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Tipping the SCALE: Will Alternative Data Promote or Impede Fair Lending Goals?

Vanessa G. Perry and Ann B. Schnare

April 2021

Note: We would like to thank the National Association of REALTORS® for providing financial support for this paper. The opinions expressed are our own, and do not necessarily reflect the positions of NAR.

Executive Summary

It has been more than 50 years since the passage of the Fair Housing Act, yet the homeownership rates of Blacks continue to be some 30 percentage points below those achieved by non-Latinx Whites. The relatively large Black-White homeownership gap reflects a variety of complex forces, ranging from continuing discrimination in the housing and mortgage markets to ongoing disparities in household incomes and debt burdens to policies that serve to disadvantage minority households. The onset of the Covid-19 pandemic is likely to exacerbate these issues, given the disparate impact the virus is having on both the physical and economic health of communities of color.

This paper focuses on the extent to which alternative ways of evaluating credit risk in the mortgage market could foster—or impede—the achievement of fair housing goals and increase homeownership rates, particularly for Black Americans. The mortgage market primarily relies on credit-bureau data to assess an applicant's creditworthiness—a critical element of the underwriting process. Yet for a variety of reasons, Blacks are more likely to have weak or missing credit scores than other segments of the population. This has led many housing advocates to call for the use of alternative data that could either enhance or replace the data contained in a typical credit report.

Our analysis focuses on three major types of alternative data that could be used in the evaluation of a consumer's creditworthiness:

- **Credit Proxies**, which capture the consumer's payment history on on-going bills such as rent, utilities, cable, and telecommunications;
- **Banking Data**, which capture activity in the consumer's banking and checking accounts; and
- **Non-Financial Personal Data**, which could include anything derived from a consumer's digital footprint, ranging from their "likes" and "dislikes" to the places they visit or shop to the characteristics of their Facebook friends.

We then evaluate each type of data using a five-factor "SCALE" framework that incorporates several important considerations in addition to the data's predictive power. These include:

> **Societal Values**, i.e., Is the use of the data consistent with general social and ethical norms?
>
> **Contextual Integrity**, i.e., Does the data make sense in the context of mortgage lending?
>
> **Accuracy**, i.e., Does the data accurately reflect the household's situation?
>
> **Legality**, i.e., Would the use of the data have a disparate impact on protected classes?
>
> **Expanded Opportunity**, i.e., Would the use of the data expand access to mortgage credit by increasing the number of qualified borrowers or by reducing borrowing costs while maintaining or improving the accuracy of credit decisions?

Failure to meet any of these criteria does not necessarily mean that the data should not be used, nor does it imply that policymakers must intervene to prohibit or discourage their use. However, viewing alternative data sets through this multifaceted lens serves to highlight their potential strengths and weaknesses from a fair housing perspective, and will hopefully lead to better decisions on the part of credit providers, regulators, and Congress.

In general, application of the SCALE framework supports the use of “credit proxies” such as the timely payment of rent and utilities, as well as certain types of aggregate banking data, for example, net monthly cashflows, total savings, and the payment of certain ongoing financial obligations that can serve as credit proxies. However, because of fair lending, ethical, and contextual concerns, we believe that the use of more granular banking data (e.g., where and how the household spends its money), as well as the plethora of data that can be harvested from social media (e.g., Facebook friends, shopping patterns, internet searches, “likes”, etc.), should generally be discouraged.

Based on these findings, we offer five broad recommendations to policymakers:

- **First**, existing legislative efforts to encourage the reporting of credit proxies such as rent, utilities, and telecom payments to credit bureaus should be supported and strengthened by explicitly pre-empting existing state or local laws that prevent the sharing of such data. Not only does the use of such data make “sense” in the context of mortgage lending; its use has also been shown to increase the number of qualified minority borrowers.
- **Second**, bank regulators should continue to explore ways to encourage the use of certain banking data in the assessment of credit risk, for example, through efforts such as the Office of the Comptroller of the Currency’s Project REACh. In addition to providing measures of the consumer’s financial capacity, banking data can be used to capture their performance on certain ongoing bills that can be used as credit proxies. At the same time, however, other types of banking data—for example, detailed checking data on how consumers spend their money—should be discouraged since they could easily serve as proxies for the consumer’s race, ethnicity, or sex.
- **Third**, additional scrutiny should be paid to the large-scale data aggregators that are enabling the application of banking data to a wide variety of uses, including credit scoring. Most consumers have little, if any understanding of how their information is being used by these largely invisible entities that collect, catalogue, and distribute their data to Fintech companies and other consumer-authorized users. Yet the data being harvested behind the scenes are arguably far more sensitive than the information currently provided by credit bureaus. While the jury is out on whether specific legislative efforts might be required, at a minimum, it is important to ensure that these companies are held to the same privacy and transparency standards as credit reporting agencies or other providers of data used in credit models.
- **Fourth**, Congress should revisit the ECOA, the Fair Housing Act, and other applicable laws to explicitly preclude the use of most, if not all kinds of non-financial personal data in lending decisions. Putting clear restrictions on how various types of consumer data can be used in

credit decisions—and ensuring the transparency of the data to consumers—will help to address the most egregious misuses of consumer data and promote fair lending goals.

- **Finally**, policymakers should explore ways to mitigate the impact of the Covid-19 pandemic on homeownership opportunities for Blacks and other historically disadvantaged groups. However, this should not include prohibiting credit bureaus from collecting and reporting delinquency data during the pandemic or removing the forbearance flags that are currently included in credit reports. Such data could ultimately be key to understanding how consumers have responded to the challenges raised by the pandemic, which in turn could provide more accurate assessments of credit risk.

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I. Introduction

It has been more than 50 years since the passage of the Fair Housing Act, yet neighborhoods remain highly segregated and the homeownership rates of Blacks continue to be well below those achieved by Whites. The persistence of segregation and the relatively large Black-White homeownership gap reflects a variety of complex forces, ranging from continuing discrimination in the housing and mortgage markets to ongoing disparities in household incomes and debt burdens to policies that serve to disadvantage minority households. The onset of the Covid-19 pandemic is likely to exacerbate these issues, given the disparate impact the virus is having on both the physical and economic health of communities of color.

This paper focuses on the mortgage market and the extent to which alternative ways of evaluating credit risk could foster—or impede—the achievement of fair housing goals, particularly for Black Americans. At the outset, it is important to emphasize that this paper only deals with one aspect of the mortgage underwriting process, namely, the evaluation of creditworthiness. We do not address additional challenges faced by Blacks that affect virtually every aspect of obtaining a mortgage—for example, down payment requirements, higher debt levels (including student loans), and disproportionately-lower appraised home values.[1] Instead, this paper focuses on whether the use of alternative data in the evaluation of credit risk could strengthen this country's ability to meet fair housing goals.

Our analysis focuses on three major types of alternative data that could be used in the evaluation of credit risk:

- **Credit Proxies**, which measure the consumer's payment history on on-going bills such as rent, utilities, cable, and telecommunications;
- **Banking Data**, which capture activity in the consumer's banking and checking accounts; and
- **Non-Financial Personal Data**, which could include anything derived from a consumer's digital footprint, ranging from their "likes" and "dislikes" to the places they visit or shop to the characteristics of their Facebook friends.

We then evaluate each type of data using a five-factor "SCALE" framework that incorporates several important considerations in addition to the data's predictive power. The use of this framework underscores the basic ethical judgment that underlies this country's fair lending laws, namely, the fact that a particular variable may be predictive does not necessarily imply that it should be used in the granting of credit.

The remainder of this paper is divided into five parts. To provide some context, we begin with a brief review of the current state of Black homeownership in this country and how it might be affected by

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[1]For a discussion of these well-documented impacts, see Vanessa G. Perry (2019), "A Loan at Last? Race and Racism in Mortgage Lending," in Race in the Marketplace: Crossing Critical Boundaries, G.D. Johnson, K.D. Thomas, A.K. Harrison, S. A. Grier, editors: Palgrave MacMillan: Cham, Switzerland, 173-192.

the Covid-19 pandemic,[2] followed with a description of the role of credit bureaus, the types of data they provide, and the use of credit scores, particularly in the mortgage market.[3] We then examine how various kinds of "alternative" data could be used to supplement or replace traditional credit reports, and apply our five-factor SCALE framework to assess the broader social, ethical, and legal concerns that may be associated with their use. Finally, we summarize our conclusions and present our recommendations for policymakers, including the extent to which existing fair lending laws need to be amended to protect consumers in the digital age.

II. The Current State of Black Homeownership

Systemic racism affects virtually every aspect of our society, ranging from ed to health care to employment[4]. The housing market is no exception. Not only do the majority of Blacks continue to live in highly segregated neighborhoods, but they also continue to have homeownership rates that are well below those that have been achieved by Whites.

In 2020, 46.4 percent of Black households owned their homes, compared to 75.8 percent of non-Latinx whites. (See Figure 1.) This roughly 30-percentage point gap in the homeownership rates of Blacks and non-Latinx Whites has persisted for most of the past 50 years. The gap narrowed somewhat in the early 2000s—in large part due to the explosion of subprime lending—but then widened in the years immediately following the 2008 housing collapse, which produced a wave of foreclosures that hit communities of color particularly hard. While Black homeownership rates increased by some 5 percentage points just last year, the Black-White homeownership gap today is roughly the same as the gap that existed in 1960, eight years before the passage of the 1968 Fair Housing Act.

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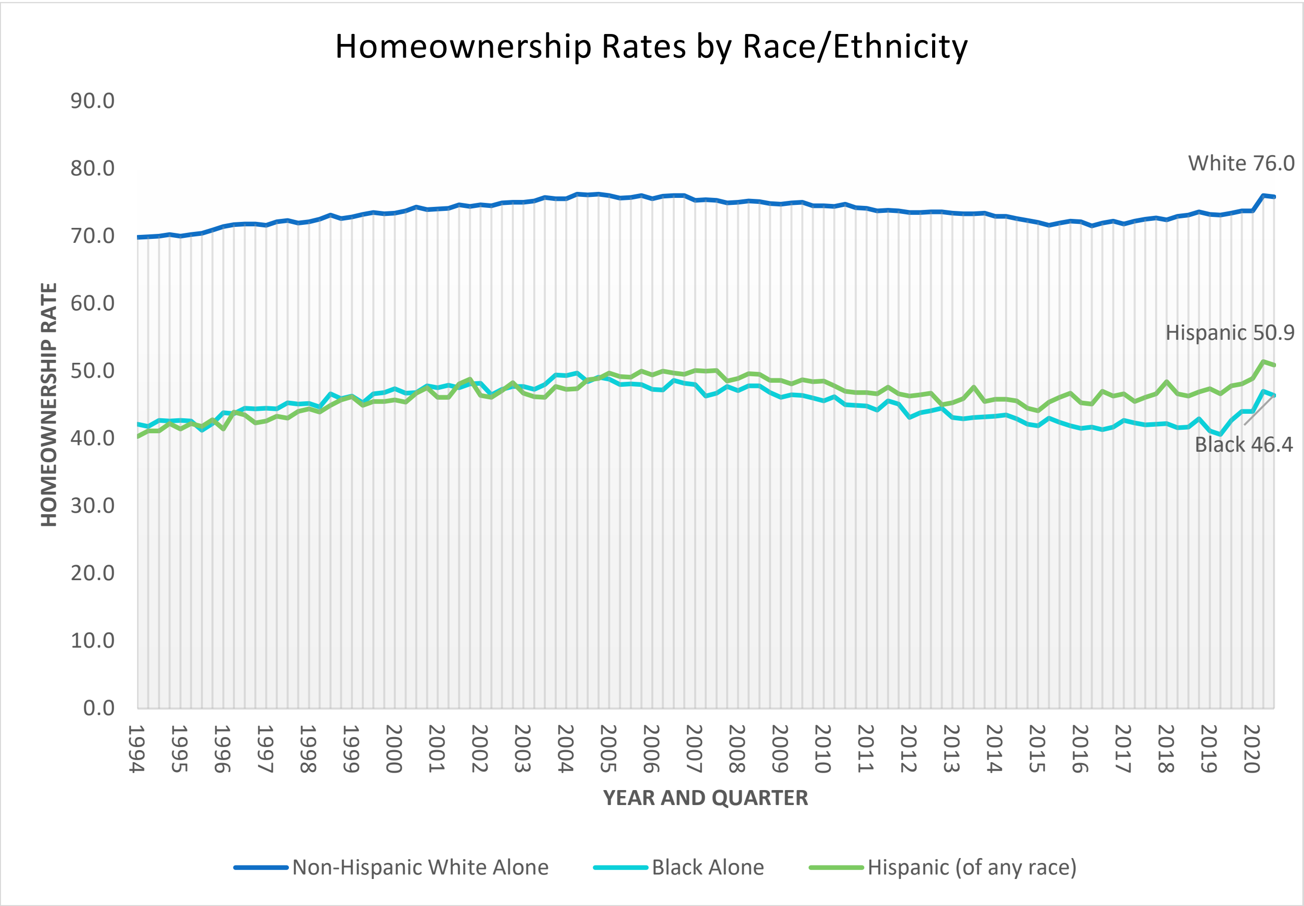
[2] For a fuller review, see Vanessa G. Perry, "2020 State of Homeownership in Black America Report," the National Association of Real Estate Brokers, https://www.nareb.com/shiba-report/

[3] See Ann B. Schnare, "Credit Bureaus in the Digital Age: Recommendations for Policy Makers," September 2019; and Consumer Financial Protection Bureau (CFPB), "Key Dimensions and Processes in the U.S. Credit Reporting System: A review of how the nation's largest credit bureaus manage consumer data," December 2012. https://www.consumerfinance.gov/dataresearch/research-reports/key-dimensions-and-processes-in-the-u-s-credit-reporting-system/.

[4] DiPrete, T.A. and Eirich, GM (2006),"Cumulative advantage as a mechanism for inequality: a review of theoretical and empirical developments," *Annual Review of Sociology*, 32(1), 271-297; Education: Reardon, S.F., Weathers, E.S., Fahle, E.M., Jang, H., & Kalogrides, D. (2019), "Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps," Stanford Center for Education and Policy Analysis, Working Paper 19-06, https://cepa.stanford.edu/content/separate-still-unequal-new-evidence-school-segregation-and-racial-academic-achievement-gaps; Allen, W.R., McLewis, C., Jones, C., Harris, D. (2018), "From Bakke to Fisher: African American Students in U.S. Higher Education over Forty Years," RSF: The Russell Sage Foundation Journal of the Social Sciences, 4 (6) 41-72; DOI: 10.7758/RSF.2018.4.6.03; Employment: Bertrand, M., and Mullainathan, S.(2004), "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," *The American Economic Review*, 94(4): 991-1013; Priest, N., & Williams, D. R. (2018), "Health Care: Racial discrimination and racial disparities in health," In B. Major, J. F. Dovidio, & B. G. Link (Eds.), Oxford library of psychology. *The Oxford handbook of stigma, discrimination, and health* (p. 163–182). Oxford University Press; Williams DR, Wyatt R.(2015), "Racial Bias in Health Care and Health: Challenges and Opportunities," *JAMA*, 2015;314(6):555–556.;

Figure I – The Black-White Homeownership Gap Remains at 30 Points[5]



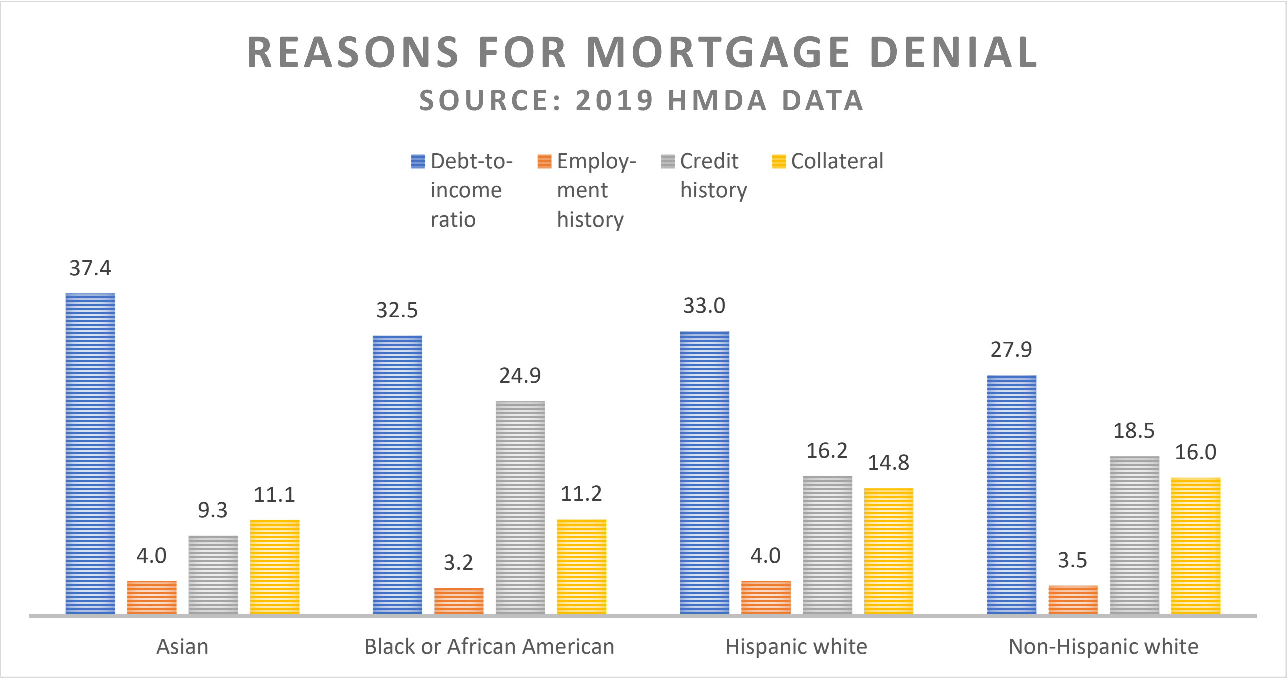
The reasons that this gap persists are multifaceted and complex.[6] Undoubtedly, access to affordable mortgage credit plays a role, as does the industry's reliance on credit-bureau data to assess the borrower's credit risk. Due to wealth disparities, the higher costs of financial services, and the cumulative effects of racial discrimination and redlining, access to mortgage credit has historically been a challenge for Black and Latinx communities. These challenges were exacerbated by the 2008 housing crisis, which led to steeper declines in housing values and higher foreclosure rates in minority

[5] Source: U.S. Census Bureau, Current Population Survey/Housing Vacancy Survey, October 27, 2020.
[6] For a fuller review, see Vanessa G. Perry, "2020 State of Homeownership in Black America Report," the National Association of Real Estate Brokers, https://www.nareb.com/shiba-report/.

neighborhoods. The aftermath of these events—including lost household savings and depreciated asset values—is undoubtedly reflected in current credit data.[7]

Because of these various factors, it is not surprising that Blacks are more likely to be rejected for a mortgage, a pattern that has persisted for many years. In 2019, for example, some 15.9percent of all Black applicants were rejected for a mortgage, compared to 7.0 percent of non-Latinx Whites. As shown in Figure 2, most lenders cited relatively low credit scores and relatively high debt-to-income ratios as the primary reasons for rejection. While high debt levels were the most common reason for rejection for every demographic group, credit history appears to be particularly problematic for Black applicants. For example, credit history accounted for some 30 percent of rejections for Blacks, compared to 23 percent for non-Latinx Whites, 21 percent for Latinxs, and only 13 percent for Asian applicants.

Figure II – Black Mortgage Applicants More Likely to Be Denied Due to Credit History



The industry's reliance on credit-bureau data in the underwriting process disproportionately affects Blacks in two important ways. First, since credit bureau data typically exclude payments on everyday necessities such as rent and utilities, they provide only a partial view of a household's performance on

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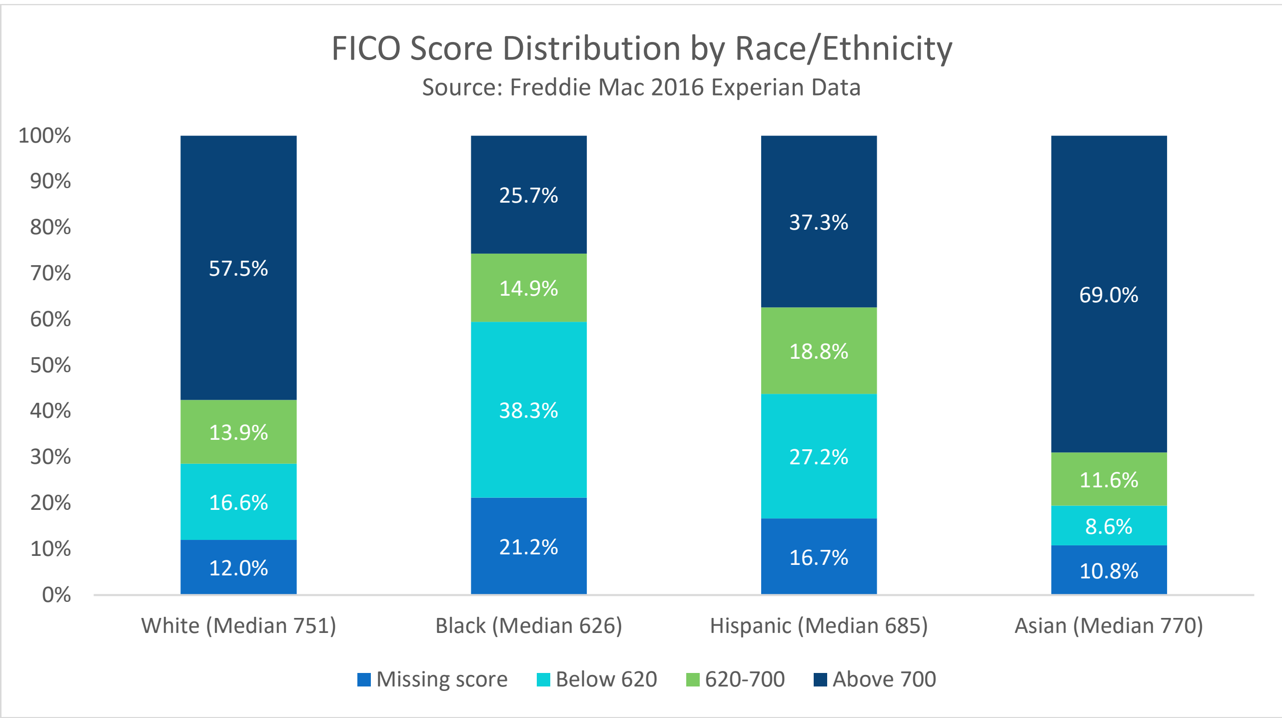
[7] National Consumer Law Center (2016). Past Imperfect: How Credit Scores and Other Analytics "Bake In" And Perpetuate Past Discrimination, Racial Justice & Equal Economic Opportunity Project, May, http://www.nclc.org/images/pdf/credit_discrimination/Past_Imperfect050616.pdf.

all its recurring bills. As shown in Figure 3 below, median credit scores are significantly lower for Blacks than they are Whites, and a higher proportion of Blacks have FICO scores below 620. As described in more detail below, research has shown that the inclusion of so-called credit proxies such as utility and rent payments in an individual's credit file would generally lead to an increase in credit scores, particularly for Blacks.

Figure III – Black Households are More Likely to Have Credit Scores Below 620



Reliance on bureau data also has a direct—and profound—effect on segments of the population with non-existent or thin credit scores—the so-called "credit-invisibles." While these individuals are generally precluded from obtaining a mortgage, a lack of credit history is not the same as having a poor credit history. Again, as shown in Figure 3, Blacks are disproportionately affected by the lack of a robust credit file. Over 21 percent of Black adults do not have a credit score, compared to just 12 percent of Whites. This pattern is consistent with research conducted by the Consumer Finance Protection Bureau, which found that Black consumers at the typical home-buying age were about twice as likely to be credit invisible as non-Latinx Whites.[8]

[8] See https://www.consumerfinance.gov/data-research/research-reports/data-point-credit-invisibles/. Accessed July 13, 2020.

The impact of a weak or non-existent credit file may affect access to mortgage credit in other important ways. For example, one paper put it this way:

> *"Consider a couple, where one person is credit invisible, and the other has a strong credit score. Lenders will advise the couple to have one loan applicant—the member with the credit score. As a result of this, the couple's measured income is lower than their actual income, meaning that they might fail lenders' debt-to-income (DTI) test. In other words, if both members of the couple earn the same income, the DTI will appear on the loan application to be twice the size that it actually is. Thus, a couple where one person has a strong credit score, the other has no history of poor credit performance, and where income is more than sufficient to meet any reasonable ability to repay requirement, could wind up unable to get a mortgage."*[9]

These and other examples of the barriers faced by potentially credit-worthy borrowers have led to calls to use alternative data in the evaluation of credit risk as a way of closing the homeownership gap.

The Covid-19 Pandemic has only increased the need to address these issues, given its profound and disparate impact on communities of color.[10] While the long-term effects of the pandemic are difficult to predict, judging from experiences with past economic crises, the prospects for increasing or even sustaining the current level of Black homeownership are likely to be highly challenging without substantial, deliberate, and targeted public policy interventions. Black people are at higher risk of contracting COVID-19 or experiencing severe illness.[11] Black workers have experienced higher rates of job loss and unemployment during the pandemic and are more likely to work in "front-line" jobs, and Black-owned small businesses have been less likely to survive during the pandemic[12].

Surprisingly, despite the slowdown in the economy and the rise in unemployment, average FICO scores are now at an all-time high.[13] While FICO warns that the impact on credit scores can take some time—as families draw down their savings and furloughs turn into permanent job losses—the government's initial efforts to mitigate the economic consequences of the pandemic have obviously played a role. Stimulus payments in the CARES Act, forbearance programs, and enhanced unemployment benefits have undoubtedly helped many borrowers stay financially afloat over much of the period. In fact, the number of borrowers with serious delinquencies (defined as more than 90 days overdue) dropped from 8.1 percent in January to 7.3 percent in July, while the average credit card balance fell from $6,934 to $6,004. These patterns suggest that many consumers have used at least

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[9] Richard K. Green and Ashlyn A. Nelson, "Credit scoring has both directly and indirectly affected the ability of people of color to access low-cost home loans," in Vanessa Perry, op. cit., p. 2-23.
[10] Rashawn Ray, "Why are Blacks dying at higher rates from COVID-19?" Brookings, Thursday, April 9, 2020, https://www.brookings.edu/blog/fixgov/2020/04/09/why-are-Blacks-dying-at-higher-rates-from-covid-19/.
[11] See https://dsl.richmond.edu/socialvulnerability/.
[12] Mills, C.K.and Battisto, J.(2020), "Double Jeopardy: Covid-19's Concentrated Health And Wealth Effects In Black Communities, August, Federal Reserve Bank of New York, https://www.newyorkfed.org/medialibrary/media/smallbusiness/DoubleJeopardy_COVID19andBlackOwnedBusinesses.
[13] See https://www.cnbc.com/2020/10/18/why-average-fico-credit-score-hit-new-record-highs-during-the-pandemic.html.

some of their government stimulus checks to pay down their existing debt. The fact that FICO scores have yet to decline also reflects a provision in the Cares Act that prohibits the reporting of missed payments for borrowers who have negotiated a forbearance agreement with their lenders.[14]

Of course, the trends observed for average FICO scores in the population as a whole may well obscure adverse trends that are already occurring within the Black community. But even if this is not the case, how long this situation will last is a matter of speculation that will ultimately depend on the government's willingness to provide additional assistance to the households and businesses affected by the pandemic and how long it takes for the economy to recover. In any event, to the extent that existing forbearance agreements come to an end and the reporting of serious delinquencies becomes more frequent, the homeownership gains achieved by Blacks immediately preceding the pandemic are likely to be reversed, making efforts to find alternative ways to measure credit risk more important than ever before.

III. Credit Bureaus, Credit Scores, And the Evaluation of Mortgage Risk

The mortgage market has traditionally evaluated credit risk based on three broad criteria known as the three "Cs" of mortgage underwriting:

- **Collateral**, defined as the ratio of the loan to the underlying value of the property;
- **Capacity**, defined as the household's total monthly debt payments (including the mortgage) as a share of their monthly income; and
- **Creditworthiness** (previously known as "*character*"), defined as the household's proven history of meeting their financial obligations.

The assessment of the third factor—the household's creditworthiness—is typically based on data obtained from the nation's credit bureaus.

Three nationwide credit bureaus dominate the credit reporting space today: Equifax, Experian, and TransUnion. Each provides detailed information on the credit histories of individual consumers, otherwise known as credit reports. While the reports provided by the bureaus differ somewhat, their basic content is the same. For example, a typical credit report will include detailed information on the consumer's various credit lines (e.g., payment history, outstanding balances, credit limits, etc.); any reported collections, bankruptcies, or foreclosures; and a list of entities that have requested the reports for the evaluation of a new credit application. In some cases, credit reports will also contain information on a consumer's payment history on other recurring bills (e.g., utility, telecom, rent), although the coverage is limited.

[14]Consumer groups have advocated that this places too much burden on consumers, who must initiate and negotiate agreements with each of their different creditors. Instead, they have argued for a temporary moratorium on the reporting of all delinquencies—a provision that was included in the initial House bill but was ultimately dropped.

Due to the sensitive nature of the data they provide, the operations of credit bureaus are strictly limited to the purposes allowed under the Fair Credit Reporting Act (FCRA), which include the granting of credit, employment, or insurance. These same limitations apply to other, more specialized credit reporting agencies that focus on specific types of credit (e.g., payday loans, utility, and telecom payments, etc.) or on other kinds of data (e.g., residential and employment history, checking account use, etc.) that are used in various FCRA-covered transactions. Note that the data assembled by credit bureaus are either collected from public records or supplied voluntarily by banks and other creditors who are both willing and able to accept the obligations established by the FCRA. In other words, under the current legal and regulatory regime, credit reporting is entirely voluntary, as opposed to mandated—a reality that ultimately limits the types of information that the bureaus can collect.

Traditionally, potential creditors evaluated a consumer's creditworthiness by examining the numerous trade lines and other information contained in their credit file. While there were broad guidelines for this assessment—for example, no more than a certain number of missed payments over a certain period—this manual process was time-consuming, error-prone, and inherently subjective. This began to change with the emergence of statistical tools known as "credit scores," which were developed by William Fair and Earl Isaac in the 1950s and subsequently branded as "FICO Scores." Initially, credit scores were used almost exclusively by retailers. However, as banks' issuances of unsecured credit cards began to explode, so did their use of credit scores. The widespread adoption of credit scores became a reality in the early-1990s when Freddie Mac and Fannie Mae made them part of their underwriting requirements and automated underwriting systems (AUS), and in the process, extended their use to the mortgage market.

Research has shown that the use of credit scores and automated underwriting in the mortgage market has broadened access to credit, especially for Black, Latinx, and lower-income borrowers.[15] Nevertheless, traditional credit scores do not always capture the unique situations, capacities, and needs of particular segments of the population, for example, recent immigrants. Moreover, while roughly ninety percent of all consumers over eighteen years of age have credit files at one or more of the credit bureaus, some 26 million consumers do not have credit files and another 20 million have files that are either "too thin" or "too old" to receive a traditional credit score.[16] These 46 million so-called "credit invisibles"—who are disproportionately Black and Latinx—are often caught in a vicious circle where their *current* lack of credit makes it virtually impossible to qualify for credit *going forward*.

The desire to broaden consumers' access to mortgage credit has led many housing advocates to call for the use of "alternative" or "non-traditional" data to supplement the information currently available in consumers' credit reports. For example, the recently released "Contract With Black America", promoted by the Rapper Ice Cube in collaboration with several scholars and activists, calls for "Credit

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[15]Susan Wharton Gates, Vanessa Gail Perry, and Peter M. Zorn, "Automated Underwriting in Mortgage Lending: Good News for the Underserved?" Housing Policy Debate, Volume 13, Issue 2, 2002. https://www.researchgate.net/publication/239749502_Automated_underwriting_in_mortgage_lending_Good_news_for_the_underserved.
[16]Kenneth P. Brevoort, Philipp Grimm, and Michelle Kambara, *Data Point: Credit Invisibles*. Consumer Financial Protection Bureau, May 2015. http://files.consumerfinance.gov/f/201505_cfpb_datapoint-credit-invisibles.pdf.

services [to] be reformed to *mandate* consideration of individual consumer data on rent, utility, cellphone, and other like bill payments."[17] (emphasis added) However, from a fair lending perspective, it is important to recognize that not all kinds of alternative data are the same, nor should they be treated equally. In the era of big data, everything from information obtained from a consumer's banking accounts to data harvested from their social media or shopping patterns could be used to measure credit risk. While some kinds of alternative data are clearly related to the *individual* consumer's financial situation—and hence, their willingness and ability to handle additional debt—others have less to say about the individual consumer and more to say about the *average* financial situation of their social network and the socioeconomic group to which they belong.

IV. Assessing the Implications for Fair Housing

There are certain minimum requirements that any kind of alternative data must meet in order to be useful for scoring purposes.[18] For example, they must:

- Comply with all existing laws and regulations, including the Fair Housing Act, the Equal Credit Opportunity Act (ECOA), and the FCRA
- Have proven predictive power over various stages of the credit cycle
- Be available from public sources or voluntarily supplied by data furnishers who are willing to assume the legal and regulatory burdens imposed by existing laws
- Be transparent to the consumer and verifiable by the data furnisher

However, even assuming that a particular kind of data meets all of these criteria, there are other—and equally important tests—that should be met, namely, that use of the data should be considered "fair," "appropriate," and inherently "justified." These concepts not only relate to concerns over disparate impact. They also relate to broader ethical and moral judgments about the type of society we want to have.

According to some observers, credit scoring models are inherently value-laden algorithms[19] based on pre-existing biases[20] that are used in decisions that have profound social and economic implications for consumers and society. Virtually all scoring models predict certain aspects of future behavior (e.g., late payments on credit lines or other financial obligations) as a function of past behavior, and some behaviors matter more than others (e.g., late mortgage payments are weighted more heavily than a late credit card payment). Scoring models also imply value judgments about the legitimacy of the circumstances that may have led to a serious delinquency, for example, the inclusion of a forbearance flag, which is currently being debated by policymakers, or medical collections, which are no longer part of the FICO score. Other value judgments relate to how a model accounts for the consumer's "credit

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[17] https://contractwithBlackamerica.us/
[18] See Ann B. Schnare, "Alternative Credit Scores and the Mortgage Market: Opportunities and Limitations," December 2017. Available at www.progressivepolicy.org/publications/updated-credit-scoring-mortgage-market/.
[19] Martin, K. 2018. Ethical Implications and Accountability of Algorithms. Journal of Business Ethics.
[20] Friedman B., Nissenbaum H. (1996) Bias in Computer Systems ACM Transactions on Information Systems, 14 (3), pp. 330-347.

mix," which often implies that certain forms of credit are more acceptable than others, e.g., installment loans versus credit cards. But perhaps the ultimate judgment embedded in scoring models is the low or non-existent credit scores that are assigned to consumers who do not rely on traditional forms of credit, for example, credit cards, mortgages, or auto loans.

There is no doubt that scoring models perform well in terms of their predictive power, and as such, it is clear why they are used legitimately across many industries in the assessment of credit risk. Most models are based on years of data and millions of records; they have been subjected to the most sophisticated analytical techniques, as well as state-of-the-art tests of predictive accuracy, reliability, and generalizability across different sub-populations and periods. Indeed, as noted earlier, compared to manual underwriting, the use of credit scores and automated underwriting in the mortgage industry has been shown to increase the number of qualified borrowers, particularly for Black and Latinx homebuyers. Nevertheless, despite the proven track record of traditional scoring models, discussions about whether they should include (or be replaced by) new kinds of data raise important ethical and legal issues for those who develop and apply the scoring algorithms in business decisions. The use of such data also has implications for those who produce them.

To examine these issues, we have developed a five-factor "SCALE" framework that evaluates alternative data sources through both a fair lending and ethical lens. The framework reflects a body of prior research on business ethics, privacy, and credit scoring. Note that in making our assessments, *we assume that the data meets the basic standards of "predictive power" that should apply to any scoring model*. Given this assumption, we use the SCALE framework to assess how various types of alternative data score on each of these criteria and why—or why not—they should be used in credit decisions.

The SCALE Framework

The SCALE framework evaluates data from the categories in question based on five different criteria:

Societal Values, i.e., Is the use of the data consistent with established social and ethical norms?

Contextual Integrity, i.e., Does the use of the data make sense in the context of mortgage credit?

Accuracy, i.e., Does the data accurately reflect the household's situation?

Legality, i.e., Does the use of the data have a disparate impact on protected classes?

Expanded Opportunity, i.e., Does the use of the data expand access to credit by increasing the number of qualified borrowers and/or by reducing borrowing costs while maintaining or improving the accuracy of credit decisions?

Failure to meet any of these criteria does not necessarily mean that the data should not be used, nor does it imply that policymakers must intervene to prohibit or discourage their use. Rather, viewing alternative data sets through this multifaceted lens is designed to highlight their potential strengths and weaknesses, and hopefully lead to better decisions on the part of credit providers, regulators, and Congress.

Societal Values: The first criteria—societal values—measures the extent to which the use of a particular variable conforms to broad social and ethical norms. As noted by Kirsten Martin, who has written extensively on the ethics of big data algorithms, ethical norms and social responsibility considerations should govern the inclusion of any variable in a scoring model.[21] In particular, she argues that model developers should consider the variable's use in similar applications in other industries, the larger social and societal context, and relevant historical factors.

Privacy is a core value in U.S. society. Not surprisingly, the privacy of individual- and household-level data has been a subject of heated debate within the media, and among consumers and policymakers. The Fair Credit Reporting Act of 1970, the Financial Monetization Act of 1999, and the USA Freedom Act of 2015 were enacted to ensure transparency in the collection and retention of consumer data, require privacy disclosures to consumers, and restrict government access to these data. However, as a result of increasing digitization and the advent of "big data", there has been increasing pressure on companies and the government to address privacy concerns posed by technological innovations that fall outside of the scope of these laws.

For example, GPS location data is now widely used by businesses to estimate consumer preferences for targeted marketing.[22] However, in the context of credit scoring, GPS location could lead to very precise inferences about a person's personal, demographic, social, and economic characteristics, as well as their consumption practices and lifestyle. Research suggests that consumers consider the use of location data as a violation of their privacy, which could ultimately harm their trust in a company and the equity of its brand. Thus, the use of GPS location in scoring models would likely be controversial due to its inconsistency with extant legal and ethical paradigms focused on privacy protections.

The use of certain types of banking data—for example, the incidence of negative account balances or transaction irregularities—could also prove to be problematic. Recently introduced credit scoring models incorporate data on consumers who maintain reserves in bank accounts over time. These data are proxies for household income, which heretofore has not been included in credit scores. Similarly, a recently proposed credit scoring innovation would include a measure of a consumer's ability to continue making payments on debt during times of economic stress.[23] By definition, whether or not a person can save beyond their obligations would place lower-income consumers at a distinct and unfair disadvantage.

The credit scoring industry is already taking action to correct against this kind of implicit income bias. Based on evidence of the disproportionate impact of late medical payments on credit ratings, in 2017 the three major credit bureaus agreed to standardize medical debt reporting practices and reduce or

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[21] For example, see Martin, K. 2019. Designing Ethical Algorithms. MISQ Executive. June 2019; Martin, K. 2018. Ethical Implications and Accountability of Algorithms. Journal of Business Ethics, 160, 835–850
[22] Martin, K and Helen Nissenbaum. 2020. What is it About Location? Berkeley Technology Law Journal, 35(1).
[23] Richard K. Green and Ashlyn A. Nelson (2020), "Credit Scoring Has Both Directly and Indirectly Affected the Ability of People of Color to Access Low-Cost Home Loans," in the 2020 State of Homeownership in Black America Report, V.G. Perry, National Association of Real Estate Brokers, https://www.nareb.com/shiba.

in some cases eliminate the weight placed on these factors in credit scoring models.[24] The bureaus adopted these changes in response to pressure from consumer advocates and state regulators to help alleviate the negative financial consequences of inadequate access to healthcare and/or expensive health insurance coverage, especially for consumers with lower or moderate incomes. Thus, predictiveness aside, given the dominant socio-cultural paradigm concerning income inequality and especially those whose circumstances may have resulted from systemic racism and cumulative disadvantage, including data that disproportionately affect those with lower incomes in credit scoring may be questionable.

Contextual Integrity: The second criteria—contextual integrity—relates to whether the use of these data makes sense in the granting of a mortgage or other forms of credit. According to the theory of Contextual Integrity (CI), the appropriateness of any data, especially private information about individuals, depends on whether it conforms with contextual norms.[25] In other words, regardless of its predictive potential, is the factor relevant to the domain in which it is used? For example, one might find a significant statistical relationship between college GPA and the likelihood of timely loan payments, but this relationship may be specious, spurious, and/or irrelevant to the context in question.

There are numerous examples of how seemingly unrelated social media data—for example, membership in a club—are being evaluated for potential predictors of credit risk.[26] Likewise, sources such as smartphone records, including location, call, and text information, are also being investigated for potential inclusion in credit scoring models.[27] In the U.S. and other countries, innovations in credit scoring involving social network and social media data have the potential to be used to predict future repayment behavior.[28] Despite their potential for predicting credit behavior, these variables may not meet the CI criterion because they have no conceptual or practical connection to payment decisions. It would be unreasonable to argue, for example, that a person made late payments because of certain social media connections.

[24] Michelle Andrews, "Credit Agencies to Ease Up on Medical Debt Reporting," NPR, July 11, 2017, https://www.npr.org/sections/health-shots/2017/07/11/536501809/credit-agencies-to-ease-up-on-medical-debt-reporting
[25] Helen Nissenbaum, Privacy in Context: Technology, Policy, And the Integrity of Social Life (2010); Martin, K and Helen Nissenbaum. 2020. What is it about Location? Berkeley Technology Law Journal, 35(1).
[26] Hardekopf, Bill (2015), "Your Social Media Posts May Soon Affect Your Credit Score," Fortune, October 23, https://www.forbes.com/sites/moneybuilder/2015/10/23/your-social-media-posts-may-soon-affect-your-credit-score-2/#22e35f4bf0e4
[27] Martin, Emmie (2017), "The most important thing you don't know about your iPhone bill," CNBC Money, https://www.cnbc.com/2017/09/08/your-wireless-carrier-can-affect-your-credit-score.html; Kharif, Olga (2016), "No Credit History? No Problem. Lenders Are Looking at Your Phone Data," Bloomberg Markets, November 25, https://www.bloomberg.com/news/articles/2016-11-25/no-credit-history-no-problem-lenders-now-peering-at-phone-data
[28] Wei, Yanhao, Pinar Yildirim, Christophe Van den Bulte, and Chrysanthos Dellarocas (2016), "Credit Scoring with Social Network Data," Marketing Science, 35(2):234-258; National Credit Educational Services (2016), "How Social Media Affects Your Credit Score and Financing Opportunities," http://ncesnow.org/how-social-media-affects-your-credit-score-and-financing-opportunities/

A recent study examined the use of a consumer's digital "footprint" (i.e., website visits) to predict loan defaults.[29] The authors found evidence that digital footprint data can not only enhance the predictive accuracy of traditional credit scores; they could also be a viable alternative to the credit bureau data that is currently used in scoring models. However, in considering the potential use of such data, it would be important to understand the extent to which web traffic relates to payment behavior to ensure that these data are truly relevant to the context of credit scoring. For example, is a consumer who visits Astrology.com daily any more or less creditworthy than one who consistently logs in to nytimes.com?

Accuracy: The third criteria—accuracy—relates to the extent to which the data are reliable, error-free, and widely available under varying macroeconomic conditions and across all major demographic, economic, and social groups. For example, given the lower homeownership rates of Black and Latinx households, rent payments are a particularly important alternative data source for these two groups. However, rent data are more likely to be collected from large-scale property management companies, and less likely to be collected from independent or smaller landlords. This may be problematic for Black and Latinx renters, who are more likely to live in smaller properties.[30] Thus, while including rental payments may expand opportunities for consumers who do not use traditional forms of credit, these data may have systematic gaps in their availability and coverage for minorities.

Another aspect of the data's accuracy relates to its susceptibility to manipulation. For example, a scoring model may find that certain aspects of consumer behavior are statistically related to credit risk, for example, the websites that they visit or the time of day they apply for a loan. However, while the model may be effective in its initial stages, nothing would prevent consumers from simply changing their behavior when they learn how it is affecting their credit scores—thereby undermining the model's predictive power. In the end, the use of social media data is relatively new and could easily change over time, making its long-term predictive power largely untested.

Legality: The fourth—and critically important—criterion is whether the credit scoring factor has a negative and disparate impact on protected classes. Race, ethnicity, and national origin are among the variables explicitly prohibited by law from inclusion in scoring models.[31] In addition, the Fair Housing Act embodies a disparate impact standard designed to "permit plaintiffs to counteract unconscious prejudices and disguised animus that escape easy classification as disparate treatment." This disparate impact standard allows consumers to hold banks liable for underwriting and pricing discrimination by identifying significant outcome disparities that have no necessary business justification. Consumers

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[29] "On the Rise of the FinTechs—Credit Scoring using Digital Footprints", Tobias Berg, Valentin Burg, Ana Gombović, Manju Puri, Federal Deposit Insurance Corporation Working Paper Series, National Bureau of Economic Research September 2018, FDIC CFR WP 2018-04, https://www.fdic.gov/bank/analytical/cfr/2018/wp2018/cfr-wp2018-04.pdf
[30] According to the Urban Institute, Blacks and Latinxs rent 44 percent of all units in two-to-four-unit buildings, compared to only 35 percent of the units in buildings with 50 or more units. See https://www.urban.org/urban-wire/owners-and-renters-62-million-units-small-buildings-are-particularly-vulnerable-during-pandemic
[31] These include the Equal Credit Opportunity Act, which was implemented by the Board of Governors of the Federal Reserve System's Regulation B in 1974, and the 1968 Fair Housing Act.

are not required to prove the bank *intended* to disadvantage Blacks, merely that the bank's practices caused such effect *without sufficient business justification*.

It is easy to see how the use of certain credit proxies and non-financial personal data could run afoul of these criteria. For example, GPS data could be troublesome from a legal perspective because, due to longstanding practices of redlining and discrimination, location has a strong correlation with race, ethnicity, and socioeconomic status. Thus, not only could the use of such data be inconsistent with socio-cultural norms; it could also violate anti-discrimination laws. Likewise, detailed expenditure data or the consumer's digital footprint could also be used as a proxy for gender. While this would again represent a potential violation of fair housing laws, the use of gender is not explicitly prohibited in other sectors, for example, the provision of auto insurance.[32]

Expanded opportunity: Finally, the fifth criterion relates to the extent to which inclusion of a variable would significantly expand the community's access to credit—for example, by reducing the un-scoreable population—while maintaining or enhancing the model's predictive power. Significant improvements in credit access could easily outweigh other social or contextual concerns that may be related to the data's use. For example, while industry experts have long argued that the addition of utility payment data would increase the number of "scoreable" consumers, some community groups continue to oppose their use since they believe it would disadvantage low-income consumers. Similar arguments have been made about the inclusion of banking data. For example, the Petal credit card model uses data on inflows and outflows from a consumer's bank accounts to measure payment consistency and volatility.[33] Petal claims that, when combined with a traditional credit score, its cashflow underwriting approach "expands credit access for new-to-credit consumers." However, in these and other cases, the real questions become whether such data improve access for consumers who are currently underserved by existing models, whether these models can measure credit risk effectively, and how these models perform relative to the *status quo* or other alternatives.

Expanded access could also be achieved by significantly reducing borrowing costs, which would make homeownership more affordable. For example, the inclusion of certain kinds of data could significantly enhance the predictive power of the model, which in turn should lead to lower mortgage rates by reducing the expected rate of default. (Alternatively, increases in the model's predictive power could enable the lender to serve a greater segment of the population at the same projected level of risk.) The use of other kinds of data could conceivably lower costs by increasing the efficiency of the mortgage underwriting process. However, while more affordable mortgages should lead to higher homeownership rates for the population at large, different subgroups could well be affected

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[32] Only seven states currently prohibit the use of gender as a factor in auto insurance pricing, although women continue to pay higher rates than men in 25 U.S. states. See https://www.nytimes.com/2019/01/18/your-money/car-insurance-gender-california.html; https://www.washingtonpost.com/transportation/2019/02/11/gender-can-no-longer-be-used-calculate-auto-insurance-rates-california-other-states; and Women Now Pay More Than Men for Car Insurance in 25 States (Even Though Men Are Riskier Drivers)
[33] https://finlab.finhealthnetwork.org/companies/petal/.

differently. If this occurs, policymakers would be faced with a difficult trade-off between the benefits that would accrue to the majority of the population and the potential harm it might cause to others.

V. The Use of Alternative Data to Measure Mortgage Risk

In many respects, the different types of alternative data that have been proposed to measure credit creditworthiness in the mortgage market—credit proxies, banking data, and non-financial personal data—represent a continuum in terms of the policy issues that they raise. On the one hand, there is a relatively strong justification for incorporating credit proxies into the evaluation of credit risk, an option that is increasingly feasible in the digital age. On the other hand, the use of a consumer's digital footprint for decision-making purposes is far more controversial since, among other things, it could have a disparate impact on protected groups.[34] Issues associated with the use of banking data fall somewhere in between these two extremes. While banking data has always been part of the mortgage underwriting process—for example, most lenders require information on the borrower's checking and savings account balances—the potential use of granular expenditure data extracted from these accounts raises the same basic issues as the use of non-financial personal data.

Credit Proxies

The first type of alternative data—which we have labeled "credit proxies—attempt to measure a consumer's so-called creditworthiness" by capturing their performance on recurring financial obligations that are typically not reported to credit bureaus. These could include the consumer's monthly rent, utility, and telecom payments. They could also include insurance payments, regular remittances to family members living abroad, and performance on payday loans. While not strictly forms of credit, including a consumer's track record for meeting at least some of these obligations is certainly consistent with social norms and makes sense in the context of mortgage lending.

The use of credit proxies has also proven to be an effective way of expanding access to credit, especially for consumers with thin or non-existent credit files.[35] For example, one study estimated that the inclusion of telecom and utility data in traditional scoring models would increase acceptance rates by about ten percent for the overall population, and by more than twenty percent for Blacks, Latinxs, and consumers making less than $20,000 a year.[36] Other studies have found that the inclusion of rental payments would also have a significant and positive impact on consumers' access to credit.[37]

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[34] For a seminal analysis of these issues, see Solon Barocas and Andrew D. Selbst, "Big Data's Disparate Impact," California Law Review, 2916. http://dx.doi.org/10.15779/Z38BG31

[35] For a review of these studies, see Rachel Schneider and Arjan Schutte. "The Predictive Value of Alternative Credit Scores," Center for Financial Services Innovation Report, November 2007. https://cfsinnovation.org/research/the-predictive-value-of-alternative-credit-scores/

[36] Michael A. Turner, Alyssa Stewart Lee, Ann B. Schnare, Robin Varghese, and Patrick D. Walker, "Give Credit Where Credit Is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data," Policy and Economic Research Council and the Brookings Institution Urban Markets Initiative Report. 2006. https://www.brookings.edu/research/give-credit-where-credit-is-due-increasing-access-to-affordable-mainstream-credit-using-alternative-data/

[37] See Experian, "Credit for Renting: The Impact of Positive Rent Reporting on Subsidized Housing Residents," Experian Rent Bureau White Paper. 2014. https://www.experian.com/content/dam/marketing/na/assets/im/rentbureau/white-papers/experian-rentbureau-credit-for-rent-analysis2.pdf; Scott M. Stringer, New York City Comptroller, "Making Rent Count: How NYC Tenants Can Lift Credit Scores and Save Money,"

While the inclusion of rent or utility payments was generally found to have a positive impact on consumers' access to credit, the opposite was true for remittance payments.[38]

But despite the demonstrated value of such data—particularly rent, utility, and telecom payments—and their obvious relevance to the measurement of "creditworthiness", they are rarely reported to credit bureaus, and when they are, they are typically restricted to collections. According to FICO, only about two and one-half percent of credit files have utility or telecom data that contain both positive and negative payment history, while less than one percent of files have such information on rental payments.[39] While each of the credit bureaus has proprietary databases that include at least some of these kinds of data—which when used for credit decisions are covered by the Fair Credit Reporting Act (FCRA)—they are not included in the consumer's standard credit report. Instead, the data are marketed separately and sometimes used to create "alternative" credit scores for consumers with little, if any credit history.

One such alternative database is owned by the National Consumer Telecom & Utilities Exchange (NCTUE®), which is operated solely for the benefit of its members, including cable companies, telecoms, and energy utilities.[40] According to its marketing materials, NCTUE now has payment data on roughly 225 million consumers with over 460 million reported trade lines. However, while it is difficult to estimate coverage rates, they appear to be relatively high for cable and cell phone providers, but relatively low for "traditional" public utilities such as local telephone companies and energy providers. This most likely reflects the voluntary nature of credit reporting. While cable and cell phone providers must actively compete for customers—and obviously benefit from information on a consumer's performance on similar accounts—"traditional" public utilities are required to serve their district, which could make them less willing to assume the various responsibilities imposed by FCRA.

Legislation introduced in both the House and the Senate in 2018 has attempted to encourage the voluntary reporting of utility, telecom, and rental data by amending the FCRA to clarify federal law concerning the reporting of such information.[41] However, while a step in the right direction, some have argued that the bills would not be enough to encourage widespread reporting. For example, neither bill would explicitly pre-empt existing state or local laws that prevent the sharing of such data, nor would they make reporting mandatory. As a result, according to Ballard Spahr, it is "unlikely that

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October 2017. https://newsroom.transunion.com/transunion-analysis-finds-reporting-of-rental-payments-could-benefit-renters-in-just-one-month.
[38] See CFPB, "Report on the Use of Remittance Histories in Credit Scoring", 2014. http://files.consumerfinance.gov/f/201407_cfpb_report_remittance-history-and-creditscoring.pdf
[39] FICO, "Truth Squad: Can Scoring Rental Data Vastly Improve Credit Access?" May 10, 2017. https://www.fico.com/blogs/risk-compliance/truth-squad-can-scoring-rental-data-vastly-improve-credit-access/
[40] See Schnare, op. cit., 2019, p. 24.
[41] The latest version of the bill—The Credit Access and Inclusion Act of 2018 (S. 3040)—was introduced in June 2018 and is similar to one that was passed by the House in 2017 (H.R. 435). The Senate bill would amend the FCRA to "allow a person or the Secretary of Housing and Urban Development [to furnish] information related to the performance of a consumer in making payments … under a lease agreement with respect to a dwelling or … pursuant to a contract for a utility or telecommunications service." See https://www.govtrack.us/congress/bills/115/s3040

individual landlords and smaller utility companies would find that the benefits of furnishing accurate information to consumer reporting agencies outweigh the costs and risks associated with FCRA."[42]

The highly dispersed ownership structure of rental housing also makes the collection of rental data extremely challenging. While a few large landlords currently report to credit bureaus, most rental housing is owned by individuals or smaller providers who have little, if any incentive to share their data—and assume the responsibilities that such data sharing would bring. A number of web applications have attempted to fill the gap by serving as intermediaries between consumers, their landlords, and the credit bureaus; however, the use of such apps has been relatively limited to date. Thus, while the proposed legislation may help to remove reporting barriers for HUD-assisted housing—which is specifically cited in the legislation and accounts for about 10 percent of all rental units[43]—its potential impact on the private rental market remains unclear.

As noted earlier, some community groups have argued against the reporting of utility data to credit bureaus, believing that it would disadvantage low-income households. However, they fail to recognize that delinquencies are reported whenever an account goes to collection, and that the failure to report positive payment histories only serves to penalize consumers who consistently pay their bills on time. This is especially relevant in light of recent "suppression and deletion" proposals to prohibit the reporting of late payments during the COVID-19 pandemic. However, others have argued that utility and telecom companies should voluntarily report positive payment data to offset the negative effects of a relatively short-term span of late payments on a consumer's credit history.[44] Indeed, as demonstrated by the studies cited above, the net benefits that would arise from a more systematic reporting of telephone, utility, and rental payments would help more consumers than it would hurt, with the largest benefits accruing to Blacks, people of Latinx descent, recent immigrants, and lower-income consumers who are less likely to have a "scorable" credit report.

Aggregated Banking Data

Another type of "alternative" data would draw on information obtained from the consumer's checking and savings accounts to augment or even replace traditional credit reports. The use of such data would enable one to construct broad indicators of a consumer's financial well-being, including average balances at the end of each month and average inflows and outflows. It would also enable one to evaluate the consumer's individual financial transactions, including their specific sources and uses of funds. While banking data has long been used as an input to the underwriting process—for example, mortgage lenders typically require copies of the consumer's recent bank statements to verify the funds required for their down payment—there is no central repository or clearinghouse for banking

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[42] Taylor R. Steinbacher, "Proposed Credit Reporting Changes Pass House with Mixed Reviews," *Consumer Finance Monitor*, Ballard Spahr, August 2018. https://www.consumerfinancemonitor.com/tag/credit-access-and-inclusion-act-of-2017/

[43] According to HUD, roughly 4.65 million households receive some form of HUD assistance, compared to a total number of occupied rental units of 43 million. https://www.huduser.gov/portal/datasets/assthsg.html and https://www.statista.com/statistics/187577/housing-units-occupied-by-renter-in-the-us-since-1975/

[44] For example, see Michael Turner, "Credit Reporting and COVID-19 — It's Not a Sophie's Choice," Inside Sources, August 07, 2020, https://www.insidesources.com/credit-reporting-and-covid-19-its-not-a-sophies-choice/

data, making it cumbersome to use. However, the digitalization of banking data and the emergence of large-scale financial data aggregators has greatly expanded its potential uses, including for credit scoring

Savings, checking and money market account data would undoubtedly provide a powerful predictor of a consumer's ability to manage their financial obligations. For example, combined with information on a consumer's outstanding debts, information on their average discretionary income at the end of the month would provide a clearer indication of how much additional credit they could support, which in underwriting terms is known as the consumer's "capacity" to handle the loan. The data could also be used to document the consumer's history of paying ongoing bills such as utility and telecom payments—in other words, it could be used to construct so-called "credit proxies". However, until recently, general privacy concerns—as well as the inherent value of this information—has made banks unable or unwilling to share their data. While there were a few proprietary data sources that provided limited information on a consumer's use of their checking accounts—for example, the frequency of overdrafts—comprehensive information on a consumer's various banking accounts simply did not exist.

This is changing rapidly with the emergence of Fintechs that offer a range of mobile financial services to consumers who are willing to give them access to their financial data. Rather than collect the data themselves—which would be a cumbersome, costly, and time-consuming process—Fintechs typically rely on third-party data aggregators to supply them with the necessary data. These financial aggregation companies partner with multiple financial institutions to access, compile and store their customer data; they then sell the requisite data to Fintech companies to support a variety of services, including personal finance and investment applications.[45] The services facilitated by these financial data aggregators have undoubtedly provided enormous benefits to consumers, as illustrated by their rapid adoption. However, as discussed in a later section, they have also led to concerns about transparency, privacy, and equitable access.

While still in its infancy, the application of aggregate banking data is steadily making inroads into the mortgage and credit scoring industries. For example, in 2017 Fannie Mae announced a pilot program, known as Single Source Verification (SSV), which allows lenders to validate a borrower's income, assets, and employment with reports provided by FNMA-approved data aggregators. In the following year, FICO partnered with Experian and Finicity (a data aggregator) to introduce a new credit score—the UltraFICO™ Score—that augments traditional credit reporting data with transactional information drawn from a consumer's banking account, including the age of the account, the frequency of activity, and evidence of savings (e.g., the average ratio of inflows to outflows).[46] And in early 2019, Experian launched a product known as Experian Boost that allows consumers to voluntarily augment their FICO score with banking data capturing their cell phone, utility, and/or streaming services payments such as

[45]Michael Deleon, "A buyer's guide to data aggregation," February 19, 2019, https://tearsheet.co/data/a-buyers-guide-for-data-aggregation/
[46] See https://www.fico.com/en/newsroom/experian-fico-and-finicity-launch-new-ultrafico-credit-score.

Netflix or Hulu.[47] According to Experian, such data has led to an increased credit score for 75 percent of consumers with scores below 680.[48]

A 2019 report by FinRegLab, an independent non-profit research organization, confirmed the potential efficacy of banking cash-flow data in the evaluation of consumer credit risk.[49] The study was based on data from consumers' deposit and pre-paid card accounts that were obtained from six non-bank financial services providers. Among other things, it found that "that cash-flow variables and scores can provide meaningful predictive power among populations and products similar to those studied where traditional credit history is not available or reliable."[50] The study also found that "cash-flow data frequently improved the ability to predict credit risk among borrowers that are scored by traditional systems as presenting a similar risk of default" and that such data "appeared to provide independent predictive value across all groups rather than acting as proxies for demographic groups." In other words, the use of such data could not only help to underwrite consumers without traditional credit scores. It could also improve the predictive power of traditional credit scores across various subsets of the population.

In considering these and other potential uses of banking data, it is important to recognize that these applications rely on the consumer's express consent to use their banking data for a specific purpose. In other words, unlike traditional credit data, it is up to the consumer—and not the entity receiving the funds—to determine what will be and will not be reported and used. And unlike traditional bureau data, these so-called "consumer permission data" are not routinely reported to any entity. The use of banking data also depends on the willingness of the consumer's bank to give third-party data aggregators access to their files, who in turn supply the data that is currently fueling the FinTech industry. According to industry accounts, financial data aggregators now have access to about 95 percent of all bank accounts[51] and, while not widely recognized, archive these data. Despite its potential promise, use of banking data for credit scoring has been relatively limited to date. Indeed, given the multitude of scores that are in the market today, there is no real assurance that a potential creditor will rely on a score that incorporates these kinds of data even if the consumer has supplied them. However, this could certainly change over time if the use of such data becomes more common.

In response to broad concerns over the need to promote financial inclusion, the OCC recently announced an initiative known as Project REACh (Roundtable for Economic Access and Change). As part of the initiative, which includes leaders from the banking, advocacy, and non-profit sectors, the OCC will attempt to promote inclusion for credit invisibles. According to the OCC:

> *"Nearly 50 million Americans—disproportionately including poor and minority Americans—lack a credit score and cannot obtain mortgages, credit cards, or other lending products. Yet many people in this segment of society pay rent, utilities, and other recurring financial*

[47] https://www.forbes.com/advisor/credit-cards/experian-boost-review/
[48] https://www.experian.com/blogs/ask-experian/does-paying-utility-bills-help-your-credit-score/
[49] FinRegLab, "The Use of Cash-Flow Data in Underwriting Credit: Empirical Research Findings," July 2019
[50] FinRegLab, "Fact Sheet: Cash-Flow Data in Credit Underwriting."
[51] Michael Deleon, op. cit.

> *obligations. Project REACh intends to work with technology partners to synthesize a credit score from alternative data, and the OCC could validate such a score for banks to use."*[52]

While the initiative is still in its formative stages, the OCC's express approval of an alternative score (or scores) for potential use by banks would go a long way to bringing the promise of such data to reality.

Despite these potential benefits, some observers have argued that opening banking data to a broader array of uses, including credit scoring, poses a threat to consumer privacy and the security of their data. According to Sheila Bair, a former commissioner of the Federal Deposit Insurance Corporation (FDIC):

> *"If the credit bureaus want to start routinely accessing our bank accounts, they should be subject to bank-like regulation. I've been a critic of big U.S. banks in certain areas, but I do believe their information security systems are substantially superior to the credit bureaus and that is due, in large part, to their regulated status."*[53]

A representative of the Center for Financial Services Innovation agreed with this assessment, noting that: "We're getting to where we have larger sets of data housed in institutions that the entire financial services industry rests on, and they don't have the same regulation and security protocols a regulated bank would have,"[54] adding that the CFPB focuses more on consumer protection and less on the safeguards that need to be put in place to guard against a potential breach.

In addition to these security and privacy concerns, the use of certain types of banking data could conceivably raise fair lending concerns. For example, while checking data could conceivably be used to generate credit proxies such as rent, utility, and telephone payments—which would be a positive development—more detailed use of the consumer's checking data—for example, where and how they spend their money—could have a disparate impact on protected classes since expenditure patterns are often proxies for the consumer's race, ethnicity, or sex. In terms of the SCALE index, the use of detailed expenditure data could also violate general social and contextual norms. Because of these concerns, policymakers might wish to limit the use of banking data to broad measures that reflect the consumer's overall financial well-being—for example, average balances, inflows, and outflows—and make the application of more granular banking data subject to prior approval by the applicable regulatory body.

Non-Financial Personal Data

The third—and potentially most controversial—kind of "alternative" data includes a wide variety of non-financial personal data that can be harvested from a consumer's digital footprint (e.g., social

[52] https://www.occ.gov/topics/consumers-and-communities/minority-outreach/project-reach-fact-sheet.pdf
[53] Penny Crosman, "New UltraFICO score stokes concerns about data privacy," *American Banker*, October 25, 2018. https://www.americanbanker.com/news/new-ultrafico-score-stokes-concerns-about-data-privacy
[54] Ibid.

networking, on-line purchases, web searches, etc.), their cell phone use (e.g., type of device, time and volume of calls, etc.) or even through the administration of so-called "psychometric" questionnaires.[55] Some of these data have been shown to be related to credit risk.[56] For example, studies have found that iOS users are generally better credit risks than Android users, as are consumers who applied for credit late at night as opposed to at other times of the day. Likewise, consumers with email addresses that use their names appear to be less risky than consumers whose email addresses are obscure. These types of non-traditional data are now being considered as alternatives to traditional credit reports in emerging markets where credit reporting is limited or non-existent. However, in countries with robust credit reporting regimes, the use of such data has largely been confined to marketing and other related purposes.

This is beginning to change with apps such as www.lenddo.com and www.eflglobal.com, which are using certain kinds of non-financial personal data in FCRA-covered transactions. Whether or not the use of such data will succeed in the long run is difficult to tell and will ultimately depend on their demonstrated value to lenders, consumers, and the broader society. However, whenever non-financial data are used for credit decisions, both the user and data provider will be subject to the same legal and regulatory requirements that govern the distribution and use of credit reports, including the FCRA, the ECOA, the GBLA, the Fair Housing Act, and other applicable laws.

It is not always clear that large-scale data aggregators understand the issues involved or the legal requirements associated with the use of their data. For example, Facebook's use of its data to block housing advertisements to consumers living in certain zip codes or with certain interests (e.g., support dogs, Latin America, child care providers, etc.) has been cited by HUD as a violation of fair lending laws.[57] Facebook also settled a series of lawsuits based on these allegations filed by a group of fair housing organizations in 2019, agreeing to changes to the firm's prior policies that permitted advertisers to target housing, employment, and credit ads to Facebook users based on race, color, gender, age, national origin, family status, and disability.[58] According to a ProPublica report, while Facebook's new advertising algorithms do not include prohibited characteristics, such as gender or age, they continue to result in bias because they include factors that correlate with these

[55] Entrepreneurial Finance Lab, "Alternative Credit Scoring in Emerging Markets," January 7, 2015. https://www.eflglobal.com/alternative-credit-scoring-emerging-markets.
[56] For a detailed discussion, see Tobias Berg, Valentin Burg, Ana Gombović, and Manju Puri, "On the Rise of the FinTechs—Credit Scoring using Digital Footprints", FDIC Center for Financial Research, FDIC CFR WP 2018-04, July 2018. https://www.fdic.gov/bank/analytical/cfr/2018/wp2018/cfr-wp2018-04.pdf.
[57] Ben Lane. "HUD accuses Facebook of enabling housing discrimination." *Housing Wire*, August 17, 2018. https://www.housingwire.com/articles/46505-hud-accuses-facebook-of-enabling-housing-discrimination?eid=324620953&bid=2211333.
[58] National Fair Housing Alliance, "Civil Rights Advocates Settle Lawsuit with Facebook: Transforms Facebook's Platform Impacting Millions of Users," March 19, 2019, https://nationalfairhousing.org/facebook-settlement/.

characteristics. These cases illustrate the dangers inherent in proceeding into largely uncharted territory with inadequate knowledge or regulatory guidance on the applicable rules of the road.[59]

More generally, even if certain data prove to be highly predictive, its use may violate many SCALE criteria, which could ultimately limit or prevent its actual use in FCRA-covered transactions. The question becomes not only "Can we do it?" but also, "Should we?" Much like the issue of racial or geographic profiling, the issue of whether such data are predictive is ultimately less important than other overriding economic, social, or ethical concerns. For example, the use of certain kinds of data—such as a consumer's Facebook friends or shopping patterns—could have a disparate impact on Blacks, Latinx, and other protected classes even if such prohibited factors are not explicit inputs to the decision model.[60] In such instances, the burden falls on the creditor to demonstrate that there is a legitimate business justification. Indeed, the persistence of racial, ethnic, and economic segregation and disparities has led some detractors to argue that the use of social networking data or shopping patterns for decision purposes will only serve to foster racial and ethnic stereotypes and perpetuate discrimination and income inequality.

It may also be more difficult to verify the accuracy of certain kinds of non-financial personal data or to explain the results to the consumer if the use of such data leads to a credit denial—requirements that are necessary to be FCRA-compliant. For example, frequent bar attendance may well be a statistical predictor of loan performance, but what if the consumer claims that she never drinks? And how does a potential creditor tell a consumer that she was turned down for a loan because her educational background, cell phone use, or Facebook interests are generally associated with a higher credit risk? Any statistical scoring model is based on the *average* performance of consumers with similar characteristics. But it is one thing to base a credit decision on financial considerations—for example, a consumer's demonstrated handling of credit—and quite another to base it on the average behavior of groups with similar interests, habits, or "likes." This is the same basic problem, on a macro scale, that led to the regulation of credit bureaus to begin with, namely, using data such as reputation, ethnicity, or gender to assess a consumer's creditworthiness.

Because of such concerns, some creditors may simply be unwilling to use certain types of personal data to protect their corporate image and their resulting customer base, even if that data is both predictive and readily verifiable. For example, as one study points out, while consumers' ability to make good on their financial obligations is undoubtedly affected by local economic conditions, the geographic region is rarely, if ever part of the credit scoring models most lenders use.[61] According to the authors, "this is most likely due to a concern that the inclusion of such factors could lead to serious public relations problems … even though there is no legal restriction on the use of such geographic

[59] Ava Kofman and Ariana Tobin, "Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement," Dec. 13, 2019, https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement.
[60] For a detailed discussion, see Solon Barocas and Andrew Selbst, op. cit.
[61] Raphael Bostic and Paul Calem, "Privacy Restrictions and the Use of Data at Credit Registries", in *Credit Reporting Systems and the International Economy*, edited by Margaret J. Miller, Boston: MIT Press, 2003, pp. 311-334

factors in making credit decisions."[62] Indeed, concerns over their corporate image may help to explain why Facebook's efforts to develop partnerships with several of the nation's largest banks have thus far been unsuccessful. It is one thing to assess an individual's creditworthiness based on their past performance on various kinds of financial obligations. It is quite another thing to make a credit decision based on the average performance of other consumers with similar personal characteristics or interests. Not only does this violate the notion of individual accountability; it also raises the specter of "guilt by association."

Certain kinds of personal data may also be susceptible to manipulation by the consumer, which will ultimately limit its predictive power over time. For example, a consumer's LinkedIn page may well provide information from a consumer's resume (e.g., educational attainment, job title, etc.) that might initially boost the predictive power of traditional credit scores. But once its use becomes common knowledge, what would stop consumers from altering the information they provide to the website? Likewise, data on the consumer's cell phone use or shopping patterns may in the short term be predictive, but once consumers understand how their data is being used, what is to stop them from changing their habits over time? More generally, in order to be useful for credit decisions, the data must be accurate, retain its predictive power over various stages of the credit cycle, and be resistant to manipulation.

Finally, the voluntary nature of credit reporting may also serve as a barrier to the development and use of certain types of non-financial personal data. FCRA imposes significant requirements on the data furnisher to verify and ensure the accuracy of their data, and to make its use transparent to the consumer. For some large-scale data aggregators, this might be a price they are simply unwilling to pay, especially if the use of their data for FCRA-related activities is not an integral part of their overall business strategy. While this may change over time, a general reluctance to take on the full responsibilities of an FCRA-compliant data provider could prove to be a near-term barrier for the use of certain kinds of personal data for credit and other covered purposes.

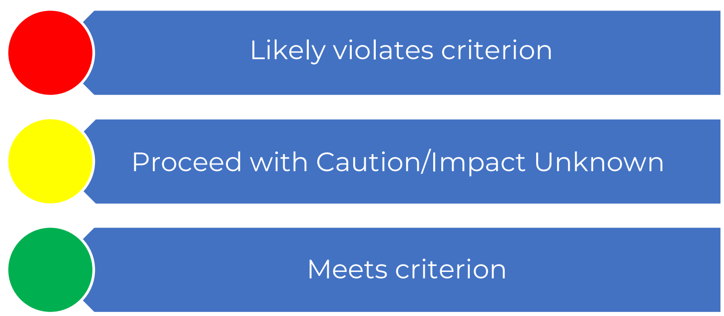
Evaluation of Alternative Data Using the SCALE Framework

Figure IV summarizes our assessment of the various kinds of alternative data based on the criteria embedded in the SCALE framework. At the outset, it is important to recognize that many variables *currently* used in the construction of credit scores would not score high on every SCALE criterion. For example, Black and Latinx consumers are more likely to have student debt due to systemic differences in household wealth and homeownership rates. As a result, student debt will likely have a disproportionate impact on younger Black consumers since such debt will inevitably reduce their ability to meet their other financial obligations. Indeed, the same might be said for credit cards since minorities are less likely to have family members who are able and willing to bail them out in the event of a financial crisis. Nevertheless, since performance on these kinds of financial obligations scores high on other SCALE criteria—including context, accuracy, and legality—and since this paper does not

[62] Ibid, p. 316

attempt to address the systemic racism that affects virtually every aspect of American life, we have restricted our analysis to additional data that could be used to measure "creditworthiness".

To evaluate the potential efficacy and fair housing implications of these alternative data sources, we have used the analogy of a traffic light, where potential applications are classified as "green", "yellow" or "red."



Note that in instances where we were unable to assess the impact of a particular variable, we have assigned a yellow flag. While we do not believe that a particular data set must score a "green" on all five criteria, a predominance of red and yellow ratings should give policymakers a reason to pause.

Figure IV: Alternative Data Vary on SCALE Criteria

	Societal Values	Contextual integrity	Accuracy	Legality	Enhanced Opportunity
	S	C	A	L	E
Credit Proxies					
Utility Payments					
Telecom payments					
Rent Payments					
Cable payments					
Payday lending					
Remittances					
Aggregated Banking Data					
Bank account(s) age					
Monthly Cashflows					

	Societal Values	Contextual integrity	Accuracy	Legality	Enhanced Opportunity
	S	C	A	L	E
Bounced Checks					
Recurring Payments/ Credit Proxies					
Other Transactions					
Non-financial personal					
Social Media Activity					
Smartphone records					
GPS location					
Shopping Patterns					

Credit Proxies: Not surprisingly, except for payday lending, the various credit proxies identified in the chart score high on most, if not all of the five SCALE criteria. Not only does their use make sense in the context of mortgage lending—particularly with respect to rent and utility payments—they generally meet the other SCALE criteria, including the proven ability to expand homeownership for minority households. While accurate rent payment data is admittedly difficult to collect, particularly from smaller landlords, its use should be encouraged given its positive impact on consumers with thin or non-existent credit files. Much the same can be said about the information on a consumer's ongoing utility, telecom, and cable payments.

However, data on payday lending—which some have proposed as an alternative way to measure a consumer's creditworthiness—is more problematic. Payday loans are used primarily by underbanked Black and Latinx consumers. For example, some 12 percent of African Americans have reported using a payday loan, compared to 4 percent for White respondents. Moreover, the industry is highly dispersed, largely unregulated, and known to be prone to abusive practices. In general, payday loan products have significantly higher interest rates—and higher rates of delinquencies and defaults—than credit cards or other types of consumer loans. While higher rates might be justified based on the underlying risks involved, the stark differences in the use of these products would likely have a negative and disparate impact on Black borrowers if these data were to be included in credit scores. Thus, from a fair lending perspective, it is difficult to support their use.

Banking Data: The inclusion of banking data in credit scores should also be explored, although with caution. Banking data has always been part of the underwriting process, for example, to verify the borrower's income and down payment source. As a result, broad banking data such as net monthly inflows and outflows score high on the SCALE criteria. However, the potential use of detailed information on how and where the consumer spends their money is far more problematic despite the "financial" nature of the data. For example, *how* one spends their money clearly differs for men and women, and *where* one spends their money is intricately linked to where one lives—and, given the segregated society in which we live, to one's racial or ethnic group. Thus, unless properly regulated, the use of expenditure data derived from a consumer's credit card or checking account could clearly have a disparate impact on protected classes that would violate fair lending laws. Their use could also violate other criteria embedded in the SCALE framework, including Societal Values and Contextual Integrity.

There are already examples of financial data aggregators that provide services that mimic credit reporting as well as providing analytics based on these data. Many consumers are unaware that data aggregators have access to their login credentials, and reportedly only about 20 percent know that data aggregators can access their information until permission to do so is actively revoked.[63] Disparities in consumer awareness and information about these providers, and in particular, when prior consent is required, how to identify or correct errors, have potential fair lending implications. Furthermore, if underrepresented minority consumers are less likely to utilize certain kinds of financial services, such as what we know about differential usage of banking and brokerage accounts (e.g., the 'unbanked' are disproportionately minorities), there may be systematic disparities in coverage of these aggregated data sources.

Non-Financial Personal Data: Finally, the use of non-financial personal data should be considered with great caution. A recent Treasury report called for greater regulatory guidance on the use of personal data in credit decisions to remove the uncertainty that might otherwise limit innovation in this area. In particular, it concluded that "regulators should provide regulatory clarity for the use of new data and modeling approaches that are generally recognized as providing predictive value consistent with applicable law for use in credit decisions."[64] The report also recommended, "prudent experimentation intending to work through various issues raised, which may, in turn, require new approaches to supervision and oversight."[65] While these regulatory initiatives would certainly be steps in the right direction, a more fundamental question needs to be addressed, namely, is the fact that certain types of data are predictive enough to justify their use in credit decisions?

Based on the five SCALE criteria, the answer to this question would generally appear to be "no." As noted earlier, there are racial and ethnic variations in location, access to goods, services, and opportunities, as well as different levels and types of "social capital", i.e., social networks and contacts that reflect where consumers live, where they went to school, and who they know. [66] Because of these differences, the use of data extracted from the consumer's digital footprint—for example, their GPS locations, shopping patterns, Facebook friends, or academic GPAs—is likely to have a disparate and negative impact on protected classes. As Barocas and Selbst discuss in detail, these negative

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[63] Rabin, Konstantin, "The new age of Fintech - What you need to know about data aggregators," February 11, 2020, https://www.finextra.com/blogposting/18444/the-new-age-of-fintech---what-you-need-to-know-about-data-aggregators
[64] US Treasury, op. cit., p.138
[65] Ibid. p. 138
[66] Grier, Sonya A. and Vanessa G. Perry (2018), "Dog Parks and Coffee Shops: Gentrification and Diversity in Urban Neighborhoods", Journal of Public Policy and Marketing, 37(1), 23–38.

impacts—which could reflect the inadvertent consequences of data mining or deliberate acts of discrimination--would be extremely difficult, if not impossible to detect,[67] rendering most enforcement efforts ineffective.

In addition, the use of a consumer's personal data in the evaluation of credit risk raises clear ethical concerns—concerns that apply to everyone, not just protected classes. As noted earlier, the fact that a certain factor is predictive does not necessarily mean that it should be used for decision-making purposes. For example, research has found that women are generally better mortgage risks than men, but existing laws prohibit the use of the borrower's sex in making lending decisions. In effect, by imposing these restrictions, "…Congress decided that the adverse effects of using prohibited bases … were sufficiently contrary to the societal notion of fairness that the potential losses in economic efficiency were justified."[68] In the end, these same moral and ethical considerations should be used to determine whether information gleaned from a consumer's digital footprint should be used in credit decisions or instead be viewed as "private" and therefore "out-of-bounds."

The use of many types of non-financial data is also likely to score low with respect to contextual integrity and data accuracy. For example, why should a consumer's Facebook "friends" or "likes" be used in credit decisions? If it is part of the credit decision, FCRA will require creditors to reveal this to consumers—a requirement that would make them reluctant to use it in the first place. Or what would prevent a consumer from changing their shopping patterns or website searches once it becomes known that a certain factor has a negative impact on their credit score? While models relying on such information may be predictive in their initial stages, their efficacy would inevitably diminish over time.

Finally, to the best of our knowledge, the jury is out on whether the use of non-financial personal data in credit scoring models would help to expand access to credit (hence, our "Yellow" rating in Figure IV.) As noted earlier, while models based on such data are being used in underdeveloped countries where credit bureaus do not exist, their impact here is largely unknown. Presumably, the application of artificial intelligence (AI) that incorporates non-financial personal data could lead to significant reductions in the size of the "un-scoreable" population. It could also increase the precision of scoring models, leading to significant cost reductions that open doors for many households who could not otherwise afford a loan. At the same time, however, for the reasons noted above, it is also possible—and in our view, highly likely—that the use of non-financial personal data would have a disparate impact on minorities even if it led to an overall decline in mortgage rates. If this occurs, policymakers will face an ethical dilemma similar to that encountered with international trade, namely, do the benefits that accrue to the majority of the population outweigh the potential costs to workers in affected industries? In terms of credit scoring, the question becomes "should an increase in a model's predictive power—and the benefits it might bring in terms of overall cost savings and mortgage access—outweigh the potential harm to protected classes?" Indeed, that is the basic issue that our SCALE framework attempts to address.

[67] Solon Barocas and Andrew D. Selbst, op. cit.
[68] Bostic and Calem, op. cit., pp. 330-331

VI. Summary

This paper examined the fair lending implications of various kinds of alternative data that could be used to measure credit risk in the mortgage market, focusing on ways to reduce the large and persistent homeownership gap that has existed between Blacks and non-Latinx Whites for most of the past 50 years. To do this, we evaluated three broad categories of alternative data—credit proxies, banking data, and non-financial personal data—using a five-factor SCALE framework that was designed to capture the potential ethical, contextual, and legal concerns that might be associated with the data's use, as well as its accuracy and potential impact on access to credit for protected classes and underserved communities.

In general, our analysis supports the use of so-called "credit proxies" such as the timely payment of rent, utilities, and telecom bills, as well as certain types of aggregate banking data, for example, net monthly inflows or outflows and total savings. However, because of fair lending concerns and the persistence of segregation, the use of certain types of granular banking data (e.g., where and how the household spends its money) as well as data that can be harvested from social media (e.g., Facebook friends, shopping patterns, internet searches, "likes", etc.) should be discouraged, if not explicitly prohibited.

The Covid-19 pandemic only heightens concerns about the future of Black homeownership. While average credit scores have yet to be affected—in fact, they have actually risen—the longer-term impact on communities of color is likely to be profound, given the disparate impact of the virus on both their health and unemployment rates. Depending on the speed of the economic recovery, as forbearance agreements begin to expire, serious delinquencies are likely to rise and the homeownership gains achieved by Black households in the year immediately preceding the pandemic are likely to be reversed, making efforts to find alternative ways to measure credit risk more important than ever before.

As noted above, some aspects of alternative data—societal values, contextual integrity, and accuracy—may make credit providers reluctant to use them. For example, since FCRA requires lenders to disclose the reasons a loan was rejected, they may avoid using factors such as where the consumer went to school or how she spends her money due to public relations and other concerns. Likewise, given the requirements that FCRA imposes on data providers, many data aggregators may conclude that the benefits of supplying the data are dwarfed by the potential costs. Nevertheless, while these frictions may limit the use of certain kinds of data in the short run, they are unlikely to persist, placing a burden on policymakers to address the issues head-on.

One approach would be to subsume these issues under the general rubric of "privacy concerns" and pass legislation similar to the European Union's General Data Privacy Regulation (GDPR), which prohibits the use of a consumer's personal data without their explicit permission but allows a "carve-out" for credit bureaus. However, while California has passed its own version of such a bill, the prospects for such sweeping legislation at the federal level seem challenging at best. As a result, we believe that a better approach would be to capitalize on the basic legal and regulatory framework that is currently in place and work to ensure that the use of alternative data in the mortgage market enhances—and does not impede—homeownership opportunities for Blacks and other historically disadvantaged groups.

VII. Public Policy Recommendations

Given the considerations discussed in the sections above, we offer the following recommendations for policymakers.

First, existing legislative efforts to encourage the reporting of credit proxies such as rent, utilities, and telecom payments should be supported and strengthened by explicitly pre-empting existing state or local laws that prevent the sharing of such data. Some consumer groups, including the National Consumer Law Center, oppose the reporting of utility and telecom bills, arguing that for some consumers, it is better to have no credit than bad credit. However, these community groups fail to recognize that negative payment data is already reported whenever an account goes to collection and that the failure to report positive payment histories only serves to penalize consumers who consistently pay their bills on time. Indeed, as demonstrated by the studies cited above, the net benefits that would arise from a more systematic reporting of telephone, utility, and rental payments would help more consumers than it would hurt, with the largest benefits accruing to Black, Latinx, recent immigrants, and lower-income consumers who are less likely to have a "scorable" credit report.

Second, bank regulators should continue to explore ways to encourage the use of certain banking data in the assessment of credit risk. While much of this data is already being used in mortgage underwriting, its digitalization would undoubtedly make the process more efficient and could lead to better lending decisions. As noted earlier, it could also provide a way of collecting data on credit proxies such as the timely payment of utilities, telecom bills, and conceivably, even rent. For the so-called "underbanked"—which largely consists of recent immigrants—the addition of such data would likely have little if any impact. Moreover, the use of certain types of banking data could conceivably raise fair lending concerns. For example, if lending decisions are based on a detailed analysis of the consumer's checking data—for example, where and how the consumer spends his money—this could easily have a disparate impact on protected classes since expenditure patterns are often correlated with the consumer's race, ethnicity, or sex. As a result, we believe that the use of banking data in credit decisions should generally be limited to broad measures that reflect the consumer's overall financial well-being or that serve as commonly accepted credit proxies, and that the use of more granular banking data should be strictly limited and subject to prior approval by an applicable regulatory body.

A third, and related recommendation, relates to the financial data aggregation industry that is enabling the application of banking data in a wide variety of uses, including credit scoring. As noted earlier, most consumers have little, if any idea on how their information is being used by the largely invisible entities that actually collect, catalogue, and distribute their data to Fintech companies and other consumer-authorized users. Yet the data being harvested behind the scenes are arguably far more sensitive than the information currently provided by credit bureaus. Recently, data aggregators have been scrutinized by policymakers for potential violations of consumer privacy under the FTC

Act.[69] While the jury is still out on whether specific legislative efforts might be required, at a minimum, it is important to ensure that financial data aggregators are held to the same privacy and transparency standards as credit reporting agencies or other providers of data used in credit models.[70]

Fourth, Congress should revisit the ECOA, the Fair Housing Act, and other applicable laws to explicitly preclude the use of most, if not all kinds of non-financial, personal data in lending decisions. Putting clear restrictions on how various types of consumer data can be used in credit decisions—and ensuring the transparency of the data to consumers—will help to address the most egregious misuses of consumer data and promote fair lending goals. Controlling the use, as opposed to the collection of such data, is the basic approach taken by the FCRA and provides a model for broader efforts related to consumer privacy. As Former Secretary of Homeland Security Michael Chertoff argues in his recent book, the era of big data "requires both a loosening of what information can be collected by the government and at the same time a tightening of the standards under which that information can be inspected, analyzed, and used." [71]

Finally, policymakers need to explore ways to mitigate the impact of the Covid-19 pandemic on homeownership opportunities for Blacks and other historically disadvantaged groups going forward. However, we do not support efforts to prohibit credit bureaus from collecting and reporting delinquency data during the pandemic, as some community groups have proposed, nor do we support effects to remove the forbearance flags that are currently included in credit reports. Indeed, such data could ultimately be key to understanding how consumers have responded to the challenges raised by the pandemic, which in turn could provide more accurate assessments of credit risk going forward. For example, the fact that a consumer had the wherewithal to seek forbearance in the face of economic difficulties could actually have a positive impact on their credit score. While the developers and providers of credit scores are undoubtedly dealing with these issues, FHA and the GSEs should also be encouraged to play a role through special programs and research.

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[69] https://www.wyden.senate.gov/imo/media/doc/011720%20Wyden%20Brown%20Eshoo%20Envestnet%20Yodlee%20Letter%20to%20FTC.pdf?mod=article_inline
[70] CFPB, "Consumer-authorized financial data sharing and aggregation," October 18, 2017, https://files.consumerfinance.gov/f/documents/cfpb_consumer-protection-principles_data-aggregation_stakeholder-insights.pdf
[71] See M. Chertoff, Exploding Data; Reclaiming Our Cyber Security in the Digital Age, Boston: Atlantic Monthly Press, 2018, p. 203.