Perceived Racial Threats Increase Demand for Conservative Media: Evidence from Black Lives Matter Protests and Fox News Ratings

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Abstract

With the growing evidence that the content on Fox News Channel (FNC) influences its viewers' attitudes and behaviors, it is important that we better understand the real-world factors driving demand for FNC, especially among those who are not already frequent viewers. Yet, our ability to identify these factors is plagued by difficult methodological issues, most notably, the selection problem of inferring the determinants of demand from content. This study overcomes these challenges by exploiting the substantial spatial and temporal variation in the Black Lives Matter (BLM) protests during 2020, the year of George Floyd's murder and other prominent police killings of Black Americans, to examine whether perceived racial threats increased FNC viewership. We construct a census block group-week panel of BLM protests and FNC ratings during 2020. With this spatial panel, we test whether the local occurrence of a BLM protest increased the portion of the local population watching FNC in the subsequent period. We find that the number of FNC viewers rose by approximately 2% following a BLM protest. At the same time, we find evidence that viewership of CNN, a moderate news channel, was unaffected and possibly declined. Our results, which survive robustness checks, tests of the modeling assumptions, and replication at the census tract level, can be interpreted as causal under reasonable assumptions. The findings provide real-world evidence that perceived racial threats increase demand for conservative media.

Keywords: Conservative Media, Racial Threat, Protests, Black Lives Matter

Introduction

Recent studies find that watching Fox News Channel (FNC), the highest rated cable news channel in the United States (US), affects viewers' attitudes and factual beliefs (Broockman and Kalla, 2022; Levin et al., 2023) and increases support for conservative ideology and vote share for Republican Party candidates (DellaVigna and Kaplan, 2007; Hopkins and Ladd, 2014; Martin and Yurukoglu, 2017; Galletta and Ash, Forthcoming). This research largely uses field and natural experiments exploiting variation in the availability of FNC to identify the consequences of consuming FNC. While offering valuable insights into the effects of FNC, this "supply-side" approach tells us little about the factors influencing the *demand* for FNC among potential viewers. Yet, if the content on FNC has an independent causal effect on viewers' attitudes and beliefs, political identities, and voting behavior, it is critical that we better understand the factors that drive greater demand for FNC, and conservative media, more broadly.[1]

There are two related methodological issues that encumber our ability to study the demand for conservative partisan media. The first regards what can be inferred about demand from media content. Previous research has found that the content of conservative media focuses on threats that are likely to induce fear, anxiety, and outrage in viewers (*e.g.*, increasing crime rates, rising racial diversity), arguing that this content drives higher ratings (Berry and Sobieraj, 2013; Klein, 2020; Confessore, 2022). This claim, however, is difficult to empirically verify because the content on FNC is both a cause and an effect of consumer demand (Levin et al., 2023). As a result, if the content of media like FNC reflects existing consumer demand for programming that invokes fear, anxiety, and outrage (Gentzkow and Shapiro, 2010; Kim, Lelkes and McCrain, 2022), we cannot infer from content alone that real-world events that feel threatening would increase demand for conservative partisan media, especially among those who are not already high consumers. Since it is precisely these

[1] Since we are only examining conservative partisan media in this study, we use the term, "conservative media", in order to distinguish it from the general term, "partisan media" (Levendusky, 2013).

low-frequency consumers for whom conservative media has been shown to have its greatest impact (Boxell, Gentzkow and Shapiro, 2017; de Benedictis-Kessner et al., 2019), examining the real-world factors that increase demand, especially on the extensive margin (*i.e.*, the proportion consuming any conservative media), benefits from an approach that does not rely primarily on analyzing the content found on FNC, among other conservative media outlets.

Second, while laboratory and survey experiments help overcome the challenges posed by selection, they are limited in their ability to measure underlying sources of demand. This is in part due to the challenge of capturing the opportunity costs of consuming cable news. That is, while experimental designs are ideal for causally identifying preferences for types of media and consequences of media after study participants are shown different types of stimuli (Levendusky, 2013; Chopra, Haaland and Roth, 2022), these "forced exposure" designs often have low stakes and thus a limited ability to detect the types of real-world events that increase viewership. Moreover, while researchers have recently increased the stakes by paying subjects to watch CNN (a moderate cable news channel (Budak, Goel and Rao, 2016)) instead of FNC (Broockman and Kalla, 2022), the intent of these experiments is still to manipulate the supply of conservative media in order to study the consequences of its consumption, not to identify the determinants of viewers' demand.[2]

We gain traction on identifying the factors influencing demand by testing whether Black Lives Matter (BLM) protests in the US during 2020 increased viewership of FNC. Put differently, we leverage the spatial and temporal variation in BLM protests to examine whether some Americans' perceptions of a localized racial threat resulted in more Americans consuming conservative media. The sudden nationwide proliferation of BLM protests following the murder of George Floyd by Minneapolis police on May 25, 2020 (and other prominent police killings) has two key features that allow us to identify changes in demand for conservative media. First, research has shown that rising perceived racial threats to the dominant status

[2]Similar work exploring the effects of conservative media on attitudes and beliefs also exploits exogenous shocks in the supply (accessibility) of media (Adena et al., 2015; Durante, Pinotti and Tesei, 2019; Wang, 2021) or use experimental designs that manipulate the supply of partisan media (Guess et al., 2021).

position of white Americans explain, among other consequences, shifts towards conservative politics and the Republican Party (Mutz, 2018; Jardina, 2019; McVeigh and Estep, 2020). Thus, the explosive growth of a movement dedicated to racial equality, which, by some accounts, was possibly the largest protest movement in American history (Buchanan, Bui and Patel, 2020), likely posed a perceived threat to and induced fear and anxiety in many white Americans (Rose, 2020; Smith and King, 2021; Field et al., 2022). Second, the unexpected outbreak of large-scale protests created substantial spatial and temporal variation in the incidence of BLM protests, and therefore a source of variation in perceived racial threats.

The specificity of our data allows us to precisely estimate the relationship between local protests and FNC viewership. Using the Crowd Counting Consortium (CCC) (Pressman and Chenoweth, 2022) data on the timing and location of BLM protests in 2020 (N = 2,341), we construct a measure of whether a BLM protest occurred in any county in each week during 2020. We then use this measure to predict FNC viewership ratings at the census block group (CBG) level in a sample that includes approximately 30% of the US population.[3] Our measure of FNC ratings, as licensed from The Nielsen Company, is a weekly estimate of the percent of the local market population that is viewing a channel. This measure is ideal for analyzing whether the local occurrence of a BLM protest predicts an increase in the number of CBG residents who viewed FNC during the subsequent week.

Using a fixed-effects counterfactual estimator in a linear model with CBG and week fixed effects, we find the occurrence of a BLM protest increased the average FNC ratings by roughly 2% during the following week. This suggests that if a BLM protest had occurred in each county across the US, more than 50,000 additional viewers would have watched the next week (compared to the average weekly FNC viewership of roughly 2.4 million). At the same time, we find some evidence that the same local occurrence of a BLM protest likely did not affect CNN's ratings, and potentially reduced viewership. The results for CNN indicate

[3]A CBG is the 2$^{\text{nd}}$ lowest level of spatial aggregation used by the US Census. Each CBG typically contains between 600 and 3,000 residents. We explain below why we do not use the entire sample of FNC ratings for each CBG.

that we are not simply capturing a general increase in cable news viewership due to local protests, and instead identify an increase in demand for conservative media specifically.

Two features of our data and analysis allow us to interpret these results causally under reasonable assumptions. First, our results take into account likely confounders. The inclusion of CBG fixed effects adjusts for time-invariant factors, such as demographic characteristics that might lead to greater FNC viewership (*e.g.*, share of population who are non-college educated, white, elderly). The inclusion of week fixed effects adjusts for temporal variation in cable news viewership (*e.g.*, rising viewership due to proximity to the 2020 election). In addition, the results are robust to the inclusion (and omission) of time-varying lagged values of FNC and CNN ratings (*i.e.*, lagged outcome variables), an areas' history of BLM and antifascist ("antifa") protests (*i.e.*, counties' cumulative counts of the protests up to and including the week prior to treatment), and an indicator of whether an antifa protest occurred during the same week at the BLM treatment event. The results also are robust to including the interaction of CBG and week fixed effects, which adjusts for differential trends across CBGs over time (Angrist and Pischke, 2009). The second feature is that we obtain consistent results when using a matrix completion (MC) estimator, which helps account for unobserved time-varying confounders by approximating and estimating the unobservable attributes (Athey et al., 2021; Liu, Wang and Xu, Forthcoming). In addition to these features, diagnostic tests indicate that our preferred model of FNC ratings meet critical assumptions of spatial panel fixed-effect designs (Liu, Wang and Xu, Forthcoming).

Our findings contribute to a large literature on the causes and consequences of biased media on social and political outcomes. We provide a credible design using real-world data to demonstrate that perceived racial threats, even in the form of mostly peaceful protests, can lead to an increase in the number of people watching FNC. While this finding is consistent with a growing scholarship on racial threat and conservative politics, it indicates that this increased consumption is not simply a result of the manufacturing of threats by conservative media or already high-propensity FNC consumers increasing their consumption. Our findings help complete the story of a media pathway from perceived racial threats to greater polarization. Our work also joins a series of studies examining the short-run effects of the BLM protests in the wake of George Floyd's murder on social and political outcomes, such as voting behavior and public opinion (Reny and Newman, 2021; Dunivin et al., 2022; Mutz, 2022; Shuman et al., 2022). While some of this research shows that the protests had positive effects on racial justice outcomes, especially in terms perceptions of racial discrimination (Mutz, 2022) and public discourse (Dunivin et al., 2022), our work suggests that there may have been unintended and unwanted consequences. Namely, the protests increased Americans' viewership of conservative media, which, according to the scholarship on FNC's effects, may have led to a decrease in accurate factual beliefs (Broockman and Kalla, 2022; Levin et al., 2023), an increase in polarization and Republican vote share (DellaVigna and Kaplan, 2007; Hopkins and Ladd, 2014; Martin and Yurukoglu, 2017), and a rightward shift in policy (Galletta and Ash, Forthcoming).

Data

We construct a CBG-weekly panel of BLM protest and FNC ratings (N = 3,372,600). We describe these and other variables used below. All variable sources and summary statistics can be found in SI Tables S1.

Protest events

To record whether a BLM or antifa protest took place in a county during a given week of 2020, we used data from the CCC (Pressman and Chenoweth, 2022). The CCC is a publicly available database of protest events in the US, compiled through crowdsourced event detection and various sources, such as online news sites and social media. Once an event is nominated for inclusion in the CCC database, the project's co-directors, research assistants, and numerous volunteers review the event's information and update the database

(Fisher et al., 2019). We manually identified BLM and antifa protests in the database using information on their participants; if participants were BLM or antifa groups, we encoded the event as such. For example, actors like “Black Lives Matter Seattle-King County” and “Black Lives Matter DC” led to the protest being designated as “BLM”. “Salt Lake City Antifascist Coalition”, “Antifa Equity Outreach”, and similar participants resulted in an “antifa” label. Labels are not mutually exclusive. Once all events during 2020 were labeled as “BLM” or “antifa” (or neither), we created a binary variable indicating whether a county experienced a BLM or antifa protest during each week of 2020. We then constructed related variables summing the number of BLM or antifa protests a county had experienced up to a given week for each week during 2020. The former is our main predictor. The latter variables, capturing counties’ “histories” of protest, are used as a time-varying control. We identified 2,341 BLM and 10 antifa protests, respectively.

The CCC database includes information on events’ number of participants (Fisher et al., 2019; Sobolev et al., 2020), which could be used to estimate the effect of protest size on FNC and CNN viewership. Unfortunately, 63% and 50% of BLM and antifa protests, respectively, are missing size information. There are other protest databases available for use, such as the well-known Armed Conflict Location & Event Data Project (ACLED). While we know of no systematic comparison of CCC, ACLED, and other options, recent research on protest in the US during 2020 report very similar results when using either CCC or ACLED (Karell et al., Forthcoming).

Cable news ratings

We licensed weekly FNC and CNN ratings during 2020 from The Nielsen Company. Nielsen defines a channel’s ratings as the portion of an area’s population that is viewing that channel (Policy and Guidelines, 2020). This gives us a measure of FNC and CNN viewership on the extensive margin (as opposed to, for instance, a measure of per capita amount of television watched).

Nielsen can provide weekly cable news ratings for the entire US during 2020. However, the cost for the complete countrywide and year-long dataset exceeded our available resources. Therefore, we obtained FNC and CNN ratings for a sample comprising 67,452 CBGs (28% of all CBGs) and 28,732 tracts (35% of all tracts), consisting of 31% of the total US population. Specifically, we licensed data consisting of the weekly zip code level FNC and CNN ratings for 20 large Designated Market Areas (DMAs), which are formed by multiple counties.[4] Our sample includes counties – and constitutive CBGs and tracts – in the following DMAs: Atlanta, Austin, Boston, Chicago, Dallas and Fort Worth, Detroit, Kansas City, Los Angeles, Louisville, Memphis, Nashville, New York City, Norfolk (Virginia), Philadelphia, Phoenix, San Francisco, Seattle, St. Louis, Tampa, and Tucson. We then apportioned the zip code level ratings into CBGs and tracts using 2019 crosswalks provided by the US Department of Housing and Urban Development.

While we cannot be sure that the spatial units in our sample of 20 DMAs perfectly represent those across the US, we take confidence from the fact that they are located in each region of the country and capture roughly a third of the total population. Moreover, the counties captured by our sample are very similar to all US counties across a range of sociodemographic characteristics, as well as voting behavior in the 2016 US presidential election. Specifically, the mean values of sampled counties' sociodemographic and political characteristic are within one standard deviation of the population's means (Table S1). (We compare county-level distributions of characteristics because that is the geography with a wide range of sociodemographic data available from the US Census's 2019 American Community Survey.)

Analytical strategy

With the variables capturing protests and cable news ratings (and wildfire smoke), we construct two panel datasets: CBG-week (N = 3,372,600) and tract-week (N = 1,436,600). We

[4] Nielsen divides the US into DMAs, each based on a large population center.

conduct our primary analysis with the CBG panel and a secondary analysis with the tract panel. Using both geographies helps guard against potential biases resulting from aggregating social phenomena into spatial units (Schutte and Kelling, 2022). Note, however, that checking the robustness of results with larger geographies – in our case, tracts relative to CBGs – poses a harder test of statistical relationships because there are fewer observations. The tract dataset, for example, reduces our observations by 57%.

We examine whether the FNC or CNN ratings in CBGs (tracts) tend to increase because of a BLM event occurring in CBGs' (tracts') counties any time in the preceding week. We analyze this relationship by estimating the average treatment effect on the treated (ATT) using the fixed effects counterfactual (FEct) estimator (Liu, Wang and Xu, Forthcoming). Counterfactual estimators like FEct draw on data under the untreated condition to build models, then use these models to impute counterfactuals of the treated observations. Doing so helps avoid negative weights – observations of (treated) early adopters never serve as controls for late adopters – and corrects biases resulting from treatment effect heterogeneity, both of which are problems with conventional two-way fixed effects (TWFE) models that have recently generated concern (Blackwell and Glynn, 2018; Imai and Kim, 2019; de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021).

Our main analysis consists of a set of three models, each regressing FNC or CNN ratings on the BLM protest indicator variable with week and CBG (tract) fixed effects. The models differ by their additional specification. First, we fit a TWFE model with CBG (tract) and week fixed effects and no other covariates. Second, we add three time-varying controls to the TWFE: the occurrence of an antifa protest during the preceding, or treatment, week, counties' histories of BLM events (up to an including the week preceding the treatment week), and counties' histories of antifa events (also up to an including the week prior to the treatment week). This is our preferred model.

The third model further adds lagged outcomes to the preferred specification. Including the lagged outcomes could be redundant because, as controls, they would adjust for many of the factors already accounted for by the unit and time fixed effects. However, since they vary over time, adjusting for lagged outcomes potentially helps also adjust for unobserved time-varying confounders. Because of these advantages and disadvantages, as well as recent insights into the "bracketing relationship" between TWFE and lagged dependent variable (LDV) approaches, which indicate that TWFE and LDV models can provide upper and lower bounds of the true expected ATT (Angrist and Pischke, 2009; Ding and Li, 2019; Marsh, 2022; Xu, 2022), we see our third model as a way to obtain the lower bounds of the ATT.

We use all three models to analyze both FNC and CNN, and we fit all models using both the CBG and tract panel datasets. Units have staggered adoption and can switch between treatment and control conditions. All models equally weight observations when computing the ATT because the propensity to receive treatment varies over both units and time. We estimate uncertainty by using non-parametric block bootstrap clustered at the unit level.

Using the preferred model, we conduct two diagnostic assessments of the modeling assumptions (*i.e.*, functional form, exogeneity, and meeting the feasibility condition) (Liu, Wang and Xu, Forthcoming). The first is a placebo test. For this test, we assume that the occurrence of a BLM protest happened two weeks earlier than it in fact did. We then use the FEct estimator to obtain an overall ATT estimate for these pretreatment periods (up to and including the actual treatment period, for a total of three weeks before the outcome is observed). This placebo ATT should not be statistically different from zero.

We examine whether this placebo ATT is different from zero by using two one-sided tests (TOST) to check whether we can reject the null hypothesis that the placebo ATT falls outside a prespecified range (in our case, ± 0.36 multiplied by the standard deviation of the residualized untreated outcome (Hartman and Hidalgo, 2018)). This procedure is a modified equivalence test developed by Liu, et al. (Liu, Wang and Xu, Forthcoming), and has the advantage of being robust to potential biases due to outliers or confounders.

The second test is a carryover test, or an evaluation of whether BLM protests continue to exert an effect on FNC viewership after they cease. While a continued effect does not threaten our arguments, a lack of carryover aligns better with modeling assumptions (Liu, Wang and Xu, Forthcoming). To test for carryover, we use the same framework as the placebo test, except we compute ATTs for the three weeks after the treatment ends. Once again, if there is no continuing effect, we should not observe evidence of BLM protest increasing FNC or decreasing CNN. Successful tests, or no evidence of placebo or carryover effects, offer evidence that the modeling assumptions are met.

We evaluate the robustness of our results by fitting three supplemental models, each using the preferred model specification. First, we add two more controls: indicators of whether a BLM or antifa event occurred in a county during the same week the FNC and CNN ratings are measured. These contemporaneous protest variables help address an alternative explanation of why BLM protest may cause an increase in FNC viewership and a decrease in CNN viewership. Namely, it is possible that a BLM (or antifa) protest is so distasteful to conservatives, that they are more likely to stay home to avoid the activity and thus consume more television, including FNC. Meanwhile, liberals are more likely to leave the home to join the protests, leading to lower ratings for the channels they tend to watch, perhaps including CNN. Adjusting for contemporaneous protests with our first robustness check model helps us rule out the possibility that our estimates are capturing the physical avoidance of (or participation in) active BLM/left-wing protests rather than the post-protest effect on perceptions of racial threat.

Our second robustness check model adds an interaction of CBG (tract) and week fixed effects to the main model, which accounts for differential trends across units over time (Angrist and Pischke, 2009). Our third check is a model using a matrix completion (MC) estimator. The MC estimator, a generalization of factor-augmented models, helps us account for unobserved time-varying confounders by seeking to approximate and estimate the unobservable attributes (Athey et al., 2021; Liu, Wang and Xu, Forthcoming). The MC tuning parameter is selected using k-fold cross validation (Liu, Wang and Xu, Forthcoming). As with the three main models, we conduct these three robustness checks at both the CBG and tract levels.

The models equally weight observations when computing the ATT and use non-parametric block bootstrap clustered at the unit level to estimate uncertainty.

Finally, we conduct a placebo treatment test to evaluate the soundness of the study's design. In this test, the main models are replicated with a different treatment variable, or placebo. The placebo should be similar to the focal treatment – in our case, a newsworthy, localized, and potentially threatening event that varies across space and time – but which would not affect our outcome (viewership ratings) through the mechanism we propose (perceived racial threat). If we find evidence that the placebo treatment predicts the outcome, this is evidence that the design may be flawed (Eggers, Tunon and Dafoe, 2021).

For our placebo treatment, we selected natural disasters and the environmental threat they pose, and specifically the sustained local presence of hazardous smoke caused by the geographically widespread and devastating forest fires of 2020 (Burke et al., 2021; Anguiano, 2020). We chose to use just one type of disaster due to the possibility that different types of disasters engender heterogeneous cable-news viewership responses.

We construct our placebo treatment indicator using a database of county-day estimates of PM2.5 levels, or particular matter in the air that are two and a half microns or less in width (and are particularly hazardous to humans) due to wildfire smoke across the US during 2020 (Childs et al., 2022). If these levels corresponded to air quality levels of "unhealthy", "very unhealthy", or "hazardous" (*i.e.*, PM2.5 readings greater than 150) for three or more days during a week, we encoded the week as experiencing a wildfire smoke event. This is the placebo treatment. We use a threshold of three days to ensure that we are not measuring unsystematic variances in wind direction.

This test consists of estimating eight models. Beginning with the CBG level data, we use the FEct estimator to regress FNC ratings on the indicator of environmental threat during the prior week. This model includes CBG and week fixed effects. Next, we fit a second model that adjusts for the BLM treatment and covariates from our preferred model (and also includes unit and time fixed effects). We then use these two model specifications to also estimate the effect of environmental threat on the following week's CNN ratings. And, as with the main analysis, we replicate this placebo treatment test with the tract-level panel dataset. All the eight models compute the ATT by equally weighting observations and estimate uncertainty using non-parametric block bootstrap clustered at the unit level.

We estimate all the described models and implement the diagnostic tests using the guidelines and software presented in Liu, et al. (Liu, Wang and Xu, Forthcoming).

Results

We examine whether BLM protests increased FNC viewership during the subsequent week by estimating the ATT using the FEct estimator. This estimator helps account for two recently identified methodological problems when using TWFE models to analyze panel data: negative weights and biases resulting from treatment effect heterogeneity (Blackwell and Glynn, 2018; Imai and Kim, 2019; de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). In our analysis, units have staggered adoption and can switch between treatment and control conditions. We weight observations equally when computing the ATT and obtain uncertainty estimates using non-parametric block bootstrap clustered at the unit level.

Figure 1 plots the estimated ATTs and 95 percent confidence intervals obtained by regressing FNC or CNN ratings on the BLM protest indicator variable with three model specifications. The left-side panel shows the results when using the CBG panel. Our baseline model, which includes only the outcome and treatment variables and CBG and week fixed effects, indicates that the occurrence of at least one BLM event predicts a statistically significant increase in subsequent FNC ratings ($p < 0.001$).

Our preferred model, Model 2, adds three time-varying controls: the occurrence of an antifa protest (or not) during the same week as the treatment BLM protest, the county's history of BLM protest up to the treatment week, and the county's history of antifa events

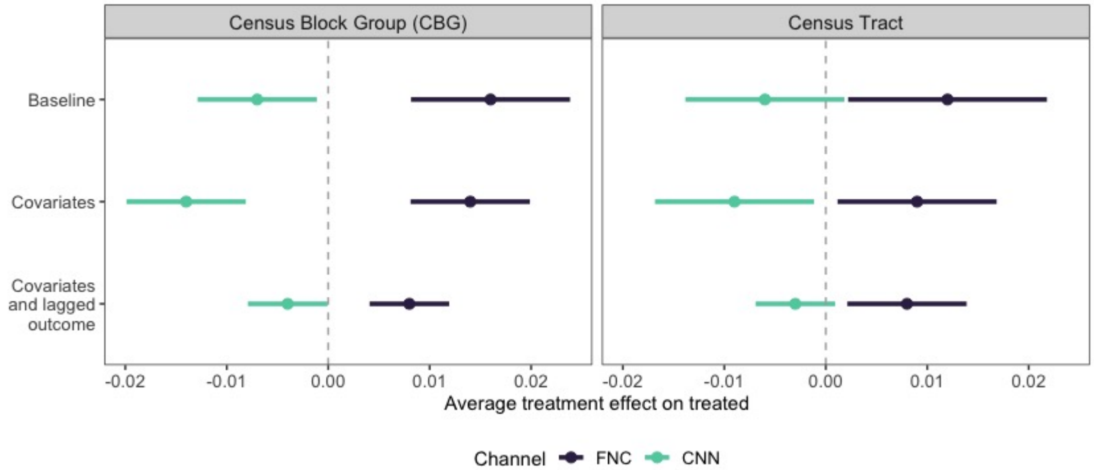

Figure 1: Effect of local BLM protest on FNC and CNN viewership during 2020, estimated at the census block group (CBG) and tract levels with three different model specifications. Bars denote 95 percent confidence intervals. Each model includes unit and week fixed effects. Complete results are shown in Tables S2 (CBG) and S3 (tract).

up to the treatment week. The antifa controls help us discern whether it is BLM protests, and thus likely racial threat, that is increasing FNC ratings rather than left-wing protests, in general. This model indicates that a local BLM protest predicts a 0.014 percentage point increase in FNC ratings ($p < 0.001$). By comparison, the mean of our measure of FNC ratings was approximately 0.67, *i.e.*, Nielsen's mean estimate of the share of people who were viewers in a given week (0.67%). These results and estimates suggest that a BLM protest increased the average FNC ratings by more than 2% during the following week.

Model 3 adds a lagged dependent variable to the preferred model's specification. As explained above, we interpret the third model's estimate as a lower bound of the ATT. Once again, we obtain consistent results; the model estimates a 0.008 percentage point increase ($p < 0.001$). The complete results for each of these three models are reported in Table S2.

Diagnostic assessments of the preferred model's modeling assumptions indicate that the assumptions are met. A placebo test suggests that we would observe no effect of a BLM protest if it occurred two weeks earlier than it in fact did. A carryover test shows that the effect "switches off" after the BLM protest. See Table S4 for the complete results.

We check the robustness of the results with three supplemental models. First, we adjust for the effect of contemporaneous protests, or BLM and antifa protests occurring during the same week that the ratings are measured. These controls help address the possibility that rising FNC ratings are due to an increase in the likelihood that conservatives stay home during the occurrence of a BLM protest and thus watch more television. (For the CNN outcome, this robustness check addresses the possibility that lower CNN ratings are due to liberals being out of the home to participate in protests and thus watching less television.) The second supplemental model adds to the preferred model an interaction of CBG and week fixed effects, which allows us to relax the parallel trends assumption of standard TWFE models and accounts for differential trends across CBGs over time (Angrist and Pischke, 2009). The third supplemental model uses the MC estimator with the preferred modeling specification to help account for unobserved confounding. The results of all three robustness checks are consistent with our main results, and presented in Table S5.

The left panel of Figure 1 also presents the estimates obtained when modeling CNN ratings. Interestingly, we find evidence of a statistically significant negative relationship between a BLM protest and subsequent CNN ratings (also presented in columns 4-6, Table S2). Like the FNC results, these results are robust to the supplemental models' alternative specifications, although the model using the MC estimator suggests that the negative relationship may be statistically insignificant (Table S5). However, despite these successful robustness checks, the preferred model's CNN results should be interpreted with caution. The diagnostic assessments suggest that its modeling assumptions may not be met (see Table S4 for results). Nevertheless, we see the totality of the CNN results as indicating that BLM protests did not increase CNN ratings, and perhaps even decreased them. This is evidence that the FNC analysis is not capturing a general increase in cable news viewership, but rather identifying a growing demand for conservative media specifically.

It is possible that our results reflect the choice to use the CBG level. As shown in the right-side panel of Figure 1, we therefore replicate our analysis at the next highest level of spatial aggregation, the census tract level (N = 1,436,600). Unsurprisingly, given the greater than 50% reduction in the number of observations, our estimates become less precise. Yet, the relationship between BLM protests and subsequent FNC ratings remains positive and statistically significant at conventional levels in each model. See Table S3 (columns 1-3) for complete results. Our preferred model of FNC (Model 2) once again passes the tests of modeling assumptions (Table S4), and the supplemental models offer consistent results (Table S6).

As also shown in Figure 1 (right), each model off CNN ratings at the tract level obtains negative ATT estimates, and our preferred model's estimates remain statistically significant. These results are robust to the supplemental models' alternative specifications and MC estimator (although the MC model's results are once again not statistically significant at conventional levels) (Table S6). However, the tests of modeling assumptions suggest that the preferred model may not meet the assumptions, leading us to interpret the tract-level CNN results similarly as the CBG-level CNN results. Namely, BLM protests do not appear to have increased CNN viewership, and perhaps even decreased viewership. In sum, the results of the census-tract analysis provide us with confidence that our CBG-level findings are not biased due to the effects of aggregating social phenomena into specific spatial units (Schutte and Kelling, 2022).

Finally, we conduct a placebo treatment test (Eggers, Tunon and Dafoe, 2021) using the environmental threat posed by sustained wildfire smoke in place of our main treatment, BLM protests. The test results indicate that the placebo treatment does not predict FNC viewership. When using the CBG panel, the ATT is negative but not statistically significant at conventional levels. When using the tract panel, the ATT is positive and not statistically significant. Interestingly, we find a positive and statistically significant relationship between sustained wildfire smoke and CNN viewership. These findings lend support to our study's design and further increase confidence in our argument that BLM protests increased FNC viewership due to perceived racial threat and not because it was understood as a kind of general threat. Complete results for the placebo treatment test are shown in Tables S7

(CBG) and S8 (census tract).

Discussion

In this paper, we exploit the widespread spatial and temporal variation in BLM protests during 2020 to study whether perceived racial threats increase viewership of Fox News, a conservative US cable news channel with the country's highest ratings. We find evidence that the local occurrence of a BLM protest did increase the number of people watching FNC. At the same time, we find that viewership for the primary moderate competitor, CNN, likely decreased or was unaffected by local BLM protests. These findings are consistent with the argument that perceived racial threats can lead some people to consume conservative media.

Our results add to a growing scholarship on perceived racial threats and conservative politics (Mutz, 2018; Jardina, 2019; McVeigh and Estep, 2020) by highlighting a media pathway between the perception of threats and political attitudes and behavior. They additionally contribute to the literature on partisan media and political polarization (Iyengar et al., 2019). Scholars using natural, laboratory, and survey experiments have found that watching FNC has a causal effect on its viewers' attitudes and behavior (DellaVigna and Kaplan, 2007; Hopkins and Ladd, 2014; Martin and Yurukoglu, 2017; Broockman and Kalla, 2022; Galletta and Ash, Forthcoming). Their identification strategies use natural or designed exogenous shocks to the supply of conservative media. While this approach provides valuable insights into the consequences of consumption, they are not intended to address difficult selection and methodological obstacles to understanding what increases demand for conservative media, especially on the extensive margin. Our strategy of using spatial and temporal variation in BLM protests during the 2020 allows us to examine one such factor – how rising perceived racial threats affect demand for FNC.

While more research is needed to fully understand the range of possible determinants of demand for conservative media, our findings have important implications. In particular, combining the growing supply-side evidence on the influence of FNC and other conservative media with our demand-side insights can describe a complex protest-and-media process by which real-world collective action interacts with partisan media in a way that leads to greater polarization. At the same time, our work highlights how scholars investigating partisan media and its effects could more fully consider designs able to separate the factors influencing demand on the extensive margin versus the intensive margin.

A final implication is that our preferred model indicates that the estimated decline in CNN ratings following a BLM protest was approximately the same size as the increase in FNC viewership. While our data does not allow us to explore the presence of a substitution effect, future work could use observational data such as ours in combination with survey and field experimental designs to explore substitution dynamics between types of media.

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Supplementary Information

for

Perceived Racial Threats Increase Demand for Conservative Media: Evidence from Black Lives Matter Protests and Fox News Ratings

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February 2023

Table S1: Summary Statistics

	All counties				Counties in sample			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Population	101,868	327,345	66	10,081,570	179,088	409,388	395	5,198,275
Median household income (USD)	52,648	14,990	12,441	142,229	57,132	16,402	25,283	116,100
White (non-Hispanic) share	0.74	0.23	0	1	0.76	0.18	0.09	1
Median age of adult white males	43.47	5.39	22	68.6	42.28	4.87	26.7	59.6
Non-citizen residents share	0.03	0.04	0	0.33	0.03	0.03	0	0.23
Share with bachelors degree	0.15	0.07	0	0.55	0.16	0.08	0.06	0.47
Share with internet service subscription	0.29	0.05	0.08	0.42	0.29	0.04	0.17	0.42
Share of adults not in labor force	0.34	0.07	0.14	0.78	0.33	0.07	0.2	0.61
Gini coefficient	0.44	0.04	0.3	0.71	0.44	0.04	0.33	0.61
Republican vote share (2016)	0.67	0.16	0.04	0.97	0.63	0.19	0.1	0.95
Total BLM protests	0.14	0.71	0	10	0.32	1.15	0	10
Total antifa protests	0.01	0.06	0	2	0.01	0.09	0	2
N	3220				542			

Note: County-level descriptive statistics. Data from the 2019 American Community Survey and MIT Election Data and Science Lab.

Table S2: Effect of BLM Protest on FNC and CNN Ratings, CBG Level

	FNC			CNN		
	(1)	(2)	(3)	(4)	(5)	(6)
BLM protest	0.016	0.014	0.008	-0.007	-0.014	-0.004
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Covariates	N	Y	Y	N	Y	Y
Lagged outcome	N	N	Y	N	N	Y
CBG FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Units	67,452	67,452	67,452	67,452	67,452	67,452
Observations	3,372,600	3,372,600	3,305,148	3,372,600	3,372,600	3,305,148

Note: Fixed effects counterfactual estimates of average treatment effect on treated. Units are US Census CBGs; observations are CBG-weeks. Bootstrapped standard errors in parentheses.

Table S3: Effect of BLM Protest on FNC and CNN Ratings, Tract Level

	FNC			CNN		
	(1)	(2)	(3)	(4)	(5)	(6)
BLM protest	0.012	0.009	0.008	-0.006	-0.009	-0.003
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)
Covariates	N	Y	Y	N	Y	Y
Lagged outcome	N	N	Y	N	N	Y
Tract FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Units	28,732	28,732	28,732	28,732	28,732	28,732
Observations	1,436,600	1,436,600	1,407,868	1,436,600	1,436,600	1,407,868

Note: Fixed effects counterfactual estimates of average treatment effect on treated. Units are US Census tracts; observations are tract-weeks. Bootstrapped standard errors in parentheses.

Table S4: Results of Diagnostic Tests of the Main Models

	CBG		Tract	
	FNC	CNN	FNC	CNN
BLM protest placebo ATT	0.003 (0.003)	-0.014 (0.003)	-0.004 (0.005)	-0.013 (0.004)
TOST p-value	0.000	0.000	0.000	0.000
BLM protest carryover ATT	-0.038 (0.003)	-0.031 (0.003)	-0.050 (0.005)	-0.025 (0.005)
TOST p-value	0.000	0.000	0.000	0.000
Units	67,452	67,452	28,732	28,732
Observations	3,372,600	3,372,600	1,436,600	1,436,600

Note: Diagnostic tests use fixed effects counterfactual estimates of BLM protests' effect on FNC or CNN ratings during the subsequent week obtained with models with the main model's specification. Table shows values for average treatment effects on the treated (ATT) and two one-sided tests (TOST). Bootstrapped standard errors in parentheses.

Robustness of main results: Alternative models

Table S5: Alternative Models Estimating the Effect of BLM Protest on FNC or CNN Ratings, CBG Level

	FEct contemporaneous protest		FEct unit time trend		Matrix completion	
	FNC	CNN	FNC	CNN	FNC	CNN
BLM protest	0.015	-0.013	0.020	-0.017	0.011	-0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)
Covariates	Y	Y	Y	Y	Y	Y
Contemporaneous protest	Y	Y	N	N	N	N
CBG FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Unit-specific time trend	N	N	Y	Y	N	N
Units	67,452	67,452	67,452	67,452	67,452	67,452
Observations	3,372,600	3,372,600	3,372,600	3,372,600	3,372,600	3,372,600

Note: Table shows average treatment effect on treated estimated using fixed effects counterfactual (FEct) and matrix completion estimators. The first model FEct model adjusts for contemporaneous BLM and antifa events; the second model includes a unit-specific time trend. Units are US Census CBGs; observations are tract-weeks. Bootstrapped standard errors in parentheses.

Table S6: Alternative Models Estimating the Effect of BLM Protest on FNC or CNN Ratings, Tract Level

	FEct contemporaneous protest		FEct unit time trend		Matrix completion	
	FNC	CNN	FNC	CNN	FNC	CNN
BLM protest	0.010	-0.009	0.014	-0.014	0.011	-0.001
	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)
Covariates	Y	Y	Y	Y	Y	Y
Contemporaneous protest	Y	Y	N	N	N	N
Tract FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Unit-specific time trend	N	N	Y	Y	N	N
Units	28,732	28,732	28,732	28,732	28,732	28,732
Observations	1,436,600	1,436,600	1,436,600	1,436,600	1,436,600	1,436,600

Note: Table shows average treatment effect on treated estimated using fixed effects counterfactual (FEct) and matrix completion estimators. The first model FEct model adjusts for contemporaneous BLM and antifa events; the second model includes a unit-specific time trend. Units are US Census trcts; observations are tract-weeks. Bootstrapped standard errors in parentheses.

Placebo treatment test

Table S7: Effect of Wildfire Smoke on FNC and CNN Ratings, CBG Level

	FNC		CNN	
	(1)	(2)	(3)	(4)
Wildfire smoke	-0.001	-0.003	0.075	0.078
	(0.014)	(0.014)	(0.021)	(0.022)
CBG FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
BLM treatment and covariates	N	Y	N	Y
Units	67,452	67,452	67,452	67,452
Observations	3,372,600	3,372,600	3,372,600	3,372,600

Note: Fixed effects counterfactual estimates of average treatment effect on treated. Units are US Census CBGs; observations are CBG-weeks. Bootstrapped standard errors in parentheses.

Table S8: Effect of Wildfire Smoke on FNC and CNN Ratings, Tract Level

	FNC		CNN	
	(1)	(2)	(3)	(4)
Wildfire smoke	0.062	0.061	0.103	0.105
	(0.071)	(0.070)	(0.016)	(0.016)
Tract FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
BLM treatment and covariates	N	Y	N	Y
Units	28,732	28,732	28,732	28,732
Observations	1,436,600	1,436,600	1,436,600	1,436,600

Note: Fixed effects counterfactual estimates of average treatment effect on treated. Units are US Census tract; observations are tract-weeks. Bootstrapped standard errors in parentheses.