# Contents

# A Controls

We obtain a rich set of county-level controls from the American Community Survey 5-year averages, collected in 2018. These data are publicly available from ACS from `https://www.census.gov/programs-surveys/acs/news/data-releases/2018/release.html`. Our main specifications include:

- % of the population with less than a high school education
- % of the population with a college degree or higher
- % of the population younger than 30
- % of the population older than 60
- % of population between 18 and 64 that is below the poverty level
- Share of households that are headed by a woman without a husband present
- the county-level unemployment rate
- the county-level labor force participation rate
- % of the population employed in manufacturing
- the median household income
- % of the population that is rural
- % of the population that speaks only English
- % of the population that is white
- % of the population that is black
- total population (logged)
- Turnout in 2020 primary
- Support for Sanders in 2016

# B Trajectory Balancing Weights

To bolster our assumption that we are capturing exogenous variation in exposure to Covid-19 at the time of the primary election, we use trajectory balancing methods to reweight our control counties to match our treated counties (Hazlett and Xu, 2018). Unlike the motivating use case for this method where the outcome is measured multiple times per unit, we only observe a county's vote choice once. As such, we target the method to balance treated and control counties on their pre-treatment covariates as well as on their full history of exposure. The results of this weighting procedure are summarized in Figure 1. By matching on the full history of Covid-19 cases, we bolster our claim that the comparison is between those counties who voted on March 17th and those who voted earlier but were otherwise identical.

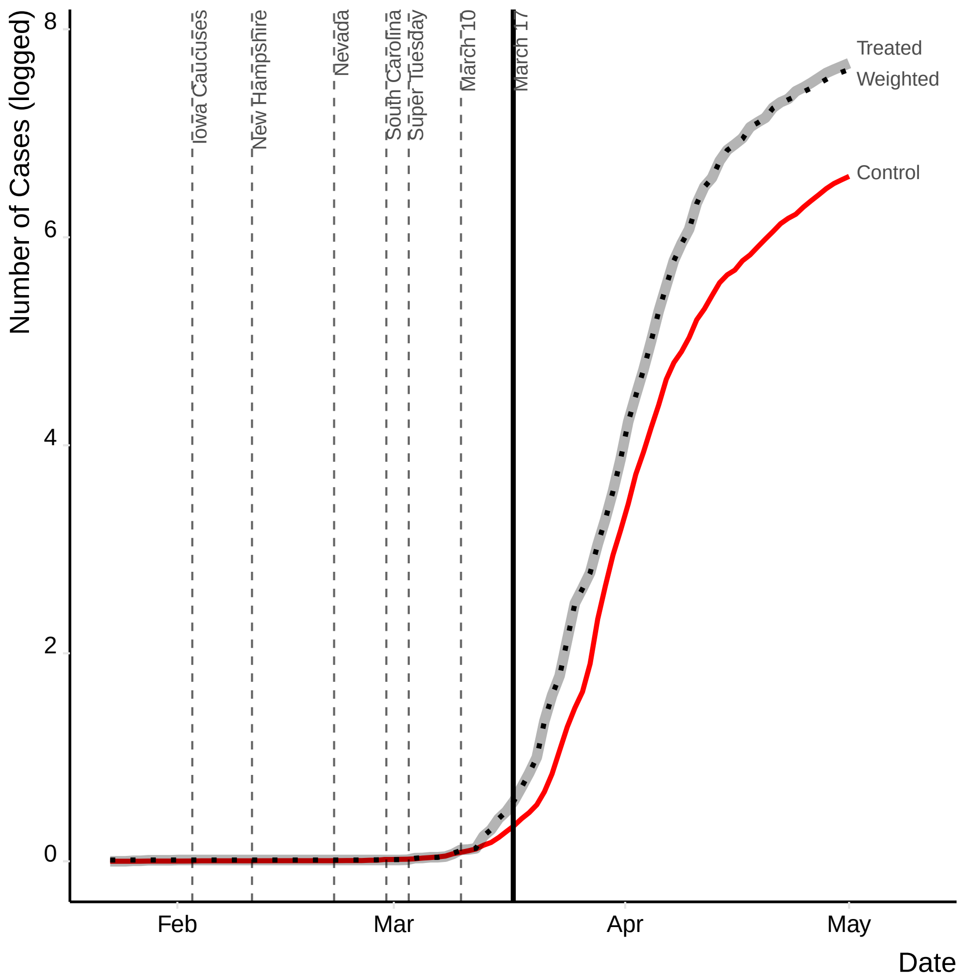


Figure 1: Trajectory balancing example for counties that voted on March 17th with one or more confirmed case in their DMA. We implement trajectory balancing (Hazlett and Xu, 2018) to re-weight the control counties that voted prior to March 17th (in red) to more closely resemble the treated counties (thick gray) in terms of the trajectory of the outbreak and pre-treatment covariates. The comparison of Sanders support is thus between those treated counties that voted on March 17th, and the re-weighted control counties given by the dotted black line that voted earlier.

# C “Localness” of the DMA Fixed Effects

Our simplest regression specification uses DMA fixed effects to compare counties in the same media environment who voted at different times. Since we assign the exposure measure at the DMA-level, these fixed effects mean that counties located within DMAs that don’t cross state lines are dropped, since their treatment measure is collinear with the fixed effect. The benefit of this estimation strategy is that we compare counties in the same area who happen to fall on two sides of a state border, one of which voted earlier than the other. The downside is that we rely on a subset of counties that differ from those that are dropped, although this problem only obtains for the first set of results that rely on these fixed effect specifications. Table 1 summarizes these differences, highlighting that the counties driving the first set of results differ systematically from those that are dropped from the analysis. These covariates are ordered by the t-statistics of a t-test difference in means, in which negative statistics mean that the counties we drop have smaller values for the covariates than those we keep. As illustrated, while there are important differences between these counties, again we note that these differences largely work against our main findings. In particular, we note that the counties we keep were more supportive of Sanders in 2016 (46.1 versus 39.7), suggesting that any selection bias introduced by our sample works against our main findings of a penalty for Sanders in 2020.

| | variable | avg_0 | avg_1 | p_value | t_value |
|---|---|---|---|---|---|
| 1 | pct sanders16 | 39.7 | 46.1 | 0 | -8.9 |
| 2 | caucus switch | 0.1 | 0.2 | 0 | -8.6 |
| 3 | Speak only English | 86.8 | 92 | 0 | -8.5 |
| 4 | Manufactur | 11.7 | 13.5 | 0 | -6 |
| 5 | Labor Force Part Rate pop 16 over | 56.9 | 59 | 0 | -5.8 |
| 6 | caucus | 0 | 0.1 | 0 | -5.3 |
| 7 | White | 81.1 | 84.7 | 0 | -5 |
| 8 | POPPCT RURAL | 54.4 | 60.3 | 0 | -4.2 |
| 9 | CollUp | 29 | 30.2 | 0.01 | -2.6 |
| 10 | Md inc hhs | 49,328.1 | 49,575.1 | 0.7 | -0.4 |
| 11 | 60Up | 24.8 | 24.8 | 1.0 | 0 |
| 12 | LT30yo | 37.4 | 37 | 0.1 | 1.4 |
| 13 | Below poverty level AGE 18 64 | 9.4 | 8.9 | 0 | 2.9 |
| 14 | turnout pct 20 | 9.1 | 8.2 | 0 | 3.1 |
| 15 | Black or African American | 11 | 8.3 | 0 | 3.9 |
| 16 | tot pop | 167,608 | 76,765.9 | 0 | 4.5 |
| 17 | LTHS | 15 | 13.5 | 0 | 5 |
| 18 | Unem rate pop 16 over | 6.9 | 6.2 | 0 | 5.6 |
| 19 | Female hher no husbandhh | 11.9 | 10.8 | 0 | 6 |

Table 1: Balance table comparing counties that we drop (0) and that we keep (1) with DMA fixed effects.

# D Considering Alternative Explanations

## D.1 Evidence of Anxiety: Robustness

Our theorized mechanism rests on the assumption that differences in the exposure to the pandemic cause differences in anxiety, which then generate differences in observed vote shares for Sanders. In the body of our paper, we demonstrate that there is daily evidence of cross-sectional relationships between exposure to the virus and Google searches for the term "coronavirus", which we interpret as a proxy for anxiety.

Our second measure of anxiety is a weekly measure of county-level mobility, derived from GPS-enabled cell phones. We posit that a reduction in movement reflects increased concern about the health risks associated with the virus and is thus a proxy for anxiety that varies over space and time in the first weeks of March. We obtain data on county-level mobility by week from Cuebiq (2020). Cuebiq partners with 86 smartphone apps to collect individual-level location data from opted-in users. These data are aggregated from individual cell phone GPS data which measures a box around all locations observed for users on a given day and calculates mobility as the (logged) distance between opposite corners of this box.[1] We measure these county-level values every week from January 20th (when the first US-based cases were reported in Washington state) to April 13th. Figure 2 plots a series of regressions predicting changes in county-level mobility as a function of DMA-level cases of Covid-19. As illustrated, there is no meaningful relationship between this behavior and cases until after Super Tuesday, at which point the coefficients become significantly negative, suggesting that anxiety over the health risks of the pandemic grew over the first few weeks of March and, importantly, that they were correlated with geographic variation in exposure during these weeks.

These estimates are likely confounded with changes in federal and state policies on social distancing, particularly if these policies are correlated with geographic variation in the outbreak. However, we emphasize that these estimates are based on DMA-level cases, many of which cut across state borders. Since the vast majority of the policies aimed at reducing movement were enacted at the state level, a pure story of responding to policy initiatives is unable to fully explain the variation in DMA-level cases that we use to identify these coefficients.[2] In sum, we argue that these negative coefficients suggest that the geographic

[1] These individual daily data are aggregated up to the county-week and placed on an index ranging from 1 to 5 based on the median mobility of all users in a county. Values on this index correspond to approximately:

- 1: 10 meters
- 2: 100 meters
- 3: 1 kilometer
- 4: 10 kilometers
- 5: 100 kilometers

[2] All states except ND, SD, NE, IA, WY, and AR had stay at home orders; all states but SD, NE, WY,

variation in exposure that we use to predict vote choice is also correlated with reduced mobility in ways that aren't purely reflecting government policies, which we interpret as evidence of a meaningful association between exposure and anxiety.

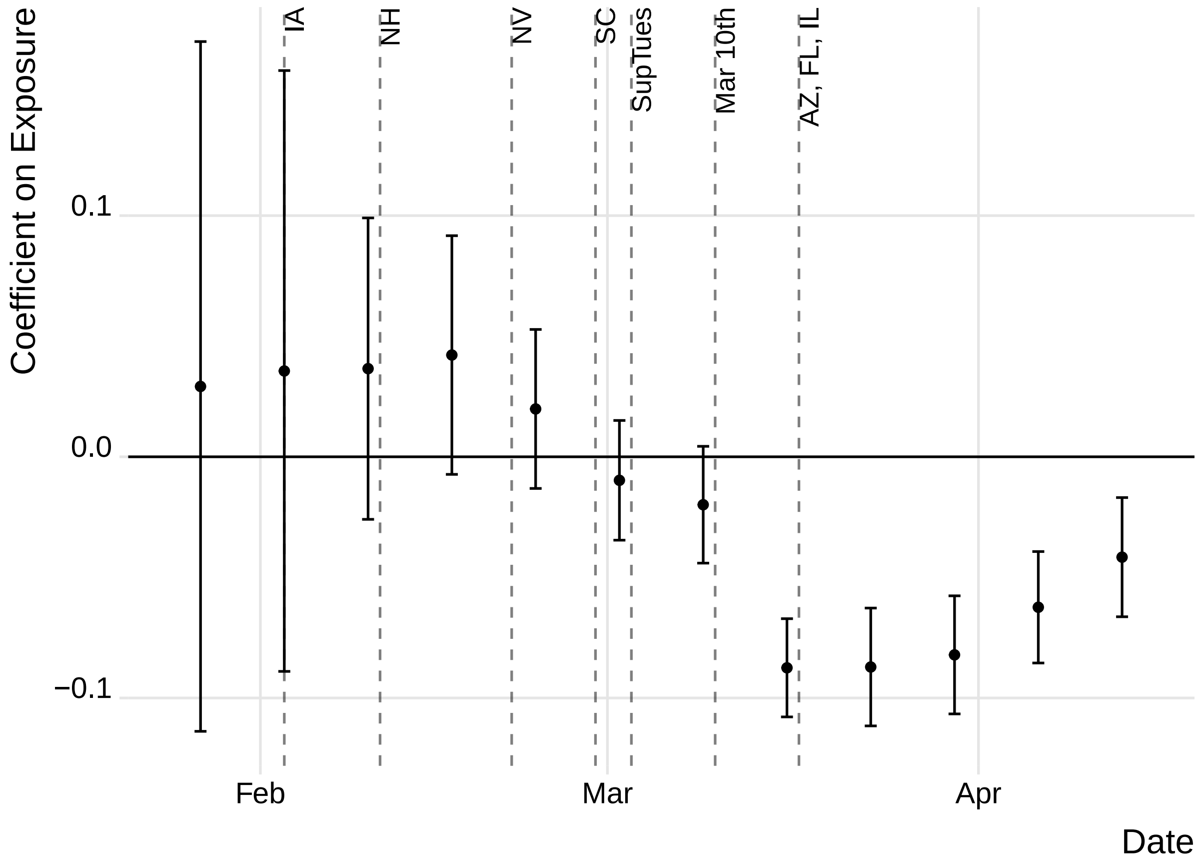


Figure 2: Weekly (x-axis) coefficients (y-axis) on the relationship between DMA-level cases and county-level mobility, including state random effects. Vertical dashed bars indicate primary dates.

## D.2 "Party Decides" Placebo Tests

The main results suggest that exposure to the novel coronavirus results in a greater decline in support for a Sanders presidency than what we observe in relatively insulated counties or those that voted prior to the outbreak. However, even with our matching and weighting strategies to argue that the outbreak is as-good-as-randomly assigned conditional on observables, there remains a concern with regards to timing. Specifically, our definition of "exposure" is defined as any county residing within a DMA that had confirmed cases of the

UT, and AR closed non-essential businesses; all states but ND banned large gatherings; every state declared a state of emergency.

virus as of March 9th, 2020. Effectively, this definition risks conflating other contemporaneous changes in the political landscape that occurred between Super Tuesday (March 3rd), and the 10 states that voted afterwards (7 on March 10th, 3 on March 17th). Specifically, this period saw the Democratic party rally around the establishment candidacy of Joseph Biden as several candidates dropped out of the race and endorsed Biden.

To confirm our results are not simply picking temporal variation and the momentum shift that occurred on Super Tuesday, we run a placebo test in which we permute our explanatory variable and compare the diff-in-diff results prior to, and following Super Tuesday. If our main results are driven by the "party decides" phenomenon, we should still find a significant negative relationship between Sanders' declining vote share and our permuted treatment. We bootstrap sample our data, each time drawing a permuted explanatory variable, and re-estimate our main specifications. As illustrated in Figure 3, our results are all null, regardless of whether we are comparing the pre-party decides voting behavior to Super Tuesday, March 10th, or March 17th.

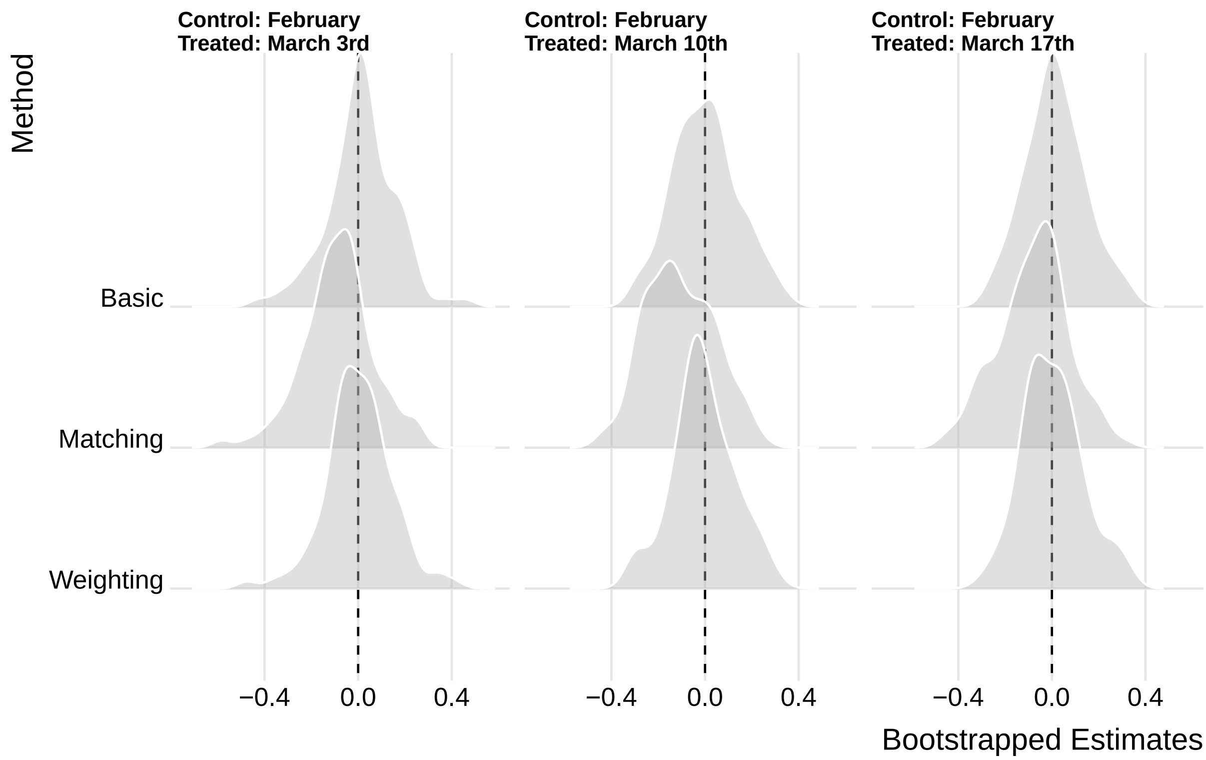


Figure 3: Permutation test results for different choices of the pre- and post-outbreak cutoff, estimated using diff-in-diff. Densities represent 100 bootstrapped estimates of the impact of exposure on the change in support for Sanders when the DMA-level Covid-19 cases are randomly reshuffled. Consistent null results suggest that our main findings are not spuriously conflating the timing of the outbreak with the Democratic Party rallying around Biden.

The main diff-in-diff results use outbreak dates to separate treated and control elections as per Table 2, meaning that all elections prior and including a given cutoff are defined as control, and all elections following the cutoff are treated. We also re-run our analyses by conducting a series of pairwise comparisons in which one election is defined as control and the other is defined as treated. Doing so allows us to identify where (and more precisely, when) our effects obtain. We treat all primary elections prior to Super Tuesday as one group in order to include multiple states in each treatment and control condition. Figure 4 summarizes these results for every specification at our disposal. The Democratic party consolidated support behind Biden ahead of Super Tuesday. As Figure 4 demonstrates, the results do not depend on comparing the period before Super Tuesday to the period after, and thus are not collinear with a "party consolidation" effect, though we cannot rule out that such an effect may also contribute to the findings in the panel comparing Super Tuesday to pre-Super Tuesday voting states.

| **Start Date** | **Control** | **Treatment** |
|---|---|---|
| March 1st | Feb | ST, March 10th, & March 17th |
| March 3rd | Feb & ST | March 10th & March 17th |
| March 10th | Feb, ST, & March 10th | March 17th |

Table 2: Treatment and control elections by outbreak "start date". February (Feb) primaries include IA, NH, NV, and SC. Super Tuesday (ST) primaries include AL, AR, CA, CO, ME, MA, MN, NC, OK, TN, TX, UT, VA and VT. March 10th primaries include ID, MI, MS, ND, and WA. March 17th primaries include AZ, FL, and IL. (Ohio's was postponed due to the outbreak.)

These results also serve as simple placebo tests by treating the later election as the control data, and the earlier as the treated data. As illustrated, these cases reveal a positive estimate, suggesting that Sanders did better in those areas that would be exposed on March 17th, but were not yet. Similar results hold if we look instead at the difference-in-differences specification election-by-election. As illustrated in Figure 5, the penalty against Sanders in Covid-exposed counties did not begin until after Super Tuesday.

## D.3 Turnout

An alternative explanation for the results summarized in our manuscript is that the outbreak differentially reduced turnout among different voting groups. One plausible scenario might be that those most threatened by exposure might be less likely to turn out. If this group is also more likely to support Sanders, it would suggest an alternative explanation for the effects we document. Of course, Sanders' popularity among young voters is well-documented, while the elderly are most threatened by the virus. As such, if this mechanism is operating, it should be the case that older voters are *less* likely to turn out, and that therefore we should see an *increase* in support for Sanders from younger voters, working against our main results.

Nevertheless, we predict variation in primary turnout by exposure across age-groups,

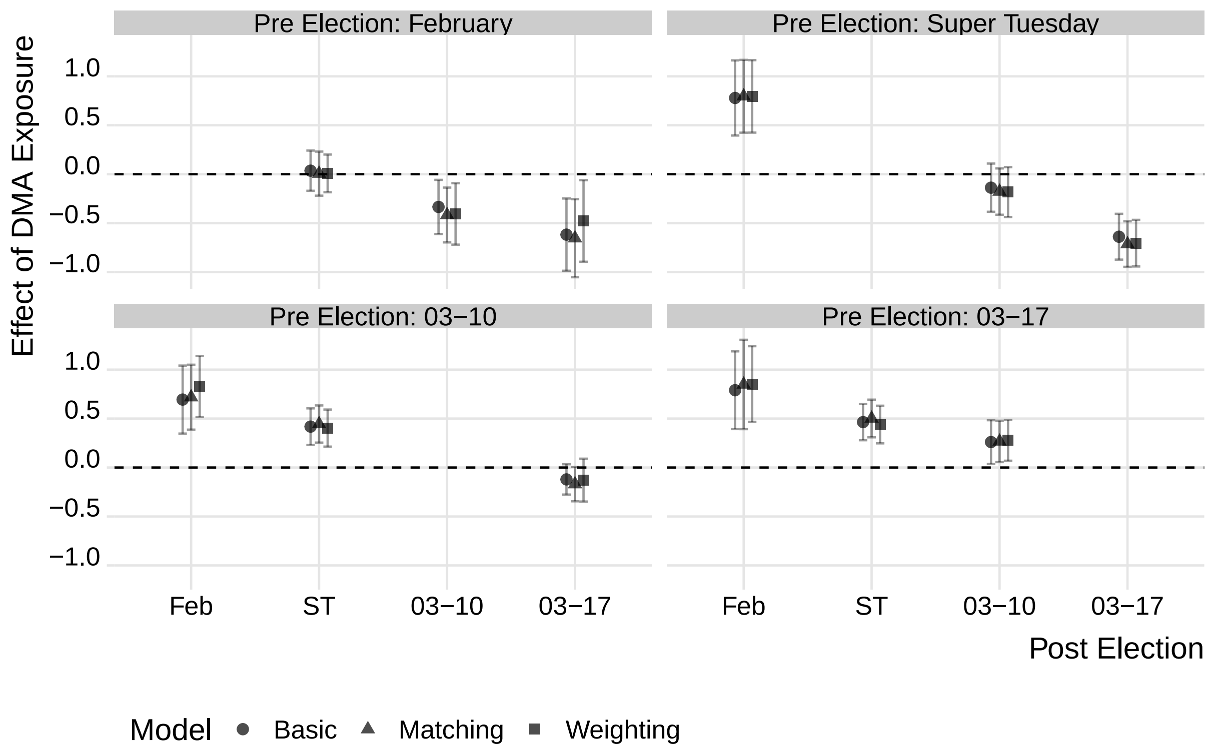


Figure 4: Pairwise election comparisons by definition of pre-outbreak election (panel titles) and post-outbreak comparison elections (x-axes).

estimating an interacted specification of the following form:

$$\text{turnout}_{ct} = \beta_0 + \beta_1 \text{Covid}_{ct} + \beta_2 \text{Age}_c + \beta_3 \text{Covid}_{ct} \times \text{Age}_c + \gamma \mathbf{X}'_c + \varepsilon_{ct} \tag{1}$$

where $\text{Age}_c$ is the share of the county's population that is older than 60 or younger than 30. We are interested in the $\beta_3$ coefficient which captures the interacted relationship between turnout and exposure to Covid-19 by age. As illustrated in Figure 6, there is little evidence to suggest that such an age-based turnout dynamic is active.

An alternative turnout story is that the Sanders campaign was effectively finished after Biden's convincing victory in South Carolina on February 29th. In this scenario, a number of would-be Sanders voters were planning on casting what were effectively protest votes, and those in COVID-exposed areas didn't bother since the "costs" of doing so were higher. If this were the case, we should expect to see a decline in turnout in more pro-Sanders counties following the South Carolina primary. As illustrated in Figures 7 and 8, there is little descriptive evidence that pro-Sanders voters stayed home after the South Carolina primaries.

To confirm this visual intuition, we run a set of regressions date-by-date, in each case predicting county-level turnout in 2020 with the same county's support for Sanders in 2016, controlling for the share of the population over 60, the share with a college degree, the unemployment rate, and the share that is white. As illustrated in Figure 9, there is

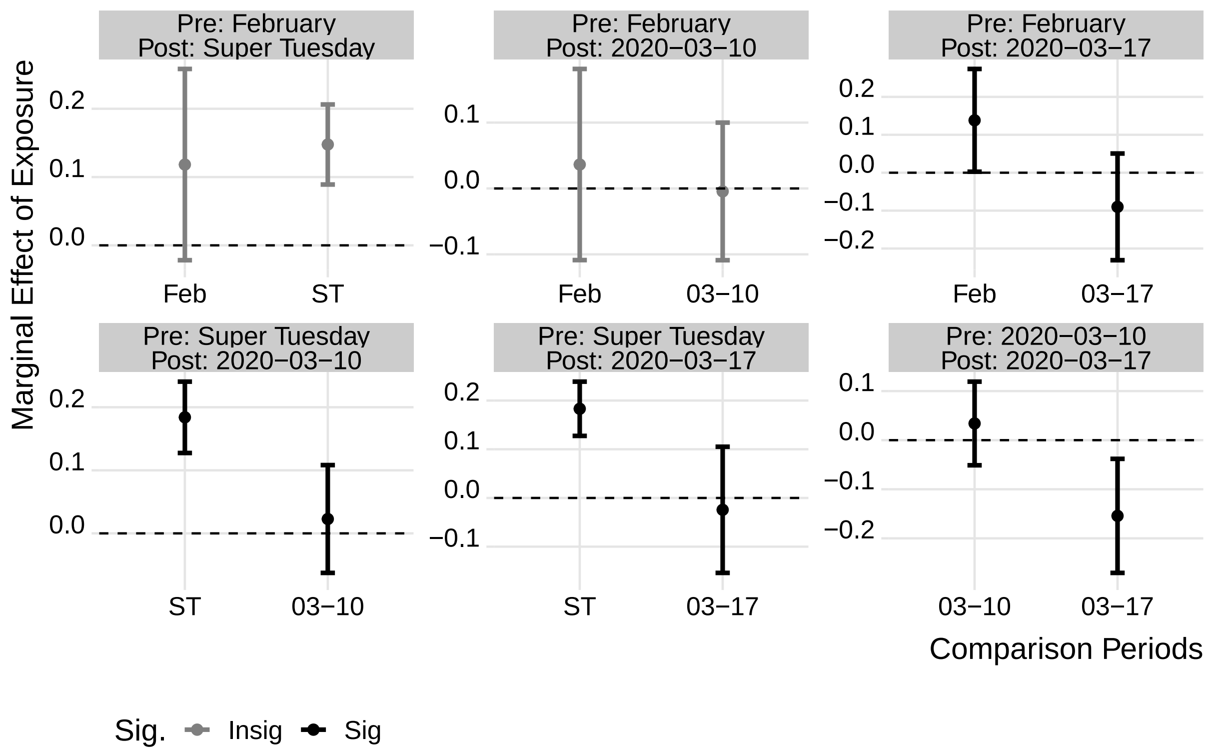


Figure 5: Pairwise election comparisons by definition of pre- and post-outbreak election.

no evidence suggesting that 2016 Bernie supporters stayed home after the South Carolina primary. To the contrary, there is a significant but small positive association between pro-Sanders counties in 2016 and 2020 turnout on Super Tuesday.

## D.4 Selection Effects

Our results would be spurious if the outbreak disproportionately affected parts of the country that were already anti-Bernie to begin with. Although our matching and weighting strategies are one solution to minimizing this risk, we can also evaluate the identification challenge directly. We replace our main outcome variable with Sanders' 2016 voteshare, testing whether 2020 exposure rates also predict 2016 Sanders support. We find, if anything, a source conservative bias as shown in Figure 10. Specifically, the counties that were more exposed to the outbreak in 2020 were, if anything, *more* supportive of Sanders in 2016, revealing a selection effect that works against our main results.

## D.5 Economic Policy Preferences

The Covid-19 pandemic influenced more than just individuals' anxiety over their health. It also precipitated a painful economic contraction in which the stock market lost

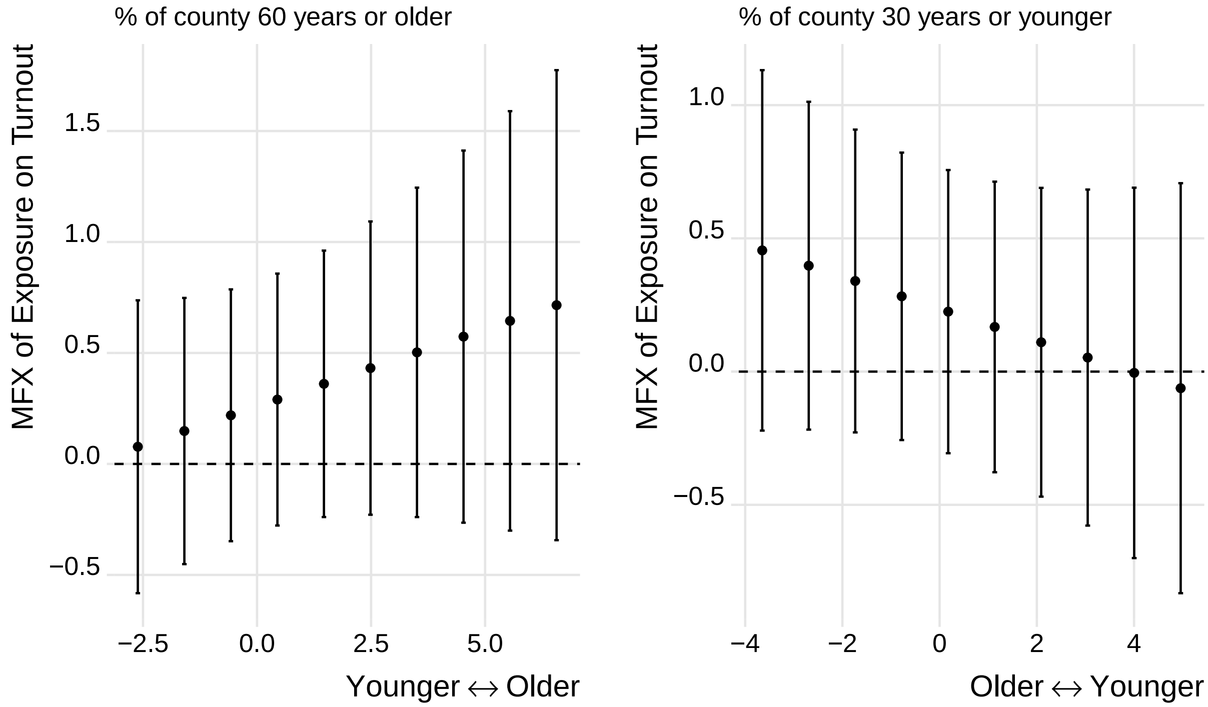


Figure 6: Marginal effects of exposure on logged turnout (y-axes) across counties with smaller and larger proportions of their population older than 60 years of age (left panel) and younger than 30 years of age (right panel).

over 20% of its value in the span of a week. An alternative story explaining the shift toward Biden focuses on the stock market contraction and the increased value of his relatively Wall Street-friendly policy position.

To examine whether the decline in support for Sanders was due not to a political flight to safety but rather due to his economic policy position, we examine how evaluations of the economy evolved between insulated and exposed areas in the early days of March. Our main results exploit variation in exposure and voting behavior across both geography and time. For the economy story to be true, it would require that places more exposed to the virus grew concerned about the economy earlier than those relatively insulated.

Survey results from the Nationscape survey (Tausanovitch et al., 2019) illustrate a clear pessimistic shift in March of 2020 in both insulated and exposed congressional districts (see Figure 11). While the exposed districts were more pessimistic in March, they were also more pessimistic in the months prior to the outbreak. A difference-in-differences regression confirms that the pre- and March differences between exposed and insulated areas are not significantly different from each other, as illustrated in Figure 12.

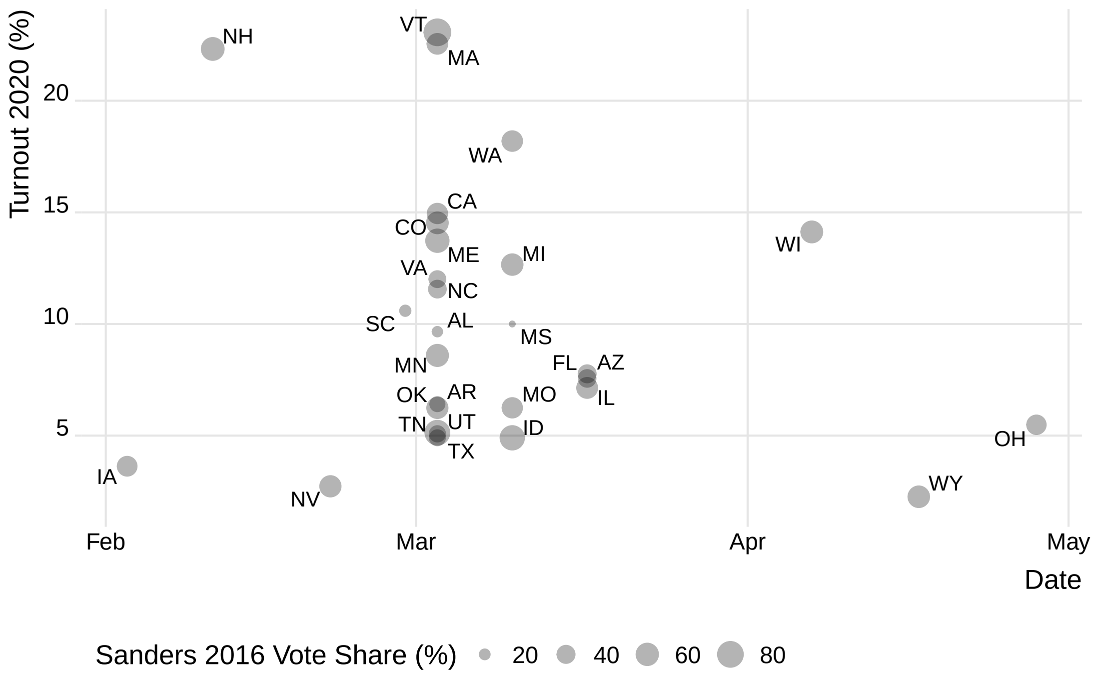


Figure 7: Average state-level turnout in the 2020 primary election (y-axis) by primary date (x-axis). Each point represents a state, sized by the overall average support for Sanders in the 2016 primary election. While there appears to be a secular decline in turnout over time, there is little evidence that this decline was starker in pro-Bernie states following Biden's victory in South Carolina on February 29th.

# E Balance and Weighting Robustness

We achieve good balance on both the matching and weighting strategies employed in the body of our paper. Figure 13 plots the improvements to balance on observables between treated and control units generated by our choice of nearest-neighbor matching using minimized Mahalanobis distance. And Table 3 summarizes the differences in treated and control covariates prior to, and following the `cbps` weights. In both cases, we successfully adjust our data to better reflect the distribution of observables in an experimental context in which treatment is randomly assigned.

We also confirm the robustness of our main findings to different choices about the matching strategy and the balancing weights. Specifically, we re-estimate our main findings replacing the `CBPS` method of Blackwell et al. (2009) with optimal weights (Zubizarreta, 2015), and replacing the nearest neighbor matching strategy with coarsened exact matching (CEM, Blackwell et al. 2009). The former robustness check yields substantively and statistically similar findings to our main results, as illustrated in Table 5.

Moving from nearest neighbor matching based on Mahalanobis distance to the CEM method requires us to reduce the number of county-level covariates we use for matching. This

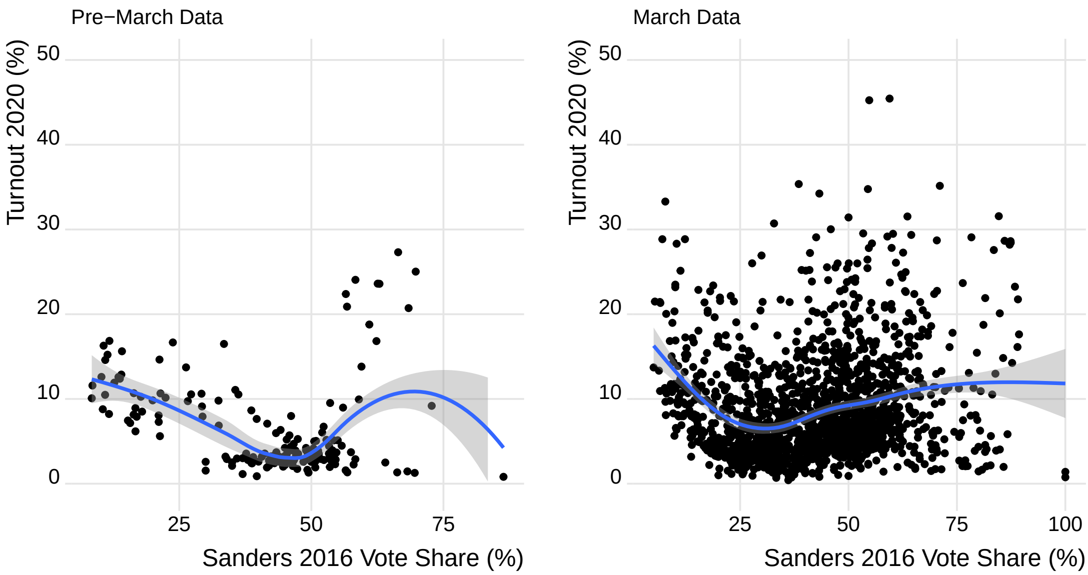


Figure 8: Scatter plots of Sanders' 2016 vote share (x-axes) against turnout in the 2020 primary (y-axes), measured prior to the March elections, and during the March elections. While the most anti-Sanders counties had higher turnout in both periods, there is little evidence suggesting that Bernie supporters disproportionately stayed home after the Biden's victory in South Carolina on February 29th.

Table 3: Balance Results for `CBPS`

| | Covs | Diff_Unm | Bal_Test_Unm | Diff_Match | Bal_Test_Match |
|---|---|---|---|---|---|
| 1 | prop.score | | | 0.150 | |
| 2 | sc_CTY_LTHS | -0.600 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 3 | sc_CTY_CollUp | 0.590 | Not Balanced, >0.05 | 0.040 | Balanced, <0.05 |
| 4 | sc_CTY_LT30yo | -0.190 | Not Balanced, >0.05 | -0.060 | Not Balanced, >0.05 |
| 5 | sc_CTY_60Up | 0.160 | Not Balanced, >0.05 | 0.070 | Not Balanced, >0.05 |
| 6 | sc_CTY_Below_poverty_level_AGE_18_64 | -0.570 | Not Balanced, >0.05 | -0.020 | Balanced, <0.05 |
| 7 | sc_CTY_Female_hher_no_husbandhh | -0.510 | Not Balanced, >0.05 | -0.010 | Balanced, <0.05 |
| 8 | sc_CTY_Unem_rate_pop_16_over | -0.240 | Not Balanced, >0.05 | 0.010 | Balanced, <0.05 |
| 9 | sc_CTY_Labor_Force_Part_Rate_pop_16_over | 0.360 | Not Balanced, >0.05 | -0.050 | Balanced, <0.05 |
| 10 | sc_CTY_Manufactur | -0.210 | Not Balanced, >0.05 | -0.040 | Balanced, <0.05 |
| 11 | sc_CTY_Md_inc_hhs | 0.620 | Not Balanced, >0.05 | 0.040 | Balanced, <0.05 |
| 12 | sc_CTY_POPPCT_RURAL | -0.560 | Not Balanced, >0.05 | -0.050 | Balanced, <0.05 |
| 13 | sc_CTY_Speak_only_English | -0.310 | Not Balanced, >0.05 | -0.050 | Not Balanced, >0.05 |
| 14 | sc_CTY_White | 0.330 | Not Balanced, >0.05 | -0.050 | Balanced, <0.05 |
| 15 | sc_CTY_Black_or_African_American | -1.170 | Not Balanced, >0.05 | 0.020 | Balanced, <0.05 |
| 16 | ln_CTY_tot_pop | 0.510 | Not Balanced, >0.05 | 0.050 | Not Balanced, >0.05 |
| 17 | sc_turnout_pct_20 | 0.420 | Not Balanced, >0.05 | 0.030 | Balanced, <0.05 |
| 18 | caucus_switch | 0.060 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |

is due to the default parameter settings yielding only two matched observations, precluding our ability to estimate treatment effects. We reduce our set of covariates to select the following six across which we can obtain reasonably good performance on our balance tests while also obtaining enough observations for statistical inference:

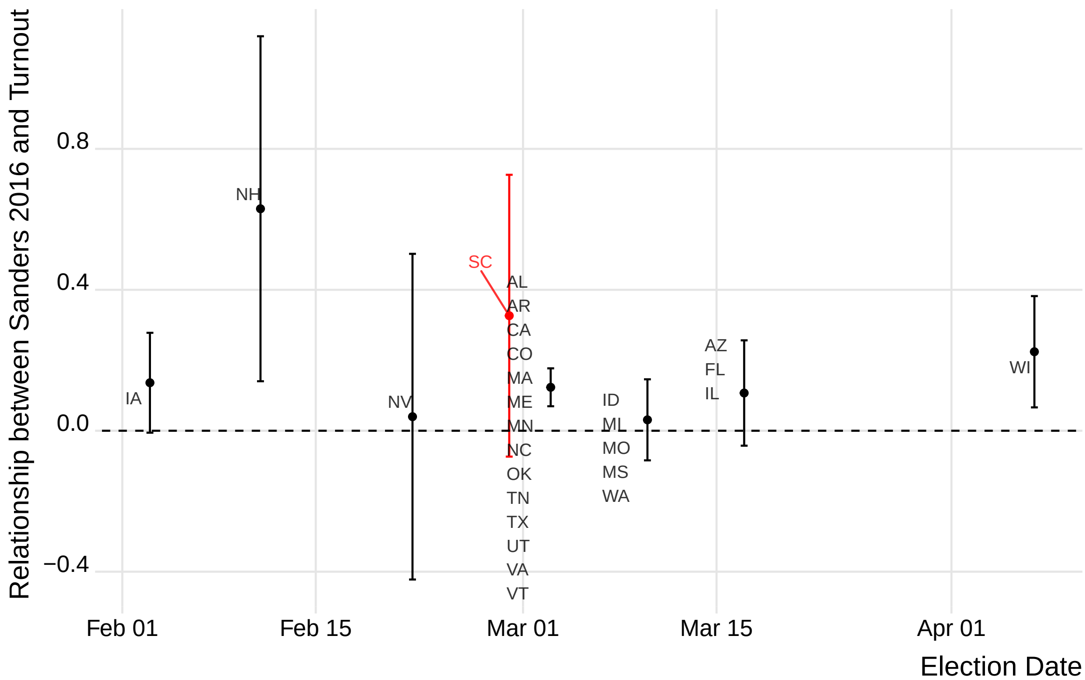


Figure 9: Coefficients (y-axis) estimate the relationship between a county's 2020 turnout and their support for Sanders in 2016, estimated date-by-date (x-axis). South Carolina primary indicated in red. Ensuing primaries show no evidence of a negative relationship between 2020 turnout and 2016 support for Sanders.

Table 4: Balance Results for `optweight`

| | Covs | Diff_Unm | Bal_Test_Unm | Diff_Match | Bal_Test_Match |
|---|---|---|---|---|---|
| 1 | sc_CTY_LTHS | -0.530 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 2 | sc_CTY_CollUp | 0.540 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 3 | sc_CTY_LT30yo | -0.170 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 4 | sc_CTY_60Up | 0.140 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 5 | sc_CTY_Below_poverty_level_AGE_18_64 | -0.490 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 6 | sc_CTY_Female_hher_no_husbandhh | -0.460 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 7 | sc_CTY_Unem_rate_pop_16_over | -0.180 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 8 | sc_CTY_Labor_Force_Part_Rate_pop_16_over | 0.290 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 9 | sc_CTY_Manufactur | -0.260 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 10 | sc_CTY_Md_inc_hhs | 0.590 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 11 | sc_CTY_POPPCT_RURAL | -0.550 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 12 | sc_CTY_Speak_only_English | -0.330 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 13 | sc_CTY_White | 0.300 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 14 | sc_CTY_Black_or_African_American | -1.160 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 15 | ln_CTY_tot_pop | 0.520 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 16 | sc_turnout_pct_20 | 0.450 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |
| 17 | caucus_switch | 0.070 | Not Balanced, >0.05 | 0 | Balanced, <0.05 |

- % 60 and older
- % with bachelor's degree
- Median household income

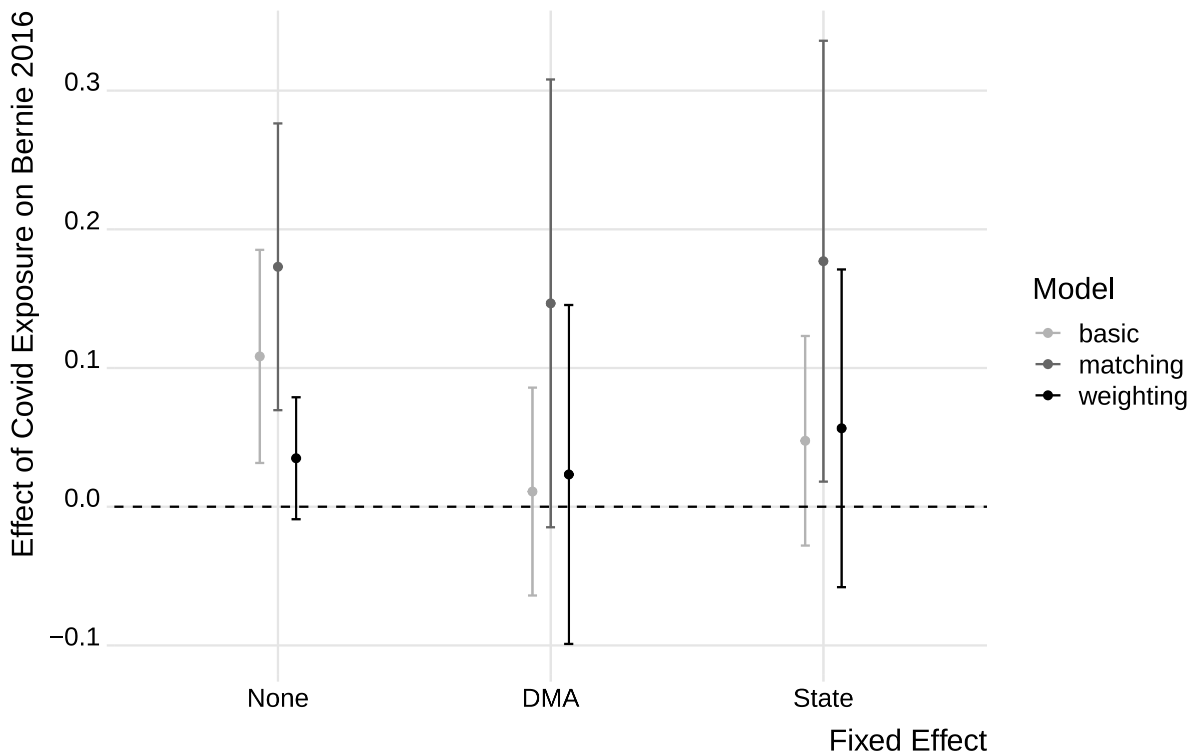


Figure 10: Coefficient estimates connecting Sanders' 2016 vote share with 2020 exposure to Covid-19, as of their election date. X-axis indicates different choices for fixed effects.

- % speak only English
- County unemployment rate
- % White

These choices reduce the number of total observations to 304 but yield substantively and statistically similar results to our main findings, as illustrated in Table 5. The balance test results are visualized in Figure 14.

# F Survey Experiment

We fielded an online survey experiment between May 11th and May 20th, 2020. We used a convenience sample of 650 Amazon Mechanical Turk workers ("Turkers"). While the Turker population is not representative of Americans writ large (Berinsky, Huber and Lenz, 2012), researchers have been successful in replicating lab experiments on the platform (Berinsky, Huber and Lenz, 2012; Crump, McDonnell and Gureckis, 2013; Clifford, Jewell and Waggoner, 2015). We conducted power analysis prior to fielding the survey using the `DeclareDesign` package for `R` to identify this sample size as necessary for identifying effects

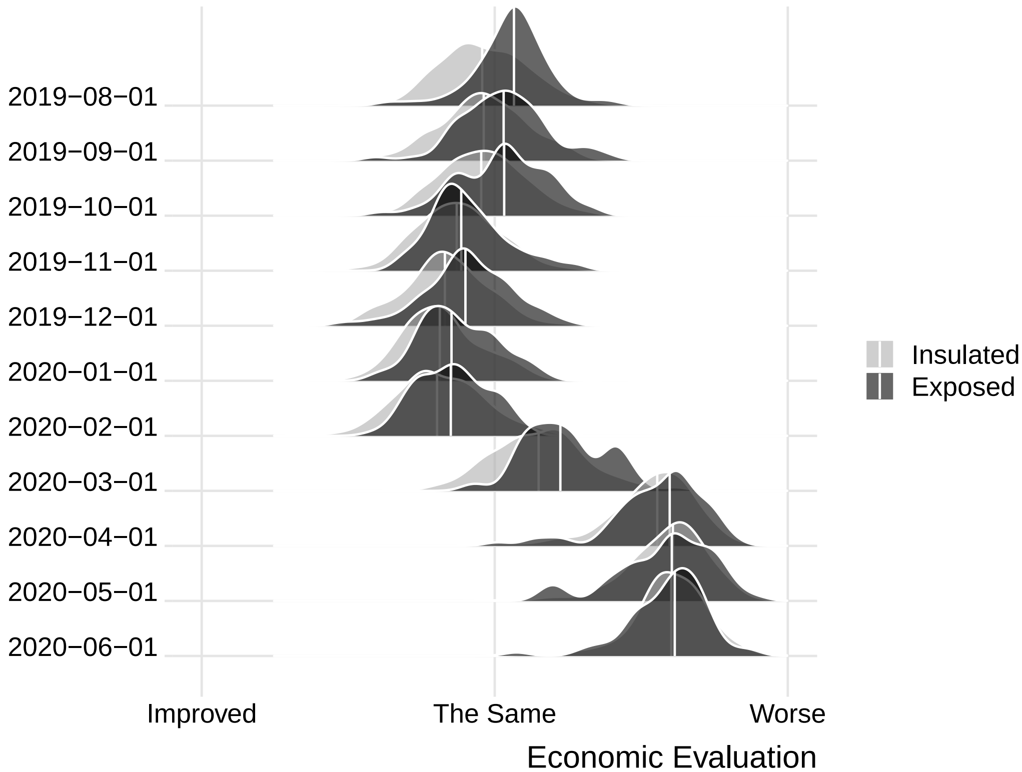


Figure 11: Economic evaluations by month between insulated (light gray) and exposed (dark gray) Congressional Districts, measured in March.

commensurate to half what we observe in our analysis of the real-world primary vote share. IRB approval was obtained prior to fielding the survey.

Our survey consisted of four parts and was designed to be completed in approximately five minutes. The first section following the consent page asked the respondents to read a paragraph describing the COVID-19 pandemic and projecting the severity of the outbreak over the next year (i.e., into summer of 2021). After reading this description, respondents were presented with descriptions of two hypothetical challengers running for executive office, and asked to indicate which candidate they preferred on a 4-item Likert scale. The third section of the survey asked respondents to provide basic demographic information (age, sex, race, party affiliation) and also to indicate whether they personally had been infected by the virus and whether they knew personally anyone who had. The last section presented respondents with the alternative description of the pandemic, ensuring that all participants were given equal information.

Our core quantity of interest is the relationship between support for mainstream candidates in response to heightened anxiety. To operationalize this, we randomly varied the description of the future of the COVID-19 pandemic to be either reassuring or pessimistic. We then described the two hypothetical challengers as either mainstream or anti-establishment. The treatment text and the candidate descriptions are summarized below.

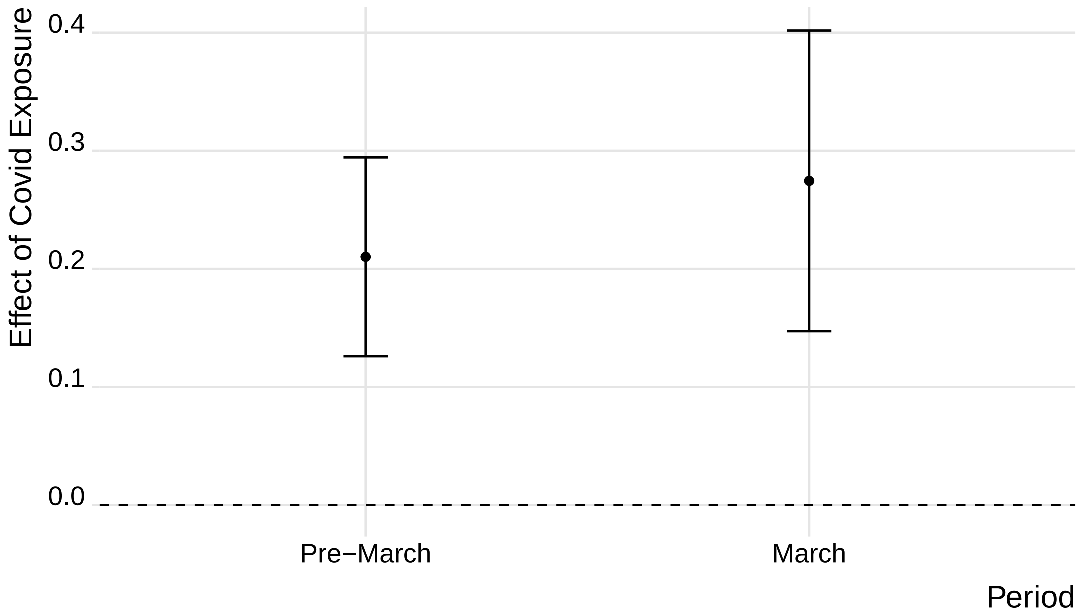


Figure 12: Difference-in-differences results comparing economic evaluations in insulated and exposed districts prior to March and in March. Positive values indicate more negative views of the economy.

## Treatment Text

**Optimistic:** Some experts believe the worst of the COVID-19 pandemic is behind us. Multiple states, and perhaps the country as a whole, are likely beyond their initial peak of COVID infections.[3] The death toll predicted by leading models has been lowered, suggesting the effect of the virus will not be as terrible as initially feared.[4] There are more than 60 candidate vaccines now in development worldwide, and several have entered early clinical trials in human volunteers.[5] There are also promising signs that existing anti-retroviral drugs may be effective in substantially reducing the severity and lethality of COVID-19 infection.[6]

**Pessimistic:** Some experts believe that COVID pandemic will continue to rage for many months to come. A well-respected group of pandemic experts believe COVID is "likely to keep spreading for at least another 18 months to two years—until 60% to 70% of the population has been infected."[7] Many experts also believe that loosening COVID-induced restrictions on mobility will lead to a 2nd wave of infections even worse than the initial

[3]New York Times. "Coronavirus in the US: Latest Map and Case Count."

[4]Raymond, Adam. "Key Coronavirus Model Now Predicts Many Fewer US Deaths." New York Magazine; Shaw, Adam. "Top Coronavirus Model Significantly Lowers Total Estimates of US Deaths in New Projection." Fox News.

[5]Lanese, Nicoletta. "When Will a COVID-19 Vaccine be ready?" Livescience

[6]Feuerstein & Herper. "Early peek at data on Gilead coronavirus drug suggests patients are responding to treatment." Statnews.

[7]Fox, Maggie. "Expert Report Predicts Up to Two More Years of Pandemic Misery." CNN.

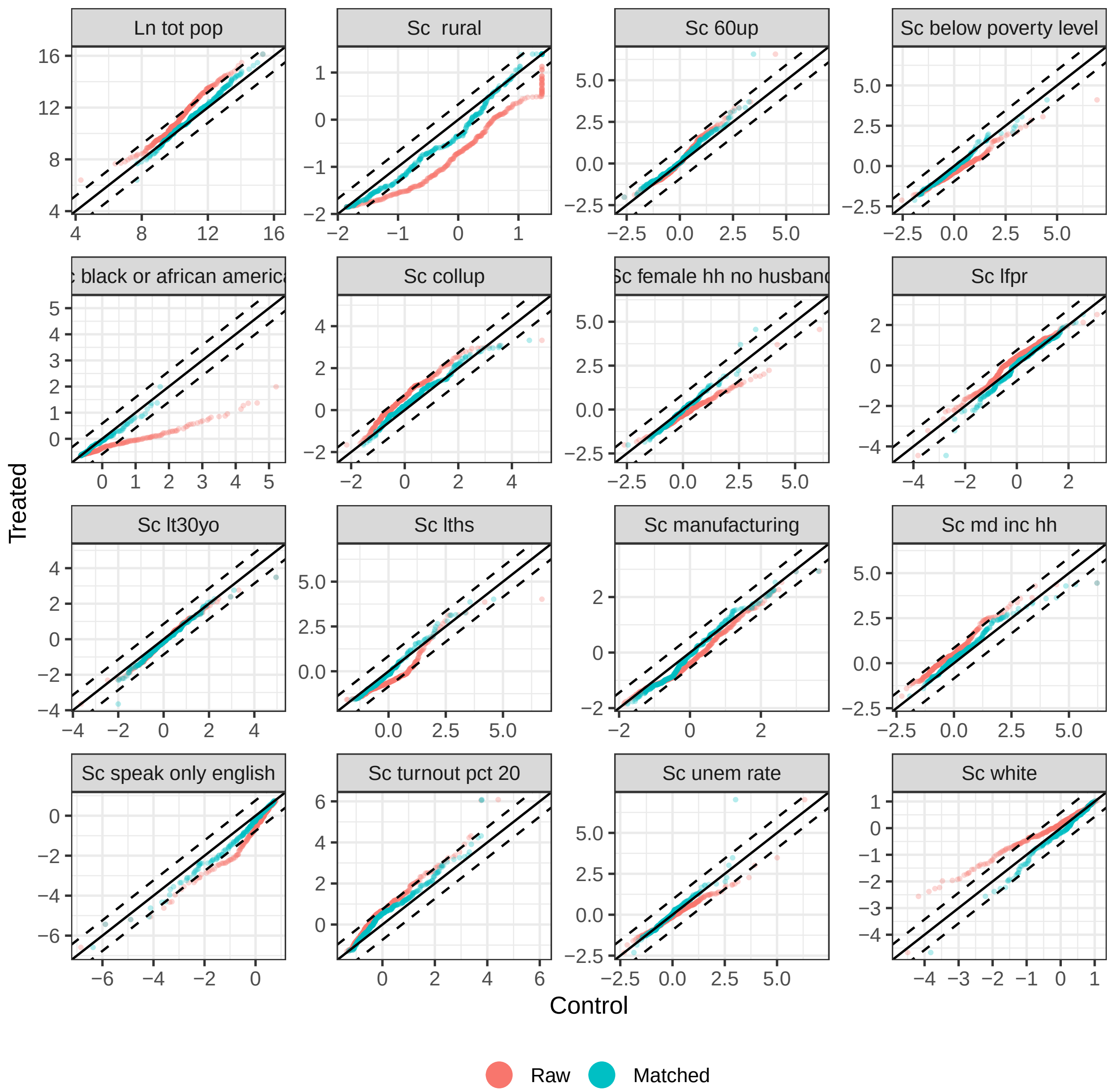


Figure 13: Balance of treated and control covariates before (red) and after (blue) matching. 45 degree line indicates perfect match.

wave.[8] In addition, current figures may be markedly underestimating the death toll to date[9] – suggesting that not only will the situation worsen in the months to come, but will do so by further declining from a status quo that is already worse than many realize.

[8]Weiss, Elizabeth. "When Will a Second Wave of the Coronavirus Hit, and What Will it Look Like?" USA Today.

[9]Wu, Jin and Allison McCann. "28,000 Missing Deaths: Tracking the True Toll of the Coronavirus Crisis." New York Times.

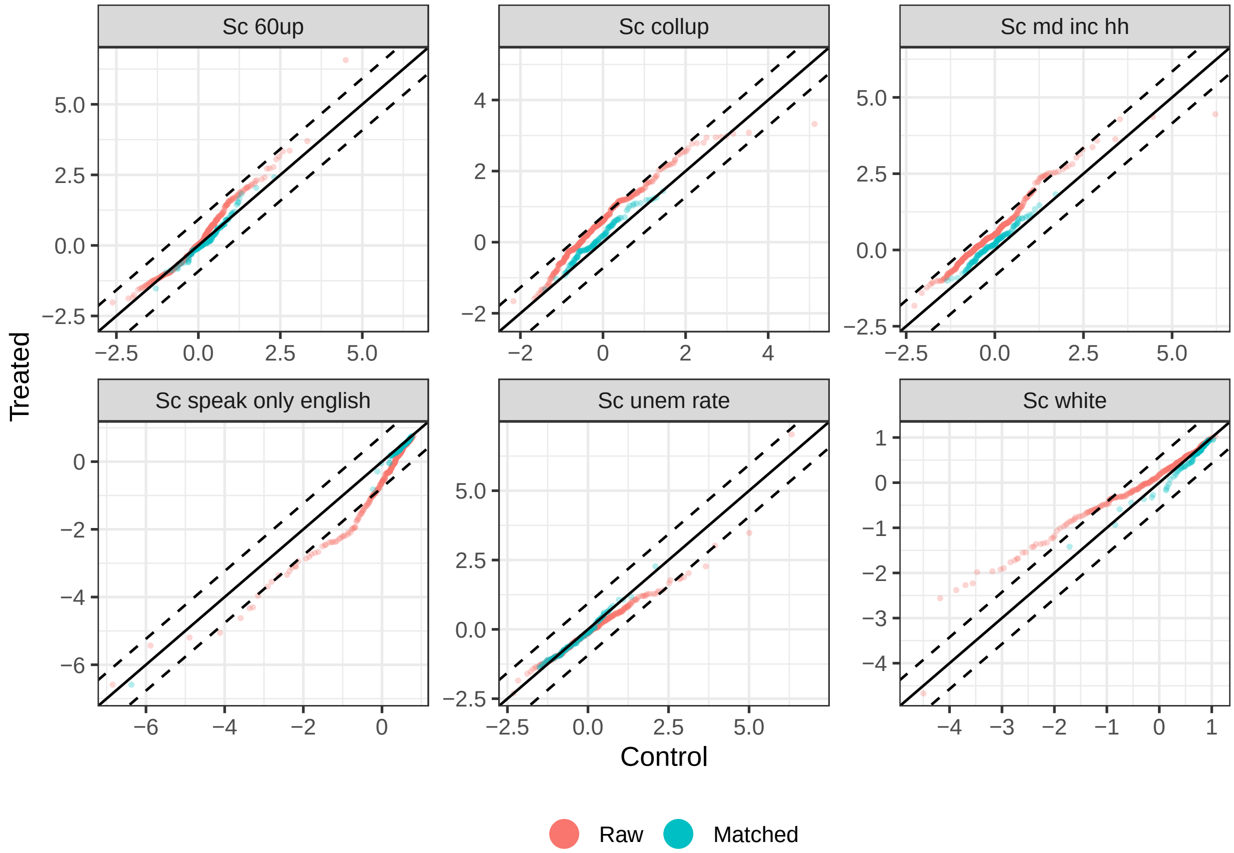


Figure 14: Balance performance across covariates using CEM (Blackwell et al., 2009).

## Candidate Descriptions

The following descriptions were provided in which candidate A was always the anti-establishment candidate (or "disruptive") and candidate B was always the mainstream candidate (or "safe"). The remainder of the sentences were randomly assigned to either candidate A or candidate B.

*Disruptive:* Candidate A seeks fundamental transformation of the economic, social, and political order. He believes that the system is broken, and the time for radical change is now. [SENTENCE 2]. [SENTENCE 3]. [SENTENCE 4].

*Safe:* Candidate B believes in strengthening existing economic, social, and political institutions. He believes that we must come together and re-invest in our system, strengthening its foundations to support generations to come. [SENTENCE 2]. [SENTENCE 3]. [SENTENCE 4].

**Sentence 2**

He is 48 years old, and was born and brought up in your area, before going to university to study physics.

He is 45 years old; he lives in the district and studied business at university.

**Sentence 3:**

After university he trained as an accountant, and set up a company ten years ago; it now employs seven people.

He is a lawyer and runs a busy local practice.

**Sentence 4 - Policy Platform:**

NONE (Roughly half of respondents received no 4th sentence)

He is passionate about achieving universal access to high-quality health care.

He is passionate about achieving universal access to high-quality education.

## F.1 Ethical Considerations

Research documentation and data that support the findings of this study are openly available in the APSR Dataverse at `https://doi.org/10.7910/DVN/S5YMS7` (Bisbee, 2021). To allow full assessment of the experiment, and in line with APSA Principles & Guidance, we outline here the basic procedures we follow. This research, conducted with IRB approval, occurred entirely on the online platform M-Turk. The IRB ruled this research exempt, determining there was no harm to participants – in part because we did not collect any personally identifying information. Participants were restricted to US residents of eligible voting age (above 18; thus no children were in the subject pool), and were compensated at what would be substantially more than the US minimum wage (75 cents for an activity taking less than 5 minutes – the average time to completion was 3.67 minutes). While the experimental design allows us only limited understanding of the subject pool's diversity, of 664 respondents the sample was 60% male, 39% female, and ¡1% other; the sample was 10% Hispanic, 80% white, 9% African American, and 11% identifying as another race. We do not believe that participation likely differentially benefited or harmed any participating groups.

## F.2 Survey Analysis

Our main results assume that the spread of the Covid-19 virus across the United States was as-good-as-random. However, it may be that the virus hit anti-Sanders locations earlier than others. If this were to be true, it would mean that our findings of an anti-Sanders effect of exposure is a spurious byproduct of selection bias. To test the possibility of this selection effect, we rely on weekly survey data from Tausanovitch et al. (2019) which measures Sanders favorability by Congressional District. These data cover the period between July 2019 and

April 2020, allowing us to examine whether the pandemic hit areas predisposed to vote again Sanders earlier in its spread.

We look for descriptive evidence of the pandemic's spread penalizing Sanders in two ways. First, we plot the distribution of Sanders' support by districts that were insulated (gray) and exposed (black) by month in Figure 15. We define districts as "insulated" or "exposed" based on their March and April number of cases. Specifically, if these districts were in the top quartile of Covid-19 cases during these months, they are classified as exposed. Otherwise they are insulated. Figure 15 illustrates that, if anything, the pandemic hit more pro-Sanders districts earlier, meaning that the selection bias should work against our findings that exposed voters were less likely to vote for Sanders.

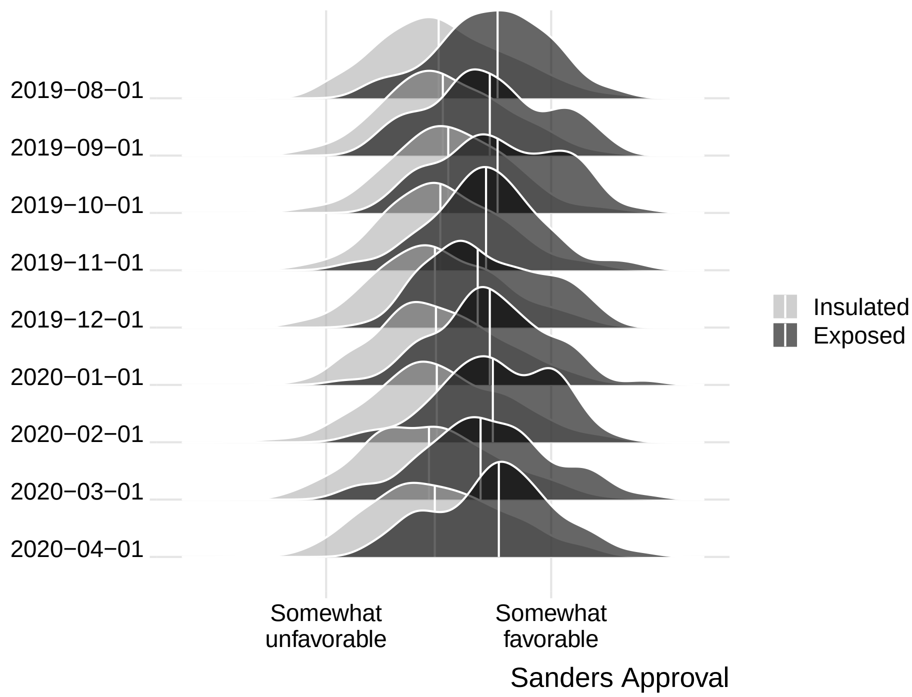


Figure 15: Histograms of favorability (x-axis) toward Bernie Sanders by month (y-axis) in congressional districts that were in the top quartile (black) or lower quartiles (gray) of Covid-19 cases in the months of March and April, 2020.

Second, we plot the week-by-week relationship between the number of Covid-19 cases and Sanders approval in Figure 16. Again, we find evidence suggesting that areas with more cases were also those more favorable toward Bernie Sanders, regardless of what week we examine. Taken together, these results reaffirm that, to the extent that the virus did not spread randomly with respect to politics, it did so in a way to bias against our findings.

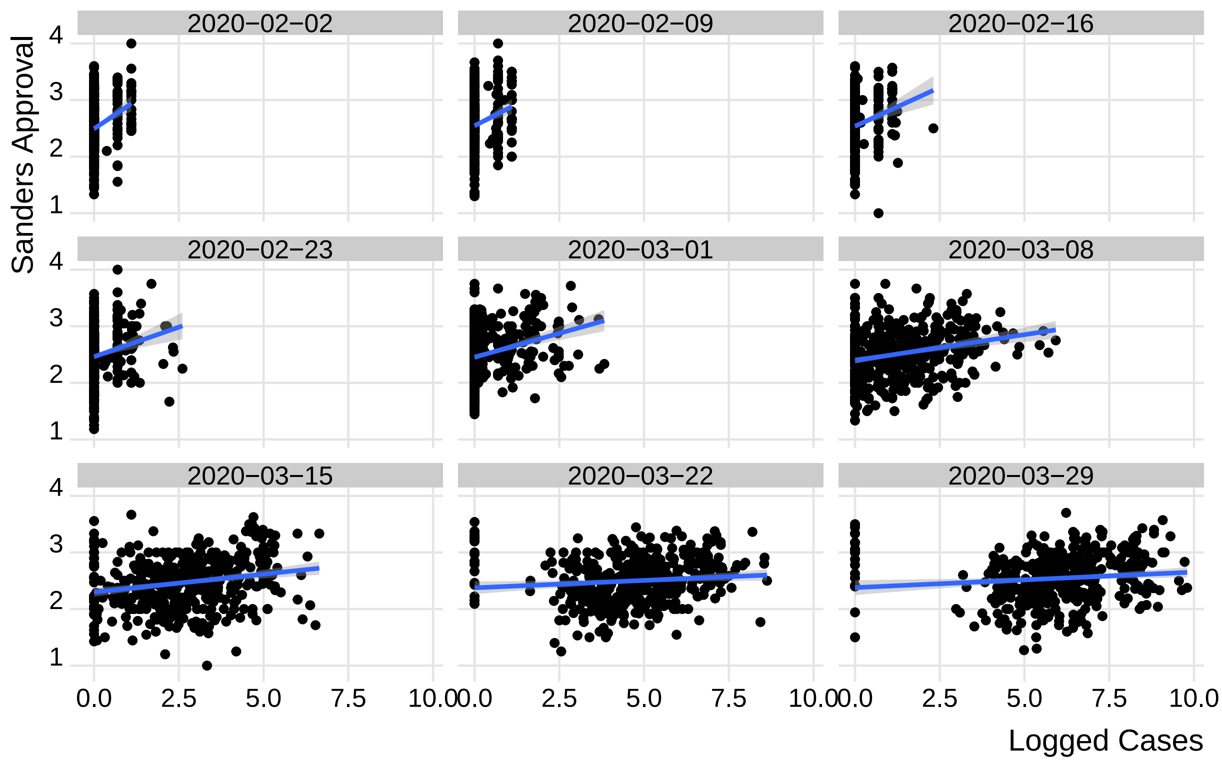


Figure 16: Week-by-week scatterplots of logged Covid-19 cases (x-axis) and average Sanders favorability (y-axis).

# G Sanders v Biden Ideological Placement

We interpret the choice facing Democratic primary voters as one between the safety of the familiar (Biden) versus the uncertainty of the extreme (Sanders). We list a number of pieces of evidence in support of this interpretation in our paper, including exit poll data from CNN, the candidates' own self-image, and evidence from Azevedo, Jost and Rothmund (2017) suggesting that Sanders supporters were less likely to support the economic, gender, or general systems of societal organization. We also used survey data from Pew Research Center's American News Pathways data tool to summarize how Democrats themselves placed Sanders and Biden in terms of their ideology between February and March of 2020.[10] As illustrated in Figure 17, there is convincing evidence that Democratic voters saw Sanders as the more ideologically extreme candidate, and Biden as the more moderate candidate. Insofar as these ideological placements map on to feelings of safety (for Biden) versus uncertainty (for Sanders), we argue that these patterns further bolster our interpretation of the primary choice as between the safety of the familiar versus the uncertainty of the unknown.

[10] https://www.pewresearch.org/pathways-2020/DEM20IDEO_a/political_party_ideology/us_adults

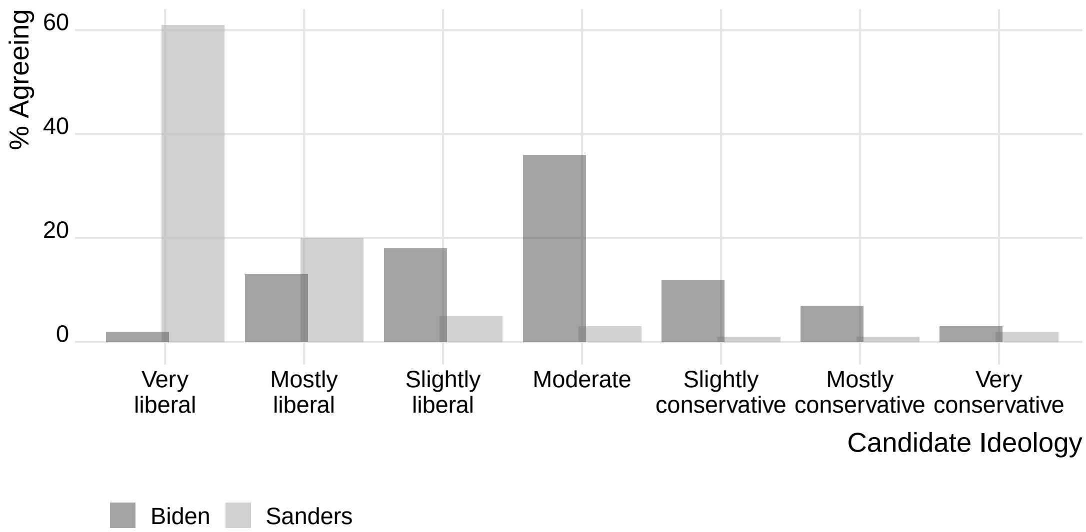


Figure 17: Average placement of Biden (dark gray) and Sanders (light gray) on a left-right ideological spectrum (x-axis). Data from Pew Research Center's American News Pathways data tool.

# H Generalizability

## H.1 Democratic Party House Primary

Simple descriptive plots summarized in Figure 18 suggest that the electoral fortunes of the anti-establishment candidates for the house declined both over the course of the 2020 primary season, as well as over the geographic variation in Covid-19 exposure.

## H.2 France Diff-in-Diff

The French municipal elections were held on March 15th, 2020 and on June 28th, 2020. Voting data at the Department level is obtained from `https://www.data.gouv.fr/fr/datasets/elections-municipales-2020-resultats-1er-tour/` for the first wave, and `https://www.data.gouv.fr/fr/datasets/municipales-2020-resultats-2nd-tour/` for the second wave of voting. We mapped these voting results to the number of Covid-19 cases in each area using data from `https://www.data.gouv.fr/fr/datasets/donnees-de-laboratoires-infra-`

We estimate a diff-in-diff model predicting the vote share for mainstream and non-mainstream parties for Department $d$ with the following specification:

$$VS_d = \lambda_d + \beta_1 Main_d + \beta_2 Post + \beta_3 Main_d \times Post + \varepsilon_d \tag{2}$$

where $\lambda_d$ are Department-fixed effects.

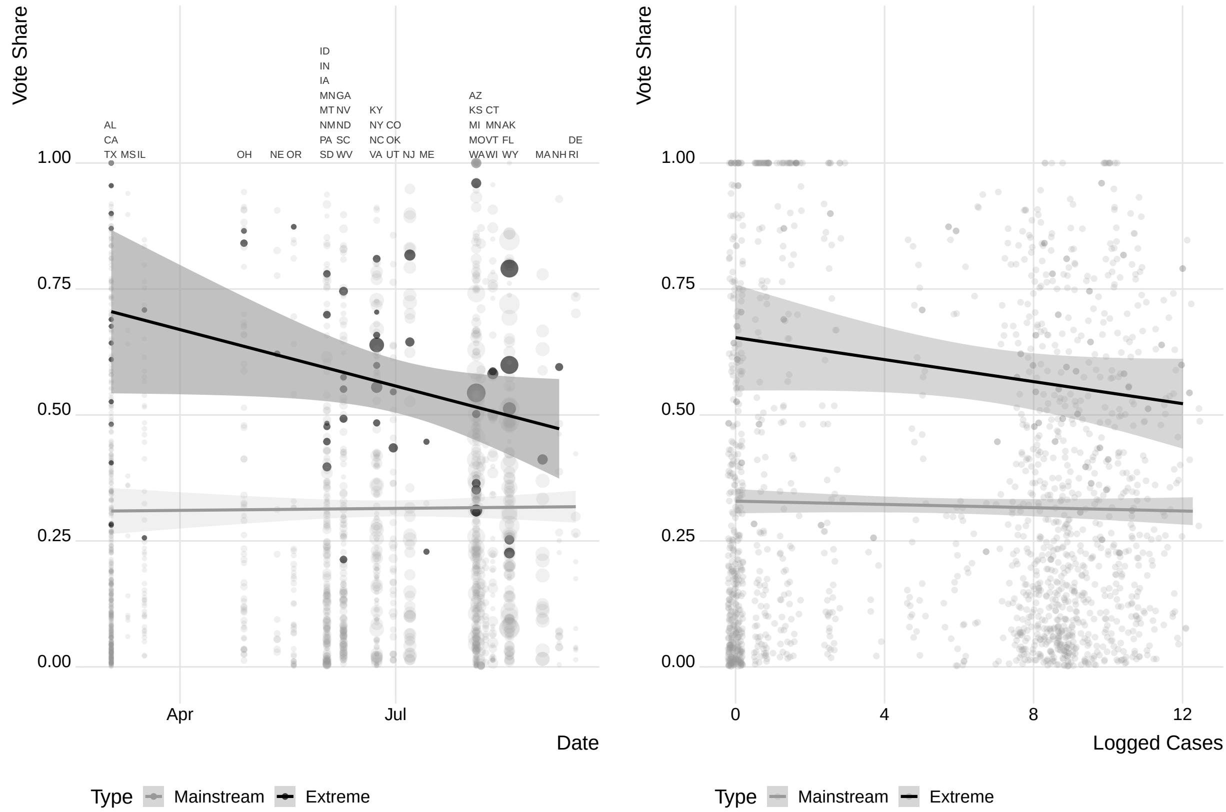


Figure 18: Extreme (black) versus mainstream (gray) vote shares (y-axes) by date (top panel) and logged cases (bottom panel).

This specification only focuses on the temporal source of variation, and compares the electoral fortunes of non-mainstream parties between when voters went to the polls in March and June. The inclusion of Department fixed effects makes this a comparison of how these parties fared *in the same area*. However, it is possible that all non-mainstream parties experienced a secular decline in support for some other reason, such as the strategic decision of "first you choose, then you discard".[11] Under the two-round system, strategic voting can result in a penalty against less popular candidates and parties in the second round, providing an alternative explanation for the penalty to non-mainstream parties we observe in the data (Dolez, Laurent and Blais, 2017).

We implement an alternative specification that predicts non-mainstream vote share as a function of geographic variation in exposure to Covid-19, measured as logged deaths. Formally, we estimate:

$$VS_{d,t} = \lambda_d + \delta_t + \beta_1 Main_d + \beta_2 Deaths_{d,t} + \beta_3 Main_d \times Deaths_{d,t} + \varepsilon_{d,t} \qquad (3)$$

Here, the subscript $t$ refers to the election date – either March 15th or June 28th. By implementing both Department ($\lambda_d$) and date ($\delta_t$) fixed effects, we isolate variation due to the

[11] https://blogs.lse.ac.uk/europpblog/2017/05/12/understanding-the-campaign-dynamics-of-the-french-pre

change in Covid-19 cases between the two elections across Departments. In both specifications, we find substantively similar results, depicted as marginal effect plots in Figure 19. The decline in support for the non-mainstream parties is strongly correlated with exposure to Covid-19, consistent with our theorized mechanism of a political flight to safety.

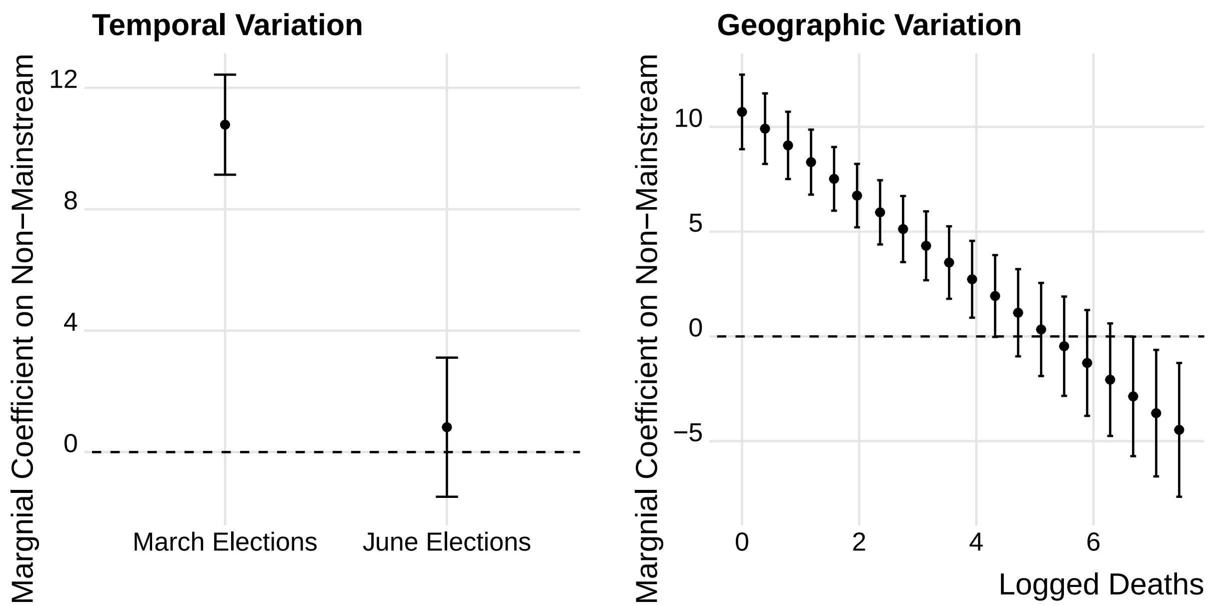


Figure 19: Diff-in-diff results for support for non-mainstream parties in the French municipal elections of 2020. Left panel summarizes Equation 2 in which the difference between mainstream and non-mainstream vote shares is compared across the March and June rounds. Right panel summarizes Equation 3 in which the difference between mainstream and non-mainstream vote shares is compared across different levels of Covid-19 exposure, measured with logged deaths.

Table 5: CEM Robustness

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Exposure Dummy | −1.068** | −0.482* | −0.994** | −0.943** | −0.656* | −0.940** |
| | (0.387) | (0.230) | (0.338) | (0.325) | (0.296) | (0.323) |
| LTHS | −0.038 | −0.040 | −0.083 | −0.062 | 0.135 | −0.014 |
| | (0.049) | (0.123) | (0.113) | (0.054) | (0.179) | (0.116) |
| Coll. Up | 0.019 | 0.147 | 0.070 | −0.0003 | 0.159 | −0.018 |
| | (0.052) | (0.207) | (0.067) | (0.041) | (0.121) | (0.075) |
| Lt30yo | −0.052 | −0.309† | −0.044 | −0.055 | −0.372** | −0.005 |
| | (0.049) | (0.165) | (0.062) | (0.034) | (0.140) | (0.060) |
| 60up | −0.175*** | −0.257 | −0.176** | −0.218*** | −0.450*** | −0.185*** |
| | (0.049) | (0.180) | (0.054) | (0.043) | (0.100) | (0.053) |
| Below poverty level | 0.041 | 0.086 | 0.042 | 0.037 | 0.111 | 0.053 |
| | (0.030) | (0.104) | (0.050) | (0.031) | (0.106) | (0.056) |
| Female HH no hus | −0.023 | −0.013 | 0.055 | −0.034 | −0.149 | −0.009 |
| | (0.037) | (0.075) | (0.057) | (0.037) | (0.214) | (0.048) |
| Unem rate | −0.020 | 0.285† | −0.019 | −0.026 | 0.094 | 0.002 |
| | (0.024) | (0.158) | (0.040) | (0.027) | (0.077) | (0.044) |
| LFPR | 0.057 | 0.012 | −0.017 | 0.051 | −0.073 | −0.008 |
| | (0.040) | (0.149) | (0.039) | (0.040) | (0.153) | (0.044) |
| Manufacturing | −0.040 | 0.154† | 0.005 | −0.054* | 0.195** | −0.019 |
| | (0.031) | (0.086) | (0.042) | (0.022) | (0.073) | (0.044) |
| Med HH Inc | −0.149** | 0.052 | −0.139* | −0.192*** | −0.097 | −0.075 |
| | (0.048) | (0.189) | (0.065) | (0.053) | (0.141) | (0.073) |
| Rural | −0.031 | −0.039 | −0.030 | −0.014 | −0.089 | −0.002 |
| | (0.021) | (0.068) | (0.043) | (0.020) | (0.170) | (0.044) |
| Speak only english | −0.195*** | −0.295 | −0.229** | −0.217*** | −0.251 | −0.183* |
| | (0.041) | (0.235) | (0.086) | (0.044) | (0.227) | (0.087) |
| White | 0.069 | −0.279 | 0.100* | 0.071 | −0.371† | 0.106† |
| | (0.050) | (0.225) | (0.045) | (0.055) | (0.211) | (0.055) |
| Black | −0.083 | −0.380 | 0.002 | −0.135* | −0.644* | 0.069 |
| | (0.052) | (0.375) | (0.076) | (0.060) | (0.285) | (0.091) |
| Tot pop | 0.025 | 0.094 | 0.006 | 0.039 | −0.013 | 0.026 |
| | (0.025) | (0.062) | (0.024) | (0.028) | (0.072) | (0.027) |
| Turnout 2020 | 0.135*** | 0.020 | 0.070 | 0.201*** | 0.515* | 0.203*** |
| | (0.034) | (0.267) | (0.063) | (0.024) | (0.207) | (0.041) |
| Caucus switch | −0.024 | 0.279 | 0.693* | | | |
| | (0.679) | (1.130) | (0.332) | | | |
| Pcttw sanders16 | 0.026*** | 0.051** | 0.032*** | 0.026*** | 0.044*** | 0.036*** |
| | (0.004) | (0.016) | (0.005) | (0.004) | (0.010) | (0.005) |
| Observations | 1,882 | 375 | 1,882 | 1,710 | 304 | 1,710 |
| $R^2$ | 0.817 | 0.803 | 0.899 | 0.860 | 0.898 | 0.924 |
| County Controls | Y | Y | Y | Y | Y | Y |
| DMA FEs | Y | Y | Y | Y | Y | Y |

*Notes:* DMA-cluster robust SEs in parentheses.† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

# References


Azevedo, Flávio, John T Jost and Tobias Rothmund. 2017. ""Making America great again": System justification in the US presidential election of 2016." *Translational Issues in Psychological Science* 3(3):231.

Berinsky, Adam J, Gregory A Huber and Gabriel S Lenz. 2012. "Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk." *Political analysis* 20(3):351–368.

Bisbee, James. 2021. "Replication Data for: Flight to Safety: Covid-Induced Changes in the Intensity of Status Quo Preference and Voting Behavior.".
**URL:** *https://doi.org/10.7910/DVN/S5YMS7*

Blackwell, Matthew, Stefano Iacus, Gary King and Giuseppe Porro. 2009. "cem: Coarsened exact matching in Stata." *The Stata Journal* 9(4):524–546.

Clifford, Scott, Ryan M Jewell and Philip D Waggoner. 2015. "Are samples drawn from Mechanical Turk valid for research on political ideology?" *Research & Politics* 2(4):2053168015622072.

Crump, Matthew JC, John V McDonnell and Todd M Gureckis. 2013. "Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research." *PloS one* 8(3).

Cuebiq, Analysis. 2020. "Mobility Insights.".
**URL:** *https://www.cuebiq.com/visitation-insights-covid19/*

Dolez, Bernard, Annie Laurent and André Blais. 2017. "Strategic voting in the second round of a two-round system: The 2014 French municipal elections." *French Politics* 15(1):27–42.

Hazlett, Chad and Yiqing Xu. 2018. "Trajectory balancing: A general reweighting approach to causal inference with time-series cross-sectional data." *Available at SSRN 3214231* .

Tausanovitch, Chris, Lynn Vavreck, Tyler Reny, Alex Rossell Hayes and Aaron Rudkin. 2019. "Democracy fund+ UCLA nationscape methodology and representativeness assessment.".

Zubizarreta, José R. 2015. "Stable weights that balance covariates for estimation with incomplete outcome data." *Journal of the American Statistical Association* 110(511):910–922.