AI, CONSUMER CREDIT, AND DISCRIMINATION: A COMPARATIVE LOOK AT CANADA AND THE UNITED STATES

STEPHANIE BEN-ISHAI AND MANDY BEDFORD

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STEPHANIE BEN-ISHAI * AND MANDY BEDFORD[†]

I. INTRODUCTION

In late 2019, an Indigenous man and his 12-year-old granddaughter were detained by Vancouver police after they attempted to open a bank account.¹ This incident followed other reports of male-to-female transgender people who had been locked out of their online bank accounts due to their voices sounding too deep to correlate with the female name on their accounts.² In some instances, the "solution" was for the bank to effectively "out" the individual as transgender on their file without their consent.³

As shocking as these examples are, they illustrate how discrimination continues to persist in the consumer lending sphere in Canada. "Commercial racial profiling," where a person of color is treated with more suspicion than other customers, remains common.⁴ Perhaps as a result of this mentality, businesses run by women are less than half as likely as male-owned businesses to seek financial

^{*} Professor of Law and University Distinguished Research Professor, Osgoode Hall Law School. The support provided by the Canadian Foundation for Legal Research for the research for this article is gratefully acknowledged. We are grateful for the feedback from the participants at the 2020 Dalhousie University Faculty of Law Purdy Crawford Workshop and Professor Brooks' leadership in organizing the event. We are also grateful for the feedback from the participants in the 2020 Third International & Comparative Insolvency Conference at the Sandra Day O'Connor College of Law and Professor Coordes' leadership in organizing the event. We are grateful to Professors Samuel Singer and Sarah Paterson for comments on an earlier draft of this article. All errors are our own.

[†] JD University of Ottawa, 2020; Articling Student at Gowling WLG Canada in Ottawa.

¹ Angela Sterritt, *Indigenous Grandfather and 12-Year-Old Handcuffed in Front of Vancouver Bank After Trying to Open an Account*, CBC NEWS (Jan. 9, 2019), http://www.cbc.ca/news/canada/british-columbia/indigenous-girl-grandfather-handc uffed-bank-1.5419519.

² Alana Cole, *Manitoba Woman says she was Locked out of her Online Banking because of Deep Voice*, CBC NEWS (Feb. 1, 2019), http://www.cbc.ca/news/canada/manitoba/banking-account-manitoba-1.5002885; Christin Scarlett Milloy, *Trans Customers Locked out of TD Bank Accounts*, DAILY XTRA (Dec. 22, 2014), http://www.dailyxtra.com/trans-customers-locked-out-of-td-bank-accounts-65644.

³ See Milloy, supra note 2.

⁴ Sterritt, *supra* note 1.

support or loans from banks.⁵ Similar trends have been reported among other visible minority groups.⁶ While these attitudes have unfortunately persisted, the consumer lending industry has begun to adopt algorithms to guide its decisions.⁷ This has raised questions about what role these tools are playing in eradicating or perpetuating discrimination, particularly when it's decision-making processes are unclear.

Recently, the Apple Card's algorithm came under public scrutiny when users claimed the algorithm perpetuated gender discrimination. In early November 2019, a prominent web developer tweeted that his wife had received a credit limit of only \$57 for the card – and a fraction of the credit limit that he had been granted.⁸ This was despite the fact that he and his wife file joint tax returns, live in a common property state, and she has the higher credit score.⁹ This thread promptly went viral, and was corroborated by other married couples, including, notably, Apple co-founder Steve Wozniak.¹⁰ The credit card's decision-making processes were under investigation from the New York Department of Financial Services at the time of publication. In response to the situation, the developer said, "My belief isn't there was some nefarious person wanting to discriminate. But that doesn't matter. How do you know there isn't an issue with the machinelearning algo[rithm] when no one can explain how this decision was made?"¹¹

While these examples may appear isolated, or the result of a glitch in the algorithm, or a well-intentioned mistake, poor access to consumer credit has significant consequences for economic advancement.¹² Student loans are used to

⁵ Nicholas Sokic, *BMO's \$3-Billion Fund for Women-Owned Businesses Taps into Segment Growing Faster than any Other*, THE FIN. POST (Nov. 1, 2019),

http://business.financialpost.com/entrepreneur/fp-startups/bmos-3-billion-fund-for-w omenowned-businesses-taps-into-segment-growing-faster-than-any-other.

⁶ Daphne Rixon & Peter Goth, *Credit Union Commercial Lending: Mitigating Risk Through Recording, Monitoring, and Reporting*, CONSUMER CREDIT UNION ASS'N, https://www.cssg.ca/webfiles/CU_Commercial_Lending-RixonGoth.pdf (last visited Nov. 23, 2020).

⁷ Robert Bartlett et al., *Consumer-Lending Discrimination in the FinTech Era* (Nat'l Bureau of Econ. Rsch., Working Paper 25943), https://www.nber.org/papers/w25943.

⁸ Sridhar Natarajan & Shahien Nasiripour, *Viral Tweet About Apple Card Leads to Goldman Sachs Probe*, BLOOMBERG (Nov. 9, 2019), http://www.bloomberg.com/news/articles/2019-11-09/viral-tweet-about-apple-card-lea ds-to-probe-into-goldman-sachs.

⁹ Id.

¹⁰ Id.

¹¹ Id.

¹² This is not to detract at all from the powerful arguments made by Professor Atkinson challenging the proposition that equality can be bought with a loan and making clear that

invest in skills that lead to better economic opportunities. Credit cards can be used to make large purchases and gain a financial benefit from those expenditures through cash-back or points programs. Lines of credit can help pay for major, unexpected expenses like a car repair, a leaky roof, or temporary medical expenses. Car loans can help people get to their jobs unconstrained from a bus route or schedule. Mortgages can provide families with the security of a home and a fixed address, as well as providing a potential source of funds in retirement. The availability and price of this credit will help determine how well-placed individuals are to handle life's financial surprises and build a stable economic future.

Arguably, neither the Canadian or American system is adequately set up to address the problem of a lender or credit scoring agency using algorithms to discriminate against minority groups. Both suffer from regulatory fragmentation – in Canada across jurisdictions, and in the United States across agencies with similar and overlapping mandates. This state of affairs could be positive if the governments could tailor regulations to their jurisdictions and try novel policy ideas. However, that does not appear to be the case in either Canada or the United States.

This article will first examine the role that algorithms are playing in the consumer lending process, and how existing inequalities can be ingrained and perpetuated by new uses of this technology, particularly by credit scoring agencies, which perform both the credit reporting and credit rating functions. It will then examine how credit scoring and discrimination in financial services are regulated in both Canada and the United States. Exploring the American experience is critical to understanding how the issue may manifest itself in Canada, which is at an earlier stage in using this technology and, as a result, has less in the way of data and regulatory experimentation. Finally, the paper will conclude with a call for data collection to determine the scope of the issue specific to Canada, and provide early recommendations for how the issue could be addressed, including by describing best practices for algorithms, regardless of sector.

regulation needs to account for both the potential upside value of borrowing and the particular vulnerabilities that debt creates for socioeconomically marginalized groups. *See* Abbye Atkinson, *Rethinking Credit as Social Provision*, 71 STAN. L. REV. 1093, 1101-02 (2019); Abbye Atkinson, *Borrowing Equality*, 120 COLUM. L. REV. 1403, 1412-13 (2020).

II. The Role of Artificial Intelligence (AI) in Furthering Discrimination

A. AI in Credit Scoring and Financial Services

It has been estimated that by 2020, financial institutions globally will have invested roughly \$10 billion in AI, and 76% of C-Suite executives agree that AI will be a critical, differentiating feature in the future.¹³ In the cards and payments sphere, 84.5% of transactions used AI of some form.¹⁴ Chatbots and robo-advisors are two visible ways in which banking and lending have adopted the technology.¹⁵ The World Economic Forum has identified four ways that AI will add value to the financial sector: improving the speed and efficiency of existing processes, improving the accuracy of existing activities and forecasts, finding new ways to derive value, and tailoring products to customer needs.¹⁶

One of the more popular ways that AI is being used in the consumer lending sphere is by using non-traditional factors to assess an applicant's credit worthiness. For example, the major credit scorer FICO, announced a partnership with the alternate credit scorer, Lenddo, to develop risk scores for Indian consumers with limited credit history.¹⁷ Ford Credit has also worked with an external fintech company to improve its data and models on borrowers through machine learning.¹⁸ Some initial research illustrates that these non-credit history factors are equal to or more effective than traditional credit bureau scoring.¹⁹ Data points such as owning an iPhone or Android device, visiting a price comparison

¹³ R. Jesse McWaters, *The New Physics of Financial Services: Understanding How Artificial Intelligence is Transforming the Financial Ecosystem*, WORLD ECON. F. 9 (Aug. 2018), http://www3.weforum.org/docs/WEF New Physics of Financial Services.pdf.

¹⁴ Task Force on Artificial Intelligence of the HouseFinancial Services Committee, 116th Cong. 3 (2019) (written testimony of Bonnie Buchanan, Surrey Business School, the University of Surrey).

¹⁵ Task Force on Artificial Intelligence of the HouseFinancial Services Committee, 115th Cong. 3 (2019) (written testimony of R. Jesses McWaters, Financial Innovation Lead, World Economic Forum).

¹⁶ McWaters, supra note 13, at 18.

¹⁷ FICO and Lenddo Partner to Extend Credit Reach in India, FICO (Oct. 3, 2016), www.fico.com/en/newsroom/fico-and-lenddo-partner-to-extend-credit-reach-in-india-1 0-03-2016.

¹⁸ Ford Credit and ZestFinance Team up to Enhance Risk Modeling, Better Serve Consumers and Lower Credit Losses, FORD MEDIA CTR. (Aug. 25, 2017), http://media.ford.com/content /fordmedia/fna/us/en/news/2017/08/25/ford-credit-a nd-zest-finance-team-up.html.

¹⁹ Tobias Berg et al., On the Rise of FinTechs – CreditScoring Using Digital Footprints 4 (FDIC Ctr. for Fin. Res., Working Paper, 2018), http://www.fdic.gov/bank/analytical/cfr/2018/wp2018/cfr-wp2018-04.pdf.

website immediately before a retail website, and the applicant having their name in an email address have all been linked with lower rates of default.²⁰

A central challenge with AI, which was illustrated by the Apple Card example, is that it is often not clear how the algorithm it arrived at its decision. Ensuring that these decisions can be reviewed and understood is referred to as explainability.²¹ TD Bank recently identified a few areas in AI that require human validation, including explainability and ensuring that it does not develop a negative bias against certain groups or individuals.²² However, this may be difficult to realize in practice. According to the Financial Innovation Lead at the World Economic Forum, "AI models [are] sophisticated systems...this makes it almost impossible to follow how the provided inputs led to the outputs of an AI model, and often even the developers who built a model cannot fully explain how it works."²³ Even beyond these concerns, there are yet others who posit that increased explainability will have negative consequences for accuracy.²⁴ Edwards and Veale state that systems with more variables tend to be more accurate and perform better. However, they are also much harder to explain than simpler, less accurate systems.²⁵ In the lending context, the relative rarity of default makes it more difficult to model, so lenders necessarily increase the complexity of the algorithm to be accurate.²⁶

B. Discrimination

Discrimination, while easy to identify in theory, is often more difficult to pinpoint in practice. The clearest definition for discrimination is "unequal treatment of persons or groups on the basis of their race or ethnicity."²⁷ The

²⁰ Id. at 3.

²¹ Ron Schmelzer, *Understanding Explainable AI*, FORBES (Jul. 23, 2019), http://www.forbes.com/sites/cognitiveworld/2019/07/23/understanding-explainable-a i/#2d6a14757c9e.

²² Michael Rhodes, *How the Banking Industry is Working to Help Code the Right Values into Artificial Intelligence*, THE FIN. POST (Sept. 18, 2019), https://financialpost.com/opinion/how-the-banking-industry-is-working-to-help-code the-right-values-into-artificial-intelligence.

²³ McWaters, *supra* note 13, at 6.

²⁴ Ashley Deeks, *The Judicial Demand for Explainable Artificial Intelligence*, 119 COLUM. L. REV. 1829, 1834 (2019).

²⁵ Lilian Edwards & Michael Veale, Slave to the Algorithm? Why a 'Right to an Explanation' is Probably Not the Remedy You Are Looking For, 16 DUKE L. & TECH. REV. 19, 59 (2017).
²⁶ Id. at 60.

²⁷ Devah Pager & Hana Shepherd, *The Sociology of Discrimination: Racial Discrimination in Employment, Housing, Credit, and Consumer Markets*, 34 ANN. REV. SOC. 181, 182 (2008).

Canada Human Rights Act,²⁸ which applies to most lenders and all credit card companies, defines discrimination as a "practice on one or more prohibited grounds of discrimination or on the effect of a combination of prohibited grounds."²⁹ The Canada Human Rights Act also sets out a number of grounds of discrimination, including race, national origin, religion, gender, sexual identity, family status, genetic characteristics, and disability.³⁰

In assessing if discrimination has taken place, scholars and American courts distinguish between differential treatment, and disparate impact.³¹ Differential treatment is more obvious; it and takes place when people are treated unequally due to their race or some other protected characteristic.³² By contrast, disparate impact takes place when individuals are treated equally on the face of the law or policy, but where one group is favored over another.³³ For example, a policy that the bank only lends to men would constitute differential treatment. Conversely, a policy that requires the bank to only lend to people who are six feet or taller would create a disparate impact for women, who are less likely, on average, than men to be over six feet tall.

Proxy discrimination occurs when a lender makes a discriminatory choice based on neutral characteristic that is correlated with a minority group.³⁴ The use of big data makes it easier for proxy discrimination to take place, even when the algorithm makes an explicit attempt to avoid outright discrimination. For example, a lender may decide to prioritize mortgages in the more affluent areas of a city, rather than in poorer ones. On its face, the lender has made a decision to serve areas with income, which might imply a safer lending risk. However, particularly in the United States, some geographic locations tend to be tightly correlated with race.³⁵ As this simple example illustrates, this discrimination can occur unintentionally and with other considerations, like profitability, in mind. While some obvious proxies can be removed from an algorithm's decision-making process, it becomes infinitely more difficult when it considers a

³³ Id.

²⁸ R.S.C. 1985, c H-6.

²⁹ *Id.* at s. 3.1.

 $^{^{30}}$ *Id.* at s. 2.

³¹ Pager & Shepherd, *supra* note 27, at 182.

³² *Id*.

³⁴ Anya E.R. Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1268 (2020).

³⁵ *Id.* at 1268-69.

multiplicity of variables and how they interact together. If location of residence is not permitted, should spending history? Television habits? The composition and habits of social media contacts?³⁶ In short, AI can take the problem of proxy discrimination and turn it into a "pervasive concern for all antidiscrimination regimes that seek to limit the use of predictive traits that are directly predictive."³⁷

There is a more opaque picture in Canada about the prevalence and effects of racial based discrimination and disparities. For instance, Statistics Canada only began reporting the unemployment numbers for specific visible minorities in August 2020.³⁸ Previously, Statistics Canada tracked three major groups – white, Indigenous, or "visible minority."³⁹ The prior categorization made it impossible to explore the nuances and differences between groups, and to measure individual communities' progress.

These data gaps are pervasive. Not only is there no concrete data in the Canadian consumer lending context, but there are also gaps in measuring differences in education, attainment of leadership positions, incarcerated populations, and health care, among many others.⁴⁰ Canada's peers in the international community, including the United States, the United Kingdom, and New Zealand, all have much more comprehensive data-collection programs for ethnic origin. A recent example of this gap arose in the context of COVID-19, when both the Ontario and federal governments were faced with questions about why data about the race of patients infected with the virus was not being released.⁴¹ Ontario eventually mandated that its public health units collect race-based data, although such collection was not taking place at a federal level until the end of August 2020.⁴² Both the United States and United Kingdom have released this data, and found that there is a higher incidence of infection and

³⁸ The Business and Community Newsletter - August 2020, STAT. CANADA, (Aug. 27, 2020), https://www150.statcan.gc.ca/n1/pub/11-632-x/11-632-x2020004-eng.htm.

⁴¹ Ryan Flanagan, *Does COVID-19 Discriminate? This is How Some Canadians are Harder-Hit*, GLOB. NEWS (Apr. 15, 2020), http://www.ctvnews.ca/health/coronavirus/does-covid-19discriminate-this-is-how-so me-canadians-are-harder-hit-1.4897298.

⁴² The Canadian Press, *Ontario Proposing All Health Units Collect Race-Based Data on COVID-19*, THE NAT'L POST (Jun. 15, 2020), http://nationalpost.com/pmn/news-pmn/canada-news-pmn/ontario-proposing-all-hea lth-units-collect-race-based-data-on-covid-19.

³⁶ *Id.* at 1276, 1282.

³⁷ *Id.* at 1282.

³⁹ Tavia Grant & Denise Balkissoon *How Canada's Racial Data Gaps Can be Hazardous to Your Health*, GLOB. AND MAIL (Feb. 6, 2019), www.theglobeandmail.com/canada/article-how-canadas-racial-data-gaps-can-be-hazar dous-to-your-health-and/.

⁴⁰ Id.

severity among communities of African descent than the general population.⁴³ This is only one example of where a lack of data may be obscuring the true experience of minority communities. Without comprehensive and accurate data, it is difficult for governments and regulators to make appropriate decisions about how to respond to these complex issues.⁴⁴ Without good information, it is as if the problem does not exist at all.

C. Algorithms in Consumer Lending

In their simplest form, algorithms are data-crunchers. They take in information, analyze it, and deliver a result based on their parameters. To build one, you need both a historical dataset and to know what a successful result will look like.⁴⁵ Machine learning algorithms utilize both input and output variables to train the code in implicit logic.⁴⁶ Crucially, these algorithms are also the environments where it is most difficult to involve a human overseer because it "learns" the relationships in data which may not be readily apparent.⁴⁷In the context of lending, a developer will consider their algorithm a success if it can determine who is, or is not, likely to repay them, and what terms are appropriate. This subjectivity of measuring algorithmic success has led to them being described as "opinions embedded in code."⁴⁸

The first challenge comes from the inferences that the algorithm draws from the datasets. Consider a simple hypothetical in an insurance context. More accidents take place in densely populated areas of cities, where there are more stops and starts, more cars, and more distractions than with rural driving. These areas also have disproportionately higher numbers of visible minorities. A deeplearning program could learn that there is a relationship between a concentration of minority populations and car accidents, and thus developing an implicit racial bias. Such a bias could lead the AI to conclude that a minority driver is more

⁴³ Id.

⁴⁴ Eric Andrew-Gee & Tavia Grant, *In the Dark: The Cost of Canada's Data Deficit*, THE GLOB. & MAIL (May 7, 2019), http://www.theglobeandmail.com/canada/article-in-the-dark-the-cost-of-canadas-data deficit/.

⁴⁵ Cathy O'Neil, *The Era of Blind Faith in Big DataMust End*, TED (2017), www.ted.com/talks/cathy_o_neil_the_era_of_blind_faith_in_big_data_must_end/trans cript?language=en#t-107383.

⁴⁶ Edwards & Veale, *supra* note 25, at 25.

⁴⁷ Id.

⁴⁸ O'Neil, *supra* note 45.

likely to be at fault in a crash with multiple drivers, inadvertently leading to higher premiums for that minority driver.⁴⁹ These inferences can be drawn without the intent of the designer or engineer because of the way AI itself can "learn" new information.

The second challenge arises from the creator who is guiding the algorithm's learning not being a neutral party. Most, but not all, discrimination comes from people who are not aware of it.⁵⁰ Psychological research has indicated that these implicit biases can happen even when they directly conflict with conscious thought.⁵¹ This bias presents additional challenges for those seeking to stamp out discrimination. As Kleinberg et al. put it, "Without some kind of formal discrimination or a "smoking gun" document, the only other direct way to tell whether someone discriminated in a specific case may be to ask them. Even setting aside the risk they lie, they honestly might not even know themselves."⁵²

The final challenge comes from using a dataset based on past performance. Basing such a dataset on past performance can produce a skewed prediction of a dataset's future performance. This is especially true for groups that have previously been economically marginalized or dispossessed, including women and ethnic minorities. This problem can also arise when the information is skewed to favor one group over another, or simply when a dataset with too few points within it.⁵³ For instance, imagine a hiring algorithm collected information about where applicants went to high school, but not how they performed academically. With the information present, the algorithm may eliminate candidates from poorly performing schools (which in the United States in particular, tend to have more students belonging to a visible minority group), even if they had been exceptional students.⁵⁴ Similar biases can also enter into the algorithm if the dataset is imbalanced and then reweighted. In a dataset where

⁴⁹ Example drawn from Jonathan Vanian, *Unmasking A.I.'s Bias Problem*, FORTUNE (Jun. 25, 2018), http://fortune.com/longform/ai-bias-problem/.

⁵⁰ Jon Kleinberg, *Discrimination in the Age of Algorithms*2 (NBER Working Paper No. 25548, Feb. 2019).

⁵¹*Id.* at 11.

⁵² Id. at 14.

⁵³ *Id.* at 24.

⁵⁴ Id. at 22.

most information is from men, a delinquent female borrower would have a greater overall impact than a delinquent male borrower.⁵⁵

This is not to say that algorithms do always and will always represent the worst of humanity's impulses. In fact, they can be used to contribute to more equitable outcomes. By using this technology, there is potential to limit disparate impacts, reduce discrimination relative to human decision-making, and make more accurate predictions than humans in ways that "disproportionately benefit disadvantaged groups."⁵⁶ The problem is simply how to design these instruments with fairness in mind.

D. Discrimination in Consumer Lending

Part of the challenge in the consumer lending context is that the supposedly "neutral" information used to evaluate loan applications has been shown to not be neutral at all. Two major application inputs, income and location, can be influenced by an applicant's race and immigration status, particularly in the United States.⁵⁷ White Americans possess several times the amount of wealth of African Americans, even within the lowest income quintile.⁵⁸ In that country, African Americans and Latino customers tend to have lower credit scores, and are more likely to lack a robust credit history.⁵⁹

People of color are also substantially more likely to have errors in their credit history, which are fiendishly difficult to correct.⁶⁰ According to a 2012 Federal Trade Commission study, one in four consumers had "at least one potentially material error" in one of their three major credit reports, and 5.2% of consumers had errors that could result in more expensive loans.⁶¹ A 2005

⁵⁵ *Id.* at 23.

⁵⁶ *Id.* at 33.

⁵⁷ Edward Ongweso Jr, *Trump Wants to Make it Basically Impossible to Sue for Algorithmic Discrimination*, VICE NEWS (Aug. 6, 2019),

 $http://www.vice.com/en_ca/article/gyzx94/trump-wants-to-make-it-basically-impossi ble-to-sue-for-algorithmic-discrimination.$

⁵⁸ Pager & Shepherd, *supra* note 27, at 189.

⁵⁹ AMY TRAUB, DEMOS, ESTABLISH A PUBLIC CREDIT REGISTRY 6 (2019), http://www.demos.org/sites/default/files/2019-03/Credit%20Report_Full.pdf.

⁶⁰ Id.

⁶¹ FED. TRADE COMM'N, REPORT TO CONGRESS UNDER SECTION 319 OF THE FAIR AND ACCURATE CREDIT TRANSACTIONS ACT OF 2003 (Dec. 2012), http://www.ftc.gov/sites/default/files/documents/reports/section-319-fair-and-accura te-credit-transactions-act-2003-fifth-interim-federal-trade-commission/130211factareport.pdf.

Canadian study found that 18% of respondents had inaccuracies in their credit report which took an average of four hours to correct.⁶² Errors can arise when files are mixed or mis-merged (for instance, John Smith from Kansas has his credit information mixed with another John Smith from Vermont), identity theft, and furnisher errors.⁶³ All of this is made more difficult to assess since credit scoring companies do not allow audits of their underlying algorithms, and the system in general remains opaque for commentators and consumers wishing to improve their credit scores.⁶⁴ Attempts to learn about one's credit score can have negative consequences on it.⁶⁵

Even in circumstances where loans were approved, minority borrowers in the United States tend to face higher borrowing costs. A 2019 NBER study found that Latino and African Americans pay 7.9 and 3.6 additional basis points respectively on their mortgages due to discrimination.⁶⁶ This differential costs these groups an additional \$765 million in mortgage interest annually.⁶⁷ When "similarly situated" applicants are compared, minority applicants received roughly 6% more rejections from in-person lenders than non-minority applicants, representing 750,000 to 1.3 million applicants.⁶⁸ This may be due, at least in part, to a lack of available options. Particularly in the United States, less-advantageous loans can be targeted to certain neighborhoods on the basis that homes in these neighborhoods appreciate more slowly.⁶⁹ One reason why this may be the case is a lack of access to all, or even most, necessary available information about loan products. An equitable marketplace is one where all consumers have access to all the information they need to make an informed decision, and they need to have

⁶² SUSAN LOTT, PUB. INT. ADVOC. CTR., CREDIT REPORTING: HOW ARE CONSUMERS FARING? 6 (2005), http://www.piac.ca/wpcontent/uploads/2014/11/piac_credit_reporting.pdf.

⁶³ CHI CHI WU, NAT'L CONSUMER L. CTR., AUTOMATED INJUSTICE: HOW A MECHANIZED DISPUTE SYSTEM FRUSTRATES CONSUMERS SEEKING TO FIX ERRORS IN THEIR CREDIT REPORTS 7-13 (2009), http://www.nclc.org/images/pdf/pr-reports/report-automated injustice.pdf.

⁶⁴ Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 10-11 (2014).

⁶⁵ Id. at 12.

⁶⁶ Bartlett et al., *supra* note 7, at 5.

⁶⁷ Id.

⁶⁸ Id. at 7.

⁶⁹ Pamela Foohey & Nathalie Martin, *Reducing the Wealth Gap Through Fintech "Advances" in Consumer Banking and Lending*, U. ILL. L. REV. (forthcoming 2021) (manuscript at 44-45).

the ability to access their preferred choice.⁷⁰ In the United States, the ability to "shop around" for the best available loan terms has historically been restricted through practices like a lack of bank relationship, or marketing that emphasizes higher-cost loan products.⁷¹ This more "hidden" bias is in addition to more blatant discrimination that exists in lending.

Redlining, a practice where lenders use highly general criteria to draw distinctions in populations, often among racial lines, is illegal in the United States.⁷² However, in the wake of the Great Financial Crisis, banks have been making fewer loans to African American borrowers. In one recent redlining settlement, a bank approved 1,886 mortgages in 2014 with only 25 being granted to African Americans.⁷³ Rather than explicitly barring lending to "Neighborhood X", as in the past, banks are avoiding making these "risky" loans to minority groups through deliberately placing branches and services in areas with fewer marginalized groups.⁷⁴ This kind of discrimination is not being enabled through algorithms, although it is easy to see how lenders with these practices could enshrine their biases into the technology.

For some groups, potential lenders can become aware of their minority status in ways that are more explicit than drawing inferences from the individual's neighborhood or where they went to school. For transgendered individuals who transition from one first name to another, their previous name remains listed on their credit report.⁷⁵ Surname changes in other contexts, such as after a marriage, are more easily accommodated.⁷⁶ The result is that any time the consumer's credit report is accessed, whether for a job, mortgage, or to rent an apartment, their identity as a transgendered person is revealed, often for years after the individual has transitioned to their new name. In order to avoid being forcibly outed, some people have reportedly created entirely new financial identities with their new name. This drastic measure robs them of the benefits of an established credit

⁷⁰ *Id.* at 44.

⁷¹ Bartlett et al., *supra* note 7, at 6.

⁷² Solon Barocas & Andrew D Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 689-90 (2016).

⁷³ Rachel L. Swarns, *Biased Lending Evolves, and Blacks Face Trouble Getting Mortgages*, N.Y. TIMES (Oct. 30, 2015), http://www.nytimes.com/2015/10/31/nyregion/hudson-city-bank-settlement.html.

⁷⁴ Id.

 ⁷⁵ Lars Z. Mackenzie, *The Afterlife of Data: Identity, Surveillance, and Capitalism in Trans Credit Reporting*, 4 TRANSGENDER STUD. Q. 45, 50 (Feb. 2017).
 ⁷⁶ Id.

history, with direct consequences for both the cost and availability of consumer credit products.⁷⁷

III. THE REGULATORY CONTEXT

A. Canada

i. Lenders

Canada has two major agencies which are responsible for regulating lenders: the Office of the Superintendent of Financial Institutions (OSFI) and the Federal Consumer Agency of Canada (FCAC).⁷⁸ The OSFI is largely responsible for overseeing deposit-taking institutions for safety and soundness, including for managing systemic risk.⁷⁹ The OSFI enforces legislative requirements on banks or lenders.⁸⁰ If a bank or federally regulated credit union faces solvency issues, the OSFI will step in with one of its four intervention protocols to either save the institution or allow it to wind up with minimal disruption for the broader financial system.⁸¹

The FCAC was designed to regulate federally regulated financial institutions, including credit card lenders, from a consumer protection perspective.⁸² One way it accomplishes this is through receiving and investigating complaints about financial institutions if internal resolution processes were unsuccessful.⁸³ After an investigation, the FCAC will issue a non-binding recommendation to the lending institution to resolve the situation.⁸⁴ Despite the

⁷⁷ Id. at 54-55.

⁷⁸ Note that our focus here is on federally regulated financial institutions. However, we recognize the existence of a range of other lenders, such as payday lenders, that are partly provincially regulated and also may be using AI in their lending practises.

⁷⁹ Office of the Superintendent of Financial InstitutionsCanada, *Guide to Intervention for Federally Regulated Deposit-Taking Institutions* 1,

http://www.osfi-bsif.gc.ca/Eng/Docs/Guide_Int.pdf (last visited Feb. 19, 2021).

⁸⁰ Office of the Superintendent of Financial InstitutionsAct, R.S.C. 1985, c 18 (3d. Supp.) Part I, § 4(2) (Can.).

⁸¹ Id.

⁸² Financial Consumer Agency of Canada's Mandate, FIN. CONSUMER AGENCY OF CAN. (June 21, 2019),

https://www.canada.ca/en/financial-consumer-agency/corporate/mandate.html. ⁸³ Jacqueline J. Williams, *Canadian Financial Services Ombudsmen: The Role of*

Reputational Persuasion, 20 BANKING FINANCE L. REV. 41, 44 (2005). ⁸⁴ Id. at 47.

current lack of powers to enforce a settlement, these recommendations are usually followed due to the FCAC's influence.⁸⁵ The FCAC also oversees lender compliance with codes of conduct, public commitments in favor of consumers, and legislative obligations, as well as conducts research on financial trends for the federal government.⁸⁶ To date, neither of Canada's lending regulators addressed the use of algorithms in consumer lending decisions. Since the FCAC is an inherently reactive regulatory agency, it is unlikely that it would be the impetus for a new Code of Conduct on the use of algorithms without clear pressure.⁸⁷

ii. Credit Scoring Agencies

Oversight of credit scoring agencies in Canada is split between federal and provincial governments. With respect to regulating the use of data or other personal information in the private sector, the federal government is largely responsible through the Personal Information Protection and Electronic Documents Act (PIPEDA).⁸⁸ Organizations regulated by PIPEDA must comply with key privacy principles and permit the individual the right to access their personal information.⁸⁹ Some of these principles include the importance of obtaining an individual's consent for collecting personal information, limiting use and retention, and ensuring that the information is as accurate as is required for the purpose it will be used for.⁹⁰ However, provincial legislation on information protection in Alberta, British Columbia, and Quebec applies instead of PIPEDA because those regimes are "substantially similar" to the federal statute.⁹¹

⁸⁵ Id.

⁸⁶ FINANCIAL CONSUMER AGENCY OF CANADA, FCAC HISTORY (Jun. 24, 2019), http://www.canada.ca/en/financial-consumer-agency/corporate/history.html.

⁸⁷ For more on the FCAC and its enforcement processes, see Stephanie Ben-Ishai, Consumer Protection Issues and "Non-Banks": A Comparative Analysis, 54 TEX. INTL. L. J. 327, at 343-48 (2019).

⁸⁸ Personal Information Protection and Electronic Documents Act, S.C. 2000, c 5, s. 3 [hereinafter PIPEDA] (Note that as of the time of publication, amendments to PIPEDA have been introduced which would, among other things, change the name of the law to the Electronic Documents Act).

⁸⁹ MIGUEL BERNAL-CASTILLERO & NANCY HOLMES, CANADA'S FEDERAL PRIVACY LAWS (Library of Parliament Publication No. 2007-44-E,2020), http://lop.parl.ca/staticfiles/PublicWebsite/Home/ResearchPublications/Background Papers/PDF/2007-44-e.pdf.

⁹⁰ *Id.* at Appendix.

⁹¹ LOTT, *supra* note 62, at 17; PIPEDA, *supra* note 88, at s. 26(2)(b).

The regulation of credit scoring organizations as a whole takes place at the provincial level. These laws set out granular requirements about dispute resolution, the use of credit scores, and who has access to credit reports. For example, many provinces require that a lender advise customers if their application was denied because of their credit report.⁹² Provincial legislation generally covers four areas: limitations on how credit reports can be used, limits on the types of information collected, requirements to disclose credit reports, and accuracy provisions.⁹³ Quebec is the only province that grounds its consumer reporting provisions within its privacy laws.⁹⁴ New Brunswick enacted a credit reporting law for the first time in 2018.⁹⁵ The territories do not have similar legislation in place.⁹⁶

All provinces except for Nova Scotia and Quebec require information based on ancestry, country of origin, religion, and other protected grounds to be excluded from the calculation.⁹⁷ It is unclear how those laws would address proxy variables, although it would arguably be within the spirit of the legislation to exclude it. Potentially complicating this requirement is that most provinces require that the most accurate and fair processes are used to arrive at a credit score.⁹⁸ If proxy variables, which often contain information about an individual's protected characteristics, are shown to be more accurate, it is unclear which statutory provision will prevail. Proven violations of credit reporting legislation can incur a range of penalties from \$1,000 to \$250,000.⁹⁹

⁹⁴ Id.

⁹⁶ LOTT, *supra* note 62, at 9.

⁹⁷ Credit and Personal Reports Regulation, Alta. Reg. 193/99, s. 4(1) (Can.); Business Practices and Consumer Protection Act, S.B.C. 2004, c 2, s. 109 (Can.); Personal Investigations Act, C.C.S.M. c P34, s. 4(a) (Can.); Credit Reporting Services Act, S.N.B. c 27, s. 10(2) (Can.); Consumer Protection and Business Practices Act, R.S.N.L. 2009, c C-31.1, s. 39(h) (Can.); Consumer Reporting Act, R.S.O. 1990, c C33, s. 9(3)(1) (Can.); Consumer Reporting Act, R.S.P.E.I. c C-20, s. 9(3)(1) (Can.); Credit Reporting Act, S.S. 2004, c C-43.2, s. 18(m) (Can).

⁹⁸ Those provinces are Alberta, New Brunswick, Nova Scotia, Ontario, Prince Edward Island, and Saskatchewan.

⁹⁹ Act Respecting the Protection of Personal Information in the Private Sector, L.R.Q. c P-39.1, s. 91 (Can.) (fines of \$1,000 for a first offence of collecting, holding, communicating to third parties); Credit Reporting Services Act, S.N.B. c 27, s. 45(1) (Can.) (fines of up to \$250,000 for a

⁹² LOTT, *supra* note 62, at 7-8.

⁹³ Id. at 19.

⁹⁵ FINANCIAL AND CONSUMER SERVICES COMMISSION OF NEW BRUNSWICK, *Credit Reporting Act Aims to Provide Clarity and Protection for Consumers* (Sept. 28, 2018), http://www2.gnb.ca/content/gnb/en/news/news_release.2018.09.1207.html.

B. United States

i. Lenders

Banks receive their license to operate through a charter, which can be granted by a state or the federal government.¹⁰⁰ The jurisdiction that issued the charter has the authority to act as the primary regulator for that institution.¹⁰¹ Most community banks are chartered at the state level, while the majority of the banking industry's assets are held by nationally-chartered institutions.¹⁰² However, the federal government and its statutes apply to almost all lending institutions through a variety of mechanisms. Qualifying for deposit insurance, undertaking certain activities, or being a member of the Federal Reserve System all attract federal regulations.¹⁰³

Due to the patchwork of lending regulators in the United States, there are several statutes and organizations responsible for monitoring and punishing discrimination in lending. These include, but are not limited to, the Department of Housing and Urban Development (HUD), the Department of Justice, the Office of the Comptroller of the Currency, the Office of Thrift Supervision, the Federal Deposit Insurance Corporation, the Federal Trade Commission, and the Federal Housing Finance Board.¹⁰⁴ There are also several laws which prohibit discrimination, depending on the type of lending product sought, and the type of protected ground at issue. For example, discrimination in mortgage lending is barred by the Home Mortgage Disclosure Act,¹⁰⁵ and the Americans with Disabilities Act¹⁰⁶ applies to discrimination against individuals with disabilities.

corporation found to violate the statute). For more on the relationship between federal and provincial regulation, see Appendix A.

¹⁰⁰ See EDWARD V. MURPHY, WHO REGULATES WHOM AND HOW? AN OVERVIEW OF U.S. FINANCIAL REGULATORY POLICY FOR BANKING AND SECURITIES MARKETS (Jan. 30, 2015), http://fas.org/sgp/crs/misc/R43087.pdf.

¹⁰¹ *Id.* at 2.

¹⁰² CONGRESSIONAL RESEARCH SERVICE, WHO REGULATED WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 24 (Mar. 10, 2020), http://fas.org/sgp/crs/misc/R44918.pdf.

¹⁰³ Id. at 25.

¹⁰⁴ FEDERAL DEPOSIT INSURANCE CORPORATION, POLICY STATEMENT ON DISCRIMINATION IN LENDING, (last updated Dec. 31, 2019), http://www.fdic.gov/regulations /laws/rules/5000-3860.html#fdic5000policyso3 [hereinafter POLICY STATEMENT].

¹⁰⁵ 12 U.S.C. § 2801.

¹⁰⁶ 42 U.S.C. § 1210.

The main anti-discrimination law in the extension of credit is the Equal Credit Opportunity Act (ECOA).¹⁰⁷ Similarly, the Fair Housing Act¹⁰⁸ focuses on real estate transactions, including loans to build, buy, or repair a home. Both laws set out a number of practices the lender cannot engage in based on protected grounds, including:

- Selectively encouraging applicants to inquire about credit applications;
- Refusing to extend credit or use different standards in deciding to extend credit or not, including to evaluate potential collateral;
- Treating a borrower differently in servicing a loan or using default remedies; or
- Using different standards to package or pool a loan for sale on a secondary market.¹⁰⁹

Additionally, lenders cannot in any way express a preference on the type of applicant using protected grounds (i.e. they can't say that their preference is to only lend to a particular group), or indicate that it will treat applicants differently based on a protected ground (i.e. they can't only offer help in completing the application to one group and not another).¹¹⁰

The ECOA is administered by the Federal Trade Commission (FTC) and the Consumer Finance Protection Bureau (CFPB).¹¹¹ Any lending institution with \$10 billion or more in assets is regulated by the CFPB with respect to consumer compliance.¹¹² For smaller institutions, consumer compliance issues are regulated by the Federal Reserve, state-level regulators, or the Office of the Comptroller of the Currency, depending on the lending institution's charter.¹¹³ For the majority of consumers with a complaint about discriminatory lending, the CFPB will investigate, and potentially pursue a civil action against the lender.¹¹⁴ Similarly,

¹¹⁴ See What Protections Do I Have Against Credit Discrimination?, CONSUMER

¹⁰⁷ 15 U.S.C. §1691.

¹⁰⁸ 42 U.S.C. § 3601.

¹⁰⁹ 15 U.S.C. § 1691(a); POLICY STATEMENT, *supra* note 104.

¹¹⁰ 15 U.S.C. § 1691(a); POLICY STATEMENT, *supra* note 104.

¹¹¹ Federal Trade Comm'n, *Your Equal Credit Opportunity Rights* (Jan. 2013), http://www. consumer.ftc.gov/articles/0347-your-equal-credit-opportunity-rights.

¹¹² JULIE STACKHOUSE, FEDERAL RESERVE BANK OF ST. LOUIS, WHY ARE THERE SO MANY BANK REGULATORS? (Apr. 25, 2017), http://www.stlouisfed.org/on-the-economy/2017/april/why-many-bank-regulators

¹¹³ Id. For more on the responsibilities of regulators, see Appendix B.

FINANCIAL PROTECTION BUREAU, http://www.consumerfinance.gov/fair-lending/ [hereinafter Discrimination Protections] (last visited Dec. 9, 2019).

the HUD will investigate any alleged violations of the Fair Housing Act, and will either encourage an agreement or take legal action.¹¹⁵ Both organizations use a disparate impact test to determine if discrimination has taken place.¹¹⁶

ii. Credit Scoring Agencies

Credit scoring agencies are overseen by the Fair Credit Reporting Act,¹¹⁷ which is administered by the CFPB for large agencies. The law requires that the agencies follow reasonable procedures to ensure accuracy and conduct reasonable investigations of consumer disputes within 30 days.¹¹⁸ In practice, supervisory authority is shared with the FTC, and both agencies have similar enforcement tools, including investigation, civil penalties, and ordering monetary relief for consumers.¹¹⁹ The Fair Credit Reporting Act imposes a regulatory floor, which the states are welcome to build on with their own additional legislation.¹²⁰ For instance, roughly half the states permit credit scores to be used as an insurance underwriting factor, while four have banned its use in certain insurance contexts.¹²¹ In 2017, New York state required that credit scoring agencies register with the state's Department of Financial Services in response to a well-publicized data breach.¹²²

http://www.ccir-ccrra.org/Documents/View/2711.

¹¹⁵ Learn About the FHEO Complaint and Investigation Process, HOUSING AND URBAN DEVELOPMENT ADMINISTRATION,

http://www.hud.gov/program_offices/fair_housing_equal_opp/complaint-process (last visited Dec. 9, 2019).

¹¹⁶ Daniel H. Burd, *HUD Issues Proposal to Conform "Disparate Impact" Rule to Supreme Court's Inclusive Communities Decision*, THE NAT'L LAW REVIEW (Sept. 5, 2019), http://www.natlawreview.com/article/hud-issues-proposal-to-conform-disparate-impac t-rule-to-supreme-court-s-inclusive.

¹¹⁷ 15 U.S.C. § 1681.

¹¹⁸ CONSUMER REPORTING AGENCIES: CFPB SHOULD DEFINE ITS SUPERVISORY EXPECTATIONS, GOVERNMENT ACCOUNTABILITY OFFICE (July 2019), http://www.gao.gov/assets/710/700294.pdf.

¹¹⁹ Id.

¹²⁰ Kyle Murray, *Does the Government Control the Credit Bureaus?*, LEXINGTON LAW (Oct. 3, 2017),

http://www.lexingtonlaw.com/blog/credit-101/does-the-government-control-the-credit bureaus.html.

¹²¹ USE OF CREDIT SCORES BY INSURERS: CREDIT SCORING WORKING GROUP, CANADIAN COUNCIL OF INSURANCE REGULATORS (June 2011),

¹²² Ashley Southall, *Cuomo Proposes Stricter Regulations for Credit Reporting Agencies*, N.Y. TIMES (Sept. 18, 2017),

Recently, as part of a settlement with thirty state governments, America's three largest credit scoring agencies committed to a National Consumer Assistance Plan. This plan included a commitment to use the most recent reporting format, requiring debt collectors to update the status of unpaid debts, and implementing an enhanced dispute resolution process for customers with mixed files or who were victims of fraud or identity theft.¹²³ The authors are not aware of any suits against credit scoring agencies in the Canadian context, or examples where the regulators had similarly collaborated on enforcement actions.

Establishing discrimination from mortgage lenders or insurance companies may soon become more difficult in the United States. In August 2019, the HUD proposed a new rule that shifted the onus of proving "disparate impact" to the plaintiff.¹²⁴ Currently, if a party alleges discrimination against their lender or insurance provider, the defendant is required to illustrate that their criteria was the most appropriate under the circumstances.¹²⁵ Given the complexity of establishing bona fide discrimination, this change would make any legal action more expensive. The President and Chief Executive Officer of the National Fair Housing Alliance has described the proposed change as elevating "the bar so high that it is virtually insurmountable."¹²⁶

IV. RECOMMENDATIONS AND BEST PRACTICES

A. Analysis of the Status Quo

In Canada, the provinces have enacted a "regulatory floor," which lenders and credit-scoring agencies will find relatively consistent across the country. Any benefits which may have been derived from competition between jurisdictions do not appear to have materialized with respect to actual enforcement. Additionally, having a regulatory agency in each province, no matter how small, will result in

http://www.nytimes.com/2017/09/18/nyregion/equifax-hack-credit-reporting-agencies - regulations.html.

¹²³ News About the National Consumer Assistance Plan, NAT'L CONSUMER ASS'N PLAN (June 9, 2016), http://www.nationalconsumerassistanceplan.com/news/news-release/.

¹²⁴ HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42854 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100).

¹²⁵ Tracy Jan, *HUD Raises the Bar for Bringing Discrimination Claims*, WASH. POST (Aug. 16, 2019),

http://www.washingtonpost.com/business/2019/08/16/hud-raises-bar-bringing-discrimination-claims/.

¹²⁶ Id.

some regulators having more investigative resources than others. In a situation where bona fide discrimination is taking place across the country, it is unclear how well-positioned all regulators will be to detect and enforce their provincial statutes.

Even more concerning is that regulators do not seem to openly contemplate that discrimination on the basis of a protected ground might be taking place. Unlike the CFPB in the United States, Canadian oversight agencies do not offer FAQs or question and answer sections on the issue of discrimination by a credit scoring agency or consumer lending institution. Other agencies, including the HUD, have similarly released rules and guidance about what criteria must be met to establish discrimination in lending for potential complainants. In December 2019, the CFPB and Federal Trade Commission hosted a workshop on the accuracy of credit reporting, including how new technologies and data management practices could be used to improve accuracy.¹²⁷ This workshop was a follow up to a 2012 FTC report on the accuracy of credit information and a multi-state settlement in 2015.¹²⁸ While regulatory enforcement may be weakening as a result of the new rule from HUD and dramatic funding cuts to the CFPB, it appears that at least American regulators are grappling with the problem of discrimination in lending.¹²⁹ All three credit scoring agencies implicated in the settlement-Equifax, Experian, and TransUnion-operate in Canada. The lack of regulatory response from Canadian regulators raises questions about the accuracy of their databases for Canadian customers.¹³⁰

As discussed earlier in this article, it has been difficult in the United States to establish bona fide discrimination in lending, even with the established tests and history of litigation in this area. This will only get more difficult with the proliferation of financial lending technologies and the use of algorithms to assist in decision making. Regardless of what regulations are or are not eventually put

¹²⁷ CFPB and FTC to Host December Workshop on Accuracy in Consumer Reporting, CONSUMER FIN. PROT. BUREAU (Sept. 19, 2019), http://www.consumerfinance.gov/aboutus/newsroom/cfpb-and-ftc-host-december-workshop-accuracy-consumer-reporting/. 128 Id

¹²⁹ Kate Berry, Kraninger Wants More Money for the CFPB. White House has a Different Plan, THE AM. BANKER (Feb. 20, 2020), http://www.americanbanker.com/news/kraningerwants-more-money-for-cfpb-white-house-has-a-different-plan.

¹³⁰ See Attorney General DeWine Announces Major National Settlement with Credit Reporting Agencies, OHIO ATT'Y GEN. (May 20, 2015), http://www.ohioattorneygeneral.gov /Media/News-Releases/May-2015/Attorney-Gener al-DeWine-Announces-Major-National-S.

into place to regulate this practice, the reason why an algorithm arrives at a conclusion is often unclear to its creators. Regulators will need to develop institutional knowledge and subject-matter expertise to ensure that they can identify gaps or misconduct that may occur. Developing this expertise will be no small feat for regulators, particularly given the rate of advancement in this area. Regrettably, in Canada, neither the provincial regulatory agencies, nor the FCAC appear to contemplate the challenges that the inevitable shift towards algorithms will create for their compliance efforts.

B. A Call to Canadian Regulators

One of the central challenges with stamping out discrimination in consumer lending is that we have a poor grasp on the scope of the problem in Canada. Given that the United States has a history of grappling with this problem, and that Canadian credit scoring agencies also operate in the United States, it is reasonable to infer that Canadian consumers are impacted by similar issues. However, inferences are not a sufficient basis for new oversight and regulations. More data is needed to determine the scope of the problem, assess the groups who are affected, and inform regulators about the best practices to correct it. Without this information, it will also be difficult to convince legislators and regulators of the necessity to act. All regulators and government agencies, and especially Statistics Canada, should begin collecting and releasing information about applicants' ethnicity as a matter of routine data collection. As important as this information will be in a consumer lending context, it will also provide vitally important information about health and economic circumstances that can inform policy choices.

Similarly, provincial regulators should conduct an audit or investigation regarding the prevalence of missing and erroneous information within credit scoring agencies and assess whether some groups are disproportionately affected by these issues. Regulators should work with their American counterparts, particularly those who were involved in the 2015 multi-state settlement, to learn from their investigative methods. While the issues identified in 2015 are hopefully no longer relevant, an audit will provide meaningful information about the scope of the problem in a Canadian context. The results should be made publicly available to help inform Canadians about the accuracy of these vitally important scores. Additionally, if widespread issues are revealed, the results of the

investigation may prompt legislative or regulatory changes to ensure that information can be efficiently updated by its holders.

Only after regulators have a comprehensive scope of the problem in Canada should further regulation and resourcing be considered. If the hypothesis that discrimination is occurring in consumer lending in Canada is correct, then the model of the CFPB should be considered. The agency is focused on providing information and advocacy for consumers, which results in clear, plain language resources. In contrast, both the FCAC and the current dispute resolution process for credit-scoring agencies direct the consumer to the institution's dispute resolution process. This can be especially problematic in cases of discrimination, which are difficult to definitively prove even within the context of litigation. By initially encouraging complainants to "go it alone," this process makes it harder to identify widespread, systematic problems with a lender or credit scoring agency. The CFPB takes a more direct approach in advocating for the consumer. Not only does this approach reduce the potential sophistication disparity between a consumer and a major institution, it also acts as an information collection mechanism.

Finally, regulators should think seriously about the best way to regulate these institutions as they move to automate their decision-making processes. Given the resources and sophistication required to keep pace with these developments, the current fragmented model may no longer be appropriate. It may be more appropriate to pool resources into a central regulator—akin to the Capital Markets Regulatory Authority—or to work directly with the FCAC on consumer-facing issues. A central regulator would be able to develop the subjectmatter expertise in order to effectively regulate the concerns coming from AI and big data. Hosting this within the FCAC would have efficiency benefits, since it should already be contemplating how to oversee banks and other lenders' use of algorithms. A central organization would also have the advantage of collecting a national picture of organizations' practices to identify trends and patterns. Since most credit scoring agencies operate across the country, the agencies themselves would have the benefit of a single point of contact on these issues, rather than working with ten different regulators.

More broadly, Canadian regulators at large should begin having conversations about how algorithms should be regulated to ensure that they do not perpetuate existing inequalities. Outside of the lending context, there are other

proposals in the United States which would place more onus on companies using algorithms. The Algorithmic Accountability Act, 2019¹³¹ would direct the Federal Trade Commission to create rules to evaluate "highly sensitive" AI. Major companies with \$50 million or more in annual revenues, those that hold information on at least 1 million devices or people, or those that act as data brokers would be affected by the Act.¹³² These rules would require companies to assess whether their algorithms are biased or discriminatory and to assess the privacy and security risks to consumers.¹³³ Any issues that arise in reporting would need to be addressed promptly.¹³⁴ Other suggestions for how algorithms can be effectively regulated are discussed in the next section.

C. Best Practices to Consider

i. Good Data Modified for Fairness

There is an undeniable truth in the maxim of "garbage in, garbage out" for algorithms. Developers of machine learning algorithms should be mindful of the flaws in their data in order to avoid further entrenching structural biases and inequalities. Part of ensuring a good dataset requires seeking information from underrepresented groups, ensuring that any gaps in the data are addressed through re-weighting, and working to eliminate as much bias as possible from the engineering process.¹³⁵ Since there are lingering problems with data collection of underrepresented groups, re-weighting may be the more realistic course to correct the data in the short term. Part of this setup demands that the organization developing the algorithm have an acceptable definition of "fairness." Even within an organization, this may be difficult to reconcile. For instance, a credit card's marketing team may favor outcomes that maximize the number of customers,

¹³¹ H.R. 2231, 116th Cong. (2019).

¹³² Adi Robertson, A New Bill Would Force Companies to Check Their Algorithms for Bias, THE VERGE (Apr. 10, 2019),

http://www.theverge.com/2019/4/10/18304960/congress-algorithmic-accountability-act-wyden-clarke-booker-bill-introduced-house-senate.

¹³³ Id.

¹³⁴ *Id*.

¹³⁵ Anna Jacobson, *Fairness in the Age of Algorithms*, UC BERKELEY SCH. OF INFO., (Apr. 27, 2019), http://medium.com/berkeleyischool/fairness-in-the-age-of-algorithms-feb11c56a709.

while the risk management team would favor fewer, safer customers.¹³⁶ The company would also need to define what unintended consequences would be unacceptable. For example, if subprime loans were shown to be profitable, a company may find itself making predatory loans it would not have made without the algorithm.¹³⁷

A related proposal, de-coupling proxy variables and attributes, could lead to further problems. First, an evaluation of what criteria is relevant is fundamentally a qualitative one that could itself be a source of algorithmic bias. Any attempt to solve this problem "would necessarily wade into the highly charged debate over the degree to which the relatively less favorable position of protected classes warrants the protection of antidiscrimination law in the first instance."¹³⁸ As Barocas and Selbst put it, "the only way to ensure that decisions do not systematically disadvantage members of protected classes is to reduce the overall accuracy of all determinations."¹³⁹ They go further to state that the attempt to rectify this issue would bring the two competing principles of antidiscrimination law, anti-classification, and anti-subordination, into conflict.¹⁴⁰ In order to correct systemic biases, it may be necessary to collect more information on an individual's protected characteristics, which may only further entrench an individual's identity as a member of that group.¹⁴¹

ii. Audits

The use of audits, akin to a review of financial statements or test results, may help uncover where the algorithm is going astray. There are various mechanisms that could accomplish this, including through code reviews, surveying consumers, a data scraping audit, or a "sock puppet" or a "collaborative" audit, where either fake or real profiles are used to run an audit.¹⁴²

¹³⁶ Anand Rao & Ilana Golbin, *What is Fair When it Comes to AI Bias?*, STRATEGY + BUS. (Apr. 12, 2019), http://www.strategy-business.com/article/What-is-fair-when-it-comes-to-AI-bias?gko= 827c0.

¹³⁷ Karen Hao, *This is How AI Bias Really Happens – and Why It's so Hard to Fix*, MIT TECH. REV. (Feb. 4, 2019), http://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happensand-wh y-its-so-hard-to-fix/.

¹³⁸ Barocas & Selbst, *supra* note 72, at 722.

¹³⁹ *Id.* at 721-22.

 $^{^{140}}$ Id. at 723.

¹⁴¹ Prince & Schwarcz, *supra* note 34, at 1315.

¹⁴² Sandvig et al., Auditing Algorithms: Research Methods for Detecting Discrimination on Internet Platforms, (May 22, 2014) (paper presented to Data and Discrimination: Converting

One difficulty that can arise from a physical test of the audit is that the new information fed into the algorithm could alter its behavior.¹⁴³

The European Union Agency for Fundamental Rights also suggests that companies should run algorithm audits regularly to ensure that it is not producing unlawful outcomes.¹⁴⁴ This could be accomplished by having a technical expert evaluate the software and code used for the algorithm or conducting randomized testing.¹⁴⁵Other scholars suggest that algorithm audits should be conducted by regulatory groups, such as the Federal Trade Commission in the United States.¹⁴⁶ The results of this audit could then be followed up through a "Privacy and Civil Liberties Assessment" which would publicize the algorithm's potential effects on privacy and marginalized groups.¹⁴⁷ Regardless of who conducts the audit, they would need substantial information from the company being audited, including the source code, original datasets, and programmers' notes describing the correlations, variables, and inferences embedded in the algorithm.¹⁴⁸

A related option to ensure that organizations who choose to use algorithms can be appropriately motivated to consider the associated risks would be to adopt a model similar to the Senior Managers Regime in the United Kingdom. This regulatory structure places substantial emphasis on individual accountability in an attempt to encourage regulated institutions to be proactive about their regulatory compliance.¹⁴⁹ Establishing a similar regime to oversee AI and algorithms could motivate credit scoring agencies and other groups using these technologies to ensure that they are adopting the technology only after thoroughly assessing the potential risks for perpetuating discrimination and other potential harms.

¹⁴⁸ *Id.* at 25.

Critical Concerns into Productive Inquiry, a preconference at the 64th Annual Meeting of the International Communication Association),

http://www.personal.umich.edu/~csandvig/research/Auditing%20Algorithms%20--%2 0Sandvig%20--%20ICA%202014%20Data%20and%20Discrimination%20Preconference.p df.

 $^{^{143}}$ Id. at 10-15.

¹⁴⁴ EUR. UNION AGENCY FOR FUNDAMENTAL RTS., #BIGDATA:

DISCRIMINATION IN DATA-SUPPORTED DECISION MAKING (2018),

http://fra.europa.eu/sites/default/files/fra_uploads/fra-2018-focus-big-data_en.pdf. ¹⁴⁵ *Id.* at 6.

¹⁴⁶ Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 24-25 (2014).

¹⁴⁷ Id. at 26.

¹⁴⁹ FIN. CONDUCT AUTH., THE SENIOR MANAGERS AND CERTIFICATION REGIME: GUIDE FOR INSURERS (2019), https://www.fca.org.uk/publication/policy/guide-for-insurers.pdf.

iii. Use Algorithms to Enhance Transparency

One suggestion proposed by Citron and Pasquale is to use scoring systems to help make credit scoring systems more transparent through interactive modeling. One of the current critiques of credit scoring is that it is often difficult for consumers to know how behavior will affect their credit scores outside of "be responsible with your credit." For instance, it is unclear how different credit utilization rates and loan repayment behaviors will affect a credit score. Allowing individuals to enter various scenarios, similar to the popular children's "Choose your own Adventure" series, will allow consumers to gain a better understanding of their credit scores.¹⁵⁰ Increased transparency about how the algorithm operates, particularly in a controlled environment, could also act as a check on covertly discriminatory practices. At a minimum, this could allow third parties including researchers, governments, and potential litigants to more easily identify instances of proxy discrimination than under current frameworks.¹⁵¹

Edwards and Veale similarly propose that algorithms can be simplified through more technology. Rather than "opening up" a black box to trace its decision-making process, a simpler model can be "wrapped around" it in an attempt to explain it.¹⁵² These models have the advantages of leaving the source data largely untouched and avoiding the trade secrecy concerns that "opening the box" would cause.¹⁵³ However, using technology to explain technology comes with its own issues. Without external validation, it is possible that the second algorithm could miss or replicate errors present in the original decision-maker. Additionally, without some minimum standards, a wide variation in explainability among companies is likely.

This option is not without its costs and trade-offs. Ensuring that the algorithm and underlying data are able to be validated by external groups will require additional expense to set up that necessary infrastructure. The desire or requirement to make this information available may be resisted by corporate users on the grounds that it could disclose their trade secrets to competitors. Current license agreements typically bar users from repurposing the original data for

¹⁵⁰ Citron & Pasquale, *supra* note 146, at 28-29.

¹⁵¹ Prince & Schwarcz, *supra* note 34, at 1312.

¹⁵² Edwards & Veale, *supra* note 25, at 61.

¹⁵³ *Id.* at 65.

commercial purposes.¹⁵⁴ Information will need to be anonymized to ensure that applicants can remain anonymous, and in compliance with privacy laws. Important questions about exactly who should be able to access this information will need to be answered in order to ensure a consistent field for all participants.¹⁵⁵

V. CONCLUSION

Thirty years since the public advent of the internet, the implications of this technology are still to shaping our lives. The innovation of using algorithms and big data to make consumer lending decisions has enormous potential to ensure that consumers without traditional credit histories still have access to products that can improve their lives. However, we have also seen some early indications that it can be used to contribute towards existing inequalities in ways that will be much harder to correct in the future. Whether or not regulators are prepared for it, the industry is shifting to adopt these measures every day.

Especially in Canada, it is imperative that we have the appropriate data to identify if there is an issue that needs to be addressed and start to determine how we would combat these issues when they arise. As with any new technology, mistakes and unintended consequences will be made. The risk that these will tend towards discriminatory outcomes is particularly high when the industry practice proxy variables are used. Thus, it is not so much a question of "if" but "when" these issues will arise. Without adequate information, we could entrench existing and unfair disparities in a way that would be hard to correct and will have direct consequences on the most vulnerable citizen's futures.

¹⁵⁴ Mauro Cesa & Luke Clancy, *To Model the Real World, Quants Turn to Synthetic Data*, RISK.NET (Apr. 27, 2020), http://www.risk.net/risk-management/7532751/to-model-the-real-world-quants-turn-to -synthetic-data.

¹⁵⁵ Prince & Schwarcz, *supra* note 34, at 1313.

APPENDIX A

	AB ¹⁵⁶	BC ¹⁵⁷	MB ¹⁵⁸	NB ¹⁵⁹	NL ¹⁶⁰	NS ¹⁶¹	ON ¹⁶²	PEI ¹⁶³	QC ¹⁶⁴	SK165
Limits on	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х
Revealing										
Information										
Protected	Х	Х	Х	Х	Х		Х	Х		Х
Grounds										
Report	Х	Х	Х	Х	Х	Х	Х	Х		Х
Exclusions										
Accuracy	Х			Х		Х	Х	Х		Х
and										
Fairness										
Explanation		X –	X - 10	X –		X -				
if Denied a		30	days	15		immediately				
Benefit		days		days						
Dispute	Х	Х	Х	Х		Х	Х	Х	Х	Х
Resolution										
Process										

Statutory Expectations for Credit Scoring Agencies

¹⁵⁶ Consumer Protection Act, R.S.A. 2000, c C-26.3 (Can.); Credit and Personal Reports Regulation, Alta. Reg. 193/99 (Can.).

¹⁵⁷ Business Practices and Consumer Protection Act, S.B.C. 2004, c 2 (Can.).

¹⁵⁸ Personal Investigations Act, C.C.S.M. c P34 (Can.); Personal Investigations Regulation, Man. Reg. 392/87 (Can.). ¹⁵⁹ Credit Reporting Services Act, S.N.B. c 27 (Can.).

¹⁶⁰ Consumer Protection and Business Practices Act, R.S.N.L. 2009, c C-31.1 (Can.).

¹⁶¹ Consumer Reporting Act, R.N.S. c 93 (Can.).

¹⁶² Consumer Reporting Act, R.S.O. 1990, c C33 (Can.).

¹⁶³ Consumer Reporting Act, R.S.P.E.I. c C-20 (Can.).

¹⁶⁴ Act Respecting the Protection of Personal Information in the Private Sector, L.R.Q. c P-39.1 (Can.).

¹⁶⁵ The Credit Reporting Act, S.S. 2004, c C-43.2 (Can.).

Issue	Appropriate Authority
Privacy Breach from a Credit Scoring	Consumer based in Alberta, BC, or
Agency	Quebec? –
	Provincial Privacy Commissioner
	Consumer based elsewhere in Canada? -
	Federal Privacy Commissioner
Complaint about a Credit	Provincial financial services commission
Scoring Agency	or agency
Discrimination against an individual or	Was it a credit union? – Likely the
group	province's
from a financial institution	financial services regulator, but it may be
	the
	FCAC if it was federally-regulated
	Was it a bank or insurance company? -
	FCAC

Relationship Between Federal and Provincial Regulators in Canada

APPENDIX B

U.S. Banking Regulatory Structure¹⁶⁶

	State- Chartered Institution, Member of the Federal Reserve	State-Chartered, Not a Member of the Federal Reserve	Nationally-Chartered
Primary Federal Regulator	Federal Reserve	Federal Deposit Insurance Corporation	Federal Deposit Insurance Corporation
Consumer Compliance Regulator (less than \$10 billion in assets)	Federal Reserve	State regulator	Office of the Comptroller of the Currency
Consumer Compliance Regulator (more than \$10 billion in assets)	Consumer Financial Protection Bureau	Consumer Financial Protection Bureau	Consumer Financial Protection Bureau

¹⁶⁶ Adapted from STACKHOUSE, *supra* note 112.