

I. INTRODUCTION

In November of 2017, ProPublica ran a story describing how Facebook allows housing advertisers exclude certain categories of users by protected classes.¹ ProPublica bought dozens of rental housing advertisements on Facebook and asked that African Americans, mothers of high school kids, people interested in wheelchair ramps, Jews, expats of Argentina, and Spanish speakers not be shown the content.² Facebook approved the ads within minutes.³

The federal Fair Housing Act (FHA) makes it unlawful to discriminate in the sale or rental of housing because of race, color, religion, sex, national origin, or disability.⁴ Specifically, section 804(c) of the FHA makes it unlawful “[t]o make, print, or publish . . . any notice, statement, or advertisement, with respect to the sale or rental of a dwelling that indicates any preference, limitation, or discrimination based on [a protected class].”⁵ By allowing ProPublica to exclude those groups of people from housing advertisements, Facebook violated the text of the Fair Housing Act.⁶

This, however, is a fairly straightforward violation under the FHA’s advertising provision. What if instead of being open about their exclusionary desires, ProPublica and Facebook hid their intentions in a complexly-layered algorithm that already knew which users were African American, mothers of high school kids, interested in wheel chair ramps, and the like?

In targeting certain individuals for their products, companies may rely on predictive analysis and existing data to create individual profiles to determine which audiences are best suited to buy.⁷ However,

1. Julia Angwin et al., *Facebook (Still) Letting Housing Advertisers Exclude Users by Race*, PROPUBLICA (Nov. 21, 2017, 1:23 PM), <https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin> [<https://perma.cc/5VHL-ZSSD>].

2. *Id.*

3. *Id.* It is worth noting that ProPublica was not actually trying to discriminate against these protected classes; it was doing this for research purposes regarding Facebook’s advertising practices.

4. 42 U.S.C. § 3604 (2012).

5. *Id.* § 3604(c).

6. As of this writing, a similar complaint, this time from the U.S. Department of Housing and Urban Development (HUD), is moving through the courts. Ben Lane, *HUD Accuses Facebook of Enabling Housing Discrimination*, HOUSINGWIRE (Aug. 17, 2018), <https://www.housingwire.com/articles/46505-hud-accuses-facebook-of-enabling-housing-discrimination> [<https://perma.cc/ST68-F7H4>]. In its complaint, HUD alleges that Facebook “invites advertisers to express unlawful preferences by offering discriminatory options, allowing them to effectively limit housing options for these protected classes under the guise of ‘targeted advertising.’” *Id.*

7. See Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 94-95 (2014).

the algorithmic techniques used to make these decisions may reflect the widespread biases that persist in society at large and can deny historically disadvantaged and vulnerable groups full participation in the housing market.⁸ It is conceivable that, given the history of discrimination, nearly all available data will reflect racial disparities.⁹ In relying on these algorithms, companies may, intentionally or otherwise, produce discriminatory effects. In addition, it may be nearly impossible to find a demonstrable intent to discriminate given the secretive nature of companies' algorithmic practices.¹⁰

Not only is it plainly unlawful, but excluding classes of people from the housing market makes it more difficult for these people to accumulate wealth to pass on to their children.¹¹ Property ownership is an important means of wealth accumulation—particularly for lower income and minority families.¹² This, in turn, creates an increase in wealth disparities between classes of people over time.¹³

8. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 671 (2016).

9. *Algorithms and Civil Rights: Understanding the Issues*, CIVIL RIGHTS INSIDER (Fed. Bar Assoc. Civil Rights L. Section, New York, N.Y.), Winter 2018, at 3, <http://www.fedbar.org/Image-Library/Sections-and-Divisions/Civil-Rights/Civil-Rights-Winter-2018.aspx> [<https://perma.cc/SDT5-LCV8>].

10. *See generally* FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* (2015).

11. CHRISTOPHER E. HERBERT ET AL., *IS HOMEOWNERSHIP STILL AN EFFECTIVE MEANS OF BUILDING WEALTH FOR LOW-INCOME AND MINORITY HOUSEHOLDS? (WAS IT EVER?)*, HARVARD UNIV., JOINT CTR. FOR HOUS. STUDIES (2013), <http://www.jchs.harvard.edu/sites/default/files/hbtl-06.pdf> [<https://perma.cc/D3XW-Z9ZD>].

12. U.S. DEP'T HOUS. & URBAN DEV., *WEALTH ACCUMULATION AND HOMEOWNERSHIP: EVIDENCE FOR LOW-INCOME HOUSEHOLDS* (2004); Laura Shin, *The Racial Wealth Gap: Why A Typical White Household Has 16 Times the Wealth of A Black One*, FORBES (Mar. 26, 2015, 8:00 AM), <https://www.forbes.com/sites/laurashin/2015/03/26/the-racial-wealth-gap-why-a-typical-white-household-has-16-times-the-wealth-of-a-black-one/#8dbdda91f45e> [<https://perma.cc/U8N9-2Q5V>]; *see also* Akilah Johnson, *That Was No Typo: The Median Net Worth of Black Bostonians Really Is \$8*, BOSTON GLOBE (Dec. 11, 2017), <https://www.bostonglobe.com/metro/2017/12/11/that-was-typo-the-median-net-worth-black-bostonians-really/ze5kxC1jJelx24M3pugFFN/story.html> [<https://perma.cc/FR6S-QSGM>].

13. *See* Janelle Jones, *The Racial Wealth Gap: How African-Americans Have Been Shortchanged Out of the Materials to Build Wealth*, ECON. POL'Y INST.: WORKING ECON. BLOG (Feb. 13, 2017, 12:01 PM), <https://www.epi.org/blog/the-racial-wealth-gap-how-african-americans-have-been-shortchanged-out-of-the-materials-to-build-wealth/> [<https://perma.cc/3J6B-J83J>]; Richard D. Kahlenberg, *An Economic Fair Housing Act*, CENTURY FOUND. (Aug. 3, 2017), <https://tcf.org/content/report/economic-fair-housing-act/> [<https://perma.cc/9D6Y-3SHA>] (finding that houses appreciate less rapidly in predominantly black neighborhoods, which helps explain why the median income for black households is sixty percent that of white households; however, the black median household net worth is just five percent of white median household net worth); Shin, *supra* note 12.

The law has always been slow to adapt to changing technologies. In the era of Big Data, especially with regards to civil rights, it is essential to be at the forefront of the changing world to protect those who are particularly vulnerable in our society. This Note will explore how a disparate-impact theory of liability may be used to explore whether certain algorithms amassed by large collections of data can be challenged as having discriminatory effects and accordingly violate the Fair Housing Act—specifically as it relates to targeted advertising.

II. THE FAIR HOUSING ACT

A. *The FHA's Prohibition Against Unlawful Advertising Practices*

The federal Fair Housing Act was passed in 1968—in the wake of the assassination of Dr. Martin Luther King, Jr. and the release of the Kerner Commission Report.¹⁴ This Report concluded that “[o]ur nation is moving toward two societies, one black, one white—separate and unequal.”¹⁵ It found that “[n]early two-thirds of all non-white families living in the central cities today live in neighborhoods marked with substandard housing and general urban blight.”¹⁶ Ultimately, the Commission recommended that a “comprehensive and enforceable federal open housing law [be enacted] to cover the sale or rental of all housing.”¹⁷ Thus, the Fair Housing Act was born with a goal: “[T]o replace residential ghettos with ‘truly integrated and balanced living patterns.’”¹⁸

14. *Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc.*, 135 S. Ct. 2507, 2516 (2015).

15. NAT'L ADVISORY COMM'N ON CIVIL DISORDERS, REPORT OF THE NATIONAL ADVISORY COMMISSION ON CIVIL DISORDERS 1 (1968) [hereinafter Kerner Commission Report], <http://www.eisenhowerfoundation.org/docs/kerner.pdf> [<https://perma.cc/35BC-XZHL>].

16. *Id.* at 24. Arguably, the same could be said of American society today. See Richard Rothstein, *America Is Still Segregated. We Need to be Honest About Why*, *GUARDIAN* (May 16, 2017, 10:48 AM), <https://www.theguardian.com/commentisfree/2017/may/16/segregation-us-neighborhoods-reasons> [<https://perma.cc/CF23-K7JJ>]; see also U.S. GOV'T ACCOUNTABILITY OFFICE, K-12 EDUCATION: BETTER USE OF INFORMATION COULD HELP AGENCIES IDENTIFY DISPARITIES AND ADDRESS RACIAL DISCRIMINATION 42 (2016), <https://www.gao.gov/assets/680/676745.pdf> [<https://perma.cc/Q83S-KBBZ>] (finding that even sixty years after the *Brown v. Board of Education* decision, segregation in schools still persists); see John Eligon & Robert Gebeloff, *Affluent and Black, and Still Trapped by Segregation*, *N.Y. TIMES* (Aug. 20, 2016), <https://www.nytimes.com/2016/08/21/us/milwaukee-segregation-wealthy-black-families.html?mtrref=www.google.com&gwh=BB462A7A688723234B817AF2B682676C&gwt=pay> [<https://perma.cc/6UHR-RKJL>].

17. Kerner Commission Report, *supra* note 15, at 14.

18. Robert G. Schwemm, *Discriminatory Housing Statements and § 3604(c): A New Look at the Fair Housing Act's Most Intriguing Provision*, 29 *FORDHAM URB. L.J.* 187, 194 (2001) (quoting 114 *CONG. REC.* 3422 (1968) (remarks of Senator Mondale)).

As previously mentioned, the Fair Housing Act, generally, prohibits discrimination in the sale or rental of housing and in the course of other housing practices if the discrimination is due to race, color, religion, sex, familial status, or national origin.¹⁹ Section 804(c) makes it unlawful “[t]o make, print, or publish, or cause to be made, printed, or published any notice, statement, or advertisement . . . that indicates any preference, limitation, or discrimination based on [a protected class].”²⁰

The Fair Housing Act contains what is known as the “Mrs. Murphy” exemption.²¹ Generally, the Fair Housing Act does not apply to any single-family household sold or rented by the owner, provided the owner meets several statutorily-defined criteria.²² However, this exemption does not apply to discriminatory advertisements.²³ By excluding the advertising provision from the FHA’s main exemption, “Congress established a system where even the smallest housing providers . . . are barred from making discriminatory statements.”²⁴

B. Section 804(c) Should Cover Advertising Decisions Made by Algorithms

At first glance, it may seem that a targeted advertising practice may not necessarily be covered as a notice, statement, or advertisement within the purview of section 804(c). However, under the U.S. Department of Housing and Urban Development’s (HUD) regulations promulgated under the Fair Housing Act,²⁵ discriminatory notices, statements, and advertisements include: “[s]electing media or locations for advertising the sale or rental of dwellings which deny particular segments of the housing market information about housing opportunities because of [a protected class].”²⁶ These regulations also include the

19. 42 U.S.C. § 3604 (2012).

20. 42 U.S.C. § 3604(c) (2012). For case law regarding § 3604(c), see Schwemm, *supra* note 18, at 213-51.

21. See 42 U.S.C. § 3603(b)(1) (2012); Schwemm, *supra* note 18, at 191 n.10. For more on the “Mrs. Murphy” exemption, see James D. Walsh, Note, *Reaching Mrs. Murphy: A Call for Repeal of the Mrs. Murphy Exemption to the Fair Housing Act*, 34 HARV. C.R.-C.L. L. REV. 605 (1999).

22. 42 U.S.C. § 3603(b)(1) (2012).

23. 42 U.S.C. § 3603(b)(1)(B) (2012); 42 U.S.C. § 3604(c) (2012).

24. Schwemm, *supra* note 18, at 192.

25. The Secretary of the Department of Housing and Urban Development is authorized to promulgate regulations to carry out her functions, powers, and duties under the FHA. 42 U.S.C. § 3608 (2012); see also 42 U.S.C. § 3535(d) (2012) (giving the Secretary general authority to promulgate regulations).

26. 24 C.F.R. § 100.75(e)(3) (2018).

act of “[r]efusing to publish advertising for the sale or rental of dwellings . . . because of [a protected class].”²⁷

At the time of its enactment, section 804(c) was contemplated to apply to oral communications (statements) and published notices and advertisements.²⁸ However, given Congress’s intent to make the FHA broader than the civil rights laws that came before it, HUD’s regulations confirm that the FHA can apply to new technologies that produce problematic statements, notices, and advertisements.²⁹

Therefore, in a challenge against a housing provider’s practice of targeted advertisements, courts will likely defer to HUD’s interpretation of section 804(c) to include algorithms that help select an advertisement’s recipients if these algorithms are found to discriminate based on a protected class.³⁰ In addition, “plaintiffs . . . [need not] point to a particular statement suggesting a discriminatory preference in order to establish a discriminatory advertising claim.”³¹ It is enough to show that the housing provider excluded members of a protected class.³² To understand how the FHA works in this context, this Section will now dive into the disparate-impact case law and explain what it takes to have standing under the FHA.

C. *Disparate-Impact Theory of Liability Under the FHA*

Recently, the U.S. Supreme Court, in *Texas Department of Housing & Community Affairs v. Inclusive Communities Project, Inc.*, found that a disparate-impact theory of liability exists under the Fair Housing Act.³³ This theory attacks discriminatory effects of housing-related actions rather than discriminatory intent.³⁴ In that case, Inclusive Communities Project brought a disparate-impact

27. 24 C.F.R. § 100.75(c)(4) (2018).

28. Schwemm, *supra* note 18, at 206-12.

29. *See id.* at 211.

30. *See Chevron U.S.A., Inc. v. Nat. Res. Def. Council, Inc.*, 467 U.S. 837 (1984) (finding that courts will defer to an agency interpretation if a statute is silent or ambiguous with respect to a specific issue and the agency’s interpretation is reasonable). Thus, courts will likely use *Chevron* deference in following HUD’s interpretation of section 804(c).

31. *Martinez v. Optimus Props., LLC*, No. 2:16-cv-08598-SVW-MRW, 2017 WL 1040743, at *5 (C.D. Cal. Mar. 14, 2017).

32. *See, e.g., Guevara v. UMH Props., Inc.*, No. 2:11-cv-2339-SHL-tmp, 2014 WL 5488918, at *6 (W.D. Tenn. Oct. 29, 2014).

33. *Tex. Dep’t of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc.*, 135 S. Ct. 2507, 2525 (2015). While lower courts had applied their own disparate-impact frameworks under the FHA, this 2015 decision solidified that this theory of liability does in fact exist. *See, e.g., Gallagher v. Magner*, 619 F.3d 823, 833 (8th Cir. 2010); *Reinhart v. Lincoln Cty.*, 482 F.3d 1225, 1229 (10th Cir. 2007); *Huntington Branch v. Town of Huntington*, 844 F.2d 926, 934 (2d Cir. 1988).

34. *See Inclusive Cmty.*, 135 S. Ct. at 2522.

claim under the FHA and alleged that the Texas Department of Housing and Community Affairs—the agency responsible for distributing low-income housing tax credits—caused “segregated housing patterns by allocating too many tax credits to housing in predominately black inner-city areas and too few in predominately white suburban neighborhoods.”³⁵

In finding disparate-impact claims cognizable under the FHA, the Court reasoned that this form of liability will help to ensure that housing providers’ priorities can be achieved without “arbitrarily creating discriminatory effects or perpetuating segregation.”³⁶ Importantly, the Court held that “disparate-impact liability under the FHA also plays a role in uncovering discriminatory intent: It permits plaintiffs to counteract unconscious prejudices and disguised animus that escape easy classification as disparate treatment. In this way disparate-impact liability may prevent segregated housing patterns that might otherwise result from covert and illicit stereotyping.”³⁷

To prove a disparate impact exists under the FHA, the plaintiff must make a showing that a housing practice causes or predictably will cause a discriminatory effect.³⁸ A disparate-impact claim will fail if the plaintiff “cannot point to a defendant’s policy or policies causing that disparity.”³⁹ This “robust causality requirement ensures that ‘[r]acial imbalance . . . does not, without more, establish a prima facie case of disparate impact’ and thus protects defendants from being held liable for racial disparities they did not create.”⁴⁰ The Court in *Inclusive Communities* reasoned that “[w]ithout adequate safeguards at the prima facie stage, disparate-impact liability might cause race to be used and considered in a pervasive way and ‘would almost inexorably lead’ governmental or private entities to use ‘numerical quotas,’ and serious constitutional questions then could arise.”⁴¹ Thus, a plaintiff must offer “proof of disproportionate impact, measured in a plausible way.”⁴²

Once a plaintiff establishes a prima facie case, the burden shifts to the defendant to prove that the housing practice has a “legally sufficient justification” that is “necessary to achieve one or more substan-

35. *Id.* at 2510.

36. *Id.* at 2522.

37. *Id.*

38. *Id.* at 2514; see also 24 C.F.R. § 100.500(e)(1) (2018) (Department of Housing and Urban Development’s disparate-impact rule).

39. *Inclusive Cmty.*, 135 S. Ct. at 2523.

40. *Id.* (quoting *Wards Cove Packing Co., Inc. v. Atonio*, 490 U.S. 642, 653 (1989)).

41. *Id.* (quoting *Wards Cove*, 490 U.S. at 653).

42. *Mt. Holly Gardens Citizens in Action, Inc. v. Twp. of Mount Holly*, 658 F.3d 375, 382 (3d Cir. 2011).

tial, legitimate, nondiscriminatory interests” in order to shield itself from disparate-impact liability.⁴³ Similar to the Title VII employment context, the defendant must demonstrate that the practice has a manifest relationship to the interest in question.⁴⁴ If the defendant meets this burden, the plaintiff may still prevail upon proving that “the substantial, legitimate, nondiscriminatory interests supporting the challenged practice could be served by another practice that has a less discriminatory effect.”⁴⁵

Thus, using this framework, which will be expounded in detail later, algorithms determining who housing providers should target in their advertisements may be challenged as a housing practice causing discriminatory effects.⁴⁶ Briefly noted, it is highly conceivable that if a plaintiff makes a *prima facie* showing of disparate impact tied to a housing provider’s advertising practices, a defendant will be able to argue that the algorithm satisfies a legitimate, nondiscriminatory interest—namely, the interest in discovering how best to allocate advertising resources. However, as also discussed later, and which may be used in the plaintiff’s showing of a less discriminatory alternative, the algorithms used may be loaded with unintentional biases that must be checked.⁴⁷ First, the remainder of this Section will briefly discuss standing and further defenses to FHA liability.

D. *Standing Under the Fair Housing Act*

In a disparate-impact challenge, and any other Fair Housing Act challenge for that matter, standing is conferred to the limits of Article III of the U.S. Constitution.⁴⁸ Therefore, in a disparate-impact challenge upon an algorithm, standing will likely not stand as a barrier as long as the aggrieved person has some connection to the hous-

43. 24 C.F.R. § 100.500(b) (2018).

44. Implementation of the FHA’s Discriminatory Effects Standard, 78 Fed. Reg. 11460, 11470 (proposed Feb. 15, 2013) (to be codified at 24 C.F.R. pt. 100); *see also* Ricci v. DeStefano, 557 U.S. 557, 562, 592 (2009) (finding that objective examinations for firefighters qualifying for a promotion were sufficiently related to job performance, and that there was no proof of a less discriminatory testing alternative); Griggs v. Duke Power Co., 401 U.S. 424, 431 (1971) (“If an employment practice which operates to exclude . . . [minorities] cannot be shown to be related to job performance, the practice is prohibited.”). For an example of a successful defense to an FHA claim, *see* Eastampton Ctr., LLC v. Twp. of Eastampton, 155 F. Supp. 2d 102, 119 (D.N.J. 2001) (controlling residential growth through a land use code was found to be a legitimate interest under municipality police power).

45. 24 C.F.R. § 100.500(c)(3) (2018).

46. *See infra* Part IV.

47. *See infra* Part III.

48. *See* Havens Realty Corp. v. Coleman, 455 U.S. 363, 372 (1982); Gladstone Realtors v. Vill. of Bellwood, 441 U.S. 91, 108 (1979).

ing practice in question. The FHA permits “[a]n aggrieved person” to bring a civil action for an alleged violation.⁴⁹ An aggrieved person is any person who claims to have been injured by a discriminatory housing practice or believes that he or she will be injured by a discriminatory housing practice that is about to occur.⁵⁰

Courts have repeatedly written that the FHA’s definition of a person who is “aggrieved” reflects a congressional intent to confer standing broadly.⁵¹ Congress intended standing under the FHA to extend to the full limits of Article III of the Constitution, and therefore, courts “lack the authority to create prudential barriers to standing in suits” brought under the FHA.⁵² Accordingly, standing has been extended to people not explicitly discriminated against,⁵³ organizations whose purpose is to fight discrimination,⁵⁴ and even cities alleging that discriminatory practices harmed their residents.⁵⁵

E. Potential Communications Decency Act Concerns

Finally, by way of introduction to the FHA, the Communications Decency Act (CDA) may become a potential shield for defendants. Under section 230 of the CDA, information content providers are not to be treated as the “publisher or speaker of any information provided by another information content provider.”⁵⁶ An “information content provider” is defined as “any person or entity that is responsible, in whole or in part, for the creation or development of information provided through the Internet or any other interactive computer service.”⁵⁷ Thus, an entity will be immune from liability under section 3604(c) if they are an internet service provider (or information con-

49. 42 U.S.C. § 3613(a) (2012).

50. 42 U.S.C. § 3602(i) (2012). “Person” under the FHA is defined broadly, as well. *See* 42 U.S.C. § 3602(d) (2012).

51. *See, e.g.*, *Bank of Am. Corp. v. City of Miami*, 137 S. Ct. 1296, 1303 (2017).

52. *Havens Realty Corp.*, 455 U.S. at 372; *Gladstone Realtors*, 441 U.S. at 103 n.9.

53. *See* *Trafficante v. Metro. Life Ins. Co.*, 409 U.S. 205, 207-08, 211 (1972) (finding standing for a white tenant that claimed injury due to the loss of the social benefits of living in an integrated community when a landlord allegedly discriminated against nonwhite rental applicants).

54. *See* *Havens Realty Corp.*, 455 U.S. at 368-69, 379 (finding standing for a fair housing organization who provided housing counseling services and investigated complaints concerning housing discrimination by finding that discriminatory actions frustrated the organization’s mission).

55. *See* *Bank of Am. Corp.*, 137 S. Ct. at 1300-01, 1303 (finding standing for a city that claimed financial injury as a result of banks intentionally issuing riskier mortgages on less favorable terms to African-American and Latino customers).

56. 47 U.S.C. § 230(c)(1) (2012).

57. *Id.* § 230(f)(3).

tent provider) who does not have a role in creating or developing discriminatory content.

The Ninth Circuit, in *Fair Housing Council of San Fernando Valley v. Roommates.com, LLC*, dealt with immunity under the CDA in regards to a FHA violation.⁵⁸ Roommates.com, a website designed to match people renting out spare rooms with people looking for a place to live, required subscribers to create profiles with answers to a series of questions before being allowed to search listings or post housing opportunities.⁵⁹ The website, in addition to requesting basic information such as name and location, “require[d] each subscriber to disclose his sex, sexual orientation and whether he would bring children to a household.”⁶⁰

In reading section 230 of the CDA, the Ninth Circuit held that since Roommates.com required its users to provide the offending content via the questions asked in building a profile, the website became the “developer” of that information, and thus, the CDA did not shield it from liability under the FHA.⁶¹

III. PREDICTIVE ANALYTICS—BIG DATA AT WORK

A. *What Information is Collected and How is it Collected? The Basics*

In the digital age, every aspect of our lives has the potential to be tracked, labeled, and combined to form individual profiles about who we are.⁶² As the Federal Trade Commission (FTC) reported in 2016,

[w]ith a smartphone now in nearly every pocket, a computer in nearly every household, and an ever-increasing number of Internet-connected devices in the marketplace, the amount of consumer

58. *Fair Hous. Council of San Fernando Valley v. Roommates.com, LLC*, 521 F.3d 1157, 1164 (9th Cir. 2008).

59. *Id.* at 1161.

60. *Id.* While sexual orientation is not a protected class under the federal FHA, it is protected under the relevant California statute also at issue in the case. See CAL. GOV'T CODE § 12955(a) (West 2018).

61. *Id.* at 1166 (“By requiring subscribers to provide the information as a condition of accessing its service, and by providing a limited set of pre-populated answers, Roommate becomes much more than a passive transmitter of information provided by others; it becomes the developer, at least in part, of that information.”). For an example of a case that granted an Internet service provider immunity under the CDA for an FHA violation, see *Chi. Lawyers’ Comm. for Civil Rights Under Law, Inc. v. Craigslist, Inc.*, 519 F.3d 666, 672 (7th Cir. 2008). There, Craigslist, Inc. was granted immunity because they did not “cause” particular statements to be made in violation of the FHA; rather, they simply acted as a passive transmitter of information. *Id.* at 671-72.

62. See John Naughton, *Why Big Data Has Made Your Privacy a Thing of the Past*, GUARDIAN (Oct. 5, 2013, 7:05 PM), <https://www.theguardian.com/technology/2013/oct/06/big-data-predictive-analytics-privacy> [<https://perma.cc/E46L-SKN7>].

data flowing throughout the economy continues to increase rapidly. The analysis of this data is often valuable to companies and to consumers, as it can guide the development of new products and services, predict the preferences of individuals, help tailor services and opportunities, and guide individualized marketing.⁶³

This amassing of data is gathered through all of our interactions with digital interfaces, including but not limited to: online transactions, search queries, health records, social networking interactions, global positioning satellites, and email.⁶⁴ Until recently, lenders even used a person's Facebook friends as a metric for creditworthiness.⁶⁵ Out of the digital sphere, individual profiles are supplemented by information in public records, consumer surveys, sweepstakes entries, loyalty programs, and the like.⁶⁶ Quite simply, companies collect bits of data from a variety of sources that allow them to know who we are, where we live, and what we do.⁶⁷

For example, in 2012, the New York Times Magazine revealed that Target was able to predict if a customer was pregnant using what is called in the trade as "predictive analytics."⁶⁸ On a mission to target advertisements to pregnant women in their second trimester, Target collected vast amounts of data for several decades on as many customers as possible by assigning shoppers a "unique code" that kept tabs on everything they bought.⁶⁹ Linked to these unique codes was customer information: demographic information, which part of town they lived in, how long it took to drive to the store, estimated salary, what websites they visited, and which credit cards they carried, among other information.⁷⁰

63. FED. TRADE COMM'N, *BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION?* i (2016) [hereinafter *FTC REPORT: BIG DATA*].

64. Omer Tene & Jules Polonetsky, *Big Data for All: Privacy and User Control in the Age of Analytics*, 11 *NW. J. TECH. & INTELL. PROP.* 239, 240 (2013); Crawford & Schultz, *supra* note 7, at 96.

65. See Laura Lorenzetti, *Lenders Are Dropping Plans to Judge You by Your Facebook Friends*, *FORTUNE* (Feb. 24, 2016), <http://fortune.com/2016/02/24/facebook-credit-score/> [<https://perma.cc/X7HK-PM8V>]. It is quite possible that these plans were not dropped, and even if they were, the data gathered from these practices would likely still remain.

66. *FTC REPORT: BIG DATA*, *supra* note 63, at 4; see Natasha Singer, *Mapping, and Sharing, the Consumer Genome*, *N.Y. TIMES* (June 16, 2012), <http://www.nytimes.com/2012/06/17/technology/acxiom-the-quiet-giant-of-consumer-database-marketing.html?ref=natashasinger> [<https://perma.cc/45ET-7D4G>].

67. See Singer, *supra* note 66; see also *FTC REPORT: BIG DATA*, *supra* note 63, at 4 ("[S]ome data brokers store billions of data elements on nearly every U.S. consumer.").

68. Charles Duhigg, *How Companies Learn Your Secrets*, *N.Y. TIMES MAG.* (Feb. 16, 2012), <http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?pagewanted=all&r=0> [<https://perma.cc/MM3M-A6VP>] (internal quotation marks omitted). This article provides an exquisitely detailed account of how Target analyzed the data they gathered.

69. *Id.*

70. *Id.*

Additionally, Target could *buy* data about customers' ethnicity, job history, magazines read, if they ever declared bankruptcy or got divorced, the year they bought their house, where they went to college, what kinds of topics they talk about online, whether they prefer certain brands of coffee, paper towels, cereal or applesauce, political leanings, reading habits, charitable giving, and the number of cars they own.⁷¹ From here, Target's analytics experts were able to pinpoint which customers were pregnant and which were specifically in their second trimester because, according to one statistician, "[w]e knew that if we could identify them in their second trimester, there's a good chance we could capture them for years."⁷²

Social media platforms also gather large swaths of data about consumers based on their interactions with the platform.⁷³ For example, social media platforms can collect data by tracking a user's web and app browsing habits and essentially follow a user across the Internet through the use of "cookies" even after a user has logged out of the platform.⁷⁴ It is no secret that Facebook, for example, amasses a fortune on selling personal data to marketers and third parties.⁷⁵ Facebook is able to sell data on every "like" a person makes on the site, the types of clothing a user's household buys on other websites, in-

71. *Id.*

72. *Id.*; see also FTC REPORT: BIG DATA, *supra* note 63, at 4-5.

73. For a brief introduction on the numerous types of data points Facebook collects, see Caitlin Dewey, *98 Personal Data Points That Facebook Uses to Target Ads to You*, WASH. POST (Aug. 19, 2016), https://www.washingtonpost.com/news/the-intersect/wp/2016/08/19/98-personal-data-points-that-facebook-uses-to-target-ads-to-you/?utm_term=.72bebc6258a [<https://perma.cc/FGE4-6D9Y>]; see also Andreea M. Belu, *The Massive Data Collection by Facebook – Visualized*, DATAETHICS (June 26, 2017), <https://dataethics.eu/en/facebooks-data-collection-sharelab/> [<https://perma.cc/UYH5-B9PW>]; Larry Kim, *You Won't Believe All the Personal Data Facebook Has Collected on You*, MEDIUM (Dec. 7, 2016), <https://medium.com/the-mission/you-wont-believe-all-the-personal-data-facebook-has-collected-on-you-387c8060ab09> [<https://perma.cc/6ZSJ-XYJ5>].

74. Christina Bonnington, *Stop Facebook from Using Your Web History for Ad Targeting*, WIRED (June 19, 2014, 6:30 AM), <https://www.wired.com/2014/06/facebook-ad-tracking/> [<https://perma.cc/4VM4-89C9>]; see also Joanna Geary, *Tracking the Trackers: What Are Cookies? An Introduction to Web Tracking*, GUARDIAN (Apr. 23, 2012, 12:08 PM), <https://www.theguardian.com/technology/2012/apr/23/cookies-and-web-tracking-intro> [<https://perma.cc/757Y-5FMC>]. To illustrate the amount of power Facebook possesses to gather data about us, recently in the European Union, Facebook was ordered to stop tracking nonmembers on third-party sites for data collection. Samuel Gibbs, *Facebook Ordered to Stop Collecting User Data by Belgian Court*, GUARDIAN (Feb. 16, 2018, 11:14 AM), <https://www.theguardian.com/technology/2018/feb/16/facebook-ordered-stop-collecting-user-data-fines-belgian-court> [<https://perma.cc/4AN4-PW36>].

75. See Hope King, *Facebook is Making More Money Off You than Ever Before*, CNN (Jan. 27, 2016, 6:48 PM), <http://money.cnn.com/2016/01/27/technology/facebook-earnings/index.html> [<https://perma.cc/W3PJ-NJEP>]; see also Mark Hachman, *The Price of Free: How Apple, Facebook, Microsoft and Google Sell You to Advertisers*, PCWORLD (Oct. 1, 2015, 3:00 AM), <https://www.pcworld.com/article/2986988/privacy/the-price-of-free-how-apple-facebook-microsoft-and-google-sell-you-to-advertisers.html> [<https://perma.cc/AAA8-RBRY>].

formation on whether a user buys beauty products, information on whether a user spends money on products for kids or pets, and information on countless other personal data points stored on the site and to sites and apps across the technological spectrum.⁷⁶ Inevitably, this data is charged with protected class implications and presents issues under the FHA if used by housing providers to target and exclude certain individuals.

B. How Data is Used to Create Individual Profiles

The previous Section described the types of data gathered in detail to demonstrate what information is potentially at the fingertips of housing providers. With this wealth of data and teams of behavioral and cognitive scientists, companies can use predictive analytics to develop and test inferences about how individuals will act in the marketplace.⁷⁷ This data mining “automates the process of discovering useful patterns, revealing regularities upon which subsequent decision making can rely.”⁷⁸

A key to decisionmaking through data gathering comes in the form of proxies. Companies use proxies, or substitute stand-in data, when they lack data for the behaviors they are most interested in.⁷⁹ The easiest conceivable proxy can be demonstrated with the use of zip codes. For example, a company may attempt to draw statistical correlations between a person’s zip code and their potential to pay back a loan or hold a job given that zip codes typically contain individuals of the same socioeconomic status.⁸⁰ Accordingly, instead of rejecting a loan or job applicant outright based on his or her race, for example, a creditor could use an applicant’s zip code as a proxy for race and thus attempt to mask their unlawful discrimination.⁸¹

To describe proxies using some of the points mentioned previously, a housing provider could deny or disfavor an applicant for a home or refuse to advertise to them based on whether the individual spends

76. Dewey, *supra* note 73.

77. See FTC REPORT: BIG DATA, *supra* note 63, at 4-5; Duhigg, *supra* note 68.

78. Barocas & Selbst, *supra* note 8, at 677.

79. CATHY O’NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 17-18, 108 (Crown Publ’g Grp. 2016) (describing that hiring programs settle for proxies since they cannot possibly incorporate information about how job applicants will actually perform at a job).

80. *Id.*; see also Katherine Noyes, *Will Big Data Help End Discrimination—or Make it Worse?*, FORTUNE (Jan. 15, 2015), <http://fortune.com/2015/01/15/will-big-data-help-end-discrimination-or-make-it-worse/> [<https://perma.cc/7CGW-ES8N>].

81. For an in-depth study on discrimination by proxy, see ANUPAM DATTA ET AL., PROXY DISCRIMINATION IN DATA-DRIVEN SYSTEMS: THEORY AND EXPERIMENTS WITH MACHINE LEARNED PROGRAMS (2017), <https://arxiv.org/pdf/1707.08120.pdf> [<https://perma.cc/H47R-FPVT>].

money on products for kids.⁸² Clearly, this data point is highly correlative to familial status—a protected class under the FHA—and thus may act as a proxy for this class. In the same vein, instead of outright refusing an applicant based on religion, a housing provider could disfavor individuals based on their “likes” on Facebook and their web-browsing history if they can infer that these data points are correlative to a certain religion and thus act as a proxy. Relatedly, instead of disfavoring an applicant outright based on gender, a housing provider could infer gender from a user’s history of buying beauty products, household products, and specific types of clothing just from the information Facebook collects on an individual.⁸³ The amount of proxies that can be developed are endless.

In *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, Cathy O’Neil discusses proxies and their use in several industries.⁸⁴ Her description of how e-scores operate to determine creditworthiness provides a useful comparison for the housing context. Credit card companies can access data on web browsing and purchasing patterns. Companies can, perhaps correctly, infer that a person “clicking for new Jaguars is richer than the one checking out a 2003 Taurus on Carfax.com.”⁸⁵ They can also pick up the location of the visitor’s computer, real estate data, and all of the data points mentioned previously to draw inferences about wealth and their potential ability to pay back a loan.⁸⁶ However, as discussed below, the data used to make these inferences may reflect persistent biases in society and exclude certain classes of people from opportunities—particularly in the housing market.⁸⁷

C. Downsides and Potential Liability in Big Data Use

This Section discusses the crux of the issue. The combination of proxies are merely inferences and have the potential to irrationally exclude individuals who may not fit the assumptions. What about the individual who happens to live in a statistically-impovertised zip code but actually has the means to be a low-risk subject of a loan? What about the individual who happens to like 2003 Tauruses more than Jaguars but due to the fact that he clicked on the former, he has

82. See Dewey, *supra* note 73. Facebook is able to, in fact, collect this information and sell it to housing providers in order for housing providers to create individual profiles on applicants.

83. See *id.*

84. See generally O’NEIL, *supra* note 79.

85. *Id.* at 143.

86. *Id.* at 144.

87. See *infra* Part III.C.

a lower e-credit score? What about the individual that happens to do all of the “wrong” things for a predictive algorithm?

Proxies have the potential to place certain individuals in a negative light if the proxies do not best represent them. The FTC has warned that “[i]f companies use correlations to make decisions about people without understanding the underlying reasons for the correlations, those decisions might be faulty and could lead to unintended consequences or harm for consumers and companies.”⁸⁸ These potential inaccuracies can result in “more individuals mistakenly being denied opportunities based on the actions of others.”⁸⁹

An algorithm is only as good as the data it works with. As described previously, predictive analytics are used to locate targeted audiences by attempting to locate statistical relationships in a dataset by “automat[ing] the process of discovering useful patterns[] [by] revealing regularities upon which subsequent decision making can rely.”⁹⁰ Data miners, who must “translate some amorphous problem into a question that can be expressed in more formal terms that computers can parse. . . . [Thus, these miners] may unintentionally parse the problem in such a way that happens to systematically disadvantage protected classes.”⁹¹ Solon Barocas and Andrew D. Selbst describe that it is up to data miners to decide what is “good” for a particular business; that decision, however, may require a high degree of subjectivity and reliance on existing data.⁹²

A succinct description of the type of algorithm this Note is concerned with is provided by University of California, Berkeley professor, Moritz Hardt. He writes that “[a] *learning algorithm* is loosely speaking any algorithm that takes historical instances (so-called *training data*) of a decision problem as input and produces a decision rule or *classifier* that is then used on future instances of the problem.”⁹³ He notes that “a learning algorithm is designed to pick up statistical patterns in training data. If the training data reflects existing

88. FTC REPORT: BIG DATA, *supra* note 63, at 9.

89. *Id.* The report further describes a case in which a credit card company had to settle FTC allegations claiming that the company “failed to disclose its practice of rating consumers as having a greater credit risk because they used their cards to pay for marriage counseling, therapy, or tire-repair services, based on its experiences with other consumers and their repayment histories.” *Id.* (citing *FTC v. CompuCredit Corp.*, No. 1:08-cv-1976-BBM-RGV (N.D. Ga. June 10, 2008)).

90. Barocas & Selbst, *supra* note 8, at 677.

91. *Id.* at 678.

92. *See id.* at 679.

93. Moritz Hardt, *How Big Data Is Unfair*, MEDIUM (Sept. 26, 2014), <https://medium.com/@mrtz/how-big-data-is-unfair-9aa544d739de> [<https://perma.cc/NH58-4R92>].

social biases against a minority, the algorithm is likely to incorporate these biases.”⁹⁴

In their work, Barocas and Selbst describe the admissions process of St. George’s Hospital in the United Kingdom to demonstrate how a computer-programmed algorithm can have negative effects on historically disadvantaged groups.⁹⁵ The hospital developed a computer program to help sort medical school applicants based on its previous admissions decisions.⁹⁶ However, the hospital historically disfavored racial minorities and women with credentials otherwise equal to other applicants.⁹⁷ As a result, the algorithm perpetuated existing disadvantages within the hospital.⁹⁸ As Barocas and Selbst pointedly noted:

Were an employer to undertake a similar plan to automate its hiring decisions by inferring a rule from past decisions swayed by prejudice, the employer would likewise arrive at a decision procedure that simply reproduces the prejudice of prior decision makers. Indeed, automating the process in this way would turn the conscious prejudice or implicit bias of individuals involved in previous decision making into a formalized rule that would systematically alter the prospects of all future applicants. For example, the computer may learn to discriminate against certain female or black applicants if trained on prior hiring decisions in which an employer has consistently rejected jobseekers with degrees from women’s or historically black colleges.⁹⁹

By using this reasoning, it is conceivable that algorithms that determine who to target for housing may suffer from the same problems. What about an algorithm that favors individuals who are homeowners? Unfortunately, that algorithm would favor white individuals, given that 72.7 percent of whites own a home compared to African Americans who have a 42.1 percent homeownership rate and Asian Americans who have a 58.2 percent ownership rate.¹⁰⁰

What about an algorithm that favors individuals based on the number of cars they own or if they bought auto parts recently?¹⁰¹ It is

94. *Id.*

95. See Barocas & Selbst, *supra* note 8, at 682 (citing Stella Lowry & Gordon Macpherson, *A Blot on the Profession*, 296 BRIT. MED. J. 657, 657 (1988)).

96. See Barocas & Selbat, *supra* note 8, at 682.

97. *Id.*

98. *Id.*

99. *Id.*

100. U.S. CENSUS BUREAU, QUARTERLY RESIDENTIAL VACANCIES AND HOMEOWNERSHIP, THIRD QUARTER 2018 (2018), <https://www.census.gov/housing/hvs/files/currenthvspress.pdf> [<https://perma.cc/53GV-Y96M>] (Table 7).

101. See Dewey, *supra* note 73.

easy to hypothesize that an algorithm with this kind of data baked into it will show some preference based on gender. What about an algorithm that favors individuals who spend money on products for kids?¹⁰² That data point clearly carries familial status implications.

What about an algorithm that favors certain college alumni? Housing providers could target colleges that favor certain races over others. What about what their political leanings are? A 2015 study by the Pew Research Center found that 49 percent of whites are members of the Republican party, while 80 percent of African Americans are members of the Democratic party.¹⁰³ An algorithm that favors Republicans would clearly exclude a majority of African Americans. Data points may have baked in biases regardless of whether they correctly or incorrectly reflect the tendencies of certain protected classes.

In a jurisdiction that includes age as a protected class under its own Fair Housing Act, an algorithm that includes data on users' technology information—such as online shopping habits, social media presence, whether users are early or late adopters of technology, and whether users own a gaming console—can readily discriminate on the basis of age.¹⁰⁴ For a state that includes sexual orientation as a protected class, the fact that Facebook can determine a user's sexual orientation on “likes” alone,¹⁰⁵ even if a user withholds their sexual orientation information, is clearly very problematic if a housing provider uses that information in its predictive analytics.¹⁰⁶

Using the Target case study as an example, it is entirely possible that housing providers possess all of this data and use it to make unlawful housing-related decisions. As Kate Crawford of Microsoft Research and Jason Schultz of NYU School of Law acutely describe:

102. *See id.*

103. *A Deep Dive into Party Affiliation: Sharp Differences by Race, Gender, Generation, Education*, PEW RES. CTR. (Apr. 7, 2015), <http://www.people-press.org/2015/04/07/a-deep-dive-into-party-affiliation> [<https://perma.cc/96HG-VSNL>].

104. *See* 775 ILL. COMP. STAT. 5/1-102(A) (2018); *see* N.Y. EXEC. LAW § 296(5)(a) (McKinney 2018); *see also* Dewey, *supra* note 73.

105. Daizhuo Chen et al., *Enhancing Transparency and Control When Drawing Data-Driven Inferences About Individuals*, 5 BIG DATA 197, 198-99 (2017); Teo Armus, *Facebook Can Tell Whether You're Gay Based on a Few 'Likes,' Study Says*, NBC NEWS (Nov. 22, 2017, 5:04 PM), <https://www.nbcnews.com/feature/nbc-out/facebook-can-tell-if-you-re-gay-based-few-likes-n823416> [<https://perma.cc/E8R7-MH9KJ>]; Rebecca J. Rosen, *Armed With Facebook 'Likes' Alone, Researchers Can Tell Your Race, Gender, and Sexual Orientation*, ATLANTIC (Mar. 12, 2013), <https://www.theatlantic.com/technology/archive/2013/03/armed-with-facebook-likes-alone-researchers-can-tell-your-race-gender-and-sexual-orientation/273963/> [<https://perma.cc/34KQ-6QAC>].

106. California, Colorado, and Illinois are three states, for example, that have added sexual orientation as a protected class. *See* CAL. GOV'T CODE § 12955 (2018); COLO. REV. STAT. § 24-34-502 (2018); 775 ILL. COMP. STAT. 5/1-102(A) (2018).

The use of Big Data may allow landlords and real estate companies to shift away from general advertising in media outlets and circumvent anti-discrimination enforcement mechanisms by isolating correlative attributes that they can use as a proxy for traits such as race or gender. . . .

. . . .

. . . Big Data may eliminate housing suppliers' need to disclose their potentially discriminatory preferences in their advertisements. Instead, the housing providers could design an algorithm to predict the relevant PII [personally identifiable information] of potential buyers or renters and advertise the properties only to those who fit these profiles. . . . Just as Big Data may be used to prevent candidates from seeing loans that might be advantageous to them, housing suppliers could potentially use Big Data to discriminate, all while circumventing the fair housing laws.¹⁰⁷

Absent intentional circumvention of fair housing laws, there still exists unintentional consequences which, under a disparate-impact theory of liability (to be discussed later), may still be unlawful.¹⁰⁸ The White House, in a 2014 report entitled *Big Data: Seizing Opportunities, Preserving Values*, addressed how Big Data will transform the way we live and work.¹⁰⁹ The Report's introduction states that "[a] significant finding of this report is that [B]ig [D]ata analytics have the potential to eclipse longstanding civil rights protections in how personal information is used in housing, credit, employment, health, education, and the marketplace."¹¹⁰ In its discussion on a policy framework to address these issues, the Report notes that Big Data can cause discrimination against individuals and groups due to "the inadvertent outcome of the way [B]ig [D]ata technologies are structured and used."¹¹¹ Notably, the Report publicizes that the "combination of circumstances and technology [in automated decisionmaking] raises difficult questions about how to ensure that discriminatory effects resulting from automated decision processes, whether intended or not, can be detected, measured, and redressed."¹¹² This same concern is articulated by Frank Pasquale in his book *The Black Box*

107. Crawford & Schultz, *supra* note 7, at 100-01.

108. *See infra* Part IV.

109. EXEC. OFFICE OF THE PRESIDENT, *BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES* (2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [<https://perma.cc/BV8R-UGXN>].

110. *Id.* (introductory letter).

111. *Id.* at 51.

112. *Id.* at 64. The report also notes that "[t]he technologies of automated decision-making are opaque and largely inaccessible to the average person"; this concern will be addressed later in this Note. *Id.*

Society: The Secret Algorithms That Control Money and Information where he writes:

Automated systems claim to rate all individuals the same way, thus averting discrimination. They may ensure some bosses no longer base hiring and firing decisions on hunches, impressions, or prejudices. But software engineers construct the datasets mined by scoring systems; they define the parameters of data-mining analyses; they create the clusters, links, and decision trees applied; they generate the predictive models applied. Human biases and values are embedded into each and every step of development. Computerization may simply drive discrimination upstream.¹¹³

Further, there is a concern about those who live on what Jonas Lerman calls “[B]ig [D]ata’s margins.”¹¹⁴ Lerman is concerned about the “billions of people” that remain on Big Data’s margins because “they do not routinely engage in activities that [B]ig [D]ata and advanced analytics are designed to capture.”¹¹⁵ This lack of engagement with data-capturing activities risks distorting datasets and can leave people, whether due to “poverty, geography, or lifestyle,” out of the decisionmaking algorithms.¹¹⁶ The risk, Lerman posits, is that “[i]n a future where [B]ig [D]ata, and the predictions it makes possible, will fundamentally reorder government and the marketplace, the exclusion of poor and otherwise marginalized people from datasets has troubling implications for economic opportunity, social mobility, and democratic participation.”¹¹⁷ Thus, if a person has less of a data footprint, he or she may be less likely to receive advertisements for certain products if a particular algorithm favors consumers with more of an online presence.¹¹⁸

Over-representation of a particular class is also an issue of concern when assessing the discriminatory effects of Big Data usage. As Barocas and Selbst point out, “[i]f a sample includes a disproportionate representation of a particular class (more or less than its actual incidence in the overall population), the results of an analysis of that sample may skew in favor of or against the over- or underrepresented class.”¹¹⁹ Thus, if housing providers gather information from sources

113. PASQUALE, *supra* note 10, at 35.

114. Jonas Lerman, *Big Data and Its Exclusions*, 66 STAN. L. REV. ONLINE 55, 57 (2013).

115. *Id.* at 56.

116. *Id.* at 57.

117. *Id.* at 59.

118. See Michael Fertik, *The Rich See a Different Internet Than the Poor*, SCI. AM. (Feb. 1, 2013), <https://www.scientificamerican.com/article/rich-see-different-internet-than-the-poor/> [<https://perma.cc/7MTZ-CSV5>].

119. Barocas & Selbst, *supra* note 8, at 686.

that collect more from a certain class than others, the data pool itself will be skewed and create a disparate impact.

A serious risk of liability arises if members of a protected class are excluded from datasets. By its nature, predictive analytics and the decision-making that results are products of the data that make up the algorithm.¹²⁰ If the data is inherently skewed towards some groups of people and away from others, whether by relying on past decisions that may be the result of prior biases or by relying on proxies for protected class characteristics, the decisionmaking process is problematic.

Similarly, there are issues in the artificial intelligence world regarding machines exhibiting serious racial and gender biases on their own with the potential to inherently discriminate based on protected classes.¹²¹ Famously, in 2016, Microsoft created a bot on Twitter in order to learn about “conversational understanding.”¹²² Microsoft had the bot engage in automated discussions with Twitter users.¹²³ Their experiment resulted in the bot spouting obscene racist and sexist statements, disputing the existence of the Holocaust, and advocating for genocide.¹²⁴ There has also been a study showing that the facial-recognition systems of Microsoft, IBM, and Face++ (a Chinese startup) failed to recognize dark-skinned females more than light-skinned males with a thirty-four percent higher rate of error on the former.¹²⁵ The study found that as skin shades on women got darker,

120. See *supra* Part III.B.

121. Navneet Alang, *Turns Out Algorithms Are Racist*, NEW REPUBLIC (Aug. 31, 2017), <https://newrepublic.com/article/144644/turns-algorithms-racist> [<https://perma.cc/Q3T8-UP9A>]; Stephen Buranyi, *Rise of the Racist Robots - How AI Is Learning All Our Worst Impulses*, GUARDIAN (Aug. 8, 2017, 2:00 AM), <https://www.theguardian.com/inequality/2017/aug/08/rise-of-the-racist-robots-how-ai-is-learning-all-our-worst-impulses> [<https://perma.cc/2Q3Q-333C>]. For an in-depth study on how software designed to predict future criminals was found to be biased against African Americans, see Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/6BZT-4HKV>].

122. Daniel Victor, *Microsoft Created a Twitter Bot to Learn from Users. It Quickly Became a Racist Jerk.*, N.Y. TIMES (Mar. 24, 2016), <https://www.nytimes.com/2016/03/25/technology/microsoft-created-a-twitter-bot-to-learn-from-users-it-quickly-became-a-racist-jerk.html> [<https://perma.cc/2EDQ-P6YE>].

123. *Id.*

124. *Id.*

125. Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, 81 PROC. OF MACHINE LEARNING RES. 1, 3-4 (2018), <http://proceedings.mlr.press/v81/buolamwini18a/buolamwini18a.pdf> [<https://perma.cc/9S3T-DLC6>]; Parmy Olson, *Racist, Sexist AI Could Be A Bigger Problem Than Lost Jobs*, FORBES (Feb. 26, 2018, 12:26 PM), <https://www.forbes.com/sites/parmyolson/2018/02/26/artificial-intelligence-ai-bias-google/#28366abb1a01> [<https://perma.cc/67V4-6NSF>].

the chances of the algorithms predicting their gender accurately “came close to a coin toss.”¹²⁶

The use of Big Data in decision-making can provide real benefits to society. Predictive analytics can predict market demand and thus increase operational efficiency so companies can figure out how to best devote their resources; this will increase profits, optimize prices, and increase overall consumer happiness.¹²⁷ Regardless of the positive effects, it is essential to understand the potential downsides of Big Data usage in order to locate unlawful discrimination (even if unintentional) that may be incorporated within it.¹²⁸

IV. APPLYING A DISPARATE-IMPACT THEORY OF LIABILITY TO CHALLENGE AUTOMATED DECISION MAKING UNDER THE FAIR HOUSING ACT

A. *The Black Box of Automated Decision Making*

At the outset, it is important to note that the data collection industry and the algorithms that result from the use of data historically lack transparency.¹²⁹ Financial institutions and data brokers have for years “strived mightily to deflect minimal demands for accountability.”¹³⁰ As recently as 2014, the FTC concluded that there is “a fundamental lack of transparency about data broker industry practices” and that data collection and its use “takes place behind the scenes, without consumers’ knowledge.”¹³¹ Therefore, challenging that the decisionmaking processes within algorithms violate the FHA may prove to be a difficult endeavor.

Outside of the industry itself masking its decisionmaking processes, the artificial intelligence world contains its own “black box” prob-

126. Olson, *supra* note 125.

127. See Jacob LaRiviere et al., *Where Predictive Analytics Is Having the Biggest Impact*, HARV. BUS. REV. (May 25, 2016), <https://hbr.org/2016/05/where-predictive-analytics-is-having-the-biggest-impact> [<https://perma.cc/9CPY-62MT>]; Joe McKendrick, *The Downstream Benefits of Predictive Analytics*, FORBES (Oct. 30, 2015, 11:24 AM), <https://www.forbes.com/sites/joemckendrick/2015/10/30/the-downstream-benefits-of-predictive-analytics/#ac870097347e> [<https://perma.cc/UG34-3MMK>].

128. See Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1037 (2017) (“[A]utomated algorithms can generate racially problematic outcomes even if that was not the intent of the algorithms’ programmers.”).

129. FED. TRADE COMM’N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY (2014) [hereinafter FTC REPORT: DATA BROKERS]; see generally PASQUALE, *supra* note 10.

130. PASQUALE, *supra* note 10, at 23 (citing Meredith Schramm-Strosser, *The “Not So” Fair Credit Reporting Act: Federal Preemption, Injunctive Relief, and the Need to Return Remedies for Common Law Defamation to the States*, 14 DUQ. BUS. L.J. 165, 170-71 (2012)).

131. FTC REPORT: DATA BROKERS, *supra* note 129, at vii.

lem.¹³² This problem has been described as “the inability to discern exactly what machines are doing when they’re teaching themselves novel skills.”¹³³ Stanford professor and computational social scientist, Dr. Michal Kosinski, has warned “that artificial intelligences often excel by developing whole new ways of seeing, or even thinking, that are inscrutable to us.”¹³⁴ An algorithm formed in this manner would surely be difficult to break apart and analyze as it would be nearly impossible for even the scientist that developed the artificial intelligence to explain how the algorithm was reaching its decisions.¹³⁵ The issues presented by this phenomenon, also called “deep learning,” is described as such:

You can’t just look inside a deep neural network to see how it works. A network’s reasoning is embedded in the behavior of thousands of simulated neurons, arranged into dozens or even hundreds of intricately interconnected layers. . . .

. . . .

. . . It is the interplay of calculations inside a deep neural network that is crucial to higher-level pattern recognition and complex decision-making, but those calculations are a quagmire of mathematical functions and variables. “If you had a very small neural network, you might be able to understand it But once it becomes very large, and it has thousands of units per layer and maybe hundreds of layers, then it becomes quite understandable.”¹³⁶

There is a concern that employers, banks, and others (such as housing providers) could turn their attention to more complex machine-learning approaches just to make their automated decision-making processes unreviewable.¹³⁷ This issue is particularly prevalent, as described above, when machines learn to be racist or discriminatory on their own without having a specific goal in mind.¹³⁸ The secrecy and unintelligibility of algorithmic processes presents a challenge in using the disparate-impact theory of liability. These challenges will arise specifically when attempting to identify which data

132. *Id.*

133. Cliff Kuang, *Can A.I. Be Taught to Explain Itself?*, N.Y. TIMES MAG. (Nov. 21, 2017), https://www.nytimes.com/2017/11/21/magazine/can-ai-be-taught-to-explain-itself.html?_r=0 [<https://perma.cc/78VJ-DE5V>].

134. *Id.*

135. Will Knight, *The Dark Secret at the Heart of AI*, MIT TECH. REV. (Apr. 11, 2017), <https://www.technologyreview.com/s/604087/the-dark-secret-at-the-heart-of-ai/> [<https://perma.cc/MA5Q-8BTJ>].

136. *Id.*

137. *Id.*

138. See *supra* notes 120-25 and accompanying text.

points contribute to a disparate impact without being related to a legitimate housing interest.

B. Establishing Prima Facie Case of Disparate Impact—An Algorithm as the Challenged Policy

As described in detail above, standing under the FHA is broad, and a plaintiff must first make a claim that a housing practice has a discriminatory effect which “actually or predictably results in a disparate impact on a group of persons or creates, increases, reinforces, or perpetuates segregated housing patterns because of [a protected class].”¹³⁹ As Robert Schwemm writes, this requires

(1) identifying a particular policy or practice of the defendant that is being challenged; (2) showing a sufficiently large disparity in how this policy affects a class of persons protected by the FHA compared with others; and (3) proving that this disparity is actually caused by the defendant’s challenged policy.¹⁴⁰

This Note posits the idea that an algorithm that determines to whom a housing provider should target advertisements may be the subject of a disparate-impact claim. Under section 3604(c) of the FHA, a housing provider may not “make, print, or publish, or cause to be made, printed, or published any notice, statement, or advertisement . . . that indicates any preference, limitation, or discrimination . . . that indicates any preference, limitation, or discrimination . . . that indicates any preference, limitation, or discrimination based on [a protected class].”¹⁴¹ HUD has interpreted this provision to apply to “[s]electing media or locations for advertising . . . which deny particular segments of the housing market information about housing opportunities because of [a protected class].”¹⁴² Algorithms that decide the “media or locations” for advertising thus result in discriminatory effects on a protected class (without adequate business justification) are unlawful.¹⁴³

The most difficult aspect of a prima facie case will be showing that a sufficiently large disparity exists in how an advertising algorithm affects a protected class compared to others. A plaintiff would need to show that an algorithmic process excludes individuals of a protected class with adequate data demonstrating “gross statistical

139. 24 C.F.R. § 100.500(a) (2018); *see also* Tex. Dep’t of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc., 135 S. Ct. 2507, 2514 (2015).

140. Robert G. Schwemm & Calvin Bradford, *Proving Disparate Impact in Fair Housing Cases After Inclusive Communities*, 19 N.Y.U. J. LEGIS. & PUB. POL’Y 685, 693 (2016).

141. 42 U.S.C. § 3604(c) (2012).

142. 24 C.F.R. § 100.75(e)(3) (2018).

143. *Id.*

disparities” to convince a court that a harm has occurred.¹⁴⁴ The plaintiff must offer “proof of disproportionate impact, measured in a plausible way.”¹⁴⁵

There has yet to be a case challenging an algorithm as a policy in the FHA disparate-impact framework. Given the secrecy of the algorithms and the difficulty in amassing enough data to prove that a protected class is statistically excluded more than others, it may prove to be nearly impossible. To bring such a claim would require a method of investigation that could track demographics of people shown an advertisement in a given area versus the demographics of people that are not in that area. Additionally, it may prove to be a challenge to bring such an investigation due to the quick nature of housing rentals. Such an investigation would need to be conducted swiftly in order to gather enough data for a disparate-impact claim.

C. *Business Justification—Weeding Out Irrelevant Data Points*

If a plaintiff can demonstrate a statistical disparity in targeted advertising created by an algorithm, the burden shifts to the defendant to prove that the policy (here, the algorithm) is necessary to achieve “one or more substantial, legitimate, nondiscriminatory interests.”¹⁴⁶ Conceivably, this may be an easy burden to meet. The defendant can simply argue that the algorithm satisfies their legitimate interest in discovering how best to allocate their advertising resources. However, as explained previously, these algorithms may be charged with biases, and thus, this prong is where automated decisionmaking can best be challenged under the FHA.¹⁴⁷

Courts that have analyzed disparate-impact claims have found that the policy challenged must be sufficiently related to a business interest.¹⁴⁸ In *Griggs v. Duke Power Co.*, the U.S. Supreme Court noted that under the business-justification prong in the Title VII disparate-impact framework, “Congress has placed on the employer the burden of showing that any given requirement must have a *manifest relationship to the employment in question*.”¹⁴⁹ Here, the Court held that “[i]f an employment practice which operates to ex-

144. *Mt. Holly Gardens Citizens in Action, Inc. v. Twp. of Mount Holly*, 658 F.3d 375, 382 (3d Cir. 2011) (quoting *Hazelwood Sch. Dist. v. United States*, 433 U.S. 299, 307-08 (1977)); see also Schwemm & Bradford, *supra* note 140, at 697 n.53 (listing cases that considered statistical disparities in disparate-impact challenges).

145. *Mt. Holly Gardens*, 658 F.3d at 382.

146. 24 C.F.R. § 100.500(b)(1)(i) (2018).

147. See *supra* Part III.

148. See *Griggs v. Duke Power Co.*, 401 U.S. 424, 431 (1971) (rejecting the defendant’s business justification because the policy was not sufficiently related to job performance).

149. *Id.* at 432 (emphasis added).

clude Negroes cannot be shown to be related to job performance, the practice is prohibited.”¹⁵⁰

This is the most interesting prong of the three-part test, and it has the potential to change the way in which algorithms that make up automated decisionmaking are formed. Because the challenged policy must be sufficiently related to a housing-related interest, a plaintiff should argue that there are data points within the algorithm that do *not* meet this criterion. That is, because some of the data points that exist within the algorithm have little to nothing to do with housing, the algorithm must be null and void. If successful, algorithms would contain less of the problems identified in Section III of this Note.¹⁵¹

Consider a hypothetical that uses the ninety-eight example data points that Facebook collects and the broad scope of information available to data brokers generally.¹⁵² Suppose Facebook collects those data points and sells that personal information to a data broker, which is then used as part of a housing provider’s algorithm to determine to whom advertisements will be targeted towards. The algorithm, whether intentionally or not, creates statistically producible results that show discriminatory effects against Hispanic individuals by failing to advertise to them. The algorithm contains data on individuals’ Amazon purchases, credit card information, number of cars they own, magazines read, Facebook “likes,” preferences in TV shows, types of restaurants eaten at, household composition, and it even marks preferences for certain behaviors within these data points.¹⁵³ Or, more obviously, the algorithm contains data on individuals’ current zip code, ethnicity, education history, language, and how long it takes them to travel to and from work.¹⁵⁴ Regardless of intent, these data points may prefer non-Hispanics over Hispanics based on behaviors within the data points.

Under the disparate-impact theory, a plaintiff should be able to argue that some of these data points are irrelevant to a housing provider’s legitimate purpose and only exist to create discriminatory effects without justification. For example, take a data point like household composition. In 2012, 17 percent of Latino households were headed by single parents with children.¹⁵⁵ In that same year, only six

150. *Id.* at 431.

151. *See supra* Part III.C.

152. *See Dewey, supra* note 73.

153. *Id.*

154. *Id.*

155. Linda A. Jacobsen et al., *Household Change in the United States*, 67 POPULATION BULLETIN 1, 6 (2012), <http://www.prb.org/pdf12/us-household-change-2012.pdf> [<https://perma.cc/DPM8-BQ5A>].

percent of white families were of the same composition.¹⁵⁶ Therefore, an algorithm that disfavors single parents with children will, by its nature, disproportionately disfavor Latinos. Algorithms that contain zip codes are similarly correlative to designate people by race and class.¹⁵⁷ For data points like Facebook “likes,” preferences in TV shows, and types of restaurants eaten at, a plaintiff can argue that these clearly do not relate to a legitimate housing purpose and exist only as means to discriminate by proxy. It is under this prong of the disparate-impact framework where the issues framed in Section III of this Note can be addressed.

D. Identifying Less Discriminatory Alternatives—Cleaning Up the Algorithm

If a defendant meets its burden under the second prong of the disparate-impact framework, the burden shifts to the plaintiff to identify less discriminatory alternatives that would still satisfy the defendant’s legitimate business purposes.¹⁵⁸ If the plaintiff fails to successfully argue that an entire algorithm is null and void based on irrelevant data points within it, this prong can be used to signal particularly troublesome data points that may be highly correlative with a protected class. Like the preceding prong, the plaintiff can argue that certain data points have no correlation with an individual’s standing in the housing market and thus “clean up” the algorithm—all while easing some of the concerns mentioned in Section III of this Note.¹⁵⁹

V. CONCLUSION

Using a disparate-impact theory of liability is by no means the perfect solution to combating discrimination, intentional or otherwise, in automated decisionmaking. This framework is rife with problems considering the difficulty of establishing a prima facie case. This Note presents this solution as one method by which to weed out data points that are unrelated to whether an individual would be a good fit for housing. It creates algorithms that contain less of the problems that result from automated decisionmaking.

156. *Id.*

157. Anna Clark, *The Tyranny of the Zip Code*, NEW REPUBLIC (Mar. 8, 2013), <https://newrepublic.com/article/112558/zip-code-history-how-they-define-us> [<https://perma.cc/7CEH-EWBJ>]; Jeff Larson et al., *How We Examined Racial Discrimination in Auto Insurance Prices*, PROPUBLICA (Apr. 5, 2017), <https://www.propublica.org/article/minority-neighborhoods-higher-car-insurance-premiums-methodology> [<https://perma.cc/7V39-9JAG>].

158. 24 C.F.R. § 100.500(c)(3) (2018).

159. See *supra* Part III.C.

This solution is a step toward what must be an industry-wide overhaul in how we combat the inherent biases in Big Data. As Frank Pasquale writes, “[w]ithout a society-wide commitment to fair data practices, digital discrimination will only intensify.”¹⁶⁰ If anything, awareness of the scope of the problem will lead to a legal regime that increases transparency and accountability in the algorithms that make the countless number of automated decisions in our day-to-day lives.

To create such an overhaul, there must be mechanisms in place to audit the algorithms in which housing providers rely upon. There must be ways to check the type of data that shape predictive analytics and the methods used to report algorithms that produce disparate impacts.¹⁶¹ These methods must be devised by keeping in mind that it may be necessary to keep some of the elements of a decision policy secret.¹⁶² If the data that made up algorithms were 100 percent transparent, privacy concerns would arise from data that is not meant to be shared broadly.¹⁶³ Therefore, the transparency of algorithms either has to be done on a personal basis with those who are allegedly affected by the algorithm or through a regulatory structure that entrusts a governmental body with the authority to check the data that shapes predictive analytics.¹⁶⁴

One method, as posited by Andrea Roth, is for lawmakers to consider “pretrial disclosure and access rules for machines.”¹⁶⁵ These rules would be analogous to qualifying traditional “expert[s]” at trial.¹⁶⁶ In the civil context, the Federal Rules of Evidence require experts to prepare a written report that includes the facts or data relied upon in order to testify at trial.¹⁶⁷ Applying these principles to machine sources, Roth writes that “a jurisdiction might require the proponent of a machine ‘expert’ . . . to dis-

160. PASQUALE, *supra* note 10, at 21.

161. See O’NEIL, *supra* note 79, at 211 (arguing for “crowdsourcing campaigns” to offer feedback on errors and biases in data sets and models).

162. Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 658 (2017).

163. See *id.* (describing that various laws may prevent full disclosure of certain data points).

164. See 5 U.S.C. § 552(a) (2012) (the Privacy Act of 1974 may be used as a regulatory structure to balance individual privacy rights and governmental interests). To cure some concerns about the government handling such data, the Privacy Act establishes a system of information practices that “governs the collection, maintenance, use, and dissemination of information about individuals that is maintained in systems of records by federal agencies.” *Privacy Act of 1974*, U.S. DEP’T JUST., <https://www.justice.gov/opcl/privacy-act-1974> [<https://perma.cc/L3JN-PWAF>].

165. Andrea Roth, *Machine Testimony*, 126 YALE L.J. 1972, 1981 (2017).

166. See *id.* at 2027.

167. *Id.* (citing FED. R. CIV. P. 26(a)(2)(B)(ii)).

close the substance and basis of the machine's conclusion."¹⁶⁸ Roth concludes that a jurisdiction "might therefore require access to the machine's source code."¹⁶⁹

Roth also argues that jurisdictions might also require "meaningful access to the machine before trial, so the opponent can both review the machine's code, if it is disclosed, and also input different assumptions and parameters into the machine . . . to see what the machine then reports."¹⁷⁰ In the fair housing context, access to the algorithms that shape advertising decisions is absolutely essential to a disparate-impact claim. Laws promoting transparency in automated decision-making are necessary to meet the goals of the FHA and the disparate-impact theory of liability. These laws are necessary to end the discriminatory housing practices that increase residential segregation by "counteract[ing] unconscious prejudices and disguised animus that [can] escape easy classification as disparate treatment."¹⁷¹

168. *Id.*

169. *Id.*

170. *Id.* at 2028.

171. *Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc.*, 135 S. Ct. 2507, 2522 (2015).