CENTER FOR
DEMOCRACY
& TECHNOLOGY

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To: Board of Governors of the Federal Reserve System, Docket No. OP-1743
Bureau of Consumer Financial Protection, Docket No. CFPB-2021-0004
Federal Deposit Insurance Corporation, RIN 3064-ZA24
National Credit Union Administration, Docket No. NCUA-2021-0023
Office of the Comptroller of the Currency, Docket ID OCC-2020-0049

Re: Request for Information on Financial Institutions' Use of Artificial Intelligence, including Machine Learning

The Center for Democracy & Technology (CDT) respectfully submits these comments to the Board of Governors of the Federal Reserve System, Bureau of Consumer Financial Protection, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency ("Agencies") in response to their request for information regarding financial institutions' use of artificial intelligence (AI). CDT is a nonpartisan, nonprofit 501(c)(3) organization that for over 25 years has been dedicated to advancing civil rights and civil liberties in the digital world and challenging exploitative and discriminatory uses of technology.

AI systems, like any human-controlled consumer practice, can violate existing federal consumer protection and antidiscrimination laws, including the Fair Credit Reporting Act (FCRA), Equal Credit Opportunity Act (ECOA), and Fair Housing Act (FHA). For example, AI systems often use or "learn" proxies for traits that are protected under the ECOA and FHA,[1] and the use of biased data can violate consumers' rights under these laws.[2] Yet, AI's complexity and opacity has obscured covered entities' compliance practices – or lack thereof – making it inherently difficult to hold AI systems accountable under these laws.

Accordingly, CDT joins the comments of our fellow civil rights, consumer, technology policy, and other advocacy organizations that sets forth some of the risks arising from the use of AI systems

[1] Historical discrimination causes certain attributes to be common in a protected class. Some machine learning (ML) systems learn to treat those attributes similarly to how the protected class itself has been historically treated.

[2] *See* Will Douglas Heaven, *Bias Isn't The Only Problem With Credit Scores—and No, AI Can't Help*, MIT TECHNOLOGY REVIEW (June 17, 2021), https://www.technologyreview.com/2021/06/17/1026519/racial-bias-noisy-data-credit-scores-mortgage-loans-fairness-machine-learning/ (explaining that marginalized consumers tend to have less data in their credit histories, which creates inaccurate credit scores that AI systems use to produce inequitable outcomes).

and makes recommendations regarding how the Agencies should address those risks. We submit these comments separately to emphasize a few points on which the Agencies should provide clarification regarding how financial institutions and third parties must fulfill existing legal obligations when developing and using AI systems. Specifically, the Agencies should:

- Clarify through guidance and regulation that use of AI systems that embed bias violates legal antidiscrimination obligations, and provide guidance about how to identify and mitigate risks arising from different types of AI training data.
- Require financial institutions to be transparent to consumers about why and how their AI systems use their data, and to ensure that AI decision-making is explainable, so as to bridge the information and enforcement gaps that otherwise prevent plaintiffs from holding institutions liable for use of AI systems that violate fair lending and other laws.
- Make clear that financial institutions bear responsibility to ensure that third-party AI systems they use do not result in discrimination, and provide guidance on how small community institutions that lack technical or policy expertise can meaningfully scrutinize the AI systems they use.

AI systems must be designed to minimize discriminatory outcomes and expand access to economic opportunity, avoiding the use of biased data that does not reflect actual risk.
(This section addresses questions 4, 5, 6, 8, and 12.)

A variety of traditional and alternative data can inform credit and other consumer finance decisions positively or adversely. This data includes credit scores and credit history, income, employment history, educational data, criminal records, public records, account history and banking activity, spending patterns, debt balances, or web and app activity and communications.[3] The types of data that financial entities use vary across institutions or even across decisions within a single institution.[4]

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[3] Karen Hao, *The Coming War on The Hidden Algorithms That Trap People in Poverty*, MIT TECH. REVIEW (Dec. 4, 2020),
https://www.technologyreview.com/2020/12/04/1013068/algorithms-create-a-poverty-trap-lawyers-fight-back/;
FINREGLAB, THE USE OF CASH-FLOW DATA IN UNDERWRITING CREDIT 8 (2019), https://finreglab.org/wp-content/uploads/2019/07/FRL_Research-Report_Final.pdf.

[4] *See Equitable Algorithms: How Human-Centered AI Can Address Systemic Racism and Racial Justice in Housing and Financial Services: Hearing before the H. Comm. on Fin. Serv. Task Force on Artificial Intelligence*, 117th Cong. (2021) [hereinafter *Hearing on Equitable Algorithms*].

As a result, the quality of data used to develop AI systems is critical. As CDT and others have demonstrated, data used to train AI systems can reflect, find proxies for, or otherwise further entrench historical discrimination. An employer's algorithm-driven selection tool can reproduce hiring biases when it is trained to look for data that current employees have in common, filtering out applicants who do not resemble existing employees.[5] Government benefits systems have used algorithm-driven methods that arbitrarily reduce or terminate public benefits, obligating families to make an impossible choice between providing care and keeping up with expenses.[6] Law enforcement's use of predictive policing and algorithmic risk assessments have been shown to treat race, skin color, and disability as indicators of higher threat, leaving marginalized people with criminal records that are not a result of criminal behavior.[7] The use of AI systems in financial services is subject to the same risks of biases resulting from the underlying data. Moreover, the discriminatory outcomes of AI in these other domains can affect the employment, payment history, and criminal history on which consumer finance decisions traditionally rely. Thus, the data used to develop AI systems throughout the economy raises real risks of bias in consumer finance decisions on multiple levels.

As a mitigation measure, instead of a consumer or merchant's traditional credit history, some researchers have proposed using alternative data specific to a consumer or merchant's *current* financial circumstances, such as cash flow, recurring living expenses, online purchases, current job and income, and education.[8] In theory, AI systems that use such alternative data could produce more equitable outcomes than systems that rely only on credit scores, if the data is more analogous to the purpose for which services are rendered (e.g., rental payment history

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[5] CENTER FOR DEMOCRACY & TECHNOLOGY, ALGORITHM-DRIVEN HIRING TOOLS: INNOVATIVE RECRUITMENT OR EXPEDITED DISABILITY DISCRIMINATION? 5-6 (2020), https://cdt.org/wp-content/uploads/2020/12/Full-Text-Algorithm-driven-Hiring-Tools-Innovative-Recruitment-or-Expedited-Disability-Discrimination.pdf; MIRANDA BOGEN & AARON RIEKE, UPTURN, HELP WANTED: AN EXAMINATION OF HIRING ALGORITHMS, EQUITY, AND BIAS 29-36 (2018), https://www.upturn.org/static/reports/2018/hiring-algorithms/files/Upturn%20--%20Help%20Wanted%20-%20An%20Exploration%20of%20Hiring%20Algorithms,%20Equity%20and%20Bias.pdf.

[6] Hao, *supra* note 3; LYDIA X. Z. BROWN, ET AL., CENTER FOR DEMOCRACY & TECHNOLOGY, CHALLENGING THE USE OF ALGORITHM-DRIVEN DECISION-MAKING IN BENEFITS DETERMINATIONS AFFECTING PEOPLE WITH DISABILITIES 4 (2020), https://cdt.org/wp-content/uploads/2020/10/2020-10-21-Challenging-the-Use-of-Algorithm-driven-Decision-making-in-Benefits-Determinations-Affecting-People-with-Disabilities.pdf.

[7] Julia Angwin et al., Machine Bias, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing; Lydia X. Z. Brown & Ridhi Shetty, *Critical Scrutiny of Predictive Policing is a Step to Reducing Disability*, CENTER FOR DEMOCRACY & TECHNOLOGY (July 23, 2020), https://cdt.org/insights/critical-scrutiny-of-predictive-policing-is-a-step-to-reducing-disability-discrimination/.

[8] FINREGLAB, *supra* note 3.

may better predict the consistency of mortgage payments).[9] Some financial technology services claim they have expanded opportunity by extending credit offers based on merchant data such as sales history and business performance,[10] or consumer data such as education or employment.[11]

However, as the House Committee on Financial Services Task Force on Artificial Intelligence recently addressed, alternative data may still preclude equitable AI systems if the data is not examined for potential bias.[12] For example, recent reports explain that educational data can include average standardized test scores of incoming students, as well as post-graduation income levels that have not been adjusted for racial and other disparities.[13] Though the CFPB and FDIC have discouraged their use, these educational variables have resulted in higher student loan interest rates charged to graduates of minority-serving institutions than to graduates from other schools.[14] Thus, alternative data sources, while holding some promise, still need to be examined as potential sources of bias.

Moreover, the Agencies should make clear that merely adjusting or removing biased data will not completely remedy AI bias in consumer finance decisions. For example, some consumers who have lost their jobs due to the COVID-19 pandemic have been denied unemployment benefits because of flawed algorithmic systems and were consequently unable to afford rent and utility payments.[15] Falling behind on those payments hurt their credit scores and resulted in

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9 JUNG CHOI ET AL., URBAN INSTITUTE, FINTECH INNOVATION IN THE HOME PURCHASE AND FINANCING MARKET 4 (2019), https://www.urban.org/sites/default/files/publication/100533/fintech_innovation_in_the_home_purchase_and_financing_market_2.pdf.

10 Mary Ann Azevedo, *How Shopify Aims to Level the Playing Field with Its Machine Learning-driven Model of Lending*, TECHCRUNCH (April 28, 2021, 11:00 AM), https://techcrunch.com/2021/04/28/how-shopify-aims-to-level-the-playing-field-with-its-machine-learning-driven-model-of-lending/.

11 *See Hearing on Equitable Algorithms*, *supra* note 4 (testimony of Dave Girouard, CEO of Upstart), https://financialservices.house.gov/uploadedfiles/hhrg-117-ba00-wstate-girouardd-20210507.pdf (claiming that Upstart's model is more inclusive because it uses employment, education, and other data "beyond the FICO score"). *See also* STUDENT BORROWER PROTECTION CENTER, INEQUITABLE STUDENT AID 13 (2021), https://protectborrowers.org/wp-content/uploads/2021/03/SBPC_Inequitable-Student-Aid.pdf (describing the various types of alternative data, including employment and education).

12 *Hearing on Equitable Algorithms*, *supra* note 4.

13 STUDENT BORROWER PROTECTION CENTER, *supra* note 11, at 16; RELMAN COLFAX PLLC, FAIR LENDING MONITORSHIP OF UPSTART NETWORK'S LENDING MODEL 22-23 (2021), https://www.relmanlaw.com/media/cases/1088_Upstart%20Initial%20Report%20-%20Final.pdf.

14 RELMAN COLFAX PLLC, *supra* note 13, at 17, 21.

15 Hao, *supra* note 3.

eviction proceedings that were added to public records. As a result, flaws in the one set of AI algorithms led to negative data that in turn could cause adverse outcomes in future AI-driven credit assessments. However, the remedy for such scenarios is not simply removing these negative factors from consumers' records. That will only make consumers more "credit invisible," with little to no credit history. Consumers cannot access credit without a credit history, but they cannot build that history without access to credit. AI systems should be designed to affirmatively improve and expand access to financial services for historically marginalized communities.

The Agencies should clarify through guidance that AI systems that use biased data or that otherwise perpetuate bias violate fair lending laws. New guidance or regulations should specify the kind of data that should and should not be used to train AI systems or to make consumer finance decisions, defining legitimate purposes of financial AI systems and requiring institutions to only use the data needed to fulfill those purposes. Further, developers and users must be ready to explain how the use of alternative datasets, and the design of the system itself, benefits consumers.

Consumers and advocates are at a disadvantage when an AI systems' data inputs and designs are not sufficiently explainable so as to evaluate potential disparate impact.
(This section addresses questions 1, 2, 3, 11, 13, 14, 15, and 17.)

Across various uses of AI systems, consumers, researchers, and even entities who use or develop the systems can struggle to identify the reasons an opaque AI system resulted in an adverse action.[16] The lack of transparency and explainability creates significant and potentially insuperable obstacles for consumers to protect and vindicate their rights. Agencies should clarify through guidance, regulations, and enforcement that AI systems used for consumer financial decisions must be transparent and explainable.

Consumers need transparency about how AI systems will use their data before they are evaluated.

As the RFI mentions, the ECOA requires creditors to notify credit applicants of the principal

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[16] *See* AARON KLEIN, REDUCING BIAS IN AI-BASED FINANCIAL SERVICES, BROOKINGS INSTITUTION (2020), https://www.brookings.edu/research/reducing-bias-in-ai-based-financial-services/ (describing how AI-driven methods may be incompatible with the explainability that fair lending laws require); *supra* notes 5-7 (identifying areas where the lack of explainability harms consumers).

reasons for taking adverse action for credit or to provide applicants with a disclosure of their right to request these explanations. Applicants should be informed pre-application regarding the specific data that will be used to evaluate their applications, rather than receiving notice only after adverse actions. This is necessary so that applicants can provide supplemental information and verify that the data that will be considered is correct. When this data is inaccurate, consumers have little success in correcting it, even when they are able to communicate with a human to explain errors, provide context, and process corrections.[17]

AI systems should not be used for credit assessments and similar high-stakes tasks if its data use and design are not easily articulable and readily explained *at the design and deployment stages*. Designing for explainability is vital because post-hoc explanations are less reliable for retracing the relationships that the system identified to produce its results.[18] Post-deployment, failure to correct inaccuracies in credit records upon request violates the ECOA, but without knowing the data AI systems are using, consumers are unlikely to recognize errors in credit records that are affecting the systems' outcomes.[19] As human involvement decreases, the ability to trace adverse actions to flawed data diminishes even further.

Explainability is needed for challenging AI-driven practices under current law.

To demonstrate disparate impact in challenging a practice under the FHA, plaintiffs must demonstrate causality.[20] A plaintiff cannot rely on a statistical disparity to make their case without showing that a particular practice, such as the defendant's use of its AI system, caused the disparity.[21] In order to make this showing, plaintiffs need access to information and data to show the role that the AI system played in the challenged practice and how the system arrived at its output.

Further, to rebut a defense under the ECOA or the FHA that a practice satisfies a legitimate business interest, the plaintiff must demonstrate the existence of a less discriminatory alternative that would satisfy the same legitimate, nondiscriminatory business interest. When

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[17] Mitchell Clark, *Credit Agencies Can't Tell My Sister and Me Apart*, THE VERGE (May 12, 2021, 9:00 am), https://www.theverge.com/22421193/credit-reporting-infrastructure-errors-experian-equifax-transunion.

[18] Andrew D. Selbst and Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1113-15 (2018), https://ir.lawnet.fordham.edu/cgi/viewcontent.cgi?article=5569&context=flr.

[19] 12 C.F.R §1002.6(b)(6)(ii).

[20] Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Communities Project, 576 U.S. 519, 538-39 (2015).

[21] *Id.* at 539.

the practice is AI-driven, this may require the plaintiff to examine the AI system to discern whether its design is suited to its purpose, comparing it against other less discriminatory practices that satisfy the same business interest.[22] Absent robust transparency and explainability, consumers and advocates simply would not have the necessary insight into these systems to meet their legal burden and meaningfully challenge the use of these systems.

The Agencies must clarify that financial institutions are required to ensure the necessary explainability and set up robust enforcement mechanisms with clear, meaningful consequences.

The Agencies' model risk management principles can aid evaluation of AI systems for compliance with fair lending laws and provide for the necessary transparency and explainability.[23] To avoid harms caused by data-driven decision-making models, the Agencies' principles currently advise financial institutions to secure the necessary expertise to develop a model that fulfills an appropriate purpose as intended. The Agencies' principles advise financial institutions to establish effective controls and validation processes. They advise financial institutions to establish governance that ensures correct, appropriate, and limited use and that mitigates the model's weaknesses. The Agencies also recommend supplementing models' results with other information.

The Agencies' model risk management principles are generally consistent with the Civil Rights Principles for the Era of Big Data. Last year, CDT joined a coalition to update the Civil Rights Principles, which are intended to advance equity in the development of decision-making technologies.[24] The Civil Rights Principles call for decision-making technologies to ensure just outcomes, preserve constitutional rights, serve historically marginalized communities, collect and use personal data responsibly, enhance individual rights, and be accountable. To this end, the Agencies must expand on and enforce existing guidance to mandate transparency and explainability for AI systems, so that plaintiffs, researchers, advocates, and government bodies

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[22] *See* Deven R. Desai and Joshua A. Kroll, *Trust But Verify: A Guide To Algorithms And The Law*, 31 HARVARD J. LAW & TECH, at 9-10 (2017), https://jolt.law.harvard.edu/assets/articlePDFs/v31/31HarvJLTech1.pdf (explaining that a consumer's dignity in the algorithmic decision-making process requires "a meaningful technical way to look under the hood.")

[23] FED. DEPOSIT INS. CORP., FIL-22-2017, SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT (2017) [hereinafter SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT], https://www.fdic.gov/news/financial-institution-letters/2017/fil17022.pdf.

[24] LEADERSHIP CONFERENCE ON CIVIL & HUMAN RIGHTS, CIVIL RIGHTS PRINCIPLES FOR THE ERA OF BIG DATA (2020, https://www.civilrightstable.org/principles/.

can pinpoint why and how an AI system is causing disparate impact.[25]

As part of that guidance, Agencies should also make clear the importance of staffing decisions in increasing financial institutions' ability to ensure explainability goals are met. Financial institutions, both large and small, also claim they lack sufficient staff and resources to diagnose discrimination in their own or third-party AI systems, leaving discriminatory outcomes to go unchecked without proper channels for recourse.[26] Financial institutions with greater capacity often fail to recruit technical and policy experts who also have marginalized identities and therefore better anticipate discriminatory impacts of AI systems and better understand what is necessary to make those systems explainable and transparent.[27] Both expertise and lived experience are necessary to achieve the degree of explainability that enables a meaningful examination of an AI system's disparate impact.

Further, the Agencies must commit to robust enforcement. Without material consequences for failing to align AI model management with the aforementioned principles, consumers will continue to carry a disproportionate burden in disparate impact claims. Current remedies are insufficient. For instance, the CFPB's use of No-Action Letters (NALs) fails to adequately protect consumers. In practice, NALs offer a temporary safe harbor exempting recipients from regulatory compliance.[28] One financial AI service that uses education data, as described above, received an initial NAL from the CFPB in 2017 and a renewed NAL in 2020, each in effect for three years.[29] Despite reports in 2020 regarding the discriminatory impact of using education data, the AI service is shielded until 2023.[30]

The Agencies' principles advise financial institutions to provide internal incentives for analyzing

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[25] *See* Anya Prince and Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1311-13 (2020), https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3572098_code499486.pdf?abstractid=3347959&mirid=1&type=2 (describing how transparency-oriented reforms can help these stakeholders isolate the subsets or aspects of AI systems that are causing certain disparate impacts).

[26] *See Hearing on Equitable Algorithms*, *supra* note 4.

[27] MAJORITY STAFF OF H. COMM. ON FIN. SERV., 116TH CONG., REP. ON DIVERSITY AND INCLUSION: HOLDING AMERICA'S LARGE BANKS ACCOUNTABLE 43-44 (2020), https://docs.house.gov/meetings/BA/BA13/20200212/110498/HHRG-116-BA13-20200212-SD003-U1.pdf.

[28] Policy on No-Action Letters, 84 Fed. Reg. 48,229 (Sept. 13, 2019). The 2019 amendments to the NAL policy removed the previously required disclaimer that stated that an NAL does not grant a safe harbor.

[29] Consumer Financial Protection Bureau, No-Action Letter to Upstart (Nov. 30, 2020), https://files.consumerfinance.gov/f/documents/cfpb_upstart-network-inc_no-action-letter_2020-11.pdf.

[30] RELMAN COLFAX PLLC, *supra* note 13, at 24.

and validating AI systems, but the institutions' management must themselves be incentivized to do so. A recent FICO survey revealed that most financial sector executives either do not understand their companies' AI systems or do not prioritize responsible AI practices.[31] The NALs and principles guide improvements to AI systems, but they do not provide for accountability without enforcement. Therefore, the Agencies should directly scrutinize each financial institution's use of AI systems, test the models themselves, and establish and enforce standardized transparency and explainability rules.

Financial institutions who use third-party AI services cannot hide behind those third parties to evade responsibility for the inputs and impact of the AI systems.
(This section addresses questions 9, 10, and 16.)

In many cases, financial institutions may rely on AI developed and/or operated by third parties. Agencies should make explicit that this does not absolve them of responsibility. Regardless of institutional size, capacity, and technical expertise, the Agencies have recognized that senior management is responsible for ensuring a critical analysis of their AI system's limitations, assumptions, and potential improvements takes place.[32] When those systems or capabilities are provided by third parties, financial institutions are responsible for assessing risks arising from those third-party relationships, doing due diligence in selecting third-party partners, managing contract structuring, and overseeing quality control of third-party services.[33] The Agencies' guidance should expressly state that financial institutions' responsibility extends to third-party AI services.

That responsibility should extend to situations in which it may not be obvious that AI is being used. For example, when using social media platforms to advertise, financial institutions should take into account the impact of algorithm-based targeted advertising on consumers' access to financial services. The Agencies should recognize that social media platforms sometimes target

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[31] *New Report from Corinium and FICO Finds that Lack of Urgency Around Responsible AI Use is Putting Most Companies at Risk*, PRNEWSWIRE (May 25, 2021, 8:00 PM), https://www.prnewswire.com/news-releases/new-report-from-corinium-and-fico-finds-that-lack-of-urgency-around-responsible-ai-use-is-putting-most-companies-at-risk-301298434.html.

[32] SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT, *supra* note 23.

[33] FED. DEPOSIT INS. CORP., FIL-19-2019, TECHNOLOGY SERVICE PROVIDER CONTRACTS (2019), https://www.fdic.gov/news/financial-institution-letters/2019/fil19019.pdf (directing financial institutions' management to consult the Agencies' Guidance for Managing Third-party Risk and examination booklets on principles for supervision of and outsourcing to technology service providers).

ads based on proxies for protected traits.[34] Like the Federal Trade Commission, the Agencies must warn financial institutions and third-party AI services against using AI to target advertising in ways that may lead to disparate impact in lending patterns under fair lending laws.[35] With respect to targeted advertising, the FHA prohibits advertisements that indicate a discriminatory preference, and the ECOA prohibits entities who regularly refer applicants to creditors from doing so on a discriminatory basis.[36]

Some third-party AI services are subject to their own obligations under fair lending laws. These services that develop or implement AI systems on behalf of financial institutions could be liable under the ECOA as entities who participate in credit decisions or refer applicants or prospective applicants to creditors.[37] They could be liable under the FHA as entities who make mortgage loans and impose terms and conditions for them.[38] And they could be liable under the FCRA as entities who evaluate and assemble consumer information used to determine eligibility for certain financial services.[39]

Smaller community institutions that lack technical and policy expertise and capacity altogether cannot overcome regulatory barriers to compete with large financial institutions. Although some have suggested this requires regulatory changes to make it easier for AI providers to partner with community institutions, regulations must be clarified, not eased.[40] Community institutions and third-party AI services have a joint responsibility for ensuring that their systems comply with fair lending laws. Since community institutions may depend far more on third-party AI systems, they must be able to use these systems without evading their due diligence obligations.

The Agencies should empower community institutions in particular to manage risk in third-party AI systems by guiding and facilitating audits. New guidance must provide for community

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[34] Desai, *supra* note 22, at 18-19.

[35] FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? UNDERSTANDING THE ISSUES FTC REPORT, FEDERAL TRADE COMMISSION (2016), at 20-21, https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf.

[36] 12 C.F.R §1002.2(l); 42 U.S.C §3604(c).

[37] 12 C.F.R §1002.2(l).

[38] 24 C.F.R §100.120.

[39] 15 U.S. Code § 1681a(d)-(f).

[40] *See Hearing on Equitable Algorithms*, *supra* note 4. Upstart's CEO Dave Girouard agreed with Rep. Barry Loudermilk that a big concern of small financial institutions is that too much time and due diligence are needed every time they want to form a partnership with a third-party AI service.

institutions to connect with external technical and policy expertise. It must articulate specific factors and inquiries that community institutions should incorporate into selecting and regularly reviewing the third-party AI systems they use. The Agencies can also explore certification or similar processes to incentivize financial institutions and third-party AI services to proactively examine their compliance.

Conclusion

CDT strongly encourages the Agencies to clarify regulations to ensure that AI systems are designed at the front-end to produce equitable outcomes and then proactively tested for disparate impact and compliance with fair lending laws. Financial institutions must be responsible for the purposes for which their AI systems are used, the training data they use, the expertise needed to design and examine the systems, and their impact on consumers who have historically been barred from economic opportunity. The Agencies need to back up their regulations and guidance with robust enforcement mechanisms to ensure compliance.

Respectfully submitted,

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