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Media visibility and social tolerance: Evidence from USA

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Abstract

I study the impact of media visibility of people of colour on the rate of hate crimes motivated by race or ethnicity in the United States. To do so, I construct a novel measure of state-level media visibility of people of colour between 2007 and 2013. Comparing state-level variation in the hate crime rate with a measure of the one-year lagged state-level variation in media visibility, I find that an increase in media visibility reduces the number of hate crimes. The effect is not larger in states that used to be pro-slavery, but larger in states that are more prone to spontaneous emotional outbursts of hate. The result, which is robust to several checks, is in the line with the argument that "visibility matters."

Keywords: Media, Information and knowledge; Economics of minorities; Crime

JEL Classification: L82; D83; J15; K42

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1. Introduction

It is often argued that an increase in media visibility of a minority group has a positive effect on the public opinions and beliefs about that minority group. One reason behind this is that media visibility of a group is a form of recognition that signals the relative social worth of that group (Hilton-Morrow and Battles, 2015). It can also increase information about the minority group that replaces incorrect or false beliefs and reduces prejudice, teaches the majority group about the minority group's struggles, perspectives, and opinions, and reduce the majority group's speed of implicit association between the minority group and negative traits (Allport, 1956; Bolzendahl and Myers, 2004; Fisher, et al., 2007; Greenberg, 1988; Reingold and Foust, 1998). If media visibility influences the accuracy of individual beliefs, it also affects the efficiency of democratic and economic systems (Della Vigna and Gentzkow, 2010). Recently, economists have become interested in the role of media on social tolerance, in particular when studying the role of negative media portrayals on nationalism and ethnic conflicts (DellaVigna et al., 2014; Yanagizawa-Drott, 2014). The effect of general media visibility, however, on social tolerance has been largely ignored.

In this paper, I use a novel measure of state-level variation in exposure to people of colour on television to study the effect of general media visibility of people of colour on social tolerance toward that group.[1] I find that media visibility does matter. In my first set of results I find, after controlling for time varying covariates and for year, state and US census fixed effects, that an increase in media visibility of people of colour on television significantly reduces the number of hate crimes per 100.000 state populations the following year. In my second set of results I find that the results are not larger in states with a history of being less tolerant toward people of colour, proxied by whether the state used to be a member of the Confederate States of America, but it is larger in states where the population is more likely to make emotional and spontaneous racist outbursts, proxied by the state's relative amount of hate speech on Twitter following US

[1] A person of color refers to an individual that is Black, Latino/a, Asian-Pacific Islander, or "Other".

President Barack Obama's re-election in 2012.[2] I also use the number of racist hate groups per 100.000 state population as an alternative measure of social tolerance to study whether media visibility affects very intolerant individuals. I find no evidence that it does. This is indicative evidence that overall media visibility does not shift the whole distribution of tolerance. Instead, it seems to influence individuals at the margin with a relatively high level of social tolerance to begin with.

As far as I am aware, this paper is the first to study the effect of general media visibility on hate crimes against people of colour. I focus on hate crimes against people of colour in the US for several reasons. First, people of colour constitutes a large share of the US population – 37.9 percent in 2010 (Smith et al. 2016) – and the group's relative status and rights, and inequalities in terms of wealth, health and wellbeing, racial profiling, etc. are continuously is at the centre of the political debate. Second, social tolerance is linked to several outcomes of interest to economists, such as income, wages, wage-differentials, growth, and happiness.[3] Hate crimes are arguably the most extreme forms of social (in)tolerance. Social tolerance is also linked to social conflicts and can change voting preferences (US Department of Justice, 2001).[4] Third, determinants of hate crime is an under-researched area that is quickly gaining more recognition. For example, in April 2017 the US Justice of Department announced a new subcommittee on hate crimes. Fourth, the media in the US has a long history of underrepresenting people of colour and this has lead to a lot of discussions on the matter.[5,6] In other countries, several broadcasting

[2] The Confederate States of America was a pro-slavery secessionist government created in 1861.

[3] See, for example, Charles and Guryan (2008), Florida and Gates (2001), Florida and Mellander (2010), Inglehart et al. (2008) Ottaviano and Peri (2006).

[4] The US Department of Justice writes: "Of all crimes, hate crimes are most likely to create or exacerbate tensions, which can trigger larger community-wide racial conflict, civil disturbances, and even riots" (US Department of Justice, 2001).

[5] In 2016, 28.3 percent of all speaking characters on screen (movie and television) in USA were from underrepresented racial or ethnic groups, which is 9.6 percentage points below the proportion in the US population (Smith et al., 2016). 22 percent of the stories on broadcasting networks failed to include any black or Asian speaking characters and over 50 fail to include an

companies have adopted policies to increase minority group representation with the motivation that representation is important.[7] But do such changes in media content influence attitudes or do they simply reflect changes in attitudes in these societies. This paper aims to address that question. In doing so, it contributes to the to need to empirically understand the malleability of attitudes towards minority groups in order to understand the reason behind and address discrimination (Carrel et al., 2015).

My empirical analysis uses a novel measure of state-level variation in exposure to people of colour on television. I construct my key independent variable by multiplying the annual proportion of series regular people of colour characters on broadcasting networks in USA between 2006 and 2012 with the predetermined 2003 state-level number of hours spent watching nonreligious television and movies. This gives me a plausible exogenous state-level variation of media visibility of people of colour on television between 2006 and 2012. In order to separate the effect of media visibility on the hate crime rate from other confounding factors, I compare state-level variation in the hate crime rate with my measure of the one-year lagged state-level variation in media visibility of people of colour. I also perform a number of checks to study the validity of the assumptions in my identification strategy. First, I show that viewers do not adjust their television watching habits given the media visibility of people of colour. Second, I show that producers and writers of shows do not change their content as a result of changes in the hate crime rate or general social tolerance. Third, a placebo test also shows that media visibility of people of colour does not affect crimes that social tolerance should not affect, such as vehicle

Asian speaking character. Smith et al. (2016) concludes that the media industry underperforms on racial and ethnic diversity when it comes to leads in films, series regulars on television, and all speaking characters.

[6] For example, this was heavily discussed during the 2015 and 2016 Academy Award (Oscar) ceremonies, where none of the 20 nominees in the four actor categories were non-white, and in 2017, when several winners were people of colour.

[7] The UK broadcaster BSkyB has an initiative to have at least 20 percent of its "significant roles" go to Black, Asian or other minority backgrounds (BAME). The British Broadcasting Company (BBC) has a similar plan to increase BAME representation to 15 percent over a period of three years starting in 2014 (Sweney, 2014). In 2015 Swedish broadcasting company SVT introduced a similar policy to increase media visibility of minority groups (TT, 2015).

theft and larceny. Finally, I show that media visibility of LGBT characters does not affect the rate of hate crimes motivated by race or ethnicity the following year. Taken together, this suggests that I capture the causal effect of general media visibility of people of colour on social tolerance towards people of colour.

This paper is related to several strands of literature. First, it is related to the small number of studies on the determinants on hate crimes (e.g. Gale et al., 2002; Green and Rich, 1998; Kruger and Pischke, 1997). Within this literature, this paper is the first study the role of media visibility. Second, this paper relates to the literature on the effects of media on a variety of outcomes. Many of these study the role of targeted media in shaping voting behaviour and political outcomes (DellaVigna and Kaplan 2007; Gerber et al., 2011). A smaller group of papers study the effect of (negative) radio propaganda on nationalism and genocide (DellaVigna et al., 2014; Yanagizawa-Drott, 2014). Banerjee and Datta Gupta's (2015) study the effect of a TV show with a strong positive social message on caste-based discriminatory behaviour in India. As far as I am aware, this study is the first to look at the role of general media visibility of people of colour on television on social tolerance towards people of colour. By looking at non-targeted media visibility, it is therefore perhaps the most related to the literature on the effect of media exposure through the introduction of (cable) television on individual behaviour and beliefs on divorce, fertility, domestic violence, and female autonomy, as well as cognitive skills, voter turnout and public spending (Chong and La Ferrara, 2009; Ferrara et al., 2012; Gentzkow, 2006; Gentzkow and Shapiro, 2008; Jensen and Oster, 2009; Kearney and Levine 2015; Strömberg, 2004) and perhaps the closest to Mastrorocco and Minale (2016) who look at the role of exposure to media in shaping beliefs and perceptions, in particular crime perceptions.

The rest of the paper is organized as follows. Section 2 describes the data and provides some descriptive statistics. Section 3 presents the identification strategy. Section 4 presents and discusses the results. Section 5 presents the results from a set of specification checks and placebo tests. Section 6 concludes.

2. Data and descriptive statistics

This study combines data from a number of sources. Information on the number of hate crimes and motivating bias in each state comes from the FBI's hate crime master file and was provided by the National Archive of Criminal Justice Data (NACJD). Information on alternative crimes comes from the FBI Uniform Crime Reports. Information on people of colour on broadcasting networks comes from GLAAD (formerly the Gay and Lesbian Alliance Against Defamation), and time spent watching television comes from the American Time Use Survey (ATUS).[8] Socioeconomic and demographic variables come from the US Census and the Jewish Yearbook.[9] Data on per capita alcohol consumption comes from the National Institute of Alcohol Abuse and Alcoholism.[10] Data on the number of hate tweets after Barack Obama's re-election in 2012 comes from Floating Sheep and data on the number of hate groups was kindly provided by the Southern Poverty Law Center.[11,12] Table 1 and Table 2 present the definitions and descriptive statistics of the key variables.

TABLE 1—DEFINITION OF KEY VARIABLES IN THE ANALYSIS

Name of variable	Definition
Hate crime rate	Total number of hate crimes motivated by race or ethnicity per 100.000 state population, after adjusting for state population coverage of submitting agencies
Ln(hate crime rate)	The natural logarithm of the hate crime rate
Ln(real GDP per capita)	State-level logged real GDP per capita

[8] URL: https://www.icpsr.umich.edu/icpsrweb/NACJD/; www.fbi.gov; www.glaad.org; www.bls.gov/tus.

[9] URL: www.census.gov; www.ajcarchives.org.

[10] http://pubs.niaaa.nih.gov/publications/surveillance102/CONS13.pdf

[11] Floating Sheep (floatingsheep.org) is the homepage of a research team at the Department of Geography at the University of Kentucky, USA. The department uses digital online life and you (DOLLY), which contains billions of geolocated tweets that allows for research and analysis. Research using DOLLY has been published in several academic journals.

[12] URL: https://www.splcenter.org.

Unemployment rate	Percent of state population that is unemployed
Police	Percent of state GDP allocated toward police and law enforcement
Jew	Percent of state population that is Jewish
Black or African American	Percent of state population that is Black or African-American
Median age for men	State-level median age for men
Median age for women	State-level median age for women
Minimum bachelor's	Percent of state population with at least a bachelor's degree
Alcohol consumption	Per capita number of units of alcohol (ethanol) consumed in each state, based on population ages 14 and older
Prison	Number of incarcerated individuals per 100.000 state population
Same-sex couples	Percent of state population who report that they live in a same-sex relationship
Ln(Larceny)	The natural logarithm number of the number of larceny crimes per 100.000 state population. Adjusted by the FBI for underreporting
Ln(Motor theft)	The natural logarithm number of the number of motor vehicle thefts per 100.000 state population. Adjusted by the FBI for underreporting

TABLE 2—DESCRIPTIVE STATISTICS OF MAIN VARIABLES

Name of variable	Definition
Hate crime rate	1.424 (0.894)
Ln(Hate crime rate)	0.129 (0.724)
ln(real GDP per capita)	10.736 (0.180)
Unemployment rate	7.121 (2.168)
Police	0.574 (0.129)
Jew	1.453 (1.800)

Black or African American	9.076
	(7.707)
Medan age for men	36.533
	(2.359)
Medan age for women	39.122
	(2.531)
Minimum Bachelor	28.084
	(4.979)
Alcohol	2.432
	(0.549)
Prison	389.824
	(123.002)
Same-sex marriage	0.493
	(0.181)
Ln(Larceny)	7.568
	(0.199)
Ln(Motor vehicle theft)	5.267
	(0.503)
Observations	262

Notes: The sample consists of states where the average population coverage of hate crimes between 2007 and 2013 is above 80 percent and there is full information for all variables.

2.1. Hate crime data

Hate crime data originally comes from the FBI hate crime master file. The FBI has published crime statistics each year since 1995 in its Uniform Crime Report and the National Archive of Criminal Justice Data provides the data in an accessible format. This analysis uses the FBI's definition of hate crime as it applies to the Uniform Crime Reports Hate Crime Statistics Program. A hate crime is defined as a crime "motivated by racial, religious, disability, sexual orientation, and ethnicity/national origin basis" (FBI, 2000). In other words, a hate crime is a crime against a member of a group simply because they belong to that group (US Department of

Justice, 1990).[13] The biases covered by the FBI statistics are race, religion, sexual orientation, ethnicity/national origin, and disability, and the FBI statistics include annual state-level data on the number of hate crimes reported to the FBI and the bias that motivated the hate crime.

Figure 1 shows the 1992–2013 development of the total number of hate crimes reported to the FBI, the number of participating agencies, and the percent of the US population covered by the reporting agencies. The development of the number of submitting agencies and the percentage of the population covered closely follow each other. This is expected as different agencies cover different regions of the United States. Figure 1 also shows a sharp increase in the number of agencies submitting statistics and the percentage of the US population covered between 1992 and 1996, followed by a trend of gradually increasing coverage up until and including 2011. During this period, the number of agencies submitting data increases from 6181 to 14575. This trend is broken in 2012 when there is a large drop in the number of participating agencies to 12022, and the population coverage falls from 92 percent in 2011 to 79 percent in 2012. There is also a large drop in the total number of hate crimes from 6222 to 5796. Figure 1 highlights the importance to take population coverage into account when analysing hate crimes. The proportion of the state population covered by the reporting agencies also varies across state and year, and the number of hate crimes reported to the FBI is most likely not the same as the true number of hate crimes committed.

[13] Medoff (1999) lists several characteristics of a hate crime that have been found to separate it from other crimes (for example assault, homicide, and robbery). First, the perpetrators are less likely to know the victim (Bureau of Justice Statistics, 1985). Second, the hate crimes tend to include personal violence and be excessively brutal (Levin and McDevitt, 1993). Third, property is likely to be destroyed or damaged and not stolen (Berk, 1990). Fourth, the perpetrators are often first-time offenders (Harry, 1990). Fifth, hate crimes also often include a larger cost of committing the crime to the perpetrators since the offenders often have to search for the victim in areas where they do not themselves live (Flanney, 1997).

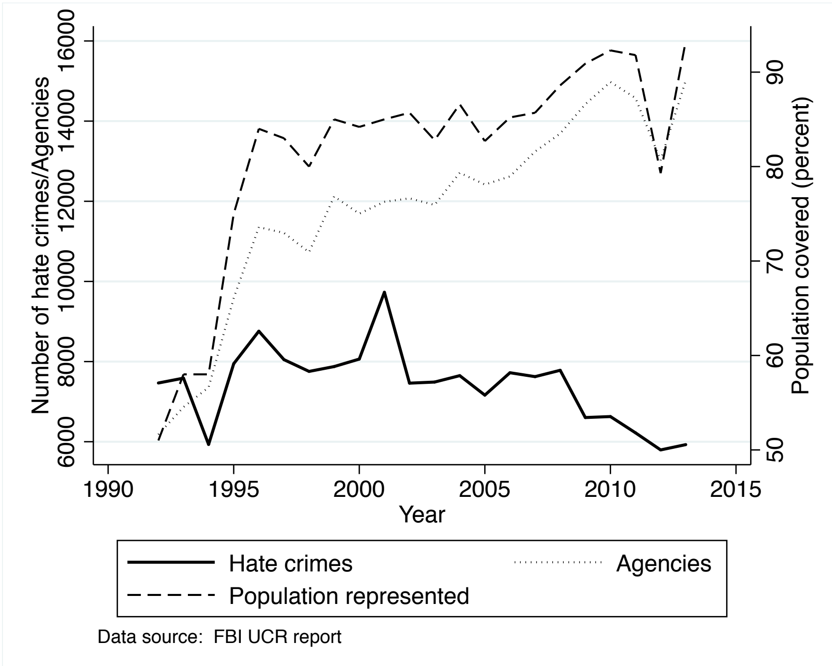

FIGURE 1. TOTAL NUMBER OF HATE CRIMES, REPORTING AGENCIES, AND PERCENT POPULATION COVERED 1992-2013

The outcome variable in the analysis is the logged total number of hate crimes motivated by the victim's race or ethnicity per 100.000 state population, after adjusting for the population share covered by the agencies submitting the data to the FBI. I am able to exclude hate crimes motivated by an anti-white bias and capture the rate of hate crimes of people that can be assumed to be people of colour. I divide the number of hate crimes by the proportion of the state population covered by the reporting agencies to obtain an estimate of the number of hate crimes that would be reported if 100 percent of the state's population were covered by the reporting agencies. This procedure may introduce a source of error in the data. States with low population coverage are likely to have less precision in their data compared with states with high population coverage. The low precision can lead to an overestimate or underestimate of the actually committed number of hate crimes, depending on the relationship between reporting behaviour of agencies and the prevalence of hate crimes.[14] Also, some states are inconsistent in their reporting. One such state is Alabama, which has a population coverage that ranges from 79 percent in 2010 to 3 percent in 2012. Inconsistent reporting is a potential problem if it means that state officials do not take hate crime reporting seriously or that the state's curriculum for identifying, reporting, and responding to hate crimes has changed throughout time. To address the issue of underreporting by agencies, I exclude states where the average population coverage between 2007 and 2013 is below 80 percent. This roughly corresponds to excluding the bottom 25 percent.[15] The mean hate crime rate in the final sample is 1.42 hate crimes per 100.000 state population. The three states with the lowest rate of hate crimes motivated by the victims' race or ethnicity are Iowa (0.10), Florida (0.16), and Wyoming (0.17). The three states with the highest crime rates are District of Columbia (4.53), New Jersey (4.40), and North Dakota (4.16). This does not necessarily mean that states with low hate crime rates are more tolerant. For example, it could reflect that states differ in their attitudes toward hate crimes, reporting behaviour, and police training.

2.2. A Measure of media visibility

I use data from two sources to construct a novel state-level measure of media visibility over time. National-level data on the proportion of scripted series regular people of colour characters on broadcasting networks for each season between 2006 and 2012 comes from GLAAD.[16,17] The

[14] If the agencies that supply data to the FBI are in the areas where crimes take place, then it leads to an overestimate of the true number of hate crimes committed. If, on the other hand, agencies tend to not report hate crimes, then it leads to an underestimate of the true number of hate crimes committed.

[15] The bottom 25 percent have an average population coverage below 82 percent

[16] Since 2005, GLAAD has published an annual report called "Where Are We on TV" in which the organization presents statistics on the total and proportion of scripted series regular characters on broadcasting and cable networks who belong to different minority groups. Since 2006, the report has included people of color. "People of color" refers to individuals that are Black, Latino/a, Asian-Pacific Islander or "others".

[17] The television season starts in June and ends in May the following year.

broadcasting networks included in GLAAD's statistics are ABC, CBS, FOX, NBC, and The CW.[18] Figure 2 shows the proportion of people of colour on broadcasting networks between 2006 and 2012. The proportion varies between 0.21 and 0.24.

State-level data on the number of hours that the state population watches nonreligious television and movies in 2003 comes from the ATUS. Figure 3 shows that there is large variation in the total number of hours. In Delaware, the population spends 1155 hours watching nonreligious television and movies in 2003. This is almost twice as much as North Dakota where the population spends 600.5 hours watching nonreligious television and movies in 2003.

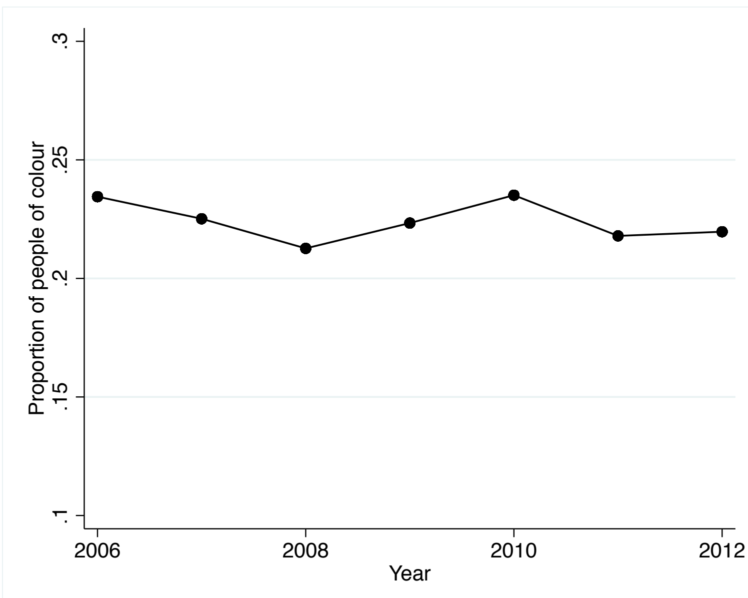

FIGURE 2. PROPORTION OF SERIES REGULAR PEOPLE OF COLOR, 2006-2012

[18] The main difference between a broadcasting network and a cable network is that a broadcasting network airs content through public airways and is financed via advertisement, whereas a cable network airs content through cable operators and is financed via a fee for each subscriber. Since viewers pay a monthly fee for a cable network, the individuals who have access to shows on cable networks may be a selected sample with characteristics that correlate with social tolerance. Also, cable networks have been known to produce shows that target certain segments of the population. To avoid any selection bias, I use statistics only from broadcasting networks.

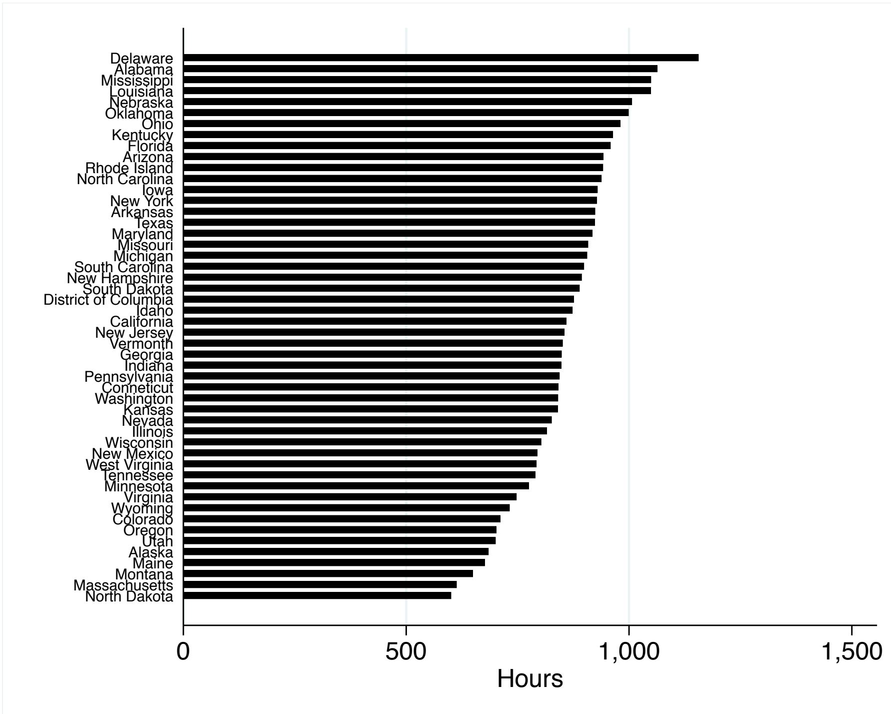

FIGURE 3. STATE-LEVEL NUMBER OF HOURS OF TELEVISION WATCHING IN 2003

To construct a state-level measure of media visibility of people of colour over time I multiply the state-level number of hours of television watching in 2003 by the proportion of people of colour on broadcasting networks at the national level between 2006 and 2012. This gives me a variable that can be interpreted as a rough measure of the state-level media visibility of people of colour on broadcasting networks between 2006 and 2012.

I use the predetermined 2003 viewing statistics instead of contemporaneous not to confound the effect of media visibility on the hate crime rate with changing habits of television watching over time. It is likely that the state-level of number of hours of television watching in 2003 is correlated with future state-level of number of hours of television watching, but it is unlikely that television watching in 2003 is correlated with any omitted variables that jointly influence media visibility of people of colour in year *t-1* and the hate crime rate in year *t*. Figure 4 shows the correlation between the state-level number of hours spent watching television in 2003 and each year between 2006 and 2012. As expected, there is a positive correlation between 2003's value and all future years used in the analysis. The positive correlation confirms that the states that watch relatively more television in 2003 keep on watching relatively more television between 2006 and 2012. It is therefore possible to use the 2003 predetermined state level television watching to estimate future values of state level television watching.

Because of the construction of the media visibility variable, all states experience the same direction of change and proportional change in the number of hours over time. Since states watch different amounts of television, however, the size of the absolute change differs between the states. The “treatment” and “control” groups are therefore differentiated by the 2003 predetermined number of hours of television watching. The mean number of hours of media visibility per year is 192 and there is variation over the years. The overall standard deviation in the sample is 26 hours, but there is a large difference between the between- and within-variation in media visibility. The between standard deviation is 25.5 hours, whereas the within standard deviation is 6.5 hours.

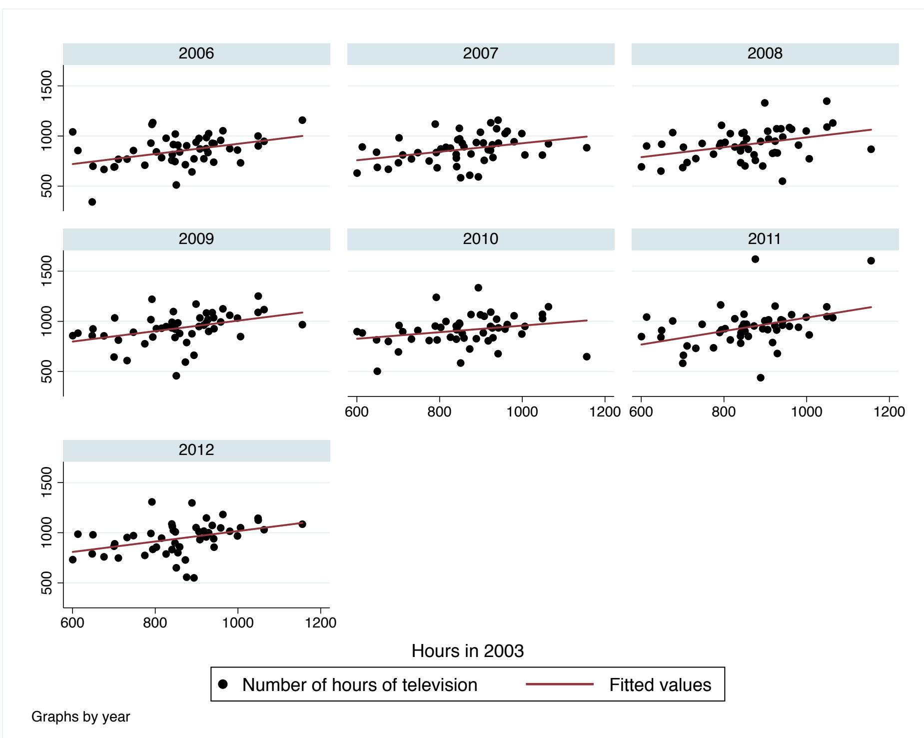

FIGURE 4. CORRELATION BETWEEN HOURS OF TELEVISION IN 2003 AND 2006-2012.

To illustrate the variation that I use for identification, Figure 5 shows the estimated total number of hours and change in hours of media visibility of people of colour between 2006 and 2012 for the two states with the most and least number of hours of television watching in 2003: Delaware and North Dakota. As can be seen, both the total and the change in the number of hours of media visibility differ between the states. The variation is larger in Delaware (Standard deviation: 9.25 hours) since the state population watches more television than the state population in North Dakota (Standard deviation: 4.8 hours).[19] The distributions of the key variables logged hate crime rate and media visibility are illustrated in the two histograms in Figure 6. Both variables are normally distributed.

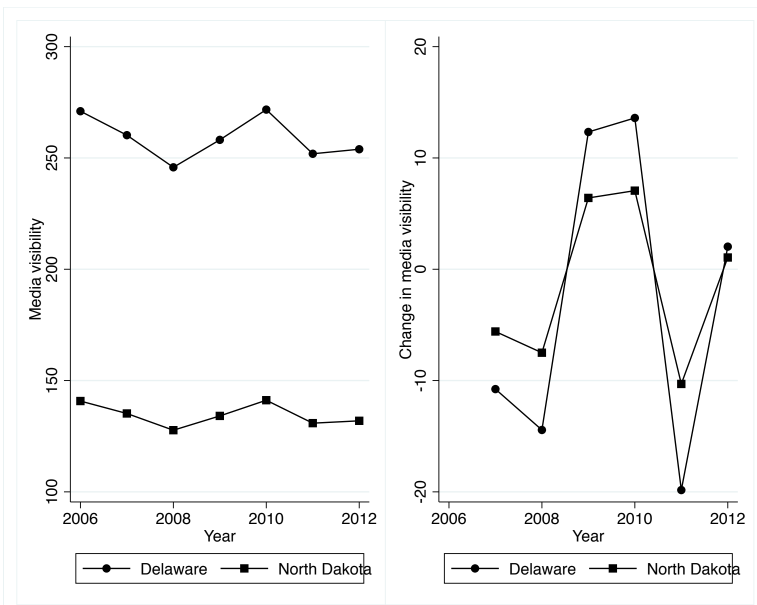

FIGURE 5. TOTAL AND CHANGE IN MEDIA VISIBILITY FOR DELAWARE AND NORTH DAKOTA

[19] Remember that I use the state-level number of hours of television to get an estimate of state-level media visibility of people of color and not to estimate the actual number of hours of media visibility.

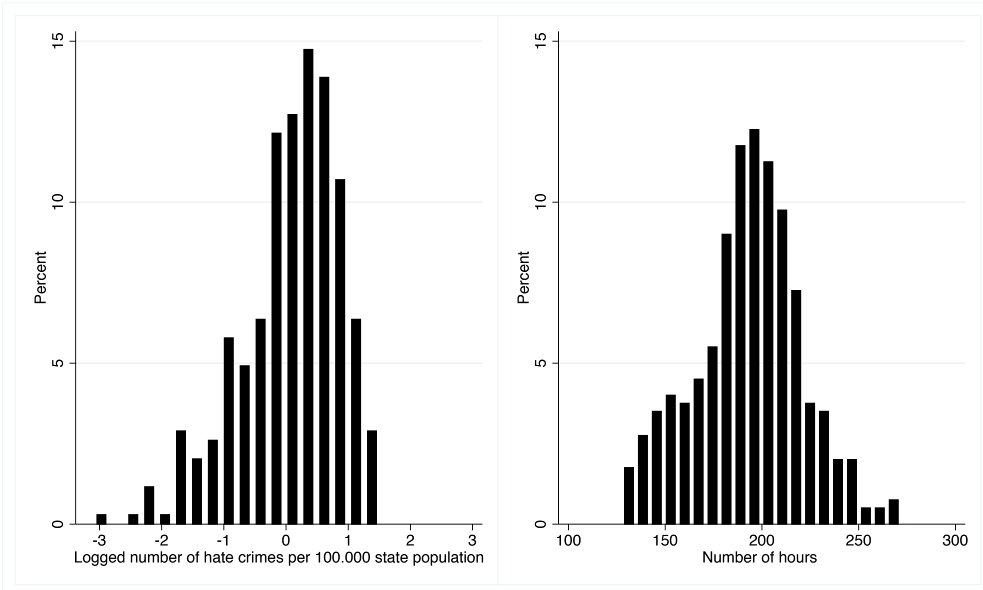

FIGURE 6. DISTRIBUTION OF THE LOGGED HATE CRIME RATE AND HOURS OF MEDIA VISIBILITY

2.3. Additional control variables

I have state-level data on two sets of time-varying control variables. The first set includes socioeconomic variables. I include information on logged real GDP per capita and the unemployment rate. I also include information on the percentage of state GDP that is allocated toward police and law enforcement. Increasing the likelihood that offenders are caught, prosecuted, and sentenced, and taking actions that deter crime is one of the direct ways that states can influence the hate crime rate. Increasing the percentage of GDP allocated toward law enforcement can have two opposite effects on the hate crime rate. It can increase the hate crime rate because more individuals are caught, prosecuted, and convicted of the offense. Or, it can act as a preventive action and decrease the hate crime rate. I also include a measure of the number of incarcerated individuals per 100.000 state population.

The second set of controls is demographic variables. I include information on the percent of the state population that has at least a bachelor's degree. Education is said to be one of the most important factors when it comes to increasing social tolerance, and so the variable is expected to have a negative effect on the hate crime rate. I also use information on the percent of the state population that is Black or African-American and the percent of the population that is Jewish. Both groups are common targets of hate crimes, but it is unclear whether an increase in the percentage of the minority group should have a positive or negative effect. An increase in the African-American and Jewish populations can lead to a more diverse and tolerant society because of greater interaction and familiarity, thus reducing hate crimes. Or, it can increase the fears that the minority group is trying to challenge the dominant group, thus increasing hate crimes (Becker, 1957). I also include information on the median age for women and men. Younger individuals tend to be more tolerant, but it is also younger individuals who tend to commit hate crimes. Therefore, it is unclear whether median age is expected to be positively or negatively related to the hate crime rate. I also include information on the percentage of same-sex couples at the state level. It is likely that there are more same-sex couples in states that are more tolerant, and changes in the percent of same-sex couples can therefore be thought to capture state-level changes when it comes to social tolerance. I also include information on the per capita number of units of alcohol (units of ethanol) consumed in each state to capture any effect of alcohol consumption on spontaneous violent behaviour towards minority groups.

Lastly, I have information on motor vehicle theft and larceny crime rates from the FBI Uniform Crime Reports. Unlike hate crimes, the FBI adjusts these data for underreporting by agencies. I use this data in two ways. First, it allows me to control for contemporaneous crime rates in the main analysis. Second, it allows me to perform a falsification test. Specifically, I use data on motor vehicle theft and larceny to test whether media visibility appears to affect these crimes. I expect the effect of media visibility on these crimes to be very small and insignificant since few hate crimes are classified as motor vehicle theft or larceny.

3. Identification strategy

To distinguish the effect of media visibility on the hate crime rate from confounding factors, I exploit the between-state variation induced by the fact that states are exposed to different amounts of media visibility of people of colour because they watch different amounts of television. If media visibility is effective in changing attitudes and tolerance towards people of colour, then I expect to see relatively larger changes in rates of hate crimes in states with a larger television viewership.

Formally, I estimate a state fixed effects OLS panel data model. I follow convention and use the log of the outcome per 100.000 state population as the dependent variable (Cheng and Hoekstra, 2013). The advantage with state fixed effects is that it controls for unobserved heterogeneity across states and exploits state-level variation over time to estimate the effect of media visibility of people of colour on the hate crime rate. Formally, the model can be written as:

$$(1) \qquad \ln(\text{hate crime}_{i,t}) = \beta_0 \text{Media Visibility}_{i,t-1} + \beta_1 X_{i,t} + s_i + u_t + \gamma_r \times u_t + \nu_{i,t}$$

Here, $\ln(\text{hate crime}_{i,t})$ is the logged state population coverage adjusted number of hate crimes motivated by race or ethnicity per 100.000 population in state *i* in year *t*. $\text{Media Visibility}_{i,t-1}$ is the one-year lagged media visibility of scripted series regular people of color characters or persons on broadcasting networks in state *i* in year *t*. It is constructed by multiplying the proportion of people of colour characters on broadcasting networks in year *t* with the predetermined 2003 state-level number of hours spent watching nonreligious television and movies. $X_{i,t}$ is a vector of control variables that includes the two sets of socioeconomic and demographic control variables, and the two crime rates. s_i and u_t control for state and year fixed effects. $\gamma_r \times u_t$ are US Census region-by-year fixed effects that allow states in different regions to follow different trends and allow for region specific shocks over time.[20] $\nu_{i,t}$ is a robust error term clustered at the state level. The model is estimated with weights for state population size. Because the dependent variable is logged and media visibility is linear, β_0 is interpreted as the

[20] The US Census regions are West, Midwest, Northeast, and South.

$\beta_0 \times 100$ percent change in the number of hate crimes per 100.000 state population associated with a unit increase in the media visibility of people of colour per year.

I use the one-year lagged value of media visibility for three reasons. First, it is unlikely that there is an instantaneous effect from an increased exposure to minority characters since the audience has to build up a sense of bond with them. This is similar to the introduction of a new friend in one's social network. It takes time to form a friendship and form beliefs and opinions about that person. Second, the television season runs from the middle of one year to the middle of the next year. This means that the exposure to people of colour characters in year *t* is actually only for the latter six months of the year. The rest of the data is for all 12 months of the year, which therefore also includes last season's exposure to people of colour characters. Using the contemporary value will therefore most likely bias the estimate. Third, it reduces the risk of reverse causality in which people are exposed to more people of colour on television because they are watch more television and commit fewer hate crimes.

4. Results

4.1. Main results

I now turn to whether media visibility of people of colour affects the hate crime rate. To the extent that media visibility affects social tolerance and the media visibility has been positive, I expect that there is a negative effect of an increase in media visibility on the hate crime rate the following year.

I start with the raw relationship between the one year lagged media visibility and hate crime rate. Figure 7 shows the correlation between the two variables. There is a negative relationship between the number of hours of media visibility of people of colour and the logged hate crime rate the following year.

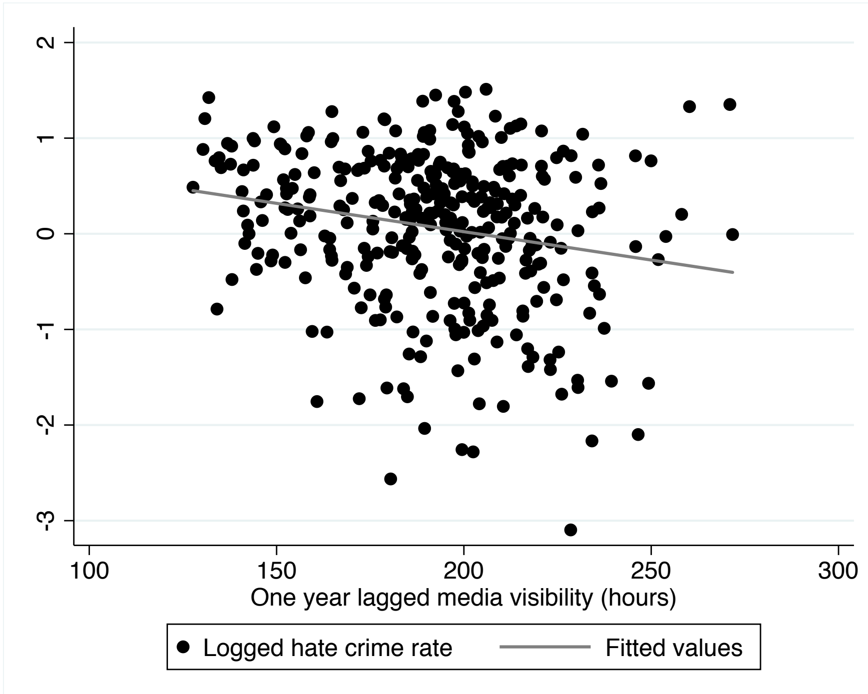

FIGURE 7. LAGGED NUMBER OF HOURS OF MEDIA VISIBILITY AND LOGGED HATE CRIME RATE

Next, I investigate the relationship more closely and estimate equation (1). Table 3 presents the results. All model specifications include state and year fixed effects. Column 1 presents the results when only the one-year lagged media visibility is included. Column 2 adds socioeconomic and demographic controls that vary at the state-year level. Column 3 adds US Census region-by-year fixed effects. Column 4 adds crime rates for motor vehicle theft and larceny to capture general trends in crime. Robust standard errors are clustered at the state level and weights for state population size is used.

The results in Table 3 provide evidence of a significant and negative effect of media visibility of people of colour on the rate of hate crimes motivated by race or ethnicity. The effect of media visibility on the hate crime rate is significant in all models that include state-level controls, US

Census region-by-year fixed effects, and contemporaneous crime rates.[21] The results do not change much depending on the model specification. An increase in media visibility of people of colour appears to increase social tolerance and lower the hate crime rate.

TABLE 3—FIXED EFFECTS RESULTS ON THE EFFECT OF MEDIA VISIBILITY ON THE LOGGED HATE CRIME RATE

	(1)	(2)	(3)	(4)
Media visibility$_{t-1}$	-0.0418	-0.0560**	-0.0502**	-0.0494**
	(0.0255)	(0.0208)	(0.0213)	(0.0219)
Observations	265	262	262	262
R^2	0.266	0.330	0.435	0.440
Number of states	38	38	38	38
State and year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	Yes
Region-by-year fixed effects			Yes	Yes
Contemporaneous crime rates				Yes

Notes: The table shows fixed effects results. Each column represents a separate regression. The dependent variable is the logged total number of hate crimes motivated by race or ethnicity per 100.000 state population, adjusted for population coverage by reporting agencies. The unit of observation is state. The cut-off is an average state population coverage above 80 percent. Robust standard errors clustered at state level are in parenthesis. The model is estimated with weights for state population. State controls include logged real GDP per capita (2005 dollars), the unemployment rate, percentage of GDP allocated towards the police, percentage of the population with at least a bachelor's degree, percentage population that is Jewish, percentage of the population that is Black or African-American, the median age for women and men, percentage same-sex couples, number of incarcerated individuals per 100.000 state population, and the number of alcohol units consumed. The number of observations is reduced in column 2-4 because of missing values for some state controls. *** p<0.01, ** p<0.05, * p<0.1.

[21] I have performed the analysis without the three states with the highest number of hours of television watching (Delaware, Oklahoma, and Ohio) to test if these three states are driving the results. As expected, the estimated size of the effect falls slightly but the interpretation of the results does not change.

It is possible that the effect of an increase in media visibility on the hate crime rate is linear and not non-linear. Therefore, I also use the (non-logged) rate of hate crimes motivated by race or ethnicity per 100.000 state population at the outcome variable of interest. The results remain the same. An increase in media visibility leads to fewer hate crimes per 100.000 state population the following year.[22,23]

4.2. Heterogeneous effects

The result in Table 3 focuses on the effect of media visibility on the hate crime rate for the average state in the data. It is possible, however, that the effect of media visibility on the hate crime rate depends on whether the state has a relatively high or low degree of social tolerance. For example, the effect can be lower in relatively tolerant states because the state populations already have a high degree of interaction with and social tolerance toward minorities, or higher because the state populations are more willing to reflect on their preconceived opinions and beliefs about minority groups. Similarly, the effect of media visibility can be higher in less tolerant states because state populations are less likely to interact with minority groups and therefore have the most to learn from media visibility of a minority group, or lower because the state populations have such low degree of tolerance that they are less affected by media visibility of minority groups.

In this section, I use two definitions of state tolerance to study whether the effect of media visibility is greater in states with a relatively high or low degree of social tolerance. The first one is former membership status in the Confederate States of America (CSA). The second is whether the state had a relatively high or low amount of hate speech on Twitter after US President Barack

[22] Results available upon request.
[23] I am unable to use the logged media visibility as the treatment since this would get rid of the between-state variation in the media visibility.

Obama's 2012 re-election. On the whole, my findings suggest that the answer depends on which of the definitions of social tolerance is used.

4.2.1 Former Confederate States of America member status

The first definition of a state's level of social tolerance is based on whether the state used to be a member of the CSA. The CSA was a confederation of secessionist states that wanted to keep or expand slavery. It was formed after the election of Abraham Lincoln in 1860 and existed between 1861 and 1865 during the American Civil War. The seven founding states in the Deep South region were Alabama, Florida, Georgia, Louisiana, Mississippi, South Carolina, and Texas. Arkansas, North Carolina, Tennessee, and Virginia in the Upper South later joined (Foner and Garraty, 1991). The confederate states have a history of being conservative and less tolerant toward minorities, especially Blacks and African-Americans.

Table 4 presents the result when I add an interactive variable that captures the additional effect of media visibility of people of colour on the hate crime rate in the 11 states that used to be members of the CSA to the model. The coefficient of the additional effect in former CSA states is close to zero and insignificant in all model specifications. This result does not support the hypothesis that the effect of media visibility differs between states of different degrees of social tolerance.

TABLE 4—HETEROGENEOUS EFFECTS BY FORMER CONFEDERATE STATE STATUS

	(1)	(2)	(3)	(4)
Media visibility$_{t-1}$	-0.0372	-0.0498**	-0.0502**	-0.0493**
	(0.0242)	(0.0218)	(0.0211)	(0.0218)
Media visibility$_{t-1}$×Confederate$_i$	-0.00400	-0.00614	-0.000117	0.000539
	(0.00877)	(0.00739)	(0.0154)	(0.0148)
Observations	265	262	262	262
R^2	0.268	0.333	0.435	0.440
Number of states	38	38	38	38
State and year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	Yes
Region-by-year fixed effects			Yes	Yes
Contemporaneous crime rates				Yes

Notes: The table shows fixed effects results. Each column represents a separate regression. The dependent variable is the logged total number of hate crimes motivated by race or ethnicity per 100.000 state population, adjusted for population coverage by reporting agencies. The unit of observation is state. The cut-off is an average state population coverage above 80 percent. Robust standard errors clustered at state level are in parenthesis. The model is estimated with weights for state population. State controls include logged real GDP per capita (2005 dollars), the unemployment rate, percentage of GDP allocated towards the police, percentage of the population with at least a bachelor's degree, percentage population that is Jewish, percentage of the population that is Black or African-American, the median age for women and men, percentage same-sex couples, number of incarcerated individuals per 100.000 state population, and the number of alcohol units consumed. The number of observations is reduced in column 2-4 because of missing values for some state controls. *** p<0.01, ** p<0.05, * p<0.1.

4.2.2 Hate speech on Twitter following US President Obama's re-election in 2012

The second definition of a state's level of social tolerance uses a contemporaneous measure. There was a large spike in hate speech on Twitter the day after US President Barack Obama's re-election in November 2012. Researchers at Floating Sheep collected all geocoded hate tweets between November 1 and November 7 in 2012 and used these to calculate a measure of how much hate speech there was in each state. To do so, they first aggregated all geocoded hate tweets (number of total tweets = 395) to state level and normalized them by comparing them with the total number of geocoded tweets in that state during the same period.[24] They then calculated a type of Location Quotient (LQ) measure that captures each state's share of hate speech relative to its total number of tweets.[25] If the LQ is equal to 1, then the state has relatively the same number of hate speech tweets as its total number of tweets after the 2012 election. An LQ above (below) 1 therefore suggests that the state had more (less) racist tweets after the 2012 election than it normally does.[26]

Table 5 presents the LQ scores of the states included in Floating Sheep's analysis.[27] Many of the racist tweets were from southern states. This is expected, as these are the more historically conservative states. However, some states stand out. For example, North Dakota and Utah, two states that were never a part of the CSA have relatively high LQ values.[28]

The LQ measure is interesting because not only does it capture the level of online racist behaviour at the state level but also an "in the spur of the moment" reaction and expression of hate that can act as an alternative indicator of the state level of social tolerance to, for example, population surveys or historical definitions. Since hate crimes tend to be more violent than other crimes, it is also possible that states where there was more of an emotional reaction to the re-election of an African-American to remain President also have more people who are more likely to react emotionally when faced with a person who belongs to a minority group that they have a

[24] Geocoded tweets make up only about 1 to 5 percent of the total number of tweets. The number of hate tweets is expected to be much larger (floatingsheep.org).

[25] The formula for the LQ used by Floating Sheep is: $\mathrm{LQ_i} = \frac{\mathrm{Hate\ Tweets_i} / \sum_{i=1}^{50} \mathrm{Hate\ Tweets_i}}{\mathrm{Total\ Tweets_i} / \sum_{i=1}^{50} \mathrm{Total\ Tweets_i}}$

[26] Matthew Zook. "Mapping Racist Tweets in Response to President Obama's Re-election. November 8, 2012. URL: www.floatingsheep.org

[27] Some states are excluded due to lack of geocoded tweets.

[28] Matthew Zook. "Mapping Racist Tweets in Response to President Obama's Re-election. November 8, 2012. URL: www.floatingsheep.org

negative bias toward. It is also possible that it is a better indicator of a type of racism that is visible only under extreme events.

TABLE 5—RANKING OF STATES BY THEIR LQ MEASURE OF THE LEVEL OF HATE SPEECH ON TWITTER

State	LQ value
Alabama	8.1
Mississippi	7.4
Georgia	3.6
North Dakota	3.5
Utah	3.5
Louisiana	3.3
Tennessee	3.1
Missouri	3.0
West Virginia	2.8
Minnesota	2.7
Kansas	2.4
Kentucky	1.9
Arkansas	1.9
Wisconsin	1.9
Colorado	1.9
New Mexico	1.6
Illinois	1.5
North Carolina	1.5
Virginia	1.5
Oregon	1.5
District of Columbia	1.5
Ohio	1.4
South Carolina	1.4
Texas	1.3
Florida	1.3
Delaware	1.3
Nebraska	1.1
Washington	1.0
Maine	0.9
New Hampshire	0.8

Pennsylvania	0.7
Michigan	0.6
Massachusetts	0.5
New Jersey	0.5
California	0.5
Oklahoma	0.5
Connecticut	0.5
Nevada	0.5
Iowa	0.4
Indiana	0.3
New York	0.3
Arizona	0.2

Notes: This table shows the LQ measure for the 42 states with enough tweets to be included in the analysis performed by Floating Sheep.

I use the LQ measure to construct the variable Hate speech. It is a dummy variable that takes the value 1 if the state has an LQ measure above the median, which is 1.81, and 0 if it has an LQ measure below the median. This classifies 15 states as having a low level of social tolerance and 27 states as having a high level of social tolerance. I then interact this variable with the media visibility variable to construct a variable that captures the additional effect of media visibility that is specific for states with a low level of tolerance. Table 6 presents the results. The estimated general effect of media visibility of people of colour on the hate crime rate is larger compared to the results presented in Table 3. A possible explanation is that the states in this analysis are required to have some hate speech tweets for the LQ to be calculated. This sample may therefore exclude the most tolerant states.[29]

More interestingly, the estimated additional effect of media visibility of people of colour in states where there was a lot of hate speech on Twitter after President Obama's re-election is significant and negative in all but the most basic model. This finding supports the hypothesis that

[29] The estimated overall effect of media visibility on the hate crime rate falls by around 1 percentage point when I also include states that are not used to calculate the LQ measure and set the Hate Speech dummy equal to zero for these states.

the effect of media visibility differs between states of different degrees of social tolerance and that the effect is greater in states where social tolerance is lower.

TABLE 6—HETEROGENEOUS EFFECTS BY RACIST TWEETS AFTER US PRESIDENT BARACK OBAMA'S 2012 REELECTION

	(1)	(2)	(3)	(4)
Media visibility$_{t-1}$	-0.0544*	-0.0743***	-0.0849***	-0.0833***
	(0.0282)	(0.0224)	(0.0211)	(0.0231)
Media visibility$_{t-1}$×Hate speech$_i$	-0.0125	-0.0151*	-0.0190**	-0.0184**
	(0.00817)	(0.00847)	(0.00817)	(0.00890)
Observations	216	213	213	213
R^2	0.278	0.347	0.479	0.481
Number of states	31	31	31	31
State and year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	Yes
Region-by-year fixed effects			Yes	Yes
Contemporaneous crime rates				Yes

Notes: The table shows fixed effects results. Each column represents a separate regression. The dependent variable is the logged total number of hate crimes motivated by race or ethnicity per 100.000 state population, adjusted for population coverage by reporting agencies The unit of observation is state. The cut-off is an average state population coverage above 80 percent. Robust standard errors clustered at state level are in parenthesis. The model is estimated with weights for state population. State controls include logged real GDP per capita (2005 dollars), the unemployment rate, percentage of GDP allocated towards the police, percentage of the population with at least a bachelor's degree, percentage population that is Jewish, percentage of the population that is Black or African-American, the median age for women and men, percentage same-sex couples, number of incarcerated individuals per 100.000 state population, and the number of alcohol units consumed. The number of observations is reduced in column 2-4 because of missing values for some state controls. *** p<0.01, ** p<0.05, * p<0.1.

4.2.3. Discussion of the results when looking at heterogeneous effects

The findings presented in this section provide some evidence that the effect of media visibility on social tolerance is greater in states that are less tolerant. What can explain the different results when using two different classifications of tolerance? A possible explanation is that former CSA member status does not capture today's state-level degree of tolerance, whereas the amount of hate speech on Twitter does. For example, North Dakota and Utah are classified as tolerant when defined by former CSA status but intolerant when defined by hate speech on Twitter. If the landscape of tolerance, or at least the landscape of the expression of tolerance in terms of hate crimes, is different from what it was 150 years ago, then using hate speech online may be a better way of classifying states as tolerant or not.

Another possible explanation is that individuals in former CSA member states are less tolerant but that the hate crime rate does not capture this. This may be because racism is more accepted in these states or that hate crimes are not prioritized or recognized. The average hate crime rate for crimes motivated by race is 0.98 in former CSA member states and 1.46 in former non-CSA member states. This discrepancy might be because the attitude toward hate crimes is different in these states or because the hate crime legislation is different.

4.3. Who does media visibility affect? Hate groups as an alternative outcome

If media visibility has an effect on social tolerance to the degree that it affects the hate crime rate, then another question is who it affects – those with relatively more or less tolerance towards minority groups? To test whether media affects people that can be assumed to be very intolerant, I use information provided by The Southern Poverty Law Center (SPLC) on the number of hate groups in each state between 2007 and 2013. [30] I classify the hate groups into racist or non-racist toward people of colour depending on the views that they promote. Examples of hate groups that are racist towards people of colour are Ku Klux Klan groups, neo-Nazi groups, White nationalist groups, racist skinhead groups, neo-Confederates, anti-immigration, racist music groups, and Holocaust deniers. The non-racist hate groups include anti-gay groups and Black separatist groups. I calculate the number of racist hate groups per 100.000 state population. The mean number of racist hate groups is 0.31 per 100.000 state population. An advantage with the hate

[30] URL: http://www.splcenter.org

group data compared to the hate crime data is that I do not have to take reporting behaviour by agencies into account. This increases the number of observations.

TABLE 7—THE EFFECT OF MEDIA VISIBILITY ON THE NUMBER OF HATE GROUPS

	(1)	(2)	(3)	(4)
Media visibility$_{t-1}$	-0.00135	-0.00213	-0.00358	-0.00358
	(0.00479)	(0.00506)	(0.00544)	(0.00547)
Observations	343	338	338	338
R^2	0.0534	0.131	0.185	0.187
Number of states	49	49	49	49
State and year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	Yes
Region-by-year fixed effects			Yes	Yes
Contemporaneous crime rates				Yes

Notes: The table shows fixed effects results. Each column represents a separate regression. The dependent variable is the logged total number of racist hate groups per 100.000 state population. The unit of observation is state. Robust standard errors clustered at state level are in parenthesis. The model is estimated with weights for state population. State controls include logged real GDP per capita (2005 dollars), the unemployment rate, percentage of GDP allocated towards the police, percentage of the population with at least a bachelor's degree, percentage population that is Jewish, percentage of the population that is Black or African-American, the median age for women and men, percentage same-sex couples, number of incarcerated individuals per 100.000 state population, and the number of alcohol units consumed. The number of observations is reduced in column 2-4 because of missing values for some state controls. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 presents the results for all types of racist hate groups. The effect of media visibility is close to zero and insignificant in all model specifications. This suggests that while media visibility of people of colour does seem to be able to influence individuals' social tolerance, the way it does so is limited in the sense that individuals that are very intolerant are not affected.

This suggests that other methods are required to increase social tolerance of individuals that are attracted to these types of groups.[31]

Does this finding cast a doubt on the main results using hate crimes? I do not believe so. The relationship between hate groups and hate crimes is ambiguous and it is not a priori obvious. On the one hand, hate groups may encourage criminal or violent behaviour that is in line with the beliefs of the hate group. On the other hand, hate groups may allow like-minded individuals to meet and discuss their frustrations, thereby making them less likely of criminal or violent behaviour (Mulholland, 2011). The results are in line with Ryan and Leeson (2010) who finds that the number of hate groups is not related to the number of hate crimes.

5. Checks and placebo tests

Having established that there is a negative effect of media visibility of people of colour on the rate of hate crimes motivated by race or ethnicity the following year, I now present several checks and tests to demonstrate that the assumptions of the identification strategy hold true.

In order for the measure of media visibility to capture the effect of media on social tolerance, the state-level television watching habits should not change due to changes in media visibility of people of colour. Table 8, column (1) presents the results when the one-year lagged media visibility variable is used to predict the number of hours of television watching the following year. Media visibility does not predict the number of hours spent watching television.

It is possible that producers of shows respond to changes in the hate crime rate or social tolerance in general by changing the number of minority group characters in their shows. If this is the case, then this invalidates the identification strategy. I therefore test whether media visibility is influenced by last year's hate crime rate. Table 8, column (2) presents the results. The results show little indication that media visibility is influenced by last year's hate crime rate.

[31] It is possible that media visibility influences the number of members of hate groups. Unfortunately, I do not have data on the size of the hate groups.

One test of the identifying assumptions is to examine whether media visibility of people of colour affects crimes that are thought to be unrelated to social tolerance. I therefore examine whether media visibility affects the logged motor vehicle theft crime rate and logged larceny crime rate. I expect these crime rates to be unaffected by media visibility since relatively few hate crimes are classified as motor vehicle theft or larceny. Table 8, column (3) and (4) show the results for motor vehicle theft and larceny. The estimate of the effect of media visibility is close to zero and insignificant in all model specifications.

If the theory behind and the identifying assumptions of the model hold, there should be a much smaller or no effect of media visibility of LGBT characters on social tolerance towards people of colour. I use GLAAD's data on series regular LGBT characters on broadcasting networks to test this. Table 8, column (5) presents the results when I look at the effect of one year lagged media visibility of LGBT characters on the rate of hate crimes motivated by race or ethnicity. The results show no indication that media visibility of LGBT characters matter for social tolerance towards people of colour.

TABLE 8—CHECKS AND PLACEBO TESTS

	(1) Hours of television watching	(2) Media visibility	(3) Motor vehicle theft	(4) Larceny	(5) LGBT media visibility
Media visibility$_{t-1}$	-2.546		0.0030	-0.0002	0.0029
	(7.023)		(0.0041)	(0.0018)	(0.0176)
Ln(hate crime rate$_{t-1}$)		0.235			
		(0.196)			
Observations	263	225	263	263	262
R^2	0.201	0.993	0.937	0.853	0.433
Number of states	38	38	38	38	38
State and year fixed effects	Yes	Yes	Yes	Yes	Yes

State controls	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effects	Yes	Yes	Yes	Yes	Yes
Contemporaneous crime rates	Yes	Yes	No	No	Yes

Notes: The table shows fixed effects results. Each column represents a separate regression. The dependent variable is the hate crime rate per 100.000 state population. Column (1) presents the results when testing whether media visibility predicts the number of hours of television watching the following year. Column (2) presents when testing whether the hate crime rate influences media visibility the following year. Column (3) and (4) presents the results when testing whether media visibility influences crimes besides hate crimes. Column (5) presents the results when testing the effect of LGBT media visibility on the hate crime rate. The cut-off is an average state population coverage above 80 percent. Robust standard errors clustered at state level are in parenthesis. The model is estimated with weights for state population. State controls include logged real GDP per capita (2005 dollars), the unemployment rate, percentage of GDP allocated towards the police, percentage of the population with at least a bachelor's degree, percentage population that is Jewish, percentage of the population that is Black or African-American, the median age for women and men, percentage same-sex couples, number of incarcerated individuals per 100.000 state population, and the number of alcohol units consumed. *** p<0.01, ** p<0.05, * p<0.1.

6. Conclusion

This paper studies the effect of general media visibility of people of colour on social tolerance towards people of colour, as measured by the number of hate crimes motivated by race or ethnicity. The results show that media visibility matters. An increase in media visibility of people of colour significantly reduces the hate crime rate the following year. The result is robust to changes in the model specification, a number of checks and placebo tests. The effect is not larger in states that used to be members of the pro-slavery secessionist CSA but in states where the population is more likely to express emotional and spontaneous outbursts of racism, as measured by the state's relative amount of hate speech on Twitter after US President Barack Obama's 2012 re-election. Individuals who are very intolerant, however, do not appear to be affected by media visibility, as I find no effect on the number of hate groups.

My findings show that general media visibility of a minority group can have an important effect on the level of social tolerance toward that minority group. This is in line with theories that suggest that the more exposure that individuals have to minority groups, the more correct information they receive about them and the more they learn about them and their worldviews. In turn, this reduces any prejudice or negative bias that they might have. The findings in this study are also in line with results in other studies that have found that mass media can have an impact on individuals' behaviour and beliefs.

With respect to policy implications, my findings suggest that an increase in media visibility of minority groups can be an important tool to increase social tolerance toward minority groups. In a world where countries are becoming more international and multicultural, media visibility that is positive and non-stereotypic can be one way to reduce any potential conflict in society that may arise between the majority and minority groups.

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