

Evaluating Policies Early in a Pandemic: Bounding Policy Effects with Nonrandomly Missing Data

Supplementary Appendix

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December 21, 2022

This supplementary appendix contains additional details for (i) alternative estimation strategies to the doubly robust estimator used in the main text, (ii) more primitive conditions for rationalizing Assumption 5 in the main text, (iii) some alternative strategies involving extra assumptions that can be used to deliver tighter bounds than the main bounds in the text (up to point identification), and (iv) additional results for the application on Tennessee’s expanded testing policy.

S-A Alternative Estimation Strategies

In this section, we discuss an alternative estimation strategy based on matching. In particular, for each county in Tennessee, we find a “match county” from among its six surrounding states based on pre-policy county characteristics, Z_{lt^*-1} . Then, we compute an estimate of the *ATT* by taking the average outcome experienced by counties in Tennessee relative to average outcomes among their matches.

In practice, to construct the matched dataset, we match based on the same covariates used in the main text: the seven day lags of the cumulative number of tests, confirmed cases, and deaths per 1000 people in the county as well as the log of county population. We pick matches from comparison counties without replacement. To actually construct the matches, for county l in Tennessee, we construct its match by choosing the county in comparison states that minimizes the Mahalanobis distance (Rosenbaum and Rubin (1985))

$$d(Z_{lt^*-1}, Z_{jt^*-1}) = (Z_{lt^*-1} - Z_{jt^*-1})' \hat{S}^{-1} (Z_{lt^*-1} - Z_{jt^*-1})$$

where j indexes counties in comparison states and \hat{S} is the estimated covariance matrix of Z_{jt^*-1} for the entire sample. Finally, we drop Shelby County (where Memphis is) due to not having a close match. This results in a matched dataset that includes 91 counties in Tennessee. For inference, we

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cluster standard errors by match along the lines of Abadie and Spiess (2022). Results using matching are provided in Figure S-7 below.

S-B Additional Discussion of Assumption 5

This section gives some more primitive conditions for Assumption 5 to hold. We consider the following conditions (to conserve on notation, we omit conditioning on Z_{it^*-1} below):

Extra Conditions:

- (i) $P(C_{ilt^*}(1) = 1 | T_{ilt^*}(1) = 0, D_l = 1) \leq P(C_{ilt^*}(0) = 1 | T_{ilt^*}(1) = 0, D_l = 1)$
- (ii) $P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 1, D_l = 1) \geq P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 0, D_l = 1)$
- (iii) $T_{ilt^*}(1) = 0 \implies T_{ilt^*}(0) = 0$

Extra Condition (i) says that the probability of untested individuals having Covid-19 does not increase under the policy relative to the absence of the policy holding the group of untested individuals fixed (here, it is equal to the group that would be untested under the policy). This condition is very similar to the weak monotonicity of the outcome in the treatment assumption discussed in Chen, Flores, and Flores-Lagunes (2018). It is also similar to, though somewhat weaker than, the Monotone Treatment Response (MTR) assumption of Manski (1997).

Extra Condition (ii) says that, if the policy had not been implemented, the probability of having Covid-19 is greater for the “compliers” (i.e., group of individuals that would be tested if the policy is implemented but not tested if the policy is not implemented) than for the “never-takers” (i.e., the group of individuals that would not be tested in either case).¹ This is similar to the Monotone Treatment Selection assumption of Manski and Pepper (2000).

Extra Condition (iii) says that untested individuals under the policy would have also been untested if the policy had not been implemented. This is an MTR-type of assumption (Manski (1997)) for being tested and would hold either if exactly the same individuals are tested whether or not the policy is implemented or if the policy strictly expands testing.

¹Another way to explain this condition is that there is positive self-selection into taking the test among individuals that become tested under the policy but would not have been tested without the policy.

Next, notice that Assumption 5 holds if the following difference is less than or equal to 0.

$$\begin{aligned}
& P(C_{ilt^*}(1) = 1, T_{ilt^*}(1) = 0 | D_l = 1) - P(C_{ilt^*}(0) = 1, T_{ilt^*}(0) = 0 | D_l = 1) \\
&= \underbrace{\left(P(C_{ilt^*}(1) = 1 | T_{ilt^*}(1) = 0, D_l = 1) - P(C_{ilt^*}(0) = 1 | T_{ilt^*}(1) = 0, D_l = 1) \right)}_{\text{Term (A)}} P(T_{ilt^*}(1) = 0 | D_l = 1) \\
&+ \underbrace{\left(P(C_{ilt^*}(0) = 1 | T_{ilt^*}(1) = 0, D_l = 1) - P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, D_l = 1) \right)}_{\text{Term (B)}} P(T_{ilt^*}(1) = 0 | D_l = 1) \\
&+ P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, D_l = 1) \underbrace{\left(P(T_{ilt^*}(1) = 0 | D_l = 1) - P(T_{ilt^*}(0) = 0 | D_l = 1) \right)}_{\text{Term (C)}}
\end{aligned}$$

where the equality holds by adding and subtracting $P(C_{ilt^*}(0) = 1 | T_{ilt^*}(1) = 0, D_l = 1)P(T_{ilt^*}(1) = 0 | D_l = 1)$ and $P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, D_l = 1)P(T_{ilt^*}(1) = 0 | D_l = 1)$. Term (A) ≤ 0 holds immediately by Extra Condition (i). Next, consider Term (B). For the first quantity in Term (B), notice that Extra Condition (iii) implies that

$$P(C_{ilt^*}(0) = 1 | T_{ilt^*}(1) = 0, D_l = 1) = P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 0, D_l = 1) \quad (\text{S-B.1})$$

because Extra Condition (iii) says that individuals who are not tested with the policy would have also been untested without the policy (so that conditioning on $T_{ilt^*}(0) = 0$ is redundant). For the second quantity in Term (B),

$$\begin{aligned}
& P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, D_l = 1) \\
&= P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 0, D_l = 1) P(T_{ilt^*}(1) = 0 | T_{ilt^*}(0) = 0, D_l = 1) \\
&+ P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 1, D_l = 1) P(T_{ilt^*}(1) = 1 | T_{ilt^*}(0) = 0, D_l = 1)
\end{aligned}$$

which holds by the law of total probability. Then, applying Extra Condition (ii) implies that

$$P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, D_l = 1) \geq P(C_{ilt^*}(0) = 1 | T_{ilt^*}(0) = 0, T_{ilt^*}(1) = 0, D_l = 1) \quad (\text{S-B.2})$$

Combining Equations (S-B.1) and (S-B.2) implies that Term (B) ≤ 0 . That Term (C) ≤ 0 immediately holds by Extra Condition (iii).

To conclude this section, it is worth pointing out that the extra conditions outlined above are stronger than are needed for Assumption 5 to hold, but they provide one set of plausible, low-level conditions where Assumption 5 would hold.

S-C Tighter Bounds under Additional Conditions

In this section, we develop tighter bounds on ATT_C relative to the ones in the main text under some additional assumptions. For this section, we maintain Assumptions 1 and 3 to 5 as well as Extra Conditions (i)-(iii), the primitive conditions to rationalize Assumption 5 in Appendix S-B. We take as a starting point the expression for $ATT_C(Z_{lt^*-1})$ in Equations (6) to (8). These conditions

immediately imply that $\phi_1(Z_{lt^*-1}) \leq \phi_0(Z_{lt^*-1}) \leq \gamma_0(Z_{lt^*-1})/\tau_0(Z_{lt^*-1})$ which we use below. The first inequality means that the probability of having had Covid-19 among untested individuals in treated locations is less than or equal to the probability of having had Covid-19 among untested individuals in untreated locations conditional on locations having similar pre-treatment characteristics, and this holds by the same sort of arguments as in Appendix S-B. The second inequality holds by Assumption 1. The same conditions further imply that $\tau_1(Z_{lt^*-1}) \geq \tau_0(Z_{lt^*-1})$.

Next, we introduce a first assumption that can lead to tighter bounds. Along the lines of Remark 1, we consider an assumption that the fraction of untested individuals who have had Covid-19 is not “too different” between treated and untreated locations with similar pre-treatment characteristics.

Assumption S-C.1. *The difference between Covid-19 infection rates among untested individuals conditional on pre-treatment characteristics for untreated locations relative to treated locations is uniformly bounded with the bound given by*

$$\phi_0(Z_{lt^*-1}) - \phi_1(Z_{lt^*-1}) \leq \alpha$$

for some $\alpha \geq 0$.

Assumption S-C.1 does not affect the upper bound from Proposition 4, but it does increase the lower bound. In particular, the lower bound is now given by $\gamma_1(Z_{lt^*-1}) - \gamma_0(Z_{lt^*-1}) - \alpha(1 - \tau_1(Z_{lt^*-1})) - \frac{\gamma_0(Z_{lt^*-1})}{\tau_0(Z_{lt^*-1})}(\tau_1(Z_{lt^*-1}) - \tau_0(Z_{lt^*-1}))$; this bound comes essentially immediately from the same types of arguments as in Proposition 4. This bound is generally tighter than the one in Proposition 4. And it is interesting to consider the limiting cases. When $\alpha = 0$, then the difference in the bounds arises because the difference between $\tau_1(Z_{lt^*-1})$ and $\tau_0(Z_{lt^*-1})$ is less than $1 - \tau_0(Z_{lt^*-1})$. On the other hand (and slightly abusing notation), if α were equal to $\gamma_0(Z_{lt^*-1})/\tau_0(Z_{lt^*-1})$ (which is its maximum possible value under the conditions in the main text), then these bounds reduce to the same ones in Proposition 4.

In practice, we note that it is likely to end up being quite *ad hoc* how to set a plausible value of α . On the one hand, as noted in the text, our largest bounds on policy effects occur in cases where the policy eliminates all Covid-19 cases among the untested, but the rate of actual Covid-19 cases would be the same for the untested as for the tested without the policy. In practice, this case seems unlikely and choosing some smaller value of α can rule out this case. That being said, it also seems unlikely that $\alpha = 0$. In particular, α would tend to be positive in cases where (i) there are some Covid-19 cases among the untested and either (ii) the policy expands testing and there is self-selection into the test (as is very likely to be the case in our application on Tennessee) or (iii) the policy actually reduces Covid-19 cases (as seems to be the case for our application on Tennessee and might be the case in other policy evaluation studies for early pandemic policies). Besides the two limiting cases, though, it seems difficult to interpret different values of α .

Finally, we consider an even stronger assumption, but one that leads to point identification.

Assumption S-C.2. *The probability of having had Covid-19 among the untested in treated locations is the same as the probability of having had Covid-19 among the untested in untreated locations conditional on pre-treatment characteristics. Moreover, this probability is constant across pre-treatment characteristics, and this probability is known. That is,*

$$\phi_1(Z_{it^*-1}) = \phi_0(Z_{it^*-1}) = \beta$$

for some β that is known to the researcher.

Under Assumption S-C.2, it follows immediately from Equations (6) to (8) that ATT_C is point identified, and it is given by

$$ATT_C = \mathbb{E}[\gamma_1(Z_{it^*-1}) - \gamma_0(Z_{it^*-1})|D_l = 1] + \beta \mathbb{E}[\tau_0(Z_{it^*-1}) - \tau_1(Z_{it^*-1})|D_l = 1]$$

Relative to Assumption S-C.1, this assumption implies that $\alpha = 0$ and that the probability of having Covid-19 among the untested is somehow known. This is likely to be a very strong assumption in practice, but in early-pandemic applications, it is likely to effectively be required in order to point identify causal effects of the policy on actual Covid-19 cases. One way that this sort of assumption can be operationalized in practice is the following. There exist estimates of the actual number of Covid-19 cases (as distinct from confirmed cases) for some locations at different points in time for the early part of the pandemic (e.g., Figure S-1 below). In the context of our application, for example, the IHME provides daily estimates of the actual number of cases at the state-level. Given this estimate (and given that it is constant across counties), one can back out the probability of having Covid-19 among the untested. In particular, along the lines of Equation (1), we have that

$$\begin{aligned} P(C_{ilt^*} = 1|D_l = 1) &= P(C_{ilt^*} = 1|T_{ilt^*} = 1, D_l = 1)P(T_{ilt^*} = 1|D_l = 1) \\ &\quad + P(C_{ilt^*} = 1|T_{ilt^*} = 0, D_l = 1)P(T_{ilt^*} = 0|D_l = 1) \end{aligned}$$

and every term on the right hand side of this equation is identified except for $P(C_{ilt^*} = 1|T_{ilt^*} = 0, D_l = 1)$. However, if we replace the left hand side, $P(C_{ilt^*} = 1|D_l = 1)$, with an existing estimate of the fraction of individuals that have had Covid-19, then we can recover $P(C_{ilt^*} = 1|T_{ilt^*} = 0, D_l = 1)$ and set β equal to this value. Thus, under Assumption S-C.2, we can point identify the effect of the policy.

Next, we use this approach in the context of our application on Tennessee’s expanded testing policy. On May 9, the IHME estimates that there had been 50,100 cumulative cases in Tennessee (for comparison, there had been 14,528 confirmed cases on the same date) which corresponds to 0.73% of Tennessee’s population. As an aside, these estimates come from information about confirmed cases, hospitalizations, deaths, and seroprevalence studies;² see Barber et al. (2022) for a detailed

²There are several state-level seroprevalence studies; probably most relevant is Bajema et al. (2021) though, to our knowledge, this same sort of information is not available at the county-level, and the sample sizes tend to be small

discussion. This estimate is towards the lower end of the state-level bounds on per capita actual Covid-19 cases presented in Figure S-6. If the IHME estimate is taken as the truth, then we can back out the fraction of untested individuals who have had Covid-19; doing this, we calculate that 0.47% of untested individuals in Tennessee had had Covid-19 by May 9 (relative to 5.9% of tested individuals). Plugging this in for ϕ_1 and ϕ_0 in from Equations (6) to (8), we therefore estimate that the policy reduced the number of actual Covid-19 cases by 1.29 per 1000 people. Continuing to take the IHME estimate of the overall infection rate as being true, this suggests that the policy reduced the number of Covid-19 cases in Tennessee by about 15% relative to what they would have been without the policy.

To conclude this section, we emphasize that the discussion above requires a number of extra assumptions that were not required for our bounding approach in the main text. In particular, as discussed above, it is unlikely that $\alpha = 0$ (which is required here). Even it were, it is additionally unlikely that β is the same across counties with different characteristics (in particular, it seems unlikely that β would be the same across counties with different values of Z_{it^*-1} such as having had a much different number of Covid-19 cases and/or tests or for locations with much different populations). Moreover, the underlying data used to estimate the overall probability of having had Covid-19 is not likely to be very precise at the frequency needed to study state-level policies (due to pooling information across time and locations). The main advantage of this approach is that it delivers a point estimate of the effect of the policy on the number of actual Covid-19 cases. And, among different possible approaches that could deliver point identification, this one seems likely to be the most reasonable choice. However, if this were the only type of result reported on the effects of a policy early in the pandemic, it would not be clear whether the results were due to the actual effects of the policy or whether they were due to the extra assumptions from above. Thus, while our approach in the main text does not result in point identification, finding evidence that a policy does indeed reduce the number of actual Covid-19 cases without requiring these extra sort of conditions is likely to be substantially more credible.

S-D Additional Results on Tennessee’s Expanded Testing Policy

This section provides some additional discussion of Tennessee’s expanded testing policy and several descriptive figures regarding the data used in the application as well as a number of additional results for the application on Tennessee’s expanded Covid-19 testing policy.

for particular states (e.g., Bajema et al. (2021) provides monthly repeated cross sections data from July to September 2020 with close to 1000 observations collected in Tennessee in each cross section). See also Arora et al. (2021) for a detailed database of seroprevalence studies.

More Details on Tennessee’s Expanded Testing Policy

As discussed in the main text, in the early part of the Covid-19 pandemic, Tennessee conducted more Covid-19 tests than most other states. For example, on April 27, Tennessee was one of nineteen states meeting minimum testing requirements suggested by the Harvard Global Health Institute and was second in the United States (only behind Utah) in terms of availability of surplus tests (Begley (2020)). Among the seven states in the Southeast used in the application, Tennessee was conducting 2,778 more tests than its minimum requirement on April 27; the next closest state was Mississippi which was conducting 379 more tests than its minimum requirement while Alabama, Arkansas, Georgia, Kentucky, and North Carolina were 652, 241, 5,354, 1,772, and 913 tests per day below their minimum testing requirements. Moreover, by May 15, Tennessee was one of only seven states exceeding revised minimum testing thresholds from the Harvard Global Health Institute (Jha, Jacobson, Friedhoff, and Tsai (2020)).

Initially, Tennessee’s large number of tests was driven by direct payments to labs that processed Covid-19 tests. That was soon followed by Tennessee’s open-testing policy which removed eligibility requirements on residents for being tested. In particular, on Wednesday, April 15, 2020, Tennessee’s governor Bill Lee announced free testing in the state for anyone who wanted a test (Nashville Tennessean (2020)). That Saturday, April 18, more than 6,500 Tennessee residents were tested at 20 different testing locations across the state (Humbles (2020)). Unlike almost all other states at that time, obtaining a test did not require an individual to be showing symptoms or to be in a high risk group. These tests were also available on the weekends of April 25 and May 2. Over the course of those three weekends, more than 23,000 people were tested at 67 different locations across the state.

Additional Results/Figures

Figure S-1 plots the number of confirmed cases and estimated number of actual cases (these estimates are from the Institute for Health Metrics and Evaluation) from February to December 2020. Notice the large gap between confirmed and estimated cases and how this gap is largest (at least in relative terms) in the early part of the pandemic.

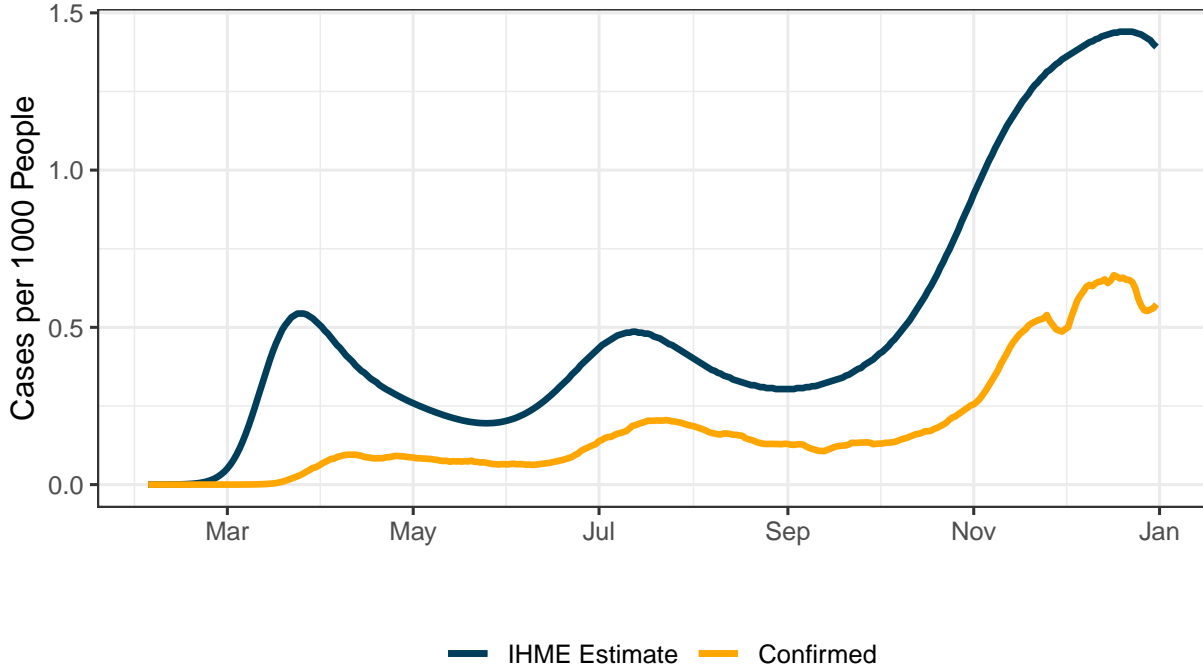
Figure S-2 provides county-level data about tests and confirmed cases for counties in Tennessee. This is analogous to the state-level plot of similar data in Figure 1 in the main text.

Figure S-3 provides state-level data on Covid-19 deaths and hospitalizations.

Figure S-4 provides information about county-level deaths for counties in Tennessee.

Figure S-5 provides the county-level bounds on Covid-19 cases for counties in Tennessee and Alabama on March 31 and April 25. As discussed in the main text, the bounds are somewhat narrower on April 25 than they were on March 31. For example, the median width of the bounds is 0.099 in Tennessee on March 31, but it is 0.059 on April 25. Focusing on the bounds on April 25, it is immediately clear that the bounds on the per capita number of actual cases tend to be noticeably tighter in Tennessee counties than in Alabama counties. The median width of the bounds is 0.059

Figure S-1: Estimated and Confirmed Covid-19 Cases



Notes: Plots of the seven day moving average of new confirmed cases per 1000 people (the yellow line) and IHME estimates of new actual cases (the blue line) in the United States from February 4, 2020 to December 31, 2020. The IHME estimates are based on confirmed cases, hospitalizations, deaths, and seroprevalence studies; see Barber et al. (2022) for additional details on how these estimates are calculated.

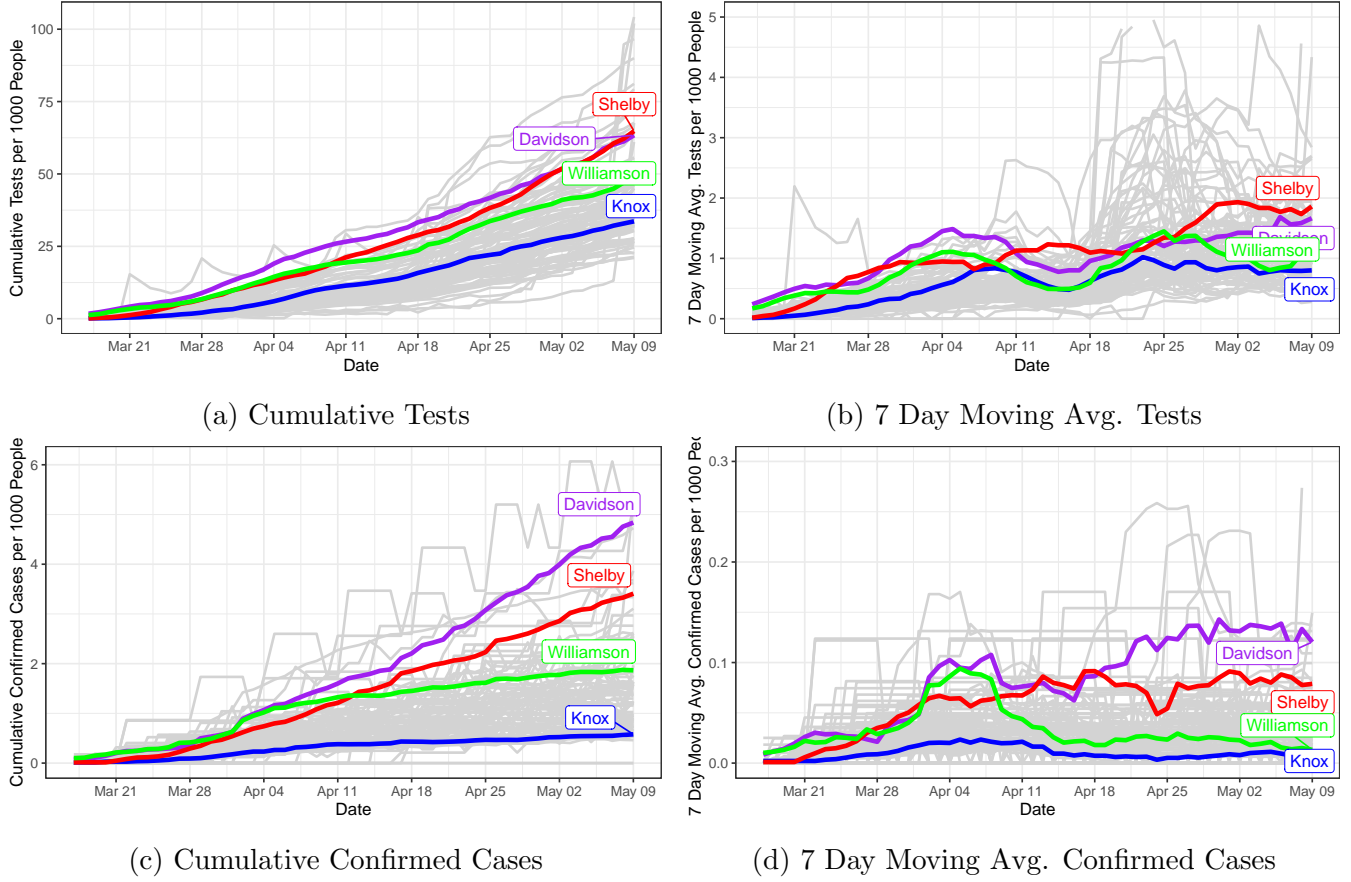
Sources: For confirmed cases, CDC COVID Data Tracker, <https://covid.cdc.gov/covid-data-tracker/#trends-dailycases>. For IHME estimates, SARS-CoV-2 Daily and Cumulative Infection Estimates 2019-2021, https://ghdx.healthdata.org/record/ihme-data/covid_19_cumulative_infections.

in Tennessee and 0.086 in Alabama. This difference is even more pronounced for other comparison states. For example, the median length of the bounds for Georgia on April 25 is 0.270. This pattern arises because, relative to the other states surrounding Tennessee, Alabama was the second highest testing state by April 25.

Figure S-6 provides state-level bounds on per capita actual Covid-19 cases using the approach for bounding actual cases discussed in the main text.

Results using the matching estimator described in Appendix S-A are provided in Figure S-7. These results are very similar to the results using the doubly robust estimator described in the main text. In particular, the estimated effects of the policy on tests are virtually identical. The estimated effects on the number of confirmed cases is somewhat smaller here. For example, in the main text, we estimated that on May 9 there had been about 0.9 fewer confirmed cases per 1000 people under the policy than there would have been without the policy. Here, we estimate about 0.5 fewer cumulative cases per 1000 people though these estimates are not statistically different from each other. In both cases, the standard errors are somewhat larger using the matching estimator. This is not surprising

Figure S-2: Tests and Confirmed Cases by County in Tennessee



Notes: The figure provides cumulative and seven day moving averages of tests and confirmed cases for all counties in Tennessee excluding Bledsoe, Trousdale, and Lake. The highlighted counties are Davidson (county of Nashville), Shelby (county of Memphis), Knox (county of Knoxville), and Williamson (suburban county of Nashville).

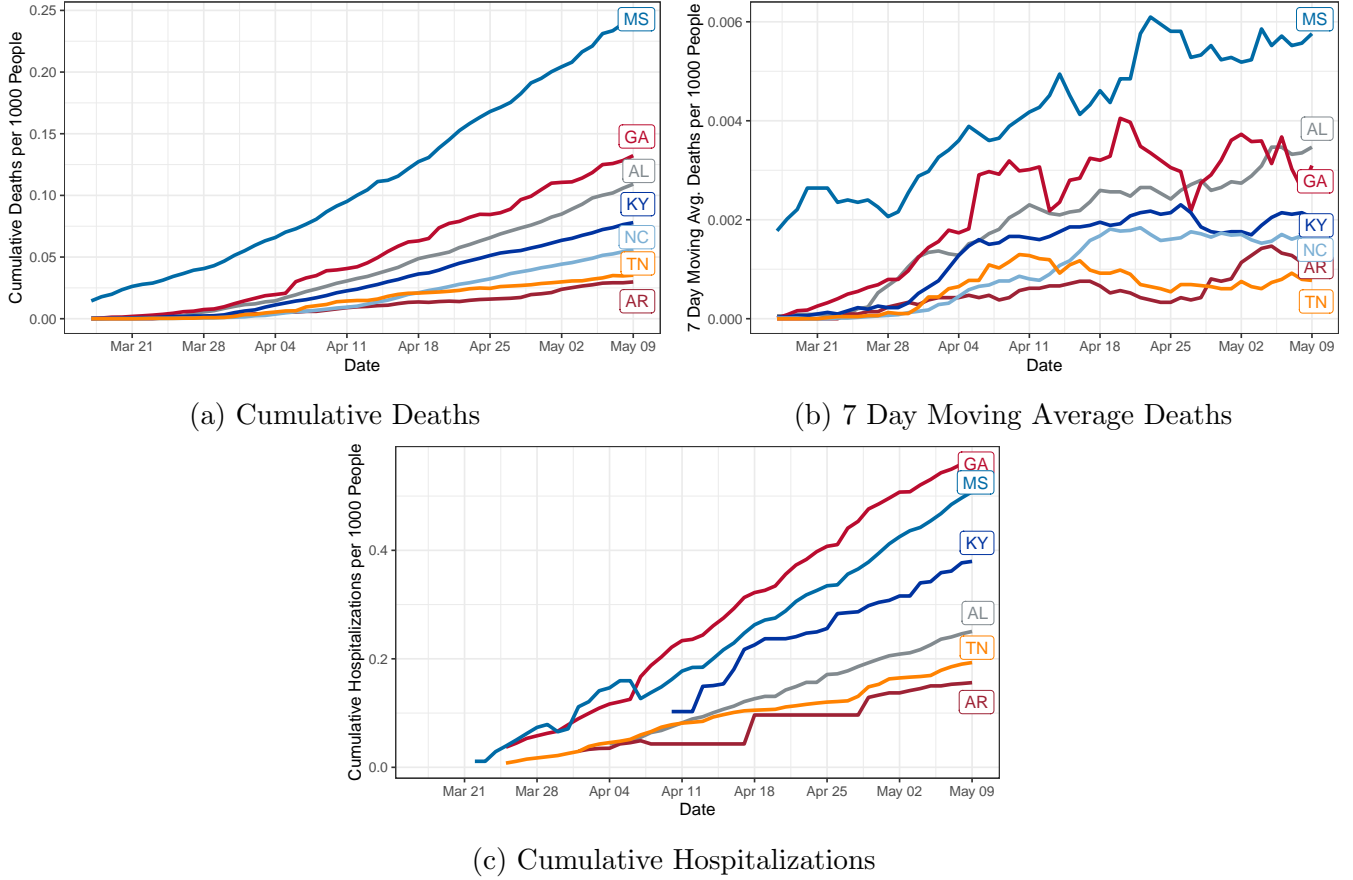
Sources: CDC COVID Data Tracker, COVID-19 Integrated County View

as it effectively uses fewer observations from the untreated group of counties. The bounds are also broadly similar to the main text; relative to the main text, the bounds are somewhat tighter here though the qualitative results are the same as in the main text.

Next, consider the case where the policy's implementation date is set to be March 25 rather than April 1. Recall that, in the main text, we argued that it was not immediately obvious where to set the date of the policy due to tradeoffs regarding capturing the full effect of Tennessee's expanded testing policy, using valid comparison counties, and not leaving out useful comparison counties. The results in Figure S-8 are very similar to the ones reported in the main text. If anything, we estimate slightly larger effects on testing and virtually the same effects on confirmed cases and actual cases due to the policy in this case. This is in line with our arguments from the main text where setting the policy date earlier would tend to additionally capture the effects of the earlier (and smaller) part of Tennessee's policy.

Figure S-9 provides similar results but for the case where the policy's implementation date is set to be April 18 (the date where the open-testing policy was implemented) rather than April 1. For

Figure S-3: Deaths and Hospitalizations by State



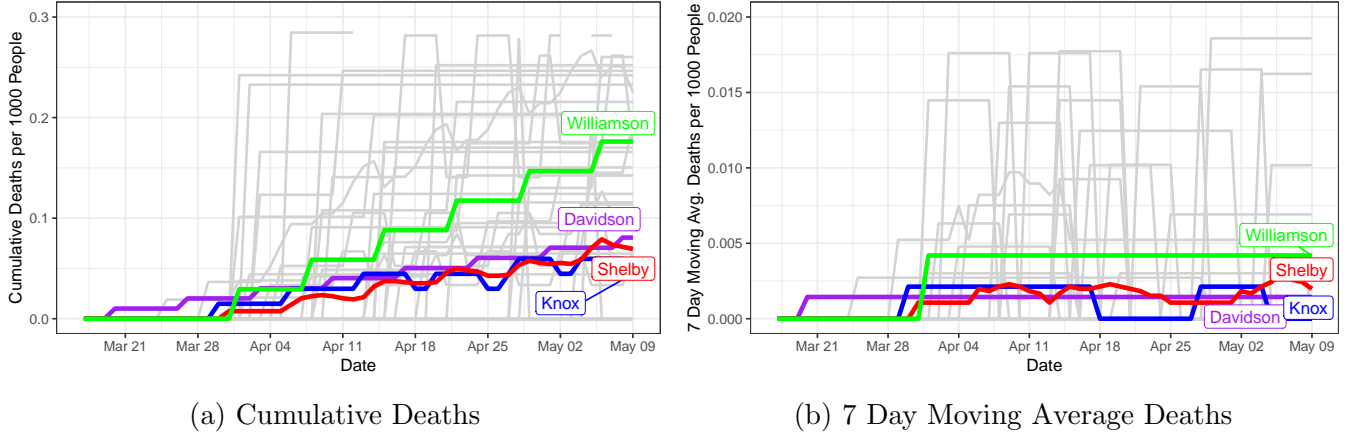
Notes: The figure provides (i) the cumulative and seven day moving average of deaths and (ii) cumulative hospitalizations for Tennessee, Alabama, Arkansas, Georgia, Kentucky, Mississippi, and North Carolina (hospitalizations are not available for North Carolina) from March 18 to May 9, 2020; not all dates are available for hospitalizations.

Sources: For deaths: CDC COVID Data Tracker, https://covid.cdc.gov/covid-data-tracker/#trends_totaldeaths. For hospitalizations, The COVID Tracking Project, <https://covidtracking.com/>

these results, our estimates of the effects of the policy, both on cumulative tests and confirmed cases, are smaller than when we set the implementation date earlier. This is in line with our expectations given the related discussion in the main text. For example, notice that there are some statistically significant effects of the policy in the pre-policy periods in this case. These effects are not included in the cumulative effects for dates after April 18. There are also somewhat tighter bounds in this case as well. That said, all of the results in this case are still qualitatively the same as above and in the main text: the policy is estimated to have increased the number of tests while decreasing the number of confirmed cases and actual cases.

Next, Figure S-10 provides a robustness check on our results from the main text by including the change in the number of confirmed cases in the prior week as an additional covariate. As discussed in the main text, our motivation for the particular covariates that we include comes from models of pandemics from the epidemiology literature. Some variations of these models, particularly ones that

Figure S-4: Deaths by County in Tennessee



Notes: The figure provides cumulative and seven day moving averages of deaths for all counties in Tennessee excluding Bledsoe, Trousdale, and Lake. The highlighted counties are Davidson (county of Nashville), Shelby (county of Memphis), Knox (county of Knoxville), and Williamson (suburban county of Nashville).

Sources: CDC COVID Data Tracker, COVID-19 Integrated County View

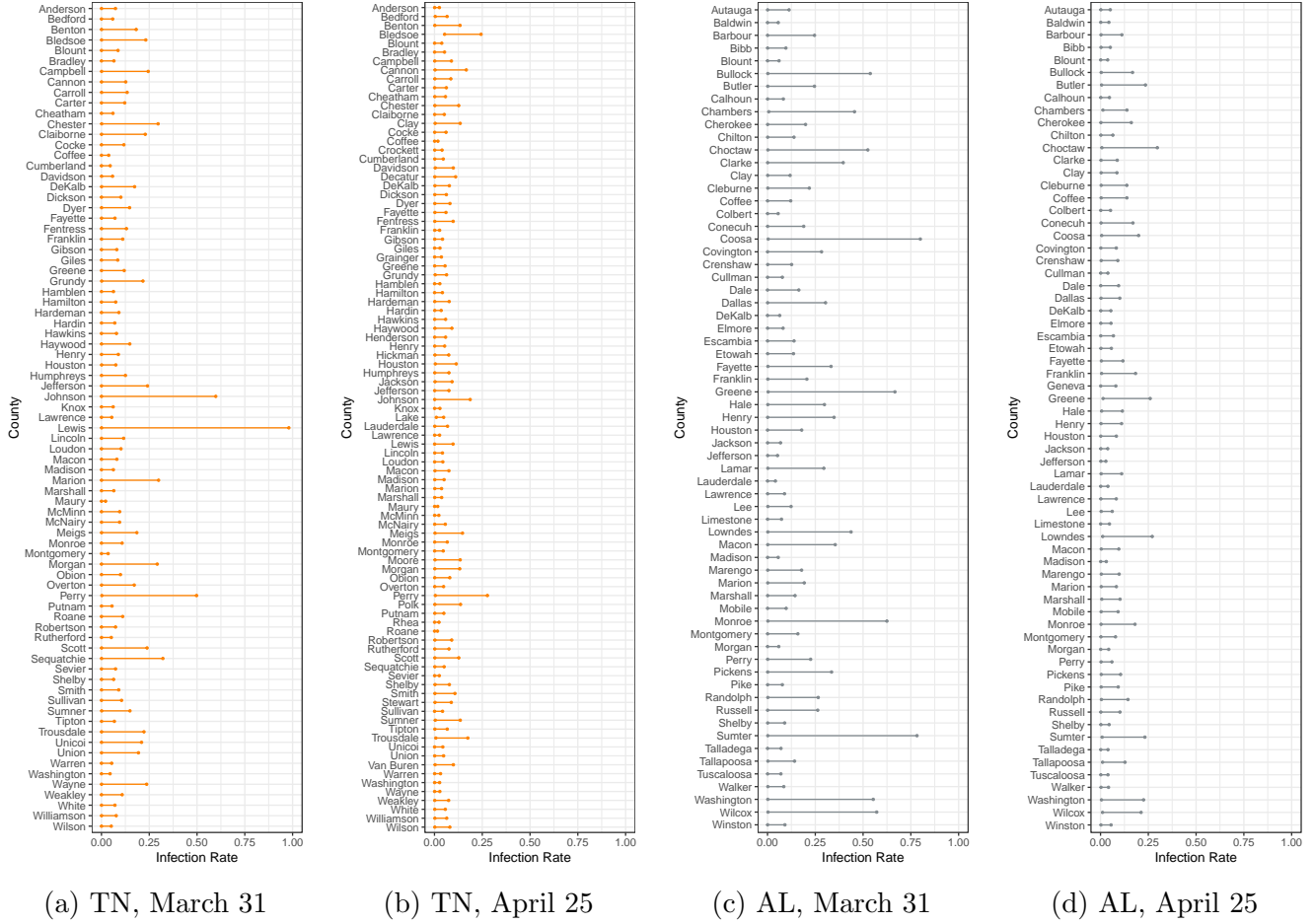
include location-specific unobserved heterogeneity, can suggest including the pre-treatment change in the number of cases as an additional covariate. These results are very similar to the ones reported in the main text.

Figure S-11 provides an additional robustness check where we replace the log of county population with the county’s population density as a covariate. The results are quite similar to the ones in the main text. Here, we estimate essentially the same effect of the policy on testing and marginally larger effects on the number of confirmed and actual Covid-19 cases than in the main text.

Next, we provide results that exclude counties from Arkansas from being in the comparison group in Figure S-12. Recall that, unlike all the other states that we consider, Arkansas did not implement a stay-at-home order. The estimates that exclude Arkansas are very similar to the ones in the main text — the estimated effect of the policy on tests is virtually identical to that presented in the main text, and the effect on confirmed cases is slightly larger (i.e., more negative) here than in the main text. Likewise, the upper bound on actual cases is somewhat more negative (indicating a slightly larger estimate of the effect of the policy).

Next, we provide estimates of the effects of the policy on deaths Figure S-13. We estimate large effects of the policy on deaths: by May 9, we estimate that the policy had reduced the number of Covid-19 deaths by about 0.11 per 1000 people. These are quite large effects. For example, with a 1% infection fatality rate, it would indicate that the policy had reduced the number of actual cases by about 11 per 1000 people which is notably larger than our estimates above. We tend to favor the estimates using confirmed cases that we have emphasized in the main text though. The main reason is that the number of deaths per county is quite small this early in the pandemic (e.g., there had been 241 total deaths in Tennessee by May 9, and there are 95 counties in Tennessee). This same issue also suggests that these results are likely to be more sensitive to our needing to impute

Figure S-5: County-Level Bounds on Total Per Capita Covid-19 Cases

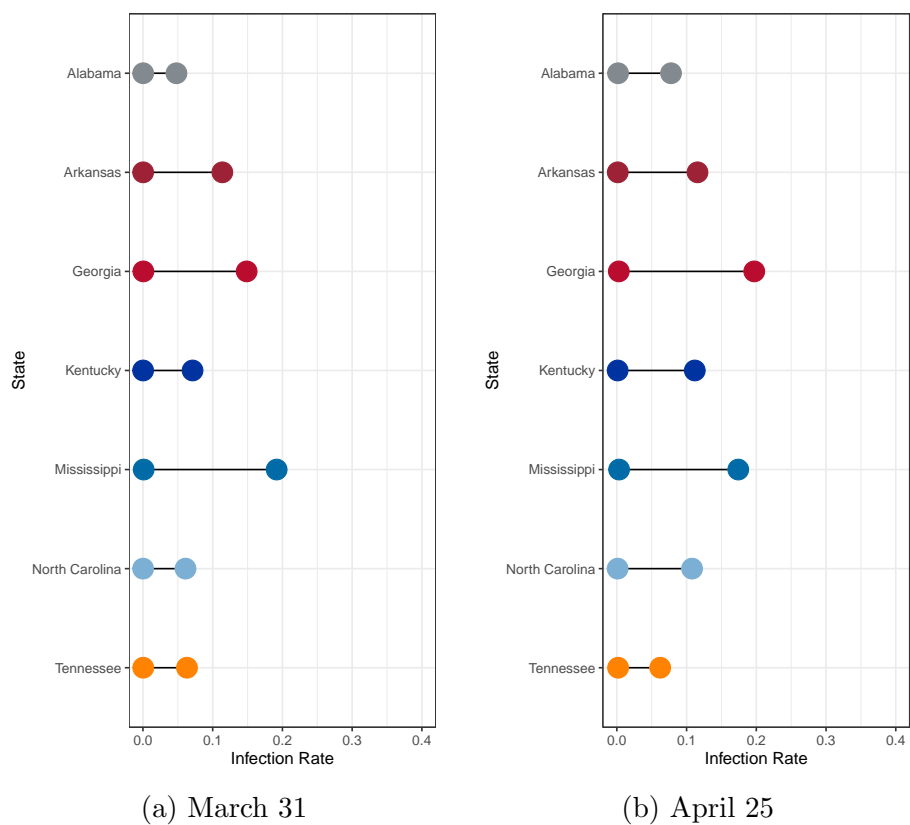


Notes: Bounds on the total (unobserved) per capita Covid-19 cases by county in Tennessee and Alabama using the bounds described in the main text.

“suppressed” numbers of deaths at the county level (recall that 42% of the county-level data on deaths is suppressed in our data which indicates that the seven-day moving average of deaths was positive in that county at that point in time but small enough to not be included for privacy reasons). That being said, at least qualitatively, these results are in line with those from the main text and suggest that Tennessee’s policy decreased the number of Covid-19 cases in Tennessee.

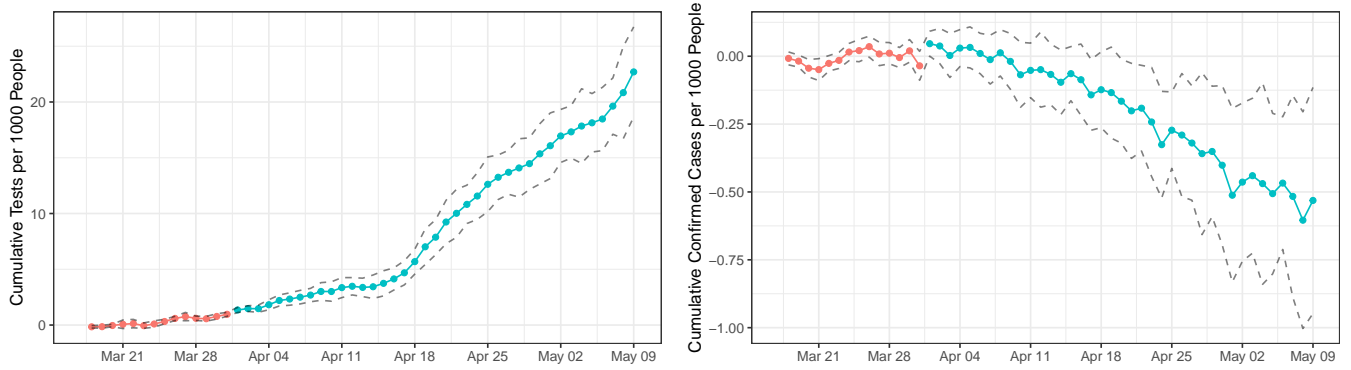
Finally, we provide estimates of the effect of Tennessee’s testing policy on trips to work. The data for trips to work comes from Google’s Covid-19 Community Mobility Reports (<https://www.google.com/covid19/mobility/>). These are aggregated cell phone data that Google has published to help researchers studying Covid-19. We focus primarily on county-level trips to work and how this variable evolves over time. It is reported as a percentage change relative to pre-Covid trips to work. These results move around more than the results for tests, confirmed cases, and actual cases above. However, most notably, our estimates indicate that the policy increased the number of trips to work from about the beginning of May. This is broadly in line with our earlier results and could arguably be due to individuals being more willing to work when the number of local Covid-19 cases is lower.

Figure S-6: State-Level Bounds on Total Per Capita Covid-19 Cases



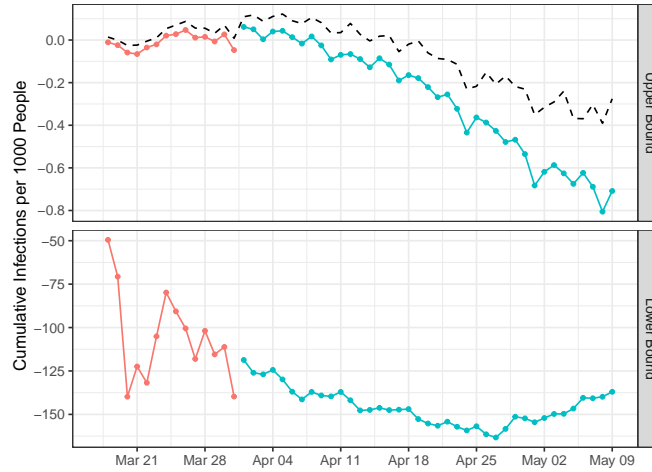
Notes: Bounds on the total (unobserved) per capita actual Covid-19 cases by state using the bounds described in the text.

Figure S-7: Tests, Confirmed Cases, and Bounds on Actual Cases using Matching



(a) Cumulative Tests

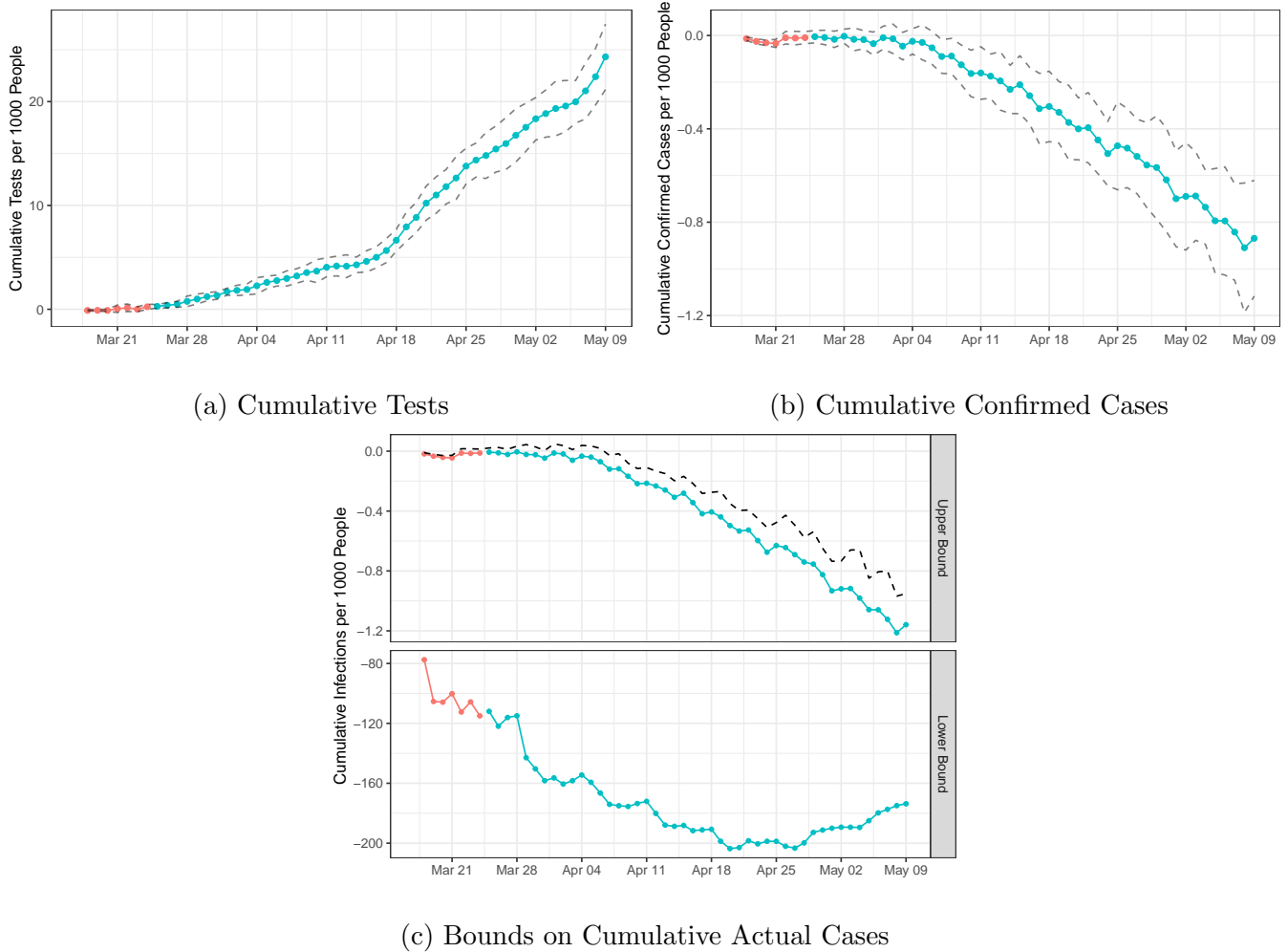
(b) Cumulative Confirmed Cases



(c) Bounds on Cumulative Actual Cases

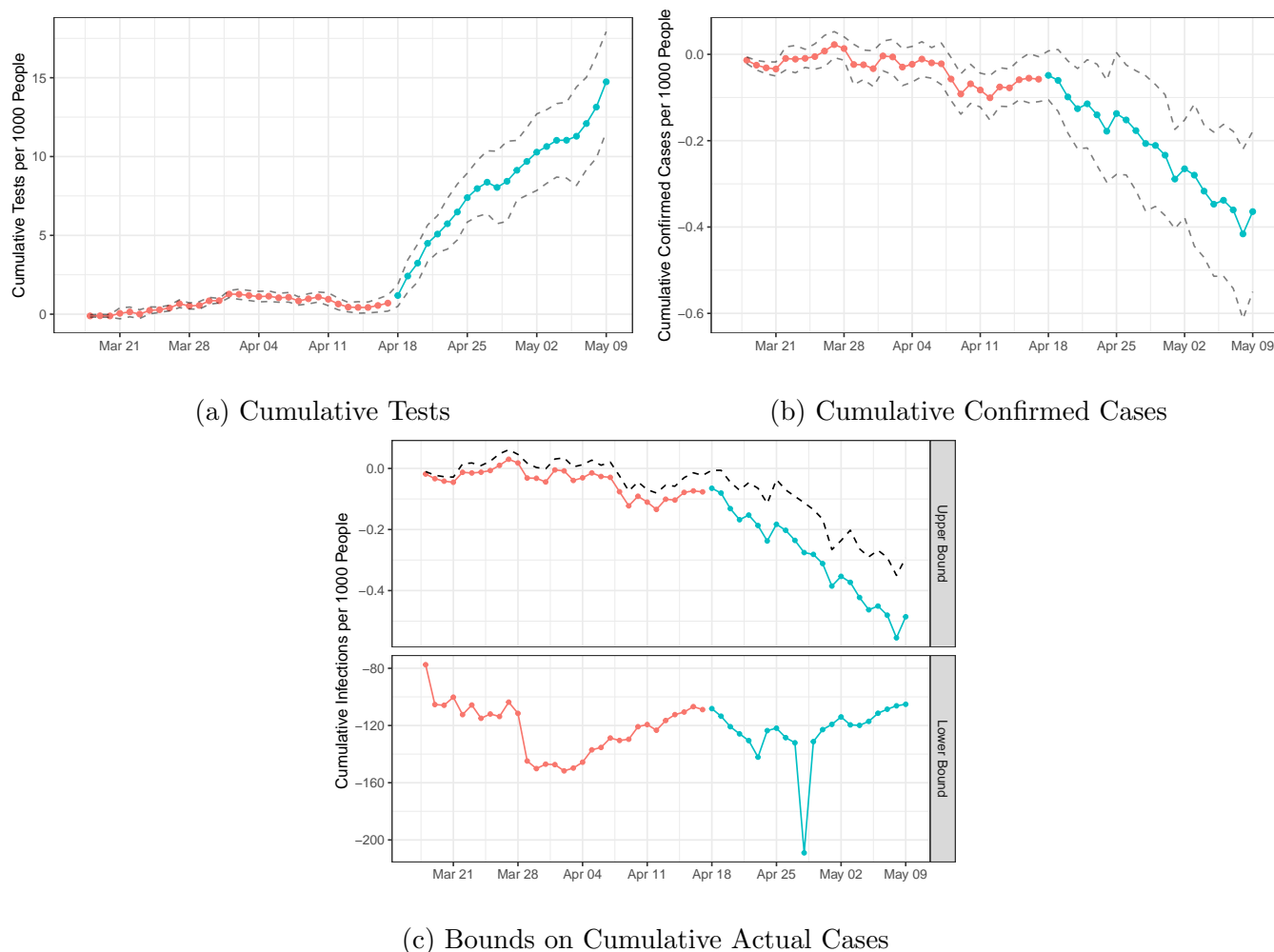
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the matching estimator described in Appendix S-A. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

Figure S-8: Tests, Confirmed Cases, and Bounds on Actual Cases using March 25 Policy Date



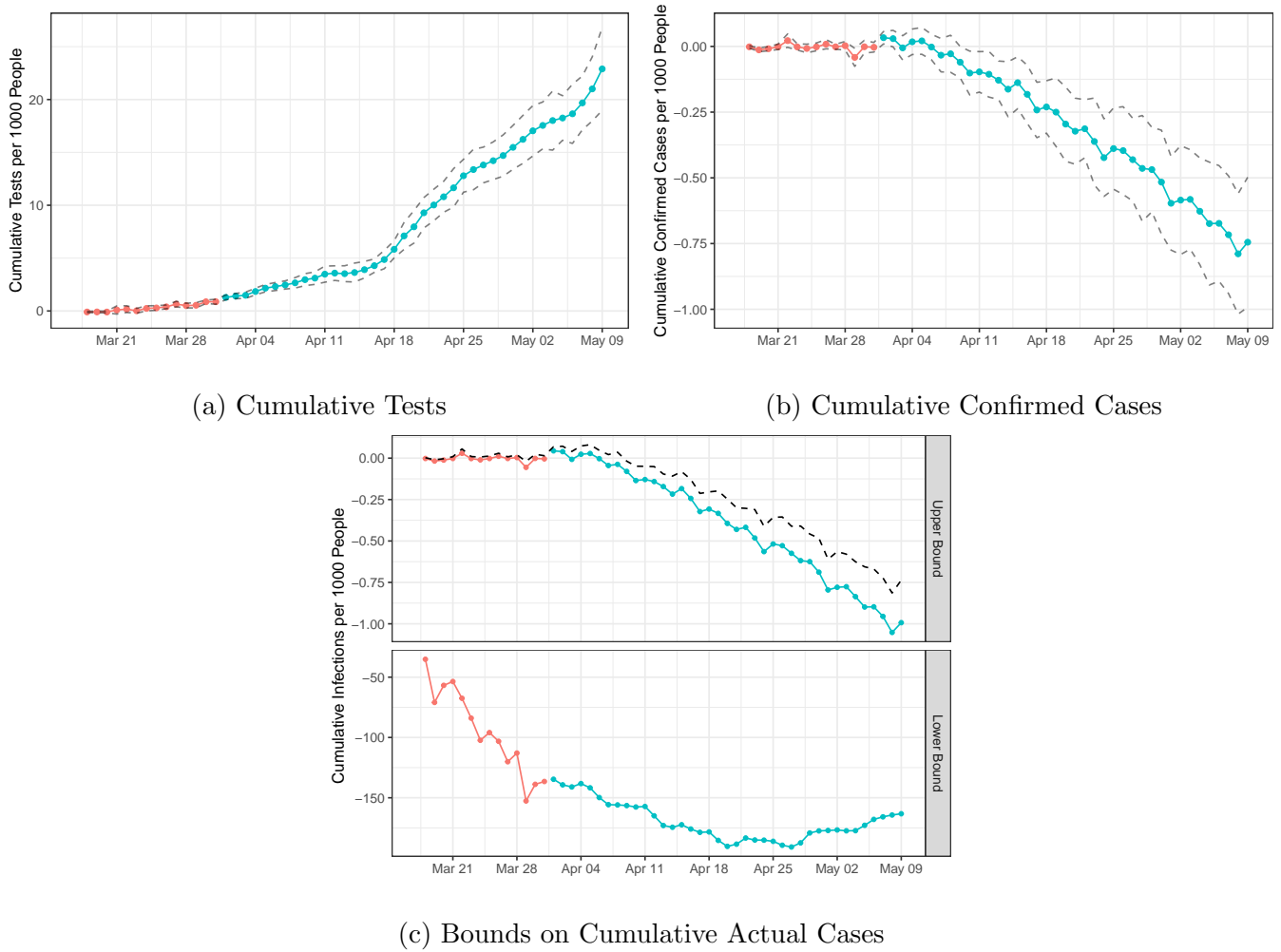
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the approach described in the main text while setting the policy date to be March 25 rather than April 1. The red points in the figure are estimates before March 25 while the blue points are for after March 25. The dashed line provides a 90% confidence interval.

Figure S-9: Tests, Confirmed Cases, and Bounds on Actual Cases using April 18 Policy Date



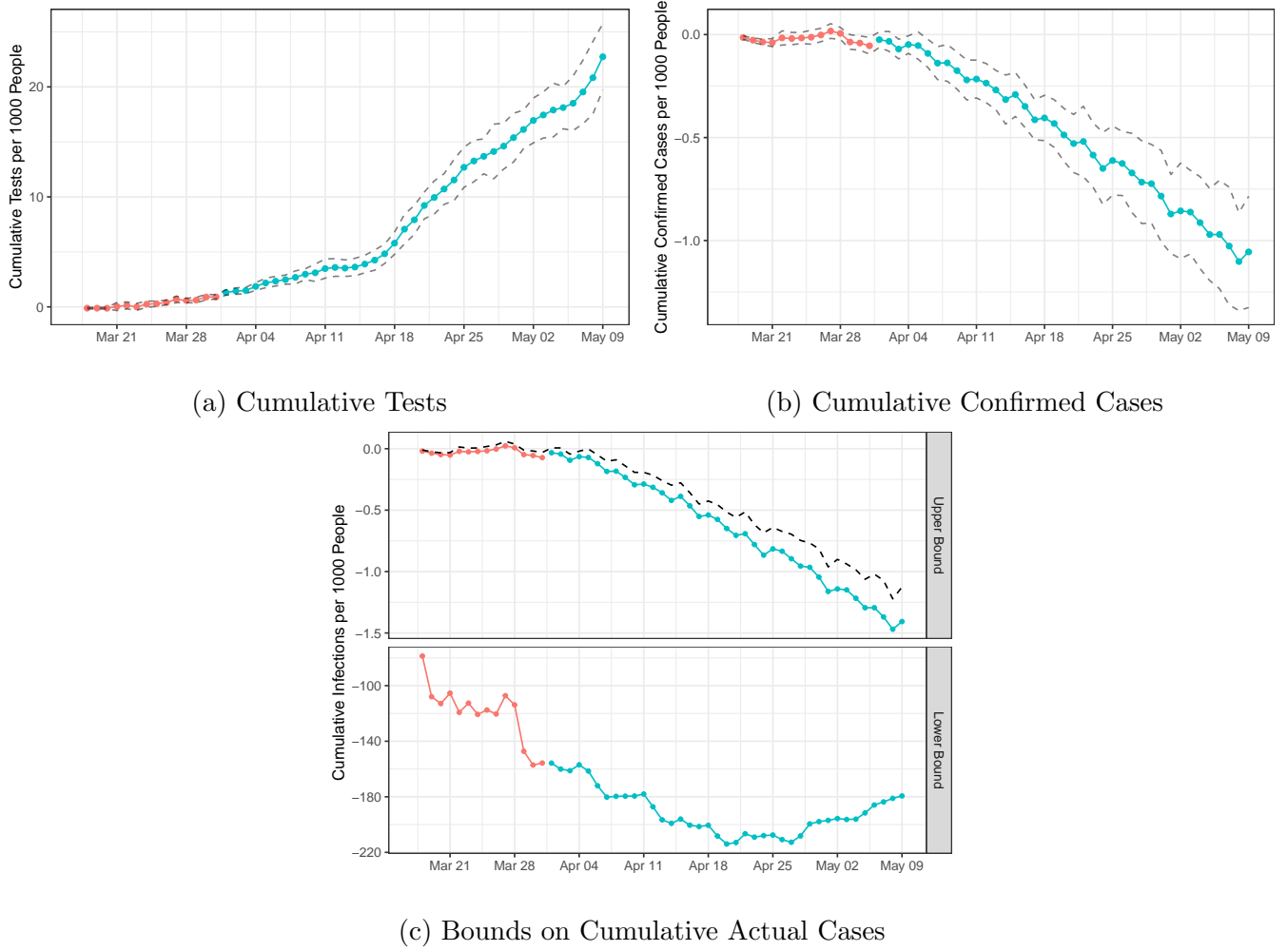
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the approach described in the main text while setting the policy date to be April 18 rather than April 1. The red points in the figure are estimates before April 18 while the blue points are for after April 18. The dashed line provides a 90% confidence interval.

Figure S-10: Tests, Confirmed Cases, and Bounds on Actual Cases including Pre-Treatment Change in Confirmed Cases



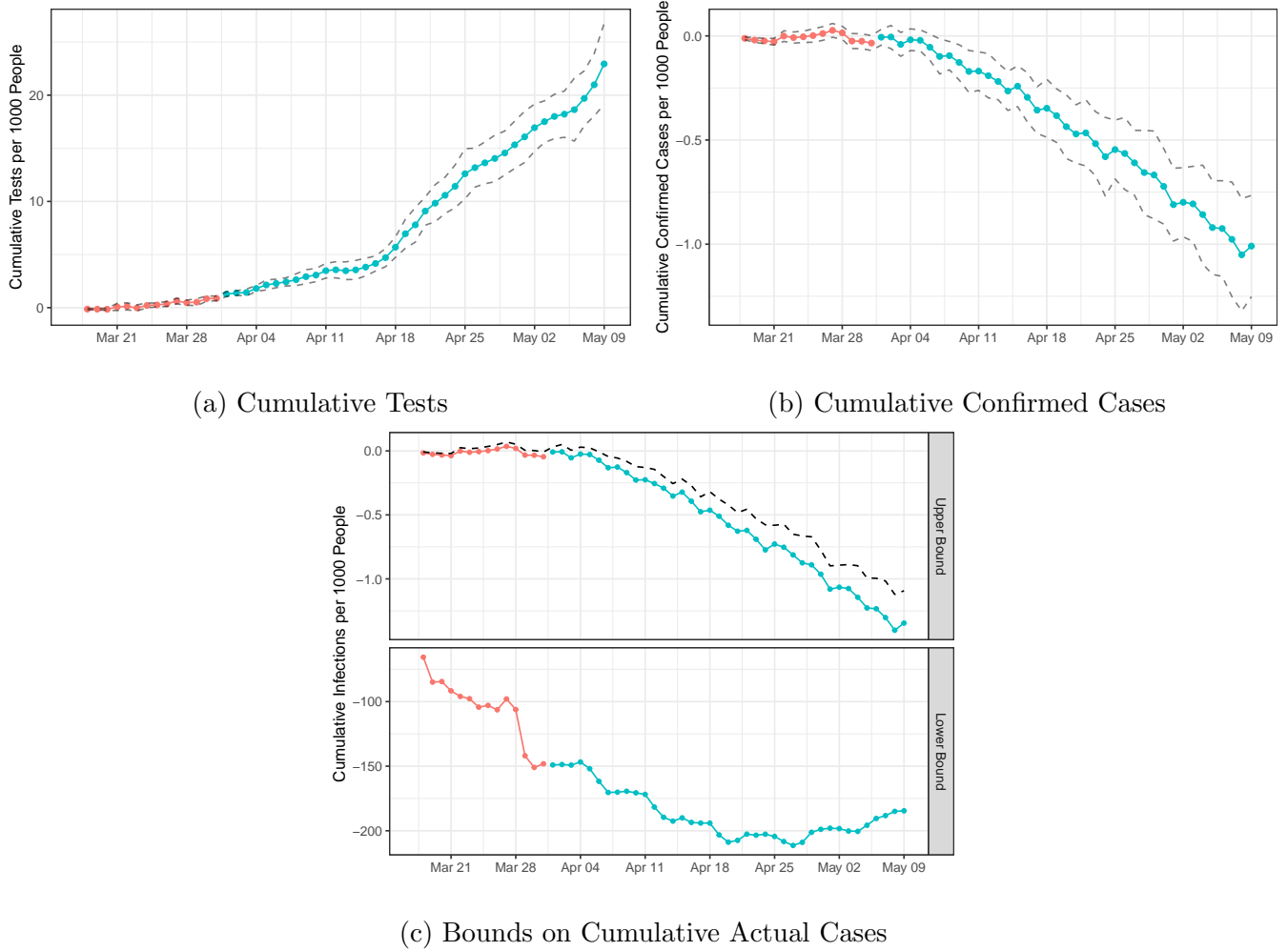
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the approach described in the main text except that it additionally includes the change in confirmed cases in the prior week as an additional covariate. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

Figure S-11: Tests, Confirmed Cases, and Bounds on Actual Cases using Population Density rather than Log Population



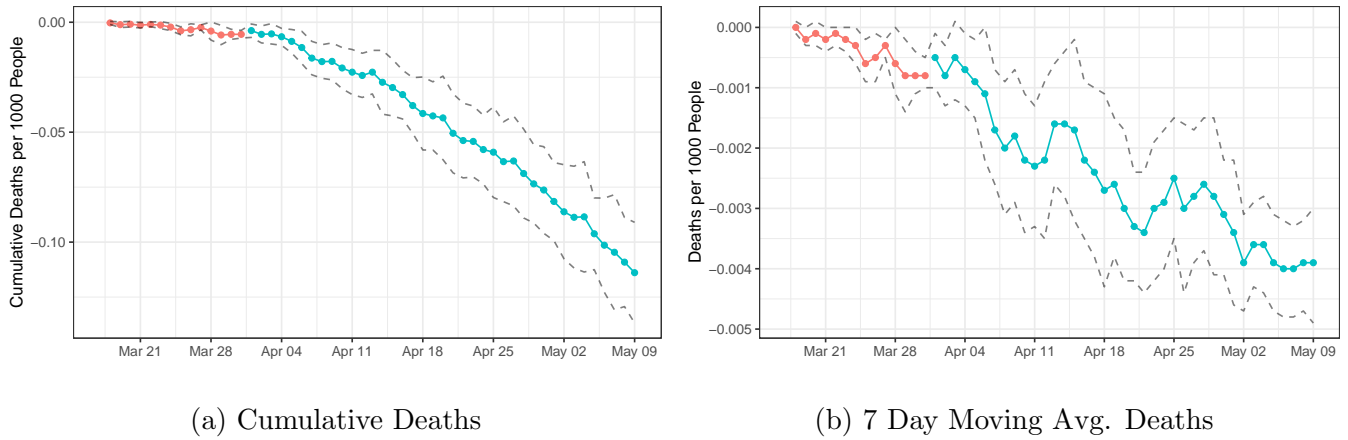
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the approach described in the main text except that it uses population density as a covariate rather than the log of county population. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

Figure S-12: Tests, Confirmed Cases, and Bounds on Actual Cases without Arkansas



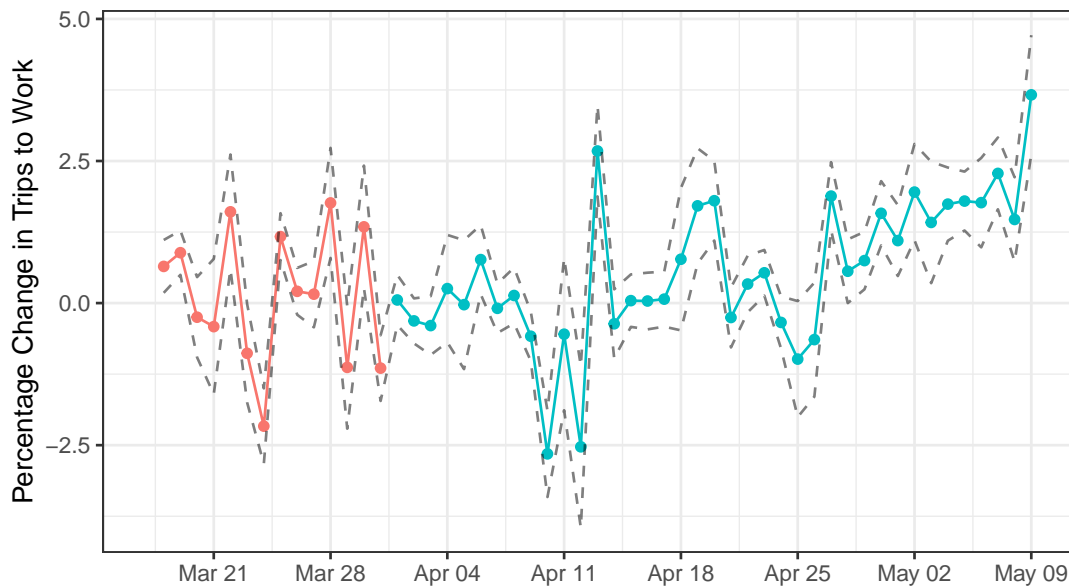
Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative tests per 1000 people, cumulative confirmed cases per 1000 people, and bounds on actual cases per 1000 people using the approach described in the main text except that the results in this figure exclude counties in Arkansas from being in the comparison group. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

Figure S-13: Policy Effects on Deaths



Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on cumulative deaths per 1000 people and the seven day moving average of deaths per 1000 people using the approach described in the text. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

Figure S-14: Policy Effects on Trips to Work



Notes: The figure provides estimates of the effects of Tennessee's expanded testing policy on the percentage change in trips to work using the approach described in the text. The data used for this plot is a subset of 464 counties of the original 692 counties where mobility data is available. The red points in the figure are estimates before April 1 while the blue points are for after April 1. The dashed line provides a 90% confidence interval.

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