1 Local news availability does not increase
2 pro-social pandemic response

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Abstract

Local media provide a bevy of pro-social and civic benefits because they provide essential information about peoples' local communities. The COVID-19 pandemic has created the conditions to test whether these conclusions can be extended beyond traditional political or civic domains, as the crisis had a particularly idiosyncratic spread across the United States. In a period of competing information and regulations, as well as rampant partisanship, a high volume of local media in an area should have led to a more pro-social response to the pandemic, as local residents had greater opportunities to learn about the risks specific to their communities and what their local and state officials were asking them to do. In particular, those with more local news available should have stayed home more and gone out for unnecessary travel less. I test this theory by combining county mobility data with counts of the local newspapers available in each county and other local demographic measures. After controlling for these other demographics and addressing potential confounding through weighting, I find no substantive effect of local newspaper volume on mobility change. This lack of a causal effect of local news availability on pro-social behavior uptake has implications for how we think about local media's role and efficacy in their communities.

One of the challenges in the American response to the COVID-19 pandemic has been the local variation in the virus's spread. While New York and other Northeastern states faced the brunt of the virus's impact in March and April 2020, the American South became the national epicenter in June and July 2020. Even inside a single state, the virus's spread and effects have varied between regions. Complicating matters, the federal government has not provided unifying guidance, leaving each state and locality to develop its own restrictions and regulations, heightening the pandemic's geographic idiosyncrasy. As such, most Americans have taken up following news about the pandemic at the local level [1], which has meant turning to and placing increased trust in local news outlets' information about the pandemic and how to respond to it [1, 2]. In fact, much has been made about how local news is an optimal pathway for combating misinformation about the pandemic [3, 4].

However, local news outlets have been disappearing across the United States for more than a decade [5, 6]. Today, almost 200 counties have no newspapers and more than 1,400 have only one newspaper [5]. In the current moment, that means that some counties are potentially better positioned to follow and respond to the pandemic by adopting the types of responses advocated for by health experts, such as mask-wearing, hand washing, and social distancing. This study tests whether counties with healthier local news economies responded in a more pro-social manner than those with less healthy local news economies.

53 It is possible that a positive association between local news availabil-
54 ity and the uptake of pro-social health behaviors does exist, as other
55 pro-social effects of local news availability are well documented. For ex-
56 ample, newspaper closures lead to declines in the rates at which people
57 contact public officials, boycott products or services, join civic groups,
58 and act as an officer for the groups to which they belong [7]. Similarly,
59 the disappearance of local newspapers leads to less accountability of
60 local governments [8]. Exacerbating the accountability issues, declines
61 in local political news have are associated with declines in the politi-
62 cal knowledge necessary to evaluate politicians and reductions in voter
63 turnout [9, 10].

64 In all of these examples, local newspapers promote pro-social behav-
65 ior by making it easier for the mass public to learn about politics. This
66 accountability function of the local news is a byproduct of providing
67 citizens with information about local politics and government to which
68 they would otherwise not have access. The same could be true about
69 COVID-19 and how best to respond, given that it is also an unfamiliar
70 topic for which there is a sizable information asymmetry between elites
71 and the mass public and that the pandemic and government responses
72 have been locally idiosyncratic.

73 To test whether local news affects the adoption of pro-social responses
74 to COVID-19, I take advantage of differences in news availability be-
75 tween counties. By leveraging this variation in the volume of local news-
76 papers available in a county, I generate an estimate of the causal effect
77 of the volume of local news on changes in travel for retail and recreation
78 and time spent at home for thousands of American counties. An initial
79 set of models accounting for county-level pandemic features and local
80 demographics shows no substantive local-news effect.

81 Even so, the effect of local-news availability may be contingent on
82 citizens becoming aware that there is a crisis about which they need
83 to learn more. For each county, I identify two such moments: March
84 11th, the day that Tom Hanks announced his COVID-19 diagnosis, the
85 NBA began canceling games, and the World Health Organization de-
86 clared COVID-19 a pandemic, and the day that their state-issued stay-
87 at-home orders. To account for the possibility that these events affected
88 information-seeking behavior, I estimated a model controlling for a se-
89 lection of pandemic features and county-level demographics, as well as
90 the interaction between newspaper volume and the period from which
91 an observation was drawn. These models show that following these
92 events, counties with more local news did not have significantly greater
93 mobility change.

Results

Main Effect of Newspaper Volume

The simplest models I estimated find the expected relationship between the volume of local newspapers available and pro-social behaviors, decreases in retail and recreation travel and increases in spending time at home, to be significant. A one-standard-deviation increase in the number of newspapers available in a county is associated with a 0.083 standard-deviation increase in the percentage point change in staying at home (95% CI = (0.044, 0.12), $p = 2.96 \times 10^{-5}$). Alternatively, the same one-standard-deviation increase in the number of newspapers is associated with a 0.11 standard-deviation decrease (95% CI = (-0.16, -0.063), $p = 4.65 \times 10^{-6}$) in the percentage-point change from baseline in travel for recreation or retail purposes. Full details can be found in Model 1 of Tables 1 and 2.

However, we should reasonably expect county-wide movement behavior during the COVID-19 pandemic to be affected by the severity of any outbreak in the county. As such, the second set of models I estimated included controls for the number of cases and deaths related to COVID-19 in each county, an indicator for whether the county's governor had issued a statewide stay-at-home order, a measure of how far into the 76-days the observation came, and the interaction between these last two variables.

Even controlling for these pandemic features, there is still evidence of a significant relationship between local news volume and pro-social behavior adoption. As we can see in Figure 1, the one-standard-deviation change in newspaper count, according to this model, produces a 0.035 standard-deviation increase in the percentage change from baseline for staying at home (95% CI = (0.0066, 0.063), $p = 0.016$). Similarly, the relationship between newspaper count and travel for recreation or retail purposes is also still significant and in the expected direction ($\beta = -0.050$, 95% CI = (-0.081, -0.019), $p = 0.0014$). The associated details can be found in Model 2 of Tables 1 and 2.

Do these relationships hold while controlling for county demographic and structural features, such as partisan lean? To answer this question, I re-estimated the models, now including controls for county demographic and structural features. Results from these models are visualized in Figure 2. With these additional controls, the estimated relationship changes direction for both staying at home ($\beta = -0.018$, 95% CI = (-0.029, 0.0061), $p = 0.0028$) and retail or recreation related travel ($\beta = 0.021$, 95% CI = (0.011, 0.029), $p = 7.73 \times 10^{-6}$). Full results are in Model 3 of Tables 1 and 2.

Beyond these flips, what we see in both contexts is that a few factors have strong relationships with changes in behavior. For both, the presence of a stay-at-home order has the largest effect (Residential: $\beta =$

1.06, 95% CI = (0.98, 1.14), $p < 2 \times 10^{-16}$; Retail & Recreation: $\beta = -1.10$, 95% CI = (-1.19, -1.01), $p < 2 \times 10^{-16}$). Time, measured in days, is also a strong predictor of mobility change in both cases. A one-standard deviation jump forward in time is associated with a 0.96 standard-deviation increase in staying home (95% CI = (0.90, 1.03), $p < 2 \times 10^{-16}$) and a 0.92 standard-deviation decrease in recreation-and-retail travel (95% CI = (-0.96, -0.87), $p < 2 \times 10^{-16}$). However, we see that the interaction between these two variables is large and in the opposite direction of the individual main effects ($\beta_{Residential} = -1.26$, 95% CI_{Residential} = (-1.35, -1.17), $p_{Residential} < 2 \times 10^{-16}$; $\beta_{Retail\&Recreation} = 1.40$, 95% CI_{Retail\&Recreation} = (1.27, 1.51), $p_{Retail\&Recreation} = 2 \times 10^{-16}$). This suggests that the relationship between stay-at-home orders and behavior change wanes with time.

Notably, the county's partisan lean is significantly associated with both types of mobility change (Residential: $\beta = 0.083$, 95% CI = (0.054, 0.11), $p = 1.69 \times 10^{-8}$; Retail & Recreation: $\beta = -0.084$, 95% CI = (-0.11, -0.056), $p = 3.35 \times 10^{-9}$). These relationships are substantially larger than those between both types of mobility change and newspaper volume. These results align with the observations made elsewhere about the influence of partisanship in responding to the threat of the virus [11].

Even so, the model specifications in Model 3 of Tables 1 and 2 are likely biased by confounding. Covariates like a county's education and income levels are likely related to both the treatment, newspaper availability, and the outcomes, change in behavior. To account for this possibility, I conducted non-parametric covariate balancing propensity score weighting. I generated weights based on the time-invariant county-level covariates. This procedure reduced the average correlation between each covariate and treatment, as seen in Supplementary Figure 2.

Using the weights output from the propensity score model, I re-estimated the models. Addressing potential confounding, these results are more consistent estimates of the effect of local news availability on behavior change than those produced in earlier models. Yet, as we can see in Figure 3, the estimated effects are statistically insignificant for staying at home ($\beta = 0.0087$, 95% CI = (-0.030, 0.048), $p = 0.66$). But, we do observe a significant effect on traveling for retail or recreation purposes ($\beta = -0.035$, 95% CI = (-0.069, -0.00081), $p = 0.045$). Notably, this significant effect on change in travel for retail and recreation is less than half the magnitude of the effect of partisanship ($\beta = -0.083$, 95% CI = (-0.11, -0.054), $p = 9.70 \times 10^{-9}$) and a small fraction of the observed effect of the presence of a statewide stay-at-home order ($\beta = -1.14$, 95% CI = (-1.24, -1.045), $p < 2 \times 10^{-16}$). Complete specifications are reported in Model 4 of Tables 1 and 2.

Given that both analyses are sufficiently powered – power estimates indicate that the chance of a false negative is approximately 0 in both cases – the most likely conclusion is that there is no significant effect of local newspaper availability on staying home, but a small effect on

184 changes in travel for retail and recreation purposes.

185 Of course, my operationalization of the treatment variable as the
186 count of newspapers in a county makes a few assumptions about the
187 nature of the hypothesized treatment effect. However, I also estimated
188 all of the same models with two additional operationalizations of news
189 availability. In the first, I used the standardized and centered log count
190 of newspapers. In the second, I used a binary indicator coded to 1 if
191 a county had any newspaper. As shown in Supplementary Tables 1-
192 4, these operationalizations do not lead to substantively different con-
193 clusions. Local news availability has no meaningful effect on behavior
194 change in either context.

195 **Changing Effects over Time**

196 While modeling the effects of local newspaper volume across the entire
197 76-day period from February 15th, 2020, to April 30th, 2020, reveals
198 no substantive relationship between the number of newspapers in a
199 county and that county's change in mobility, these models do not ac-
200 count for the possibility that the effect of local news is moderated by
201 other time-dependent changes in the information environment. These
202 possible information-environment changes include changes in the re-
203 ported severity of COVID-19 or the implementation of location-specific
204 policies. To account for these possible moderation effects, I conducted
205 a second analysis evaluating the effect of local news volume in three
206 periods: before and up through March 11th, 2020; then from March
207 12th, 2020, up till a state put in place stay-at-home orders; and, then,
208 the period following the implementation of stay-at-home orders.

209 Given that this analysis is effectively a difference-in-difference de-
210 sign, the model assumes that counties with differing numbers of local
211 newspapers had similar trends before the changes in the information
212 environment. To validate the parallel trends assumption, I plotted the
213 relationship between time and change in behavior, with regression lines
214 added for the observations up through March 11th, 2020, and those
215 that came after, as seen in Supplementary Figure 3. As we can see,
216 before this date, the average behavioral changes between counties with
217 low and high amounts of local news are similar.

218 With this assumption met, I estimated linear models regressing daily
219 behavior change on the interaction between the number of newspapers
220 in a county and the period into which each observation falls, as well as
221 the same county-level covariates included in the first set of models.

222 As we can see in Model 1 of Tables 3 and 4 and Panels A and B of
223 Figure 4, the effect of local newspaper volume is significantly moder-
224 ated by time in the unweighted models. In the period between March
225 12 and the implementation of statewide shutdowns, a one-standard-
226 deviation increase in local newspaper volume was associated with an

227 additional 0.054 standard-deviation increase in staying at home (95%
 228 CI = (0.015, 0.094), $p = 0.0068$). In the period between the implemen-
 229 tation of statewide shutdowns and April 30, that same one-standard-
 230 deviation increase in local newspaper volume produced an additional
 231 0.073 standard-deviation increase in staying home (95% CI = (0.028,
 232 0.12), $p = 0.0016$). In regards to travel for retail or recreation purposes,
 233 a one-standard-deviation change in newspaper volume did not produce
 234 a statistically significant change in the period from March 12 to the imple-
 235 mentation of statewide orders ($\beta = -0.028$, 95% CI = (-0.067, 0.011), p
 236 = 0.16), while the same one-standard-deviation increase in newspaper
 237 volume produced an additional 0.068 standard-deviation decrease in
 238 going out for these purposes following the implementation of statewide
 239 stay-at-home orders (95% CI = (-0.11, -0.029), $p = 0.00066$).

240 However, if we apply the same non-parametric covariate balancing
 241 propensity score weighting used in the prior section, the results change
 242 substantially. With this weighting, the the effect of local newspaper vol-
 243 ume on staying home, while statistically insignificant, is actually nega-
 244 tive in the latter two time periods (March 12 - Order: $\beta = -0.12$, 95%
 245 CI = (-0.26, 0.017), $p = 0.085$; After Order: $\beta = -0.12$, 95% CI = (-0.27,
 246 0.024), $p = 0.10$). Similarly, in the period from March 12 till the imple-
 247 mentation of statewide stay-at-home orders, the effect of local newspa-
 248 per volume on travel for retail or recreation purposes changes sign from
 249 negative to positive and is statistically insignificant ($\beta = 0.074$, 95% CI
 250 = (-0.048, 0.20), $p = 0.24$). Yet, in the period following the implemen-
 251 tation of statewide orders till April 30, the effect is insignificant, but in
 252 the expected negative direction ($\beta = -0.066$, 95% CI = (-0.16, 0.023), p
 253 = 0.15). Full results are in Model 2 of Tables 3 and 4, with associated
 254 predictions visualized in Panels C and D of Figure 4.

255 To contextualize the estimated effects across all four models, I plotted
 256 the predicted standard-deviation change in mobility during each period
 257 for counties ranging from 0 to 40 papers in Figure 4. Even when the
 258 interaction effects are significant (Panels A and B), the effects' substan-
 259 tive impacts are still small. A change from 0 to 40 papers in a county
 260 — a change of over 11 standard deviations in the number of papers) —
 261 in the period after statewide orders only produces a predicted change
 262 in staying home of about 0.24 standard deviations. For travel for re-
 263 tail or recreation purposes, the same change in the same period only
 264 leads to a decrease of 0.30 standard deviations in mobility based on the
 265 unweighted model.

266 These results do not substantively change if I operationalize the treat-
 267 ment variable as a binary indicator for the presence of any local news-
 268 papers or as the log of the count of newspapers in a county, as shown
 269 in Supplementary Tables 5-8.

Discussion

Local news has the potential to generate a positive effect on the adoption of pro-social responses to the COVID-19 pandemic. To test whether such effects have materialized, I analyzed the publicly available mobility reports provided by Google regarding staying home and traveling for retail and recreation purposes. Models regressing change in mobility on the volume of local news, pandemic-related features, and structural and demographic features showed that, when accounting for potential confounding, there was no substantive relationship between the number of newspapers in a county and that county's mobility change. Even considering variation in the effect over distinct periods, while still accounting for potential confounding, does not produce evidence supporting the hypothesis that an abundance of local news increased pro-social response uptake. Operationalizing treatment as a binary indicator of the presence of any local newspaper does not change the substantive results.

These results are normatively concerning because they suggest that the pro-social impact of local news may be limited. While local news promotes healthy civic engagement, such as by promoting voter turnout [9, 10], it does not appear to be counteracting the partisan response to the COVID-19 pandemic, which is likely due to differences in how partisan media and elites from both parties framed the severity of the virus [12, 13], as well as the activation of mass partisan animus as health behaviors became politicized [14]. As such, my results point towards a substantial limitation for local news to promote pro-social behavior in politically polarized contexts. The implications of such a limitation are concerning, given the possibility of partisan media and elites politicizing essential civic issues, such as voting by mail [15], thus turning attitudes and behavior related to these issues into opportunities to signal one's partisan identity. If issues become strongly politicized and polarized, it is not clear that local media can undo such position-taking.

But, should I have expected to find an effect in the first place? While local news availability leads to more pro-social civic behavior, such as voting, the comparison to pro-social COVID-19 response may not fit. One could argue that COVID-19 is a singular national-level crisis and disaster covered across all levels of journalism, while local elections are highly idiosyncratic and are likely to only be covered by local outlets. However, positioning the COVID-19 pandemic at the opposite binary of local elections would be misplaced.

To begin with, this assumption inaccurately characterizes local elections. Local elections are unique cases of a much larger national event. Local elections are specific instances of the two national parties competing. When local news disappears, citizens turn to national media and partisan heuristics to make their decisions, leading to less split-

315 ticket voting [16]. Similarly, the expansion of political coverage brought
316 about by the Internet has led to an increase in national considerations
317 when voting in local elections [17]. Both of these results demonstrate
318 how local elections exist along a local-national spectrum. Local news
319 leads citizens to consider the local context of the election, but it is an
320 oversimplification to argue that local elections are truly low-information
321 affairs.

322 Furthermore, this strong differentiation between local-election cov-
323 erage and COVID-19 coverage also inaccurately characterizes the pan-
324 demic. COVID-19 is not a monolithic story. While there is a strong
325 national element playing out, local communities have had a distributed
326 and asynchronous experience of dealing with the pandemic. These dif-
327 ferences have manifested in differing regulations across states, coun-
328 ties, and municipalities regarding staying at home, face coverings, and
329 testing [18]. As such, local contexts are highly important and local news
330 sources have much to offer, which both Democrat and Republican politi-
331 cians have indicated [19].

332 That being said, one could argue that a high degree of choice does
333 not matter inside a county or community. As long as there is a path-
334 way, citizens could access helpful and necessary information. Yet, I
335 account for this possibility through an additional operationalization of
336 news availability that codes news availability as a binary variable, coded
337 to 1 when a county has any number of newspapers and 0 when they
338 have no newspapers. This operationalization produces substantively
339 similar results in both the stay-at-home and travel for retail and recre-
340 ation contexts: having any newspaper at all does not lead to behavior
341 change.

342 Similarly, one could argue that news consumers are more likely to
343 turn to TV news, especially local TV news, during a crisis. Nielsen data
344 lends credence to this theory; local TV news viewership was up about
345 7% in major media markets, with greater effects among younger view-
346 ers [20]. Larger than that, the major broadcast evening-news programs
347 saw a 42% year-over-year increase in viewers during the week of March
348 16th [21] and cable news saw viewership sore to record or near-record
349 highs in April [22]. Even so, *The New York Times* report on Internet
350 audience behavior indicates that major market newspapers were reg-
351 ularly experiencing audience growth above 100% in March 2020 com-
352 pared to February 2020 [2]. Without absolute audience counts, com-
353 paring growth rates could lead to false perceptions of absolute audience
354 size. Yet, these reports suggest that, behaviorally, Americans turn their
355 attention to multiple local news and information pathways simultane-
356 ously, meaning that newspaper availability should be a relevant factor
357 in communities' pandemic responses.

358 Beyond these theoretical concerns, it is important to consider the
359 practical limitations of this study. Causal inference with observational
360 data is notoriously difficult. However, one of the principal concerns with

361 regression estimates in such cases is that unobserved confounders will
362 account for observed significant relationships. In this case, though,
363 the expected relationship disappears when just controlling for observed
364 covariates. Applying covariate balancing propensity score weighting to
365 generate more consistent estimates of the treatment effect in the face
366 of potential confounding also provides no evidence of any link between
367 local news availability and the adoption of pro-social behaviors. This
368 pattern holds across the models with and without time-based interac-
369 tions.

370 My analysis also cannot account for whether increased newspaper
371 volume is associated with county residents giving more attention to the
372 local news. I assume that it does, but if this assumption is wrong, it
373 breaks the causal link between news availability and behavior change.
374 Furthermore, increased attention to local news may manifest in at-
375 tention explicitly directed to reporting on basic facts about the virus's
376 spread and not information about how and why to socially distance.

377 In the same vein, newspapers may make some production decisions
378 that affect the relationship between newspaper availability and behavior
379 change. For example, local news may not be adequately addressing the
380 information needs of community members during this time, a condition
381 that has been identified in pre-COVID-19 reporting [23, 24]. Further-
382 more, evidence suggests that in choosing whom they feature in their
383 reporting on the pandemic, newspapers are producing politicized and
384 polarized coverage of the crisis [25].

385 One particular example of how these production-decision effects may
386 play out is the difference between rural counties that share and do not
387 share a media market with a city. Those that do tend to have their local
388 news coverage focused on the urban environment and its challenges.
389 During the pandemic, this focus has led to increased coverage of the
390 pandemic's risks, which in turn has led those in these rural counties
391 sharing a media market with a city to be more likely to practice social
392 distancing [26]. (However, the observed effects were still substantively
393 small.)

394 Additionally, Google's reports note that, in some cases, the change
395 in behavior reported is based on limited data. In these cases, we should
396 assume that the estimates could change dramatically if more data could
397 have been collected during the baseline window. Furthermore, counties
398 with fewer newspapers are also more likely to be missing outcome ob-
399 servations, especially regarding staying at home. This association could
400 bias results and pose a threat to validity. As more data, especially from
401 additional sources, becomes available, these results should be tested to
402 see if they replicate.

403 Altogether, these limitations are relatively minor. The analyses pre-
404 sented here are sufficiently powered, consider a reasonable set of poten-
405 tial confounders, and ultimately apply appropriate methods for causal
406 inference. I find that, when controlling for pandemic and county de-

407 mographic features, the relationship between local newspaper volume
408 and behavior change is effectively zero in both the case of travel for re-
409 tail or recreation purposes and time spent at home. By comparison,
410 partisanship has a much larger effect in both cases.

411 As America continues to deal with the fallout of the COVID-19 pan-
412 demic, it will face new challenges to the regular social and civic func-
413 tioning of the country. Local news could play an important role in the
414 management and response to these specific challenges, given its ability
415 to inform and mobilize members of the mass public. However, assum-
416 ing that local newspapers are providing sufficient coverage of the pan-
417 demic and providing information on the recommended responses, the
418 evidence presented here indicates that local news coverage is not suffi-
419 cient to undo the politicization and polarization of issues and behavior.

420 But, this study should not be taken as evidence that local newspa-
421 pers provide diminished civic benefits. Instead, this work should be-
422 gin conversations about why those in healthy and robust local news
423 economies did not change their behavior and what types of production-
424 side changes could be implemented to promote future behavior change.
425 In particular, future research should extend the findings presented here
426 by considering the issue from an audience perspective — *who is respon-*
427 *sive to local news?* — and from a production perspective — *how can local*
428 *news outlets better position their work to lead to pro-social outcomes?* De-
429 veloping behavioral insights in these specific areas could help develop
430 a more robust and healthy information environment, undermining this
431 study's pessimistic implications.

432 **Methods**

433 **Data**

434 I collected mobility data from Google's COVID-19 Mobility Reports [27].
435 These reports, published for a set of countries and regions, compare
436 how the number of trips and the time spent in different types of loca-
437 tions have changed compared to a baseline period from January 3rd,
438 2020 to February 6th, 2020. Each report includes measures for loca-
439 tions classified as recreation or retail, groceries or pharmacies, parks,
440 transit stations, work, and residential. Certain counties did not gener-
441 ate enough data, so Google did not report any values in those cases. The
442 data used in this study cover each day from February 15th, 2020, and
443 April 30th, 2020. Supplementary Figure 1 visualizes the distribution
444 of days of mobility data available for each county.

445 I combined these mobility data with counts of the number of newspa-
446 pers operating in each county. These counts were based on the Univer-
447 sity of North Carolina at Chapel Hill's School of Media and Journalism's
448 Center for Innovation and Sustainability in Local Media's proprietary

449 database of newspapers [5]. These data were initially collected in 2018
450 and verified using a variety of trade sources.¹

451 *The New York Times* originally published the data about the number
452 of cases and deaths in each county I used in this study [28]. *The New*
453 *York Times* also originally published the data about the statewide stay-
454 at-home-orders and the dates they were issued that are used in this
455 study [18].

456 I turned to the 2018 American Community Survey (ACS), accessed
457 through the tidycensus package in R, to collect county demographic
458 measures. I combined these with data about food access from the De-
459 partment of Agriculture [29] and 2012 population density estimates
460 from ESRI [30]. Finally, I also operationalized the partisan lean for each
461 county as each county’s 2016 vote share for Hillary Clinton.

462 **Modeling**

463 To estimate the relationship between local news availability and mobility
464 behavior changes during the COVID-19 pandemic, I estimated a series
465 of linear models for the ‘Retail & recreation’ and ‘Residential’ mobility
466 data. The simplest models regressed the percentage-point change from
467 baseline in standard-deviation units for the given category on the num-
468 ber of newspapers published in a county. I followed these models by
469 estimating additional models, including controls for four COVID-19 re-
470 lated features: the number of cases on the given day, the number of
471 deaths on the given day, the number of days since the beginning of the
472 observation period, and a binary indicator for whether a statewide stay-
473 at-home order was in place. I also included the interaction between the
474 binary stay-at-home-order indicator and the measure of days since the
475 beginning of the time window to account for these orders’ time-varying
476 effects.

477 To account for further additional demographic and structural fac-
478 tors, I also estimated models with additional covariates, including those
479 for the county’s racial composition, the county’s education level, poverty
480 levels, internet access, food access, population density, and partisan
481 lean. Since some of these covariates are likely confounders related to
482 both local news availability and the response to the pandemic, I esti-
483 mated a final set of models using non-parametric covariate balancing
484 propensity score weighting [31]. This approach provides a less biased
485 causal estimate of the effect of newspaper availability on change in mo-
486 bility behavior. Supplementary Figure 2 visualizes the difference in the
487 correlation between treatment and covariates before and after applying
488 the weights generated through the balancing process.

¹More information about the database and how it was constructed can be found on
their [website](#).

489 To assess whether changes in the information about COVID-19 mod-
490 erated local news effects, I estimated models with interactions between
491 newspaper volume and time based on two major information interven-
492 tions: the corresponding announcements on March 11th, 2020, that
493 COVID-19 had reached a pandemic status, Tom Hanks had contracted
494 the illness, and the NBA was suspending its season, and the sub-
495 sequent implementations of stay-at-home orders by state governors.
496 (These orders were put in place on different dates.) To account for the
497 fact that the implementation of orders, the volume of local news avail-
498 able in a county, and the response variables all share causes, I also
499 included controls for a county's number of reported COVID-19 cases
500 and deaths, as well as the demographic and structural factors included
501 in the earlier models. These models were also re-estimated using non-
502 parametric covariate balancing propensity score weighting to account
503 for potential confounding.

504 In all cases, the outcomes and continuous predictors were centered
505 and standardized.

506 **Data Availability**

507 The figures and analyses in this paper are based on data provided by
508 Google, the University of North Carolina at Chapel Hill's School of Me-
509 dia and Journalism's Center for Innovation and Sustainability in Lo-
510 cal Media, *The New York Times*, ESRI, the United States Census, and
511 United States Department of Agriculture. Processed minimal datasets
512 necessary for reproducing analyses and figures, are available via the
513 associated [OSF repository](#) for this project.

514 **Code Availability**

515 Original code, like data, is available via the associated [OSF repository](#)
516 for this project.

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Figure 1: Regression coefficients estimated for models regressing mobility change on newspaper volume and pandemic features. Filled points indicate estimates that are statistically significant at the $\alpha = 0.05$ level. Bars mark 95% confidence intervals. Observations are at the county level. All continuous variables centered and standardized. Standard errors are clustered within counties and states. $N_{Residential} = 81,019$ and $N_{Retail} = 135,435$.

Figure 2: Regression coefficients estimated for models regressing mobility change on newspaper volume, pandemic features, and county demographic and structural measures. Filled points indicate estimates that are statistically significant at the $\alpha = 0.05$ level. Bars mark 95% confidence intervals. Observations are at the county level. All continuous variables centered and standardized. Standard errors are clustered within counties and states. $N_{Residential} = 80,938$ and $N_{Retail} = 135,287$.

Figure 3: Regression coefficients estimated for models regressing mobility change on newspaper volume, pandemic features, and county demographic and structural measures. Filled points indicate estimates that are statistically significant at the $\alpha = 0.05$ level. Bars mark 95% confidence intervals. Observations weighted based on covariate balancing propensity score weighting. Observations are at the county level. All continuous variables centered and standardized. Standard errors are clustered within counties and states. $N_{Residential} = 80,938$ and $N_{Retail} = 135,287$

Figure 4: Predicted mobility change as the number of newspapers in a county increases across three time periods: Before March 12, between March 12 and the implementation of statewide orders, and after the implementation of statewide orders. Panels present results from different models.

Table 1: Regression estimates for models estimating change in staying at home. All predictors centered and standardized unless otherwise noted. Standard errors clustered within states.

	Dependent variable: Δ Stay at Home											
	No Weighting					Weighting						
	β	s.e.	p	95% CI	β	s.e.	p	95% CI	β	s.e.	p	95% CI
Intercept	-0.077	0.022	0.00037	-0.12, -0.035	0.06	0.034	0.081	-0.0075, 0.13	-0.0033	0.035	0.92	-0.071, 0.064
Total Papers	0.083	0.02	0.00003	0.044, 0.12	0.035	0.014	0.016	0.0066, 0.063	-0.018	0.0059	0.0028	-0.029, -0.0061
Cases					0.086	0.025	0.00056	0.037, 0.14	0.064	0.021	0.003	0.022, 0.11
Deaths					-0.022	0.012	0.069	-0.046, 0.0017	-0.006	0.011	0.6	-0.028, 0.016
Time					0.96	0.032	0	0.89, 1	0.96	0.032	0	0.9, 1
Order in Effect (binary)					1.1	0.041	0	1, 1.2	1.1	0.04	0	0.98, 1.1
Time : Order in Effect					-1.3	0.048	0	-1.4, -1.2	-1.3	0.045	0	-1.3, -1.2
Population Size									0.01	0.0061	0.999	-0.0019, 0.022
Population Density									0.022	0.006	0.00018	0.011, 0.034
Median Age									-0.048	0.008	0	-0.064, -0.033
Pct. Not White									-0.034	0.014	0.017	-0.063, -0.0062
Pct. w/ College Degree									0.08	0.015	0.000000019	0.05, 0.11
Pct. Below Poverty Level									-0.0023	0.013	0.86	-0.027, 0.023
Pct. at least 2x Above Poverty Level									0.14	0.017	0	0.1, 0.17
Pct. w/ Computer and Broadband									-0.073	0.016	0.0000091	-0.1, -0.041
Pct. Speak only English at Home									0.00029	0.015	0.98	-0.029, 0.029
Pct. w/ Low Access to Food									-0.018	0.0075	0.018	-0.032, -0.003
State Capital									-0.014	0.017	0.41	-0.048, 0.02
2016 Clinton Vote Share									0.083	0.015	0.000000017	0.054, 0.11
Observations			87,979				81,019				80,938	

Table 2: Regression estimates for models estimating change in travel for retail or recreation purposes. All predictors centered and standardized unless otherwise noted. Standard errors clustered within states.

	Dependent variable: Δ Retail and Recreation Travel																													
	No Weighting								Weighting																					
	β		(1)	p		95% CI		β	s.e.	(2)		p		95% CI		β	s.e.	(3)		p		95% CI		β	s.e.	(4)		p		95% CI
Intercept	0.035	0.029	0.23	-0.022	0.091	-0.17	0.031	0.000000072	-0.23, -0.11	-0.17	0.024	0	-0.22, -0.12	-0.17	0.023	0	-0.21, -0.12													
Total Papers	-0.11	0.024	0.0000047	-0.16, -0.063	-0.05	0.016	0.0014	-0.081, -0.019	0.02	0.0046	0.0000077	0.011, 0.029	-0.035	0.017	0.045	-0.069, -0.00081														
Cases					-0.076	0.024	0.0014	-0.12, -0.029	-0.059	0.019	0.00018	-0.096, -0.022	-0.12	0.044	0.0074	-0.21, -0.032														
Deaths					0.015	0.012	0.22	-0.009, 0.039	-0.0047	0.009	0.6	-0.022, 0.013	-0.027	0.038	0.48	-0.1, 0.047														
Time					-0.9	0.023	0	-0.95, -0.86	-0.92	0.024	0	-0.96, -0.87	-0.9	0.022	0	-0.94, -0.86														
Order in Effect (binary)					-1.1	0.055	0	-1.2, -1	-1.1	0.048	0	-1.2, -1	-1.1	0.049	0	-1.2, -1														
Time : Order in Effect					1.4	0.064	0	1.2, 1.5	1.4	0.06	0	1.3, 1.5	1.4	0.053	0	1.3, 1.5														
Population Size					-0.012	0.0047	0.01	-0.021, -0.0028	0.02	0.017	0.23	-0.026, -0.016	-0.021	0.0065	0.0016	-0.033, -0.0078														
Population Density					-0.021	0.0026	0	-0.017, 0.027	0.008	0.011	0.47	-0.014, 0.03	0.025, 0.093	0.00064	0	-0.15, -0.089														
Median Age					0.0049	0.011	0.67	0.0059, 0.059	0.034	0.014	0.018	-0.011, 0.051	0.026	0.017	0.13	-0.0079, 0.06														
Pct. Not White					0.05	0.015	0.001	-0.019, 0.039	0.0061	0.018	0.73	-0.028, 0.041	-0.0022, 0.044	0.0087	0.59	-0.022, 0.012														
Pct. w/ College Degree					-0.13	0.015	0	-0.034, 0.014	0.02	0.016	0.2	-0.011, 0.051	0.026	0.017	0.13	-0.0079, 0.06														
Pct. Below Poverty Level					0.032	0.014	0.017	-0.019, 0.039	0.0061	0.018	0.73	-0.028, 0.041	-0.0022, 0.044	0.0087	0.59	-0.022, 0.012														
Pct. at least 2x Above Poverty Level					0.02	0.016	0.2	-0.011, 0.051	0.026	0.017	0.13	-0.0079, 0.06	-0.0022, 0.012	0.012	0.012	0.076	-0.0022, 0.044													
Pct. w/ Computer and Broadband					0.01	0.015	0.49	-0.019, 0.039	0.0061	0.018	0.73	-0.028, 0.041	-0.0022, 0.044	0.0087	0.59	-0.022, 0.012														
Pct. Speak only English at Home					0.028	0.011	0.014	-0.026, 0.0043	-0.0046	0.0087	0.59	-0.022, 0.012	-0.03, 0.06	0.06	0.06	0.06	-0.03, 0.06													
Pct. w/ Low Access to Food					-0.011	0.0079	0.16	-0.034, 0.035	0.015	0.023	0.51	-0.11, -0.056	-0.083	0.014	0	-0.11, -0.054														
State Capital					0.00079	0.018	0.96	-0.084	0.014	0	135, 287																			
2016 Clinton Vote Share					-0.084	0.014	0	-0.11, -0.056	-0.083	0.014	0	-0.11, -0.056	-0.083	0.014	0	-0.11, -0.054														
Observations			152, 275				135, 435				135, 287																			

Table 3: Regression estimates for models estimating change in staying at home in three different time periods. All predictors centered and standardized unless otherwise noted. Standard errors clustered within states.

	Dependent variable: Δ Stay at Home							
	No Weighting				Weighting			
	β	s.e.	(1) p	95% CI	β	s.e.	(2) p	95% CI
Intercept	-1.2	0.013	0	-1.2, -1.1	-1.1	0.026	0	-1.2, -1.1
Total Papers	-0.053	0.0093	0	-0.071, -0.034	0.084	0.052	0.11	-0.018, 0.19
March 12 - Statewide Order (binary)	1.1	0.038	0	1, 1.2	1.1	0.043	0	1, 1.2
After Statewide Order (binary)	1.9	0.038	0	1.8, 2	1.9	0.048	0	1.8, 2
Cases	0.053	0.016	0.00089	0.022, 0.085	0.19	0.059	0.0015	0.072, 0.3
Deaths	-0.024	0.013	0.063	-0.048, 0.0013	-0.082	0.039	0.036	-0.16, -0.0055
Population Size	0.0083	0.0062	0.18	-0.0039, 0.02	-0.016	0.015	0.29	-0.047, 0.014
Population Density	0.022	0.0067	0.001	0.0089, 0.035	0.031	0.0097	0.0012	0.012, 0.05
Median Age	-0.04	0.0082	0.00000085	-0.056, -0.024	-0.046	0.0085	0.000000056	-0.063, -0.03
Pct. Not White	-0.025	0.015	0.095	-0.053, 0.0043	-0.04	0.018	0.025	-0.076, -0.0052
Pct. w/ College Degree	0.083	0.016	0.0000001	0.052, 0.11	0.069	0.015	0.00000068	0.039, 0.099
Pct. Below Poverty Level	0.00065	0.013	0.96	-0.025, 0.026	-0.0091	0.015	0.54	-0.038, 0.02
Pct. at least 2x Above Poverty Level	0.13	0.017	0	0.1, 0.17	0.12	0.019	0	0.086, 0.16
Pct. w/ Computer and Broadband	-0.075	0.016	0.00000043	-0.11, -0.043	-0.079	0.021	0.000018	-0.12, -0.038
Pct. Speak only English at Home	-0.0031	0.015	0.84	-0.033, 0.027	0.014	0.017	0.43	-0.02, 0.047
Pct. w/ Low Access to Food	-0.019	0.0077	0.016	-0.034, -0.0035	-0.03	0.011	0.0068	-0.053, -0.0084
State Capital	-0.02	0.017	0.23	-0.053, 0.013	0.02	0.025	0.42	-0.028, 0.069
2016 Clinton Vote Share	0.076	0.015	0.00000018	0.047, 0.1	0.082	0.015	0	0.054, 0.11
Total Papers : March 12 - Statewide Order (binary)	0.054	0.02	0.0068	0.015, 0.094	-0.12	0.071	0.085	-0.26, 0.017
Total Papers : After Statewide Order (binary)	0.073	0.023	0.0016	0.028, 0.12	-0.12	0.075	0.1	-0.27, 0.024
Observations			83,578				80,938	

Table 4: Regression estimates for models estimating change in travel for retail and recreation purposes in three different time periods. All predictors centered and standardized unless otherwise noted. Standard errors clustered within states.

	Dependent variable: Δ Retail and Recreation Travel							
	No Weighting				Weighting			
	β	s.e.	(1) p	95% CI	β	s.e.	(2) p	95% CI
Intercept	0.960	0.012	0	0.93, 0.98	0.960	0.017	0	0.92, 0.99
Total Papers	0.043	0.009	0.00000	0.025, 0.061	-0.028	0.038	0.460	-0.1, 0.046
March 12 - Statewide Order (binary)	-1.100	0.025	0	-1.2, -1.1	-1.100	0.025	0	-1.1, -1.1
After Statewide Order (binary)	-1.800	0.043	0	-1.9, -1.7	-1.800	0.050	0	-1.9, -1.7
Cases	-0.044	0.011	0.0001	-0.065, -0.023	-0.110	0.031	0.0002	-0.17, -0.054
Deaths	0.023	0.010	0.029	0.0024, 0.043	0.064	0.020	0.002	0.024, 0.1
Population Size	-0.008	0.005	0.120	-0.018, 0.0021	-0.0003	0.013	0.980	-0.027, 0.026
Population Density	-0.022	0.003	0	-0.029, -0.015	-0.023	0.004	0.00000	-0.031, -0.015
Median Age	-0.004	0.010	0.710	-0.024, 0.016	-0.001	0.011	0.900	-0.023, 0.02
Pct. Not White	0.046	0.015	0.002	0.017, 0.075	0.063	0.017	0.0003	0.029, 0.097
Pct. w/ College Degree	-0.130	0.015	0	-0.16, -0.099	-0.120	0.017	0	-0.15, -0.086
Pct. Below Poverty Level	0.032	0.013	0.016	0.0058, 0.057	0.037	0.013	0.006	0.011, 0.063
Pct. at least 2x Above Poverty Level	0.019	0.016	0.220	-0.011, 0.05	0.028	0.016	0.082	-0.0035, 0.059
Pct. w/ Computer and Broadband	0.018	0.015	0.220	-0.011, 0.047	0.018	0.017	0.300	-0.016, 0.051
Pct. Speak only English at Home	0.029	0.011	0.011	0.0066, 0.051	0.019	0.011	0.089	-0.0029, 0.041
Pct. w/ Low Access to Food	-0.010	0.008	0.190	-0.025, 0.0048	0.001	0.010	0.930	-0.018, 0.02
State Capital	0.008	0.017	0.640	-0.026, 0.042	0.028	0.023	0.220	-0.017, 0.073
2016 Clinton Vote Share	-0.079	0.014	0	-0.11, -0.052	-0.083	0.014	0	-0.11, -0.056
Total Papers : March 12 - Statewide Order (binary)	-0.028	0.020	0.160	-0.067, 0.011	0.074	0.062	0.240	-0.048, 0.2
Total Papers : After Statewide Order (binary)	-0.068	0.020	0.001	-0.11, -0.029	-0.066	0.046	0.150	-0.16, 0.023
Observations			142,388				135,287	