Quantifying the Effects of Protests on Voter Registration and Turnout

Appendices and Supplementary Materials

August 2021

Contents

Appendix A
Locations of Protest by Cause

<u>Figure A1-8:</u> Geographic Patterns in Social Protests During the Trump Era

Figure A1
Had a Protest, 2017–2020

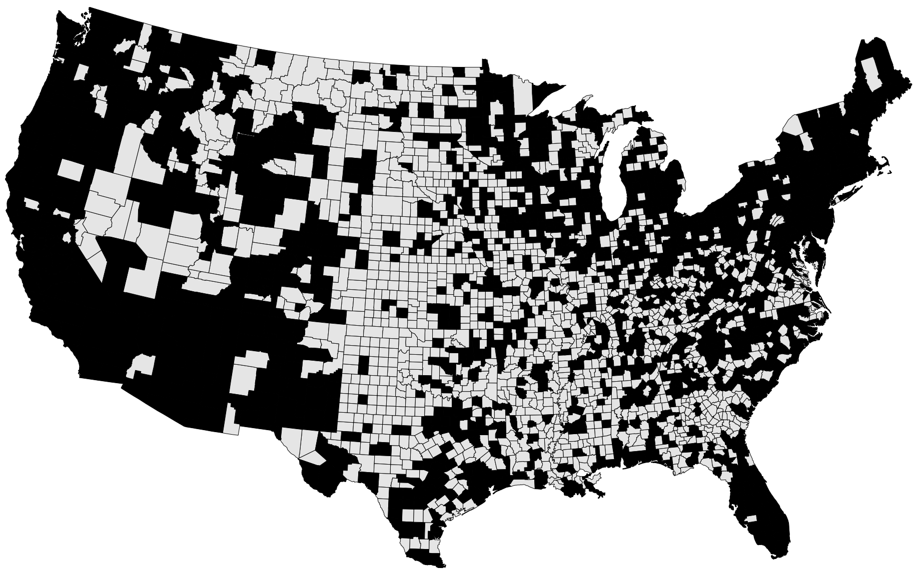


Figure A2
Average Distance to a Protest, 2017–2020

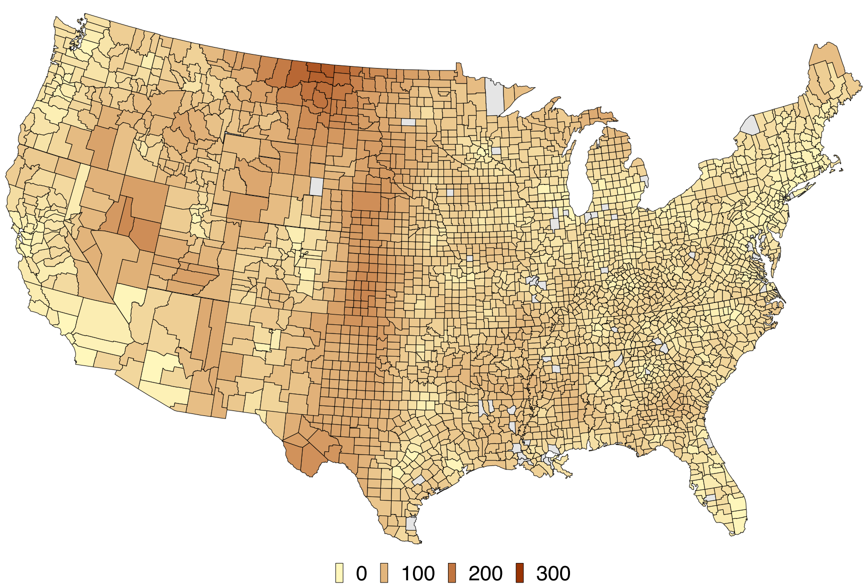


Figure A3

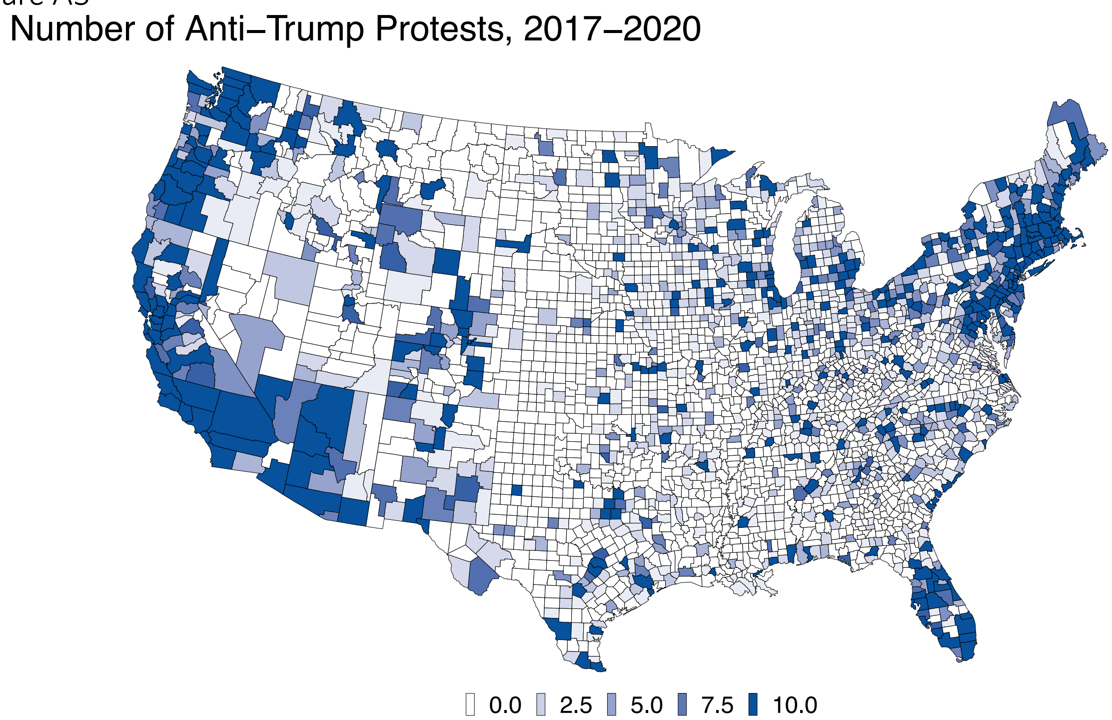


Figure A4

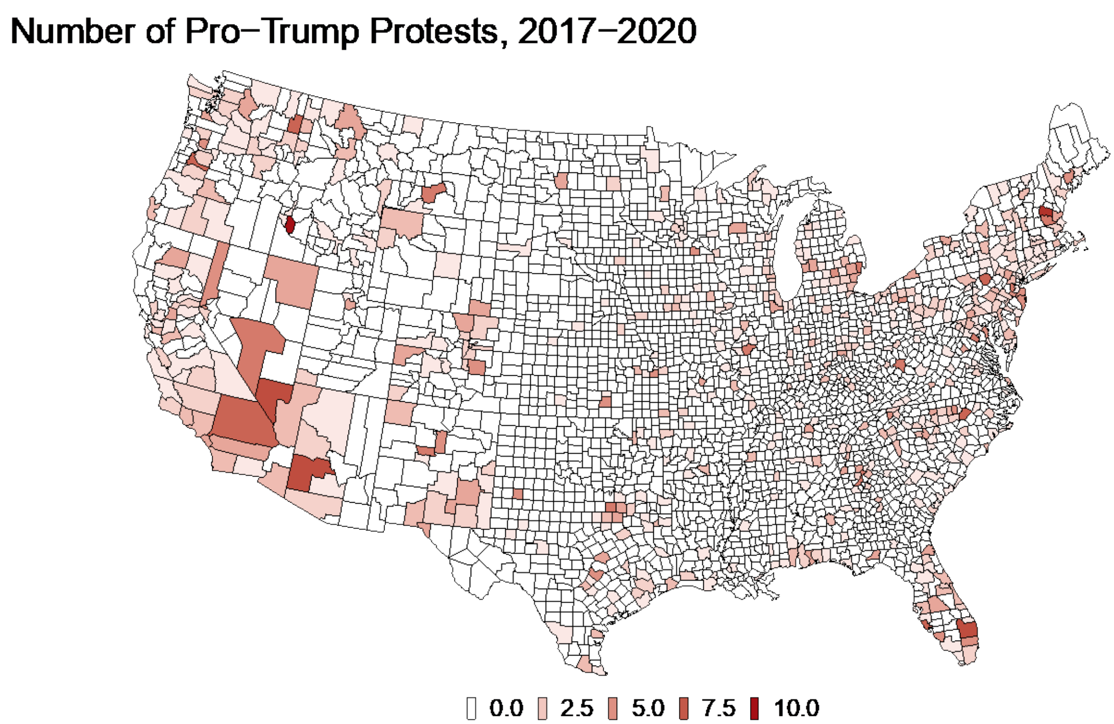


Figure A5

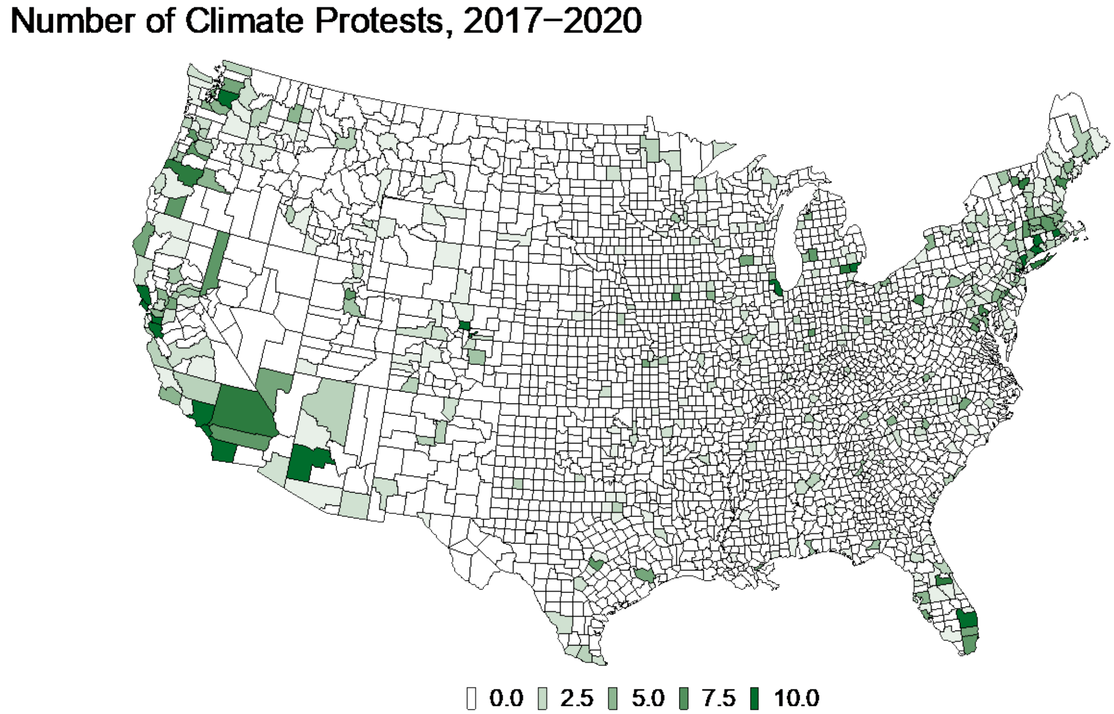


Figure A6

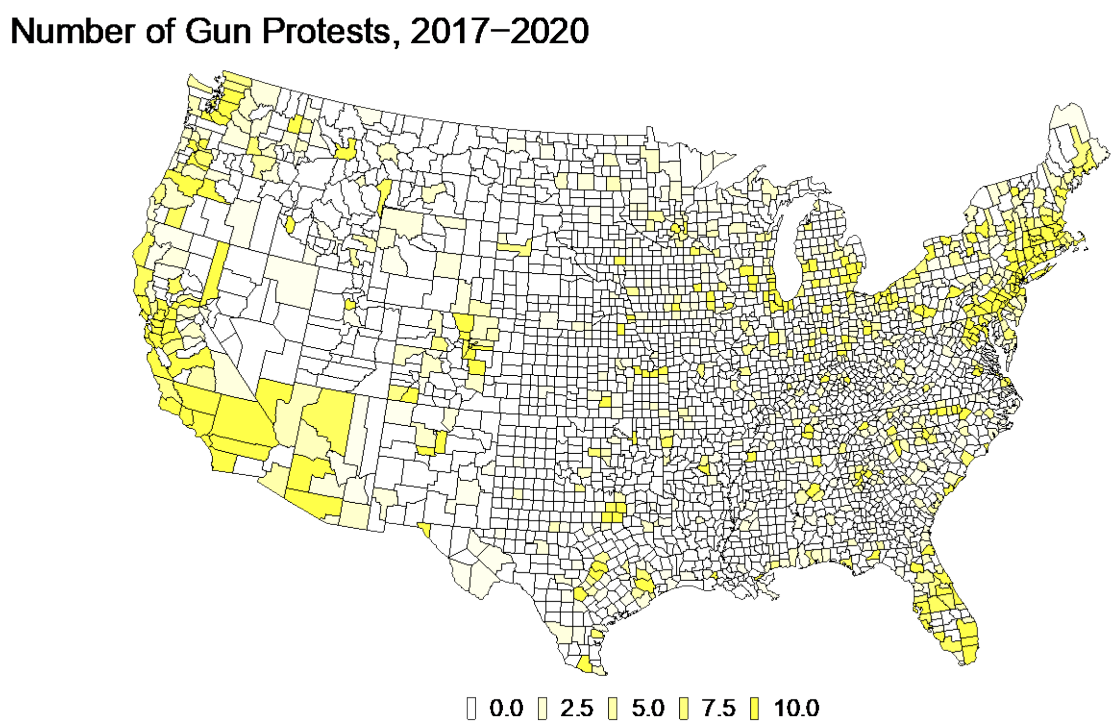


Figure A7

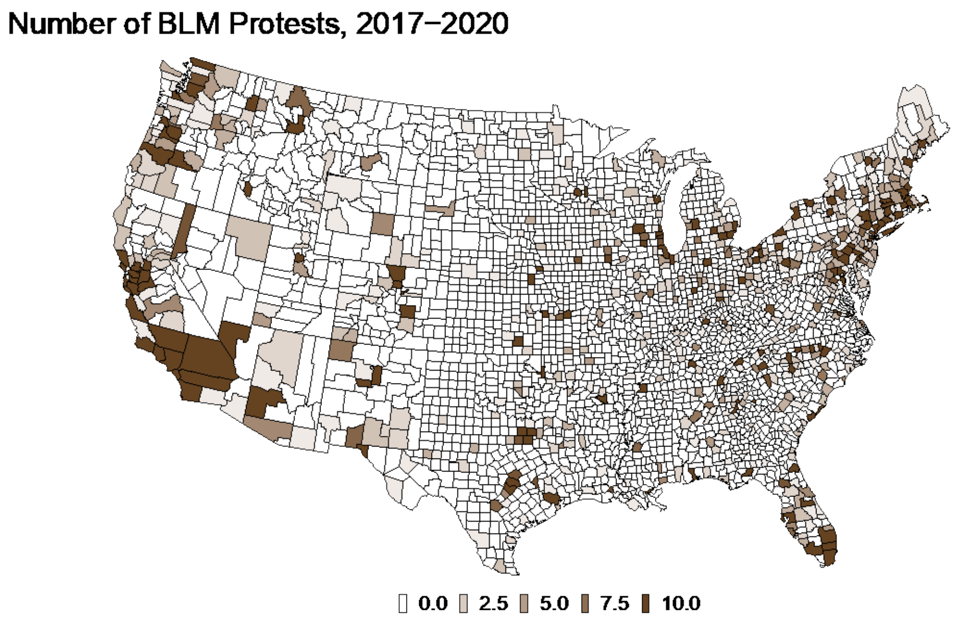
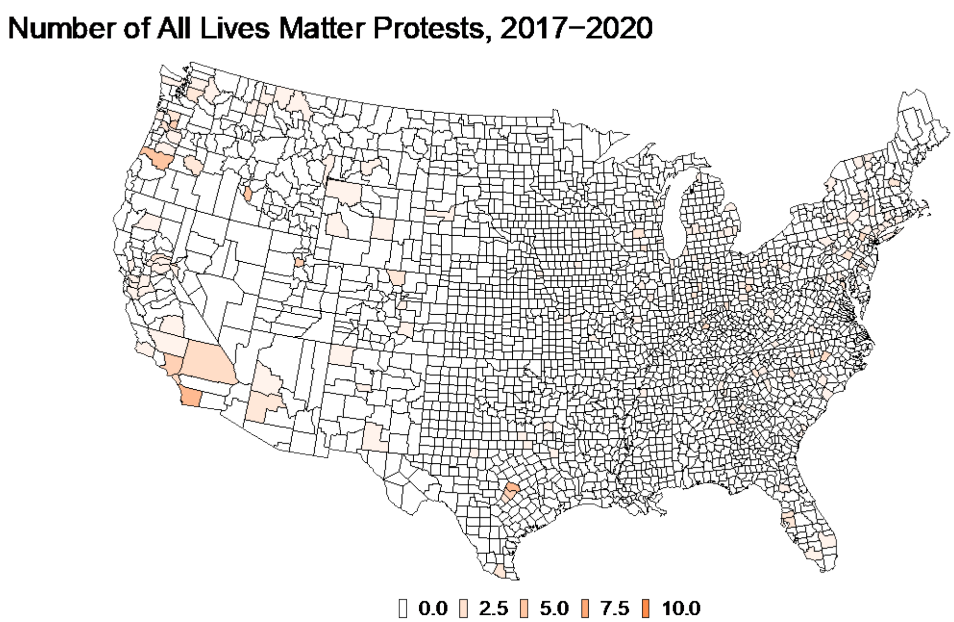


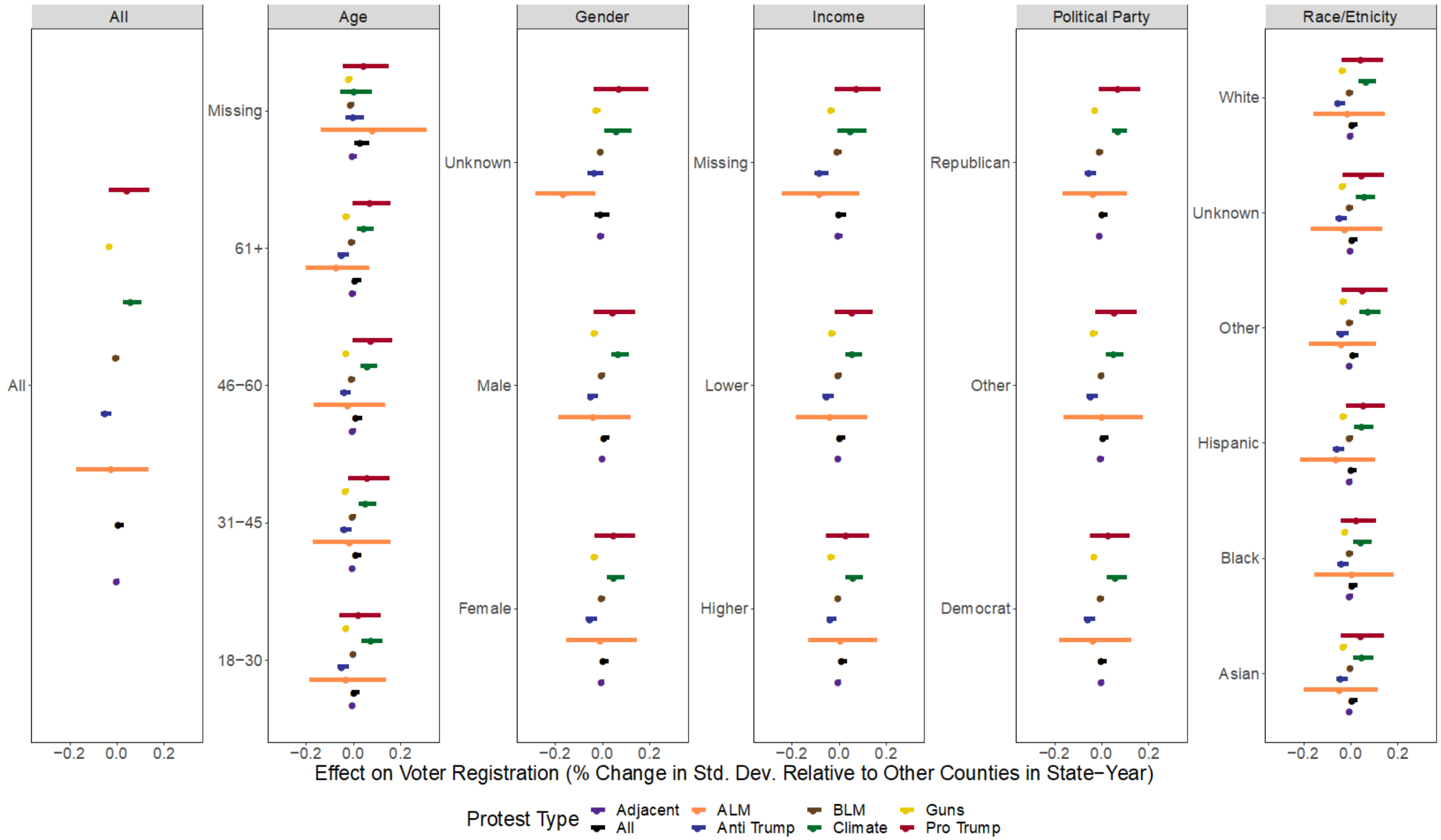
Figure A8



<u>Notes</u>: Figure maps the number of protests of various types during the Trump presidency. Areas that are shaded their darker respective colors had more protests, whereas areas that are shaded lighter had fewer protests (with white areas experiencing no protests of these respective types over the period of study). For the sake of making visualization easier, we cap the number of possible protests at 10. This data comes from the Crowd Counting Consortium (CCC) dataset that we describe in greater detail in the next section. **Takeaways**: the various types of protests have a considerable degree of geographic variation. Individuals in the heartland states rarely had protests near them. Anti-trump and black-lives matter protests occurred much more frequently than pro-trump and all-lives matter protests (respectively).

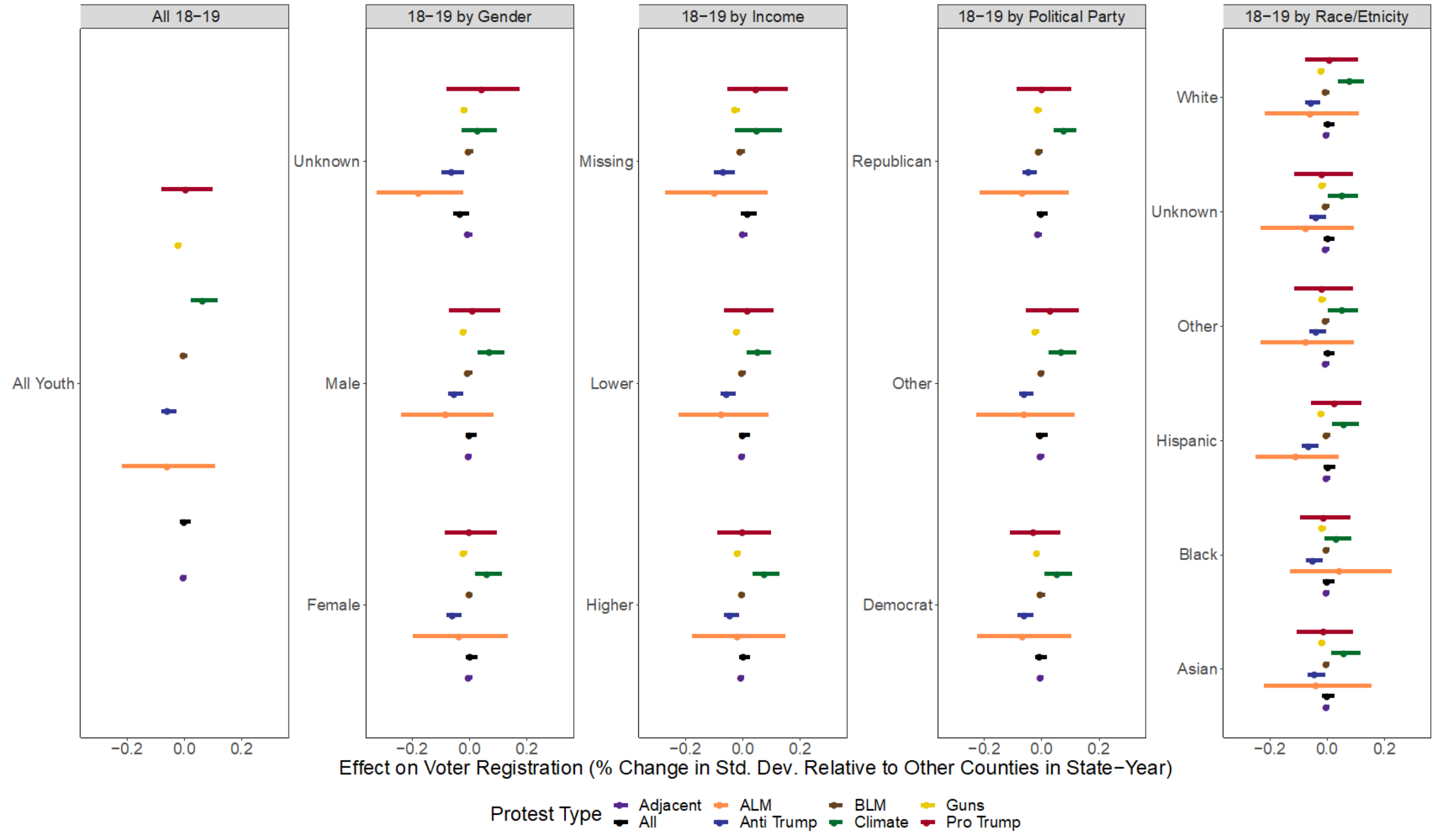
Appendix B:
Effects of Protest In the Same Count on Voter Registration by Subpopulation and Protest Cause:

Figure B1: Effect of All Protest Types on Voter Registration Patterns



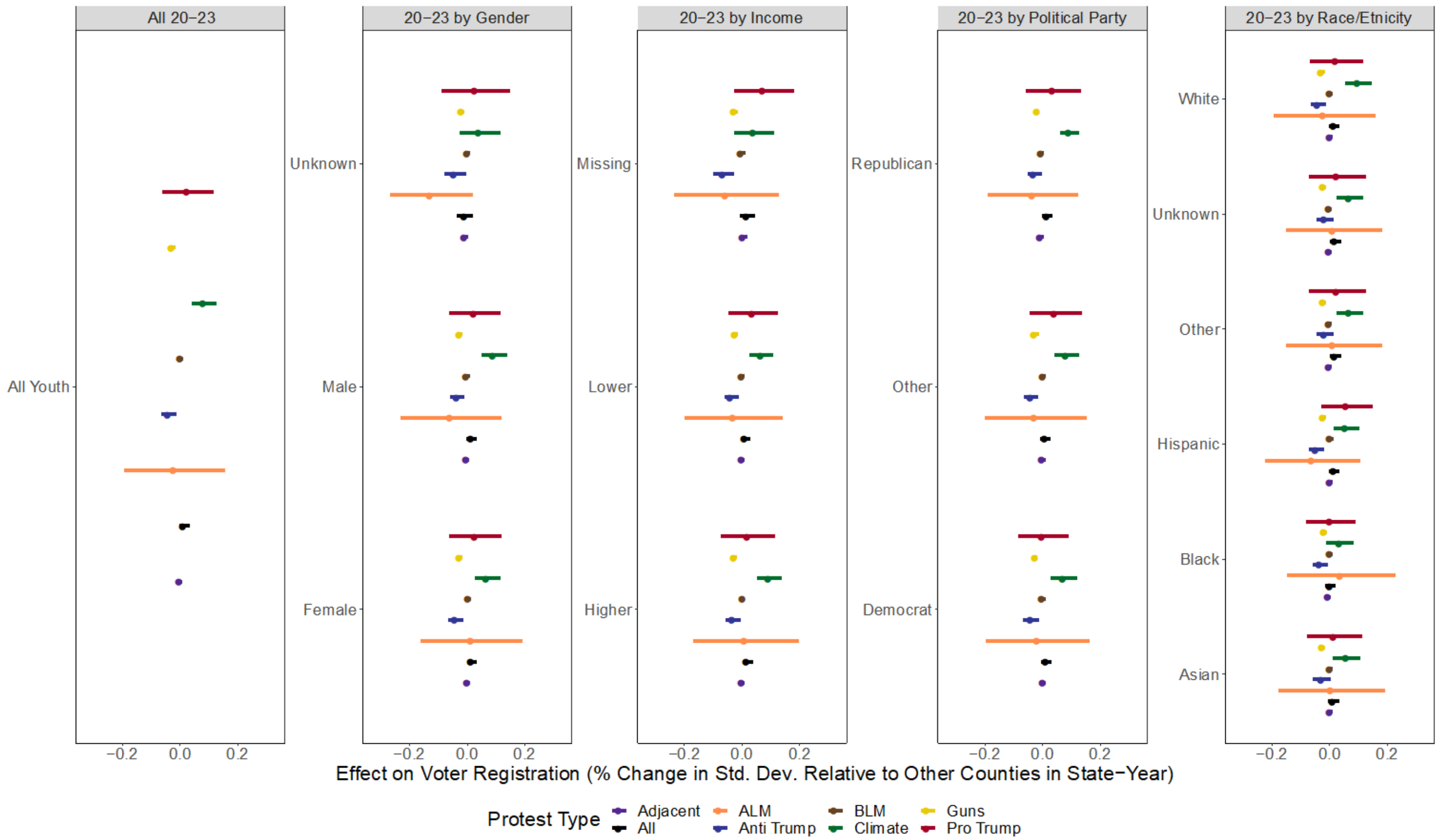
Notes: Figure is a coefficient plot of the effects of various protests (denoted by differences in colors) on the voter registration patterns of different subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "all"), protests on adjacent counties, all lives matter (i.e., "ALM"), anti-Trump, pro-Trump, black lives matter (i.e., "BLM"), climate, and guns are show. The panels display effects among all citizens, citizens by age, citizens by gender, citizens by income, citizens by political party, and citizens by race/ethnicity. **Takeaway**: aside from climate change protests (which modestly increased registration patterns of most subgroups), the average protest of these types had little to no effect on patterns of voter registration.

Figure B2: Effect of All Protest Types on 18-19-year-olds' Voter Registration Patterns



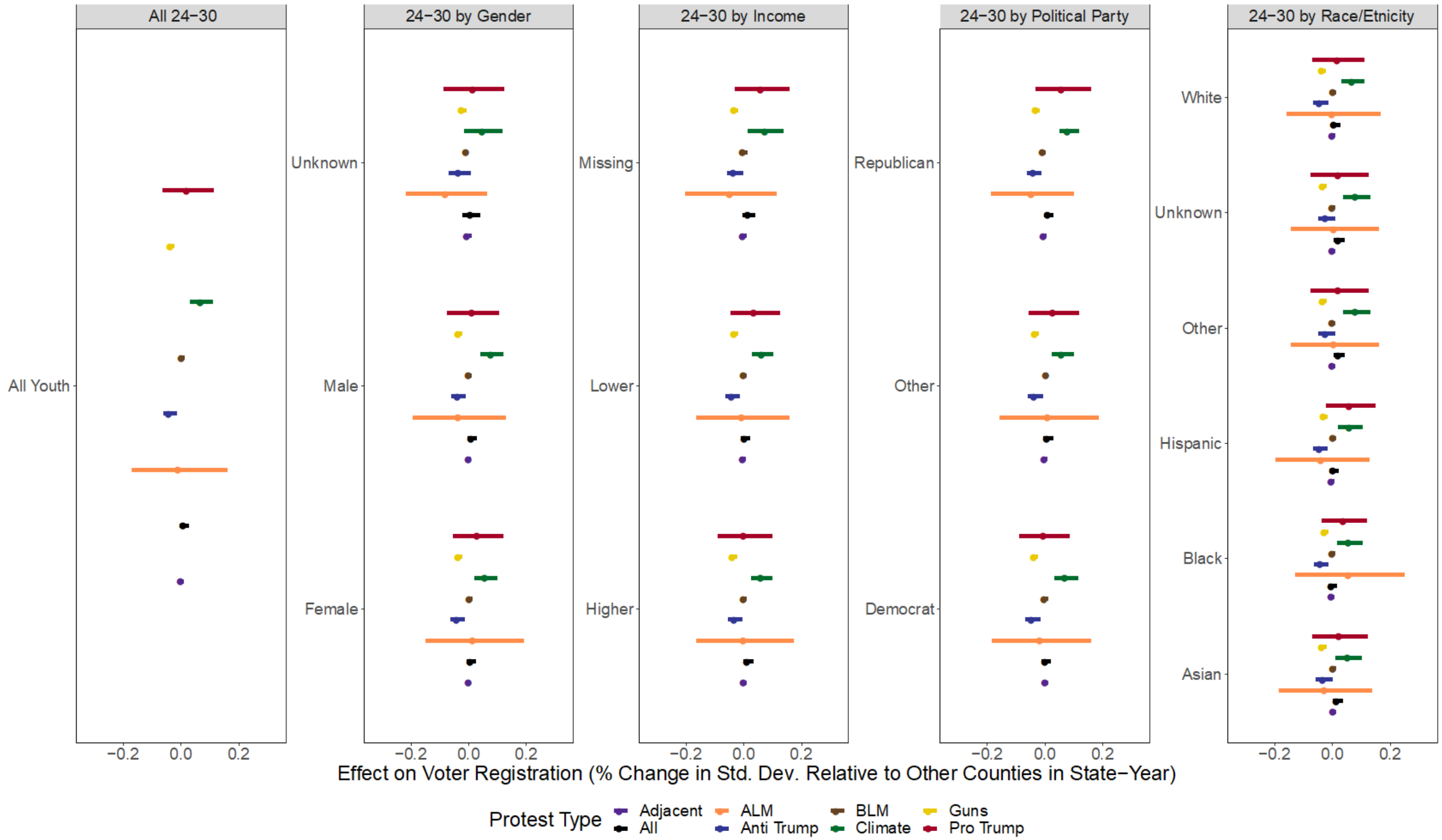
Notes: Figure is a coefficient plot of the effects of various protests (denoted by differences in colors) on the voter registration patterns of different youth (i.e., 18-19-year-olds) subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "all"), protests on adjacent counties, all lives matter (i.e., "ALM"), anti-Trump, pro-Trump, black lives matter (i.e., "BLM"), climate, and guns are show. The panels display effects among all youth (aged 18-19), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: aside from climate change protests (which modestly increased registration patterns of most youth subgroups), the average protest of these types had little to no effect on patterns of voter registration.

Figure B3: Effect of All Protest Types on 20-23-year-olds' Voter Registration Patterns



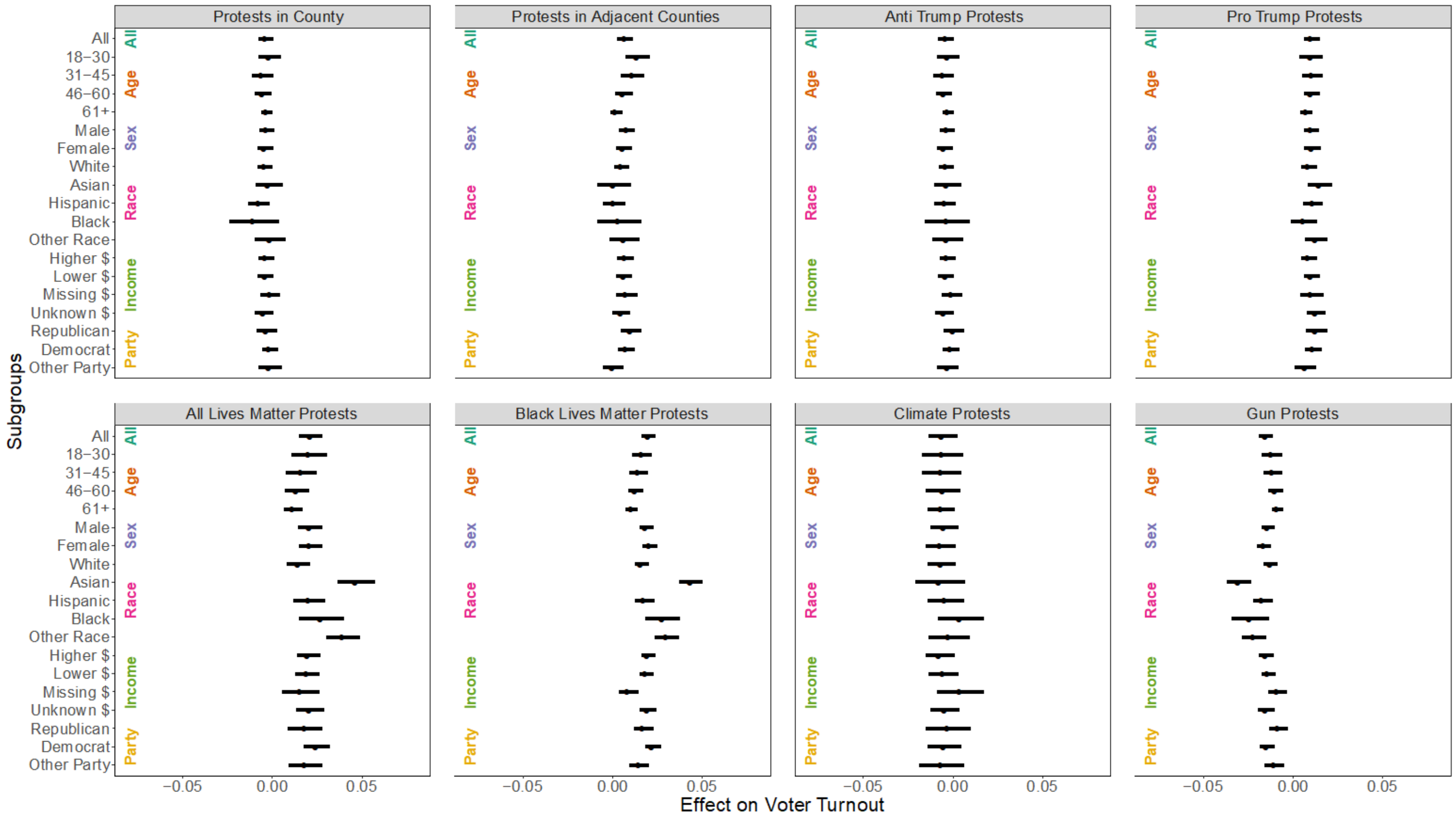
Notes: Figure is a coefficient plot of the effects of various protests (denoted by differences in colors) on the voter registration patterns of different youth (i.e., 20-23-year-olds) subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "all"), protests on adjacent counties, all lives matter (i.e., "ALM"), anti-Trump, pro-Trump, black lives matter (i.e., "BLM"), climate, and guns are show. The panels display effects among all youth (aged 20-23), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: aside from climate change protests (which modestly increased registration patterns of most youth subgroups), the average protest of these types had little to no effect on patterns of voter registration.

Figure B4: Effect of All Protest Types on 24-30-year-olds' Voter Registration Patterns



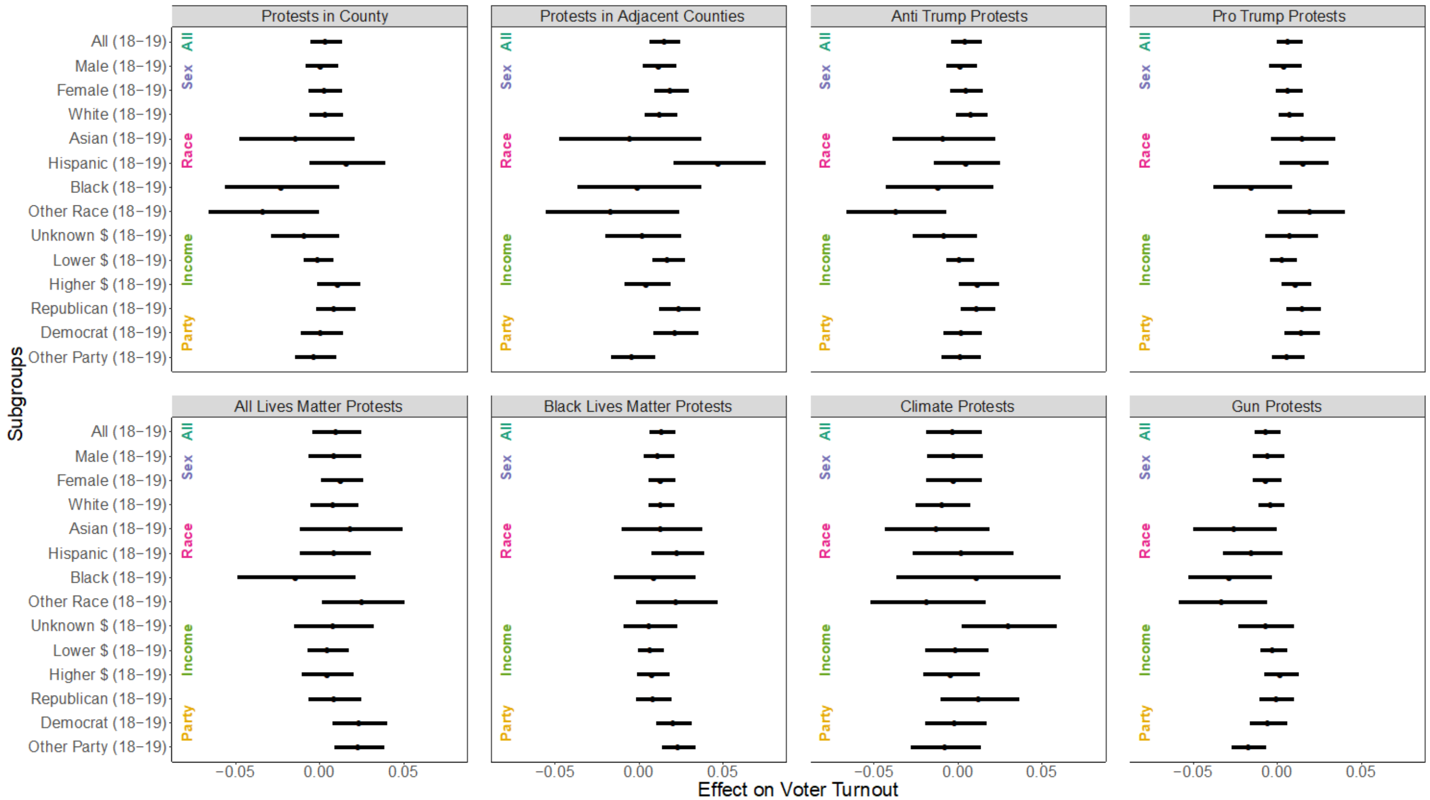
Notes: Figure is a coefficient plot of the effects of various protests (denoted by differences in colors) on the voter registration patterns of different youth (i.e., 24-30-year-olds) subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "all"), protests on adjacent counties, all lives matter (i.e., "ALM"), anti-Trump, pro-Trump, black lives matter (i.e., "BLM"), climate, and guns are show. The panels display effects among all youth (aged 24-30), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: aside from climate change protests (which modestly increased registration patterns of most youth subgroups), the average protest of these types had little to no effect on patterns of voter registration.

Figure B6: Effect of All Protest Types on Voter Turnout Patterns in the 2018 and 2020 Elections



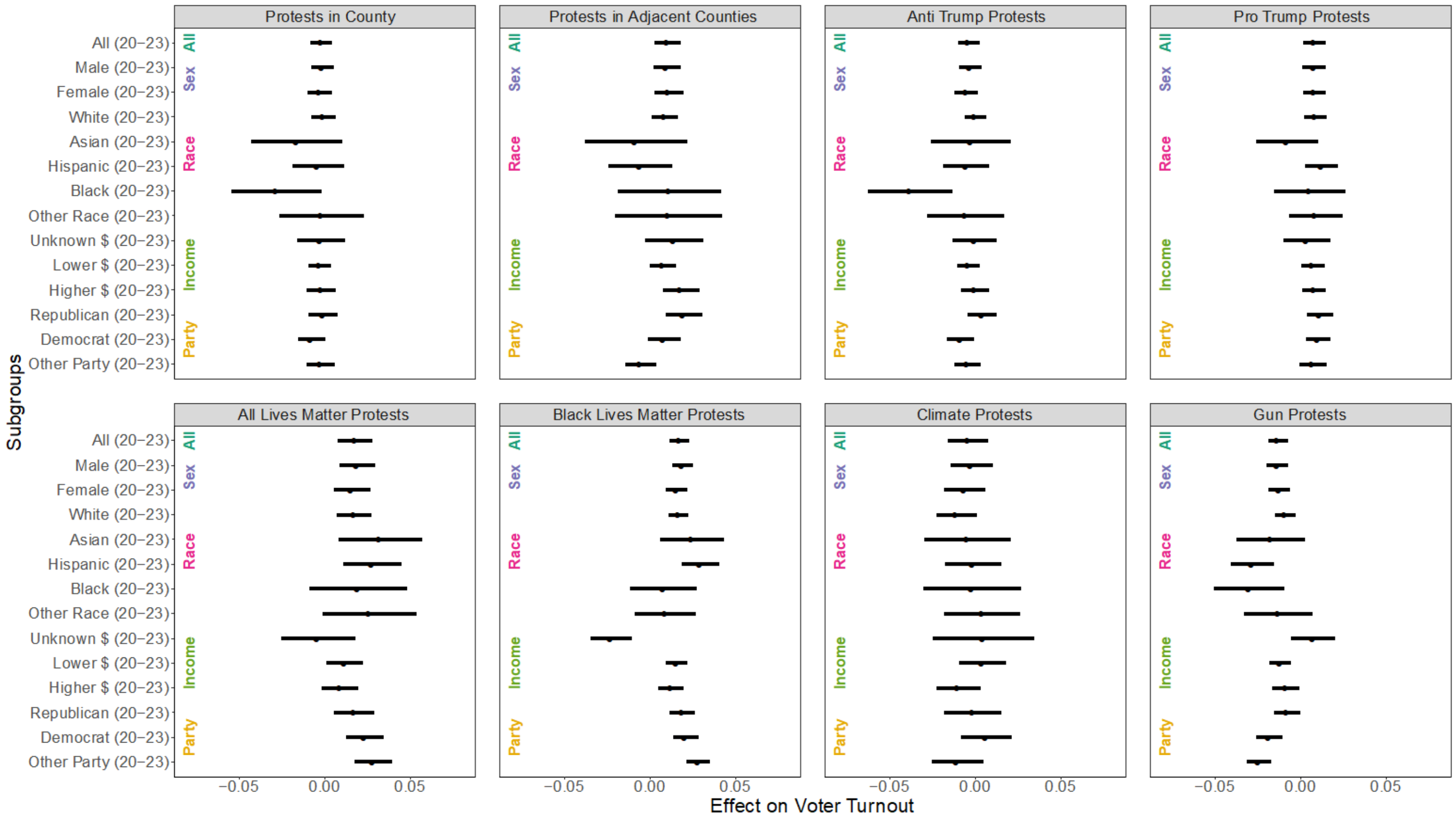
Notes: Figure is a coefficient plot of the effects of various protests (separated by the panels of the figure) on the voter turnout patterns of different subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "Protests in the County"), protests on adjacent counties, anti-Trump, pro-Trump, All Lives Matter, Black Lives Matter, climate, and guns are shown. The different shadings within the panels mark the effects of various citizens subgroups—that is, among all citizens, citizens by age, citizens by gender, citizens by income, citizens by political party, and citizens by race/ethnicity. **Takeaway**: the average protest modestly increases voter turnout in the counties in which they are held and in adjacent counties. All Lives Matter and Black Lives Matter protests increase voter turnout in the counties in which they are held. Gun control protests have a small negative impact on turnout in the counties in which they are held. All other protest types have little to no effect on the rates of voter turnout of the groups considered.

Figure B7 Effect of All Protest Types on Voter Turnout Patterns of Youth Ages 18-19 in the 2018 and 2020 Elections



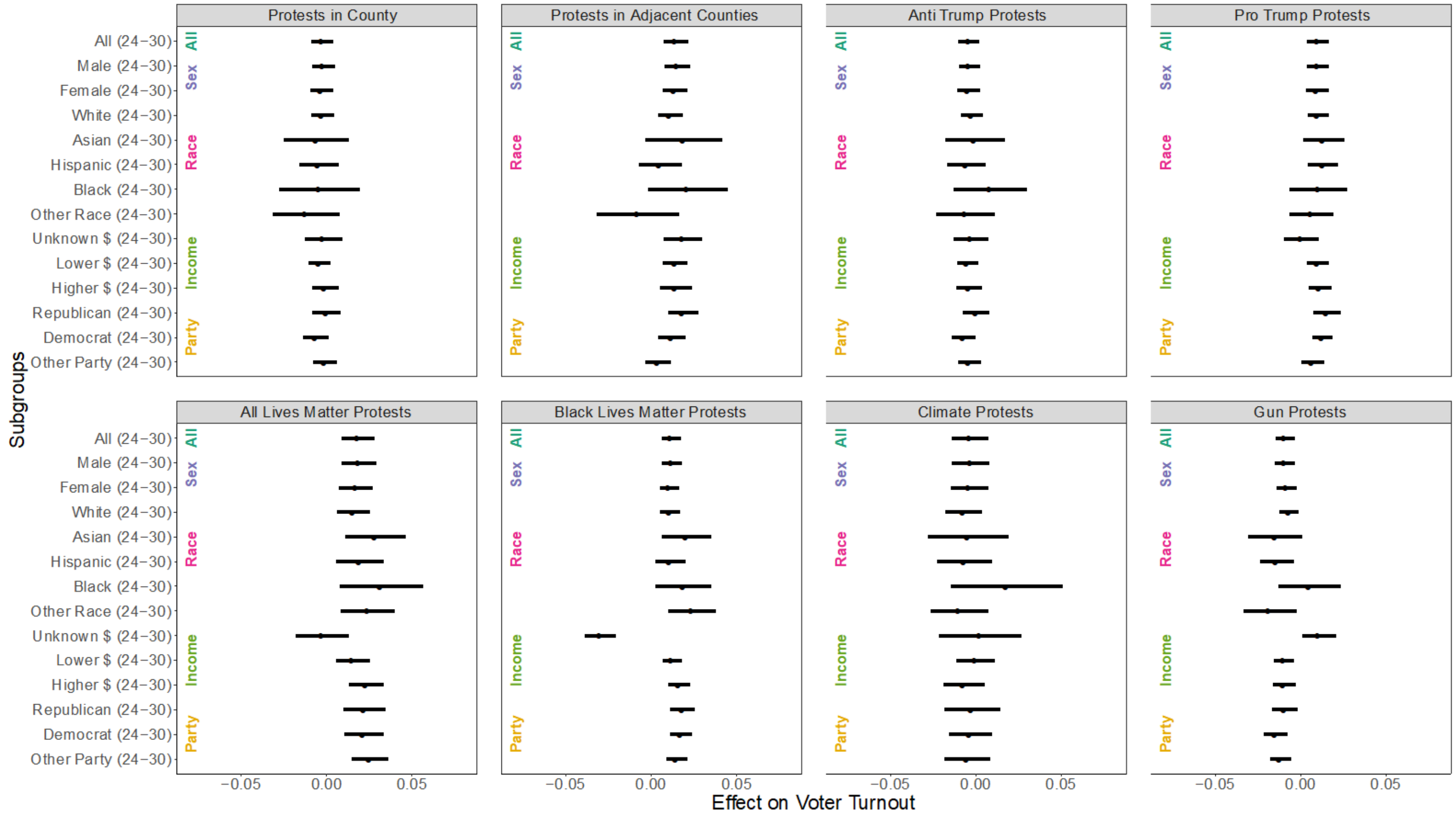
Notes: Figure is a coefficient plot of the effects of various protests (separated by the panels of the figure) on the youth (i.e., 18-19-year-olds) voter turnout patterns of different subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "Protests in the County"), protests on adjacent counties, anti-Trump, pro-Trump, All Lives Matter, Black Lives Matter, climate, and guns are shown. The different shadings within the panels mark the effects of various citizens subgroups—that is, among all youth (ages 18-19), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: the average protest modestly increases voter turnout in the counties in which they are held and in adjacent counties for most youth subgroups. All Lives Matter and Black Lives Matter protests increase voter turnout in the counties in which they are held for most youth subgroups. Gun control protests have no effect on most youth subgroups. All other protest types have little to no effect on the rates of voter turnout of the groups considered.

Figure B8: Effect of All Protest Types on Voter Turnout Patterns of Youth Ages 20-23 in the 2018 and 2020 Elections



Notes: Figure is a coefficient plot of the effects of various protests (separated by the panels of the figure) on the youth (i.e., 20-23-year-olds) voter turnout patterns of different subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "Protests in the County"), protests on adjacent counties, anti-Trump, pro-Trump, All Lives Matter, Black Lives Matter, climate, and guns are shown. The different shadings within the panels mark the effects of various citizens subgroups—that is, among all youth (ages 20-23), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: the average protest modestly increases voter turnout in the counties in which they are held and in adjacent counties for most youth subgroups. All Lives Matter and Black Lives Matter protests increase voter turnout in the counties in which they are held for most youth subgroups. Gun control protests have a small negative effect on the voter turnout of most subgroups. All other protest types have little to no effect on the rates of voter turnout of the groups considered.

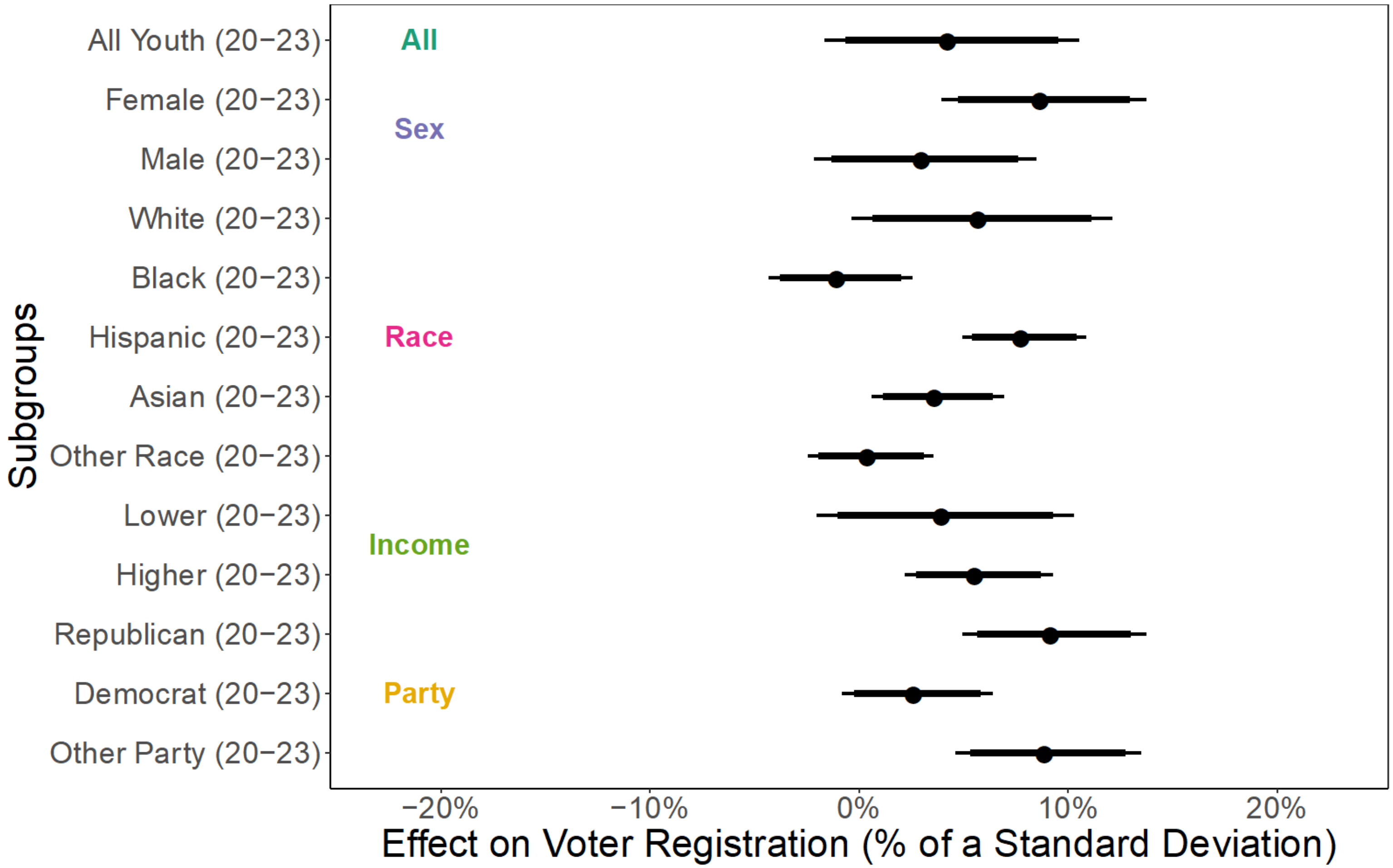
Figure B9: Effect of All Protest Types on Voter Turnout Patterns of Youth Ages 24-30 in the 2018 and 2020 Elections



Notes: Figure is a coefficient plot of the effects of various protests (separated by the panels of the figure) on the youth (i.e., 24-30-year-olds) voter turnout patterns of different subgroups. Coefficients (i.e., effect sizes) are shown with circles; bars denote the 95% confidence intervals for the effect estimates. The effect of the average protest (i.e., "Protests in the County"), protests on adjacent counties, anti-Trump, pro-Trump, All Lives Matter, Black Lives Matter, climate, and guns are shown. The different shadings within the panels mark the effects of various citizens subgroups—that is, among all youth (ages 24-30), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: the average protest modestly increases voter turnout in the counties in which they are held and in adjacent counties for most youth subgroups. All Lives Matter and Black Lives Matter protests increase voter turnout in the counties in which they are held for most youth subgroups. Gun control protests have a small negative effect on the voter turnout of most subgroups. All other protest types have little to no effect on the rates of voter turnout of the groups considered.

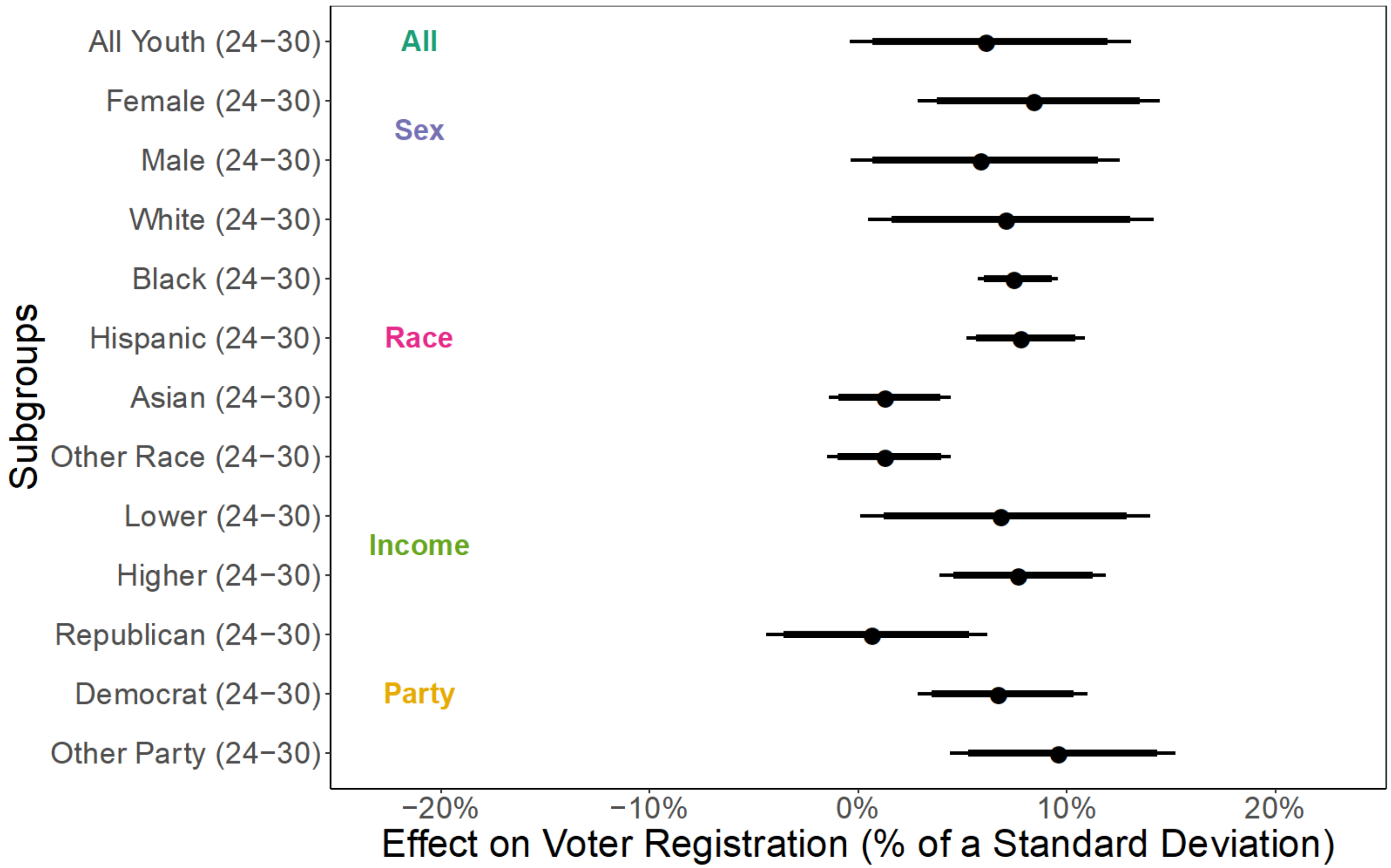
Appendix C:
RDiT Model Estimation of Causal Effect of Protests after George Floyd's Murder: Age 20-23 and Age 24-30 and Variations in Effect Across States and Age groups

Figure C1: Effect of George Floyd's Murder on Patterns of Voter Registration (RDiT), 20-23-year-olds



Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of different youth (i.e., 20-23-year-olds) subgroups. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. The different shadings mark the effects of various citizens subgroups—that is, among all youth (ages 20-23), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: on average, the George Floyd murder modestly increased the voter registration patterns of most 20-23-year-olds, albeit perhaps slightly less than among 18-19-year-olds.

Figure C2: Effect of George Floyd's Murder on Patterns of Voter Registration (RDiT), 24-30-year-olds

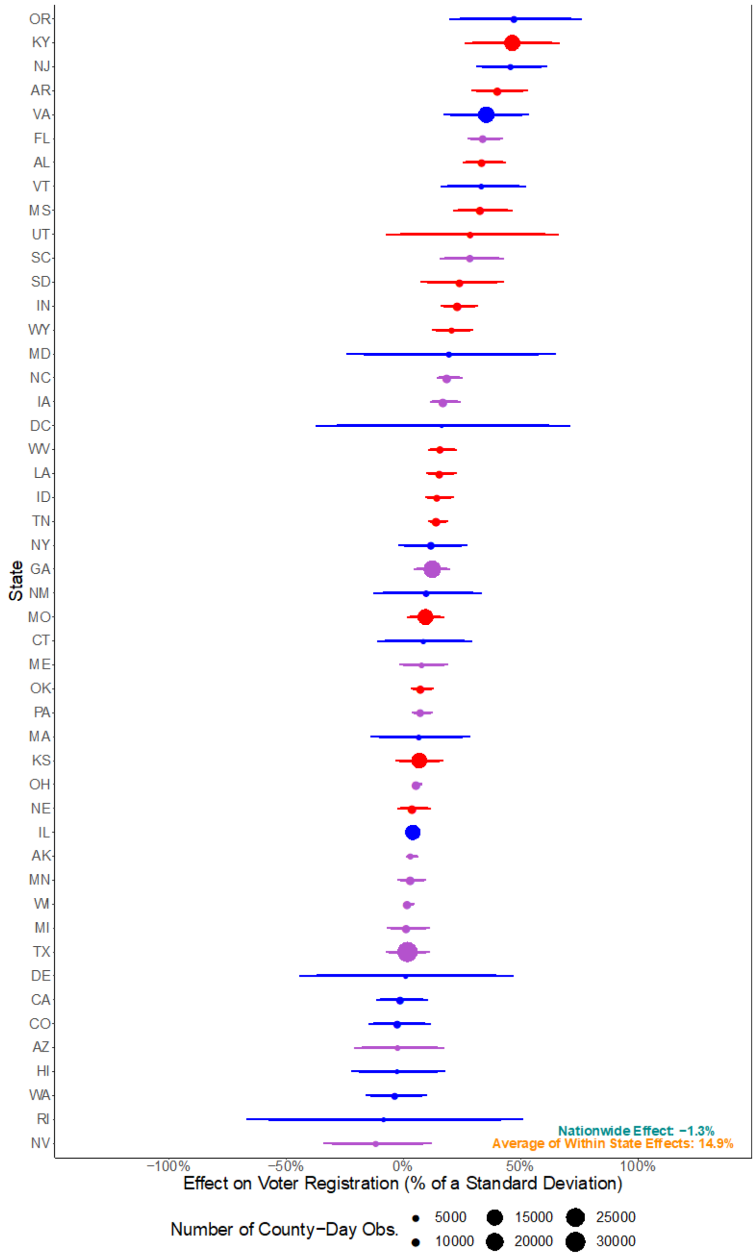


Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of different youth (i.e., 24-30-year-olds) subgroups. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. The different shadings mark the effects of various citizens subgroups—that is, among all youth (ages 24-30), youth by gender, youth by income, youth by political party, and youth by race/ethnicity. **Takeaway**: on average, the George Floyd murder modestly increased the voter registration patterns of most 24-30-year-olds, albeit perhaps slightly less than among 18-19-year-olds.

For Figures C3 through C7, following the guidance below to interpret the figures.

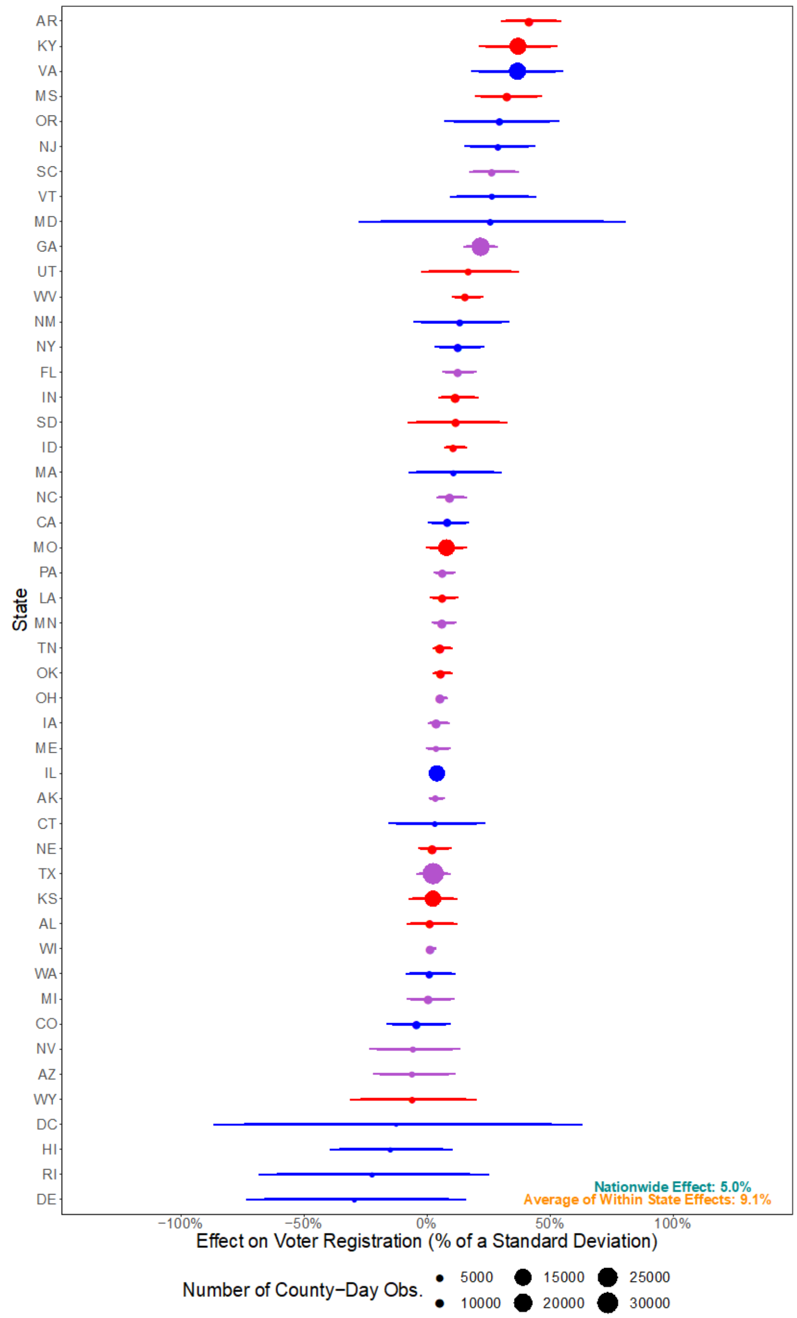
To help summarize the results from Figures I-XVII, we provide two benchmark estimates. The first is denoted with an **orange** dashed line. This estimate averages the states' individual effects. It weights all states equally; that is to say, it tells you what effect Floyd's murder had in the average or typical state. The second benchmark is denoted with a **cyan** dashed line. This line corresponds with what is shown in Figure M, which weights states according to those with more counties in them. That is to say, this approach is what we see when we allow larger states to dominate the estimation of the RDiT models. Neither of these approaches is "right"; they simply give windows into different quantities of interest in understanding the effect of Floyd's murder on voter registration.

<u>Figure C3.</u> Effect of George Floyd's Murder on Overall Registration (by State)



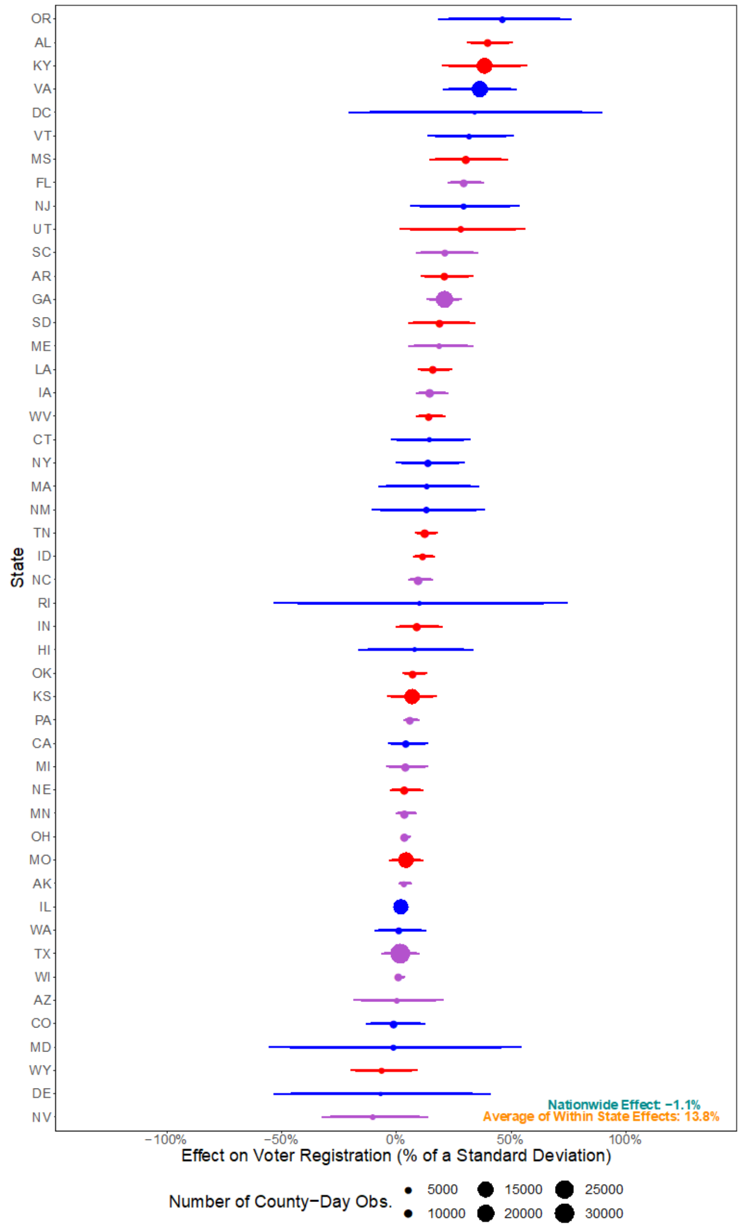
<u>Notes</u>: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C4. Effect of George Floyd's Murder on 18-30-year-olds' Registration (by State)



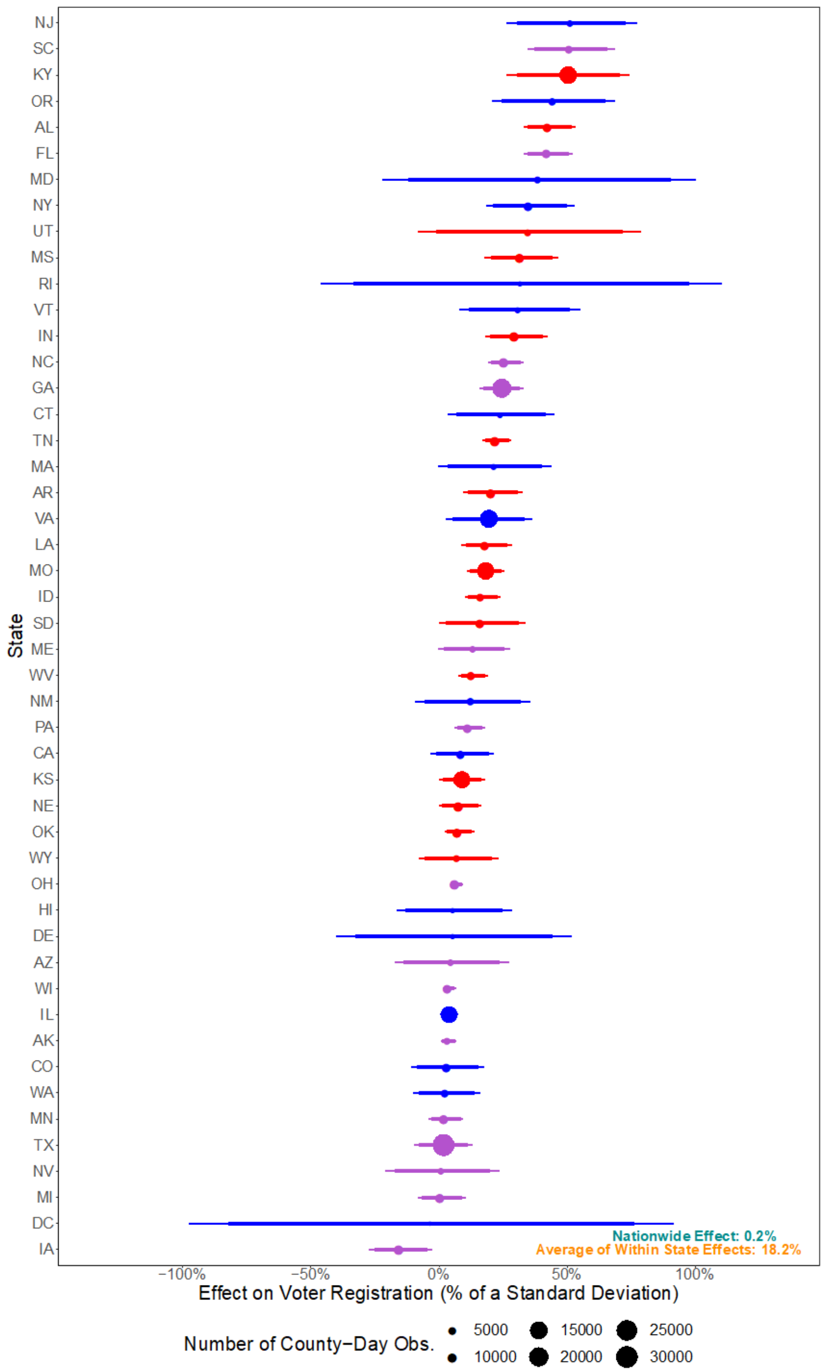
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C5. Effect of George Floyd's Murder on 31-45-year-olds' Registration (by State)



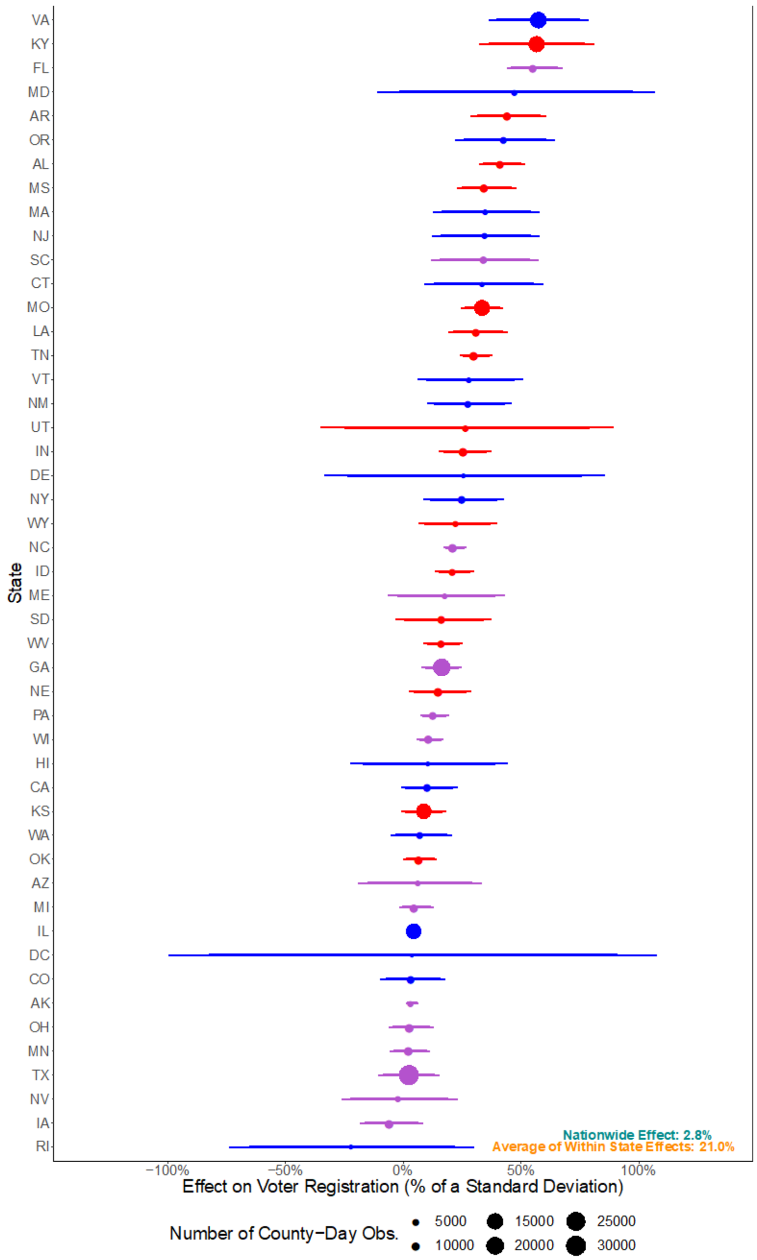
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C6. Effect of George Floyd's Murder on 46-60-year-olds' Registration (by State)



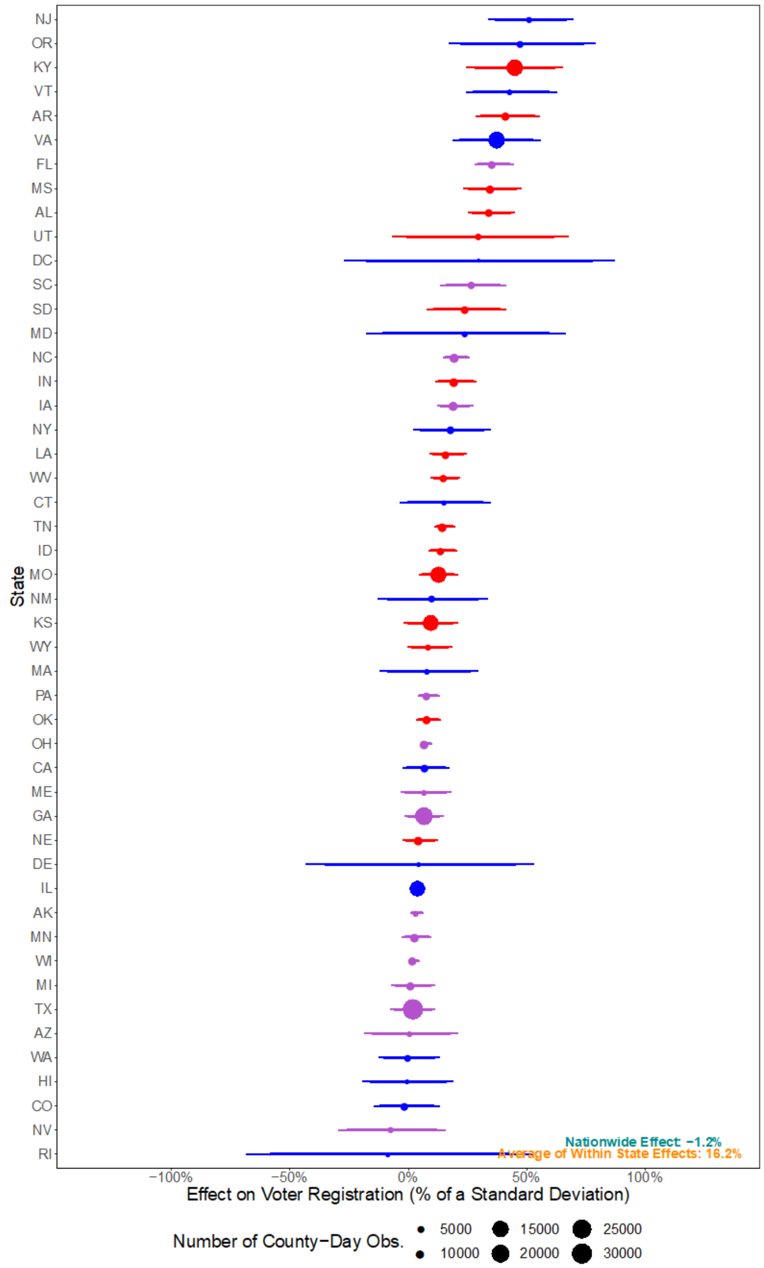
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C7. Effect of George Floyd's Murder on 61+-year-olds' Registration (by State)



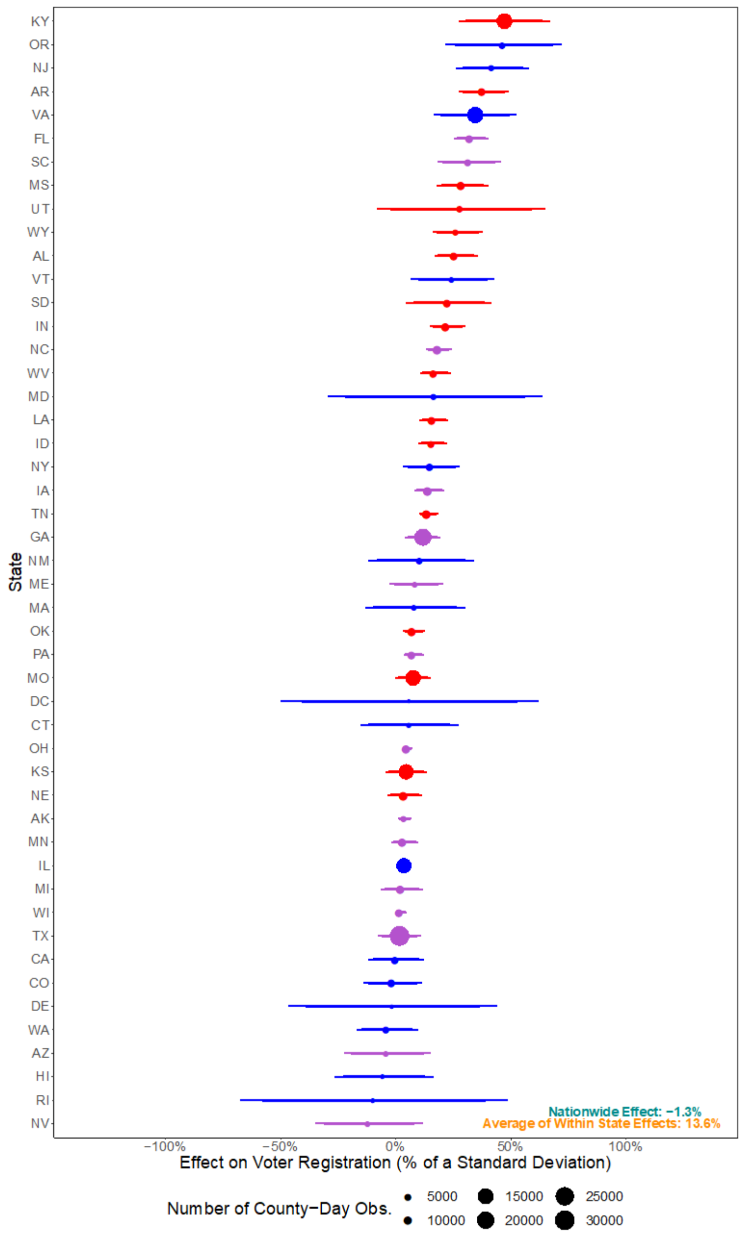
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C8. Effect of George Floyd's Murder on Males' Registration (by State)



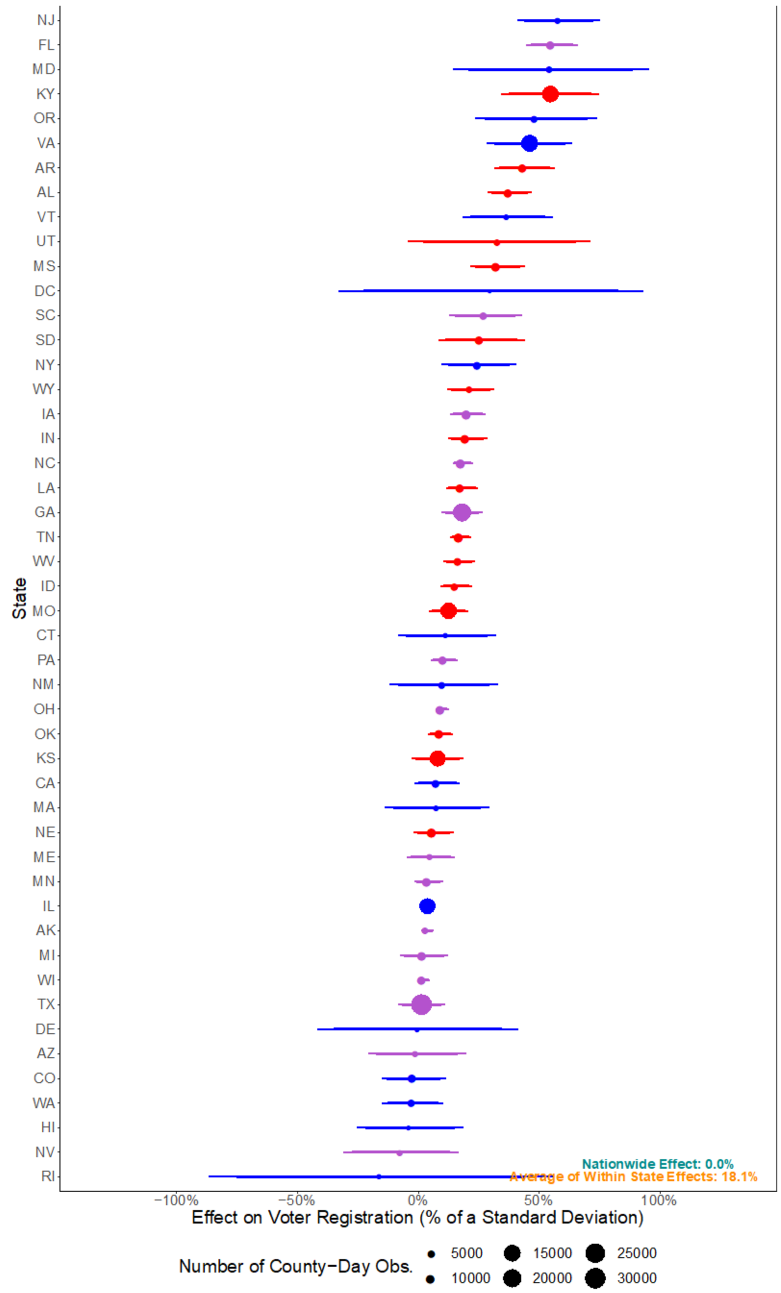
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C9. Effect of George Floyd's Murder on **Females'** Registration (by State)



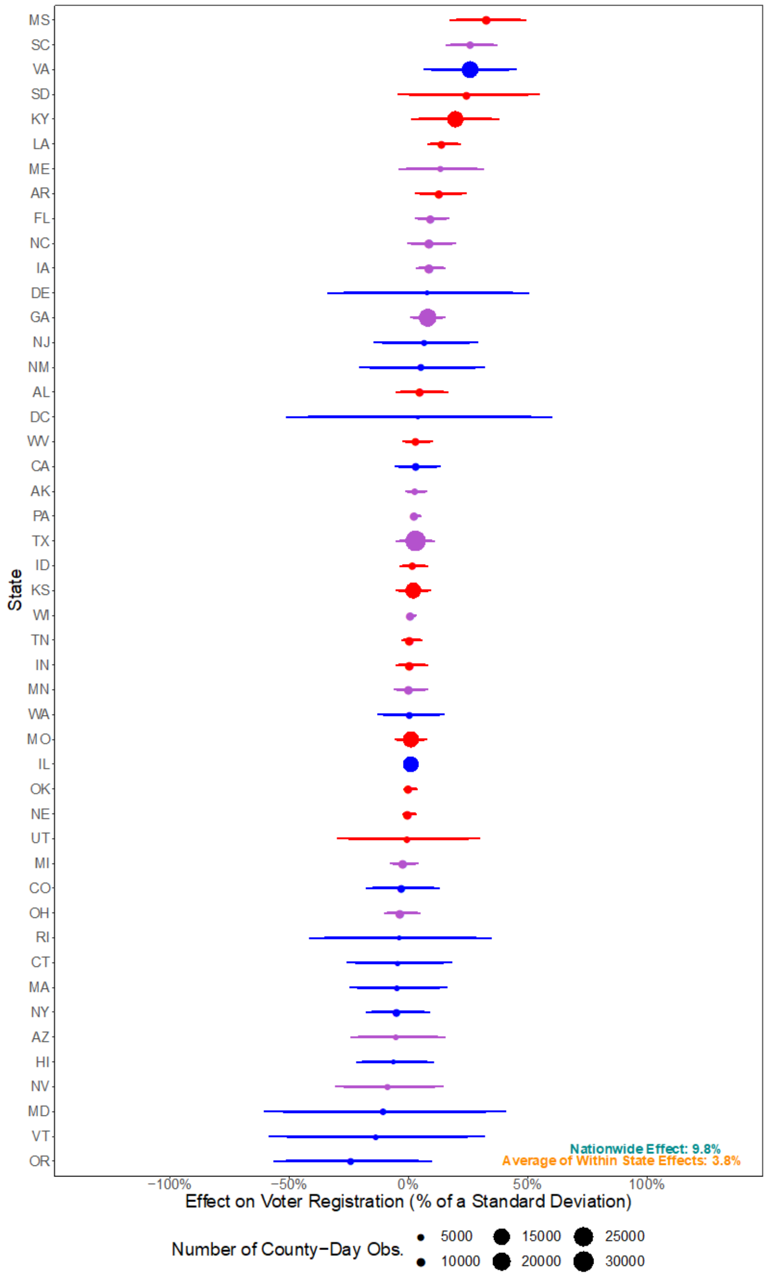
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C10. Effect of George Floyd's Murder on **Whites'** Registration (by State)



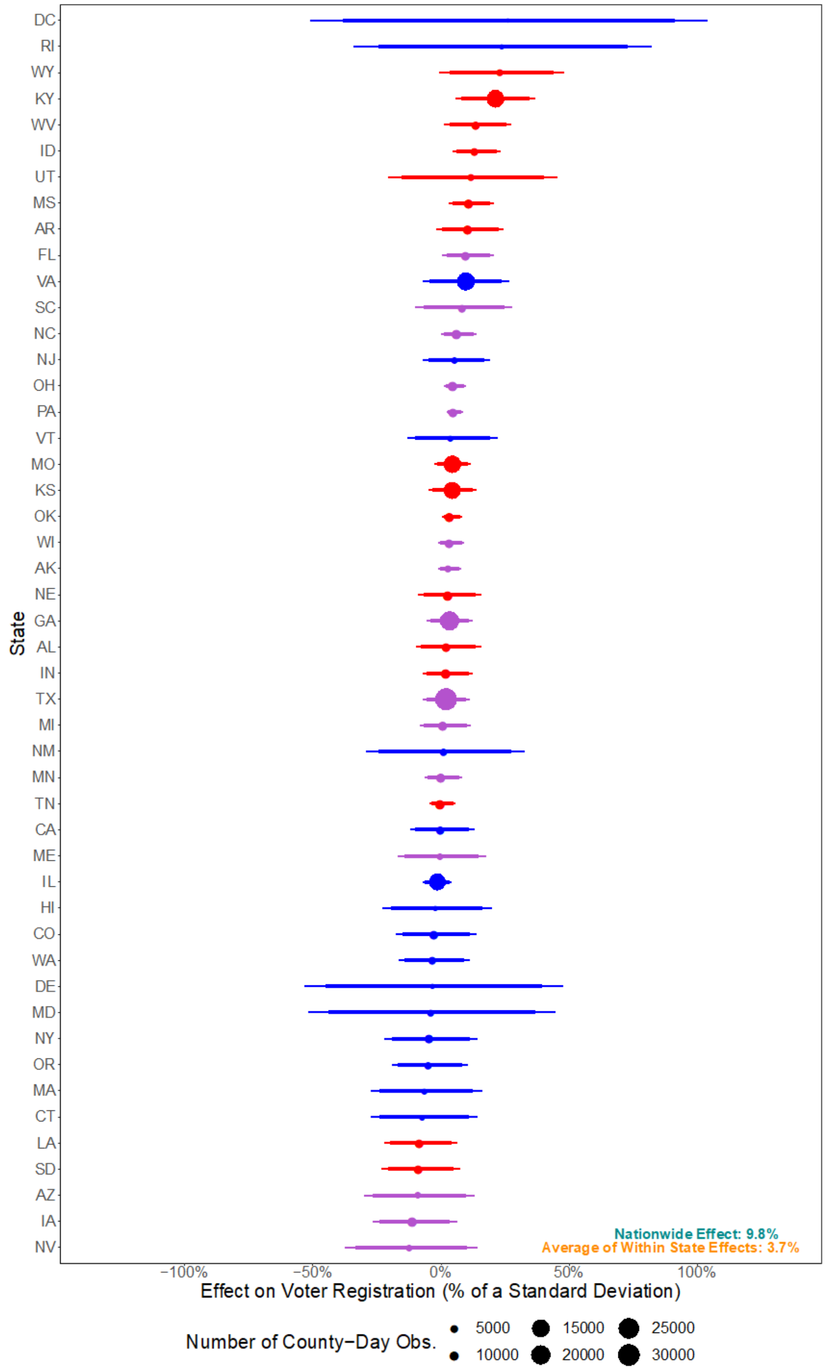
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C11. Effect of George Floyd's Murder on **Blacks'** Registration (by State)



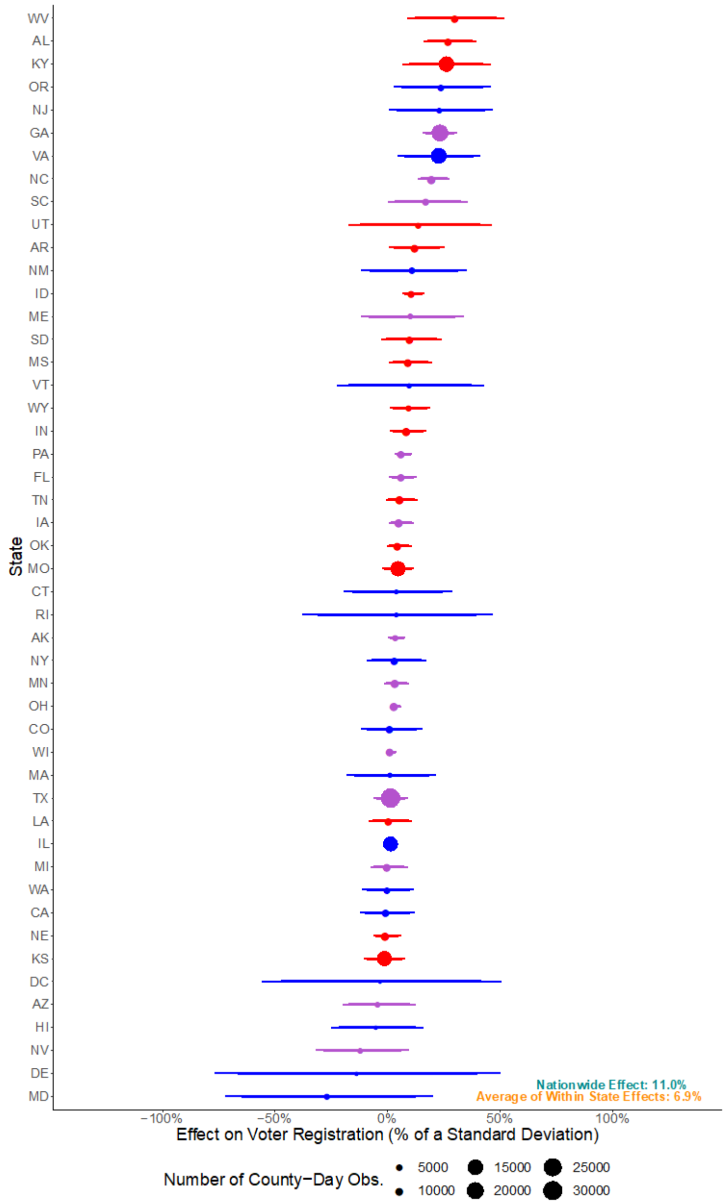
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C12. Effect of George Floyd's Murder on Asians' Registration (by State)



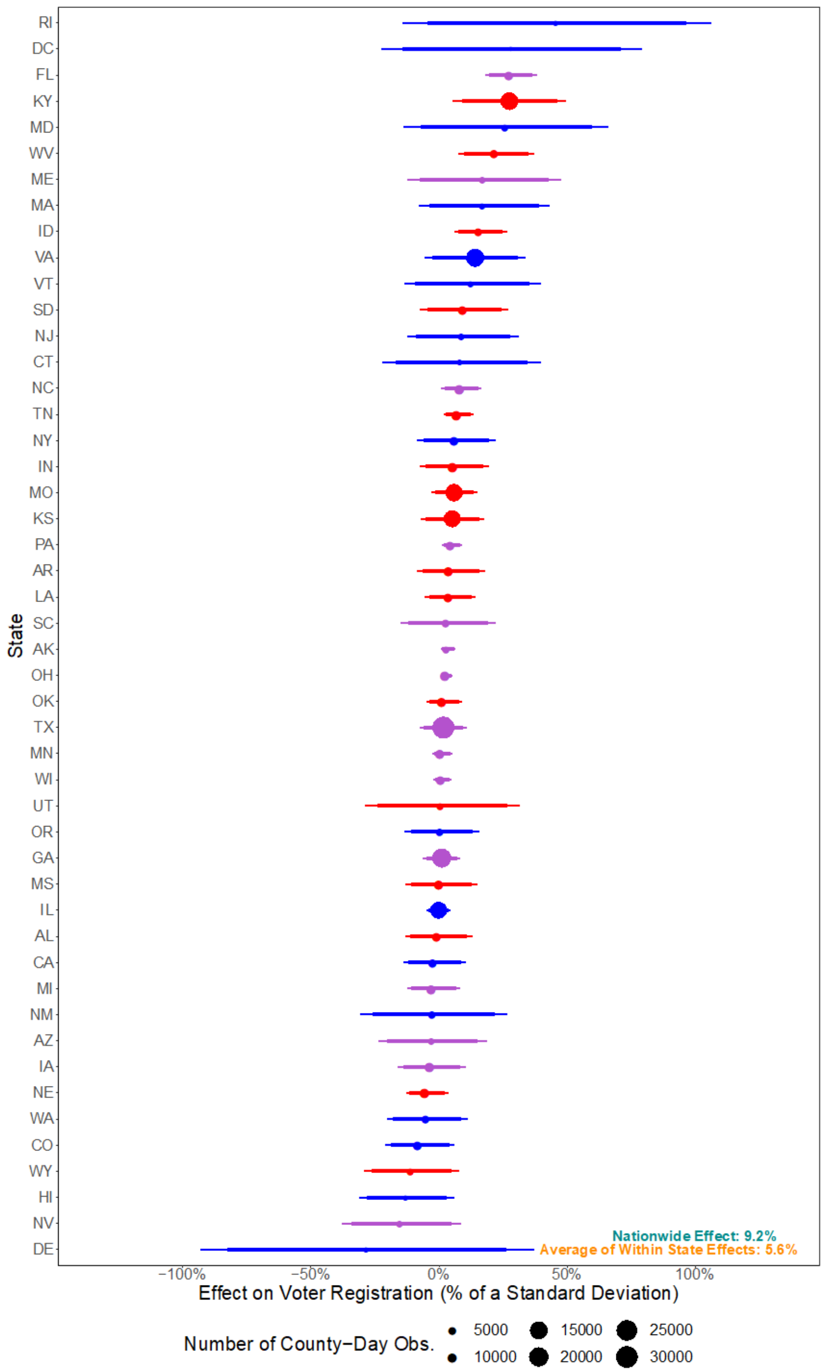
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C13. Effect of George Floyd's Murder on **Hispanics'** Registration (by State)



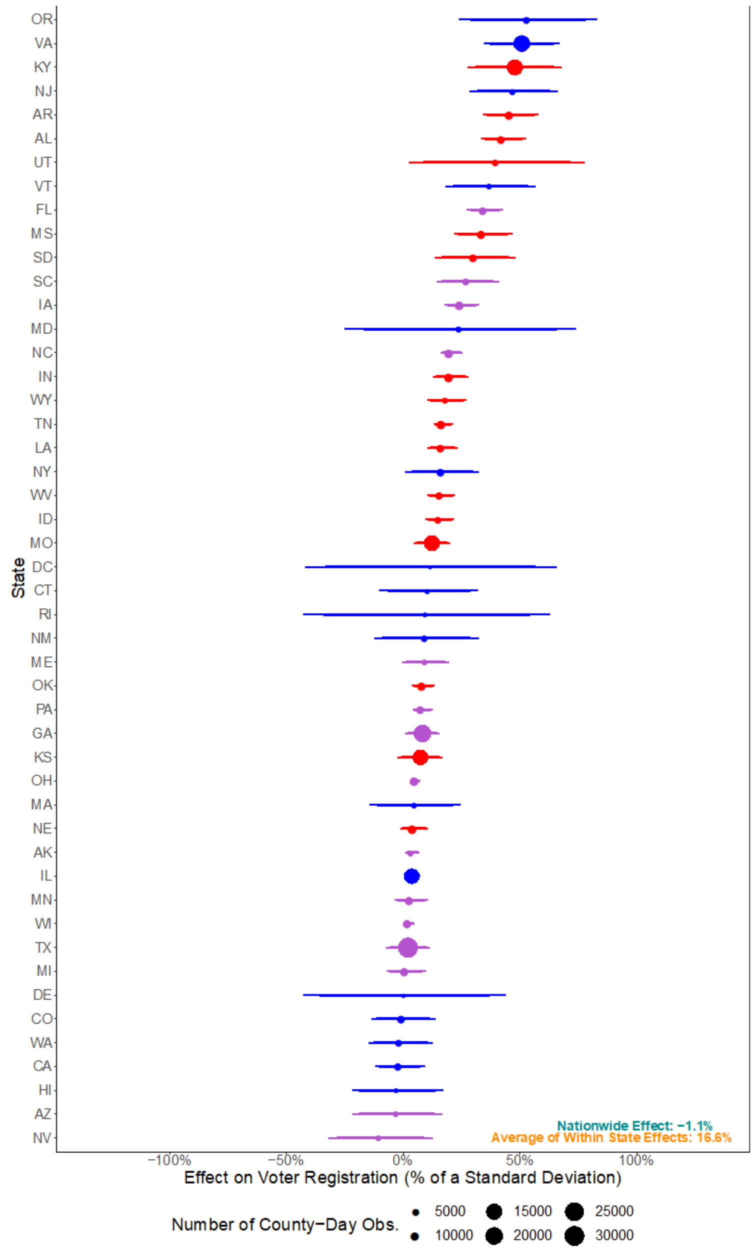
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C14. Effect of George Floyd's Murder on **Other Races'** Registration (by State)



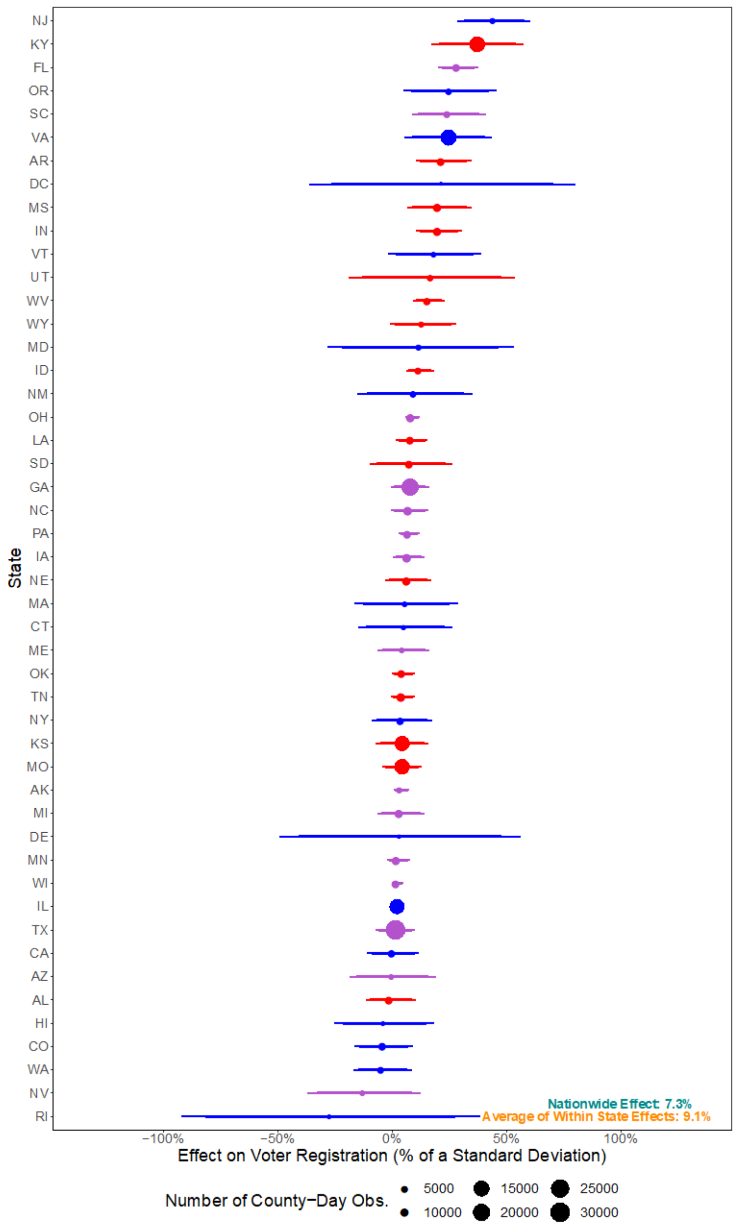
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C15. Effect of George Floyd's Murder on **Lower Income People's** Registration (by State)



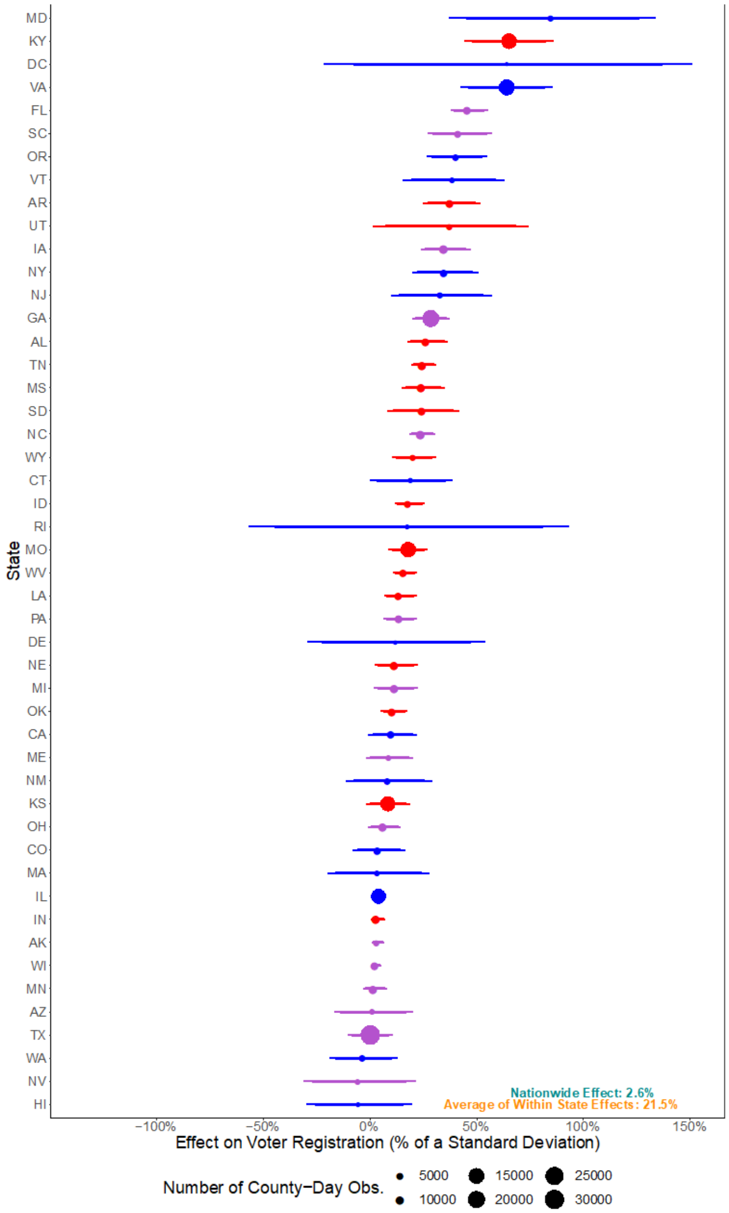
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C16. Effect of George Floyd's Murder on Higher Income People's Registration (by State)



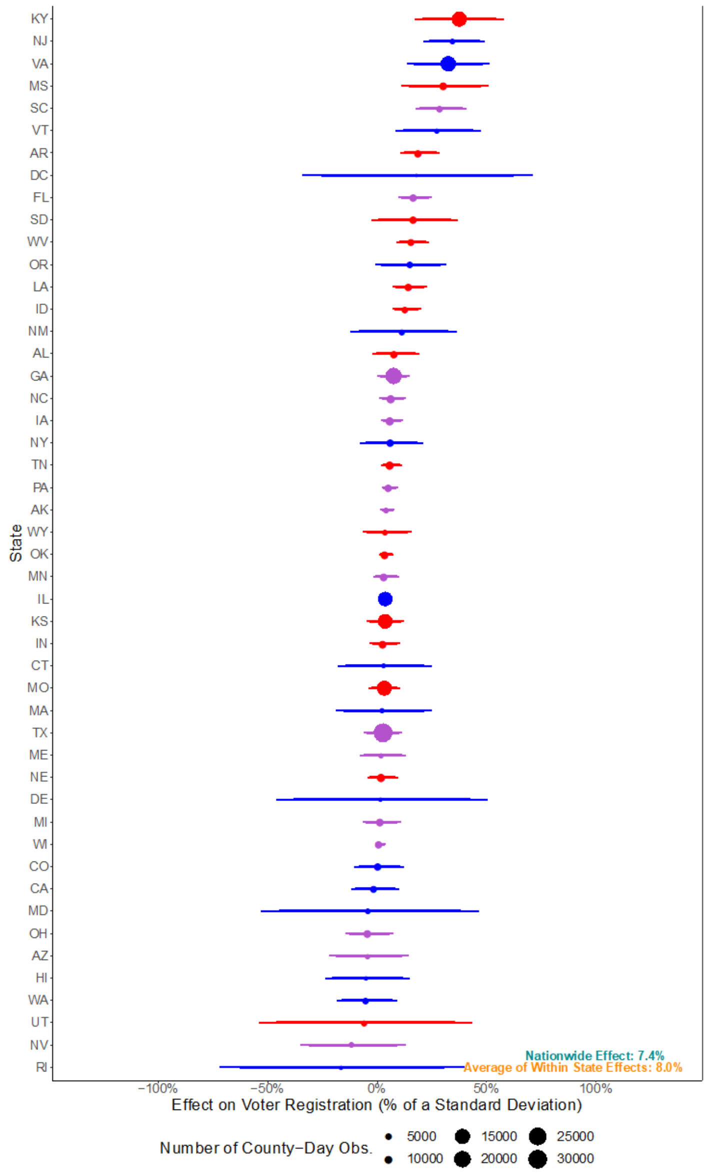
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C17. Effect of George Floyd's Murder on Republicans' Registration (by State)



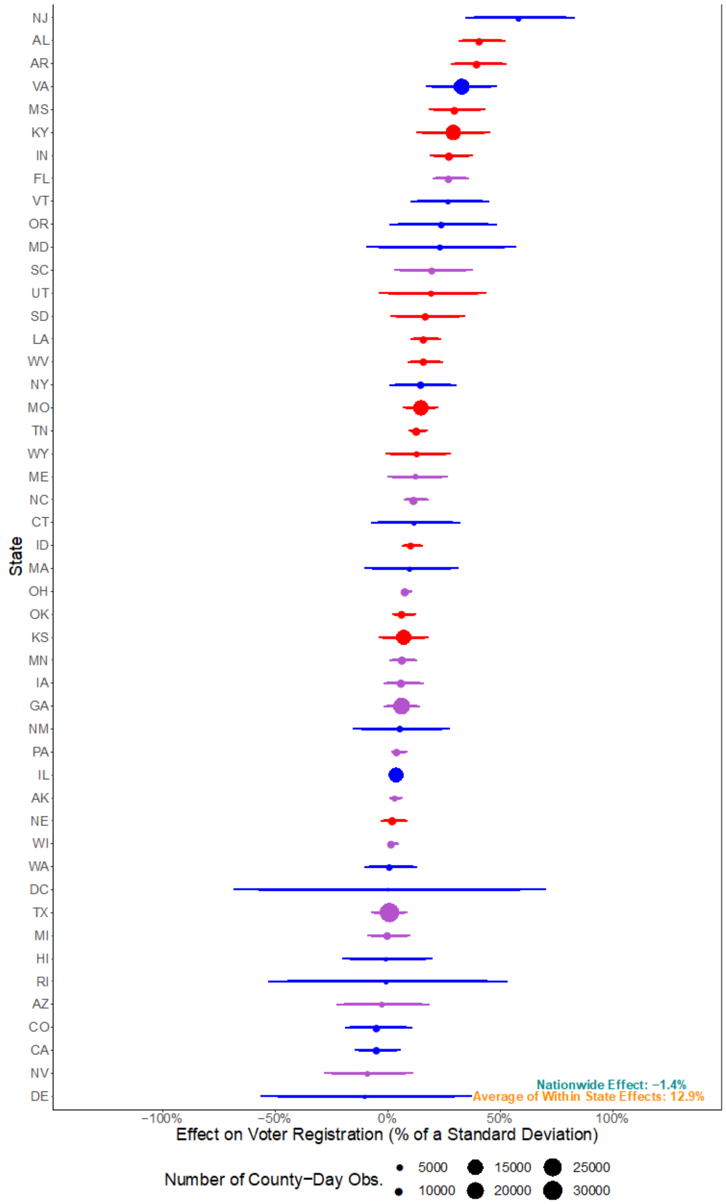
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C18. Effect of George Floyd's Murder on Democrats' Registration (by State)



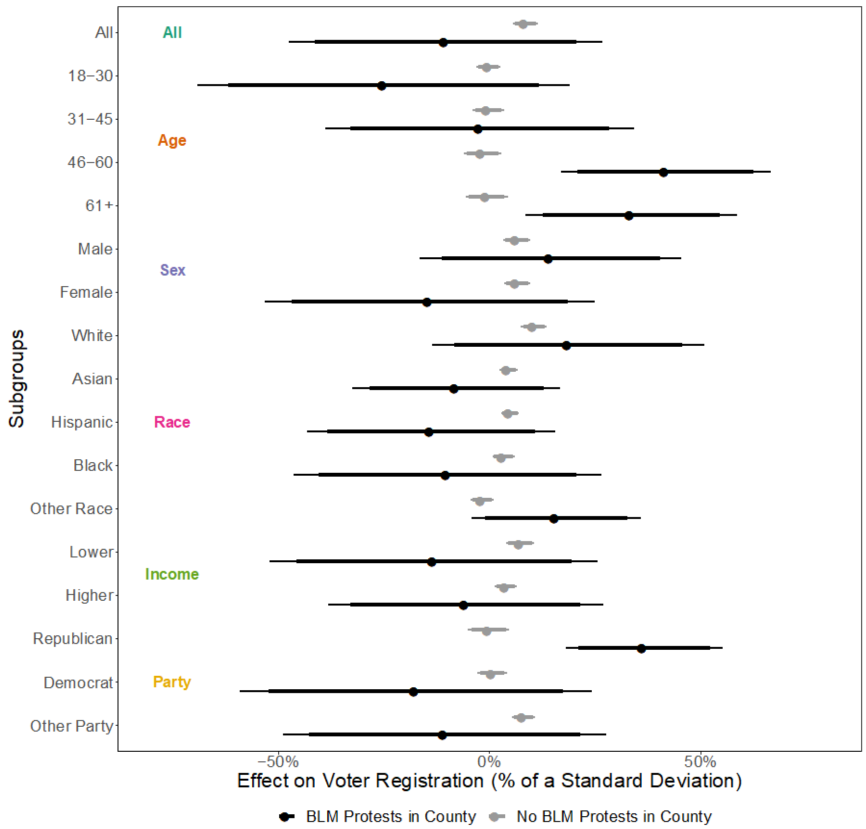
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

Figure C19. Effect of George Floyd's Murder on Other Parties' Registration (by State)



Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of subgroup listed at the top of the figure across the individual states listed on the y-axis. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Points are sized by the number of county-day observations in the respective states. The **cyan** dashed line shows the average RDiT effect when we pool all states together (see Figure M); the **orange** dashed line shows the average of the within state effects—that is the effect among the average state. The points are shaded by the tercile of democratic vote share—**blue** points/bars are states in which Biden did especially well, **purple** points/bars are tossup states between Biden and Trump, **red** points/bars are states in which Trump did especially well. **Takeaway**: there is considerable state-by-state variation in the effects of the George Floyd murder on voter registration of this subgroup.

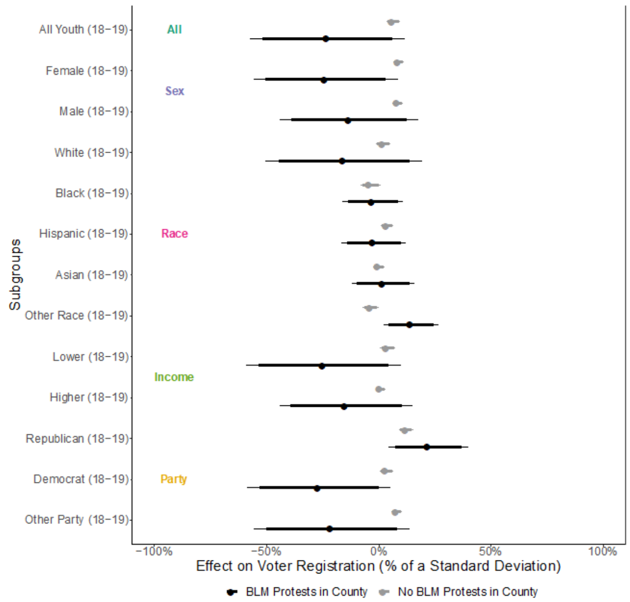
Figure C20. Effect of George Floyd's Murder on Patterns of Voter Registration, by **Protest Occurrence**



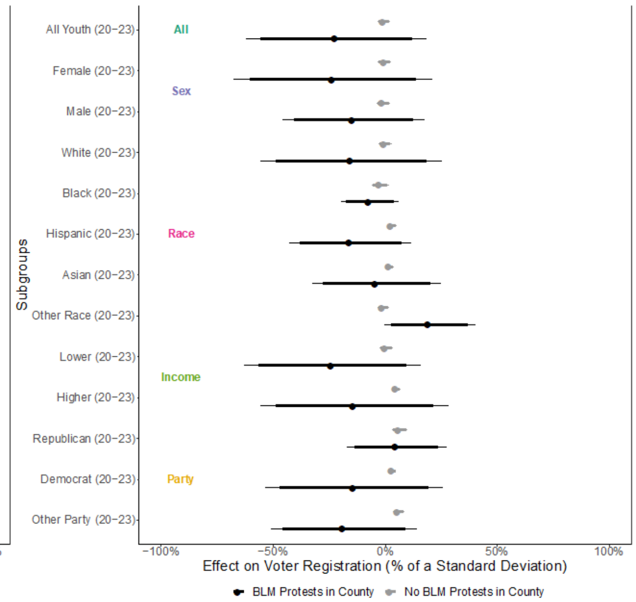
Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of listed on the left (with its corresponding shading across the figure). Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Models are broken by counties that had a BLM protest in the corresponding month in the time series. **Takeaway**: there is considerable heterogeneity in the effects of George Floyd on voter registration, with some groups being mobilized to register by having a protest in their area and others being mobilized to register by other means, such as observing the media coverage of Floyd's murder and its downstream effects.

Figure C21. Effect of George Floyd's Murder on Patterns of Voter Registration, by Protest Occurrence (Youth Subgroups)

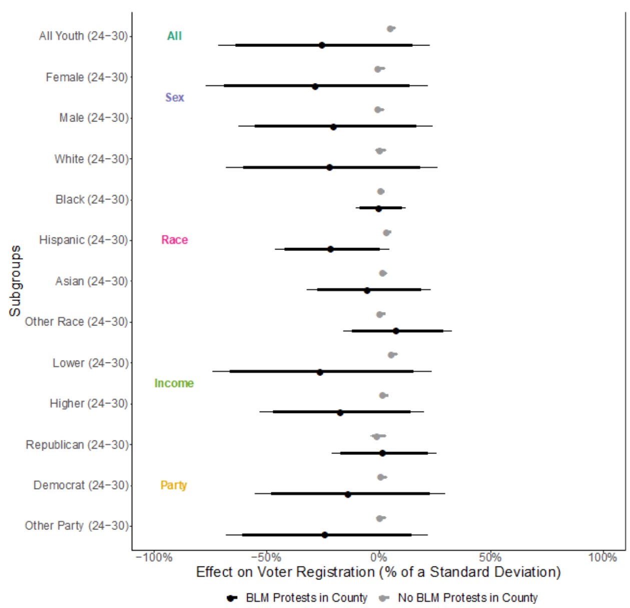
a.) Among 18-19-Year-Olds



b.) Among 20-23-Year-Olds



c.) Among 20-24-Year-Olds



Notes: Figure is a coefficient plot of the effects of the George Floyd murder on the voter registration patterns of listed on the left (with its corresponding shading across the figure). Panels show different subsets of youth. Coefficients (i.e., effect sizes) are shown with circles; thin bars denote the 95% confidence intervals for the effect estimates, while thicker bars denote 90% confidence intervals. Models are broken by counties that had a BLM protest in the corresponding month in the time series. **Takeaway**: there is considerable heterogeneity in the effects of George Floyd on voter registration, with some groups being mobilized to register by having a protest in their area and others being mobilized to register by other means, such as observing the media coverage of Floyd's murder and its downstream effects.

Appendix D: Data and Methodology

Datasets

Data for Understanding County Conditions for Protests
(from RAYSE county merge: We merged the CCC data described above with a county-level data base called RAYSE which was developed by the Center for Information and Research on Civic Learning and Engagement (CIRCLE) at Tufts University by synthesizing a large number of indicators from multiple, public datasets round five different components of civic life that tended to correlate with youth turnout; economic conditions, nonprofit density, electoral/political competitiveness, youth registration, and access to amenities/quality of life. More information can be found at https://circle.tufts.edu/sites/default/files/2020-01/rayse_index_sources_methodology.pdf. Both of the data were aggregated at county-level and were matched using State-County FIPS.

Data for Estimating the Effects of Protests on Voter Registration and Turnout
To estimate the effect of these Trump-era protests, we draw on data from two sources. First, to measure the location and timing of social protests we use data from the Crowd Counting Consortium (CCC). The CCC collects publicly available data on political crowds reported in the United States, including marches, protests, strikes, demonstrations, riots, and other actions. The CCC emerged out of a collaborative effort by Jeremy Pressman and Erica Chenoweth to provide an accurate estimate of the number of people who participated in the Women's March on Washington (and its affiliated Sister Marchers worldwide) on January 21st, 2017. Several of their colleagues expressed an interest in conducting similar kinds of efforts. Upon recognizing the growing public interest in up-to-date information on crowds—and in response to requests to continue the effort beyond the Women's March—they and their volunteer colleagues established the CCC. The CCC uses various manual and technical means of collecting and coding protests' location, date, and general details about the purpose behind the protest. The CCC data identifies the geographic location (i.e., the county), timing (i.e., the date), claim (e.g., pro-Trump or anti-Trump), and, in some instances, provides an estimate of how many people attended the protest based on media reports for the protest. In our analyses, we use the protest data from the CCC from the beginning of its inception through November 2020. We focus on the effect of protests overall, protests adjacent to a given county that they occurred in, pro-Trump, anti-Trump, climate, gun, and race-based protests. We have done extensive checking and validation of the CCC data to ensure that the protest data are of high caliber and fidelity.[1]

[1] In addition to the internal data quality checks installed by the CCC, two independent coders from our research team cleaned the CCC data and geocoded all protests according to when they occurred. The correlation between these two codings of protest location/timing was exceptionally high (r=0.972)

To measure voter registration and voter turnout, we use data from large-scale nationwide public-use voter files. In the United States, voting and registration are in the public record. That said, this data is not collected by a federal entity. Given the U.S.'s federalist system, each state collects information on whether citizens vote (but not who they vote for). These records are compiled together by firms, such as Catalist, the Data Trust, Aristotle, and (the vendor that we use) L2. These analytics firms obtain state voter files in the same way as each other and are widely used in research by academics, campaigns, and practitioners (Hersh 2015). The file that we have contains registration and voting histories of approximately 200 million individuals in the United States.[2] In addition to voting and registration, the L2 files contain information on individuals' age, gender, race/ethnicity, political party, and income (from matches they have conducted of the voter files to credit bureau data).[3]

Analytic Approach Overview

In this report, we look for effects of protests (of various types) on the voter registration and voter turnout for all citizens and citizens by various races/ethnicities, income levels, genders, political parties, and ages. In all of our analyses, we draw specific attention to young voters of various backgrounds. This focus is justified for (at least) two reasons. First, young people have traditionally low levels of political participation, but have played a key role in organizing many of the protests that occurred during the Trump presidency. And second, previous research has documented that young people's voting and registration patterns are especially malleable to external forces (Holbein and Hillygus 2016, 2020; Holbein 2017; Prior 2018). For the sake of computing power, in our analyses, we collapse these voter records from the individual to the county-month-year (for voter registration) and the county-year (for voter turnout) levels of aggregation. This means, that in our voter registration analyses, our sample size is equivalent to the number of counties in the United States (just over 3,000) times the number of months in our sample (47). This gives us a full sample size of just under 150,000 observations for our voter registration analyses. Given that we only have turnout data that overlaps with our protests data (recall that the CCC did not start collecting protest data until after Trump came into office in early 2017) in two federal elections, in our voter turnout analyses our sample size is equivalence to the number of counties (just over 3,000) times the number of elections (2). This gives us a full sample size of just over 6,000 observations for our voter turnout analyses.

Methods for Estimating the Effects of Protests on Voter Registration and Turnout

There are several ways that we can estimate the effect of protests on voter registration and voter turnout. These conceptualize what it means to be exposed to a protest in slightly different ways. First, we could treat individuals before a protest as not being exposed to a protest, but those after the protest occurred as being exposed. While we can use this

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[2] Our voter registration analyses must, of necessity, exclude New Hampshire (which does not include voter registration dates in their statewide file) and North Dakota (which does not have voter registration in the state).

[3] Age and gender are available for virtually all states. Race/ethnicity and political party are available in the voter records from some states. For those that do not have this information, it is modeled by voter file vendors. Previous research shows that these modeled race and party scores do a good job of identifying individuals of various races/ethnicities/political persuasions (Fraga, Holbein, and Skovron 2018; Igielnik et al. 2015; Fraga and Holbein 2020).

approach with both registration and turnout, only voter registration allows us to look at precise changes around the timing of the protest (because turnout is only measured during the two elections that we explore, while citizens can register at any point of time). Second, we could treat individuals who live in the same geographic area (e.g., the same county) as where a protest occurs as being exposed, but everyone else not being exposed. As in other studies that look at the effect of salient events on voter registration and voter turnout, this approach makes the implicit assumption that physical proximity is a good proxy for psychological proximity—that people closer to protests will be more affected by things that happened closer to them than those that are far away (Enos 2017; Newman and Hartman 2017, 2019; Barney and Schaffner 2019; Rogowski and Tucker 2019; Hassell, Holbein and Baldwin 2020). Again, we could use this approach for both voter registration and voter turnout. Third, recognizing that adjacent communities may also be affected, we could code individuals in nearby areas as being a part of the treatment group, but those who are not as part of the control group.

None of these approaches is perfect; all come with assumptions about how protest affect the American electorate. For example, the approach that compares voter registration and voter turnout patterns before a protest to after that protest occurs makes the assumption that nothing else occurred that could bias the relationship of interest. This assumption, while tenuous in some scenarios may be more feasible when we look precisely in the immediate aftermath of the protest. Similarly, the approach that compares areas that had a protest to areas that did not makes the assumption that those areas were not different in other ways outside of having a protest. To strengthen our assumptions, we use and combine both of these approaches in this report. Combining both information on the geographic location and the timing of protests allows us to use various panel methods for causal inference including difference-in-differences (diff-in-diffs) and regression discontinuity in time (RDiT) designs. Ultimately, using these several different approaches strengthens our ability to estimate the causal effect of protests on voter registration and voter turnout.

Difference-in-differences (Diff-in-diffs) Model

Diff-in-Diffs are a standard approach in the social sciences for estimating treatment effects with panel/longitudinal data (Abadie 2005; Angrist and Pischke 2008, 2014; Athey and Imbens; Donald and Lang 2007). In a typical difference-in-differences research design, one takes advantage of a first difference such as that in the rates of voter registration/turnout between areas that had a protest vs. those that did not and benchmarks that difference to a second difference such as the change in voter registration/turnout patterns before to after a protest is held.

In our application, our diff-in-diffs benchmark how rates of voter registration and voter turnout changed in areas that had protests relative to the rates of change in voter registration voter turnout for areas that did not have a protest. For our voter registration outcome, we aggregate the L2 voter files up to the month-year level. This allows us to examine how protests affected voter registration in that given month. Given our large sample size for voter registration—which is equal to the number of counties in our sample (roughly 3,000) * the number of months in our sample (roughly 48)—we are able to run fairly sophisticated difference-in-differences specifications which include county and month-year fixed effects as well as linear and quadratic time trends for each county. This, in essence, allows us to control for 1.) things that remain constant within counties—such as the culture and size of the county, 2.) things that remain constant within given month-years—such as seasonal patterns in voter registration, and 3.) things that force some counties to trend towards more registration over time—such as improvements in voter registration access or technologies. For our voter turnout outcome, sadly, we only have our outcome measure in two time periods—those that from the 2018 and 2020 elections. This is the case as we do not have data on protest location/timing before the start of the Trump presidency (i.e., in 2017).[4] Given our limited time series—whose sample size is equivalent to the number of counties in the United States (roughly 3,000) * the number of federal elections in our sample (2)—we have to be careful in reading too much into the turnout estimates. These can only leverage intra-county changes in voter turnout from 2018 to 2020 above and beyond what we would normally expect to see from a midterm election to a presidential election.[5] In these models, we can control for overall differences between midterm and presidential elections, but we cannot account for forces that drive differences in the changes of voter turnout rates over time and across counties that are unrelated to whether those counties had a protest in that given year.

Diff-in-diffs are not without their challenges. For example, in a difference-in-differences design, it is hard to estimate treatment effects when we have few treated units; as is the case, for example, when all protests of a specific type are relatively rare and are clustered in one time period (MacKinnon and Webb 2020). That said, this approach has a great degree of value in combining both geographic and temporal variation in protest exposure. As such, it is a flexible tool in estimating the effects of protests on voter registration and voter turnout.

Regression discontinuity designs

Regression discontinuity designs (RDDs) are also a standard research design for estimating causal effects in the social sciences (Angrist and Pischke 2008, 2014; Calonico, Cattaneo, and Titiunik 2014). For example, some scholars have used regression discontinuity methods to estimate the effect of students marginally failing a standardized test (Ahn and Vigdor 2014; Holbein 2016; Holbein and Hassell 2019; Holbein and Ladd 2017; Thistlethwaite and Campbell 1960), barely living on one side of a geographic boundary (Clinton and Sances 2018; Heissel and Norris 2018; Schafer and Holbein 2020), or winning a very close election (De la Cuesta and Imai 2016; Eggers et al. 2015; Hall 2015). RDDs leverage as-good-as-random variation and continuity in potential outcomes around an arbitrary cutoff. That is to say, in all applications of regression discontinuity designs, researchers take advantage of the fact that close to an arbitrary cutoff people are essentially randomly assigned to either a treatment or a

[4] We do not look at off-cycle elections given the large differences in contexts and ballots of areas that had local elections during the time period of study.
[5] Given our smaller sample size for our voter turnout measure, we can only include county and year fixed effects in our difference-in-differences models. These account for forces outside of protests that remain constant within counties and within years.

control group. This is because, in most cases, individuals cannot control on which side of the discontinuity or cutoff they fall—students very close to passing or failing an exam cannot precisely manipulate where they are relative to the cutoff, individuals near a geographic boundary don't often sort around it, and which candidate wins a close election with razor thin margins is essentially as-good-as random—being outside of the control of the actors at play. This is especially true when the precise location or the precise timing of the discontinuity is unknown to the actors at play.

In our application, we take advantage of the fact that the precise timing of *some* protests is not known beforehand. That is to say, within a narrow window of days around when some protests occur, potential registrants before and after the event are essentially the same—aside from being as-good-as randomly assigned to being exposed to a protest. This is only true in some cases. Some protests spring up out of the (metaphorical) woodwork without much planning. Others, however, are planned long before they actually occur and, as such, are (perhaps) located in areas that are not all-else-equal to the areas in which they do not occur. In instances where the location and timing of protests are timed well in advance, we might run the risk of having biased estimates. Essentially, in these scenarios, we would be worried that planners of protests would have protests in areas that are fundamentally different from areas that do not have protests. For example, protest planners may target protests in areas where voter registration/voter turnout of target groups was low *specifically because* they wanted to change those patterns. If this were the case, our difference-in-differences research design might actually be picking up on these forms of what researchers call selection biases. Fortunately, for some protests—including those that followed the killing of George Floyd—it is essentially random whether individuals close to the cutoff are exposed to a protest or not. Given the quasi-random nature of the George Floyd/Black Lives Matter protests—which sprung up organically in the immediate aftermath of Mr. Floyd's killing—we can look use the days around this exogenous event to look at the effect of protests on patterns of voter registration (Reny and Newman 2021).[6] (We cannot apply this same research design to our measure of voter turnout because Americans were not voting in the immediate days before and after the killing of George Floyd.)

Appendix D Figure 1 provides of visualization of our RDiT design. On the horizontal axis we plot the days before (on the left) and after (on the right) George Floyd's murder (which is denoted with a **grey** vertical dashed line). The **brown** dots show the number of protests that occurred each day in this time series. The lines show various ways of modeling the relationship between the days before/after Floyd's murder and the number of protests that occur over time, using linear, quadratic, cubic, and loess functional forms. As can be seen, starting on the day of George Floyd's shooting (May 25, 2020), there was a very large jump approximately equivalent to 300 additional protests and approximately 123,000 additional protestors. Before Floyd's murder, there were some few protests that occurred, but these

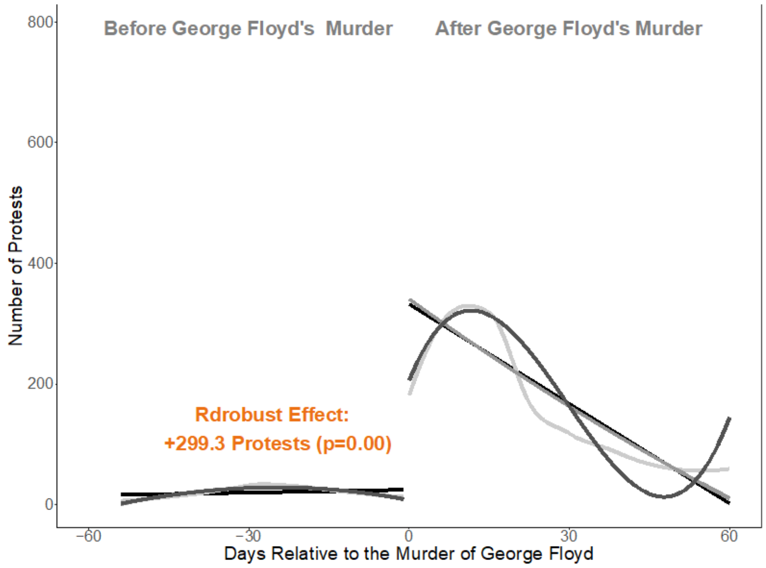
[6] Reny and Newman (2021) validate that the timing of George Floyd's murder was, as best we can tell, exogenous to other forces. Reny and Newman (2021) use that fact to examine the effect on Mr. Floyd's death on political attitudes, such as individuals' views toward the police and African Americans. We extend their research design to also look at political behaviors such as voter registration.

were fairly low and steady in the days that preceded this tragedy. In the days that immediately followed Floyd's murder, there were hundreds of protests (at the peak) and hundreds of thousands of protestors that are directly attributable to Floyd's death and subsequent media coverage of this event. Our RDiT leverages the large and unanticipated nature of the protests generated by Floyd's murder to see if there are also simultaneously jumps in voter registration at the same cutoff. In so doing, we are able to see whether the events that trigger large-scale protests also cause citizens to wield their political power in other domains.

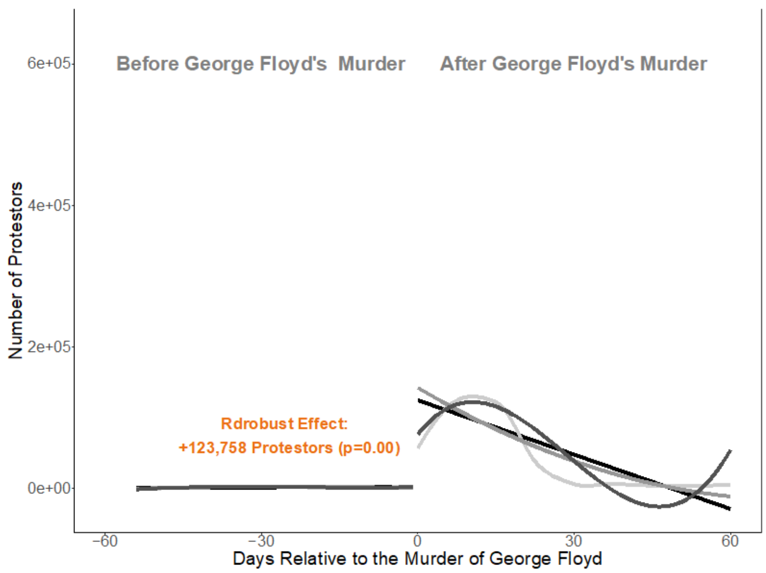
There two primary pathways by which George Floyd's murder could have affected voter registration. First, individuals who attended a protest or who lived in close geographic proximity to a protest may have been directly mobilized to register through their fellow protestors and parallel organizational groups that latched themselves onto this organize protest movement. Indeed, we have quite a bit of qualitative evidence that this registration-driven focus played a key role in some areas that had George Floyd protests. Alternatively, those who live closer to a protest may view protesting as a substitute, rather than a complement, to registering (and hopefully, ultimately, voting). A second way, however, that Floyd's murder could affect voter registration is through the media coverage that occurred in this shooting's immediate aftermath. Even if individuals did not live in an area where a protest occurred, the intense spike in media (traditional and new) coverage of Floyd's shooting and the protests that followed mean that the effects of Floyd's murder need not be constrained to areas with protests. Again, this indirect effect could be positive or negative—individuals could be mobilized or demobilized by seeing the coverage of Floyd's murder/the protests that followed—and they could vary by individual groups—perhaps being present among Republicans for different mechanistic reasons than for Democrats, for example. While we cannot test psychological mechanisms that drive one to register, one could imagine different rationales for different individual groups being mobilized/demobilized at different levels across subgroups. And exploring differences across geographic location and individual subgroups is still illuminating of the broader potential moderators driving any potential registration effects.

Appendix Figure D1: The Discontinuous Increase in Protest Activity Around the Precise Date of George Floyd's Murder—Illustrating the Regression Discontinuity in Time Design

I. Effect of Floyd Murder on the Number of Protests



II. Effect of Floyd Murder on the Number of Protestors



Notes: Figure plots the days relative to George Floyd's murder on May 25th, 2020 on the x-axis. Dates before Floyd's murder are on the left, while dates after Floyd's murder are on the right. The date of Floyd's shooting is denoted with a grey dashed line. On the y-axis are the number of protests held each day in the time series. The lines show various functional forms of the relationship between these two variables, including: linear, quadratic, cubic, and loess. As can be seen, George Floyd's murder caused a jump of about 300 additional protests. **Takeaway**: George Floyd's murder caused a large spike in protest activity that can be used to explore the effect of as-good-as random protests on patterns of voter registration.

In short, in addition to leveraging time in our RDiT models, in some specifications, we also take into account geographic proximity. We do this by sub-setting our RDiT models to each state individually, only areas that had a protest, and only areas that did not have a protest. These models allow us to explore whether Mr. Floyd's murder had any impact on patterns of voter registration that varied by the proximity to the shooting, by whether there were protests in the area, and by other social forces present in these various geographic areas.

Adjusting for population size in our models examining voter registration: In all of our model specifications for our voter registration outcome, we account for the fact that some areas/time periods are more likely to see higher numbers of voter registrations than others. This is true because some areas have higher populations and because people are much more likely in the periods leading up to an election than during off-cycle periods. While this fact is somewhat accounted for in our model specifications that include geographic and time-period fixed effects, we take one more step to account for inherent differences in registration counts. We do this by standardizing our registration counts measure with state-years. This allows us to see protests change the normal pattern of voter registration in a given state and time period above and beyond the patterns that we would normally see in that context. In addition to allowing us to account for inherent differences in registration patterns, this simple (and common) transformation also allows us to better get the sense of how large/small our effects are. For our voter registration models, our outcomes are scaled such that the estimated effects are equal to the percent of a standard deviation (i.e., a common measure of variance). That is, our effect estimates benchmark the change (if any) in registrations relative to normal/standard changes we see in the distribution of voter registration over time.

CIRCLE, the Center for Information & Research on Civic Learning and Engagement at Tufts University's Tisch College of Civic Life, served as coordinator for the research.