Negative: GSE Credit Model

By “Coach Vance” Trefethen

***Resolved: The United States federal government substantially reform the use of Artificial Intelligence technology***

Case Summary: The AFF plan changes the criteria used to evaluate loan applications for Government Sponsored Enterprises (GSEs). These are also known as “Freddie Mac” (Federal Home Loan Mortgage Corporation, FHLMC) and “Fannie Mae” (Federal National Mortgage Association, FNMA). These are government-created semi-privatized entities that buy mortgages from commercial lenders. They repackage the loans and sell them as mortgage-backed securities. They are immense corporations and are expected to be bailed out by the federal government if things go wrong, as they did in 2008 during the financial/housing crisis, in order to stabilize the economy and the housing market. The federal government’s goal in establishing these agencies was to stimulate home ownership for more Americans by providing federal guarantees that mortgages would be paid if borrowers defaulted.
 Status Quo uses the FICO score to evaluate loan risk, which is the commonly known “credit score” that everyone has heard of. AFF wants them to use more advanced systems involving AI. GSEs are already considering updating their credit scoring system, and they just need to finish studying it before the changes will be made. And Freddie Mac is already testing AI.

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Negative: GSE Credit Model

NEGATIVE GOAL / CRITERIA – 8 criteria for a good GSE credit scoring model (7 in first card + 1 in second card)

#1) Expanded credit access + 5 criteria for impact on consumers and GSE operations + #7) Reducing impact of medical debt

National Consumer Law Center 2019. (nonprofit organization headquartered in Boston, Massachusetts, specializing in consumer issues on behalf of low-income people. Legal services, government and private attorneys, as well as community organizations, work with the center to advocate for consumer reform ) 21 Mar 2019 “Re: Comments/RIN 2590-AA98, Validation and Approval of Credit Score Models” <https://www.nclc.org/images/comments-fhfa-credit-scoring-models.pdf> (accessed 25 Nov 2021)

As with the previous December 2017 Request for Input of Credit Scoring Models, we urge FHFA to equally consider the needs of and impact on consumers and to do so throughout the entire process of approving or rejecting a scoring model. FHFA’s website highlights stability and access in the housing finance market as two agency missions; incorporating the needs of consumers into the development of the proposed rule will help meet those goals. First, one of the explicit criteria for the initial credit score assessment should be whether a scoring model will expand access to mortgage credit for borrowers. [**END QUOTE]** Nowhere in either the Credit Score Assessment or Enterprise Business Assessment is there any consideration of this critical factor. FHFA does request comment on whether it should include this factor in the fair lending assessment with respect to expanding access to credit for protected classes. However, we think this consideration should be in the initial credit score assessment as a factor in any of the approaches for evaluating test results. Thus, for example, the Comparison-Based Approach should evaluate whether a new credit model produced scores that are more accurate or just as accurate but approve more borrowers than the old model. If FICO 9 has the same accuracy rate as Classic FICO but approves more borrowers without losing any predictiveness, then the GSEs should approve FICO 9. [**THEY GO ON LATER IN THE CONTEXT QUOTE**:] Second, impact on consumers should be explicitly included in the Enterprise Business Assessment. Proposed § 1254.8(b) lists five criteria for this assessment, including (1) accuracy & reliability; (2) fair lending assessment; (3) impact on GSE operations and risk management, and impact on industry; (4) competitive effects; and (5) third-party vendor review. We believe that criteria (3) should also include impact on consumers. Thus, the cost-benefit analysis discussed on criteria (3), proposed § 1254.8(b)(3), should not be limited to the benefits to the GSEs, industry operations and mortgage market liquidity, but should also include benefits to consumers in terms of greater access to mortgage credit and lower costs for borrowers. Third, benefit to consumers should explicitly include reducing the unfair impact of medical debt. Medical debt has tremendous impact on credit reports and scores, affecting one in five consumers with a credit report. As the Consumer Financial Protection Bureau has found, medical debt unfairly penalizes a consumer’s credit score by 10 points, and for a medical debt collection item that is subsequently paid, by up to 22 points (i.e. the consumer’s credit score should actually be 10 points or 22 points higher). In addition, as discussed in our comments on the December 2017 RFI on Credit Scoring Models, medical debt also has a racially disparate impact. Reducing its harm by updating to FICO 9 may also help with the yawning racial divides in mortgage lending.

And there’s an 8th criterion: Modeling for economic disruptions due to Covid and similar events is absolutely critical

RiskSpan 2020 (technology consulting firm in the residential mortgage and mortgage-backed securities industry) 11 May 2020 “Changes to Loss Models…and How to Validate Them” <https://riskspan.com/author/riskspan/page/5/> (accessed 25 Nov 2021)

Modelers have now been grappling with how COVID-19 should affect assumptions and forecasts for nearly two months. This exercise is raising at least as many questions as it is answering. No credit model (perhaps no model at all) is immune. Among the latest examples are mortgage servicers having to confront how to bring their forbearance and loss models into alignment with new realities. These new realities are requiring servicers to model unprecedented macroeconomic conditions in a new and changing regulatory environment. **[END QUOTE]** The generous mortgage forbearance provisions ushered in by March’s CARES Act are not tantamount to loan forgiveness. But servicers probably shouldn’t count on reimbursement of their forbearance advances until loan liquidation (irrespective of what form the payoff takes). The ramifications of these costs and how servicers should modeling them is a central topic to be addressed in a Mortgage Bankers Association webinar on Wednesday, May 13, “Modeling Forbearance Losses in the COVID-19 world” (free for MBA members). RiskSpan CEO Bernadette Kogler will lead a panel consisting of Faith Schwartz, Suhrud Dagli, and Morgan Snyder in a discussion of the forbearance’s regulatory implications, the limitations of existing models, and best practices for modeling forbearance-related advances, losses, and operational costs. Models, of course, are only as good as their underlying data and assumptions. When it comes to forbearance modeling, those assumptions obviously have a lot to do with unemployment, but also with the forbearance take-up rate layered on top of more conventional assumptions around rates of delinquency, cures, modifications, and bankruptcies. [**THEY GO ON LATER IN THE CONTEXT QUOTE:]** The unique nature of this crisis requires modelers to expand their horizons in search of applicable data. For example, GSE data showing how delinquencies trend in rising unemployment scenarios might need to be supplemented by data from Greek or other European crises to better simulate extraordinarily high unemployment rates. Expense and liquidation timing assumptions will likely require looking at GSE and private-label data from the 2008 crisis. Having reliable assumptions around these is critically important because liquidity issues associated with servicing advances are often more an issue of timing than of anything else.

Affirmative burden

It’s up to the Affirmative to prove with evidence they meet these 8 criteria, since it’s their burden of proof to win a change in policy. If they don’t prove all of these, you should vote Negative and wait for a better policy to be developed. And we’ll show you that this is already underway in our Inherency arguments.

TOPICALITY

1. No substantial reform

Status Quo already uses AI for mortgage credit scoring

Jeff Kauflin 2020 (journalist) FORBES 18 Nov 2020 “New Freddie Mac Partnership Will Mean ‘Tens Of Thousands Of New Mortgages Per Year For People Of Color,’ Says Zest AI CEO” <https://www.forbes.com/sites/jeffkauflin/2020/11/18/zest-ai-inks-deal-with-freddie-mac-to-boost-mortgage-approvals/?sh=dd806dc12a02> (accessed 25 Nov 2021)

Freddie Mac, the company created by the U.S. government in 1970 to fund mortgages and increase home ownership, [will start](https://www.prnewswire.com/news-releases/zest-ai-joins-forces-with-freddie-mac-to-help-make-homeownership-possible-for-more-americans-301176336.html) using fintech company Zest AI to help assess the risk of people defaulting on their mortgages. Freddie Mac funded [1.3 million](http://www.freddiemac.com/perspectives/david_brickman/20201029_financial_results_3q2020.page) U.S. mortgages in the third quarter of 2020 alone.  Founded in 2009, Los Angeles-based Zest uses artificial intelligence to try to help lenders approve more loans (without increasing defaults), approve them faster and reduce racial discrimination.

INHERENCY

1. Status Quo will update when studies are completed

They need more time to study alternative credit models, and they’re studying it right now

Jann Swanson 2020. (journalist) Fannie/Freddie Adopt Not-so-New Credit Score Model 12 Nov 2020 MORTGAGE NEWS DAILY <http://www.mortgagenewsdaily.com/11122020_credit_scoring_gses.asp> (accessed 24 Nov 2021)

The Federal Housing Finance Agency (FHFA) announced on Tuesday that it has validated and reapproved the Classic FICO credit score model for use by Fannie Mae and Freddie Mac for assessing the creditworthiness of mortgage borrowers. The Agency said this would allow the GSEs "to continue supporting the mortgage market while assessing more modern credit score models that were submitted in response to the 2020 Joint Enterprise Credit Score Solicitation."

GSEs will update their credit model when the studies are completed

Jann Swanson 2020. (journalist) Fannie/Freddie Adopt Not-so-New Credit Score Model 12 Nov 2020 MORTGAGE NEWS DAILY <http://www.mortgagenewsdaily.com/11122020_credit_scoring_gses.asp> (accessed 24 Nov 2021)

Both GSEs had said the solicitation itself was merely the first of four phases described in the FHFA final rule on the validation and approval of third-party credit score model(s) that the GSEs can use. Its deadline for submissions of contenders was September 15 which brought the GSEs and their regulator hard up against the November 20 deadline imposed for the credit model decision by the 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act. FHFA called the approval of the FICO product an incremental step in meeting the requirements of the Act. It said it expects it will take the GSEs an additional year to complete the validation and approval process of the remaining credit score models submitted in response to the solicitation.

Freddie Mac (one of the GSE’s) is testing AI now

Rachel Stone 2019 (journalist) 24 Sept 2019 “Freddie Mac testing underwriting software that uses alternative data” <https://www.spglobal.com/marketintelligence/en/news-insights/trending/jkbrpm42jgcvganwk_lu1w2> (accessed 25 Nov 2021)

One of the U.S.'s largest housing finance firms is testing alternative data to better evaluate borrowers seeking to secure a mortgage. Freddie Mac has been using underwriting software from financial technology firm ZestFinance Inc., a partnership first reported by *The Wall Street Journal*. That software, which looks at data beyond the traditional credit score and purports to evaluate it differently, could make mortgages more available for certain applicants, including first-time home buyers and minorities, said people familiar with the matter. The Los Angeles, Calif.-based startup develops artificial intelligence software to enable financial companies to access thousands of additional data sources to better evaluate the risk that an applicant will not repay a loan. Whereas conventional methods of credit scoring rely on about 20 to 50 variables, artificial intelligence can consume an infinite number of variables and is more resilient to data that might be messy or not always accurate, a person familiar with the matter said. ZestFinance has launched models with tens of thousands of variables.

HARMS / SIGNIFICANCE

1. No one harmed with Status Quo credit scores

Status Quo FICO scores aren’t hurting anyone and alternatives would be worse

Joanne Gaskin 2015 (Senior Director, Scores & Analytics at FICO) 18 Dec 2015 “FICO: There is no Monopoly on the GSEs Credit Scoring Model” <https://themreport.com/news/government/12-18-2015/fico-there-is-no-monopoly-on-the-gses-credit-scoring-model> (accessed 24 Nov 2021)

The implication that the GSEs use of the FICO Score is locking potential buyers out is without merit. Today, 190 Million consumers receive a FICO Score. There are an additional 28 Million consumers that have information at the three major credit bureaus but no not obtain a FICO Score for the following reasons: inactive credit” (e.g. 3-4 years since any account was last updated), “collection-only” (i.e., this is the only information in their credit file), or they have only a single account that is “too new” (less than 6 months payment history). Scoring these individuals is not only analytically unsound but will lock many consumers into low scores effectively freezing them out of mainstream credit. It is punitive to return a low score to these consumers whose credit status is frozen in time – often as a result of a period of prior financial distress. Furthermore, returning a score for consumers who have a single tradeline less than 6 months old or have collection-only information in their credit files will not qualify them for a mortgage. Lastly, a consumer without a credit score can avail themselves of the GSEs manual underwriting process as a pathway to homeownership.

SOLVENCY

1. More study needed

Before AI can be used for credit scoring, it has to be tested to prove itself on the issue of bias using outcome-focused testing

Talia Gillis 2019 (Empirical Law and Finance Fellow and SJD Candidate, Harvard Law School. PhD Candidate in Business Economics, Department of Economics and Harvard Business School) 1 Nov 2019 “False Dreams of Algorithmic Fairness” <https://www.forbes.com/sites/jeffkauflin/2020/11/18/zest-ai-inks-deal-with-freddie-mac-to-boost-mortgage-approvals/?sh=dd806dc12a02> (accessed 25 Nov 2021)

I end the Article by discussing possible paths forward. I argue that regulators should develop a framework for an ex ante consideration of the effects of an algorithmic pricing rule. This can be achieved by applying a credit pricing rule, before it is used by a lender, to a dataset of hypothetical lenders. The regulator can then examine the outcomes of the pricing rule to determine whether the pricing rule discriminates. This type of outcome-focused testing brings to the forefront the demonstration of disparities, which is formally part of the first stage of a disparate impact complaint in traditional fair lending law. My proposed testing framework develops this type of analysis and adapts it to the machine learning context.

AI credit models MUST be tested first to prove they’re not more discriminatory than status quo methods

National Consumer Law Center 2021 (non-profit specializing in low-income consumer issues, with an emphasis on consumer credit. NCLC provides legal and technical consulting and assistance on consumer law issues to legal services, government, and attorneys representing low-income consumers ) 1 July 2021 “Re: Request for Information and Comment on the Financial Institutions’ Use of Artificial Intelligence, Including Machine Learning“ <https://www.nclc.org/images/pdf/credit_reports/comments_RFI_AI.pdf> (accessed 25 Nov 2021)

The disparate impact standard is flexible enough to respond to the latest innovations in the credit market, as it has in the past. Under the three-step analysis, if testing of an AI model used in underwriting reveals that it disproportionately disadvantages a protected class, and produces inaccurate results that are not predictive of credit quality, there is not a legitimate business justification for using such a model. Moreover, even if the AI model were accurate and predictive, it could be that a more traditional credit assessment is a less discriminatory alternative. The Agencies should require financial institutions to test AI models used in underwriting and other parts of the credit transaction to ensure the outputs are empirically derived, statistically sound and accurately predict risk or achieve other valid objectives.

Unanswered questions and exaggerated claims for AI in the lending industry

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The lack of a definition for AI, combined with the lack of transparency, may create consumer protection issues. Since we don’t know what companies actually use when they claim to employ AI, we don’t know if they are making exaggerated claims to create an impression of accuracy and sophistication. For example, many consumers have experienced chatbots supposedly using AI that make nonsensical responses. This leads to some fundamental questions about the use of AI in financial services: How do we evaluate if the AI is actually an improvement or effective for the purpose for which it is being used? Who is evaluating if an AI model is predictive or even functional? For regulated financial institutions, it would be the prudential regulator’s role to examine AI used for credit underwriting and risk management—we certainly hope that the examiners will be focused on this. But we urge that examinations not be limited to those areas, and that the Agencies examine the use of AI for other purposes such as customer service, servicing, and collections. The CFPB should examine the use of AI by other non-bank supervised entities (such as mortgage and student loan servicers and debt collectors) to assess the impact on consumers— especially for racial disparities.

More study is needed to determine the best ways to protect against discrimination in lending using machine learning

Talia Gillis 2019 (Empirical Law and Finance Fellow and SJD Candidate, Harvard Law School. PhD Candidate in Business Economics, Department of Economics and Harvard Business School) 1 Nov 2019 “False Dreams of Algorithmic Fairness” <https://www.forbes.com/sites/jeffkauflin/2020/11/18/zest-ai-inks-deal-with-freddie-mac-to-boost-mortgage-approvals/?sh=dd806dc12a02> (accessed 25 Nov 2021)

Given the unsuitability of input-based approaches in the algorithmic setting, there is a need to rethink how to analyze discrimination in the algorithmic setting. This is true for both disparate treatment and disparate impact. For disparate treatment, we have no reliable way to detect proxies for protected characteristics. For disparate impact, we need new tools to evaluate the effects of algorithmic pricing that are appropriate for machine learning, as restricting variables upstream can have a limited or surprising effect on the disparities downstream. One challenge in developing an outcomes-based test is that there are currently widespread and far-reaching disagreements over the theoretical foundations and boundaries of the discrimination doctrine. The exact details about the implementation of the test rely on a clear definition of what discrimination law aims to achieve.

Example: Lender “Upstart” rolled out an AI model after telling the government it was unbiased… and then we found out it was biased – because no outside study was done first

National Consumer Law Center 2021 (non-profit specializing in low-income consumer issues, with an emphasis on consumer credit. NCLC provides legal and technical consulting and assistance on consumer law issues to legal services, government, and attorneys representing low-income consumers ) 1 July 2021 “Re: Request for Information and Comment on the Financial Institutions’ Use of Artificial Intelligence, Including Machine Learning“ <https://www.nclc.org/images/pdf/credit_reports/comments_RFI_AI.pdf> (accessed 25 Nov 2021)

Despite Upstart’s claims that there was no unlawful discriminatory impact in Upstart’s systems, the Student Borrower Protection Center (SBPC) identified in February 2020 that Upstart’s AI model charged higher interest rates to hypothetical students who attended community colleges, historically black colleges and universities (HBCUs), and Hispanic serving institutions (HSIs).30 SBPC used hypothetical applicants, identical in every way except for their higher education institution, to ascertain that the interest rates increased based on what type of school the borrower attended. As SBPC warned in that report, “[B]y considering the college or university attended by the consumer, a lender may capture disparate patterns in college attendance across class and race, thereby introducing bias in the underwriting process.” That bias had infected Upstart’s AI. Upstart failed to adequately police its own technology for discriminatory impact. And, as SBPC’s report illustrated, despite Upstart’s claims that its AI model yielded higher acceptance rates for borrowers of color than traditional models, those same borrowers were charged more than similarly situated white borrowers which still resulted in a discriminatory impact. The CFPB failed to independently test Upstart’s assertions, instead relying on the representations of the company rather than conducting its own analysis.

2. Bad data

The information used by “Big Data” to develop their models in the lending industry is full of errors

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Leveraging new types of data and analytical techniques could potentially benefit consumers. However, both traditional and alternative data reflect deeply ingrained structural inequalities in education, employment, housing and access to credit. Some forms of alternative data also raise additional concerns regarding accuracy, relevance and predictability, and how data used in these models could potentially worsen existing disparities. Non-financial Big Data, for example, including web browsing history, social media profile, and friends and family data may not be accurate or predictive of credit quality. An NCLC report on Big Data highlighted that information collected on consumers by four data brokers was riddled with errors. The information was often inaccurate and incomplete and primarily gathered without the consumer’s knowledge. There was no easy mechanism for consumers to dispute the accuracy of the information.

DISADVANTAGES

1. Worse for minorities – the Fuster Study

Application of Machine Learning to mortgage lending will discriminate against minorities

Andreas Fuster, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther 2018. (Fuster: Swiss National Bank. Goldsmith-Pinkham: Yale School of Management. Ramadorai: Imperial College London and CEPR. Walther: Imperial College London. ) Nov 2018 “Predictably Unequal? The Effects of Machine Learning on Credit Markets” <https://www.gc.cuny.edu/CUNY_GC/media/CUNY-Graduate-Center/PDF/Programs/Economics/Other%20docs/SSRN-id3072038.pdf> (accessed 25 Nov 2021)

We confirm that the machine learning technology delivers significantly higher out-ofsample predictive accuracy for default than the simpler logistic models. However, we find that predicted default propensities across race and ethnic groups look very different under the more sophisticated technology than under the simple technology. In particular, while a large fraction of borrowers belonging to the majority group (e.g., White non-Hispanic) gain, that is, experience lower estimated default propensities under the machine learning technology than the less sophisticated logit technology, these benefits do not accrue to the same degree to some minority race and ethnic groups (e.g., Black and Hispanic borrowers).

Machine Learning credit scoring creates a significant penalty associated with being a minority

Andreas Fuster, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther 2018. (Fuster: Swiss National Bank. Goldsmith-Pinkham: Yale School of Management. Ramadorai: Imperial College London and CEPR. Walther: Imperial College London. ) Nov 2018 “Predictably Unequal? The Effects of Machine Learning on Credit Markets” <https://www.gc.cuny.edu/CUNY_GC/media/CUNY-Graduate-Center/PDF/Programs/Economics/Other%20docs/SSRN-id3072038.pdf> (accessed 25 Nov 2021)

We find that the machine learning model is predicted to provide a slightly larger number of borrowers access to credit, and to marginally reduce disparity in acceptance rates (i.e., the extensive margin) across race and ethnic groups in the borrower population. However, the story is different on the intensive margin—the crossgroup disparity of equilibrium rates increases under the machine learning model relative to the less sophisticated logistic regression models. This is accompanied by a substantial increase in within-group dispersion in equilibrium interest rates as technology improves. This rise is virtually double the magnitude for Black and White Hispanic borrowers under the machine learning model than for the White non-Hispanic borrowers, i.e., Black and Hispanic borrowers get very different rates from one another under the machine learning technology. For a risk-averse borrower behind the veil of ignorance, this introduces a significant penalty associated with being a minority.

Fuster Study methodology – data is specific to US mortgage market

Andreas Fuster, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther 2018. (Fuster: Swiss National Bank. Goldsmith-Pinkham: Yale School of Management. Ramadorai: Imperial College London and CEPR. Walther: Imperial College London. ) Nov 2018 “Predictably Unequal? The Effects of Machine Learning on Credit Markets” <https://www.gc.cuny.edu/CUNY_GC/media/CUNY-Graduate-Center/PDF/Programs/Economics/Other%20docs/SSRN-id3072038.pdf> (accessed 25 Nov 2021)

Armed with the intuition from our simple models, we therefore go to the data to understand the potential effects of machine learning on an important credit market, namely, the US mortgage market. We rely on a large administrative dataset of close to 10 million US mortgages originated between 2009 and 2013, in which we observe borrowers’ race, ethnicity, and gender, as well as mortgage characteristics and default outcomes. We estimate a set of increasingly sophisticated statistical models to predict default using these data, beginning with a simple logistic regression of default outcomes on borrower and loan characteristics, and culminating in a Random Forest machine learning model (Ho, 1998; Breiman, 2001).

A/T “Non-unique because Status Quo has bias already” – But AI bias is worse: It’s undetectable and will go unchallenged

National Consumer Law Center 2021 (non-profit specializing in low-income consumer issues, with an emphasis on consumer credit. NCLC provides legal and technical consulting and assistance on consumer law issues to legal services, government, and attorneys representing low-income consumers ) 1 July 2021 “Re: Request for Information and Comment on the Financial Institutions’ Use of Artificial Intelligence, Including Machine Learning“ <https://www.nclc.org/images/pdf/credit_reports/comments_RFI_AI.pdf> (accessed 25 Nov 2021)

Financial institutions’ use of AI models may lead to unlawful discrimination and abusive practices in the credit process, including in underwriting, pricing, and credit decisions. Machine learning, the most powerful form of artificial intelligence, heightens this risk because it makes non-intuitive connections using large volumes of data that result in decisions that may not be readily understandable or explainable in an adverse action notice. Discriminatory credit practices will go unrecognized and unchallenged.

2. Housing Market Crash II. If you try to beat Disad-1 about racial bias, you’ll end up with Disad-2

Blattner Study finds: Flawed data leads to bad decisions by AI

Edmund L. Andrews 2021 (former economics reporter for [The New York Times](https://en.wikipedia.org/wiki/The_New_York_Times) who served as a technology reporter in Washington, European economics correspondent and Washington economics correspondent) 6 Aug 2021 How Flawed Data Aggravates Inequality in Credit <https://hai.stanford.edu/news/how-flawed-data-aggravates-inequality-credit> (accessed 25 Nov 2021)

Banks and other lenders are turning to artificial intelligence to develop increasingly sophisticated models for scoring credit risk. But even though credit-scoring companies are legally prohibited from considering factors like race or ethnicity, critics have long worried that the models contain hidden biases against disadvantaged communities, limiting their access to credit. Now [a preprint study](https://arxiv.org/abs/2105.07554) in which researchers used artificial intelligence to test alternative credit-scoring models finds that there is indeed a problem for lower-income families and minority borrowers: The predictive tools are between 5 and 10 percent less accurate for these groups than for higher-income and non-minority groups.
**END QUOTE. HE GOES ON LATER IN THE ARTICLE TO WRITE QUOTE:**

“We’re working with data that’s flawed for all sorts of historical reasons,” says [Laura Blattner](https://www.gsb.stanford.edu/faculty-research/faculty/laura-blattner), an assistant professor of finance at the [Stanford Graduate School of Business](https://www.gsb.stanford.edu/), who co-authored the new study with Scott Nelson of the University of Chicago Booth School of Business.

Blattner Study finds AI can’t overcome minority bias except by knowingly giving loans to people with low credit scores

Edmund L. Andrews 2021 (former economics reporter for [The New York Times](https://en.wikipedia.org/wiki/The_New_York_Times) who served as a technology reporter in Washington, European economics correspondent and Washington economics correspondent) 6 Aug 2021 How Flawed Data Aggravates Inequality in Credit <https://hai.stanford.edu/news/how-flawed-data-aggravates-inequality-credit> (accessed 25 Nov 2021)

Some experts have argued that the algorithms run into trouble because financial institutions are legally prohibited from incorporating factors like ethnicity, gender, or race into their models. Those prohibitions are intended to prevent discrimination, but they can also block lenders from recognizing differences between groups that might actually elevate some borrowers’ credit scores. The study finds that is not a problem.  Even when Blattner and Nelson created scoring models that were fine-tuned to minority and low-income borrowers, the scores were still less accurate for those groups. There is no simple solution, Blattner says. But one possible strategy would be for financial companies to run experiments in which they approve loans to people with relatively low credit scores. “If you’re a bank, you could give loans to people and see who pays,” says Blattner. “That’s exactly what some fin-tech companies are doing: giving loans and then learning.”

Link: GSEs are led by incompetents and doing risky behavior

Meghan Milloy 2017 (Director of Financial Services Policy at the American Action Forum) 28 Sept 2017 “FANNIE MAE AND FREDDIE MAC AND THE NEED FOR REFORM” <https://www.americanactionforum.org/solution/fannie-mae-freddie-mac-need-reform/#ixzz7DGlBeEHR> (accessed 25 Nov 2021)

Fifth, policymakers must ensure that history does not repeat itself in the housing finance market. More specifically, reform should promote best practices within FHFA and should work to bolster a strong, competitive primary market. Just two years ago, nearly seven years after the GSEs went into conservatorship, [the FHFA reported](https://fhfaoig.gov/Content/Files/EVL-2015-004_0.pdf) that the two were still engaging in risky behavior that could put taxpayers and the economy at risk. Let’s not forget that between 1998 and 2004, the Office of Federal Housing Enterprise Oversight (OFHEO) – then the regulator of the GSEs – found that Enron-style accounting at Fannie Mae had resulted in $10.6 billion in losses. More recently, FHFA reported that Fannie Mae hired an employee unqualified to be its chief auditor, and FHFA failed to act.

Impact: Low credit score lending = Either massive taxpayer cost from another bailout like during the 2008 crash… or systemic financial market crash if GSE’s are allowed to fail

Meghan Milloy 2017 (Director of Financial Services Policy at the American Action Forum) 28 Sept 2017 “FANNIE MAE AND FREDDIE MAC AND THE NEED FOR REFORM” <https://www.americanactionforum.org/solution/fannie-mae-freddie-mac-need-reform/#ixzz7DGlBeEHR> (accessed 25 Nov 2021)

There were several flaws in the securitization and collateralization process that made things worse. Fannie Mae and Freddie Mac, as well as Countrywide and other private label competitors, lowered the credit quality standards of the mortgages they securitized. A mortgage-backed security was therefore “worse” during the crisis than in the preceding years because the underlying mortgages were generally of poorer quality. This turned a bad mortgage into a worse security. Mortgage originators took advantage of these lower credit quality securitization standards and the easy flow of credit to relax the underwriting discipline in the loans they issued. As long as they could resell a mortgage to the secondary market, they didn’t care about quality. In addition to feeding poorly originated mortgages into the system, the GSEs proved to be so deeply interconnected with the broader financial system that policymakers were forced to step in to prevent their failure. In September 2008, the Federal Housing Finance Agency (FHFA) put  Fannie Mae and Freddie Mac into conservatorship. Policymakers in effect promised that “the line would be drawn between debt and equity,” such that equity holders were wiped out, but GSE debt would be worth 100 cents on the dollar. They made this decision because banking regulators (and others) treated the GSEs’ debt as equivalent to Treasuries. A bank cannot hold all of its assets in debt issued by General Electric or AT&T, but it can hold it all in Fannie or Freddie debt. The same is true for many other investors in the United States and around the world. These investors assumed GSE debt was perfectly safe, and, as a result, they weighted it too heavily in their portfolios. Policymakers were convinced that this counterparty risk faced by many financial institutions meant that any write-down of GSE debt would trigger a chain of failures through the financial system. In addition, GSE debt was used as collateral in short-term lending markets, and, by extension, their failure would have led to a sudden, massive, contraction of credit beyond what actually occurred. Finally, mortgage markets depended so heavily on the GSEs for securitization that policymakers concluded their sudden failure would effectively halt the creation of new mortgages. All three reasons led policymakers to conclude that Fannie and Freddie were too interconnected with the system to be permitted to fail.