Discrimination in Online Ad Delivery

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Abstract

A Google search for a person's name, such as "*Trevon Jones"*, may yield a personalized ad for public records about Trevon that may be neutral, such as "*Looking for Trevon Jones? …"*, or may be suggestive of an arrest record, such as "*Trevon Jones, Arrested?..."*. This writing investigates the delivery of these kinds of ads by Google AdSense using a sample of racially associated names and finds statistically significant discrimination in ad delivery based on searches of 2184 racially associated personal names across two websites. First names, previously identified by others as being assigned at birth to more black or white babies, are found predictive of race (88% black, 96% white), and those assigned primarily to black babies, such as DeShawn, Darnell and Jermaine, generated ads suggestive of an arrest in 81 to 86 percent of name searches on one website and 92 to 95 percent on the other, while those assigned at birth primarily to whites, such as Geoffrey, Jill and Emma, generated more neutral copy: the word "arrest" appeared in 23 to 29 percent of name searches on one site and 0 to 60 percent on the other. On the more ad trafficked website, a black-identifying name was 25% more likely to get an ad suggestive of an arrest record. A few names did not follow these patterns: Dustin, a name predominantly given to white babies, generated an ad suggestive of arrest 81 and 100 percent of the time. All ads return results for actual individuals and ads appear regardless of whether the name has an arrest record in the company's database. Notwithstanding these findings, the company maintains Google received the same ad text for groups of last names (not first names), raising questions as to whether Google's advertising technology exposes racial bias in society and how ad and search technology can develop to assure racial fairness.

Keywords: online advertising, public records, racial discrimination, data privacy, information retrieval, computers and society, search engine marketing

[1] v0.14 Preprint available at http://dataprivacylab.org/projects/onlineads/1071-1.pdf

Introduction

Have you ever been arrested? Imagine the question not appearing in the solitude of your thoughts as you read this paper, but appearing explicitly whenever someone queries your name in a search engine. Perhaps you are in competition for an award, an appointment, a promotion, or a new job, or maybe you are in a position of trust, such as a professor, a physician, a banker, a judge, a manager, or a volunteer, or perhaps you are completing a rental application, selling goods, applying for a loan, joining a social club, making new friends, dating, or engaged in any one of hundreds circumstances for which an online searcher seeks to learn more about you. Appearing alongside your list of accomplishments is an advertisement implying you may have a criminal record, whether you actually have one or not. Worse, the ads don't appear for your competitors.

A person's criminal record begins when he is arrested for a crime. Job applications frequently include questions such as:

- "Have you ever been arrested?"
- "Have you ever been charged with a crime?"
- "Other than a traffic ticket, have you been convicted of a crime?"

Advantages of knowing such information when hiring or engaging with a person relate to trustworthiness. Because others often equate a criminal record with not being reliable or honest, protections exist for those having criminal records.

If someone is falsely accused of a crime, pleads not guilty, and charges are dismissed, in the U.S., he may file suit against the person who brought the charges. For example, if a private citizen files a false criminal charge against you, or falsely makes a complaint to a police officer that results in your arrest, and if no conviction results, you may be able to sue the accuser for malicious prosecution.

If an employer disqualifies a job applicant based solely upon information indicating an arrest record, the company may face legal consequences. The U.S. Equal Employment Opportunity Commission ("EEOC") is the federal agency charged with enforcing Title VII of the Civil Rights Act of 1964, a law in the United States which applies to most employers, prohibiting employment discrimination based on race, color, religion, sex, or national origin, and through guidance issuance in 1973, extended to persons having criminal records [1,2]. Title VII does not prohibit employers from obtaining criminal background information. However, certain uses of criminal information, such as a blanket policy or practice of excluding applicants or disqualifying employees based solely upon information indicating an arrest record, can result in a charge of discrimination. To make a determination, the EEOC uses an "adverse impact test," which measures whether practices, intentional or not, have a disproportionate effect. If the ratio of the effect on groups is less than 80%, the employer may be held responsible for discrimination [3].

So what about online ads suggesting someone with your name has an arrest record, even when no one with your name has ever been arrested? The malicious prosecution approach does not apply. Title VII does not apply either, unless you have an arrest record and can prove the potential employer used the ad or information from the company sponsoring the ad.

Further, the advertiser may argue that the ads are commercial free speech –a constitutional right to display the ad associated with your name. The First Amendment of the U.S. Constitution protects advertising, as granted under the landmark U.S. Supreme Court decision, Central Hudson Gas & Electric Corp. v. Public Service Commission of New York, Supreme Court of the United States, 447 U.S. 557 (1980). In Central Hudson, the Supreme Court sets out a four-part test for assessing government restrictions on commercial speech, which begins by determining whether the speech is misleading. Are online ads suggesting the existence of an arrest record misleading if no one having the name has an arrest record?

Assume the ads are free speech: what happens when these ads appear more often for one racial group than another? Not everyone is being equally affected by the free speech. Is that free speech or is it racial discrimination?

Racism is "any attitude, action or institutional structure which subordinates a person or group because of their color . . . Racism is not just a matter of attitudes; actions and institutional structures can also be a form of racism" [4]. *Racial discrimination* results when a person or group of people is treated differently based on their racial origins [5]. Power is a necessary precondition, for it depends on the ability to give or withhold benefits, facilities, services, opportunities etc., from someone who should be entitled to them, and are denied on the basis of race. *Institutional or structural racism* is a system of procedures/patterns whose effect is to foster discriminatory outcomes or give preferences to members of one group over another [6].

Notice that racism can result, even if not intentional and that online activity may be so ubiquitous and intimately entwined with technology design that technologists may now have to think about societal consequences like structural racism in the technology they design. Such considerations are beyond this paper, but they frame the relevant legal, societal and technical landscape in which this work resides.

The investigation, chronicled in this writing, reports on an observed phenomenon, that some online ads suggestive of arrest records appear more often for one racial group than another among a sample of racially associated names. Because online ad delivery is a socio-technical construct, its study requires blending sociology and computer science, and so this writing presents such a blend.

Problem Statement

Given online searches of racially identifying names, show that associated personalized ads suggestive of an arrest record do not differ by race.

Our hypothesis: no difference exists in the delivery of ads suggestive of an arrest record responding to online searches of racially associated names. Then, when presented with evidence of a pattern to the contrary, examine the pattern's credibility, likelihood and circumstances of occurring.

What is the suspected pattern of ad delivery? Below are three groups of ad hoc real-world examples that jointly describe concerns.

Earlier this year, a Google search for "*Latanya Farrell*" yielded the two ads appearing in Figure 1a. The first ad implies she may have been arrested, was she? After clicking on the link and paying the requisite subscription fee, we learn that the company has no arrest record for her (Figure 1b). A Google search for "*Latanya Sweeney*" and "*Latanya Lockett*" also yields ads suggestive of arrests. We find no arrest record for "*Latanya Sweeney*" but we do for "*Latanya Lockett*" (Figure 1). The ads appeared on google.com and on a newspaper website to which Google supplies ads, reuters.com (Figure 1c). All the ads in question link to instantcheckmate.com.

In comparison, searches for "*Kristen Haring*", "*Kristen Sparrow*" and "*Kristen Lindquist*" did not yield any instantcheckmate.com ads, only competitor ads (Figure 2a, 2c, and 2e), even though the company's database reports having records for all three names and arrest records for "*Kristen Sparrow*" and "*Kristen Lindquist* (Figure 2d and 2f).

Searches for "*Jill Foley*", "*Jill Schneider*" and "*Jill James*" displayed instantcheckmate.com ads with neutral copy; the word "arrest" did not appear in the ads even though arrest records for all three names appear in the company's database (Figure 3).

Lastly, we consider a proxy for race associated with these names. Figure 4 shows Google images appearing for image searches of "*Latanya*", "*Latisha*", "*Kristen*" and "*Jill*", respectively. There appears a racial distinction. The faces associated with "*Latanya*" and "*Latisha*" (Figure 4a and 4b) tend to be black, while white faces dominate the images of "*Kristen*" and "*Jill*" (Figure 4c and 4d).

Together, these handpicked examples (Figures 2, 3 and 4) describe the suspected pattern –ads suggesting arrest tend to appear with names associated with blacks and neutral ads or no ads tend to appear with names associated with whites, regardless of whether the company has an arrest record associated with the name. The remainder of this paper describes a journey to establish an instance of the pattern worthy of scholarly consideration and statistical assessment.

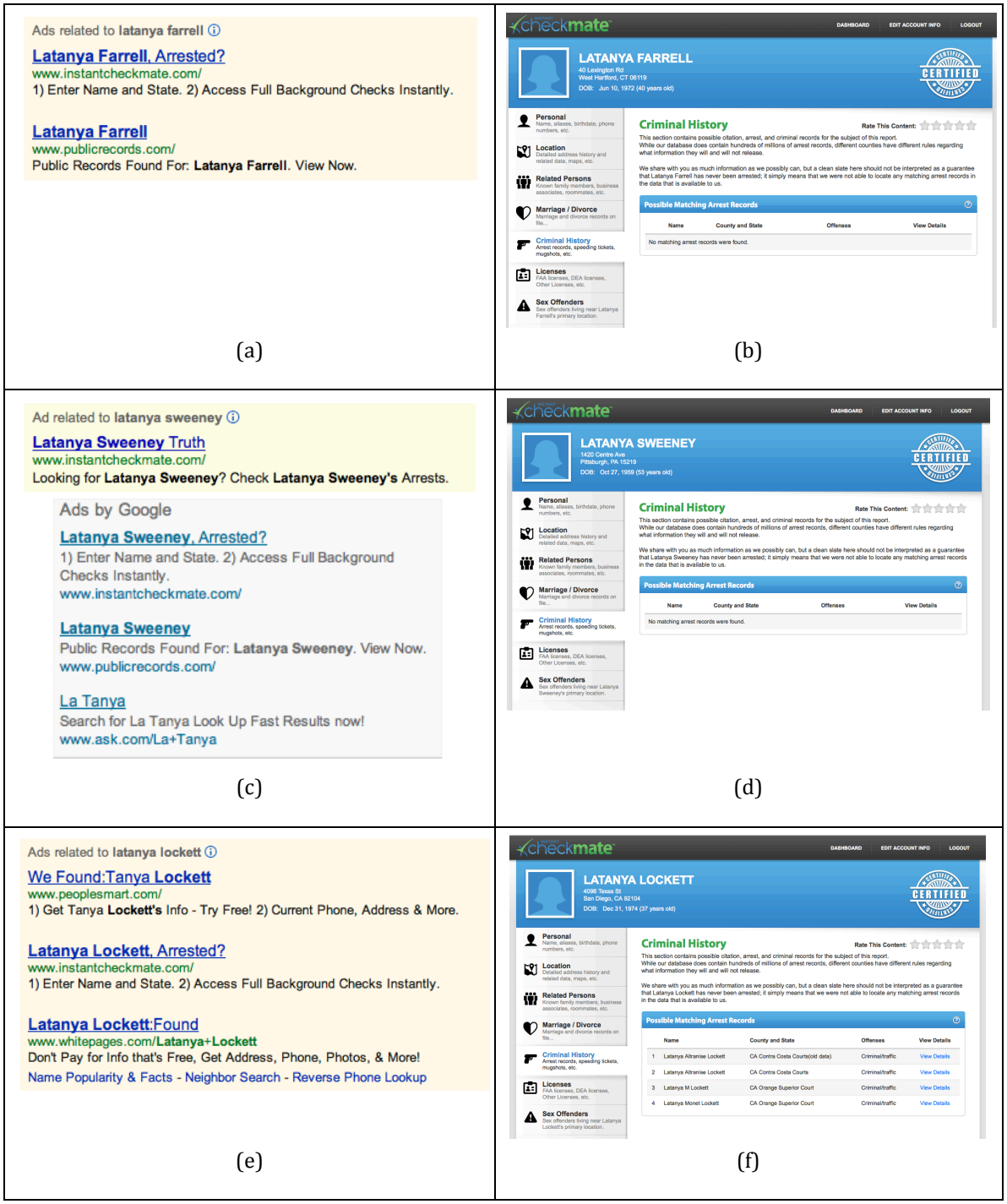

Figure 1. Sample ads and criminal reports for "latanya farrell" (a,b), "latanya sweeney" (c,d), and "latanya locket"(e,f) appearing on google.com (a,b,c) and reuters.com (c bottom). Criminal reports from instantcheckmate.com (b,d,f).

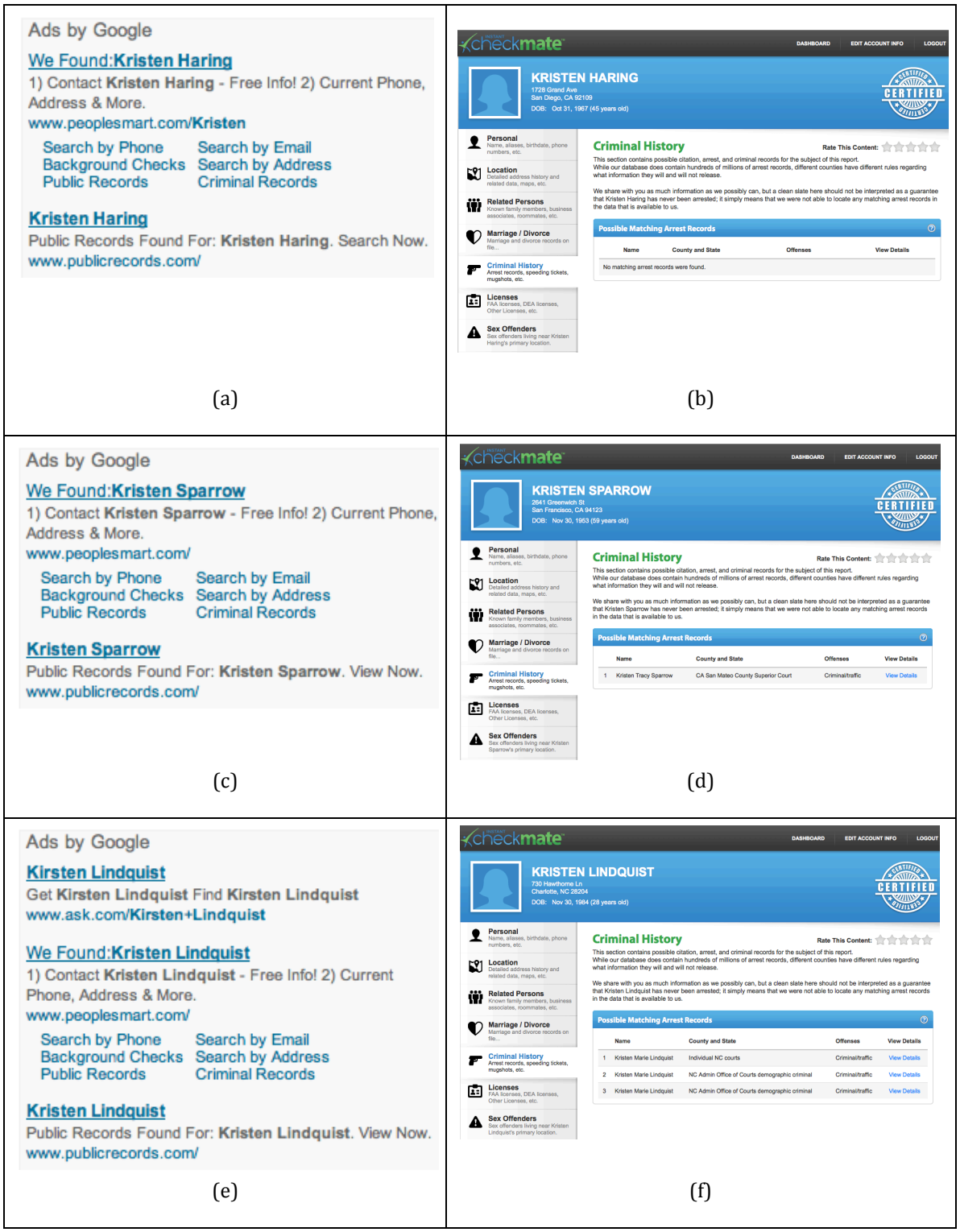

Figure 2. Sample ads and criminal reports for "kristen haring" (a), "kristen sparrow" (b), and "kristen lindquist" (c), appearing on reuters.com (a,c,e). Criminal reports from instantcheckmate.com (b,d,f).

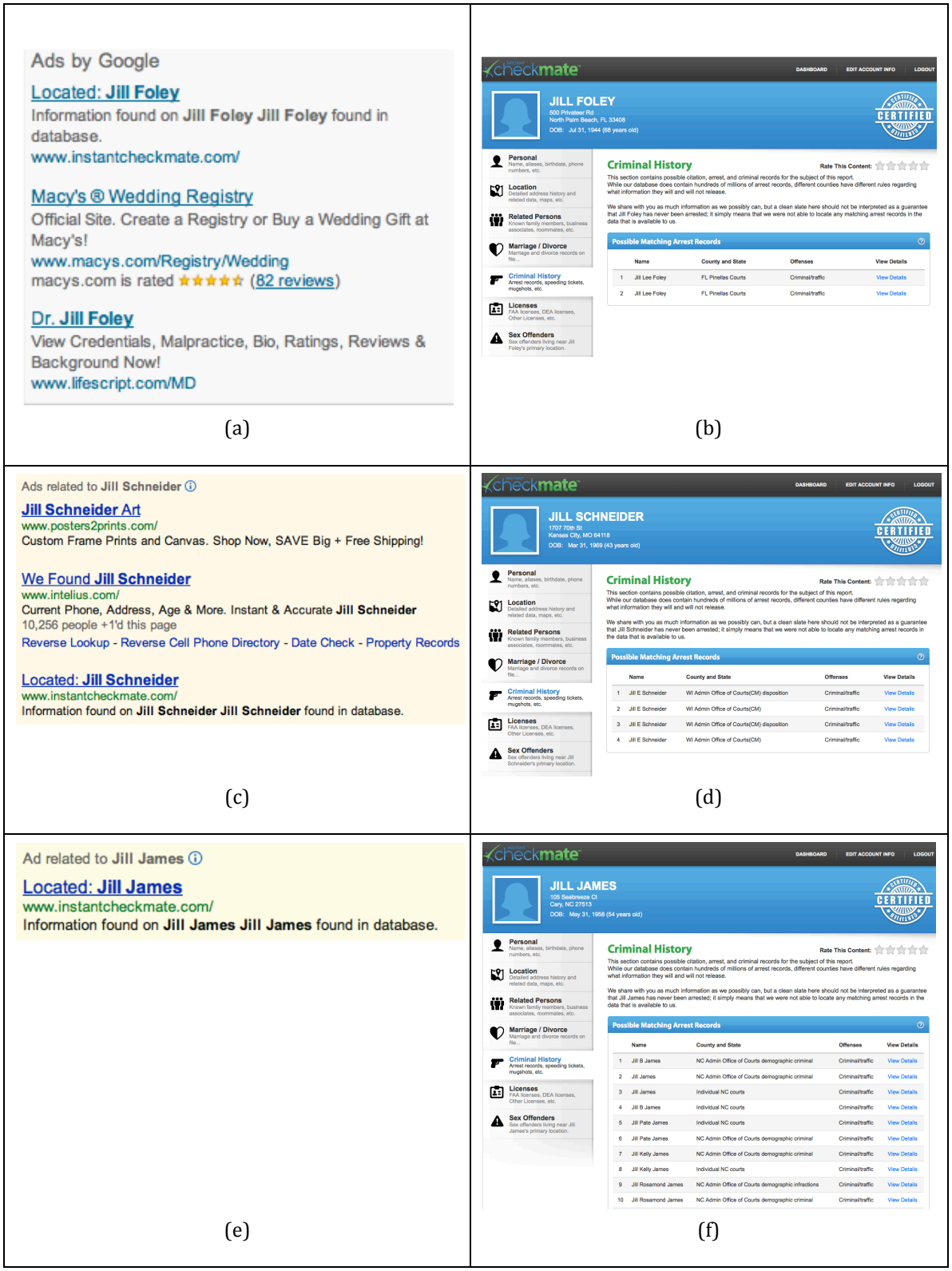

Figure 3. Sample ads and criminal reports for "jill foley" (a,b), "jill schneider" (c,d), and "jill james"(e,f) appearing on google.com (c,e) and reuters.com (a). Criminal reports from instantcheckmate.com (b,d,f).

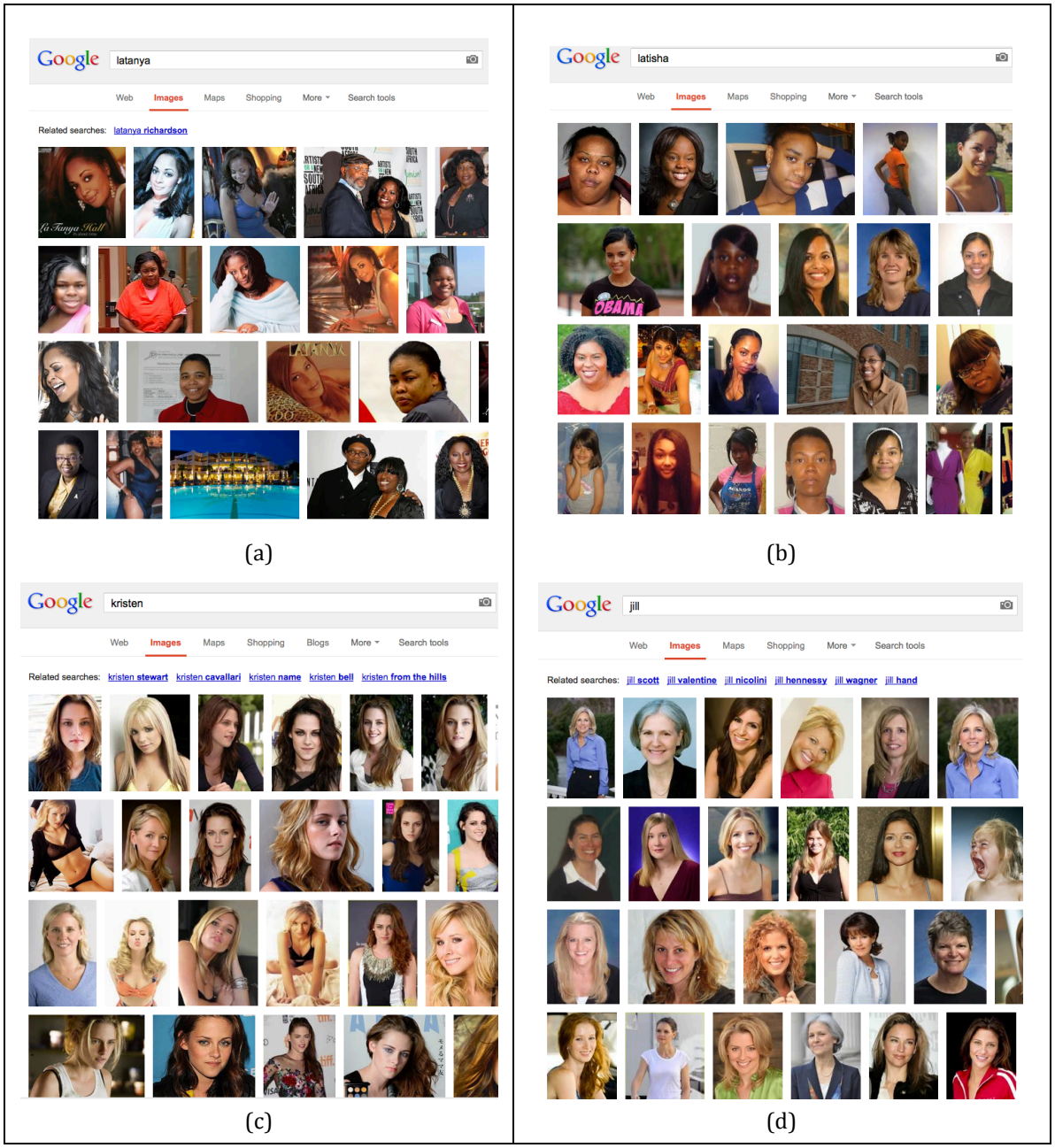

Figure 4. Sample face images on google.com retrieved for searches "latanya" (a), "latisha" (b), "kristen" (c), and "jill" (d).

Google AdSense

Who generates the ad's text? Who decides when and where an ad will appear? What is the relationship between Google, Reuters and Instant Checkmate in the previous examples? An overview of Google AdSense, the program that delivered the ads in Figures 1, 2, and 3, explains entities and relationships.

In printed newspapers and magazines, ad space and ad content are fixed. Everyone who purchases the publication sees the same ad in the same space. But websites are different. Online ad space, not bound by the same physical limitations, can be dynamic, with ads tailored to the reader's search criteria, content interests, geographical location, and so on. Any two readers (or the same reader returning to the same website) might view different ads.

Google AdSense is the largest provider of dynamic online advertisements, placing ads for millions of sponsors on millions of websites [7]. In the first quarter of 2011, Google earned US $2.43 billion ($9.71 billion annualized), or 28% of total revenue, through Google AdSense [8]. AdSense has operational variations, but for simplicity, this writing only describes those features of Google AdSense specific to the Instant Checkmate ads in question.

When a reader enters search criteria in an enrolled website, Google AdSense embeds ads believed to be relevant to his search in the web page of results. Figures 1, 2, and 3 show ads delivered by Google AdSense in response to various "*firstname lastname*" searches.

To place an online ad, a "sponsor" provides Google with search criteria, copies of possible ads to deliver once a match occurs, and a financial bid (an amount the sponsor is willing to pay) if a reader clicks the delivered ad.[2] Google operates a real-time auction across bids for the same search criteria, usually displaying the ad having the highest bid first, the second highest second, and so on, and may elect not to show any ad if it considers the bid too low or if showing the ad exceeds a threshold (e.g. a maximum account total for the sponsor). In Figures 1, 2, and 3, Instant Checkmate sponsors the ads, which in most cases appears first among ads, implying Instant Checkmate had the highest bid.

A website owner wanting to "host" online ads enrolls in AdSense and changes his website to include special software that sends information about the current reader (e.g., search criteria) to Google and in exchange, receives corresponding ads from Google. The displayed ads have the banner "Ads by Google" when appearing on sites other than google.com. For example, reuters.com is an AdSense host, and entering "*Latanya Sweeney*" in the search bar at reuters.com generated a new web page having ads delivered by Google, bearing the banner "Ads by Google" (Figure 1c).

[2] This writing conflates two interacting Google programs: Google Adwords allows advertisers to specify search criteria, ad text and bids and Google AdSense delivers the ads to host sites.

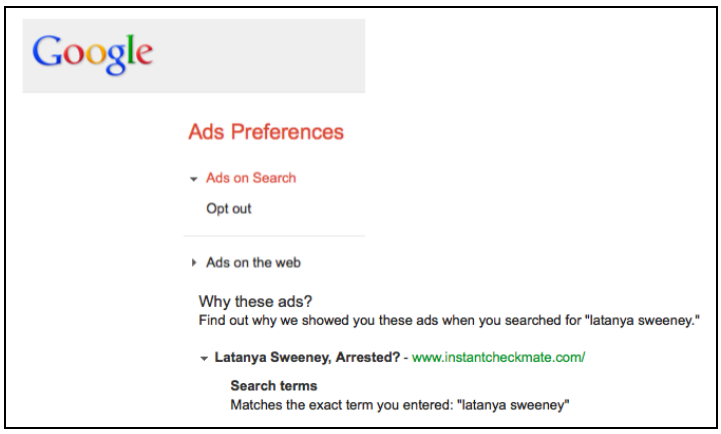

Figure 5. Google explanation for delivering ad "*Latanya Sweeney, Arrested*?" –matches the exact first and last name searched.

There is no cost associated with displaying an ad, but if the reader actually clicks the ad, the sponsor pays the promised bid, which is split between Google and the host. Clicking the "*Latanya Sweeney*" ad on reuters.com (Figure 1c) would cause Instant Checkmate to pay its bid to Google, which splits it with Reuters.

Search Criteria

What search criteria did Instant Checkmate specify? Are ads randomly delivered? Do ads rely only on the first name? Will ads be delivered for made-up names too? Google AdSense provides answers to these questions too. Ads displayed on google.com allow readers to learn why a specific ad appeared. Clicking the circled "i" in the ad banner (e.g., Figure 1c) provides a web page explaining the ads (e.g., Figure 5). Doing so for ads in Figures 1, 2, and 3, reveals that the ads appeared because the search criteria associated with the bid matched the exact first and last name combination searched. Because bids presumably relate to records the company sells, the names would likely be the first and last names of real people, and because searches are online, ads may be more effective for people having online identities.

In summary, search criteria associated with ads:

- has to be both first and last names;
- should be names of real people; and,
- may prefer names of people with an online identity.

The next sections describe systematic construction of a list of racially associated first and last names for real people. It is not presumed that Instant Checkmate placed bids or Google delivered ads using any such list. Instead, the list allows us to have a qualified sample of racially associated names for testing ad delivery.

Black and White Identifying Names

"Black-identifying" and "white-identifying" first names are those for which a significant number of people have the name and the frequency is sufficiently higher in one race than another. Heavily cited prior academic work provides exemplars.

In 2003, Bertrand and Mullainathan did a field experiment in which they provided resumes to job posts that were virtually identical except some of the resumes had black-identifying names and others had white-identifying names [9]. Their "Job Discrimination Study" showed significant discrimination against black names: white names received 50% more callbacks for interviews even though the resumes otherwise had identical qualifications.

The Job Discrimination study used a correlation of names given to black and white babies in Massachusetts between 1974 and 1979, defining black-identifying and white-identifying names as those that have the highest ratio of frequency in one racial group to frequency in the other racial group.

	White Female	Black Female	White Male	Black Male
(a)	Allison Anne Carrie Emily Jill Laurie Kristen Meredith	Aisha Ebony Keisha Kenya Latonya Lakisha Latoya Tamika	Brad Brendan Geoffrey Greg Brett Jay Matthew Neil	Darnell Hakim Jermaine Kareem Jamal Leroy Rasheed Tremayne
(b)	Molly Amy Claire Emily* Katie Madeline Katelyn Emma	Imani Ebony* Shanice Aaliyah Precious Nia Deja Diamond	Jake Connor Tanner Wyatt Cody Dustin Luke Jack	DeShawn DeAndre Marquis Darnell* Terrell Malik Trevon Tyrone
(c)		Latanya Latisha		

Figure 6. Black-identifying and white-identifying first names from (a) the Job Discrimination Study [9], (b) Fryer and Levitt [11], and (c) observation in Figure 4. Emily, a white female name, Ebony, a black female name, and Darnell, a black male name, appear in both (a) and (b), giving a total of 63 distinct first names.

In the popular book "Freakonomics," Levitt and Dubner report the top 20 whitest- and blackest-identifying girl and boy names [10]. The list comes from earlier work by Fryer and Levitt, which shows a pattern change in the way Blacks named their children starting in the 1970's, which they correlate with the Black Power Movement [11]. They postulate that the movement influenced how Blacks perceived their identities and they give as evidence that before the movement, names given to black and white children were not distinctly different, but after the movement, the emergence of distinctly black names appear.

Similar to the Job Discrimination Study, the list used by Fryer and Levitt comes from names given to black and white children recorded in California birth records from 1961-2000 (over 16 million births).

We need a list of racially associated names in order to test ad delivery, so we use the union of lists from these prior studies augmented with two black female names, "*Latanya*" and "*Latisha*", from earlier observations. Figure 6 enumerates our list, having eight names for each of the categories: white female, black female, white male, and black male from the Job Discrimination Study (Figure 6a), and the first eight names for each category from the Fryer and Levitt work (Figure 6b). Removing duplicates gives a total of 63 distinct first names.

Full Names of Real People

Having a list of racially associated first names (Figure 6) is a start, but testing ad delivery requires a real person's first and last name ("full name"). How do we get full names? Web searches provide a means to locate and harvest full names by: (1) sampling names of professionals appearing on the Web; and, (2) sampling names of people active on social media sites and blogs ("netizens"). The subsections below describe the steps.

Harvesting Full Names of Professionals

Professionals often have their own websites or have biographical information appearing on institutional websites, listing titles and positions, and describing prior accomplishments and current activities. Several professions, such as research, medicine, law, and business, often have degree designations, such as PhD, MD, JD or MBA, associated with people in that profession. A Google search for a first name and a degree designation typically yields lists of people having that first name and degree. We use these kinds of searches to harvest a sample of full names of professionals having racially associated first names; Figure 8a itemizes the steps.

Here is a walk through the method of Figure 8a. The goal is to acquire a list of at least 10 full names for each racially associated first name. For each first name in the list of racially associated first names (Figure 6): perform a Google search with that first name and a degree designation (Step 1.1); harvest full names from the search

results, up to 3 pages of results, avoiding duplicate names; and, for each full name recorded, visit its associated web page, and if an image is discernible, record whether the person appears black, white, or other. Archive each web page visited, preserving images and content.

Here are two examples. Figure 9a shows results for a Google search of "*Ebony PhD"*. The results immediately reveal links for real people having "*Ebony"* as a first name – specifically, "*Ebony Bookman"*, "*Ebony Glover"* (highlighted), "*Ebony Baylor"* and "*Ebony Utley"*. We harvest the full names appearing on the first three pages of search results, using searches with other professional endings, such as *JD*, *MD*, or *MBA* as needed to find additional names in order to get at least 10 full names for "*Ebony*". Clicking on the link associated with "*Ebony Glover*" provides more information about her (Figure 9b), including an image. We record that the *Ebony Glover* in the study appears black.

Similarly, Figure 9c shows search results for "*Jill PhD*"—a list of professionals whose first name are *Jill*. Visiting links yields web pages with more information about each person. For example, Figure 9d shows an extract of *Jill Schneider* 's web page, and from the associated image, we record that the *Jill Schneider* in this study is white.

Step 1 **For each** $name_i$ in the list of racially associated first names in Figure 6, **do**:
- 1.1 Perform a Google search for "$name_i$ $degree_j$" where $degree_j$ is one of {*PhD*, *MD*, *JD*, *MBA*}.
- 1.2 **For each** result page, up to 3 pages, **do**:
  - Preserve a copy of the page
  - Record first and last names of people, avoiding duplicates.
  - **For each** full name recorded, **do**:
    - Click on the associated link. Preserve a copy of the resulting page.
    - If personal image appears, record whether the person appears black, white, or other.
  - **Repeat** Steps 1.1 and 1.2 with another $degree_j$ if the number of full names for $name_i$ is less than 10.

(a)

Step 1 **For each** $name_i$ in the list of racially associated first names in Figure 6, **do**:
- 1.1 Perform a PeekYou search for "$name_i$"
- 1.2 **For each** result page, up to 2 pages, and 10 recorded full names for $name_i$ **do**:
  - Preserve a copy of the page
  - Record first and last names of people, avoiding duplicates.
  - **For each** full name recorded, note whether associated image appears black, white, or other.

(b)

Figure 8. Method for harvesting racially associated first and last names of (a) professionals using Google search and (b) netizens using PeekYou.

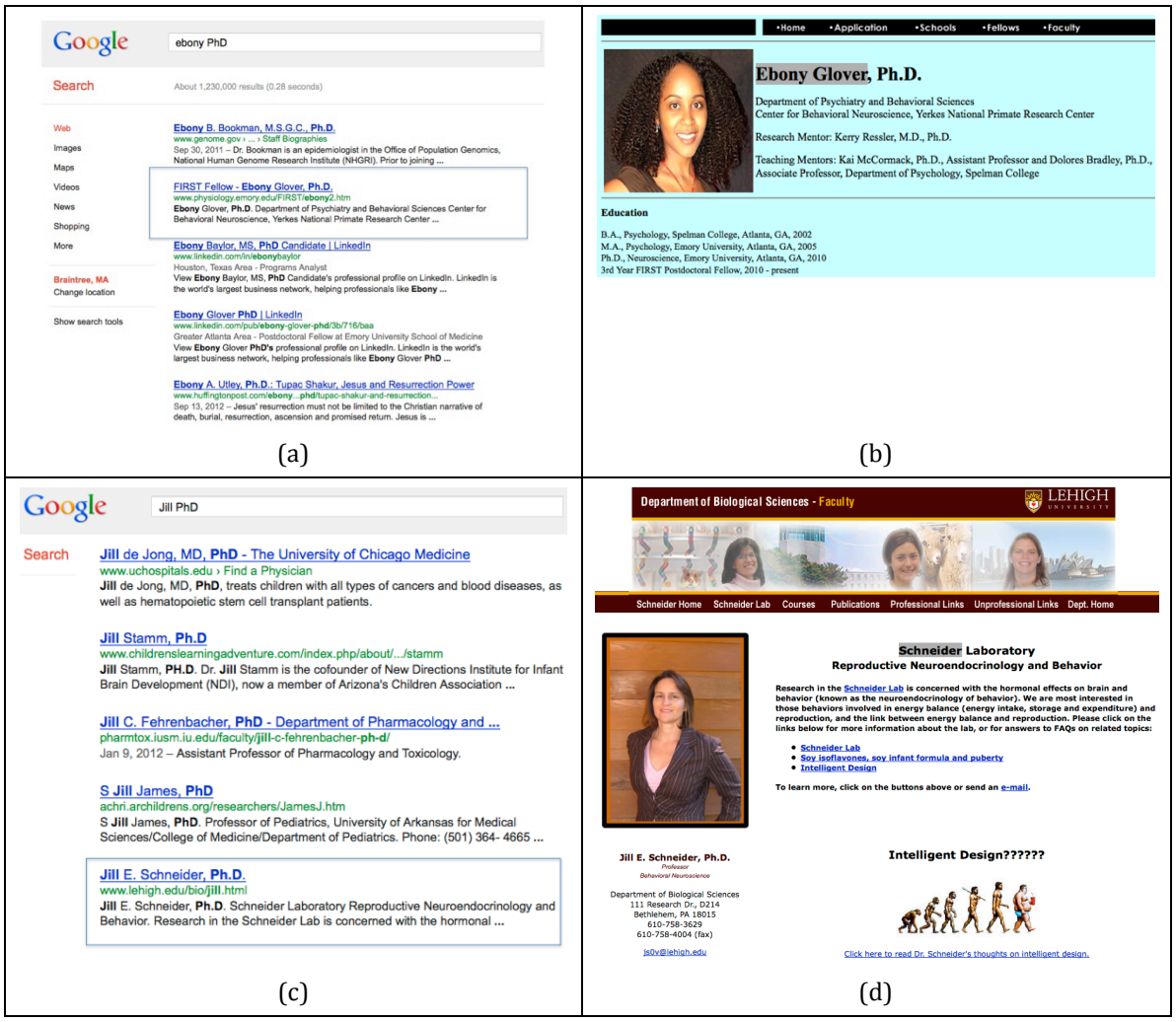

Figure 9. Extracts of search and web pages for first names and degree designations. (a) Search "*Ebony Phd*". (b) "*Ebony Glover*" page. (c) Search "*Jill Phd*" (d) "*Jill Schneider*" page.

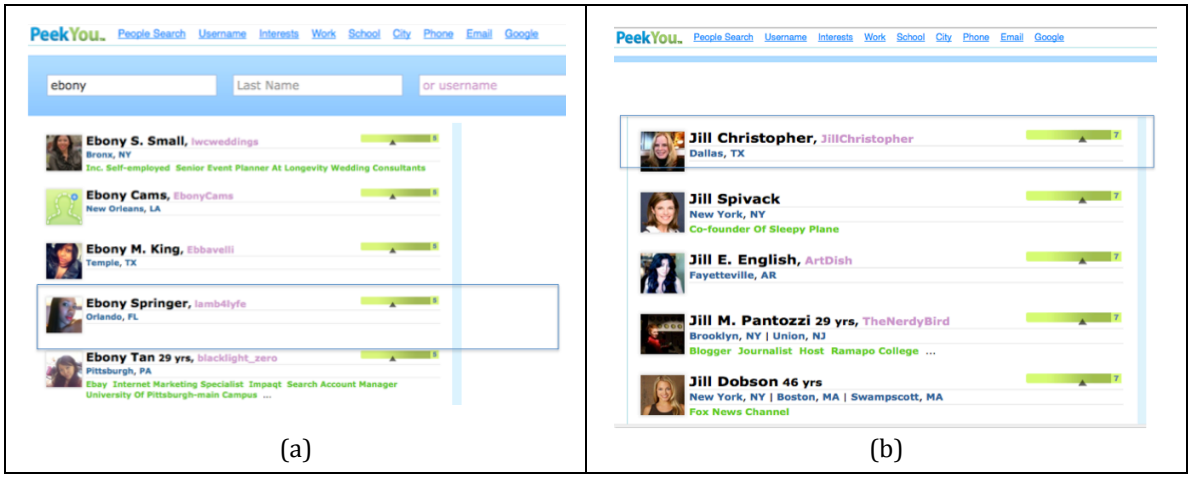

Figure 10. Extracts of search pages for netizens using PeekYou.com for first names (a) "*Ebony*" and (b) "*Jill*". Highlighted records are (a) "*Ebony Springer*" and (b) "*Jill Christopher*".

Harvesting Full Names of Netizens

The website peekyou.com ("PeekYou") compiles and disambiguates online and offline information on individuals, thereby connecting residential information with Facebook and twitter users, bloggers, and others, and assigns its own rating of size for each person's on-line footprint. Search results from peekyou.com ("PeekYou search") lists people having the highest score first, second highest second, and so on, and includes an image of the person. Celebrities and public figures tend to list first, having the highest PeekYou scores, followed by bloggers, tweeters and the rest. We use PeekYou searches to harvest a sample of full names of netizens having racially associated first names; Figure 8b itemizes the steps.

Harvesting names of netizens (Figure 8b) is similar but simpler than harvesting names of professionals (Figure 8a). For each name in the list of racially associated first names (Figure 6), perform a PeekYou search with that first name (Step 1.1); harvest full names from the search results, up to 2 pages of results, avoiding duplicate names; and, for each full name recorded, note whether the person in the associated image appears black, white, or other. Archive each web page, preserving images and content.

Here are two examples. Figure 10a shows some results from a PeekYou search of "*Ebony"* as a first name, listing "*Ebony Small*", "*Ebony Cams*", "*Ebony King*", "*Ebony Springer*" (highlighted), and "*Ebony Tan*". Similarly, Figure 10b shows some PeekYou search results for "*Jill*" as a first name, listing "*Jill Christopher*" (highlighted), "*Jill Spivack*", "*Jill English*", "*Jill Pantozzi*", and "*Jill Dobson*". We harvest these and other full names appearing on the first two pages of results and for each recorded image, report the race of the person if discernible. We record "*Ebony Glover*" in this study appears black and "*Jill Christopher*" white.

Results from Harvesting Full Names

Armed with the approach just described, from September 24 through October 22, 2012, I harvested 2184 racially associated full names of people with an online presence and using the images associated with those names, was able to confirm that the racially associated first names in Figure 6 are predictive of race (88% black and 96% white). Figures 11 and 12 summarize results. Below is a discussion.

Google searches of first names and degree designations were not as productive as first name lookups on PeekYou, 1002 to 1182 harvested names, respectively. White male names, "*Cody*", "*Connor*", "*Tanner*" and "*Wyatt*", retrieved results with those as last names not first names, the black male name, "*Kenya*", was confused with the country, and black names, "*Aaliyah*", "*Deja*", "*Diamond*", "*Hakim*", "*Malik*", "*Marquis*", "*Nia*", "*Precious*", "*Rasheed*" retrieved less than 10 full names. Only "*Diamond*" posed a problem with PeekYou searches –seemingly confused with other online entities. Other than "*Diamond*", all other searches contributed full names, and so unless noted otherwise, we exclude "*Diamond*" from further consideration.

FIRST NAME			FULL NAMES			IMAGES					
Name	Race	Gender	Professionals	Netizens	Full Names	None	Black	%	White	%	Other
Aaliyah	Black	Female	5	14	19	7	12	100%	0	0%	0
Aisha	Black	Female	22	32	54	13	36	88%	5	12%	0
Allison	White	Female	14	14	28	4	0	0%	23	96%	1
Amy	White	Female	42	25	67	24	0	0%	40	93%	3
Anne	White	Female	19	16	35	7	1	4%	27	96%	0
Brad	White	Male	19	18	37	13	0	0%	24	100%	0
Brendan	White	Male	15	25	40	16	3	13%	20	83%	1
Brett	White	Male	13	15	28	5	0	0%	23	100%	0
Carrie	White	Female	17	16	33	10	0	0%	21	91%	2
Claire	White	Female	30	26	56	18	1	3%	37	97%	0
Cody	White	Male	0	30	30	14	0	0%	16	100%	0
Connor	White	Male	0	30	30	6	1	4%	23	96%	0
Darnell	Black	Male	12	14	26	11	14	93%	1	7%	0
DeAndre	Black	Male	16	13	29	14	15	100%	0	0%	0
Deja	Black	Female	0	24	24	3	18	86%	3	14%	0
DeShawn	Black	Male	13	14	27	14	11	85%	2	15%	0
Diamond	Black	Female	0	0	0						
Dustin	White	Male	36	30	66	24	0	0%	42	100%	0
Ebony	Black	Female	14	45	59	9	46	92%	4	8%	0
Emily	White	Female	15	15	30	3	0	0%	26	96%	1
Emma	White	Female	33	27	60	27	2	6%	30	91%	1
Geoffrey	White	Male	19	15	34	4	0	0%	29	97%	1
Greg	White	Male	20	20	40	17	0	0%	23	100%	0
Hakim	Black	Male	4	13	17	9	7	88%	1	13%	0
Imani	Black	Female	12	13	25	6	19	100%	0	0%	0
Jack	White	Male	28	30	58	30	0	0%	24	86%	4
Jake	White	Male	29	30	59	27	1	3%	30	94%	1
Jamal	Black	Male	11	18	29	8	10	48%	4	19%	7
Jay	White	Male	15	14	29	6	3	13%	18	78%	2
Jermaine	Black	Male	14	14	28	13	15	100%	0	0%	0
Jill	White	Female	20	14	34	4	0	0%	30	100%	0
Kareem	Black	Male	18	15	33	10	17	74%	0	0%	6
Katelyn	White	Female	50	30	80	29	0	0%	51	100%	0
Katie	White	Female	37	13	50	26	0	0%	24	100%	0
Keisha	Black	Female	11	29	40	11	28	97%	1	3%	0
Kenya	Black	Female	4	0	4	1	3	100%	0	0%	0
Kristen	White	Female	20	14	34	7	0	0%	27	100%	0
Lakisha	Black	Female	13	15	28	15	13	100%	0	0%	0
Latanya	Black	Female	13	15	28	13	13	87%	2	13%	0
Latisha	Black	Female	13	15	28	7	19	90%	2	10%	0
Latonya	Black	Female	21	15	36	11	23	92%	2	8%	0
Latoya	Black	Female	12	15	27	12	15	100%	0	0%	0
Laurie	White	Female	13	15	28	7	1	5%	20	95%	0
Leroy	Black	Male	11	14	25	7	9	50%	7	39%	2
Luke	White	Male	35	25	60	31	1	3%	27	93%	1
Madeline	White	Female	37	29	66	36	2	7%	28	93%	0
Malik	Black	Male	1	17	18	6	12	100%	0	0%	0
Marquis	Black	Male	5	14	19	3	15	94%	1	6%	0
Matthew	White	Male	18	26	44	12	0	0%	32	100%	0
Meredith	White	Female	18	15	33	5	2	7%	26	93%	0
Molly	White	Female	41	29	70	27	0	0%	42	98%	1
Neil	White	Male	18	12	30	11	0	0%	17	89%	2
Nia	Black	Female	0	11	11	0	8	73%	3	27%	0
Precious	Black	Female	0	12	12	4	7	88%	1	13%	0
Rasheed	Black	Male	1	16	17	6	8	73%	2	18%	1
Shanice	Black	Female	12	14	26	6	18	90%	1	5%	1
Tamika	Black	Female	14	15	29	12	17	100%	0	0%	0
Tanner	White	Male	0	30	30	12	0	0%	18	100%	0
Terrell	Black	Male	13	15	28	7	17	81%	4	19%	0
Tremayne	Black	Male	15	12	27	14	12	92%	1	8%	0
Trevon	Black	Male	12	14	26	12	14	100%	0	0%	0
Tyrone	Black	Male	19	17	36	13	19	83%	3	13%	1
Wyatt	White	Male	0	30	30	17	0	0%	13	100%	0
		Totals	1002	1182	2184	756	508		881		39

Figure 11. Summary of harvesting 2184 full names of professionals and neitzens from the Web (middle group) using racially associated first names (leftmost group), and race observations of online images (rightmost group). A total of 1428 images, 508 black, 881 white and 39 other.

NUMBER OF FULL NAMES (BASED ON FIRST NAME DESCRIPTION)

	Black	White	Totals	
Male	483	592	1075	49%
Female	352	757	1109	51%
Totals	835	1349	2184	
	38%	62%		

(a)

		IMAGE LABELS: Black	IMAGE LABELS: Not Black	Predicitve Value
BLACK FIRST NAME	Black	490	68	88%
	Not Black	18	852	98%
		Sensitivity 96%	Specificity 93%	

(b)

		IMAGE LABELS: White	IMAGE LABELS: Not White	Predicitve Value
WHITE FIRST NAME	White	831	39	96%
	Not White	50	508	91%
		Sensitivity 94%	Specificity 93%	

(c)

Figure 12. Descriptive statistics of harvested full names (a) and analysis of first names as a classifier for blacks (b) and for whites (c).

Figure 11 shows the number of full names harvested for each first name. Names contributing the most number of full names have white first names, e.g. "*Katelyn*" (80), "*Molly*" (70), "*Amy*" (67), "*Dustin*" (66) and "*Madeline*" (66), purposefully oversampled to test whether comparable PeekYou scores have any effect on ad delivery. Names contributing the least number of full names have black first names, "*Hakim*" (17), "*Rasheed*" (17), "*Precious*" (12), "*Nia*" (11) and "*Kenya*" (4).

The average number of full names for each first name is 35, with a median of 30, and standard deviation 16. For black first names, the average number of full names for each of the 31 first names is 27, with median 27, and standard deviation 11, and for the 31 white first names, the average is 44, median 35, and standard deviation 16.

Of the 2184 full names harvested, 835 (38%) are associated with black first names and 1349 (62%) with white first names, and 1075 (49%) with male first names and 1109 (51%) with female names; see Figure 12a.

Most images associated with black-identifying names were of black people (88%) and an even greater percentage of images associated with white-identifying names were of white people (96%). A total of 1428 names had discernible black (508), white (881) or other (39) images (Figure 11). We examine black and white names separately as predictors of race (Figures 12b and 12c). Of those having black associated first names, 490 images were of blacks, 68 images were not, 18 images

having white first names were of blacks, and 852 names had neither black first names nor images of blacks. Similarly, 831 images of whites had white first names, 50 images of whites did not have white first names, 39 had white first names but non-white images, and 508 had neither white first names nor images of whites.

Some first names associated as black had perfect predictions (100%) –"*Aaliyah*", "*DeAndre*", "*Imani*", "*Jermaine*", "*Lakisha*", "*Latoya*", "*Malik*", "*Tamika*", and "*Trevon*" —and the worst predictors of blacks were "*Jamal*" (48%) and "*Leroy*" (50%). Figure 11 has details. Even more first names associated with whites, 12 of 31 names or 39%, made perfect predictions –"*Brad*", "*Brett*", "*Cody*", "*Dustin*", "*Greg*", "*Jill*", "*Katelyn*", "*Katie*", "*Kristen*", "*Matthew*", "*Tanner*" and "*Wyatt*" –and the worst predictors of whites, "*Jay*" (78%) and "*Brendan*" (83%"), were not bad. These findings strongly support the use of these names as racial indicators in this study.

Sixty-two full names (or 62/2184 = 3%) appeared in the list twice even though the people were not necessarily the same. No name appeared more than twice, so overall, Google and PeekYou searches tended to yield different names.

Ad Delivery

We now have a set of first and last names suggestive of race. What ads appear when these names are searched? To answer this question, we examine ads delivered on two sites, Google.com and Reuters.com, in response to searches of each full name, once at each site.

The method is straightforward. For each full name, visit Google.com, search for the name and record which ads display. Repeat the process at Reuters.com, clearing the browser's cache and cookies before each search and preserving copies of web pages received. Figure 13 enumerates these steps.

As examples, Figure 14 shows ads delivered in response to searches of "*Lakisha Simmons*", "*Laurie Ryan*", "*Darnell Bacon*", and "*Brendan Watson*" on google.com and reuters.com. We preserve the capture of all ads, not just those of Instant Checkmate.

Step 1	**For each** *fullname*$_i$ in the list of racially associated full names, **do**:
1.1	Clear the browser cache and cookies.
1.2	Search Google.com for "*fullname*$_i$"
1.3	Preserve copies of any of up to the first 3 pages of results having ads.
1.4	Record which ads display.
1.5	Clear the browser cache and cookies.
1.6	Search Reuters.com for "*fullname*$_i$"
1.7	Preserve a copy of the resulting page.
1.8	Record which ads display.

Figure 13. Method for harvesting ads appearing in responses to searches of full names on google.com and reuters.com.

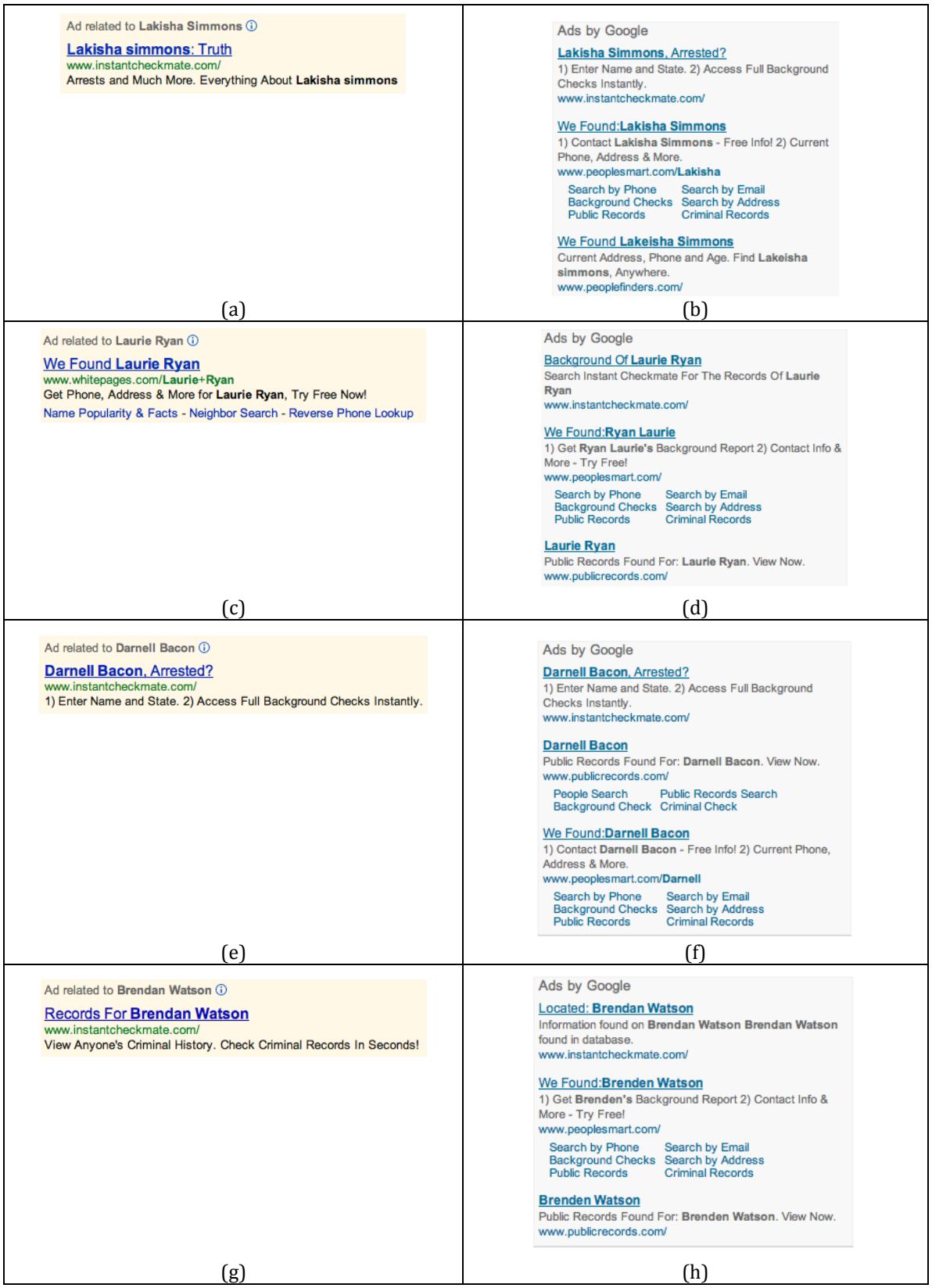

Figure 14. Ads in response to full name searches on google.com (a,c,e,g) and reuters.com (b,d,f,h) for "*Lakisha Simmons*", "*Laurie Ryan*", "*Darnell Bacon*", and "*Brendan Watson*".

Results from Ad Delivery

From September 24 through October 23, 2012, I searched 2184 full names on google.com and reuters.com, as described above. Execution took place at different times of days, different days of week, with different IP and machine addresses operating in different parts of the United States using different browsers. I manually searched 1373 of the names and used automated means ("Webshot" [12]) for the remainder (812 names). Here are 15 findings about ads and names, followed by four supplemental observations.

1. No more than three ads ever appeared for a search, whether manual or automated, regardless of website, Google or Reuters. No company's ad listed more than once on a page.

2. Far fewer ads appeared on google.com than on reuters.com. A total of 5337 ads appeared, 4473 (84%) on reuters.com and only 864 (16%) on Google, even when examining up to three pages of search results on google.com, and Google showed fewer ads per page, typically 1 (median) compared to 3 (median) on Reuters. In terms of the 2184 full names, ads appeared exclusive to Reuters (1221), Google (17) and on both (604) for a total of 1842 (84%) names having ads; 342 names had no ads at all. Reuters displayed ads for 1826 (84%) names and Google for 622 (28%). Figures 15a and 15c have summary statistics.

3. Most ads were for government-collected information ("public records") about the person. Public records in the United States often include a person's address, phone number, criminal history, and professional and business licenses, though specifics vary among states. Of the 5337 total ads captured, all but 1161 were for public records, or conversely, 4176 ads (78% of all ads) were for public records. Figure 15a has a distribution.

4. Ads for public records appeared for most names. Of the 2184 names, 1705 (78%) had at least one ad for public records about the person being searched. Reuters showed ads for 1598 names and Google for 544 names. Figure 16 has details.

5. More Instant Checkmate ads appeared than for any other company. Four companies accounted for more than half of all ads: instantcheckmate.com (1557 of 5337 or 29%), publicrecords.com (861 or 16%), peoplesmart.com (589, 11%), and peoplefinders.com (542, 10%). All ads for these companies sold public records. Ad distribution was different on Google's site; Instant Checkmate still had the most ads (431 of 864 or 50%), but Intelius, another seller of public records, while not in the top four overall, had the second most ads (127 or 15%) on google.com. Figure 15a lists details.

6. Instant Checkmate ads dominated the topmost ad position. On reuters.com, ads for Instant Checkmate listed first in 892 (49%) of the 1826 searches having ads on Reuters. The next closest, publicrecords.com, was a distance back having the topmost spot only 142 times, but most frequently appearing in the second and third positions. Figure 15b summarizes ad positions.

7. Ads for public records appeared more often in black names than white. Regardless of company, proportionately more ads appeared for names having a black-identifying first name. PeopleSmart ads appeared for 270 white and 280 black names, being disproportionately higher for blacks, 41% (280 of 679) to 29%. PublicRecords ads appeared 10% more often for black (54%) than white (44%) names, and Instant Checkmate ads 2.45% more often for blacks (72% to 69%). Figure 15d lists findings.

8. Instant Checkmate ads accounted for the largest percentage of ads in most first name categories, except for "*Kristen*", "*Connor*", and "*Tremayne*", which have uncharacteristically fewer ads. Instant Checkmate ads appeared for an average of 70% of all full names in a first name group receiving ads on Reuters (median 76%, standard deviation 0.21, 63 first name groups). For example, Instant Checkmate ads appeared on Reuters for 90-100% of all full names having ads whose name began "*Kenya*", "*Latoya*", "*DeShawn*", "*Emily*", "*Jay*", "*Greg*", "*Brendan*", "*Brad*", "*Leroy*", "*Dustin*", "*Neil*" or "*Jill*". In three cases, Instant Checkmate ads fell under 25% despite competition: "*Tremayne*" (91% PublicRecords, 23% Instant Checkmate), "*Connor*" (80% PublicRecords, 20% Instant Checkmate), and "*Kristen*" (58% PublicRecords, 16% Instant Checkmate). Figure 16 shows results by first name group.

9. Instant Checkmate had the most variability in ad copy. Almost all ads for public records included the name of the person in the ad itself, making each ad virtually unique, but beyond personalization, there was little variability in ad templates. Of the 534 PeopleFinder ads appearing on Reuters, all but 11 used the same personalized template, "We found *fullname.* Current Address, Phone and Age. Find *fullname*, Anywhere", where the person's first and last name replaces *fullname*. PublicRecords used 5 templates and PeopleSmart 7, but Instant Checkmate used more than all others combined, 18 templates in 1126 ads. Figure 17 displays ad texts and frequencies for all four companies.

10. Only Instant Checkmate ads included the word "arrest". While Instant Checkmate's competitors, PeopleSmart, PublicRecords, and PeopleFinders, also sell criminal history information, none of their ads included the word "arrest". In the 18 templates of Instant Checkmate ads found on Reuters, 8 of them include the word "arrest"; see Figure 17 for details.

11. Instant Checkmate ads having "arrest" in its text appeared less often than ads not including the word on Reuters. Of the 1126 Instant Checkmate ads appearing on Reuters, 544 (48%) include the word "arrest" and 582 (52%) do not. Figure 19 provides details.

12. A greater percentage of Instant Checkmate ads having "arrest" in ad text appeared for black identifying first names than for white first names. Of the 1126 Instant Checkmate ads on Reuters, 488 displayed with black-identifying first names, 291 (60%) of which had "arrest" in ad text. Of the 638 ads displayed with white-identifying names, 308 (48%) had "arrest". These results are statistically significant, $X^2(1)=14.32$, $p < 0.001$; there is less than a 0.1% probability that these data can be explained by chance. The results also have an adverse impact ratio (40%/52%) of 77%, satisfying the EEOC's and U.S. Department of Labor's 80% adverse impact test if this were employment. Figure 15e shows analysis.

13. More white identifying first names top the list of neutral Instant Checkmate Ads than do black names. On reuters.com, the highest percentage of neutral ads, where the word "arrest" does not appear in ad text, were ads for "*Jill*" (77%) and "*Emma*" (75%), both white-identifying names. Names receiving the highest percentage of ads with "arrest" in the text are "*Darnell*" (84%), "*Jermaine*" (81%) and "*DeShawn*" (86%), all black-identifying first names. Some names appear opposite this pattern. "*Dustin*", a white-identifying name, generated "arrest" ads in 81% of searches with that first name, and "*Imani*", a black-identifying name, received neutral copy in 75% of "*Imani*" searches. Figure 19 provides results by first name groups.

14. Instant Checkmate ads appearing on google.com often used different ad text than on Reuters. While the same neutral and arrest ads having dominant appearances on Reuters also appeared frequently on Google, ads on google.com included an additional 10 templates, all using the word "criminal", a word also suggestive of arrest, or the word "arrest". These new templates appeared in 89 of the 432 ads (21%). Figure 20 lists the Instant Checkmate ad templates found on google.com.

15. On google.com, a greater percentage of Instant Checkmate ads suggestive of arrest displayed for black associated first names than white. Of the 432 Instant Checkmate ads appearing on google.com, 90% (388) were suggestive of arrest regardless of race. Of the 366 ads that appeared for black-identifying names, 335 (92%) were suggestive of arrest. Far fewer ads displayed for white-identifying names (66 total), and 53 (80%) were suggestive of arrest. These results are statistically significant, $X^2(1)=7.71$, $p < 0.01$; there is less than a 1% probability that these data can be explained by chance. The adverse impact ratio (8%/20%) of 40%, which would satisfy the EEOC adverse impact test if this were employment. Figure 15f shows analysis and Figures 21 and 22 show distributions.

Here are four supplemental observations.

16. A greater percentage of Instant Checkmate ads having the word "arrest" in ad text appeared for black identifying first names than for white identifying first names within professional and netizen subsets. Of the 2184 names in the study, 599, harvested using professional designations, had Instant Checkmate ads on Reuters with 217 having black associated names, 136 (63%) of which received ads with the word "arrest" in ad text compared to only 178 (47%) of 382 white associated names, a statistically significant difference ($X^2(1)=14.34$, $p < 0.001$). Netizens also had a higher percentage of black names having ads with the word "arrest" in 155 (57%) of 271 ads for black identifying names compared to 130 (51%) of 256 ads for white identifying names.

17. People behind the names used in this study are diverse. Examining source webpages for the names reveals all kinds of people. Political figures include State Representatives Aisha Braveboy ("arrest" ad) and Jay Jacobs (neutral ad) of Maryland, Jill Biden (neutral ad), wife of U.S. Vice President Joe Biden, and Claire McCaskill, whose campaign advertisement for the U.S. Senate is alongside an Instant Checkmate ad having the word "arrest" (Figure 23). Names mined from academic websites include graduate students, researchers, administrators, staff, and accomplished academics, such as Amy Gutmann, President of the University of Pennsylvania and Chair of the U.S. Presidential Commission for the Study of Bioethical Issues. Dustin Hoffman ("arrest" ad) is among names of celebrities. A smorgasbord of athletes appears, from local to national fame, including numerous high school stars (assorted neutral and "arrest" ads). The youngest person associated with the study was a missing 11-year-old black girl.

18. PeekYou, the primary source of names for Netizens in this study, assigns a score to each name estimating the name's overall presence on the Web. As expected, celebrities get the highest scores, 10's and 9's. Of the 2184 names in the study, 1143 were harvested from PeekYou with scores, and only 4 of these had a PeekYou score of 10 and 12 had a 9 score. Dustin Hoffman is a 9. Only 2 ads appeared for these high scoring names. Other than that, an abundance of ads appeared across the remaining spectrum of PeekYou scores. Figure 25 shows distributions of Peek You scores.

19. Different Instant Checkmate ads appear for the same person. Of the 2184 names, 228 names had Instant Checkmate ads on both Reuters and Google, but only 42 of these names received the same ad. The other 186 (82%) names received different ads across the two sites. Search results on Reuters for the 62 duplicate names that appeared in the study show different ads for 37 (60%) names, the same ad for 7 names, and no ad for 18. At most, three distinct ads appeared across Reuters and Google for the same name; Figure 24 has examples.

	Reuters	Google	Totals	
instantcheckmate	1126	431	1557	*29%*
peoplesmart	550	39	589	*11%*
publicrecords	770	91	861	*16%*
peoplefinders	535	7	542	*10%*
facebook	29		29	*1%*
intelius	56	127	183	*3%*
whitepages	61	33	94	*2%*
ask	175	13	188	*4%*
usa-people-search	73		73	*1%*
other (public records)	53	7	60	*1%*
not public records	1045	116	1161	*22%*
Totals	4473	864	5337	
	84%	*16%*		

(a)

Ad Position on Reuters

	1st	2nd	3rd	Totals
instantcheckmate	**892**	157	77	1126
peoplesmart	110	252	188	550
publicrecords	142	**350**	**278**	770
peoplefinders	128	202	205	535
facebook	2	9	18	29
intelius	5	25	26	56
whitepages	7	17	37	61
ask	60	73	42	175
usa-people-search	12	27	34	73
other (public records)	14	19	20	53
			Ads for public records	3428
			Other ads (not public records)	1045
			Total ads on Reuters	4473

(b)

	Reuters	Google	Totals
Names having Ads	1826	622	
Exclusive to Reuters or Google	1221	17	1238
Ads/Name: Average	2.4	1.4	
Ads/Name: Median	3	1	
Standard Deviation	0.8	0.7	
		Names having No Ads	342
		Names with Ads on Both Reuters and Google	604
		Total Full Names	2184

(c)

Public Record Ads on Reuters by Type of First Name

	BLACK		WHITE		Totals	Ratio	Difference (*p*-value)
instantcheckmate	488	72%	638	69%	1126	1.04	2.45%
peoplesmart	280	41%	270	29%	550	1.40	11.86%
publicrecords	368	54%	402	44%	770	1.24	10.45%
peoplefinders	264	39%	271	29%	535	1.32	9.39%
intelius	37	5%	19	2%	56		3.38%
Total names	679		919		1598		

(d)

INSTANT CHECKMATE ADS ON REUTERS

	OBSERVED						EXPECTED	
	BLACK		**WHITE**		Totals		**BLACK**	**WHITE**
Arrest Ads	291	60%	308	48%	599	53%	260	339
Neutral Ads	197	40%	330	52%	527	47%	228	299
Totals	488		638		1126			

(e)

INSTANT CHECKMATE ADS ON GOOGLE

	OBSERVED						EXPECTED	
	BLACK		**WHITE**		Totals		**BLACK**	**WHITE**
Arrest Ads	335	92%	53	80%	388	90%	329	59
Neutral Ads	31	8%	13	20%	44	10%	37	7
Totals	366		66		432			

(f)

Figure 15. Summary statistics for (a) ads appearing on Reuters and Google; (b) ad positions on Reuters; (c) results by names; (d) ads for public record appearing on Reuters by racially associated first name; (e) Chi-Square test for Instant Checkmate ads on Reuters; and, (f) Chi-Square test for Instant Checkmate ads on Google.

FIRST NAME			NAMES WITH PUBLIC RECORD ADS			NUMBER OF FULL NAMES WITH PUBLIC RECORD ADS ON REUTERS											
Name	Race	Full Names	Reuters	Google	Distinct	instantcheckmate		peoplesmart		publicrecords		peoplefinders		intelius			
Aaliyah	Black	19	13	3	14	4	31%	2	15%	13	100%	0	0%	8	62%		
Aisha	Black	54	47	26	50	37	79%	24	51%	25	53%	26	55%	1	2%		
Allison	White	28	17	0	19	12	71%	2	12%	6	35%	7	41%	1	6%		
Amy	White	67	41	0	43	27	66%	18	44%	19	46%	10	24%	0	0%		
Anne	White	35	20	2	20	16	80%	0	0%	6	30%	5	25%	2	10%		
Brad	White	37	32	9	32	30	94%	13	41%	9	28%	4	13%	0	0%		
Brendan	White	40	36	12	36	34	94%	10	28%	15	42%	6	17%	0	0%		
Brett	White	28	25	4	25	21	84%	6	24%	9	36%	4	16%	0	0%		
Carrie	White	33	23	7	24	17	74%	6	26%	7	30%	1	4%	0	0%		
Claire	White	56	40	0	43	31	78%	14	35%	7	18%	13	33%	0	0%		
Cody	White	30	16	0	17	9	56%	8	50%	13	81%	1	6%	0	0%		
Connor	White	30	20	0	21	4	20%	2	10%	16	80%	1	5%	1	5%		
Darnell	Black	26	23	20	25	19	83%	6	26%	12	52%	7	30%	0	0%		
DeAndre	Black	29	21	9	24	15	71%	6	29%	13	62%	8	38%	3	14%		
Deja	Black	24	15	13	19	11	73%	0	0%	11	73%	7	47%	1	7%		
DeShawn	Black	27	22	13	22	21	95%	7	32%	16	73%	1	5%	1	5%		
Diamond	Black																
Dustin	White	66	52	4	53	47	90%	20	38%	28	54%	6	12%	0	0%		
Ebony	Black	59	47	28	49	39	83%	11	23%	28	60%	15	32%	0	0%		
Emily	White	30	20	0	21	19	95%	2	10%	4	20%	1	5%	0	0%		
Emma	White	60	36	0	39	20	56%	17	47%	22	61%	8	22%	1	3%		
Geoffrey	White	34	27	7	29	24	89%	9	33%	13	48%	5	19%	0	0%		
Greg	White	40	37	11	39	35	95%	6	16%	10	27%	14	38%	1	3%		
Hakim	Black	17	9	4	11	5	56%	2	22%	4	44%	5	56%	1	11%		
Imani	Black	25	16	8	18	8	50%	4	25%	11	69%	7	44%	4	25%		
Jack	White	58	31	0	35	25	81%	9	29%	13	42%	10	32%	0	0%		
Jake	White	59	29	1	32	20	69%	8	28%	8	28%	8	28%	2	7%		
Jamal	Black	29	24	11	26	11	46%	9	38%	8	33%	16	67%	1	4%		
Jay	White	29	19	5	20	18	95%	2	11%	3	16%	5	26%	0	0%		
Jermaine	Black	28	22	20	22	16	73%	14	64%	13	59%	7	32%	0	0%		
Jill	White	34	29	12	29	26	90%	7	24%	11	38%	8	28%	0	0%		
Kareem	Black	33	28	19	28	21	75%	11	39%	13	46%	6	21%	1	4%		
Katelyn	White	80	63	0	72	26	41%	8	13%	34	54%	54	86%	3	5%		
Katie	White	50	26	0	27	14	54%	13	50%	10	38%	7	27%	1	4%		
Keisha	Black	40	30	14	36	24	80%	16	53%	8	27%	13	43%	3	10%		
Kenya	Black	4	4	2	4	4	100%	1	25%	0	0%	3	75%	2	50%		
Kristen	White	34	19	1	22	3	16%	10	53%	11	58%	7	37%	0	0%		
Lakisha	Black	28	26	18	26	15	58%	15	58%	5	19%	17	65%	0	0%		
Latanya	Black	28	24	17	24	19	79%	19	79%	13	54%	4	17%	0	0%		
Latisha	Black	28	22	19	23	17	77%	5	23%	12	55%	20	91%	0	0%		
Latonya	Black	36	34	17	34	26	76%	17	50%	17	50%	14	41%	1	3%		
Latoya	Black	27	26	20	27	25	96%	9	35%	15	58%	6	23%	0	0%		
Laurie	White	28	19	6	19	14	74%	5	26%	8	42%	6	32%	0	0%		
Leroy	Black	25	24	22	24	22	92%	13	54%	11	46%	5	21%	0	0%		
Luke	White	60	38	0	38	23	61%	18	47%	18	47%	4	11%	2	5%		
Madeline	White	66	41	0	53	11	27%	17	41%	24	59%	36	88%	1	2%		
Malik	Black	18	14	8	15	8	57%	2	14%	4	29%	7	50%	3	21%		
Marquis	Black	19	17	13	17	14	82%	5	29%	9	53%	0	0%	0	0%		
Matthew	White	44	29	9	29	24	83%	5	17%	10	34%	6	21%	0	0%		
Meredith	White	33	25	4	30	18	72%	8	32%	14	56%	12	48%	1	4%		
Molly	White	70	49	0	52	26	53%	12	24%	28	57%	10	20%	1	2%		
Neil	White	30	20	5	21	18	90%	7	35%	6	30%	3	15%	2	10%		
Nia	Black	11	5	2	5	4	80%	0	0%	4	80%	0	0%	1	20%		
Precious	Black	12	7	2	8	2	29%	3	43%	2	29%	2	29%	1	14%		
Rasheed	Black	17	13	6	17	6	46%	6	46%	6	46%	9	69%	2	15%		
Shanice	Black	26	19	14	20	13	68%	6	32%	13	68%	4	21%	1	5%		
Tamika	Black	29	22	18	25	18	82%	15	68%	14	64%	9	41%	0	0%		
Tanner	White	30	18	2	20	15	83%	1	6%	9	50%	3	17%	0	0%		
Terrell	Black	28	24	18	24	20	83%	11	46%	14	58%	11	46%	1	4%		
Tremayne	Black	27	22	14	26	5	23%	13	59%	20	91%	10	45%	0	0%		
Trevon	Black	26	23	8	23	9	39%	3	13%	15	65%	14	61%	0	0%		
Tyrone	Black	36	36	33	36	30	83%	25	69%	19	53%	11	31%	1	3%		
Wyatt	White	30	22	4	23	11	50%	7	32%	11	50%	6	27%	0	0%		
	Totals		1598	544	**1705**	1126		550		770		535		56			

Figure 16. Counts of ads for public records by first name.

instantcheckmate

C 382	**Located: *fullname*** Information found on *fullname fullname* found in database.
AC 2	**Located: The Person** Information found on them Person found in database.
G* 96	**We found *fullname*** Search Arrests, Address, Phone, etc. Search records for *fullname*.
S* 4	**We found Them** Search Arrests, Address, Phone, etc. Search records for *fullname*.
I 40	**Background of *fullname*** Search Instant Checkmate for the Records of *fullname*
U 9	**Background of Anyone** Search Instant Checkmate for the Records of *fullname*
J 17	***fullname*'s Records** 1) Enter Name and State. 2) Access Full Background Checks Instantly.
X 3	**Anyone's Records** 1) Enter Name and State. 2) Access Full Background Checks Instantly.
K* 195	***fullname*: Truth** Arrests and Much More. Everything About *fullname*
O* 67	***fullname* Truth** Looking for *fullname*? Check *fullname*'s Arrests
L* 176	***fullname*, Arrested?** 1) Enter Name and State. 2) Access Full Background Checks Instantly.
V* 2	**Uh Oh, Arrested?** 1) Enter Name and State. 2) Access Full Background Checks Instantly.
AD* 1	**Found: *fullname*** We have the story on *fullname fullname*'s arrests, relatives,etc.
AF* 3	***Fullname* - Found** Learn the truth about *fullname* Check *fullname*'s arrests & more.
AE 4	**Research *fullname*** We have details on *fullname*. *fullname*'s full background & info.
M* 55	***fullname* Located** Background Check, Arrest Records, Phone, & Address. Instant, Accurate
N 62	**Looking for *fullname*?** Comprehensive Background Report and More on *fullname*
AI 8	**Looking for People in the US?** Comprehensive Background Report and More on *fullname*

peoplesmart

A 7	**We found: *fullname*** 1) Get *firstname's* Background Report 2) Contact info & More -try Free!
T 87	**We found: *fullname*** 1) Get Aisha's Background Report 2) Current Contact Info - Try Free!
D 105	**We found: *fullname*** 1) Contact *fullname* -Free Info! 2) Current Address, Phone & More.
Q 348	**We found: *fullname*** 1) Contact *fullname* -Free Info! 2) Current Phone, Address & More.
AG 1	**We found *firstname*** Get *firstname* in CA's Email, Address, Phone, Public Records & More Easy!
AH 1	**We found *firstname* In *lastname*** 1)Get *firstname*'s Info – Try Now! 2)Current Phone, Address & More.
R 1	**Looking For *fullname*?** Get *fullname*'s Phone, Email Address, Public Records & More Now!

publicrecords

B 570	***fullname*** Public Records Found For: *fullname*. View now.
P 128	***fullname*** Public Records Found For: *fullname*. Search now.
F 13	**Records: *fullname*** Database of all *lastname*'s in the Country. Search now.
Z 2	***Fullname* Info** View Contact Information For Free Quick & Easy Search Results!
H 56	***fullname*** We have Public Records For: *fullname*. Search Now.

peoplefinders

E 523	**We found *fullname*** Current Address, Phone and Age. Find *fullname*, Anywhere.
Y 8	**We found *fullname*** 1)Get Phone/ Address/ Age Instantly! 2) Find Anyone, Anywhere for Free.
AA 2	**Find *fullname*** Get current and past addresses and phone numbers. Instant results!
AB 1	**We Found Them for Free** Current Address, Phone and Age. Find *fullname* Anywhere.

Figure 17. Templates for ads for public records on Reuters, replace *fullname* with person's first and last name. Letter identifies text. Number is number of occurrences of text. *arrest ad.

FIRST NAME			INSTANT CHECKMATE																					PEOPLESMART								PUBLICRECORDS					PEOPLEFINDERS			
Name	Race	Full Names	C	AC	G	S	I	U	J	X	K	O	L	V	AD	AF	AE	M	N	AI	Totals	A	T	D	Q	AG	AH	R	Totals	B	P	F	Z	H	Totals	E	Y	AA	AB
Aaliyah	Black	19	1	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	4	0	1	0	1	0	0	0	2	6	3	1	0	3	13	0	0	0	0
Aisha	Black	54	21	0	6	0	1	0	1	0	2	0	1	0	0	0	0	2	3	0	37	3	6	11	4	0	0	0	24	21	2	1	0	1	25	24	0	2	0
Allison	White	28	5	0	0	0	0	0	0	0	5	1	0	0	0	0	0	0	1	0	12	0	1	0	1	0	0	0	2	3	1	0	0	2	6	7	0	0	0
Amy	White	67	4	0	3	0	2	0	2	0	3	3	3	0	1	2	1	1	2	0	27	0	0	4	14	0	0	0	18	13	4	0	0	2	19	10	0	0	0
Anne	White	35	4	0	1	0	0	0	1	0	5	1	2	0	0	0	0	2	0	0	16	0	0	0	0	0	0	0	0	5	0	0	0	1	6	5	0	0	0
Brad	White	37	8	0	3	0	0	0	1	0	7	3	7	0	0	0	0	1	0	0	30	0	2	2	9	0	0	0	13	8	1	0	0	0	9	4	0	0	0
Brendan	White	40	13	0	2	0	0	1	0	0	8	1	2	0	0	0	0	1	5	1	34	0	7	0	3	0	0	0	10	13	2	0	0	0	15	6	0	0	0
Brett	White	28	12	0	1	0	0	0	0	1	1	2	2	0	0	0	0	1	1	0	21	0	0	1	5	0	0	0	6	8	1	0	0	0	9	4	0	0	0
Carrie	White	33	9	0	3	0	0	1	0	0	2	0	0	0	0	0	0	1	1	0	17	0	0	0	6	0	0	0	6	5	2	0	0	0	7	1	0	0	0
Claire	White	56	11	0	2	0	2	0	0	0	10	2	1	0	0	1	0	2	0	0	31	0	0	9	5	0	0	0	14	7	0	0	0	0	7	13	0	0	0
Cody	White	30	2	0	2	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	9	0	0	2	6	0	0	0	8	9	3	1	0	0	13	1	0	0	0
Connor	White	30	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	4	0	0	1	1	0	0	0	2	11	4	1	0	0	16	1	0	0	0
Darnell	Black	26	1	0	1	0	0	0	1	0	5	1	9	0	0	0	0	0	1	0	19	0	3	0	3	0	0	0	6	9	2	0	0	1	12	7	0	0	0
DeAndre	Black	29	4	0	0	0	0	0	0	0	4	1	3	0	0	0	0	2	1	0	15	0	1	3	2	0	0	0	6	12	1	0	0	0	13	8	0	0	0
Deja	Black	24	2	0	2	0	0	0	0	0	1	0	4	0	0	0	0	0	2	0	11	0	0	0	0	0	0	0	0	5	3	1	0	2	11	7	0	0	0
DeShawn	Black	27	1	0	8	1	1	0	0	0	2	1	5	0	0	0	0	1	0	1	21	0	1	1	5	0	0	0	7	14	1	0	0	1	16	1	0	0	0
Diamond	Black																																							
Dustin	White	66	5	0	4	0	1	0	0	0	26	1	6	0	0	0	0	1	3	0	47	0	0	4	15	1	0	0	20	22	5	0	1	0	28	6	0	0	0
Ebony	Black	59	6	0	6	0	2	0	1	0	8	5	5	0	0	0	0	1	5	0	39	1	2	0	8	0	0	0	11	24	2	0	0	2	28	14	1	0	0
Emily	White	30	7	0	1	0	0	1	2	0	2	3	1	0	0	0	0	1	1	0	19	0	1	0	1	0	0	0	2	2	1	1	0	0	4	1	0	0	0
Emma	White	60	12	0	1	0	0	0	1	0	3	0	1	0	0	0	0	0	2	0	20	0	0	3	14	0	0	0	17	16	5	0	0	1	22	8	0	0	0
Geoffrey	White	34	17	0	2	0	0	0	0	0	1	0	1	0	0	0	0	3	0	0	24	0	2	1	6	0	0	0	9	7	4	0	0	2	13	5	0	0	0
Greg	White	40	18	0	1	0	1	0	0	0	4	0	6	0	0	0	0	2	3	0	35	0	1	0	5	0	0	0	6	7	3	0	0	0	10	12	2	0	0
Hakim	Black	17	1	0	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	5	0	0	0	2	0	0	0	2	2	1	0	0	1	4	5	0	0	0
Imani	Black	25	3	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	1	0	8	0	1	1	2	0	0	0	4	3	3	0	0	5	11	7	0	0	0
Jack	White	58	14	0	0	0	1	0	0	0	6	1	2	0	0	0	0	0	1	0	25	0	0	2	7	0	0	0	9	12	1	0	0	0	13	9	1	0	0
Jake	White	59	9	0	1	0	1	0	0	0	3	0	1	0	0	0	1	3	1	0	20	0	0	4	4	0	0	0	8	5	3	0	0	0	8	8	0	0	0
Jamal	Black	29	5	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	11	0	2	1	6	0	0	0	9	7	0	0	0	1	8	16	0	0	0
Jay	White	29	8	0	0	1	2	0	0	0	4	0	2	0	0	0	0	0	1	0	18	0	1	0	1	0	0	0	2	3	0	0	0	0	3	4	1	0	0
Jermaine	Black	28	2	0	0	0	0	0	0	0	3	0	9	1	0	0	0	0	1	0	16	0	3	3	8	0	0	0	14	13	0	0	0	0	13	6	0	0	1
Jill	White	34	18	0	3	0	2	0	0	0	0	3	0	0	0	0	0	0	0	0	26	0	1	3	3	0	0	0	7	7	3	1	0	0	11	8	0	0	0
Kareem	Black	33	9	0	0	0	0	0	1	0	3	0	4	0	0	0	0	0	4	0	21	0	5	0	6	0	0	0	11	12	1	0	0	0	13	6	0	0	0
Katelyn	White	80	12	0	2	0	2	0	0	0	3	2	2	0	0	0	1	1	1	0	26	0	0	2	6	0	0	0	8	19	8	0	0	7	34	54	0	0	0
Katie	White	50	8	0	0	0	1	0	0	0	2	2	0	0	0	0	0	1	0	0	14	0	0	1	12	0	0	0	13	7	3	0	0	0	10	7	0	0	0
Keisha	Black	40	12	0	2	0	2	0	0	0	3	1	3	0	0	0	0	0	1	0	24	3	3	3	6	0	0	1	16	8	0	0	0	0	8	13	0	0	0
Kenya	Black	4	1	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	4	0	0	1	0	0	0	0	1	0	0	0	0	0	0	3	0	0	0
Kristen	White	34	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	0	3	0	7	0	0	0	10	6	3	0	0	2	11	7	0	0	0
Lakisha	Black	28	6	0	1	0	1	0	0	0	0	1	6	0	0	0	0	0	0	0	15	0	2	1	12	0	0	0	15	5	0	0	0	0	5	17	0	0	0
Latanya	Black	28	11	0	0	0	0	0	0	0	1	0	7	0	0	0	0	0	0	0	19	0	6	4	9	0	0	0	19	11	2	0	0	0	13	4	0	0	0
Latisha	Black	28	5	0	3	0	1	0	0	0	1	1	5	0	0	0	0	1	0	0	17	0	0	0	5	0	0	0	5	11	1	0	0	0	12	20	0	0	0
Latonya	Black	36	6	0	2	1	1	0	1	0	1	4	8	0	0	0	0	1	1	0	26	0	0	0	17	0	0	0	17	15	2	0	0	0	17	13	1	0	0
Latoya	Black	27	6	0	3	0	1	0	0	0	5	2	6	0	0	0	0	1	1	0	25	0	0	0	9	0	0	0	9	10	4	0	0	1	15	6	0	0	0
Laurie	White	28	2	0	2	0	0	1	0	0	5	0	3	0	0	0	0	1	0	0	14	0	2	0	3	0	0	0	5	6	2	0	0	0	8	6	0	0	0
Leroy	Black	25	6	1	4	1	1	0	0	0	3	0	2	0	0	0	0	2	2	0	22	0	1	0	12	0	0	0	13	7	3	0	0	1	11	4	1	0	0
Luke	White	60	7	0	2	0	4	1	0	0	1	3	3	0	0	0	0	1	1	0	23	0	0	3	14	0	1	0	18	12	4	0	0	2	18	4	0	0	0
Madeline	White	66	2	0	0	0	0	1	0	1	1	1	0	0	0	0	1	3	0	1	11	0	0	7	10	0	0	0	17	17	5	0	0	2	24	36	0	0	0
Malik	Black	18	2	0	0	0	1	0	0	0	1	1	2	0	0	0	0	0	1	0	8	0	0	0	2	0	0	0	2	3	0	0	0	1	4	7	0	0	0
Marquis	Black	19	4	0	1	0	0	0	0	0	0	1	8	0	0	0	0	0	0	0	14	0	1	1	3	0	0	0	5	8	1	0	0	0	9	0	0	0	0
Matthew	White	44	8	0	2	0	0	0	2	0	7	0	4	0	0	0	0	1	0	0	24	0	3	1	1	0	0	0	5	7	2	1	0	0	10	5	1	0	0
Meredith	White	33	9	0	0	0	0	2	0	0	2	2	1	0	0	0	0	1	0	1	18	0	3	1	4	0	0	0	8	12	2	0	0	0	14	12	0	0	0
Molly	White	70	6	0	1	0	1	0	1	0	9	6	0	0	0	0	0	1	1	0	26	0	0	2	10	0	0	0	12	18	8	0	0	2	28	10	0	0	0
Neil	White	30	6	0	4	0	1	0	0	0	2	2	2	0	0	0	0	1	0	0	18	0	2	1	4	0	0	0	7	5	1	0	0	0	6	3	0	0	0
Nia	Black	11	1	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	2	0	1	0	1	4	0	0	0	0
Precious	Black	12	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	2	0	2	1	0	0	0	0	3	2	0	0	0	0	2	2	0	0	0
Rasheed	Black	17	1	0	0	0	0	0	0	0	0	1	2	0	0	0	0	1	0	1	6	0	3	0	3	0	0	0	6	6	0	0	0	0	6	9	0	0	0
Shanice	Black	26	6	0	0	0	0	0	0	0	3	0	4	0	0	0	0	0	0	0	13	0	3	0	3	0	0	0	6	9	1	0	0	3	13	4	0	0	0
Tamika	Black	29	5	0	1	0	2	0	0	0	0	2	2	0	0	0	0	5	0	1	18	0	2	7	6	0	0	0	15	9	3	1	0	0	13	8	0	0	0
Tanner	White	30	6	0	0	0	0	0	0	0	1	1	2	0	0	0	0	1	5	0	16	0	0	0	1	0	0	0	1	6	3	0	0	0	9	4	0	0	0
Terrell	Black	28	1	0	1	0	3	0	0	0	3	0	9	0	0	0	0	2	0	0	19	0	2	2	7	0	0	0	11	11	2	0	0	1	14	10	0	0	0
Tremayne	Black	27	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	1	1	5	0	4	3	6	0	0	0	13	15	2	2	0	2	21	11	0	0	0
Trevon	Black	26	2	0	2	0	0	0	0	0	0	2	1	0	0	0	0	2	1	0	10	0	1	1	2	0	0	0	4	8	3	1	1	1	14	13	0	0	0
Tyrone	Black	36	3	0	1	0	0	0	1	0	8	1	13	0	0	0	0	1	2	0	30	0	3	4	17	0	0	0	24	17	0	0	0	3	20	11	0	0	0
Wyatt	White	30	3	0	1	0	1	0	0	0	2	0	0	0	0	0	0	1	2	0	10	0	0	3	4	0	0	0	7	7	1	0	0	2	10	6	0	0	0
	Totals		382	2	96	4	40	9	17	3	195	67	176	2	1	3	4	55	62	8	1126	7	87	105	348	1	1	1	550	570	128	13	2	56	769	523	8	2	1
											1126														550								769					534			

Figure 18. Distribution of ad templates in Figure 17 by first name as they appeared on Reuters.com.

INSTANT CHECKMATE ADS ON REUTERS

		Total Ads	Arrest Ads		Neutral Ads	
Aaliyah	Black	4	3	75%	1	25%
Aisha	Black	37	11	30%	26	70%
Allison	White	12	6	50%	6	50%
Amy	White	27	16	59%	11	41%
Anne	White	16	11	69%	5	31%
Brad	White	30	21	70%	9	30%
Brendan	White	34	14	41%	20	59%
Brett	White	21	7	33%	14	67%
Carrie	White	17	6	35%	11	65%
Claire	White	31	18	58%	13	42%
Cody	White	9	7	78%	2	22%
Connor	White	4	2	50%	2	50%
Darnell	Black	19	16	84%	3	16%
DeAndre	Black	15	10	67%	5	33%
Deja	Black	11	7	64%	4	36%
DeShawn	Black	21	18	86%	3	14%
Diamond	Black					
Dustin	White	47	38	81%	9	19%
Ebony	Black	39	25	64%	14	36%
Emily	White	19	8	42%	11	58%
Emma	White	20	5	25%	15	75%
Geoffrey	White	24	7	29%	17	71%
Greg	White	35	13	37%	22	63%
Hakim	Black	5	4	80%	1	20%
Imani	Black	8	2	25%	6	75%
Jack	White	25	9	36%	16	64%
Jake	White	20	8	40%	12	60%
Jamal	Black	11	5	45%	6	55%
Jay	White	18	7	39%	11	61%
Jermaine	Black	16	13	81%	3	19%
Jill	White	26	6	23%	20	77%
Kareem	Black	21	7	33%	14	67%
Katelyn	White	26	10	38%	16	62%
Katie	White	14	5	36%	9	64%
Keisha	Black	24	9	38%	15	63%
Kenya	Black	4	2	50%	2	50%
Kristen	White	3	1	33%	2	67%
Lakisha	Black	15	8	53%	7	47%
Latanya	Black	19	8	42%	11	58%
Latisha	Black	17	11	65%	6	35%
Latonya	Black	26	17	65%	9	35%
Latoya	Black	25	17	68%	8	32%
Laurie	White	14	11	79%	3	21%
Leroy	Black	22	12	55%	10	45%
Luke	White	23	10	43%	13	57%
Madeline	White	11	5	45%	6	55%
Malik	Black	8	4	50%	4	50%
Marquis	Black	14	10	71%	4	29%
Matthew	White	24	14	58%	10	42%
Meredith	White	18	6	33%	12	67%
Molly	White	26	17	65%	9	35%
Neil	White	18	11	61%	7	39%
Nia	Black	4	2	50%	2	50%
Precious	Black	2	1	50%	1	50%
Rasheed	Black	6	4	67%	2	33%
Shanice	Black	13	7	54%	6	46%
Tamika	Black	18	10	56%	8	44%
Tanner	White	16	5	31%	11	69%
Terrell	Black	19	15	79%	4	21%
Tremayne	Black	5	2	40%	3	60%
Trevon	Black	10	7	70%	3	30%
Tyrone	Black	30	24	80%	6	20%
Wyatt	White	10	4	40%	6	60%
	Totals	1126	599	53%	527	47%

ARREST ADS SORT	
86%	DeShawn
84%	Darnell
81%	Jermaine
81%	Dustin
80%	Hakim
80%	Tyrone
79%	Terrell
79%	Laurie
78%	Cody
75%	Aaliyah
71%	Marquis
70%	Brad
70%	Trevon
69%	Anne
68%	Latoya
67%	DeAndre
67%	Rasheed
65%	Latonya
65%	Molly
65%	Latisha
64%	Ebony
64%	Deja
61%	Neil
59%	Amy
58%	Matthew
58%	Claire
56%	Tamika
55%	Leroy
54%	Shanice
53%	Lakisha
50%	Allison
50%	Connor
50%	Kenya
50%	Malik
50%	Nia
50%	Precious
45%	Jamal
45%	Madeline
43%	Luke
42%	Emily
42%	Latanya
41%	Brendan
40%	Jake
40%	Tremayne
40%	Wyatt
39%	Jay
38%	Katelyn
38%	Keisha
37%	Greg
36%	Jack
36%	Katie
35%	Carrie
33%	Brett
33%	Kareem
33%	Kristen
33%	Meredith
31%	Tanner
30%	Aisha
29%	Geoffrey
25%	Emma
25%	Imani
23%	Jill
	Diamond

NEUTRAL ADS SORT	
77%	Jill
75%	Emma
75%	Imani
71%	Geoffrey
70%	Aisha
69%	Tanner
67%	Brett
67%	Kareem
67%	Kristen
67%	Meredith
65%	Carrie
64%	Katie
64%	Jack
63%	Greg
63%	Keisha
62%	Katelyn
61%	Jay
60%	Jake
60%	Tremayne
60%	Wyatt
59%	Brendan
58%	Emily
58%	Latanya
57%	Luke
55%	Jamal
55%	Madeline
50%	Allison
50%	Connor
50%	Kenya
50%	Malik
50%	Nia
50%	Precious
47%	Lakisha
46%	Shanice
45%	Leroy
44%	Tamika
42%	Claire
42%	Matthew
41%	Amy
39%	Neil
36%	Deja
36%	Ebony
35%	Latisha
35%	Latonya
35%	Molly
33%	DeAndre
33%	Rasheed
32%	Latoya
31%	Anne
30%	Brad
30%	Trevon
29%	Marquis
25%	Aaliyah
22%	Cody
21%	Laurie
21%	Terrell
20%	Hakim
20%	Tyrone
19%	Dustin
19%	Jermaine
16%	Darnell
14%	DeShawn
	Diamond

Figure 19. Distributions of Instant Checkmate ads having the word "arrest" or not ("neutral") appearing on Reuters.com.

Ad Templates on Reuters and Google		Ad Templates on Google Only	
C 33	**Located: *fullname*** Information found on *fullname fullname* found in database.	AJ* 30	***fullname*'s Records** Did you know *fullname*'s criminal history is searchable?
G* 24	**We found *fullname*** Search Arrests, Address, Phone, etc. Search records for *fullname*.	AP* 2	***fullname*'s Records Online?** Did you know *fullname*'s criminal history is searchable?
I 2	**Background of *fullname*** Search Instant Checkmate for the Records of *fullname*	AM* 9	**Anyone's Records Online?** Did you know *fullname*'s criminal history is searchable?
U 1	**Background of Anyone** Search Instant Checkmate for the Records of *fullname*	AK* 2	**Records For Anyone in US** View Anyone's Criminal History. Check Criminal Records in Seconds!
J 6	***fullname*'s Records** 1) Enter Name and State. 2) Access Full Background Checks Instantly.	AN* 9	**Records For *fullname*** View Anyone's Criminal History. Check Criminal Records in Seconds!
K* 52	***fullname*: Truth** Arrests and Much More. Everything About *fullname*	AL* 26	**Records For *fullname*?** Find the Truth About *fullname* View Criminal Records in Seconds.
O* 7	***fullname* Truth** Looking for *fullname*? Check *fullname*'s Arrests	AQ* 3	**Records For People in the US?** Find the Truth About *fullname* View Criminal Records in Seconds.
L* 200	***fullname*, Arrested?** 1) Enter Name and State. 2) Access Full Background Checks Instantly.	AO* 6	**Find *fullname*** Criminal records, phone, address, & more on *fullname*
V* 10	**Uh Oh, Arrested?** 1) Enter Name and State. 2) Access Full Background Checks Instantly.	AS* 1	**We Found *fullname* | InstantCheckmate.com** Search Arrests, Address, Phone, etc Search records for *fullname*.
M* 6	***fullname* Located** Background Check, Arrest Records, Phone, & Address. Instant, Accurate	AT* 1	***fullname*'s Records | InstantCheckmate.com** Did you know *fullname*'s criminal history is searchable?
N 2	**Looking for *fullname*?** Comprehensive Background Report and More on *fullname*		

Figure 20. Templates for ads for public records on Google.com, replace *fullname* with person's first and last name. Letter identifies text. Number is number of occurrences of text. Asterisk (*) denotes an ad suggestive of an arrest record.

FIRST NAME			INSTANT CHECKMATE ADS ON GOOGLE																													
Name	Race	Full Names	C	AC	G	S	I	U	J	X	K	O	L	V	AD	AF	AE	M	N	AI	AJ	AP	AM	AK	AN	AL	AQ	AO	AS	AT	Totals
Aaliyah	Black	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Aisha	Black	54	4	0	0	0	0	0	0	0	3	1	3	1	0	0	0	4	0	0	1	1	1	0	0	4	0	0	0	0	23
Allison	White	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Amy	White	67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Anne	White	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Brad	White	37	0	0	1	0	0	0	0	0	0	0	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	8
Brendan	White	40	1	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0	0	0	11
Brett	White	28	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	3
Carrie	White	33	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Claire	White	56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cody	White	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Connor	White	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Darnell	Black	26	0	0	0	0	0	0	1	0	0	0	13	0	0	0	0	0	0	0	2	0	1	0	0	1	0	0	0	0	18
DeAndre	Black	29	0	0	0	0	0	0	0	0	3	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Deja	Black	24	0	0	2	0	0	0	0	0	1	0	4	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	10
DeShawn	Black	27	0	0	0	0	0	0	1	0	3	0	6	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	12
Diamond	Black																															
Dustin	White	66	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Ebony	Black	59	1	0	0	0	0	1	0	0	3	0	17	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	26
Emily	White	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Emma	White	60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Geoffrey	White	34	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	5
Greg	White	40	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	6
Hakim	Black	17	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3
Imani	Black	25	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3
Jack	White	58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jake	White	59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jamal	Black	29	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	1	0	0	6
Jay	White	29	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	4
Jermaine	Black	28	0	0	1	0	0	0	1	0	1	0	10	1	0	0	0	0	0	0	2	0	0	0	2	0	0	1	0	0	19
Jill	White	34	5	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	9
Kareem	Black	33	2	0	1	0	0	0	0	0	3	0	10	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	18
Katelyn	White	80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Katie	White	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Keisha	Black	40	1	0	1	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	12
Kenya	Black	4	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Kristen	White	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lakisha	Black	28	0	0	1	0	0	0	0	0	1	0	7	0	0	0	0	0	0	0	2	0	1	0	0	2	0	0	0	0	14
Latanya	Black	28	2	0	1	0	1	0	0	0	1	1	6	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	15
Latisha	Black	28	1	0	0	0	0	0	1	0	3	0	11	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	18
Latonya	Black	36	0	0	1	0	0	0	0	0	2	1	4	0	0	0	0	1	0	0	3	0	0	1	0	0	0	0	1	0	14
Latoya	Black	27	0	0	2	0	0	0	0	0	0	1	10	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	15
Laurie	White	28	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Leroy	Black	25	2	0	2	0	1	0	0	0	0	0	9	1	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	19
Luke	White	60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Madeline	White	66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Malik	Black	18	0	0	1	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	7
Marquis	Black	19	0	0	0	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	1	0	0	2	1	0	0	1	12
Matthew	White	44	1	0	0	0	0	0	0	0	1	0	4	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	8
Meredith	White	33	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Molly	White	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Neil	White	30	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	4
Nia	Black	11	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Precious	Black	12	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Rasheed	Black	17	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3
Shanice	Black	26	2	0	0	0	0	0	1	0	1	0	9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	14
Tamika	Black	29	1	0	4	0	0	0	1	0	3	0	5	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	16
Tanner	White	30	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Terrell	Black	28	0	0	0	0	0	0	0	0	4	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	15
Tremayne	Black	27	2	0	0	0	0	0	0	0	1	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
Trevon	Black	26	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	5
Tyrone	Black	36	0	0	1	0	0	0	0	0	8	0	16	0	0	0	0	0	0	0	3	0	0	0	0	2	0	0	0	0	30
Wyatt	White	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
		Totals	33	0	24	0	2	1	6	0	52	7	200	10	0	0	0	6	2	0	30	2	9	2	9	26	3	6	1	1	432
			432																													

Figure 21. Distribution of ad templates in Figure 20 by first name as they appeared on Google.com.

INSTANT CHECKMATE ADS ON GOOGLE

		Total Ads	Arrest Ads		Neutral Ads	
Aaliyah	Black	0	0		0	
Aisha	Black	23	19	83%	4	17%
Allison	White	0	0		0	
Amy	White	0	0		0	
Anne	White	0	0		0	
Brad	White	8	8	100%	0	
Brendan	White	11	10	91%	1	9%
Brett	White	3	2	67%	1	33%
Carrie	White	2	1	50%	1	50%
Claire	White	0	0		0	
Cody	White	0	0		0	
Connor	White	0	0		0	
Darnell	Black	18	17	94%	1	6%
DeAndre	Black	7	7	100%	0	
Deja	Black	10	9	90%	1	10%
DeShawn	Black	12	11	92%	1	8%
Diamond	Black				0	
Dustin	White	1	1	100%	0	
Ebony	Black	26	24	92%	2	8%
Emily	White	0	0		0	
Emma	White	0	0		0	
Geoffrey	White	5	3	60%	2	40%
Greg	White	6	5	83%	1	17%
Hakim	Black	3	3	100%	0	
Imani	Black	3	3	100%	0	
Jack	White	0	0		0	
Jake	White	0	0		0	
Jamal	Black	6	5	83%	1	17%
Jay	White	4	4	100%	0	
Jermaine	Black	19	18	95%	1	5%
Jill	White	9	4	44%	5	56%
Kareem	Black	18	16	89%	2	11%
Katelyn	White	0	0		0	
Katie	White	0	0		0	
Keisha	Black	12	11	92%	1	8%
Kenya	Black	2	2	100%	0	
Kristen	White	0	0		0	
Lakisha	Black	14	14	100%	0	
Latanya	Black	15	11	73%	4	27%
Latisha	Black	18	16	89%	2	11%
Latonya	Black	14	14	100%	0	
Latoya	Black	15	15	100%	0	
Laurie	White	1	1	100%	0	
Leroy	Black	19	16	84%	3	16%
Luke	White	0	0		0	
Madeline	White	0	0		0	
Malik	Black	7	7	100%	0	
Marquis	Black	12	12	100%	0	
Matthew	White	8	7	88%	1	13%
Meredith	White	2	2	100%	0	
Molly	White	0	0		0	
Neil	White	4	3	75%	1	25%
Nia	Black	2	2	100%	0	
Precious	Black	2	2	100%	0	
Rasheed	Black	3	2	67%	1	33%
Shanice	Black	14	11	79%	3	21%
Tamika	Black	16	14	88%	2	13%
Tanner	White	1	1	100%	0	
Terrell	Black	15	15	100%	0	
Tremayne	Black	6	4	67%	2	33%
Trevon	Black	5	5	100%	0	
Tyrone	Black	30	30	100%	0	
Wyatt	White	1	1	100%	0	
	Totals	432	388	90%	44	10%

ARREST ADS SORT	
100%	Brad
100%	DeAndre
100%	Dustin
100%	Hakim
100%	Imani
100%	Jay
100%	Kenya
100%	Lakisha
100%	Latonya
100%	Latoya
100%	Laurie
100%	Malik
100%	Marquis
100%	Meredith
100%	Nia
100%	Precious
100%	Tanner
100%	Terrell
100%	Trevon
100%	Tyrone
100%	Wyatt
95%	Jermaine
94%	Darnell
92%	Ebony
92%	DeShawn
92%	Keisha
91%	Brendan
90%	Deja
89%	Kareem
89%	Latisha
88%	Matthew
88%	Tamika
84%	Leroy
83%	Greg
83%	Jamal
83%	Aisha
79%	Shanice
75%	Neil
73%	Latanya
67%	Brett
67%	Rasheed
67%	Tremayne
60%	Geoffrey
50%	Carrie
44%	Jill
	Aaliyah
	Allison
	Amy
	Anne
	Claire
	Cody
	Connor
	Diamond
	Emily
	Emma
	Jack
	Jake
	Katelyn
	Katie
	Kristen
	Luke
	Madeline
	Molly

NEUTRAL ADS SORT	
56%	Jill
50%	Carrie
40%	Geoffrey
33%	Brett
33%	Rasheed
33%	Tremayne
27%	Latanya
25%	Neil
21%	Shanice
17%	Aisha
17%	Greg
17%	Jamal
16%	Leroy
13%	Matthew
13%	Tamika
11%	Kareem
11%	Latisha
10%	Deja
9%	Brendan
8%	DeShawn
8%	Keisha
8%	Ebony
6%	Darnell
5%	Jermaine
	Aaliyah
	Allison
	Amy
	Anne
	Brad
	Claire
	Cody
	Connor
	DeAndre
	Diamond
	Dustin
	Emily
	Emma
	Hakim
	Imani
	Jack
	Jake
	Jay
	Katelyn
	Katie
	Kenya
	Kristen
	Lakisha
	Latonya
	Latoya
	Laurie
	Luke
	Madeline
	Malik
	Marquis
	Meredith
	Molly
	Nia
	Precious
	Tanner
	Terrell
	Trevon
	Tyrone
	Wyatt

Figure 22. Distributions of Instant Checkmate ads having the word "arrest" or not ("neutral") appearing on Google.com.

Ads by Google

Support Claire McCaskill
Claire McCaskill Fights for Middle Class America. Give to Her Campaign
www.clairemccaskill.com/

Claire McCaskill: Truth
Arrests and Much More. Everything About Claire McCaskill
www.instantcheckmate.com/

Donate to the DSCC Now
Only You Can Keep the Senate Blue In 2012. Give to the DSCC Today!
www.dscc.org/Donate
Join the DSCC! - Donate Now!

Figure 23. Example ads displayed in response to search of "*Claire McCaskill*" on Reuters.com (right), Claire McCaskill, U.S. Senator from Missouri (left). An ad having the word "arrest" appears below an ad for her U.S. Senate campaign.

Ads by Google

Latonya Evans, Arrested?
1) Enter Name and State. 2) Access Full Background Checks Instantly.
www.instantcheckmate.com/

Ads by Google

Latonya Evans's Records
1) Enter Name and State. 2) Access Full Background Checks Instantly.
www.instantcheckmate.com/

Ad related to Latonya Evans ⓘ

Latonya Evans's Records
www.instantcheckmate.com/
Did you know Latonya Evans's criminal history is searchable?

Ads by Google

Latisha Smith Located
Background Check, Arrest Records, Phone, & Address. Instant, Accurate
www.instantcheckmate.com/

Ads by Google

Latisha smith: Truth
Arrests and Much More. Everything About Latisha smith
www.instantcheckmate.com/

Ads related to Latisha Smith ⓘ

Latisha Smith, Arrested?
www.instantcheckmate.com/
1) Enter Name and State. 2) Access Full Background Checks Instantly.

Ad related to Latisha Smith ⓘ

Latisha Smith, Arrested? - 1) Enter Name and State.
www.instantcheckmate.com/
2) Access Full Background Checks Instantly.

Figure 24. Examples of different ad copy appearing for searches of "*Latonya Evans*" (left) and "*Latisha Smith*" (right).

OVERALL

PeekYou Score	Number of Names with Score	%	Number of Ads	%
2	33	3%	11	33%
3	94	8%	45	48%
4	170	15%	80	47%
5	226	20%	111	49%
6	152	13%	66	43%
7	382	33%	164	43%
8	70	6%	21	30%
9	12	1%	2	17%
10	4	0%	0	0%
Total	1143		500	
			44%	
Average	5.6			
Standard Dev	1.6			
Median	6			

BLACK IDENTIFYING FIRST NAMES

PeekYou Score	Number of Names with Score	%	Number of Ads	%
2	33	7%	11	33%
3	94	20%	45	48%
4	116	24%	61	53%
5	158	33%	94	59%
6	40	8%	26	65%
7	31	6%	15	48%
8	5	1%	1	20%
9	0	0%	0	
10	0	0%	0	
Total	477		253	
	42%		53%	
Average	4.4			
Standard Dev	1.3			
Median	4			

WHITE IDENTIFYING FIRST NAMES

PeekYou Score	Number of Names with Score	%	Number of Ads	%
2	0	0%	0	
3	0	0%	0	
4	54	8%	19	35%
5	68	10%	17	25%
6	112	17%	40	36%
7	351	53%	149	42%
8	65	10%	20	31%
9	12	2%	2	17%
10	4	1%	0	0%
Total	666		247	
	58%		37%	
Average	6.5			
Standard Dev	1.1			
Median	7			

Figure 25. Distributions of Netizen names and ad delivery by PeekYou scores for those names having PeekYou scores, which are values PeekYou assigns to names as an estimate of the person's presence on the Web.

Conclusion and Future Work

This study raises more questions than it answers. Here is the one answer provided. Our hypothesis states that no difference exists in the delivery of ads suggestive of an arrest record based on searches of racially associated names. Our findings reject this hypothesis. A greater percentage of ads having "arrest" in ad text appeared for black identifying first names than for white identifying first names in searches on Reuters.com, on Google.com, and in subsets of the sample. Results of Chi-Square tests on these patterns were statistically significant. On Reuters.com, a host of Google AdSense ads, a black-identifying name was 25% more likely to get an ad suggestive of an arrest record, $X^2(1)=14.32$, $p < 0.001$; there is less than a 0.1% probability that these data can be explained by chance.

Why is this discrimination occurring? Is this Instant Checkmate, Google, or society's fault? Answering these questions is beyond the scope of this writing, but navigating the terrain requires further information about the inner workings of Google AdSense. Google understands that an advertiser may not know which ad copy will work best, so an advertiser may give multiple templates for the same search string and the "Google algorithm" learns over time which ad text gets the most clicks from viewers of the ad. It does this by assigning weights (or probabilities) based on the click history of each ad copy. At first all possible ad copies are weighted the same, they are all equally likely to produce a click. Over time, as people tend to click one version of ad text over others, the weights change, so the ad text getting the most clicks eventually displays more frequently. This approach aligns the financial interests of Google, as the ad deliverer, with the advertiser. Figure 24 provides examples in which Instant Checkmate provided multiple ad templates for searches of "*Latonya Evans*" and "*Latisha Smith*".

Did Instant Checkmate provide ad templates suggestive of arrest disproportionately to black-identifying names?[3] Or, did Instant Checkmate provide roughly the same templates evenly across racially associated names but society clicked ads suggestive of arrest more often for black identifying names? Google uses cloud-caching strategies to deliver ads quickly, might these strategies bias ad delivery towards ad templates previously loaded in the cloud cache? Is there a combinatorial effect?

This paper is a start and more research is needed; however, online advertising is dynamic and easy to change. In order to preserve research opportunities, prior to any announcement of this work, I captured additional results for 50 hits on 2184 names across 30 websites serving Google Ads to learn the underlying distributions of ad occurrences per name. While analyzing these data may prove illuminating, in the end, the basic message presented in this writing does not change. There is discrimination in delivery of these ads.

[3] During a conference call with the founders of Instant Checkmate and their lawyer on December 21, 2012, the company's representatives asserted that Instant Checkmate gave the same ad text to Google for groups of last names (not first names).

In the broader picture, technology can do more to thwart discriminatory effects and harmonize with societal norms. Ads responding to name searches appear in a specific information context and technology controls that context. A reader enters a name then views web content and news stories specific to that name. Dynamic ads are a part of that context. Alongside news stories about high school athletes and children can be ads bearing the child's name and suggesting arrest. This seems concerning on many levels. For example, even if the child has an arrest record, juvenile records are typically exempt from public record disclosure. The juxtaposition of ads also provide context. Claire McCaskill provides an example where an ad suggestive of arrest appears alongside an ad for her U.S. Senate campaign. Search and ad technology already reason extensively about context and appropriateness when deciding the best content to deliver to the reader [13]. Many factors are often known about the reader at the time of ad delivery, e.g., browsing history, geographical location, and shopping behavior [14]. With some expansion, technology could additionally reason about social and legal implications of content and context too. For example, well-known computer scientist Cynthia Dwork and her colleagues have already been working on algorithms that assure racial fairness [15]. This area seems ripe for further research and development.

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