The Internet and Racial Hate Crime:

Offline Spillovers from Online Access

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Abstract

We empirically investigate the effect of the Internet on racial hate crimes in the United States from the period 2001–2008. We find evidence that, on average, broadband availability increases racial hate crimes. We also document that the Internet's impact on these hate crimes is not uniform in that the positive effect is stronger in areas with higher levels of racism, which we identify as those with more segregation and a higher proportion of racially charged search terms, but not significant in areas with lower levels of racism. We analyze in depth whether Internet access will enhance hate group operations but find no support for the idea that this mechanism is driving the result. In contrast, we find that online access is increasing the incidence of racial hate crimes executed by lone wolf perpetrators. We describe several other mechanisms that could be driving the results. Overall, our results shed light on one of the many offline societal challenges from increased online access.

Keywords: Internet, broadband, online-offline interaction, hate crime, hate groups, race, econometrics, panel models

JEL Codes: L86, L96, H40, K42, C26

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1. Introduction

Widespread Internet penetration is associated with several benefits, but it has also introduced unique societal challenges as documented by other research.[2] One such challenge is online hate content. The Internet provides an accessible, affordable, unscreened, and anonymous channel for posting and sharing hate ideologies. Anecdotally, this has led to an increase in hate-related websites.[3] In 2011, close to 14,000 sites were reported to contain hate-related content, representing a six-fold increase from that in 2000.[4] In particular, over 65 percent of the active hate sites tracked by the anti-bigotry NGO, Southern Poverty Law Center, is found to contain racial and ethnicity related hate ideologies (SPLC 2009). More recently, a multitude of hate activity has appeared on social media and networking sites such as Facebook, Twitter, and YouTube (Gerstenfeld 2013) and extremist social media sites such as *NewSaxon*, all of which further facilitates the ease with which racial extremists link to one another [5]

It is not clear, however, whether or how the increase in online hate content affects offline racial hate crimes.[6] There are a number of channels through which greater Internet availability may increase the number of hate crimes committed. For example, increased Internet access may increase the efficiency with which extremists can spread hate ideology and connect with like-

Mechanism-1

[2] For example, Ayyagari et al. (2011) draw a connection between online enabled technologies and stress, Bhuller et al. (2013) uncover a positive relationship between sex crimes and Internet availability, Chan and Ghose (2014) and Greenwood and Agarwal (2015) find a link between online classified ads and HIV incidence, and White and Horvitz (2009) show how online medical searches can lead to unfounded escalations of concerns about common illnesses (i.e., cyberchondria).
[3] In fact, extremists were among the earliest to adopt Internet technologies. For instance, hate groups were utilizing Internet Relay Chat channels (e.g., #Nazi and #Klan), online newsgroups (e.g., alt.politics.white-power and alt.revisionism), and listservs to spread hate agendas even before the first hate site, Stormfront, was launched in 1995.
[4] Figures for online hate activity for various years come from the Digital Terror and Hate Report issued by the Simon Wiesenthal Center.
[5] Available at http://www.civilrights.org/publications/hatecrimes/exploiting-internet.html, accessed on May 27, 2015.
[6] For ease of readability, the term *hate crimes* is used henceforth to refer to racial hate crimes. These crimes are traditional offenses that are committed against individuals or groups based on real or perceived social and physical traits including race.

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minded members. Anecdotally, there is evidence that hate related material found on the Internet has led to hate crimes (Wolf 2004). For example, Benjamin Nathaniel Smith, who went on a shooting spree in 1999 that targeted racial and ethnic minorities, told a documentary film maker: "It wasn't really 'til I got on the Internet, read some literature of these groups that … it really all came together" (Wolf 2004). Another way in which greater Internet availability may increase the

Mechanism-2

number of hate crimes committed is by facilitating the training of individuals to commit hate crimes. For example, the Tsarnaev brothers reportedly relied on online instructions to build the pressure cooker bombs used in the 2013 Boston marathon bombing.[7] To the best of our knowledge there has been no systematic study about whether increased access to online hate content would increase offline hate crimes. In addition, it would be useful to get a better understanding of conditions under which offline hate crimes increase so as to motivate proper policy responses.

To empirically examine these issues, we use geographic and temporal variation in county-level broadband availability to study the effect of Internet penetration on hate crime in the United States between 2001 and 2008. We find evidence that increases in the number of broadband providers leads to increases in racial hate crimes, on average. The relationship between Internet

Identification strategy

access and these hate crimes further holds after using an instrumental variable (IV) approach to address endogeneity and is robust to a number of auxiliary checks and falsification tests. The

alternative mechanism

positive relationship does not appear to be due to increased crime reporting or reclassification of crimes over time. The positive relationship between Internet penetration and offline racial hate crime is most evident in areas with higher levels of racism, as indicated by higher levels of segregation and higher propensity to search for racially charged words. On the other hand, we

[7] Todd Wallack and Beth Healy, "Tsarnaev brothers appeared to have scant finances," *The Boston Globe*, April 24, 2013. Available at: http://www.bostonglobe.com/metro/2013/04/23/tsarnaev-brothers-appeared-have-scant-finances/ZbNBuN2Gcz8IOFddKDIU0N/story.html

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observe that Internet access does not have an impact on racial hate crimes in areas with lower levels of racism. We do not find any evidence that an increase in Internet access leads to an increase

possible mechanisms

in local hate group formation, and the presence of a local hate group does not seem to strengthen the link between Internet penetration and hate crimes. However, Internet access appears to increase the incidence of racial hate crimes committed by "lone wolf" actors.

This paper aims to make the following contributions: First, we believe our study is the first to document the relationship between the Internet and hate crime using a large-scale dataset and econometric techniques. This finding should be of interest to an ongoing academic effort to document some of the downsides to increased online access (e.g., Ayyagari et al. 2011; Bhuller et al. 2013; Chan and Ghose 2014; Greenwood and Agarwal 2015; White and Horvitz 2009) that has been enabled by the platform nature of the Internet in connecting disparate groups of users (Bailey and Bakos 1997; Bennett, Seamans and Zhu 2015; Parker and Van Alstyne 2005). Second, we document conditions under which the positive relationship is present, which we believe can help motivate policy responses. Specifically, we focus on two salient factors─entropy scores (Massey and Denton 1988) and racially charged search terms (Stephens-Davidowitz 2014)─that show interesting moderating effects of the Internet on hate crime. We therefore believe that our findings should be of interest to policy-makers, interest groups, NGOs, and academics. Third, we provide insights into some plausible mechanisms driving the relationship between the Internet and hate crimes. In particular, our results appear to challenge the general notion that the Internet has played a role in the increase in hate group formation. Additionally, the analyses found some support that Internet-induced hate crimes arise mainly from lone-wolf perpetrators.

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Here we will look for: Y - outcomes of interest
T, X - Treatment Variables

2. Data

To examine the link between Internet penetration and hate crime, we combine detailed data from various official sources including the Federal Bureau of Investigation (FBI), the Federal Communications Commission (FCC), the U.S. Census Bureau, and the U.S. Bureau of Labor Statistics. Hate crime data come from the FBI's annual report, *Hate Crime Statistics*. We restrict our empirical focus to the years 2001–2008 because the population coverage in the hate crime data is relatively stable for this time period.[8] Table 1 provides the descriptive statistics of our data.

Y Our main dependent variable is *hate crime*$_{it}$, which is the number of hate crimes in county *i* in year *t*. In the study sample, close to two-thirds of reported hate crimes arise from racial-bias motivations (60.4%), making it by far the most typical form of bias-motivated crime in the United States. The distinct divide in prevalence between racially motivated crimes and other categories of hate crimes drives our main focus on racially motivated hate crimes. Moreover, the nature of hate crime varies as a function of the target group, and the prevalence of each type of hate crime is affected by a different set of predictor variables (Glaser et al. 2002).[9]

T,X Our main independent variable is the average number of broadband providers in county *i* in year *t*, *Internet*$_{it}$, which we use to measure broadband availability.[10] We choose to focus on broadband access to the Internet over other forms of access such as dial-up, as extant research shows that broadband adoption significantly increases the overall usage of the Internet, heightens the consumption of online content in quantity and diversity, and affects a range of online and

[8] The coverage is over 80% for this time period, with a high of 88.6% in 2008 and a low of 82.8% in 2003.The high coverage of *Hate Crime Statistics* is an effort due in part to local agencies consistently furnishing hate crime reports to the FBI, voluntarily. In states that do not impose data collection statutes (e.g., Alabama, Georgia, and Mississippi), some agencies have nevertheless chosen to submit their reports.

[9] Though the FBI data on hate crime is unlikely to suffer from documentation issues and ambiguous classification, it may still face the problem of changing levels in reporting behavior (DiIulio 1996). We address the potential effects of crime reporting trends through a separate test described in Section 6.

[10] Counts of ZIP code level providers are averaged across each county to derive this measure.

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offline activities (Hitt and Tambe 2007; Kolko 2010a). Specifically, the reduction in waiting times for loading images, sounds, and videos via broadband availability facilitates the likelihood and willingness to consume hate content online.

Data on broadband availability comes from FCC Form 477, which reports the number of broadband providers offering broadband services at 200 kilobits per second or faster in a ZIP code.[11] The FCC data is the only comprehensive indicator of U.S. broadband availability that has been recorded annually since 1999 (Kolko 2010b), and is extensively used by policy makers and academics to assess broadband availability (California Public Utilities Commission 2006; Grubesic 2008; Kolko 2012; Seamans and Zhu 2014; Xiao and Orazem 2011). Using data on the number of broadband providers from the FCC and proprietary data on broadband use from Forrester Research, Kolko (2010b) shows that the extent of broadband availability increases monotonically with the number of broadband providers.[12] Given that broadband policies often work by adding providers to an area via public provision, subsidization, and regulation, it is meaningful in a policy context to employ the number of broadband providers as a proxy for Internet

Non-ideal Measurement

penetration.

As noted in past literature, the use of the FCC data to measure broadband availability may introduce measurement error for certain study contexts (Greenstein and Mazzeo 2006; GAO 2006, 2009; Kolko 2010b; Xiao and Orazem 2011).[13] For example, there may be business but not residential subscribers in a given ZIP code, so the FCC's count will overstate residential broadband availability. In addition, the FCC does not report the actual number of providers for locations with

[11] Broadband providers include telephone-line DSL, cable modems, wireless, satellite, and power-line technologies.
[12] To assess the integrity of the broadband provider data, we correlate it with household Internet adoption data at the state level. Results show a strong positive correlation between broadband providers and the Internet measures from two other official data sources (see Table A1 of the Online Appendix).
[13] The FCC does not report whether providers serve consumers or businesses, how much they charge for service, the speed of their service, and whether they provide service to the whole or only part of a ZIP code.

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Potential measurement error

one to three providers, instead grouping them into a single category. Following Kolko (2012), we assign a value of two to ZIP codes reported as having one to three providers, which introduces measurement error in our estimations. Below we describe an IV approach to help account for endogeneity, which also helps address the measurement error inherent in our measure of broadband availability.

We combine hate crime and broadband availability measures with demographic, socioeconomic, and crime-related variables from a variety of official sources which allow us to control for the underlying propensity of hate crimes across locations.

Regression adjustment

The U.S. Census and the U.S. Bureau of Labor Statistics provide county-level information on population density, age proportions, race proportions, international migration rates, number of persons below the poverty line, employment level, and size of various industry sectors. These demographic and socioeconomic factors are important for controlling for characteristics which are known to influence crime rates (Bell et al. 2013; Dollard et al. 1939; Glaser and Sacerdote 1999; Hansmann and Quigley 1982; Kelly 2000; Sampson et al. 1997), although there is some debate about the relative importance of some of the characteristics as they pertain to hate crime in particular. For example, Dollard et al. (1939) argue that economic factors are important determinants of hate crime, and others, including Green and Rich (1998), find evidence of a positive relationship between unemployment and hate crime. On the other hand, Krueger and Pischke (1997) find no relationship between unemployment and hate crime. While not the focus of our research, we discuss the impact of our control variables on hate crime in our setting, thereby shedding additional light on a topic that has been subject to much debate in prior literature. We also account for crime-related prevalence by controlling for the number of police employees and prevailing crime levels. The FBI database *Law Enforcement Officers Killed and Assaulted* provides information on the

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annual count of police employees by county, and the FBI's *Uniform Crime Report* provides counts of general crime levels by county. All log transformed variables are constructed using log(X+1) to account for zero values.

3. Empirical Methodology

We first motivate our approach with graphical evidence of the positive relationship between broadband availability and hate crime. Figure 1 provides scatter plots of number of broadband providers (x-axis) and number of racial hate crimes (y-axis) for each of the years 2001 to 2008. The plots include a linear trend, which indicates a positive relationship between the number of broadband providers and racial hate crimes. OLS results (provided in Online Appendix Table B1) include the full set of controls and confirm the statistical relationship apparent in the raw data. The OLS results may be biased due to endogeneity or measurement error, so we next describe our econometric approach to address these issues and more rigorously investigate the relationship between Internet providers/availability and hate crime.

3.1. Cross Sectional IV Specification

Our baseline cross-sectional regression is of the following specification:

$$\ln(1 + y_{\mathrm{it}}) = \alpha + \beta \ln(1 + Internet_{\mathrm{it-1}}) + \lambda X_{it-1} + \varepsilon_{\mathrm{i}} \quad (1)$$

for each year 2001−2008, where y_{it} is the number of racial hate crimes in county *i* for year *t*, $Internet_{it-1}$ is the number of broadband providers in county *i* for year *t-1*, and X_{it-1} includes various demographic, socioeconomic, and crime-related characteristics of county *i* in year *t-1*. In these specifications, all covariates are lagged by one period to avoid simultaneity biases. In all regressions, we report robust standard errors, clustered at county *i*.

To address potential endogeneity issues such as omitted variable biases and measurement

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error in broadband availability, we apply an IV identification strategy on our cross-sectional specification. Specifically, we run IV regressions on Equation (1) by instrumenting for *Internet* using the *Slope* of the local terrain. This is the same instrument used by Kolko (2012). To be a valid instrument, slope should directly affect broadband availability and not directly affect hate crime. The slope instrument identifies cross-sectional variance in the costs to broadband providers in extending Internet service to an area. As noted by the Government Accounting Office (GAO 2006) and Prieger (2003), terrain features such as slope affect the cost to extend broadband service in an area. Since much of the cost in providing broadband service comes from the fixed costs in setting up telecommunications infrastructure, providers would face high cost barriers to deploy broadband services in areas with steep terrain. This negative relationship is empirically confirmed in Kolko (2012). In Figure 2, we provide scatter plots of terrain slope (x-axis) and the number of broadband providers (y-axis), as well as a trend line. Across the years, we observe a consistent negative relationship between the two variables. Note, however, that the negative relationship appears weaker in early years and stronger in later years. This suggests that the relationship between terrain slope and number of broadband providers may vary by year, which we will exploit in our panel IV approach described in Section 3.2.

Instrument!

Justification for the instrument is almost always qualitative / anecdotal

The exclusion restriction holds if slope does not have a direct effect on the incidence of racial hate crime, independent of its relationship with Internet availability. Terrain characteristics such as slope are unlikely to bear direct effects on hate crime, as these criminal acts are largely induced by human ideologies, prejudices, and influences. Although there may not be direct effects on hate crime, the slope of a location may be linked to crime incidence indirectly. Locations with flat terrains are likely to be urbanized areas that may possess demographic and economic features associated with higher incidence of crime levels (Glaeser and Sacerdote 1999). To account for

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these effects, demographic, socioeconomic, and crime-related variables mentioned earlier are included in the first stage regressions as controls.[14] In later sections, we describe additional checks that are performed to test the exclusion restriction.

3.2. IV Fixed Effects Specifications

The idea of Fixed Effects

An additional issue we face is that the relationship between hate crimes and broadband providers may be heterogeneous across locations (Cornwell and Trumbull 1994). Unobserved local conditions such as the level of racial intolerance, discriminatory cultures and practices may cause some counties to experience a greater effect from broadband availability on its incidence of hate crimes. In order to address this issue, we specifically pool racial hate crime data across the years 2001–2008 and use county-level fixed effects models of the following type:

$$\ln(1 + y_{it}) = \alpha + \beta \ln(1 + Internet_{it-1}) + \lambda X_{it-1} + C_i + Y_t + \varepsilon_{it} \quad (2)$$

where y_{it} is the number of racial hate crimes in county i in year t, $Internet_{it-1}$ is the number of broadband providers in county i in year t-1, and X_{it-1} includes various time-varying demographic, socioeconomic, and crime characteristics of county i in year t-1. The county-level fixed effects C_i help address the unobserved heterogeneity across counties that may explain the observed relationship between number of broadband providers and racial hate crime. We include year dummies Y_t to account for temporal shocks such as the occurrence of terrorism that may produce shifts in racial attitudes (e.g., the September 11, 2001 terrorism incident).

To simultaneously address endogeneity and measurement error issues, we rely on panel IV regressions in which we instrument for broadband providers using a variant of terrain slope. Specifically, we interact the slope values with year dummies to construct instruments that allow for heterogeneous time impacts on broadband growth. We then include these instruments in IV

[14] A correlation table consisting of the correlations of slope and covariates is provided in Online Appendix Table B2.

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regressions that follow Equation (2). The approach of utilizing cross-sectional instruments interacted with time dummies has been used in past research (e.g., Forman and van Zeebroeck 2013, Stevenson 2008), and, we believe, is valid in our setting. Notably, the slope of terrain not only affects the number of broadband providers in the cross-section, but also influences the *growth rate* of broadband providers over time. That is, the number of broadband providers at locations with steep terrain will increase at a slower rate, compared to areas with flat terrain. Reports have noted a similar trend in favor of this argument, in that broadband growth has been unevenly focused on areas that already have broadband capabilities, namely the urban areas, but proceeds sluggishly in rural and remote areas over the years (OCED 2008). We verify graphically that the broadband growth patterns within our dataset are similar (see Online Appendix Figure A1).

3.3 Alternative Model Specifications

Alternative specifications are used to assess the IV assumptions and stability of the results. First, we follow Kolko (2012) and use a first-difference IV model of the following form:

$$\ln\left(\frac{1+y_{it+1}}{1+y_{it}}\right) = \alpha + \beta \ln(1 + Internet_{it+1} - Internet_{it}) + \lambda X_{it} + \delta X_{it} \times \ln(1 + Internet_{it+1} - Internet_{it}) + \Lambda Z_{it} + \varepsilon_{it} \quad (3)$$

where the dependent variable is the log change in racial hate crime, the independent variable is the log change in broadband providers, accompanied by covariates (X_{it}), interactions of these covariates with the log change in broadband providers, and additional controls (Z_{it}) to account for local economic growth and crime trends.[15] Whereas the fixed effects specification detailed in Equation (2) requires us to use slope-year interacted instruments, the first-differences specification detailed in Equation (3) allows us to use slope alone as an instrument. County-level effects are

[15] The choice of variables to be interacted with change in broadband providers follows closely those proposed by Kolko (2012), including population density, population size, median household income, and college attainment percentage. Road density is also included as a covariate as per the specification in Kolko (2012).

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controlled for in either case, either by differencing out or by including a county-specific intercept. Thus, the results from Equation (3) will serve to cross-validate the directionality of the results from the panel IV model.

Second, we collapse the data set into pre- and post-intervention periods to check whether our results are sensitive to measurement issues that arise from serially correlated outcomes (Bertrand et al. 2004). To do this, we supplement the current set of racial hate crime data with that from 1992 to 1998. We then create a pre-broadband period and a post-broadband period and use average values of racial hate crimes and broadband providers for each county in each of these two periods. We also check that the results using this approach are robust to alternate cut-offs for the definition of pre and post. Finally, we run a large number of robustness tests with additional controls, alternative functional forms, and outlier removal. Various falsification checks are also employed to assess whether the main results arise spuriously and to test for the possibility of alternative explanations.

4. Results

4.1. Cross-Sectional IV Regression

Table 2 reports our IV regression results linking broadband availability to racial hate crime. We report both the first stage and second stage coefficients in the same table. Across all years, we see that the slope coefficient is consistently negative and significant in the first stage results, satisfying the correlation requirement that instruments should have with the endogenous regressor, conditional on other covariates. This result supports the claims in Kolko (2012) and the negative trend observed in Figure 2. To assess whether slope suffers from problems of being a weak instrument, we check the significance of the first-stage F-statistics and find that they are all

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significant above the 1% level. We further contrast the F-statistics with the Stock and Yogo (2005) critical thresholds for weak instruments. Across all years, the F-statistics surpass the critical value, suggesting that the slope variable does not suffer from weak instrument biases.

Next, we turn to the second stage regression results. We observe that the coefficients for broadband providers are positive and significant in all years, except in 2001.[16] We also note that the magnitude of the relationship differs across the years. Contrasting the year with the smallest significant coefficient (2006) to the year with the largest significant coefficient (2002), we see that a one-unit increase in broadband providers produces a 66.8 and 271.4 percent, respectively, increase in racial hate crimes, mapping out to 1,176 to 4,779 annual cases of racial hate crime across all counties.[17]

The regression results also reveal other relationships that are of interest. Poverty, police staffing, and crime levels appear to be positively correlated with the incidence of racially motivated crimes, although we find little effect from the rate of unemployment on racially motivated hate crime, in line with findings in Krueger and Pischke (1997). Locations with higher mean ages appear to experience more racial hate crimes in general. This trend agrees with the findings of von Hippel et al. (2000), which reasoned that older individuals are less likely to inhibit innate prejudices. In addition, employment levels hold a negative but not significant relationship with racial hate crimes. Finally, the negative relationships between racial hate crimes and proportion of African Americans and foreign nationals seem to suggest that a larger presence of racial/national minorities in a community may reduce racial tensions, possibly by introducing greater familiarity and acceptance.

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[16] We note that cross-sectional OLS results across the years also produce a similar result (Online Appendix Table B1).

[17] A one-unit increase in broadband providers corresponds to an approximately 65% increase in the average number of providers (1.56). We estimate the annual increase in racial hate crimes by multiplying the percentage increases (66.8 and 271.4) by the average annual number of racial hate crimes across the study period (1,761).

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As a robustness check, we repeat the above analysis for ethnicity hate crimes.[18] Given that a significant proportion of the online hate content contains racial and ethnicity ideologies (SPLC 2009), we expect to see a similar positive relationship between online access and ethnicity hate crimes. Results for ethnicity hate crimes are provided in Table B3 of the Online Appendix. The Internet appears to also have a positive effect for ethnicity hate crimes, although the magnitude of this effect is not as large as that for racial hate crimes. Contrasting the smallest and largest coefficients, we see that a one-unit increase in broadband provider brings about 15.6 to 188.6 percent increase in ethnicity hate crimes.

4.2. Panel IV Regression Results

Table 3 gives the results of our fixed effects IV regressions. Model 1 is the IV regression based on the pooled sample in which we use slope as the instrument along with year fixed effects. In Models 2 and 3, we include slope-year dummies as instruments and add county-fixed effects, respectively. We further estimate a model that includes additional covariates to reflect the sizes of common industries in urbanized locations in Model 4. As expected, the instrument is negatively associated with broadband availability and this relationship is significant under various model specifications. Of greater importance, we observe that the magnitudes of the interaction terms are generally increasing over the years; interaction terms for early years (i.e., 2004 and earlier) tend to hold smaller coefficient values, while those for later years tend to hold larger coefficient sizes. This set of estimates supports our argument that the slope of terrain affects the rate at which broadband providers enter into locations over time. The first stage F-statistics are all significant above the 1%

[18] Victims of ethnicity hate crimes are targeted as a result of their nationality and cultural heritage. The FBI identifies ethnicity hate crimes as separate from racial hate crimes.

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level and they surpass the critical values indicated by the threshold given by Stock and Yogo (2005), indicating that the slope-year instrument is quite strong.

In the second stage results, the estimates for broadband providers are all positive and significant, suggesting that racial hate crimes increase as broadband availability increases. Results from Model 3 suggest that a one-unit increase in broadband providers leads to a 21.39 percent increase in racial hate crimes, which equates to 865 additional annual incidents of racially driven crimes in the United States. We further find that the estimates for broadband providers in Model 4 remain qualitatively similar after including additional urbanization factors that may correlate with terrain slope. However, goodness-of-fit for Model 4 performed worse in terms of root mean square error. Taken jointly, this indicates that the existing framework of covariates and fixed effects in Model 3 are sufficiently robust in capturing extraneous effects that may affect the exclusion restriction, without undermining model fit. The over-identification statistics in the full models indicate that the exclusion restriction of our instruments cannot be rejected at conventional levels, indicating that the slope-time instrument does not correlate with the error term in the explanatory equation. We also performed an auxiliary check on the exclusion restriction by regressing racial hate crimes on the instrument and the abovementioned covariates and find that the instrument is not correlated with racial hate crimes after controlling for these demographic, socioeconomic, and crime-related factors (see Online Appendix Table B4).

We next provide analyses that further explore the nature of the relationship between broadband providers and racial hate crimes in Table 4. In particular, we consider situations in which there are indicators that racial and ethnic differences are salient. In line with the Dollard et al. (1939) frustration-aggression hypothesis, we expect the effects to be heightened in these situations. We use two state-level variables to identify these situations, and we then split the sample

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using the median values of these measures. The level of racism at a location is likely indicated by the intensity of its racial segregation (Cell 1982). A common racial segregation measure used in sociology is *entropy*, which indicates the level of integration or segregation exhibited in a subarea's population composition (Massey and Denton 1988).[19] Lower levels of entropy reflect lower levels of racism and vice versa. In fact, Glaeser (2005) writes: "Hatred declines when there is private incentive to learn the truth. Increased economic interactions with a minority group may provide that incentive (p. 45)." In addition, we use on an online measure of racial animus, using the volume of Google search queries that include racially charged language (Stephens-Davidowitz 2014).[20]

Models 1 and 2 of Table 4 examine the impact of broadband availability split by entropy scores, and Models 3 and 4 examine the impact of broadband availability split by racially charged online searches. The results show an interesting pattern. The coefficient on broadband providers is positive and significant for the areas with above-median segregation and racially charged search, but not significant for the areas with below-median segregation and racially charged search. Thus, while increased Internet access leads to an *increase* in hate crime, on average, there are situations in which Internet access does not affect hate crime incidence. These findings suggest that the Internet's impact on hate crime is not uniform and is predominantly present in areas with higher racism tendencies.[21]

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[19] Gentzkow and Shapiro (2011) use similar indices of segregation to construct measures of ideological segregation.
[20] Stephens-Davidowitz creates the index by averaging the counts of searches for racial epithets in each market from 2004-2007. He notes that the racial epithet is typically preceded or followed by search terms including "hate" or "joke(s)."
[21] In additional checks included in the Online Appendix Table B5, we break out locations by high and low proportion of poverty and employment. These characteristics are chosen for additional focus given prior literature and our results from the cross-sectional panel. Poverty in particular appears to be a strong moderator of the relationship between the Internet and hate crime.

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5. Robustness Checks

In this section, we investigate the robustness of the main results to a variety of alternative specifications, models, and other tests. By performing these checks, we hope to rule out as many alternative explanations as possible. We proceed in several steps. First, as discussed in Section 3.3, we show that our findings are robust to alternate model specifications. These robustness tests help to rule out the possibility that our findings arise because of model misspecification. Second, we show that our findings are robust to a large number of robustness tests with additional time-varying and time-invariant covariates, as well as to the removal of outliers. These tests help to rule out the possibility that our findings are biased by omitted variables. Finally, we conduct several tests to rule out our findings being driven by changes in crime reporting behavior over time or by changes in hate crime classification over time. Collectively, these tests help to rule out our findings having arisen spuriously because of other factors that are changing at the same time as broadband penetration.

5.1. Results Using Alternate Models

As described in Section 3.3, we utilize two approaches to address concerns with potential model misspecification. First, we cross-validate the coefficient signs and significance using a first difference model specification that relies on a different identification strategy as described in Equation (3). The results in Online Appendix Table B6 show that the broadband provider coefficient in the first difference specification holds a positive and significant relationship with racial hate crime trends.[22] First stage results also suggest that the slope does not suffer from weak instrument issues. For the second approach, we adopt the pre- and post-intervention specification

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[22] The magnitude of the broadband provider estimate in Model 1 of Table B6 is comparable to its equivalent counterpart (Model 3) of Table 3, lending weight to the validity of the results under the panel IV framework.

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in Bertrand et al. (2004) to assess the stability of the results with respect to serial correlations issues that may be present in multiple-period panels. Analyses using the collapsed dataset (Online Appendix Table B7) indicate a positive and significant relationship between Internet availability and racial hate crime, which provides further confidence in the validity of the baseline results.

We also perform a falsification check using lagged values of racial hate crime to rule out that the relationship is arising spuriously. A significant coefficient in this check would suggest that there is some omitted variable that drives the trends in racial hate crimes and broadband expansion simultaneously, as values of the predictor variable should not be related to past values of the outcome variable. Under a stricter test, we look for a relationship between racial hate crimes in the period 1992−1998 and broadband availability in the period 1999−2006. Given limited availability and accessibility to online hate content in the pre-broadband period, coefficients on broadband availability are expected to be smaller and nonsignificant. Significant estimates would suggest that the IV is correlated with underlying location-specific trends in racial hate crimes, which undermines its exclusion restriction. In addition, these two falsification checks could jointly reveal potential inflation of estimates that the slope-time instrument creates.[23] We find no evidence of significant correlations between the broadband availability and racial hate crime in both falsification checks (see Online Appendix Table B8).

5.2. Results Using Additional Covariates and Removal of Outliers

Next, we explore the robustness of the results to the inclusion of additional or alternate control variables in order to assuage potential concern about omitted variables bias. Broadband availability may increase more rapidly in locations that have large population sizes and rapid income growth—factors that are also known to correlate with crime levels (Glaeser and Sacerdote 1999;

[23] In the case where slope-time instrument artificially inflates estimates, we would expect to see significant estimates.

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Levitt 1999).[24] In addition to these two factors, racial hate crimes may be driven by the racial composition of the location, which may be associated with broadband growth due to differences in the socioeconomic status of these racial groups. To assess the potential impact of this endogeneity bias on our baseline estimates, we examine the coefficient magnitudes and significance of broadband providers with respect to the inclusion of population size, median household income, proportion of Whites, and proportion of Asians as additional covariates. We also run these additional models using non-log model specifications to assess result stability with respect to non-logarithm transformation. The coefficients on our broadband measure in logged models are of comparable magnitudes to the baseline estimate in Table 3 (see Online Appendix Table B9). Improvements in model fit from including these covariates are marginal, suggesting that the estimation framework of Equation (2) performs well. Moreover, our results do not appear to be affected by the log-transformation process which smoothens out skewed data points.

We also check the robustness of our cross-section results after adding additional nontime-varying covariates such as college attainment proportion, entropy scores, racially charged searches, and road density, as these variables may correlate with unobserved factors that are related with slope and crime levels. College attainment levels may affect the intensity of Internet usage and is also indicative of the population size of young adults, the largest population group who constitute the group committing hate crimes. Entropy and racially charged search are indicators of racism that are likely to be correlated to neighborhood segregation patterns. These are added to control for residential segregation that might result from steep slope features. Road density is a proxy for transportation costs of a location, which in turn is correlated with the slope of the terrain

[24] For instance, the probability of incarceration for committing crimes is lower in places with large populations as the pool of potential suspects is larger, thereby giving rise to a positive link between population size and crime rates. Also, families with high household incomes tend to cluster in better neighborhoods with lower crime rates.

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and the ease of accessing target victims in the area. Results remain qualitatively similar even after including these variables (see Online Appendix Table B10).

Next we remove potential outlier years, which might upwardly bias our main results. The prevalence of racial hate crimes may reach abnormally high levels in periods experiencing external shocks. Our dataset includes the period in which the major terrorist attack on September 11, 2001, took place. Anger, frustration, and fear after a terrorist attack can result in indiscriminate, racially based attacks on innocent individuals who appear to be of Muslim, Middle Eastern, or South Asian descent (Kaplan and Moss 2003). We rerun the baseline regression models after removing observations from 2001 and 2002, and obtain similar result to those in Table 3 (see Online Appendix Table B11).

Crime Reporting: Important Alternative Mechanism

5.3. Checks on Crime Reporting and Classification

Finally, we consider the possibility that the positive link between racial hate crime and broadband availability may be an artifact of heightened levels of crime reporting that coincided with the period of broadband expansion, or may be due to changes in classification of what constitutes a hate crime. To this end, we first assess the effect of broadband providers on the likelihood of crime reporting via a separate dataset constructed through the combination of the National Crime Victimization Survey (NCVS) and the FCC.[25] These results are provided in Table 5. The coefficients on broadband providers are not statistically significant, suggesting that broadband availability does not shift crime reporting behaviors. Thus, it is unlikely that the relationship between Internet access and racial hate crime is driven by an increase in crime reporting behavior facilitated by better broadband availability

Are you persuaded with this argument?

[25] Details of the NCVS dataset and the regression specifics are provided in Online Appendix C.

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We also examine the regression coefficients for additional types of crime (see Online Appendix Table B12). Aggravated and simple assault are commonly committed forms of hate crime. A reclassification of these crimes as hate crime via the increased ability to recognize their inherent bias motivations may result in an artificial spike in hate crime statistics, which may coincide with the broadband growth trends. However, the coefficient on broadband providers is not significant, suggesting that crime reclassification is unlikely. We also assess the impact of broadband providers on alternative crimes that are unlikely to be affected by the growth in broadband usage. For this, we focus on murder, robbery, and burglary as alternative crimes.[26] The presence of a statistical relationship between the incidence of these crimes and broadband providers would suggest that the observed relationships in the main results arise spuriously. However, we find the coefficients on broadband providers are not significant across these alternative crimes, providing additional confidence that the main results are not spurious.

6. *Post Hoc* Analyses

In Section 4 we provide evidence that increased Internet access leads to an *increase* in hate crime, on average, but that there are situations in which Internet access does not affect hate crime prevalence. The results from Table 4 suggest that the positive relationship between Internet penetration and racial hate crimes increases in areas with more segregation (higher entropy scores) and more racially charged search behavior, but that the relationship is not affected by Internet access in areas with less segregation (lower entropy scores) and less racially charged search

[26] According to FBI statistics, most hate crimes manifest through assault, intimidation, and vandalism/property damage, with very few (if notany) manifesting via murder, robbery, and burglary. Less than 2% of hate crimes fall under murder, robbery or burglary. Also, the latent risk factors for murder, robbery, and burglary are not known to have any relationships with Internet availability, unlike other crimes such as rape and other sexual offenses, which are found to be exacerbated by increased access to online pornography (Bhuller et al 2013).

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behavior. In this section we conduct additional *post hoc* analyses to uncover the potential mechanism underlying these results.

There are several pathways through which the Internet might increase offline hate crime. We focus our discussion on two potential pathways. First, online hate sites can be used to recruit individuals to offline hate groups and coordinate group efforts. In fact, both hate group membership and the number of hate groups increased dramatically during the 2000s (Potok 2010). Given that Internet usage is highly prevalent among youths, hate groups have utilized specific strategies for recruiting youths including the use of online membership forms, subscription-based mailing lists, hate-related music, video games, and other activities on hate sites (Gerstenfeld et al. 2003; Schafer 2002). Internet communications can also help hate groups in the coordination of their activities by facilitating the interactions between committed group members to discuss strategies and tactics (Anti-Defamation League 2001). Content analyses of hate websites suggest a fair amount of grass-roots mobilization (Bostdorff 2004). For instance, the Imperial Klans of America posted an invitation on the White Camelia Knights' website to a "Unity Gathering" in Kentucky. Thus, a potential mechanism through which access to/use of the Internet increases hate crimes is the enhancement of offline hate group operations through more efficient recruitment and coordination.

Another major pathway through which access to/use of the Internet might increase offline hate crime is by advocating for racial based ideologies online and compelling individuals to act on the hate agenda by carrying out hate crimes on their own, as was apparently the case for Benjamin Nathaniel Smith. Adams and Roscigno (2005), using text-based analysis of material from six supremacist websites, find that in addition to recruitment, the texts of these websites advise on courses of action that one could take. They specifically write that a "relatively new strategy that

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makes these organizations a legitimate threat is the 'lone wolf' approach to social action" (p. 771). In fact, survey responses in our NCVS data revealed that over sixty-four percent of hate crimes in the United States during the period 2004−2008 were committed by single perpetrators, lending plausibility to the idea that the mechanism through which the Internet induces more hate crime is by motivating more individual-based hate crimes (Appendix C). Below, we elaborate potential ways to further investigate the role of hate group recruitment and lone-wolf attacks in the link between Internet and increased hate crimes.

To examine whether use of/access to the Internet increases hate crimes via the enhancement of offline hate group operations through more efficient recruitment and coordination, we perform several analyses using hate group data obtained from the Southern Poverty Law Center (SPLC).[27] We use a specification similar to Equation (2) to estimate the relationship between broadband providers and number of offline hate groups. If the Internet enables hate groups to recruit members more effectively, we would expect the coefficient on broadband providers to be positive and significant. Note that this rests on the assumption that the number of hate groups is positively correlated with the number of members. There is some anecdotal evidence in support of this assumption (Mulholland 2010), but it is possible that the number of hate groups is uncorrelated with total hate group membership. Models 1 and 2 of Table 6 analyze the relationship between the Internet and number of hate groups. The coefficients on broadband providers are negative but statistically insignificant in both of these models.[28] Thus there is little support for the notion that

[27] Founded in the 1970s, the SPLC is the leading center in tracking and exposing activities of hate groups. SPLC provides data on city and state location of hate groups on its website http://www.splcenter.org/get-informed/hate-map. We obtained historical data on hate group locations using the Internet Archive https://archive.org/.

[28] The SPLC has noted an increase in the number of hate groups between 2000 and 2008 (see http://www.splcenter.org/home/2013/spring/the-year-in-hate-and-extremism). The insignificant result here suggests that the Internet is unlikely to be responsible for the increase in hate group formation.

the Internet has led to an increase in offline hate group formation (although it is possible that hate group membership has increased without the number of hate groups increasing).

Second, we explore the impact of broadband providers on racial hate crimes in areas with varying levels of hate group presence. Specifically, we contrast the effect of broadband providers in counties with at least one hate group during the study period to that of counties with no hate groups in all years of the same period. If the underlying mechanism is that the Internet facilitates the coordination of attacks by offline hate groups, then we would expect counties with one or more hate groups to experience a larger effect than counties with no hate groups. Models 3 and 4 of Table 6 provide results from our baseline specification (Table 3, Column 3) after splitting the sample into those counties with no hate groups and those with one or more hate groups. The coefficient on broadband providers is positive and significant in Model 3 (counties with no hate groups) and negative but insignificant in Model 4 (counties with one or more hate groups). Thus, it does not appear that hate crime increases more in counties with hate groups.

In order to examine whether hate content motivates lone wolves to engage in hate crimes, we perform several analyses using additional hate crime perpetrator information obtained from the FBI. In order to perform this analysis, we obtained the hate crime yearly master records directly from the FBI. These records contains perpetrator information about the hate crimes committed.[29] We proceeded by identifying racial hate crimes that were committed by a single perpetrator versus those that were committed by more than one perpetrator. The number of perpetrators in the dataset is recorded by the police officer(s) in charge of the hate crime incident and it denotes the number of known offenders who are involved in executing the crime. This information is largely derived

[29] An email request was made to the FBI to access the master records. Requests can be made via crimestatsinfo@ic.fbi.gov.

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from the accounts of the victims and the efforts of police investigations. We sum the number of racial hate crimes committed by single and multiple perpetrators separately by county and year. We then use each of these counts as dependent variables and replicate the regression specification in Table 3, Column 3. These results are presented in Columns 5 and 6 of Table 6. When the dependent variable is the log count of racial hate crimes committed by single perpetrators, the coefficient on the number of broadband providers is positive and significant, and similar in magnitude to the main results. When the dependent variable is the log count of racial hate crimes committed by multiple perpetrators, the coefficient on the number of broadband providers is positive but not significant. To better understand the lone-wolf mechanism, we did a further investigation via a split-sample analysis to explore the impact of Internet access on the incidence of racial hate crimes committed by single and multiple perpetrators for locations with high and low levels of racism. Similar to our previous analysis in Table 4, racism levels are measured by entropy scores and incidence of racially charged searches. Based on this analysis, we find that the impact of Internet access largely induces lone-wolf attacks in areas with a high level of racism. In contrast, racial hate crimes committed by multiple perpetrators do not exhibit any meaningful patterns by racism levels. These results are reported in Table B14 of the Online Appendix.

In summary, the results in Table 6 provide suggestive evidence that the main result is driven by the number of single perpetrator acts of hate crime, which is consistent with the explanation that our results are driven by lone-wolf actors. In contrast, the results of our analyses on the role of hate groups does not lend much support to the idea that the primary mechanism through which the Internet increases hate crimes is through the enhancement of offline hate group operations through more efficient recruitment and coordination. However, additional work is needed in order

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to fully understand what role, if any, hate groups play in mediating the link between the Internet and hate crime.

7. Discussion and Implications

The Internet, like other information and communications technologies (ICTs), has had both positive and negative spillovers to society (Kling 1996). In this paper, we study the link between broadband availability and racial hate crimes. We use slope of terrain as an instrument for the number of broadband providers and a fixed effects framework to address potential endogeneity issues. Our results provide evidence consistent with the idea that an increase in Internet access leads to an increase in racial hate crimes, on average. This increase is most evident in areas with higher levels of racism, as indicated by more segregation and higher propensity to search for racially charged words. On the other hand, we observe that Internet access does not have an impact on racial hate crimes in areas with lower levels of racism. We do not find any evidence that an increase in Internet access leads to an increase in local hate group formation, and the presence of a local hate group does not seem to strengthen the link between Internet access and hate crime. However, Internet access appears to increase the incidence of racial hate crimes committed by lone-wolf perpetrators. Our findings provide several key insights for academics, policy makers, and law enforcement officials on the societal challenges related to Internet growth.

First, our study is the first to use a large-scale dataset to empirically quantify the impact of Internet access on hate crimes—in particular, racially motivated hate crimes. We further show that this positive relationship is unlikely to be driven by an increase in crime reporting or reclassification schemes over time. Translating the coefficient estimates from our cross sectional IV regression to raw counts, the results suggest that a one unit increase in broadband providers

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could lead to between 1,200 and 4,800 additional cases of hate crime per year. We also note that hate crime has tangible and intangible costs. Tangible costs to victims include property damage, medical expenses, lost earnings due to injuries, and to society through police protection costs, legal and adjudication costs, and correction costs (McCollister et al. 2010). Intangible costs of these crimes involve pain and suffering for the victims, and emotions of fear and anger directed toward members of the same racial community (Anderson 2012).[30]

Second, the findings on the moderating impact of racism indirectly support the notion that Internet facilitates the specialization of individual interests (Van Alstyne and Brynjolfsson 2005). A heightened effect of online access on racial hate crimes in areas with higher levels of racism suggests that individuals go online to engage in the construction and affirmation of individual racial identities (Byrne 2007; Daniels 2009). This finding contributes to the literature on how users interact with the online medium and the resulting consequences of increased Internet usage (e.g., Kraut et al. 1998; Teo et al. 1999; Wellman et al. 2003). In particular, the specialization of interests allows the Internet medium to amplify the messages, values, and ideas that are posted on it (Earl and Schussman 2003), which have the opposite effect of promoting the more inclusive, democratic society that was envisioned by early thought leaders regarding usage of the Internet (Jenkins and Thorburn 2003).

Third, we find little evidence that increased Internet access facilitates offline hate group operations (e.g., member recruitment and organizing planned attacks).[31] This result is perhaps not

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[30] These costs can be quite large. The 2011 Norway massacre and 2013 Boston marathon bombing are instances of bias-motivated crimes linked to online hate materials (Beirich 2014; Bergen and Rowland 2014), that have dire consequences including multiple deaths, injuries, business disruptions, subsequent copycat terror acts, and social instability, which can in turn fuel retaliatiatory responses as evidenced in the post-September 11 spike in hate crimes. NBC reports the financial loss of the Boston bombing to be over $330M (see http://usnews.nbcnews.com/_news/2013/04/29/17975443-adding-up-the-financial-costs-of-the-boston-bombings).

[31] As seen in Table B13 of the Online Appendix, the number of hate groups does not hold a significant relationship with racial hate crimes at the county-level analysis. Similar results are found when the analysis is conducted at the

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surprising given the mixed evidence linking hate groups to hate crimes. For example, Daniels (2009) found in her interview studies that while online hate content holds the danger of eroding ideas and values of racial equality, it is ineffective at recruiting teenagers into hate groups. A qualitative study on the major white extremist sites reveal that their recruitment efforts are more reactive than proactive, and are far less aggressive than suggested by the media (Ray and Marsh 2001). Ryan and Leeson (2011) find no relationship between hate groups and hate crime, and suggest that "hate groups, though populated by hateful people, may be a lot of hateful bluster" (p. 260). As their quote suggests, it is possible that hate groups provide an outlet that serves to ultimately *reduce* the number of hate crimes by allowing racists to express their frustrations in less physical ways (Glaser et al. 2002). Mulholland (2010) finds support for the idea that hate groups are more likely to form in areas with fewer government services. In these situations, hate groups serve as a social and/or economic net. On the other hand, there may be reasons to believe that hate groups do lead to greater hate crime. For example, Dharmapala and McAdams (2005) use a formal economic model to argue that a desire for fame or esteem may in part drive individuals to commit hate crimes, and Adamczyk et al (2014) find a positive relationship between hate groups per capita and ideologically motivated homicide attacks.

Fourth, we find some evidence that much of the increase in racially motivated hate crime is due to an increase in crimes committed by single perpetrators. While further work is needed in order to fully understand the mechanisms, we believe a fruitful avenue to consider is the role played by lone wolf, single perpetrators and how Internet communication facilitates the grooming of these individuals. Spaaij (2010) notes an increasing threat from lone-wolf extremists who carry

state level. This suggests that the null result holds even when accounting for the possibility of individuals travelling out of local vicinities for organized hate group activities.

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out attacks individually and independently from established organizations. The increase in lone-wolf attacks may arise partly due to a change in hate group strategy that involves adopting a leaderless resistance operating model. In this process, racial extremists are employing the Internet to provide ideological motivation, encouragement, and justification through online propaganda and instructions to spur like-minded individuals in carrying out lone-wolf attacks.[32] In particular, Ray and Marsh (2001) found evidence that all major white-extremist sites have promoted the lone-wolf mentality to varying degrees. Moreover, an online "Lone Wolf Point System" was instituted by the racial extremist, Alex Curtis, on his website to encourage and reward individuals who engage in lone-wolf attacks on victims.[33] In addition to these findings, the split sample results suggest that the impact of online access on lone-wolf attacks tends to be stronger in locations where there are preexisting levels of racism. In line with the notion of specialization of personalized interests, it is likely that racially biased individuals tend to self select into the personal consumption of online content that supports their racial ideologies, which in turn motivate and incite them toward being lone-wolf extremists. The lack of a distinct pattern for racial hate crimes executed by multiple perpetrators further suggests that the selective viewing of online hate content is largely an individual process.

This paper has several limitations. First, given that experimental variation of broadband availability across counties does not exist, we have to rely on variation generated by instrumental variables for identification. While the diagnostic checks provide statistical validation of our IV, future research may wish to explore alternative IVs and verify our findings. Second, while we have examined two potential mechanisms through which Internet access might affect hate crime,

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[32] For instance, the White American Resistance has listed lone wolf tactics on its hate site: http://www.resist.com/Articles/literature/LawsForTheLoneWolfByTomMetzger.htm.
[33] Available on http://archive.adl.org/learn/ext_us/curtis.html?LEARN_Cat=Extremism, accessed on June 2, 2015.

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additional research is needed to study each of these mechanisms in greater depth. In addition to these two mechanisms, future research may wish to explore alternative mechanisms that are beyond the scope of this study. For instance, our work did not examine micro-level online interactions that hate crime perpetrators had prior to committing the crimes. Future work may wish to examine the various online communication patterns involved in the grooming process of racial extremists. In particular, are offline communications used in conjunction with online media at some point in time, and do "to-be perpetrators" communicate with the other extremists using more intimate forms of online communication (e.g., email, site messaging) as opposed to broadcast types of communication (e.g., forum thread discussions, public poll responses)? Knowledge of the communication patterns of perpetrators can allow for a better understanding of the online process of inciting and motivating perpetrators to action. In addition, another alternative mechanism could be that enhanced Internet access may provide a faster and more voluminous inflow of information related to the attacks on U.S. troops in foreign countries, which may in turn incite extremists to perpetrate hate crimes locally. It is important to test such alternative mechanisms as the pertinent policy implications can be very different from that of increased hate crimes induced by a growth in online hate propaganda. Finally, forward-looking questions on this topic remain unanswered due to the nascent nature of technological events. For instance, with the increased use of video and social networking sites in the last six years,[34] will Internet access promote even more hate crimes, and will this lead to new and sophisticated forms of bias-driven activity?

Our findings also suggest some possible policy implications. By assessing the impact of Internet access on racial hate crimes over the years, the study results serve to evaluate the early

[34] Reuters report that the use of sites like YouTube, Facebook and Twitter by militant and hate groups grew by almost 20% from 2009 to 2010. See http://www.reuters.com/article/2010/03/15/us-internet-hate-idUSTRE62E40O20100315.

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policies that were erected to keep the effects of online hate content at bay. First, given that online access continues to exert a positive influence on racial hate crimes despite existing efforts in monitoring and screening online hate content,[35] it is reasonable to infer that these technologically driven solutions fall short in addressing an issue that is inherently social in nature (Daniels 2009). In particular, extremists' use of sophisticated techniques in presenting racial ideologies online (e.g., cloaked websites and implicit messages) could undermine the effectiveness of these technological solutions.[36] Instead of engaging in a technological rat race with extremists, it may be more worthwhile to incorporate critical multiple literacies of digital media, anti-racism, and social justice in the education curriculum for youths, so that individual users can be skillful in analyzing online content, criticizing stereotypes, values, and ideologies, and be competent in interpreting the multiple meanings and messages found in online media (Kahn and Keller 2005). Second, the fact that most of the increase in hate crimes is concentrated in areas with a history of racism, and that there appears to be no impact on hate crimes in areas with lower levels of racism, implies that policies drawn to combat online hate content would need to consider the peculiar pattern users take in traversing the Internet. Empowered by online search engines and automatic filters, Internet users are able to play an active role in choosing information sources to interact with, making them more likely to seek out content that is aligned with their personal preferences (Van Alstyne and Brynjolfsson 2005). Given that users are unlikely to seek out online content that is counter to their viewpoints, strategies aimed at shining light on hate and exposing the lies

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[35] The FBI has been monitoring websites of hate groups since the early 2000s. See http://www.firstamendmentcenter.org/fbi-steps-up-monitoring-of-hate-groups-web-sites. Most public libraries and schools frequented by children use filtering software to screen out hate content from search results (Daniels 2009).

[36] Since the monitoring and filtering software can only respond to certain predetermined words or themes, new websites and social media sites devoted to hate propaganda may not even be identified as such.

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underlying online hate propaganda may have limited applicability.[37] As such, findings from this study suggest a need to consider alternative strategies apart from counter-speech tactics, which cannot be effectively deployed on the same online medium as hate propaganda. Third, our findings suggest that efforts directed at identifying and stopping lone wolves might be an effective means to mitigate the proliferation of hate crimes induced by the Internet. Given that lone wolves can come from various backgrounds and have widely varying motives for their actions (Spaaij 2010), a major challenge is to distinguish individuals who intend to commit actual hate crimes from those who have radical beliefs but stay within the law. The use of big data techniques to search for digital traces on online hate sites and communities may be an appropriate solution. Going forward, this motivates the need to develop additional data-driven approaches within the MIS field in order to harvest and analyze large volumes of texts (e.g., Brynielsson et al. 2013; Cohen et al. 2014), with specific goals of identifying potential lone-wolf attackers.

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[37] Christopher Wolf, chair of the Anti-Defamation League's Internet Task Force, listed such a strategy to combat online hate content, available at http://www.firstamendmentcenter.org/hate-speech-online.

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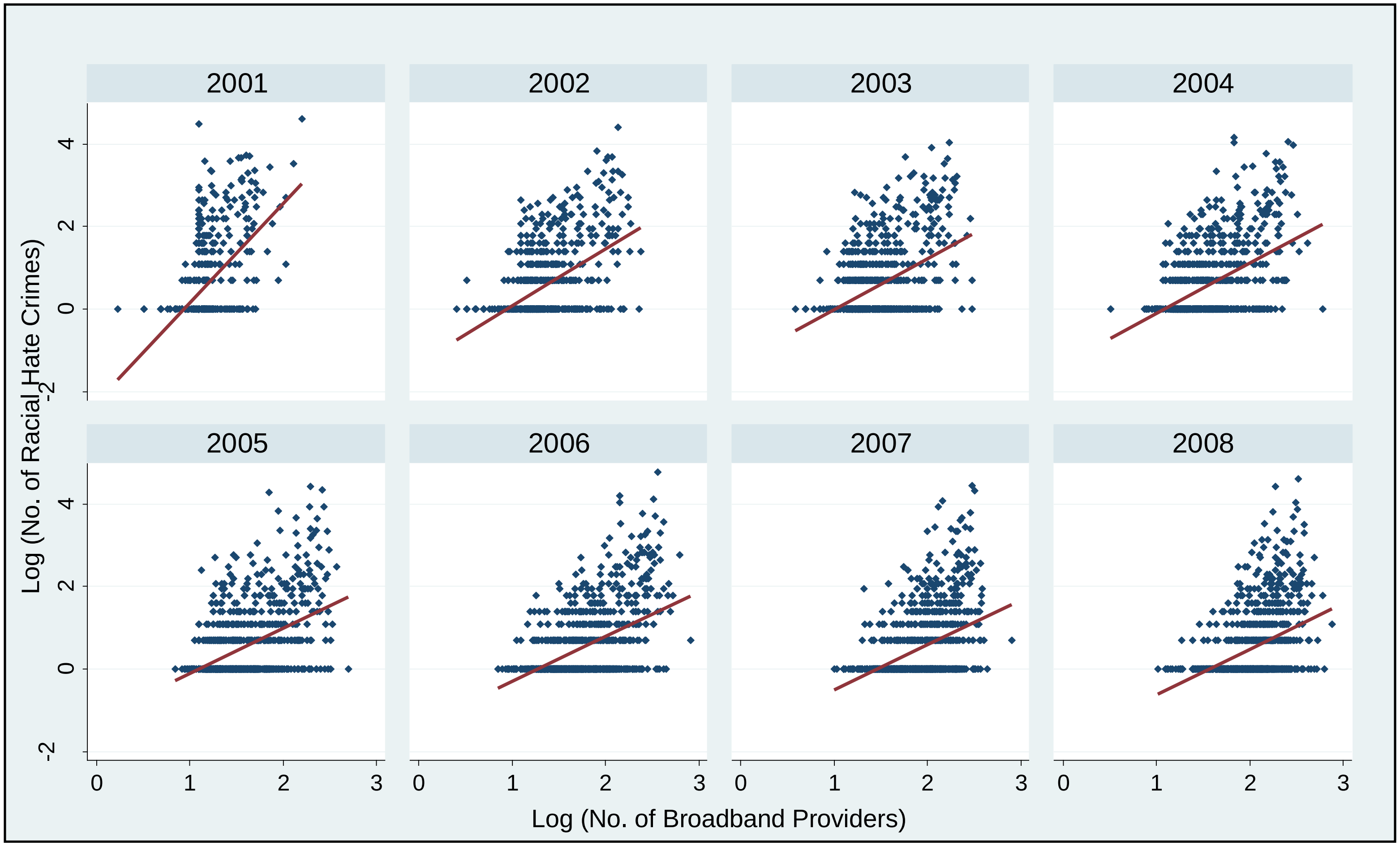

Figure 1: Relationship between racial hate crimes andthe number of broadband providers

Notes: One-year lagged values of number of broadband providers are matched to racial hate crime observations from the study period (2001 to 2008) to derive this graph. As seen, the positive slope is particularly steep for 2001, the year when the September 11 terrorism incident took place.

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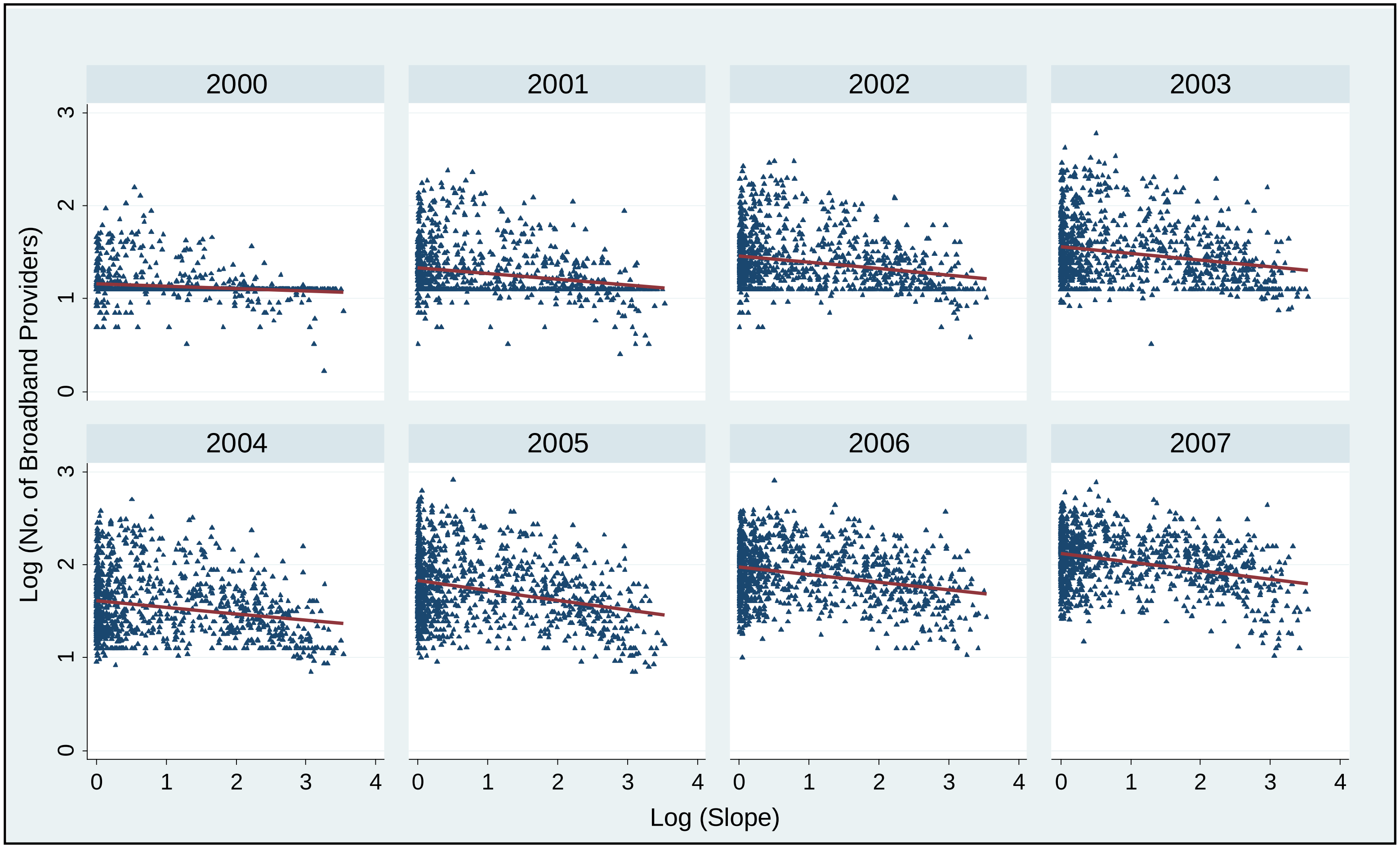

Figure 2: Relationship between thenumber of broadband providers and slope

Notes: Since one-year lagged values of broadband providers are used in our analyses, we show the graphical correlation between broadband providers and slope for 2000 to 2007. A trend is apparent in this graph: counties with low slope values (situated on the left side of each cell) are gaining more broadband providers than counties with high slope values (situated on the right side of each cell) over time. The trend leads to a stronger negative relationship over the years (i.e., steeper downward-sloping red line), which motivates the use of the slope-year interaction term as an instrument variable.

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Table 1: Descriptive Statistics (N = 8200)

Variables	Mean	Std. Dev.	Min.	Max.	Description	Source
Dependent Variables:						
No. of Racial Hate Crimes	1.718	5.65	0	118.00	Count of crimes with anti-Black, anti-White, anti-American Indian, anti-Asian and anti-Multiple races biases	FBI
Log (No. of Racial Hate Crimes)	0.477	0.80	0	4.78		
No. of Religion Hate Crimes	0.656	3.39	0	79.00	Count of crime with anti-Jewish, anti-Catholic, anti-Protestant, anti-Islamic, anti-other religion anti-Atheism and anti-multiple religion biases	FBI
Log (No. of Religion Hate Crimes)	0.190	0.54	0	4.38		
No. of Sexual Orientation Hate Crimes	0.398	1.69	0	51.00	Count of crimes with anti-male homosexuals, anti-female homosexuals, anti-homosexuals, anti-heterosexuals, and anti-bisexuals biases	FBI
Log (No. of Sex. Orientation Hate Crimes)	0.172	0.44	0	3.95		
No. of Ethnicity Hate Crimes	0.378	1.85	0	62.00	Count of crimes with anti-Hispanic, and anti-other national origin biases	FBI
Log (No. of Ethnicity Hate Crimes)	0.152	0.43	0	4.14		
No. of Disability Hate Crimes	0.036	0.38	0	16.00	Count of crimes with anti-physical disability and anti-mental disability biases	FBI
Log (No. of Disability Hate Crimes)	0.018	0.14	0	2.83		
Broadband Availability and Instrument:						
Avg. No. Broadband Providers	4.268	2.41	1.33	17.38	Average number of broadband providers across county	FCC
Log (Avg. No. of Broadband Providers)	1.562	0.42	0.22	2.91		
Slope	3.607	5.85	0	33.43	Steepness of the terrain	Arc GIS
Log (Slope)	0.937	1.01	0	3.54		
Demographic Factors:						
Population Density	261.86	768.47	0	11999	Population per square mile	US Census
Log (Population Density)	4.553	1.33	0	9.39		
Population Size	0.124M	0.214M	2068	2.057M	Annual population estimates for counties	US Census
Log (Population Size)	10.922	1.21	7.63	14.54		
Mean Age	38.189	2.51	29.34	52.80	Average age of population, calculated across different age groups	US Census
Log (Mean Age)	3.666	0.06	3.41	3.99		
No. of International Migrants	286.85	1002.05	0	15827	Annual inflow of foreign migrants to county	US Census
Log (No. of International Migrants)	3.324	2.15	0	9.67		
Proportion of African American	0.093	0.13	0	0.80	Ratio of African American to total population	US Census
Proportion of Whites	0.879	0.14	0.17	0.99	Ratio of Whites to total population	US Census
Proportion of Asians	0.011	0.02	0	0.20	Ratio of Asians to total population	US Census

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Socioeconomic Indicators:						
Median Household Income	41239	10916	17345	107200	Median household income in each county	US Census
Log (Median Household Income)	10.596	0.24	9.76	11.58		
No. of People in Poverty	13041	23734	203	407333	Count of people below the poverty level	US Census
Log(No. of People in Poverty)	8.732	1.15	5.32	12.92		
Employment Percentage	0.948	0.02	0.86	0.99	Percentage of employed individuals out of the employable population	BLS
Crime-related factors:						
No. of Police Employees	279.22	604.24	0	8342	Annual number of staff including police officers in police agencies	FBI
Log (No. of Police Employees)	4.653	1.34	0	9.03		
No. of Crimes	723.44	1455.75	0	21075	Annual number of crimes reported	FBI
Log (No. of Crimes)	5.186	2.01	0	9.96		
Industry sector size:						
Utilities Industry Payroll	10764	39261	0	0.692M	Total annual payroll of employees in industry with NAICS code 22 (in $1000)	US Census
Log (Utilities Industry Payroll)	2.943	4.44	0	13.45		
Information Industry Payroll	79703	278490	0	6.00M	Total annual payroll of employees in industry with NAICS code 51 (in $1000)	US Census
Log (Information Industry Payroll)	8.099	3.70	0	15.61		
Finance & Insurance Industry Payroll	181874	677938	0	13.7M	Total annual payroll of employees in industry with NAICS code 52 (in $1000)	US Census
Log (Finance & Insurance Ind. Payroll)	9.831	2.28	0	16.44		
Professional, Sci. & Tech. Industry Payroll	189627	703088	0	15.3M	Total annual payroll of employees in industry with NAICS code 54 (in $1000)	US Census
Log (Professional, Sci. & Tech. Ind. Payroll)	9.481	2.72	0	16.55		
Administrative and Support Industry Payroll	95713	262142	0	2.69M	Total annual payroll of employees in industry with NAICS code 56 (in $1000)	US Census
Log (Admin. & Support Industry Payroll)	8.720	3.52	0	14.81		

Notes. Hate crime data are from the years 2001 to 2008, while the regressors are from 2000 to 2007. Statistics are tabulated at the county-year level for all variables. All log transformed variables are constructed using log(X+1). Payroll information for each industry sector is used as a proxy to denote the size of each industry for each county.

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Main results

Table 2: Cross Sectional IV Regressions for Racial Hate Crimes

	Year 2001 (1)	Year 2002 (2)	Year 2003 (3)	Year 2004 (4)	Year 2005 (5)	Year 2006 (6)	Year 2007 (7)	Year 2008 (8)
1st stage DV: Log (No. of BB Providers)								
Log (Slope)	-0.012***	-0.032***	-0.051***	-0.057***	-0.042***	-0.080***	-0.042***	-0.057***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log (Population Density)	0.028***	0.058***	0.075***	0.084***	0.073***	0.089***	0.071***	0.067***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Log (Mean Age)	0.101	0.173	-0.311**	-0.114	-0.100	-0.075	-0.327***	-0.443***
	(0.08)	(0.12)	(0.13)	(0.14)	(0.15)	(0.15)	(0.12)	(0.12)
Log (No. International Migrants)	0.031***	0.047***	0.040***	0.027***	0.058***	0.055***	0.047***	0.044***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Proportion of African Americans	-0.015	0.143**	-0.082	-0.060	-0.176***	-0.158**	0.183***	0.168***
	(0.04)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.05)
Log (No. of People in Poverty)	0.035***	0.067***	0.094***	0.141***	0.101***	0.095***	0.027*	0.034***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Employment Percentage	1.236***	3.930***	2.424***	3.489***	2.471***	2.137***	1.285***	-0.054
	(0.42)	(0.50)	(0.48)	(0.49)	(0.56)	(0.58)	(0.47)	(0.46)
Log (No. of Employees in Police Force)	-0.032***	-0.034**	-0.038**	-0.044***	-0.031*	-0.018	0.002	-0.008
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Log (No. of Crimes)	0.004	-0.001	-0.001	-0.003	-0.004	-0.013***	-0.007*	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2nd stage DV: Log (No. of Racial Hate Crimes)								
Log (No. of BB Providers)	2.322	2.620***	1.582***	1.254***	1.224**	1.022***	1.573***	1.180***
	(1.86)	(0.74)	(0.43)	(0.39)	(0.53)	(0.27)	(0.55)	(0.40)
Log (Population Density)	-0.034	-0.131***	-0.063*	-0.035	-0.051	-0.052	-0.078*	-0.037
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Log (Mean Age)	0.230	-0.239	0.928*	0.787*	0.821*	0.261	0.833*	0.343
	(0.40)	(0.45)	(0.47)	(0.44)	(0.42)	(0.40)	(0.47)	(0.45)
Log (No. International Migrants)	-0.005	-0.096**	-0.048*	0.009	0.021	-0.013	-0.002	-0.015
	(0.07)	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)
Proportion of African Americans	-0.024	-0.561**	-0.309*	-0.178	-0.166	0.169	-0.537**	-0.331
	(0.16)	(0.25)	(0.16)	(0.16)	(0.16)	(0.17)	(0.23)	(0.20)
Log (No. of People in Poverty)	0.119*	0.041	0.121**	0.038	0.003	0.064*	0.090**	0.085**
	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Employment Percentage	2.487	-5.798*	1.448	-1.127	-2.225	-1.239	-3.607**	0.019
	(3.16)	(3.51)	(1.91)	(2.03)	(1.98)	(1.53)	(1.67)	(1.40)
Log (No. of Employees in Police Force)	0.145**	0.174***	0.104***	0.112***	0.125***	0.131***	0.098***	0.139***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Log (No. of Crimes)	0.024*	0.037***	0.043***	0.030*	0.051***	0.060***	0.055***	0.080***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	1025	1025	1025	1025	1025	1025	1025	1025
First stage F-statistics	49.319	34.781	37.519	37.338	37.99	38.898	31.285	36.229
Stock Yogo Critical Value	8.96	8.96	8.96	8.96	8.96	8.96	8.96	8.96
Root MSE	0.6424	0.7075	0.6706	0.6609	0.6682	0.6452	0.6963	0.6718

Notes. All models are 2SLS regressions. Robust clustered standard errors are reported in parentheses. All regressors in the second stage are lagged by one period to avoid simultaneity biases. Following Stock et al. (2002), we report Stock and Yogo (2005) critical values for maximal IV size > 15%. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

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Table 3: Panel IV Regressions, Baseline Specifications

	(1)	(2)	(3)	(4)
1st Stage DV: Log (No. of BB Providers)				
Log (Slope)	-0.049***			
	(0.00)			
Log (Slope) * Year = 2001		-0.038***	-0.039***	-0.043***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2002		-0.048***	-0.041***	-0.047***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2003		-0.052***	-0.042***	-0.051***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2004		-0.043***	-0.036***	-0.041***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2005		-0.085***	-0.079***	-0.085***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2006		-0.060***	-0.053***	-0.062***
		(0.01)	(0.01)	(0.01)
Log (Slope) * Year = 2007		-0.074***	-0.064***	-0.072***
		(0.01)	(0.01)	(0.01)
2nd stage DV: Racial Hate Crimes				
Log (No. of BB Providers)	1.448***	1.208***	0.387**	0.332*
	(0.16)	(0.16)	(0.19)	(0.19)
Log (Population Density)	-0.058***	-0.044***	0.066*	0.063
	(0.01)	(0.01)	(0.04)	(0.04)
Log (Mean Age)	0.544***	0.478***	3.052***	3.434***
	(0.15)	(0.15)	(0.97)	(1.08)
Proportion of African Americans	-0.011	-0.000	0.007	0.009
	(0.01)	(0.01)	(0.01)	(0.01)
Log (No. of People in Poverty)	-0.208***	-0.181***	-0.010	-0.033
	(0.06)	(0.06)	(1.78)	(2.05)
Employment Percentage	0.067***	0.082***	0.092	0.093
	(0.02)	(0.02)	(0.10)	(0.10)
Log (No. of employees in Police Force)	0.125***	0.124***	0.026	0.055
	(0.01)	(0.01)	(0.04)	(0.04)
Log (No. of Crimes)	0.049***	0.047***	-0.012	-0.005
	(0.01)	(0.00)	(0.01)	(0.01)
Year Fixed Effects	✓	✓	✓	✓
County Fixed Effects			✓	✓
Industry Size Controls				✓
Observations	8200	8200	8200	7530
First Stage F-statistics	323.152	45.943	25.687	28.228
Stock-Yogo Critical Value	8.96	11.29	11.29	11.29
Hansen J Statistics	-	17.471	6.692	6.755
P-value of Hansen J Statistics	-	0.008	0.35	0.344
Root MSE	0.6724	0.6551	0.4199	0.4282

Notes. All models are 2SLS IV regressions. We estimate the baseline specification by incrementally adding slope-year instruments and county fixed effects in Models 1 to 3. In Model 4, we estimate the basic specification with the addition of industry size covariates, which are captured by the annual aggregate payrolls of various industries common in urbanized locations. Robust clustered standard errors are reported in parentheses. All covariates are lagged by one period to avoid simultaneity biases. Following Stock et al. (2002), we report the Stock and Yogo (2005) critical values for maximal IV size > 15% (for just-identified models) and for relative bias > 10% (for over-identified models). Demographic controls include population density, mean age, no. of international migrants and proportion of African Americans; socioeconomic controls include no. of people in poverty and employment percentage; crime-related controls include no. of police employees and no. of crimes at the county level.* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

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Another way to think about splitting data -> interaction term

Table 4: Panel IV Regressions, Split Sample Specifications

Subsample Description:	Low Entropy	High Entropy	Low Racially Charged Search	High Racially Charged Search
	(1)	(2)	(3)	(4)
2nd Stage DV: Racial Hate Crimes				
Log (No. of BB Providers)	-0.242	0.945***	-0.770	0.507**
	(0.21)	(0.33)	(0.82)	(0.20)
Log (Population Density)	0.272**	0.098**	0.033	0.108*
	(0.13)	(0.05)	(0.04)	(0.06)
Log (Mean Age)	2.784**	3.387*	1.276	5.527***
	(1.14)	(1.77)	(1.30)	(1.49)
Proportion of African Americans	0.016	-0.008	0.015	-0.001
	(0.01)	(0.02)	(0.01)	(0.02)
Log (No. of People in Poverty)	0.512	0.075	-0.493	1.776
	(1.51)	(3.72)	(2.55)	(2.04)
Employment Percentage	0.254**	-0.049	0.550*	0.033
	(0.12)	(0.16)	(0.32)	(0.12)
Log (No. of employees in Police Force)	-1.770**	-0.992	2.425	-1.337
	(0.90)	(1.26)	(2.27)	(0.92)
Log (No. of Crimes)	0.078	-0.045	0.026	0.062
	(0.06)	(0.05)	(0.06)	(0.06)
Year Fixed Effects	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓
Observations	4144	4056	3952	4024
First Stage F-statistics	19.412	11.522	2.242	28.105
Stock-Yogo Critical Value	11.29	11.29	11.29	11.29
Hansen J Statistics	5.933	9.091	7.788	4.531
P-value of Hansen J Statistics	0.431	0.169	0.254	0.605
Root MSE	0.403	0.45	0.431	0.416

Notes. All models are 2SLS IV regressions. Models 1 - 4 replicate Model 3 from Table 3A and split the sample into below (low) and above (high) median value for entropy score (Models 1-2) and racially charged search score (Models (3-4). Robust clustered standard errors are reported in parentheses. All covariates are lagged by one period to avoid simultaneity biases. Following Stock et al. (2002), we report the Stock and Yogo (2005) critical values for maximal IV size > 15% (for just-identified models) and for relative bias > 10% (for over-identified models). Demographic controls include population density, mean age, no. of international migrants and proportion of African Americans; socioeconomic controls include no. of people in poverty and employment percentage; crime-related controls include no. of police employees and no. of crimes at the county level.* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

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No effect for the Crime Reporting: What can be wrong about this result?

Table 5: Effect of Broadband on Crime Reporting Behavior

	Logistic Regression			
	Zero for 1995 and earlier		Zero for 1990 and earlier	
	(1)	(2)	(3)	(4)
Log (No. of BB Providers)	-0.007	-0.004	0.000	0.003
	(0.01)	(0.01)	(0.01)	(0.01)
MSA and Year-quarter Dummies	✓	✓	✓	✓
Demographic Controls		✓		✓
Crime-related Controls		✓		✓
Observations	131237	131232	88343	88338
Log Pseudo-Likelihood	-86140.36	-78290.00	-58047.85	-52885.21

Notes. The dependent variable is a binary variable denoting whether the respondent reported the crime. In Models 1 and 2, the broadband providers are imputed with zeros for the years 1995 and earlier. In Models 3 and 4, the broadband providers are imputed with zeros for the years 1990 and earlier. All regressions include MSA dummies and year-quarter dummies. Robust clustered standard errors are reported in parentheses. Demographic controls include race, gender, household income, marital status, and educational attainment of the respondent. Crime-related controls include the crime location and crime type. Five observations were dropped in Models 2 and 4, as the covariates predicted the outcomes perfectly. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

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Mechanisms: Lone Wolfs

Table 6: Hate Groups and Single vs. Multiple Perpetrator Effects

	No. of Hate Groups		Log (No. Racial Hate Crimes)		Log (No. Racial Hate Crimes)	
2nd stage DV:	Log Specification	Non-log Specification	Counties with no hate groups	Counties with hate groups	Single Perpetrator	Multiple Perpetrators
Listed at the top of each column	(1)	(2)	(3)	(4)	(5)	(6)
BB Providers Measure	-0.200	-0.042	0.440*	-0.070	0.229**	0.043
	(0.15)	(0.03)	(0.26)	(0.26)	(0.12)	(0.06)
Log (Population Density)	-0.002	0.040	0.065**	0.047	-0.004	0.013
	(0.02)	(0.07)	(0.03)	(0.05)	(0.01)	(0.01)
Log (Mean Age)	-1.694***	-3.848***	1.572*	4.212**	1.596***	-0.156
	(0.54)	(1.07)	(0.95)	(1.82)	(0.49)	(0.31)
Log (No. International Migrants)	-0.003	-0.007	-0.001	0.013	-0.003	0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Proportion of African Americans	-1.476**	-1.734	-0.001	-0.541	1.125*	0.257
	(0.73)	(1.28)	(1.49)	(3.12)	(0.66)	(0.42)
Log (No. of People in Poverty)	0.117	0.187	-0.034	0.390**	-0.027	0.042
	(0.07)	(0.12)	(0.10)	(0.15)	(0.06)	(0.03)
Employment Percentage	0.106	-0.212	0.066	-2.242*	-0.787*	0.404
	(0.40)	(0.73)	(0.85)	(1.33)	(0.41)	(0.26)
Log (No. of Employees in Police Force)	0.000	-0.011	0.002	0.074	-0.004	-0.000
	(0.02)	(0.03)	(0.04)	(0.08)	(0.02)	(0.01)
Log (No. of Crimes)	0.004	-0.000	-0.010	-0.014	0.003	-0.002
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.00)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	7175	7175	4976	3224	8200	8200
First Stage F-statistics	17.497	42.377	12.244	19.201	18.737	18.737
Stock-Yogo Critical Value	11.12	11.12	11.29	11.29	11.29	11.29
Hansen J Statistics	3.907	1.418	6.226	12.486	2.159	8.865
P-value of Hansen J Statistics	0.563	0.922	0.398	0.052	0.905	0.181
Root MSE	0.2108	0.4192	0.3646	0.4900	0.233	0.1393

Notes. All models are 2SLS IV regressions. Models 1 and 2 are examining the impact of broadband providers on hate group incidence. Model 1 is a log specification where both the dependent and independent variables are logged; Model 2 is a non-log specification which regresses number of hate groups on number of broadband providers. Models 3 and 4 examine the effect of broadband providers on racial hate crime across locations without and with hate group presence, respectively. Models 5 and 6 examine the impact of broadband providers on the incidence of racial hate crimes committed by single perpetrator and multiple perpetrators, respectively. Covariates used are similar to that in Table 3. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

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