Algorithmic Discrimination: A Framework and Approach to Auditing & Measuring the Impact of Race-Targeted Digital Advertising

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Summary

The algorithmic systems and platforms that facilitate race-based targeted advertising and marketing are the focal point of increased scrutiny by civil rights activists, advocacy organizations, policymakers, technologists, and others. Consensus is growing that these automated, algorithmic systems discriminate against and produce tangible harms that disproportionately impact communities and people of color. However, we collectively know less about the demonstrable ways that racial discrimination takes place in our contemporary digital advertising ecosystem. Further, we have fewer ways to think about how to conceptualize and document the potential impacts and harms of race-based advertising in both legacy media forms and especially in today's digital media landscape, which is driven by search engines, digital advertising and marketing platforms, and a complex infrastructure of advertising and data technologies that create the systems and structures defining the business of advertising and marketing today.

This report and the research that produced it aims to accomplish the following:

1. Illuminate how marketers and advertisers target individuals and communities based on race in today's digital advertising systems.
2. Identify policy challenges and interventions to help mitigate the impact of algorithmic discrimination in advertising and marketing practice.
3. Provide an alternative way of conceptualizing, measuring, and documenting the potential impacts and/or harms produced by race-based target marketing and advertising structured by digital marketing and advertising platforms.
4. Help the research and policy community think about what types of data can be marshaled to better understand the ways that racial targeting works in today's digital advertising landscape and to help formulate methods for utilizing data to shape our understanding about how this industry practice produces discriminatory impacts and harms.
5. Provide grounding for all of the above in the systemic, structural, and historical context at the intersection of critical race theory, technological development, and advertising practice.

By understanding the systemic, structural, and historical underpinnings of today's digital advertising industry and by conceptualizing the impact and specific harms produced by today's digital advertising ecosystem through the practice of race-targeted marketing and advertising, I aim to do a small part to accomplish this goal: dismantling systemic racism, reversing inequality, and ensuring that all people can participate, prosper, and reach their full potential. A further goal of this paper is to help the research and policy community think about what types of data can be marshaled to better understand the ways that racial targeting works in today's digital advertising landscape and to help formulate methods for utilizing data to shape our understanding about how this industry practice produces discriminatory impacts and harms.

2.0

The Advent of the (Ad) Algorithm:

A Brief History of Data, Computation, and Race-Targeted Advertising

In order to develop a complex and nuanced understanding for policymaking about the impact of algorithmic discrimination in automated targeted advertising, we need to first understand both the history of race-targeted advertising and marketing and the historical development of advertising technologies and systems. Doing so helps us to better understand the ways that their origins were intertwined and gave rise to our current digital advertising ecosystems.

The historical context I will provide offers the following:

1. Targeting is fundamental to advertising and marketing, so much so that it defines it. The historical origins of audience targeting and its inextricable connection to advertising, marketing, broadcasting, journalism, and the media industries more broadly demonstrate that targeting is an intentional practice.
2. The power to computationally process large amounts of data to model and predict group-based, consumer behavior made race highly salient to an advertising and marketing industry that once viewed itself as race-neutral and apolitical.[1] Advertising and marketing's computational turn normalized race as a salient audience segment, and therefore a target audience who could be exploited to amass profits, within the consumer market at large and within the advertising and marketing industries in particular.
3. That race-based targeting was normalized within the complex, expanding, and lucrative advertising and marketing industries also legitimized the practice among consumers, including non-white consumers and within non-white communities that shoulder the greater risk of harm from race-based targeting. On the one hand, non-white consumers gained access to, and saw themselves benefitting from, goods and services through marketing and advertising that began to be targeted to them. On the other hand, non-white professionals sought economic advancement by carving out unique roles and niches within the advertising and marketing and broader media industries.[2]
4. Interlocking racial, computational, and spatial logics fuel the advertising and marketing industry's development. Race-based advertising and marketing practices are sustained by the complex, networked infrastructures that allow racial discrimination writ large to persist, particularly in the forms of segregation. This includes the segregation of people geographically (including digital space, as I will detail later), computationally as "datafied" consumer subjects,[3] and as audience segments in advertising and marketing practice.

On the Rise: Advertising, Marketing, and Broadcast Journalism

Advertising and marketing are distinct, yet closely related business practices. In simple terms, commercial advertising is about message—communications designed and deployed to persuade people to buy goods and services. Marketing is about people—identifying and/or developing audiences that advertisers want to purchase particular goods and services. Both are linked together through the media or channels through which advertising messages are communicated to audiences.

Given this relationship, it comes as no surprise that the modern advertising and marketing industries emerged together, historically, alongside the advent and increased public usage of mass media. This includes radio beginning in earnest in the 1930s and television in the 1950s and, more prominently, the 1960s. The drive to use radio to sell products (advertising) required advertisers to know and understand their audiences. As Philip Napoli noted in his historical account of the rise of the advertising and marketing industries, depression-era economic pressures forced advertisers to know their audiences even better as a means to help justify advertising budgets.[4] These economic pressures and the opportunities for radio, and later television, to increase revenues for broadcasters through advertising birthed the field of marketing and its handmaiden—audience research.

The Computational Turn

Race and computation figure into this mix of new media channels, the burgeoning new industries of advertising and marketing, and the field of journalism early in the story on two different fronts, highlighted in the 1950s and 1960s from both outside of and adjacent to commercial advertising.

In 1959, Ithiel De Sola Pool was a new political science professor at the Massachusetts Institute of Technology. He was well-versed in the kinds of new public opinion and other forms of market research frontiers by people like statistician George Gallup and salesman-turned-pollster Elmo Roper, among others. Like his compatriots, Pool believed that by gaining enough knowledge about human behavior, he could mathematically simulate and ultimately predict such behavior. Part of Pool's theory of simulation was that human behavior could be modeled, not by focusing on individual behavior per se, but by modeling individuals as part of the groups with which they powerfully identify. This modeling included groups associated with religion, income, geography, political party, and race. What set Pool apart from many of his predecessors interested in the study of human behavior was that in 1959, as a member of the MIT faculty, he had access to the computational power necessary to test the veracity of his predictive modeling theories—a power that could only be exercised by a modern computer.

Pool harnessed this power in an effort to predict the potential outcomes of the 1960 U.S. presidential election, as a consultant to the Democratic Party and its candidate, John F. Kennedy. After aggregating data from prior presidential election polls, Pool simulated past voter behavior as the basis for his prediction. He put it this way:

> "Computers can be used to follow step-by-step the logical consequences of a series of events occurring in systems so complex that no formula exists for reaching the desired results. In such systems, which can be described but are not capable of being mathematically optimized, simulation permitting us to state the initial conditions and explore the consequences of specific changes over time. Simulation is, in short, an acting-out in the computer, of a history of events within a s*ystem. It replicates step-by-step the processes as they occur in time*" (emphasis added).[5]

Pool's computer simulation became the big bang moment that spawned the possibilities for algorithmically driven marketing and advertising, whether used for commercial or political interests (between which there was little distinction at the time).

But, the outcome of Pool's simulation was an equally important marker. Pool's modeling predicted that Kennedy would win only by emphasizing civil rights in his campaign strategies, communications, and policy agenda. As I explain in my book *Black Software*, Pool's simulation advised Kennedy's team to push the civil rights issue "not because it was morally right. Not because it was best for America's democracy. The advice to make civil rights a Kennedy campaign centerpiece was a scientific response to a political predicament. The Democratic Party had a Negro problem. Particularly, it had been hemorrhaging them in droves over the prior two election cycles."[6]

Pool's simulation crystallized the salience of race and racial group identification as a powerful predictor of voting behavior. It solidified racial groups as relevant in the relatively new and expanding industries of computationally driven advertising and marketing. But it was audience research in the service of TV journalism that helped to make race—Black people in particular at the time—the targets of commercial markets. The voting blocs that Pool could now behaviorally measure became the basis for the burgeoning advertising and marketing industries' target audiences.

Making (Target) Markets: Audience Research, TV News, and Civil Rights

CBS created the Television Audience Research Institute in 1944[7] as a means to experiment with and document the outcomes of its explorations with television as a commercial broadcasting medium. Advertising—then frequently in the form of "sponsorship"—served as the primary source of revenue. CBS wanted to understand what qualities defined good broadcasting—primarily in the form of television news broadcasting. Good broadcasting would be determined by what drew the most viewers to its news programming.

To better understand and maximize the relationship between how CBS structured and framed its television news programming and its opportunity to attract the greatest audiences, they contracted the services of a relatively new audience research company, Social Research Incorporated (SRI), which was led and staffed by a team of anthropologists and sociologists. Ultimately the SRI consultants persuaded CBS that they should frame their television news programming around the desires of those who were members of the middle and lower classes who were interested in what became known as "action news," characterized by drama, violence, and "news you can use."[8] SRI also highlighted the degree to which Black people at the time (now approaching the mid-1960s) were both part of that class contingent, and increasingly had access to and got their news from both newspapers and television news.[9]

Like Pool with his simulation theory, CBS had an opportunity to test the veracity of their SRI consultants' advice about how to structure and frame its news programming to capture the greatest audience. The place for the test was the Los Angeles television market, led by CBS affiliate KNXT. The programming it tested was its news program, *CBS Reports*. The subject for the test was the Watts rebellion of 1965. More specifically, the *CBS Reports* program titled "Watts: Riot or Revolt," was aired in December 1965 and packaged for SRI's specified audiences, containing all of the visual, audio, and other features recommended by SRI. The program was a stunning success in terms of the news format and audience reach. And, it was—ironically or not—sponsored by the largest and fastest growing computing technology company at the time, IBM.[10]

If Pool's election experiment cemented the salience of race and racial groups for predicting human behavior, then the airing of CBS's "Watts: Riot or Revolt" solidified racial groups (Black people in this case) as a target market. The moment crystallized for audience researchers, advertisers, and marketers (of products both commercial and political) that Black people had access to the primary channels of communication through which advertising messages were broadcast. Broadcasters, advertisers, and marketers also observed that Black people, construed as audiences, seemed to demonstrate monolithic patterns of behavior when it came to television viewing and other market-based choices. Each of these observations began to normalize Black audiences, and race-based audiences more broadly, as legitimate "target" markets.

Race and Representation in the Future of the Ad Industries

From the late 1960s throughout the late 1970s as the collective purchasing power of African Americans in particular began to relatively skyrocket, advertising and marketing professionals accepted and encouraged the reality that non-white audiences make attractive target audiences.[11] Like whites, Black and brown people spend money too, purchase many of the same products, and aspire to live the good life that advertising messages began to promote. Advertising from the 1960s forward treated race-based target marketing as a given and as legitimate practice. The social and economic landscape throughout these decades produced a normalization, rather than repudiation of race-based targeting. Race-based targeting, a central component of the broader advertising and marketing industry, was seen as opening up, rather than foreclosing economic and employment opportunity and advancement for people and communities of color in a growing middle class.

The conversation taking place throughout the professional and research literatures (which at the time were closely tied to one another) tended to focus on twin issues about representation. First, why were non-white people, particularly in the form of advertising models and other advertising talent, excluded from advertising messages? This line of questioning focused not so much on the effectiveness of representing advertising subjects that matched advertising targets, but on the propriety of non-white people and communities not sharing the economic benefits of an advertising industry that became content to advertise to non-whites and drive consumption among non-white audiences, but hoard the tremendous profits being accrued by a virtually all-white industry.[12]

Second, how did advertisers best target Black and brown consumers? This line of questioning focused largely on whether the representation of non-whites (physically and linguistically) in advertising messages most effectively appealed to non-white target audiences and whether marketers effectively segmented these race-based markets to account for the heterogeneity of consumers within them.[13]

Race-Targeted Advertising in Public Policy: Civil Rights and Consumer Protection

Ideas about whether, how, and in what domains to regulate advertising have, from the beginning, been intimately intertwined with race. I focus here on two ideas. The first emerged in civil rights legislation, specifically in section 1901.203 Title VIII of the Civil Rights Act of 1968, which prohibited racial discrimination in the "sale, rental, or financing of housing." A long list of defined forms of racial discrimination called out in the legislation specified that this included "any advertising either directly or through visual representation a preference for applicants of a particular race or ethnic origin." It also specified that "words indicative of the race or ethnic background of the dwelling or landlord such as "White private home," or "all Black subdivision," may not be used in advertising housing financed or to be financed by the Farmers Home Administration or its successor agency under Public Law 103-354. Further, the statute stated that "*selection of advertising media and the areas to be covered by any advertising must be made to reach potential applicants of all races or ethnic origins*" (emphasis added).[14]

Early challenges of newspaper publishers' and advertisers' violations of these new federal laws first prominently emerged in a set of documents and studies submitted as part of a U.S. Senate Fair Housing hearing in 1971. One such report, prepared by the Washington Center for Metropolitan Studies, under commission by the Department of Housing and Urban Development, made the following claim: "Real estate advertising in newspapers is biased. This applies to many individual advertisements as well as to the total pattern which is used by the real estate industry to advertise."[15] The evidence and examples marshaled in the study called out three forms of practices directly prohibited by the fair housing legislation. The first practice included examples that used illegal expressions such as "in white home." The second practice included examples where all-Black models were used to advertise homes in predominantly Black communities (with the interpretation that these homes and the areas in which they exist are *for Black people*). The third practice included examples that excluded advertising to non-whites for homes in predominantly white neighborhoods. The Washington Center concluded its written testimony for the hearing saying, "As each day passes without regulation and guidelines for advertising, as defined in Title VIII, section 804(s), HUD must assume more and more responsibility for aiding and abetting the real estate industry's desire to keep the housing market segregated."[16]

While objections to race-targeted advertising based on civil rights violations persisted throughout the 1970s and following years, a second objection began to emerge in the late 1970s and 1980s. In addition to pointing out that race-targeted advertising (representationally and geographically) excluded people from opportunities based on race (discrimination, in the aforementioned housing example), advocates alleged that advertising harmed targeted consumers. Alarms about deceptive advertising have been raised in tandem with debates about legal remedies since the early 1960s.[17] However, the earliest articulation of advertising as a race-based consumer harm that I am aware of appears in the article "The Problem of Black Consumers and Commercials" in 1983.[18] While the article begins with a curious introduction that seems far afield from the topic at hand, the author ultimately provides a theory of race-based advertising harms framed not in civil rights but in consumer protection terms.

Griffin's argument amounts to little more than advertising is harmful because it is deceptive and it leads consumers to purchase dangerous products (that generally cause physical harms). However, Griffin frames these consumer harms with an equivalence that is curious to me, and useful in the argument I later make regarding the need to rethink how we frame race-based harms accrued to people of color as a result of race-targeted advertising. Griffin states that "White Americans, as well as their Black counterparts, are victimized consumers.... Blacks and whites alike purchase gimmicks, games, gadgets and dangerous toys."[19] The equivalent risk of harm among Black and white consumers as a result of advertising seems counter to the author's reasoning for highlighting the particular risks of advertising on Black consumers.

Three things stand out to me about this argument. First, the equivalence that Griffin uses to frame Black and white consumers approximates the model of fairness that underlies the discriminatory advertising prohibitions set forth in the Fair Housing Act cited earlier. That is, the statute defines non-discriminatory advertising as advertising the same thing to all audiences, regardless of race. Second, Griffin does not invoke the disparate impact theory as a means to distinguish actual harm and risk of harm to Black consumers—particularly when this means of evidencing discrimination is on the rise, in employment, fair housing, education, and other areas of litigation.[20] Third, implicit within his argument—the part that is buried in a footnoted quote—Griffin alludes to the reason we should distinguish Black and other non-white consumers from white consumers. His premises provide a fitting foundation for why disparate impact may not be the only lens through which to conceptualize harm and impact—particularly in the case of race-targeted advertising. “Non-white low-income families, particularly Negroes, are doubly disadvantaged; their poverty is compounded by racial discrimination, and they have comparatively few opportunities to improve their social standing in the community.”[21]

3.0
Algorithmic Discrimination

Four arguments emerge from the advertising and marketing industry's historical origins and early development, prompting several questions about our contemporary moment:

- How should we define the problem of racial targeting in advertising and marketing practice? What makes targeting discriminatory and harmful?
- How do we identify and define discriminatory racial targeting in the complex, automated, and algorithmically driven technologies that characterize today's advertising technology systems and infrastructure?
- What theory of discrimination and discriminatory harms should guide us in this digital environment? Is disparate impact—the prevailing means for defining racial discrimination—appropriate and sufficient for defining what discrimination means in the context of automated, race-based ad targeting?
- Is "fairness" an adequate framework for framing, identifying, and addressing the impacts and harms produced by race-targeted advertising?

I provide a brief answer to each of these questions in the next few chapters, and provide a framework for exploring racial targeting consistent with both those answers and with the four conclusions I drew from the country's intersecting racial, computational, and advertising and marketing history.

Defining the Problem of Racial Targeting in Advertising and Marketing Practice

In this section, I first offer a framework for conceptualizing the risks, impacts, and harms to minoritized individuals and communities produced by automated, algorithmically driven, race-targeted advertising. Second, I outline a method and process for identifying and investigating the existence, outcomes, and potential impacts of targeting. The foundation for this methodology and my later critiques related to fairness specifically emanate from recent co-authored work led by Matthew Bui, in a paper titled *Targeted Ads as a Case of Algorithmic Discrimination*.[22] This paper extends that work significantly, driven by what Bui et al. lay out as the need to develop new frameworks for conceptualizing race-based ad targeting in a way that lends itself to policy remedies that are more justice-oriented.

What's Wrong with Targeting?

Defining racial targeting—whether through traditional media or algorithmic platforms—as harm in and of itself helps us to conceive the linkage between advertising and marketing practice and the collective harms it produces beyond that of any individual consumer. This is especially the case inasmuch as racial targeting, like targeting consumers based on age, income, consumer habits, or any other reason, is intentional. Targeting is intentional, and the imagined and constructed targets of digital advertising increasingly become so (individual targets) the closer they move from audience target to engaged audience member, with respect to advertising and marketing communications, to being party to a transaction as a result.

In 2012, I began serving as an expert witness on behalf of the plaintiffs in *Saint-Jean v. Emigrant Mortgage Co*. The case, filed in U.S. District Court for the Eastern District of New York in 2011 alleged that the bank sold predatory mortgage products, violating the Fair Housing Act, Equal Credit Opportunity Act, and the New York City Human Rights Law.[23] In one line of argument, the plaintiff's attorneys, representing the firm Relman, Dane & Colfax, charged that Emigrant's advertising and marketing practices targeted prospective mortgage seekers in Black and Hispanic neighborhoods—a phenomenon now commonly referred to as reverse redlining or predatory inclusion.[24] I examined the evidence, argued in my written report, defended the report in a lengthy deposition, and then testified before a judge and jury that Emigrant's advertising and marketing did indeed constitute reverse redlining.

The defense in this case raised two primary questions in objection to my testimony, questions I had faced in a previous case alleging similar actions[25]: Isn't targeting accepted marketing and advertising practice, and if so, what's wrong with it? My answer of course was that while targeting is accepted marketing and advertising practice, it is wrong when a company sells a product that is fundamentally harmful, and it is discriminatory when that company exclusively targets that product to racially marginalized and historically underserved groups.

The defense sought to exclude my testimony throughout the legal proceeding on the grounds that I was called as an expert on race and advertising and marketing practice, not as an expert on either mortgage products and financing, or the tenets of the Community Reinvestment Act, which Emigrant used to defend its targeting of Black and brown communities with its mortgage products. Ultimately, the judge in the case overruled these objections and allowed me to testify that targeted advertising and marketing practice, and the predatory nature of both practice and product, go hand in hand. The judge recognized, as I argue here, that race-targeted advertising promoting the sale of fundamentally destructive products are part and parcel of the harms wrought by the transaction, whether that is foreclosure, bankruptcy, massive debt accrual, or the collective consequences that these repeated harms produce—the extraction of wealth and erosion of social capital in Black and brown communities.[26]

Race Proxy: The Salience and Masking of Racial Identity in Digital Practice

In my 2014 article, "Racial Formation, Inequality and the Political Economy of Web Traffic,"[27] I identified what was then, and continues to be, a contradiction in the way that race and racial identity are treated in digital context, by platforms ranging from search engines like Google to social media platforms like Facebook (Meta). There, I briefly demonstrated the ways that, on the one hand, platforms did not provide explicit ways for users to identify themselves by race or ethnicity in the same ways that gender, religious affiliation, and other identity markers are often solicited. On the other hand, it was clear in both the architecture in which systems for classifying websites were built and in the results produced by Internet searches that race was exceptionally salient in the political economy of the Web—especially inasmuch as advertising is the backbone of these major search and social media platforms.[28] This phenomenon, along with the findings about how search engines help to segregate Internet traffic and thereby differently confer visibility to race-oriented websites, is what Chris Gilliard and Hugh Culik[29] have popularized more broadly as "digital redlining," a term coined as early as 2007 but not explicitly used to refer to race-related phenomena.

This phenomenon became increasingly clear in 2019 when Facebook was sued for civil rights violations by allowing users of its advertising platform to target based on race, facilitating discrimination in housing, employment, and potentially more.[30] It ended the practice and Google followed suit in 2020 when it made it no longer possible for housing and real estate advertisers to use zip codes in their ad targeting.[31] However, these examples of curtailing zip code-based ad targeting still mask the ways that complex algorithms that serve up ads and search results that maintain the salience of race for consumer marketing.

This practice also means that zip codes remain one of our best ways to identify racial targeting in digital advertising systems, especially at a time when platforms are doing away with the most explicit ways to target specific consumer demographics. As in the political realm, where explicit racial targeting by political candidates was once considered both negative and frequently a violation of the Voting Rights Act,[32] more recent strategies to "cue" or "appeal" to race have been designed to be subtle and implicit.[33] In similar ways, the fact that advertisers can no longer use actual race indicators or racial proxies like zip codes as specific targeting variables on the largest ad platforms does not mean that the intent to discriminate—or put a different way, the intent to target based on race—has suddenly been diminished.

Identifying and Defining an Approach to Identifying and Auditing Digital Ad Targeting: The Case of Payday Lending

This section outlines a process for identifying racial targeting in the area of financial services advertising and demonstrating a range of potential impacts and harms. I conducted two interrelated studies—algorithm audits—of different types of digital advertising and marketing that share the following common foundations.

- **Focus on payday lending:** Each of the studies I present focuses on a single issue: payday lending. While payday lending and payday lenders are not in and of themselves predatory, they have historically been known to disproportionately target and impact borrowers of color.[34] Focusing on this single advertising issue area helps to distinguish lenders across a spectrum, ranging from legitimate to potentially predatory; identify and compare the geographic targeting of competing lenders; and identify a broader variety of players in a given sector that comprise the online ecosystem in which the search for and advertising of payday lending products and services takes place.
- **Use of zip codes as race proxy:** In the absence of explicit racial indicators, I use zip codes as a proxy for race, for all of the reasons I previously mentioned. To enhance the relationship between geographical locations and race that makes zip codes a reliable proxy, I modeled the following framework and studies on zip codes that have the highest concentration of a single racial group, in this case, Black and white populations. In my first study, I used the zip codes with the top 10 highest percentage of either Blacks or whites, so long as the population of those zip codes exceeded 3,000. This resulted in zip codes that are scattered across the United States (though predominantly in the South, Northeast, and Midwest). In my second study, I modeled a single geographical area where African Americans are represented in high concentrations within multiple contiguous zip code tabulation areas. This also provided the ability to address issues of racial advertising targeting alongside other measures of equity as outlined in the PolicyLink National Equity Atlas.[35]
- **Analysis of advertising types:** The studies here analyzed two different, but related, forms of advertising and marketing—display advertising and paid and organic search.
  - Display advertisements consist of text and/or audiovisual content pushed to users on websites they visit.
  - Paid and organic search results refer to content that is curated and ranked for users (typically by a search engine, like Google) searching for specific content. Advertisers can pay to have their content appear in prominent places within search results (typically at the top or bottom). Other results are rank ordered for users through search engine algorithms that arbitrate website and content visibility.

Typically, commercial websites attempt to game the search engine's algorithms in order to rank more highly, and therefore become more visible to users in search results. This is typically done through either, or a combination of, advertising technology (ad tech) infrastructures (software embedded within websites) and/or marketing professionals who manipulate website content and structure in order to improve website "quality" (the key overall factor used by algorithms to rank websites).

First, it is important to point out that display advertising, paid search, and organic search all constitute advertising. Second, website "quality" provides a useful data point for identifying lender websites that are more likely to be predatory in nature, and it helps to characterize the general web context that users become connected to and immersed in when searching for information about payday lenders. Third, the status of lenders' website ad tech infrastructures provides an indication of a lenders' ability and/or propensity to target.

Data Sources and General Methodology

The primary data for the following studies came from the website semrush.com, a marketing data platform that tracks and produces data about the content, sale, and distribution of online advertising, website user traffic, quality, visibility, and search engine result rankings. Keywords are the basis for the advertising auctions that arbitrate display advertising, paid search, and organic search results. Google explains that:

> When someone searches, the Google Ads system finds all ads whose keywords match that search; From those ads, the system ignores any that aren't eligible, like ads that target a different country or are disapproved based on a policy violation; Of the remaining ads, only those with a sufficiently high Ad Rank may show. Ad Rank is a combination of your bid, ad quality, the Ad Rank thresholds, the context of the person's search, and the expected impact of extensions and other ad formats.[36]

Google adds that, "the most important thing to remember is that even if your competition bids higher than you, you can still win a higher position—at a lower price—with highly relevant keywords and ads."[37]

Building the initial foundation for the Semrush advertising data used for these studies was a three-step process:

1. **Choose keywords.** Choosing keywords that users looking for payday loan information are likely to use generated a list of websites that were vying for traffic based on those specified keywords. After some exploration, I developed a keyword set that included 57 of the top keywords associated with payday loans (see Appendix A for the keyword list). Once entered, Semrush identified websites vying for position on one or more of these keywords.
2. **Choose location.** By using Semrush's "position tracking" tool (designed to aid marketers in "multitargeting across multiple locations"[38]), I narrowed my keyword analysis to a geographical location based on zip code. This resulted in the tool generating traffic and visibility data for website ranking on the given keywords in the specified geographical area, thereby providing the ability to control and compare data across locations.
3. **Discover competitors.** The final step of this initial process of collecting the data needed to investigate targeting was to explore the platform's competitor discovery data. This data includes comparative data for all of the websites that rank on one or more of my specified keywords. It also includes the following metrics: domain name of the ranked website; visibility rank, which ranks the site's visibility for the specified keyword on a low-high, 100-point scale; visibility difference, which is the difference in the site's ranking in the current week compared to the previous week; estimated traffic to the domain and the difference in generated traffic from the following week; the total number of keywords, of the specified set of keywords, for which the domain ranked; and the average position rank of the domain in Google search results, along with the average rank's standard deviation.

Depending on the type of advertising being analyzed, I specified whether I wanted data associated with the domains' paid Google advertising or organic search. Finally, I downloaded the results of each set of data for each of the specified zip code locations to form the basis of a dataset that I augmented with additional data sourced both from, and beyond, the Semrush platform. Figures 1 and 2 illustrate each of the above points.

Figure 1. Semrush Position Tracking & Competitive Analysis Platform Showing Configuration Details

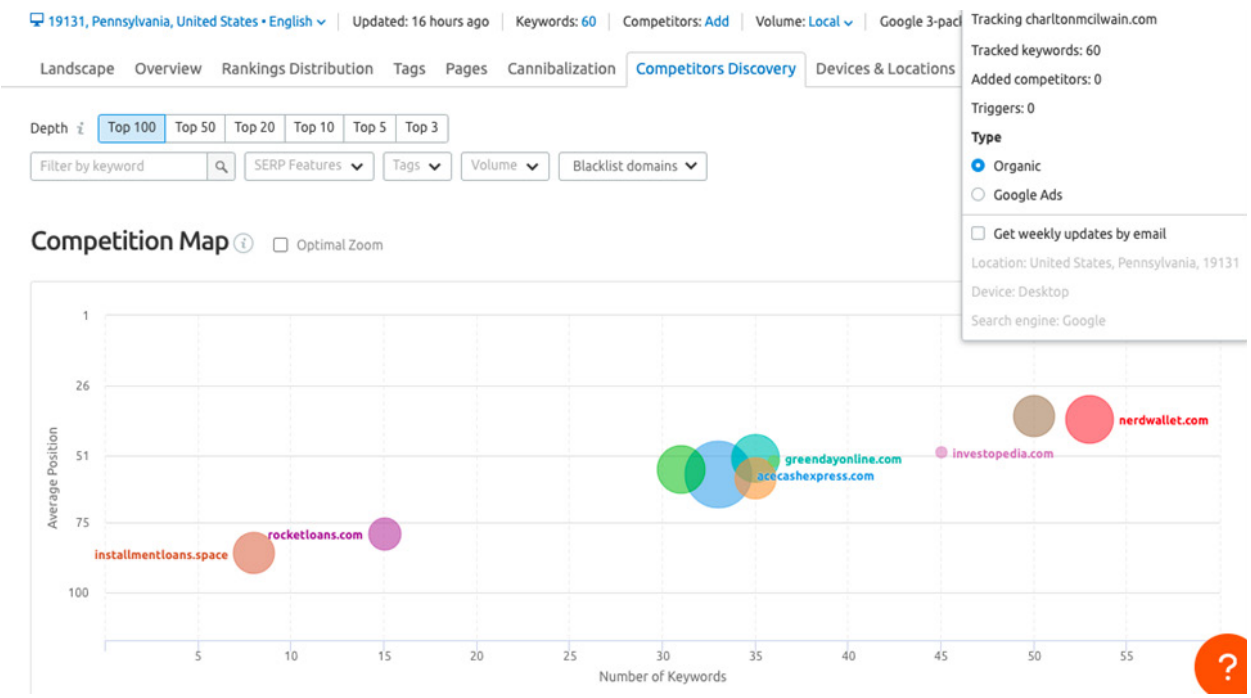


Figure 2. Semrush Position Tracking & Competitive Analysis Platform Results Data

Competitors 1 - 10 (2542)

	Domain	Visibility Feb 27	Visibility Diff	Estimated Traffic Feb 27	Estimated Traffic Diff	Keywords	Avg pos
1.	acecashexpress.com		↑0.86	85.08	↑1.54	33	58.57 ± 42
2.	nerdwallet.com		↓0.60	34.15	↓-11.51	53	38.37 ± 36
3.	creditninja.com		↑3.97	23.70	↑6.91	31	56.43 ± 43
4.	greendayonline.com		↓0.80	13.53	↑0.42	35	52.57 ± 43
5.	installmentloans.space		↑1.09	20.51	↑0.72	8	86.93 ± 33
6.	creditkarma.com		↓0.53	14.73	↑0.95	50	37.15 ± 34
7.	opploans.com		↓1.04	28.98	↑3.50	35	59.87 ± 40
8.	rocketloans.com		↑0.90	7.66	↓0.00	15	79.45 ± 37
9.	investopedia.com		↑0.34	17.54	↓-3.57	45	50.17 ± 35
10.	advanceamerica.net		↑0.13	11.13	↑0.51	36	53.77 ± 40

Display Advertising, Targeting Intention, and Modeling Impact

Which payday lenders demonstrate intent to target? This is a "top of the funnel" question. Which lenders are targeting based on race? This question is further down the funnel. I begin with the first, and offer this claim: one way to distinguish whether and which payday lending companies are targeting based on race is to identify those armed with the capabilities to target. The greater the ad tech infrastructure a company builds to target, the greater the likelihood that it will target based on race.

Ad Infrastructure as a Measure of Targeting Intent

To determine what websites demonstrated an intention to target, I did the following. First, I followed the three-step process specified above: chose keywords, chose location, and discovered competitors. These steps included display advertising results for 1,142 domains competing for payday loan-related keywords, within the top 10 Black and top 10 white zip codes (see Appendix B for zip code and related data). Second, I purchased data from Wappalyzer.com[39] about each of the 1,142 domains in the dataset, which yielded an exhaustive list of technologies used by each website. The technologies of most interest for my purposes were those in the following categories:

- A/B testing,
- advertising,
- analytics,
- customer data platforms,
- retargeting.

For each technology found on each respective website in the dataset, I coded whether or not that technology was present on the website. I then created a variable that included the total count of technologies present on each respective website, as well as the total count of each technology found in a given category (a website might use multiple advertising technologies for instance). Finally, I created a total ad tech index that indicated the proportion of ad tech found on each website out of the possible number of ad tech products. Lower scores indicated a lower presence of ad tech, and higher scores indicate a greater ad tech presence. Table 1 shows the mean scores and their standard deviations.

Table 1. Ad Tech Index Scores as Measure of Intent to Target

Ad Tech Category	Mean	Standard Deviation
Advertising	0.16	0.25
A/B testing	0.18	0.29
Analytics	0.35	0.38
Customer data platforms	0.15	0.28
Retargeting	0.15	0.26
Total Ad Tech	0.25	0.28

This represents one broad way to determine what websites intend to target. We could say that websites below the mean demonstrate less of an intent to target, than those at or above the mean do. Means and standard deviations provide more detailed distinctions between sites about their motivations, with those falling at higher standard deviations above the mean demonstrating even greater motivation to discriminate. Using this as a guide, a total of 165 of the websites on the list demonstrate an intent to target (see list of websites in Table 2). Sites that demonstrate an intent to target utilize, on average, 13 different technologies, including one A/B testing application, three advertising applications, six analytics applications, one customer data platform application, and one retargeting application.

While there were, of course, a number of competing ad tech providers for each of these advertising and marketing activities that facilitated targeting, the ones described here predominate within this dataset of payday lenders. They illustrate clearly how they facilitate audience targeting broadly—individually and in relationship to each other. That is, one gets a clear sense that a site armed with these technologies intends to target consumers in a significant way. But, as mentioned earlier, targeting defines marketing and advertising, and marketing and advertising are targeting. So, the next relevant question to address is, does a payday loan company's digital advertising strategy reveal an intention to target consumers based on race?

How Ad Tech Infrastructures Facilitate Targeting

To get a better sense of how these ad tech infrastructures facilitate targeting, here is how each of the most frequently used products in each of these categories (represented in the research dataset) describe their product and company.

A/B Testing: Optimizely. Optimizely facilitates targeting by providing A/B testing capabilities to improve the content of, engagement with, and outcomes from advertising and marketing content. A/B testing provides a way to test the performance of two different versions of content on actual or potential audiences. In their words, Optimizely let's you "Use the world's most powerful front-end A/B and multipage experimentation product built for the enterprise; leverage experimentation and personalization to create winning experiences; deliver targeted messaging, personalized offers and recommend the most relevant content for your users."[40]

Advertising: Google Advertising. Google Ads is an advertising platform. It facilitates advertising production, audience targeting, and performance metrics for display or search-based advertising. It states that users can "Get in front of customers when they're searching for businesses like yours on Google Search and Maps. Only pay for results, like clicks to your website or calls to your business... With Google Ads you can reach more relevant customers within your budget. Plus, our smart technology will help you improve your ads over time to get more of the results that matter to your business."[41]

Analytics: Google Analytics. Google Analytics is a service that allows a user to track customer traffic to, and engagement with its website, particularly with its advertising. "Understand what works by measuring traffic sources, interactions with your content, and more. Create custom website goals that matter most to your business, such as signups or e-commerce purchases. See the impact of your digital marketing on your bottom line by measuring revenue, return on investment (ROI) and return on ad spend (ROAS). Analytics is built to integrate seamlessly with Google's other media and publisher products, including Google Ads. Advertise more effectively by linking your Ads account to Analytics. Easily turn your website events into ad conversions, then access Google's advanced machine learning capabilities to optimize ad campaigns for traffic, CPA, ROI or ROAS.[42]

Customer Data Platform: Adobe Experience Platform Identity Service. A customer data platform facilitates behavioral targeting and engagement with a company's customers by aggregating and storing data specific to individual users. Adobe Experience puts it this way: "Delivering relevant digital experiences requires having a complete understanding of your customer. This is made more difficult when your customer data is fragmented across disparate systems, causing each individual customer to appear to have multiple 'identities.' Adobe Experience Platform Identity Service provides you with a comprehensive view of your customers and their behavior by bridging identities across devices and systems, allowing you to deliver impactful, personal digital experiences in real time. With Identity Service, you can: Ensure that your customers receive a consistent, personalized, and relevant experience through each interaction; Stitch together several different identities from disparate sources and create a comprehensive view of your customers; and Utilize an identity graph to map different identity namespaces, providing you with a visual representation of how your customers interact with your brand across different channels."[43]

Retargeting: Google Remarketing Tag. Retargeting applications facilitate website owners' ability to continue to track and serve ads to users once they have visited and left the company's website. "Google's new Remarketing Tag helps you to easily create remarketing lists by allowing you to place one tag across all pages on your site. ... Now you can reach specific audiences with relevant messaging and tag your entire site with ease."[44]

Differential Representation Indicates Race-Based Targeting Intent

A website's ad tech infrastructure can demonstrate a company's intention to target—including race-based targeting. But, finding additional evidence about race-based targeting intention specifically requires that we look at advertisers' actual practice. The display advertising dataset was based on payday loan company's advertising in all or mostly Black or white zip codes. This data provided two ways to demonstrate whether companies intentionally targeted consumers in mostly Black zip codes, mostly white zip codes, or some combination of the two. First, we can define a company's intent to target by identifying sites that are exclusive to either the Black or white zip codes. Second, we can define it by those that choose to advertise in some Black zip codes but not others. Third, we can define it by the number of predominantly Black zip codes in which a company advertises. Based on these parameters, 45 sites advertised exclusively in Black zip codes, and 76 advertised exclusively in white zip codes (Table 2). Here, exclusivity to one set of zip codes and/or their overrepresentation in Black zip codes demonstrates an intent to target.

While these indicators demonstrated the factual basis for which sites intended to target based on race, the consequences and differential meaning of ad exclusivity or overrepresentation do not become clear until we know more about the sites and the products they represent. That is, this information established who targeted whom, but it did not yet answer the full question, which is, who is targeting *what* to whom? Before addressing that question, in the context of modeling impact, I identified one additional means to demonstrate a site's targeting intent.

Table 2. Sites Demonstrating Targeting Intent Through Ad Exclusivity and/or Overrepresentation

Black Zip Codes Exclusive	White Zip Codes Exclusive		Overrepresented in Black Zip Codes
1ffc.com	allproductsweb.com	mintfinancialgroup.com	10bestpersonalloans.com
24cash.ca	apruve.com	mylendly.com	247loanpros.com
acimacredit.com	autorepairloansnow.com	nation.com	albanypark.com
allbirthdayfreebies.com	bankatfirst.com	nationaldebtrelief.com	albert.com
amone.com	beenverified.com	nearside.com	aspiration.com
bcu.org	bestonlinemortgageloan.com	northbaycash.com	bestmoney.com
bedplanet.com	bestreviews.com	onevip.com	biz2credit.com
Blackhawknetwork.com	burrow.com	originpc.com	bluevine.com
butchsautobody.com	businesshomepage.solutions	pigeonloans.io	cardcash.com
capitalpaymentssolutions.com	capitalone.com	pingpongx.com	carshield.com
cashnetusa.com	capitaloneshopping.com	pls247.com	chime.com
cbautojobs.com	cash.com	protectmycar.com	credible.com
concordautoprotect.com	chargeafter.com	seedfi.com	creditkarma.com
conns.com	chase.com	shop411.com	creditstrong.com
consumeraffairs.com	checkintocash.com	sleepnumber.com	easypayfinance.com
creditfresh.com	circleup.com	smartanswersonline.com	experian.com
creditunion1.org	consumersadvocate.org	stockwiseauto.com	fastloanadvance.com
dcu.org	consumersearch.com	surveyjunkie.com	fastloandirect.com
earnin.com	directhit.com	td.com	figure.com
easternbank.com	dutrac.org	top10bestpersonalloans.com	fundera.com
farmershomefurniture.com	easyautolenders.com	top10mortgageloans.com	fundinghero.com
firstrepublic.com	eiloan.com	topwealthinfo.com	graceloanadvance.com
freedomfinancialnet.com	essentialoan.com	tuitionchart.com	howstuffworks.com
gotoloans.com	financesavingsplan.com	unison.com	info.com
laddercredit.com	findinfoonline.com	upfurnish.com	intuit.com
leaseville.com	firstpeoples.com	upgrade.com	laddercredit.com
loansmee.net	fundthatflip.com	varomoney.com	lanterncredit.com
modoloan.com	getsearchinfo.com	walletgenius.com	lendingpoint.com
mybobs.com	giftcash.com	watersbodyshop.com	lendingtree.com
mypoints.com	go2bank.com	zinchfin.com	lendstart.com
nickelodeonbirthdayclub.com	gopher.com		loansmarket.com
oneparkfinancial.com	homrest.com		moneylion.com
payoff.com	informationvine.com		motiveloan.com
perfectgift.com	insideweather.com		mysynchrony.com
plastiq.com	izitosearch.com		nerdwallet.com
point.com	joinhoney.com		netcredit.com
quick2lend.com	kasasa.com		onemainfinancial.com
regionalfinance.com	key.com		quick2lend.com
sdfcu.org	lavishgreen.com		quickenloans.com
southstreetautocare.com	lendr.online		sofi.com
suburbanautofinance.com	life123.com		top10personalloans.com
tokloans.com	loanbuilder.com		upstart.com
topconsumerreviews.com	lpiloans.com		wayfair.com
westtownbank.com	mapquest.com		wefixmoney.com
wrench.com	mdg.com		
	meblefurniture.com		

Differential Reach as a Measure of Race-Based Targeting Intent
One additional way to define racial targeting is to ask the question, how hard does a site/company work to reach their advertising targets? In this dataset, that question can be addressed with the keyword “matches count” variable. Advertisers participating in digital ad auctions bid on, and compete with other advertisers for visibility to audiences searching for specific keywords. Competing for attention on multiple keywords associated with a site’s content and/or product offerings increases the chances of one’s ad being shown to audience members searching for that term. As such, we can say that the number of keywords on which a site competes for visibility with a specific audience indicates their intent to target.[45]

Recall that our dataset was based on approximately 60 keywords associated with payday lending. This means that every site in the dataset competes for at least one keyword and as many as 60. Comparing and determining sites’ effort to reach their audience, as determined by the racial makeup of the zip code in which they advertise, demonstrates the intent to target. Or, it would be more accurate to say that it reflects a more intensive intention to target based on race. In this dataset, payday loan advertisers expended greater reach into Black zip codes compared to white zip codes. On average, advertisers competed for visibility on three keywords, compared to four keywords for advertisers competing in Black zip codes. This represents a statistically significant difference ($p < .001$). That disparity grows significantly when we look at the sites competing exclusively in either Black or white zip codes. In this case, advertisers competing in Black zip codes compete for three times the number of keywords than those competing in white zip codes.

Modeling Impact
The logic of this dataset and method for analyzing race-based ad targeting impact was determined by two primary quantifiable factors that have less to do with the advertisement itself and were more about the company and product being sold to audiences. The first was site reputation, and the second was audience exposure. While the majority of sites in this dataset were payday lenders, they were not all necessarily predatory lenders. So, the question becomes, how can we distinguish between sites that are more or less predatory? These data limit the ability to determine the predatory nature of the product being sold by the respective companies. In light of this, what we do have are two proxies that don’t so much indicate predation, but reputation.

This dataset included two measures of website trustworthiness/reputation/quality. Semrush’s *authority score*[46] is given to every domain in its database. Using a proprietary algorithm, the company rates a domain’s impact not on users, but on other websites, based on a combination of factors that include characteristics such as the number of links a website has to and from other quality websites (think power laws in social network theory); a website’s links to more popular and well-trafficked websites; the domain’s age, and a number of factors similarly included in Google’s (now deprecated) "page rank" algorithm. Google still uses a multi-algorithm ranking system to help determine what websites to serve up based on user search queries. In fact, inasmuch as *authority score* is based on the reputation and popularity of websites, this score is inextricably linked to Google's ranking system. While the utility of Semrush's authority score is to help marketers better game the system for search visibility (in Google, Bing, and other search engines), the score (and Google's manual about what goes into their various algorithm weights)[47] are insightful for understanding why Semrush's authority score is a useful barometer for separating quality and legitimate payday lending sites from those that are potentially predatory.

I used a second measure of website quality to help distinguish potentially predatory lending sites from other payday lenders. This measure is Majestic.com's *trust flow*. Like Semrush, Majestic is a SaaS (i.e., software as a service) company that facilitates digital marketing professionals, primarily for the purpose of search engine optimization. As such, its trust flow score is a similar measure of website quality intended to be used to help marketers to determine how to maximize their visibility in search.[48] In this dataset, *source authority* and *trust flow* are highly correlated ($r=.642$, $p<.001$). For demonstration purposes here, however, I report on the two separately rather than reducing them to a single variable.

For the relevant 165 sites in the payday lending display advertising dataset that demonstrated intent to target based on race, the fact that they intended to target is one step. The next was to ascertain whether what they targeted to consumers was, to some degree, potentially harmful, using the website trust measures we have at our disposal. The question then is, how trustworthy are the payday lending websites advertising in Black zip codes (those in general, and those with the intent to target)? In comparison, how trustworthy are those sites that exclusively advertise in white zip codes? Answering these two questions provides us the means to determine potential impacts and harms that might accrue to those in Black zip codes, and whether the impact potential is disproportionate to those residing in those zip codes.

The array of scores in Table 3 tells a story. First, the trust and authority scores in the payday lending display advertising competitive landscape are, to begin with, low. When I compared scores for websites advertising in Black zip codes with those in white zip codes, they were numerically the same for authority scores, and statistically the same (that is, there was not a statistically significant difference) for trust flow scores. When I looked at sites advertising in exclusively white and Black zip codes, however, you can see a distinct difference. Those sites targeting exclusively Black zip codes had scores that were significantly below all that advertised in Black zip codes, and they were significantly below those that exclusively advertised in exclusively white zip codes. Scores of sites advertising exclusively in white zip codes were only slightly below (to a statistically nonsignificant degree) the group of all sites that advertised in white zip codes.

Table 3. Mean Authority & Trust Flow Scores

	Mean Trust | Authority	SD	N
All	35 | 48	19 | 28	1142
Black zip codes	33 | 48	18 | 28	280 | 513
White zip codes	38 | 48	20 | 29	306 | 629
Black exclusive	26 | 35	17 | 28	83 | 83
White exclusive	38 | 45	25 | 27	144 |144
Black over indexers	35 | 48	19 | 28	42 | 42

Based on these measures, I concluded that the potential impact/harm of race-targeted advertising is that Black users are disproportionately exposed to sites that are at greater risk of being potentially predatory. Users in white zip codes on the other hand are exposed to a wider array of sites that offer potentially greater opportunities and less risk of harm. To add some additional color to this analysis, we can look at a few examples of the kinds of sites targeting display advertising exclusively in white and Black zip codes.

For instance, it is in exclusively Black zip codes that we find known predatory lending companies like CashNetUSA, which during the height of the coronavirus epidemic charged Black consumers upwards of 300% in interest for loans,[49] and NetCredit, who has made predatory lending warning lists as recently as January 2022.[50] On the other hand, it is hard not to notice the array of reputable banks like Chase, CapitalOne, and TD Bank that pack the list of advertisers exclusively in white zip codes, along with an array of consumer education and advocacy sites that help users sift through loan and lender information. Both reputable banks and financial institutions as well as consumer education sites are examples of the type of sites rarely included among financial institutions advertising exclusively to Black zip codes.

Theories of Discrimination and Discriminatory Acts in a Digital Environment: The Advantages and Limitations of Disparate Impact Analysis

Some may observe that this analysis of race-based digital ad targeting resembled a somewhat typical disparate impact analysis. It demonstrates the fact of, and means through which, payday loan and similar businesses in the financial services sector differentially target Black consumers with more potentially risky product offerings through their digital advertising. It also demonstrates the ways in which some of these companies limit access to Black consumers by advertising more high-quality products, services, and resources almost exclusively to white consumers.

Part of the purpose of this study was to provide and demonstrate a method for conducting such an analysis, and to demonstrate whether clear patterns emerged to justify such a study as a framework for, and as means to audit, digital advertising practices for evidence of racial targeting. It was also my purpose, through this framework, to demonstrate the degree to which these patterns represent a combination of intentional decision-making on the part of site/company advertising and marketing professionals and algorithmic decisions facilitated through the google ad network that these companies use to distribute their display advertisements in conjunction with their keyword ad auction system (which is what these data track).

Finally, I wanted to, through this framework and analysis, identify some limitations of disparate impact as a primary, sole, or even most appropriate way to conceptualize and approach the auditing of racial discrimination in digital ad targeting. For all the good that this approach provides, it lacks the ability to provide two key things that are necessary not only to establish a pattern or practice of discrimination but also to conceptualize and identify evidence of harm.

First, in the absence of (and access to) data—that is either guarded by and/or untrackable to advertisers and the companies that comprise the complex ad tech infrastructure—we cannot properly measure any one individual's exposure to online targeted advertising.

Second, and also as a result of our lack of access to the right data, we don't typically have the means to identify user outcomes. While we might in the best of possible present worlds gain access to ad conversion data—that is, users who clicked on an ad and were exposed to its content—we don't have access to what follows from a user's decision to take their search for payday lending to the next step. That is, digital advertising engagement metrics are siloed to the public from user business decisions—in this case, the decision to begin, complete, and experience the aftermath of entering into a contractual financial transaction.

The lack of access to structured data linking targeted ad engagement and conversion metrics to consumer business decisions means that it is difficult, if not impossible to, codify specific, individual-level harms. This makes it difficult to provide what is frequently desired by legal professionals and policymakers—a direct link between the pattern or practice that disparately impacts a member of a protected group and an individual or group of individuals directly and negatively affected by that specific pattern or practice.

To be clear, I am not arguing that disparate impact analyses in the framework that I propose and demonstrate are not useful. To the contrary, finding the disparate pattern is powerful and necessary. It just may not be enough, in some circumstances.

Digital Hoods: Networked Model of Race-Based Ad Targeting

Dr. Robin Stevens and colleagues' concept of the "digital hood" provides a useful, supplementary framework to effectively demonstrate the potential harms and impacts accrued in minoritized neighborhoods as a result of race-based targeted advertising. Stevens' group uses the digital hood concept to track the "dynamic and somewhat concerning interplay between the geographic neighborhood and the digital neighborhood."[51] Her focus was young people, and her concern was that young people from underserved neighborhood environments began to play out negative behaviors in digital space in ways that replicated those behaviors in their geographical neighborhood. I am interested, however, in using this concept as a potential lens through which to better understand how the online world's encroachment on life lived in geographical space compounds, exacerbates, and sustains a history of discriminatory effects, through race-based targeted advertising.

Payday lending harms individuals whose desperation may lead them to initiate a financial transaction that adversely impacts their financial opportunities and that of their families. But the damage can go much further than that, going beyond the individual to collective harm. For instance, the constant and normative practice of bombarding and concentrating cigarette, alcohol, and fast-food advertisements and establishments in Black and brown neighborhoods, and the relative absence of banks and healthy food, for instance, significantly harms not just individuals but also the neighborhood and community collectively.[52]

Is Fairness an Adequate Framework? Conceptualizing the Impacts of Predatory Advertising as Compounding Harms

Framework and Method

Different from a disparate impact analysis, a network analysis of targeted ads (in this study) is a constellation of relationships between nodes (websites, that represent payday loan and other financial services sector organizations) and aggregated users connected to a geographical place—a zip code (another node)—where users reside. Different from statistical analyses, the object of focus is not a collection of cases, whether those cases represent people or an action like an ad placement. In network analyses, the relationship matters most. The characteristics of nodes are also important, but only inasmuch as they help to shed light on the relationships between nodes in the network.

A network approach to codifying the presence and potential harms of race-based advertising targeting makes sense for a number of reasons.

- First, the context of internet search on which digital advertising is based is a dynamic process, constituted as a relationship between users and the information source we engage to find the things we want and need.
- Second, automated and algorithmically driven search engine features and the variety of ad tech systems detailed earlier form a relationship with users. They “know” us—insofar as they track, gather, store, retrieve, and utilize user data to help provide us what they think we need or want.
- Third, these systems have relationships with us insofar as they know not only what we look for, how we consume the information served, and our consumer-constructed or actual identities. They also purport to know—more or less—where we live and what surrounds us in our geographical contexts. I can search for payday loans in a Pennsylvania zip code, but the first results I get are still going to be located near me because Google knows that I live in Brooklyn, New York, because of its access to my IP address, mobile location data, search behavior, and more.
- Fourth and finally, networks—particularly in the way that they make relationships (edges) visible and legible—help us to see different kinds of patterns. These patterns can help us better grasp the kind of power and influence that nodes wield in specific geographical spaces, and the potential impacts and harms that might accrue to that geographical community, beyond any one or set of individuals.

The framework and analysis that follow begins with these questions:

- What relationship does online targeted advertising have, not just with the people who engage with the advertisement, but with the geographical space in which advertising audiences live?
- What payday loan and similar financial services have a greater relationship to a given geographical area and the people who reside there by virtue of their advertising and the company’s geographical locations?
- What other potentially adverse consumer products and services exist alongside payday lenders in the users’ geographical space?
- What types of companies and industries seem to wield more power given the strength of their relationship with the geographical space?
- What can we infer from the answers to each of these questions about what the potential impacts and harms could be to the neighborhood and its neighbors, collectively?

Design

The base of data for this study was derived through the same process as the prior study. I searched for websites competing for the same 57 keywords associated with payday lending. From here, the process diverged in the following ways:

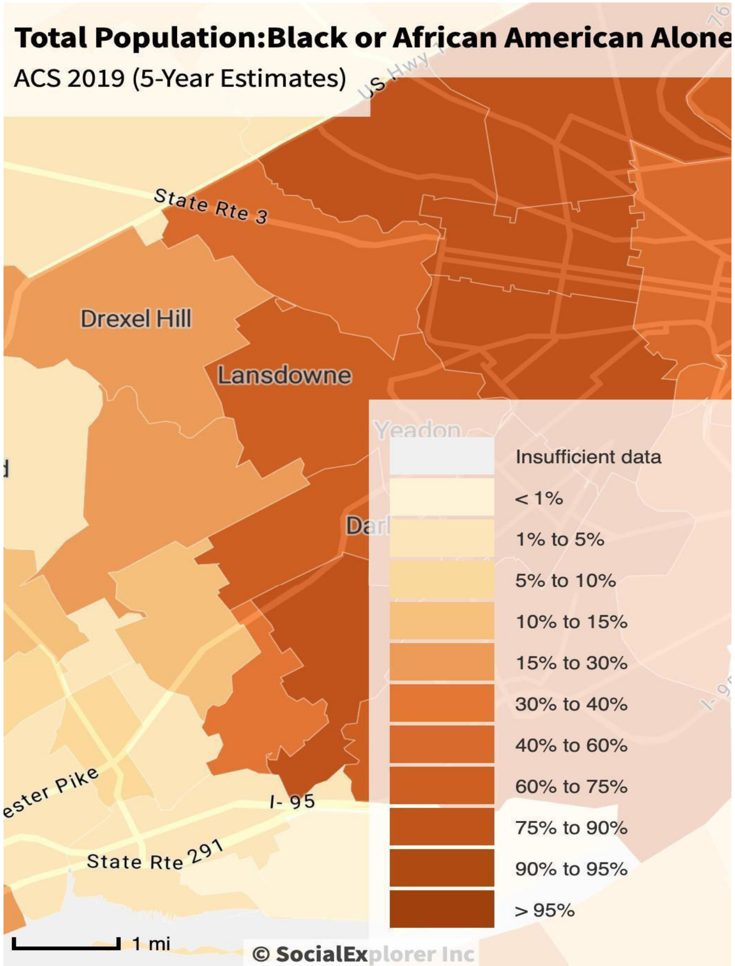
- I included both competitors in the display advertising space and those in the organic search space. This captured sites trying to attract their target audience through display ads and in their search results as a product of the user's keyword search.
- I searched in a single geographical location, comprising 15 contiguous zip codes where the population is majority Black. These include the following zip codes in Philadelphia, Pennsylvania: 19023, 19050, 19079, 19121, 19126, 19131, 19132, 19138, 19139, 19141, 19143, 19144, 19150, 19151, 19153.
- Through Google Maps, I also collected a set of businesses and organizations operating in these zip codes using the search term "payday loan," followed by the zip code (payday loan 19023, for example).
- I created a directed network graph that graphed relationships between the following nodes: source nodes included payday lending keyword advertisers (websites) targeting one or more of the specified zip codes. Target nodes included zip codes as advertising targets and business entities located within the zip code's geographical area.
- I added a number of node attributes to the graph, as well as edge attributes, that describe some aspect of the relationship between nodes. The final network graph includes 3,380 separate nodes, comprising 32,808 edges or relationships between nodes.

My analysis proceeded as follows. First, I provided an overall picture of the Philadelphia neighborhood's concentration of online advertising by sites in the payday lending space, and then separately the concentration of payday lending and related establishments operating in the specified geographical area. Second, I investigated entities among both the online and geographical-based entities that dominate and have the potential for proportional impact. Third, I drew some brief conclusions about how we might think about impact and harm, given the network data.

Geographical Immersion

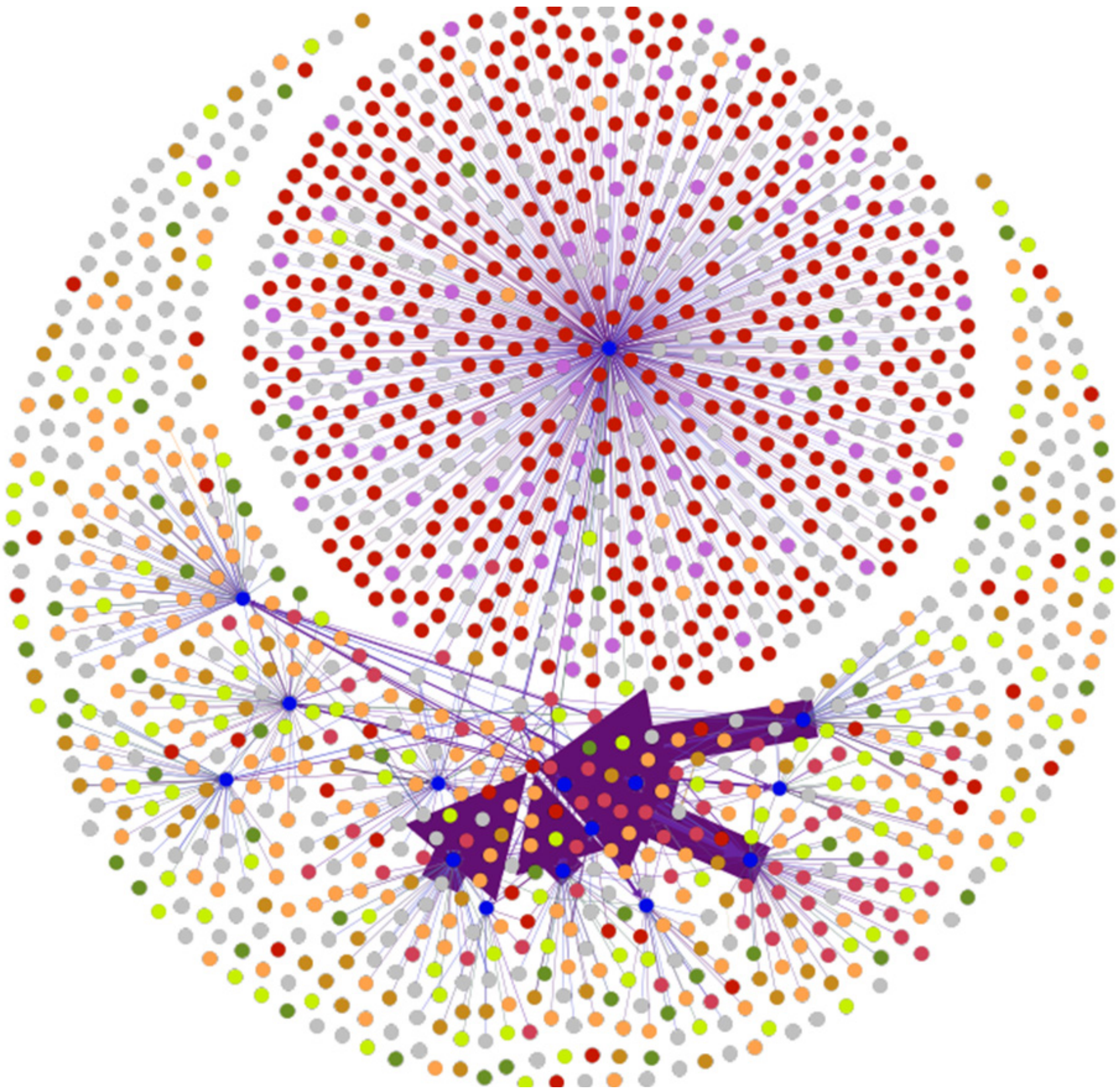
The image in Figure 3 displays the approximate geographical area graphed using the selected Philadelphia area zip codes, particularly the darker shaded areas to the right, which signify the concentration of Black/African American residents. When I begin to add the various graphed visualizations to this, you can begin to see a story unfold.

Figure 3. Graphed Zip Codes



The first network graph in Figure 4 solely captures business and organization entities within this geographical region. Its nodes are connected at two possible points; in-links from the Google Maps search to the entities located in the neighborhood and links back to the online domain via the respective business/organization's website URLs. Each node (circle) represents either one of our targeted zip codes or a business/organization, each of which were categorized by their primary business or organizational purpose and represented in these images by color.[53] Arrows represent the source, direction and target of the relationship. The thickness of the arrows represent the strength of the relationship between the two nodes.

Figure 4. Graphed Entities Across All Zip Codes



Given that our graph doesn't include data specifying relationships between the specific entities here, what you see are individual nodes scattered throughout. The prevalence of certain colors represents greater representation of those entities in the geographical area. The colors seen most here are red and light blue. Here, two cluster formations stand out right away and tell the first piece of our story. This network comprises two connected components. The first component—the circle—depicts a single zip code (19153), indicated by the blue dot at the center of the circle. It primarily contains digital connections concentrated in the area. The second component, the shape resembling a crescent moon surrounding the circle, includes the business and organization entities found within their respective zip codes and, for some, their corresponding digital spaces.

Figure 4, we might say, represents the realities of the everyday experience of those who reside in the respective Philadelphia zip codes included here. People encounter businesses and organizations as they move through their geographical spaces. These businesses offer access to the things that residents need and want. Many of these entities are accessible online. Someone needs cash from their bank account and doesn't want to pay a fee. They search "ATM near me" and discover in the search results that there is an ATM near them. Then they bike five blocks to the Bank of America ATM.

For those whose bank accounts are empty or are short on cash—to pay the rent, make a car payment, buy groceries, or pay for an emergency dental procedure—resources are easily discoverable online, and they lead to specific places and people with whom to find what one needs. The problem is that what is most readily at hand are the risky loan services that dot the area (in red). The accessible resources within this part of the city are rife with payday lenders, check cashing establishments, services offering cash advances, car title loans, and the like. Brick and mortar establishments offering such services comprise more than one-third of the array of establishments in the area. This is more than double the number of restaurants (green dots); five times the number of grocery stores (dark gray dots); 15 times more than the number of health food establishments (light gray dots); and 5 times the number of legitimate banks, credit unions, and financial service education establishments (lightest gray dots).

If we conceptualize digital and geographical experience as one in the same, then what we see represented here is the broadening of the opportunity structure—through the "pull" of internet search—to discover, engage, and potentially transact with one of these risky financial institutions. This is in addition to the broadened opportunity represented just by the introduction of online lenders, which researchers and consumer protection advocates have been sounding the alarm about for more than a decade.[54] This is reflected in this network by two entities represented in the crescent part of this network formation, the large arrows pointing to a single red dot that represents the company Ace Cash Express, which is tethered in digital space to two sites: acecash.com and acecashexpress.com. Ace has been embroiled in litigation for almost two decades by both private and public litigants.

> On September 6, 2001 a class action lawsuit was filed against Ace Cash Express in the United States District Court for the Northern District of Texas. The Complaint alleged that Ace Cash Express exploited low-income consumers by charging outrageous and illegal interest rates on payday loans and used unfair, deceptive, and abusive practices to make and collect on those loans. The complaint called Ace Cash Express an illegal enterprise which amounted to a "massive loan-sharking operation.[55]

Ace Cash operates offices in every Philadelphia zip code in this network and has a diversified web presence. Residents throughout the area can find Ace online and in their neighborhood streets, making its offerings digitally and physically accessible. This accessibility is compounded when we add the digital advertising layer to the network.

Figure 5 displays the networked geography of 15, mostly Black, Philadelphia zip codes, with the network of websites using display advertising and paid search to vie for the attention of users searching for keywords associated with payday loans. What we see in this diagram are three concentric circles, each connected to each through links that crisscross both geographical and digital space. At the center of the densely packed core lies each zip code. They are surrounded by a wall of ads and search results emanating from payday lending sites, most of which offer potentially risky loan products, including a plethora of what I call loan education/broker sites that both help provide information about and link users to lenders who then potentially offer risky products. The layer surrounding the core largely represents websites connected both to risky payday lending sites in that core and to the physical spaces in these Philadelphia zip codes. The outer layer largely represents the brick-and-mortar companies and organizations residing in these zip codes, themselves with their respective connections into digital space. Figure 6 presents a closer look into that core, with some of the site names distinguishable to give a sense of what they offer, or purport to offer.

Figure 5. Network of Sites Vying for Visibility in Black Zip Codes Through Paid Advertising

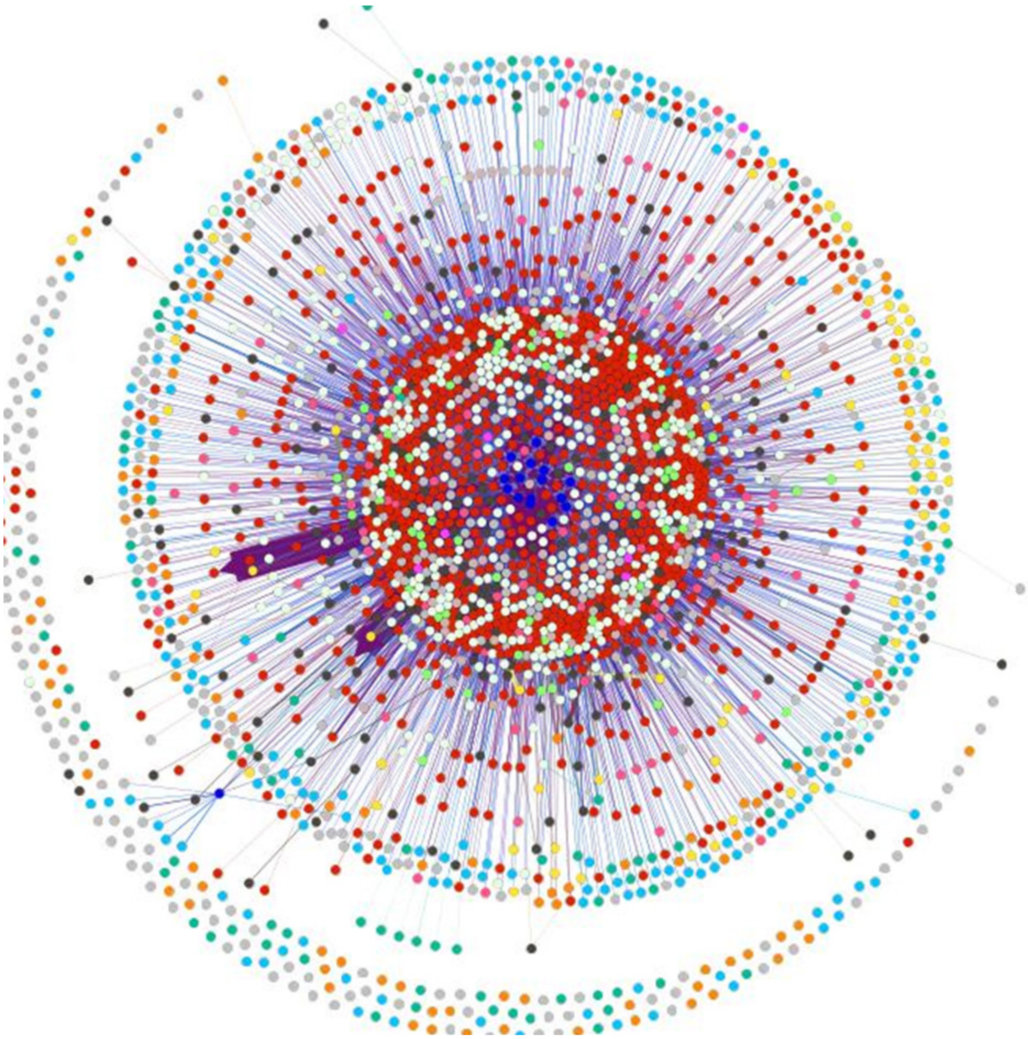
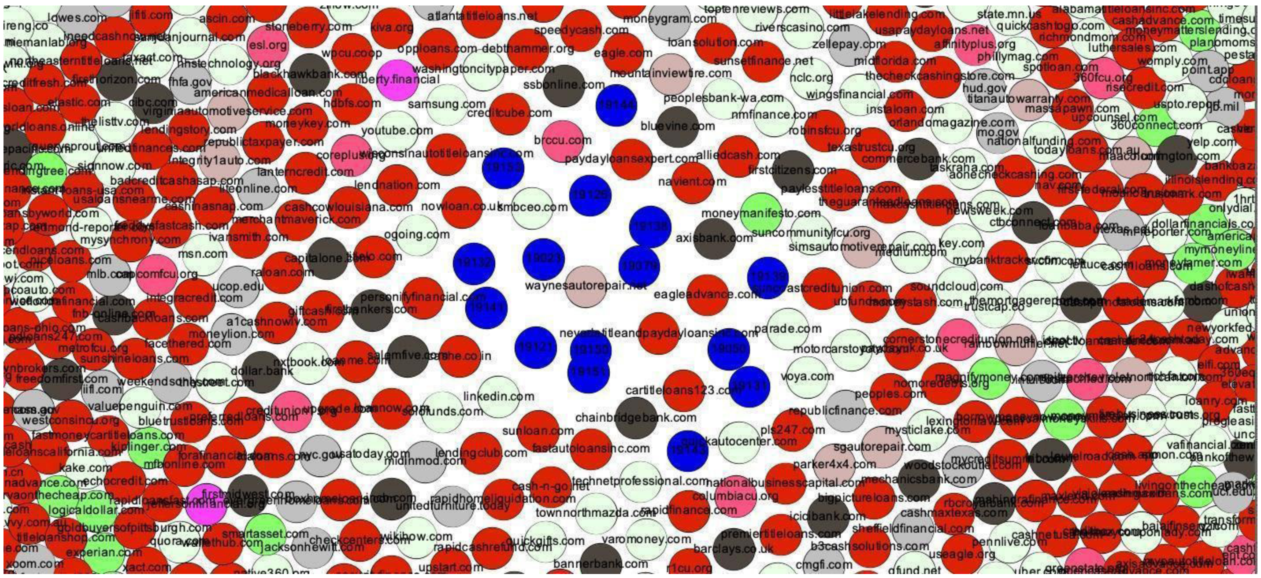
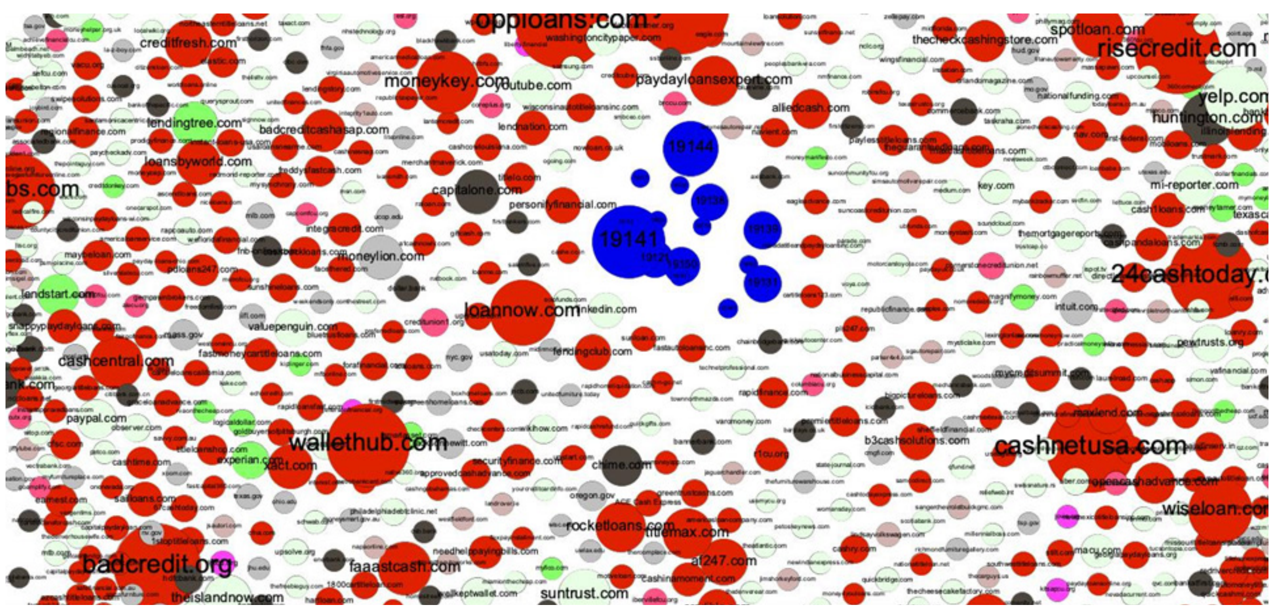


Figure 6. Primary Sites Vying for Visibility Through Paid Search



We can look at other aspects of the network to ascertain which of the sites in this core and throughout this network are wielding the most power in terms of their visibility, effort to reach the mostly Black consumers represented in these area codes, and the degree of advertising push they exert through the network. In Figure 7, individual node sizes indicate their relative power in the network, as measured by the weighted degree of individual nodes.

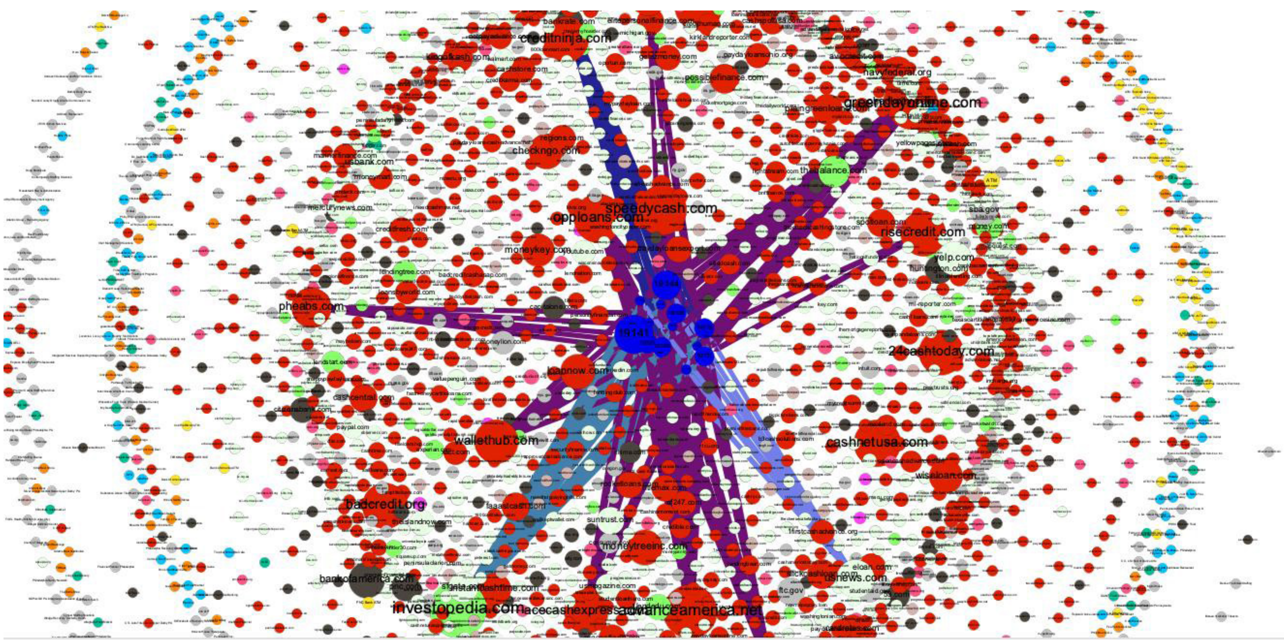
Figure 7. Core Nodes Sized by Weighted Degree



In Figure 8, we see this in two ways. Power in the inverse is represented by the sizes of the blue nodes, our respective Philadelphia zip codes. These are the most frequent targets of the payday lending entities and similar sites that appear in this network. Zip code 19141 stands out as the most frequent target, followed by 19144 and then others. These are the places where the risk of impact is potentially greatest. Then we see the largest nodes (top 10) surrounding them these include, in order from highest degree: Ace Cash Express (its geographical sites), investopedia.com, advanceamerica.net, greendayonline.com, speedycash.com, opploans.com, checkintocash.com, cashnetusa.com, acecashexpress.com, and badcredit.org.

In Figure 8, we see a slightly different representation of power, based on those digital sites competing for keyword visibility through display advertising or paid search. The color of the arrows from the sites to their target zip codes represent a range from dark gray, to light blue, to navy blue to purple.

Figure 8. Sites Vying for Greatest Payday Loan KW Visibility



These represent sites competing for 46 of 57 of our seed keywords associated with payday loans. Again, these are the sites competing far above average for these keywords. Topping that list is Investopedia. Other newcomers to this list include wellsfargo.com, pheabs.com, checkcity.com, and netcredit.com.

This network illustrates the push and pull that animates the experience of life lived not in two distinct places—the geographical and the digital—but in one place where both dimensions of life converge. The need to find immediate means to make ends meet pulls citizens into their communities—either physically or through online searches—hunting a loan to tide them over. But, when you add the extreme push of these products into the community through display advertising, paid search, and even unpaid efforts to game ranking algorithms for visibility, there is no better word than predatory to describe it. The predatory nature of many of these payday and similar types of loan products is clear in terms of the way that exorbitant interest rates, compounding fees, and other loan terms doom customers to mounting debt and the havoc that wreaks in consumers' lives. But the predatory nature of digital advertising here is equally clear. It is predatory in the intentional targeting. It is predatory in the ad tech surveillance infrastructure that literally stalks consumers of payday loans and similar services through their search histories, data profiles, retargeting efforts, and their front doorsteps. And, it is predatory in the way that all of that is purposefully pushed not just to individual people, but into whole communities whose economic health is on the brink of deterioration or has already deteriorated.

4.0
Research Conclusions

Though much is left to be explored and explained, I draw four conclusions from the work presented here. First, key players within the digital advertising industry—not just companies selling goods and services—should be seen as at least partially responsible for the discriminatory harms they facilitate. In today's digital advertising economy, digital platforms structure the game, ad tech purveyors facilitate playing the game and gaming the system, and marketers and advertisers play the game, producing outcomes that financially benefit them to the detriment of the targeted consumers who fall prey to their predatory products. In fact, in some ways, the platform companies themselves do more than facilitate given the degree to which they also incentivize race-based targeting (to the degree that targeting results in greater visibility in the digital advertising economy). Given the intentionality of race-based targeting and the predatory nature of certain products in the open market, we should conceive of the full scope of technology platforms and software companies that aid and abet them as a party to the harms produced by those predatory products. This is consistent with and expands recent efforts to hold technology platforms accountable for facilitating discrimination.

Second, we should think about and begin to define and describe the harms of predatory advertising in terms of its impact not just on individuals, but on the collective communities in which we live. If we begin to adjust our thinking away from the idea that the online world and "real life" are distinct spaces and places, then we can begin to more clearly see the collective impacts of predatory lending on and in the communities in which we live, work, raise children, care for family, and entertain ourselves. We can then push with others in our communities to protect our interests. For instance, the PolicyLink National Equity Atlas provides disaggregated data up to the county level, which helps us to put the zip codes I modeled in this study in greater context. In a nutshell, people of color fall considerably below whites in terms of overall prosperity score indicators, including economic vitality, readiness, and connectedness.[56] By seeing and considering the push and pull of internet search and advertising as part of the fabric of everyday life and experience lived in and across geographical spaces characterized by varying levels of economic prosperity, we can better keep in view the far reaching effects of the wealth extraction and economic deterioration wrought by payday and other predatory lending practices. This view also helps us to see the ways that predatory advertising compounds and is implicated in those harms.

Third, despite its utility and necessity in identifying predatory advertising patterns, disparate impact as a framework for conceptualizing racial discrimination in the area of digital advertising targeting is limited. The lack of specific access to the right kinds of data further problematizes the use of limited racial proxies at our disposal, namely zip codes. Given that location data used in the digital advertising arena is fraught with issues of reliability, basing disparate impact analyses on such proxies proves challenging. Further, disparate impact analyses presume that the best way to produce and validate evidence of racial discrimination is by comparing protected groups against the benchmark of white performance. This presumption diminishes, in some respects, the impact of harms accrued to people and communities of color, which is related to our final conclusion.

Fourth, conceptualizing the impacts of predatory advertising as compounding harms illuminates the ways in which the concept of fairness, as a policy framework for mitigating algorithmic discrimination, is limited. A fairness remedy to the problem of predatory advertising would be to equalize the costs and benefits equally across demographic communities. If all communities and demographic groups were equally targeted by advertising, both good and bad, then no group is being unfairly subjected to any greater risk of harm than the other, according to the logic of fairness and the logic of disparate impact. But, this logic presumes a false equivalence. It dismisses the fact that people and communities have histories. It assumes that all people are similarly situated with respect to the economic situation in which they live, in the communities in which they live. There was a reason that my second study—modeling race-based advertising targeting as connected to geographies and communities—did not include a comparison to similarly situated white communities. That is because, in many respects, there are no similarly situated white communities. This is to say and emphasize that the impact of targeted advertising on communities of color should be measured against itself and its own compounded histories of discrimination.

5.0
Potential Policy Directions

Drawing on the frameworks and analyses offered in the previous sections, I want to close by identifying potential policy directions that I believe are worth considering. To be clear, these are starting points, not fully developed policy proposals, meant to help seed ideas for potential policy interventions that may help us address the wide-ranging challenges that algorithmic discrimination in general, and race-targeted advertising more specifically, present, especially as they are so closely intertwined with an array of predatory products and practices that are and have historically been targeted at people and in communities of color. I preface my brief suggestions by pointing out the reality that there is a "too big to fail" element to the digital advertising sector. I am not concerned that significantly intervening into, and limiting what is done in that sector would devastate local, national, or global economies. I simply mean to point out that we are trying to address a practice that has been central to advertising virtually since its origins. Further, the array of technologies that make targeting possible and incentivize it to the degree that much of the digital economy is built around it is inextricably linked throughout the infrastructure of our contemporary digital systems. This link has the effect of rendering some forms of policy interventions unrealistic, unmeasurable, and unenforceable, in my view. The policy directions mentioned below reflect, to the degree possible, interventions that could and should be pursued, but within the scope of what is realistically within the realm of the possible.

Alternative Lending Systems

In the same way that geographical and digital spaces converge in everyday life, solutions to problems that emerge are also integrated. This means that sometimes the solution to what appears as a "technical" problem may necessitate a "non-technical" solution. When it comes specifically to the problem of predatory advertising in the area of payday and similar forms of lending, one potential intervention lies more in the realm of lending rather than technical systems. It seems clear, from my analysis and the extant literature and evidence about payday lending, that one fruitful direction would be to erect alternative lending systems that are not incentivized by massive profit generation.

We have such systems in place of course, tied to specific areas of "productive" activity in the form of government subsidized/guaranteed education loans, mortgages, small business loans, and the like. Personal financing, however, has rarely, if ever, been a target of opportunity for such alternative lending systems that are specifically government based. So, one option would be for federal and/or state governments to initiate such an alternative system for short-term personal financing needs that are not subject to exorbitant interest rates, high fees, and catastrophic consequences for temporary non-payment or even default. A second approach would be for the government to partner with private or nonprofit sector organizations to innovate and build such systems—similar to the kinds of alternative systems, infrastructures, and exchange economies that Lisa Servon highlighted in her 2017 book *The Unbanking of America*.[57] In the absence of national regulations banning or significantly curtailing the payday loan industry, its predatory practices will survive and thrive, aided and abetted by digital platforms, unless there are real alternatives.

Transparency and Accountability

Transparency and accountability are of course a common set of principles undergirding the ethical uses and regulation of technology. In the context of targeted advertising this might come in the form of compulsory industry-wide or company-specific audits through some of the methods I outlined earlier in this report. These audits would articulate, quantify, and demonstrate who companies are targeting, for what, through what channels, and with what messages (something that is important to this equation, but not directly addressed in the studies conducted in this report). That is, the digital advertising industry as a whole should have to account for who is targeting what to whom, when, how much, and to what effect. In this last respect, the effect part of such an accountability measure would be to require companies targeting protected groups with suspected predatory products to account for and present data that demonstrated the results of their predatory advertising. This could take the form of initiated and consummated loan transactions, and the terms of their respective loan agreements. This would help regulators and the public have access to data that is privacy preserving, but which accounts for the full scope of predatory activity, from the marketing and advertising through resulting financial transactions, to the outcomes of those transactions.

An additional accountability measure would be to provide oversight and grant clearance for certain bad actors with histories of predatory products—either from a public body like the Consumer Financial Protection Bureau or Federal Trade Commission or an industry body, for example the Association of National Advertisers, or some combination of the two—before they can market and advertise their products to people residing in particular areas. These measures would be something akin to the "preclearance" measures that were once a vital part of the Voting Rights Act.[58] In essence, bad actors would have to demonstrate before the fact that what they purport to advertise and that their advertising targets are not likely to place protected groups at risk—especially those residing in communities that have historically been negatively affected—before they can advertise. Similarly, bodies could also preclear specific types of advertisements, given what is known about targeting practices in terms of representing the target audience in advertising.[59]

Algorithmic Auditing and Testing

Despite the fact that companies like Facebook removed specific demographic categories from its list of options for advertisers to choose from for the purposes of audience targeting, or despite Google removing zip codes as options for the same purpose, we need to also ensure that the "lookalike" (a curious term in the context of racial identity) audiences that have been put in their place do not implicitly facilitate the same discriminatory targeting that using explicit racial categories did. Ad platforms that automate the construction of such audiences for users should be required to regularly test and demonstrate for regulatory bodies that there is no pattern overlap between lookalike audiences constructed from the mountain of behavioral data that these platforms and the variety of ad tech software generates, and members or communities where members of protected groups predominate. This would not require platforms to reveal the intellectual property that produces these audiences, but it would require them to produce outcome data about whether, where, and when those audiences and racial group identities converge.

Search Suppression

Given that platforms such as Google dominate both the digital advertising and search engine economies (which, of course, in many respects are one and the same), it is perfectly within these companies' sphere of influence to use their vast arbitration powers over search and visibility to help disincentivize bad actors in predatory industries like payday lending from participating on its platforms. That is, companies could, if properly compelled to do so, suppress information about, advertising of, and opportunities to engage with content related to known predatory industries and actors. It could accomplish this in a number of ways:

- Outright ban purveyors of predatory products targeting protected groups from advertising on its platforms.
- Tag those company's sites and content and rank them lower in terms of "quality" and thereby lessen their potential for visibility.
- Charge such companies a premium for visibility generated through their ad auction systems.
- As a public service, prominently display forms of warning content about specific predatory products and companies that show up when users search for keywords that trigger these companies in search results.

These are just some of the many ways at the disposal of ad platforms to arbitrate the visibility of things that we know will compound harms to individuals from protected groups and communities where they reside.

A critical component of many of these policy measures dealing directly with platforms themselves is having relevant, up-to-the-moment data that helps to understand, analyze and visualize the impacts of racial targeting in the digital advertising and marketing sector alongside what is happening in geographical space. That is, having access to and utilizing ad targeting data to include as a key indicator of neighborhood economic and social well-being could go a long way to helping us also see the broader ways that predatory advertising and marketing, and the predatory products they help to push to consumers of color, compound harms collectively in communities.

6.0
Appendix A:
Predatory Lending Keyword List

$255 payday loans online

$500 loan

360 loans

auto repair financing

auto title loans

bad credit line of credit

borrow money

car repair credit card

car title loans

car title loans near me

cash advance credit line

cash advance loans

cash advance online

cash for gift cards near me

cash loans

check advance

check advance near me

check cashing place near me

direct lenders for

easy online loans

easy payment furniture

fast cash loans

finance loan

get a loan today

guaranteed installment

guaranteed loan approval

i need money now

installment loan process

installment loans

installment loans

instant line of credit online

lender

loan places near me

loans

loans for bad credit

loans for bad credit

loans without credit check

no credit check auto repair near me

no credit check direct

online finance loan

online line of credit

online loan app

online loans

online only installment

online only loans

online personal loan

payday advance online

payday loans near me

personal loan finance

personal loans no credit check

rapid cash

sell gift cards near me

title loans near me

title loans online

verge credit

what is a fast cash loan

who buys gift cards near me

7.0
Appendix B:
Zip Codes Used in Study 1

Zip code	Location	Population	% Black	% White
36083	Tuskegee, AL	7,316	87%	
36088	Tuskegee Institute, AL	4,646	97%	
20743	Capitol Heights, MD	37,888	85%	
07017	East Orange, NJ	36,471	80%	
200747	District Heights, MD	40,484	89%	
48203	Highland Park, MI	23,063	90%	
20745	Oxon Hill, MD	27,790	68%	
02126	Mattapan, MA	29,620	78%	
38762	Mound Bayou, MS	2,482	99%	
60472	Robbins, IL	4,904	86%	
15563	Stoystown, PA	3,027		98%
41572	Virgie, KY	3,561		99%
15935	Hollsopple, PA	3,460		97%
15956	South Fork, PA	2,675		99%
62467	Teutopolis, IL	4,259		98%
16025	Chicora, PA	5,194		98%
52031	Bellevue, IA	5,102		97%
61911	Arthur, IL	5,330		98%
25123	Leon, WV	3,333		96%
47993	Williamsport, IN	3,661		96%

8.0

Appendix C:

Ad Tech Category Descriptions

Retargeting	A/B Testing	Advertising	Analytics		Customer Data Platform
AdRoll	Adobe Target	AdRoll	Acquia Personalization	Heap Hotjar	Adobe Experience Platform
Criteo	Bloomreach Search & Advertising	Amazon Advertising	Adobe Analytics	HubSpot	BlueConic
Google Remarketing Tag	ContentSquare	AppNexus	Akamai mPulse	Inspectlet	Cooladata
Steelhouse	Convert	Criteo	Amplitude	Kount	Emarsys
	Decibel	Facebook Ads	AppDynamics	Linkedin Insight Tag	mParticle
	Dynamic Yield	Google Ads	Appsflyer	Matomo Analytics	Salesforce Audience Studio
	Google Optimize	LiveIntent	Bloomreach Search & Merchandising	Medallia	Segment
	Kibo Personalizatio n	Microsoft Advertising	Branch	Microsoft Clarity	Tealium
	Optimizely	Pinterest Ads	Braze	Mixpanel	Treasure Data
	VWO	Reddit Ads	bugsnag	Moat	Cool Data
		Tcsquared	Clicktale	Mouse Flow	
		Snappixel	Cloudflare Browser Insights	New Relic	
		Tatari	Cloudflare Browser Insights	Orbi	
		Vdx.tv	ComScore	Parse.ly	
		SpotX	Content Square	Paypal Marketing Solutions	
		Taboola TheTradeDesk	Crazy Eg	Pinterest Conversion Tag	
		Twitter Ads	Datadog	Quantcast Measure	
		Simpli.fi	Decibel	Quantum Metric	
		33Across	Dreamdata	Quora Pixel	
		Doubleclick Floodlight	Dynatrace	Riskified	
		Outbrain	Elastic APM	Sift	
		Podsights	Facebook Pixel	Snowplow Analytics	
		Prebid	Full Story	Tik Tok Pixel	
		Rakuten Advertising	Google Ads Conversion Tracking	Trackjs	
		Google Publishing Tag	Google Analytics	Twitter Analytics	
		TripleLeft	Google Call Conversion Tracking	VWO	
		Google Adsense		Webtrends	
		Index Exchange		Zoominfo	

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