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Broadband Internet, Market Demographics and Hate Groups

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Abstract

We argue that the Internet increases hate when there is better matching between buyers and sellers ("direct effect") and decreases hate when the processing of online information discredits the seller's reputation ("indirect effect"). Using data from United States commuting zones, we show that contemporary and traditional white-supremacist hate groups are more prevalent in markets with higher Internet penetration and the Internet's effect is stronger in youthful markets and weaker in educated markets. We interpret this as evidence that educated consumers are more objective when investigating information distributed over the Internet compared to youthful consumers, and that policy should address both the local supply and the demand for hate-based content. For example, policies that restrict minors' access to cyberhate overlook the importance of decreasing demand by teaching young people how to employ the necessary critical-thinking and fact-checking skills to debunk the misinformation that pervades the Internet.

Keywords

Hate, Internet, Search Costs, Social Media

1. Introduction

The expression of hate towards an entire group of people is economically relevant when it results in market failure. For example, xenophobia can lead to inefficient search and the mis-match of trades in consumer and labor markets; hate crimes, and their remedies, attract scarce criminal justice resources from federal and local governments; and political polarization can disrupt public discourse, delay public financing, and cause ineffective lawmaking. A growing economics literature focuses on the Internet and social media as some of the main reasons for the rise of hate, xenophobia, and polarization around the world. We contribute to this literature by estimating the effects of broadband Internet access on the prevalence of white-supremacist hate groups in the United States. We argue that the Internet impacts hate groups through its contrasting direct and indirect effects and show that the indirect effect varies plausibly with local market demographics that measure shifts in the demand for hate.

Before the diffusion of modern information technology, white supremacists would spend substantial resources to produce and distribute low-quality pamphlets to limited audiences in local markets. They now use low-cost computers, smartphones, and Internet connections to distribute high-quality multimedia worldwide (Potok, 2000). Prominent white nationalists such as Mike Peinovich and Donald Black are examples of hate-based entrepreneurship that employs modern information technology (Squire & Gais, 2021). Peinovich founded the alt-right blog "The Right Stuff" and hosted the hate-based podcast "The Daily Shoah". Black, who received computer training when imprisoned for his role in the 1981 attempted coup in Dominica, was an early adopter of the latest computers and broadband to keep the Stormfront website connected to "everybody in the white nationalist movement, to everyone in the world" (Barbaro, 2017).

Theory suggests that advances in information technology can impact the market for hate in two significant ways. On the one hand, a standard supply-and-demand model with transaction costs would assume that the Internet increases supply when it lowers the seller's marginal cost of producing and distributing hate-based products and increases demand when it lowers the buyer's cost of searching for products with suitable prices and features (Stigler, 1961; Bakos, 2001). These "direct effects" place upward pressure on the quantity of hate in the market through better matching of buyer preferences and seller offerings. The effect on prices is ambiguous. This is the well-known frictionless commerce prediction from Brynjolfsson and Smith (2000). On the other hand, search models would assume that the Internet decreases demand when content providers post information that debunks the false claims about out-groups, when consumers have access to more diverse information sources or pre-existing cognitive frameworks, and when hate groups are exposed to the scrutiny of law enforcement and the general public (Ellison, 2005; Glaeser, 2005; Phillips, 2016). These "indirect effects" place downward pressure on the quantity of hate through information processing that discredits the hate-monger's messaging and reputation.

Holding supply constant, the effect of the Internet on the quantity of hate traded is also expected to be higher in markets where consumers are more willing to accept the hate-creating messages delivered by hate groups. For example, the effect of Internet access on the demand for hate will be more pronounced in markets when populated by demographic groups that are less concerned about discerning truth from falsehood (Lee & Leets, 2002; Grossman & Hopkin's, 2016). For example, entrepreneurs of hate use memes and tasteless Internet humor to push hateful stories on young, impressionable, white males without parental scrutiny (Southern Poverty Law Center, SPLC, 2018a; Squire & Gais, 2021). Here, the indirect effect is likely weak and does not greatly affect the impact of Internet penetration on the demand for hate. By contrast, increases in the number of educated consumers are expected to mitigate the Internet's effect on the demand for hate when they are more efficient and objective when investigating information distributed over the Internet to learn the truth about hate-creating stories (Glaeser, 2005). In this case, the indirect effect has a relatively larger impact on the demand for hate and decreases the Internet's effect on the equilibrium quantity of hate in the market.

Ultimately, the relationship between the Internet and the demand for hate is an empirical question. However, estimating demand is problematic without local data on hate-group sales and prices. We overcome this limitation by specifying a reduced-form model of hate-group entry into commuting zones as a function of supply-and-demand factors, and the number of rivals. We identify demand shifts in the model indirectly with the principle of revealed preference. We assume that all else held constant, a hate group is more likely to be observed in a local market when consumer demand and hate-group payoffs in that market are greater than the payoffs from deploying its resources somewhere else. Under this assumption, we can test whether, conditional on control variables, there is a systematic relationship between the marginal effect of an increase in Internet access on the probability of entry and exogenous demographics that approximate consumer preferences, such as education and age. The sign of these cross partials shed light on whether the underlying demand curves for hate are shifting outward or inward, and on the relative importance of the Internet's indirect effect on the hate-group payoffs.

There are two main issues when estimating the model. The first concerns unobserved time-invariant heterogeneity that is correlated with some of the covariates in our model. Because our model is nonlinear, we control for this correlation with Mundlak (1978)-Chamberlain (1980) fixed effects. Because Internet access is not randomly assigned, unobserved market- and time-varying factors may also confound the effects of the Internet on the prevalence of hate groups in local markets. We control for this source of endogeneity with the two-step estimation approach used by Petrin and Train (2010). The excluded variables come from Internet service provider (ISP) decisions to deploy high-speed Internet to their local consumers. Deployment should be faster in areas with more houses per road mile because ISP costs are lower, and in areas with more skilled labor, because of stronger business demand for Internet services. The key identifying assumption is that conditional on controls, hate groups do not consider local shocks that affect Internet deployment when making their own market-entry decisions.

Using data from United States commuting zones in 2000, 2010, and 2017, we show a steep decline in the total number of local hate-group chapters from 273 in 2000 to 81 in 2017. We then use the estimates from our market-entry model to show that contemporary (i.e., Neo-Nazis, Racist Skinheads) and traditional hate groups (i.e., Ku Klux Klan, or KKK) are more prevalent in markets with higher Internet penetration. This suggests that the Internet's direct effects on the quantity of hate traded in the representative market dominate the indirect effects. The findings are robust to alternative specifications that include variables that interact Internet penetration with exogenous measures of education and age, a specification that employs linear two-stage least squares (2SLS), alternative definitions of hate groups, and a specification that treats immigration as endogenous.

We also estimate that a one percentage-point increase in Internet penetration is, on average, associated with a 0.9 (0.9) percentage-point increase in the probability of observing one contemporary (traditional) hate group, and that these marginal effects differ across markets. For example, the Internet's effect on the probability of observing one contemporary (traditional) group is 0.8 (0.8) percentage points when evaluated at a low level of educated adults (i.e., the 5th percentile of the number of native-born, non-Hispanic whites aged 25 and older with at least a high-school degree and age 25) and declines to a statistically insignificant 0.04 (0.02) percentage points when evaluated at an elevated level of educated adults at the 95th percentile. This suggests that the indirect effect has a relatively large impact on the demand for hate in educated markets, whereas the same effect appears to be weaker in youthful markets.

Previous economic studies of hate focused on geographical, historical and income explanations (Jefferson & Pryor, 1999; Green, Glaser, & Rich, 1998; Mulholland, 2010; Ryan & Leeson, 2011). Our paper contrasts this research by using broadband Internet penetration across commuting zones and time to examine the relationship between information technology and hate. In this respect, our paper is closer to the literature on the political-economy effects of the Internet and social media (Zhuravskaya, Petrova, & Enikolopov, 2020). For instance, Boxell, Gentzkow and Shapiro (2017) find that the growth in polarization is largest for those least likely to use the Internet and social media. This suggests that these technologies are not the main drivers of polarization. Kawakatsu et al. (2021), however, argue that partisanship occurs when interests are heavily shaped by peer-to-peer learning, with little independent exploration. Similarly, Müller and Schwarz (2023) show that increases in anti-Muslim sentiment since the start of President Trump's 2016 presidential campaign were in counties with high Twitter usage. Amorim, Lima and Sampaio (2022) find a positive relationship between high-speed Internet penetration and the 2011 Occupy Movement protests. Bursztyn et al. (2019) find that the diffusion of social media in Russia resulted in more hate crimes in areas with a high level of national sentiment. Melnikov (2023) shows that following the deployment of third-generation (3G) wireless technology in the United States, Democratic voters became more liberal, and Republicans became more conservative.

Our finding of heterogenous Internet effects aligns with studies on the Internet and education outcomes. For example, Chen et al. (2021) find that increased Internet expenditures increased both graduation rates and disciplinary problems for public school students. Controlling for the general trend in the number of hate groups, our finding that the positive relationship between the Internet and hate increases with the in-group population of youth is new and consistent with an outward shift in the demand curve for hate. While this finding supports laws that require publicly-funded schools to restrict minors' access to cyberhate on their networks, this policy prescription overlooks the importance of the youth employing the critical-thinking and fact-checking skills to debunk the misinformation that pervades the Internet. Blanket policies are also incongruent with the National Security Council's (NSC, 2021, p. 22) conclusion that the population must have the digital skills and literacy to use the Internet productively while avoiding the harmful content disseminated by malicious actors online. In short, good policy must address both the supply and the demand for hate-based content to mitigate the Internet's effect on hate, xenophobia, and polarization, and it must also serve the local market's preferences and skills.

The paper is organized as follows. The next section discusses white supremacist hate in the United States. Section 3 introduces the data. Section 4 describes the empirical model and estimation approach. The results are presented in Section 5 and Section 6 concludes.

2. White Supremacist Hate in the United States

2.1. Hate, Xenophobia, and Polarization

Hate, xenophobia, and political polarization are related. Piazza (2020) argues that political hate speech towards minorities dehumanizes opponents and increases polarization, while Finkel et al. (2020) describe polarization as "one party holding a basic abhorrence for their opponents". Bloch and Myers (2018) note that nativists will "confront employers that are perceived to be hiring immigrants". The SPLC (2018b) defines hate organizations by their attacks on groups of people by way of their nationality, race, religion, and sexuality. Glaeser (2005) defines group-level hatred as "the willingness of members of one group to pay harm to members of another group". Harm can be explicitly or implicitly paid from one group to another, and can be non-violent, violent or "too-violent". For example, Beirich and Buchanan (2018) note that the largest anti-Muslim group in the United Sates, ACT for America, has political influence, but cannot control the inflow of violent doctrine from extreme ideologies. Moreover, after the Unite the Right rally in Charlottesville in 2017, many Neo-Confederate members distanced themselves from the group because they believed it was a violent para-military organization. More generally, hate groups in the Charlottesville region likely faced increased police and public scrutiny after the rally.

Following passage of the federal Hate Crime Statistics Act in 1990, many law enforcement agencies across the country agreed to report to the uniform crime reporting (UCR) program on crimes motivated by race, gender identity, religion, disability, sexual orientations, or ethnicity. However, the reporting of these explicit expressions of hate are voluntary and incomplete throughout the United

States. The Federal Bureau of Investigation's (FBI's) reporting protocols are also subjective. Among other things, the local reporting officer must decide whether the offense is a hate crime, what bias-motivation category it belongs to, and the pertinent characteristics of the victim and the offender. In the latter case, the UCR only records the race, gender, and ethnicity of the offender, and not their ideologies, motivations, and preferences. Given the data limitations on hate crimes, we measure local consumption of hate by the number of white-supremacist hate groups in each commuting zone in the United States. The advantage is that white-supremacist hate groups are well defined and measured by the Anti-Defamation League (ADL), FBI, and SPLC. They are also categorized according to the ideologies, motivations, and preferences of their different subgroups.

2.2. Hate as an Economic Good

The variable of interest is hatred by members of white supremacist in-groups towards out-groups. In return for membership dues and other payments, hate-group consumers receive utility from interactions with fellow hate-group members and their consumption of hate-based goods that lower the utility of out-groups. Each in-group consumer will have an optimal amount of utility-decline they prefer for the out-group. When aggregated, this market demand helps determine the expected payoffs for hate groups through memberships, with or without excludability conditions, profits, and/or the power to influence other persons.

The interpretation of hate groups as optimizing agents specializing in the supply of hate-based products and earning non-trivial revenues has qualitative support. Fryer and Levitt (2012) explain the rise of the KKK in the early 1920s in terms of the benefits of group membership, such as personal protection and networking, and the costs, such as social stigma. They argue that the Klan was a multi-level marketing structure run by incentivized sales agents selling hatred, religious intolerance, and fraternity to educated professionals in a time where there was tremendous demand. They also estimate that in 1924, initiation fees, dues, and profits from the sale of robes in Indiana generated nearly $4.4 million (in 2011 dollars) for the national Klan leader, $2.6 million for the Indiana head, and $330,000 for the lead salesman.

Modern organizations require regular membership dues or donations, and sell merchandise, propaganda, and podcast subscriptions. They also charge fees for organizing concerts, conferences, and rallies (ADL, 2017). Ezekiel (2002) estimates that there were about 25,000 KKK, Neo-Nazi and Racist Skinhead members in 1994. About 150,000 persons purchased hate literature, made contributions to hate groups or attended rallies. More than 400,000 persons read hate literature. The National Alliance grossed over $1 million a year in revenue in the early 2000s and had over 1400 paying members. More recently, Crowdfunders and crypto trading have emerged as sources of revenue. The 20 most recognized hate groups generated over $20 million in contributions, grants, and sales from these sources in 2014 and 2015 (Paynter, 2017). Stiffman (2016) estimates that the average annual revenue of 52 tax-exempt hate groups equaled $1.9 million in 2015, ranging from zero to $29.8 million. Klinenberg (2022) found that a $11 discount increased membership to the Oath Keepers.

2.3. White Supremacy

The American Association of Physical Anthropologists (AAPA, 2019) define white supremacy as the belief that white people are superior and should dominate other races. The SPLC began monitoring white supremacist activity in the 1980s amid a resurgence of the KKK and other groups. Their listing of hate groups categorized white supremacists as KKK, Neo-Nazi, Racist Skinhead, and "Other". KKK is the most infamous of United States hate groups. Although Black Americans have typically been their primary target for hate, they have also attacked Jews, immigrants, members of the LGBTQ community and Catholics. Neo-Nazis hate a similar set of out-groups, share a love for Nazi Germany, and are intensely anti-Semitic. Racist Skinheads are a violent movement preparing for the hoped-for white revolution and race war (SPLC, 2021). The "Other" category includes groups and publishers endorsing a variety of doctrines that are not easily classified as typical white supremacist groups (SPLC, 1996, 2021).

Local demographics incentivize hate groups to segment markets and target different consumer preferences. We assume the KKK supplies a traditional brand of white supremacy that celebrates Confederate and Southern heritage and directs relatively less-violent actions and messages largely towards Black Americans. For example, the Knights of the Ku Klux Klan have attempted to put a "kinder, gentler" face on the KKK by courting the mainstream media and portraying itself as a modern white civil rights organization[1]. We assume that Neo-Nazi and Racist Skinhead hate groups supply a contemporary brand that celebrates nationalism and white supremacy and directs violent actions and messages towards non-whites and immigrants. Neo-Nazis and Racist Skinheads also have a national and international market presence with branded merchandise, record labels, publishing houses, websites, and annual meetings and concerts. They view the KKK, as old-fashioned noting that their online activism is "feeble" and that they are unable to adapt to the changing messaging and tactics of the radical right (Beirich & Buchanan, 2018). We abstract away from the other groups for now but check the robustness of our results to other hate group definitions in Section 5.

The SPLC assigns local hate-group branches and chapters to the city or county where they are located and active. Hate-group activities include marches, rallies, speeches, meetings, leafleting, publishing literature, and criminal acts. **Table 1** presents SPLC (2001, 2011, 2018b) data on white supremacist chapters by Census Regions in 2000, 2010 and 2017. The number of local chapters decreased slightly from 282 in 2000 to 273 in 2010. During this period, the number of traditional group chapters increased from 93 to 102 and the number of contemporary group

[1]See https://www.splcenter.org/fighting-hate/extremist-files/group/knights-ku-klux-klan.

chapters decreased from 189 to 173. This period was followed by a steep decline in the total number of local chapters from 273 in 2010 to 81 in 2017. The number of traditional chapters fell from 102 in 2010 to 44 in 2017, and the number of contemporary chapters declined from 171 to 37 over the same period. About 44 percent of the total number of local hate-group chapters were located in the South in the 2000s. This concentration is most pronounced for traditional hate-group chapters, where about 67 percent of local chapters were located in the South. The fewest number of local chapters are in the Northeast and the West.

Table 1. Local hate-group chapters.

Census Region	2000			2010			2017		
	T	C	Total	T	C	Total	T	C	Total
Northeast (NE)	9	30	39	4	26	30	2	8	10
Midwest (MW)	22	50	72	20	44	64	7	19	26
South (S)	57	60	117	73	56	129	29	5	34
West (W)	2	43	45	3	41	44	4	5	9
Multiple Census Regions+	3	6	9	2	4	6	2	0	2
Total	93	189	282	102	171	273	44	37	81
NE & MW++	0	1	1	0	1	1	0	0	0
NE & S	0	1	1	1	1	2	1	0	1
MW & S	3	3	6	1	1	1	1	0	1
MW & W	0	1	1	0	1	2	0	0	0
Traditional	**2000**			**2010**			**2017**		
	T			T			T		
KKK	93			102			44		
Total	93			102			44		
Contemporary	**2000**			**2010**			**2017**		
		C			C			C	
Neo-Nazi		154			111			27	
Racist Skinhead		35			60			10	
Total		189			171			37	

NOTES. T is traditional, C is contemporary. +Some hate groups located in commuting zones that span multiple states are located in Multiple Census Regions. ++NE & MW, NE & S, MW & S, and MW & W report groups located in Multiple Census Regions. The SPLC does not count entities that appear only in cyberspace because they are likely individual web publishers who falsely portray themselves as groups. *SOURCE.* SPLC (2001, 2011, 2018b).

3. Data

3.1. Sample Market

The sample market is a commuting zone described by the United States Department of Agriculture (Tolbert & Sizer, 1996; USDA, 2012). Commuting zones are local labor market areas comprising adjoining counties that closely reflect the local economy where people live, work and commute. A nice feature of this definition is that it captures potential consumers in a neighboring county or parish who can easily commute to a local hate group's headquarters to participate in meetings, rallies, and other events. The definition is also empirically useful as it includes markets with no hate groups. In contrast, larger markets such as a state are always likely to have at least one hate group. The important assumption for our analysis of local direct and indirect effects is that the location where a hate group is observed is also the location where the hate group operates. If our local market definition is too narrow, such that we don't include all the hate groups that are actually in the market, we may conclude that there is less entry either because of high fixed costs or the degree of competition is strong, and we will overstate the cutoff parameters in hate-group entry model (Aguirregabiria, 2017).

Table 2. United States population, immigration, and Internet penetration 1980 to 2017.

United States population												
Region	1980				2000				2017			
	Pop	Imm	Non-White	Int	Pop	Imm	Non-White	Int	Pop	Imm	Non-White	Int
Northeast	47.6	9.0	16.4	0	51.92	14.3	25.5	14.5	54.6	17.9	33.7	85.9
Midwest	57.3	3.6	12.4	0	62.57	6.0	17.6	9.8	66.4	8.0	23.1	77.2
South	73.3	4.0	25.5	0	97.39	9.5	33.1	9.3	120.6	13.1	41.7	79.7
West	40.7	10.7	25.2	0	59.94	20.0	39.3	13.4	73.6	21.0	47.5	85.9
Total	218.9	6.2	20.0	0	271.8	11.9	29.5	11.3	315.11	14.7	37.8	81.7
Immigrants												
Region	1980		2000		2017							
	Imm+	Non-White	Imm+	Non-White	Imm+	Non-White						
Northeast	4.3	35.1	7.4	64.3	9.8	73.6						
Midwest	2.1	32.1	3.7	60.8	5.3	70.1						
South	2.9	57.2	9.2	77.7	15.8	82.2						
West	4.4	63.0	11.9	80.6	15.5	82.3						
Total	13.6	48.3	32.4	73.8	46.3	79.0						

NOTES. Pop is population in millions. Imm is the population share of immigrants. Non-White is the population share of non-whites including Hispanics. Imm+ is immigrants in millions. Int is the share of residents in the market with a fixed Internet connection over 200 kbps in at least the downstream or upstream direction. *SOURCE.* ACS (2016, 2017, 2018), Ruggles et al. (2022), NTIA (2001, 2010), and FCC (2022).

The hate-group data are from 2000, 2010 and 2017. We sample this period because, as documented in **Table 2**, it corresponds to the diffusion of high-speed Internet to about ten percent of residents in 2000 to over 80 percent in 2017, and because 2017 was the most recent hate group data available from the SPLC. This period also captures relatively large changes in both the number and composition of immigrants living in the United States, which are also documented in **Table 2**, and in the **Appendix**. This variation is useful for identifying the relationships between broadband Internet access and hate-group payoffs and between foreign-born populations and payoffs in Section 5.

3.2. Variables

We measure three dependent variables indicating the presence of white supremacist hate in local markets. $Any\ Hate_{mt}$ equals the number of contemporary and traditional hate-group chapters in commuting zone m in year t. $Contemporary\ Hate_{mt}$ equals the number of contemporary chapters in commuting zone m in year t. $Traditional\ Hate_{mt}$ equals the number of traditional chapters in commuting zone m in year t. The dependent variables do not count redundant chapters when a hate-group branch has multiple chapters in a zone. We use $Any\ Hate_{mt}$ initially in a univariate ordered probit model that assumes all hate groups are the same. We then relax this assumption and permit different brands of hate in the bivariate ordered probit model, using $Contemporary\ Hate_{mt}$ and $Traditional\ Hate_{mt}$ as the dependent variables.

We match the number of hate groups in the 722 commuting zones in the continental United States to demographics for the years 2000, 2010 and 2017. Most of these variables are constructed from the IPUMS from the 1980, 1990, and 2000 decennial census, and the American Community Survey (ACS). We pool the 2009-2011 and the 2016-2018 ACSs for 2010 and 2017, respectively. The IPUMS data are matched to commuting zones using relationship files from Autor and Dorn (2013) and Autor, Dorn, and Hanson (2019). We use data from IPUMS (Ruggles et al., 2022), Kneebone and Torres (2015), the FCC (2022), the NTIA (2001, 2010), the Association of Religion Data Archives (2025), and David Leip's Atlas of United States Presidential Elections (2025) to construct market-level measures of the in-group, information technology, and other market conditions. The **Appendix** provides a detailed description of the variables used in the empirical analysis.

Following the market-entry literature, both $Uneducated\ Pop_{mt}$ (the number of native-born, non-Hispanic whites without high-school degrees and age 25 and above) and $Educated\ Pop_{mt}$ (the number of native-born, non-Hispanic whites with at least a high-school degree and age 25 and above) are measured as counts to approximate market size. In-group preferences are measured by $In\text{-}Group\ Income_{mt}$ (the median income of households headed by a native-born, non-Hispanic white) and $Out\text{-}Group\ Income_{mt}$ (the median income for households headed by an out-group member who is non-white, Hispanic, or an immigrant). Local preferences are measured by: $Evangelical_{mt}$ (the share of the population that is evangelical Protestant); $Protestant_{mt}$ (the share of the population that is mainline Protestant); $Republican_{mt}$ (the share of total voters who voted Republican in the most-recent Presidential election); $Youth_{mt}$ (the share of the in-group population of children, aged 19 and younger)[2]; $Immigration_{mt}$ (the share of the population that was not born in the United States); $Native\ Non\text{-}White_{mt}$ (the share of the native population that is Black, Hispanic, Asian, or Other Race); $Confederate_m$ (equals one when market m is in one of the former Confederate States of America, and zero otherwise); and $Klan\ 1924_m$ (equals one when market m had an active KKK chapter during the Klan's second rise from 1915 in 1924, and zero otherwise)[3]. Information technology is measured by $Internet_{mt}$ (the share of residences with a fixed Internet connection over 0.2 Mbps in at least the downstream or upstream direction).

3.3. Summary Statistics

Table 3 tabulates all the market structures in the sample. The dominant market structure is no white supremacist hate groups. Entry by one contemporary group is the second most likely outcome, followed by entry by one traditional group. Entry by one contemporary and one traditional group are the most likely market structures for the remaining outcomes, followed closely by markets that contain two contemporary groups and no traditional groups. The number of markets with four or more contemporary groups has fallen over time. The maximum number of traditional groups in a market has also fallen over time from three to two, and there are only two markets with two traditional hate groups in 2017. Given these distributions, we set $Contemporary\ Hate_{mt}$ to three in our empirical model when the number of groups in a market equals three or more and set $Traditional\ Hate_{mt}$ to two when the number of groups equals three. The maximum number of $Any\ Hate_{mt}$ is set to five. The implication from these restrictions is that the marginal effect of additional entrants beyond their truncated levels equals zero.

Table 4 presents means and standard deviations for the independent variables in our empirical model. Columns two and three show that markets with at least one contemporary or one traditional hate group have a higher share of immigrants and native non-whites in their local population, more uneducated (and educated) in-group persons, and more in-group persons with higher incomes. They are also more likely to have had an active KKK chapter during the second rise of the Klan and are more likely to be located in former Confederate states. These same markets have lower shares of mainline Protestants and Republican voters.

[2]For robustness, we also measured youth with the population aged 13 to 18 years, and the population aged 14 years or younger, respectively. The results, not reported, are similar to those discussed in Section 5.

[3]We use the IPUMS variable RACHSING to define our race and Hispanic variables. We also include three border-year interaction terms, $Border_m \times YEAR\ 2000_t$, $Border_m \times YEAR\ 2010_t$, and $Border_m \times YEAR\ 2017_t$, where $Border_m$ equals one when market m is located in California, Arizona, New Mexico, or Texas, and zero otherwise, to control for unobserved time-varying shocks to immigration in the border states.

Columns four and five show that markets with at least one contemporary hate group have similar residential Internet penetration compared to markets with at least one traditional group, a higher share of immigrants in their local population, more uneducated (and educated) in-group persons, and higher out-group median incomes. These same markets have lower shares of Evangelicals and Republican voters and are less likely to be located in former Confederate states.

Table 3. Hate-group tabulations.

2000-2017				*Contemporary*			
Traditional	0	1	2	3	4	5+	Total
0	1761	139	29	15	10	3	1957
1	129	36	13	1	0	3	182
2	15	7	1	0	0	1	24
3	2	1	0	0	0	0	3
Total	1907	183	43	16	10	4	2166
2000				*Contemporary*			
Traditional	0	1	2	3	4	5+	Total
0	554	60	17	9	4	2	646
1	37	15	10	0	0	0	62
2	6	4	1	0	0	0	11
3	2	1	0	0	0	0	3
Total	599	80	28	9	4	2	722
2010				*Contemporary*			
Traditional	0	1	2	3	4	5+	Total
0	552	58	10	5	5	1	631
1	57	16	3	1	0	3	80
2	7	3	0	0	0	1	11
Total	616	77	13	6	5	2	722
2017				*Contemporary*			
Traditional	0	1	2	3	4	5+	Total
0	655	21	2	1	1	0	680
1	35	5	0	0	0	0	40
2	2	0	0	0	0	0	2
Total	692	26	2	1	1	0	722

SOURCE. SPLC (2001, 2011, 2018b).

Table 4. Summary statistics.

Variables	Full Data	No	Any	C	T	2000	2010	2017
Any Hate$_{mt}$	0.29	-	1.55	1.78	1.57	0.39	0.36	0.11
	(0.72)	-	(0.91)	(1.04)	(0.88)	(0.84)	(0.81)	(0.39)
Contemporary Hate$_{mt}$	0.17	-	0.91	1.42	0.42	0.25	0.21	0.05
	(0.52)	-	(0.89)	(0.71)	(0.72)	(0.62)	(0.58)	(0.26)
Traditional Hate$_{mt}$	0.11	-	0.58	0.28	1.13	0.12	0.14	0.06
	(0.35)	-	(0.61)	(0.53)	(0.34)	(0.38)	(0.39)	(0.25)
Internet$_{mt}$	45.65	46.75	40.88	40.08	40.58	9.27	54.96	72.72
	(28.96)	(28.96)	(28.50)	(29.47)	(27.81)	(4.09)	(11.99)	(14.52)
Immigration$_{mt}$	5.64	5.32	7.05	8.34	5.65	4.84	5.82	6.27
	(5.37)	(4.96)	(6.73)	(7.47)	(5.44)	(5.05)	(5.46)	(5.51)
Native Non-White$_{mt}$	17.28	16.87	19.08	18.08	20.83	15.51	17.34	19.01
	(14.42)	(14.80)	(12.54)	(11.40)	(13.37)	(14.10)	(14.46)	(14.52)
Uneducated Pop$_{mt}$	17.33	10.64	46.42	57.71	39.94	23.77	15.68	12.52
	(29.43)	(14.86)	(51.36)	(58.87)	(41.61)	(40.01)	(23.97)	(18.93)
Educated Pop$_{mt}$	162.41	95.13	454.97	594.66	359.26	149.06	164.92	173.26
	(348.76)	(188.82)	(625.27)	(717.34)	(550.54)	(333.84)	(349.46)	(362.44)
In-Group Income$_{mt}$	36.54	35.76	39.94	42.04	38.14	37.23	35.19	37.20
	(6.78)	(5.93)	(8.86)	(8.97)	(8.70)	(6.63)	(6.48)	(7.03)
Out-Group Income$_{mt}$	26.81	26.50	28.17	30.09	25.97	27.87	25.19	27.38
	(6.22)	(6.01)	(6.93)	(6.59)	(6.54)	(6.15)	(5.79)	(6.39)
Evangelical$_{mt}$	24.53	24.45	24.84	19.23	31.71	27.19	23.07	23.32
	(17.67)	(17.82)	(17.03)	(14.16)	(17.41)	(20.83)	(16.48)	(14.89)
Protestant$_{mt}$	14.96	15.63	12.02	12.26	11.88	17.73	15.07	12.07
	(10.93)	(11.61)	(6.48)	(6.65)	(6.05)	(11.87)	(10.83)	(9.19)
Republican$_{mt}$	58.27	59.33	53.68	51.15	56.40	57.29	56.06	61.47
	(12.91)	(13.15)	(10.71)	(9.78)	(10.98)	(10.92)	(12.63)	(14.35)
Youth$_{mt}$	24.66	24.64	24.73	24.93	24.61	26.71	24.14	23.12
	(2.75)	(2.84)	(2.31)	(2.42)	(2.07)	(2.21)	(2.26)	(2.41)
Klan 1924$_{m}$	0.47	0.40	0.75	0.78	0.77	0.47	0.47	0.47
	(0.50)	(0.49)	(0.43)	(0.42)	(0.42)	(0.50)	(0.50)	(0.50)

Continued

Confederate$_m$	0.34	0.32	0.44	0.31	0.59	0.34	0.34	0.34
	(0.47)	(0.46)	(0.50)	(0.46)	(0.49)	(0.47)	(0.47)	(0.47)
Border$_m$	0.14	0.15	0.13	0.13	0.12	0.14	0.14	0.14
	(0.35)	(0.35)	(0.33)	(0.34)	(0.33)	(0.35)	(0.35)	(0.35)
Density$_{mt}$	14.25	10.83	29.13	34.53	25.24	13.67	14.76	14.33
	(17.14)	(11.78)	(26.39)	(29.90)	(22.49)	(16.32)	(17.50)	(17.57)
Commercial$_{mt}$	5.90	5.57	7.33	8.02	6.77	5.72	5.99	5.97
	(1.97)	(1.59)	(2.67)	(2.74)	(2.46)	(1.84)	(2.13)	(1.91)
B$_{mt}$	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.01)
Total Any Hate$_{mt}$ $^{+}$	0.29	-	1.57	1.82	1.61	0.39	0.38	0.11
	(0.76)	-	(1.03)	(1.19)	(1.04)	(0.84)	(0.90)	(0.39)
Total Contemporary Hate^{+}	0.18	-	0.98	1.53	0.46	0.26	0.24	0.05
	(0.62)	-	(1.12)	(1.05)	(0.95)	(0.68)	(0.75)	(0.28)
Total Traditional Hate$_{mt}$ $^{+}$	0.11	-	0.59	0.29	1.14	0.13	0.14	0.06
	(0.36)	-	(0.64)	(0.55)	(0.39)	(0.41)	(0.39)	(0.25)
Contemporary State Hate$_{mt}$	1.50	1.52	1.42	1.21	1.64	0.05	2.21	2.23
	(1.34)	(1.33)	(1.38)	(1.35)	(1.41)	(0.23)	(1.12)	(0.98)
Traditional State Hate$_{mt}$	0.77	0.73	0.92	0.78	1.09	0.03	1.68	0.59
	(0.89)	(0.87)	(0.94)	(0.91)	(0.96)	(0.17)	(0.58)	(0.78)
Observations	2166	1761	405	259	209	722	722	722

NOTES. Full data is pooled over 722 commuting zones and three time periods. No is no hate groups, Any is contemporary plus traditional groups, C is contemporary, T is traditional. Standard deviations in parentheses. $^{+}$*Total Any Hate$_{mt}$*, *Total Contemporary Hate$_{mt}$* and *Total Traditional Hate$_{mt}$* do not impose cap on the number of hate groups in a commuting zone.

4. Empirical Method

4.1. Market Entry

There are no data on sales and prices to estimate the demand for hate and its relationship with information technology. We overcome these limitations by using hate-group counts and market demographics to estimate hate-group entry into commuting zones as a function of supply-and-demand factors, and the number of rivals. We use our estimates to measure the marginal effects of the Internet on the probability of hate-group entry into a market. We then test how the marginal effects vary with exogenous covariates that approximate consumer preferences and infer whether the underlying demand curves for hate are shifting outward or inward.

We assume that contemporary and traditional hate groups supply independent products and specify separate market-entry models for each product type. There are $n_{imt} = 1, \cdots, N_{imt}$ potential hate group entrants deciding to be active or not in local market $m = 1, \cdots, M$ at time $t = 1, \cdots, T$, where $i = 1, 2$ indicates contemporary and traditional hate, respectively. All groups are assumed to be homogenous within their product type, contemporary or traditional, and to not switch between product types. The present value of net benefits for a hate group in the market following post-entry competition with n_{imt} active groups is represented by the indirect payoff function $\pi_{imt}(n_{imt})$. Payoffs $\pi_{imt}(n_{imt})$ are expected to decrease with the number of hate groups in the market and all groups know their own and rivals' payoffs. Each hate group makes its entry decision market-by-market at each point in time and groups will continue to enter a market until it is no longer valuable to do so. Holding costs and demand conditions constant, the equilibrium number of hate groups for type i in market m, at time t, are described by:

$$\pi_{imt}\left(n_{imt}^{*}\right) \geq 0 \text{ and } \pi_{imt}\left(n_{imt}^{*}+1\right) < 0 \tag{1}$$

Estimation requires the specification of payoffs. Following Toivanen and Waterson (2005) and Manuszak and Moul (2008), we specify reduced-form entry equations for contemporary and traditional hate groups, respectively. The unobserved payoffs for hate-group type i are:

$$\pi_{imt}\left(n_{imt}\right): \pi_{imt} = \alpha_{im} + \tau_{it} + X'_{mt}\beta_i + g_i\left(n_{imt}, \mu_i\right) + \varepsilon_{imt} \tag{2}$$

where α_i are market fixed effects, τ_i are time fixed effects, X are supply-and-demand characteristics of the market, $g_i(\cdot)$ are market structure functions that describe the number of rivals, $n_i = 1, \cdots, N_i$ are the number of hate groups in the market, β are market coefficients, $\mu_i(1), \mu_i(2), \cdots, \mu_i(N_{imt})$ are market structure coefficients that measure the effects on entry from additional rivals, and ε_i are random errors measuring the market characteristics observed by hate groups but not by the researcher. Assuming $\mu_i(1) \leq \mu_i(2) \leq \cdots \leq \mu_i(N_{imt})$ and given that $\overline{\pi}_{imt} = \alpha_{im} + \tau_{it} + X'_{mt}\beta_i$, the probability of observing $n_{imt} = n_i$ hate groups in equilibrium in terms of the thresholds for the unobserved random variables is:

$$P\left[\mu_1(n_1) - \overline{\pi}_{1mt} \leq \varepsilon_{1mt} < \mu_1(n_1+1) - \overline{\pi}_{1mt}, \mu_2(n_2) - \overline{\pi}_{2mt} \leq \varepsilon_{2mt} < \mu_2(n_2+1) - \overline{\pi}_{2mt}\right] \tag{3}$$

Equations (1) through (3) can be specified as a probability model of market entry with the number of hate groups as the dependent variables. We first set the unknown competition coefficients or "cutoffs" for the boundary conditions to $\mu_i(0) = \infty$ and $\mu_i\left(n_{imt}^{*}+1\right) = -\infty$. We then assume that conditional on regressors, mean-zero ε_{1mt} and ε_{2mt} are independent and identically distributed bivariate standard normal with unit variances and correlation ρ over m and t. The probability of the number of contemporary and traditional groups in each market and period is:

$$\begin{aligned} P\left[n_{1mt}=n_1, n_{2mt}=n_2\right] = {} & \Phi\left[\mu_1\left(n_1+1\right)-\bar{\pi}_{1mt}, \mu_2\left(n_2+1\right)-\bar{\pi}_{2mt}, \rho\right] \\ & -\Phi\left[\mu_1\left(n_1\right)-\bar{\pi}_{1mt}, \mu_2\left(n_2+1\right)-\bar{\pi}_{2mt}, \rho\right] \\ & -\Phi\left[\mu_1\left(n_1+1\right)-\bar{\pi}_{1mt}, \mu_2\left(n_2\right)-\bar{\pi}_{2mt}, \rho\right] \\ & +\Phi\left[\mu_1\left(n_1\right)-\bar{\pi}_{1mt}, \mu_2\left(n_2\right)-\bar{\pi}_{2mt}, \rho\right] \end{aligned} \tag{4}$$

where Φ is the bivariate standard normal cumulative distribution. Given independence, we can add the log likelihoods for all the observations in Equation (4) and estimate market entry with maximum likelihood estimation (MLE). The assumption that the data are independent and identically distributed conditionally on regressors ensures consistent estimation of the coefficients on market characteristics and the number of competitors.

4.2. Estimation Issues

Our initial concern is that the unobserved time-invariant market heterogeneity is correlated with elements of the market characteristics vector, X_{mt}. Standard MLE of a probit model with market fixed effects is problematic because of the incidental parameters problem. Wooldridge (2002) and Papke and Wooldridge (2008) suggest using the Mundlak (1978)-Chamberlain (1980) device that uses a linear projection on the time averages of market characteristics to control the correlation between unobserved heterogeneity and these covariates. We follow their approach by assuming a conditional normal distribution for heterogeneity with linear expectation and constant variance. We then use $T^{-1}\Sigma_t x_{mt}$ to calculate the 1 × K vector of time averages for the exogenous variables and add this vector of time averages $\bar{X}_m$ to payoffs as additional variables. This correlated random effects (CRE) approach has an intuitive interpretation—after adding the controls for heterogeneity, the partial effects are the effects of changing X_{mt} on local market entry while holding the time average constant (Wooldridge, 2019).

Another concern is unobserved market- and time-varying factors that may confound the effects of information technology on hate-group payoffs. One possibility is the tendency of consumers to prefer online news and social media that reinforces their political viewpoint, instead of analyzing the facts of the story. This local preference for media bias will be positively correlated with the demand for high-speed Internet and the demand for hate when a majority of consumers use the Internet to reinforce their tastes. The preference for media bias will be negatively correlated with the demand for high-speed Internet and positively correlated with the demand for hate when a majority of consumers use the Internet to objectively reject the promotion and consumption of hate. As such, estimates of the impact of the Internet on payoffs will have an upward bias when consumers use the Internet to reinforce their viewpoints and a downward bias when consumers use the Internet objectively. The standard instrumental-variable techniques typically used to alleviate this bias produce inconsistent estimates in our discretechoice model because the Internet and the random errors enter the model nonlinearly. We follow Petrin and Train (2010) by employing a two-step control-function approach to correct hate-group payoffs for the endogeneity of the Internet.

To fix ideas, let the share of residences in the market with the Internet (s_{mt}) be endogenous and additively separable in observed exogenous variables and unobserved factors:

$$s_{mt} = s\left(Z_{mt}, \bar{X}_m, \bar{W}_m, \varphi\right) + v_{mt} \tag{5}$$

where $Z_{mt} = \left[\tilde{X}_{mt}, W_{mt}\right]$ is a 1 × R (> K) vector of all the exogenous variables in the system, $\tilde{X}_{mt}$ is a 1 × (K − 1) vector of market characteristics absent the scalar s_{mt}, $\bar{W}_m$ is a 1 × (R − K) vector of the within-market means of the instrumental variables, φ is a vector of estimated parameters, and v_{mt} is the unobserved factors. The vectors $\bar{X}_m$ and $\bar{W}_m$ enter Equation (5) as a result of the Mundlak-Chamberlain treatment of unobserved heterogeneity. The vector W_{mt} contains the excluded instrumental variables that are used to identify the effects of the endogenous variable on hate-group payoffs.

Decomposing ε_{imt} into its mean conditional on v_{mt}, and deviations around the mean, results in $\varepsilon_{imt} = E\left[\varepsilon_{imt} \middle| v_{mt}\right] + e_{imt}$. By construction, these deviations are uncorrelated with v_{mt}, and therefore not correlated with s_{mt}. The control function $h\left(v_{mt}, \omega_i\right)$ equals the conditional expectation of ε_{imt}, where the vector ω_i contains the control function's parameters. Substituting the control functions into each hate group's payoff function gives:

$$\pi_{imt} = \bar{X}'_m \xi_{xi} + \bar{W}'_m \xi_{wi} + \tau_{it} + X'_{mt}\beta_i - \mu_i\left(n_{imt}\right) + h_i\left(v_{mt}, \omega_i\right) + e_{imt} \tag{6}$$

where ξ_{xi} and ξ_{wi} are parameters to be estimated and e_{imt} is the mean-zero random error in payoffs. Conditioning on the part of the endogenous variable correlated with the unobserved payoffs, $h_i\left(v_{mt}, \omega_i\right)$, controls for omitted variable bias and MLE of the bivariate ordered probit model will now produce consistent estimates.

A related issue concerns the measurement of high-speed Internet as 0.2 Mbps in at least the downstream or upstream direction. This was the FCC's broadband definition until 2010, when it changed to four Mbps downstream and one Mbps upstream, before changing again in 2015 to 25 Mbps downstream and three Mbps upstream. Given the popularity of video conferencing and remote teamwork, the FCC justified these changes to accommodate video streaming along with basic browsing[4]. Because we do not have local data on residential subscribers with these higher speeds, we use $Internet_{mt}$ to approximate the true value of quality-adjusted high-speed Internet penetration. Measurement error in this variable will lead to biased estimates of the effects of information technology on hate-group payoffs and inflated standard errors. However, since $Internet_{mt}$ is already treated endogenous in our two-step maximum likelihood estimator, the potential bias from meas-

[4]See, for example, https://broadbandnow.com/report/fcc-broadband-definition.

urement error should not be a serious problem[5].

We estimate the corrected hate-group payoff functions with two steps. Step-one estimates Equation (5) by pooled ordinary least squares (OLS). The residuals provide estimates of v_{mt} that form the control functions. Step-two includes the control functions in the hate group's payoff functions and estimates Equation (6) by maximum likelihood. Because v_{mt} are estimated, they introduce additional variance into the estimator of the bivariate ordered probit model. We use nonparametric bootstrap, which accounts for the sequential two-step nature of our estimator, to obtain consistent standard errors for the coefficient estimates in Equation (6). Although our estimator assumes independent data, this is unlikely to hold in the sample when the payoffs within each commuting zone share common characteristics through time. When this dependence is large, the estimated standard errors may be problematic. We address this during estimation by using a cluster-pairs bootstrapping program that samples clusters of observations within a commuting zone, with replacement, to account for arbitrary within-market correlations (Cameron & Trivedi, 2010). Each replication estimates the first-step information technology regression, recovers the residuals, and estimates the bivariate-ordered-probit model with maximum likelihood and corrected standard errors. The bootstrap includes 1000 iterations. Because we do not specify an explicit structure of correlation, our likelihood approximates the true likelihood and is termed pseudolikelihood. The hypothesis tests in Section 5 are Wald tests.

5. Results

5.1. Identification

The effects of market characteristics and the number of players on payoffs are identified by within-market time variation in the demographics and the number of hate groups across all markets. The effects of the Internet are identified by within-market time variation in Internet penetration across all markets, and by the exclusion restrictions. We use the cost and demand shifters, $Density_{mt}$ (the number of households per local road mile in the market) and $Commerical_{mt}$ (the ten-year lagged share of participants in the local labor market from the finance, insurance, and real estate sectors; computer and data processing services, as well as the communications industries), as excluded instruments for $Internet_{mt}$. Residential Internet is more likely in markets where network costs can be defrayed over more premises. The total miles of local roads in the commuting zone approximates the size and common cost of the outside plant used to connect the Internet to each household. When more houses per road mile reduces the average cost of deployment and maintenance, $Density_{mt}$ will be positively correlated with *Inter-*

[5]Appendix notes that county-level data on the number of fixed residential Internet connections are not available in 2000 for measuring $Internet_{m}$ and are interpolated. The involves computing 2000 to 2010 ratios in broadband penetration for an MSA and applying those ratios to county-specific 2010 data and then aggregating up to commuting zones. Because the MSA data are estimates from a survey, and the 2000 data are interpolated, $Internet_{mt}$ is measured with error. This measurement error is alleviated with our two-step maximum likelihood estimator.

net_{mt}. Forman, Goldfarb, Greenstein (2012) argue that skilled labor drives business demand for high-speed Internet. $Commerical_{mt}$ is positively correlated with $Internet_{mt}$ when more employment in the communications, data processing, finance, insurance, and real estate sectors increases the network's quality and provides complementary revenue to Internet service providers[6]. The key identifying assumption is that conditional on controls, hate groups do not consider local shocks to Internet deployment when making their own market-entry decisions.

Column one of **Appendix** presents the results from the first-step OLS regression of $Internet_{mt}$ on the Mundlak-Chamberlain controls, year fixed effects, and all the exogenous variables in Z_{mt}. This first step has an R-squared of 0.907. An F-test rejects the null that the estimated coefficients on the excluded instruments jointly equal zero ($F(2, 721) = 19.85$; Prob > F = 0.00). The estimated coefficients on $Density_{mt}$ and $Commerical_{mt}$ are statistically different from zero and enter the first-step regression with their expected positive signs. Several other coefficients in this regression are statistically significant and have economic interest. For example, Internet penetration increases with the educated in-group's population, and with immigration. This latter result is consistent with foreign-born persons locating in inner-city, urban markets where the cost of deploying the Internet is also lower. We use the OLS estimates to calculate the residuals and to construct the control function $h(\hat{v}_{mt}, \omega) = \omega\hat{v}_{mt}$ for inclusion in the hate-group payoff functions.

5.2. Hate Group Payoffs and Marginal Effects

Table 5 presents ordered-probit estimates of market entry by hate groups. For comparison, columns one through three report the results with no control functions and columns four through six report the preferred results with the corrections for the endogeneity of the Internet. The estimated coefficient on $Internet_{mt}$ equals 0.011 and is statistically different from zero at the five percent level in the uncorrected specification of contemporary payoffs. This estimate increases to 0.098 and is significant at the five percent level in the corrected specification. The relationship between the Internet and traditional payoffs follows a similar pattern. The estimated coefficient on $Internet_{mt}$ is an imprecise −0.002 in the uncorrected specification and rises to a statistically significant 0.077 in the corrected specification. The negative bias on the uncorrected estimates is consistent with the media bias story that unobserved preferences for objective information from the Internet are inversely correlated with the local demand for hate.

The estimated coefficients on the controls for market size and preferences are important determinants of entry. Because larger markets have more customers and payoffs, an increase in market size is expected to increase hate-group payoffs and the likelihood of entry. The estimated coefficient on $Uneducated\ Pop_{mt}$ is pos-

[6] $Commerical_{mt}$ is lagged because current shocks to the demand for technical workers may affect the Internet and the supply and demand of hate. Since infrastructure is a function of current and historical investments, the historical supply of workers affects current Internet quality and penetration but should not directly affect hate-group payoffs.

itive and significant at the ten percent level and suggests that demand is increasing in the number of in-group adults that did not graduate from high school. The negative and significant coefficient on *Educated* Pop_{mt} in the contemporary payoff is consistent with the notion that educated in-group adults are less likely to accept the hate-creating messages delivered by hate groups and may help debunk the veracity of these messages. The estimated coefficients on *In-Group* $Income_{mt}$ and *Out-Group* $Income_{mt}$ in the contemporary equation have opposite signs. This suggests that an increase in the out-group's status relative to the in-group increases contemporary group payoffs and their likelihood of market entry. These results align with Glaeser's (2005) argument that hate is an economic good and that hate groups rationally spread hatred to satisfy in-group preferences. Market size and relative income are not significant in the traditional hate-group payoffs. The estimated coefficient on $Youth_{mt}$ in the contemporary equation is positive and significant at the ten percent level and supports the SPLC's (2018a) observation that contemporary hate groups target young audiences. The coefficients on $Republican_{mt}$ are positive in contemporary and traditional payoffs.

Table 5. Ordered probit estimates of market entry.

Variables	MLE With No Control Functions			Two-Step MLE With Control Functions			Difference
	Any Hate	*Contemporary*	*Traditional*	*Any Hate*	*Contemporary*	*Traditional*	$C - T^{+}$
$Internet_{mt}$	0.006	0.011**	−0.002	0.092**	0.098**	0.077*	0.022
	(0.005)	(0.004)	(0.007)	(0.036)	(0.042)	(0.042)	(0.050)
$Immigration_{mt}$	−0.062	−0.013	−0.141**	−0.166**	−0.119	−0.239**	0.120
	(0.047)	(0.053)	(0.071)	(0.078)	(0.087)	(0.103)	(0.123)
Native Non-White$_{mt}$	−0.053**	−0.043	−0.063**	−0.057*	−0.051	−0.065*	0.014
	(0.025)	(0.030)	(0.031)	(0.031)	(0.036)	(0.036)	(0.045)
Uneducated Pop_{mt}	0.004*	0.004	−0.003	0.008*	0.008*	−0.000	0.008
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)
Educated Pop_{mt}	−0.002**	−0.004***	0.001	−0.005***	−0.007***	−0.002	−0.005
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
In-Group $Income_{mt}$	−0.034	−0.071***	0.024	−0.025	−0.063*	0.033	−0.096***
	(0.022)	(0.027)	(0.028)	(0.027)	(0.033)	(0.033)	(0.045)
Out-Group $Income_{mt}$	0.031*	0.065***	−0.018	0.022	0.056**	−0.026	0.083***
	(0.016)	(0.022)	(0.018)	(0.019)	(0.025)	(0.021)	(0.030)
$Evangelical_{mt}$	−0.006	−0.004	−0.005	−0.015	−0.012	−0.013	0.001
	(0.004)	(0.007)	(0.004)	(0.015)	(0.016)	(0.015)	(0.016)

Continued

Protestant$_{mt}$	−0.004	−0.022	0.007	−0.037	−0.057*	−0.023	−0.033
	(0.020)	(0.023)	(0.023)	(0.027)	(0.030)	(0.031)	(0.039)
Republican$_{mt}$	0.023***	0.006	0.020*	0.041***	0.024*	0.035**	−0.011
	(0.009)	(0.009)	(0.012)	(0.013)	(0.014)	(0.016)	(0.019)
Youth$_{mt}$	0.016	0.050	−0.066	0.138*	0.171*	0.043	0.128
	(0.050)	(0.059)	(0.068)	(0.078)	(0.089)	(0.091)	(0.123)
Klan 1924$_{m}$	0.412***	0.477***	0.311***	0.430***	0.488***	0.349***	0.139
	(0.088)	(0.110)	(0.101)	(0.110)	(0.131)	(0.126)	(0.160)
Confederate$_{m}$	0.089	−0.127	0.370***	0.100	−0.124	0.392**	−0.516**
	(0.122)	(0.139)	(0.137)	(0.164)	(0.178)	(0.176)	(0.209)
Year 2010$_{t}$	−0.017	−0.306	0.174	−3.634**	−4.006**	−3.129*	−0.876
	(0.258)	(0.286)	(0.344)	(1.569)	(1.789)	(1.796)	(2.125)
Year 2017$_{t}$	−0.824**	−1.231***	−0.324	−5.920***	−6.428**	−4.981**	−1.447
	(0.382)	(0.427)	(0.497)	(2.208)	(2.515)	(2.519)	(2.983)
Border 2000$_{mt}$	−0.190	0.042	−0.539*	−0.337	−0.118	−0.654	0.536
	(0.183)	(0.198)	(0.290)	(0.257)	(0.264)	(0.658)	(0.628)
Border 2010$_{mt}$	0.065	−0.075	0.207	0.400	0.263	0.524*	−0.261
	(0.171)	(0.224)	(0.204)	(0.248)	(0.303)	(0.286)	(0.363)
Border 2017$_{mt}$	−0.121	−0.372	0.164	0.062	−0.170	0.345	−0.516
	(0.234)	(0.373)	(0.249)	(0.384)	(1.754)	(0.717)	(1.853)
One Group (μ_{i1})	1.453**	2.201***	1.632**	2.392***	3.040***	2.619**	
	(0.645)	(0.775)	(0.789)	(0.827)	(0.982)	(1.022)	
Two Groups (μ_{i2})	2.417***	3.256***	2.807***	3.380***	4.127***	3.803***	
	(0.647)	(0.781)	(0.778)	(0.824)	(0.988)	(1.009)	
Three Groups (μ_{i3})	3.151***	3.940***		4.128***	4.820***		
	(0.654)	(0.799)		(0.831)	(1.003)		
Four Groups (μ_{i4})	4.036***			5.006***			
	(0.668)			(0.843)			
Five Groups (μ_{i5})	4.873***			5.811***			
	(0.690)			(0.865)			

Continued

Estimated v_{mt}				−0.090**	−0.090**	−0.082**
				(0.036)	(0.042)	(0.042)
Estimated ρ		0.106			0.085	
		(0.065)			(0.067)	
Relevance: $Internet_{mt}$				χ^2 (2, 721) = 19.16***		
				(0.00)		
Joint CRE		χ^2 (22) = 101.58***				
		(0.00)				
CRE	χ^2 (11) = 56.00***	χ^2 (11) = 42.30***	χ^2 (22) = 44.39***			
	(0.00)	(0.00)	(0.00)			
Coefficient Equality		χ^2 (29) = 218.34***				
		(0.00)				

NOTES. 2166 observations. Estimated regressions include Mundlak controls for unobserved heterogeneity. Robust standard errors for estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses. P-value of the Chi-Squared statistic for the Wald test reported in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level. Joint Control Function tests the null that the control function coefficients jointly equal zero across equations. Control Function tests the null that the control function coefficients jointly equal zero within each equation. Joint CRE tests the null that the correlated random effects jointly equal zero across equations. CRE tests the null that the correlated random effects jointly equal zero within each equation. Coefficient Equality tests the null that all the payoff coefficients are the same across the contemporary and traditional equations. [+]Differences in estimated coefficients from the Contemporary and Traditional Hate Group equations ($C - T$). Robust standard errors for differences in estimated coefficients, clustered by commuting zone and bootstrapped with 1,000 iterations, in parentheses.

White supremacists often spread stories that out-groups threaten their culture and rights. A particular application is that the Civil Rights Act of 1964, the Immigration and Nationality Act of 1965 and other immigration policies have contributed to whites in the United States being systematically replaced by the out-group population. We find no evidence that increases in the size of the local market's native non-white and immigrant populations increase the likelihood of entry by white-supremacist hate groups. The estimated coefficients on $Native\ Non\text{-}White_{mt}$ and $Immigrant_{mt}$, respectively, are all negative in contemporary and traditional payoffs. These findings are more in line with the contact hypothesis, which argues that increased interactions between in- and out-groups make it easier for the in-group to learn the truth about out-groups and lowers their demand for hate (Allport, 1954; Billings, Chyn, & Haggag, 2021). It is also possible that the increase in the size of these out-groups is associated with their increased willingness to contact authorities about incidences of hate which would decrease the supply of hate.

Geography and history also explain hate-group entry. Because consumers in former Confederate states are likely to have stronger preferences for Confederate and Southern heritage, the estimated positive coefficient on $Confederate_m$ in traditional group payoffs is expected. Similarly, the second rising of the KKK in the 1920s openly supported nationalism, white supremacy, and Protestant Christianity. Preferences for these historical ideologies are apparent in the relatively large estimated positive coefficients on $Klan\ 1924_m$ in contemporary and traditional payoffs. The estimated coefficients on $Protestant_{mt}$ are negative in contemporary and traditional payoffs but are imprecisely estimated[7,8].

Finally, the number of hate groups in the market, $\mu_i\left(n_{imt}\right)$, are specified as dummy variables equal to one when there are n_{imt} hate groups in the market and zero otherwise. The estimated coefficients on the number of hate groups in the market have plausible magnitudes in all of the preferred specifications and they are precisely estimated. They show that the payoffs for both types of hate groups decline with the number of intra-brand rivals in the local market.

Table 6 presents the marginal effects of our independent variables on the probability of observing hate groups, $\partial P[n_i(.)]/\partial X$, where $n_i(.)$ measures one, two and three hate groups, respectively. Columns one and two of row one show that a one percentage-point increase in broadband Internet penetration is associated with a 0.90 percentage-point increase in the probability of observing one contemporary hate group and with a 0.90 percentage point increase in the probability of observing one traditional group. This suggests that the Internet's direct effects, which includes the reduction in search and other transactions costs, on the quantity of hate traded in the representative market dominate the indirect effects, which include the lower cost of objectively evaluating hate-based messages.

The demand for hate should be relatively higher in markets where there is less ability or desire to discern online truth from fiction. Fictional cyberhate stores, for example, are often targeted toward younger and less-educated persons because they raise less scrutiny and suspicion through suspension of disbelief. Inexperienced teenagers can also consume racist ideas on the Internet with no exchange of contrasting ideas, and with no parental disapproval (Kawakatsu, 2021). Similarly, less-educated consumers are likely less efficient and less objective when evaluating hate-creating stories (Glaeser, 2005). Less- and more-educated groups may

[7]Column seven of **Table 5** presents differences in the estimated coefficients from contemporary and traditional payoffs. Allowing the supply-and-demand coefficients to differ is important. Significant differences in the coefficients for $In\text{-}Group\ Income_{mt}$ and $Out\text{-}Group\ Income_{mt}$ indicate that the demand for contemporary hate is more sensitive to changes in economic conditions than traditional hate. Differences for $Confederate_{mt}$ suggest that traditional groups may target audiences that celebrate Confederate history and culture.

[8]Appendix explores the sensitivity of our findings to alternative hate group-definitions that consider anti-immigrant, anti-Muslim, Neo-Völkisch and White Nationalist groups, and to alternative bin definitions in our ordered-probability model. Summary statistics are presented in Appendix. Estimates of the market-entry model estimates are presented in Appendix and are qualitatively similar to our preferred specification.

also be more likely to readily accept information that conforms with their beliefs. For example, some uneducated persons may uncritically accept online anti-immigrant messages, while some educated persons may categorically reject anti-immigrant messages, even when the facts stated are true. Together, these demographic effects suggest that hate-group messaging and acceptance is stronger in younger and less-educated markets and more demand for hate will lead to more trades and to increased probability of hate-group market entry.

Table 6. Marginal effects on the probability of market entry.

	One Group		Two Groups		Three Groups
	Contemporary	*Traditional*	*Contemporary*	*Traditional*	*Contemporary*
$Internet_{mt}$	0.009**	0.009*	0.002**	0.002*	0.002**
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
$Immigration_{mt}$	−0.011	−0.026**	−0.003	−0.006**	−0.002
	(0.008)	(0.011)	(0.002)	(0.003)	(0.002)
$Native\ Non\text{-}White_{mt}$	−0.005	−0.007*	−0.001	−0.002*	−0.001
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
$Uneducated\ In\text{-}Group\ Pop_{mt}$	0.001*	−0.000	0.000*	−0.000	0.000**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$Educated\ In\text{-}Group\ Pop_{mt}$	−0.001***	−0.000	−0.000**	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$In\text{-}Group\ Income_{mt}$	−0.006*	0.004	−0.001*	0.001	−0.001*
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
$Out\text{-}Group\ Income_{mt}$	0.005**	−0.003	0.001**	−0.001	0.001**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
$Evangelical_{mt}$	−0.001	−0.001	−0.000	−0.000	−0.000
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
$Protestant_{mt}$	−0.005*	−0.003	−0.001*	−0.001	−0.001*
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
$Republican_{mt}$	0.002*	0.004**	0.001*	0.001**	0.000*
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
$Youth_{mt}$	0.016**	0.005	0.004*	0.001	0.003**
	(0.008)	(0.010)	(0.002)	(0.002)	(0.002)
$Klan\ 1924_{m}$	0.047***	0.039***	0.011***	0.008***	0.008***
	(0.013)	(0.014)	(0.003)	(0.003)	(0.002)

Continued

$Confederate_{mt}$	−0.011	0.045**	−0.003	0.010**	−0.002
	(0.015)	(0.020)	(0.004)	(0.005)	(0.003)
$Year\ 2010_{mt}$	−0.039	−0.093*	−0.049*	−0.232**	−0.263***
	(0.038)	(0.051)	(0.029)	(0.109)	(0.096)
$Year\ 2017_{mt}$	−0.062**	−0.064	−0.019	−0.324***	−0.343***
	(0.030)	(0.047)	(0.025)	(0.102)	(0.077)
Border 2000	−0.010	−0.054**	−0.002	−0.010**	−0.002
	(0.021)	(0.023)	(0.005)	(0.004)	(0.004)
Border 2010	0.028	0.069*	0.007	0.021	0.006
	(0.032)	(0.042)	(0.010)	(0.018)	(0.008)
Border 2017	−0.014	0.042	−0.003	0.012	−0.003
	(0.034)	(0.043)	(0.009)	(0.015)	(0.007)

NOTES. 2166 Observations. Estimated marginal effects are based on a change from zero to one for indicator variables. Robust standard errors for estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level. The reported marginal effects equal the sample's average marginal effect. Estimated marginal effects for the probability of observing two or three hate groups are available upon request.

Panel A of Table 7 tests the youth hypothesis by letting the effect of the Internet on the probability of entry vary by the share of the in-group population of minors, aged 19 and younger ($Youth_{mt}$). Focusing on contemporary groups, a one percentage-point increase in Internet penetration evaluated at a low level of young people's share of the in-group population (i.e., 5th percentile of the sample data's $Youth_{mt}$) increases the probability of observing one hate group by 0.4 percentage points. The marginal effect of increased Internet penetration equals 1.3 percentage points when evaluated at a high share of young people (i.e., 95th percentile of the sample data's $Youth_{mt}$), and the estimated 0.9 percentage point increase in the Internet's marginal effect across the distribution of $Youth_{mt}$ is significant at the five percent level. The increase is smaller and insignificant for traditional groups. The marginal effect of the Internet on the likelihood of observing a traditional hate group increases from 0.7 percentage points at a low level of young in-group members to one percentage point at the elevated level.

Panel B of Table 7 tests the education hypothesis by evaluating the marginal effects of Internet on hate at different levels of the educated in-group's population. Focusing on contemporary groups, the Internet's marginal effect equals 0.8 percentage points when evaluated at a low level of educated population and falls to 0.04 percentage points when evaluated at an elevated level of education. The resulting 0.76 percentage-point drop in the Internet's estimated marginal effect is significant at the one percent level. The effects are similar for traditional groups but the decrease in the Internet's estimated marginal effect is not significant. Panel C examines the relationship between a market's uneducated population and the Internet's marginal effect on the probability of observing one hate group. While the marginal effect of the Internet rises from 0.9 percentage points to 1.4 percentage points at low and high levels of uneducated adults in the contemporary equation, these estimated differences are not significant. The Internet's estimated marginal effect on the probability of observing a traditional group remains essentially unaffected by the size of a market's uneducated in-group population.

Table 7. Cross-partial effects of the Internet on the probability of market entry.

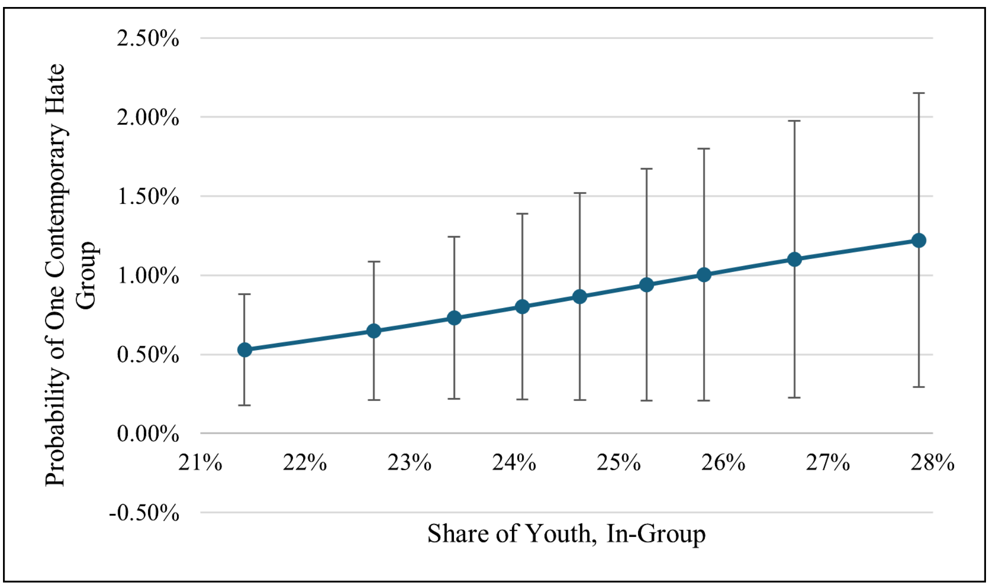
	A: By Share In-Group Youth			B: By Educated In-Group Size			C: Uneducated In-Group Size		
Contemporary Groups	Percentiles								
	5th	50th	95th	5th	50th	95th	5th	50th	95th
One Entrant	0.004***	0.009***	0.013***	0.0080***	0.0065***	0.0004*	0.009**	0.010**	0.014*
	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.0002)	(0.004)	(0.004)	(0.007)
Two Entrants	0.001***	0.002*	0.005	0.003**	0.002**	0.0001	0.0020**	0.002**	0.004
	(0.0004)	(0.001)	(0.003)	(0.001)	(0.0008)	(0.0001)	(0.0008)	(0.0009)	(0.003)
Three Entrants	0.0009**	0.002*	0.005	0.004*	0.003**	0.0006***	0.0009	0.001*	0.002*
	(0.0004)	(0.001)	(0.005)	(0.002)	(0.002)	(0.0002)	(0.0006)	(0.0006)	(0.001)
	Differences in Percentiles								
	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th
One Entrant	0.004**	0.004*	0.009**	−0.006***	−0.0015	−0.0076***	0.004	0.0005	0.005
	(0.002)	(0.003)	(0.004)	(0.002)	(0.0010)	(0.003)	(0.004)	(0.0005)	(0.004)
Two Entrants	0.002	0.001	0.004	−0.002**	−0.0006	−0.002**	0.002	0.0002	0.002
	(0.002)	(0.001)	(0.003)	(0.0007)	(0.0004)	(0.001)	(0.003)	(0.0001)	(0.003)
Three Entrants	0.003	0.001	0.004	−0.003*	−0.0007	−0.0035*	0.001	0.00010*	0.001
	(0.004)	(0.001)	(0.005)	(0.002)	(0.0006)	(0.002)	(0.001)	(0.00005)	(0.001)
Traditional Groups	Percentiles								
	5th	50th	95th	5th	50th	95th	5th	50th	95th
One Entrant	0.007**	0.009**	0.01*	0.008**	0.008**	0.002	0.0085**	0.0085**	0.0085
	(0.003)	(0.004)	(0.006)	(0.004)	(0.0035)	(0.004)	(0.004)	(0.004)	(0.006)
Two Entrants	0.001	0.002*	0.003	0.004	0.003	0.001	0.002**	0.002**	0.002
	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)

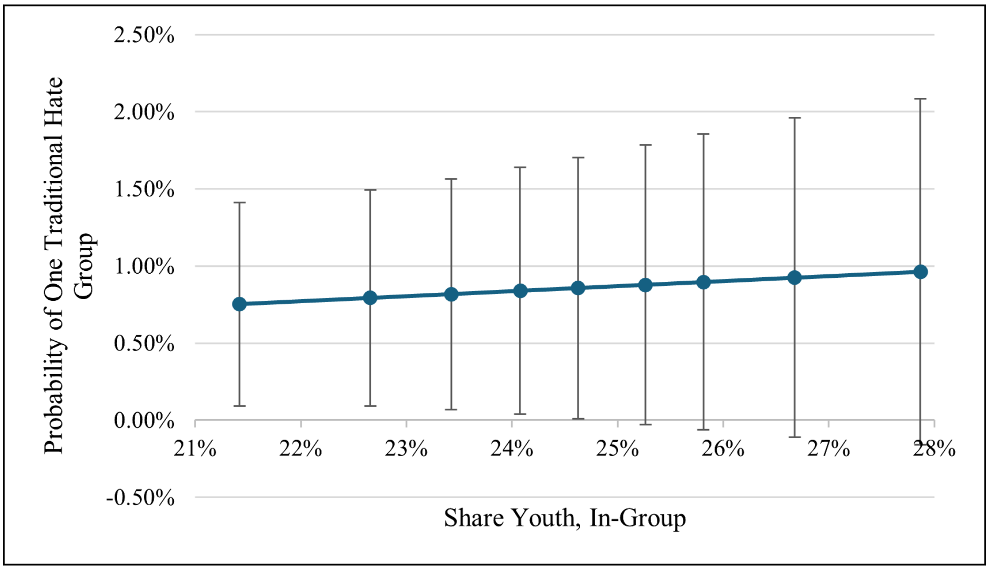
Continued

	Differences in Percentiles								
	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th
One Entrant	0.001	0.001	0.003	−0.0055	−0.0005	−0.006	−0.0001	−0.00001	−0.0001
	(0.002)	(0.003)	(0.005)	(0.005)	(0.0007)	(0.005)	(0.0027)	(0.0003)	(0.003)
Two Entrants	0.0008	0.0006	0.001	−0.002	−0.0003	−0.003	−0.00003	−0.000004	−0.00004
	(0.003)	(0.0015)	(0.004)	(0.004)	(0.0006)	(0.004)	(0.0015)	(0.0001)	(0.0016)

NOTES. Estimated marginal effects are for an increase in $Internet_{mt}$ on the probability of observing the indicated number of entrants in the average market, evaluated at the 5th, 50th, and 95th percentiles for *Youth, Educated In-Group Size,* and *Uneducated In-Group Size*. The reported marginal effects equal the sample's average marginal effect for an ordered Probit specification. These estimates do not account for inter-equation effects because results from the bivariate probit model do not reject the null hypothesis that there is no correlation between the errors from the $Contemporary_{tm}$ and *Traditional* ordered Probit equations. Robust standard errors for estimated marginal effects, clustered by commuting zone and bootstrapped with 1,000 iterations, in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level.

For easier analysis, **Figure 1** provides a visual presentation of the tests of the youth and education hypotheses for one hate group in the market. Along with **Table 7**, these results show that the strongest statistical evidence that having more younger persons in the market gives a higher marginal effect of the Internet on hate than having fewer younger persons comes from one contemporary entrant. Similarly, the strongest evidence that having more educated persons gives a lower marginal effect also comes from one contemporary entrant. Given a single entrant indicates whether or not a hate group exists in a location, our results may reflect a decrease in the probability of exit, where the preferences of younger and educated persons provide sufficient demand to help some existing contemporary hate groups in their local market.

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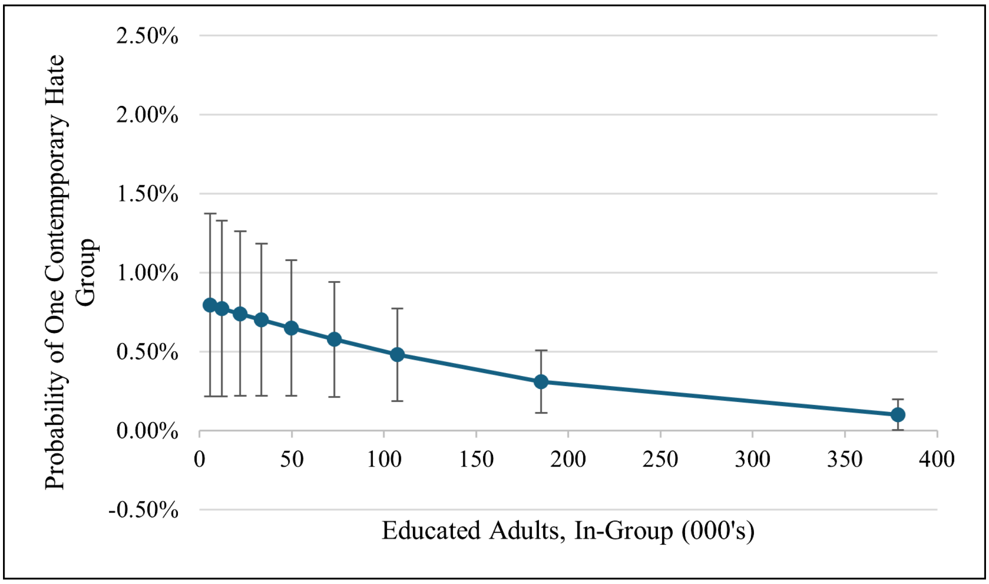
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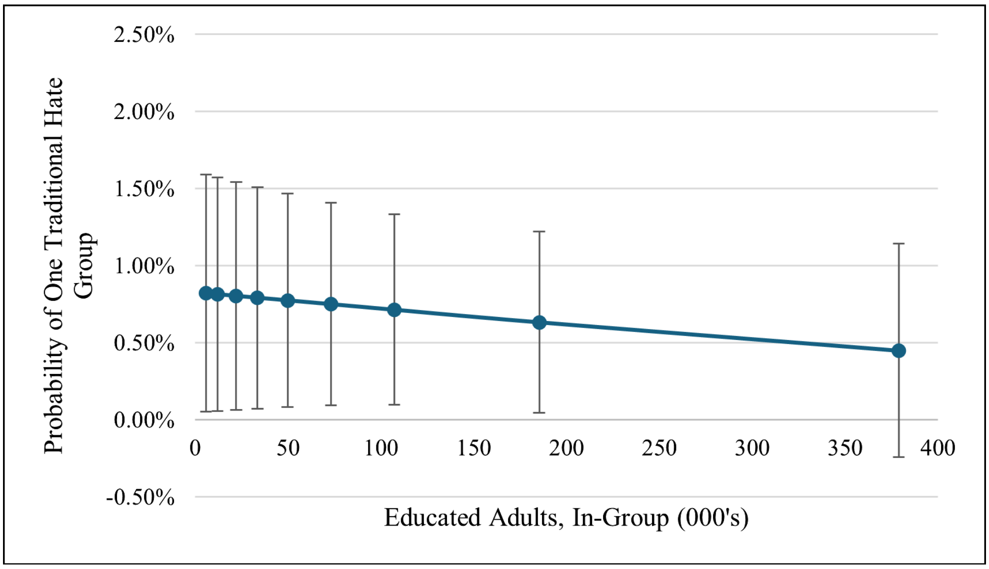
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Probability of One Traditional Hate Group
Educated Adults, In-Group (000's)

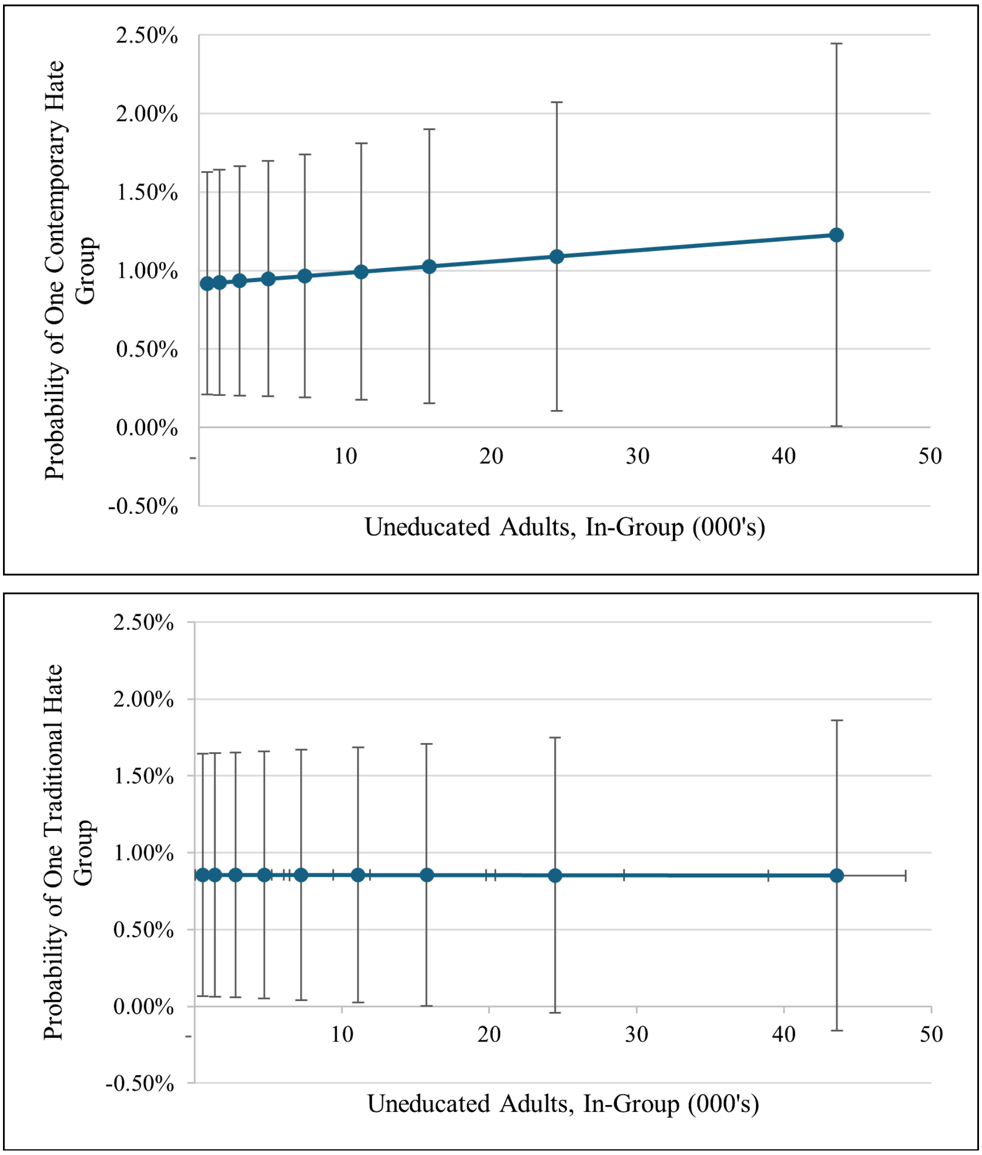


Figure 1. Marginal effects of the Internet on the probability of one hate group (base model). *NOTES.* Estimated marginal effects are for an increase in *Internet* on the probability of observing one contemporary or traditional hate group, evaluated at the deciles for *Youth*, *Educated In-Group Population,* and *Uneducated In-Group Population*. The reported marginal effects equal the sample's average marginal effect for an ordered-probit specification. The estimates do not account for inter-equation effects because results from the bivariate probit model do not reject the null hypothesis that there is no correlation between the errors from the *Contemporary* and *Traditional* ordered-probit equations. The 95 percent confidence intervals are based on robust standard errors for estimated marginal effects, clustered by commuting zone and bootstrapped with 1000 iterations.

5.2. Robustness

The ordered-probability model is well suited for measuring marginal effects. However, because we use a nonlinear estimator, the identifying assumption for $Density_{mt}$ and $Commerical_{mt}$ is not directly testable with standard diagnostics. We assess its plausibility with an alternative linear specification and the two-stage least squares

(2SLS) estimator. The results are reported in columns one and two of **Appendix**. The Hansen J statistics cannot reject the null that the overidentification restrictions in the linear model are appropriate. Hausman-Wu endogeneity tests reject the null hypothesis that $Internet_{mt}$ is exogenous in all the linear model specifications. The effects of variables that control for market demographics, market size, consumer preferences, and geography and history also prove robust to the linear specification. For example, the estimated coefficients on $Educated\ Pop_{mt}$, $Uneducated\ Pop_{mt}$, $In\text{-}Group\ Income_{mt}$, $Out\text{-}Group\ Income_{mt}$, and $Youth_{mt}$ have the same signs and significance in the linear and bivariate ordered probit specifications.

The results in **Table 7** largely rely on the ordered probit model's functional form to measure the heterogeneous effects of the Internet across markets through the cross-partial effects. To make sure these results hold up with more flexibility in the specification, **Table 8** presents results from ordered probit specifications with the age and education interactions, $Internet_{mt} \times Youth_{mt}$, $Internet_{mt} \times Educated\ Pop_{mt}$, and $Internet_{mt} \times Uneducated\ Pop_{mt}$[9]. The results presented in columns two through six cannot reject the null hypothesis that the coefficients on $Internet_{mt} \times Youth_{mt}$ in the traditional equation, and $Internet_{mt} \times Educated\ Pop_{mt}$ and $Internet_{mt} \times Uneducated\ Pop_{mt}$ in the contemporary and traditional equations equal zero. Moreover, the coefficients on $Internet_{mt}$ in these specifications remain positive and statistically significant, except for the positive and marginally significant coefficient on $Internet_{mt}$ in the traditional-hate equation that includes the interaction $Internet_{mt} \times Educated\ Pop_{mt}$. The results indicate that the Internet's marginal effect on contemporary group payoffs is increasing in a market's share of youth. The coefficient on $Internet_{mt} \times Youth_{mt}$ is positive and significant at the five percent level and the coefficient on $Internet_{mt}$ is negative and insignificant in the contemporary equation[10]. Overall, the inclusion of interaction variables has only a small impact on the relationship between the Internet's marginal effect on entry and market demographics. The cross-partial effects, presented in **Table 9** and **Figure 2**, are similar to those in **Table 7**.

[9]We treat these interaction variables as endogenous and include interactions between our excluded exogeneous variables and age and education, $Commercial_{mt} \times Youth_{mt}$, $Density_{mt} \times Youth_{mt}$, $Commercial_{mt} \times Educated\ Pop_{mt}$, $Density_{mt} \times Educated\ Pop_{mt}$, $Commercial_{mt} \times Uneducated\ Pop_{mt}$ and $Density_{mt} \times Uneducated\ Pop_{mt}$, in our vectors of excluded exogenous variables Z_{mt} (Wooldridge, 2002). Columns two and three of **Appendix**, along with columns one through four of **Appendix**, present the results from the first-step OLS regression of $Internet_{mt}$, $Internet_{mt} \times Youth_{mt}$, $Internet_{mt} \times Educated\ Pop_{mt}$, and $Internet_{mt} \times Uneducated\ Pop_{mt}$ on the Mundlak-Chamberlain controls, year fixed effects, and all the exogenous variables in Z_{mt}. An F-test rejects the null that the estimated coefficients on the excluded instruments jointly equal zero in all of the first-step $Internet_{\mathrm{mt}}$ regressions, and the $Internet_{mt} \times Youth_{mt}$ and $Internet_{mt} \times Uneducated\ Pop_{mt}$ regressions. The instruments are not relevant in the $Internet_{mt} \times Educated\ Pop_{mt}$ regression.

[10]For completeness, columns three through eight of **Appendix** presents results from 2SLS estimates of our linear specification with the age and education interaction variables, $Internet_{mt} \times Youth_{mt}$, $Internet_{mt} \times Educated\ Pop_{mt}$, and $Internet_{mt} \times Uneducated\ Pop_{mt}$, while **Appendix** presents results from similar specification with census division-year fixed effects. The resulting cross-partial effects, reported in **Appendix**, show evidence that having more younger and uneducated persons in the market gives a higher marginal effect of the Internet on contemporary hate than having fewer younger and uneducated persons.

Table 8. Ordered probit estimates of market entry with *Internet*$_{mt}$ interacted with demographics.

Variables	*Internet*$_{mt}$ × *Youth*$_{mt}$		*Internet*$_{mt}$ × *Educated Pop*$_{mt}$		*Internet*$_{mt}$ × *Uneducated Pop*$_{mt}$	
	Contemporary	*Traditional*	*Contemporary*	*Traditional*	*Contemporary*	*Traditional*
Internet$_{mt}$	−0.014	0.084**	0.101*	0.047	0.093**	0.128**
	(0.035)	(0.041)	(0.054)	(0.032)	(0.046)	(0.059)
Internet$_{mt}$ × *Youth*$_{mt}$	0.005**	−0.0002				
	(0.002)	(0.002)				
Internet$_{mt}$ × *Educated Pop*$_{mt}$			0.00001	0.00008		
			(0.00004)	(0.00005)		
Internet$_{mt}$ × *Uneducated Pop*$_{mt}$					0.00007	−0.001
					(0.0003)	(0.001)
Immigration$_{mt}$	−0.077	−0.281***	−0.108	−0.228***	−0.111	−0.288**
	(0.082)	(0.103)	(0.126)	(0.088)	(0.090)	(0.119)
Native Non-White$_{mt}$	−0.062*	−0.067*	−0.055**	−0.074*	−0.056	−0.056
	(0.036)	(0.038)	(0.024)	(0.040)	(0.037)	(0.043)
Uneducated Pop$_{mt}$	0.004	−0.003	0.017	0.079	0.009	−0.045
	(0.004)	(0.005)	(0.044)	(0.067)	(0.014)	(0.031)
Educated Pop$_{mt}$	−0.006***	−0.002	−0.008	−0.014	−0.007**	0.007
	(0.002)	(0.003)	(0.006)	(0.008)	(0.003)	(0.006)
In-Group Income$_{mt}$	−0.091***	0.026	−0.065*	0.013	−0.058	−0.011
	(0.033)	(0.034)	(0.038)	(0.030)	(0.036)	(0.043)
Out-Group Income$_{mt}$	0.062**	−0.026	0.057***	−0.025	0.057**	−0.034
	(0.024)	(0.021)	(0.022)	(0.021)	(0.026)	(0.025)
Evangelical$_{mt}$	−0.018	−0.013	−0.011	−0.012	−0.010	−0.018
	(0.016)	(0.016)	(0.022)	(0.008)	(0.016)	(0.021)
Protestant$_{mt}$	−0.045	−0.027	−0.057	−0.013	−0.053*	−0.039
	(0.031)	(0.031)	(0.037)	(0.027)	(0.032)	(0.036)
Republican$_{mt}$	0.026*	0.039**	0.025	0.047**	0.021	0.056***
	(0.014)	(0.017)	(0.016)	(0.021)	(0.016)	(0.020)
Youth$_{mt}$	−0.128	0.075	0.178**	−0.005	0.166*	0.136
	(0.114)	(0.129)	(0.071)	(0.101)	(0.095)	(0.130)

Continued

Klan 1924$_m$	0.484***	0.360***	0.471***	0.315**	0.447***	0.308**
	(0.131)	(0.131)	(0.073)	(0.144)	(0.138)	(0.147)
Confederate$_m$	−0.127	0.439**	−0.112	0.379**	−0.130	0.393*
	(0.176)	(0.176)	(0.227)	(0.176)	(0.181)	(0.201)
Year 2010$_t$	−4.668**	−3.264	−4.086*	−1.748	−3.805**	−5.023**
	(1.978)	(2.205)	(2.424)	(1.459)	(1.917)	(2.417)
Year 2017$_t$	−6.937***	−5.201*	−6.544*	−3.045	−6.103**	−7.940**
	(2.658)	(2.949)	(3.383)	(2.085)	(2.736)	(3.460)
Border 2000$_{mt}$	−0.438	−0.887	−0.107	−0.479	−0.126	−0.688
	(0.319)	(0.705)	(0.352)	(0.445)	(0.268)	(0.664)
Border 2010$_{mt}$	0.236	0.411	0.252	0.391*	0.241	0.627*
	(0.307)	(0.312)	(0.354)	(0.215)	(0.315)	(0.347)
Border 2017$_{mt}$	−0.018	0.299	−0.239	0.136	−0.267	0.377
	(1.736)	(0.813)	(3.081)	(0.253)	(1.816)	(0.818)
One Group (μ_{i1})	−3.349	4.966	3.135***	2.586**	3.262***	3.466***
	(4.202)	(4.485)	(1.135)	(1.111)	(1.020)	(1.180)
Two Groups (μ_{i2})	−2.259	6.169	4.231***	3.786***	4.352***	4.674***
	(4.199)	(4.484)	(1.145)	(1.115)	(1.025)	(1.168)
Three Groups (μ_{i3})	−1.566		4.927***		5.042***	
	(4.199)		(1.124)		(1.035)	
Estimated v_{mt} (*Internet*$_{mt}$)	0.023	−0.063	−0.092*	−0.052	−0.087*	−0.134**
	(0.037)	(0.043)	(0.055)	(0.033)	(0.045)	(0.059)
Estimated v_{mt} (*Internet*$_{mt}$ × *Youth*$_{mt}$)	−0.005**	−0.001				
	(0.002)	(0.002)				
Estimated v_{mt} (*Internet*$_{mt}$ × *Educated Pop*$_{mt}$)			−0.00002	−0.0001		
			(0.00004)	(0.0001)		
Estimated v_{mt} (*Internet*$_{mt}$ × *Uneducated Pop*$_{mt}$)					0.000005	0.001
					(0.0004)	(0.001)
Estimated ρ	0.083		0.077		0.070	
	(0.070)		(0.070)		(0.069)	

Continued

Relevance: $Internet_{mt}$	χ^2 (4, 721) = 12.62***	χ^2 (4, 721) = 12.59***	χ^2 (4, 721) = 11.91***
	(0.00)	(0.00)	(0.00)
Relevance: $Internet_{mt}$ × $Youth_{mt}$	χ^2 (4, 721) = 9.84***		
	(0.00)		
Relevance: $Internet_{mt}$ × $Educated\ Pop_{mt}$		χ^2 (4, 721) = 1.77	
		(0.13)	
Relevance: $Internet_{mt}$ × $Uneducated$			χ^2 (4, 721) = 12.30***
Pop_{mt}			(0.00)

NOTES. 2166 observations. Estimated regressions include Mundlak controls for unobserved heterogeneity. Robust standard errors for estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses. P-value of the Chi-Squared statistic for the Wald test reported in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level. Joint Control Function tests the null that the control function coefficients jointly equal zero across equations. Control Function tests the null that the control function coefficients jointly equal zero within each equation. Joint CRE tests the null that the correlated random effects jointly equal zero across equations. CRE tests the null that the correlated random effects jointly equal zero within each equation. Coefficient Equality tests the null that all the payoff coefficients are the same across the contemporary and traditional equations. +Differences in estimated coefficients from the Contemporary and Traditional Hate Group equations (*C* - *T*). Robust standard errors for differences in estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses.

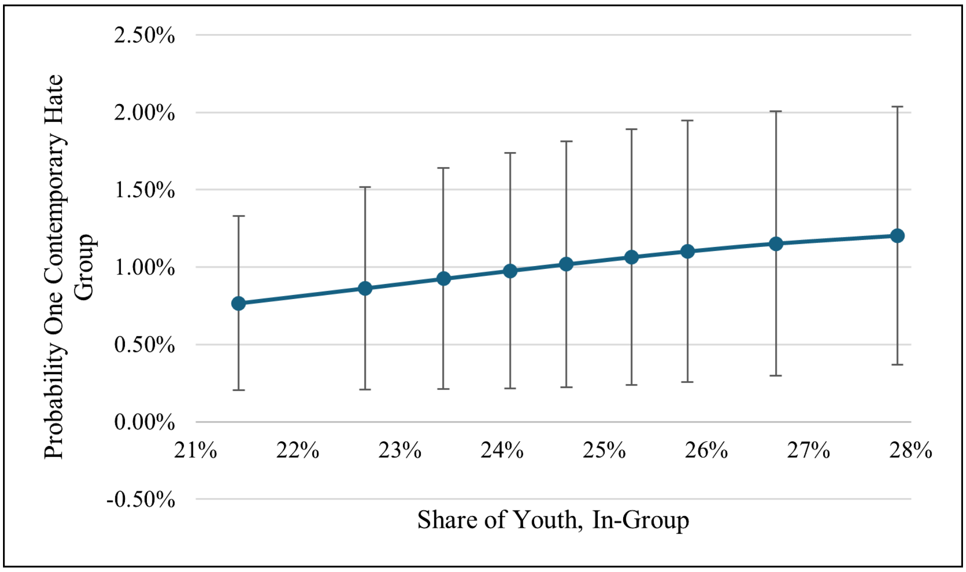
Table 9. Cross-partial effects of the Internet on the probability of market entry from specifications with interacted demographics.

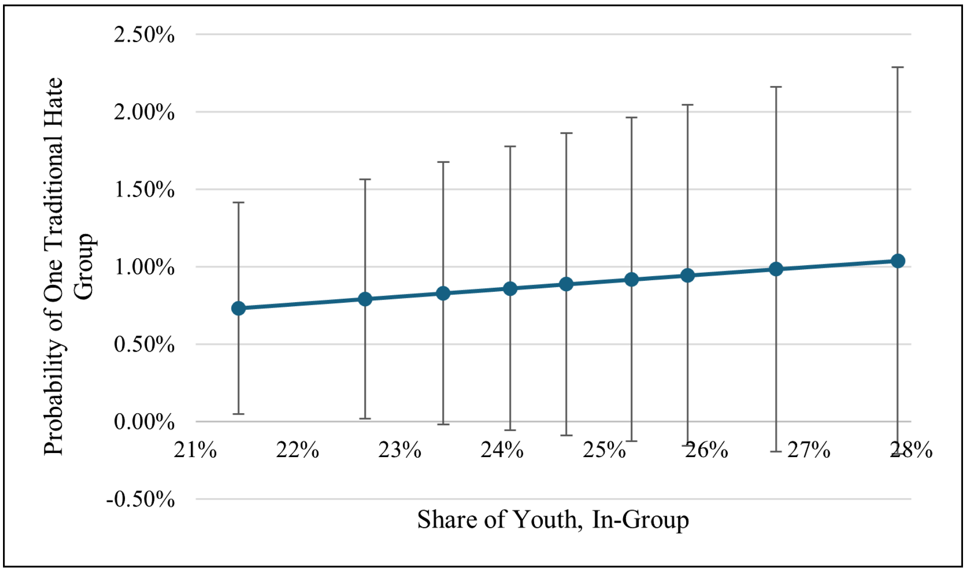
	A: By Share In-Group Youth			B: By Educated In-Group Size			C: By Uneducated In-Group Size		
	Percentiles								
Contemporary Groups	5th	50th	95th	5th	50th	95th	5th	50th	95th
One Entrant	0.007***	0.010**	0.012***	0.008***	0.006***	0.0004	0.008**	0.009***	0.015*
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.0009)	(0.004)	(0.003)	(0.009)
Two Entrants	0.002*	0.003*	0.005**	0.002**	0.002**	0.0001	0.002	0.002*	0.005
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.005)
Three Entrants	0.002	0.003	0.005	0.004**	0.004**	0.0006	0.001	0.0007	0.003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.0006)	(0.002)	(0.002)	(0.009)
	Differences in Percentiles								
	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th
One Entrant	0.002	0.003	0.005**	−0.006***	−0.002	−0.007***	0.006	0.0007	0.007
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.008)	(0.002)	(0.008)

Continued

Two Entrants	0.002	0.001	0.003	−0.002**	−0.006	−0.002**	0.003	0.0002	0.003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.0005)	(0.001)	(0.005)	(0.0004)	(0.005)
Three Entrants	0.003	0.001	0.004	−0.003*	−0.0008	−0.004*	0.002	0.0001	0.002
	(0.003)	(0.001)	(0.004)	(0.002)	(0.0006)	(0.002)	(0.01)	(0.0004)	(0.010)
Traditional Groups	Percentiles								
	5th	50th	95th	5th	50th	95th	5th	50th	95th
One Entrant	0.007**	0.009*	0.011*	0.004	0.003	0.0003	0.009***	0.006**	0.0002
	(0.003)	(0.005)	(0.007)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)
Two Entrants	0.001	0.002	0.003	0.004	0.003	0.0005	0.011**	0.007**	0.0005
	(0.001)	(0.002)	(0.005)	(0.003)	(0.002)	(0.001)	(0.005)	(0.003)	(0.001)
	Differences in Percentiles								
	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th	95th - 50th	50th - 5th	95th - 5th
One Entrant	0.002	0.002	0.004	−0.003	−0.0006	−0.004	−0.006**	−0.003**	−0.009**
	(0.002)	(0.003)	(0.005)	(0.003)	(0.0008)	(0.003)	(0.003)	(0.001)	(0.003)
Two Entrants	0.001	0.001	0.002	−0.002	−0.0007	−0.003	−0.007**	−0.003	−0.010*
	(0.004)	(0.002)	(0.005)	(0.002)	(0.0009)	(0.003)	(0.003)	(0.002)	(0.005)

NOTES. Estimated marginal effects are for an increase in $Internet_{mt}$ on the probability of observing the indicated number of entrants in the average market, evaluated at the 5th, 50th, and 95th percentiles for *Youth, Educated In-Group Size*, and *Uneducated In-Group Size*. The reported marginal effects equal the sample's average marginal effect for an ordered Probit specification. These estimates do not account for inter-equation effects because results from the bivariate probit model do not reject the null hypothesis that there is no correlation between the errors from the $Contemporary_{tm}$ and $Traditional_{tm}$ ordered Probit equations. Robust standard errors for estimated marginal effects, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level.

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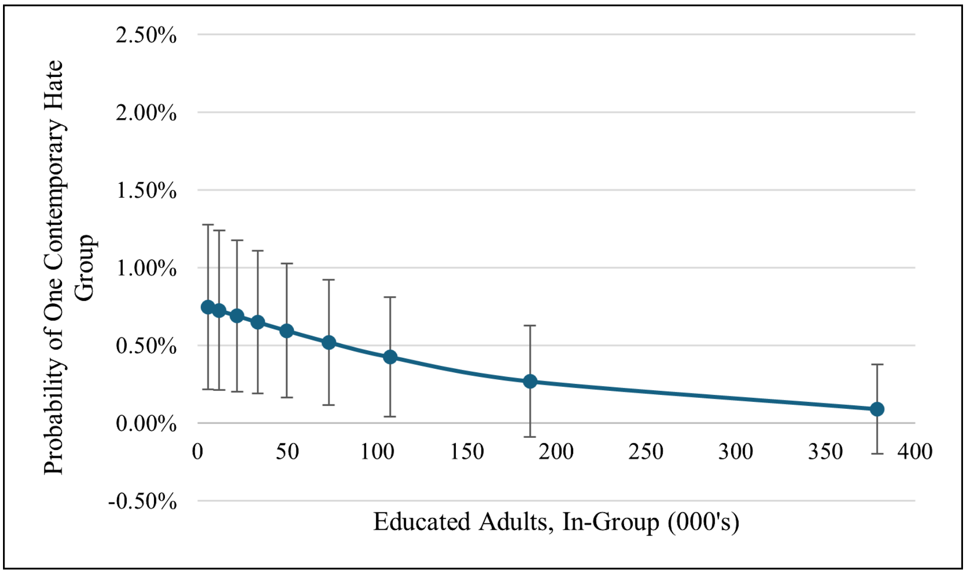
Share of Youth, In-Group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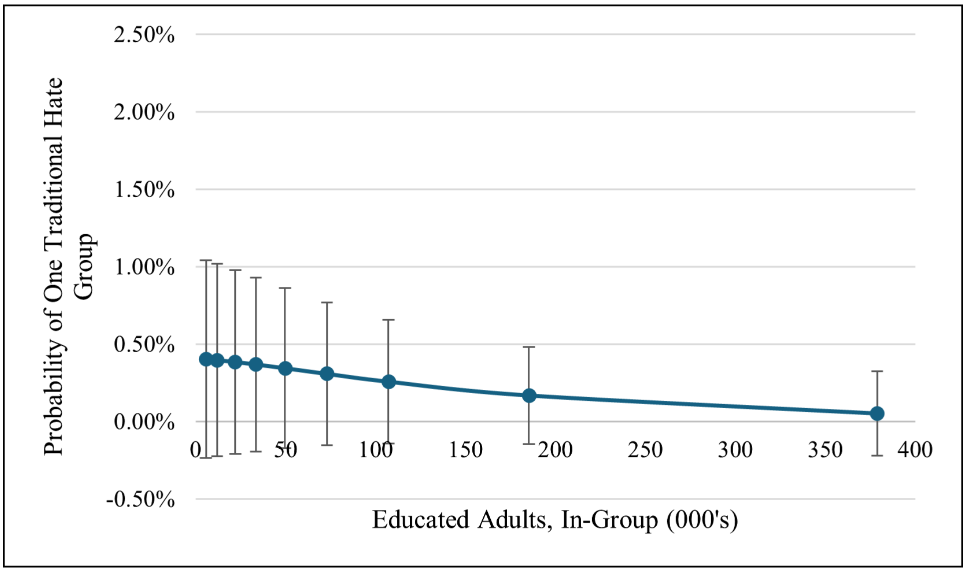
Probability of One Contemporary Hate Group
Educated Adults, In-Group (000's)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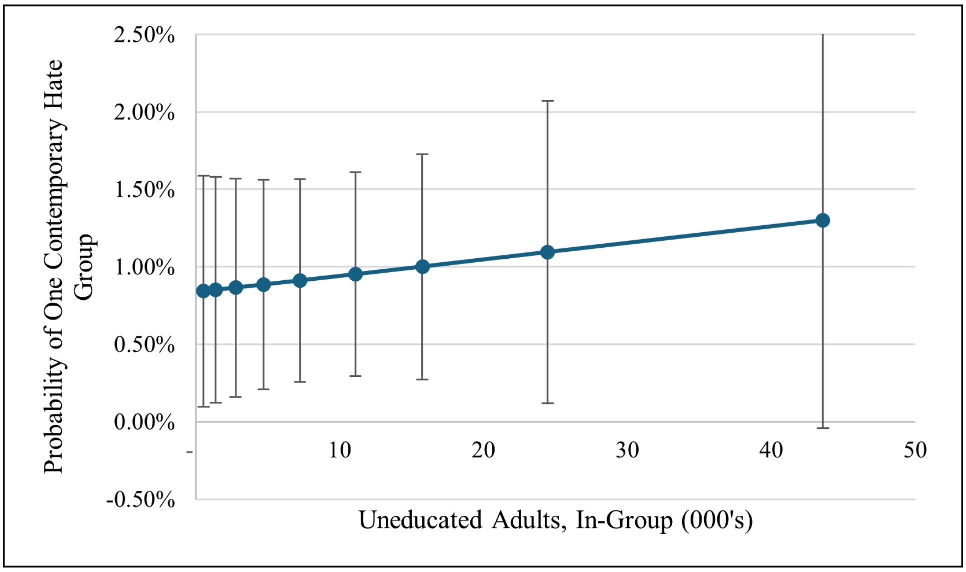
Probability of One Traditional Hate Group
Educated Adults, In-Group (000's)



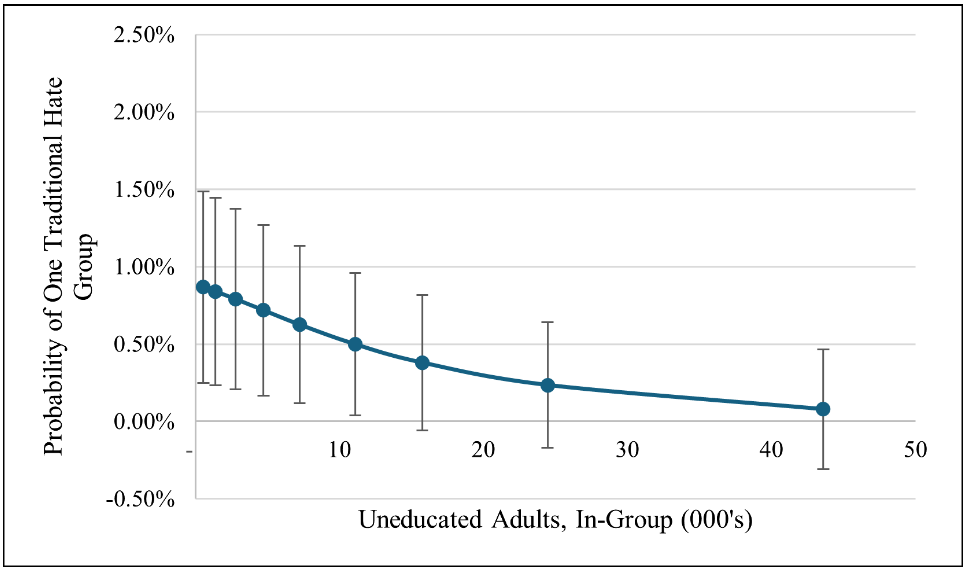


Figure 2. Marginal effects of the Internet on the probability of one hate group (interaction model). *NOTES.* Estimated marginal effects are for an increase in *Internet* on the probability of observing one contemporary or traditional hate group, evaluated at the deciles for *Youth*, *Educated In-Group Population,* and *Uneducated In-Group Population*. The reported marginal effects equal the sample's average marginal effect for an ordered-probit specification. The estimates do not account for inter-equation effects because results from the bivariate probit model do not reject the null hypothesis that there is no correlation between the errors from the *Contemporary* and *Traditional* ordered-probit equations. The 95 percent confidence intervals are based on robust standard errors for estimated marginal effects, clustered by commuting zone and bootstrapped with 1000 iterations.

If $Density_{mt}$ and $Commerical_{mt}$ are relevant and valid instruments, the ordered-probability model should be robust to omitted variables. For an informal test, we include a parsimonious specification that omits the controls for religion, politics, age, and whether a market is located in a border state. We also include a specification that adds *Contemporary State Hate*$_{mt}$ (the number of statewide contemporary groups in the market) and *Traditional State Hate*$_{mt}$ (the number of statewide traditional groups in the market) in the payoff functions. See **Appendix** for the counts of statewide hate groups. The results from these alternative specifications are reported in columns one through four of Table 10 and reported coefficients are consistent with the results presented in Table 5.

Table 10. Ordered probit estimates of market entry with endogenous $Internet_{mt}$ and $Immigration_{mt}$, and with state hate groups.

Variables	Parsimonious Specification		State Hate		Endogenous Internet and Immigration	
	$Contemporary_{mt}$	$Contemporary_{mt}$	$Contemporary_{mt}$	$Traditional_{mt}$	$Contemporary_{mt}$	$Traditional_{mt}$
$Internet_{mt}$	0.084**	0.083**	0.111**	0.090*	0.083**	0.071*
	(0.036)	(0.040)	(0.050)	(0.053)	(0.040)	(0.040)
$Immigration_{mt}$	−0.027	−0.100	−0.341	−0.579	−0.100	−0.234**
	(0.071)	(0.087)	(0.389)	(0.476)	(0.087)	(0.102)
$Native\ Non\text{-}White_{mt}$	−0.075**	−0.053	−0.035	−0.037	−0.053	−0.071*
	(0.030)	(0.035)	(0.046)	(0.052)	(0.035)	(0.036)
$Uneducated\ In\text{-}Group\ Pop_{mt}$	0.009**	0.005	0.005	−0.004	0.005	−0.001
	(0.005)	(0.004)	(0.007)	(0.008)	(0.004)	(0.005)
$Educated\ In\text{-}Group\ Pop_{mt}$	−0.008***	−0.006***	−0.006*	−0.000	−0.006***	−0.001
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
$In\text{-}Group\ Income_{mt}$	−0.064**	−0.089***	−0.053	0.050	−0.089***	0.034
	(0.029)	(0.034)	(0.038)	(0.043)	(0.034)	(0.033)
$Out\text{-}Group\ Income_{mt}$	0.058**	0.059**	0.054**	−0.028	0.059**	−0.027
	(0.023)	(0.025)	(0.026)	(0.023)	(0.025)	(0.022)
$Evangelical_{mt}$		−0.014	−0.017	−0.018	−0.014	−0.013
		(0.017)	(0.021)	(0.021)	(0.017)	(0.016)
$Protestant_{mt}$		−0.045	−0.074*	−0.041	−0.045	−0.019
		(0.030)	(0.041)	(0.042)	(0.030)	(0.031)
$Republican_{mt}$		0.021	0.028*	0.038**	0.021	0.033**
		(0.013)	(0.015)	(0.017)	(0.013)	(0.016)
$Youth_{mt}$		0.164*	0.189*	0.092	0.164*	0.034
		(0.084)	(0.114)	(0.128)	(0.084)	(0.090)
$Klan\ 1924_m$	0.512***	0.471***	0.463***	0.306*	0.471***	0.309**
	(0.128)	(0.130)	(0.169)	(0.179)	(0.130)	(0.123)
$Confederate_m$	−0.099	−0.197	−0.106	0.504	−0.197	0.295*
	(0.167)	(0.174)	(0.290)	(0.316)	(0.174)	(0.176)
$Year\ 2010_t$	−3.550**	−0.133	−4.467**	−3.427	−0.133	−0.521
	(1.566)	(0.273)	(2.048)	(2.110)	(0.273)	(0.677)

Continued

Year 2017$_t$	−5.660***	0.421	−7.132**	−5.470*	0.421	0.664**
	(2.162)	(0.309)	(2.896)	(2.982)	(0.309)	(0.300)
Border 2000$_{mt}$		−0.318	0.396	−0.084	−0.318	0.460
		(1.793)	(0.579)	(0.897)	(1.793)	(0.772)
Border 2010$_{mt}$		−2.439	0.890	1.284	−2.439	−2.806*
		(1.629)	(0.836)	(0.940)	(1.629)	(1.657)
Border 2017$_{mt}$		−4.844**	0.513	1.149	−4.844**	−4.613*
		(2.355)	(1.959)	(1.249)	(2.355)	(2.383)
Contemporary State Hate		−0.193**			−0.193**	−0.0004
		(0.078)			(0.078)	(0.079)
Traditional State Hate		−0.358***			−0.358***	−0.059
		(0.118)			(0.118)	(0.136)
One Group (μ_{i1})	1.950***	3.573***	4.824*	5.379	3.573***	3.073***
	(0.554)	(1.067)	(2.929)	(3.560)	(1.067)	(1.096)
Two Groups (μ_{i2})	3.026***	4.672***	5.921**	6.563*	4.672***	4.260***
	(0.559)	(1.075)	(2.928)	(3.556)	(1.075)	(1.086)
Three Groups (μ_{i3})	3.710***	5.362***	6.629**		5.362***	
	(0.564)	(1.093)	(2.948)		(1.093)	
Estimated v_{mt} (Internet)	−0.078**	−0.073*	−0.103**	−0.095*	−0.073*	−0.077*
	(0.036)	(0.039)	(0.049)	(0.053)	(0.039)	(0.040)
Estimated v_{mt} (Immigration)			0.333	0.433		
			(0.395)	(0.463)		
Estimated ρ	0.086	0.086	0.086		0.086	
	(0.068)	(0.068)	(0.067)		(0.068)	
Relevance: *Internet$_{mt}$*	χ^2 (2, 721) = 20.83***	χ^2 (2, 721) = 20.24***	χ^2 (3, 721) = 14.0***		χ^2 (2, 721) = 20.24***	
		(0.00)	(0.00)		(0.00)	
Relevance: *Immigration$_{mt}$*			χ^2 (3, 721) = 34.0***			
			(0.00)			

NOTES. 2166 observations. Estimated regressions include Mundlak controls for unobserved heterogeneity. Robust standard errors for estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses. P-value of the Chi-Squared statistic for the Wald test reported in parentheses. ***Significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level. Joint Control Function tests the null that the control function coefficients jointly equal zero across equations. Control Function tests the null that the control function coefficients jointly equal zero within each equation. Joint CRE tests the null that the correlated random effects jointly equal zero across equations. CRE tests the null that the correlated random effects jointly equal zero within each equation. Coefficient Equality tests the null that all the payoff coefficients are the same across the contemporary and traditional equations. +Differences in estimated coefficients from the Contemporary and Traditional Hate Group equations (*C* - *T*). Robust standard errors for differences in estimated coefficients, clustered by commuting zone and bootstrapped with 1000 iterations, in parentheses.

Although not the main focus of our study, the finding that local immigration is not positively related to hate-group formation is interesting because it suggests that in-person interactions can counter online expressions of hate. It also contrasts the literature that relates immigration and trade to populist, far-right politics. For instance, Tabellini (2020) finds that post-World War I immigration to the United States reduced Democrat votes. Gennaioli and Tabellini (2019) show that French voters adopted more extreme positions on globalization and immigration in 2017 and tempered their views on income redistribution. Autor et al. (2020) find that Chinese import competition increased polarization in the United States and made voters more conservative. A possible explanation for our finding is selection on unobservables, with immigrants being attracted to local places with favorable culture, diversity, and economic opportunities. If these places are less likely to have white-supremacist hate groups, simple comparisons between low- and high-immigration commuting zones may produce estimates of the effects of immigration on hate group entry that are biased downward. We explore this possibility with the Bartik instrument and the control-function approach described in Section 4.

The Bartik (1991) instrument is motivated by the tendency of immigrants to settle in origin-country-specific enclaves. Enclaves are measured by each market's lagged origin-country shares of the total origin-country populations in the United States. The shares allocate the number of contemporary immigrants from different origin countries to their local markets. Following Card (2009), we construct the Bartik instrument for $Immigration_{mt}$ as:

$$B_{mt} = \Sigma_k z_{mk,1980} g_{kt} \tag{7}$$

where $\Sigma_k z_{mk,1980} = \left(N_{mk,1980}/N_{k,1980}\right)\left(1/Pop_{mt}\right)$, $N_{mk,1980}$ is the number of immigrants from country k living in market m in 1980, $N_{k,1980}$ is the number of immigrants from origin-country k living in the United States in 1980, $N_{mk,1980}/N_{k,1980}$ is market m's share of the total number of immigrants from origin-country k living in the United States in 1980, Pop_{mt} is market m's population at time t, and g_{kt} is the number of immigrants arriving in the United States from country k in each period's previous ten years. We use the last seven years, from 2010 to 2017, for $t = 2017$.

Our approach assumes that the growth in the number of persons arriving in the United States from different source countries are exogenous national shocks and the shares are exogenous local exposures to these shocks. Since our sample data are a panel with local shares fixed to 1980, the time variation in our Bartik instrument comes from differences in the national growth rates of immigrants between source countries, which measures the relative size of the national shocks. Following Goldsmith-Pinkham, Sorkin and Swift (2020), our model examines whether markets with high shares of a particular immigrant community experience differential changes in hate-group entry following shocks whose effect depends on the relative size of that community. The effects of $Immigration_{mt}$ on hate-group payoffs are identified by within commuting-zone variation in the share of the population not born in the United States, time variation in the Bartik instrument, and by the Bartik's exclusion restrictions. Conditional on market controls, the exclusion restrictions assume that local shares of immigrants in 1980, and changes in national shocks, are independent of the unobserved factors that affect changes in the probability of hate group entry into local markets.

Appendix presents results from the first-step OLS regressions of $Internet_{mt}$ and $Immigration_{mt}$, respectively, on the Mundlak-Chamberlain controls, year fixed effects, and the exogenous variables in Z_{mt}, including the Bartik instrument, B_{mt}. Focusing on immigration, this first-step regression has an R-squared of 0.758 and an F-test rejects the null that the estimated coefficients on the three excluded instruments jointly equal zero ($F(3, 721) = 34.0$; $Prob > F = 0.00$)[11]. The estimated coefficient on B_{mt} is positive and statistically different from zero at the one percent level. Several other coefficients are statistically significant and have economic interest. For example, immigration is more prominent in the border states and increases over time. It also increases with the number of educated in-group persons and the in-group's median income. Immigration decreases with the number of uneducated in-group persons in the local market, and the shares of Evangelicals and Protestants in the local market.

We use the first-step OLS estimates of $Internet_{mt}$ and $Immigration_{mt}$ to calculate residuals and to construct the Internet and immigration controls that are included in the contemporary and traditional payoff functions. Columns five and six of **Table 10** report the results from the step-two bivariate-ordered probit model with control functions that correct for the endogeneity of $Internet_{mt}$ and $Immigration_{mt}$. Conditional on the relevance and validity of the Bartik instruments, there is little evidence for the endogeneity of immigration. The coefficients on estimated immigration's control function in the contemporary and traditional hate-group equations are statistically insignificant and there is no evidence of a positive relationship between the number of immigrants in the local market and white supremacist hate groups. This null result provides an interesting counter to some of the findings in the globalization, immigration and political polarization literature from Gennaioli and Tabellini (2019), Autor et al. (2020), and Tabellini (2020), etc.

6. Conclusion

We argued that the Internet increases hate when the Internet increases the demand and supply of hate by reducing search and other transaction costs. Indirect effects can offset these direct effects when other content providers use the Internet to expose hate groups and their members, and post material that debunks hate-based messages. The demand for hate falls when buyers use the information posted online to evaluate objectively hate-groups and their messages. We used the revealed preferences of white supremacists to estimate a market-entry model for hate groups. Using data from United States commuting zones, we show that con-

[11]An F-test rejects the null that the excluded instruments jointly equal zero ($F(3, 721) = 14.0$; $Prob > F = 0.00$) in the step-one $Internet_{mt}$ equation.

temporary and traditional white-supremacist hate groups are more prevalent in markets with higher Internet penetration. This implies that the Internet's direct effects of better matching on the quantity of hate traded dominates the indirect information processing effect in the representative market.

Information effects are stronger in educated markets, consistent with an inward shift in the demand curve for hate and fewer trades, and weaker in youthful markets. The finding on youth supports laws, such as the Children's Internet Protection Act of 2000, requiring publicly-funded schools to monitor and restrict minors' access to cyberhate[12], and the French and Australian bans on under-15s and under-16s, respectively, from accessing social media. However, these policy prescriptions overlook the importance of the youth learning how to employ critical thinking and fact checking skills to debunk the false claims and misinformation that pervade the Internet.

Our finding that the effects of Internet on equilibrium quantities of hate differ by socio-demographic factors provides support for the NSC's (2021) conclusion that policies addressing hate-based online content must address both the supply and demand of this content. Children, and others, must develop digital, critical-thinking, and fact-checking skills needed to use the Internet productively while avoiding the harmful content disseminated by malicious actors online (NSC, 2021, p. 22). Moreover, the finding that the effects of Internet access on the equilibrium quantities of hate are heterogeneous suggests that the appropriate policy responses should vary by market and that while national guidelines may be needed, local implementation of policy details may produce the best results.

There are several interesting findings in this paper. If nothing else, it provides a useful counterpoint to the research that espouses large positive externalities from broadband to support their favorite policies. Moreover, several findings are new and should motivate further investigation into the incentives and tradeoffs facing hate groups. One possibility is extending the data beyond 2017 to explore the relevance of our findings in a rapidly evolving technological and social landscape. Another possibility is a structural model that extends our independent homogenous game to heterogenous players supplying different product types (Mazzeo, 2002). This could be a fruitful way to measure the potential substitutability between contemporary and traditional hate, and other types of hate, such as the hate from far-right, anti-government nativist groups. This would permit deeper insights into hate-group incentives to differentiate themselves from rivals, for example, that are not possible with our reduced-form model. If possible, future work could use choice experiments to directly measure the propensity of consumers to use online hate as a direct substitute for the physical proximity of local hate-group chapters. Finally, exploring the relationships between the rule of law, hate groups and hate crimes could be beneficial.

[12]Growing bipartisan concern over the effects of social media on the mental health of young users has resulted in proposals requiring schools to use content filters to limit youths from using the Internet and social media on their networks to be eligible for E-Rate funds (Lima, 2023).

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Availability of Data and Materials' Statement

The appendices and datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

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