# Supplemental Appendix

# Who Watches the Watchmen?

# Local News and Police Behavior in the United States

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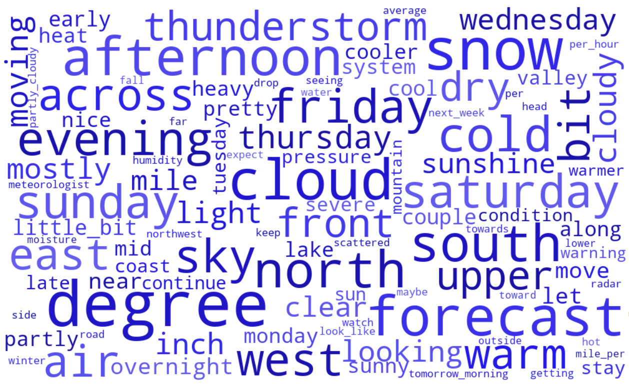
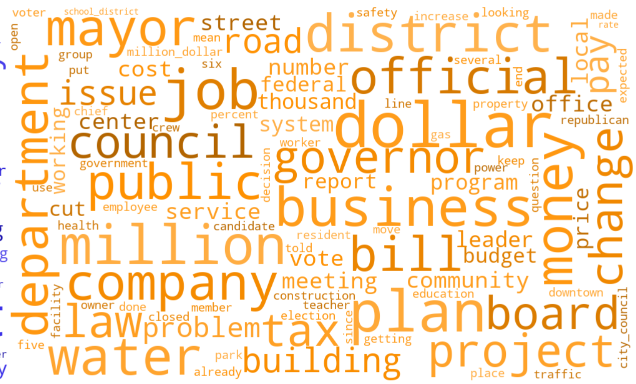
**Appendix Figure 1A:** Local News Topics, World Clouds



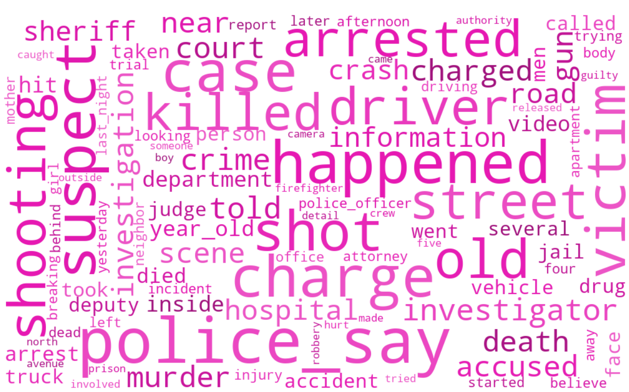

(a) Weather




(b) Politics


(c) Sports


(d) Miscellaneous




(e) Crime

Notes: This figure shows word clouds of the 50 words and bigrams that have the highest probability of being generated by a given topic. The size of the word is proportional to the word's probability.

**Appendix Figure 1B:** Local News Topics, Weights

| Weather | | Politics | | Sports | | Misc. | | Crime | |
|---|---|---|---|---|---|---|---|---|---|
| Unigram or Bigram | Weight | Unigram or Bigram | Weight | Unigram or Bigram | Weight | Unigram or Bigram | Weight | Unigram or Bigram | Weight |
| degree | 0.010 | dollar | 0.006 | season | 0.008 | kid | 0.005 | police_say | 0.006 |
| snow | 0.009 | plan | 0.005 | san | 0.008 | community | 0.003 | happened | 0.006 |
| cloud | 0.008 | job | 0.005 | play | 0.007 | local | 0.003 | suspect | 0.005 |
| forecast | 0.008 | million | 0.004 | win | 0.007 | something | 0.003 | case | 0.005 |
| afternoon | 0.007 | business | 0.004 | sport | 0.006 | find | 0.003 | charge | 0.005 |
| south | 0.007 | district | 0.004 | coach | 0.005 | event | 0.003 | shot | 0.005 |
| north | 0.007 | money | 0.004 | football | 0.005 | every | 0.003 | victim | 0.005 |
| cold | 0.006 | water | 0.004 | fan | 0.005 | great | 0.003 | old | 0.004 |
| evening | 0.006 | mayor | 0.004 | player | 0.005 | food | 0.003 | shooting | 0.004 |
| sky | 0.006 | company | 0.004 | high_school | 0.003 | com | 0.003 | driver | 0.004 |
| saturday | 0.006 | public | 0.004 | head | 0.003 | getting | 0.003 | arrested | 0.004 |
| sunday | 0.006 | official | 0.003 | field | 0.003 | place | 0.003 | street | 0.004 |
| friday | 0.006 | department | 0.003 | great | 0.003 | center | 0.002 | killed | 0.004 |
| west | 0.005 | bill | 0.003 | final | 0.003 | give | 0.002 | investigator | 0.004 |
| across | 0.005 | project | 0.003 | top | 0.003 | sure | 0.002 | crime | 0.004 |
| air | 0.005 | governor | 0.003 | second | 0.003 | love | 0.002 | told | 0.004 |
| bit | 0.005 | law | 0.003 | run | 0.003 | world | 0.002 | court | 0.004 |
| east | 0.005 | tax | 0.003 | guy | 0.003 | keep | 0.002 | investigation | 0.003 |
| warm | 0.005 | council | 0.003 | four | 0.003 | hope | 0.002 | death | 0.003 |
| thunderstorm | 0.005 | change | 0.003 | point | 0.003 | thank | 0.002 | charged | 0.003 |
| upper | 0.005 | board | 0.003 | college | 0.003 | never | 0.002 | gun | 0.003 |
| front | 0.004 | building | 0.003 | six | 0.003 | let | 0.002 | near | 0.003 |
| dry | 0.004 | road | 0.003 | diego | 0.003 | free | 0.002 | murder | 0.003 |
| thursday | 0.004 | pay | 0.003 | best | 0.003 | dog | 0.002 | accused | 0.003 |
| cloudy | 0.004 | issue | 0.003 | san_diego | 0.003 | friend | 0.002 | scene | 0.003 |

Notes: This figure shows the 25 words and bigrams that have the highest probability of being generated by a given topic.

**Appendix Figure 2A:** Crime Bigrams, Word Clouds


(a) Frequency (b) Relatively Frequency

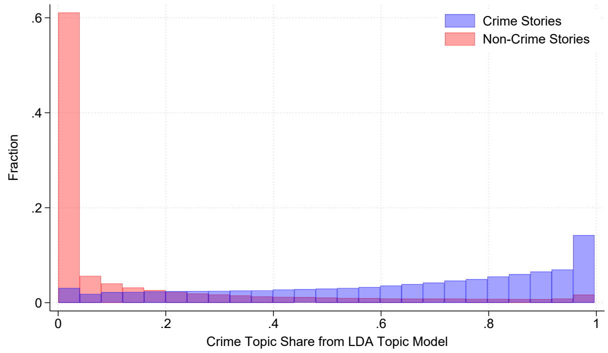
Notes: This figure shows word clouds of the 50 bigrams with the highest frequency (Panel (a)) and of the 50 bigrams with the highest relative frequency (Panel (b)). The frequency is the number of times the bigram appears in the crime library. The relative frequency is the number of times the bigram appears in the crime library over the number of times the bigram appears in the non-crime library. The size of the words is proportional to the value.

**Appendix Figure 2B:** Crime Bigrams, Weights

| Bigram | Frequency | Bigram | Relative Frequency |
|---|---|---|---|
| police_department | 890 | police_union | 999.000 |
| district_attorney | 786 | murder_charge | 999.000 |
| police_said | 663 | criminal_possession | 999.000 |
| law_enforcement | 550 | internal_affair | 221.790 |
| pleaded_guilty | 520 | affair_bureau | 184.380 |
| prosecutor_said | 471 | pleading_guilty | 184.380 |
| attorney_office | 467 | browne_said | 171.909 |
| york_police | 385 | according_criminal | 171.019 |
| police_commissioner | 378 | officer_fired | 165.674 |
| year_prison | 339 | man_accused | 160.330 |
| raymond_kelly | 335 | vance_manhattan | 154.986 |
| paul_browne | 328 | possession_weapon | 152.314 |
| enforcement_official | 305 | federal_agent | 149.641 |
| defense_lawyer | 304 | corruption_case | 146.969 |
| federal_district | 298 | criminal_complaint | 141.625 |
| commissioner_raymond | 297 | official_misconduct | 138.953 |
| chief_spokesman | 272 | spokesman_paul | 133.608 |
| manhattan_district | 269 | sexual_assault | 132.272 |
| federal_prosecutor | 264 | browne_police | 124.701 |
| city_police | 263 | enforcement_official | 116.430 |
| department_chief | 230 | maximum_sentence | 100.206 |
| browne_said | 193 | witness_stand | 93.526 |
| assistant_district | 188 | attempted_murder | 93.526 |
| said_police | 184 | people_arrested | 93.526 |

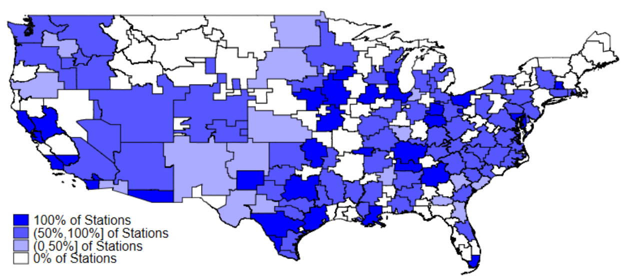
Notes: This figure reports the 25 bigrams with the highest frequency and the 25 bigrams with the highest relative frequency. The frequency is the number of times the bigram appears in the crime library. The relative frequency is the number of times the bigram appears in the crime library over the number of times the bigram appears in the non-crime library. We set the relative frequency equal to 999 in cases in which the bigram only appears in the crime library.

**Appendix Figure 3:** Validation of Local Stories Classification



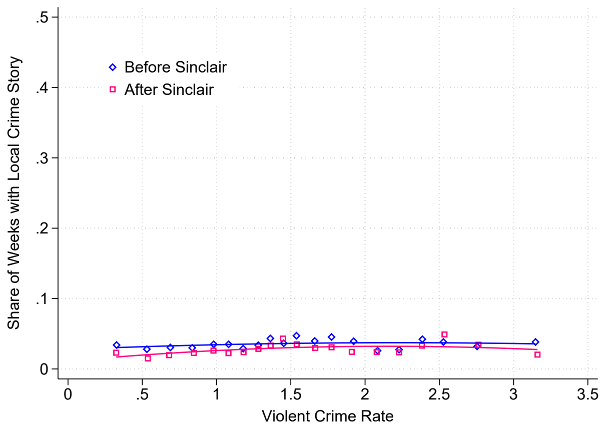

Notes: This figure shows a histogram of the crime topic share separately by whether local stories are classified to be about crime or not according to the methodology described in Section 3. Crime topic shares are from an unsupervised LDA model trained on local stories. Stories are defined to be local if they mention at least one of the municipalities with more than 10,000 people in the media market.

**Appendix Figure 4:** Map of Media Markets Included in the Content Sample

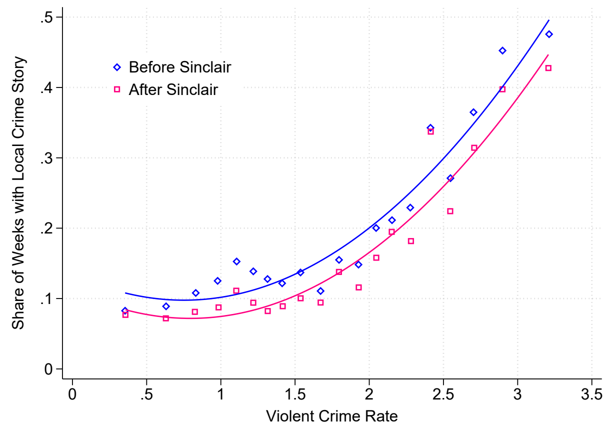



Notes: This map shows the share of stations for which we have content data continuously from 2010-2017 across media markets in the United States. Darker colors correspond to higher shares of media market stations included in the content data. 61% of media market have at least one station included in our sample, and for 88% of them the sample includes more than half of the stations present in the market.

**Appendix Figure 5:** Relationship Between Violent Crime Rates and Share of Weeks with Local Crime Story Before and After Sinclair Ownership, by Covered Status



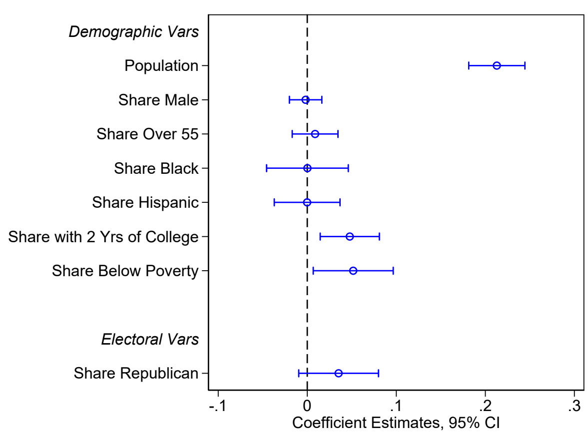

(a) Non-Covered Municipalities



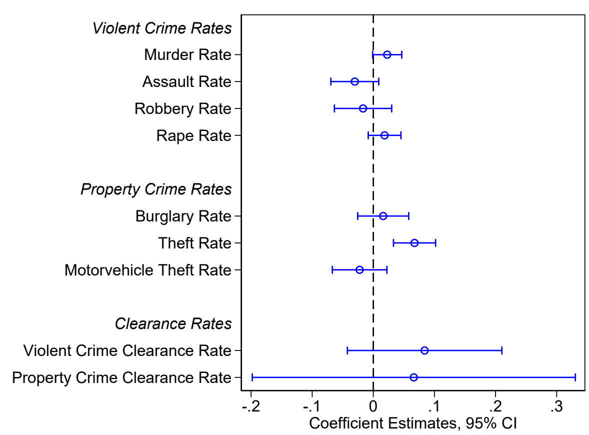

(b) Covered Municipalities

Notes: This figure shows how the relationship between violent crime rates and local crime reporting changes with Sinclair ownership, by whether a municipality is covered at baseline or not. Panel (a) shows a binned scatter plot of the relationship between the municipality's violent crime rate and the share of weeks in a year in which the station reports a local crime story about the municipality, separately before and after Sinclair acquires the station, for non-covered municipalities. Panel (b) shows the same binned scatter plot for covered municipalities. The sample is restricted to stations that are ever owned by Sinclair. Covered municipalities are mentioned in the news more than the median municipality in 2010. Crime rates are IHS crimes per 1,000 people, winsorized at the 99% level.

**Appendix Figure 6:** Differences Between Covered and Non-Covered Municipalities




(b) Socio-economic Characteristics




(b) Crime and Clearance Rates

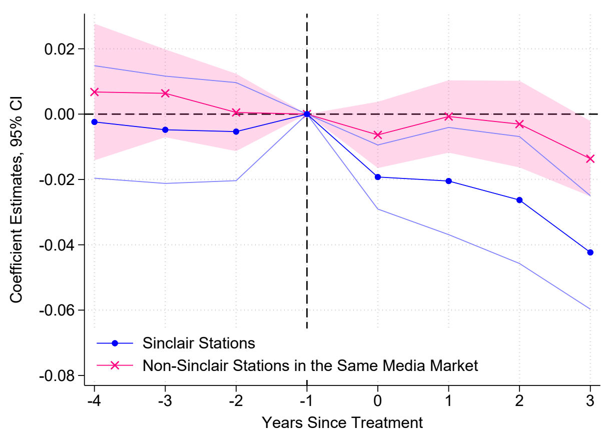
Notes: This figure shows along which dimensions covered and non-covered municipalities differ. We report coefficient estimates together with 95% confidence intervals from a regression of an indicator variable for the municipality being covered at baseline on standardized socio-economic characteristics of the municipality, crime and clearance rates in 2010, and media market fixed effects. All coefficients are estimated in the same regression, but we report them in two separate graphs for ease of exposition. Given that all independent variables are standardized, the coefficients represent the effect of a one standard deviation increase. Standard errors are clustered at the media market level. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes. Crime rates are IHS crimes per 1,000 people. Both clearance rates and crime rates are winsorized at the 99% level.

**Appendix Figure 7:** Correlation of Coverage Over Time

| | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|
| 2010 | 1.000 | 0.970 | 0.960 | 0.961 | 0.956 | 0.946 | 0.953 | 0.948 |
| 2011 | 0.970 | 1.000 | 0.972 | 0.966 | 0.961 | 0.952 | 0.957 | 0.951 |
| 2012 | 0.960 | 0.972 | 1.000 | 0.968 | 0.960 | 0.953 | 0.956 | 0.953 |
| 2013 | 0.961 | 0.966 | 0.968 | 1.000 | 0.968 | 0.958 | 0.957 | 0.954 |
| 2014 | 0.956 | 0.961 | 0.960 | 0.968 | 1.000 | 0.966 | 0.963 | 0.958 |
| 2015 | 0.946 | 0.952 | 0.953 | 0.958 | 0.966 | 1.000 | 0.972 | 0.964 |
| 2016 | 0.953 | 0.957 | 0.956 | 0.957 | 0.963 | 0.972 | 1.000 | 0.971 |
| 2017 | 0.948 | 0.951 | 0.953 | 0.954 | 0.958 | 0.964 | 0.971 | 1.000 |

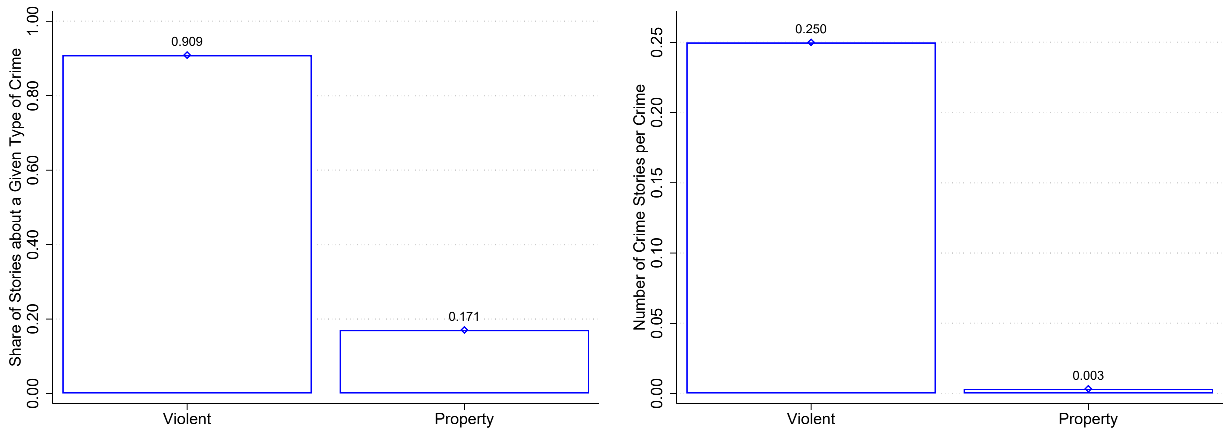
Notes: This figure shows that covered status persists over time. In particular, it shows the correlation of the share of weeks that a given municipalities appears in the news in different years. The sample is restricted to media markets that never experience Sinclair entry.

**Appendix Figure 8:** Effect of Sinclair Ownership for Sinclair Stations and Stations in the Same Media Market on the Probability of Having a Local Crime Story, by Year since Treatment




Notes: This figure shows the effect of Sinclair entry on the probability that a station reports local crime stories about covered municipalities relative to non-covered municipalities, by year since treatment, separately for stations owned by Sinclair and for non-Sinclair stations in Sinclair media markets. We report coefficient estimates and 95% confidence intervals from a regression of an indicator variable for the station reporting a local crime story about the municipality on the interaction between indicator variables for years since Sinclair entry and an indicator variable for whether the municipality is covered at baseline, defined separately for Sinclair and non-Sinclair stations, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects. The sample excludes always treated media markets. The omitted category is T-1. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level, but the effect is constrained to be the same by year since treatment. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix Figure 9:** Local Crime News of Violent and Property Crimes

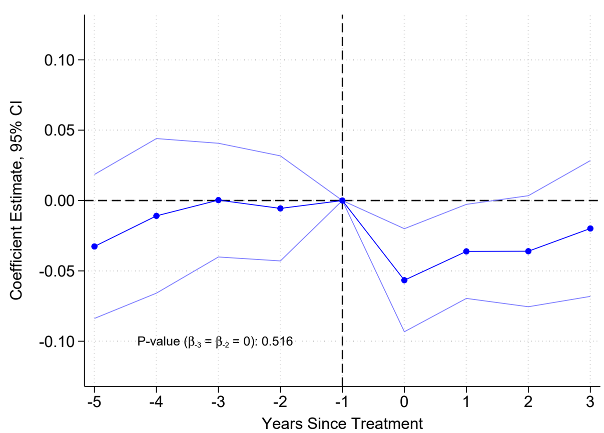



(a) Share of Crime Stories

(b) Crime Stories per Offense

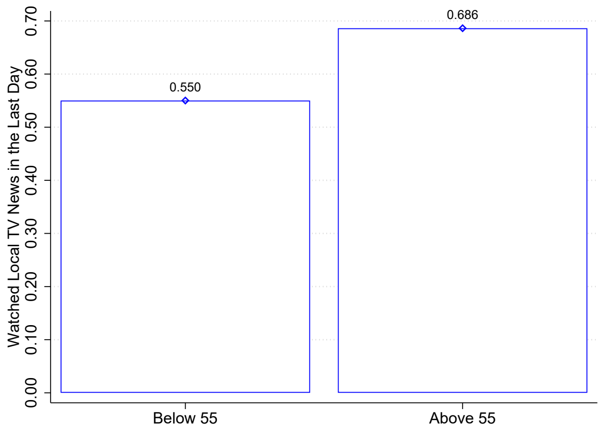
Notes: This figure shows what crimes are covered in local TV news. Panel (a) shows the average share of a municipality's crime stories that are about violent crimes (i.e., murder, assault, rape, and robbery) and property crimes (i.e. burglary, theft, and motor vehicle theft). Panel (b) shows the average number of crime stories per reported offense across municipalities. 8% of stories are about both a violent and a property crime. Note that this does not exactly correspond to the probability that a crime of a given type appears in the news because we have information on news coverage only for one randomly selected day per week. In both graphs, the sample is restricted to 2010 and to media market that never experience Sinclair entry.

**Appendix Figure 10:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, by Year since Treatment, Estimated Including Data for 2009

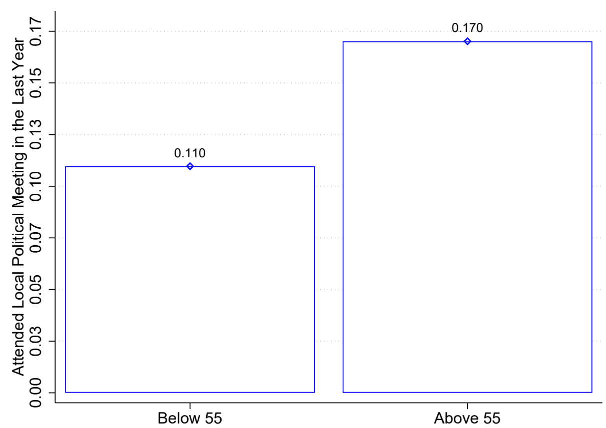



Notes: This figure shows the effect of Sinclair entry on the violent crime clearance rate of covered municipalities relative to non-covered municipalities, by year since treatment, using data that include 2009. We report coefficient estimates and 95% confidence intervals from a regression of the municipality's violent crime clearance rate on the interaction between indicator variables for years since Sinclair entry and an indicator variable for whether the municipality is covered at baseline, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (4)). The sample excludes always treated media markets. The omitted category is T-1. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix Figure 11:** Local News Viewership and Political Participation, by Age




(a) Watched Local TV News




(b) Attended a Local Political Meeting

Notes: This figure reports the share of people who reported watching local TV news in the last day (Panel (a)) or attended a local political meeting in the last year (Panel (b)), separately for individuals below and above 55.

**Appendix Table 1:** Sample Summary

| | Overall | Included in the Content Analysis |
|---|---|---|
| | (1) | (2) |
| # of Stations | 835 | 325 |
| # of Stations Ever Controlled by Sinclair | 121 | 38 |
| # of Stations Ever Owned and Operated by Sinclair | 110 | 37 |
| # of Stations Ever Owned and Operated by Cunningham | 10 | 1 |
| # of Stations Ever Controlled by Sinclair through a Local Marketing Agreement | 10 | 4 |

Notes: This table presents summary counts for full-powered commercial TV stations affiliated with a big four network 2010-2017, separately for all stations (column (1)) and for the sample of stations included in the content analysis (column (2)).

**Appendix Table 2:** Descriptive Statistics

| | Municipalities in the Analysis | | | All Municipalities | | | P-value |
|---|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Panel A: Content | | | | | | |
| Had a Local Story | 2253 | 0.267 | 0.269 | | | | |
| Had a Local Crime Story | 2253 | 0.103 | 0.171 | | | | |
| | Panel B: Crime and Clearance Rates | | | | | | |
| Property Crime Rate | 1792 | 4.075 | 0.526 | 2365 | 4.065 | 0.539 | 0.767 |
| Violent Crime Rate | 1792 | 1.674 | 0.814 | 2365 | 1.714 | 0.807 | 0.229 |
| Property Crime Clearance Rate | 1792 | 0.191 | 0.119 | 2365 | 0.192 | 0.117 | 0.802 |
| Violent Crime Clearance Rate | 1792 | 0.461 | 0.255 | 2365 | 0.466 | 0.251 | 0.676 |
| | Panel C: Municipality Characteristics | | | | | | |
| Population | 1792 | 59219 | 159090 | 2365 | 58653 | 217781 | 0.825 |
| Share Male | 1792 | 0.487 | 0.025 | 2365 | 0.487 | 0.026 | 0.773 |
| Share Over 55 | 1792 | 0.232 | 0.064 | 2365 | 0.236 | 0.065 | 0.060 |
| Share Black | 1792 | 0.117 | 0.159 | 2365 | 0.115 | 0.157 | 0.578 |
| Share Hispanic | 1792 | 0.158 | 0.187 | 2365 | 0.155 | 0.188 | 0.675 |
| Share with 2 Years of College | 1792 | 0.365 | 0.149 | 2365 | 0.360 | 0.147 | 0.276 |
| Share Below Poverty Line | 1792 | 0.136 | 0.078 | 2365 | 0.139 | 0.078 | 0.328 |
| Share Republican | 1792 | 0.475 | 0.159 | 2365 | 0.468 | 0.156 | 0.231 |

Notes: This table reports descriptive statistics for the main variables considered in the analysis and for municipality characteristics. Columns (1) to (3) restrict the sample to municipalities included in the main analysis; columns (4) to (6) include all municipalities with more than 10,000 inhabitants. Column (7) reports the *p*-value of the difference between the two samples from a regression of the specified characteristic on a dummy for the municipality being included in the analysis, with standard errors clustered at the media market level. The content analysis includes 2253 municipalities. 1792 of these municipalities are also in the police behavior analysis. The reference sample additionally includes 573 municipalities that satisfy the conditions to be included in the police behavior analysis, but are located in media markets for which we have no content data (see Appendix B for a detailed explanation). Content and crime and clearance rates are measured in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes. Crime rates are IHS crimes per 1,000 people. Both clearance rates and crime rates are winsorized at the 99% level.

**Appendix Table 3:** Sinclair Entry and Media Market Characteristics

| Dependent Variable | Pop. | Share Male | Share Male 15 to 30 | Share White | Share Hispanic | Unempl. | Income per Capita | Turnout | Share Repub. |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Panel A: All DMAs | | | | | | | | |
| Sinclair | 0.001 | 0.017 | -0.001 | 0.009 | 0.104 | -0.265 | 0.009* | 0.003 | -0.002 |
| | (0.004) | (0.021) | (0.028) | (0.063) | (0.080) | (0.170) | (0.005) | (0.002) | (0.007) |
| Observations | 1648 | 1648 | 1648 | 1648 | 1648 | 1648 | 1648 | 618 | 618 |
| Clusters | 206 | 206 | 206 | 206 | 206 | 206 | 206 | 206 | 206 |
| Outcome Mean in 2010 | 13.561 | 49.412 | 10.783 | 83.240 | 11.808 | 9.454 | 3.539 | 0.432 | 0.515 |
| | Panel B: DMAs in Content Data | | | | | | | | |
| Sinclair | 0.000 | 0.029 | -0.008 | 0.089 | 0.086 | -0.045 | 0.006 | -0.000 | 0.003 |
| | (0.005) | (0.021) | (0.031) | (0.085) | (0.105) | (0.208) | (0.006) | (0.003) | (0.007) |
| Observations | 904 | 904 | 904 | 904 | 904 | 904 | 904 | 339 | 339 |
| Clusters | 113 | 113 | 113 | 113 | 113 | 113 | 113 | 113 | 113 |
| Outcome Mean in 2010 | 14.157 | 49.290 | 10.833 | 80.730 | 14.215 | 9.564 | 3.580 | 0.422 | 0.511 |

Notes: This table shows the relationship between Sinclair entry and socio-economic and political trends. We regress the outcome on an indicator variable for Sinclair entry, media market fixed effects, and year fixed effects. The sample includes all media markets in Panel A, and is restricted to media markets in the content data in Panel B. Standard errors are clustered at the media market level. The dataset is a media market by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Population and income per capita are defined in logs.

**Appendix Table 4:** Effect of Sinclair Ownership on Slant of Non-Local Crime Stories

| Dependent Variable | Share of Stories About… | | Has Non-Local Story About… | | |
|---|---|---|---|---|---|
| Type | Non-Local Crime | Non-Local Police | Police Misconduct | Crime and Drugs | Crime and Immigrants |
| | (1) | (2) | (3) | (4) | (5) |
| Sinclair | 0.002 | 0.001 | -0.026** | 0.074*** | 0.066*** |
| | (0.003) | (0.002) | (0.013) | (0.025) | (0.020) |
| Observations | 31120 | 31120 | 31120 | 31120 | 31120 |
| Clusters | 113 | 113 | 113 | 113 | 113 |
| Stations | 325 | 325 | 325 | 325 | 325 |
| Outcome Mean in 2010 | 0.070 | 0.057 | 0.032 | 0.800 | 0.188 |
| Station FE | X | X | X | X | X |
| Month FE | X | X | X | X | X |
| Media Market Controls | X | X | X | X | X |

Notes: This table shows the effect of Sinclair ownership on the coverage and slant of non-local crime stories. We define a story to be local if it mentions at least one of the municipalities with more than 10,000 people in the media market. All other stories are non-local. We define a story to be about crime following the methodology described in Section 3 (column (1)). We define a story to be about police if it contains the word "police" (column (2)), and about police misconduct if it contains both "police" and "misconduct" (column (3)). We define a story of be about crime and drugs if the story is about crime and in contains any of the following strings: "drug", "drugs", "marijuana", "cocaine", "meth", "ecstasy" (column (4)). Finally, we define a story of be about crime and immigrants if the story is about crime and in contains any of the words "immigration", "immigrant", "migrant", "undocumented" (column (5)). We regress the outcome on an indicator variable for the station being owned by Sinclair, baseline media market characteristics interacted with month fixed effects, station fixed effects, and month fixed effects. The characteristics included are log population, share male, share male between 15 and 30, share white, share Hispanic, share unemployed, and log income per capita. Standard errors are clustered at the media market level. The dataset is a station by month panel. Treatment is defined at the monthly level.

**Appendix Table 5:** Effect of Sinclair Ownership on Slant of Local Crime Stories

| Dependent Variable | Share of Local Crime Stories About… | | |
|---|---|---|---|
| Type | Police Misconduct | Crime and Drugs | Crime and Immigrants |
| | (1) | (2) | (3) |
| Sinclair | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.008) | (0.003) |
| Observations | 30858 | 30858 | 30858 |
| Clusters | 113 | 113 | 113 |
| Stations | 325 | 325 | 325 |
| Outcome Mean in 2010 | 0.005 | 0.181 | 0.015 |
| Station FE | X | X | X |
| Month FE | X | X | X |
| Media Market Controls | X | X | X |

Notes: This table shows the effect of Sinclair ownership on the slant of local crime stories. We define a story to be local if it mentions at least one of the municipalities with more than 10,000 people in the media market. We define a story to be about police misconduct if it contains both "police" and "misconduct" (column (1)). We define a story of be about crime and drugs if the story is about crime and in contains any of the following strings: "drug", "drugs", "marijuana", "cocaine", "meth", "ecstasy" (column (2)). Finally, we define a story of be about crime and immigrants if the story is about crime and in contains any of the words "immigration", "immigrant", "migrant", "undocumented" (column (3)). We regress the outcome on an indicator variable for the station being owned by Sinclair, baseline media market characteristics interacted with month fixed effects, station fixed effects, and month fixed effects. The characteristics included are log population, share male, share male between 15 and 30, share white, share Hispanic, share unemployed, and log income per capita. Standard errors are clustered at the media market level. The dataset is a station by month panel. Treatment is defined at the monthly level.

**Appendix Table 6:** Effect of Sinclair Ownership on the Probability of Having a Local Story, by Whether the Story is about Crime

| Dependent Variable | Had a Local Story | | |
|---|---|---|---|
| Decomposition | Any | Crime | Non-Crime |
| | (1) | (2) | (3) |
| Sinclair * Covered | -0.032** | -0.018*** | -0.023 |
| | (0.014) | (0.007) | (0.014) |
| Observations | 3143360 | 3143360 | 3143360 |
| Clusters | 113 | 113 | 113 |
| Municipalities | 2253 | 2253 | 2253 |
| Stations | 325 | 325 | 325 |
| Outcome Mean in 2010 | 0.248 | 0.092 | 0.221 |
| Station by Week FE | X | X | X |
| Covered by Week FE | X | X | X |
| Station by Municipality FE | X | X | X |
| Sinclair * Controls | X | X | X |

Notes: This table shows the effect of Sinclair ownership on the probability that a station reports a local story about covered municipalities relative to non-covered municipalities, overall (column (1)) and by whether the story is about crime (columns (2) and (3)). We regress the outcome on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix Table 7:** Effect of Sinclair Ownership on the Probability of Having a Local Crime Story, by Political Leaning of the Municipality

| Dependent Variable | Had Local Crime Story | |
|---|---|---|
| Share Republican | >= Median | < Median |
| | (1) | (2) |
| Sinclair * Covered | -0.016** | -0.020** |
| | (0.007) | (0.010) |
| Observations | 1567082 | 1559558 |
| Clusters | 99 | 86 |
| Municipalities | 1123 | 1116 |
| Stations | 285 | 249 |
| Outcome Mean in 2010 | 0.079 | 0.104 |
| Station by Week FE | X | X |
| Covered by Week FE | X | X |
| Station by Municipality FE | X | X |
| Sinclair * Controls | X | X |

Notes: This table shows the effect of Sinclair ownership on the probability that a station reports local crime stories about covered relative to non-covered municipalities, by whether the municipality's Republican vote share in the 2008 presidential election was above (column (1)) or below the median (column (2)). We regress an indicator variable for the station reporting a local crime story about the municipality on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, interactions between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, and share below the poverty line. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix Table 8:** Effect of Sinclair Ownership on the Probability of Having a Local Crime Story, by Type of Crime

| Dependent Variable | Had Local Crime Story | |
|---|---|---|
| Type of Crime | Violent | Property |
| | (1) | (2) |
| Sinclair * Covered | -0.017*** | -0.005 |
| | (0.006) | (0.004) |
| Observations | 3143360 | 3143360 |
| Clusters | 113 | 113 |
| Municipalities | 2253 | 2253 |
| Stations | 325 | 325 |
| Outcome Mean in 2010 | 0.089 | 0.025 |
| Station by Week FE | X | X |
| Covered by Week FE | X | X |
| Station by Municipality FE | X | X |
| Sinclair * Controls | X | X |

Notes: This table shows the effect of Sinclair ownership on the probability that a station reports local crime stories about covered municipalities relative to non-covered municipalities, by whether the story is about a violent (column (1)) or property crime (column (2)). We regress an indicator variable for the station reporting a local crime story about the municipality on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, interactions between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is at the monthly level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix Table 9:** Effect of Sinclair Entry on Violent Crime Rates

| Type of Crime | All | Murder | Assault | Robbery | Rape |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Panel A: Dependent Variable as Crime Rates | | | | |
| Sinclair * Covered | 0.028 | 0.003 | 0.012 | 0.046*** | -0.026 |
| | (0.035) | (0.004) | (0.035) | (0.017) | (0.024) |
| Observations | 14336 | 14336 | 14336 | 14336 | 14336 |
| Clusters | 112 | 112 | 112 | 112 | 112 |
| Municipalities | 1792 | 1792 | 1792 | 1792 | 1792 |
| Outcome Mean in 2010 | 1.674 | 0.034 | 1.235 | 0.721 | 0.300 |
| | Panel B: Dependent Variable as Dummy = 1 if ≥ 1 Crime | | | | |
| Sinclair * Covered | - | 0.029 | -0.001 | -0.010 | 0.045** |
| | - | (0.036) | (0.004) | (0.014) | (0.017) |
| Observations | - | 14336 | 14336 | 14336 | 14336 |
| Clusters | - | 112 | 112 | 112 | 112 |
| Municipalities | - | 1792 | 1792 | 1792 | 1792 |
| Outcome Mean in 2010 | - | 0.462 | 0.910 | 0.964 | 0.932 |
| Media Market by Year FE | X | X | X | X | X |
| Covered by Year FE | X | X | X | X | X |
| Municipality FE | X | X | X | X | X |
| Sinclair * Controls | X | X | X | X | X |

Notes: This table shows the effect of Sinclair entry on the crime rates of covered municipalities relative to non-covered municipalities, for different types of violent crimes. We regress the municipality's crime rate for a given type of violent crime on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Crime rates are IHS crimes per 1,000 people, winsorized at the 99% level.

**Appendix Table 10:** Effect of Sinclair Entry on Property Crime Rates

| Dependent Variable | Property Crime Rate | | | |
|---|---|---|---|---|
| Type of Crime | All | Burglary | Theft | MVT |
| | (1) | (2) | (3) | (4) |
| Sinclair * Covered | 0.053** | 0.065** | 0.045 | 0.026 |
| | (0.023) | (0.028) | (0.028) | (0.029) |
| Observations | 14336 | 14336 | 14336 | 14336 |
| Clusters | 112 | 112 | 112 | 112 |
| Municipalities | 1792 | 1792 | 1792 | 1792 |
| Outcome Mean in 2010 | 4.075 | 2.435 | 3.754 | 1.241 |
| Media Market by Year FE | X | X | X | X |
| Covered by Year FE | X | X | X | X |
| Municipality FE | X | X | X | X |
| Sinclair * Controls | X | X | X | X |

Notes: This table shows the effect of Sinclair entry on the crime rate of covered municipalities relative to non-covered municipalities, for different types of property crimes. We regress the municipality's crime rate for a given type of property crime on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Crime rates are IHS crimes per 1,000 people, and are winsorized at the 99% level. MVT stands for motor vehicle theft.

**Appendix Table 11:** Effect of Sinclair Entry on the Property Crime Rate, Differences-in-Differences Decomposition

| Dependent Variable | Property Crime Rate | | | |
|---|---|---|---|---|
| Sample | Non-Covered | | Covered | |
| | (1) | (2) | (3) | (4) |
| Sinclair | 0.004 | 0.015 | -0.013 | -0.007 |
| | (0.037) | (0.035) | (0.026) | (0.024) |
| Observations | 6480 | 6480 | 7856 | 7856 |
| Clusters | 86 | 86 | 112 | 112 |
| Municipalities | 810 | 810 | 982 | 982 |
| Outcome Mean in 2010 | 3.922 | 3.922 | 4.201 | 4.201 |
| Municipality FE | X | X | X | X |
| Year FE | X | X | X | X |
| Controls * Year FE | | X | | X |

Notes: This table shows the effect of Sinclair entry on the property crime rate using a differences-in-differences specification estimated separately for non-covered (columns (1) and (2)) and covered (columns (3) and (4)) municipalities. We regress the outcome on an indicator variable for Sinclair presence in the media market, municipality fixed effects, and year fixed effects. Columns (2) and (4) additionally control for baseline municipality characteristics interacted with year fixed effects. The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Crime rates are IHS crimes per 1,000 people, winsorized at the 99% level.

**Appendix Table 12:** Effect of Sinclair Entry on Police Spending and Employment

| Dependent Variable | Police Expend. Per Capita | Judicial Expend. Per Capita | Police Employees per 1,000 People | Police Employees per 1,000 People | Police Officers per 1,000 People |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Sinclair * Covered | -0.001 | -0.002 | 0.132 | -0.046 | -0.033 |
| | (0.004) | (0.002) | (0.168) | (0.028) | (0.020) |
| Observations | 8551 | 8551 | 9574 | 14335 | 14335 |
| Clusters | 109 | 109 | 111 | 112 | 112 |
| Municipalies | 1389 | 1389 | 1518 | 1792 | 1792 |
| Outcome Mean in 2010 | 0.242 | 0.019 | 2.978 | 2.385 | 1.858 |
| Media Market by Year FE | X | X | X | X | X |
| Covered by Year FE | X | X | X | X | X |
| Municipality FE | X | X | X | X | X |
| Sinclair * Controls | X | X | X | X | X |

Notes: This table shows the effect of Sinclair entry on the spending and employment of police departments of covered municipalities relative to non-covered municipalities. We regress the outcome on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. All outcomes are winsorised at the 99% level.

**Appendix Table 13:** Effect of Sinclair Entry on Low-Level Arrests

| Dependent Variable | Number of Low-Level Arrests |
|---|---|
| | (1) |
| Sinclair * Covered | 0.107*** |
| | (0.033) |
| Observations | 9312 |
| Clusters | 98 |
| Municipalities | 1164 |
| Outcome Mean in 2010 | 6.620 |
| Media Market by Year FE | X |
| Covered by Year FE | X |
| Municipality FE | X |
| Sinclair * Controls | X |

Notes: This table shows the effect of Sinclair entry on low-level arrests in covered municipalities relative to non-covered municipalities. We regress the number of low-level arrests in the municipality on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Arrests are under the IHS transformation, winsorized at the 99% level.

**Appendix Table 14:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, by 55+

| Share 55+ | >= Median | < Median |
|---|---|---|
| | (1) | (2) |
| | Panel A: Had a Local Crime Story | |
| Sinclair * Covered | -0.017** | -0.019** |
| | (0.007) | (0.009) |
| Observations | 1551198 | 1579204 |
| Clusters | 102 | 100 |
| Municipalities | 1119 | 1118 |
| Stations | 302 | 297 |
| Outcome Mean in 2010 | 0.074 | 0.107 |
| Station by Week FE | X | X |
| Covered by Week FE | X | X |
| Station by Municipality FE | X | X |
| Sinclair * Controls | X | X |
| | Panel B: Violent Crime Clearance Rate | |
| Sinclair * Covered | -0.065** | -0.006 |
| | (0.028) | (0.027) |
| Observations | 7088 | 7056 |
| Clusters | 98 | 93 |
| Municipalities | 886 | 882 |
| Outcome Mean in 2010 | 0.462 | 0.461 |
| Media Market by Year FE | X | X |
| Covered by Year FE | X | X |
| Municipality FE | X | X |
| Sinclair * Controls | X | X |

Notes: This table shows heterogeneous effects by whether the share of the population over 55 was above (column (1)) or below the median in 2010 (column (2)). In Panel A, the table shows the effect of Sinclair ownership on the probability that a station reports local crime stories about covered municipalities relative to non-covered municipalities. We regress the outcome on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level. In Panel B, the table shows the effect of Sinclair entry on the violent crime clearance rate of covered municipalities relative to non-covered municipalities. We regress the municipality's violent crime clearance rate on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level. In both panels, the characteristics included are log population, share male, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix Table 15:** Effect of Sinclair Ownership on the Probability of Having a Local Crime Story, by Whether the Story is about a Crime Incident or an Arrest

| Dependent Variable | Had Local Crime Story | |
|---|---|---|
| Story Related to | Crime | Arrest |
| | (1) | (2) |
| Sinclair * Covered | -0.018*** | -0.002 |
| | (0.007) | (0.002) |
| Observations | 3143360 | 3143360 |
| Clusters | 113 | 113 |
| Municipalities | 2253 | 2253 |
| Stations | 325 | 325 |
| Outcome Mean in 2010 | 0.084 | 0.019 |
| Station by Week FE | X | X |
| Covered by Week FE | X | X |
| Station by Municipality FE | X | X |
| Sinclair * Controls | X | X |

Notes: This table shows the effect of Sinclair ownership on the probability that a station reports local crime stories about covered municipalities relative to non-covered municipalities, by whether the story is about a crime incident or an arrest. Arrest-related stories are stories that contain crime bigrams related to arrests or prosecutions (e.g., "police arrested" or "murder charge") or include the string "arrest." Crime-related stories are all other crime stories. We regress an indicator variable for the station reporting a local crime-related (column (1)) or arrest-related (column (2)) story about the municipality on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

## Appendix A: Institutional Setting

### Media Markets

A media market, also known as designated market area (DMA), is a region where the population receives the same television and radio station offerings. Media markets are defined by Nielsen based on households' viewing patterns: a county is assigned to a media market if that media market's stations achieve the highest viewership share. As a result, media markets are non-overlapping geographies. Counties can be split across media markets, but this happens rarely in practice. As noted by Moskowitz (2021), only 16 counties out of 3130 are split across media markets. Similarly, while media markets are redefined by Nielsen every year, only 30 counties changed their media market affiliation between 2008 and 2016.

Multiple local TV stations belong to the same market. We focus on stations that are affiliated to one of the big-four networks (ABC, CBS, FOX, and NBC) as they they tend to take up most of the viewership and be the ones producing local newscasts. In fact, 85% of local TV stations that do so belong to this category (Papper (2017)). Networks are publishers that distribute branded content. Affiliated stations, although under separate ownership, carry the television lineup offered by the network while also producing original content. With few exceptions, each network has a single affiliate by media market. Note that we exclude low-powered stations (which are sometimes affiliated to a big four network, especially in smaller markets) as they generally have limited geographic reach and smaller viewership.

### Law Enforcement in the United States

Law enforcement in the United States is highly decentralized. Municipal police departments are the primary law enforcement agencies in incorporated municipalities: they are responsible for responding to calls for service, investigating crimes, and engaging in patrol within the municipality's boundaries. Municipal police departments are led by a commissioner or chief that is generally appointed (and removed at will) by the head of the local government.

Non-incorporated areas fall instead under the responsibility of county police, state police, or sheriff's offices, depending on the state's local government statutes. Tribal departments have jurisdictions on Native-American reservations, while special jurisdiction agencies such as park or transit police provide limited policing services within specified areas. Sheriff's offices are also responsible for the functioning of courts. Sheriffs are the only law enforcement heads that are elected. Finally, the FBI has jurisdiction over federal crimes (i.e., crimes that violate U.S. federal legal codes or where the individual carries the criminal activity over multiple states). However, most crimes are prosecuted under state criminal statutes. We refer to Owens (2020) for more details on the functioning of law enforcement agencies in the United States.

# Appendix B: Data Cleaning

## Coverage of Local Crime

**Separating Newscasts into News Stories.** We segment each newscast into separate stories using an automated procedure based on content similarity across sentences. We begin by selecting the number of stories each newscast is composed of using texttiling (Hearst (1997)), an algorithm that divides texts into passages by identifying shifts in content based on word co-occurrence. We then divide sentences into passages using the Content Vector Segmentation methodology proposed by Alemi and Ginsparg (2015), which identifies content shifts by leveraging the representation of sentences into a vector space using word embeddings. In addition, we show that our results are robust to a simple segmentation procedure that separates the newscast into stories of 130 words, based on the fact that the average person speaks at around 130 words per minute.

**Measuring Coverage of Local Crime.** We use the segmented transcripts to measure whether a municipality appears in a crime story using the following procedure:

1. We define a story to be about a municipality if the name of the municipality appears in it. If multiple municipalities' names appear in the same story, we define the story to be local to all of them (76.5% of local crime stories mention a single media market municipality, 18.5% mention two municipalities, and the remaining 4% mention three or more).

2. We defines a story to be about crime if it contains a bigram that is much more likely to appear in an external pre-tagged crime-related library as opposed to a non-crime-related one. The crime-related training library we consider are articles from the Metropolitan Desk of the New York Times with the tags Crime Statistics, Criminal Offenses, or Law Enforcement 2010-2012, that we download from Factiva. The non-crime-related training library is composed by all other Metropolitan Desk articles over the same time period. Each library is composed of all bigrams contained in the articles. We focus on bigrams because they tend to convey more information than single words. We remove punctuation and stop words and lemmatize the

remaining words using WordNet's lemmatizer. We use articles from the New York Times as they are a readily available, previously tagged corpus, but focus on the Metropolitan Desk to capture language that is appropriate to local news stories.

We define a bigram to be about crime if it is ten times more likely to appear in the crime-related library versus the non-crime-related one. Focusing on the relatively frequency of bigrams between the two libraries allows us to filter out common use bigrams (e.g., "New York", "last year") that are likely to appear in the corpus but are not specific to crime. We additionally filter out uncommonly used bigrams that might show up only because of noise by excluding bigrams that appear in the crime library less than 50 times.

3. We create an indicator variable equal to one if a given municipality was mentioned in a crime story by a given station in a given week.

**Interpolation.** To maximize sample size in the presence of short gaps in the data, we replace missing observations in spells shorter than two consecutive months using linear interpolation. In particular, we linearly interpolate the number of crime stories in which a municipality is mentioned in a given week. We define our main outcome, which is an indicator variable equal to one if the municipality was mentioned in a station's crime story in a given week, based on the interpolated variable. 3% of total observations are missing in the raw data and get replaced using this procedure.

## UCR Data

**Identifying and Cleaning Record Errors.** UCR data have been shown to contain record errors and need extensive cleaning (Maltz and Weiss (2006), Evans and Owens (2007)). Following the state of the art in the crime literature, we use a regression-based method to identify record errors and correct them. The method is similar to procedures used, among others, by Evans and Owens (2007), Chalfin and McCrary (2018), Weisburst (2019) and Ba and Rivera (Forthcoming), but most closely follows Mello (2019).

For each city, we fit the time series of crimes and clearances 2009-2017 using a local linear regression with bandwidth two. We compute the absolute value of the percent difference between actual and predicted values (adding 0.01 to the denominators to avoid dealing with zeros) and identify an observation to be a record error if the percent difference exceeds a given threshold. The threshold is computed as the 99th percentile of the distribution of percent differences for cities within a population group.[1] We substitute observations that are identified as record errors using the predicted value from the time-series regression. We follow this procedure to clean the crime and clearance series of each type of crime (property, violent, murder, assault, robbery, rape, burglary, theft, and motor vehicle theft). Overall, around 1% of observations are substituted using this procedure.

**Population Smoothing.** To define crime rates we use a smoothed version of the population count included in the UCRs, again following the crime literature. In particular, we fit the population time series of city using a local linear regression with a bandwidth of 2 and replace the reported population with the predicted values. This is necessary because population figures are reported yearly, but tend to jump discontinuously in census years (Chalfin and McCrary (2018)).

**Sample Definition.** Our starting sample is composed by municipalities with more than 10,000 people with a municipal police department (2629 municipalities). This excludes 116 municipalities, mainly located in California, that contract their contract out law enforcement services to the local sheriff's office.

To create a balanced sample, we exclude municipalities that do not continuously report crime data to the FBI 2010-2017 (235 municipalities) and do not have at least one violent and one property crime in every year (29 municipalities). This leaves us with 2365 municipalities. The empirical strategy requires restricting the sample to municipalities located in media markets included in the content data, which further drops 568 municipalities. The final sample includes 1792 municipalities.

**Crime Reporting Issues.** It is important to note that our findings on crime rates refer to crimes that the public reports to the police, so changes in crime reporting behavior might be potentially conflated with changes in crimes. Given that our results on crime rates are quite stable across crime

[1] Mello (2019) supports this choice by noting that the percent differences tend to be more dispersed for smaller than for larger cities, perhaps because the number of crimes and arrests is increasing with city size. We follow the same size categories: 10,000-15,000, 15,000-25,000, 25,000-50,000, 50,000-100,000, 100,000-250,000, and >250,000.

types, we believe that our results are unlikely to be purely explained by a differential reporting behavior on part of the public. In particular, violent crimes such as murders and assaults are less likely to be under-reported, so we are not concerned that the null effect on violent crime rates is masking a different dynamic. Similarly, to the extent that under-reporting is less likely for crimes crimes that involve insured goods such as burglaries and vehicle thefts (as insurance companies often would not honor theft claims without a police report), we do not believe that changes in reporting behavior can explain our findings. Under-reporting is less concerning for our results on clearance rates, as the police can only investigate crimes that are known to them. While it is true that there is potential for manipulation in clearance statistics, for manipulation to fully explain the result it would need to be systematic and at quite a large scale, which we believe is implausible.

## Google Trends Data

The Google Trends API normalizes the search interest between 0 and 100 for the time and location of each query. In particular, "each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. [...] The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics" (Stephens-Davidowitz (2014)). We modify the script provided by Goldsmith-Pinkham and Sojourner (2020) to query the Google Trends API.

Importantly, the Google Trends API limits the number of geographic locations per query to five. We ensure comparability across media markets and time by including that the New York media market in all our queries, and normalizing search volume to the one of New York media market following Goldsmith-Pinkham and Sojourner (2020). The Google Trends API censors observations that are a below an unknown threshold. Google Trends data by municipality are censored with a very high frequency, which makes it impossible to construct a panel of municipalities over time.

## Gallup Data

The Gallup Poll Social Series surveys are public opinion surveys that Gallup has been conducting monthly since 2001. The surveys focus on a specific topic each month (e.g., the October survey focuses on crime perceptions), but a question on what is the most important problem facing the country is always asked. Gallup interviews approximately 1,000 individuals per month, which gives us a total of almost 99,000 individual observations 2010-2017.

The Gallup data do not include municipality identifiers, but we use the reported zip codes to link observations to specific municipalities. Zip codes are missing for 1.7% of the observations, which we drop. We begin by intersecting zip codes and municipality shapefiles using ArcGIS. To avoid assigning zip codes to municipalities that they very minimally intersect with, we drop all intersections that are less than 1% of the zip code area. Zip codes are not subdivisions of municipalities and can cross municipal boundaries. If a zip code intersects one municipality only, we assign it to that municipality. If a zip code intersects multiple municipalities, we assign it to the municipality that has the largest overlap with the zipcode.

Following this procedure, we are able to assign 51,000 respondents to specific municipalities. Of them, almost 34,000 are in municipalities included in the police behavior analysis. We aggregate the individual-level survey data at the municipality by year data, and define the outcome as an indicator variable equal to one if at least one respondent in the municipality reported crime as being the most important problem facing the nation.

## Appendix C: Classifying Local Crime News

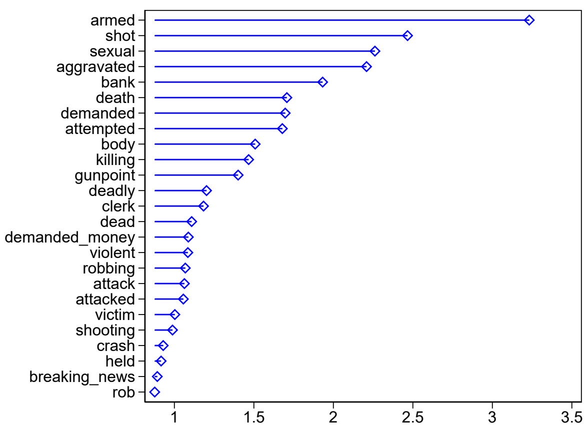
We build a classifier model that assigns a specific type of crime to each of the 464,356 local news stories about this topic in our sample. To train the model, we need a sub-sample of the stories to be labeled with the correct crime type. We create this sub-sample by performing a naive keyword search, using the following keywords:

1. Murder: MURDER, HOMICID, KILLE;
2. Assault: ASSAULT;
3. Robbery: ROBBE;
4. Rape: RAPE, SEXUAL ASSAULT;
5. Burglary: BURGLAR;
6. Theft: THIEF, STEAL, STOLE, THEFT.

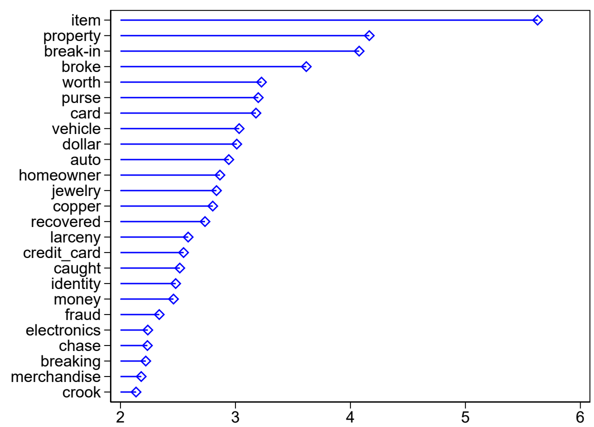
We selected these terms to minimize the presence of false positives. In fact, we checked using the full vocabulary that these keywords return words and bigrams that appear to be closely related to the crime considered. The training sample is then defined to be the sample of crime stories that contain at least one of the keywords (226,503 stories). Because it is difficult to distinguish between assault and rapes and burglary and theft, we classify stories into two categories: stories about violent crimes (murder, assault, robbery, and rape) and stories about property crimes (burglary and theft). Because a story can potentially cover different types of crimes, we train separate binary models for each category.

We use this sub-sample to train a classifier model. In particular, we train a support vector machine model using stochastic gradient descent. The features that are used to predict the label are the most frequent 25,000 words and bigrams in the full corpus. We exclude the keywords used to define the original labels from the features, as they contain significant information for the training sample, but we already know that we will not be able to leverage this information for out-of-sample predictions. The features are TF-IDF weighted. We train the model on 80% of the sample, and use the remaining 20% as a test sample to evaluate model performance. We find that the three models perform well, with F1-scores of 0.84 (violent) and 0.80 (property). Appendix C Figure 1 shows the most predictive feature for each category. Reassuringly, the features selected by the different models appear to intuitively link to the respective crimes. We use the models to predict the category of the remaining 237,853 stories. Using this method, we are able to assign a crime type to almost all local crime stories. Overall, 38,177 stories (8%) are classified as having both a violent and a property crime.

**Appendix C Figure 1:** Most Predictive Features for News Type Classifier




(a) Violent




(b) Property

Notes: This figure shows the most predictive features for the classification models used to identify the content of local crime news.

## Appendix D: Robustness Checks

### Robustness of the Effect of Sinclair Ownership on Coverage of Local Crime

Appendix D Table 1 shows that the effect of Sinclair ownership on news coverage of local crime is robust to a number of concerns. Column (1) reports the baseline estimates for reference.

**Robustness to Data Cleaning and Sample.** We begin by showing that the choices we make when cleaning the content data and defining the outcome do not matter for the effect on the probability that a municipality appears in the news with a crime story. First, columns (2) and (3) show that the result is not affected if we identify crime stories using bigrams that are less (more) distinctively about crime, i.e., bigrams that are five (twenty) times more likely to appear in the crime-related versus the non-crime-related library. In addition, not replacing missing observations using linear interpolation as described in Appendix B (column (4)) or segmenting newscasts using a fixed number of words (column (5)) leaves the result unchanged. Similarly, restricting the sample to the same set of municipalities included in the analysis of clearance rates does not impact the result (column (6)).

**Robustness to Treatment Definition.** Columns (7) and (8) show robustness to using alternative definitions of Sinclair ownership. In the baseline analysis, we consider a station to be controlled by Sinclair in all months after acquisition, independently of whether Sinclair retains ownership of the station or not. Column (7) shows that focusing on stations directly owned and operated by Sinclair does not affect the result. Finally, in column (8) we show that the result is unchanged if we only include markets that Sinclair entered as part of a group acquisition, where endogenous entry is less likely to be a concern.

### Robustness of the Effect of Sinclair Entry on Clearance Rates

Appendix D Table 2 shows that the effect of Sinclair entry on the violent crime clearance rate is robust to decisions taken during data cleaning and alternative ways of defining Sinclair entry. Appendix D Table 3 shows robustness to alternative ways of defining the covered status of a municipality. In both tables, column (1) reports the baseline estimates for reference.

**Robustness to Data Cleaning.** We begin by showing that the result is not sensitive to the data cleaning procedure. First, in column (2) we show that not winsorizing the outcome only minimally impacts the estimates. In addition, column (3) shows that the result is virtually unchanged if we do not replace record errors using the regression-based procedure described in Appendix B.

**Robustness to Treatment Definition.** We also show that using alternative definitions of Sinclair ownership does not affect the result. The estimates are robust to dropping media markets where Sinclair divested a station (column (4)) and considering only media markets where Sinclair directly owns and operates a station (column (5)). Finally, we consider the possibility that Sinclair acquisitions might correlate with trends in covered relative to non-covered municipalities. In column (6), we shown that this is unlikely to explain our results: the coefficient is unchanged when we only consider markets that Sinclair entered as part of multi-station deals, where acquisitions are less likely to be driven by specific media market conditions.

**Robustness to Covered Status Definition.** Finally, we show that our main result is also robust to alternative ways of identifying covered and non-covered municipalities. In our baseline specification, we define a municipality to be covered if it is mentioned in the news more than the median municipality in 2010. This decision is motivated by the fact that having control and treatment of similar size helps with power, but it is potentially concerning for two reasons.

First, this could be seen as an ad hoc decisions. In Appendix D Table 3 we show that the main result does not change if we split municipalities at the median after having residualized coverage on media market fixed effects (column (2)), if we predict covered status based on observable characteristics (column (3)), or if we measure coverage in different time periods (columns (4) to (6)), although in some cases the estimates lose significance.

Second, splitting at the median implies that municipalities close to the median might end up with a different covered status while receiving similar news coverage at baseline. To speak to this concern, we begin by showing in Appendix D Figure 1 that the effect on the violent crime clearance rate is increasing in pre-treatment coverage. In addition, we estimate a "donut" version of our baseline specification dropping municipalities between the 40th and 60th percentile of baseline coverage. Appendix D Table 3 column (7) shows that the point estimate is barely affected by imposing this sample restriction. Finally, we show in column (8) that our main result is robust to a matching specification.[2]

## Robustness to Heterogeneous Effects in TWFE Models

Recent work in the econometrics literature has highlighted that two-way fixed effects (TWFE) regressions recover a weighted average of the average treatment effect in each group and time period (de Chaisemartin and D'Haultfœuille (2020)). This is problematic because weights can be negative, which means that if treatment effects are heterogeneous, the TWFE estimates might be biased. No formal extension of these concepts to higher dimensional fixed effect models, such as the ones we use in this paper, is available as far as we are aware. Nonetheless, we provide four pieces of evidence consistent with the effect on the violent crime clearance rate being robust to concerns related to heterogeneous treatment effects in TWFE regressions.

First, we note that issues with negative weights are most severe when the majority of units in the sample are treated at some point. The fact that we have a large number of media markets that never experience Sinclair entry suggests that negative weights might have limited relevance in our setting. To quantify this statement, we implement the diagnostic test proposed by Jakiela (2021) by focusing on two specifications that only exploit the staggered timing of Sinclair entry, separately for covered and non-covered municipalities. We find that 31% of all treated observations receive a negative weight when we focus on non-covered municipalities (28% when we focus on covered municipalities). Consistent with what theory suggests, these observations are all in always treated units after 2014, as shown by the heat maps in Appendix D Figure 2. Because our event-study

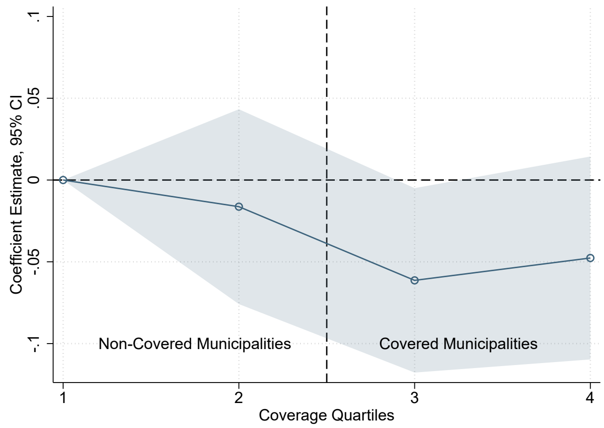
[2]We define a sample of covered municipalities and non-covered municipalities which are similar on a set of pre-specified characteristics, among municipalities in the top and bottom 40th percentile of the baseline coverage distribution. We match with common support and without replacement. The resulting sample includes 1366 municipalities, split between 658 covered and 658 non covered municipalities. To perform our matching algorithm, we employ the following set of covariates: log population, demographic characteristics (namely, share male, share over 55, share black, share Hispanic, and share with 2 years of college), economic characteristics (share below the poverty line) and, finally, political leaning (Republican vote share in the 2008 election). These are measured at baseline (i.e., in 2010) to avoid any post-treatment bias.

graphs exclude always treated observations but display patterns that are very much in line with our two-way fixed effects estimates, we are not concerned that the negative weights of always treated observations post-2014 drive our results.

Second, we ask directly whether there is evidence of treatment effect heterogeneity, again following Jakiela (2021). Appendix D Table 4 shows that we cannot reject that the slope of the relationship between the residualized outcome variable and the residualized treatment variable is linear, which suggests that the homogeneity assumption might not be off-base in our setting. In line with this result, Appendix D Figure 3 shows that event study graphs estimated using the robust estimators developed by de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) display treatment effects consistent with our baseline estimates. Given that the differences-in-differences estimates that underlie our main effects are robust to allowing for treatment effects to be heterogeneous, we are confident in our triple differences estimates as well.

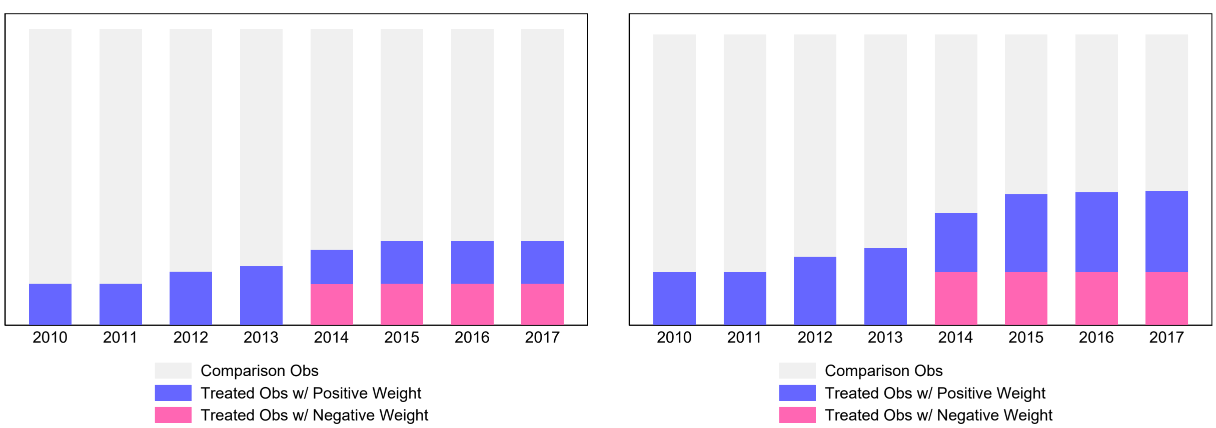
Finally, we show that our results are robust to artificially eliminating variation from the staggered timing of Sinclair entry. This is important to the extent that the issue of negative weights in staggered designs arises in part from using earlier treated units as control for later treated units (Goodman-Bacon (2021)), in line with what Appendix D Figure 2 also shows in our case. We eliminate variation from staggered timing by running regressions including only media markets that are either never treated or that are acquired at specific points in time, for all years in which Sinclair entered more than three media markets. Appendix D Table 5 shows that out of the four years we consider, three reproduce a negative coefficient. The magnitude of the effect is larger in two of them and not significant in one, but larger standard errors produce confidence intervals consistent with the main point estimate. Instead, we do not find a similar effect if we focus on media markets entered in 2013 only.

**Appendix D Figure 1:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, by Coverage Quartile




Notes: This figure shows the effect of Sinclair entry on the violent crime clearance rate by a municipality's coverage quartile. We regress the municipality's violent crime clearance rate on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for the municipality's baseline coverage quartile, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (similar to equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Baseline coverage quartiles are defined based on the number of times the municipality is mentioned in the news in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix D Figure 2:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, Test for Negative Weights in TWFE Models

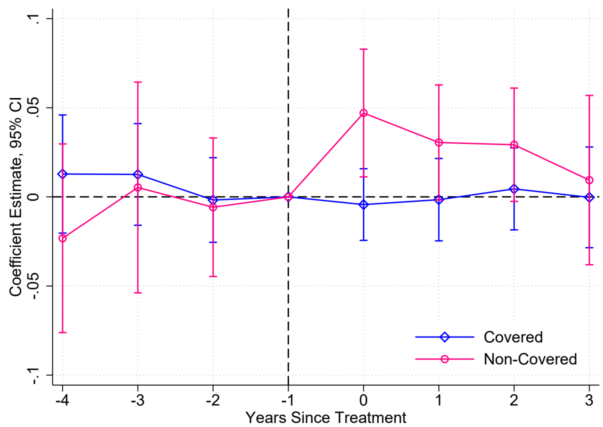



(a) Non-Covered Municipalities

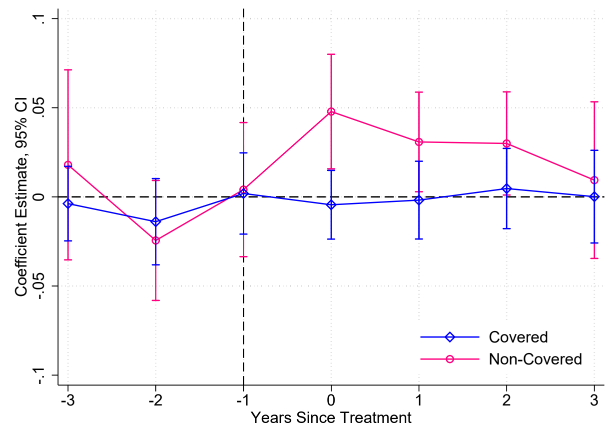
(b) Covered Municipalities

Notes: The figure shows the weights used to calculate the two-way fixed effects estimates of the impact of Sinclair entry on the violent crime clearance rate, for two differences-in-differences designs that only exploit variation from the staggered timing of Sinclair entry separately for covered and non-covered municipalities. The weights are calculated following Jakiela (2021).

**Appendix D Figure 3:** Effect of Sinclair Entry on the Violent Crime Clearance Rate by Year since Treatment, Robustness to Heterogeneous Effects in TWFE Models




(a) de Chaisemartin and D'Haultfoeoeuille (2020)




(b) Calloway and Sant'Anna (2021)

Notes: This figure shows the effect of Sinclair entry on the violent crime clearance rate by year since treatment, estimated separately for covered and non-covered municipalities using an estimator robust to heterogeneous treatment effects in TWFE models. The starting point is a TWFE model that regresses the outcome on year and municipality fixed effects. We estimate placebo coefficients leading up to treatment and dynamic treatment effects using the robust estimator proposed by de Chaisemartin and D'Haultfoeoeuille (2020), which we report together with 95% confidence intervals from 1000 bootstrap repetitions in panel (a) and using the estimator proposed by Calloway and Sant'Anna (2021) in panel (b). The analysis is run separately for covered and non-covered municipalities, but we report the coefficients on the same graph for ease of comparison. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is defined at the yearly level. A media market is considered treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix D Table 1:** Effect of Sinclair Ownership on the Probability of Having a Local Crime Story, Robustness to Data Cleaning and Treatment Definition

| Dependent Variable | Had Local Crime Story | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Baseline | Data Cleaning and Sample | | | | | Treatment Definition | | |
| Robustness to… | | Less Restrictive Crime Story Definition | More Restrictive Crime Story Definition | No Imputation | Fixed Division of Newscasts into Stories | Same Sample as UCR Analysis | Drops Divested Stations | Stations Owned and Operated by Sinclair Only | Group Acquis. Only |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Sinclair * Covered | -0.018*** | -0.021*** | -0.018*** | -0.018*** | -0.023*** | -0.017** | -0.018*** | -0.019*** | -0.015** |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.007) |
| Observations | 3143360 | 3143360 | 3143360 | 3054074 | 3143360 | 2502984 | 3143360 | 3143360 | 3132074 |
| Clusters | 113 | 113 | 113 | 113 | 113 | 112 | 113 | 113 | 112 |
| Municipalities | 2253 | 2253 | 2253 | 2253 | 2253 | 1792 | 2253 | 2253 | 2245 |
| Stations | 325 | 325 | 325 | 325 | 325 | 324 | 325 | 325 | 322 |
| Outcome Mean in 2010 | 0.092 | 0.099 | 0.072 | 0.091 | 0.107 | 0.102 | 0.092 | 0.092 | 0.092 |
| Station by Week FE | X | X | X | X | X | X | X | X | X |
| Covered by Week FE | X | X | X | X | X | X | X | X | X |
| Station by Municipality FE | X | X | X | X | X | X | X | X | X |
| Sinclair * Controls | X | X | X | X | X | X | X | X | X |

Notes: This table shows the robustness of the effect of Sinclair ownership on the probability that a station reports a local story about covered municipalities relative to non-covered municipalities. We regress an indicator variable for the station reporting a local crime story about the municipality on the interaction between an indicator variable for the station being owned by Sinclair and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for the station being owned by Sinclair and baseline municipality characteristics, station by week fixed effects, covered status by week fixed effects, and station by municipality fixed effects (equation (1)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Column (1) reports the baseline estimates. Column (2) identifies crime stories using bigrams that are five (instead of ten) times more likely to appear in the crime library then in the non-crime library. Column (3) identifies crime stories using bigrams that are twenty (instead of ten) times more likely to appear in the crime library then in the non-crime library. Column (4) leaves spells shorter than eight weeks for which we have no content data as missing. Column (5) segments the newscasts into stories using a fixed number of words per story (see Appendix B for further details). Column (6) restricts the sample to municipalities also included in the crime analysis. Column (7) restricts treatment to stations owned and operated by Sinclair. Column (8) drops stations that were not acquired by Sinclair as part of multi-station deal. Standard errors are clustered at the media market level. The dataset is a municipality-station pair by week panel. There are multiple stations in each media market covering the same municipalities, and the municipality-station pair is the cross-sectional unit of interest. Treatment is defined at the monthly level. Covered municipalities are mentioned in the news more than the median municipality in 2010.

**Appendix D Table 2:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, Robustness to Data Cleaning and Treatment Definition

| Dependent Variable | Violent Crime Clearance Rate | | | | | |
|---|---|---|---|---|---|---|
| | Baseline | Data Cleaning | | Treatment Definition | | |
| Robustness to… | | No Winsorizing | No Imputation | Drops DMAs with Divested Stations | Stations Owned and Operated by Sinclair | Group Acquis. Only |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Sinclair * Covered | -0.033** | -0.037** | -0.035** | -0.032* | -0.023* | -0.031* |
| | (0.016) | (0.017) | (0.017) | (0.016) | (0.014) | (0.018) |
| Observations | 14336 | 14336 | 14336 | 14304 | 14336 | 13840 |
| Clusters | 112 | 112 | 112 | 111 | 112 | 104 |
| Municipalities | 1792 | 1792 | 1792 | 1788 | 1792 | 1730 |
| Outcome Mean in 2010 | 0.461 | 0.462 | 0.461 | 0.461 | 0.461 | 0.459 |
| Media Market by Year FE | X | X | X | X | X | X |
| Covered by Year FE | X | X | X | X | X | X |
| Municipality FE | X | X | X | X | X | X |
| Sinclair * Controls | X | X | X | X | X | X |

Notes: This table shows the robustness of the effect of Sinclair entry on the violent crime clearance rate of covered municipalities relative to non-covered municipalities. We regress the municipality's violent crime clearance rate on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Column (1) reports the baseline estimates. Column (2) does not winsorize clearance rates, while column (3) does not correct for likely erroneous observations using the methodology described in Appendix B. Column (4) drops media markets with stations that were eventually divested. Column (5) restricts treatment to media markets with stations owned and operated by Sinclair. Column (6) drops markets that were not entered by Sinclair as part of multi-station deals. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is at the yearly level. A media market is treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix D Table 3:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, Robustness to Covered Status Definition

| Dependent Variable | Violent Crime Clearance Rate | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Baseline | Covered Status Definitions | | | | | Donut | |
| Robustness to… | | Residualized | Predicted | Jan-Jun 2010 | Jul-Dec 2010 | Jan-Jun 2011 | Donut | Matching |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Sinclair * Covered | -0.033** | -0.031** | -0.025 | -0.028* | -0.024 | -0.043** | -0.038** | -0.035* |
| | (0.016) | (0.014) | (0.016) | (0.014) | (0.016) | (0.017) | (0.018) | (0.018) |
| Observations | 14336 | 14336 | 14336 | 14336 | 14336 | 14336 | 11600 | 10928 |
| Clusters | 112 | 112 | 112 | 112 | 112 | 112 | 112 | 112 |
| Municipalities | 1792 | 1792 | 1792 | 1792 | 1792 | 1792 | 1450 | 1366 |
| Outcome Mean in 2010 | 0.461 | 0.461 | 0.461 | 0.461 | 0.461 | 0.461 | 0.452 | 0.459 |
| Media Market by Year FE | X | X | X | X | X | X | X | X |
| Covered by Year FE | X | X | X | X | X | X | X | X |
| Municipality FE | X | X | X | X | X | X | X | X |
| Sinclair * Controls | X | X | X | X | X | X | X | X |

Notes: This table shows the robustness of the effect of Sinclair entry on the violent crime clearance rate of covered municipalities relative to non-covered municipalities. We regress the municipality's violent crime clearance rate on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Column (1) reports the baseline estimates, in which covered municipalities are municipalities mentioned in the news more than the median municipality in 2010. Column (2) defines a municipality as being covered if the residual from a regression of its baseline coverage in 2010 on media market fixed effects is above the median. Column (3) uses covered status predicted from a LASSO regression of the baseline municipality characteristics, the baseline municipality characteristics squared, and the baseline municipality characteristics cubed. In columns (4), (5), and (6), covered municipalities are municipalities mentioned in the news more than the median municipality in the first half of 2010, in the second half of 2010, and in the first half of 2011 respectively. Column (7) drops municipalities with baseline news coverage between the 40th and 60th percentile in 2010, while column (8) implements propensity score matching on the same sample. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is at the yearly level. A media market is treated in a given year if Sinclair was present in the market in the January of that year. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix D Table 4:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, Test for Heterogeneous Treatment Effects in TWFE Model

| Dependent Variable | Residualized Violent Crime Clearance Rate | |
|---|---|---|
| Sample | Non-Covered | Covered |
| | (1) | (2) |
| Residualized Treatment | 0.025** | -0.005 |
| | (0.012) | (0.007) |
| Treatment | -0.001 | -0.001 |
| | (0.004) | (0.003) |
| Treatment * Residualized Treatment | 0.011 | 0.009 |
| | (0.020) | (0.012) |
| Observations | 6480 | 7856 |

Notes: This table test whether treatment effect are likely to be heterogeneous across treated units following Jakiela (2021). We regress the residualized outcome on the treatment, the residualized treatment, and the interaction between the two, separately for non-covered (column (1)) and covered municipalities (column (2)). The residualized outcome is the residual from a regression of the municipality's violent crime clearance rate on municipality and year fixed effects. The treatment is an indicator variable for Sinclair presence in the media market. The residualized treatment is the residual from a regression of the treatment on municipality and year fixed effects. The dataset is a municipality by year panel. Treatment is at the yearly level. A media market is treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

**Appendix D Table 5:** Effect of Sinclair Entry on the Violent Crime Clearance Rate, No Staggered Timing

| Dependent Variable | Violent Crime Clearance Rate | | | |
|---|---|---|---|---|
| Media Markets Treated in… | 2012 | 2013 | 2014 | 2015 |
| | (1) | (2) | (3) | (4) |
| Sinclair * Covered | -0.101** | 0.008 | -0.020 | -0.030** |
| | (0.047) | (0.043) | (0.020) | (0.014) |
| Observations | 9536 | 9192 | 10168 | 9544 |
| Clusters | 62 | 59 | 71 | 63 |
| Municipalities | 1192 | 1149 | 1271 | 1193 |
| Outcome Mean in 2010 | 0.439 | 0.434 | 0.442 | 0.438 |
| Media Market by Year FE | X | X | X | X |
| Covered by Year FE | X | X | X | X |
| Municipality FE | X | X | X | X |
| Sinclair * Controls | X | X | X | X |

Notes: This table shows the robustness of the effect of Sinclair entry on the violent crime clearance rate of covered municipalities relative to non-covered municipalities to eliminating variation in treatment coming from the staggered timing of Sinclair entry. We restrict the sample to media markets never exposed to Sinclair and entered by Sinclair in the year specified in the column header, for years in which Sinclair entered more than three media markets. We regress the municipality's violent crime clearance rate on the interaction between an indicator variable for Sinclair presence in the media market and an indicator variable for whether the municipality is covered at baseline, the interaction between an indicator variable for Sinclair presence in the media market and baseline municipality characteristics, media market by year fixed effects, covered status by year fixed effects, and municipality fixed effects (equation (3)). The characteristics included are log population, share male, share over 55, share black, share Hispanic, share with 2 years of college, share below the poverty line, and Republican vote share in the 2008 presidential election. Standard errors are clustered at the media market level. The dataset is a municipality by year panel. Treatment is at the yearly level. A media market is treated in a given year if Sinclair was present in the market in the January of that year. Covered municipalities are mentioned in the news more than the median municipality in 2010. Clearance rates are defined as total number of crimes cleared by arrest or exceptional means over total number of crimes, winsorized at the 99% level.

## Appendix E: Persuasion Rates

To the magnitude of our effects into perspective, we estimate a persuasion rate that measures the share of the TV station's viewers who were convinced to be worried about crime as the result of exposure to Sinclair's content. Persuasion rates are generally defined as:

$$f = \frac{y_T - y_C}{e_T - e_C} \times \frac{1}{1 - y_0} \times 100. \tag{1}$$

We set $y_T - y_C$ to be equal to 0.034 (see Table 5 column (1)) and $y_0$ to be equal to 0.05 (see footnote 25). We use two different types of data sources to get at exposure: surveys and audience data.

We begin by discussing exposure rates using three different survey sources: the 2010 Cooperative Congressional Election Studies (Ansolabehere (2012)), Nielsen's Local Watch Report (Nielsen (2017)), and a survey from Pew Research (Matsa (2018)). In the CCES data, approximately 60% of individuals report watching local TV news the day before being surveyed. The share of adults watching local TV news is instead 46% and 37% according to the Nielsen and Pew Research data respectively.

When using survey data, we need to make assumptions regarding which TV stations people watch. As a first approximation, there are four news-producing TV stations by media market (these are the big-four affiliates our paper focuses on, that tend to be the only ones producing local news content). We calculate persuasion rates under two different assumptions on TV viewers' switching behavior:

1. Suppose first that TV viewers only ever watch one channel. Then, we can assume that one fourth of all TV viewers will be exposed by the change in content of Sinclair. We can therefore set $e_T - e_C$ to be equal to $0.25 \times 0.60 = 0.15$ (CCES), $0.25 \times 0.46 = 0.115$ (Nielsen) and $0.25 \times 0.37 = 0.09$ (Pew Research). This gives us persuasion rates respectively equal to $f_1^{CCES} = 23.8\%$, $f_1^{NIELSEN} = 31.6\%$ and $f_1^{PEW} = 39\%$, which are at the higher end of the spectrum of persuasion rates.

2. Suppose instead that TV viewers switch across channels and are exposed to all local TV

newscasts over some period of time. Then, we can set $e_T - e_C$ to be equal to the viewership rate reported in the different surveys. This gives us persuasion rates respectively equal to $f_2^{CCES} = 6\%$, $f_2^{NIELSEN} = 7.7\%$ and $f_2^{PEW} = 9.66\%$. These smaller estimates are in line with many other estimates of persuasion rates.

We can also calculate exposure using audience data. Using the replication data from Martin and McCrain (2020), we get that the average news rating is 4.7%, where news ratings are defined to be the share of TV households that are watching a given program at a certain point in time. This corresponds to 4.5% of the overall population (around 96% of US households are classified as TV households according to Nielsen). Using this number as our exposure rate, we calculate a persuasion rate of approximately $f^{RATINGS} = 78\%$. While this is a very high persuasion rate, it is likely to be a (substantial) overestimate, as ratings data do not take into account that different individuals might be viewing newscasts of the same station at different points during the day or over different periods of time (in other words, it is likely that different people would watch and therefore be exposed to the news in the morning and in the evening or over the course of a week). Still, we consider it a helpful upper bound.