_Iyear_2020	7.057	3.038	2.32	.022	1.046	13.068	**
Constant	-149.634	168.617	-0.89	.377	-483.295	184.028	

Mean dependent var	63.545	SD dependent var	6.962
R-squared	0.710	Number of obs	145
F-test	20.806	Prob > F	0.000
Akaike crit. (AIC)	829.490	Bayesian crit. (BIC)	883.071

**** p<.01, ** p<.05, * p<.1*

TABLE 24: Linear regression on Turnout (2016)
– Without Outliers, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.236	.098	-2.40	.022	-.436	-.036	**
leaning_dem	-.25	3.216	-0.08	.938	-6.786	6.286	
percent_children	-1.619	1.721	-0.94	.354	-5.116	1.879	
percent_elderly	-1.027	.749	-1.37	.179	-2.55	.496	
avg_hh_size	-11.279	28.609	-0.39	.696	-69.419	46.861	
percent_married_male	.704	3.2	0.22	.827	-5.799	7.206	
percent_married_fe~e	-.083	3.548	-0.02	.982	-7.293	7.128	
percent_bach	.477	.463	1.03	.309	-.463	1.417	
unemp_rate	.84	1.224	0.69	.497	-1.647	3.327	
log_median_hh_income	15.94	29.126	0.55	.588	-43.252	75.131	
percent_poverty	.783	1.206	0.65	.52	-1.667	3.233	
percent_male	-1.952	7.409	-0.26	.794	-17.01	13.105	
median_age	-.086	.87	-0.10	.922	-1.855	1.683	
percent_minority	.017	.172	0.10	.921	-.333	.367	
gini	-125.529	68.391	-1.84	.075	-264.517	13.459	*
Constant	91.639	282.551	0.32	.748	-482.575	665.852	

Mean dependent var	59.944	SD dependent var	6.340
R-squared	0.739	Number of obs	50
F-test	5.934	Prob > F	0.000
Akaike crit. (AIC)	290.432	Bayesian crit. (BIC)	321.024

**** p<.01, ** p<.05, * p<.1*

TABLE 25: Linear regression on Turnout (2020)
– Without Outliers, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.205	.064	-3.20	.003	-.335	-.075	***
leaning_dem	4.384	1.651	2.66	.012	1.028	7.739	**
percent_children	-1.566	.968	-1.62	.115	-3.533	.401	
percent_elderly	-.904	.667	-1.36	.184	-2.259	.452	
avg_hh_size	16.539	15.39	1.07	.29	-14.738	47.816	
percent_married_ male	1.338	1.583	0.85	.404	-1.879	4.555	
percent_married_f e~e	-.559	1.894	-0.30	.77	-4.407	3.289	
percent_bach	.585	.324	1.81	.079	-.072	1.243	*
unemp_rate	.312	1.299	0.24	.811	-2.328	2.952	
log_median_hh_in come	15.428	21.784	0.71	.484	-28.841	59.698	
percent_poverty	1.416	1.237	1.14	.26	-1.098	3.93	
percent_male	.819	3.78	0.22	.83	-6.862	8.5	
median_age	.347	.908	0.38	.705	-1.498	2.192	
percent_minority	-.146	.115	-1.27	.211	-.379	.087	
gini	-77.268	52.202	-1.48	.148	-183.355	28.819	
Constant	-161.765	278.263	-0.58	.565	-727.264	403.735	

Mean dependent var	67.948	SD dependent var	5.959
R-squared	0.801	Number of obs	50
F-test	6.722	Prob > F	0.000
Akaike crit. (AIC)	270.664	Bayesian crit. (BIC)	301.256

**** p<.01, ** p<.05, * p<.1*

TABLE 26: Difference-in-Differences Regression on Turnout, absorbing indicators – Without Outliers, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	.003	.069	0.04	.964	-.135	.141	
leaning_dem	-1.638	1.202	-1.36	.179	-4.054	.778	
percent_children	1.162	1.434	0.81	.422	-1.721	4.044	
percent_elderly	.804	.906	0.89	.379	-1.017	2.624	
avg_hh_size	-29.195	25.813	-1.13	.264	-81.069	22.679	
percent_married_ male	2.838	1.782	1.59	.118	-.744	6.42	
percent_married_f e~e	-4.97	2.629	-1.89	.065	-10.254	.313	*
percent_bach	3.414	1.649	2.07	.044	.101	6.727	**
unemp_rate	-.263	.906	-0.29	.773	-2.083	1.558	
log_median_hh_in come	-1.238	46.89	-0.03	.979	-95.467	92.991	
percent_poverty	-.503	1.364	-0.37	.714	-3.244	2.237	
percent_male	10.793	7.714	1.40	.168	-4.709	26.295	
median_age	1.628	1.7	0.96	.343	-1.789	5.045	
percent_minority	.726	.653	1.11	.272	-.587	2.039	
gini	-21.902	156.622	-0.14	.889	-336.645	292.841	
_Iyear_2016	-12.805	5.604	-2.28	.027	-24.066	-1.543	**
_Iyear_2020	-17.725	9.069	-1.95	.056	-35.949	.499	*
Constant	-500.987	431.406	-1.16	.251	-1367.93	365.956	

Mean dependent var	63.545	SD dependent var	6.962
R-squared	0.931	Number of obs	145
F-test	20.675	Prob > F	0.000
Akaike crit. (AIC)	619.283	Bayesian crit. (BIC)	669.887

**** p<.01, ** p<.05, * p<.1*

Appendix E:

TABLE 27: Simple regression on Turnout (All Years)
– Population Weighted, No Proxy, No Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.108	.056	-1.93	.055	-.219	.002	*
Constant	64.291	.895	71.82	0	62.521	66.06	***

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.025	Number of obs	147
F-test	3.733	Prob > F	0.055
Akaike crit. (AIC)	980.077	Bayesian crit. (BIC)	986.058

**** p<.01, ** p<.05, * p<.1*

TABLE 28: Linear Regression on Turnout (All Years)
– Population Weighted, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.13	.066	-1.95	.053	-.261	.002	*
leaning_dem	1.761	1.361	1.29	.198	-.932	4.453	
percent_children	-1.024	1.503	-0.68	.497	-3.997	1.949	
percent_elderly	-.829	.81	-1.02	.308	-2.431	.773	
avg_hh_size	12.503	21.741	0.58	.566	-30.512	55.518	
percent_married_ male	3.366	1.801	1.87	.064	-.197	6.929	*
percent_married_f e~e	-3.361	2.044	-1.64	.103	-7.406	.684	
percent_bach	.813	.472	1.72	.087	-.12	1.746	*
unemp_rate	.069	.445	0.15	.877	-.812	.95	
log_median_hh_in come	2.352	21.355	0.11	.912	-39.899	44.603	
percent_poverty	1.173	.73	1.61	.111	-.272	2.618	
percent_male	7.075	4.505	1.57	.119	-1.839	15.99	
median_age	1.39	.735	1.89	.061	-.065	2.845	*
percent_minority	-.132	.085	-1.54	.126	-.3	.037	
gini	-172.431	53.69	-3.21	.002	-278.657	-66.205	***
_Iyear_2016	-2.281	1.647	-1.39	.168	-5.539	.977	
_Iyear_2020	8.638	3.921	2.20	.029	.88	16.396	**
Constant	-309.842	274.706	-1.13	.261	-853.354	233.67	

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.738	Number of obs	147
F-test	25.249	Prob > F	0.000
Akaike crit. (AIC)	819.197	Bayesian crit. (BIC)	873.024

**** p<.01, ** p<.05, * p<.1*

TABLE 29: Linear regression on Turnout (2012)
– Population Weighted, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.211	.122	-1.73	.094	-.46	.039	*
leaning_dem	1.302	3.145	0.41	.682	-5.13	7.734	
percent_children	2.318	2.112	1.10	.281	-2.001	6.637	
percent_elderly	.365	1.461	0.25	.805	-2.624	3.354	
avg_hh_size	-29.872	30.246	-0.99	.331	-91.732	31.987	
percent_married_male	-.802	5.563	-0.14	.886	-12.18	10.576	
percent_married_fe~e	-.882	6.375	-0.14	.891	-13.921	12.156	
percent_bach	1.628	.707	2.30	.029	.183	3.073	**
unemp_rate	.085	.889	0.10	.925	-1.734	1.904	
log_median_hh_income	-46.341	56.839	-0.82	.422	-162.589	69.908	
percent_poverty	-.353	2.575	-0.14	.892	-5.62	4.914	
percent_male	1.388	15.014	0.09	.927	-29.319	32.095	
median_age	.597	1.857	0.32	.75	-3.201	4.395	
percent_minority	-.087	.226	-0.39	.702	-.549	.374	
gini	-217.791	148.014	-1.47	.152	-520.514	84.932	
Constant	614.674	841.3	0.73	.471	-1105.979	2335.326	

Mean dependent var	62.653	SD dependent var	6.061
R-squared	0.728	Number of obs	45
F-test	3.472	Prob > F	0.002
Akaike crit. (AIC)	253.526	Bayesian crit. (BIC)	282.432

**** p<.01, ** p<.05, * p<.1*

TABLE 30: Linear regression on Turnout (2016)
– Population Weighted, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.174	.153	-1.14	.261	-.484	.135	
leaning_dem	-.765	5.176	-0.15	.883	-11.274	9.743	
percent_children	.076	2.598	0.03	.977	-5.199	5.35	
percent_elderly	-.59	1.039	-0.57	.574	-2.7	1.52	
avg_hh_size	-10.851	41.892	-0.26	.797	-95.897	74.195	
percent_married_male	.058	4.474	0.01	.99	-9.025	9.14	
percent_married_fe~e	-.288	4.965	-0.06	.954	-10.367	9.79	
percent_bach	.989	.824	1.20	.238	-.684	2.663	
unemp_rate	.871	1.736	0.50	.619	-2.653	4.396	
log_median_hh_income	-16.984	50.13	-0.34	.737	-118.753	84.785	
percent_poverty	-.061	1.885	-0.03	.974	-3.887	3.765	
percent_male	2.85	10.597	0.27	.79	-18.664	24.363	
median_age	1.85	1.574	1.18	.248	-1.346	5.046	
percent_minority	.029	.225	0.13	.898	-.429	.487	
gini	-132.502	102.881	-1.29	.206	-341.361	76.357	
Constant	116.164	493.781	0.24	.815	-886.264	1118.592	

Mean dependent var	59.861	SD dependent var	6.304
R-squared	0.749	Number of obs	51
F-test	3.031	Prob > F	0.003
Akaike crit. (AIC)	289.204	Bayesian crit. (BIC)	320.113

**** p<.01, ** p<.05, * p<.1*

TABLE 31: Linear regression on Turnout (2020)
– Population Weighted, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	-.162	.107	-1.51	.141	-.38	.056	
leaning_dem	5.182	2.613	1.98	.055	-.122	10.486	*
percent_children	-1.782	1.091	-1.63	.111	-3.997	.433	
percent_elderly	-1.044	.942	-1.11	.276	-2.957	.87	
avg_hh_size	30.014	23.041	1.30	.201	-16.762	76.79	
percent_married_ male	.719	2.925	0.25	.807	-5.219	6.656	
percent_married_f e~e	.225	3.072	0.07	.942	-6.012	6.462	
percent_bach	.285	.516	0.55	.584	-.763	1.333	
unemp_rate	.187	1.89	0.10	.922	-3.65	4.024	
log_median_hh_in come	24.964	33.777	0.74	.465	-43.607	93.534	
percent_poverty	1.717	1.797	0.96	.346	-1.931	5.365	
percent_male	-.099	6.316	-0.02	.988	-12.92	12.723	
median_age	1.316	1.682	0.78	.439	-2.1	4.731	
percent_minority	-.172	.162	-1.06	.297	-.501	.158	
gini	-99.092	104.041	-0.95	.347	-310.306	112.122	
Constant	-272.539	430.15	-0.63	.53	-1145.791	600.713	

Mean dependent var	67.873	SD dependent var	5.924
R-squared	0.801	Number of obs	51
F-test	6.925	Prob > F	0.000
Akaike crit. (AIC)	265.218	Bayesian crit. (BIC)	296.128

**** p<.01, ** p<.05, * p<.1*

TABLE 32: Difference-in-Differences Regression on Turnout, absorbing indicators – Population Weighted, Without Proxy, Without Squared Closeness

turnout	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
closeness_gap	.034	.067	0.51	.611	-.1	.168	
leaning_dem	-2.231	1.038	-2.15	.037	-4.316	-.145	**
percent_children	1.269	1.291	0.98	.33	-1.323	3.862	
percent_elderly	.189	.785	0.24	.811	-1.388	1.765	
avg_hh_size	-22.424	15.802	-1.42	.162	-54.162	9.315	
percent_married_ male	4.625	1.86	2.49	.016	.888	8.361	**
percent_married_f e~e	-6.476	2.573	-2.52	.015	-11.643	-1.309	**
percent_bach	1.348	1.768	0.76	.449	-2.203	4.898	
unemp_rate	-1.277	.617	-2.07	.044	-2.517	-.037	**
log_median_hh_in come	48.144	42.127	1.14	.259	-36.472	132.759	
percent_poverty	.875	1.207	0.72	.472	-1.55	3.299	
percent_male	13.296	6.281	2.12	.039	.68	25.911	**
median_age	3.883	2.016	1.93	.06	-.165	7.931	*
percent_minority	.642	.697	0.92	.362	-.759	2.042	
gini	-143.397	180.029	-0.80	.429	-504.997	218.203	
_Iyear_2016	-11.094	5.573	-1.99	.052	-22.287	.1	*
_Iyear_2020	-15.766	10.789	-1.46	.15	-37.436	5.903	
Constant	-1173.547	451.44	-2.60	.012	-2080.292	-266.803	**

Mean dependent var	63.495	SD dependent var	6.944
R-squared	0.952	Number of obs	147
F-test	47.310	Prob > F	0.000
Akaike crit. (AIC)	566.212	Bayesian crit. (BIC)	617.049

**** p<.01, ** p<.05, * p<.1*

Appendix F:

FIGURE 1: Closeness vs Turnout, 2012

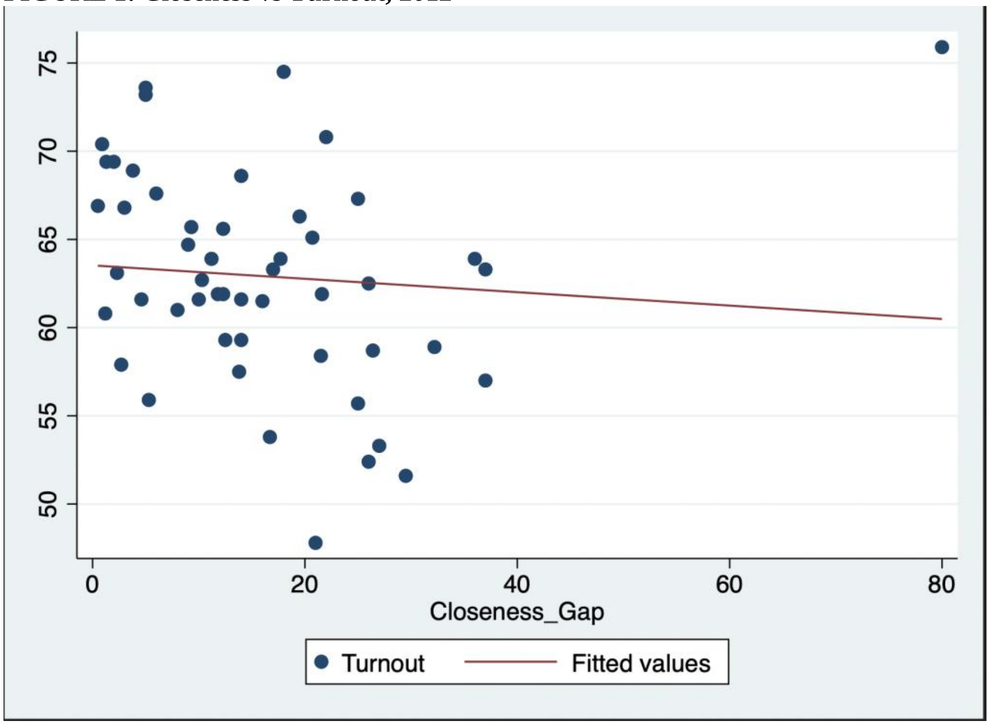


FIGURE 2: Closeness vs Turnout, 2016

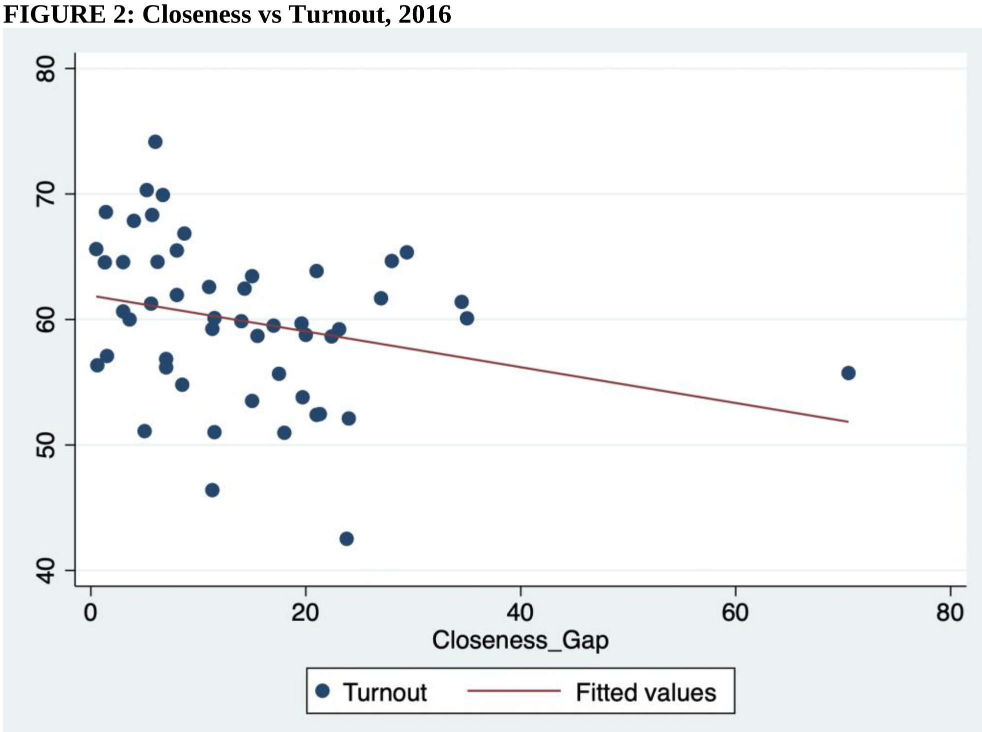
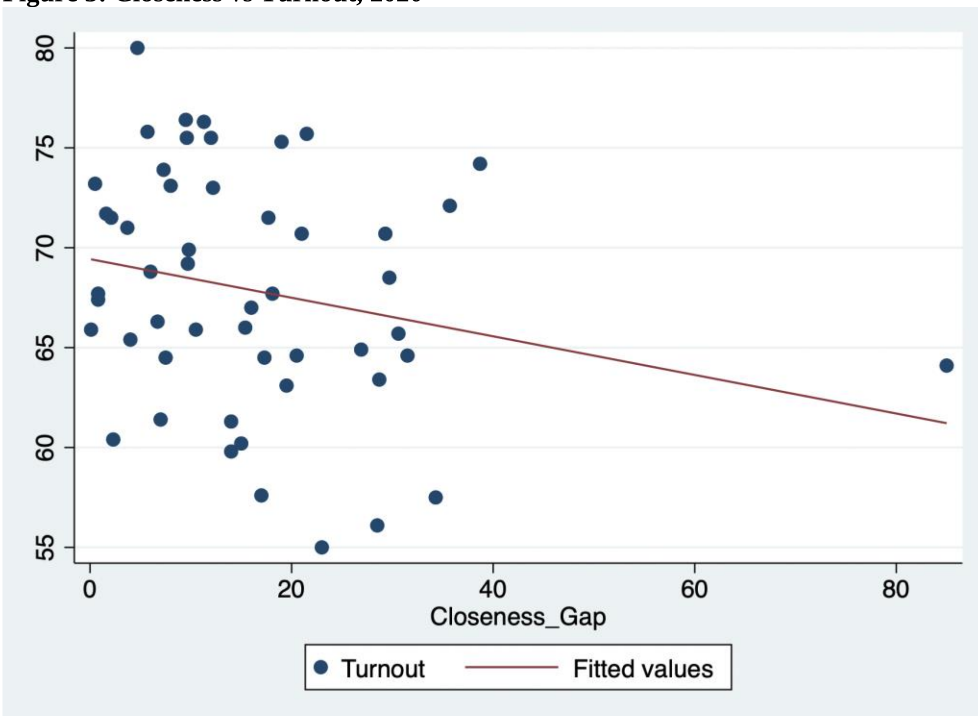


Figure 3: Closeness vs Turnout, 2020



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