Discriminatory Effects of Credit Scoring on Communities of Color

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About the National Fair Housing Alliance
Founded in 1988 and headquartered in Washington, DC, the National Fair Housing Alliance is a consortium of more than 220 private, non-profit fair housing organizations, state and local civil rights agencies, and individuals from throughout the United States. Through comprehensive education, advocacy and enforcement programs, NFHA protects and promotes equal access to apartments, houses, mortgage loans and insurance policies for all residents of the nation.

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Introduction

Our current credit scoring systems have a disparate impact on people and communities of color. These systems are rooted in our long history of housing discrimination and the dual credit market that resulted from it. Moreover, many credit scoring mechanisms include factors that do not just assess the risk characteristics of the borrower; they also reflect the riskiness of the environment in which a consumer is utilizing credit as well as the riskiness of the types of product a consumer uses.

Until only a few decades ago, communities and people of color explicitly were not permitted access to low-cost government and other mainstream loans. In the 1930s the Home Owners Loan Corporation and at least through the 1950s the Federal Housing Administration and the Veterans Administration used blatantly discriminatory rating systems and “Residential Security Maps” to deem communities of color high-risk. Banks, real estate agents, appraisers, and others also perpetuated redlining and segregation in the housing markets. The passage of the federal Fair Housing Act of 1968 improved conditions, but even up until the mid 1970s, federal regulatory agencies refused to acknowledge their enforcement responsibilities under the Act. It was not until civil rights groups sued the agencies that the federal government began to collect information on the mortgage lending practices of the institutions it regulated, and to establish and implement fair lending examination procedures.

Because of this history of racial discrimination, segregated neighborhoods formed and people of color had limited access to affordable, sustainable credit. Instead of accessing mainstream credit available to white borrowers and white neighborhoods, people of color were relegated to using fringe lenders and paying much more than they would otherwise have had to. While segregation and housing discrimination have abated somewhat, we still live in an extraordinarily segregated society. Access to credit is still often based on where we live rather than our individual ability to repay that credit. As this paper will explore, people of color were steered to subprime loans even when they qualified for prime loans, contributing to the fact that the foreclosure crisis has hit communities of color even worse than it has hit the rest of the country.

Credit scoring systems in use today were built upon and continue to rely upon the very dual credit market that continues to discriminate against people of color. For example, these systems penalize borrowers for using the type of credit disproportionately used by borrowers of color. Even fair lending defense attorneys who represent major banks readily admit that credit scoring has a differential impact on people of color. In a recent article, attorneys at K&L Gates assert that, “even the most basic lending standards, such as credit scores and [loan-to-value]

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1 For example, according to 2010 Census numbers, 65 percent of individuals in large metropolitan areas still live in areas of high segregation between whites and African-Americans. Gurian, Craig, “New maps show segregation alive and well,” Remapping Debate, April 20, 2011.
requirements, ‘impact’ racial and ethnic groups differently.” While there has been some discussion recently by the industry about the existence of the disparate impact theory under the Fair Housing Act and other long-established laws, disparate impact has been recognized by all eleven circuit courts that have ruled on the matter as a legally acceptable means by which parties can assert claims under the Fair Housing Act.

As we all look for solutions to the foreclosure crisis, lenders, regulatory agencies and policymakers promote tighter underwriting standards as a solution to improving the quality of loan performance and strengthening the economy. What they mean in part, however, is requiring higher credit scores for the best and most affordable products. This, of course, places the focus for improving loan performance on borrowers. But many studies and analyses have demonstrated that inappropriate loan products and their components were key factors driving the subprime crisis. Factors including product type, presence of a yield spread premium, distribution channel, inflated appraisals, and prepayment penalties helped significantly to predict whether a loan would fail. Even major credit repositories and credit scoring companies, including Vantage Score and FICO, admit that credit scores declined in predictive value leading up to and during the foreclosure crisis. So why are some looking to increased reliance on credit scoring as a way of originating well-performing mortgages and solving the crisis?

The use of credit scoring and its disparate impact go far beyond the lending sector, affecting access to many other financial products and services. Credit and other scoring mechanisms are being used by employers to evaluate job applicants, insurers to determine auto, life and homeowners insurance, and landlords to screen tenants. Credit scoring modelers and companies are finding even more creative ways to broaden the use of these systems. A recent proposal in the state of Texas would use credit scores to determine utility rates. Credit scores

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2 Hancock, Paul; Brody, Melanie Hibbs; McDonough, Jr., David G; Malpass, Melissa S.; Shinohara, Tori K., “Supreme Court vs. HUD: The Race to Decide ‘Impact or Intent’,” Legal Insight, K&L Gates, November 17, 2011.

3 In addition, since the Fair Housing Act was amended in 1988, the U.S. Department of Housing and Urban Development has acted in administrative proceedings and in other contexts with the full understanding that disparate impact claims are cognizable under the Act, as has the U.S. Department of Justice in its actions. Further, the Consumer Financial Protection Bureau recently announced that it would utilize all tools at its disposal, including the disparate impact theory, to pursue lenders who discriminate against consumers in violation of the Equal Credit Opportunity Act. The Bureau specifically stated that it would use the disparate impact theory in bringing actions under ECOA. See http://www.consumerfinance.gov/pressreleases/consumer-financial-protection-bureau-to-pursue-discriminatory-lenders/. The Federal Reserve also recognizes disparate impact as a way to prove ECOA claims.

4 Stillman, Jim, “Your Credit Score Determines the Availability of Credit . . . and the Cost,” Yahoo! Voices, June 20, 2007.
are even being used to determine which patients are more likely to take their medication as prescribed.5

The expanded use of scoring mechanisms has caused great consternation among consumer and civil rights groups as well as policymakers. For example, insurance companies use credit-based insurance scores to determine pricing. Yet, studies by the Missouri and Texas Departments of Insurance have found that insurance scoring discriminates against low-income people and consumers of color because of the racial and economic disparities inherent in scoring mechanisms.6 The Missouri study concluded that a consumer’s race was the single most predictive factor determining a consumer’s insurance score and, consequently, the consumer’s insurance premium.

The relationship between insurance credit scores and race is so strong that even though the Federal Trade Commission (FTC) used data selected by the industry in a 2007 FTC report, it found that credit scoring discriminates against low-income people and consumers of color, and that insurance scoring was a proxy for race.7 The FTC report also confirms that, despite growing reliance on credit-based insurance scores, scant evidence exists to prove there is a causal relationship between a consumer’s score and auto insurance losses. Without the need to demonstrate such a connection, insurers could theoretically use any arbitrary consumer characteristic, such as hair color or zodiac sign, that demonstrates a correlation to a specific outcome, to price insurance products.

This report focuses primarily on the use of credit scores by lenders, not other industries. This report provides only an abbreviated overview of other critical issues facing consumers when it comes to credit scoring and reporting. These issues are significant and help to demonstrate the urgent need to reform this system. For example, credit scoring systems are based on information obtained from consumer credit reports, even though credit reports are often rife with errors that are difficult to correct. Credit scoring systems are also a mystery to consumers because credit scoring companies maintain that their systems are proprietary and cannot be revealed. These issues are covered in great detail by recent reports by Demos8 and the

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5 The FICO Medication Adherence Score will be used by insurers and medical care facilities to identify patients who will need additional follow up services to insure they take their medication. Parker-Pope, Tara, “Keeping Score on How You Take Your Medicine,” New York Times, June 20, 2011.
8 Fremsted, Shawn, Traub, Amy, Discrediting America: The Urgent Need to Reform the Nation’s Credit Reporting Industry, Demos, June 2011.
Consumer Financial Protection Bureau9 and a survey by the Consumer Federation of America and VantageScore.10

Fixing our current credit scoring system is not only a moral imperative consistent with our national policies and beliefs about fairness and justice; it is also a legal obligation as outlined by the federal Fair Housing Act and the Equal Credit Opportunity Act. We hope this paper will assist with the dialogue at this conference as well as our national dialogue on how to move forward and out of our financial and foreclosure crises.

This paper begins in Section I with a discussion of the historical discrimination that led to our dual credit market, including subprime lending and the foreclosure crisis. Section II contains a detailed analysis of why credit scoring has a discriminatory impact. Section III discusses the legal obligation that the federal government and the financial industry have to promote fair housing. Section IV offers recommendations for how to fix our broken approach to credit scoring.

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I. The Nation’s Dual Credit Market Rooted in Discrimination

Credit scoring systems penalize borrowers who have anything other than mainstream, prime loans. As described below, people and communities have been excluded from mainstream affordable credit based on race and national origin. In the past, this was explicitly promoted by the federal government and the private industry with discriminatory rating systems, and is continued even today by banks like SunTrust and Wells Fargo. And it has been aided by the blanketeting of subprime loans in communities of color and fostered by continued patterns of segregation and the dual credit market. Because many of the factors that make up credit scoring systems rely on this dual credit market and its inherent discrimination, credit scoring contributes to the self-perpetuating cycle of restricted access to credit that has a dramatic disparate impact on communities of color.

A. Overt Historical Discrimination

In the not-so-distant past, government and private industry explicitly used race and national origin in assessing borrower risk. For example, the Home Owners Loan Corporation (HOLC), a federal agency established in 1933 in response to the foreclosure crisis associated with the Depression, institutionalized “redlining.” HOLC utilized a discriminatory risk rating system whereby prospective borrowers were favored if their neighborhood was deemed “new, homogeneous, and in demand in good times and bad.” Properties would be ranked low (and thus judged high-risk) if they were “within such a low price or rent range as to attract an undesirable element,” which often meant that they were located near an African-American neighborhood. The so-called “Residential Security Maps” used to make these classifications labeled the lowest ranking neighborhoods “fourth grade,” and shaded them in red. According to housing scholars William J. Collins and Robert A. Margo, “the agency’s revisions were unprecedented. Private financial institutions incorporated the new rating system in their own appraisals, thereby beginning the widespread institutionalization of the practice known as ‘redlining.'” As discriminatory policies and practices continued to persist within the real estate sector, private banks began to adopt the underwriting guidelines established by the federal government in the HOLC program.

Subsequently, the HOLC risk rating system came to inform the Federal Housing Administration (FHA) and Veterans Administration (VA) loan programs in the 1940s and 1950s. The FHA made it possible to purchase a house with just a 10 percent down payment, as opposed to the customary 33 percent required before its establishment. Loan terms were also extended for up to 30 years. The VA program provided similar benefits, all while following the FHA in rating

12 Ibid.
properties in large part on the basis of the “stability” and “harmoniousness” of neighborhoods.14

As a result, the new benefits of a reduced down payment and better loan terms reached only some Americans. According to FHA’s policy, “If a neighborhood is to remain stable, it is necessary that properties shall continue to be occupied by the same racial and social classes. Changes in social or racial occupancy contribute to neighborhood instability and the decline of value levels.”15 To implement this policy, the FHA even went so far as to recommend the use of restrictive covenants to ensure neighborhood stability and racial homogeneity.16

The notion that race had a direct impact on property values was broadly adopted by the appraisal industry, and appraisers were trained to evaluate properties using race as a factor. McMichael’s Appraising Manual, for example, provided the following ranking of race and nationality by impact on real estate values (in order of preference):17

1. English, Germans, Scotch
2. North Italians
3. Bohemians or Czechs
4. Poles
5. Lithuanians
6. Greeks
7. Russians, Jews (lower class)
8. South Italians
9. Negroes
10. Mexicans

Such lists remained in appraisal manuals long after the Fair Housing Act was passed in 1968.

Similar policies were employed in the insurance industry, as homeowners insurance companies adopted policies that resulted in either the outright denial of insurance in communities of color or the availability only of policies that provided inadequate protection at excessive costs to consumers.

Even after passage of the Fair Housing Act, these discriminatory practices received tacit approval from the federal banking regulatory agencies. It was not until 1976, when a coalition of civil rights groups sued them for failing to enforce the Fair Housing Act, that the federal banking regulatory agencies acknowledged that they had any enforcement responsibilities

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under the Act.\textsuperscript{18} The settlement required the agencies to collect information on the mortgage lending practices of the institutions they regulated, and to establish and implement fair lending examination procedures.

Understanding the historical context of discrimination and redlining practices is significant in any discussion on credit scoring. Because borrowers of color could not access credit in the mainstream market, a dual credit market developed – a market that was separate and unequal – a market where white borrowers had ready access to more regulated, lower-cost, affordable and sustainable credit products while borrowers of color were relegated to unregulated, higher-cost and more unsustainable sources of credit. These fringe markets were – and in some cases still are - the primary source of credit for communities of color.

B. Subprime Lending and Its Long-Term Discriminatory Effects

In many cases, the banking and insurance industries simply replaced their explicitly discriminatory standards with policies and practices that were non-discriminatory on their face, but maintained a disparate impact. (It is worth noting, as described below, that some companies also maintained overtly racially discriminatory policies.) By setting minimum loan values, employing tiered interest rate policies, refusing to make loans in some neighborhoods, and offering only market value homeowners insurance in some neighborhoods, banks and insurance companies continued to discriminate in the marketplace.

Many lenders, recognizing that borrowers of color represented a growth market, developed initiatives to heavily target this market segment. Indeed subprime lenders (and some subsidiaries of prime lenders) took advantage of communities that mainstream lenders shunned. In a representative case, the St. Louis Equal Housing and Community Reinvestment Alliance alleged that a large local bank had not made a single loan to an African-American borrower from 2003 to 2008.\textsuperscript{19} Moreover, all of the banks’ branches were located in areas with less than two percent African-American population. Nationwide, African-Americans and Latinos were much more likely to receive a subprime loan than their white counterparts according to HMDA data. In both 2005 and 2006, roughly 54 percent of African-Americans and 47 percent of Latinos received subprime loans compared to approximately 17 percent of whites.\textsuperscript{20} A study conducted by the National Community Reinvestment Coalition found that there are fewer commercial bank branches in communities of color.\textsuperscript{21}

Instead of targeting this market with safe, lower-cost, affordable and sustainable loans, borrowers of color were targeted for unsustainable, higher-cost, subprime mortgages.

\textsuperscript{18} National Urban League et. al. v. Office of the Comptroller of the Currency, et al , 1976
\textsuperscript{19} Rivas, Rebecca S., “Housing Alliance calls out Midwest BankCenter for not loaning to blacks.” The St. Louis American, October 14, 2009.
Subprime lenders have long boasted and prided themselves on being the primary providers of credit to African-American, Latino and other underserved groups. Countrywide, at one time the nation’s largest lender and a major originator of subprime loans, boasted that it was the number one lender to borrowers of color.\(^22\) The Department of Justice (DOJ) recently settled an unprecedented $335 million lawsuit with Countrywide because of its discriminatory practices, which included steering African-American and Latino borrowers who qualified for prime loans into subprime mortgages.\(^23\) Some of the nation’s other top subprime lenders have either settled major discrimination lawsuits or are currently defending themselves against such allegations. These lenders include Long Beach, Ameriquest, Delta Funding, Household Finance, Associates, Citi, and Wells Fargo.

And while banks and others continued to defend the use of credit scores as the great equalizer, many borrowers with high credit scores received subprime mortgages even when they qualified for prime credit. Many would-be prime consumers were instead steered into subprime and Alt-A mortgages because of the higher short-term profits lenders could garner. For example, an analysis conducted by First American Loan Performance found that 41 percent of subprime loans made in 2004 went to borrowers who actually would have qualified for a prime rate loan.\(^24\) Another study, commissioned by The Wall Street Journal, revealed that in 2005, 55 percent of subprime borrowers would have qualified for a prime loan. The Wall Street Journal analysis also found that in 2006 that number had jumped to as high as 61 percent.\(^25\) Federal Reserve Governor Edward Gramlich noted that half of subprime borrowers had credit scores of 620 or higher.\(^26\)

The recently amended lawsuit filed by the City of Baltimore against Wells Fargo provides a glaring example of how lenders purposefully targeted African-Americans and Latinos for higher priced mortgages in outrageously discriminatory ways.\(^27\) Two affidavits filed by former Wells Fargo employees revealed that Wells Fargo:

- Specifically targeted African-American communities for subprime loans but did not do so in white communities;


\(^{25}\) Kirchhoff and Block, “Subprime Loan Market Grows Despite Troubles”, USA Today, December 14, 2004. (At the time of his statement, a score of 620 qualified a borrower for a prime loan.)

\(^{26}\) Mayor and City Council of Baltimore v. Wells Fargo Bank, N.A. and Wells Fargo Financial Leasing, Inc. Third Amended Complaint for Declaratory and Injunctive Relief and Damages, October 21, 2010.
• Targeted African-American churches for the purpose of selling subprime loans. Employees of color were tapped to make presentations to the churches. A white employee was told she could only attend the presentations at African-American churches if she “carried someone’s bag;”

• Used derogatory language to refer to African-American consumers. African-Americans were referred to as “mud people” and “niggers.” And employees referred to loans in African-American neighborhoods as “ghetto loans.” And they referred to Prince George’s County as the “subprime capital” of Maryland. Comparatively, Wells employees felt that predominately white counties like Howard County, Maryland were bad places for subprime mortgages;

• Gave employees substantial financial incentives for steering borrowers who actually qualified for prime mortgages into the subprime market.

America’s separate and unequal financial system is a direct result of the bias perpetuated by both the private and public sectors. Here are some statistics that demonstrate our dual financial system:

• African-American and Latino homebuyers “face a statistically significant risk of receiving less favorable treatment than comparable whites when they ask mortgage lending institutions about financing options;” 28

• The denial rate for first lien mortgages for African-American borrowers was 2.5 times higher than the rate for Non-Hispanic white borrowers in 2010. 29

• In 2008, African-Americans were 2.63 times more likely and Hispanics more than two times more likely than their white counterparts to receive a higher-priced loan. 30

• Even higher-income African-Americans and Latinos received a disproportionate share of subprime loans. According to one study that analyzed more than 177,000 subprime loans, borrowers of color were more than 30 percent more likely to receive a higher-rate loan than white borrowers, even after accounting for differences in creditworthiness. 31

• Borrowers residing in zip codes whose population is at least 50 percent non-white were 35 percent more likely to receive loans with prepayment penalties

than financially similar borrowers in zip codes where non-whites make up less than 10 percent of the population.32

It follows, then, that borrowers of color are disproportionately represented in foreclosure claims and that communities of color experience higher foreclosure rates than the general population. A recent study released by the Center for Responsible Lending reveals that a home owned by an African-American family is 76 percent more likely to go into foreclosure that a home owned by a white family.33 The Center for Responsible Lending estimates that African-American and Latino communities will lose $194 billion and $177 billion respectively in housing wealth as a result of the foreclosure crisis including the resulting depreciation of living near foreclosed properties.34

These high rates of foreclosure caused by discriminatory practices have resulted in thousands of bank-owned (also known as real estate-owned or REO) properties in communities of color. A recent undercover investigation by NFHA and its members shows that discrimination by the banks continues even after foreclosure.35 The investigation found striking disparities in the maintenance and marketing of foreclosed properties in white areas compared those in neighborhoods of color. Investigators used 39 different factors to evaluate the maintenance and marketing of REO properties, subtracting points for broken windows and doors, water damage, overgrown lawns, no “for sale” sign, trash on the property, and other deficits. Overall, REO properties in communities of color were 42 percent more likely to have more than 15 maintenance problems than properties in white neighborhoods. NFHA has since filed housing discrimination complaints against Wells Fargo and U.S. Bancorp for disparities in the maintenance and marketing of REO properties.

C. The Proliferation of Fringe Lenders in Communities of Color

As described above, fringe lenders – including payday lenders and check cashers – have historically been a primary source of credit for underserved borrowers and are highly concentrated in communities of color. One analysis revealed that there were more payday lender outlets in the country than all McDonalds and Burger King restaurants combined.36 These fringe lenders saturate predominantly African-American and Latino neighborhoods. A study of fringe lenders in California found that payday lenders were nearly eight times as concentrated in neighborhoods with the largest shares of African Americans and Latinos as

34 Ibid.
compared to white neighborhoods, draining nearly $247 million in fees per year from these communities.\textsuperscript{37} The study includes several maps of communities throughout California showing this pattern. Below is a map of Los Angeles depicting the heavy concentration of payday lenders in African-American and Latino communities. Conversely, there are few mainstream bank facilities in predominantly African-American and Latino communities.

![Map of Los Angeles depicting the heavy concentration of payday lenders in African-American and Latino communities.](image)

Map: Center for Responsible Lending

Conversely, there are few mainstream bank facilities in predominantly African-American and Latino communities. Borrowers who are targeted by fringe lenders and shunned by mainstream financial institutions are susceptible to volatile credit markets. Consumers who access credit from fringe lenders will undoubtedly have lower credit scores because the products these institutions peddle have abusive terms that carry higher delinquency and default rates.

II. Credit Scoring Has a Discriminatory Impact and Is Not the Best Measure of Risk

Have a mortgage from a finance company? Your credit will likely be lower than if you had gotten the loan from a depository lending institution. Lose that same home to foreclosure because you can no longer make the inflated payments? Your credit score just went down again.

\textsuperscript{37}Li, et. al. Predatory Profiling: The Role of Race and Ethnicity in the Location of Pay Day Lenders in California, Center for Responsible Lending, March 26, 2009.
As described above, people of color were disproportionately steered to subprime loans and targeted by fringe lenders. Because credit scoring systems and other automated valuation systems are promoted as a great equalizer and a non-discriminatory way of measuring credit risk, one might then think that credit scores would not rely on discriminatory assumptions to measure risk. In fact, that is exactly what the systems do in some instances. For example, some scoring mechanisms assume that a borrower who received a loan from a finance company is a worse credit risk than one who got a loan from a depository institution – when, in fact, the opposite may be true. A credit scoring system that relies on this false premise penalizes the borrower who simply may not have had access to a mainstream lender but had abundant access to fringe lenders.

Indeed, credit scoring mechanisms are a reflection of the lending and finance systems which produce the data upon which the mechanisms are built. Oftentimes, credit scoring mechanisms assess the riskiness of the lending environment, product type or loan features a consumer uses rather than the risk profile of the consumer.

Let us use an analogy to illustrate this point. Suppose a test has been developed to determine how safe or risky someone is as a car driver. In this test, the driver has to drive through a path and navigate a series of cones and obstacles. However, the driver is placed in a car that is essentially a lemon. The brakes do not work, there is no steering wheel fluid in the car so that it does not turn well, and the transmission is malfunctioning along with other problems. The driver completes the course and is given a low score having knocked over several cones or run into some of the obstacles on the course. But then, this same driver is placed into a different car and asked to drive the same course again. This time the car is not a lemon. It is in pristine condition – with no problems. The second time through, the driver passes with flying colors and receives a high score.

Did the driver change? No. But what did change is the vehicle in which the driver was placed. So the test, while accurately measuring how well the driver navigated the course, was more a reflection of the quality of the vehicle in which the driver was placed than the ability or riskiness of the driver. Similarly, credit scoring mechanisms are often a reflection or measurement of the lending environment or loan product type – and not so much the risk profile of the borrower.

Consumers of color are ill-served by the financial mainstream and disproportionately access credit in more volatile financial environments – these consumers disproportionately get the lemons of the financial services world. As a result, current credit scoring mechanisms which do not evaluate or calibrate scores based on the safety or soundness of the lending environment, may actually cause harm to borrowers of color by misjudging them.

A. Limited Scope, Quality and Transparency of Credit Information
The information used to build credit scoring models can come from many different sources; however, modelers have tended to rely heavily on credit reporting data from credit bureaus. The quality or accuracy of the scoring model is intrinsically tied to the quality of data upon which the model is based: the better the data quality, the better the scoring system. If modelers are relying on limited data or inaccurate data, they will develop scoring models that are less effective and have limited predictive power and market applicability. The less predictive a scoring model, the greater the likelihood for miscalculating risk.

Companies can use data purchased from third party sources or their own privately held data to develop their scoring systems. Larger companies that have abundant information about a large number of consumers oftentimes use their own in-house data to either develop their own unique scoring systems or to enhance systems that they might obtain from an outside source. But, by and large, the data upon which scoring models are built are purchased from large credit repositories, and these data are often flawed. A study conducted by the National Association of State Public Interest Research Groups revealed the following: ³⁸

- Four out of five credit reports contained errors;
- 25 percent of credit reports contained significant errors that would result in the denial of credit;
- 54 percent had inaccurate personal information;
- 30 percent listed closed accounts as open; and
- 8 percent did not list major credit accounts.

Not only can the data that credit modelers use be flawed but it can be incomplete. Not all creditors report consumer information to credit repositories. Indeed, some positive credit information from fringe lenders is typically not reported while negative information is almost always reported. Take the case of payday lenders, which, as illustrated above, are concentrated in communities of color. According to the Community Financial Services Association of America, “Payday advances are not reported to traditional credit bureaus.”³⁹ If a consumer obtains a payday loan, the fact that the consumer has paid off the debt on time is not reported to credit bureaus. However, unpaid payday loans are often reflected on the consumer’s credit report. The Consumer Federation of America reports that unpaid payday loans can lead to negative credit ratings as well as difficulty in opening bank accounts.⁴⁰

Creditors are not required to report consumer data to the credit repositories. Nor, if they do report, are they required to report positive data as well as negative data. A creditor can decide to forgo submitting any data, or to report only negative data to the credit repositories. Some

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creditors may opt not to submit data because they do not wish to pay reporting costs. Others may not want other companies to be able to identify – and poach – their best paying customers. And while a creditor may not be able or willing to report positive data on a regular basis, the creditor can report negative data to the credit repositories by having the matter referred to a collections agency or by filing an action against the consumer to collect on the alleged debt. This tilts the entire system against the consumer, especially those who access credit outside of the financial mainstream.

Smaller creditors like community development financial institutions (CDFIs) that want to report positive data may be prohibited from doing so because of their size. An informal survey conducted by NFHA underscores the difficulty of collecting comprehensive information on consumer credit habits. The major credit repositories are structured to collect data from larger creditors with a large number of consumer files. Some repositories require creditors to have at least 500 files when reporting data; others require 1,000 files. These numbers are often beyond the reach of CDFIs and other community-based institutions.

In addition to posing accuracy and access challenges, credit scoring mechanisms lack transparency. The formulas are proprietary and not disclosed to the public. In addition, there are a number of individual factors that help determine the score, only some of which are public. It is not clear exactly how the factors used in the credit scoring systems affect a consumer’s score. There are potentially thousands of variables that can be included in a scoring system. These variables can be comprised of individual components as well as combined components and might include such elements as the number of: 30-day late payments; inquiries; inquiries by subprime lenders; open trade lines; late mortgage loan payments; or installment loans. They might also include length of employment or length of individual revolving loan accounts.

Each variable is purportedly tested to determine first if it is related to a particular outcome, such as likelihood for a mortgage loan default or for filing an insurance auto claim. Then the variables are tested to determine how they should be weighted within the credit scoring formula. There is a level of subjectivity to the process and experts who develop the systems make the final determination as to which variables are to be included in the formulas and how much weight each is given.

It is important to note that credit scoring modelers are trying to determine whether a particular variable has a correlation to a particular outcome. But the mere presence of a correlative relationship between a particular variable and a certain outcome does not in and of itself indicate a causal relationship. For example, variable testing may indicate that there is a correlation between gas company credit cards and higher rates of mortgage loan defaults; but this does not mean that having a gas company credit card will cause a consumer to default on a mortgage.

It stands to reason that not all variables with a correlative relationship can or should be used in a credit scoring system. For example, some analyses have shown that hair or eye color can
correlate to certain types of insurance claims. Other analyses have revealed links between zodiac signs and frequency of auto claims. If we were to follow these data, those born under the sign of Taurus or Virgo would pay higher premiums than Cancers or Aquarians. It also follows that neither race nor national origin nor any proxies that stand for them should be used in a credit scoring system, not only because it flies in the face of our nation’s laws and policies, but because it makes as little sense as using a zodiac sign to price car insurance.

**B. Disparate Impact of Credit Scoring Factors**

While it is no longer legal to evaluate risk using protected class characteristics, current credit scoring systems still have a significant disparate impact on people of color and other underserved consumers because some seemingly facially-neutral factors actually have discriminatory effects.

Take, for example, the factors used by the FICO scoring system, which is widely-known and often touted as the industry standard for use in mortgage lending. While many independent variables and their weighting in the FICO scoring system are unknown and proprietary, several broad categories that impact the score are public: payment history; amounts owed; length of credit history; new credit; and types of credit used. The chart below from one of FICO’s websites illustrates the value assigned to each of these categories.

![FICO Score Categories Chart](http://www.myfico.com/CreditEducation/WhatsInYourScore.aspx)

All of these categories pose concerns about disparate impact and unintended discriminatory outcomes, and affect access to sustainable, affordable, and fair credit. Below is a more detailed description of the fair lending concerns related to each category of the FICO scoring system.

**Payment History – 35% of FICO Score**

41 “Allstate: Virgos have most crashes,” United Press International

While the Allstate press release announcing the findings was tongue-in-cheek, the data and analysis were real. “Allstate zodiac joke bombs,” CNN Money, February 2, 2011.

See also “Aquarius with the fewest claims, Taurus lives more dangerously,” Allianz Suisse, February 17, 2011.

42 Chart developed by Fair Isaac: [http://www.myfico.com/CreditEducation/WhatsInYourScore.aspx](http://www.myfico.com/CreditEducation/WhatsInYourScore.aspx).
The payment history component of the score includes information about whether borrowers make timely debt payments, including some subprime loans. As mentioned above, subprime loans carry much higher default and delinquency rates\(^43\) – not necessarily because of the borrower traits, but more often because of the aspects and features of the loans themselves. Because African-Americans and Latinos are targeted for subprime loans, the data suggest that these groups will undoubtedly experience higher rates of poor performance in payment history.

A unique study that compared two similar groups of low- and moderate-income borrowers demonstrates this point.\(^44\) The study compared two mortgage loan portfolios, one comprised of loans made through a program that provided low-cost fixed rate loans, and the other a portfolio of subprime loans. Using propensity score match methodology, the researchers were able to isolate borrowers with similar characteristics in the two groups. The divergent variables between the two groups were the loan terms and conditions, and the channel borrowers used to obtain the mortgages. While the traits of both groups of borrowers were similar, the loan performance outcomes were not. The default rate for the subprime portfolio was *four times higher* than that for the lending program portfolio for low- and moderate-income borrowers.

Moreover, the study found compelling evidence that loan characteristics and origination channel had a significant impact on loan performance. Specifically, the existence of prepayment penalties, adjustable interest rates, and elevated costs negatively impacted the loans’ performance – even after controlling for credit score. Additionally, loans originated through broker channels resulted in higher default rates.

These data conflict with the underlying assumption behind scoring mechanisms. This study and others suggest that a borrower may well end up with a damaged credit score not because the borrower was more risky or negligent but rather because the borrower obtained a loan through a broker or received loan terms that increase the likelihood of delinquency and default. Existing credit scoring systems do not distinguish between risk caused by borrower behavior and risk caused by loan terms and conditions. Thus, risky loans are likely to have a negative

\(^43\) According to Mortgage Bankers Association National Delinquency Survey Data released 5/19/2010, the seasonally adjusted delinquency rate was 6.17% for prime fixed loans, 13.52% for prime ARM loans, 25.69% for subprime fixed loans, 29.09% for subprime ARM loans, 13.15% for FHA loans, and 7.96% for VA loans. Foreclosure starts rate was .69% for prime fixed loans, 2.29% for prime ARM loans, 2.64% for subprime loans, 4.32% for subprime ARM loans, 1.46% for FHA loans, and .89% for VA loans. These trends have held steady. The same data released 8/29/2009 revealed the following: the seasonally adjusted delinquency rate was 6.41% for prime loans, 25.35% for subprime loans, 14.42% for FHA loans, and 8.06% for VA loans. The foreclosure inventory rate was 3% for prime loans, 15.05% for subprime loans, 2.98% for FHA loans, and 2.07% for VA loans.

\(^44\) Lei Ding, Roberto G. Quercia, Janneke Ratcliff, and Wei Li, *Risky Borrowers or Risky Mortgages: Disaggregating Effects Using Propensity Score Models*, Center for Community Capital, University of North Carolina at Chapel Hill, September 13, 2008.
impact on the borrowers’ credit scores, even though those borrowers may have had a perfect payment record had they been able to obtain a less risky loan.

*Amounts Owed – 30% of FICO Score*

The FICO score calculation of amounts owed is comprised of multiple factors and FICO does not reveal in detail all of these factors and how they are weighted. However, the company does report that this category takes into consideration the amount of credit available to a borrower for certain types of revolving and installment loan accounts. To the extent that underserved communities have restricted access to credit, and in particular, the type of credit that will likely be reported in a positive fashion to credit repositories, this category can pose a disparate discriminatory impact.

A study by the San Francisco Federal Reserve Board provide an analysis of individuals who do not have a checking or savings account in the region. These “unbanked” tend to be low-income, young, non-white adults who lack a college degree. The analysis goes on to reveal that approximately half of African-Americans and Latinos fall into this category and that the unbanked are concentrated in lower-income census tracts without a checking or savings account. This analysis also documents the preponderance of payday lenders and check cashers in predominately African-American and Latino neighborhoods.

The lack of access to mainstream lenders may well impact the ability of underserved consumers to obtain revolving or installment lines of credit from such lenders. And if these borrowers experience undue difficulty in accessing quality credit, they may well suffer a lower credit score from a system that considers how much “extra” credit they may have available in certain revolving and installment accounts.

Here again, this component is not only measuring the ability of the borrower to effectively manage credit accounts but is also measuring the extent to which a consumer actually has access to certain types of credit accounts.

*Length of Credit History- 15% of FICO Score*

Presumably, the longer a borrower has had an account, and to the extent that the account is reported to the credit repositories, the higher the borrower’s credit score. If this is indeed the case, then borrowers with little access to credit that is reported to the credit repositories will be negatively impacted by this component.

We provide a fairly detailed analysis above of how mainstream creditors historically discriminated against communities of color. Moreover, as referenced above, borrowers of color

are much less likely than their white counterparts to have access to mainstream banks and consequently are much more likely to access credit from fringe lenders who do not report positive data to the credit repositories. This means that borrowers of color will be less likely to have trade lines with a significant amount of history.

This factor also penalizes borrowers who deal on a cash basis, access credit outside of the financial mainstream, have been shut out from accessing traditional credit, or obtain credit from lenders who do not report positive data. Borrowers with these circumstances are disproportionately persons of color.

**New Credit- 10% of Credit Score**

This component takes into consideration the number of newly opened accounts a consumer has. FICO does not provide details on just how a consumer’s credit score will be affected if the consumer establishes new credit. FICO advises consumers to avoid opening new lines of credit as this might result in lowering the credit score. Further, opening new accounts will lower the average account age of credit lines and this will result in a lower credit score.

This component also considers the number of credit accounts a consumer pursues. So if a consumer is shopping for a mortgage or applying for credit at different places, the consumer’s credit score can be negatively impacted. To guard against any negative impact, FICO advises consumers to shop for a mortgage loan within a short window of time.

There are two areas of concern with respect to disparate outcomes under this component. The first is the higher likelihood that consumers of color will be among those who are accessing new credit accounts. As discussed above, credit access is a major challenge for underserved groups and these groups are much more likely to be unbanked. It stands to reason, therefore, that underserved groups will be among those who are newly entering the credit markets and therefore, establishing new accounts.

The second area of concern emanates from the higher mortgage loan declination rates for borrowers of color. As described earlier, HMDA data reveal that borrowers of color are much more likely than their white counterparts to be declined for a loan. These higher declination rates suggest that borrowers of color may be more likely to apply to additional lenders for a loan approval.

If mortgage loan inquiries or applications are undertaken in a short time frame, there may be no negative impact on a consumer’s credit score. However, if a consumer applies for a mortgage with one lender, is declined, and then applies for a mortgage with another lender, this process may well negatively impact the consumer’s credit score due to the longer lapse in time between

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46 “How to Repair Your Credit and Improve Your FICO Credit Score,” Available at: http://www.myfico.com/crediteducation/improveyourscore.aspx
loan inquiries. More analysis and research needs to be conducted to determine if borrowers of color have a higher incidence of shopping for a mortgage with different lenders over longer periods of time and ultimately how that might impact their credit scores.

Types of Credit Used – 10% of FICO Score

Again, FICO does not reveal exactly how it calculates the type of credit a borrower may use in generating a credit score; however, there is evidence that certain types of credit, like credit provided by finance companies, are treated less favorably than credit provided by mainstream lenders, like depository banking institutions. According to the Federal Reserve Board, “Many credit-scoring models consider the number and type of credit accounts you have. A mix of installment loans and credit cards may improve your score. However, too many finance company accounts or credit cards might hurt your score.”47 If this is indeed the case, this category also presents dangerous implications for borrowers of color.

FICO, in a guide developed to advise consumers on how to improve their credit scores, suggests that consumers who have installment loans and credit cards that are reported to the credit repositories will have a more favorable analysis in the FICO credit scoring system.48 Here again, consumers who access credit outside of the financial mainstream will be penalized by this type of an analysis.

This component may more largely assess the quality of the environment or type of loan product a consumer accesses rather than the risk characteristics of the consumer.

C. Existing Credit Scoring Systems Do Not Adequately Predict Risk

The current crisis has revealed that credit scoring mechanisms are an insufficient measure for predicting and managing performance. While FICO is designed to assess risk and predict a borrower’s performance, recent analyses demonstrate the ineffectiveness of the scoring mechanism. Default rates for all borrowers have increased precipitously, regardless of credit score, and one study found that “higher FICO scores have been associated with bigger increases in default rates over time.”49

In the years before the economic crisis, it was common for lenders to put aside more thorough and comprehensive underwriting criteria which allowed unique and compensating factors to be evaluated, and instead to substitute them with flimsy underwriting standards. If a borrower had a higher credit score, the lender could truncate the underwriting process by foregoing a fully documented underwriting review. In order to maximize short-term profits, lenders took

48 Ibid.
49 Demyanyk, Yuliya, “Did Credit Scores Predict the Subprime Crisis?” The Regional Economist, Federal Reserve Bank of St. Louis, October, 2008.
great strides to increase volume. One way to increase volume was to shorten the time it took to approve a loan.

Sound underwriting criteria such as verifying savings and other deposits, income and employment or documenting timely rental payments were largely disregarded. Lenders gave substantially more weight to the credit score factor. In that environment, the FICO score became a proxy for sound underwriting. Whereas the credit score might have been an important tool to add to the underwriting toolbox, instead it was over-valued in the underwriting process. Even FICO admits that lenders were too reliant on the model.50

A study published by the Federal Reserve Bank of St. Louis looked at credit scores and borrowers who received subprime mortgages.51 The study revealed that, for borrowers with the lowest FICO scores (500 – 600), the rate of seriously delinquent loans was twice as large in 2007 as it was in 2005. Comparatively, for borrowers with the highest FICO scores (above 700), the rate of seriously delinquent loans was almost four times as large in 2007 as it was in 2005. Borrowers with lower FICO scores saw a 100 percent increase in seriously delinquent loans while borrowers with higher FICO scores saw a 300 percent increase in seriously delinquent loans. The study’s author concludes that “the credit score has not acted as a predictor of either true risk of default of subprime mortgage loans or of the subprime mortgage crisis.” The heavy reliance on FICO during the most recent housing boom has contributed to the system’s ineffectiveness. Even industry analysts have recognized the flaws in FICO.52 In a document written to clients, an analyst at CIBC World Markets called FICO scores “virtually meaningless.”53

Borrowers with higher FICO scores are in many cases acting the way borrowers with very low scores are predicted to act. Some analysts in reviewing private loan portfolios have found that in some cases loan characteristics were more predictive of loan performance than the borrower’s FICO score. Indeed, both FICO54 and TransUnion have released reports that indicate that borrowers with higher FICO scores are performing in uncharacteristic ways. These borrowers, in a trend never before seen, are more likely to pay their credit card debt than their mortgage loan debt. This offers additional proof that a credit score alone cannot predict long-term mortgage performance.

Many lenders that either do not rely on credit scoring mechanisms at all or minimally rely on them experience default rates that are lower than the industry average. For example, Golden West Financial, a lender that did not rely on the FICO score because of its non-predictive nature,

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51 Ibid footnote 49.
experienced a default rate of 0.75 percent while the industry average for the same class of loans was 1.04 percent. Golden West relied on careful underwriting, including income and asset verification and employed a different mechanism for compensating appraisers. Instead of compensating an appraiser based on the number of appraisals completed, Golden West compensated appraisers on the accuracy of the appraisal over the life of the loan. Underscoring the tenuous reliability of the FICO score, a Golden West representative reported that some of Golden West’s best clients had very low FICO scores and some of their worst clients had high FICO scores. In addition, the North Carolina State Employees’ Credit Union indicated that for their borrowers who would be classified as subprime, the default rate is 1.25 percent, well below the industry average. NCSE attributes the higher default rates among subprime loans to higher interest rates and poor underwriting practices.

D. Risky Loan Products and Unsafe Lending Environments – Not Borrowers – Were Clearly the Culprit

When looking at which loans failed and which were successful over the past ten years, the picture becomes clear. Loan terms and conditions were the largest part of the problem, not the borrowers. Failed underwriting processes and unsuitable loan products were higher contributors to poor loan performance than were the credit characteristics of the borrower. Even borrowers with good credit who paid their bills on time, quickly found themselves in trouble after getting a predatory or subprime loan or accessing credit in an unsafe environment.

We saw similar outcomes among corporations like Lehman Brothers and Bear Stearns that turned more and more to risky investment products and tenuous financial deals. Just as the creation and sale of unregulated complex derivative investment products was a bad idea, and led otherwise sound companies into ruin, so was the creation and sale of unwise mortgage loan products with highly risky features, like pre-payment penalties, and negative amortization which led otherwise good consumers into default.

Some lenders might improve overall loan performance by improving the quality of the underwriting process. In a presentation on the impact of the Qualified Residential Mortgage requirements, a number of organizations, including NFHA, the National Association of Realtors® and the Mortgage Bankers Association, highlighted a number of factors that are most important in decreasing default risk. Those factors included full loan documentation and verification processes. These critical underwriting components were identified as key elements in improving loan portfolio performance and management.

The organizations also cite risky loan features including:

55 Ibid.
56 Ibid.
57 The presentation deck is available by contacting the National Fair Housing Alliance or any of the other sponsoring organizations.
• negative amortization loans;
• interest-only loans;
• loans with balloon payments;
• loans exceeding 30 years in maturity;
• prepayment penalties;
• unverified income, employment, assets and other debts i.e., no-doc or low-doc loans;
• underwriting for ARMs based on an introductory rate rather than the fully-indexed interest rate;
• total points and fees exceeding three percent of loan amount;
• unstable or undocumented payment history;
• ARM reset caps above two percentage points per year;
• investor loans;
• yield spread premiums; and
• piggyback seconds.

These same risky loan features have been identified in proposed regulations for the Qualified Mortgage and Qualified Residential Mortgage requirements.

Perhaps instead of concentrating so much of the risk analysis on the borrower, more attention should be paid to evaluating the products themselves, the environment in which the credit is provided and the underwriting process used by the mortgage lender.

III. Why the Federal Government and Lenders Have an Obligation to Change the System

All federal agencies and their grantees associated in any way with housing and community development have a special obligation to further the purposes of federal Fair Housing Act. The law covers policies and practices that have a disparate impact on protected classes. To the extent that credit scoring has a disparate impact, the federal government and its grantees must take action.

The federal Fair Housing Act – passed in 1968 – has the dual mission of eliminating housing discrimination and promoting residential integration. The Fair Housing Act requires that government agencies spend funds dedicated to housing and community development in a manner that “affirmatively furthers fair housing.” This obligation is not limited to the Department of Housing and Urban Development; rather it applies to a wide range of government agencies, including those with regulatory or supervisory authority over financial institutions, as stated in Section 808(d) of the Fair Housing Act:

All executive departments and agencies shall administer their programs and activities relating to housing and urban development (including any Federal agency having regulatory or supervisory authority over financial institutions) in a manner affirmatively to further the purposes of this subchapter and shall cooperate
with the Secretary [of Housing and Urban Development] to further such purposes. 58 (emphasis added)

Executive Orders and other provisions of the Fair Housing Act related to affirmatively furthering fair housing provide additional guidance on this obligation. 59 The Obama Administration has also affirmed its commitment to fair housing and fair lending. 60

This affirmative obligation has been interpreted to apply to efforts to eliminate segregation. This is important to the well-being of our nation because where we live determines our access to opportunities, wealth, and resources. 61 In this context, equal access to credit, financial services and products cannot be overstated. The largest federal housing program ever, the Troubled Asset Relief Program (TARP) provided funding for major banks and insurance companies. As recipients of these funds, these entities are also required to affirmatively further fair housing with TARP and any other government funds. 62 Credit scoring systems, which are clearly related to housing and community development, are also covered by this provision of our nation’s fair housing laws.

IV. Policy and Enforcement Solutions to Improve Credit Scoring Systems

Because of the significance that credit scoring has for a wide range of access issues, such as credit access, employment opportunity, and insurance availability, credit scoring mechanisms need major improvements if not a complete overhaul. Intrinsic and persistent discrimination in the lending markets and America’s dual and unequal credit market have contributed to serious credit access problems for borrowers and communities of color. Below are some recommendations on how to improve credit scoring mechanisms and suggestions on how to monitor and evaluate these systems.

58 42 U.S.C. Sec. 3601 et seq.
59 Section 805 of the Fair Housing Act lays the groundwork for this mandate by detailing discrimination in residential real estate-related transactions; Section 808 of the Act spells out the responsibility of the Secretary of Housing and Urban Development (HUD) to administer the Act, and the Act’s application to other federal agencies; and Executive Order 11063, 59 signed on November 20, 1962, and Executive Order 12892, 59 signed on January 17, 1994, together state the responsibilities of all federal agencies to administer their programs in a manner that affirmatively furthers fair housing and clarify what is meant by programs and activities relating to housing and urban development.
61 Carr and Kutty, p. 2.
62 Swesnik, Deidre; Clark, Benjamin; Goldberg, Deborah. How Tarp Funds Could (and Should) Be Used to Improve Our Neighborhoods, National Fair Housing Alliance, November 2009.
Broaden the scope of financial data utilized by underwriting and credit scoring models

One way to improve credit scoring models is to broaden the scope and quality of data upon which the systems are based. Currently the primary source of data is major credit repositories.

Credit repositories should make it easier for smaller financial institutions to report positive data. Moreover, credit repositories must be proactive and ensure that positive data from non-traditional sources can be submitted. Data should also be included from state housing finance agencies, community development financial institutions, micro-lending organizations, credit unions, and affiliation or community groups such as churches, faith-based institutions and benevolent organizations.

Broadening the scope of credit information will create a more robust data pool with additional information about and from consumers who access credit in safe, but non-traditional environments. It will also enable the credit scoring systems to more accurately assess a broader range of consumers. This will in turn lessen the likelihood that a consumer will be incorrectly characterized or categorized in various credit scoring systems.

Finally, credit repositories must create mechanisms to correct the current system’s slant toward the reporting of only negative data. For example, a mechanism that allows consumers to report and submit verifiable and documented information about their credit payment histories could be designed. Consumers are paying debt obligations on time that do not get reflected in the credit repository data and this has a huge negative impact on communities of color.

Improve the quality of data

Credit bureaus must make it easier for consumers to correct erroneous information on their credit reports. Incorrect information can lead to low credit scores and credit denials and limit access to quality, affordable credit.

Improving data quality will also contribute to better scoring models that more accurately assess consumer risk. Improving the performance of scoring models should be the goal of everyone involved with providing credit to consumers. It should also be the goal of regulators that oversee financial institutions and credit reporting agencies. Ensuring that consumers have access to quality credit will expand opportunities for consumers, promote healthy financial practices, and contribute to the growth of consumer net worth.

Make the system more transparent

It has taken years to get agencies to reveal the limited information that they currently do about how various factors impact a consumer’s credit score. Yet, there is much we don’t know. This can lead housing professionals and credit and housing counselors to give inaccurate information to consumers about how effectively to manage their credit. Moreover, since
different scoring mechanisms are used for different reasons, it may well be the case that when a consumer does something to improve their insurance score, for example, the consumer’s credit score will be negatively impacted.

Consumers and consumer counselors are generally uninformed about what should be done to impact positively the consumer’s score. Making the scoring systems more transparent will help consumers better manage their financial affairs. Making the system and the data more transparent will also help advocates, financial institutions, federal regulators, and legislators.

**Adequately assess the impact of credit scoring mechanisms on underserved groups**

The Consumer Financial Protection Bureau, other federal banking regulators, and federal enforcement agencies including DOJ and HUD should examine the impact of credit scoring mechanisms on underserved groups and the population as a whole. The regulators should also conduct disparate impact analyses of credit scoring systems. It is imperative that the data that regulatory and enforcement agencies use to undertake these analyses come from a broad range of sources. For example, regulators cannot rely predominantly on industry-developed data upon which to conduct these evaluations.

Credit score developers should also conduct similar analyses of their own systems to identify any fair lending concerns and to implement less discriminatory alternatives.

**Reduce the over-reliance on credit scoring mechanisms**

Credit-scoring mechanisms are an insufficient measure for predicting and managing performance as the current crisis has revealed. Borrowers are not behaving as their credit scores would indicate. Lenders, investors, regulators and legislators must caution against using credit scores as a replacement for underwriting or the only assessment of risk. There are many factors that affect loan risk including the presence of pre-payment penalties, inefficient appraisals, poor documentation practices, and other abusive loan features. The credit score may be the least significant factor when it comes to risk analysis. Therefore, lenders, investors, regulators and legislators must adopt approaches that objectively consider other elements that impact risk.

**Evaluate product risk**

In addition to reducing the reliance on credit scoring systems, federal regulators and legislators should push for the evaluation of credit and financial services products. Additionally, underwriting systems and practices should be evaluated for their level of risk. This information should be readily available so consumers will know which products and which underwriting practices pose the most risk and will therefore likely contribute to a negative credit score. Providing objective information to consumers about threats associated with the products or
services they are considering will enable consumers to make informed and sound financial decisions.

As discussed above, multiple studies reveal that unsafe products and unsavory underwriting practices have a significant impact on loan performance and credit risk. It therefore is quite practical to consider these functions in the risk analysis. Focusing analyses on borrower characteristics will not improve the quality of the assessment of risk; rather, objectively considering all factors that contribute to credit risk will result in a better analysis of risk exposure.

**Fix credit scores for victims of discrimination**

Repairing credit scores damaged by discrimination or any other practice should be included in complaint settlements and remedies. For example, the recent Justice Department settlement with Countrywide demonstrated the discrimination against African Americans and Latinos in steering and fees. Thousands of families who should have received prime loans were steered to subprime loans. It is reasonable to assume that their credit scores were negatively impacted by the mere fact that they received a more expensive subprime loan. Those borrowers should be made whole and their remedies should include restoring their damaged credit scores.

Regulators, enforcement agencies, and the courts should fix credit scores as a matter of course as part of remedies and settlements. In fact, this has already been done in some settlements between banks and fair housing organizations and consumer groups. When predatory lending was especially rampant in the early 2000s, fair housing organizations were sometimes successful in complaint settlements in getting a borrower’s credit history amended. In consultation with the credit reporting agency, the bank would have the trade line that applied to the predatory loan deleted from the borrower’s credit report. This, in turn, erased the loan from the borrower’s history as if it had never been made. In recent years, however, some lenders have not agreed to delete the trade line entirely and instead have agreed only to report the loan as “satisfied.” This means that the credit report shows that there is no debt remaining on the loan but any history of late payments and other blemishes remains on the credit report for the time allotted by the credit scoring agency. Unfortunately, because of the opacity of credit scoring mechanisms, it is hard to tell which approach might be best for a specific consumer at any given time.
Conclusion

By 2042, the majority of people in this country will be people of color. Given these changing demographics, it is past time to figure out how to make our nation’s credit system work equally for everyone. When civil rights groups called for a foreclosure moratorium on subprime loans more than five years ago, predicting that the nation was headed for a financial and foreclosure crisis and referencing the disproportionate damage these loans were causing in communities of color, Federal Reserve Chair Ben Bernanke told the groups that the problem of foreclosure would be contained and restricted to the subprime market. The Mortgage Bankers Association responded that, “Each loan is an individual transaction and situation, one which needs to be addressed individually between the lender and the borrower.”

We all know now that these responses to the burgeoning crisis did not make sense and that regulators and the industry failed to see the breadth of the ensuing crisis, despite the warnings made by civil rights and consumer protection groups. The foreclosure problems not only went beyond the U.S. subprime market but turned into an international economic crisis of proportions not seen since the Depression.

Credit scoring mechanisms are negatively impacting the largest growing segments of our country and economy. America cannot be successful if increasing numbers of our residents are isolated from the financial mainstream and subjected to abusive and harmful lending practices. Credit scores affect more and more of our daily activities and determine everything from whether we can get a job and provide for our families to whether we will be able to successfully own a home and build wealth for future generations. The current credit scoring systems work against the goal of moving qualified consumers into the financial mainstream because they are too much a reflection of our broken dual credit market. This paradigm must change.

We believe that the recommendations presented here are important steps towards broadening access to good credit for all qualified borrowers.

63 “Civil rights groups urge freeze on foreclosures,” Los Angeles Times, April 6, 2007.
64 “MBA Chairman Robbins Responds to Call for Moratorium on Foreclosures,” Mortgage Bankers Association news release, April 4, 2007.
Credit reports and scores reflect stunning racial disparities. Credit reporting and credit scoring are supposed to be entirely objective, with no room for flawed tools such as human judgment (and the biases built into human minds). Yet for the past two decades, study after study has found that African American and Latino communities have lower credit scores as a group than whites (and Asians, when the data is available). For a list of studies, see page 5.

Why do all these studies show such racial disparities in credit scores? Is it because communities of color are somehow less responsible? Are there cultural differences? No, these are not the explanations. Instead, the explanation lies in the very nature of judging humans based on past behavior. By doing so, credit scores necessarily incorporate elements of past inequality.

Communities of color have less income than white Americans – African Americans earn only 64 cents for every dollar earned by whites, and Latinos earn only 73 cents. This difference is due to racial inequality in many settings, such as segregation in education, hidden biases in employment, and the collateral consequences of mass incarceration. But the disparity in assets is even more stunning: African American families own less than seven cents for every dollar in wealth owned by white families, while Latino households own less than eight cents for every dollar of white wealth. With fewer assets to draw on, people of color – and the friends and family who they might turn to – are far less able to cushion the blow of financial catastrophes, such as job losses, income reductions, sickness, or unplanned expenses.

How Discrimination Lowers the Credit Scores of Communities of Color

The racial wealth gap has a very real impact on the ability of consumers to pay their bills. For example, a study by investigative journalists at ProPublica found that, even accounting for income, the rate of judgments from debt collection lawsuits was twice as high in mostly black communities as it was in mostly white ones. ProPublica’s conclusion as to the reason for this
disparity: the racial wealth gap makes it far more difficult for African Americans to recover from a financial setback or come up with a few hundred dollars to pay an emergency bill.

This racial wealth gap didn’t happen by accident. It was caused by centuries of discrimination, redlining, and exclusion. For example, the very practice of redlining was invented by the Federal Housing Administration, which refused to guarantee home loans made in African American communities, thus depriving them of the ability to accumulate wealth through homeownership. During the early years of Social Security, unemployment insurance, and the minimum wage, these programs did not cover domestic and agricultural workers — two of the most significant occupations for African Americans.

This discrimination is not ancient history. In the years before the most recent foreclosure crisis, homeowners of color were disproportionately targeted for predatory mortgages. These communities suffered grossly higher rates of foreclosure, wiping out nearly $400 billion in their wealth, and having a devastating impact on their financial health and their credit scores. Current discriminatory practices that have an outsized economic impact include racial profiling/law enforcement bias, employment discrimination, housing segregation, and the re-emergence of old-fashioned redlining. When minorities are disproportionately targeted by law enforcement, it has a devastating economic impact, not only on offenders but also on their families and communities. African Americans and Latinos are also disproportionately affected when municipalities discriminatorily imposed fees and fines to obtain revenue, i.e., the “Ferguson” issue. All of these practices drain precious dollars from minority families, making it a struggle to keep up with everyday bills, with one resulting risk being harm to credit histories.

Using the Past to Judge Carries on its Biases into the Future

Credit scoring is a reflection of the racial economic divide and wealth gap in this country. Its use also perpetuates that same racial and economic inequality. The use of credit reports and scores entrenches inequality by dictating a consumer’s access to future opportunities. Credit history is used as a gatekeeper for many important necessities – employment, housing (both rental and homeownership), insurance, and of course, affordable credit. Because of poor credit histories, minority consumers are disproportionately denied jobs, credit, insurance, housing and other services, or are forced to pay more. The drain on income affects their ability to pay their current bills, let alone build assets to move ahead. They cannot obtain loans on affordable terms to buy homes or start small businesses. The historic and current discrimination that is reflected in credit histories causes communities of color to move even further and further behind.

Challenging Economic Racism

In light of the troubling racial disparities reflected in credit reports and scores, they should not be used outside of the credit context absent the most compelling justification. For example,
there’s no evidence that credit history is a valid predictor of job performance and, with extremely limited exceptions, employers simply shouldn’t use credit reports in employment.

With respect to insurance, insurers claim that there is a correlation between credit scores and insurance losses. However, there is no good explanation for why a person with a lower credit score is supposedly more likely to cause greater losses to insurers. Insurers argue that this correlation is because someone “who is reckless with credit may also be reckless with driving or irresponsible about maintaining a home” – a weak argument since many people have poor scores due to job loss or illness. More importantly, correlation may simply be due to correlation with income and wealth. Consumers with lower scores simply may have fewer financial resources, and thus are more likely to file a claim rather than “eating” the loss. Consumers shouldn’t be penalized because they don’t have resources to forego filing a claim that they are legitimately entitled to file.

With respect to lending, the quandary is that credit histories and scores are useful tools for lenders, but they perpetuate past inequalities. The issue for our society is whether we continue with these same tools knowing that it not only hurts communities of color, but that the disparate impact of this tool reflects centuries of discrimination, exclusion, and exploitation.

One simple reform is to restrict or even eliminate the practice of risk-based pricing, in which lenders charge higher rates to consumers with lower credit scores. While lenders argue that higher prices are justified as compensation for the risk of lending to lower-scoring borrowers, expensive loan terms can make the loan much more onerous and difficult to repay. Given that consumers of color have historically been targeted for predatory lending, credit scores should not be used to justify high-rate loans.

Another straightforward reform is to expand the use of “second change” or special purpose programs. Second change programs, sometimes offered by community development financial institutions, give consumers who have fallen on hard times a chance to rebuild their credit histories. Special purpose programs are specifically aimed at increasing access to for minority communities, especially small business credit, and are explicitly permitted under federal law. Another option is to reduce the time limits on negative information in credit reports to three years as a way to minimize the vicious cycle aspect of low credit scores. There is nothing special about the current time limits of seven years for most information and ten years for bankruptcies, and some countries have shorter limits.

A deeper but more difficult reform, which would require significant research by data scientists, would be to develop new tools or to adjust the current tools to account for discrimination. New methods of analysis should be explored. Such tools might include the use of Big Data, i.e., analysis of massive amounts of data consumers generate through every day activities that is not traditionally used in underwriting. Currently, there are very real and significant concerns about the accuracy, predictiveness, and relevance of Big Data. The use of Big Data itself can also result in disparate impacts on minority communities, especially if the data is linked to a borrower’s social circles. Furthermore, there is no good explanation for why certain types of data that may statistically correlate with greater risk to lenders are relevant. However, there is
the possibility that Big Data could also be part of the solution one day, if a predictive and accurate type of analysis could be developed that is free of disparate impact.

There should also be research as to whether modifications could be made to current credit scoring models that could reduce racial disparities while maintaining – and hopefully, improving -- predictiveness. While credit scoring may have predictive value, it can also be an overly blunt instrument. Credit scoring models could be refined and modified so as to reduce racial disparities, a concept that legally is known as “a less discriminatory alternative.” Such modifications might need to actively take race into account. But that is not a radical concept. As former Supreme Court Justice Harry Blackmun once noted, “In order to get beyond racism, we must first take account of race. There is no other way.” Or as the following graphic illustrates, achieving justice or equity and eliminating the impacts of past discrimination may require treating disadvantaged groups differently.

Source: Interaction Institute for Social Change | Artist: Angus Maguire  interactioninstitute.org and madewithangus.com
Studies Showing Racial Disparities in Credit Scores

- A 2012 study by the CFPB examining credit scores for about 200,000 consumers found that the median FICO score for consumers in majority minority zip codes was in the 34th percentile, while it was in the 52nd percentile for zip codes with low minority populations. Source: Consumer Financial Protection Bureau, *Analysis of Differences Between Consumer- and Creditor-Purchased Credit Scores*, at 18, Sept. 2012, available at http://files.consumerfinance.gov/f/201209_Analysis_Differences_Consumer_Credit.pdf.

- A 2010 study by the Woodstock Institute found that in predominately African American zip codes in Illinois, over 54.2% of the individuals had a credit score of less than 620. In comparison, 20.3% of Illinois residents statewide had a credit score of less than 620, and only 16.8% of individuals in predominately white zip codes had a credit score of less than 620. In white zip codes, 67.3% of residents had a better than a 700 credit score, while 25% of individuals in predominantly African-American zip codes had credit scores above 700. In zip codes that were majority Latino, 31.4% of individuals had a credit score of less than 620, and only 47.3% had credit scores greater than 700. Source: Sarah Duda & Geoff Smith, Woodstock Institute, *Bridging the Gap: Credit Scores and Economic Opportunity in Illinois Communities of Color* 8 (Sept. 2010), available at http://www.woodstockinst.org/sites/default/files/attachments/bridgingthegapcreditscores_sept2010_smithduda.pdf.

- A 2007 Federal Reserve Board report to Congress on credit scoring and racial disparities, which was mandated by the 2003 Fair and Accurate Credit Transactions Act of 2003 (FACTA), analyzed 300,000 credit files matched with Social Security records to provide racial and demographic information. While the Federal Reserve’s ultimate conclusion was to support credit scoring, its study found significant racial disparities. In one of the two models used by the Federal Reserve, the mean score of African Americans was approximately half that of white non-Hispanics (54.0 out of 100 for white non-Hispanics versus 25.6 for African Americans) with Hispanics fairing only slightly better (38.2). Source: Board of Governors of the Federal Reserve System, *Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit* 80-81 (Aug. 2007) available at http://www.federalreserve.gov/boarddocs/rptcongress/creditscore/creditscore.pdf.

- A 2007 study by the Federal Trade Commission (FTC) on racial disparities in the use of credit scores for auto insurance, also mandated by the 2003 FACTA amendments, found substantial racial disparities, with African Americans and Hispanics strongly over-represented in the lowest scoring categories. Source: Federal Trade Commission, *Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance* 3 (July 2007) available at https://www.ftc.gov/sites/default/files/documents/reports/credit-based-insurance-
A 2006 study from the Brookings Institution found that counties with high minority populations are more likely to have lower average credit scores than predominately white counties. In the counties with a very low typical score (scores of 560 to 619), Brookings found that about 19% of the population is Hispanic and another 28% is African American. On the other hand, the counties that have higher typical credit scores tend to be essentially all-white counties. Source: Matt Fellowes, Brookings Inst., *Credit Scores, Reports, and Getting Ahead in America* 9-10 (May 2006) available at https://www.ciaonet.org/attachments/2800/uploads.

A 2004 study by Federal Reserve researchers found that fewer than 40% of consumers who lived in high-minority neighborhoods had credit scores over 701, while nearly 70% of consumers who lived in mostly white neighborhoods had scores over 701. Source: Robert B. Avery, Paul S. Calem, & Glenn B. Canner, *Credit Report Accuracy and Access to Credit*, Federal Reserve Bulletin (Summer 2004) available at https://www.federalreserve.gov/pubs/bulletin/2004/summer04_credit.pdf.

A 2004 study published by Harvard’s Joint Center for Housing Studies found that the median credit score for whites in 2001 was 738, but the median credit score for African Americans was 676 and for Hispanics was 670. Source: Raphael W. Bostic, Paul S. Calem, & Susan M. Wachter, Joint Ctr. for Hous. Studies of Harvard Univ., *Hitting the Wall: Credit As an Impediment to Homeownership* (Feb. 2004) available at http://www.jchs.harvard.edu/sites/jchs.harvard.edu/files/babc_04-5.pdf.

A 2004 study conducted by the Texas Department of Insurance on insurance scoring found that African American and Hispanic consumers constituted over 60% of the consumers having the worst credit scores but less than 10% of the consumers having the best scores. Source: Tex. Dep’t of Ins., *Report to the 79th Legislature--Use of Credit Information by Insurers in Texas* (Dec. 30, 2004) available at http://www.tdi.texas.gov/reports/documents/creditrpt04.pdf.

A 2004 study conducted by the Missouri Department of Insurance found insurance credit scores were significantly worse for residents of high-minority zip codes. The average consumer in an “all minority” neighborhood had a credit score that fell into the 18th percentile, while the average consumer in a “no minority” neighborhood had a credit score that fell into the 57th percentile. Source: Brent Kabler, Missouri Department of Insurance, *Insurance-Based Credit Scores: Impact on Minority and Low Income Populations in Missouri* (Jan. 2004) available at https://insurance.mo.gov/reports/reports/documents/credscore.pdf.

A 1997 analysis by FICO showed that consumers living in minority neighborhoods had lower overall credit scores. Source: Fair, Isaac & Co., *The Effectiveness of Scoring on Low-to-Moderate Income and High-Minority Area Populations* 22, Fig. 9 (Aug. 1997) available at http://market360online.com/sqlimages/1261/36693.pdf.
• A 1996 Freddie Mac study found that African-Americans were three times as likely to have FICO scores below 620 as whites. The same study showed that Hispanics are twice as likely as whites to have FICO scores under 620. Source: See Freddie Mac, Automated Underwriting: Making Mortgage Lending Simpler and Fairer for America’s Families (Sept. 1996) available at http://www.housingfinance.org/uploads/Publicationsmanager/9706_Aut.pdf.

Other Resources


United States Department of Justice – Civil Rights Division, Investigation of the Ferguson Police Department, Mar. 4, 2015, available at https://www.justice.gov/sites/default/files/opa/press-releases/attachments/2015/03/04/ferguson_police_department_report.pdf (discussing how law enforcement practices in Ferguson, MO were “shaped by the City’s focus on revenue rather than by public safety needs” and showed “clear racial disparities that adversely impact African Americans.”)


BIG DATA
A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK
ABOUT THE AUTHORS

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The findings and conclusions presented in this report are those of the authors alone. This report was completed on February 14, 2014; information on the chart was fact checked as of Dec. 11, 2013.
# BIG DATA

**A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK**

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EXECUTIVE SUMMARY

Approximately 64 million consumers in the United States have no credit history or lack sufficient credit history to generate a credit score, cutting off access to traditional banking services. Finding a way of getting affordable access to credit is of vital importance to the economic well-being of this population. It also represents an untapped market with the potential for big profits. So it is unsurprising that in this era of big data, information culled from Internet searches, social media, and mobile apps would be put to use towards that goal. However, it is unclear as to whether doing so will be beneficial for the low-income consumer. These products may fill a void and provide affordable access to credit to these underserved populations or they may be a means of preying on vulnerable communities.
Big data makes big promises. It promises to make better predictive algorithms that in turn can make better products available to the unbanked and underbanked. But can big data live up to this big promise?

When analyzing this use of big data, consumers and policy makers should be concerned with these questions:

1. Are the decisions based upon accurate data?
2. Can the algorithms, when fed with good data, actually predict the creditworthiness of low-income consumers?
3. Does the use of big data in reports used for credit, employment, insurance, and other purposes comply with consumer protection laws?
4. Is there the potential for a discriminatory impact on racial, geographic, or other minority groups?
5. Does the use of big data actually improve the choices for consumers?

Answering these questions has been especially challenging given the secretive and proprietary nature of the products examined. Therefore, the National Consumer Law Center (NCLC) did its own investigation of the information data brokers had on its staff and reviewed products using big data analytics.

**NCLC’s Study of Big Data Accuracy**

Big data proponents argue that multiplying the number of variables will expand access to borrowers with thin credit files. Expanding the number of data points also introduces the risk that inaccuracies will play a greater role in determining creditworthiness. Given these indications of accuracy problems, we conducted our own survey for this report of the data maintained on consumers by big data brokers. Even given our initial skepticism, we were astonished by the scope of inaccuracies among the data brokers we investigated.

In general, obtaining the data was challenging and the reports our volunteers received were riddled with inaccuracies or included little or incomplete information. Errors ranged from the mundane—a wrong e-mail address or incorrect phone number—to seriously flawed. Interestingly, eBureau touts its ability to estimate income based on its advanced models and offer insights based upon the consumer’s education. Despite that claim, seven of the fifteen consumer reports generated by eBureau contained errors in estimated income, nearly doubling the salary of one participant and halving the salary of another, and eleven of the fifteen reports incorrectly stated the volunteer’s education level. Reports purchased from Intelius and Spokeo had the most inaccuracies while the reports from Acxiom, eBureau, and ID Analytics contained very little information.
Applying the Fair Credit Reporting Act

An analysis of the Fair Credit Reporting Act, shows that many big data brokers could be considered consumer reporting agencies (CRAs) and subject to the FCRA. The FCRA imposes substantial duties on a CRA. Three of the most important functions of the FCRA deal with accuracy, disclosure, and the right to dispute items on the report. It is highly unlikely, given the size of the data set and the sources of information, that the companies that provide big data analytics and the users of that data are meeting these FCRA obligations.

Evaluating the Discriminatory Impact

Because big data scores use undisclosed algorithms, it is impossible to analyze the algorithm for potential racial discriminatory impact. According to the companies’ marketing materials, consumers are judged based upon data generated from their Internet usage, mobile applications, and social media. However, access and usage of these sources vary by race and socioeconomic status, and thus any algorithm based upon them may have racial disparities.

Different races also use the Internet differently. For example, according to Nielsen spokesman Matthew Hurst, “Black consumers are also 30 percent more likely to visit Twitter using mobile phones than the average customer.” These different ways of accessing the Internet leave a digital data trail. Yet, despite these known differences, little is known about how each of these variables is weighted or used by big data analytics.

Big Data, Better Products?

Finally, proponents of big data underwriting argue that by using a constellation of factors to price credit, the cost of credit will be reduced for low-income borrowers, thus enabling lenders to provide lower-cost small loans as alternatives to payday loans. We evaluated seven loan products that are based on big data underwriting, six of which present themselves as payday loan alternatives. Some of the features of these loans are arguably “less bad” than those offered by traditional payday lenders, but these products still fail to meet the requirements to be considered genuine, better alternatives. They still feature three-digit APRs.

Even more troubling is that all of the lenders except Presta and MySalaryLine require borrowers to provide sensitive banking information (i.e. bank name, routing number, and account number). A lender could potentially use this information to reach into a bank account and take the funds if the consumer fails to make a payment. The requirement for electronic information is of concern and may be an attempt to obtain access to the consumer’s account while evading the important protections of the Electronic Funds Transfer Act. The requirement that the borrower provide bank account information could ensure that the lender will be repaid, even if the borrower is unable to afford the loan without neglecting other expenses (like rent or food) or falling into a cycle of debt.
Conclusion and Recommendations

Unfortunately, our analysis concludes that big data does not live up to its big promises. A review of the big data underwriting systems and the small consumer loans that use them leads us to believe that big data is a big disappointment. More and more, consumers are leading robust lives online. However, as data about consumers proliferates, so does bad data.

Key Federal Policy Recommendations

- The Federal Trade Commission (FTC) should continue to study big data brokers and credit scores testing for potential discriminatory impact, compliance with disclosure requirements, accuracy, and the predictiveness of the algorithms.
- The FTC and the Consumer Financial Protection Bureau (CFPB) should examine big data brokers for legal compliance with FCRA and Equal Credit Opportunity Act (ECOA).
- The CFPB should create a mandatory registry for consumer reporting agencies so that consumers can know who has their data.
- The CFPB, in coordination with the FTC, should create regulations based upon the FTC’s research that:
  a. Define reasonable procedures for ensuring accuracy when using big data;
  b. Specify a mechanism so that consumers can do a meaningful review of their files including all data points that can be linked to that consumer (not just those that identify the consumer explicitly); and
  c. Define reasonable procedures for disputing the accuracy of information.
- The CFPB should require all of the financial products it regulates to meet Regulation B’s requirements for credit scoring models.
## Analysis of Big Data Loan Products

<table>
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<tr>
<th>PRODUCT</th>
<th>PROVIDER</th>
<th>STATE</th>
<th>COSTS</th>
<th>TERMS</th>
<th>APR WITH FEES</th>
<th>INSTALLMENT PAYMENTS</th>
<th>COLLECT ELECTRONIC BANK INFORMATION</th>
<th>FINANCIAL EDUCATION</th>
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<tr>
<td>Great Plains Lending</td>
<td>ThinkFinance</td>
<td>Nat’l</td>
<td>Varies by amount From $91.68 to $2386.84</td>
<td>Bi-weekly payments</td>
<td>Varies by amount 349.05% to 448.76%</td>
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<tr>
<td>LendUp</td>
<td>LendUp</td>
<td>CA</td>
<td>Varies by loan amount and length From $10.70 to $44</td>
<td>30 days</td>
<td>Varies by loan amount and length 199.53% to 748.77%</td>
<td>Not available to first time borrowers.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MySalaryLine</td>
<td>ThinkFinance</td>
<td>AZ, MO</td>
<td>$150 AZ: $7.50 plus 14¢ daily MO: 55¢ daily</td>
<td>Next Pay Date</td>
<td>MO: 134%</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>$300 AZ: $15 plus 29¢ daily MO: $1.10 daily</td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>$500 AZ: $25 plus 48¢ daily MO: $1.83 daily</td>
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<tr>
<td>Plain Green</td>
<td>ThinkFinance</td>
<td>Nat’l</td>
<td>Varies by amount From $189.52 to $1979.84</td>
<td>Bi-weekly payments</td>
<td>Varies by amount 299.17% to 378.95%</td>
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<tr>
<td>Presta</td>
<td>ThinkFinance</td>
<td>Nat’l</td>
<td>Varies depending on monthly payment (For an iPad 4, $23 weekly payment, $64 initial payment, effective fees of $738)</td>
<td>Weekly payments</td>
<td>Varies by product</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RISE (Formerly Payday One)</td>
<td>ThinkFinance</td>
<td>CA, DE, ID, LA, MO, NM, OH, SC, SD, TX, UT, WI</td>
<td>Varies by state, plus interest: Up to $735 in TX, $693 in OH</td>
<td>Bi-weekly payments</td>
<td>Varies by state 299.16% to 358.85%</td>
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<tr>
<td>Spotloan</td>
<td>ZestFinance</td>
<td>All states except MA, MO, ND, and WV</td>
<td>Varies by loan amount and length From $206.04 to $1372.69</td>
<td>Bi-weekly payments</td>
<td>390%</td>
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The information on this chart is based upon publicly available information found on the following products’ websites on Dec. 11, 2013.
INTRODUCTION

Approximately 64 million consumers in the United States have no credit history or lack sufficient credit history to generate a credit score, cutting off access to traditional banking services. Finding a way of getting affordable access to credit is of vital importance to the economic well-being of this population. It also represents an untapped market with the potential for big profits. So it is unsurprising that in this era of big data, information culled from Internet searches, social media, and mobile apps would be put to use towards that goal.

Big data makes big promises. It promises to make better predictive algorithms that in turn can make better products available to the unbanked and underbanked. But can big data live up to this big promise?

Big data products claiming to hold the key to unlocking the mystery of low-income consumers’ creditworthiness must be able to show that they actually do what they claim to do. Some have suggested that big data is merely noise. As Nate Silver writes in The Signal and the Noise:

> If the quantity of information is increasing by 2.5 quintillion bytes per day, the amount of useful information almost certainly isn’t. Most of it is just noise, and the noise is increasing faster than the signal. There are so many hypotheses to test, so many data sets to mine — but a relatively constant amount of objective truth.¹

According to Tomaso Poggio, an MIT neuroscientist who studies how our brains process information, the problem is that evolutionary instincts lead us to see patterns where there are none—“finding patterns in random noise.”²

Big data products must also show that they can meet not just the goals but also the ideals of consumer protection laws. They should operate with transparency, accuracy, and relevancy. Despite existing consumer protection laws giving consumers easy access to their credit reports, traditional credit reports are known to have high rates of error. Adding to the number of data points with data of questionable quality seems unlikely to result in higher rates of accuracy for consumers.

Finally, big data products must operate in a way that is fair and free from discrimination. Different communities use and access technology in different ways. The data that is mined often has different implications for different populations. Big data must not lay the groundwork for lending that discriminates against vulnerable consumers— whether intentional or unintentional.

Companies are starting to use big data to make decisions about whether to offer loans to consumers and on what terms. When analyzing this use of big data, consumers and policy makers should be concerned with these questions:

1. Are the decisions based upon accurate data?
2. Can the algorithms, when fed with good data, actually predict the creditworthiness of low-income consumers?
3. Does the use of big data in reports used for credit, employment, insurance, and other purposes comply with consumer protection laws?

4. Is there the potential for a discriminatory impact on racial, geographic, or other minority groups?

5. Does the use of big data actually improve the choices for consumers?

The public literature reveals surprisingly little about how big data brokers and users of big data operate. Unfortunately, our investigation, detailed in this report, found that big data turns out to be a big disappointment. The data brokers we investigated provided very little data and the data they did provide had many errors. Moreover, the products we reviewed failed to provide more affordable products for low-income consumers.

DIGITAL DEMOGRAPHICS

Historically, issues related to technology and privacy were seen as middle-class consumer issues. However, now that the Internet is increasingly a requirement for social and economic inclusion, these issues impact low-income consumers to a much greater extent. As low-income consumers use the Internet more, lenders and data brokers have more tools to analyze the credit potential of more low-income consumers.

The Pew Internet & American Life Project catalogs the Internet habits of individuals and families. In the lowest-income demographic surveyed, 76 percent of adults used the Internet.3 However, disparities still exist in how low-income consumers access the Internet. For example, 65 percent of consumers making less than $25,000 a year lack access to broadband in the home.4 Lower-income households with a member who owns a Smartphone are more likely than higher-income households to access the Internet primarily using a mobile device.5 Of adults that earn less than $30,000 a year, 41 percent own a Smartphone.6 Social media use among lower-income consumers is also widespread. Of households that make under $30,000 per year, 77% frequent social media sites.7

Of adults that earn less than $30,000 a year, 41% own a Smartphone; 77% frequent social media sites.

To date, these communities have been underserved by traditional lenders, so there is an opportunity for lenders to use big data to provide credit products to them. However, it is unclear as to whether doing so will be beneficial for the low-income consumer. These products may fill a void and provide affordable access to credit to these underserved populations or they may be a means of preying on vulnerable communities.
BACKGROUND ON BIG DATA

The rapid evolution of technology has ushered in the rise of what some industry analysts dub “the Decade of Big Data.” The McKinsey Global Institute defines big data as “datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.” However, in common usage (and for the purposes of this report), big data means the massive amounts of data that consumers generate in everyday life—through business transactions, e-mail messages, photos, surveillance videos, web traffic, activity logs stored in giant structured databases, or unstructured text posted on the web, such as blogs and social media. In the last decade, the amount of data generated has grown exponentially, partially due to the rise of web tracking techniques and the increasing use of Internet-enabled mobile devices. As the amount of available data has grown, innovations in computing capability, the falling cost of data storage, and advances in statistical analysis make it easier to interpret and monetize data.

The private sector, government agencies, and nonprofits are taking advantage of the proliferation of data to transform the way they operate. Private industry has harnessed the power of big data to develop sophisticated advertising campaigns. Companies target potential customers whose interests and demographic information they have identified through social networking data, web browsing history, and purchase information. Target, for example, can reliably predict which shoppers are pregnant based on the history of products purchased at the store, combined with other demographic information purchased from third-party data brokers. Overall, business customers spend $45 billion a year for data.

It’s unsurprising amidst all this digital noise that lenders would seek to capitalize on big data to drive credit decisions. Douglas Merrill is the former chief information officer (CIO) at Google and founder of ZestFinance. At Google, Merrill managed the rise of one of the world’s largest data companies. Now, he’s deploying the analytical tools and technological savvy he cultivated at the search engine behemoth to transform subprime credit underwriting.

According to Merrill, “[a]ll data is credit data.” Merrill founded ZestCash in 2009 but re-named the company ZestFinance after switching its focus from directly lending small dollar loans to selling the data analysis it provides to other lenders of subprime products. Instead of evaluating potential borrowers based on a FICO score, which uses 10-15 variables to arrive at its score, ZestFinance renders a credit decision after analyzing thousands of variables. The company runs the variables through ten different models. By expanding the number of variables, the company argues, the credit decision will more accurately reflect the risk a person presents. Subprime borrowers, who typically have poor FICO scores and therefore pay much higher interest rates on loans, may actually turn out to be good credit risks. In conjunction with the algorithms using big data, new lines of financial products have been introduced targeting unbanked and under-banked populations. However many of these products are very expensive and may not be beneficial.
THE BIG DATA ECOSYSTEM—HOW DOES IT WORK?

Thousands of companies specialize in data, but three different functions exist: data collection, data aggregation, and data analysis.

Data Collection

To understand data collection, it’s important to understand how data is created. With the introduction of Internet-enabled devices (computers, mobile phones, and tablets), the amount of data that a consumer generates is enormous. Between 2006 and 2011, the amount of data generated increased by a factor of nine to 1.8 zettabytes (1.8 trillion gigabytes). Each time a consumer visits a website, makes a purchase, or indicates a preference on Facebook or other social networking sites, data is created.

For example, a woman interested in purchasing a mystery novel will sit at her computer and open a web browser. She types “Amazon.com” into the URL line. By typing in the URL, her computer requests the page from Amazon’s server. The computer transmits its Internet Protocol (IP) address to the webpage. An IP address is similar to a brick-and-mortar address, in that each address is unique. Based on the woman’s IP address, the website’s server can predict her zip code (with varying degrees of accuracy). Amazon’s server sends the webpage and downloads a “cookie” (line of text) onto the woman’s hard drive. Several other third-party marketing firms that contract with Amazon may also download cookies. A cookie can contain various types of information, including (but not limited to) the time of her visit, the subpages she visited, and the items she purchased. Cookies also typically designate a unique ID to one’s computer. By assigning a unique ID, third-party tracking companies can see other pages a person visits, intuited preferences.

Third-party tracking companies also may embed a piece of software called a “web beacon” which not only can track which webpages a person visits, but also record the text typed in. For example, if a webpage has a beacon on it, then when a person uses the “search” function on a webpage, such as Amazon’s, that information is relayed to a third-party marketer. Subsequent pages that the person visits are summarily tracked. If the woman purchases a few mystery novels from Amazon and then books a flight for a family vacation, surfs the web for the latest political gossip, and “Googles” the best rates for car insurance, a third-party tracking company may capture every single move she makes.

A rich portrait of individuals emerges from the ability to track their online behavior. From purchase histories to search topics, a completely unedited and unmediated version of a person emerges. This data is incredibly valuable to marketers and there are few restrictions on such data in the U.S. This data can be bought and sold at will.

Web crawling is another technique that companies can use without developing a relationship with a host page. Web crawling involves the duplication and categorization of
information from websites, typically by automated means. Programmers can write software that scans websites and sorts posts. Rapleaf, a tech company, used web crawling techniques to scan posts from Facebook. Social Intelligence Corp. collects data on individuals by deploying web crawlers to analyze Facebook profiles and pictures. Individuals can be categorized based on groups that they “like” or comments posted. Based on this data, the company sells information in the form of a background check report that prospective employers may use to determine the consumer’s eligibility for employment. Photos tagged of the individual by other users may also be included in the report.

**Data Aggregation**

The ability to combine and cross-reference this data with other data creates an enormous opportunity to expand the information available about a particular individual. Data aggregation is the process of combining an array of data or data sources to compile a comprehensive portrait of an individual, behavior, or characteristic. ZestFinance, for example, combines data from alternative credit bureaus with data gleaned from web crawling to make a decision about whether to loan money to individuals.

Companies have sought to make data aggregation easier by creating platforms that reformat data to make it uniform. Zoot Enterprises, for example, buys data from fourteen major databases and allows business clients to conduct searches across all fourteen databases.

**Data Analysis**

Data analysis is completed by running either raw data or aggregated data through a series of models (usually called algorithms) to reveal patterns or test hypotheses.

While the collection, aggregation, and analysis are all distinct steps in using big data, they are not necessarily performed by separate actors. ZestFinance, for example, buys data from data brokers but also collects its own data through web crawling. It combines the data and runs it through ten separate models before rendering a credit decision. Most companies use a hybrid model where they perform their own proprietary analysis on data obtained from multiple data brokers, aggregators, or other sources. As discussed in detail in the next section, depending on the structure of the company, many of the activities of the actors performing these three steps are subject to the regulations of the Fair Credit Reporting Act.

**SUPERSIZE IT: IS BIGGER ALWAYS BETTER?**

Big data proponents argue that multiplying the number of variables will expand access to borrowers with thin credit files. Thus, they claim that big data will be used to generate a credit score that gives creditors a fuller picture of a consumer and therefore gives a more accurate and robust predication of the consumer’s ability to repay. While that potential may exist, it is unclear that this is what actually occurs. Big data only generates
better results if the algorithm is predictive and if the data that feeds it is accurate. At present, there is no mechanism in place to ensure the integrity of credit scores generated by big data.

Certainly, problems exist with the traditional credit scoring system. First, credit scores cannot predict if any particular person will actually engage in the behavior. In fact, often the probability is greater that a particular low-scoring person will not engage in the behavior. Second, many low-income consumers have low credit scores simply because they have either a “thin file” or “no file.” This means that they have very little reported credit history—often because low-income consumers are less likely to access the types of financial services that report to the traditional credit bureaus. A denial of credit to these consumers is based on the absence of credit history rather than anything negative in their credit histories.

Big data credit scoring models attempt to address both of these critiques of traditional credit scoring. They claim that by expanding the data points in their algorithms, they can create a more refined predictive score. Also, by expanding the type of data analyzed, they claim that they enable lenders to extend access to credit to traditionally underserved populations.

Creating better credit scores and increasing access to credit for the estimated 64 million consumers who have little or no information in traditional reports at the major credit bureaus (Equifax, Experian, and TransUnion) are laudable goals. However, expanding the type of information used also carries risks.

Like promoters of big data, promoters of “full file” utility credit reporting claim that using utility data will assist thin file or no-file consumers to build credit histories and gain access to credit. However, full file utility credit reporting could end up harming consumers’ credit scores or give them low scores instead of no scores. Many low-income consumers struggle to get credit.

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### Credit Score Basics

A credit scoring system is one that numerically weighs or “scores” some or all of the factors considered in the underwriting process. Factors are developed based on data about past borrowers from their files at consumer reporting agencies and sometimes from other sources. Examples of factors used in a traditional credit scoring system include:

- history of payment of past obligations,
- amounts owed,
- length of credit history, and
- types of credit already held.

The number of points received often determines whether the consumer is offered credit, how much credit is granted, and at what price.

Credit scores are used to predict the probability that consumers will engage in a particular behavior, e.g., miss a payment, default, or file for bankruptcy. Because a credit score is generated based on information in a consumer’s credit file, it will change as the information in the consumer’s credit file is updated. The leading creator of models is FICO, formerly known as Fair Isaac & Co. Even though FICO develops other types of credit scores, a credit risk score is sometimes referred to as a “FICO score.” The “Big Three” credit reporting agencies (Equifax, Experian, and TransUnion) have developed their own credit risk score model to compete with FICO, called the “VantageScore.”
customers would receive negative marks for a 30- or 60-day late payment during months when utility costs are high, even though they eventually catch up when costs are lower (e.g., in summer months for cold winter states). Financially distressed consumers could (and should) be prioritizing payment based upon whether their utilities will be shut off so they can afford to pay for food or other critical items and defer their utility payments until later. Also, the federal assistance Low Income Heating Energy Assistance Program (LIHEAP) actually requires consumers to receive a shut-off notice before they can get assistance in some states. Reporting utility information means that these consumers cannot access LIHEAP assistance without damaging their credit records. In this way, even if “full file” utility credit reporting is predictive of creditworthiness, it unfairly punishes vulnerable consumers for making the best financial decision for their families.

Given the breadth of personal and potentially sensitive information big data brokers collect, credit scoring models based upon big data must be analyzed to determine their true impact on low-income consumers. Specifically, consumers and policy makers should be concerned with the integrity of the data in three ways:

1. accuracy of the data used;
2. verifiable predictiveness of the algorithm; and
3. potential discriminatory impact.

DATA ACCURACY: GARBAGE IN, GARBAGE OUT?

While big data enthusiasts highlight important flaws in the current credit scoring system, critics have identified drawbacks to expanding credit variables from fifteen to thousands. Instead of minimizing the impact of an unimportant credit signal, a big data approach could amplify the significance of a completely irrelevant signal. Nassim Taleb, a risk engineering professor at New York University, is a vocal critic of big data. Taleb said, “…if I generate…a set of 200 variables—completely random and totally unrelated to each other—with about 1,000 data points for each, then it would be near impossible not to find in it a certain number of ‘significant’ correlations of sorts.”24 With a thousand different variables—from prepaid cell phone payments to rental payments to social media histories—the correlation among variables can confuse instead of clarify.

Expanding the number of data points also introduces the risk that inaccuracies will play a greater role in determining creditworthiness. More data does not necessarily mean better data. In a 2013 study by the Federal Trade Commission, researchers found that 20 percent of traditional credit reports had errors; 5 percent of credit reports contained errors that could result in a lower credit score, making credit inaccessible or costlier.25 The traditional credit bureaus are highly centralized and finite—there are only three—but hundreds of other consumer data brokers exist that provide alternative credit information and other types of consumer data. Even with a relatively centralized system, it can be difficult to get mistakes corrected among the “Big Three” credit bureaus (Equifax, Experian, and TransUnion). If data aggregators or data analysts harvest data from
dozens of sources, inaccuracies are harder to detect and the source of the error can be difficult to identify.

A small research study published in 2005 suggests that these accuracy problems are not merely hypothetical. Researchers requested files from two major data brokers—Acxiom and ChoicePoint—that provide lenders with alternative credit data. Eleven of eleven ChoicePoint reports contained at least one error. Although eleven testers requested their files from Acxiom, the company only mailed six. Four of the six reports reported incorrect information.26

In addition, the National Consumer Law Center’s (NCLC) 2012 report Broken Records, reviewed the inaccuracies endemic to the criminal background check industry and found criminal background checks to be rife with errors.27 Many of these background check agencies rely on unverified, incorrect, or outdated data available on the Internet, rather than doing the more difficult or expensive research to track down more accurate information.

Given these indications of accuracy problems, we conducted our own survey for this report of the data maintained on consumers by big data brokers. Even given our initial skepticism, we were astonished by the scope of inaccuracies among the data brokers we investigated.

NCLC’s Study of Big Data Accuracy

In an attempt to learn more about big data brokers, fifteen volunteers, all whom were NCLC employees, attempted to retrieve their information from four different data brokers: eBureau, ID Analytics, Intelius, and Spokeo. By either purchasing or requesting the consumer file from each of these companies, NCLC hoped to illuminate the type of data collected, the accuracy of the data, and the ease of obtaining a consumer report. Report authors Persis Yu and Jillian McLaughlin also requested reports from Acxiom. Other volunteers did not request reports from Acxiom because of the financial cost and because, in light of a New York Times article published prior to our study, no information was expected (see p. 17). Though they were all NCLC employees, the volunteers ranged in age, work experience, income, education, and social media presence.

The five big data companies chosen. We chose the five companies based on several factors, including representativeness of the industry, the variety of users likely to buy the data, and the relative ease with which information could be requested. Data from two of the five companies (Spokeo and Intelius) was purchased via a subscription or individual report.

Acxiom is believed to have amassed the world’s largest commercial database on consumers.28 It claims to provide insight into consumers’ preferences and behaviors with its data products and services.29 One of Acxiom’s products lets corporate clients purchase
hundreds of details about individuals or households, such as whether the household size, income, and even whether it has concerns about allergies, diabetes, or “senior needs.” As mentioned previously, only co-authors Persis Yu and Jillian McLaughlin attempted to obtain reports from Acxiom.

**eBureau** also generates a “score” for use by clients in determining a consumer’s credit risk. eBureau claims to analyze inputs from thousands of databases, storing billions of records in its warehouses. Interestingly, eBureau touts its ability to estimate income based on its advanced models. According to its promotional materials:

> eBureau’s Income Estimator utilizes dozens of different predictive data sources, including independently compiled sources of demographic data, real asset information, and spending behavior. Income Estimator’s sophisticated scoring model factors in 375 discrete individual, household, and neighborhood variables to produce a highly accurate estimate. It has been validated against hundreds of thousands of self-reported income records from across the US...

**ID Analytics** primarily serves clients using “identity intelligence,” which monitors the name, address, Social Security number, phone number, and date of birth consumers disclose. The company uses this information to create an alternative credit score; in theory, the alternative score predicts financial stability. For example, if consumers change addresses or phone numbers frequently, they are likely to be less stable than consumers who consistently report the same number and address. ID Analytics collects consumer information from cable providers, cell phone companies, and checking account history.

**Intelius** appeals to a broader market segment than eBureau and ID Analytics, which primarily target financial services providers. Intelius stores more than 20 billion records and compiles data on individuals for a variety of purposes—hiring, dating background checks, and fraud prevention. Intelius specifically markets its data to businesses and consumers.

**Spokeo** focuses on a consumer audience and specifies on its site that the information collected should not be used for any purpose listed under the Fair Credit Reporting Act (FCRA), including employment screening, credit decisions, and insurance eligibility (see page 26). Spokeo suggests that its site can be used to identify the holder of a telephone number, help families reunite with loved ones, and assist nonprofits and small businesses in identifying potential donors or customers.

The five companies represent a range of services, markets, and tactics. Four of the five companies are on the radar of the FTC. In December of 2012, the FTC ordered Acxiom, eBureau, ID Analytics, and Intelius to disclose to the agency their methods of data collection and privacy practices.

**Obtaining the reports.** In general, obtaining the reports was challenging. At the time, Acxiom, purportedly the world’s largest data company, required consumers to submit an online request form and then physically mail a personal check for $5 to cover the cost of processing the request. When an NCLC researcher asked if Acxiom would accept a
money order instead of a personal check, Acxiom stated that it would accept a money order only with a notarized copy of the consumer’s identification document.

On their websites, ID Analytics and eBureau provide users with a standardized process for requesting individual consumer reports. However, after our volunteers submitted the voluminous information identified on its website, eBureau sent a letter requiring each volunteer to verify his or her Social Security number by sending a copy of the card, W-2, or other official document. ID Analytics required two volunteers to submit additional information.

Two volunteers were unable to find their information when searching Spokeo, and one of those was also unable to find information from Intellius. The volunteer who received no Spokeo or Intellius information has a unique name and numerous social media accounts.

The data obtained. The reports from Acxiom, eBureau, and ID Analytics contained very little information. In contrast, the reports from Intellius and Spokeo were more robust.

**Acxiom.** Our experience was similar with that of a journalist from the *New York Times* who requested her report from Acxiom in 2012. She expected to see most of the 1,500 data points the company claims to amass per consumer. Instead, the company sent a report listing the journalist’s previous residential addresses. She wrote, “For a corporate client, the company is able to match customers by name with, say, the social networks or Internet providers they use, but it does not offer consumers the same information about themselves.” In our experience, one co-author’s Acxiom report included current and previous residential addresses as well as a very incomplete voting history; the other co-author’s Acxiom report also included an incorrect middle initial of her name, current and previous residential addresses (current address was incorrect), as well as an inaccurate and incomplete voting history.

**eBureau** claims to utilize “vast amounts of predictive data to offer instant insights across multiple industries, from higher education to financial services to automotive and insurance marketers.” Yet, the reports by eBureau only had nine fields: first name, last name, address, phone number, Social Security number, date of birth, income, education, and length of residence.

**ID Analytics** claims to help companies “optimize[] credit decisions about individuals to maximize revenue opportunities and reduce risk” through its data and algorithms. Yet, the reports it gave to our volunteers contain just ten fields: name, address, social security number, phone, date of birth, name variations, date of birth variations, Social Security number variations, address history, and phone number history.

**Intellius** claims to be “a confidential way to find people so you can reconnect or just get more info on a person.” Its People Search reports include phone numbers, address history, age and date of birth, relatives, and social media profiles.
Spokeo reports provide the most information. They include personal data such as, name, address, phone number, email address, age, marital status, education level, family members, and social media profiles. The reports also included demographic information about the volunteer who requested the file, such as area home values, occupations, median incomes, race and gender statistics, and average age.

Given the claims by each of these data broker companies, the sparse information they produced for our volunteers may only be a fraction of the data the company stores about them. Such an omission may violate the Fair Credit Reporting Act.

Accuracy. The reports our volunteers received were riddled with inaccuracies. Errors ranged from the mundane—a wrong e-mail address or incorrect phone number—to seriously flawed. One of the reports combined information about our volunteer with information about two other individuals; other reports listed wrong addresses, relatives, and occupations. Some reported home addresses in states in which the volunteer never resided. Interestingly, eBureau touts its ability to estimate income based on its advanced models44 and offer insights based upon the consumer’s education. Despite that claim, seven of the fifteen consumer reports generated by eBureau contained errors in estimated income, nearly doubling the salary of one participant and halving the salary of another, and eleven of the fifteen reports incorrectly stated the volunteer’s education level.

Reports purchased from Intelius and Spokeo had the most inaccuracies. The most common errors in both were wrong address (twelve out of fourteen volunteer reports and eight out thirteen volunteers respectively), added or omitted immediate family members (ten and seven respectively), and added or omitted social media accounts (nine and ten respectively).
Study Participants with Mistakes in Their Data Report (per Company and Category)

Of the 15 study participants’ reports, there were a number of errors. Acxiom was not included in this study.

**eBureau**

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**ID Analytics**

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<td>Age</td>
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**Intelius**

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**Spokeo**

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Verifying the Predictiveness of Big Data Credit Scores

Aside from the unverified claims by companies profiting from the algorithms used to analyze big data, consumers have no way to know whether the algorithm accurately predicts their creditworthiness. Though a similar critique is certainly true of FICO and other traditional credit scores, consumers are given a general understanding of how those scores work and roughly how different variables are weighted. This gives consumers a guidepost for predicting their own creditworthiness and potentially adjusting their behavior in order to improve their creditworthiness.

With big data, there is no independent source confirming the accuracy or reliability of the algorithms used to generate a predictive score. Nor is there transparency regarding how the score is calculated. Consumers obtaining loans based upon this score have no real way of knowing whether the loan really is tailored for them or whether this is an elaborate marketing scam.

As discussed next, the FCRA does not explicitly require credit scores to be predictive of creditworthiness. However, Regulation B, the implementing regulation for the Equal Credit Opportunity Act (ECOA), does address predictiveness. Regulation B requires that a credit scoring system satisfy four criteria:

1. The data used to develop the system must constitute either the entire pool of applicants or an appropriate sample of applicants who applied for credit within a reasonable preceding period of time;
2. The system must have the purpose of predicting applicants’ creditworthiness with respect to “legitimate business interests” of the creditor using it;
3. The system must be “developed and validated using accepted statistical principles and methodology”, and
4. The system should be periodically reviewed and re-validated as to its predictive ability and adjusted accordingly.

Regulation B itself makes limited use of this definition of a credit scoring system, referring to it only with respect to when creditors may consider information about age and public assistance status. However, the practical importance of this definition is much greater, as some of the banking regulators have required the banks they regulate to meet Regulation B’s requirements for credit scoring models. The Consumer Financial Protection Bureau (CFPB) could similarly require products that it regulates to meet these requirements.
Applying the Fair Credit Reporting Act (FCRA)

One of the most powerful tools consumers and regulators have to ensure a fair and accurate credit reporting system is the FCRA. As the use of big data purports to address some of the deficiencies of traditional credit reporting, it must also be held to the same consumer protection standards.

FCRA Background

The FCRA is a federal statute that first became effective April 25, 1971. It regulates the activities of consumer reporting agencies (CRAs), the users of reports, and those who furnish information to CRAs (furnishers). The Act also provides remedies to consumers affected by such reports.

The FCRA attempts to protect consumers’ privacy and reputations by placing various obligations on persons who use or disseminate credit information about consumers. For example, CRAs must adopt reasonable procedures to ensure that the information they disseminate is accurate and up-to-date and that it is furnished only to users with certain permissible purposes. The Act also imposes disclosure obligations for both CRAs and users. These are designed to ensure that consumers will know when a consumer report has been used as the basis of action adverse to their interests, and that consumers will know about the information being disseminated about them. CRAs also must reinvestigate information that consumers dispute and inform users of the dispute. Those who furnish information to CRAs must participate in an agency’s reinvestigation and are subject to other duties. Importantly for consumers, the Act provides consumers with a civil remedy (meaning the right to sue for damages) for most violations of the Act.

The term “consumer reporting agency” refers not just to credit bureaus, but also to many other entities that meet the statutory definition. This may include creditors, data brokers, employment screening companies, check approval companies, alternative credit bureaus, and others.

Under the FCRA, “consumer reporting agencies” (CRAs) are companies or nonprofits that provide consumer reports to third parties for the purposes of determining eligibility for credit, insurance, employment, or other business transactions. The definition of a “consumer report” is fairly broad. It is a written, oral, or other communication of any information by a CRA bearing on one of seven factors:

- a consumer’s creditworthiness,
- credit standing,
- credit capacity,
- character,
- general reputation,
- personal characteristics, or
- mode of living.
The FCRA also has a special definition for a “credit score.” However, credit scores also fall within the general definition of a consumer report.

Since a report need bear on only one of the seven factors listed in the statute, a wide variety of information about a consumer satisfies this part of the definition of a consumer report, including most of the information collected by big data brokers. For example, these reports claim to assemble details about property values and ownership; likely income and assets; an applicant’s educational background; professional licenses; phone service history; subprime credit information, such as use of a payday loan; and ownership of boats and airplanes as a way of assessing credit risk. Other information assembled in these reports from social media and spending patterns deals with personal characteristics or mode of living, and would be considered a consumer report if used to determine whether to extend credit, employment, or other purpose under the FCRA. For example, creditors believe that those who buy birdseed, snow rakes, and felt pads for furniture are good credit risks, while those who buy chrome-skulls are not. Reports of these types meet the definition of consumer report.

The second prong of the definition of a consumer report narrows the broad scope of the first prong. It requires that the information must be “used or expected to be used or collected in whole or in part” for certain purposes—determining eligibility for credit, insurance, employment, or certain other business transactions.

**Databases that Do Not Name the Consumer**

With some of the big data databases, data may be stored without specifically identifying an individual consumer by name. This does raise questions about whether these data brokers are CRAs since a consumer report is one “bearing on a consumer’s credit worthiness” and other factors. Consumer is defined in the FCRA as an individual. Thus, at a minimum, a consumer must be “an identifiable person.” Therefore, a report on an anonymous computer username is not a consumer report.

However, citing advancements in technology and the public availability of a broad range of data about consumers, the FTC clarified in its 2011 Staff Summary that information may constitute a consumer report even if it does not identify the consumer by name if it could “otherwise reasonably be linked to the consumer.”

In some cases, the consumer’s name may actually be irrelevant. Hypothetically, if an online lender uses an analysis of the websites a potential borrower views based upon the cookies on the computer applying for the loan, then the most important piece of identifying information for that consumer may be the IP address and not the potential borrower’s name. Still, since the lender is using the IP address as a proxy for an individual, a report about that IP address should be considered a consumer report because it can reasonably be linked to the consumer who will be repaying the loan.

**What Consumer Reporting Agencies Must Do Under the FCRA**

If the FCRA does apply to a big data database, it imposes substantial duties on the CRA. Three of the most important functions of the FCRA deal with accuracy, disclosure, and
the right to dispute items on the report. It is highly unlikely, given the size of the data set and the sources of information, that the companies that provide big data analytics and the users of that data are meeting these FCRA obligations.

Accuracy

The FCRA requires CRAs to use reasonable procedures to ensure maximum possible accuracy of the information in a report. Under the FCRA, the requirement of accuracy does not mean merely that the information must be technically accurate. Rather, accuracy encompasses the completeness of the information, the relevance, and the interpretation. In most jurisdictions, it is not sufficient for information to be literally true; it also cannot be misleading or incomplete.

The accuracy requirement will be a challenge to many big data brokers. The first challenge will be ensuring that data is technically accurate. The Internet is full of bad information. Moreover, ensuring that information matches the correct consumer may be nearly impossible when consumers are only identified by their first and last names. Also, consumers using shared computers may have data improperly attributed to them. Our survey of the big data companies’ reports showed a remarkable level of inaccuracy.

Completeness will also be a challenge with big data. Depending on the data source, many pieces of information will be snapshots in time. For example, a lender wanting to analyze patterns of online shopping may do so by using cookies embedded in the consumer’s web-browser. However, those cookies will not include items that were returned or that were purchased as gifts.

Finally, courts consider a consumer report to be inaccurate when it is “misleading in such a way and to such an extent that it can be expected to [have an] adverse [effect].” Information can be technically accurate but misleading in a number of ways. For example, a data broker might have information on a borrower’s educational status and list the consumer’s educational status as “completed high school.” If the consumer has also completed a four-year college program, this may be technically correct, but it implies that the consumer’s education ended after high school.

The way that information is displayed may also be misleading. NCLC’s report Broken Records described employment background checks that used line spacing that made the list of offenses appear to be longer than it actually was. A scoring model that is not actually predictive of creditworthiness could also be considered misleading. The FCRA does not explicitly require credit scores to predict what they claim to predict. However, scoring models that claim to predict creditworthiness but fail to do so are misrepresenting the consumer’s information. A score that incorrectly claims to predict a consumer’s creditworthiness portrays the consumer’s data in a light that is not true.
Disclosure

To know whether information on a consumer report is accurate, the consumer must know that such a report exists and what information it contains. For this reason, the FCRA gives consumers the right to find out what is in the files maintained by the CRA.

The law gives consumers the right to request the information in their file at a CRA—often for free. Moreover, when a user takes an adverse action relating to credit, insurance, or employment, in whole or in part because of information in a consumer report, the user must provide an adverse action notice to the consumer. This notice identifies the CRA that supplied the consumer report and gives instructions on how to obtain a report. It alerts the consumer to the existence of the report and that it contains some adverse information that the consumer should probably check. Unfortunately, compliance with this notice requirement is sparse with non-traditional consumer reports.

CRAs must clearly and accurately disclose to the consumer all information in the consumer’s file at the time of the request. A CRA violates the FCRA by refusing to provide this information or by providing only partial disclosure. The responses to the requests that our volunteers made for their consumer reports show that big data brokers are likely to fail to comply with the requirement to disclose all information in the consumer’s file. As discussed, even though data may not be explicitly identified to a certain consumer, because it can be linked to the consumer, the CRA should disclose that information.

However, even if data brokers were to provide this disclosure, the information may not be comprehensible for consumers due to its sheer volume. Therefore, meaningful disclosure may not be possible when using big data. This may prove to be a fundamental flaw with using big data for determining eligibility for credit or other FCRA-covered purposes.

Right to Dispute Inaccuracies

One of the most critical protections provided by the FCRA is the consumer’s right to dispute the accuracy or completeness of any item of information in his or her file. Upon receiving a dispute, the FCRA requires the CRA to conduct a reinvestigation, reviewing all relevant materials and contacting the source of any information. Any information that cannot be verified must be deleted.

The right to dispute information is an important safeguard necessary to ensure the accuracy of the consumer’s data and is one of the most important functions of the FCRA. However, compliance with this part of the statute may prove to be challenging, if not impossible, to data brokers collecting big data.
it may be difficult for a consumer to dispute and for the data broker to verify whether it really was the consumer visiting a certain website or making a certain purchase.

Given that unverifiable data should be deleted, theoretically, a consumer should be able to dispute all information in his or her file, and the CRA would be required to delete it if unverifiable. Given the reluctance of consumer reporting agencies historically to delete any information, whether a big data broker would comply is another matter.

Evasion of the FCRA

The FCRA’s definition of “consumer report” covers a broad range of information (see page 21). This broad scope is narrowed by purposes to which the information is used. Thus, some data brokers have attempted to avoid liability under the FCRA by claiming that their products are not used for consumer reporting purposes and that the information is not assembled for the purpose of furnishing consumer reports.

One way that these companies have attempted to evade the FCRA is by including boilerplate language in their agreements stating that the information is not a consumer report and telling users that it may not be used for any permissible purpose under the FCRA. However, this type of boilerplate should not be sufficient to exclude information from the definition of a “consumer report.” (See examples of disclaimers on page 26.)

For example, one company, Spokeo, was sued by the FTC in 2012 for marketing its products to companies in the human resources, background screening, and recruiting industries without taking the steps to protect consumers that are required under the FCRA. Spokeo settled the suit for $800,000. However, in its terms of use, Spokeo still attempts to disclaim its obligations under the FCRA.

The Spokeo disclaimer should not comply with the law. Regardless of the ultimate use of the information, if an entity providing consumer information reasonably expects or reasonably should expect that the information might be used for FCRA purposes, and the entity does not have reasonable procedures in place to limit the uses to which the information can be put, then the entity should qualify as a CRA.

The FTC has warned companies that the presence of a disclaimer stating that reports should not be used for FCRA purposes is not sufficient to avoid FCRA coverage. Boilerplate language in an agreement is not sufficient to defeat the expectation that some users who have access to reports bearing on creditworthiness or other FCRA factors might use the information for FCRA purposes. As the FTC has stated to several data brokers:

*If you have reason to believe that your [mobile application] reports are being used for employment or other FCRA purposes, you and your customers who are using the reports for such purposes must comply with the FCRA. This is true even if you have a disclaimer on your website indicating that your reports should not be used for employment or other FCRA purposes.*
Examples of Data Broker Disclaimers to Sidestep the FCRA*

**Accurint® for Collections** does not constitute a "consumer report" as that term is defined in the federal Fair Credit Reporting Act, 15 USC 1681 et seq. (FCRA). Accordingly, Accurint for Collections may not be used in whole or in part as a factor in determining eligibility for credit, insurance, employment or another permissible purpose under the FCRA.

**Intelius** FCRA Restrictions. Intelius is not a consumer reporting agency as defined in the Fair Credit Reporting Act ("FCRA"), and the information in the Intelius databases has not been collected in whole or in part for the purpose of furnishing consumer reports, as defined in the FCRA. You shall not use any of our information as a factor in (1) establishing an individual’s eligibility for personal credit or insurance or assessing risks associated with existing consumer credit obligations, (2) evaluating an individual for employment, promotion, reassignment or retention (including employment of household workers such as babysitters, cleaning personnel, nannies, contractors, and other individuals), or (3) any other personal business transaction with another individual (including, but not limited to, leasing an apartment).

**Rapleaf** Compliance with Fair Credit Reporting Act. Rapleaf is not a consumer-reporting agency ("Consumer Reporting Agency") as defined by the Fair Credit Reporting Act, 15 U.S.C. § 1681 et seq. ("FCRA") and Data Services and reports do not constitute "Consumer Reports" as that term is defined in the FCRA. You agree to not use or provide the Data Services Data for any purposes enumerated in the FCRA in lieu of obtaining a Consumer Report. Specifically, you agree not to use or provide the Data Services Data, or authorize anyone else to use or provide the Data Services Data, for the following purposes:

a. in connection with establishing a consumer's eligibility for credit or insurance to be used primarily for personal, family or household purposes, or in connection with assessing risks associated with existing credit obligations of a consumer;

b. for the purpose of evaluating a consumer for employment, promotion, reassignment or retention as an employee;

c. for any tenancy verification or in connection with any application to rent real property;

d. in connection with a determination of a consumer's eligibility for a license or other benefit that depends on an applicant's financial responsibility or status;

e. as a potential investor or servicer, or current insurer, in connection with a valuation of, or assessment of credit or prepayment risks associated with, an existing credit obligation;

f. in connection with any information, service or product sold or delivered to a "Consumer" (as that term is defined in the FCRA) that constitutes or is derived in substantial part from a Consumer Report;

g. for any other purpose covered under the FCRA; or

h. for the preparation of a Consumer Report or in such a manner that may cause such data to be characterized as a Consumer Report. You agree not take any "Adverse Action" (as that term is defined in the FCRA), which is based in whole or in part on Data Services or data, against any Consumer.

**Spokeo** You may not use Spokeo.com or any information acquired from Spokeo.com:

i) to engage in activities that would violate applicable local, state, national or international law, or any regulations having the force of law, including the laws, regulations, and ordinances of any jurisdiction from which You access Spokeo.com;

ii) to send any commercial email or text message that does not comply with CAN-SPAM, the Telephone Consumer Protection Act or any other applicable state law;

iii) to evaluate a consumer's eligibility for credit or insurance to be used primarily for personal, family, or household purposes, to evaluate a person's eligibility for employment or volunteering purposes, to evaluate a person's eligibility for a government license or benefit, to evaluate a person for renting a dwelling property, or for any other purpose specified in the Fair Credit Reporting Act (15 U.S.C. § 1681b);

iv) in any manner that may violate any local, state, federal, or international privacy law to which You may be subject on the basis of Your location or the location of the person searched.

* Examples found on select data brokers' websites; not an inclusive list.
Furthermore, while it is sufficient if the CRA anticipates a listed use, this is not even necessary. It should be enough if, in the usual course of events, one would expect the report to be used for an FCRA purpose.80

EVALUATING THE DISCRIMINATORY IMPACT
OF BIG DATA SCORES

Because big data scores use undisclosed algorithms, it is impossible to analyze the algorithm for potential racial discriminatory impact. According to the companies’ marketing materials, consumers are judged based upon data generated from their Internet usage, mobile applications, and social media. However, access and usage of these sources vary by race and socioeconomic status, and thus any algorithm based upon them may have racial disparities.

Non-Hispanic white households have greater rates of broadband adoption than other socioeconomic groups. The adoption gap is widest between non-Hispanic whites and Hispanics (14 percent difference in adoption).81 Thirty percent of whites use their mobile phone as their sole Internet connection compared to roughly 48 percent of Latinos and 39 percent of blacks.82 Households that access the Internet solely using a mobile device are also more likely to be low-income.

Different races also use the Internet differently. For example, research by Pew and the Federal Reserve Board show that blacks and Latinos use their smartphones to do their banking more than any other race or ethnicity,83 while whites are more likely to bank using a traditional desktop or laptop.84 Additionally, according to Nielsen spokesman Matthew Hurst, “Black consumers are also 30 percent more likely to visit Twitter using mobile phones than the average customer.”85 These different ways of accessing the Internet leave a digital data trail. Yet, despite these known differences, little is known about how each of these variables is weighted or used by big data analytics.

Data gathered via the Internet is coded with an IP address. An IP address can be predictive of the consumer’s zip code or even latitude and longitude.86 Significantly, based upon census data, zip code and location can function as a proxy for race and income. There is already evidence that some companies target different zip codes differently. An investigative report by the Wall Street Journal found that the office supply store Staples priced its merchandise differently depending on the zip code gleaned from the consumer’s IP address.87

While the discriminatory pricing of staplers may not be the gravest of injustices, the potential pitfalls of this type of pricing scheme raises concerns. If instead of office supply stores, banks and lenders engaged in this analysis, low-income and communities of color could be given higher interest rates and other less favorable terms.

Another potential concern relates to creditworthiness by association. Creditors have based a consumer’s creditworthiness on the characteristics of others. For example, American Express lowered a customer’s credit limit from $10,800 to $3,800, not based on
his payment history with the company, but because “[o]ther customers who have used their card at establishments where you recently shopped have a poor repayment history with American Express.” With this type of analysis, low-income consumers with pristine credit histories could find their big data credit scores lowered simply because they save costs by shopping at low-end outlets whose customers include people who have trouble paying their bills.

There is already evidence that location is being used as a proxy for a consumer’s ability to repay a debt. A recent report by TransUnion highlights this ominous trend:

…”aggregated credit data is…helpful to [debt] collectors because it can identify local credit conditions clustered around common demographics. This is especially true for consumers with little or no credit history. For example, if the consumer is living in a ZIP code where the mortgage delinquency rates are climbing or always high, the chance for collection may be significantly less than for those in ZIP codes where the delinquency rate is relatively low and stable.”

Does using location and type of device in calculating a credit score violate federal credit discrimination laws? The answer to this question is complex, and depends on the product at issue.

There are two main types of discrimination theories under civil rights law: disparate treatment and disparate impact (or the “effects” test). Disparate treatment occurs when a business or employer treats a person differently on the basis of race or another prohibited basis (gender, age, religion, etc.). Disparate impact occurs when a business’s policy or practice, neutral on its face, has a disproportionate negative impact on a protected group. Under this theory, the business’s motive in treating applicants differently might not be race or another prohibited basis, but the effect is to adversely impact a particular protected class. The classic example of disparate impact is where an employer only hires people over a certain height. Because women are, on average, shorter than men, this policy would likely result in fewer women getting hired than men.

The Equal Credit Opportunity Act (ECOA) prohibits racial discrimination in the granting of credit, and is the federal anti-discrimination law that would likely apply to companies that use big data credit scores. It prohibits not just disparate treatment, but also policies or practices that have a disparate impact.

In order to make out a “prima facie” (initial) case for disparate impact, the plaintiff must:

- **Identify** a specific policy (e.g., use of location) that has a discriminatory effect;
- **Show a disparate impact** of the policy on a group protected by anti-discrimination laws; and
- **Show causation**, i.e. a link between the policy and the disparate impact.

Making out a prima facie case of disparate impact does not necessarily mean that a practice violates the ECOA. Under the disparate impact analysis, a creditor or company can
defend its policy by showing a “business necessity.” Courts have articulated a number of different tests and definitions of “business necessity,” including “compelling need,” “manifest relationship,” “legitimate, non-discriminatory rationale,” and “demonstrably necessary.”

With respect to ECOA, regulatory interpretations of this Act state that creditors can defend a policy that produces disparate impact by showing “a demonstrable relationship between” the challenged policy and “creditworthiness.” Thus, if a variable or factor in a credit scoring model causes a disparate impact, but is “demonstrably related” to creditworthiness, it may be permissible under fair lending laws. The variable or factor, however, must be related to creditworthiness and not some other reason, such as generating maximum profit.

The business necessity analysis may differ for scoring models using large amounts of aggregated data as opposed to traditional credit reports. Traditional credit scores are based on credit histories, and supposedly measure the consumer’s likelihood of repaying a loan. There is an understandable connection between timely repayment of past obligations and the likelihood of timely repayment of future obligations, so a “demonstrable relationship” argument can be easily made. While there might be some correlation between web searches, IP address, or social media posts and the likelihood of repayment, there has been no definitive understandable reason provided as to why those data points are a good measure of creditworthiness.

Finally, one should not rule out the possibility of a disparate treatment analysis. Given the amount of personal information available online, it is possible, if not likely, that users of big data can discover the consumer’s race, gender, religion, national origin, or other characteristics that lenders are prohibited from considering.

BIG DATA, BETTER PRODUCTS?

Proponents of big data underwriting argue that by using a constellation of factors to price credit, the cost of credit will be reduced for low-income borrowers, thus enabling lenders to provide lower-cost small loans as alternatives to payday loans. However, our analysis of loans priced according to big data underwriting challenges this assumption.

Elements of an Affordable Loan Versus a Payday Loan

Payday loans are very high-cost, short term loans that ensnare borrowers in a debt trap. The finance charge for a payday loan typically ranges from $10 to $30 for every $100
borrowed. Loans typically cost 400% annual interest or more. The dangers of payday loans are well documented. Payday loans lead to repeat borrowing and escalating cost. Taking out a payday loan increases the likelihood that the borrower will lose a bank account, file for bankruptcy, be subject to eviction, delay medical care, face a utility shut-off, and become delinquent on a credit card.

In 2010, the National Consumer Law Center released a report, *Stopping the Payday Loan Trap: Alternatives that Work, Ones that Don’t*, comparing different alternatives to payday loans. According to that report, a truly affordable alternative product that avoids the pitfalls of traditional payday loans must:

- Have an annual percentage rate (APR), including fees, of 36% or less;
- Have a term of at least 90 days, or one month per $100 borrowed;
- Require multiple installment payments rather than a single balloon payment;
- Not require that the borrower turn over a post-dated check or electronic access to a bank account; and
- Be issued after an evaluation of the borrower’s ability to repay the loan.

In addition, many of the best payday loan alternatives had features that helped borrowers get on a path to financial security, such as including a savings component to the loan or offering financial education.

**NCLC Analysis of Big Data Loan Products**

Using these standards, we evaluated seven loan products that are based on big data underwriting, six of which present themselves as payday loan alternatives. Think Finance provides the technology for underwriting five of the seven loan products. Think Finance works with tribal payday lenders to provide two of those products (i.e. Great Plains Lending and Plain Green). ZestFinance provides the underwriting technology to a tribal payday lender for Spotloan and LendUp uses its own big data infrastructure.

According to their own materials, all products charge triple-digit APRs, including fees, for first-time customers. Different products offer different APRs depending on the loan amount, where the borrower obtained the loan, and the repayment schedule (see page 7). The APRs ranged from about 134% to 748%, more typical of payday loans and far more than 36%. The materials did not state how these APRs were calculated; therefore, it is not clear whether the APRs include all fees and could be even higher.

Five of the seven products require weekly or biweekly installment payments. The other two, MySalaryLine and LendUp, require full payment after a set number of days. Borrowers repay MySalaryLine loans on the next pay date while LendUp gives up to thirty days from the loan start date for the borrower’s first loan.

All of the lenders except Presta and MySalaryLine require borrowers to provide sensitive banking information (i.e. bank name, routing number, and account number). However, some of the lenders may not use this electronic information in every case.
- **LendUp** automatically deducts the owed amount from the borrower’s account that was used to deposit the loan originally.
- **MySalaryLine** works in conjunction with an employer’s payroll provider to debit the amount automatically from an employee’s next paycheck through payroll direct deposit.
- **Plain Green** and **Great Plains Lending** are also enabled to perform automatic withdrawals from a borrower’s bank account on her payday, but it is unclear whether they will deduct an amount if a borrower asks to provide payment through other means.
- **Presta** automatically charges customers’ debit or credit cards according to their payment schedule.
- **RISE** will electronically debit a payment from a borrower’s checking account unless alternate arrangements are made.
- **Spotloan** will automatically deduct payments from customers’ checking accounts, but claims it will also accept checks.

Four out of the seven products did offer financial education resources in the form of online courses. RISE, Plain Green and Great Plains Lending all offer the same “Financial U” online learning center, which is available only to borrowers. In the case of RISE, one of the ThinkFinance products, a $10 reward is offered upon successful completion of the program. Plain Green and Great Plains Lending also offer a reward for program completion, but one must borrow money to obtain information about what the reward is and how to claim it. LendUp provides its own financial education materials available to the public, which consist of informational videos followed by quizzes. Successful completion of credit courses allows LendUp borrowers to accumulate points, which can be used to achieve higher status levels, in line with LendUp’s gamification of lending. These status levels claim to open the door to better terms for future loans, including higher loan amounts and installment payments.

Some of the features of these loans are arguably “less bad” than those offered by traditional payday lenders, but these products still fail to meet the requirements to be considered genuine, better alternatives. They still feature three-digit APRs. With the exception of LendUp and MySalaryLine, all products accept installment payments; however, many of them require weekly or biweekly payments rather than monthly ones.

As mentioned previously, all but two of the lenders require borrowers to provide sensitive banking information (i.e. bank name, routing number, and account number). While some may not make use of this information in all cases, the same is true of traditional payday lenders, which typically allow borrowers to repay in person or by other means. The Electronic Funds Transfer Act generally prohibits conditioning an extension of credit on the consumer’s repayment of that debt by preauthorized electronic fund transfers. Many payday-type lenders structure their loan products to evade the important protections of this Act while still maintaining a high degree of access to the consumer’s account, and we are concerned that the lenders discussed in this report that require bank account information may be following this pattern. It may also violate the FTC’s Credit Practices Rule which prohibits creditors from using certain contract provisions that the
FTC found to be unfair to consumers. RISE, Plain Green, Great Plains, and Spotloan do allow consumers to repay their loans by alternatives means, but require consumers to provide sensitive banking information (i.e. bank name, routing number, and account number). A lender could potentially use this information to reach into a bank account and take the funds if the consumer fails to make a payment. The requirement that the borrower provide electronic information could ensure that the lender will be repaid, even if the borrower is unable to afford the loan without neglecting other expenses (like rent or food) or falling into a cycle of debt.

More importantly, it is unclear whether these lenders actually evaluate a borrower’s ability to repay, precisely because there is no information available concerning the specific methods big data uses to underwrite loans, nor is there any information available about the default rates for any of these products. The ability to repay a loan must consider more than a credit score or predictive set of algorithms. It must consider the income and assets a consumer has, in addition to the consumer’s debts and obligations. Without an understanding of the data points that go into these lenders’ underwriting algorithms, it is not possible to determine if the risk of default is being properly evaluated.

In short, loan terms for these seven products appear to be an improvement over their traditional payday lending counterparts only in that some allow installment payments and some allow repayment periods of 90 days or longer. The differences are not enough to consider the products as safe or genuine alternatives to payday loans.

CONCLUSION AND POLICY RECOMMENDATIONS

With the advances in technology, big data is more and more likely to find its way into lending decisions. As stated above, there is a need for improving affordable access to credit to low-income consumers. However, access by itself is not the ultimate goal; affordable access is the goal.

Although innovation should be encouraged, it should not go unfettered. The good intentions driving new products that aim to broaden access for low-income consumers are laudable—but they are no substitute for strong consumer protections, which remain vitally important. As new financial products emerge—especially those targeted towards low-income consumers and the unbanked or underbanked—the integrity of those products must be examined. As described, the framework is:

1. Are the decisions based upon accurate data?
2. Can the algorithms, when fed with good data, actually predict the creditworthiness of low-income consumers?
3. Does the use of big data in reports used for credit, employment, insurance, and other purposes comply with consumer protection laws?

4. Is there the potential for a discriminatory impact on racial, geographic, or other minority groups?

5. Does the use of big data actually improve the choices for consumers?

Answering these questions has been especially challenging given the secretive and proprietary nature of the products examined. Without voluntary disclosure of the methods that data brokers use to collect and analyze data, there is no way for consumer advocates to answer the first question in our framework. Fortunately, the FTC has taken an interest in the use of big data. Hopefully its analysis will give us answers to some of these questions.

Unfortunately, our analysis concludes that big data does not live up to its big promises. Consumers have the right to be judged based upon accurate and relevant information. But even our small sample found that consumer information housed by data brokers was riddled with errors—and this is just the data they were willing to give us. We suspect that error rates are actually higher. Big data brokers do not provide consumers with a meaningful way to verify the accuracy of their information, nor is there any way that inaccurate information can be disputed.

Furthermore, the use of big data in the lending arena does not appear to result in more affordable products for low-income consumers. While some loans are marginally better, for the most part, credit products using alternate data are just as expensive as payday loans.

The credit reporting system is far from perfect. It is possible that new technologies could play a role in providing low-income consumers better access to affordable credit. However, the products we reviewed do not meet that promise.

Despite the big promises, a review of the big data underwriting systems and the small consumer loans that use them leads us to believe that big data is a big disappointment. More and more, consumers are leading robust lives online. However, as data about consumers proliferates, so does bad data.

**Key Federal Policy Recommendations**

- The FTC should continue to study big data brokers and credit scores testing for potential discriminatory impact, compliance with disclosure requirements, accuracy, and the predictiveness of the algorithms.
- The FTC and the CFPB should examine big data brokers for legal compliance with FCRA and ECOA.
- The CFPB should create a mandatory registry for consumer reporting agencies so that consumers can know who has their data.

Big data brokers do not provide consumers with a meaningful way to verify the accuracy of their information, nor is there any way that inaccurate information can be disputed.
The CFPB, in coordination with the FTC, should create regulations based upon the FTC’s research that:

a. Define reasonable procedures for ensuring accuracy when using big data;

b. Specify a mechanism so that consumers can do a meaningful review of their files including all data points that can be linked to that consumer (not just those that identify the consumer explicitly); and

c. Define reasonable procedures for disputing the accuracy of information.

The CFPB should require all of the financial products it regulates to meet Regulation B’s requirements for credit scoring models.
ENDNOTES

2. Id. at 12.
11. Axiom, Things We Are Working On (June 2012).


38. Since this study was conducted, Acxiom has created an online portal, www.AboutTheData.com, for consumers to view their information. This new portal has not been analyzed as a part of this report.


40. eBureau requires consumers to provide personal information, a copy of a government-issued ID, and a current utility, phone, or credit card bill.
www.nytimes.com/2012/07/22/business/axiom-consumer-data-often-unavailable-to-
consumers.html?pagewanted=all.
43. ID Analytics, Adding a New Dimension to Determining Credit Risk, www.idanalytics.com/
datasheets/ebureau_income_estimator_datasheet.pdf.
47. Reg. B, 12 C.F.R. § 1002.2(p)(1) [§ 202.2(p)(1)]. See also Official Staff Commentary to Regulation
B § 1002.2(p)-1 [§ 202.2(p)-1].
49. Id. § 1002.2(p)(1)(ii) [§ 202.2(p)(1)(ii)].
50. Id. § 1002.2(p)(1)(ii) [§ 202.2(p)(1)(ii)].
51. Id. § 1002.2(p)(1)(iv) [§ 202.2(p)(1)(iv)]. No definition of “periodically” is given in the regulation.
See also Official Staff Commentary to Regulation B § 1002.2(p)-2 [§ 202.2(p)-2] (providing
guidance on revalidation procedures).
52. See Official Staff Commentary to Regulation B § 1002.2(p)-1 [§ 202.2(p)-1] (describing the
difference as relating only to how age is used as a predictive factor).
53. For example, the Office of the Comptroller of Currency (OCC) has required the national
banks that it regulates to ensure that the bank’s scoring models meet the validation
requirements of Regulation B’s definition of credit scoring. OCC, *Credit Scoring Models*, OCC
Lending%20Handbook.pdf. The National Credit Union Administration has similarly
required that the credit scoring systems used by the credit unions that NCUA regulates meet
the criteria of Regulation B’s definition of credit scoring. National Credit Union
gov/pdf/fairappx.pdf (inter-agency examination procedures for reviewing a financial
institution’s credit scoring models).
(8th ed. 2013).
collection score” is a consumer report).
58. FTC Staff Summary § 603(d)(1) item 6A. See National Consumer Law Center, *Fair Credit
Reporting* § 2.3 (8th ed. 2013).
2013).
64. FTC, 40 Years Staff Report Accompanying FTC Staff Summary § V(D); FTC Staff Summary § 603(d)(1) item 5A.
77. See National Consumer Law Center, *Fair Credit Reporting* § 2.5.3.2 (8th ed. 2013).
80. See National Consumer Law Center, *Fair Credit Reporting* § 2.3.5.1 (8th ed. 2013).
82. *Id.*, Slide 11.


91. Id. at § 4.3.2.5.

92. Official Staff Commentary to Regulation B, 12 C.F.R. § 202.6(a)-2.


97. Presta, the only rent-to-own product evaluated, resembles the cost of traditional lease-to-own products. We treat the Presta product as a loan product because it serves the same function as a long for the price of the item being acquired. As a form of credit, an item bought through Presta carries an APR of 202.07% for a product valued at $300.


99. 16 C.F.R. Part 444.
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CREDIT SCORING IN THE ERA OF BIG DATA

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ABSTRACT

For most Americans, access to credit is an essential requirement for upward mobility and financial success. A favorable credit rating is necessary to purchase a home or car, to start a new business, to seek higher education, or to pursue other important goals. For many consumers, strong credit is also necessary to gain access to employment, rental housing, and essential services such as insurance. At present, however, individuals have very little control over how they are scored and have even less ability to contest inaccurate, biased, or unfair assessments of their credit. Traditional, automated credit-scoring tools raise longstanding concerns of accuracy and unfairness. The recent advent of new “big-data” credit-scoring products heightens these concerns.

The credit-scoring industry has experienced a recent explosion of start-ups that take an “all data is credit data” approach, combining conventional credit information with thousands of data points mined from consumers’ offline and online activities. Big-data scoring tools may now base credit decisions on where people shop, the purchases they make, their online social media networks, and various other factors that are not intuitively related to creditworthiness. While the details of many of these products remain closely guarded trade secrets, the proponents of big-data credit scoring argue that these tools can reach millions of underserved consumers by using complex algorithms to detect patterns and signals within a vast sea of information. While alternative credit scoring may ultimately benefit some consumers, it also poses significant risks.

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** S.M. Computer Science & Technology and Policy. MIT 2016. This views expressed in this article are solely those of the authors and do not represent the opinions of their respective institutions. The authors would like to thank Taesung Lee for helpful comments and suggestions on earlier drafts. The authors also wish to thank Professors David Vladeck and Alvaro Bedoya of Georgetown Law, and Professors Danny Weitzner and Hal Abelson of MIT for their extensive guidance in the development of this article. All errors remain those of the authors alone.
Credit-scoring tools that integrate thousands of data points, most of which are collected without consumer knowledge, create serious problems of transparency. Consumers have limited ability to identify and contest unfair credit decisions, and little chance to understand what steps they should take to improve their credit. Recent studies have also questioned the accuracy of the data used by these tools, in some cases identifying serious flaws that have a substantial bearing on lending decisions. Big-data tools may also risk creating a system of “creditworthiness by association” in which consumers’ familial, religious, social, and other affiliations determine their eligibility for an affordable loan. These tools may furthermore obscure discriminatory and subjective lending policies behind a single “objective” score. Such discriminatory scoring may not be intentional; instead, sophisticated algorithms may combine facially neutral data points and treat them as proxies for immutable characteristics such as race or gender, thereby circumventing existing non-discrimination laws and systematically denying credit access to certain groups. Finally, big-data tools may allow online payday lenders to target the most vulnerable consumers and lure them into debt traps.

Existing laws are insufficient to respond to the challenges posed by credit scoring in the era of big-data. While federal law prohibits certain forms of discrimination in lending and ensures that consumers have limited rights to review and correct errors in their credit reports, these laws do not go far enough to make sure that credit-scoring systems are accurate, transparent, and unbiased. Existing laws also do little to prevent the use of predatory scoring techniques that may be geared to target vulnerable consumers with usurious loans.

This article, which has been developed as part of a collaborative effort between lawyers and data scientists, explores the problems posed by big-data credit-scoring tools and analyzes the gaps in existing laws. It also sets out a framework for comprehensive legislative change, proposing concrete solutions that would promote innovation while holding developers and users of credit-scoring tools to high standards of accuracy, transparency, fairness, and non-discrimination.

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I. INTRODUCTION

One day in late 2008, Atlanta businessman Kevin Johnson returned home from his vacation to find an unpleasant surprise waiting in his mailbox. It was a letter from his credit card company, American Express, informing him that his credit limit had been lowered from $10,800 to a mere $3,800.1 While Kevin was shocked that American Express would make such a drastic change to his limit, he was even more surprised by the company’s reasoning. By any measure, Kevin had been an ideal customer. Kevin, who is black, was running a successful Atlanta public relations firm, was a homeowner, and had always paid his bills on time, rarely carrying a balance on his card.2 Kevin’s father, who had worked in the credit industry, had taught him the importance of responsible spending and, “because of his father’s lessons,
[Kevin had] scrupulously maintained his credit since college." Yet his stellar track record and efforts to maintain “scrupulous” credit seemed to matter little, if at all, to American Express. The company had deemed him a risk simply because, as the letter put it, “other customers who had used their card at establishments where [Kevin] recently shopped have a poor repayment history with American Express.” When Kevin sought an explanation, the company was unwilling to share any information on which of businesses – many of them major retailers – contributed to American Express’s decision to slash Kevin’s limit by more than 65 percent.

Kevin Johnson was an early victim of a new form of credit assessment that some experts have labeled “behavioral analysis” or “behavioral scoring,” but which might also be described as “creditworthiness by association.” Rather than being judged on their individual merits and actions, consumers may find that access to credit depends on a lender’s opaque predictions about a consumer’s friends, neighbors, and people with similar interests, income levels, and backgrounds. This data-centric approach to credit is reminiscent of the racially discriminatory and now illegal practice of “redlining,” by which lenders classified applicants on the basis their zip codes, and not their individual capacities to borrow responsibly.

Since 2008, lenders have only intensified their use of big-data profiling techniques. With increased use of smartphones, social media, and electronic means of payment, every consumer leaves behind a digital trail of data that companies – including lenders and credit scorers – are eagerly scooping up and analyzing as a means to better predict consumer behavior. The credit-scoring industry has experienced a recent explosion of start-ups that take an “all data is credit data” approach that combines conventional credit information with thousands of data points mined from consumers’ offline and online activities. Many companies also use complex algorithms to detect patterns and signals within a

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3 Id.
4 Lieber, supra note 1.
5 Cuomo et al., supra note 2.
6 See, e.g., id. (quoting Robert Manning).
7 Tracy Alloway, Big data: Credit where credit’s due, FINANCIAL TIMES (Feb. 4, 2015), http://www.ft.com/cms/s/0/7933792e-a2e6-11e4-9e06-00144feab7de.html [https://perma.cc/7D8J-JHWY].
vast sea of information about consumers’ daily lives. Forecasting credit risk on the basis of a consumer’s retail preferences is just the tip of the iceberg; many alternative credit-assessment tools now claim to analyze everything from consumer browsing habits and social media activities to geolocation data.

While proponents of big-data credit analysis claim that these new analytical tools could revolutionize the lending industry and ultimately benefit consumers, experiences like Kevin Johnson’s are a harbinger of the hazards. For the majority of Americans, fair access to credit can be a make-or-break determinant of whether a person can buy a home, own a car, or get a college education. The use of non-transparent credit-assessment systems that judge consumers based on factors that they are not aware of and which may be beyond consumers’ control, fundamentally conflicts with the American ideal of self-determination. As one critic put it, a consumer “can get in a death spiral simply by making one wrong move, when algorithms amplify a bad data point and cause cascading effects.” This risk is all the more troubling when consumers have no way of distinguishing the “right moves” from the “wrong” ones. Unless the rules of the credit system are transparent and predictable, access to the American dream may turn upon arbitrary factors rather than merit.

Big-data assessment tools also have “the potential to eclipse longstanding civil rights protections in how personal information is used in [the] . . . . marketplace,” by using seemingly innocuous information, like consumers’ retail preferences, as proxies for sensitive attributes like race. Kevin Johnson’s story raises the troubling possibility that consumers might be penalized for activities that are associated with particular racial, ethnic, or socioeconomic groups. Rather than fostering change for the good, big-data credit-assessment tools may only shield and exacerbate preexisting forms of bias.

Finally, these new tools hold the risk that even the most careful consumers could fall victim to flawed or inaccurate data. The problem of inaccuracy has long proved a challenge...
Credit Scoring & Big Data

for traditional credit-scoring systems, which utilize a relatively limited set of data points.\textsuperscript{14} Big-data credit-assessment tools are likely to compound this problem.\textsuperscript{15} Everyone with a Netflix or Pandora account has witnessed firsthand how “smart” algorithms can draw poor inferences about users’ preferences on the basis of a few atypical searches and stray clicks. There is mounting evidence that big-data credit-scoring systems, which employ thousands of data points that are surreptitiously and continuously mined from a consumer’s offline and online activities, may incorporate a high degree of inaccurate information.\textsuperscript{16} For example, a recent report indicates mobile location data can be particularly prone to inaccuracy.\textsuperscript{17} While consumers have a legal right to correct inaccuracies in their credit reports, this may be practically impossible with big-data tools.

This paper discusses how big-data tools are transforming the credit-scoring industry and the major risks and challenges these new tools pose. We compare traditional, automated scoring tools to emerging, big-data tools, and also provide an introduction to the terminology and concepts that are necessary to understand how big-data scoring works in practice. We describe the major steps that a credit scorer might follow to design and deploy a big-data scoring model, as well as the risks to consumers at every step in the process. Finally, we address gaps in the existing legal framework and propose a legislative solution that balances innovation with the need to preserve fairness, accuracy, and transparency in credit scoring.

II. TRADITIONAL CREDIT-ASSESSMENT TOOLS

A credit score is a “summary of a person’s apparent creditworthiness that is used to make underwriting decisions,”


\textsuperscript{17} See, e.g., Steven Jacobs, Report: More Than Half of Mobile Location Data is Inaccurate, STREETFIGHT (May 14, 2015), http://streetfightmag.com/2015/05/14/report-more-than-half-of-mobile-location-data-is-inaccurate [https://perma.cc/43L2-4ULH].
as well as to "predict the relative likelihood of a negative financial event, such as a default on a credit obligation."\textsuperscript{18} Over the course of the past three decades, automated credit-scoring systems like those developed by the Fair and Isaac Corporation (FICO) have become a fundamental determinant of fiscal success for the majority of Americans.\textsuperscript{19} Without a sufficiently favorable score from a major credit bureau, a consumer likely cannot "buy a home, build a business, or send [her] children to college."\textsuperscript{20} Credit scores and reports are not only used for lending decisions. Many employers review credit reports when determining whom to hire, or when deciding whether to promote an existing employee.\textsuperscript{21} Landlords also commonly use credit reports to screen potential tenants.\textsuperscript{22}

The mainstream credit-scoring market is generally segmented into consumer-reporting agencies, or "CRAs," and companies that develop and license automated scoring methodologies.\textsuperscript{23} CRAs, including the "big three" nationwide credit bureaus – TransUnion, Experian, and Equifax\textsuperscript{24} – obtain data relating to individual consumers and compile these data into what are commonly referred to as "credit reports." CRAs generally obtain the information that goes into credit reports from credit-information "furnishers" such as credit-card companies, mortgage lenders, and potentially other sources.\textsuperscript{25} According to the Consumer Financial Protection Bureau (CFPB), each of the big-three CRAs receives approximately 1.3 billion updates for over 200 million consumer files each month.\textsuperscript{26} The information that is compiled into credit reports is

\textsuperscript{18} See Robinson + Yu, supra note 11, at 7.

\textsuperscript{19} See Yu, supra note 10, at 27 (FICO first introduced its flagship score in 1981).


\textsuperscript{23} NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING § 1.2.2 (8th ed. 2013).

\textsuperscript{24} 15 U.S.C. § 1681a(g) (CRAs operating on a "nationwide basis").


\textsuperscript{26} CONSUMER FIN. PROT. BUREAU, KEY DIMENSIONS AND PROCESSES IN THE U.S. CREDIT REPORTING SYSTEM: A REVIEW OF HOW THE NATION'S LARGEST CREDIT BUREAUS MANAGE CONSUMER DATA 21 & n.54 (Dec. 2012).
then used to score individual consumers using proprietary scoring models. In the traditional credit-scoring market, there are two main developers of credit-scoring models and software, namely FICO, and VantageScore, which is a joint venture of the big-three credit-scoring companies.\textsuperscript{27} These companies develop multiple models and products that are suited to meet the needs and information held by CRAs and lenders. FICO, for example, produces “numerous FICO scoring models that vary by version (e.g., newer and older models), by the nationwide CRA that sells the score to lenders, and by industry.”\textsuperscript{28} FICO remains the most prominent credit-modeling company. According to the CFPB, during 2010, over 90 percent of lenders used FICO scores to make lending decisions.\textsuperscript{29}

Automated underwriting is a relatively recent innovation. Prior to the 1980s, most lending decisions were entrusted to individual loan officers and specialists who evaluated applicants on an individual basis.\textsuperscript{30} These underwriting processes were not only labor-intensive, but could be influenced by personal bias. Automated scoring tools, like early iterations of the FICO score, which was not widely adopted until the early 1990s,\textsuperscript{31} were viewed as better alternatives that could increase efficiency and avoid the most egregious forms of discrimination.\textsuperscript{32}

Traditional automated scoring frameworks like the FICO score have not proved a panacea, however, and there is concern that these tools unjustifiably disadvantage certain borrowers. An astounding number of U.S. consumers – 64 million according to an Experian report – are currently classed as “unscorable,” meaning that they cannot access traditional forms of credit.\textsuperscript{33} These consumers may be “immigrants or recent college grads [with] little to no credit history,” or “people who haven’t had an active credit account for at least six

\textsuperscript{27} NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING §§ 1.2.2; 14.4.4 (8th ed. 2013).


\textsuperscript{29} NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING § 14.4.4 (8th ed. 2013).


\textsuperscript{31} See Robinson + Yu, supra note 11, at 27.

\textsuperscript{32} See id.

\textsuperscript{33} Blake Ellis, Millions Without Credit Scores not so Risky After All, CNN MONEY (Aug. 14, 2013), http://money.cnn.com/2013/08/14/pf/credit-scores [https://perma.cc/AA8Y-ZU3K].
Because traditional credit-scoring models consider a relatively limited set of data points, they may not adequately predict the creditworthiness of many “thin-file” consumers. The FICO score, for instance, principally looks at a consumer’s payment history, the amounts she owes, the length of her credit history, new credit, and types of credit she uses, while omitting factors such as employment history, salary, and other items that might suggest creditworthiness. As a practical consequence, traditional credit-scoring tools may also perpetuate unfairness by denying certain groups favorable access to credit merely because they have been excluded from the credit market in the past.

The data considered in traditional credit-scoring mechanisms can also be inaccurate. A 2013 Federal Trade Commission (FTC) study found that twenty-six percent of the consumers surveyed had errors in their credit reports, and these mistakes were material for thirteen percent of consumers, potentially resulting in denials, higher rates of interest and other less-favorable terms. These errors also disproportionately impacted individuals with lower levels of education. Even when a consumer identifies an error, the problem can take a significant amount of time to be corrected, thereby limiting the consumer’s ability to maintain good credit in the future. In one particularly egregious example, CRA TransUnion repeatedly reported the bad debts of a woman named “Judith L. Upton,” on the credit report corresponding to an entirely different individual, named “Judy Thomas.”

34 Id.
35 According to VantageScore, a major provider of credit-scoring tools, “not all of these consumers [currently classified as subprime borrowers] should be labeled subprime,” and “more than 10 million of these consumers have either prime or near-prime credit scores” when additional information is taken into consideration. See VantageScore, What lenders really think about unscorables (July 2013), http://thescore.vantagescore.com/article/67 [https://perma.cc/A38N-F59E].
36 See Robinson + Yu, supra note 11, at 9.
38 Out of a survey population of 1,001 consumers. See FED. TRADE COMM’N, supra note 14, at i-iii.
39 See id., at 29.
40 For example, in 2014, the Huffington Post reported on 69 year-old veteran who was forced out of his home as a result of an erroneously-reported debt on a credit card that he never held. The debt, which he disputed, remains on his credit score to this day. See Hunter Stuart, It’s Disturbing Likely that Your Credit Report is Wrong, HUFFINGTON POST (Aug. 11, 2014), http://www.huffingtonpost.com/2014/08/11/credit-report-bureau-mistakes-_n_5661956.html [https://perma.cc/Q83N-3JBV].
extensive attempts to rectify the error, Ms. Thomas finally sued TransUnion, ultimately winning a multi-million dollar verdict.42 Judy Thomas's experience is reflective of similar problems that other consumers have faced when they discover errors in their traditional credit reports.43

III. ALGORITHMS, MACHINE LEARNING, AND THE ALTERNATIVE CREDIT-SCORING MARKET

The perceived inability of traditional, automated credit scores to adequately capture “thin file” borrowers has prompted the emergence of alternative, big-data tools that promise lenders a way to “squeeze additional performance” out of their underwriting processes.44 Although traditional factors, such as those used by FICO, remain central to contemporary lending decisions, the credit-scoring industry is witnessing a rapid shift to new, alternative tools. Even traditional credit-reporting and scoring agencies are developing alternative models that rely on non-traditional data. Experian, for instance, is already leveraging big data to develop “universal customer profiles” that integrate information from the online and offline activities

42 Id.
43

In 2013, a similar fate befell yet another, different Judy Thomas. According to a report by 60 Minutes, Ohio resident Judy Thomas discovered that her credit reports inaccurately contained information on the debts of a Utah woman, Judy Kendall. As a result of the false information on her reports, Ms. Thomas struggled for years, unable to refinance her mortgage, obtain a new car, or even cosign for her children’s student loans. See 60 Minutes Report: 40 Million Mistakes: Is your credit report accurate?, NAT'L ASS’N OF CONSUMER ADVOCATES, (Feb. 11, 2013), http://www.consumeradvocates.org/media/news/60-minutes-report-40-million-mistakes-your-credit-report-accurate [https://perma.cc/8YVD-5W4S] (transcript of 60 Minutes report). Comedian John Oliver also recently took the big-three consumer reporting agencies to task for similarly egregious inaccuracies on various credit reports. In one example, a consumer’s application to rent an apartment was denied because his credit report falsely identified him as a terrorist. In another example, an individual by the name of Samuel Jackson discovered that his credit report included information on three separate sex offenders who had shared his name. In yet another example, a Texas woman, discovered that credit reports from all three major agencies reported her as deceased. See Chris Lee, HBO’s John Oliver Shows the Infuriating Truth About Credit Reporting Agencies, FORTUNE (Apr. 11, 2016). http://fortune.com/2016/04/11/hbo-john-oliver-reveals-the-awful-business-behind-credit-background-checks [https://perma.cc/T37G-PAQW].

of thousands of consumers. FICO has been testing out a new system that uses non-traditional data to assess thin-file borrowers; its new “FICO Score XD,” which FICO developed in collaboration with the credit bureau Equifax, uses data on consumers’ cable and cellphone accounts to predict creditworthiness. While some of the data used in these alternative tools may seem logically related to a consumer’s ability to manage a loan, for instance, utility bill payment histories, other types of “fringe data” are increasingly employed, despite the lack of an intuitive link to creditworthiness.

A number of emerging companies use proprietary “machine-learning” algorithms to sift and sort through thousands of data points available for each consumer. These companies treat their machine-learning tools as closely-guarded trade secrets, making it impossible to offer a comprehensive picture of the industry. However, some publicly-available information, particularly disclosures in patent applications, offers valuable insights into how machine-learning credit-scoring tools work and the risks that they may pose.

In this part, we provide an overview of the techniques and methodologies that big-data credit-scorers likely use to design, test, and deploy machine-learning tools to assess creditworthiness. We begin by introducing some basic terminology and concepts, and continue by describing how credit-scoring tools that use machine learning differ from traditional tools such as the FICO score. We then provide a step-wise description of how one might design and implement a

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45 See Marcus Tewksbury, The 2013 Big Data Planning Guide for Marketers, Experian Marketing Services (2013), http://www.experian.com/assets/marketing-services/white-papers/big-data-planning-guide-for-marketers.pdf [https://perma.cc/FY9T-G28A]. Experian collects offline data for individual consumers that is linked to “match keys” like a consumer’s address, credit card number, phone number, and also collects online and mobile data that is linked to match keys such as device ID, IP address, geolocation, a consumer’s Twitter “handle,” time stamp, and other identifiers.


47 Robinson + Yu refer to such information as “mainstream alternative data,” and suggest that by including factors such as payment histories into consumer credit scoring, models may be able to more effectively account for “thin-file” or “no-file” consumers who lack the traditional indicators of creditworthiness, but who otherwise may be capable of taking on credit obligations. See Robinson + Yu, supra note 11, at 23.

48 See id. at 15.
machine-learning credit-scoring tool, drawing upon the real-world example of a new big-data credit-scoring company, ZestFinance. Finally, we describe the types of problems that may occur when machine learning is used to make credit decisions, examining how such big-data tools may be non-transparent and inaccurate, may perpetuate and deepen existing forms of discrimination, and may be used to unfairly target vulnerable consumers.

A. Introduction to basic terminology and concepts

In recent years, terms like “machine learning” and “algorithmic decision-making” have become staples in the popular discourse on big data. But these terms may remain opaque and mysterious to laypeople and lawyers alike. This section attempts to demystify some of these technical terms and concepts.

We begin with the most basic building block of our discussion: the algorithm. An algorithm can be described as “any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as an output. An algorithm is thus a sequence of computational steps that transforms the input into the output.” In lay terms, algorithms are simply mathematical formulae or models. Algorithms may range in their complexity from those used to solve very simple, well-defined problems to those used to solve complicated, ill-defined problems. Here, we describe well-defined problems as structured problems, and ill-defined problems as unstructured problems. Structured problems generally have only a single, certain answer for a set of input values. For example, the arithmetic mean is an algorithm that takes a series of values as its inputs and produces the average of these values as its output. Calculating the circumference of a circle based on the circle’s radius is another example of a structured problem. Structured problems lack inherent randomness and uncertainty; as a consequence, the algorithms used to solve for structured problems generally remain fixed and do not change in response to different input variables.

49 See THOMAS H. CORMEN, CHARLES E. LEISERSEN, RONALD L. RIVEST, & CLIFFORD STEIN, INTRODUCTION TO ALGORITHMS 1 (3d ed. 2009) (emphasis omitted).
50 An illustrative example is the conversion of inches to feet. By definition, 1 inch is equivalent to 0.0254 meters. In this case, 0.0254 meters is the only right answer to the “problem” of converting 1 inch to its equivalent in meters.
Algorithms can also be used to solve highly complex, unstructured problems where there is uncertainty in the underlying process as well as in the input data. Put simply, an unstructured problem can have multiple “correct” answers, although some of these correct answers may be better than others. In such cases, the formula (or formulae) used to arrive at a solution or output is often not static and can change depending on the input data. Suresh Venkatasubramanian helpfully uses the analogy of a recipe to describe the types of algorithms used to solve unstructured problems. For most dishes, like unstructured problems, there may not be a single, correct outcome and much depends upon the ingredients (or data) available to the cook. There is, for example, no single, universal set of steps to prepare a ratatouille; optimal cooking times, ratios, seasonings, and preparatory steps may change depending on whether one uses eggplants or zucchini.

To offer another example from the commercial context, imagine that a retailer wishes to design a model that will segment customers into different groups and predict which sub-set of customers will respond favorably to targeted advertising. This customer segmentation challenge is an unstructured problem where there is likely no single “correct” formula for arriving at the desired end. The perceived relationships between customer characteristics and the customers’ predicted responses to targeted ads might change when new data is added into the mix. Much like our hypothetical ratatouille chef, the data scientist who is tasked with designing a model to solve the customer segmentation problem might discover that there are many different ways to identify the subset of customers she seeks. The underlying algorithm or algorithms that make up the retailer’s model are unlikely to remain static and can be expected to change in response to new input data.

The term “machine learning,” which scholars suggest is related to, but different from, “data mining,” describes “a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to

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52 There may also be inherent randomness or noise in the system being studied. A straightforward application of a mathematical formula would ignore the inherent noise in the system. See Harold J. Kushner & G. George Yin, Stochastic Approximation Algorithms and Applications 2 (1997).
53 Suresh Venkatasubramanian, When an Algorithm Isn't, MEDIUM (Oct. 1, 2015), https://medium.com/@geomblog/when-an-algorithm-isn-t-2f9fe01b9bb5#61b0d7a0 [https://perma.cc/U7SY-CK7Z].
54 Id.
perform other kinds of decision making under uncertainty."\textsuperscript{56} Once the process of machine learning is complete, the data scientist uses the patterns and insights detected in the data to design a final model (or set of models) that can predict a desired outcome. Returning to Venkatasubramanian’s recipe analogy, imagine that we wish to make a certain known dish (the output), but we do not have a list of all of the ingredients (the inputs), or any information regarding the proper ratios for each ingredient. One method to arrive at the final recipe would be to assemble the whole universe of potential ingredients in our kitchen and prepare random combinations of these ingredients, discarding those ingredients that do not fit, and adding and adjusting new ingredients that improve the final result. If we continue with this process of trial and error, we may eventually stumble upon a final recipe that yields a palatable result.\textsuperscript{57} The recipe analogy, although not perfect, offers a rough idea of how iterative machine learning works in practice. While this approach would be pretty inefficient in a kitchen, contemporary advances in computing power have made it possible for certain machine-learning tools to complete thousands and perhaps millions of iterations in a relatively short period of time.\textsuperscript{58}

Machine learning comes in two flavors—"supervised" machine learning, and "unsupervised" machine learning. In the case of supervised machine learning, the data scientist has a known or desired output or "target variable," and wishes to discover the relationships between that target variable and various other data points that she may have at her disposal in order to predict when or why that output will occur. By allowing the data scientist to understand the relationship between the target variable and the various relevant input values, supervised machine learning can allow the data scientist to "predict the future value of a target variable as a function of [input values]."\textsuperscript{59} Returning to our customer

\textsuperscript{56} Kevin P. Murphy, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE (2012).
\textsuperscript{57} See Venkatasubramanian, supra at note 53.
\textsuperscript{59} COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL., FRONTIERS IN MASSIVE DATA ANALYSIS 101 (2013), http://www.nap.edu/read/18374/chapter/9#101
segmentation example, a retailer might possess customer records that indicate whether certain customers have responded favorably to targeted advertising on past occasions. But the retailer may have no idea why certain customers responded as they did or what advertising techniques were effective. Depending on the body of data points available, the retailer can use a machine-learning process to understand the factors that are correlated to the retailer’s target variable—customer responsiveness to targeted advertising—and this in turn will assist the retailer in developing a more effective advertising strategy.

In the case of unsupervised machine learning, the data scientist may not have anything specific that she wishes to predict or determine, meaning that the process is not focused on understanding a known target variable. Unsupervised learning can, however, illuminate relationships between data points that may be useful in the future. Through unsupervised learning, the data scientist can “understand how the data were generated, the relationships between variables, and any special structure that may exist in the data.”

With these basic terms and concepts in mind, we next describe how big data and algorithmic decision making are changing the credit-scoring and lending industries.

B. How traditional credit-modeling tools compare to alternative, “big-data” tools

Estimating an individual’s creditworthiness is an unstructured problem. There exists no single rule to predict a borrower’s likelihood of repayment. Historically, credit-scoring companies like The Fair Isaac Corporation (FICO) have used relatively simple algorithmic solutions that integrate a limited number of categories of data. The basic FICO score, for instance, considers an individual’s payment history, outstanding debt, length of credit history, pursuit of new credit, and debt-to-credit ratio in determining a credit score. The model assigns a numeric value for each of these five variables, and then applies a pre-determined weight (in percentage

[https://perma.cc/Z49D-7FBE]. As used in this paper, the term “target variable” refers to an example of the desired output.

60 For a more complete explanation of unsupervised learning techniques and applications, see Toon Calders & Bart Custers, supra note 55, at 27-42.

61 COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL., supra note 59.

62 See Rob Berger, A Rare Glimpse Inside the FICO Credit Score Formula, DOUGHROLLER (Apr. 30, 2012), http://www.doughroller.net/credit/a-rare-glimpse-inside-the-fico-credit-score-formula [https://perma.cc/8VD7-6JSX].

63 Id.

64 Id.
terms) to each of these input values and averages them to arrive at a final credit score.\footnote{Id.}

While the FICO model may be simple to apply and relatively easy for a loan applicant to understand, this simplicity may also lead to credit decisions that are under-inclusive and that disadvantage borrowers who have not had prior access to the credit system.\footnote{See supra note 20.} An individual’s relative ability to repay a loan may depend on myriad factors, and a more nuanced model that integrates a wider variety of data points could, at least arguably, solve the under-inclusivity problem. Until very recently, lenders and underwriters faced technological constraints that limited their ability to collect, store, and analyze data about prospective applicants.\footnote{See Eva Wolkowitz & Sarah Parker, Big Data, Big Potential: Harnessing Data Technology for the Underserved Market, CENTER FOR FINANCIAL SERVICES INNOVATION 4 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf [https://perma.cc/CC72-X7RE] (“Consumer finance applications of Big Data have existed ever since credit bureaus first gathered tradeline information to assign consumer repayment risk[,] and insurance companies utilized applicant histories and demographics to set premiums[,] . . . The earliest uses of large data sets to inform financial product offerings did not differ greatly, in theory or aim, from how Big Data usage is conceived today. Rather, its use was limited by rudimentary computing power and the hurdles of gathering and normalizing data from incompatible or non-digitized sources, both of which made the process relatively inefficient.”).}

Increasingly, however, credit scorers are able to take advantage of a wide variety of non-traditional data, including information collected from social media, consumers’ retail spending histories, and other data points obtained from public platforms or procured from data brokers.\footnote{See id. at 14, 23; see also, e.g., Bill Hardekopf, Your Social Media Posts May Soon Affect Your Credit Score, FORBES (Oct. 23, 2015), http://www.forbes.com/sites/moneybuilder/2015/10/23/your-social-media-posts-may-soon-affect-your-credit-score-2/#28ba380a3207 [https://perma.cc/86XS-7F7A].} In order to effectively analyze this wealth of data on consumers’ online and offline activity, the alternative credit-scoring industry is turning to more complicated algorithms and modeling techniques.\footnote{Robinson & Yu, supra note 11, at 2.} In an ideal world, the more sophisticated the algorithms used and the more data involved, the more predictive and accurate a credit-scoring model should be. As we explore in greater detail below, however, big-data tools also pose significant risks to transparency, accuracy, and fairness.
One of the most prominent players in the alternative credit-scoring and underwriting industry is ZestFinance.\(^7\) Founded in 2009, ZestFinance offers big-data credit-scoring tools to providers of payday loans (short-term, high-interest loans), while also offering such loans through its affiliate, ZestCash.\(^71\) To date, the company has underwritten “more than 100,000 loans” and is authorized to lend to consumers in several states across the United States.\(^72\) ZestFinance touts an “all data is credit data” approach\(^73\) that combines conventional credit information with thousands of data points collected from consumers’ offline and online activities. The company’s system of proprietary algorithms analyzes several thousand data points per individual in order to arrive at a final score.\(^74\) While ZestFinance has not disclosed detailed information regarding either its data sources or the algorithms it uses, a patent application\(^75\) and marketing materials provide a window onto ZestFinance’s scoring system.

Consumers would likely be surprised at the types of information ZestFinance uses to predict creditworthiness. Although ZestFinance does rely upon some traditional credit data, other data points may appear to have little connection to creditworthiness. For example, the ZestFinance model takes into consideration how quickly a loan applicant scrolls through an online terms-and-conditions disclosure, which — according to the company’s founder — could indicate how responsible the individual is.\(^76\) Evidence that a person is willing to give up


\(^{71}\) See ZESTCASH, https://www.zestcash.com [https://perma.cc/VW2Q-ZLKG]. ZestFinance insists that it does not engage in payday lending, however as the New York Times points out, the products offered through ZestCash feature extremely high rates of interest, and ZestCash may deduct sums from borrowers’ accounts on paydays. ZeshCash is no longer in operations as of June 24, 2016. See Ann Carrns, Don’t Call them Payday Loans, but Watch the Fees, N.Y. TIMES (Feb. 15, 2012), http://bucksblogs.nytimes.com/2012/02/15/dont-call-them-payday-loans-but-watch-the-fees [https://perma.cc/L2PF-JKU2].

\(^{72}\) Lohr, supra note 70, N.Y. TIMES (Jan. 19, 2015).

\(^{73}\) See supra note 9.


social-media connections might likewise signal a high-risk borrower. ZestFinance also considers spending habits in the context of a borrower's geographic location. For instance, "paying half of one's income [on rent] in an expensive city like San Francisco might be a sign of conventional spending, while paying the same amount in cheaper Fresno could indicate profligacy." ZestFinance is only one example of an alternative credit-scoring company that claims to predict credit risk on the basis of non-traditional data. The methods and practices of the alternative credit-scoring industry as a whole remain opaque and poorly understood. According to Upturn’s David Robinson and Harlan Yu, “[t]hese companies come and go quickly, making it difficult to construct a complete snapshot of the market.” In a recent study of alternative credit-scoring models, Upturn identified a number of “fringe” data scoring products available from both established and startup credit-scoring companies (see Table 1).

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77 Id.
78 Id.
79 Robinson + Yu, supra note 11, at 14.
80 Adapted from Robinson + Yu, supra note 11, at 13-15.
What little information is available about these alternative credit-assessment tools is already provoking alarm among regulators and consumer-advocacy groups.\(^81\) There is concern that these tools are non-transparent and rely on inaccurate data collected from numerous sources, making it difficult for consumers to verify or challenge unfair decisions. As already noted above, inaccuracies in raw credit-reporting

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data have posed frequent problems for traditional credit-scoring and assessment tools.\(^{82}\)

These tools may also perpetuate and, indeed, intensify, existing bias by scoring consumers on the basis of their religious, community, and familial associations, as well as on the basis of sensitive features such as race or gender. The social-media company Facebook recently filed a patent application pertaining to a method for “[a]uthorization and [a]uthentication [b]ased on an [i]ndividual’s [s]ocial [n]etwork.”\(^{83}\) The patent application indicates that one of the method’s preferred embodiments could be used for credit scoring.\(^{84}\) The patent application explains that: “[w]hen an individual applies for a loan, the lender [could] examine[] the credit ratings of members of the individual’s social network who are connected to the individual. . . . If the average credit rating of these members is at least a minimum credit score, the lender [could] continue[] to process the loan application. Otherwise, the loan application [would be] rejected.”\(^{85}\) Although it is unclear whether Facebook’s credit-scoring tool is operational, critics have already suggested that the tool could lead to new forms of digital redlining.\(^{86}\)

There is also no certainty that all the alternative credit-assessment tools on the market are truly designed to predict creditworthiness; instead, some may be designed to identify and target vulnerable individuals with high-cost loan products. Although there is no concrete evidence showing that alternative scorers are currently using machine learning to identify such borrowers, major data brokers, some of whom are also engaged in credit reporting, have been criticized for selling so-called “sucker lists” that identify individuals who are “old, in financial distress, or otherwise vulnerable to certain types of marketing pitches.”\(^{87}\) In one high-profile example, the FTC sought a consent decree against Equifax for selling lists of potentially vulnerable consumers to companies that market fraudulent products.\(^{88}\) A 2013 Senate Commerce Committee

\(^{82}\) See, e.g., Brief for Center for Dig. Democracy as Amicus Curiae Supporting Respondents, \textit{Spokeo, Inc. v. Robins}, 135 S.Ct. 1892, No. 13-1339, 2015 WL 5302538, at *12-13; \textit{see also supra} note 16.

\(^{83}\) U.S. Patent No. 9,100,400 (filed Aug. 2, 2012).

\(^{84}\) \textit{Id.}, Col. 2, Is. 9-16.

\(^{85}\) \textit{Id.}, Col. 2, Is. 10-16.


\(^{87}\) JULIA ANGWIN, DRAGNET NATION: A QUEST FOR PRIVACY, SECURITY, AND FREEDOM IN A WORLD OF RELENTLESS SURVEILLANCE (2014).

\(^{88}\) Equifax Information Services, LLC, Complaint No. 102-3252, Fed. Trade Comm’n (2012),
report also described some of these lists, which, with titles such as “Hard Times,” “Burdened by Debt,” “Retiring on Empty,” and “X-tra Needy,” appear deliberately calibrated to single out consumers who are most susceptible to unfavorable financial products like payday loans. As one report suggests, if “secretive, data-driven scoring” can be used to identify vulnerable consumers, this could “trigger a flood of payday loan ads” targeted to these individuals.

To better understand how these risks may arise, it is useful to first understand how an alternative credit scorer might use machine-learning techniques and thousands of data points to model and predict creditworthiness.

C. Using machine learning to build a big-data credit-scoring model – how it works and potential problems

How would a data scientist go about solving the unstructured problem of measuring creditworthiness using thousands of available data points and supervised machine-learning tools? There is no single methodology to design a big-data credit-scoring tool, and every scorer’s data-driven recipe is likely to differ. To the extent generalization is possible, this part describes the three major steps that a credit scorer might follow to design its scoring tool, namely: i) defining the problem to be solved (the scorer’s definition of creditworthiness) and specifying a target variable representing the outcome the scorer wishes to predict; ii) gathering data and transforming it into useable form; and, iii) developing and refining the model through exposure to training data and through feature selection. These three steps generally reflect the process that ZestFinance outlines in its patent application for its alternative credit-scoring tool. A schematic of ZestFinance’s model and scoring system is provided in Figure I, below.

https://www.ftc.gov/sites/default/files/documents/cases/2012/10/121010equifaxcmpt.pdf


It is important to note that the supervised machine-learning process we describe in this part is highly simplified. In practice, the process of arriving at a model for a complex, unstructured problem such as predicting creditworthiness is likely to be iterative. For example, the scorer may constantly update its stock of data or integrate new types of data, which could ultimately lead to changes in the structure of the model, the model’s most significant features, or the weights assigned to these features. This part offers a simplified snapshot of some of the key steps in this ordinarily iterative process.

i) **Step 1: defining the problem and specifying the target variable**

Before using supervised machine-learning techniques to solve a problem or make predictions, the data scientist must first define the problem and determine precisely what she

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91 Adapted from U.S. Patent App. No. 14/276,632, supra note 75.
wishes to predict.\textsuperscript{92} This step may seem obvious, but in the case of an unstructured problem like predicting creditworthiness, where there is no single correct answer, articulating a proper and quantifiable definition is critical. To explain, we return to our example of the retailer who wishes to segment customers into different groups and predict which sub-set of customers are most likely to respond favorably to targeted advertising. There is no predefined formula or rule to tell us why certain customers respond to targeted ads, when others do not. The data scientist must “translate some amorphous problem into a question that can be expressed in more formal terms that computers can parse.”\textsuperscript{93}

One way to achieve this is to select a “state or outcome of interest” commonly referred to as a “target variable.”\textsuperscript{94} A target variable can be defined by reference to examples of past outcomes or varying characteristics.\textsuperscript{95} These differing outcomes or characteristics are often described as “class attributes.”\textsuperscript{96} For example, suppose our retailer previously circulated a promotional email to a list of known customers, and the email contained an offer for a product at a reduced price. Suppose further that, in order to obtain the discounted product, customers had to purchase the product at the retailer’s online shop using a discount code supplied in the email. At the end of the promotion period, the retailer would have a list of customers that responded, as well as a list of customers that did not respond. These two lists would correspond to two classes representing responsiveness to targeted advertising, which is the target variable of interest. The class attribute for this first group could be encoded as “responsive to targeted advertising.” The class attribute for the second group could be encoded as “non-responsive to targeted advertising.” The classes of customers on both the responsive list and the non-responsive list could then be used to make predictions about future customer behavior.


\textsuperscript{93} Solon Barocas & Andrew D. Selbst, \textit{Big Data’s Disparate Impact}, 104 CALIF. L. REV. (forthcoming 2016) (manuscript at *8).

\textsuperscript{94} Id. at *7-8; see also COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL., supra note 59, at 101 (describing how machine learning models allow for the “prediction of the future value of a target variable as a function of the other variables at one’s disposal, and/or at a future time”).

\textsuperscript{95} See Abbot, supra note 92.

While the retailer's approach to defining a target variable and establishing class attributes in this example might seem logical, it could also result in flawed predictions because the class groupings are broad. The class represented by the non-responsive group is the most troublesome because the retailer only knows that non-responsive customers did not purchase the product online, but cannot say why. Some non-responsive customers may truly have been uninfluenced or even negatively influenced by the ad. Others may have failed to respond for a variety of different reasons. For example, certain non-responsive customers might use automatic spam filters on their email inboxes that prevented those customers from receiving an ad that they would otherwise have found useful. Other non-responsive customers might not have actually seen the email until after the promotional period lapsed, and thus could not use the code even if they had wanted to do so. Some non-responsive customers may actually have been influenced by the email, but they may have purchased the product at brick-and-mortar stores, rather than online.97 Finally, recall that the retailer based its target variable on a sample population of customers whose email addresses were previously known to the retailer. If this sample population is not representative of the general population of all potential customers, the retailer's target variable and class groups are likely to be under-inclusive and only of partial predictive value.98

While a careful data scientist would likely anticipate these types of problems, the retailer example illustrates the challenges that a data scientist may face when attempting to reduce a complex problem into a quantifiable target variable and set of class attributes. Depending on the information available to the data scientist, there may not be a cost-effective way to increase the granularity of the class attributes, ultimately reducing the accuracy of the final model. It may also prove expensive and burdensome for the data scientist to ensure that the individuals in the initial data set reflect the same distribution of characteristics in the broader population that the data scientist wishes to study.99

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97 Dean Abbot offers a similarly illustrative example of flawed target variable definition involving cases of fraud. See Dean Abbot, supra at note 92.

98 As Kate Crawford points out, when target variables are under-inclusive due to gaps in the data set, there may be “signal problems” where “some citizens and communities are overlooked or underrepresented.” Kate Crawford, Think Again: Big Data, FOREIGN POLICY (May 9, 2013), http://foreignpolicy.com/2013/05/10/think-again-big-data [https://perma.cc/EF5B-XK8E].

99 See Toon Calders and Indrė Žliobaitė, supra at note 96, 46-47 (“Computational models typically [assume] . . . that (1) the characteristics of
Credit scoring, while more complex than our targeted-advertising example, arguably poses many of the same challenges. There is no inherent definition of "creditworthiness." Instead, as Barocas and Selbst note:

[T]he very notion of creditworthiness is a function of the particular way the credit industry has constructed the credit issuing and repayment system—one in which an individual’s capacity to repay some minimum amount of an outstanding debt on a monthly basis is taken to be a non-arbitrary standard by which to determine in advance and all-at-once whether he is worthy of credit.100

There are multiple possible options for the data scientist who wishes to define creditworthiness and establish a target variable that can be used for future predictions. One option might be to simply segment potential borrowers into classes (e.g., "very creditworthy," "creditworthy," "less creditworthy," and "not creditworthy") based on their FICO scores. Another option might be to segment borrowers based upon their income levels and credit card repayment histories. Individuals with low incomes, or those that did not regularly pay down credit card balances, might be deemed less creditworthy, whereas those with higher incomes and strong track records of repayment might be deemed more creditworthy. Either option is likely to have its shortcomings. For example, basing class groups on borrowers’ existing FICO scores could systematically exclude some populations that have been historically unrepresented in the credit market, potentially for reasons that have little to do with these groups’ capacity to be responsible borrowers.101 An approach that classifies borrowers based on their relative income levels or past repayment histories may be overly simplistic and may fail to account for other factors that bear on a particular borrower’s ability to repay a loan.

100 Barocas and Selbst, supra at note 93, at 9 (citing David J. Hand, Classifier Technology and the Illusion of Progress, 21 STATISTICAL SCI. 1 (2006)).

101 See, e.g., Blake Ellis, Millions Without Credit Scores not so Risky After All, CNN MONEY (Aug. 14, 2013), http://money.cnn.com/2013/08/14/pf/credit-scores [https://perma.cc/4GD4-PPN5].
A poorly-crafted definition could also lead to inadvertent discrimination, where “data miners [...] unintentionally parse the problem and define target variables in such a way that protected classes happen to be subject to systematically less favorable determinations.” As Calders and Zliobaite point out, the process of assigning labels to class attributes may be either objective or subjective. Subjective labeling involves some human interpretation, whereas objective labeling does not. The class attributes in our retail example are objective: customers fall within binary categories based on their responses to the targeted advertisement. Subjective class labels, by contrast, are generally non-binary, for example “the assessment of a human resource manager [regarding whether] a job candidate is suitable for a particular job.” Where class attributes are defined subjectively, “there is a gray area in which human judgment may have influenced the labeling resulting in bias.” As we note in further detail below, the class attributes that the data scientist initially selects may be adjusted and perhaps even supplanted as the machine-learning process advances. However, there is no guarantee that the machine-learning process will necessarily correct for implicit bias that is initially introduced through poorly-defined target variables or class attributes.

Alternative credit scorers promise that they can avoid problems of under-inclusiveness posed by traditional scoring systems, but so far, it remains unclear whether this truly is the case. Unfortunately, there is scarce information about how alternative credit-scoring companies like ZestFinance define “creditworthiness,” or how they set target variables and label classes of borrowers to serve as examples for their machine-learning processes. ZestFinance’s patent application does not supply its definition of creditworthiness, or describe the target variable it uses.

Although there is no clear-cut evidence that alternative credit-scoring companies are using machine-learning tools to maximize lender profitability at the expense of consumers,
rather than scoring for “creditworthiness” as the layperson might understand it, there is also no reason to assume that these companies have the borrowers’ interests at heart. A recent study of online payday lending notes that the “lenders [using] sophisticated technology and advanced algorithms to predict which applicants are most likely to repay loans...continue to charge interest rates usually in excess of 300 percent APR....”109 Experts at Upturn have also recently detailed how online “lead generators” are using sophisticated algorithmic scoring techniques to zero in on consumers at moments when they are likely to be especially vulnerable to low-value, short-term credit products with usurious interest rates and highly unfavorable terms.110 This raises the possibility that certain alternative credit scorers may not be truly interested in predicting consumer creditworthiness, but rather in finding vulnerable, high-value targets for unfavorable loans.111 Payday borrowers also “disproportionately come from poor and minority communities.”112 Rather than expanding access to underserved groups, alternative credit scorers may be employing target variables that work to the further detriment of historically disadvantaged groups.

ii) Step 2: gathering and transforming data

Once the data scientist has identified the target variable and established classes, she next gathers information associated with individuals for which the various outcomes are already known. This information will eventually constitute the “training data” that will be used throughout the machine-learning process to develop a final model. The prevailing view is that the larger the data set available for analysis, the more accurate and predictive the final model. In the era of “big data,” alternative credit-scoring companies can take advantage of the booming trade in consumer information to obtain everything from an individual’s online purchase history, criminal and arrest record, internet browsing history (collected


111 As already discussed above in Section III (B) supra, certain major credit-reporting agencies and data brokers have been subject to investigation and public criticism for selling “sucker lists” with information on financially-vulnerable consumers.

112 Id.
through tracking mechanisms such as browser “cookies”), to an individual’s “friend” groups on social-media platforms.\footnote{A New York Times report concludes, “[I]t’s as if the ore of our data-driven lives were being mined, refined and sold to the highest bidder, usually without our knowledge – by companies that most people rarely even know exist.” See Singer, supra note 8.}

ZestFinance’s approach to gathering data is illustrative. ZestFinance claims to collect thousands of data points for each individual it analyzes. These data points fall into four broad categories, namely: 1) the borrower’s data, 2) proprietary data, 3) public data, and 4) social network data.\footnote{U.S. Patent App. No. 14/276,632, supra note 75, at ¶ 0038.} The first category contains information provided directly by the applicant during the application process,\footnote{Id. at ¶ 0028.} as well as other information such as web-browser activity, which might be gleaned from the applicant’s device at the time she applies for a loan online.\footnote{Id. at ¶ 0040.} For example, if a prospective customer applies online, ZestFinance may be able to measure how long the applicant spends reviewing the terms and conditions page to determine whether she read it carefully.\footnote{Id. at ¶ 0040.} The second category, “proprietary data,” refers to information obtained from “privately or governmentally owned data stores,”\footnote{Id. at 0025.} and most likely includes material compiled by major data brokers such as Acxiom.\footnote{See Singer, supra note 8. According to Singer, as of 2012, Acxiom’s “servers process[ed] more than 50 trillion data transactions,” and that the company’s “database contains information about 500 million active consumers worldwide, with about 1,500 data points per person. That includes a majority of adults in the United States.”}

This second category is perhaps the broadest, and may encompass everything from an individual’s online and offline purchase history to health and medical data.\footnote{According to Adam Tanner, data brokers may increasingly be able to gather information on individuals’ prescription histories in a manner that sidesteps the protections of Federal privacy laws such as HIPAA. See Adam Tanner, How Data Brokers Make Money Off Your Medical Records, SCIENTIFIC AMERICAN (Feb. 1, 2016), http://www.scientificamerican.com/article/how-data-brokers-make-money-off-your-medical-records [https://perma.cc/WSJ2-GUX5].} The third category, “public data,” contains information that ZestFinance obtains from automated searches of the Internet and techniques such as web crawling and scraping.\footnote{U.S. Patent App. No. 14/276,632, supra note 75, at ¶ 0026.} Finally, the fourth category, “social network data,” consists of social-media activity including information aggregated from the borrower’s social media posts and “any social graph
information for any or all members of the borrower’s social network.”

Once the data scientist has collected the raw data points that will serve as training data, she must translate them into a usable form that can be processed by a computer. The ZestFinance patent provides some insights into how such a transformation process works. For instance, an individual’s raw salary might be translated into a percentile score that compares the individual’s salary to the salaries of other people who are employed in the same industry and geographic region. As another example, recall that ZestFinance collects information about the amount of time that an applicant spends reviewing a terms-and-conditions disclosure, which ZestFinance sees as an indicator of an applicant’s level of responsibility. However, this raw time measurement is not immediately useable, and ZestFinance transforms the measurement into “an ordinal variable on a 0-2 scale, where 0 indicates little or no care during the application process and 2 indicates meticulous attention to detail during the application process.”

ZestFinance’s data-transformation process does not end here, however. After converting the raw data points into useable form, ZestFinance further processes the resulting variables “using one or more algorithms (statistical, financial, machine learning, etc.) to generate a plurality of independent decision sets describing specific aspects of a borrower,” which the patent refers to as “metavariables.” ZestFinance’s metavariables appear to place applicants into categories by drawing inferences from one or more pieces of transformed data. For example, a metavariable might compare an applicant’s reported income to the average income of individuals with similar professions living in the applicant’s city, and then generate a “veracity check” that represents the likelihood that the applicant is misrepresenting her salary. As another example, ZestFinance might score the applicant on a “personal stability” scale, based upon the amount of time she has “been consistently reachable at a small number of addresses or phone numbers.” The patent explains that ZestFinance’s metavariables are “very useful at the

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122 Id. at ¶ 0027.
123 Id. at ¶ 0040-42.
124 Id. at ¶ 0042.
125 Id.
126 Id. at ¶ 0041.
127 Id. at ¶ 0044.
128 Id.
intermediate stage of constructing a credit scoring function,”¹²⁹ and may be used to determine “which ‘signals’ are to be measured [in the final scoring process], and what weight is to be assigned to each [‘signal’].”¹³⁰

The process of data collection and transformation poses a number of risks that, if left unaddressed, may lead to unfair denials of credit or extension of credit under unfavorable terms. One such risk may occur when the credit scorer has an overabundance of data points at its disposal. While the integration of more training data into a machine learning process may lead to increased accuracy in the modeling,¹³¹ it can also increase the incidence of spurious correlations.¹³² As data scientist James Kobielus notes, “[o]ne of the bedrock truths of statistics is that, given enough trials, almost any possible occurrence can happen .... The more possible events that might take place, the more potential, albeit unlikely, ‘fluke’ events there are.”¹³³ As credit-scoring algorithms integrate more inputs, it becomes more likely that an algorithm might draw a spurious correlation between a particular attribute and creditworthiness. As Kobielus further explains:

Some extreme correlations may jump right out at us and scream “Significant!” only to fade upon repeated observations. Though they may not be statistical flukes, such correlations may vanish under the influence of the statistical rule known as “regression toward the mean.” These are non-robust correlations of the sort that may be borne out by historical data sets but, when encoded in predictive models, fail to be replicated in future observations.¹³⁴

¹²⁹ The Metavariabes serve as the inputs to the final scoring model. See id. at ¶ 0043.
¹³⁰ Id. at ¶ 0045.
¹³⁴ Id.
The raw input data is also not necessarily objective; indeed, it is likely to reflect forms of preexisting bias and discrimination. As one expert has warned, “because not all data is created or even collected equally, there are ‘signal problems’ in big-data sets – dark zones or shadows where some citizens and communities are overlooked or underrepresented.”\textsuperscript{135} Such signal problems may arise where the mechanisms used to collect data favor particular groups to the exclusion of others. Kate Crawford points to the example of Boston’s “Street Bump” app to explain how the design of a data collection tool can lead to different outcomes for similarly-situated groups.\textsuperscript{136} Street Bump uses the accelerometers in motorists’ iPhones to crowd-source data on the location of potholes. As Crawford notes, “if cities begin to rely on data that only come from citizens with smartphones, it’s a self-selecting sample – it will necessarily have less data from those neighborhoods with fewer smartphone owners, which typically include older and less affluent populations.”\textsuperscript{137} If credit scorers rely on non-neutral data collection tools that fail to capture a representative sample of all groups, some groups could ultimately be treated less favorably or ignored by the scorer’s final model.

Another challenge posed by the use of extremely large data sets is the problem of accuracy, something that has long plagued traditional credit scorers who have historically relied on far fewer data points than those in the alternative scoring industry. As mentioned above, in a 2013 study, the FTC identified a high incidence of inaccuracies in traditional credit reports, leading to elevated rates of interest for certain borrowers.\textsuperscript{138} A recent study by the National Consumer Law Center that examined the consumer information held by a number of major data brokers likewise concluded that the data sources used by alternative credit scorers were “riddled with inaccuracies,” ranging from “the mundane” to the “seriously flawed.”\textsuperscript{139} According to the Electronic Privacy Information Center, because big-data credit scorers are principally “concerned with amassing a large quantity of information about an individual,” the overall quality of that data is likely to suffer.\textsuperscript{140}

\begin{footnotesize}
\begin{enumerate}
\item\textsuperscript{135} Crawford, supra note 98.
\item\textsuperscript{136} See Street Bump, http://www.streetbump.org [https://perma.cc/CXC2-75WZ].
\item\textsuperscript{137} Crawford, supra note 98.
\item\textsuperscript{138} Id.
\item\textsuperscript{139} FED. TRADE COMM’N, supra note 14, at 63-64.
\item\textsuperscript{140} See Yu et al, supra note 10, at 4.
\item\textsuperscript{141} Credit Scoring, ELECTRONIC PRIVACY INFORMATION CENTER (2016), https://epic.org/privacy/creditscoring [https://perma.cc/W94Z-HGWP].
\end{enumerate}
\end{footnotesize}
During the process of data transformation, a program may be “designed to discard minor differences that occur in identifiers, such as incorrect digits in a social security number.”\[^{142}\] These errors are often difficult to correct down the line, and credit scorers generally dedicate little time and energy to correcting errors in their datasets.\[^{143}\] In one example, TransUnion, a major national data broker and CRA, repeatedly mixed the files of two different women—Judy Thomas and Judith Upton—because of similarities in their names, their dates of birth, and their Social Security numbers.\[^{144}\] TransUnion’s mistake meant that a complete stranger’s bad debts haunted Judy Thomas for years. TransUnion only corrected the problem after Thomas sued and won a multimillion dollar jury verdict.\[^{145}\]

Finally, the process of data collection and transformation may lead to problems of transparency. Credit-scoring companies treat their data sources as proprietary trade secrets.\[^{146}\] In practice, this means that consumers have no realistic means to understand which of the many seemingly inconsequential decisions they make each day could impact their credit ratings, and even less ability to challenge their scores, or test whether the input data are accurate. This problem is likely heightened where a lender relies on thousands of data points and translates these data points into forms that, while intelligible to a computer, are not intelligible to the layperson. Assuming that a diligent applicant could first identify an error among the thousands of entries in the credit scorer’s raw data set, it is unlikely that the applicant would have the capacity to prove that the error resulted in a faulty score. As one study puts it, “[a] credit score rests upon [the scorer’s] accrual of as many records and cross-correlations of a borrower’s financial decisions as possible. [Credit scorers] then reductively collapse the entangled mass of correlations of those

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\[^{142}\] Id.
\[^{143}\] Frank Pasquale notes that agents at the main credit-reporting agencies reported spending approximately six minutes for each error they were asked to resolve. See Frank Pasquale, The Black Box Society: The Secret Algorithms that Control Money and Information 22 (2015).
activities to a three-digit number, supposedly imbued with comparative social meaning." Because the data-transformation process likely involves numerous aggregations and combinations of data points, as well as subjective decisions by the data scientist, applicants are likely to have few means to effectively challenge their scores.

iii) Step 3: developing a final model through analysis of training data and feature selection

Once the data scientist has collected and transformed the corpus of training data, the process of machine learning can begin. But not every input within the training data will prove relevant, and many inputs are likely to be discarded as the system learns what is relevant to the target variable and what is irrelevant. The machine-learning process typically involves an optimization routine that attempts to identify the most significant input variables and the appropriate weights that should be assigned to each. Here, it is helpful to recall Venkatasubramanian’s trial-and-error recipe analogy. In order to develop a final model (the recipe), the data scientist uses computer programs capable of running many successive iterations and analyzing perhaps thousands of combinations of data points in order to identify relevant factors that best correlate to the target variable of interest. This iterative process of identifying relevant inputs and discarding irrelevant inputs is described as “feature selection.” Put differently, feature selection refers to the task of choosing a subset of input attributes that are most relevant to the problem and which have the greatest predictive potential. As the machine-learning process advances, the most predictive features will be assigned greater weights and will be combined into a final model.

As discussed in the prior section, ZestFinance’s data-transformation process results in a series of metavariables that may constitute combinations of multiple data points, or may instead represent inferences drawn from particular data points. Once the data are condensed down to a few hundred metavariables for each individual, ZestFinance next undertakes a feature-selection process in which it identifies a

148 See Section III (A), supra.
149 Feature selection is an important component of any machine-learning application. Feature selection increases the signal to noise ratio by eliminating irrelevant input variables. See Isabelle Guyon & Andre Elisseeff, An introduction to variable and feature selection, 3 J. MACHINE LEARNING RES. 1157 (2003).
few significant metavariables that can be used for scoring.\textsuperscript{150} ZestFinance’s feature-selection process is not uniformly automated, and the company selects the most significant metavariables in one of two ways. In some cases, a data analyst may “curate” or manually determine which metavariables are significant, drawing from past experiences and observations of the applicant pool.\textsuperscript{151} In other instances, ZestFinance may rely on statistical algorithms to automatically identify the most significant metavariables.\textsuperscript{152} ZestFinance’s patent application provides a vague overview of the specific metavariables that go into its credit-scoring models, likely in an effort to retain trade secrecy. As a result, it is not possible to determine which of ZestFinance’s metavariables have emerged as the most significant, how they are calculated, and whether they are an accurate reflection of creditworthiness.

In the final stage of the ZestFinance scoring process, significant metavariables are fed into “statistical, financial, and other algorithms each with a different predictive ‘skill.’”\textsuperscript{153} In essence, ZestFinance’s final model is a composite of a number of other models. An applicant’s final score is an aggregate of the set of scores produced by these models. The patent does not describe how each score is weighted within the final ensemble model.

Once the data scientist has used the transformed training data to develop the final model (or series of models), the model can be deployed to make scoring and lending decisions. At this point, the scorer may not need to collect and input the same amount of data for each new prospective borrower – recall that the machine learning process allows the scorer to discard certain data points that the model determines are irrelevant. However, because creditworthiness is an unstructured problem with no single solution, the credit scorer may also be interested in constantly improving upon the model. Every time the model is deployed to score a new consumer, more data are generated. These new data can be fed back into the machine-learning process, leading to improvements in the model. Information that was previously deemed irrelevant in earlier iterations may take on new meaning as the system continues to learn.

\textsuperscript{150} This is one of the critical components of the scoring process. ZestFinance aggregates different data points for each individual. Not all of these data points are relevant; hence, ZestFinance must determine which of its thousands of input variables or transformations are relevant to ZestFinance’s creditworthiness. The resulting variables are called metavariables. See U.S. Patent App. No. 14/276,632, supra note 75, at ¶¶ 0040-47.

\textsuperscript{151} See id. at ¶ 0045.


\textsuperscript{153} Id. at ¶ 0010.
As the ZestFinance example demonstrates, the manner in which the data scientist develops and refines the final credit-scoring model can potentially create major barriers to transparency and to consumers' ability to challenge scores. The process of data transformation, metavariable development, feature selection, and, finally, the filtering of significant features through multiple models is so complex that even the most sophisticated consumer would likely find it difficult to understand, or to determine whether any inaccuracies in the raw data negatively influenced her final score.

The machine-learning and feature-selection process may also produce models that perpetuate implicit forms of bias and that inadvertently factor in sensitive characteristics such as race. As we will discuss in further detail, longstanding Federal law prohibits lenders from directly taking characteristics such as race or sex into account when making lending decisions. When a credit scorer has thousands of data points to work with, however, the machine-learning process may indirectly consider sensitive characteristics, such as race, even when those characteristics are not directly designated as input values. In many instances, “the attributes that characterize [] subjects [in the dataset] may not be independent from each other.” Attributes that are facially neutral may in fact be highly correlated with sensitive characteristics that, by law, cannot be considered. One well-known example is an individual’s zip code, which can easily serve as a proxy for a sensitive characteristic like race.

Consumers’ use of technology, shopping habits, social-media practices, and other details are likely to vary by race and other sensitive factors. “Thirty percent of whites,” for example, “use their mobile phone as their sole Internet connection compared to roughly forty-seven percent of Latinos and thirty-eight percent of blacks.” When combined with other information, mobile and Internet usage practices could potentially be used as a proxy for race. If, during the process of

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154 See discussion infra Section IV.
155 Calders & Žliobaite, supra note 96, at 47 (emphasis omitted).
156 Id.
machine learning, the model learns that race or another sensitive characteristic is highly correlated to credit risk, the model will attach greater significance to proxy variables that can serve as a stand-in for that sensitive characteristic. Even where data miners are careful, "they can still effect discriminatory results with models that, quite unintentionally, pick out proxy variables for protected classes." 

The machine-learning and feature-selection process may also produce results that are unfair because an individual's final score may not be made on the basis of the individual's own merits, but rather based on factors the individual coincidentally shares with others that the model deems risky. When a model relies on generalizations reflected in the data, individuals can be victimized by "statistically sound inferences that are nevertheless inaccurate," and which are completely beyond the individual's control. For example, a model that scores individuals on the basis of shared characteristics may penalize "low-income consumers with pristine credit histories...simply because they save costs by shopping at low-end stores." Such models may also punish individuals for being members of particular communities or families, or for their affiliations with certain political, religious, and other groups. Kevin Johnson's story provides a good example of this phenomenon in the credit context. What happened to Kevin is not likely an anomaly. In many other areas—from academic admission decisions to the realm of Google search results—big-data tools that judge individuals on the basis of shared characteristics rather than individuals' own merits have been shown to entrench existing bias.

IV. THE INADEQUACIES IN THE EXISTING LEGAL FRAMEWORK FOR CREDIT SCORING

Federal laws already regulate certain aspects of the credit-assessment industry as well as the use of credit scores and reports. The existing legal framework, however, contains multiple gaps and inadequacies. Regulators and consumers

159 Barocas & Selbst, supra note 93, at 5.
160 See id., at 18-19.
161 YU ET AL., supra note 10, at 28.
162 See Section II.
163 See, e.g., Stella Lowry & Gordon Macpherson, A Blot on the Profession, 296 BRITISH MED. J. 657 (1988) (finding that an automated system used to sort medical school applicants on the basis of previous admission decisions systematically disadvantaged racial minorities who were otherwise similarly situated to white applicants); Latanya Sweeney, Discrimination in Online Ad Delivery, 56 COMM. ACM 44 (2013) (finding that Google queries with African-American-sounding names were more likely to return advertisements for arrest records than queries using white-sounding names).
may also find it difficult to apply existing laws to many alternative forms of credit assessment because of the new data sources and technologies that these alternative tools use. This part surveys two federal laws that are particularly relevant to the credit-scoring industry, namely the Fair Credit Reporting Act (“FCRA”) and the Equal Credit Opportunity Act (“ECOA”). In addition to briefly describing the scope of the FCRA and ECOA regimes and the key requirements the laws impose, this part describes potential problems that both regulators and consumers may face when seeking to apply these laws to non-traditional, big-data credit-scoring models.

A. The Fair Credit Reporting Act (FCRA)

FCRA was enacted in 1970 to serve the dual goals of ensuring fairness in consumer credit reporting, and safeguarding consumers’ privacy through limitations on how consumer credit information can be disclosed or used.\(^\text{164}\) FCRA furthers these objectives by “requir[ing] that consumer reporting agencies adopt reasonable procedures for meeting the needs of commerce for consumer credit, personnel, insurance, and other information in a manner which is fair and equitable to the consumer, with regard to the confidentiality, accuracy, relevancy, and proper utilization of such information.”\(^\text{165}\) FCRA also seeks to ensure that consumers can access information about their scores, correct errors, and understand how their personal and credit data are being used by third parties who use it to make credit, employment, and insurance decisions.

While the activities of many alternative credit-scoring companies may trigger FCRA’s requirements, a recent study points out that “[i]t is highly unlikely, given the size of the data set and the sources of information, that the companies that provide big data analytics and the users of that data are meeting these FCRA obligations.”\(^\text{166}\) Providers of alternative credit-assessment tools may also be able to evade FCRA’s coverage if, instead of compiling information that is tied to a specific individual, credit scorers aggregate data at the household or neighborhood level, or gather and report data associated with a device or an IP address used by multiple individuals.

\(^{164}\) See Robinson + Yu, supra note 11, at 28; see also generally S. Rep. No. 91-169 (1969).


\(^{166}\) See Yu ET AL., supra note 10, at 5.
i) Information, entities, and activities governed by FCRA

Whether a particular entity or reporting activity falls under FCRA principally depends on the types of information involved, the actual or expected uses of that information, and whether the information is reported by a “consumer reporting agency” ("CRA"). FCRA governs “consumer reports,” which are defined as reports containing “any information . . . bearing on a consumer’s credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living.” The information need only satisfy one of these factors, with the practical implication that almost any information about a consumer might qualify.

While the types of information potentially relevant to FCRA are vast, information will not be considered as a consumer report unless it pertains to an “individual,” meaning an “an identifiable person.” If a company compiles data on the activities of a household, a neighborhood, and potentially a device or Internet Service Protocol (“ISP”) address, the company’s reports may not be subject to FCRA’s requirements.

Courts have held, for example, that reports containing information on individuals who share a common surname are not governed by FCRA because the reports do not pertain to single individuals. One court has suggested that reports pertaining to a house or property, and not strictly to the property’s owner, may fall outside of FCRA. Reports that purport to strip out a consumer’s personally identifying information and assign an anonymous customer ID to the information could also side-step this requirement, despite

170 McCready v. EBay, Inc., 453 F.3d 882 (7th Cir. 2006) (information pertaining to an anonymous computer username does not qualify under definition of “consumer report”).
171 See Robinson + Yu, supra note 11, at 17.
173 Fuges v. Southwest Fin. Serv., Ltd., 707 F.3d 241, 253 (3d Cir. 2012) (finding that it was not unreasonable for the defendant to interpret the FCRA’s definition of a consumer report as excluding information about encumbrances on a property, even if the property was owned by an identifiable consumer).
174 For example, Verizon assigns a “Unique Identifier Header” (“UIDH”) to each of its mobile customers, allowing the company to track users across devices, logging details on browsing habits, geolocation, and other information. See VERIZON WIRELESS, https://www.verizonwireless.com/support/unique-identifier-header-faqs [https://perma.cc/Z77M-QK3V]. The online advertising company Turn also recently came under public scrutiny for devising so-called
the fact that such identifiers may easily be linked back to a particular consumer. While the FTC has taken the position that information, even if not tied to a consumer's name, may qualify as a consumer report if it could be "reasonably linked to the consumer," it remains to be seen whether de-identification methods can be used to circumvent FCRA's requirements.

Application of FCRA further depends on whether the information an entity collects and sells constitutes a "consumer report" under the Act. In order to qualify as a "consumer report," the information must be "used or expected to be used or collected" to serve as a "factor in establishing the consumer's eligibility for" three purposes: credit, insurance, and employment. The origin and nature of the information thus make no difference to FCRA coverage; applicability turns on the purposes for which such information is collected, as well as actual or likely end-uses for the information. The individual or entity supplying the information need not have proof that the information will be used for a covered purpose; it is enough "if, in the usual course of events, one would expect that one of the uses of a report would be a listed one." As big-data models expand the types of information analyzed for credit decisions, factors not previously considered as falling within the scope of FCRA, such as geolocation and online browsing history information, may qualify under the Act.

FCRA's final definitional element further circumscribes its scope, making clear that information that nominally qualifies as a "consumer report" will not trigger the Act's requirements unless it is supplied by an entity meeting the definition of a "consumer reporting agency" ("CRA"). A CRA is defined as "[a]ny person which, for monetary fees, dues, or on a cooperative nonprofit basis . . . [r]egularly engages in whole

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178 Fair Credit Reporting, supra note 168, at § 2.3.5.1.

179 Id. at § 2.3.5.3.

or in part in the practice of assembling or evaluating consumer
credit information or other information on consumers for
the purpose of “furnishing consumer reports to third parties.” Based on this final requirement, many collection and reporting
activities may fall outside of FCRA’s bounds. For example, a
lender that develops its own mechanisms for collection and
data analytics will not trigger FCRA as long as it does not
resell that information for further use in the credit, insurance,
or employment context. The definition of CRA may also
create a loophole for big-data companies that segment their
internal operations and wall off any credit-reporting activities
from other activities, such as targeted marketing. As the
National Consumer Law Center points out, “one division of a
corporation can collect consumer reports, while another collects
business reports. As long as the business reports are not
derived from a consumer report, but are independently
collected solely for a business purpose, that division would not
act as a CRA.”

A number of companies that currently collect and
compile the types of information increasingly used to assess
creditworthiness or to make decisions under other listed FCRA
purposes have attempted to evade the Act’s application by
disclaiming any responsibility for how the information is used.
For example, Intelius, a major data broker, declares on its
website that it “is not a consumer reporting agency as defined
in the [FCRA],” and that those using its reports shall not do so
for any of the purposes set out in the FCRA. The FTC has
cracked down on certain data brokers who rely on disclaimers
to disavow responsibilities under FCRA, however, there is
evidence that these practices remain widespread among many
data brokers.

182 It should be noted that the FCRA also specifically excepts actors that only
(2012), a flexibility that may have particular importance for online lenders
that use detailed applications. See also Robinson + Yu, supra note 11, at 28.
183 Fair Credit Reporting, supra note 168, at § 2.5.2.
184 See YU ET AL., supra note 10, at 26 (setting out examples of data broker
disclaimers).
185 See, e.g., Consent Decree, United States v. Spokeo, Inc., No. CV12-05001
MMM (C.D. Cal., June 7, 2012).
186 See YU ET AL., supra note 10, at 26. For instance, Spokeo still maintains a
disclaimer on its website even after it was subject to a major FTC
ii) Key FCRA requirements and limitations on use of consumer reports

Out of concern for consumers’ privacy, once information qualifies as a “consumer report,” FCRA only permits its use for certain permissible purposes; for instance, use in connection with a consumer credit transaction. Consumer reports cannot be sold for non-permissible purposes, such as targeted marketing. A CRA must maintain reasonable safeguards to ensure information is used permissibly, and must refuse to furnish a report if it has reason to believe the recipient intends to do otherwise.

CRAs must also use reasonable procedures to guarantee the accuracy of information in consumer reports. Not only must the information in a report be literally true, it also must not be misleading or incomplete. When a lender takes an adverse action on a consumer’s application based upon information contained in a consumer report, FCRA obligates the lender to notify the consumer of the adverse action, identify the CRA that provided the report, and provide instructions on how the consumer can obtain the information in the report. The consumer has the further right to request and obtain information in the report, as well as to challenge the accuracy of the information.

In the traditional credit-scoring context, FCRA’s transparency mechanisms have provided an important, albeit imperfect, safeguard against abuses and mistakes. These measures, however, may not be effective in the alternative credit-scoring context, where the data points collected and used are increasingly vast and where scoring companies may be

189 See Trans Union Corp. v. FTC, 245 F.3d 809, 812-16 (D.C. Cir. 2001) (confirming the FTC’s finding that lists containing the names and address of individuals who have auto loans, department store credit cards, or mortgages, qualified as consumer reports under the FCRA, and that the sale of such lists for target marketing purposes was a violation of the Act).
192 See Fair Credit Reporting, supra note 168, at § 4.2.3.
193 15 U.S.C. § 1681m(a) (2012); see also Fair Credit Reporting, supra note 168, at § 3.3.6.
taking steps to circumvent FCRA’s definitional scope.\(^{196}\) Consumer advocacy groups have already raised concerns that “compliance with [the FCRA’s] notice requirement is sparse with non-traditional consumer reports.”\(^{197}\) Given that non-traditional scoring models rely on thousands of pieces of information collected from multiple sources, it will likely prove extremely difficult for consumers to identify and challenge inaccuracies in the raw data,\(^{198}\) and even more difficult to contest inferences drawn from analysis of the raw data points. By placing the burden of ensuring accuracy on the shoulders of individual consumers, FCRA’s protections may prove increasingly ineffective as scorers adopt alternative big-data models.

### iii) Key issues and challenges not addressed by FCRA

While FCRA limits uses of information in consumer reports and provides procedural safeguards to correct mistakes, it does not limit the types of information that can be used to score credit, aside from certain forms of outdated criminal records and financial records.\(^{199}\) As a consequence, consumers may have few guideposts allowing them to understand what stands behind a credit decision and what steps they can take to improve their scores. Although “a similar critique is certainly true of FICO and other traditional credit scores,” such concerns are heightened in the case of big-data alternative credit scoring, where consumers have practically zero notice as to what information is being collected about their behavior, and how it is being used.\(^{200}\)

To the extent that FCRA requires alternative credit-scoring companies to provide consumers with the opportunity to access and correct information about them, it may prove practically impossible for consumers, when dealing with big-data scoring systems that potentially integrate thousands of variables, to verify the accuracy of their scores and reports or

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\(^{196}\) For example, the FCRA does not apply to companies that collect and maintain their own data on consumers, and use it internally rather than selling it. See 15 U.S.C. § 1681a(d)(2)(A)(6) (2012). As a practical consequence, online lenders that acquire their information first-hand from consumers or through automated web-crawling will not be subject to the FCRA. See Robinson + Yu, supra note 11, at 28.


\(^{198}\) See Yu et al., supra note 10, at 25.


\(^{200}\) Yu et al., supra note 10, at 20.
to challenge decisions based on alternative models. FCRA’s transparency and reporting requirements place the burden on individual consumers to identify and contest errors and inaccuracies in the data that may impact upon their final scores. This system is likely to prove unworkable for big-data tools.

While the Equal Credit Opportunity Act (“ECOA”), discussed below, prohibits lenders from considering sensitive factors such as race when making lending decisions,201 neither law expressly prohibits the consideration of many data points that are facially unrelated to consumers’ financial practices and that may also serve as proxies for immutable or sensitive characteristics. FCRA also “does not explicitly require credit scores to be predictive of creditworthiness” at all,202 meaning that FCRA cannot prevent scorers from using big-data machine-learning tools to predict other outcomes, such as consumer vulnerability.

B. The Equal Credit Opportunity Act (ECOA)

Congress enacted ECOA in 1974 to prohibit creditors from discriminating against credit applicants on the basis of sensitive characteristics such as race, religion, national origin, sex, or marital status.203 Since its enactment, ECOA and its accompanying Regulation B have served as the primary vehicle for individuals and classes of consumers to challenge lending decisions and policies that are either patently discriminatory, or that lead to discriminatory results. Plaintiffs have two principal options to bring an ECOA claim: they can either allege disparate treatment by showing that they were specifically singled out and treated unfavorably on the basis of some sensitive characteristic such as race, or they can allege disparate impact, by showing that a facially neutral lending policy resulted in less favorable terms for members of a protected class when compared with other similarly situated borrowers.

The existing ECOA framework governs lending decisions made using big-data machine-learning tools just as it does lending decisions using traditional tools. Borrowers are likely to find, however, that it is much more difficult to make the case for either disparate treatment or disparate impact.

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201 See subsection B, infra.
202 Yu et al., supra note 10, at 20.
203 15 U.S.C. § 1691a(a)(1) (2012); see also, e.g., 12 C.F.R. § 1002.1 (2016) (“The purpose of this part is to promote the availability of credit to all creditworthy applicants without regard to race, color, religion, national origin, sex, marital status, or age, . . . “); Treadway v. Gateway Chevrolet Oldsmobile Inc., 362 F.3d 971, 975 (7th Cir. 2004).
when a lender justifies its decisions on a credit-scoring process that uses sophisticated algorithms and thousands of data points. There are several reasons for this. First, to the extent that a lender wishes to implement a lending policy that deliberately singles out members of a particular racial, ethnic, or other group, the lender likely can employ facially-neutral proxy variables in its scoring model as stand-ins for characteristics like race. Second, to the extent that lending decisions accord less favorable treatment to a protected class, the lender may be able to claim that its “objective,” data-driven, modeling processes are proof that the disparate impact is grounded in business necessity.

i) Entities and activities governed by ECOA

ECOA governs the activities of creditors and protects against discrimination in credit transactions. ECOA’s definition of “creditor” encompasses three groups: 1) “[a]ny person who regularly extends, renews, or continues credit;” 2) “any person who regularly arranges for the extension, renewal, or continuation of credit;” or 3) “any assignee of an original creditor who participates in the decision to extend, renew, or continue credit.”\(^{204}\) ECOA regulations further clarify that any “person who, in the ordinary course of business, regularly participates in a credit decision, including setting the terms of the credit,” can constitute a creditor under the Act.\(^{205}\)

ECOA defines the term “credit transaction” as “every aspect of an applicant’s dealings with a creditor regarding an application for credit or an existing extension of credit.”\(^{206}\) ECOA’s scope of coverage thus includes, but is not limited to, “information requirements; investigation procedures; standards of creditworthiness; terms of credit; furnishing of credit information; revocation; alteration, or termination of credit; and collection procedures.”\(^{207}\)

These definitions are likely to capture the activities of credit scorers even if they merely provide credit scores or credit-assessment tools, but do not make the ultimate call on whether to grant a loan. Companies that develop credit-risk modeling tools arguably “participate[] in credit decision[s]” by developing “standards of creditworthiness” even when they merely furnish the models that lenders ultimately deploy to make lending decisions. FTC Chairwoman Edith Ramirez has warned, however, that ECOA likely does not reach entities that


\(^{205}\) 12 C.F.R. § 202.2(d) (2016).

\(^{206}\) 12 C.F.R. § 202.2(m) (2016).

\(^{207}\) Id.
use scoring tools to determine whether to solicit vulnerable individuals with advertisements for subprime or other less-favorable credit products. ECOA thus may not serve as an effective check on companies that use big-data credit-scoring tools to unfairly target minority consumers with products like payday loans.

ii) Challenging discrimination under ECOA

ECOA only prohibits discrimination on a limited number of grounds, namely “race, color, religion, national origin, sex, or marital status.” ECOA further prohibits creditors from treating consumers differently because they “derive[] [income] from any public assistance program.” The scope of ECOA’s discrimination protections is potentially limiting. For instance, by its terms ECOA does not clearly prohibit discrimination on the basis of a consumer’s sexual orientation. While some courts have interpreted ECOA’s prohibition on sex discrimination as encompassing claims where an individual was denied access to credit because he or she did not comply with the lender’s expectations regarding gender norms, consumers may find it difficult to challenge lender discrimination based on sexual orientation.

Proving a violation of ECOA is burdensome, and the use of highly complex big-data credit-scoring tools may only exacerbate that difficulty. In order show discrimination under ECOA, a plaintiff must either demonstrate “disparate treatment” by proving that the lender based its lending decision on “a discriminatory intent or motive,” or “disparate treatment,” by showing that the lender’s practices or decisions have had a “disproportionately adverse effect on minorities.”

While reliance on big-data scoring tools may lessen the frequency of instances of disparate treatment by decreasing the influence of individual loan-officer discretion on lending decisions, as Barocas and Selbst point out, tools that employ

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211 See, e.g., Rosa v. Park W. Bank & Trust Co., 214 F.3d 213, 215 (1d Cir. 2000) (recognizing that “prohibited bases of discrimination under the ECOA do not include [] sexual orientation,” but finding violation of ECOA sufficiently alleged where plaintiff discrimination because his “attire did not accord with his male gender”).
213 Cf. id.
thousands of data points and complex models could also potentially be used to mask overtly discriminatory policies.\textsuperscript{214} Perhaps more likely, however, big-data tools may perpetuate existing, systemic forms of discrimination. As discussed above, machine-learning tools may foment unintentional discrimination if they define target variables in a manner that encodes existing bias, rely on inaccurate sample data, or permit the use of proxy variables for sensitive characteristics such as race.

A consumer’s best option to combat such unintentional forms of discrimination under ECOA is likely to allege disparate impact. Under current law, however, this is a difficult showing to make. ECOA’s text makes no mention of disparate impact analysis. The Supreme Court has not yet considered whether plaintiffs can bring disparate-impact claims under ECOA, though circuit courts have consistently held that such claims are available.\textsuperscript{215} ECOA’s implementing regulations make express reference to disparate impact, stating that ECOA’s “legislative history [] indicates that the Congress intended” to allow “effects test” claims akin to those permitted in the employment context.\textsuperscript{216}

The Supreme Court recently examined disparate-impact claims in the context of the Fair Housing Act (FHA) and affirmed that such claims remain viable under the FHA and similar antidiscrimination laws whose “text refers to the consequences of actions and not just to the mindset of actors, and where that interpretation is consistent with statutory purpose.”\textsuperscript{217} In \textit{Inclusive Communities Project, Inc.}, the Supreme Court also appears to have announced a more stringent standard for plaintiffs who wish to show disparate impact, cautioning that “disparate impact liability must be limited so employers and other regulated entities are able to

\textsuperscript{214} Barocas & Selbst, \textit{supra} at note 93, at 22 (“Data mining could also breathe new life into traditional forms of intentional discrimination because decision-makers with prejudicial views can mask their intentions by exploiting various machine learning techniques.”).

\textsuperscript{215} See, e.g., Golden v. City of Columbus, 404 F.3d 950, 963 (6th Cir. 2005) (noting that Supreme Court has not yet decided whether disparate impact cognizable under ECOA, but reasons that statute seems to permit disparate impact analysis).

\textsuperscript{216} 12 C.F.R. § 202.6(a) (2016), at n.2 (“Congress intended an ‘effects test’ concept, as outlined in the employment field by the Supreme Court in the cases of \textit{Griggs v. Duke Power Co.}, 401 U.S. 424 (1971), and \textit{Albemarle Paper Co. v. Moody}, 422 U.S. 405 (1975), to be applicable to a creditor’s determination of creditworthiness”).

make the practical business choices and profit-related decisions that sustain a vibrant and dynamic free-enterprise system.”

Historically, in order to make a prima facie case of disparate impact, plaintiffs were required to show three things: 1) a specifically identifiable practice or policy; 2) a statistically significant disparity in treatment between a protected group and other groups; and, 3) a causal link between the disparity and the practice or policy. It has never been sufficient for a plaintiff to simply show an imbalance between a protected group and a non-protected group, no matter how stark. In *Inclusive Communities Project, Inc.*, the Supreme Court signaled that plaintiffs face an increasingly stringent set of hurdles when identifying the policy or practice that causes the disparate impact. According to the Court, “a one-time decision may not be a policy at all.” The Court also indicated that plaintiffs might face a heightened standard for causation, noting that “[i]t may also be difficult to establish causation” where “multiple factors” stand behind the challenged decision or policy. The Court also stated that a “robust causality requirement,” will “protect defendant from being held liable for racial disparities they did not create.” Although it is not clear how the Court’s reasoning will play out in a credit-scoring context, the Court’s emphasis on “robust causality” raises the possibility that credit scorers may be able to avoid disparate impact liability if they can show that their models merely reflect and reproduce existing forms of systemic bias against minorities.

Assuming that a plaintiff can make a prima facie case of disparate impact, the defendant can still avoid liability if the defendant can make a showing of “business necessity” by “stat[ing] and explain[ing] [a] valid interest served” by the challenged policy. In order to prove “business necessity,” the defendant need not show that the challenged policy or practice was indispensable to its objective, but only that the policy was “related” to its objective or business goals. If the defendant

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218 Id. at 2518.
219 See, e.g., Wards Cove Packing Co. v. Atonio, 490 U.S. 642, 657-58 (1989) (superseded by statute on other grounds) (“As a general matter, a plaintiff must demonstrate that it is the application of a specific or particular employment practice that has created the disparate impact under attack.”).
220 See, e.g., id.
221 Inclusive Communities Project, Inc., 135 S. Ct. at 2523.
222 Id. at 2523-24.
223 Id. at 2523.
224 Id. at 2522, 2512; see also, e.g., Ricci v. DeStefano, 557 U.S. 557, 587 (2009).
225 See, e.g., Ricci, 557 U.S. at 578 (“the ‘touchstone’ for disparate-impact liability is the lack of ‘business necessity’: If an employment practice which operates to exclude minorities cannot be shown to be related to job performance, the practice is prohibited.” (internal quotations omitted)).
shows business necessity, the burden shifts back to the plaintiff to offer a policy or practice that would be equally effective in meeting the defendant’s goals, but that would not produce a disparate impact.226

There are few examples of past cases in which plaintiffs have challenged automated credit-scoring tools under ECOA using the disparate impact theory.227 As the above analysis suggests, the exacting standards set out by the Supreme Court will likely make it extremely difficult for future plaintiffs to do so, particularly when dealing with complex big-data tools that employ thousands of data points. Credit scorers have trade secrecy on their side; at present, consumers and regulators have no practical way to dig into the models to understand what drives lending decisions, and determine whether the target variables and training data are impacted by implicit forms of bias. Assuming that a plaintiff could, absent access to the models and data, pinpoint policies that lead to discriminatory outcomes, the plaintiff will still likely lose unless she can offer a non-discriminatory alternative option to model creditworthiness. Put simply, unless consumers have the ability to pull back the curtain and understand how big-data credit-scoring tools work, scorers and lenders may be able to perpetuate systemic bias with relative impunity.

V. THE CHALLENGES OF ALTERNATIVE CREDIT-SCORING AND A LEGISLATIVE FRAMEWORK FOR CHANGE

This article has attempted to describe how big-data and machine-learning techniques are changing the credit-scoring industry, as well as the difficulties that regulators and consumers will likely face when they seek to apply existing federal laws like FCRA and ECOA to alternative credit-scoring tools. As the above discussion indicates, big-data credit-scoring tools potentially present four major challenges, namely: 1) insufficient transparency, 2) input data that are potentially inaccurate, 3) the potential for biased and discriminatory scoring, and 4) the risk that these tools will be used to target vulnerable consumers. These challenges are all somewhat

227 Beaulialice v. Fed. Home Loan Mortgage Corp., No. 8:04-CV-2316-T-24-EA, 2007 WL 744646 (M.D. Fla. Mar. 6 2007), offers a rare example of a challenge to a credit-scoring algorithm under the disparate impact theory. Unfortunately, Beaulialice provides little insight into how a court might view a disparate impact claim in the credit-scoring setting as the case was dismissed on the ground that the plaintiff’s claims were barred by the doctrine of “unclean hands.” Id.
dependent on one another, meaning that the adequacy a solution to one challenge may rest upon the effectiveness of the solutions to the other challenges. For example, absent an effective mechanism to solve the transparency problem, regulators and consumers will arguably have difficulty determining whether a particular scoring system relies on data points that operate as proxies for sensitive features such as race, or whether the scoring system targets vulnerable individuals. In order to challenge instances of implicit bias in a model, regulators will need to understand how the model's target value is defined, what data points are used to score, and what the model's most important features are. Similarly, if lenders are permitted to use models that are designed to identify consumers that are financially vulnerable and more susceptible to predatory products, this could further entrench discriminatory lending patterns down the road. Any legislative solution that only addresses some, but not all, of the challenges posed by big-data credit-scoring tools will be inadequate.

We propose that each of these four challenges can be addressed through legislation that is designed to complement the existing legal framework. To that end, we offer a model bill – the *Fairness and Transparency in Credit Scoring Act* (“FaTCSA”) – that could be enacted at either the federal or state level.228 This model legislation was developed as part of a collaborative effort between data scientists at the Massachusetts Institute of Technology and legal scholars at the Georgetown University Law Center. Although the FaTSCA is designed with alternative credit-scoring tools in mind, it is broad enough in scope to encompass even traditional credit-scoring tools. In this section, we briefly summarize each of the four challenges posed by big-data credit-scoring tools, and describe the FaTSCA’s proposed solutions to those challenges.

**A. Existing transparency rules are inadequate**

As discussed above, big-data scoring systems like those used by ZestFinance are currently treated as protected trade secrets, thereby making it extremely difficult for consumers to understand what impacts their scores and what steps they should take to responsibly improve their access to credit. While we do not suggest that traditional credit-scoring models are perfect examples of transparency, the transparency problem is less acute for these tools because they employ only a

228 *See infra* p. 202, Julius Adebayo, Mikella Hurley & Taesung Lee, *Model Fairness and Transparency in Credit Scoring Act (FaTCSA)*. The Model FaTSCA is reproduced with permission of its authors. As currently drafted, the Model FaTSCA has been optimized for enactment at the state level.
handful of features that are intuitively related to consumer financial behavior, and are publically-regarded—whether rightly or wrongly—as setting consistent guideposts for defining creditworthiness. Non-traditional scoring tools, by contrast, use many factors that lack an intuitive connection to financial behavior. Consumers may also be unaware that certain of these factors are being tracked, let alone used for credit decisions. The secrecy surrounding credit scoring is likely to make it exceedingly difficult for consumers and regulators to determine whether a particular model employs inaccurate data or treats as significant sensitive features such as race. However, under existing federal laws like FCRA and ECOA, consumers and regulators are responsible for producing proof of both problems.

The Model FaTCSA proposes to address the transparency deficit by requiring that all developers and users of credit-scoring and assessment tools make routine disclosures regarding the classes and categories of data that they collect, the sources of this data, the collection methods used, and the particular data points (or combinations of data points) that individual models treat as significant.229 These disclosures must be updated routinely so that consumers and regulators can remain apprised of changes that affect credit access.230 Although these disclosures would not necessarily provide direct or conclusive evidence that a particular model uses inaccurate input data or relies on proxies for sensitive characteristics, enhanced reporting on data categories, sources, and significant features will arguably better enable consumers and regulators to identify those scoring tools and models that deserve closer scrutiny. The FaTCSA’s transparency rules would also allow consumers to gain a basic understanding of how they are scored so that they can responsibly improve their access to credit.

We anticipate that critics of the FaTCSA’s transparency proposals may raise concerns about the potential that consumers will learn how to “game” the scoring system once consumers find out what features are most significant to a particular model. While we agree that enhanced transparency could benefit consumers by allowing them to adapt their behavior to new rules, we maintain that the risk that this will lead to widespread “gaming” of the system is likely limited, and is heavily outweighed by the need to offer consumers clear guideposts to navigate the credit system. If a credit-scoring system defines certain actions or characteristics as “responsible,” and others as “irresponsible,” consumers should

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229 See id. at § 3(a), p. 204.
230 See id. at § 3(b), p. 204.
be able to change their behavior to emulate the responsible behaviors. Past experience dealing with traditional scores such as FICO supports this view. Few would argue that a consumer is “gaming” the FICO system when she diligently pays off her credit card balance at the end of the month, even if she does so with the knowledge that this behavior will ultimately improve her credit score.

Critics may also question whether the FaTCSA’s transparency proposals will negatively impact innovation by allowing competitors to reverse-engineer a particular scorer’s model. While total trade secrecy could allow certain scorers to maximize their business advantage, we maintain that this interest does not outweigh the need to ensure that consumers are informed and can challenge inaccurate, biased, and potentially predatory models. The FaTCSA’s transparency rules are designed to be selective, and to allow credit scorers to maintain a substantial degree of trade secrecy. While some experts have demanded that credit scorers disclose everything about their models, including their formulas and programming source code, the FaTCSA seeks to strike a balance between encouraging innovation and preserving transparency.

B. The burden of ensuring accuracy should not fall to the consumer

Existing laws like the FCRA establish basic accuracy requirements for the data used in credit-assessment tools, however consumers bear the burden of identifying and disputing inaccuracies. As stories like that of Judy Thomas indicate, credit scorers may not be striving to achieve high levels of accuracy with regard to their input data because the costs of doing so outweigh the marginal financial benefits of that increased accuracy. FCRA’s accuracy requirements appear to offer inadequate incentives to increase data accuracy, even in the conventional credit-scoring context where scorers are dealing with fewer types and sources of data. As credit-assessment tools integrate more data points, many of which may be difficult for consumers to verify or dispute, the law should shift the burden of accuracy to the shoulders of the credit scorers themselves.

The Model FaTCSA would require all developers and users of credit assessment tools to maintain rigorous standards of accuracy, conduct regular reviews of their data, and

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regularly self-certify that they comply.\textsuperscript{233} The FaTCSA would not only require that scorers ensure that the raw data points they use are accurate, it would also obligate scorers to have safeguards in place to make certain that all data points are verifiable and traceable to the individual consumer, such that similarities in names, social security numbers, and other identifiers do not lead to mistakes that plague responsible borrowers.\textsuperscript{234} The option for periodic inspections and audits would allow regulators to determine whether the scorers’ certifications are an accurate reflection of scorers’ actual practices and efforts to improve accuracy.\textsuperscript{235} The FaTCSA also proposes stiff penalties for inaccuracies, and would empower both regulators and citizens to police non-compliance.

\textbf{C. Better tools are needed to detect and prevent discrimination by proxy}

While federal laws offer some existing protections against discriminatory credit scoring, the current regime is likely to be insufficient to address the unique concerns raised by big-data scoring tools. Neither FCRA nor ECOA place substantial limits on the types of data used in credit scoring.\textsuperscript{236} As a consequence, there is little to prevent scoring tools from inadvertently using innocuous data points as proxies for sensitive attributes such as race. Additionally, although ECOA prohibits lenders from basing lending decisions on factors such as race, ethnicity, and sex,\textsuperscript{237} it omits other sensitive characteristics such as sexual orientation. Finally, while ECOA allows plaintiffs to bring both disparate-treatment and disparate-impact claims, courts have interpreted these tests stringently, and place an extraordinary burden on plaintiffs to prove either deliberate discrimination, or to show that an unjustified, uniform policy has led to less-favorable treatment of certain groups.\textsuperscript{238}

The Model FaTCSA would address these problems by shifting the burden to the developers and users of credit-scoring tools to ensure that their tools do not score consumers based upon immutable characteristics or certain sensitive

\textsuperscript{233} See infra pp. 206-207, Model FaTSCA, at §§ 4(d), 4(g), 5.
\textsuperscript{234} See id. at §§ 4(d), p. 206.
\textsuperscript{235} See id. at § 6, pp. 207-208.
\textsuperscript{237} See PATRICIA A. MCCOY, BANKING LAW MANUAL: FEDERAL REGULATION OF FINANCIAL HOLDING COMPANIES, BANKS AND THRIFTS § 8.02[1][a][iii] (2d ed. 2015) (“With respect to marital status, age, the receipt of public assistance benefits and immigration status, however, Congress deemed it legitimate to take those factors into account under certain circumstances”).
\textsuperscript{238} See supra Section IV(B)(ii).
affiliations, unless such scoring is otherwise permitted under federal law. The FaTCSA addresses the potential problem of proxy-based discrimination by prohibiting the use of models that "treat as significant any data points or combinations of data points that are highly correlated" to sensitive characteristics and affiliations. The FaTCSA also requires that scoring models be based on empirically-sound sample data in order to avoid situations where the training dataset used during the machine-learning and feature-selection stages does not produce a model that inadvertently favors particular groups. Credit scorers must validate and certify that they have repaired their data and have developed their models such that they avoid discrimination by proxy. The FaTSCA does not prescribe particular methodologies that scorers must use to prevent proxy-based discrimination, but rather mandates that scorers adhere to "industry best practices." The FaTSCA thus encourages the data scientists that develop these scoring systems to keep pace with new proposals and developments in the area of algorithmic accountability.

D. Credit-assessment tools should not be used to target vulnerable consumers

Given that big-data scoring tools are becomingly increasingly prevalent in the online payday-lending industry, there is a risk that these sophisticated tools will be used to identify vulnerable individuals who will be most susceptible to predatory loan products. This risk demands an immediate legislative response. At present, no federal law requires that credit-assessment tools be designed to predict a consumer's

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239 See infra pp. 206-207, Model FaTSCA, at § 4(b)-(c). Credit scorers would be permitted, for example to consider a borrower's age pursuant to the limitations already imposed by ECOA. See McCoy, supra note 237, at § 8.02[1][a][iii].

240 See infra, pp. 206-207, Model FaTSCA, at § 4(b)-(c).

241 See id. at 407, at § 4(e).

242 See id. at § 4(g).

243 See id.

244 See Section III(B).

Data scientists and lawyers have already proposed technical solutions to such problems as discrimination by proxy. One such group of experts, for example, proposes a method that could be used to "repair" training datasets at the outset to eliminate implicit bias, thereby avoiding the risk that factors like race or gender will be weighted in a final scoring model. See Michael Feldman et al., Certifying and Removing Disparate Impact, Proc. 21ST ACM SIGKDD Int'l Conf. Knowledge Discovery & Data Mining 259-68 (2015); Ifeoma Ajunwa et al., Hiring by Algorithm: Predicting and Preventing Disparate Impact (Mar. 10, 2016), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2746078 [https://perma.cc/734W-9AS7].
actual creditworthiness. Although certain predatory lending practices themselves may be prohibited, there is no requirement that credit-scoring models consider the impact that a loan product could have on a consumer’s future financial stability. The Model FaTCSA would require that all credit scores and credit assessment tools be predictive of creditworthiness, defined as a “consumer’s likelihood of repaying a loan or debt and the consumer’s ability to do so without risking serious harm to the consumer’s financial stability.” To the extent that a credit-scoring tool is designed to account for other considerations such as a lender’s profit margins, these considerations cannot override the imperative of creditworthiness.

VI. CONCLUSION

Big-data credit-scoring tools may, as their proponents claim, emerge as a way to ensure greater efficiency in underwriting while expanding access to the underbanked and to historically neglected groups. But this zeal to “build a better mousetrap” must be tempered against its possible perils. As stories like Kevin Johnson’s illustrate, bigger data does not necessarily produce better decisions. Because of the life-altering consequences that can flow from a faulty or unfair credit score, regulators must ensure that innovators proceed responsibly and have strong legal incentives to ensure that their scoring decisions are transparent, accurate, unbiased, and fair.

246 See infra p. 205, Model FaTSCA, at § 4(a).
ANNEX 1: THE MODEL FAIRNESS AND TRANSPARENCY IN CREDIT SCORING ACT

Rationale and Summary: For most Americans and their families, access to credit is an essential requirement for upward mobility and financial success. A favorable credit rating is invariably necessary to purchase a home or car, to start a new business, to seek higher education, and to pursue other goals. For many consumers, strong credit is also necessary to gain access to employment, rental housing, and essential services such as insurance. At present, however, individuals have very little control over how they are scored and have even less ability to contest inaccurate, biased, or unfair assessments of their credit. The credit scoring industry is now almost completely automated, with banks and lenders increasingly relying on opaque scoring tools that use numerous data sources and proprietary algorithms in order to determine which consumers get access to credit and on what terms. Traditional, automated credit scoring tools raise longstanding concerns of accuracy and unfairness. The recent advent of new “big-data” credit scoring products heightens these existing concerns of abuse, inaccuracy, and bias.

While little is known about emerging, big-data scoring tools, many claim to incorporate thousands of data points into their models, including such factors as a consumer’s handwriting style, social networking practices, or retail shopping habits. Alternative credit scoring may ultimately benefit some consumers, but it may also serve to obscure discriminatory, subjective, and even predatory lending policies behind a single “objective” score. There is a risk that these tools may combine facially neutral data points and treat them as proxies for immutable features such as race, thereby circumventing existing non-discrimination laws and denying credit access to certain groups. Non-transparent scoring systems may also prevent consumers from understanding what steps they should take to gain access to the economic building blocks of the American dream. While existing laws prohibit certain forms of discrimination in lending and give consumers limited rights to review and correct errors in their credit reports, these laws do not go far enough to make sure that credit scoring systems are accurate, transparent, and unbiased. Developers and users of credit assessment tools are also not required to score consumers on the basis of actual creditworthiness, raising the risk that certain products may be used to target vulnerable consumers and lure them into debt traps.
The Fairness and Transparency in Credit Scoring Act would hold developers and users of credit scoring tools to high standards of accuracy, transparency, and non-discrimination. It would prohibit credit scorers from using consumers' immutable characteristics and protected affiliations, whether directly or by proxy. The Act would also give consumers the right to understand how credit-scoring companies are evaluating their online and offline activities so that all Americans are empowered to strive for a more prosperous future. Finally, the Act would require that scores be predictive of creditworthiness, defined as a consumer’s likelihood of repaying a loan and ability to do so without risking serious harm to the consumer’s financial stability.

SECTION 1. DEFINITIONS. As used in this Act:

1. “Consumer” means any individual or group of individuals, including households, family groups, and small businesses having 5 full-time equivalent employees or fewer.

2. “Credit score” means any numerical or descriptive assessment of a consumer’s creditworthiness.

3. “Credit assessment tool” means any system, model, technique, factor, set of factors, or any other mechanism used to assess, measure, or document consumer creditworthiness.

SECTION 2. SCOPE AND APPLICABILITY. This Act applies to any entity or person (the “covered entities”) that develops, uses, purchases, sells, or otherwise furnishes to a third party any credit scores or credit assessment tools if those scores and tools are used or reasonably expected to be used for any of the following purposes:

a. To identify, target, or prescreen consumers for solicitation for credit, insurance, or financial services transactions or products;

b. To determine whether to grant or deny any form of credit to any consumer and to set the terms under which a consumer may obtain credit;

c. To determine whether to grant or deny any form of insurance to any consumer and to set the terms under which a consumer may access insurance;

d. To determine whether to grant or deny any form of residential housing to any consumer, to set the terms of a consumer’s residential lease, or to make any determinations regarding the extension or termination of a consumer’s existing residential lease; and
(e) To determine whether to grant or deny any form of employment to any consumer, to determine conditions of employment, and to make determinations regarding employee retention and promotion;

The Act applies to any covered entity having any contacts with the State of [insert State name] on any basis that is not inconsistent with the Constitution of this State or of the United States.

SECTION 3. DISCLOSURE OF CREDIT SCORING INFORMATION.

(a) Every covered entity shall publicly disclose and disseminate, in accordance with guidelines and a standardized format to be prescribed by the Attorney General, the following information regarding the credit scores and credit assessment tools that the entity develops, uses, purchases, sells, or otherwise furnishes to a third party for any covered purpose set out in Section 2:

(1) All classes and categories of data gathered pertaining to consumers, including, but not limited to, details of existing credit accounts, credit status and activity, salary and employment data, retail purchase data, location data, and social media data;

(2) The types of sources from which each data category is obtained and the collection methods used to gather such data, including the collection methods used by any third party data vendors; and

(3) A complete list of all individual data points and combinations of data points that a credit score or credit assessment tool treats as significant. Each significant data point or combination of data points must be listed by order of relative importance.

(b) Every covered entity shall make and update the public disclosures described in Section 3(a) on a semianual basis at a minimum. Every covered entity must make additional disclosures whenever there is a substantial adjustment in the categories or types data collected and used, and whenever there are any changes in the data points or combinations of data points that a credit score or credit assessment tool treats significant.

(c) Every covered entity shall make and update the public disclosures described in Section 3(a) in the following manner:
(1) By posting all disclosures on a publicly accessible, centralized source to be established by the Attorney General;

(2) By making all disclosures available to the public on the covered entity’s website in a manner that is clear and conspicuous;

(3) By making a disclosure to a consumer, in a clear and conspicuous manner that is appropriate to the circumstances, whenever a covered entity uses a credit score or credit assessment tool in any of the following circumstances:

(A) When a consumer applies to receive credit, is offered or denied credit, or is solicited with an invitation to apply for credit;

(B) When consumer applies to receive insurance, is offered or denied insurance, or is solicited with an invitation to apply for insurance;

(C) When a credit score or credit assessment tool is used as a basis to offer or deny a consumer any form of rental housing, to set the terms of a consumer’s residential lease, or to make any determinations regarding the extension or termination of a consumer’s existing residential lease; and

(D) When a credit score or credit assessment tool is used as a basis to offer or deny a consumer any form of employment, to set the terms of the employment, or to make determinations regarding employee termination or promotion.

SECTION 4. CREDIT SCORING STANDARDS. Covered entities must ensure that credit scores and credit assessment tools meet the following requirements:

(a) They must be predictive of consumer creditworthiness, defined as the consumer’s likelihood of repaying a loan or debt and the consumer’s ability to do so without risking serious harm to the consumer’s financial stability. To the extent that a credit score or assessment tool is designed to reflect other considerations such as lender profitability, these additional considerations must not outweigh the primary purpose of predicting consumer creditworthiness;

(b) They must not treat as significant a consumer’s immutable characteristics, including, but not limited to, race, color, gender, sexual orientation, national origin, and age, unless expressly permitted under an applicable federal law. They also
must not treat as significant any data points or combinations of data points that are highly correlated to immutable characteristics, unless expressly permitted under an applicable federal law;

(c) They must not treat as significant a consumer's marital status, familial status, religious beliefs, or political affiliations. They also must not treat as significant any data points or combinations of data points that are highly correlated to marital status, familial status, religious beliefs, or political affiliations;

(d) They must employ rigorous safeguards, processes, and mechanisms to ensure that all data points are accurate, verifiable, and traceable to the specific consumer. Data must be regularly tested for accuracy, verifiability, and traceability. Data points that do not meet these requirements must not be used;

(e) They must be based on data that is derived from an empirical comparison of sample groups or the population of creditworthy and non-creditworthy consumers who applied for credit within a reasonable preceding period of time;

(f) They must be developed and validated using accepted statistical principles and methodologies; and

(g) They must be consistently revalidated in accordance with industry best practices and by the use of appropriate statistical principles and methodologies, and must be adjusted as necessary in order to maintain predictive ability as well as compliance with the standards set out in Sections 4(a) – (f).

SECTION 5. CERTIFICATION OF COMPLIANCE.

(a) Every covered entity must publicly certify that the credit scores and credit assessment tools that it develops, uses, purchases, sells, or otherwise furnishes to third parties for any of the purposes listed in the Act satisfy the standards as set out in Section 4. Public certifications of compliance shall be made on a semiannual basis, and in the following manner:

(1) By posting an affidavit of compliance on a publicly accessible, centralized source to be made available by the Attorney General. This affidavit must be signed by the covered entity’s Chief Executive Officer and Chief Technology Officer;

(2) By making the affidavits of compliance available to the public on the covered entity’s website in a manner that is clear and conspicuous; and
(3) By making a disclosure to a consumer, in a clear and conspicuous manner that is appropriate to the circumstances, under any of the circumstances described in Paragraphs (c)(3)(A) – (D) of Section 3 this Act.

SECTION 6. PERIODIC STATE INSPECTIONS AND AUDITS.

(a) Covered entities must retain complete, chronological records documenting changes to credit scores and credit assessment tools, including, but not limited to, the data points collected and used, the methodologies and models employed, and any other information that reasonably relates to a covered entity’s compliance with the standards set out in Section 4 of this Act. Covered entities must also keep a record of all internal compliance tests and validation exercises, any material weaknesses identified, and the actions taken to address such weaknesses.

(b) The Attorney General retains the right to inspect, review, and audit a covered entity’s credit scores and credit assessment tools and any documentation relating to such scores and tools in order to ensure compliance with the standards set out in Section 4. The Attorney General may employ other entities, including private auditing companies and private attorneys, to act under the Attorney General’s supervision and undertake such inspections, reviews, and audits.

(c) Upon the request of the Attorney General or an entity acting under the Attorney General’s supervision, a covered entity is required to furnish the following items to the Attorney General or an entity that is acting under the Attorney General’s supervision, for purposes including inspection, review, and auditing to ensure compliance with this Act:

1. All data that is collected or used for the purpose of credit scoring;

2. The identities of all data sources and the methodologies used for data collection, including the methodologies used by any third party data vendors;

3. Full details of the credit scoring or assessment methodology, including, but not limited to, any algorithms used, source code, and scoring guidelines and procedures;

4. Evidence of compliance with the standards set out in Section 4, including, but not limited to, documentation of internal control and validation procedures, results of any compliance tests and validation exercises, and evidence of actions taken to address weaknesses and deficiencies in a credit scoring system.
(6) Any other information that the Attorney General or entity acting under the Attorney General's supervision deems relevant.

SECTION 7. PENALTIES. Any covered entity that fails to comply with the requirements of this Act may be liable for up to one percent of the entity's annual profits or $50,000 for each violation, whichever amount is greater. Any covered entity that willfully violates the requirements of this Act shall be liable for each violation for up to one percent of the entity's annual profits or $50,000 for each violation, whichever amount is greater. Nothing in this Act diminishes or restricts the application of other penalties that may be available under other state or federal laws.

SECTION 8. INVESTIGATIONS AND ENFORCEMENT.

(a) (1) The Attorney General shall investigate violations of this Act. If the Attorney General finds that a covered entity has violated or is violating any of its obligations under the Act, the Attorney General may bring a civil action against the covered entity.

(2) The Attorney General may employ another entity, including a private attorney, to investigate violations of the Act and to bring a civil action, subject to the Attorney General's supervision.

(b) (1) A consumer may bring a civil action for violation of Sections 3, 4, and 5 of this Act on behalf of the State of [insert State name].

(2) A complaint filed by a consumer under this Section shall be filed in [insert relevant court] in camera and ex parte, and may remain under seal for up to 60 days. No service shall be made on the defendant until after the complaint is unsealed.

(3) On the same day as the complaint is filed pursuant to paragraph (b)(2), the consumer plaintiff shall serve, by mail and electronic means, the Attorney General with a copy of the complaint, a summary of the evidence compiled by the plaintiff, and copies of all documents that are in the plaintiff's position and that may be relevant to the plaintiff's claims.

(4) Within 60 days after receiving the complaint and disclosure of material evidence and information, the Attorney General may elect to intervene and proceed with the action.
(5) The Attorney General may, for good cause shown, move the court for extensions of the time during which the complaint remains under seal pursuant to paragraph (b)(2). The motion may be supported by affidavits or other submissions in camera.

(6) Before the expiration of the 60-day period or any extensions obtained under paragraph (b)(5), the Attorney General shall do either of the following:

(A) Notify the court that it intends to proceed with the action, in which case the Attorney General shall conduct the action and the seal shall be lifted; or

(B) Notify the court that it declines to proceed with the action, in which case the seal shall be lifted and the consumer plaintiff shall have the right to conduct the action.

(c)(1) If, after a consumer plaintiff initiates an action and the Attorney General decides to proceed with the action, the Attorney General shall have the primary responsibility for prosecuting the action. The consumer plaintiff shall have the right to continue as a full party to the action.

(2) The Attorney General may seek to dismiss the action for good cause, notwithstanding the objections of the consumer plaintiff, if the Attorney General has notified the consumer plaintiff of the filing of the motion to dismiss and the court has provided the consumer plaintiff with an opportunity to oppose the motion and present evidence at a hearing.

(3) The Attorney General may settle the action with the defendant, notwithstanding the objections of the consumer plaintiff, if the court determines, after a hearing providing the consumer plaintiff an opportunity to present evidence, that the proposed settlement is fair, adequate, and reasonable under the circumstances.

(d)(1) If the Attorney General elects not to proceed, the consumer plaintiff shall have the same right to conduct the action as the Attorney General would have had if it had chosen to proceed. If the Attorney General so requests, the Attorney General shall be served with copies of all pleadings filed in the action and supplied with copies of all deposition transcripts.

(2) The Attorney General may, for good cause and upon timely application, intervene in the action in which it had initially declined to proceed. If the Attorney General is allowed to intervene, the consumer plaintiff shall retain principal responsibility for the action and the recovery of
the parties shall be determined as if the Attorney General had elected not to proceed.

(e) No claim for any violation of this Act may be waived or released by any covered entity, except if the action is part of a court-approved settlement of a civil action brought under this Section.

(f) For civil actions brought under this Section, the parties shall be allowed to recover as follows:

(1) If the Attorney General or entity acting under the Attorney General’s supervision initiates an action pursuant to this Section, the Attorney General or the entity acting under its supervision shall receive a fixed 33 percent of the proceeds of the action or settlement of the claim.

(2) If a consumer plaintiff initiates an action pursuant to this Section and the Attorney General does not elect to proceed with the action, the consumer plaintiff shall receive an amount not less than 33 percent and not more than 50 percent of the proceeds of the action or settlement.

(3) If a consumer plaintiff initiates an action pursuant to this Section and the Attorney General elects to proceed with the action, the consumer plaintiff shall receive at least 15 percent but not more than 33 percent of the proceeds of the action or settlement of the claim, depending upon the extent to which the consumer plaintiff substantially contributed to the prosecution of the action. The Attorney General shall receive a fixed 33 percent of the proceeds of the action or settlement of the claim.

(4) All remaining proceeds shall go to the Treasury of the State of [insert State name].

(5) If the Attorney General, an entity acting under the Attorney General’s supervision, or a consumer plaintiff prevails in or settles any action under this Section, the entity acting under the Attorney General’s supervision or the consumer plaintiff shall also receive an amount for reasonable expenses that the court finds to have been reasonably incurred, plus reasonable costs, including experts’ fees, and attorney’s fees. All expenses, costs, and fees shall be awarded against the defendant and under no circumstances shall they be the responsibility of the State.

(f) If a consumer plaintiff initiates or proceeds with an action under this section, the court may award the defendant reasonable expenses, costs, and attorney’s fees only if the defendant prevails in the action and the court finds that the
claim was frivolous, vexatious, or brought primarily for purposes of harassment.

(g) Once the Attorney General, an entity acting under the Attorney General’s supervision, or a consumer plaintiff brings an action under this Section, no other person may bring a related action under this Act based on the facts underlying the pending action.

SECTION 9. RELATIONSHIP WITH EXISTING LAWS. Nothing in this Act expands, diminishes, impairs, or otherwise affects the rights and obligations of covered entities under the Fair Credit Reporting Act, the Equal Credit Opportunity Act, or any other applicable federal laws. Nothing in Section 8 of this Act limits or restricts the right of persons to bring actions under other state and federal laws, even if these actions are based on the same or similar facts as an action brought under Section 8 of this Act.

SECTION 10. SEVERABILITY. If any provision of this Act or its application to any person or circumstance is held invalid, the invalidity does not affect other provisions or applications of this Act that can be given effect without the invalid provision or application, and to this end the provisions of this Act are severable.
ANNEX 2: THE MODEL FATSCA SECTION-BY-SECTION

Section 1. Definitions
- **Consumer**: Refers to any individual person or group of persons including households, family groups, and small businesses with fewer than five full-time employees. This definition ensures that the Act applies regardless of whether the covered entity is dealing with an individual, a group of persons, or a small family-owned business.
- **Credit Score**: A numerical or descriptive assessment of a consumer’s creditworthiness.
- **Credit Assessment Tool**: A system, model, technique, factor, set of factors, report, or any other mechanism used to score assess consumer creditworthiness. This definition encompasses traditional credit scores as well as emerging “big data” tools.

Section 2. Scope and Applicability
- **Section 2** defines “covered entities” based upon whether they develop, use, purchase, or sell credit scores or credit assessment tools for specific, defined purposes. The category of “covered entities” is broad enough to encompass lenders that use credit scores and assessment tools, even when the tools are entirely developed by third party vendors.
- The category of covered entities does not encompass all entities that might also be deemed “credit reporting agencies” (CRAs) under the Fair Credit Reporting Act (FCRA). For example, companies that merely assemble consumer data might be deemed CRAs under the FCRA, but they would not fall within the Act’s scope of application unless they also evaluate that data as part of a credit scoring or assessment exercise.
- The Act’s scope is further limited to certain specific contexts or purposes. A covered entity will fall under the Act’s requirements when the score or assessment tool is used or should be expected to be used for any of the following purposes: 1) to identify, target, or prescreen consumers for credit products, financial products, or insurance products; 2) to grant or deny credit to any applicant and to set the terms of access to credit; 3) to grant or deny insurance to any applicant and to set the terms of access to an insurance product; 4) to grant or deny residential housing to any consumer; and 5) to grant or deny employment to any applicant or make decisions regarding employee promotion and retention.
The Act applies to the fullest extent permitted by both the state and Federal Constitution.

Section 3. Disclosure of Credit Scoring Information
- This section establishes transparency minima for the types of information that covered entities must make publically available regarding their scores and tools. They must publish information regarding the categories of data collected, the sources and techniques used to acquire that data, and the specific data points that a tool uses for scoring.
- While covered entities do not need to disclose every individual data point that they collect, they must provide a particularized description of the data points or combinations of data points that their models deem significant. For example, if an assessment tool treated the number of “likes” that a Facebook user receives per week as a significant factor, the entity would be required to describe this data point with particularity, and could not merely rely on a more generic description such as “social media activity.”
- If a tool treats a combination of data points as significant when combined, the combination must be described, even though each data point may not be individually significant. Covered entities must also rank significant data points (or combinations thereof) by order of importance. This will better enable regulators and the public to ascertain whether a credit score or assessment tool is indirectly considering prohibited characteristics such as race.
- The Act does not define the term “significant” in reference to data points or combinations of data points. Significance must be determined on a case-by-case basis for each model or assessment tool given that a change in the particular type of model used may affect whether a data point is significant, even if all other factors are held constant.
- Covered entities must report the above information in three ways: 1) by disclosure on a publically accessible website established by the Attorney General; 2) by public disclosure on the entity’s own website; and, 3) through disclosures to consumers when a score or assessment tool is used in credit, insurance, rental housing, or employment transactions.

Section 4. Credit Scoring Standards
- The Act sets out minimum standards for all credit scores and assessment tools. Several have been adapted
from the Equal Credit Opportunity Act’s (ECOA) Regulation B, which requires all automated credit scoring tools that consider age as a factor to be “empirically derived, demonstrably and statistically sound.” See 12 C.F.R. 202.2(p).

- Credit scores and assessment tools must be predictive of creditworthiness, meaning a consumer’s likelihood of repaying a loan and ability to do so without risking serious harm to the consumer’s financial stability. This standard is meant to ensure that lenders will not employ credit assessment tools target vulnerable consumers, or to prioritize lender profit over a consumer’s financial stability. Scoring and assessment tools may consider other objectives as long as consumer creditworthiness remains the central focus.

- Credit scores and assessment tools must not treat as significant, either directly or indirectly, immutable characteristics such as race. This standard seeks to prevent covered entities from using facially-neutral data points as proxies for sensitive characteristics.

- Credit scores and assessment tools also must not take into account, either directly or indirectly, a consumer’s marital or familial status, or religious or political affiliations.

- If a data point or combination of data points is strongly correlated to any immutable characteristics or protected affiliations, it cannot be used. A data point can be used, however, if it is only weakly correlated to a prohibited characteristic or affiliation.

- Credit scores and assessment systems must be backed by rigorous safeguards and mechanisms to ensure that the raw data are accurate, verifiable, and traceable to the consumer. For example, covered entities must ensure that they have mechanisms in place to prevent data from consumers with similar names or social security numbers from being combined. Covered entities are obligated to verify the underlying data they collect and use, and to have robust systems in place to identify and eliminate errors.

- Credit scores and assessment tools must be developed and validated using accepted statistical principles and methodologies, as currently required under ECOA’s Regulation B. This requirement can be met if a score or assessment tool is based on an accepted modeling technique such as a regression analysis or a decision tree analysis. They must also be based on data that are derived from an appropriate sample.
Finally, scores and assessment tools must be continuously revalidated to ensure that they remain predictive, and that they remain in compliance with the Act’s other standards.

Section 5. Certification of Compliance
- Covered entities must publically report and certify that their credit scores and assessment tools meet the standards established in Section 4. They must make this self-certification of compliance through an affidavit and in the same manner as described in Section 3. Certifications must be made or updated twice per year.
- In addition to encouraging compliance, the self-certification may permit state and federal regulatory agencies such as the FTC to pursue actions against non-complying entities.

Section 6. Periodic State Inspections and Audits
- This Section authorizes the state attorney general, or a private auditing firm or attorney acting under the attorney general’s supervision, to inspect or audit a covered entity at any time to test for compliance with the standards set out in Section 4. The attorney general will be given *in camera* access to all elements of a scoring or assessment system, including algorithms, source code, and repositories of data.
- Any consumer data made available to the attorney general will not be used for purposes other than inspection or audit. It cannot be used in an investigation or proceeding against a consumer, or furnished to any other law enforcement or regulatory body for such a purpose.

Section 7. Penalties
- The Act gives a court discretionary ability to impose a penalty of up to $50,000 or one percent of the covered entity’s annual profits, whichever is greater, for each instance in which a covered entity violates the Act’s requirements. For each willful violation, the Act imposes a mandatory penalty of $50,000 or one percent of the covered entity’s annual profits, whichever is greater.

Section 8. Investigation and Enforcement
- The Act gives the state attorney general, or another entity acting under the attorney general’s supervision, primary enforcement authority. If the attorney general does not act, a consumer may bring suit on the state's
behalf. A consumer plaintiff does not need to prove any form of damage in order to have standing in the suit.

- If a consumer plaintiff initiates a suit, the attorney general will have the opportunity to intervene and either proceed with the action or seek dismissal for good cause. If, after a consumer plaintiff has initiated a suit, the attorney general intervenes and decides to proceed with the action, the consumer plaintiff can continue to participate as a full party. If the attorney general initially decides not to intervene, it may do so at a later point if the consumer plaintiff is not adequately representing the state's interests.

- The Act sets out a formula by which the attorney general, its designate, and any consumer plaintiff can share in any civil penalties awarded. The Act also allows private plaintiffs to recover reasonable expenses, costs, and attorney’s fees for successful actions or settlements. In cases where a court deems the consumer plaintiff’s suit to be frivolous or vexatious, the court may also award expenses, costs, and fees to the defendant entity.

Section 9. Relationship with Existing Laws

- The Act does not expand, diminish, or impair covered entity’s rights and obligations under the FCRA, the ECOA, or any other applicable federal law.

Section 10. Severability

- Any provisions of the Act that are invalidated, for example if they are preempted by federal law, can be severed from the Act without affecting the Act’s remaining provisions.
**Executive Summary**

As many as 70 million adults in the United States have neither traditional credit scores nor robust credit histories with one of the three major credit bureaus. These “credit underserved” individuals represent both opportunity and risk. While they offer financial institutions and other businesses the opportunity to gain customers, they also pose a significant risk to lenders and the macro-economy if credit is extended without sufficient analysis of their ability to repay. Individuals who lack credit scores are at risk, too, because access to credit is increasingly important in the modern economy.

In recent years, several companies have designed new strategies to assess creditworthiness outside the confines of traditional credit tradelines. These innovations rely on collecting and analyzing alternative or nontraditional data, such as rental and bill payment history, insurance payments, debit-card use, and public records. In many cases, these alternative credit reporting and scoring products are based on aggregating large public and proprietary sources of data that traditional scoring methodologies don’t tap.

As confirmed by previous CFSI research, there is considerable interest in these new credit-scoring products. But before widespread adoption can occur, an important question must be answered: what is the proof of their predictive and economic value?

To answer this question, many vendors that have created credit scores based on alternative data sources have conducted real-world tests, asking lenders to evaluate how well alternative scoring could have improved the performance of their credit portfolios. Several major vendors—Fair Isaac, LexisNexis and L2C—shared some of these internal test results. CFSI also reviewed an analysis by RentBureau about the correlation between historical rental payment data and the likelihood of continuing payments. This paper summarizes those analyses.

Our purpose is not to recommend any product over another, nor to compare their relative strengths and weaknesses. Rather, this paper reports on some of the existing evidence of the scores’ effectiveness and suggests areas for further evaluation.

The tests CFSI reviewed provide strong proof of the predictive value of the alternative credit scores, demonstrating the promise of basing credit decisions

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1 See Katy Jacob and Rachel Schneider, “Market Interest in Alternative Data Sources and Credit Scoring,” The Center for Financial Services Innovation, December 2006.
on a broad range of data. By using alternative data, lenders stand to reach a large group of potential borrowers about whom they currently have little or no information. For these consumers, alternative credit scores strengthen lenders' ability to:
- Reliably rank order risk;
- Efficiently evaluate applicants for credit or design offers for credit; and
- Increase approval rates while controlling for acceptable levels of risk.
The Predictive Value of Alternative Credit Scores

**Background**

Being “credit underserved” can have many unfortunate consequences. For example, individuals without credit scores have limited options to obtain a mortgage, which means homeownership—the primary way American households save and accumulate wealth—either costs more or isn’t available to them at all. Consumer credit is critical to starting a business, buying a car, weathering periods of financial hardship, and even making everyday purchases in the securest way—with a credit card. In addition, credit histories are often used to evaluate auto and home insurance, job, and rental applications.

A person’s credit report compiles information reported by lenders on credit accounts held by the consumer. Typical credit report details include payment history, outstanding balances, collection items, public records such as tax liens and bankruptcies, and a list of entities who have obtained the report. A consumer’s credit history may be summarized by the credit reporting agency into a credit risk score that predicts the risk of lending to that borrower. For example, the FICO® score from Fair Isaac assigns a number ranging from 300 to 850, calculated using the data in the report, with a higher score representing a better credit risk.

Estimates vary as to how many individuals lack traditional credit scores, ranging from 35 to 70 million adults. These individuals either have no file with the three traditional credit bureaus—Experian, Equifax and TransUnion—or have insufficient tradelines or tradelines covering too short a period to generate a score. It is sometimes assumed that many of those underserved by credit have lower or moderate incomes, but this is not always the case. In fact, they are a diverse group comprised of many segments, including many individuals who would be classified as prime or near-prime in terms of creditworthiness. Those without traditional credit scores include many immigrants, as well as younger, older, and recently divorced individuals.

*Figure 1: Size of Credit Underserved Market*

<table>
<thead>
<tr>
<th>Source</th>
<th>Market Estimate</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experian</td>
<td>35 million</td>
<td>Not “credit active”</td>
</tr>
<tr>
<td>Fair Isaac</td>
<td>54 million</td>
<td>Without credit files that can be scored, either because of no credit history (22 million) or thin files (32 million)</td>
</tr>
<tr>
<td>National Credit Reporting Association</td>
<td>70 million</td>
<td>Either no credit score or a lower credit score than their financial history and payment potential warrant</td>
</tr>
</tbody>
</table>

2 For more information, see Katy Jacob and Rachel Schneider, “Market Interest in Alternative Data Sources and Credit Scoring,” The Center for Financial Services Innovation (CFSI), December 2006, p. 3; and Katy Jacob, “Reaching Deeper: Using Alternative Data Sources to Increase the Efficacy of Credit Scoring,” CFSI, March 2006, p. 3.
The Predictive Value of Alternative Credit Scores

**Figure 2: Market Segments within Credit Underserved Market**

Source: Experian Data Reporting Prepaid Executive Roundtable April 28, 2005

**Description of Alternative Credit Scores**

Several companies have developed strategies to use data other than traditional credit tradelines to assess potential borrowers' stability, ability, and willingness to pay. The three that shared data with CFSI for this analysis are Fair Isaac, LexisNexis and L2C. All three companies produce predictive scores—analogous to the credit scores currently available through the traditional credit bureaus—that can be used to make credit decisions about credit underserved consumers. All three scores can be delivered to lenders real-time when a borrower applies for credit, or can be provided on a “batched” basis for a group of applications submitted at one time. They are based on analysis of recorded data about individual behavior and financial status other than traditional credit tradelines. As a result, they are especially predictive for potential borrowers who either have no file or a thin file with the traditional credit bureaus.³

Fair Isaac created the FICO score, the first general-purpose credit score based on traditional credit bureau data and still the most widely used score in the United States. In 2004, Fair Isaac launched the FICO® Expansion® score, which analyzes debit data, membership data, utility data, bankruptcies, judgments, liens, property and asset information, and a third-party score (included as a score-within-a-score).

³ It is worth noting that some evidence indicates that alternative data is also useful to augment decision making about “full file” individuals who have a robust traditional credit score.
Because the FICO Expansion score is FCRA compliant, it can be used to make credit decisions but not for marketing other than for “pre-approved” offers. Ninety percent of lenders who use the FICO Expansion score access it directly from Fair Isaac through a platform designed to integrate with existing point-of-sale solutions, while 10 percent access it through other providers. FICO Expansion is not currently available through the three traditional credit bureaus.

Fair Isaac’s FICO Expansion score can typically provide a score on 70 to 100 percent of lenders’ applicants who have little or no traditional credit bureau histories. Users of the FICO Expansion score include top 10 credit card issuers, installment loan lenders, student lenders, private label/retail card issuers, auto finance companies, and mortgage lenders. The FICO Expansion score uses the same score range (300-850®) and performance definition (bad performance is defined as 90 days past due or worse over 24 months) as the FICO score (see Figure 3). While odds ratios always vary according to specific portfolios or products, these similarities facilitate integration of the FICO Expansion score into lenders’ existing operations.

LexisNexis’s flagship services are its Lexis and Nexis research services, which provide web-based searchable access to more than 2,000 public record and proprietary data sources. The five billion documents that provide content for these services also provide baseline data for LexisNexis’s suite of risk-management products. LexisNexis introduced credit-risk scoring services based on nontraditional data in 2000. RiskView, introduced in 2006, is the latest generation of this product line. LexisNexis targets these services at four industries: wireless telecommunications, retailers, bank cards, and auto lenders. Six of the top 10 credit card issuers and four of the top five wireless companies use RiskView.

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4 The Fair Credit Reporting Act (FCRA) regulates the collection, dissemination, and use of consumer credit information. Lenders must comply with FCRA to use consumer credit data to decline credit or take adverse action against an existing customer. This means they may use the data only for a permissible purpose and must notify customers who are adversely affected that the action was based on information provided by the particular Consumer Reporting Agency (CRA). Consumers have the right to request a copy of their reports from the CRA and the ability to correct any errors in the information.

5 Fair Isaac, FICO, FICO Expansion and 300-850 are registered trademarks of Fair Isaac Corporation.
Alternative data analyzed by RiskView include bankruptcies, liens and judgments; criminal convictions; address and work history; phone records; professional licensures; and asset records. To generate a score, RiskView needs, at a minimum, the individual’s full name and one other indicator of identity. A RiskView score can be assessed for 31 million individuals who have no traditional credit history and 45 million whose traditional credit histories are shorter than 18 months. In working with lenders, LexisNexis has been able to provide a score for more than 90 percent of credit applicants who have either no file or a thin traditional credit history. The RiskView score is FCRA compliant. Approximately 20 percent of RiskView users access the score through through Equifax; the remainder connect through a third-party data processor or directly to LexisNexis. Half of RiskView users receive the score and reason codes only, while the other half receive more specific data about potential borrowers.

L2C, founded in 2000, specializes exclusively in alternative credit reporting and analytics. L2C began by serving telecommunications companies, relying primarily on analysis of telecommunications payment histories and building creative new analytical models. Today, L2C’s Link2Credit™ and First Score Direct™ products are used in the credit card, consumer lending, and telecommunications industries, across a broad spectrum of companies. Approximately 10 percent of L2C’s customers access the service directly through web-based connection to L2C. The other 90 percent receive it through one of the three major credit bureaus. L2C’s integration with TransUnion allows lender queries and L2C results to be transmitted between the lender and TransUnion without systems changes, while accessing the product through Equifax requires some technology integration. By early 2008, L2C expects to have the same level of integration with Equifax and Experian that it has with TransUnion. Because L2C has both FCRA and non-FCRA products, its products can be used for credit decisions and to market invitations to apply as well as pre-approved offers. Approximately 20 percent of L2C customers are using individual data records collected by L2C as well as the L2C score in their credit decisions, while 80 percent use the score alone.

L2C uses seven major data sources, which account for over one billion customer records across 1,000 data attributes. Behaviors analyzed include checking-account activity, payday lending, ID verification, fraud data, public records, check cashing, utility payments, and retail data. L2C can provide a score for 95 percent of all U.S. households. Typically, L2C needs only identity verification and one alternative tradeline to provide a score, which means the company can score 80 to 90 percent of customers with little or no current credit history.

Figure 4: Alternative Data Products

<table>
<thead>
<tr>
<th>Company Product</th>
<th>Typically Able to Score:</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fair Isaac</strong></td>
<td>70-100% of those in a lender’s applicant pool with no traditional credit score</td>
<td>Debit data, membership data, utility data, bankruptcies, judgments, liens, property and asset information and a third party score used as a score-within-a-score.</td>
</tr>
<tr>
<td><strong>LexisNexis</strong></td>
<td>Over 90% of those in a lender’s applicant pool with no traditional credit score</td>
<td>Over 300 public record attributes such as employment and address history; property and asset ownership; bankruptcies, liens and judgments; criminal records; ID verification and professional licensure.</td>
</tr>
<tr>
<td><strong>L2C</strong></td>
<td>80 – 90% of those in a lender’s applicant pool with no traditional credit score</td>
<td>Proprietary phone payment data; debit and checking account activity; multi-sourced alternative lending data (e.g., payday lending, rent-to-own); fraud/ID verification; public records; and retail data.</td>
</tr>
</tbody>
</table>
Alternative Credit Scoring Tests

As previous research by CFSI has confirmed, there is considerable interest among lenders for alternative approaches to credit decisions.\(^6\) However, there is a major question to answer before alternative credit scores are widely adopted: What is the proof of their predictive and economic value?

Lenders and the vendors providing alternative data scoring methods have conducted hundreds of tests of their effectiveness. However, this information has not generally been made public. For this analysis, three vendors provided the results of recent internal lender tests to CFSI. All of these tests were retro-tests, which means that Fair Isaac, LexisNexis, and L2C each received a pool of applicant data from a lender’s existing portfolio of loans. Lenders analyzed the applicants, generating alternative credit scores for each individual as of the time of the original credit application. The alternative credit scores were then compared to the performance data for the credit extended to those applicants. Essentially, the alternative credit score was applied to approved customers retroactively, to determine how well the score that would have been assigned at the time of application correlates with actual behavior and whether it would have improved the lender’s ability to manage risk.\(^7\)

Figure 5: Types of Test Results Reviewed

Each of the three vendors has conducted many more tests than are described below. Direct comparisons across the alternative scores or test results are neither relevant nor appropriate because the analyses they provided differ substantially, representing a variety of industries, types of portfolios, and methodologies applied. However, the data suggest several important conclusions:

1. An alternative score has meaningful predictive and economic value to lenders extending credit to individuals with thin or no traditional credit histories.

2. Alternative scores can be generated for most individuals who lack traditional credit scores, about whom lenders would otherwise have very little information on which to base their credit decisions.

3. Alternative scores provide a reasonable method of ordering risk among potential borrowers, or ranking individuals according to level of risk.

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\(^6\) Jacob and Schneider, “Market Interest in Alternative Data Sources and Credit Scoring.”

\(^7\) Because this type of retro-test addresses only approved customers, there is an issue with “reject inferencing.” However, this type of test provides a strong enough indication of the effectiveness of the alternative score that it is a standard approach for lenders to decide whether or not to rely on a particular alternative credit score.
4. Individuals with thin or non-existent traditional credit histories may be prime borrowers as well as those with higher credit risk than the general population.

5. Most lenders test an alternative score’s application to the specific loan portfolio with which they will use it. Before it can be applied effectively, it is critical to know (and lenders are demanding to know) how the alternative scoring method stacks up against a specific pool of their borrowers and product types.

CFSI reviewed the following test results:

- **Fair Isaac**: Fair Isaac has analyzed the FICO Expansion Score using data samples from more than 75 leading lenders in consumer credit, mortgage lending, auto financing, student lending, and telecommunications. Fair Isaac provided the aggregate results from tests with three large pools of data from multiple lenders, for the credit card, auto financing, and mortgage industries.

- **LexisNexis**: LexisNexis provided the results from four individual tests of RiskView with different products: credit card, wireless telecommunications, auto finance, and retail credit card. These tests are representative of more than 100 similar tests LexisNexis has completed.

- **L2C**: L2C also shared the results from a series of tests across multiple products, including auto lending, credit card, mortgage, and education loans, although all of the product tests were conducted with the same top 10 bank. L2C has tested Link2Credit or First Score Direct with more than 50 lenders.

The tests looked at the first 12 to 24 months of customer performance data and sought to correlate “bad rates” and “good:bad odds” ratios with the alternative credit score. The bad rate is the percent of borrowers who have had bad performance within the period analyzed; for almost all of the tests below, bad performance was defined as delinquency of 90 days or worse. The odds ratio is the ratio of “good performing” borrowers to “bad performing” borrowers. So, for example, a 10 percent bad rate means that one out of every 10 borrowers was 90 days delinquent or worse during the performance period. Nine of the 10 borrowers were “good performers,” so good:bad odds are 9:1.

**Fair Isaac FICO Expansion Score**

Fair Isaac's FICO Expansion score has the same range of possible scores, from 300 to 850, as the traditional FICO score. In the company’s experience, lenders who use the FICO Expansion score for credit origination risk decisions typically find that 30 to 50 percent of applications receive scores of 640 or higher. Before using FICO Expansion, most of these consumers were rejected for lack of a traditional credit score. Therefore, FICO Expansion enables lenders to approve and book at least 30 percent more credit applicants with little or no traditional credit data. The following graph shows the distribution of consumers across the FICO Expansion score range for a week.
The validation studies provided by Fair Isaac represent pooled validations containing between 10 and 20 national lenders and approximately 600,000 customers. The studies focused on credit applicants for both prime and subprime credit card, auto financing, and mortgage products. Fair Isaac analyzed credit applicants from 2004 with payment performance for 24 months. The lenders who participated include, but are not limited to:

- Bank-card issuers: American Express and HSBC;
- Auto finance lenders: DaimlerChrysler, DriveTime, and Ford Motor Credit; and
- Mortgage lenders: Credit Suisse, First Franklin, Freddie Mac, HSBC Mortgage, and Option One.

The odds ratios found in the validation study (shown below) demonstrate that the FICO Expansion score ranks risk across applicants in each industry. In other words, the odds of positive repayment are substantially higher for higher-scoring records than for lower-scoring records. Individual issuer odds spreads were even wider for prime portfolios and tighter for subprime portfolios, as would be expected.
The Predictive Value of Alternative Credit Scores

**Figure 7: Expansion Score Good:Bad Ratios for Pools of Lenders by Sector Good:Bad Odds**

<table>
<thead>
<tr>
<th>Expansion Score</th>
<th>Credit Card</th>
<th>Auto Financing</th>
<th>Mortgage</th>
</tr>
</thead>
<tbody>
<tr>
<td>520-539</td>
<td>1:4</td>
<td>1:7</td>
<td>2:2</td>
</tr>
<tr>
<td>540-559</td>
<td>2:0</td>
<td>1:8</td>
<td>2:7</td>
</tr>
<tr>
<td>560-579</td>
<td>2:6</td>
<td>2:6</td>
<td>3:6</td>
</tr>
<tr>
<td>580-599</td>
<td>6:0</td>
<td>3:3</td>
<td>4:5</td>
</tr>
<tr>
<td>600-619</td>
<td>7:2</td>
<td>4:1</td>
<td>6:8</td>
</tr>
<tr>
<td>620-639</td>
<td>11:6</td>
<td>5:5</td>
<td>10:0</td>
</tr>
<tr>
<td>640-659</td>
<td>15:7</td>
<td>6:3</td>
<td>12:3</td>
</tr>
<tr>
<td>660-679</td>
<td>22:8</td>
<td>9:2</td>
<td>18:6</td>
</tr>
<tr>
<td>680-699</td>
<td>28:5</td>
<td>11:6</td>
<td>23:1</td>
</tr>
<tr>
<td>700-719</td>
<td>33.9</td>
<td>16:1</td>
<td>27:7</td>
</tr>
</tbody>
</table>

Note: The full score range for FICO Expansion scores is 300-850; this table presents the score ranges where most of the application volume is found.

Fair Isaac also provided the following statistics to describe the predictive value seen on these portfolios. K-S measures the maximum difference between the cumulative percentage of two groups, in this case, good files and bad files. A higher value indicates that the model produced a bigger separation of goods and bads. For example, in the test results for auto-financing loans, the K-S range was 10–41. Because of the more homogenous nature of subprime borrowers, in Fair Isaac's experience, these portfolios tend to produce K-S values at the lower end of the range. The GINI coefficient indicates how the model’s predictive performance compares to random behavior by measuring the ratio of the area between a trade-off curve (which plots the accumulation of bads in the population) and a diagonal line (which represents no predictive power) and 0.5. Higher values indicate more predictive score performance, with a maximum value equal to 1. The credit card results show a range of GINI values from 0.194 to 0.440.

**Figure 8: Expansion Score K-S and GINI Coefficient for Pools of Lenders by Sector**

<table>
<thead>
<tr>
<th>K-S</th>
<th>Credit Card</th>
<th>Auto Financing</th>
<th>Mortgage</th>
</tr>
</thead>
<tbody>
<tr>
<td>17 – 35</td>
<td>10 – 41</td>
<td>17 – 35</td>
<td></td>
</tr>
<tr>
<td>0.194 – 0.440</td>
<td>0.134 – 0.546</td>
<td>0.230 – 0.472</td>
<td></td>
</tr>
</tbody>
</table>

**LexisNexis RiskView**

LexisNexis’s RiskView score ranges from 500 to 900 and is calibrated so that the ratio of goods to bads doubles approximately every 40 points. The goal was to have wide dispersement of the individuals scored across the range of scores to give lenders greater detail about potential performance. The following chart shows the rank ordering of risk apparent from the four test results that LexisNexis supplied, one each for companies in the bank card, retail, auto finance, and wireless telecommunications industries. While there are some jumps in the progression, for the most part, individuals are distributed across the risk spectrum, with higher bad rates for those with lower scores.
The Predictive Value of Alternative Credit Scores

LexisNexis also provided data demonstrating a wireless company’s increased ability to segment its consumers using RiskView. According to LexisNexis, using RiskView allows lenders to realize a 20 to 40 percent increase in the ability to segment its borrowers because they can score applicants with no credit history and apply alternative scoring methodologies to assess those with traditional credit scores.

In this sample of over 70,000 applicants (with an overall bad rate of 14.1 percent, which is typical of wireless carriers), 7,700 customers without traditional credit scores could be scored using RiskView, representing almost 11 percent of the portfolio. Importantly, this subset of the portfolio was not all subprime: the top 10 percent of this 7,700 had a default risk (based on their combined bad rate) of under 10 percent. Before applying alternative credit analysis, the wireless carrier would have turned away most of these applicants or experienced high default rates on those it accepted.

It is also worth pointing out that while the traditional credit scores and the RiskView scores move generally in the same direction (i.e., most individuals with high traditional credit scores also have high RiskView scores), at the edges the scores diverge in interesting ways. Thus, the application of the alternative score deepens the analysis the wireless carrier can apply even for a “scored” population. For example, in this sample, the lender experienced a bad rate of 11.7 percent for individuals in the traditional credit score band of 581–640. Applying a RiskView score to individuals within that score band allows the lender to segment further, identifying higher-risk consumers with RiskView scores of 501 to 560 and bad rates of 43 percent, as well as lower-risk consumers with RiskView scores of 681 and higher and bad rates under 5 percent. This effect can be seen in every score band of the traditional credit score, showing how a combination of the two approaches can better estimate loss rates.

**Figure 9: RiskView Good:Bad Ratios and Bad Rates for Four Product Portfolios**

![Graph showing RiskView Good:Bad Ratios and Bad Rates for Four Product Portfolios](image)
The Predictive Value of Alternative Credit Scores

Figure 10: Wireless Sample of Traditional Credit Score and RiskView Overlay

<table>
<thead>
<tr>
<th>Wireless Industry Data Sample: Bad Rate/# of Applicant Files</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RISK-VIEW SCORE</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>No-Score</td>
</tr>
<tr>
<td>501-560</td>
</tr>
<tr>
<td>561-620</td>
</tr>
<tr>
<td>621-680</td>
</tr>
<tr>
<td>681-740</td>
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<tr>
<td>741-800</td>
</tr>
<tr>
<td>801+</td>
</tr>
<tr>
<td><strong>Total</strong></td>
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</tbody>
</table>

L2C Link2Credit™ and First Score Direct™

L2C segments the individuals its score is designed to evaluate into three categories:
- Thin file: individuals with a traditional credit score based on three or fewer tradelines;
- Unscoreable: individuals with too few tradelines tracked by the traditional credit bureaus to calculate a score; and
- No hits: individuals with no tradeline information at the traditional credit bureaus.

Applying L2C’s scoring methodology to individuals with thin or no traditional files shows that a large percentage represent near prime or prime credit risk: almost 19 million “thin file,” 10 million “unscoreable” and 9 million “no hit” individuals have L2C scores of 600 or higher, on a scale from 300 to 800. (Note that L2C has calibrated its score to be approximately 20 points below the traditional credit score range.) L2C reports that companies using its analytical models typically increase applicant approvals by 10 to 20 percent while maintaining existing default rates. In some cases, companies using L2C have lowered default rates by as much as 25 percent while increasing their approvals by almost 10 percent.

Figure 11: L2C Estimate of Credit Risk Distribution
L2C shared data with CFSI from one test with a top 10 bank across multiple product lines, consisting of near-prime auto finance, subprime auto finance, credit cards, education, prime mortgage, and subprime mortgage. For each product, L2C analyzed the performance of its score for credit decisions according to the three segments identified above. For each segment, L2C reported its ability to calculate a score, the percent of bad-performing borrowers within the bottom decile of the score range, and the K-S within the segment.

K-S is a statistical tool that helps to measure a score’s effectiveness at spreading out the population under analysis across the risk spectrum. K-S calculates the cumulative percentage of good accounts less the cumulative percent of bad accounts at a specific score range. The absolute K-S score will vary according to application and the characteristics of the set of borrowers being analyzed. For example, a product marketed narrowly at subprime borrowers with a high expected default rate is likely to produce a portfolio with a low K-S because many of the borrowers will have similar characteristics. For that reason, for one product, a satisfactory K-S might be 35 while for another it might be 15. But in both cases, higher relative K-S scores translate to improved risk assessment.

For L2C’s analysis, the lender gave L2C the K-S it had calculated for a set of borrowers before applying the L2C score, as well as the percent of bad files in the bottom decile of this applicant pool. L2C was then able to compare these measures with the K-S and the percent of bad files in the bottom decile that resulted from the application of its alternative scoring methodology. As a result, for these specific product lines, we can see the improvement or lift in K-S from applying L2C’s analytics.

The tables below show L2C’s results for the subprime auto loan and credit card tests. For the subprime auto test, bad files were defined as accounts delinquent 60 days or more during the 12-month period analyzed. The lift in the K-S for no-hit customers of 7.7 represents a 69 percent improvement, while for thin-file applicants it was 4.9, or 26 percent. Of course, the key issue for the lender is how these results can be used to increase the number of customers receiving credit without increasing expected default rates. By using alternative credit data analysis such as L2C’s, this lender expects to increase its approval rate for applicants with no traditional credit files by 35 percent and its approval rate for applicants with thin files by 43 percent, while maintaining its current default rate. This would result in an additional 4,000 customers each quarter.

For the credit card test, a bad file was defined as 90 days delinquent or more during the 12-month period analyzed. L2C provided a significant lift over the client’s custom modeling system. It found a K-S of 35.9 on files where the client had no score and increased the K-S of thin-file customers by 30 percent. An additional 55 percent of no-score accounts and 29 percent of thin-file accounts were approved using L2C’s methodology. This represents approval of more than 50,000 additional applicants each quarter.
The Predictive Value of Alternative Credit Scores

**Figure 12: L2C Lift in KS and % Bads for Subprime Auto Portfolio**

<table>
<thead>
<tr>
<th>Segment</th>
<th>Total Sample</th>
<th>Client Model Alone</th>
<th>L2C Model Alone</th>
<th>Lift Using Both Client and L2C Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Files/Segment</td>
<td>Hit Rate</td>
<td>KS</td>
<td>% of Bads in Bottom Decile</td>
</tr>
<tr>
<td>No Hit</td>
<td>3%</td>
<td>94.4%</td>
<td>11.1</td>
<td>9.6%</td>
</tr>
<tr>
<td>Unscoreable &amp; Thin File</td>
<td>13%</td>
<td>95.8%</td>
<td>18.9</td>
<td>15.6%</td>
</tr>
<tr>
<td>Credit Scored</td>
<td>84%</td>
<td>96.8%</td>
<td>19.6</td>
<td>17.1%</td>
</tr>
<tr>
<td>All</td>
<td>100%</td>
<td>96.6%</td>
<td>19.2</td>
<td>16.8%</td>
</tr>
</tbody>
</table>

Note: Sample equals approximately 400,000 files.

**Figure 13: L2C Lift in KS and % Bads for Card Services Portfolio**

<table>
<thead>
<tr>
<th>File Thickness</th>
<th>Total Sample</th>
<th>Client Model Alone</th>
<th>L2C Model Alone</th>
<th>Lift Using Both Client and L2C Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of Files</td>
<td>Hit Rate</td>
<td>KS</td>
<td>% of Bads in Bottom Decile</td>
</tr>
<tr>
<td>No Client Model Score</td>
<td>18.3%</td>
<td>86.9%</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Very Thin</td>
<td>3.0%</td>
<td>94.5%</td>
<td>32.6</td>
<td>29.5%</td>
</tr>
<tr>
<td>Thin File</td>
<td>5.9%</td>
<td>88.2%</td>
<td>38.7</td>
<td>34.3%</td>
</tr>
<tr>
<td>Scored</td>
<td>72.8%</td>
<td>86.9%</td>
<td>49.7</td>
<td>48.5%</td>
</tr>
<tr>
<td>All</td>
<td>100%</td>
<td>87.2%</td>
<td>50.0</td>
<td>48.2%</td>
</tr>
</tbody>
</table>

Note: Sample size approximately 3 million files.

**Figure 14: Projected Customer Increases by Using L2C Score**

<table>
<thead>
<tr>
<th></th>
<th>SubPrime Auto</th>
<th>Card Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Hit Approval Increase</td>
<td>35%</td>
<td>55%</td>
</tr>
<tr>
<td>Thin File Approval Increase</td>
<td>43%</td>
<td>29%</td>
</tr>
<tr>
<td>Client New Applicants/Quarter</td>
<td>4,000/qtr</td>
<td>56,000+/qtr</td>
</tr>
</tbody>
</table>
RentBureau collects rental payment histories and incorporates them into its National Rental Data Exchange™. It then provides this information to apartment companies to use in screening applicants. In its first 15 months of operation, RentBureau collected over three million resident records.

RentBureau analyzed a representative sample of almost 45,000 lease records to determine how past payment behavior relates to write-off events within a current lease. Write-offs are defined as any situation in which there is an outstanding balance after the close of a lease, whether because of damage to the apartment, outstanding rent, or departure of a tenant. In the lease data analyzed, the write-offs were observed within 24 months after the lease was signed. Within this population, 55 percent were “ideal renters,” with fully paid rent every month. Among the non-ideal renters, higher numbers of late payments or insufficient funds strongly correlated with higher write-off rates, indicating that past rental payment behavior is highly predictive of future behavior. For renters with no late payments, the write-off rate was 18 percent, versus 65 percent for renters with eight late payments. A large proportion of write-off behavior is still unexplained by this analysis: 47 percent of the total write-offs were not preceded by any late payments. However, as RentBureau gathers more data (especially multi-lease data from individual renters), this may change; and analyzing past rental data still represents a substantial improvement over the real estate industry’s current tools to predict write-off risk.

Rental payment data is widely perceived as a potentially rich source of information about individuals who do not have robust traditional credit scores. Within RentBureau’s database, approximately 57 percent of the leases are below the Fair Market Rent, indicating a strong likelihood of overlap between this population and the traditionally unscored.

Furthermore, it seems likely that rental write-off risk correlates with credit risk, especially for mortgage lending. Further analysis needs to be completed, however, to determine whether rental payment behavior can predict future payment of specific types of credit.8

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8 The U.S. Department of Housing and Urban Development establishes Fair Market Rent guidelines annually to determine payment amounts for various housing assistance programs. Fair Market Rent in 2007 was defined as the dollar amount below which 40 percent of the standard-quality rental housing units in the metropolitan area are rented. http://www.huduser.org/datasets/fmr.html

9 CFSI is a partner in a study being conducted by the Political & Economic Research Council to evaluate this issue.
The Predictive Value of Alternative Credit Scores

Discussion

Although the tests CFSI reviewed provide strong evidence of the predictive value of alternative credit scores, many outstanding questions remain about these products. Many lenders believe that testing the effectiveness of alternative data analysis and credit scoring for a particular product or loan portfolio is necessary before adopting or using the alternative effectively, which means there is still a significant hurdle in the sales process. Some lenders have suggested that an apples-to-apples comparison of the various alternative credit scores would advance the field toward greater market adoption by enabling lenders to compare the solutions available today. It is likely that the alternative-scoring industry will continue working to provide lenders and other potential users of alternative data with a fuller economic case for their products.

Accessing and building new data sources that might provide strong predictive data (such as rent and utility payments) would help make current alternative data products more robust, and these data sources need to achieve broad coverage of the population. In addition, alternative data providers must continue to make it easier for financial institutions to integrate alternative data products into their marketing and decision making. Enlisting the major credit bureaus as resellers, for example, reduces the legal and compliance challenges facing businesses that want to use alternative data. However, relying on them as exclusive distributors raises other operational challenges. Different lenders may each incorporate alternative data into their decision-making processes in different ways.

It seems likely that alternative data will be mined further for additional insights about the market segments, behavior, and attitudes of underbanked consumers. This is a large, untapped market that is likely to include distinct consumer segments with varying demand for different types of financial services. Based on CFSI’s research regarding the underbanked in other contexts, it appears that individuals use credit off and on, and that information about alternative tradelines may be a robust source of knowledge about this consumer group. This information may be useful not only for lending but also for other purposes, such as insurance underwriting, rental and job applications, client account management, and marketing.

Conclusion

Even in this early stage of development for alternative credit scoring methodologies, the use of alternative data offers the promise of reaching many individuals about whom lenders previously had little or no data. Evidence shows that the new scoring methods clearly strengthen lenders’ ability to:

- Reliably rank order risk;
- Efficiently evaluate applicants for credit or design offers for credit; and
- Increase approval rates while controlling for acceptable levels of risk.

Contrary to common perception, these tests indicate that many underserved consumers represent prime or near-prime credit risk to lenders. Most importantly, unlike traditional credit scores, alternative credit scores can be generated for most adults in the United States, which means that widespread use of alternative data could dramatically broaden the reach of mainstream financial services companies.
About CFSI:
The Center for Financial Services Innovation (CFSI), a non-profit affiliate of ShoreBank Corporation, facilitates financial services industry efforts to serve underbanked consumers across the economic, geographic, and cultural spectrum. It provides funding and resources, enables partnerships, and identifies, develops and distributes authoritative information on how to respond to the needs of the underbanked profitably and responsibly. CFSI works with banks, credit unions, technology vendors, alternative service providers, consumer advocates, and policy makers to forge pioneering relationships, products, and strategies that will transform industry practice and the lives of underbanked consumers. For more on CFSI, go to www.cfsinnovation.com.

ShoreBank is America’s first and leading community development and environmental banking corporation. For more on ShoreBank, go to www.shorebankcorp.com.
Discriminatory Effects of Credit Scoring on Communities of Color

Lisa Rice* & Deidre Swesnik**

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* Vice President, National Fair Housing Alliance.
** Director of Public Policy and Communications, National Fair Housing Alliance. About the National Fair Housing Alliance (NFHA): Founded in 1988 and headquartered in Washington, DC, NFHA is a consortium of more than 220 private, nonprofit fair housing organizations, state and local civil rights agencies, and individuals from throughout the United States. Through comprehensive education, advocacy, and enforcement programs, NFHA protects and promotes equal access to apartments, houses, mortgage loans, and insurance policies for all residents of the nation.
I. INTRODUCTION

Our current credit-scoring systems have a disparate impact on people and communities of color. These systems are rooted in our long history of housing discrimination and the dual credit market that resulted from it. Moreover, many credit-scoring mechanisms include factors that do not just assess the risk characteristics of the borrower; they also reflect the riskiness of the environment in which a consumer is utilizing credit, as well as the riskiness of the types of products a consumer uses.

Until only a few decades ago, communities and people of color were explicitly excluded from access to low-cost government and other mainstream loans. In the 1930s, the Home Owners Loan Corporation (HOLC) used blatant discriminatory rating systems and “residential security maps” to deem communities of color to be high risk.1 The Federal Housing Authority (FHA) and Veterans Administration (VA) continued this discrimination into the 1950s.2 Banks, real estate agents, appraisers, and others also perpetuated redlining and segregation in the housing markets. The passage of the federal Fair Housing Act of 1968 improved conditions, but federal regulatory agencies refused to acknowledge their enforcement responsibilities under the Act until the mid 1970s. It was not until civil-rights groups sued the agencies that the federal government began to collect information on the mortgage-lending practices of the institutions it regulated, and to establish and implement fair-lending examination procedures.

Because of this history of racial discrimination, segregated neighborhoods formed and people of color had limited access to affordable, sustainable credit. Instead of accessing mainstream credit available to white borrowers and white neighborhoods, people of color were relegated to using fringe lenders and paying much more than they would have had to otherwise. While segregation

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and housing discrimination have abated somewhat, we still live in an extraordinarily segregated society.\(^3\) Access to credit is even now often based on where we live rather than our individual ability to repay that credit. As this Article will explore, people of color were steered to subprime loans even when they qualified for prime loans, contributing to the fact that the foreclosure crisis has hit communities of color worse than the rest of the country.\(^4\)

Credit-scoring systems in use today continue to rely upon the dual credit market that discriminates against people of color. For example, these systems penalize borrowers for using the type of credit disproportionately used by borrowers of color. Even fair-lending defense attorneys who represent major banks readily admit that credit scoring has a differential impact on people of color. In a recent article, attorneys at K&L Gates asserted “even the most basic lending standards, such as credit scores and [loan-to-value] requirements, ‘impact’ racial and ethnic groups differently.”\(^5\) While some in the financial industry have recently discussed the existence of the disparate-impact theory under the Fair Housing Act and other long-established laws, all eleven circuit courts that have considered the matter recognized disparate impact as a legally acceptable means by which parties can assert claims under the Act.\(^6\)

As we all look for solutions to the foreclosure crisis, lenders, regulatory agencies, and policymakers promote tighter underwriting standards as a solution to improving the quality of loan performance and strengthening the economy. What they mean in part, however, is requiring higher credit scores for the best and most affordable products. This, of course, places the focus of improving loan performance on borrowers. But many studies and analyses have demonstrated that inappropriate loan products and their components were

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4. See infra Part II.B.


6. See Press Release, Consumer Fin. Prot. Bureau, Consumer Financial Protection Bureau To Pursue Discriminatory Lenders, (Apr. 18, 2012), http://www.consumerfinance.gov/pressreleases/consumer-financial-protection-bureau-to-pursue-discriminatory-lenders (announcing Bureau targeting unlawful lending practices including disparate impact). In addition, since the Fair Housing Act was amended in 1988, the United States Department of Housing and Urban Development and United States Department of Justice have acted in administrative proceedings and other contexts with the full understanding that disparate-impact claims are cognizable under the Act. See id. Further, the Consumer Financial Protection Bureau (CFPB) recently announced that it would utilize all tools, including disparate-impact theory, to pursue lenders who discriminate against consumers in violation of the Equal Credit Opportunity Act (ECOA). See id. The CFPB specifically stated that it would use disparate-impact theory when bringing actions under the ECOA. See id. The Federal Reserve also recognizes disparate impact as a way to prove ECOA claims. See id.
key factors driving the subprime crisis. Factors including product type, presence of a yield-spread premium, distribution channel, inflated appraisals, and prepayment penalties helped significantly to predict whether a loan would fail. Even major credit repositories and credit-scoring companies, including VantageScore and FICO, admit that credit scores declined in predictive value leading up to and during the foreclosure crisis. So why are some looking to increased reliance on credit scoring as a way of originating well-performing mortgages and solving the crisis?

The use of credit scoring and its disparate impact go far beyond the lending sector, affecting access to many other financial products and services. Employers use credit and other scoring mechanisms to evaluate job applicants, insurers use them to determine auto, life, and homeowners insurance, and landlords use them to screen tenants. Credit-scoring modelers and companies are finding even more creative ways to broaden the use of these systems. A recent proposal in Texas would use credit scores to determine utility rates. Credit scores are even being used to determine which patients are more likely to take their medication as prescribed.

Consumers, civil-rights groups, and policymakers are greatly concerned by the expanded use of scoring mechanisms. For example, insurance companies use credit-based insurance scores to determine pricing. Yet, studies by the Missouri and Texas Departments of Insurance have found that insurance scoring discriminates against low-income people of color because of the racial and economic disparities inherent in scoring mechanisms. The Missouri study concluded that a consumer’s race was the single most predictive factor determining his or her insurance score and, consequently, his or her insurance premium.

The relationship between insurance credit scores and race is so strong that

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8. See infra Part II.

9. See Jim Stillman, Your Credit Score Determines the Availability of Credit . . . and the Cost, YAHOO! VOICES (June 20, 2007), http://voices.yahoo.com/your-credit-score-determines-availability-creditand-392590.html.

10. See Tara Parker-Pope, Keeping Score on How You Take Your Medicine, N.Y. TIMES WELL BLOG (June 20, 2011, 5:23 PM), http://well.blogs.nytimes.com/2011/06/20/keeping-score-on-how-you-take-your-medicine. Insurers and medical-care facilities use the FICO Medication Adherence Score to identify patients who need follow-up services to ensure they take their medication. See id.


12. See KABLER, supra note 11, at 39.
even though the Federal Trade Commission (FTC) used data selected by the industry in a 2007 FTC report, it found that credit scoring discriminates against low-income people of color, and that insurance scoring was a proxy for race. The FTC report also confirms that, despite growing reliance on credit-based insurance scores, scant evidence exists to prove there is a causal relationship between a consumer’s score and auto-insurance losses. Without the need to demonstrate such a connection, insurers could theoretically use any arbitrary consumer characteristic, such as hair color or zodiac sign, that demonstrates a correlation to a specific outcome, to price insurance products.

This Article focuses primarily on the use of credit scores by lenders, not other industries. It provides an abbreviated overview of other critical issues facing consumers in regard to credit scoring and reporting. These issues are significant and help to demonstrate the urgent need to reform this system. For example, credit-scoring systems are based on information obtained from consumer credit reports, even though credit reports are often rife with errors that are difficult to correct. Credit-scoring systems are also a mystery to consumers because credit-scoring companies maintain that their systems are proprietary and cannot be revealed. These issues are covered in great detail by recent reports by Demos and the Consumer Financial Protection Bureau (CFPB), and a survey by the Consumer Federation of America and VantageScore.

Fixing our current credit-scoring system is not only a moral imperative consistent with our national policies and beliefs about fairness and justice; it is also a legal obligation as outlined by the Fair Housing Act and the Equal Credit Opportunity Act. We hope this Article will assist with the dialogue at this conference as well as our national dialogue on how to move forward and out of our financial and foreclosure crises.

This Article begins with a discussion of the historical discrimination that led to our dual credit market, including subprime lending and the foreclosure crisis. Next, this Article contains a detailed analysis of why credit scoring has

14. See id. at 3.
18. See infra Part II.
a discriminatory impact.\textsuperscript{19} Then it discusses the legal obligations that the federal government and the financial industry have to promote fair housing.\textsuperscript{20} Finally, it offers recommendations for how to fix our broken approach to credit scoring.\textsuperscript{21}

II. THE NATION’S DUAL CREDIT MARKET ROOTED IN DISCRIMINATION

Credit-scoring systems penalize borrowers who have anything other than mainstream, prime loans. As described below, the financial industry excludes people and communities from mainstream, affordable credit based on race and national origin.\textsuperscript{22} In the past, the federal government and private industry explicitly promoted this behavior with discriminatory rating systems. Such practices continue today by banks, including SunTrust and Wells Fargo.\textsuperscript{23} The blanketing of subprime loans in communities of color and continued patterns of segregation and the dual credit market foster discriminatory behaviors. Because many of the factors that make up credit-scoring systems rely on this dual credit market and its inherent discrimination, credit scoring contributes to the self-perpetuating cycle of restricted access to credit that has a dramatic disparate impact on communities of color.\textsuperscript{24}

A. Overt Historical Discrimination

In the not-so-distant past, government and private industry explicitly used race and national origin in assessing borrower risk. For example, the HOLC, a federal agency established in 1933 in response to the foreclosure crisis associated with the Great Depression, institutionalized “redlining.”\textsuperscript{25} The HOLC utilized a discriminatory risk-rating system whereby prospective borrowers were favored if their neighborhood was deemed “new, homogeneous, and in demand in good times and bad.”\textsuperscript{26} Properties would be

\textsuperscript{19} See infra Part III.
\textsuperscript{20} See infra Part IV.
\textsuperscript{21} See infra Part V.
\textsuperscript{22} See infra Part II.B-C.
\textsuperscript{26} See Douglas S. Massey, Origins of Economic Disparities: The Historical Role of Housing Segregation, in SEGREGATION: THE RISING COSTS FOR AMERICA 39, 69 (James H. Carr & Nandinee K. Katty
ranked low, and thus judged high-risk, if they were “within such a low price or rent range as to attract an undesirable element,” which often meant they were located near an African-American neighborhood. The so-called “residential security maps” used to make these classifications labeled the lowest ranking neighborhoods “fourth grade,” and shaded them in red. According to housing scholars William J. Collins and Robert A. Margo, “the agency’s revisions were unprecedented. . . . [P]rivate financial institutions incorporated the new rating system in their own appraisals, thereby beginning the widespread institutionalization of the practice known as ‘red-lining.’” As discriminatory policies and practices continued to persist within the real-estate sector, private banks began to adopt the underwriting guidelines established by the federal government in the HOLC program.

Subsequently, the HOLC risk-rating system informed the FHA and VA loan programs in the 1940s and 1950s. The FHA made it possible to purchase a house with just a 10% down payment, as opposed to the customary 33% required before its establishment. Loan terms were also extended for up to 30 years. The VA program provided similar benefits, all while following the FHA in rating properties in large part on the basis of the “stability” and harmoniousness of neighborhoods.

As a result, the new benefits of a reduced down payment and better loan terms reached only some Americans. According to the FHA’s policy: “If a neighborhood is to remain stable, it is necessary that properties shall continue to be occupied by the same racial and social classes. Changes in social or racial occupancy contribute to neighborhood instability and the decline of value levels.” To implement this policy, the FHA even went so far as to recommend the use of restrictive covenants to ensure neighborhood stability and racial homogeneity.

The appraisal industry broadly adopted the notion that race had a direct impact on property values, and appraisers were trained to evaluate properties using race as a factor. McMichael’s Appraising Manual, for example, provided the following preferences of race and nationality ranked by impact on real-estate values:

27. See id. at 70.
28. Id.
29. Collins & Margo, supra note 2, at 20.
30. See Massey, supra note 26, at 71.
31. See id. at 71-72.
32. See id.
33. Frederick M. Babcock et al., Techniques of Residential Location Rating, 6 J. AM. INST. REAL EST. APPRAISERS 133, 137 (1938).
34. See Massey, supra note 26, at 71-72.
1. English, Germans, Scotch
2. North Italians
3. Bohemians or Czechs
4. Poles
5. Lithuanians
6. Greeks
7. Russians, Jews (lower class)
8. South Italians
9. Negroes
10. Mexicans

Such lists remained in appraisal manuals long after Congress passed the Fair Housing Act in 1968. The insurance industry employed similar policies, as homeowners insurance companies adopted policies that resulted in either the outright denial of insurance in communities of color or only the availability of policies that provided inadequate protection at excessive costs to consumers.

The federal banking regulatory agencies tacitly approved such discriminatory practices even after passage of the Fair Housing Act. It was not until 1976, when a coalition of civil-rights groups sued them for failing to enforce the Act, that the federal banking regulatory agencies acknowledged that they had any enforcement responsibilities. The settlement required the agencies to collect information on the mortgage-lending practices of the institutions they regulated, and to establish and implement fair-lending examination procedures.

It is important to understand the historical context of discrimination and redlining practices in any discussion on credit scoring. Because borrowers of color could not access credit in the mainstream market, a dual credit market developed—a market that was separate and unequal—a market where white borrowers had ready access to more regulated, lower cost, affordable and

sustainable credit products while borrowers of color were relegated to unregulated, higher cost and more unsustainable sources of credit. These fringe markets were, and in some cases still are, the primary credit source for communities of color.

B. Subprime Lending and Its Long-Term Discriminatory Effects

In many cases, the banking and insurance industries simply replaced their explicit discriminatory standards with policies and practices that were nondiscriminatory on their face, but maintained a disparate impact. In other cases, however, companies maintained overtly racially discriminatory policies. Banks and insurance companies continued to discriminate in the marketplace by setting minimum loan values, employing tiered interest-rate policies, refusing to make loans in some neighborhoods, and offering only market-value homeowner’s insurance in some neighborhoods.39

Many lenders, recognizing that borrowers of color represented a growing market, developed initiatives to heavily target this market segment. Indeed, subprime lenders and some subsidiaries of prime lenders took advantage of communities that mainstream lenders shunned. In a representative case, the St. Louis Equal Housing and Community Reinvestment Alliance alleged that a large local bank did not make a single loan to an African-American borrower between 2003 and 2008.40 Moreover, all of the bank’s branches were located in areas with less than 2% African-American population.41 According to nationwide Home Mortgage Disclosure Act (HMDA) data, African Americans and Latinos were much more likely to receive a subprime loan than their white counterparts.42 In 2005 and 2006, roughly 54% of African Americans and 47% of Latinos received subprime loans compared to approximately 17% of whites.43 A study conducted by the National Community Reinvestment Coalition found that there are fewer commercial bank branches in communities of color.44

Instead of targeting this market with safe, lower cost, affordable and sustainable loans, borrowers of color were targeted for unsustainable, higher cost, subprime mortgages. Subprime lenders have long boasted and prided themselves on being the primary providers of credit to African-American,

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39. See Wilke, supra note 36.
41. See id.
42. See Avery et al., supra note 24, at 96.
43. See id.
Latino, and other underserved groups. Countrywide Financial Corporation, at one time the nation’s largest lender and a major originator of subprime loans, boasted that it was the number-one lender to borrowers of color.\textsuperscript{45} The Department of Justice (DOJ) recently settled an unprecedented $335 million lawsuit with Countrywide because of its discriminatory practices, which included steering African-American and Latino borrowers who qualified for prime loans into subprime mortgages.\textsuperscript{46} Some of the nation’s other top subprime lenders have either settled major discrimination lawsuits or are currently defending against such allegations. These lenders include Long Beach, Ameriquest, Delta Funding, Household Finance, Associates, Citi, and Wells Fargo.\textsuperscript{47}

While banks and others continued to defend the use of credit scores as the great equalizer, many borrowers with high credit scores received subprime mortgages even when they qualified for prime credit. Instead, many would-be prime consumers were steered into subprime and Alt-A mortgages because of the higher short-term profits lenders could garner.\textsuperscript{48} For example, an analysis conducted by First American Loan Performance found that 41% of subprime loans made in 2004 went to borrowers who actually would have qualified for a prime-rate loan.\textsuperscript{49} Another study revealed that in 2005, 55% of subprime borrowers would have qualified for a prime loan.\textsuperscript{50} It also found that in 2006 that number had jumped to as high as 61%.\textsuperscript{51} Federal Reserve Governor Edward Gramlich noted that half of subprime borrowers had credit scores of 620 or higher.\textsuperscript{52}

\begin{itemize}
\item \textsuperscript{47} See generally NAT’L CONSUMER L. CENTER, https://www.nclc.org/unreported-decisions.html (last visited Nov. 24, 2013) (collecting unreported decisions in litigation against various lenders).
\item \textsuperscript{48} See Rajdeep Sengupta, Alt-A: The Forgotten Segment of the Mortgage Market, 2010 FED. RES. BANK OF ST. LOUIS REV. 55, 56, available at http://research.stlouisfed.org/publications/rev/10/01/Sengupta.pdf. “Typically, Alt-A mortgages are underwritten to borrowers of good credit quality—that is, those who would otherwise qualify for a prime loan in terms of their credit history. However, Alt-A borrowers do not satisfy the underwriting rules for prime loans because they are unwilling or unable to provide full documentation on their mortgage application.” Id.
\item \textsuperscript{50} See id; (noting subsequent crash of housing market and financial system).
\end{itemize}
The recently settled lawsuit filed by the City of Baltimore against Wells Fargo provides a glaring example of how lenders purposefully targeted African Americans and Latinos for higher priced mortgages in outrageously discriminatory ways. Two affidavits filed by former Wells Fargo employees revealed that Wells Fargo:

- Specifically targeted African-American communities for subprime loans, but did not do so in white communities;
- Targeted African-American churches for the purpose of selling subprime loans. Employees of color were tapped to make presentations to the churches. A white employee was told she could only attend the presentations at African-American churches if she “carried someone’s bag;”
- Used derogatory language to refer to African-American consumers. African Americans were referred to as “mud people” and “niggers.” Employees referred to loans in African-American neighborhoods as “ghetto loans.” Finally, they referred to Prince George’s County as the “subprime capital” of Maryland. Comparatively, Wells Fargo employees felt that predominately white counties like Howard County, Maryland were bad places for subprime mortgages;
- Gave employees substantial financial incentives for steering borrowers who actually qualified for prime mortgages into the subprime market.

Both the private and public sectors perpetuate the bias witnessed in America’s separate and unequal financial system. The following are statistics that demonstrate our dual financial system:

55. See Declaration of Tony Paschal, supra note 54, ¶ 8.
56. See Declaration of Elizabeth M. Jacobson, supra note 54, ¶¶ 27-28; Declaration of Tony Paschal, supra note 54, ¶ 12.
57. See Declaration of Tony Paschal, supra note 54, ¶¶ 8, 16.
58. See id. ¶ 8.
60. See Declaration of Tony Paschal, supra note 54, ¶ 8.
61. See id. ¶ 13.
• “African-American and Hispanic homebuyers face a statistically significant risk of receiving less favorable treatment than comparable whites when they ask mortgage-lending institutions about financing options;”62

• The denial rate for first-lien mortgages for African-American borrowers was 2.5 times higher than the rate for Non-Hispanic white borrowers in 2010.63

• In 2008, African Americans were 2.63 times more likely, and Hispanics more than 2 times more likely, than their white counterparts to receive a higher-priced loan.64

• Even higher income African Americans and Latinos received a disproportionate share of subprime loans.65 According to one study that analyzed more than 177,000 subprime loans, borrowers of color were more than 30% more likely to receive a higher rate loan than white borrowers, even after accounting for differences in creditworthiness.66

• Borrowers residing in zip codes with a population at least 50% nonwhite were 35% more likely to receive loans with prepayment penalties than financially similar borrowers in zip codes where nonwhites make up less than 10% of the population.67

It follows, then, that borrowers of color are disproportionately represented in foreclosure claims, and that communities of color experience higher foreclosure rates than the general population. A recent study released by the Center for Responsible Lending (CRL) reveals that a home owned by an African-American family is 76% more likely to go into foreclosure than a home owned by a white family.68 The CRL estimates that African-American and Latino

66. See id.
communities will lose $194 billion and $177 billion, respectively in housing wealth as a result of the foreclosure crisis including the resulting depreciation of living near foreclosed properties. These high rates of foreclosure caused by discriminatory practices have resulted in thousands of bank-owned (also known as real-estate-owned or REO) properties in communities of color. A recent undercover investigation by the National Fair Housing Alliance (NFHA) and some of its members revealed that discrimination by the banks continues even after foreclosure. The investigation found striking disparities in the maintenance and marketing of foreclosed properties in white neighborhoods compared to those in neighborhoods of color. Investigators used 39 different factors to evaluate the maintenance and marketing of REO properties, subtracting points for broken windows and doors, water damage, overgrown lawns, no “for sale” sign, trash on the property, and other deficits. Overall, REO properties in communities of color were 42% more likely to have more than 15 maintenance problems than properties in white neighborhoods. NFHA has since filed housing-discrimination complaints against Wells Fargo and U.S. Bancorp for disparities in the maintenance and marketing of REO properties.

C. The Proliferation of Fringe Lenders in Communities of Color

As described above, fringe lenders, including payday lenders and check cashers, have historically been a primary source of credit for underserved borrowers and are highly concentrated in communities of color. One analysis revealed that there were more payday-lender outlets in the country than McDonalds and Burger King restaurants combined. These fringe lenders saturate predominantly African-American and Latino neighborhoods. A study of fringe lenders in California found that payday lenders were nearly 8 times as concentrated in neighborhoods with the largest shares of African-Americans and Latinos as compared to white neighborhoods, draining nearly $247 million in fees per year from these communities. The study includes several maps of

69. See id. at 11.
71. See id. at 18 (giving examples of racial disparity in REO properties).
72. See id. at 14 (listing factors).
73. See id. at 2.
75. See Klein, supra note 49.
76. See Wei Li et al., Ctr. for Responsible Lending, Predatory Profiling: The Role of Race and Ethnicity in the Location of Payday Lenders in California 2 (2009), http://www.responsible
communities throughout California showing this pattern. Below is a map of Los Angeles depicting the heavy concentration of payday lenders in African-American and Latino communities.

*Map—Center for Responsible Lending*

Conversely, there are few mainstream bank facilities in predominantly African-American and Latino communities. Borrowers who are targeted by fringe lenders and shunned by mainstream financial institutions are susceptible to volatile credit markets. Consumers who access credit from fringe lenders will undoubtedly have lower credit scores because institutions peddle products having abusive terms that carry higher delinquency and default rates.

lending.org/california/ca-payday/research-analysis/predatory-profiling.pdf.
Do you have a mortgage from a finance company? Your credit will likely be lower than if you had received the loan from a depository lending institution. Did you lose that home to foreclosure because you could no longer make the inflated payments? If so, your credit score just went down again.

As described above, people of color were disproportionately steered to subprime loans and targeted by fringe lenders. One might then think that credit scores would not rely on discriminatory assumptions to measure risk because they and other automated valuation systems are promoted as great equalizers and nondiscriminatory ways of measuring credit risk. Yet, in some instances, that is exactly what they do. For example, some scoring mechanisms assume that a borrower who received a loan from a finance company is a greater credit risk than one who received a loan from a depository institution. In fact, the opposite may be true. A credit-scoring system relying on this false premise penalizes the borrower who simply may not have had access to a mainstream lender, but had abundant access to fringe lenders. Indeed, credit-scoring mechanisms reflect the lending and finance systems producing the data upon which the mechanisms are built. Oftentimes, credit-scoring mechanisms assess the riskiness of the lending environment, product type, or loan features a consumer uses rather than his or her risk profile.

A simple analogy will illustrate this point. Suppose the Department of Motor Vehicles tests a car driver to determine his or her driving abilities. In this test, the driver must drive through a path and navigate a series of cones and obstacles. But the driver is placed in a car that is essentially a lemon. The brakes do not work, it does not turn well, and the transmission malfunctions. The driver knocks over several cones, runs into obstacles, and completes the course, receiving a low score. But then, this same driver is placed into a different car and asked to drive the same course again. This time the car is not a lemon. It is in pristine condition—with no problems. The second time through, the driver passes with flying colors and receives a high score.

Did the driver change? Of course not. What changed is the vehicle the driver used. The test accurately measured how well the driver navigated the course as influenced by the quality of the vehicle, but not his or her driving abilities. Similarly, credit-scoring mechanisms often reflect the lending environment or loan-product type, but not the risk profile of the borrower.

The financial mainstream fails to properly serve consumers of color who disproportionately access credit in more volatile financial environments. The financial-services world routinely tests consumers of color using lemons. As a result, current credit-scoring mechanisms that do not evaluate or calibrate

77. *See supra* Part II.B-C.
scores based on the safety or soundness of the lending environment may misjudge consumers of color, causing them harm.

A. Limited Scope, Quality, and Transparency of Credit Information

The information used to build credit-scoring models comes from a variety of sources; however, modelers tend to rely heavily on credit-reporting data from credit bureaus. The quality or accuracy of the scoring model is intrinsically tied to the quality of data upon which the model is based: the better the data quality, the better the scoring system. If modelers rely on limited or inaccurate data, they will develop scoring models that are less effective and have limited predictive power and market applicability. The less predictive a scoring model, the greater the likelihood for miscalculating risk.

Companies can use data purchased from third-party sources or privately held data to develop scoring systems. Larger companies having abundant information about a large number of consumers oftentimes use in-house data to develop unique scoring systems or to enhance systems acquired from outside sources. But, by and large, the data upon which scoring models are built are purchased from large credit repositories, and this data is often flawed. The National Association of State Public Interest Research Groups conducted a study revealing the following:

- Overall, 79% of credit reports contained errors;
- 25% of credit reports contained significant errors that would result in denial of credit;
- 54% had inaccurate personal information;
- 30% listed closed accounts as open; and
- 8% did not list major credit accounts.78

Not only can the data be flawed, it can also be incomplete. Not all creditors report consumer information to credit repositories. Indeed, positive credit information from fringe lenders often goes unreported while negative information is almost always reported. Payday lenders, for example, are concentrated in communities of color. According to the Community Financial Services Association of America (CFSA), “[p]ayday advances are not reported to traditional credit bureaus.”79 If a consumer obtains a payday loan, the fact

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that the consumer has paid off the debt on time is not reported to credit bureaus. However, unpaid payday loans are often reflected on the consumer’s credit report. The Consumer Federation of America reports that unpaid payday loans can lead to negative credit ratings and difficulties opening bank accounts.80

Creditors are not required to report consumer data to the credit repositories. Nor, if they do report, must they report positive data along with negative data. Some creditors may opt not to submit data because they wish to avoid reporting costs, while others want to prevent competitors from identifying and poaching their best-paying customers. And while a creditor may be unable or unwilling to report positive data on a regular basis, it can report negative data by referring the matter to a collection agency or filing a collection action against the consumer. This tilts the entire system against the consumer, especially those who access credit outside of the financial mainstream.

Smaller creditors like community development financial institutions (CDFIs) that want to report positive data may be prohibited from doing so because of their size. An informal survey conducted by the NFHA underscores the difficulty of collecting comprehensive information on consumer credit habits. The major credit repositories are structured to collect data from larger creditors with a large number of consumer files. Some repositories require creditors to have at least 500 files when reporting data; others require 1000 files. These numbers are often beyond the reach of CDFIs and other community-based institutions.

In addition to posing accuracy and access challenges, credit-scoring mechanisms lack transparency. The formulas are proprietary and not disclosed to the public. While there are a number of individual factors that help determine the score, only some of them are public. It is not clear exactly how the factors used in the credit-scoring systems affect a consumer’s score. There are potentially thousands of variables that can be included. These variables can be comprised of individual and combined components, including such elements as the number of: 30-day late payments, inquiries, inquiries by subprime lenders, open trade lines, late mortgage loan payments, or installment loans. Additionally, variables might include length of employment or length of individual revolving loan accounts.

Each variable is purportedly tested to first determine if it is related to a particular outcome, such as likelihood of a mortgage loan default or filing of an auto-insurance claim. Next, the variables are weighted within the credit-scoring formula. This is done through experts who subjectively assign each variable a score.

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Notably, credit-scoring modelers are trying to determine whether a particular variable correlates to a certain outcome, but the mere presence of a correlative relationship between a variable and an outcome does not necessarily indicate a causal relationship. For example, variable testing may indicate a correlation between gas-company credit cards and higher rates of mortgage-loan defaults, but this does not mean that having a gas-company credit card will cause a consumer to default on a mortgage.

It stands to reason that not all variables with a correlative relationship can, or should, be used in a credit-scoring system. For example, some analysis shows hair or eye color correlates to certain types of insurance claims. Other analysis reveals links between zodiac signs and frequency of auto claims. Under this methodology, those born under the sign of Taurus or Virgo would pay higher premiums than Cancers or Aquarians. It also follows that credit-scoring systems should use neither race, national origin, nor any indicative proxy, not only because it flies in the face of our nation’s laws and policies, but because it makes as little sense as using a zodiac sign to price car insurance.

B. Disparate Impact of Credit-Scoring Factors

While it is illegal to evaluate risk using protected class characteristics, credit-scoring systems continue to have a significant disparate impact on people of color and other underserved consumers because some seemingly facially neutral factors actually have discriminatory effects.

Take, for example, the factors used by the FICO scoring system, which is widely known and often touted as the industry standard for use in mortgage lending. While it remains unknown how FICO weights variables in its scoring system, several broad categories impacting the score are public: payment history, amounts owed, length of credit history, new credit, and types of credit used. Below, FICO’s chart illustrates the value assigned to each variable.


83. See id.
Discriminatory Effects of Credit Scoring

Each category poses a concern about disparate impact and unintended discriminatory outcomes, as well as affects access to sustainable, affordable, and fair credit. Below is a more detailed description of the fair-lending concerns related to each category of the FICO scoring system.

1. Payment History: 35% of FICO Score

The payment-history component of the FICO score includes information about whether borrowers make timely debt payments, including some subprime loans. As mentioned above, subprime loans carry much higher default and delinquency rates, not necessarily because of the borrower’s traits, but instead because of the aspects and features of the loans. Because African Americans and Latinos are targeted for subprime loans, data suggests that they will undoubtedly experience higher rates of poor performance in payment history.

A unique study comparing two similar groups of low- and moderate-income...
The study compared two mortgage-loan portfolios, one comprised of low-cost, fixed-rate loans, and the other of subprime loans. Using propensity-score match methodology, researchers were able to isolate borrowers with similar characteristics. The divergent variables were the loan terms, conditions, and the channel used to obtain mortgages. While traits of both borrower groups were similar, performance outcomes were not. The default rate for the subprime portfolio was four to five times higher than that for the lending-program portfolio for low- and moderate-income borrowers.

Moreover, the study revealed compelling evidence that loan characteristics and origination channel significantly impacts loan performance. Specifically, prepayment penalties, adjustable interest rates, and elevated costs negatively impact the loan performance, even after controlling for credit score. Additionally, loans originating through broker channels tend to result in higher default rates.

This data conflicts with the underlying assumption behind scoring mechanisms. It, along with other studies, suggests that a borrower may end up with a damaged credit score not because the borrower was more risky or negligent, but rather because he or she obtained a loan through a broker or received loan terms that increase the likelihood of delinquency and default. Existing credit-scoring systems do not distinguish between risk caused by borrower behavior and risk caused by loan terms and conditions. Thus, risky loans are likely to negatively impact the borrowers’ credit scores, even though they may have had a perfect payment record had they been able to obtain a less risky loan.

2. Amounts Owed: 30% of FICO Score

The FICO score calculation of amounts owed is comprised of multiple factors, but FICO does not reveal details concerning each factor or how each is weighted. However, FICO reports that the amounts-owed category takes into consideration the amount of credit available to a borrower for certain types of revolving and installment loan accounts. To the extent that underserved

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88. See id. at 14.
89. See id. at 2-3.
90. See id. at 3.
91. See Ding et al., supra note 87, at 3
92. See id.
93. See id. at 28-31.
94. See id.
95. See Ding et al., supra note 87, at 28-31.
2013] DISCRIMINATORY EFFECTS OF CREDIT SCORING 955

communities have restricted access to credit, and the type of credit that loan companies may positively report to credit repositories in particular, amounts owed can pose a disparate discriminatory impact.

A study by the San Francisco Federal Reserve Board provides an analysis of individuals who do not have a checking or savings account in the region. The unbanked tend to be young, low-income, non-white adults, and without a college degree. The Board goes on to reveal that approximately half of African Americans and Latinos fall into this category, and that unbanked individuals are concentrated in lower income census tracts. The Board also documents the preponderance of payday lenders and check cashers in predominately Latino neighborhoods.

The lack of access to mainstream lenders may impact the ability of underserved consumers to obtain revolving or installment lines of credit. If these borrowers experience undue difficulty in accessing quality credit, they may well suffer a lower credit score from a system that considers how much “extra” credit they may have available in certain revolving and installment accounts. Here again, amounts owed is not only measuring the ability of the borrower to effectively manage credit accounts, but is also measuring consumer’s access to certain credit accounts.

3. Length of Credit History: 15% of FICO Score

Presumably, the longer a borrower holds an account, and to the extent that the account is reported to the credit repositories, the higher the borrower’s credit score. If this is indeed the case, then borrowers with access to credit that goes unreported to credit repositories will be negatively impacted by this component.

We provide a fairly detailed analysis above of how mainstream creditors historically discriminated against communities of color. Moreover, as referenced above, borrowers of color are much less likely than their white counterparts to have access to mainstream banks and, consequently, are much more likely to access credit from fringe lenders who do not report positive data to credit repositories. This means that borrowers of color will be less likely to have a lengthy credit history.

This factor penalizes borrowers who deal on a cash basis, access credit outside of the financial mainstream, cannot access traditional credit, or obtain

(last visited Nov. 26, 2013).

97. See Understanding the Unbanked Market in San Francisco: A Preliminary Analysis, FED. RESERVE BANK OF S.F. (on file with authors).
98. See id. at 2.
99. See id. at 5.
100. See id. at 11.
101. See supra Part II.A
102. See supra Part II.C.
credit from lenders who do not report positive data. Borrowers with these circumstances are disproportionately persons of color.  

4. New Credit: 10% of FICO Score

New credit considers the number of accounts a consumer recently opened. FICO does not provide details on how establishing new credit affects a consumer’s credit score. FICO advises consumers to avoid opening new lines of credit because it might result in a lower credit score. Further, opening new accounts lowers the average account age, causing a lower credit score.

New credit also considers the number of credit accounts a consumer pursues. Therefore, shopping for a mortgage and applying for credit at different places may negatively impact a consumer’s credit score. To guard against this, FICO advises consumers to shop for a mortgage loan within a short window of time.

There are two areas of concern with respect to disparate outcomes under new credit. First, we are concerned because there is a higher likelihood that consumers of color will access new credit accounts. As discussed above, credit access is a major challenge for underserved groups and these groups are much more likely to be unbanked and underbanked. It stands to reason, therefore, that underserved groups will be among those who are newly entering the credit markets in order to access credit for the first time and therefore, establishing or attempting to establish new accounts. FICO counts credit inquiries under the new-credit category.

The second concerning area emanates from the higher mortgage-loan declination rates for borrowers of color. As described earlier, HMDA data reveals that financial institutions are much more likely to decline a borrower of
color’s loan application than their white counterparts.\textsuperscript{110} Given these higher declination rates, borrowers of color are likely to apply to several lenders before successfully acquiring a loan.

If mortgage-loan inquiries or applications are undertaken in a short time frame, the applications may not hurt a consumer’s credit score.\textsuperscript{111} However, if a consumer applies for a mortgage with one lender, waits to be declined, and then applies for a mortgage with another lender, this process may well negatively impact the consumer’s credit score due to the longer lapse in time between inquiries. More analysis and research is needed to determine if borrowers of color have a higher incidence of shopping for a mortgage with different lenders over longer periods of time and, ultimately, how that might impact their credit scores.

5. Types of Credit Used: 10% of FICO Score

Again, FICO does not reveal exactly how the type of credit a borrower uses affects his or her credit score, however, there is evidence that certain types of credit—such as credit provided by finance companies—are treated less favorably than credit provided by mainstream lenders like depository banking institutions. According to the Federal Reserve Board, “[m]any credit-scoring models consider the number and type of credit accounts you have. A mix of installment loans and credit cards may improve your score. However, too many finance company accounts or credit cards might hurt your score.”\textsuperscript{112} If this is indeed the case, this category also presents dangerous implications for borrowers of color.

In a guide advising consumers on how to improve their credit score, FICO suggests that they have installment loans and credit cards that are reported to credit repositories.\textsuperscript{113} FICO urges that these credit sources will play a favorable role in the FICO credit-scoring system.\textsuperscript{114} But, these types of credit may actually penalize consumers who access them outside of the financial mainstream. In the end, this component may focus more on the quality of the environment or type of loan product a consumer accesses, rather than the risk characteristics of the consumer.

C. Existing Credit-Scoring Systems Do Not Adequately Predict Risk

The current crisis revealed that credit-scoring mechanisms are an insufficient measure for predicting and managing performance. While the FICO Score is

\begin{itemize}
\item \textsuperscript{110} See supra note 63 and accompanying text.
\item \textsuperscript{111} See supra note 107 and accompanying text.
\item \textsuperscript{112} 5 Tips: Improving Your Credit Score, BOARD OF GOVERNORS OF FED. RES. SYS., http://www.federalreserve.gov/consumerinfo/fivetips_creditscore.htm (last updated June 17, 2010).
\item \textsuperscript{113} See id.
\item \textsuperscript{114} See id. (discussing benefits of installment loans and credit cards).
\end{itemize}
designed to assess risk and predict a borrower’s performance, recent analysis demonstrates its ineffectiveness. Default rates for all borrowers have increased precipitously, regardless of credit score, and one study found that “higher FICO scores have been associated with bigger increases in default rates over time.”

In the years before the economic crisis, more thorough and comprehensive underwriting criteria allowing for the evaluation of unique and compensating factors were common. More recently, however, lenders began substituting the comprehensive criteria with flimsy underwriting standards. If a borrower had a higher credit score, the lender could truncate the underwriting process by foregoing a fully documented underwriting review. In order to maximize short-term profits, lenders took great strides to increase volume. One way to increase volume was to shorten the time it took to approve a loan.

Institutions largely disregarded sound underwriting criteria, such as verifying savings and other deposits, income and employment, or documenting timely rental payments. However, lenders gave substantially more weight to the credit-score factor. In that environment, the FICO score became a proxy for sound underwriting. Whereas the credit score might have safely been used as an important tool in the underwriting toolbox, it was instead overvalued, leading to poor lending decisions. Even FICO admits that lenders were too reliant on the model.

The Federal Reserve Bank of St. Louis published another study looking at credit scores and borrowers who received subprime mortgages. It revealed that, for borrowers with the lowest FICO scores (500 to 600), the rate of seriously delinquent loans was twice as high in 2007 than in 2005. Comparatively, for borrowers with the highest FICO scores (above 700), the rate of seriously delinquent loans was almost four times as high in 2007 than in 2005.

Borrowers with lower FICO scores saw a 100% increase in seriously delinquent loans while borrowers with higher FICO scores saw a 300% increase. The study’s author concludes that “the credit score has not acted as a predictor of either true risk of default of subprime mortgage loans or of the subprime mortgage crisis.”

Lenders’ heavy reliance on FICO scores during the most recent housing boom has contributed to the system’s ineffectiveness. Even industry analysts have recognized the flaws in FICO’s system. In a

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117. See Demyanyk, supra note 115.
118. See id.
119. See id.
120. See id.
121. Demyanyk, supra note 115.
122. See Stephen Gandel, Lenders Look Beyond Credit Scores To Gauge Who’s a Risk, TIME, Jan. 9,
document written to clients, an analyst at the Canadian Imperial Bank of Commerce World Markets called FICO scores “virtually meaningless.”

Borrowers with higher FICO scores are, in many cases, acting the way analysts predict borrowers with very low scores will act. In reviewing private loan portfolios, some analysts have found that loan characteristics were better predictors of loan performance than the borrower’s FICO score. Indeed, both FICO and TransUnion have reported that borrowers with higher FICO scores are performing in uncharacteristic ways. These borrowers, in a trend never before seen, are more likely to pay their credit-card debt than their mortgage-loan debt. This offers additional proof that a credit score alone cannot predict long-term mortgage performance.

Many lenders that either do not rely on credit-scoring mechanisms at all, or minimally rely on them, experience default rates that are lower than the industry average. For example:

Golden West Financial, a lender that did not rely on FICO because of its unpredictable nature, experienced a default rate of .75% while the industry average for the same class of loans was 1.04%. Golden West relied on careful underwriting, including income and asset verification and employed a different mechanism for compensating appraisers. Instead of compensating an appraiser based on the number of appraisals completed, Golden West compensated appraisers on the accuracy of the appraisal over the life of the loan. Underscoring the tentative reliability of the FICO score, a Golden West representative reported that some of Golden West’s best clients had very low FICO scores and some of their worst clients had high FICO scores. The North Carolina State Employees’ Credit Union indicated that for their borrowers who would be classified as subprime, the default rate is 1.25%, well below the industry average. NCSE attributes the higher default rates among subprime loans with higher interest rates and poor underwriting practices.


D. Risky Loan Products and Unsafe Lending Environments—Not Borrowers—Were Clearly the Culprit

When looking at loan terms and conditions over the past ten years, it becomes clear why some borrowers failed and some succeeded. Failed underwriting processes and unsuitable loan products were higher contributors to poor loan performance than were the credit characteristics of the borrower. Even borrowers with good credit, who paid their bills on time, quickly found themselves in trouble after getting a predatory or subprime loan, or accessing credit in an unsafe environment.

Analysts observed similar outcomes among corporations such as Lehman Brothers and Bear Stearns, who turned more and more to risky investment products and tenuous financial deals. Just as the creation and sale of unregulated, complex derivative investment products was a bad idea, and led otherwise sound companies into ruin, so was the creation and sale of unwise mortgage-loan products with highly risky features, like prepayment penalties and negative amortization, both of which led otherwise good consumers into default.

Some lenders might improve overall loan performance by improving the quality of the underwriting process. In a presentation on the impact of the qualified residential-mortgage requirements, a number of organizations, including NFHA, the National Association of Realtors® and the Mortgage Bankers Association, highlighted a number of factors that are most important in decreasing default risk.126 Those factors included full-loan documentation and verification processes.127 The organizations identified these critical underwriting components as key elements in improving loan-portfolio performance and management.128

The organizations also cite risky loan features including:

- negative amortization loans;
- interest-only loans;
- loans with balloon payments;
- loans exceeding thirty years in maturity;
- prepayment penalties;
- unverified income, employment, assets and other debts—no-doc or low-doc—loans;

126. See NFHA et al., Presentation on Impact of Qualified Residential Mortgage Requirements (on file with authors) (identifying factors needed to decrease default risks).
127. See id.
128. See id.
• underwriting for ARMs based on an introductory rate rather than the fully-indexed interest rate;
• total points and fees exceeding three percent of loan amount;
• unstable or undocumented payment history;
• ARM reset caps above two percentage points per year;
• investor loans;
• yield spread premiums; and
• piggyback seconds.129

Proposed regulations for the qualified mortgage (QM) and the qualified residential mortgage (QRM) have identified many of these risky loan features. Most of these features are prohibited under the final QM regulations; the final QRM regulations have not yet been released. Instead of concentrating the risk analysis on the borrower, financial analysts should evaluate available products, the environment in which the credit is provided, and the mortgage lender’s underwriting process.

IV. WHY THE FEDERAL GOVERNMENT AND LENDERS HAVE AN OBLIGATION TO CHANGE THE SYSTEM

Federal agencies, their grantees, and others associated with housing and community development, have a special obligation to further the purposes of the Fair Housing Act. The Act covers policies and practices that disparately impact protected classes.130 The federal government must act to correct any disparate impact caused by credit scoring.

The Fair Housing Act seeks to eliminate housing discrimination and promote residential integration. The Act requires government agencies to dedicate housing and community development in a manner that affirmatively furthers fair housing.131 The Act applies to government agencies having regulatory or supervisory authority over financial institutions. As stated in Section 808(d) of the Fair Housing Act:

All executive departments and agencies shall administer their programs and activities relating to housing and urban development (including any Federal agency having regulatory or supervisory authority over financial institutions) in a manner affirmatively to further the purposes of this subchapter and shall cooperate with the Secretary [of Housing and Urban Development] to further

129. See id.
131. See id. § 3608(d).
such purposes.\textsuperscript{132}

The Act, along with executive orders, further defines the obligations of federal agencies.\textsuperscript{133} The Obama Administration has also affirmed its commitment to fair housing and fair lending.\textsuperscript{134}

Courts interpret this affirmative obligation to require efforts to eliminate segregation.\textsuperscript{135} Eliminating segregation is important to our nation’s well being because where we live determines our access to opportunities, wealth, and resources.\textsuperscript{136} In this context, equal access to credit, financial services, and products cannot be overstated. The largest federal housing program ever, the Troubled Asset Relief Program (TARP) provided funding for major banks and insurance companies.\textsuperscript{137} As recipients of federal funds, these entities are required to affirmatively further fair housing with TARP, as well as any other government funds accepted.\textsuperscript{138} Fair housing laws also cover credit-scoring systems that are clearly related to housing and community development.

V. POLICY AND ENFORCEMENT SOLUTIONS TO IMPROVE CREDIT-SCORING SYSTEMS

Because credit scoring significantly affects a wide range of access issues, such as credit access, employment opportunities, and insurance availability, credit-scoring mechanisms need major improvements if not a complete overhaul. Intrinsic and persistent discrimination in the lending markets and

\textsuperscript{132} Id. (emphasis added); see id. §§ 3601-3619 (describing duties to further fair housing).


\textsuperscript{135} See Young v. Pierce, 544 F. Supp. 1010, 1018 (E.D. Tex. 1982) (“This statute explicitly commands the Secretary of HUD to act in furtherance of the ideal of fair housing . . . . A variety of cases have explicitly recognized this affirmative duty.”); see also Otero v. N.Y.C. Hous. Auth., 484 F.2d 1122, 1134 (2d Cir. 1973) (“Action must be taken to fulfill . . . the goal of open, integrated housing patterns, and to prevent the increase of segregation . . . of racial groups whose lack of opportunities the [Fair Housing] Act was designed to combat.”).


America’s dual- and unequal-credit markets continue to contribute to serious credit-access problems for borrowers and communities of color. Below, we offer some recommendations on how to improve credit-scoring mechanisms and suggest how to monitor and evaluate these systems.

A. Broaden the Scope of Financial Data Utilized by Underwriting and Credit-Scoring Models

Broadening the scope and quality of data upon which the scoring systems are based will improve credit-scoring models. Currently the primary source of data is major credit repositories. Credit repositories should make it easier for smaller financial institutions to report positive data. Moreover, credit repositories must be proactive and ensure that financial institutions can submit positive data from nontraditional sources. Models should also include data from state housing-finance agencies; CDFIs; micro-lending organizations; credit unions; and affiliation or community groups, such as churches, faith-based institutions, and benevolent organizations.

Broadening the scope of credit information will create a more robust data pool with additional information about and from consumers who access credit in safe, but nontraditional environments. It will also enable credit-scoring systems to accurately assess a broad range of consumers. This will, in turn, reduce the likelihood that a consumer will be incorrectly characterized in various credit-scoring systems.

Finally, credit repositories must create mechanisms to correct the current system’s slant toward reporting only negative data. For example, repositories could develop a mechanism that allows consumers to report and submit verifiable and documented information about their credit payment histories. Credit repository data should reflect consumers who pay debt obligations on time, a problem that negatively affects communities of color.

B. Improve the Quality of Data

Credit bureaus must make it easier for consumers to correct erroneous information on their credit reports. Incorrect information can lead to low credit scores, credit denials, and limited access to quality, affordable credit.

Improving data quality will also contribute to better scoring models that more accurately assess consumer risk. Everyone who provides credit to consumers should make improving scoring-model performance a goal. Regulators overseeing financial institutions should likewise seek to improve scoring-model performance. Ensuring that consumers have access to quality credit will expand opportunities for consumers, promote healthy financial practices, and contribute to the growth of consumer net worth.
C. Make the System More Transparent

Agencies have taken years to reveal what has amounted to very little information about how various factors impact consumer credit scores. There is much we do not know. This lack of information leads housing professionals and credit and housing counselors to ineffectively advise consumers on how to manage their credit. Moreover, because different scoring mechanisms are used for different reasons, a consumer’s credit score may be hurt when the consumer acts to improve his or her insurance score.

Consumers and consumer counselors are generally uninformed about how to positively impact the consumer’s score. Making the scoring systems more transparent will help consumers better manage their financial affairs. It will also help advocates, financial institutions, federal regulators, and legislators.

D. Adequately Assess the Impact of Credit-Scoring Mechanisms on Underserved Groups

The CFPB, federal banking regulators, and federal enforcement agencies including the DOJ and the U.S. Department of Housing and Urban Development should examine the impact of credit-scoring mechanisms, especially as they relate to underserved groups. Regulators should also analyze the disparate impact of credit-scoring systems. It is imperative that regulatory and enforcement agencies analyze data from a broad range of sources. It is crucial that regulators do not rely predominantly on industry-developed data. Credit-score developers should also analyze their own systems to identify fair-lending concerns and implement less discriminatory alternatives.

E. Reduce the Overreliance on Credit-Scoring Mechanisms

The current crisis revealed that credit-scoring mechanisms are an insufficient measure for predicting and managing consumer performance. Borrowers have not behaved as their credit scores predicted. Lenders, investors, regulators, and legislators must caution against using credit scores as a replacement for underwriting, or as the only assessment of risk. Many factors affect loan risk, including the presence of prepayment penalties, inefficient appraisals, poor documentation practices, and other abusive loan features. The credit score may be the least significant factor when it comes to risk analysis. Therefore, lenders, investors, regulators, and legislators must adopt approaches that objectively consider other elements that impact risk.

F. Evaluate Product Risk

In addition to reducing the reliance on credit-scoring systems, federal regulators and legislators should push for the evaluation of credit and financial-services products. Additionally, institutions should evaluate underwriting systems and practices for their risk level. This information should be readily
available to consumers, who will use it to understand which products and underwriting practices pose the most risk to their credit score. This transparency will enable consumers to make informed and sound financial decisions.

As discussed above, multiple studies reveal that unsafe products and unsavory underwriting practices significantly impact loan performance and credit risk. Therefore, it is quite practical to consider these functions in the risk analysis. Focusing analyses on borrower characteristics will not improve the quality of the assessment of risk; rather, objectively considering all factors affecting credit risk will result in a better understanding of risk exposure.

G. Fix Credit Scores for Victims of Discrimination

Complaints, settlements, and remedies should include repairing credit scores damaged by discrimination. For example, the recent DOJ settlement with Countrywide demonstrated discrimination against African-Americans and Latinos in steering and fees.139 Thousands of families who should have received prime loans were steered to subprime loans.140 It is reasonable to assume that their credit scores were negatively impacted by the mere fact that they received a more expensive subprime loan. Those borrowers should be made whole and their remedies should include restoring damaged credit scores.

As part of remedies and settlements, regulators, enforcement agencies, and courts should fix credit scores as a matter of course. In fact, some settlements between banks or fair-housing organizations and consumer groups already do this. When predatory lending was especially rampant in the early 2000s, fair-housing organizations were sometimes successful in getting a borrower’s credit history amended as part of a settlement. In consultation with the credit-reporting agency, the bank would have the predatory loan deleted from the borrower’s credit report. This, in turn, erased the loan from the borrower’s history, as if it had never been made. In recent years, however, some lenders have not agreed to delete the trade line entirely and instead have agreed only to report the loan as satisfied. This means that the credit report shows that there is no debt remaining on the loan, but any history of late payments and other blemishes remains on the credit report. Unfortunately, because of the opacity of credit-scoring mechanisms, it is hard to tell which approach might be best for a specific consumer at any given time.

VI. CONCLUSION

By 2042, the majority of people in this country will be people of color.141

139. See U.S. Attorney’s Office Cent. Dist. of Cal., supra note 46.
140. See id.
141. See Press Release, U.S. Census Bureau, An Older and More Diverse Nation by Midcentury (Aug. 14,
Given these changing demographics, it is past time to make our nation’s credit system work equally for everyone. When civil-rights groups called for a foreclosure moratorium on subprime loans more than five years ago, predicting that the nation was headed for a financial and foreclosure crisis while referencing the disproportionate damage these loans were causing communities of color, Federal Reserve Chairman Ben Bernanke told the groups that the problem of foreclosure would be contained and restricted to the subprime market. The Mortgage Bankers Association responded that, “[e]ach loan is an individual transaction and situation, one which needs to be addressed individually between the lender and the borrower.”

It is now obvious that such responses to the burgeoning crisis were naïve, and that regulators and industry leaders failed to recognize the breadth of the ensuing crisis despite warnings by civil-rights and consumer-protection groups. The foreclosure problems not only went beyond the nation’s subprime market, but also turned into an international economic crisis of proportions not seen since the Great Depression.

Credit-scoring mechanisms are negatively affecting the largest growing segments of our country and economy. America cannot be successful if increasing numbers of our residents are isolated from the financial mainstream, and subjected to abusive and harmful lending practices. Credit scores have an increasing impact on our daily activities, and determine everything from whether we can get a job, to whether we will be able to successfully own a home. The current credit-scoring systems work against the goal of moving qualified consumers into the financial mainstream because they are too much a reflection of our broken dual credit market. This paradigm must change.

We believe that the recommendations presented here are important steps towards broadening access to good credit for all qualified borrowers.

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In FTC Study, Five Percent of Consumers Had Errors on Their Credit Reports That Could Result in Less Favorable Terms for Loans

Consumers Should Check Their Credit Reports for Free Using AnnualCreditReport.com

FOR RELEASE

February 11, 2013


A Federal Trade Commission study of the U.S. credit reporting industry found that five percent of consumers had errors on one of their three major credit reports that could lead to them paying more for products such as auto loans and insurance.

Overall, the congressionally mandated study on credit report accuracy found that one in five consumers had an error on at least one of their three credit reports.

“These are eye-opening numbers for American consumers,” said Howard Shelanski, Director of the FTC’s Bureau of Economics. “The results of this first-of-its-kind study make it clear that consumers should check their credit reports regularly. If they don’t, they are potentially putting their pocketbooks at risk.”

The study, in which participants were encouraged to use the Fair Credit Reporting Act (FCRA) process to resolve any potential credit report errors, also found that:

- One in four consumers identified errors on their credit reports that might affect their credit scores;
- One in five consumers had an error that was corrected by a credit reporting agency (CRA) after it was disputed, on at least one of their three credit reports;
- Four out of five consumers who filed disputes experienced some modification to their credit report;
- Slightly more than one in 10 consumers saw a change in their credit score after the CRAs modified errors on their credit report; and
In FTC Study, Five Percent of Consumers Had Errors on Their Credit Reports That Could Result in Less Favorable Terms for Loans

7/25/2019

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Other study results can be found in the executive summary of the report.

“Your credit report has information about your finances and your bill-paying history, so it’s important to make sure it’s accurate,” said Charles Harwood, Acting Director of the FTC’s Bureau of Consumer Protection. “The good news for consumers is that credit reports are free through annualcreditreport.com, and if you find an error, you can work with the credit reporting company to fix it.”

About the Study

The FTC report is the first major study that looks at all the primary groups that participate in the credit reporting and scoring process: consumers; lenders/data furnishers (which include creditors, lenders, debt collection agencies, and the court system); the Fair Isaac Corporation, which develops FICO credit scores; and the national credit reporting agencies (CRAs). It is based on work with 1,001 participants who reviewed 2,968 credit reports with a study associate who helped them identify and correct possible errors on their credit reports.

Consumers in the study were selected to match the demographic and credit score information of the general public, and participants were encouraged to dispute errors that could affect their credit standing. Credit reports with potential errors identified by study participants were sent to Fair Isaac (FICO) for rescoring.

After completing the FCRA dispute process, study participants were provided with new credit reports and credit scores. The original reports were then compared with the new reports. If any modifications were made as a result of the disputes, the impact of errors on the consumer’s credit score was determined.

Congress directed the FTC to conduct a study of credit report accuracy and provide interim reports every two years, starting in 2004 and continuing through 2012, with a final report in 2014. The reports are being produced under Section 319 of the Fair and Accurate Credit Transactions Act, or FACT Act.

Information for Consumers

The FTC has a wide range of general information for consumers on credit reporting issues, including Free Credit Reports, Disputing Errors on Credit Reports, and Your Source for a Truly Free Credit Report? AnnualCreditReport.com, as well as a new consumer blog posted titled It Pays to Check Your Credit Report.

It also has information available on how credit scores affect the price of credit and insurance and what consumers need to know about their credit reports when looking for a job. Finally, the FTC has a video for consumers on how to get a free credit report.

The Commission vote authorizing the staff to issue the report to Congress was 5-0, with former Commissioner J. Thomas Rosch participating. It is the fifth interim report to Congress describing the progress the agency has made on a national study examining the accuracy of credit reports.

The Federal Trade Commission works for consumers to prevent fraudulent, deceptive, and unfair business practices and to provide information to help spot, stop, and avoid them. To file a complaint in English or Spanish, visit the FTC's online Complaint Assistant or call 1-877-FTC-HELP (1-877-382-4357). The FTC enters complaints into Consumer Sentinel, a secure, online database available to more than 2,000 civil and criminal law enforcement agencies in the U.S. and abroad. The FTC’s website provides free information on a variety of consumer topics. Like the FTC on Facebook, follow us on Twitter, and subscribe to press releases for the latest FTC news and resources.

PRESS RELEASE REFERENCE:

FTC Issues Follow-Up Study on Credit Report Accuracy

https://www.ftc.gov/news-events/press-releases/2013/02/ftc-study-five-percent-consumers-had-errors-their-credit-reports
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