Divergent Partisan Compliance with Shelter-in-Place Orders during the COVID-19 Pandemic

Alec MacMillen*
University of Chicago
amacmillen@uchicago.edu

June 12, 2020

Abstract

Shelter-in-place orders (SIPOs) have emerged as one of the preeminent policy tools used by state and local officials to prevent community spread of the novel coronavirus (COVID-19) in the United States. SIPOs are difficult to enforce, so their success relies largely on public acceptance of and compliance with the onerous restrictions they entail. Allcott et al. (2020) explore trends in mobility and find that Democratic-leaning counties are more likely to engage in social distancing than Republican-leaning counties. This paper further explores that dynamic, and focuses explicitly on the implementation of SIPOs and the changes in mobility that results in counties of different partisan persuasions. The main empirical specification finds that the 10th-percentile Republican county is likely to register 25% fewer visits to points-of-interest (POIs) than the 90th-percentile Republican county in the week that a SIPO goes into effect. This trend persists to the end of a SIPO's effective period: under the same specification, the 10th-percentile county is likely to log 30% fewer POI visits than the 90th-percentile county in the week that a SIPO is lifted, and this partisan effect is detectable even 3 weeks after a SIPO is lifted. This relationship is robust to a strict set of controls and alternate dependent variable specifications, and has significant policy implications for the long-term response to COVID-19 that will unfold over the coming months and years.

Keywords: social distancing; COVID-19; shelter-in-place orders; partisanship; mobility

*Thanks to Chris Berry, Anthony Fowler, Tammy Glazer,a nd Camilo Arias Martelo for their helpful comments and suggestions. All remaining errors are my own.

1 Introduction

Since first being identified in Wuhan province in December 2019, the novel coronavirus (COVID-19) has wreaked havoc across the globe. As of June 12, 2020, more than 7.2 million cases and 413,000 deaths have been reported worldwide, and the United States holds the dubious distinction of being the global leader in both confirmed cases (2.1 million) and deaths (116,000). COVID-19 is a highly infectious respiratory disease that spreads easily between humans, so federal, state, and local governments have sought to reduce community transmission by enforcing shelter-in-place orders (SIPOs) to encourage, and in many cases require, that citizens "stay safe, stay home" and avoid going outside for non-essential purposes. Since March 2020, 42 states have issued statewide mandatory SIPOs that have lasted anywhere from a few weeks to nearly three months. Even in states without formal SIPOs, some counties have taken the initiative to direct their residents to stay home.

SIPOs, of course, are policies of such scale that they are difficult to enforce, and their success relies largely on public compliance. Allcott et al. (2020) examine trends in travel during the first half of 2020 using metrics from mobility company SafeGraph and find that American communities are not all equal in their adherence to social distancing directives. Using data on visits to points-of-interest ("POIs") across the nation, they find that residents of Republican-leaning counties are statistically much less likely to reduce their movement as compared to their counterparts in Democratic-leaning counties. These findings have significant implications both health-wise and economically, and also serve to illustrate deep-seated cleavages in public sentiment and trust in institutions. I expand on Allcott et al.'s methodology to examine these divergent partisan trends in mobility related directly to the implementation of SIPOs. Do counties of different partisan persuasions react to SIPOs differently? If so, how do these differences persist or dissipate as time passes from the beginning of the SIPO to the end, and beyond?

2 Literature Review

Despite the short timeframe since the advent of COVID-19 and the rapidly changing nature of the situation, there is an extensive literature examining policy responses to the pandemic. Several studies have attempted to quantify the epidemiological effects of SIPOs: Courtemanche et al. (2020) find that such orders, along with bans on large gatherings, have had statistically significant effects on lowering the case growth rate. Dave et al. (2020) concur that SIPO adoption contributed to declining case rates, although they stress the majority of these benefits accrued to early adopters and high-population density states. Using a synthetic control study design, Friedson et al. (2020) find that California's SIPO reduced COVID-19 cases by 125.5 to 219.7 per 100,000 population within a month. Greenstone and Nigam (2020) take an actuarial approach and project that 3-4 months of social distancing starting in March 2020 would save 630,000 lives by October 2020, equivalent to approximately $8 trillion according to the US government's definition of the statistical value of a life.

A rich literature has also emerged using human mobility, rather than COVID-19 prevalence, as an outcome of interest. Abouk and Heydari (2020) use mobility data and an event-study design to rank the effectiveness of several policy interventions at reducing social interaction. They find that statewide SIPOs had the strongest causal impact on reducing social interactions. Conversely, Gupta et al. (2020) find that emergency declarations, not SIPOs, had the largest impact on reductions in mobility, and they thus argue that individuals will voluntarily engage in social distancing once they are aware of the health risks of failing to do so. To the extent that the timing of statewide SIPOs determines trends in mobility, Adolph et al. (2020) assert that the party membership of sitting governors explains variation in timing of these SIPOs - namely, Republican governors were significantly more likely to refrain from issuing statewide SIPOs until later than their Democratic counterparts. At the individual level, in an analysis most closely related to that of this paper, Painter and Qiu (2020) show that residents of Republican counties are less likely to stay at home after a state SIPO has been implemented relative to those in Democratic counties.[1]

A logical hypothesis from the existing literature is that SIPOs reduce COVID-19 cases and deaths vis-a-vis their impact on human mobility - by reducing or eliminating travel and daily activities outside the home, SIPOs limit opportunities for community spread. Of course, SIPOs

[1] It's worth highlighting the findings of Wright et al. (2020), who show that low-income areas comply less with SIPOs, to note that the direct relationship between partisanship and social distancing adherence may be somewhat confounded by socioeconomic factors.

are only as effective as the population is compliant, and it is for this reason that understanding the dynamics of SIPO compliance across counties of disparate ideological leanings is particularly important. Anecdotal evidence[2] suggests that there are partisan cleavages in adherence to social distancing, with such reports hitting a peak during the Memorial Day holiday weekend.[3]

This paper aims to address a gap in the existing literature by comparing partisan divergence in adherence to mandatory SIPOs during both the onset and relaxation periods. Understanding how different populations respond to government directives on social distancing will help inform policy-making around public health and economic recovery as the United States moves from handling an acute short-term crisis into managing a longer-term engagement with COVID-19.

3 Data & Methodology

3.1 Data Sources

All mobility metrics are derived from data provided by SafeGraph. SafeGraph aggregates GPS pings from approximately 45 million mobile devices to measure foot traffic patterns around a predefined set of points-of-interest (POIs), which include a wide variety of public locations. SafeGraph reports daily counts of visitors to each of approximately 5 million POIs across the United States, as well as the POI's geographic location and industry. The main dependent variable of interest, the log of POI visits by county and by day, is calculated by aggregating data reported at the POI-day level in SafeGraph's *Weekly Places Patterns* data product. Alternate dependent variable specifications (drawn from SafeGraph's *Social Distancing Metrics*) include median home and non-home dwell time, defined as the median time spent at the location designed "home" (based on historical location patterns) by all devices within a given geographic and temporal unit.

Information on the main explanatory variable, county-level partisanship, is derived from election returns provided by MIT's Election Data and Science Lab[4] that was accessed using the `elections` package in R. Data on COVID-19 cases and deaths at the county level comes from *The New York Times*.[5] The data include daily counts of cumulative cases and deaths for all counties and

[2]See popular accounts in the Economist, the Atlantic, and the New York Times.
[3]See stories from the Guardian and Vox.
[4]Harris (2020*a*)
[5]Smith et al. (2020)

county-equivalents in the United States. Killeen et al. (2020) provide a helpful dataset of county-level policy interventions, including detail on diverse interventions and effective dates. County-level implementation dates for SIPOs are sourced from this dataset and from the National Association of Counties.[6] Demographic covariates are from the 2016 5-year American Community Survey (ACS) administered by the US Census Bureau, accessed using the `tidycensus` package in R.[7] Weather data, which includes information on daily maximum temperatures, minimum temperatures, and precipitation, is provided courtesy of gridMET.[8]

3.2 Empirical Specification

Building on the model of Allcott et al. (2020), my main empirical specification takes the form:

$$log(c_{it}) = \alpha_t \rho_i + X_{it} * \gamma_t + \varepsilon_{it} \tag{1}$$

where c_{it} is the number of POI visits in county i during week t, X_{it} are non-parametric and time-varying controls, and ε_{it} is the county-specific error term. Standard errors are clustered at the county level throughout.

The chief extension beyond the methodology of Allcott et al. (2020) comes in the specification of the weekly covariates: rather than reporting a coefficient estimate for the partisan difference between Democratic and Republican-leaning counties in POI visits by *absolute* week (that is, corresponding to a specific date on the calendar), I limit my sample to the universe of counties that were ever under a mandatory SIPO and adjust weekly measures to be reported relative to the week that a SIPO started and to the week that it ended.[9] This approach discards temporal variation in the issuance of SIPOs, which allows us to estimate potentially divergent partisan trends in mobility *with respect to* the enactment of these policies themselves.

[6] Harris (2020*b*)

[7] *American Community Survey 5-year estimates* (2016)

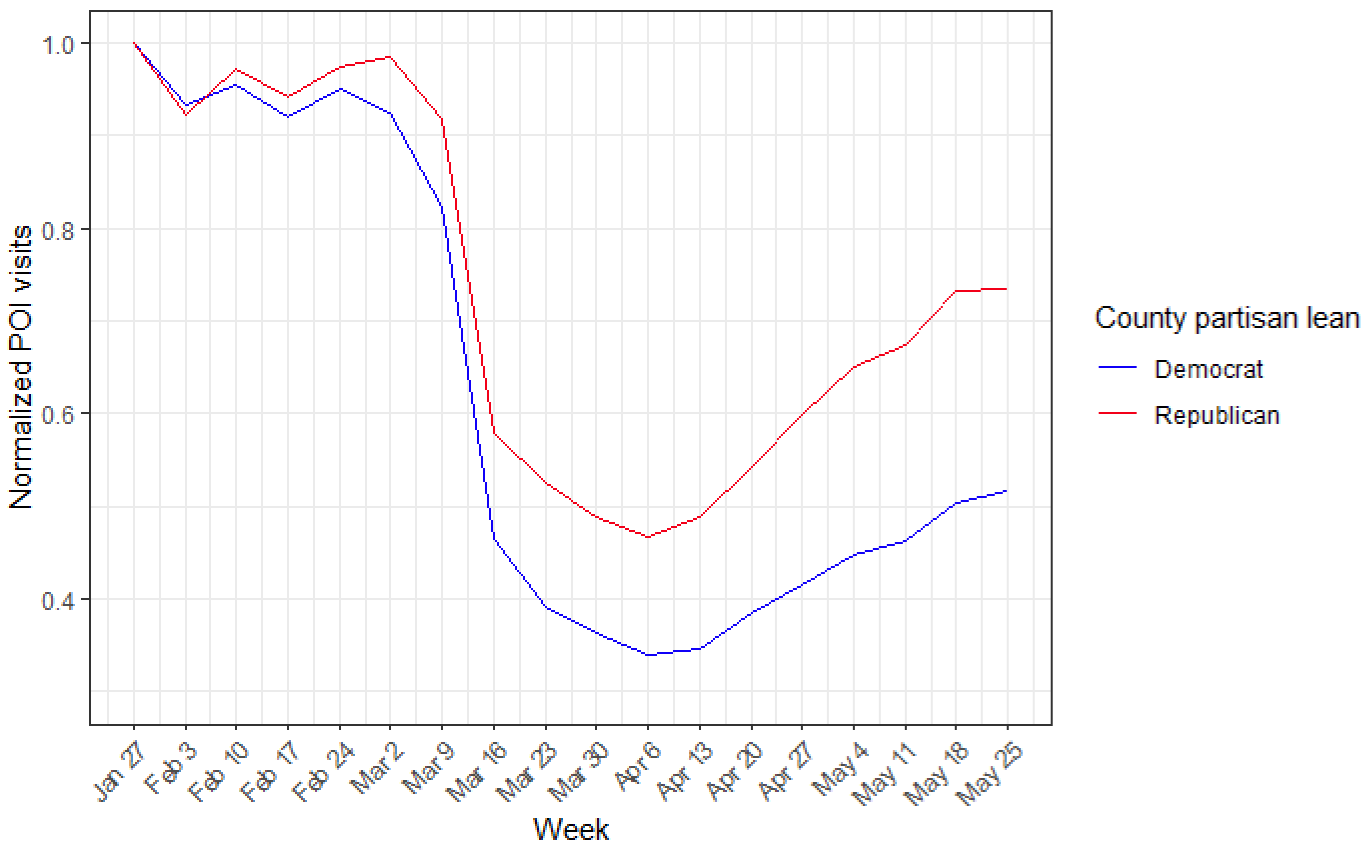
[8] Abatzoglou (2011)

[9] To clarify, I generated a *weeks_since_start* variable that counted the number of weeks since a SIPO began. Weeks before the SIPO were counted as negative and the week the SIPO began was labeled 0. Under this approach, the *weeks_since_start* value for Franklin County, Ohio (SIPO effective start date 3/24/20) for the week starting 3/16/20 would be -1, as would the value for Richland County, South Carolina (SIPO effective date 4/7/20) for the week starting 3/30/20. Allcott et al. would treat these two observations as occurring in separate weeks, but my specification treats them as occurring in the same week *relative to their local SIPO*. An analogous approach was taken for the *weeks_since_end* variable, relative to the week in which a county's SIPO was discontinued.

4 Results

Figure 1 shows a weekly time series of normalized POI visits for *all* counties in the United States, not just those that were ever under a SIPO order, for all absolute calendar weeks starting from January 27 to May 31 (i.e., the week starting May 25). Counties with a share of the vote for Trump at or higher than the country median are defined "Republican" and those below the median are labeled "Democrat."

Figure 1: Normalized POI Visits by Week and County Partisan Lean



Normalized POI visits by week and county partisan lean with the week of January 27 as the baseline. POI visits are defined as the sum total of all visits to all POIs in a given county and given seven-day period.

The figure demonstrates that total POI visits by county-week, normalized to the week of January 27, plunged steeply during the second and third weeks of March for locations of both ideological leanings. However, Republican counties "bottomed out" at a much higher minimum of POI visits (about 48% of the baseline visits count, during the week of April 6) than did Democratic counties (35% of baseline visit counts). Both sets of counties have seen continuous increase in POI visits since early April, but Republican counties had attained roughly 75% of pre-pandemic visitation levels by the week of May 25, while Democratic counties had just barely broken the 50% threshold.

Table 1 reports the results from the main empirical specification described in section 3.2 above, with a simple regression of *log_total_visits* on county partisanship with weekly coefficients and county and week fixed effects. The coefficients on weeks -8 to -3 suggest that Republican and Democratic counties behaved very similarly in terms of POI visits from 8 weeks to 3 weeks pre-SIPO (the baseline period), as illustrated by Figure 1. However, by 2 weeks before the normalized SIPO effective start date, a sharp divergence is noticeable: Republican counties see much higher POI visitation rates (0.247), and this distinction only grows sharper over time. In week 0, the effective start week of SIPOs, the coefficient estimate is 0.652, suggesting that a move from a heavily Democratic county in the 10th percentile in terms of Trump vote to a heavily Republican county in the 90th percentile would result in a 25.4% increase in POI visits.[10] The difference between Republican and Democratic counties begins to diminish as time passes after the SIPO is enacted, although it does persist quite strongly even after a full month.

[10] The 90th percentile of Trump vote share is 0.807 and the 10th percentile is 0.417: (0.807 - 0.417) * 0.652 = 0.254.

Table 1

WEEKLY PARTISAN DIFFERENCE RELATIVE TO WEEK OF SIPO START DATE
DEPENDENT VARIABLE: LOG TOTAL POI VISITS

Specification	(1)	(2)	(3)
8 weeks prior (-8)	-0.026	-0.016	0.000
	(0.010)	(0.009)	(0.000)
7 weeks prior (-7)	-0.012	-0.004	0.008
	(0.010)	(0.009)	(0.006)
6 weeks prior (-6)	-0.010	0.006	0.045
	(0.010)	(0.009)	(0.005)
5 weeks prior (-5)	-0.024	0.006	0.049
	(0.010)	(0.009)	(0.005)
4 weeks prior (-4)	-0.023	0.006	0.032
	(0.010)	(0.009)	(0.006)
3 weeks prior (-3)	0.031	0.046	0.005
	(0.010)	(0.010)	(0.007)
2 weeks prior (-2)	0.247	0.254	0.085
	(0.011)	(0.011)	(0.007)
1 week prior (-1)	0.489	0.500	0.163
	(0.011)	(0.011)	(0.007)
Week of effective date (0)	0.652	0.482	0.174
	(0.010)	(0.011)	(0.006)
1 week post (+1)	0.715	0.547	0.161
	(0.010)	(0.011)	(0.006)
2 weeks post (+2)	0.713	0.545	0.145
	(0.010)	(0.011)	(0.006)
3 weeks post (+3)	0.673	0.505	0.149
	(0.010)	(0.011)	(0.006)
4 weeks post (+4)	0.578	0.421	0.119
	(0.010)	(0.011)	(0.006)
County-time fixed effects	Yes	Yes	Yes
Demographic, health and policy controls	No	Yes	Yes
Linear time trend control	No	No	Yes
Sample size	44,316	41,837	34,454
Adj. R-squared	0.724	0.767	0.907

Coefficient estimates show the predicted percentage difference in POI visits between two hypothetical counties with 0% and 100% vote share for Donald Trump, respectively, in the 2016 US presidential election. Week enumeration is relative to the start date of the SIPO that applies to the county in question. Counties that were never under a SIPO are dropped from the sample. Standard errors are reported in parentheses and clustered at the county level.

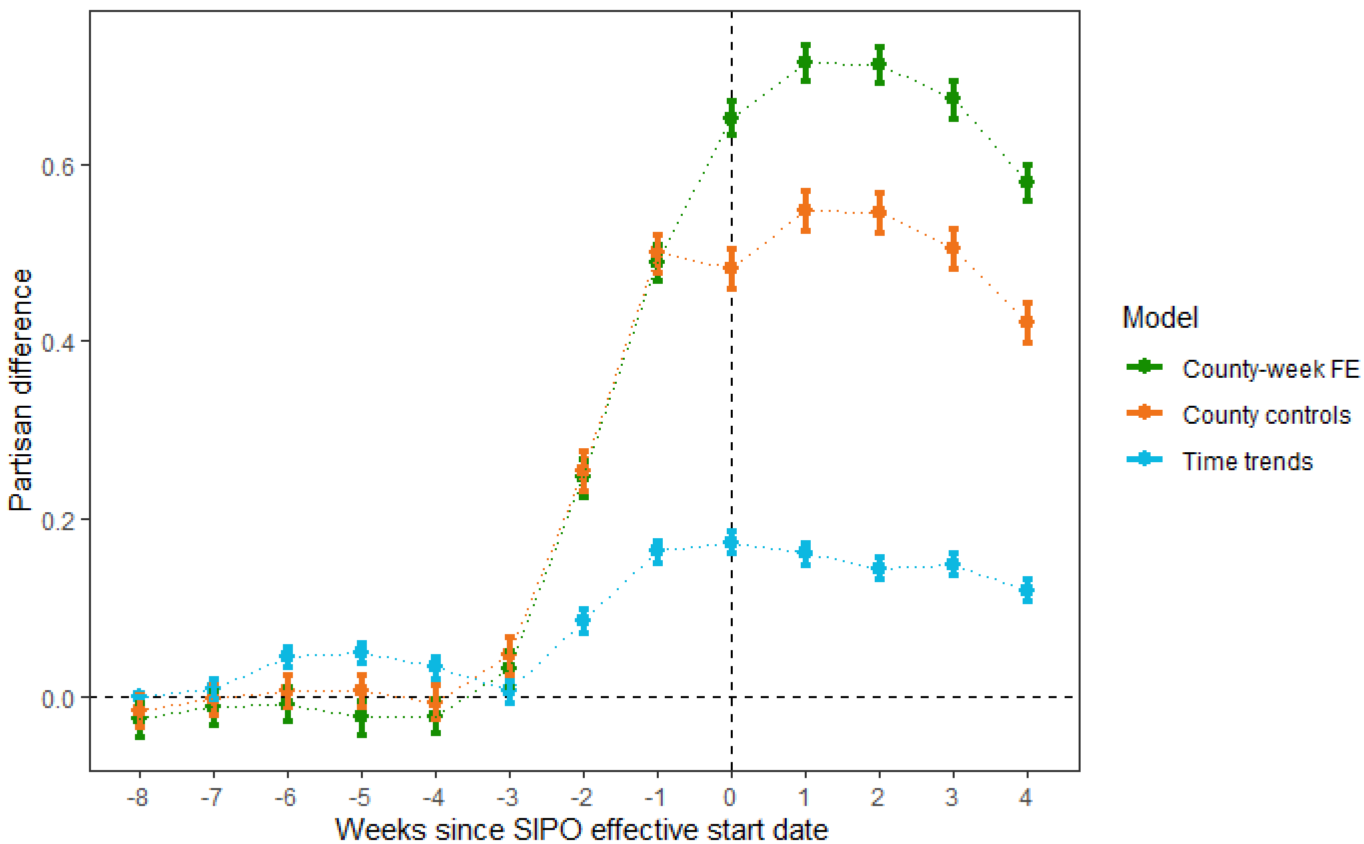
Column (2) reports weekly coefficient estimates with controls for demographics, public health, and weather taken into consideration.[11] Adding these controls attenuates the observed effect somewhat, although the stark temporal pattern of partisan divergence is preserved. These estimates suggest that moving from a strongly Democratic to a strongly Republican county in the week of a SIPO's effective start date results in an 18.8% increase in mobility as measured by POI visits, with the effect persisting to the magnitude of 16.4% 4 weeks post-SIPO implementation.

Column (3) retains the fixed effects and controls from models (1) and (2), and additionally incorporates a control for a linear time trend using a 2-week lag and lead of the dependent variable (log POI visits). Controlling for the time trend further attenuates the estimates, although the effects are still positive and statistically significant.

Figure 2 provides a graphical illustration of these coefficient estimates. The plot emphasizes the sharp divergence between counties of different partisan leanings starting 2 weeks before SIPO effective start date, and these effects peak at or approximately 1-2 weeks after SIPOs go into effect and begin to diminish thereafter. This pattern is explored narratively with a case study of Ohio in Appendix Figure 9. These results suggest that Democratic areas (which tend to be more urban, more educated, and more susceptible to outbreaks of COVID-19) actually began social distancing *before* mandatory SIPOs went into effect, perhaps reacting to or anticipating outbreaks that occurred earlier than in more rural, Republican areas. The complementary conclusion is that Republican counties were less sensitive to social distancing mandates than their Democratic counterparts, and the inclusion of controls for population density and COVID-19 incidence suggest that the gap is not due solely to the urban-rural divide or case counts.

[11] Demographic controls include county-level share of population by race, education, household income, occupation industry, and public transit usage. Public health controls include log population density, log population over 65, and a weekly decile ranking of log COVID-19 cases and deaths. Cases and deaths controls are particularly important to include because Democratic counties experience the vast majority of COVID-19 incidence, see Appendix Figure 4. Weather controls include weekly mean maximum temperature, mean minimum temperature, and mean precipitation.

Figure 2: Weekly Partisan Difference Coefficients Relative to SIPO Start Week



Weekly partisan difference coefficient

Table 2 reports weekly coefficient estimates for partisan divergence in social mobility adherence relative to the *end* dates of SIPOs. The divergence appears to diminish as the effective SIPO end date approaches, but it still persists noticeably even 3 weeks after the SIPO end date. The coefficient on the strictest model specification including time trend controls, model (3), suggests that even 3 weeks after a SIPO is lifted Republican counties are visiting POIs 10% more than Democratic counties.[12]

[12] $(0.807 - 0.417) * 0.255 = 0.100$

Table 2

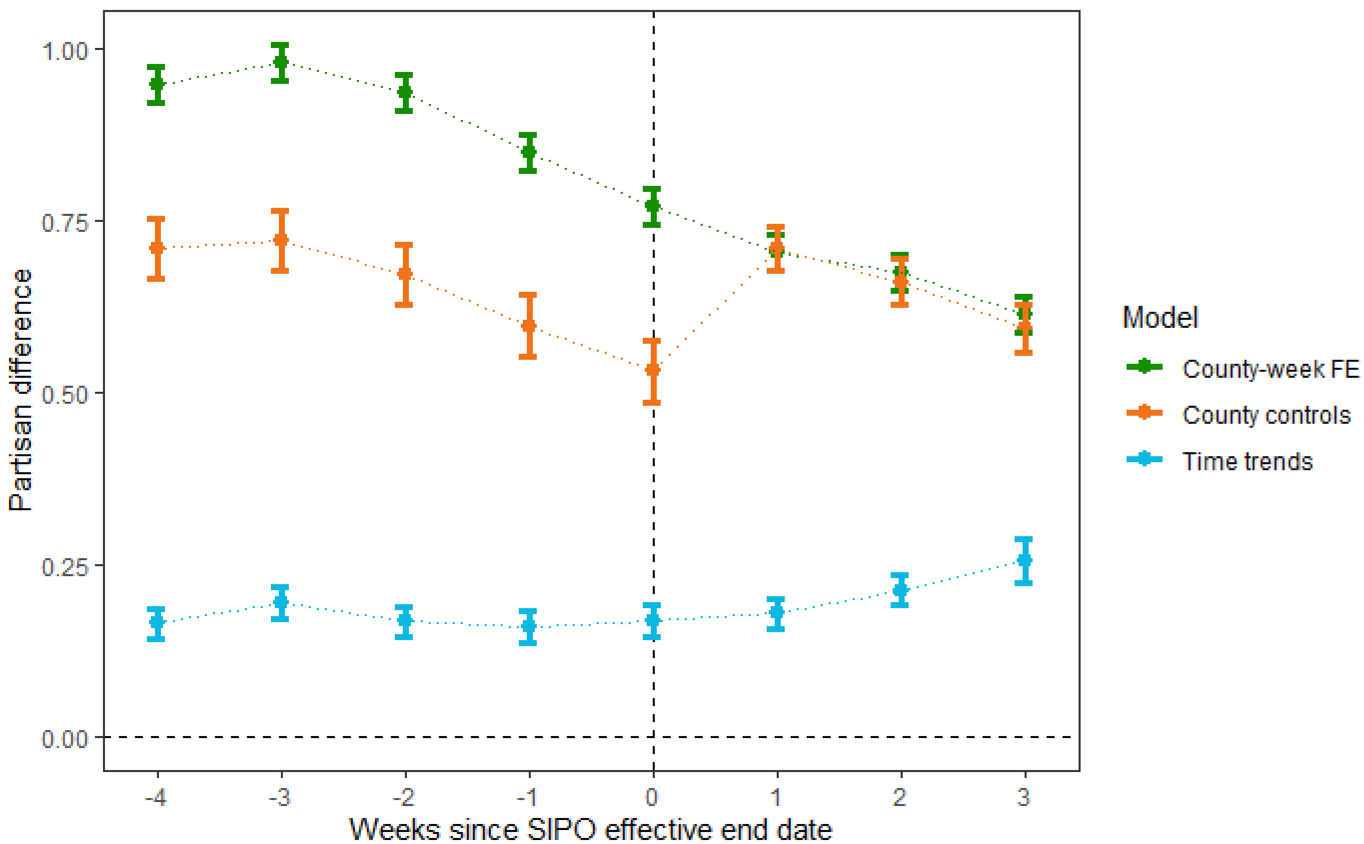
Weekly Partisan Difference Relative to Week of SIPO End Date
Dependent variable: log total POI visits

Specification	(1)	(2)	(3)
4 weeks prior (-4)	0.948	0.709	0.164
	(0.014)	(0.021)	(0.011)
3 weeks prior (-3)	0.979	0.720	0.194
	(0.014)	(0.023)	(0.011)
2 weeks prior (-2)	0.936	0.670	0.167
	(0.013)	(0.022)	(0.011)
1 week prior (-1)	0.849	0.596	0.159
	(0.013)	(0.022)	(0.012)
Week of effective date (0)	0.770	0.530	0.168
	(0.013)	(0.023)	(0.168)
1 week post (+1)	0.702	0.709	0.178
	(0.013)	(0.016)	(0.011)
2 weeks post (+2)	0.674	0.661	0.212
	(0.013)	(0.017)	(0.011)
3 weeks post (+3)	0.612	0.592	0.255
	(0.013)	(0.018)	(0.016)
County-time fixed effects	Yes	Yes	Yes
Demographic, health and policy controls	No	Yes	Yes
Linear time trend control	No	No	Yes
Sample size	30,474	28,764	23,688
Adj. R-squared	0.695	0.753	0.895

Coefficient estimates show the predicted percentage difference in POI visits between two hypothetical counties with 0% and 100% vote share for Donald Trump, respectively, in the 2016 US presidential election. Week enumeration is relative to the end date of the SIPO that applies to the county in question. Counties that were never under a SIPO are dropped from the sample. Standard errors are reported in parentheses and clustered at the county level.

The plot of weekly coefficient estimates of partisan divergence relative to SIPO end in Figure 3 indicate that the trends Allcott et al. identified are not unique to the onset of shelter-in-place orders: rather, they are a persistent feature of mobility patterns in the United States and do not disappear even weeks after a SIPO has been lifted. This trend is explored narratively with a case study of the lifting of South Carolina's SIPO in Appendix Figure 10. This finding is also robust to alternate specifications of the dependent variable, including using the count of visitors to POIs from a census block group different from the one in which the POI is located (Appendix Figures 5 & 6) and median time spent outside the home (Appendix Figures 7 & 8).

Figure 3: Weekly Partisan Difference Coefficients Relative to SIPO End Week



5 Discussion

This paper has attempted to demonstrate that divergent trends in partisan mobility during the COVID-19 pandemic identified by Allcott et al. (2020) are not ephemeral: they persist before, during and after the application of policies designed to encourage social distancing and prevent community spread, and they are not explained solely by the urban-rural divide or mere COVID-19 incidence. Allcott et al. make the case that disparate and conflicting news sources contribute to the behavioral differences, and future work in this area could focus on teasing out more of the root causes for these divergent mobility trends.

This work could also benefit from an enhanced suite of controls, including COVID-19 test availability and results, as well as controls for other policy responses aside from SIPOs including school and non-essential business closures, out-of-state travel quarantines, gathering bans, and partisan news media consumption as in Wright et al. (2020). Another interesting extension of this approach would be to examine mobility patterns in states that never enacted a statewide SIPO but nonetheless had counties that issued SIPOs at the local level. Within-state mobility variation in that scenario could provide a richer picture of the root causes behind adherence (or non-adherence) to social distancing policies.

Ultimately, without a vaccine, the United States (and the world at large) is entering a protracted battle with COVID-19 that will likely last 18 months or more. Health experts have warned that, while the curve has largely been "flattened" for the time being, social distancing is still an important tool in preventing further outbreaks and pressures on the healthcare system. As recently as June 12, Director of the National Institute of Allergy and Infectious Diseases Dr. Anthony Fauci cautioned that states should rethink their reopening strategies if they experience a spike in cases.[13] Understanding whether and how large populations respond and adhere to SIPOs is critical, given that social distancing remains the most effective impediment to COVID-19 in the absence of a vaccine. If large swaths of the country are less likely to comply with SIPOs, then perhaps other policy interventions should be explored to limit community spread. Policymakers will need the types of insight provided by this and similar research to make decisions that are, and will continue to be, life-and-death.

[13] As reported by CNN.

References

Abatzoglou, John T. 2011. "Development of gridded surface meteorological data for ecological applications and modelling." *International Journal of Climatology* http://www.climatologylab.org/gridmet.html.

Abouk, Rahi and Babak Heydari. 2020. The Immediate Effect of COVID-19 Policies on Social Distancing Behavior in the United States. Available at ssrn: https://ssrn.com/abstract=3571421.

Adolph, Christopher, Kenya Amano, Bree Bang-Jensen, Nancy Fullman and John Wilkerson. 2020. Pandemic Politics: Timing State-Level Social Distancing Responses to COVID-19. Preprint APSA.

Allcott, Hunt, Levi Boxell, Jacob Conway, Matthew Gentzkow, Michael Thaler and David Yang. 2020. Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic. Working Paper 26946 NBER.

American Community Survey 5-year estimates. 2016.

Courtemanche, Charles, Joseph Garuccio, Anh Le, Joshua Pinkston and Aaron Yelowitz. 2020. "Strong Social Distancing Measures In The United States Reduced The COVID-19 Growth Rate." *Health Affairs* Advance online publication: https://doi.org/10.1377/hlthaff.2020.00608.

Dave, Dhaval M., Andrew I. Friedson, Kyutaro Matsuzawa and Joseph J. Sabia. 2020. When Do Shelter-in-Place Orders Fight COVID-19 Best? Policy Heterogeneity Across States and Adoption Time. Working Paper 27091 NBER.

Friedson, Andrew I., Drew McNichols, Joseph J. Sabia and Dhaval Dave. 2020. Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects. Working Paper 26992 NBER.

Greenstone, Michael and Vishan Nigam. 2020. Does Social Distancing Matter? Working paper 2020-26 Becker Friedman Institute for Economics.

Gupta, Sumedha, Thuy D. Nguyen, Felipe Lozano Rojas, Shyam Raman, Byungkyu Lee, Ana Bento, Kosali I. Simon and Coady Wing. 2020. Tracking Public and Private Responses to the COVID-19 Epidemic: Evidence from State and Local Government Actions. Working Paper 27027 NBER.

Harris, Jonathan. 2020*a*. "Counties and COVID-19: Safer at Home Orders." `https://www.naco.org/resources/featured/counties-and-covid-19-safer-home-orders`.

Harris, Jonathan. 2020*b*. "Counties and COVID-19: Safer at Home Orders." `https://www.naco.org/resources/featured/counties-and-covid-19-safer-home-orders`.

Killeen, Benjamin D., Jie Ying Wu, Kinjal Shah, Anna Zapaishchykova, Philipp Nikutta, Aniruddha Tamhane, Shreya Chakraborty, Jinchi Wei, Tiger Gao, Mareike Thies and Mathias Unberath. 2020. "A County-level Dataset for Informing the United States' Response to COVID-19.".

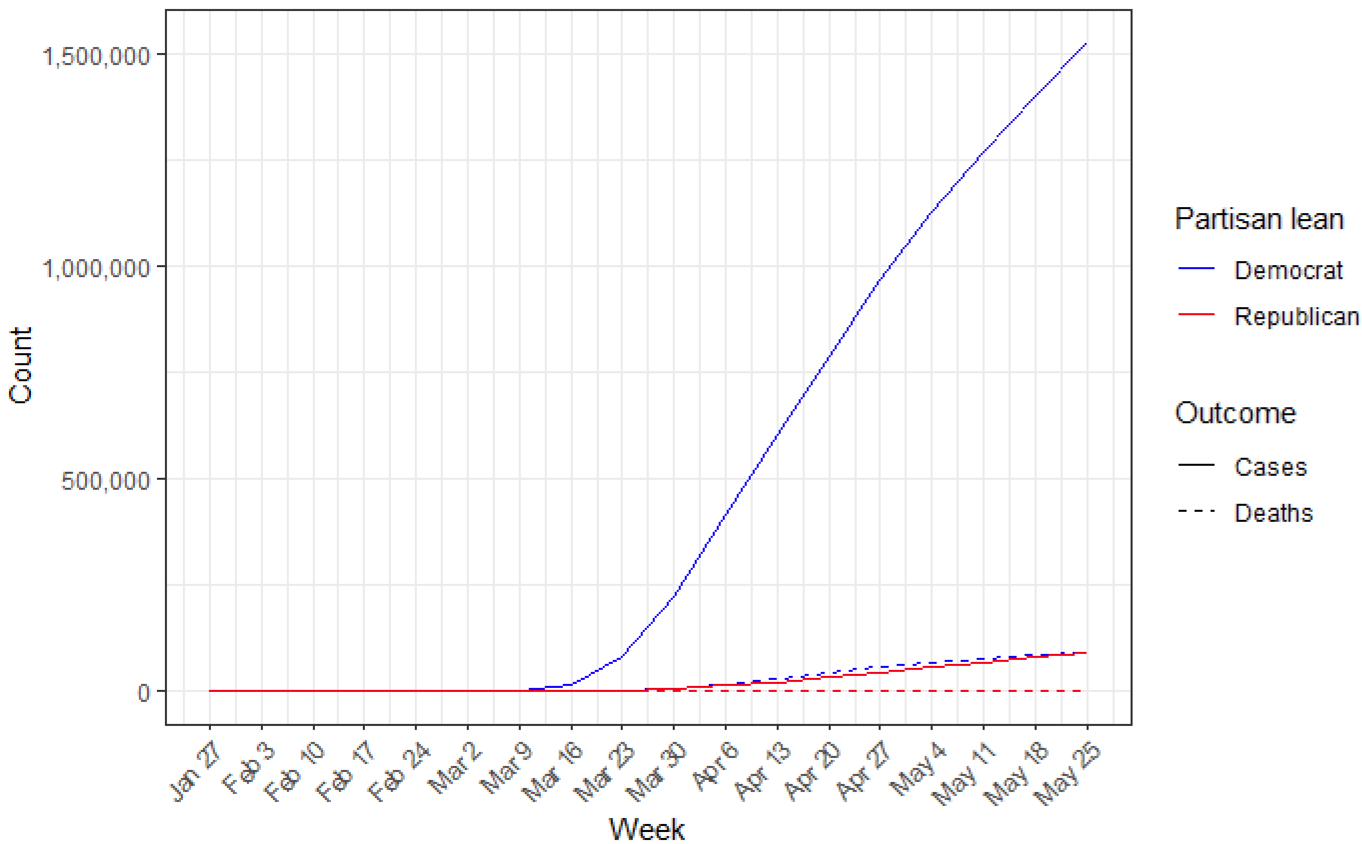
Painter, Marcus and Tian Qiu. 2020. Political Beliefs affect Compliance with COVID-19 Social Distancing Orers. Available at ssrn: https://ssrn.com/abstract=3569098.

Smith, Mitch, Karen Yourish, Sarah Almukhtar, Keith Collins, Danielle Ivory and Amy Harmon. 2020. "Coronavirus (Covid-19) Data in the United States." `https://github.com/nytimes/covid-19-data`.

Wright, Austin, Konstantin Sonin, Jesse Driscoll and Jarnickae Wilson. 2020. Poverty and Economic Dislocation Reduce Compliance with COVID-19 Shelter-in-Place Protocols. Working paper 2020-40 Becker Friedman Institute for Economics.

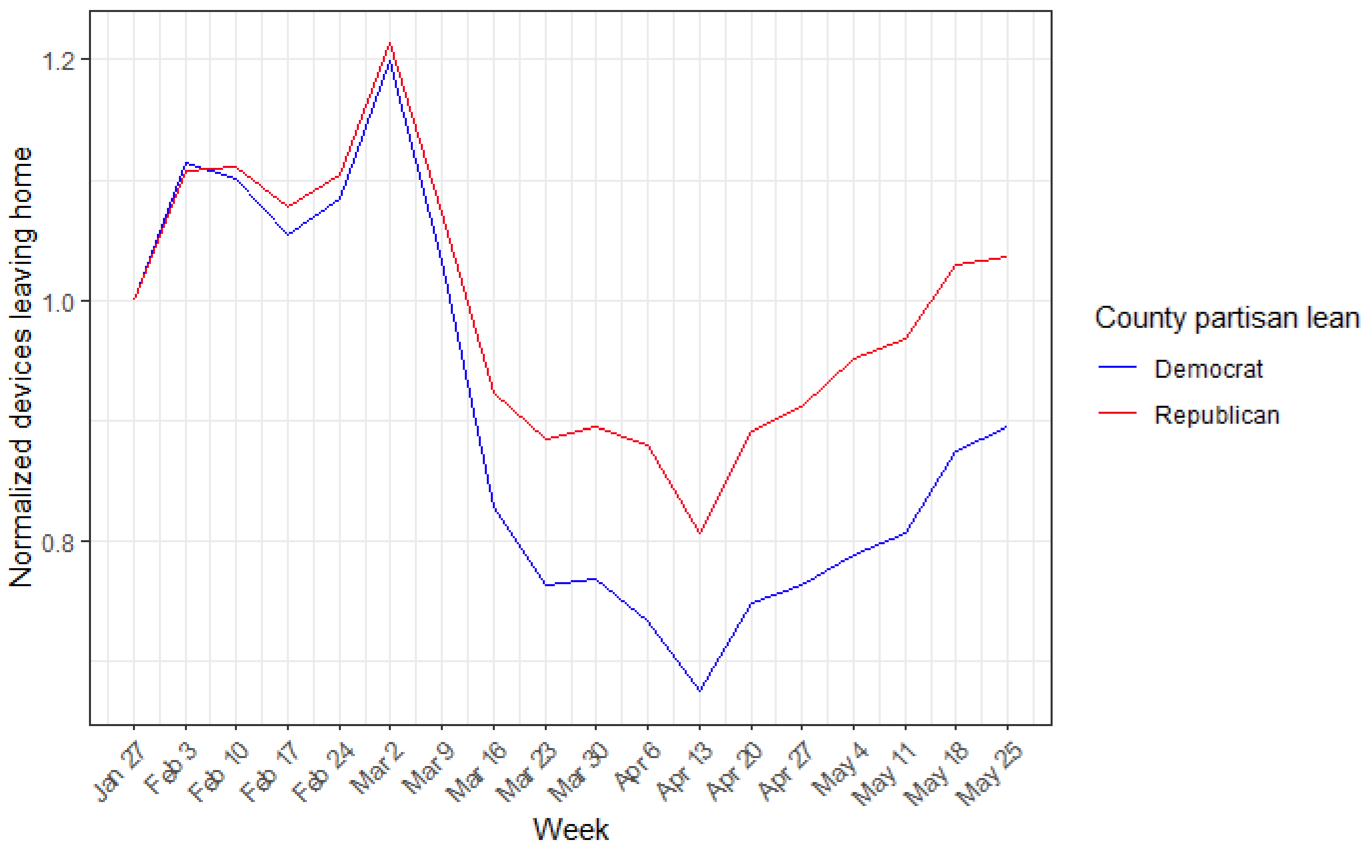
6 Appendix

Figure 4: COVID-19 Cases and Deaths by Week and County Partisan Lean



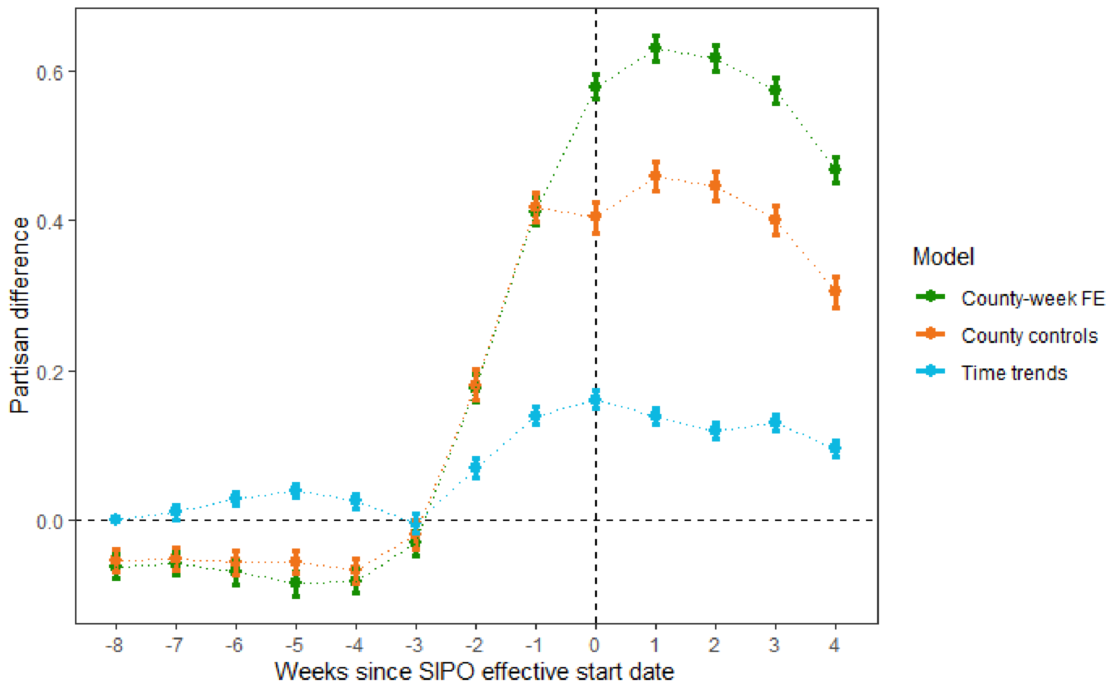
COVID-19 cumulative cases and deaths by week and county partisan lean. "Partisan lean" refers to whether a county's vote share for Donald Trump in the 2016 election fell above or below the national median.

Figure 5: Normalized Visitors from Different Census Block Groups

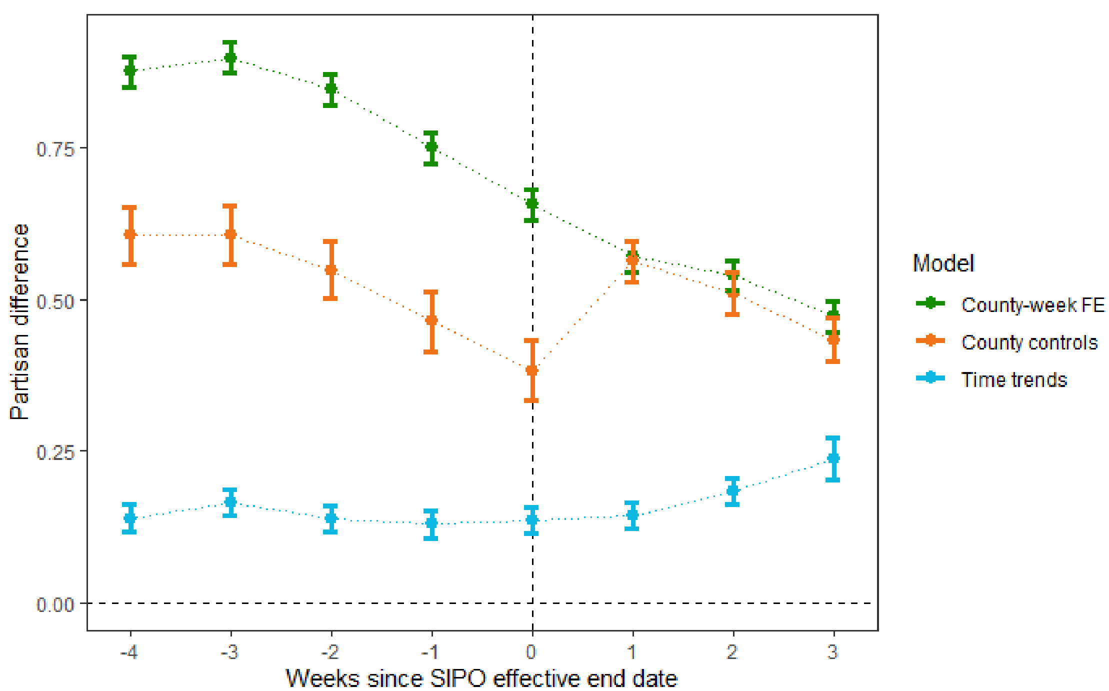


Normalized visitors to POIs from other census block groups by week and county partisan lean with the week of January 27 as the baseline.

Figure 6: Alternate Dependent Variable: Log Total Visitors from Different Block Groups

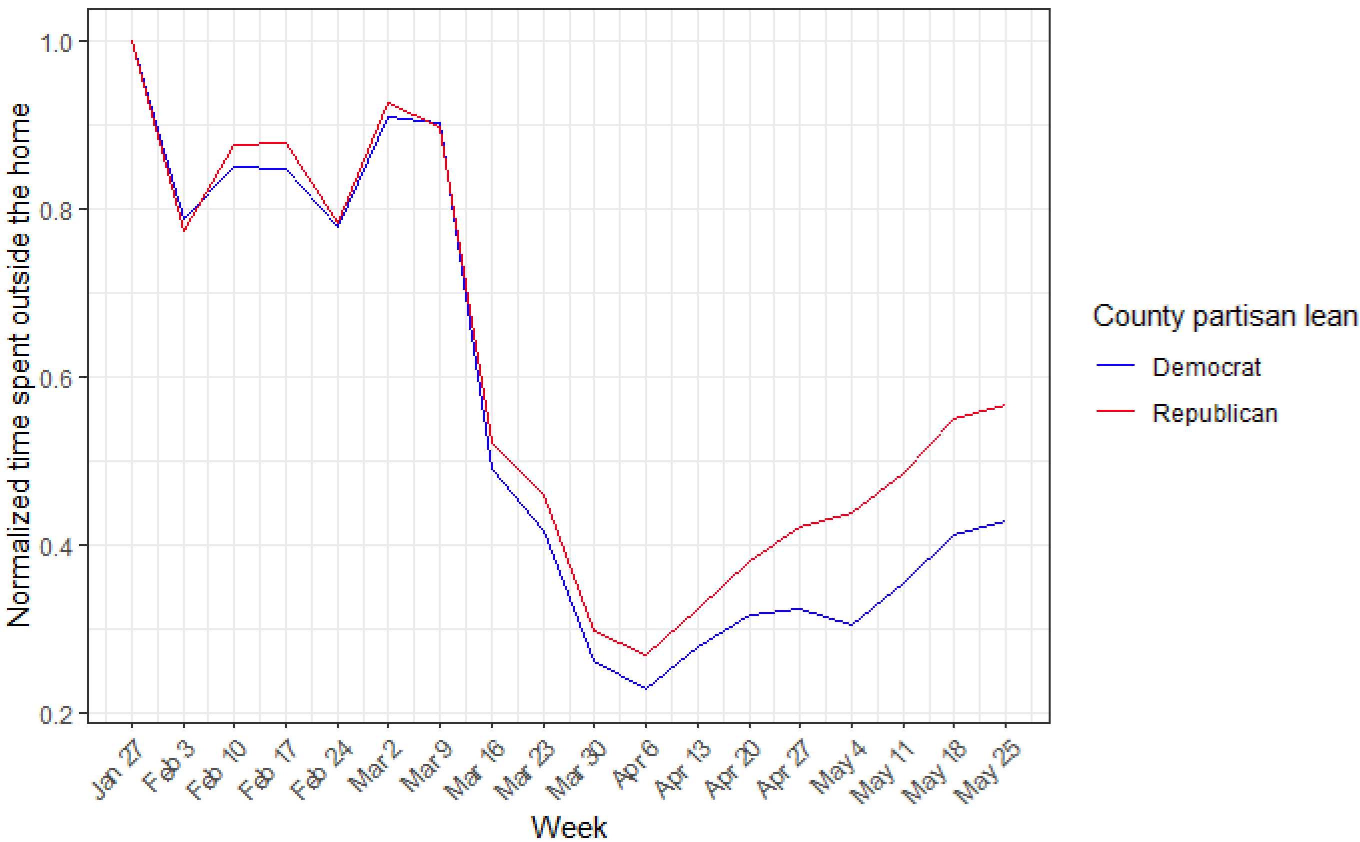


(a)



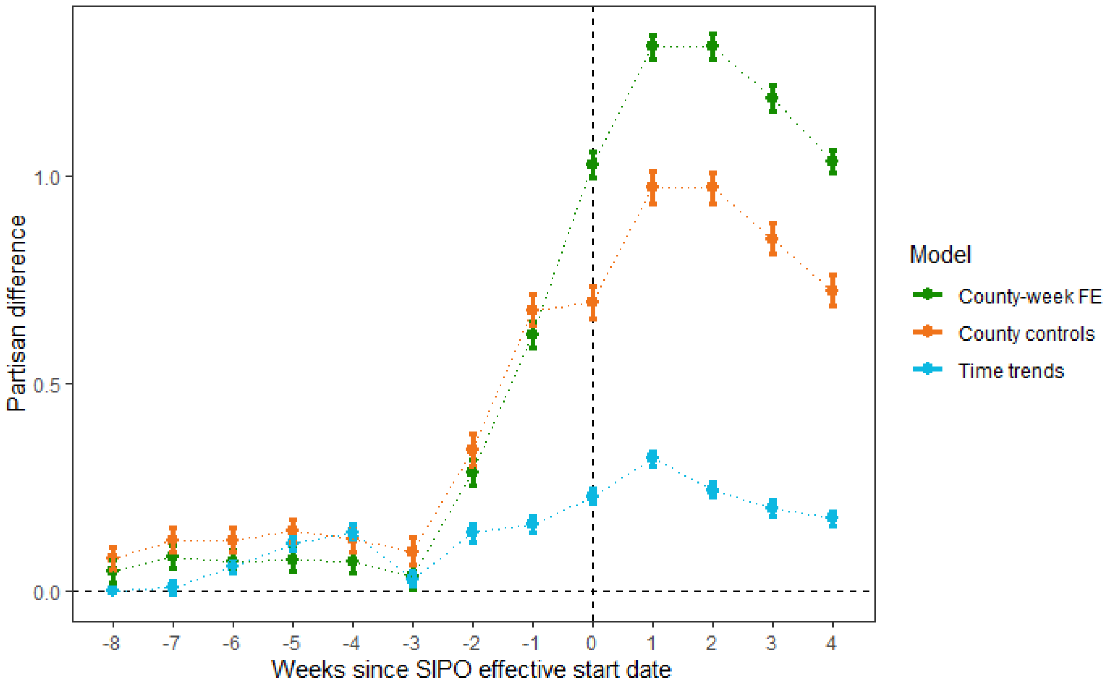
(b)

Figure 7: Normalized Time Spent Outside the Home by Week and County Partisan Lean

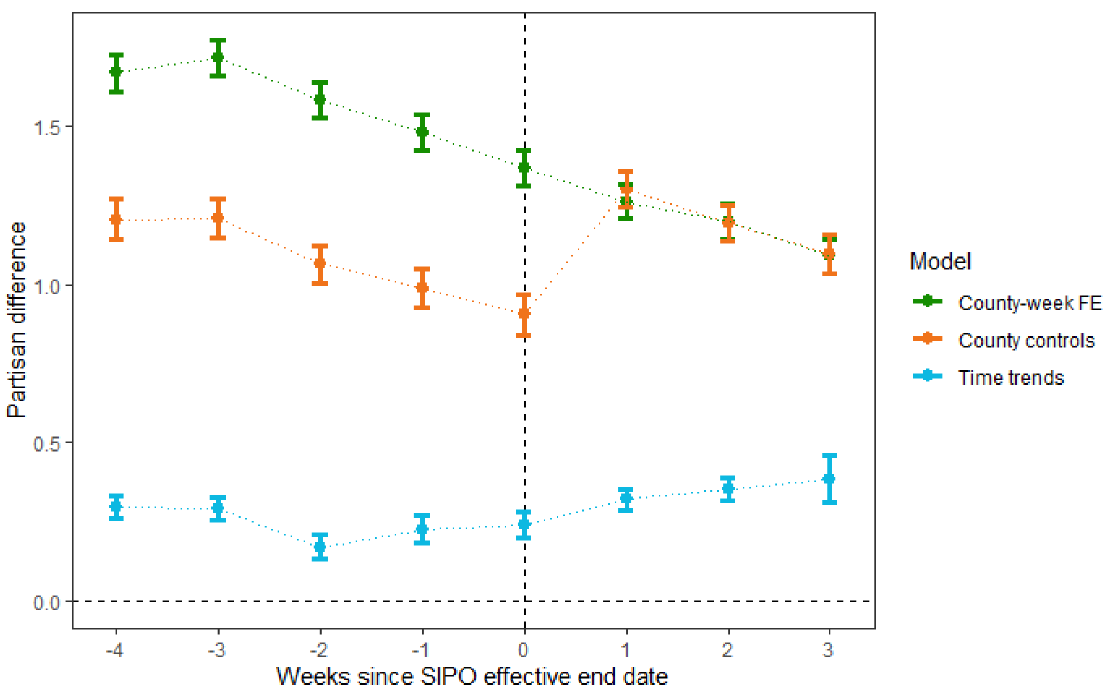


Normalized time spent outside the home by week and county partisan lean with the week of January 27 as the baseline. Time spent outside the home is defined as the median device dwell time at locations outside that device's geohash-7 home area.

Figure 8: Alternate Dependent Variable: Log Median Time Spent Outside the Home

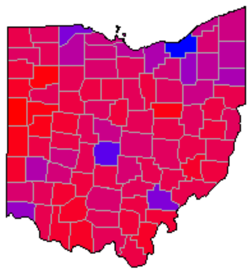


(a)



(b)

Figure 9: Normalized POI Visits in Ohio Relative to SIPO Effective Start Week

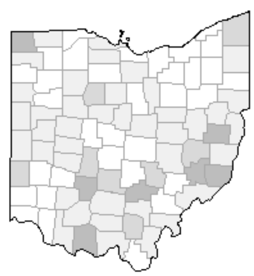


(a) 2016 presidential election

(b) 3 weeks pre-SIPO start

(c) 2 weeks pre-SIPO start

(d) 1 week pre-SIPO start

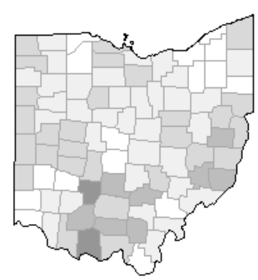


(e) Week of SIPO start

(f) 1 week post-SIPO start

(g) 2 weeks post-SIPO start

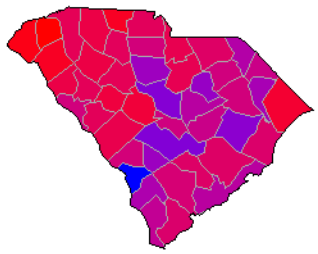
(h) 3 weeks post-SIPO start



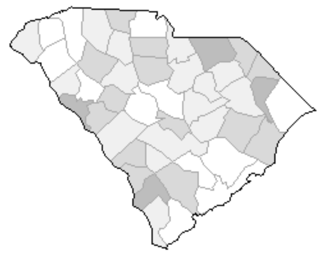
(i) 4 weeks post-SIPO start

Panel 9a shows the county-level vote in the 2016 US Presidential election in Ohio, with red counties representing votes for Donald Trump. Subsequent panels show county decile rankings in terms of POI visits for weeks relative to SIPO effective start dates. Weekly decile rankings are calculated in terms of all counties that were ever under a SIPO, normalized to n weeks since the start of the SIPO ($n \in [-3, 4]$). Darker shades represent higher deciles, i.e., more POI visits. The weekly figures illustrate that large, urban, Democratic counties like Cuyahoga, Franklin and Hamilton remained in lower deciles for POI visits throughout the period of analysis. On the other hand, smaller, rural, Republican counties (especially in the southern and eastern parts of the state) tend to rank relatively higher for POI visits, with the divergence growing more pronounced as time passes after the SIPO effective date.

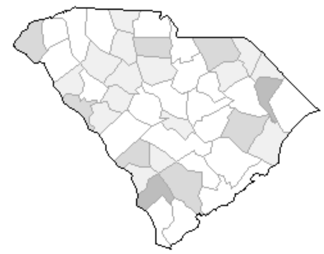
Figure 10: Normalized POI Visits in South Carolina Relative to SIPO Effective End Week



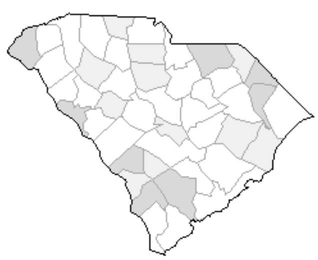
(a) 2016 presidential election



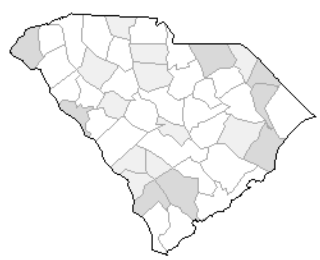
(b) 3 weeks pre-SIPO end



(c) 2 weeks pre-SIPO end



(d) 1 week pre-SIPO end

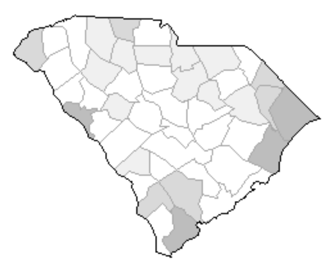


(e) Week of SIPO end

(f) 1 week post-SIPO end

(g) 2 weeks post-SIPO end

(h) 3 weeks post-SIPO end



(i) 4 weeks post-SIPO end

Panel 10a shows the county-level vote in the 2016 US Presidential election in South Carolina, with red counties representing votes for Donald Trump. Subsequent panels show county decile rankings in terms of POI visits for weeks relative to SIPO effective end dates. Weekly decile rankings are calculated in terms of all counties that were ever under a SIPO, normalized to n weeks since the end of the SIPO ($n \in [-3, 4]$). Darker shades represent higher deciles, i.e., more POI visits. The weekly figures illustrate that divergent trends in mobility at the county level observed 3 weeks before the end of South Carolina's SIPO mostly dissipate by the first week after the statewide SIPO is lifted. However, the divergence reappears in the subsequent weeks, with Democratic-leaning counties like Orangeburg and Richland remaining on the lower end of mobility rankings and Republican-leaning areas in the coastal plain showing the greatest increases in POI visits.