

Addressing Traditional Credit Scores as a Barrier to Accessing Affordable Credit

By Ying Lei Toh

Access to affordable credit is vital to consumers' economic well-being and to inclusive economic growth. Affordable credit enables consumers to better manage their finances and cope with unexpected emergencies. Further, affordable credit may empower consumers to pursue opportunities such as entrepreneurship or higher education, which can build wealth and increase socioeconomic mobility. However, many consumers continue to face difficulties obtaining the credit they need. According to the 2019 Survey of Consumer Finances (SCF), about one-quarter of consumers who desired credit reported that they did not obtain any credit or as much credit as they requested.

A major impediment to obtaining affordable credit is lenders' reliance on traditional credit scores—specifically, the FICO score and VantageScore—to assess consumers' creditworthiness. These credit scores affect not only loan approval decisions but also the interest rates consumers pay on their loans. And while these credit scores are intended to help lenders make informed decisions about consumers' risk of default, they do not always accurately reflect a borrower's ability to repay. For instance, traditional credit scores persistently penalize borrowers who have experienced derogatory credit events such as delinquencies, even when those events are no longer indicative of their ability to pay.

Ying Lei Toh is an economist at the Federal Reserve Bank of Kansas City. This article is on the bank's website at www.KansasCityFed.org

Traditional credit scores may also disproportionately punish consumers from economically disadvantaged groups, who tend to experience greater difficulties obtaining their first line of credit as both account age and length of payment history are major factors in the scores. Better understanding the obstacles these scores pose to consumer credit access—as well as potential ways to address them—is thus of critical importance to both efficient credit allocation and economic mobility.

In this article, I examine the barrier traditional credit scores pose to obtaining affordable credit in the United States and discuss efforts to address this barrier. Using data from the 2019 SCF, I find that traditional credit scores may indeed hinder a sizeable share of consumers from obtaining the credit they desire. Further, disparities in credit access across several sociodemographic groups match the disparities in their likelihood of having high traditional credit scores, suggesting lenders' reliance on traditional credit scores may drive disparities in credit access. Although using alternative data or more sophisticated statistical techniques in credit scoring and underwriting could alleviate these disparities, clearer regulatory guidance and more research will likely be necessary to promote the development and adoption of alternative credit-scoring models.

Section I reviews how traditional credit scores affect credit access in the United States. Section II examines disparities in credit scores across several sociodemographic groups and discusses their implications. Section III discusses efforts to address the barrier that traditional credit scores pose to credit access.

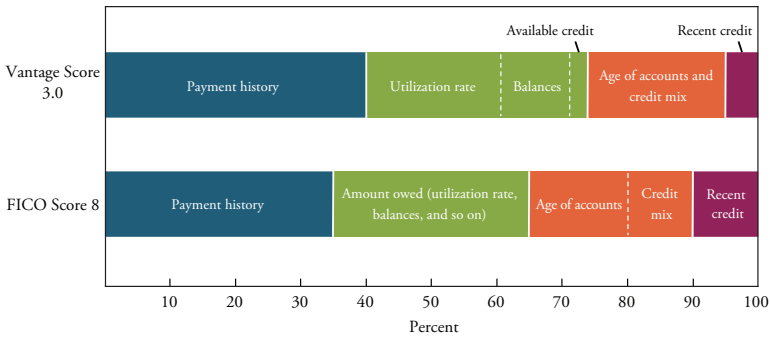
I. Traditional Credit Scores and Access to Credit

Mainstream lenders (banks and credit unions) have traditionally been the main source of affordable credit—often defined as a loan with an annual interest rate below 36 percent—for consumers (Saunders 2021). To assess the creditworthiness (or risk of default) of potential borrowers, these lenders have typically relied on credit scores. In theory, credit scores provide lenders with a standardized metric for evaluating consumers' credit risks objectively, consistently, and cheaply, helping to increase the overall availability of credit and the efficiency of credit allocation in consumer credit markets (Board of Governors of the Federal Reserve System 2007). Lenders deem consumers with lower credit

Box FICO Score and VantageScore

To obtain a FICO score or VantageScore, consumers need sufficient credit history. Consumers must have opened at least one credit account to be eligible for a VantageScore and must have at least one account that has been open for six months or longer to be eligible for a FICO score. If a consumer meets these requirements, their score is calculated based on data from their credit bureau files. The chart below shows the categories of data and their relative weighting in FICO Score 8 and VantageScore 3.0, the most commonly used versions of the two scores.

Factors that Determine a Consumer’s Credit Score



Sources: FICO and VantageScore.

Payment history. A consumer’s payment history is the most influential factor in determining both their FICO Score 8 (35 percent) and VantageScore 3.0 (40 percent). A good (and long) track record of on-time payments is critical for a high credit score.

Amount owed. A lower level of credit usage—as measured by factors such as total balance, number and type of accounts with balances, unused or available credit, and credit utilization (specifically, the balance-to-credit-limit ratio)—increases a consumer’s credit score.

Age of credit accounts and credit mix. Older accounts and a greater diversity of account types increase a consumer’s credit score.

Recent credit. Fewer recent credit accounts and applications are associated with higher credit scores.

Both the FICO score and VantageScore range from 300 to 850. A FICO score or VantageScore above 660 is considered “prime,” while a FICO score below 620 or a VantageScore below 600 is considered “subprime.”

Table 1

Reasons Borrowers Were Denied or Granted Less Credit Than Requested in Their Most Recent Loan Application

Reasons provided by lender	Percent
Lack of credit history / credit references	9.4
Credit bureau reports / credit ratings	35.9
Other credit records	8.2
Too much debt	21.6
Income / assets / other financial characteristics	10.3
No reason given / bank policy	6.3

Notes: Table is constructed by grouping similar reasons contained in variable X7585 of the 2019 SCF. “Lack of credit history / credit references” corresponds to reason codes 62 and 67; “credit bureau reports / credit ratings” corresponds to reason 63; “other credit records” corresponds to reason code 64; “too much debt” corresponds to reason code 66, “income / assets / other financial characteristics” corresponds to reason codes 65, 71, 72, 73, 76, 79, and 103; “no reason given / bank policy” corresponds to reason code -1.

Sources: Board of Governors of the Federal Reserve System and author’s calculations.

Table 2

Average Annual Percentage Rates (APRs) for Consumer Loans by FICO Score

FICO score	General-purpose credit card (percent)	Personal loan (percent)	30-year fixed rate mortgage (percent)	Used car loan (percent)
760 and above			5.99	
720	17.5	10.73–12.50	6.21	3.68
690	21.0	13.50–15.50	6.39	5.53
630	22.6	17.80–19.90	7.58	10.33
580	23.3		–	16.85
Below 580	23.9	28.50–32.00	–	20.43

Notes: APRs for general-purpose credit cards are based on data from 2020. The personal loan rates are accurate as of February 1, 2023. Mortgage rates are calculated based on a loan size of \$300,000 and are accurate as of February 7, 2022. Used car loan rates are accurate as of 2022:Q2.

Sources: Consumer Financial Protection Bureau (CFPB), Bankrate, myFICO, and Experian.

scores to be less creditworthy and are thus more likely to deny credit to these consumers or charge them higher interest rates.¹

Traditional credit scores—particularly, the FICO score and VantageScore—are derived solely from consumers’ credit history and are the type of credit scores lenders most commonly use to evaluate consumers’ creditworthiness today.² See the Box for an overview of these two scores, including the minimum requirements for obtaining them.

Data suggest that lenders rely heavily on traditional credit scores to determine whether and at what price consumers can obtain credit.

Table 1 shows that according to the 2019 SCF, which is conducted by the Board of Governors of the Federal Reserve System, almost half of consumers who applied but failed to obtain the credit they desired were unsuccessful because of reasons related to their credit bureau records (35.9 percent) or lack thereof (9.4 percent). Moreover, Table 2 shows that consumers with lower FICO scores face higher rates when obtaining various types of consumer loans. For example, a consumer with a FICO score under 580 faces a nearly 17 percentage point higher average rate for a used car loan than a consumer with a FICO score of 720 or above.

II. Implications of Relying on Traditional Credit Scores to Determine Access and Cost of Credit

Lenders' heavy reliance on traditional credit scores for credit underwriting may prevent some consumers from obtaining affordable credit—or discourage them from applying in the first place. According to the 2019 SCF, 9.3 percent of consumers age 18 and above were either denied credit or granted less credit than they requested—and about 45.3 percent of these consumers report being denied or granted less credit than requested because of their credit score.³ Additionally, 7.4 percent of consumers report that they did not apply for credit either because the interest rates were too high or because they did not think they would be approved; both reasons may be related to the lack of a high traditional credit score. In all, up to 11.6 percent of consumers ($9.3 \times 0.453 + 7.4$) may have credit needs that were unmet or undermet due to no or low credit scores.

From both a lending and consumer protection perspective, denying some consumers credit may be desirable to the extent that it prevents them from overborrowing; however, a low or nonexistent credit score may not always reflect a lack of creditworthiness. Instead, it may reflect that a consumer is new to the credit market or that they had a disadvantageous start to their credit history—for example, by not having access to a co-borrower or by having their credit histories established as a result of a third-party debt collection. Evidence suggests these reasons are especially relevant for younger consumers, low- and moderate-income (LMI) consumers, and Black or Hispanic consumers—placing populations that

may especially benefit from access to affordable credit at a particular disadvantage in obtaining it.

Consumers new to the credit market

Consumers who lack credit scores are often those who are new to the credit market, such as young adults. These consumers' creditworthiness cannot be observed through traditional credit-scoring methods because they have no or insufficient credit history to generate a credit score.⁴ Moreover, even after becoming scorable, these consumers have lower credit scores on average because they tend to have younger accounts, shorter payment histories, higher credit utilization rates (due to lower credit limits), and a larger number of recent account applications. Thus, lending decisions based solely on traditional credit scores may inefficiently deny credit for consumers new to the credit market.

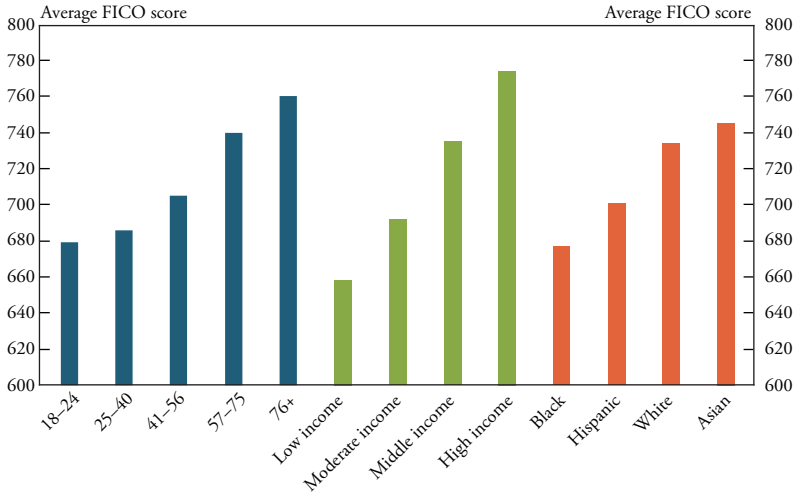
Indeed, young adults appear to be at a particular disadvantage for this reason. Brevoort, Grimm, and Kambara (2015) estimate that in December 2010, 35.5 percent of consumers between the ages of 20 and 24 had no or insufficient credit history to be scorable compared with 19.3 percent of the overall population. Moreover, Chart 1 shows that when younger consumers are scorable, they have lower credit scores on average.

Consumers with a disadvantageous start to their credit history

Traditional credit-scoring models also tend to persistently assign lower scores to consumers with less advantageous starts to their credit history, even when the disadvantages they faced did not or no longer reflect their true creditworthiness (Bach and others 2023).⁵ Consumers typically establish their credit history by obtaining their first line of credit. Although most consumers do so alone, some leverage the creditworthiness of others—for example, by having a co-borrower with good credit history or by becoming an authorized user on someone else's (often a parent's) credit line. The latter approach is more advantageous because it not only increases the likelihood of approval but may also help consumers boost their credit scores by acquiring the credit history of the established borrower (Bach and others 2023).⁶ However, many consumers are unable to obtain credit this way. For example, Brevoort and Kambara (2017) find that individuals from LMI neighborhoods are less likely to leverage the creditworthiness of others in applications than individuals from higher-income neighborhoods.

Chart 1

Younger Consumers, Black and Hispanic Consumers, and Consumers Living in Lower-Income Neighborhoods Have Lower Credit Scores on Average



Note: A neighborhood is classified as “low income” if its median family income is under 50 percent of the area median family income, “moderate income” if its median family income is between 50 and 80 percent of the area median income, “middle income” if its median family income is between 80 and 120 percent of the area median income, and “high income” if its median family income exceeds 120 percent of the area median income.
 Sources: Horymski (2022); Kramer-Mills, Landau, and Scally (2020); and ShiftProcessing.com.

A less common but more disadvantageous way of establishing one’s credit history is through bankruptcy or third-party debt collection. Credit-scoring models consider these events to be derogatory, meaning consumers who establish their credit scores this way are likely to start off with lower credit scores. Further, because records remain on consumers’ credit bureau files for seven years, derogatory events may continue to weigh on consumers’ credit scores even when they are no longer indicative of consumers’ creditworthiness. Again, Brevoort and Kambara (2017) find that individuals from LMI neighborhoods are more likely to have their credit histories established through these derogatory events than individuals from higher-income neighborhoods.

Given that LMI neighborhoods also tend to have higher shares of Black and Hispanic consumers, we may expect Black and Hispanic consumers to disproportionately experience disadvantages in establishing their credit history (Goodman and others 2022). Indeed, studies have found that the share of consumers without a credit score is higher among both LMI consumers and Black or Hispanic consumers

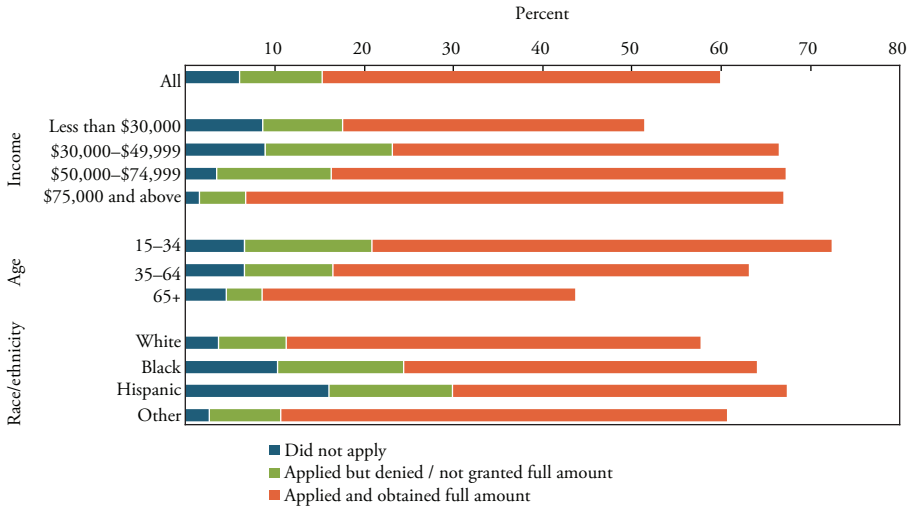
compared with higher-income and white consumers (Brevoort, Grimm, and Kambara 2015; Hepinstall and others 2022). Further, Chart 1 shows that LMI consumers and Black and Hispanic consumers have lower credit scores compared with higher-income consumers and white consumers, on average.

Moreover, Blattner and Nelson (2021) find that while credit scores are generally predictive of default risks, they are less predictive for consumers with “noisier” credit bureau files—that is, those that contain fewer records, lack diversity in account types, or include past derogatory events. These factors also tend to lower credit scores, suggesting lower credit scores may not always be indicative of lower creditworthiness—especially for consumers who are new to the credit market or had less advantageous starts to their credit histories.⁷

Indeed, data from the 2019 SCF suggest that disparities in credit scores across age, income, and racial and ethnic groups have contributed to similar disparities in credit access. Chart 2 shows that around 60 percent of consumers desired credit in the 12 months preceding the 2019 SCF.⁸ This share does not vary widely by consumer characteristic, except for age—consumers under the age of 35 were 28.7 percentage points more likely to desire credit than those 65 years or older. In contrast, the share of consumers who desired credit but had credit needs that went unmet or undermet—either because they did not apply (blue bars) or because they applied but were denied or granted less credit than requested (green bars)—varied widely across age, income, and racial and ethnicity groups. Consumers who were below age 65, earned less than \$75,000 a year, or were Black or Hispanic were substantially more likely to have their credit needs unmet or undermet. Lower-income consumers—particularly, those making less than \$50,000 a year—and Black or Hispanic consumers were less likely to have applied for credit and more likely to be denied conditional on applying compared with consumers earning \$75,000 or more a year and white consumers. And although consumers with income between \$50,000 and \$75,000 and those under the age of 65 were not substantially less likely to have applied for credit compared with higher-income and older individuals, they were more than twice as likely to be denied credit either partially or fully.

Chart 2

Disparities in Credit Access Mirror Disparities in Credit Scores across Income, Age, and Race and Ethnicity Groups



Sources: Board of Governors of the Federal Reserve System and author's calculations.

The data in this section suggest that traditional credit scores pose critical barriers to accessing affordable credit. In addition, traditional credit scores are less predictive of creditworthiness for consumers with lower or no credit scores, implying that some of these consumers may be inefficiently denied access to credit or charged higher prices. While barriers to access may be transitory for young consumers, they are likely to be persistent for lower-income and Black or Hispanic consumers, who have lower credit scores on average.⁹ These consumers would likely benefit the most from access to lower-cost credit, as both lower-income and Black or Hispanic consumers tend to lack savings that could help them cover unexpected emergencies. Access to lower-cost credit could help these groups avoid taking on high-cost debt and could enhance their economic mobility by allowing them to purchase homes, invest in the education of their children, and pursue other economic opportunities such as entrepreneurship. As such, addressing the barriers that traditional credit scores pose to credit access may be critical in enhancing economic mobility and financial inclusion.

III. Efforts to Address the Barrier of No or Low Traditional Credit Scores

Although the barriers to credit access are pervasive for consumers with no or low credit scores, federal agencies and lenders have, until recently, done relatively little to address them. Lenders traditionally addressed these barriers by offering credit-building products to consumers seeking to establish or improve their traditional credit scores, while federal agencies primarily focused on financial education. In more recent years, however, lenders (particularly, fintech lenders) and federal agencies have begun developing credit-scoring models that leverage alternative data sources and exploring the use of more advanced machine learning techniques in credit scoring. These efforts could expand the share of consumers who are scorable and improve the accuracy of credit risk prediction (particularly for underserved consumers), thereby improving overall access to credit.

Traditional credit-building products

One way financial institutions have traditionally helped consumers with low or no credit scores access low-cost credit is by offering products designed to help them build or improve their credit history. Although these products are reported to credit bureaus as standard credit products, they do not, in fact, offer consumers additional liquidity. Instead, these products require consumers to either secure the credit line with a deposit or pre-pay for the loan. This feature minimizes the default risks that lenders face, making them more willing to extend these “loans” to consumers of unknown or possibly high default risk. By obtaining and making timely payments on these products, consumers can establish or improve their credit scores.

Two common types of credit-building products are credit-builder loans (CBLs) and secured credit cards. CBLs are reported as installment loans to credit bureaus. However, unlike regular installment loans, lenders do not provide borrowers with funds upfront; instead, they require borrowers to pre-pay for their loans. Specifically, the loan is disbursed to borrowers with each installment payment that they make. For example, if a borrower took out a 12-month CBL for \$600, which implies a monthly payment of \$50 plus interest, the lender would deposit \$50 into the borrower’s account each time they made their monthly

payment. A secured credit card is an “alternative” credit card that works like a regular credit card but requires cardholders to post a security deposit (typically, equal to the credit limit) to reduce lenders’ exposure to default risk (White 2022).

Research on credit-building products is relatively scant, and previous studies find that the adoption of these products has mixed effects on consumers’ credit scores. Studies on CBLs generally find that taking out a CBL both increases the probability of having a credit score and increases credit scores for those with existing scores who also have little to no existing debt. However, studies also find that taking out a CBL can actually hurt the credit scores of consumers with a higher level of existing debt (see, for example, Burke and others 2022; CFPB 2020).¹⁰ Opening a secured credit card likewise benefits some consumers while hurting others. Santucci (2016) finds that secured cardholders who kept their cards open over the course of two years experienced an increase of about 24 points in their credit scores. CFPB (2017) suggests that secured cardholders who maintain a good payment history may even have their cards converted into unsecured credit cards and their deposits returned after a period. However, secured credit cardholders who closed their accounts within two years—whether their accounts were in good standing or otherwise—saw their credit scores decline by over 40 points (Santucci 2016). Those whose accounts were in default at the time of closure experienced an especially sharp drop in their credit scores of around 60 points.

Moreover, although credit-building products can help some consumers obtain and improve their credit scores, they are likely to have limited effects on expanding access to lower-cost credit overall. Surveys consistently find that many U.S. consumers—particularly, lower-income and younger consumers—lack basic knowledge about credit scores (see, for example, Capital One 2022, Quinn 2021, and Consumer Federation of America 2020). Thus, consumer awareness of credit-building products is likely to be low. Even when consumers are aware of these products, they may face barriers obtaining them, including insufficient funds to fulfill the deposit requirement of secured credit cards, a lack of trust in the lender, and an inability to pass the ability-to-pay (ATP) test (CFPB 2017; Levy and others 2016).¹¹

Fintech credit-building products

In recent years, some financial technology (“fintech”) firms have also begun offering credit cards that do not require consumers to have a traditional credit score to apply, providing consumers with an alternative product for building credit.¹² Instead of relying on security deposits or prepayments, these fintech lenders minimize their exposure to default risks by only lending to consumers whom they determine to be creditworthy based on alternative metrics, such as bank account data.¹³ To help consumers build their credit scores, these credit cards also have features that help maintain good payment behaviors. For instance, one fintech credit card does not allow consumers to carry a balance and offers a seven-day automatic repayment feature, which helps cardholders to make timely payments and keep their credit card utilization level low. And another rewards cardholders by increasing their credit limit if they make consistent, timely payments.

Outside studies on the effectiveness of these fintech products are limited, though data shared by the representatives of one fintech credit card provider suggest that these products have helped some consumers establish and obtain high credit scores.¹⁴ According to this provider, consumers who opened a credit card with them without a traditional credit score obtained a VantageScore of 681—a prime score—on average, 12 months after opening the card. In addition, these cards appear to help provide credit to consumers who are underserved by mainstream lenders. In particular, 40 percent of the consumers this fintech provider approved for a card in 2022 had previously been denied credit by a mainstream lender. Fintech credit cards are likely to have a small effect on expanding credit access to consumers (both directly and indirectly) at present, given that these cards are relatively new and many consumers may still not be aware of them.¹⁵ That said, these fintech credit cards have the potential to reach more consumers than secured credit cards, as they are both more accessible and provide real liquidity to cash-flow-constrained consumers.

Financial education and credit counseling

Traditionally, agencies in both the public and private sectors have engaged in efforts to improve consumers’ personal finance knowledge, including their knowledge about credit scores, borrowing, and debt management. Many consumers lack a basic understanding of credit scores;

surveys also indicate that many consumers lack financial knowledge more generally, including knowledge about borrowing (Contretras and Bendix 2021). To improve general financial literacy, many federal agencies have developed dedicated financial education websites that provide educational materials and financial management tools to consumers (Toh 2022). State and local governments have also worked to promote the inclusion of financial education in school curriculums (Contretras and Bendix 2021). In addition, various nonprofit organizations, such as the National Foundation for Credit Counseling or American Consumer Credit Counseling, offer credit counseling services that can help consumers improve their financial knowledge and better manage their debts, thereby improving their credit scores (Roll and Moulton 2016).¹⁶

Relatively little is known about the effectiveness of the various public sector financial education efforts on financial literacy, and subsequently, consumer credit behaviors and credit scores, as these efforts often lack measurable goals (GAO 2006). However, research on financial education in general suggests that these efforts may have limited effects. Financial literacy surveys consistently find that many U.S. consumers lack the financial knowledge needed to make sound financial decisions—on average, consumers only answer around half of the financial literacy questions in these surveys correctly (Contretras and Bendix 2021). Moreover, depending on the survey, the share of questions that consumers answer correctly has either been relatively stagnant or declining over time, suggesting that financial education efforts may not have been effective at improving consumers' financial knowledge.¹⁷ Studies on financial education generally find little to no effect on consumer financial behaviors, implying financial education may not help consumers obtain and improve traditional credit scores (Fernandes, Lynch, and Netemeyer 2014). However, some evidence suggests that credit counseling may improve consumers' credit scores. For example, Roll and Moulton (2016) find that consumers who underwent credit counseling reduced their debts and experienced larger increases in their credit scores compared with those who did not undergo credit counseling.

Promoting the use of alternative data in credit scoring and underwriting

More recently, lenders and federal agencies have turned their efforts to developing and promoting the use of alternative data in credit

scoring. Because traditional credit scores are generated solely from credit records from the three main credit bureaus, their predictiveness of a consumer's default risk is limited by the availability and quality of the consumer's credit bureau data. As discussed in Section II, traditional credit scores may not be as informative about the creditworthiness of consumers with no credit history or noisier credit bureau data. Moreover, past credit history may not always be a good predictor of future creditworthiness (Di Maggio, Ratnadiwakara, and Carmichael 2022).

One way to address the limitations of credit bureau data is by using alternative data in credit scoring. These alternative data may include data on bill payments (for example, rent and utilities), transactions or cash flow (for example, bank accounts), and income or assets (for example, employment history and property ownership). They may also include non-financial data—for example, on social media use or type of mobile device (FinRegLab 2020). Studies find that credit-scoring models that use alternative data (particularly, cash flow data)—either alone or as a supplement to traditional credit bureau data—are not only able to score more consumers but also perform as well as or better than traditional credit scores at predicting consumers' default risks (see, for example, Di Maggio, Ratnadiwakara, and Carmichael 2022; FinRegLab 2020; Turner and others 2006).

Both the public and private sectors have been actively developing credit-scoring models that use alternative data in recent years. In 2020, the Office of the Comptroller of the Currency (OCC) launched Project REACH (Roundtable for Economic Access and Change) to promote financial inclusion by improving access to credit and capital. One objective of Project REACH is to help develop an alternative credit-scoring system that can serve as a safe and fair tool for underwriting.¹⁸ Traditional credit score creators and credit bureaus have been developing new scoring models that include alternative data such as bill payment data (for example, Experian Boost) and transaction data (for example, UltraFICO).¹⁹ Additionally, fintech firms Petal Card and Nova Credit have developed cash-flow-based credit-scoring models—CashScore and Cash Atlas, respectively—that use permissioned transaction data to predict credit risk.

Although using alternative data in credit scoring may, in theory, expand access to low-cost credit, its effects may be limited at present due

to its low adoption by mainstream lenders (FinRegLab 2020). Many mainstream lenders may lack the motivation to use alternative data since they do not lend to subprime consumers, for whom alternative data is more predictive of credit risks. Technology or resource constraints, regulatory uncertainty, higher compliance risks associated with the use of alternative data, and a lack of data on the performance of underwriting models that incorporate alternative data are a few other factors that may hinder mainstream lenders from using alternative data in underwriting (GAO 2021).

Recent developments in both the regulatory and market spaces may encourage broader adoption of alternative data in credit underwriting, though their effects remain to be seen. In recent years, federal financial regulators have taken steps to reduce regulatory uncertainty surrounding alternative data in credit underwriting. In 2019, for example, federal financial regulators issued a joint statement encouraging responsible use of alternative data such as cash flow data in credit underwriting (Board of Governors of the Federal Reserve System and others 2019). And in 2021, the CFPB modified its definition of “qualified mortgage” under the Truth in Lending Act (Regulation Z) to allow for greater use of alternative data in mortgage lending. To further incentivize the use of alternative data, federal regulators have also stated that they may consider lenders’ use of alternative data in underwriting mortgages for LMI consumers to be an innovation, potentially helping lenders to meet Community Reinvestment Act goals (GAO 2021).²⁰ More off-the-shelf credit-scoring models that incorporate alternative data have also become available in the market in recent years; their availability may facilitate mainstream lenders’ use of alternative data in credit underwriting by addressing challenges in obtaining and integrating alternative data into their in-house underwriting models.

Exploring the use of machine learning in credit underwriting

In recent years, lenders, researchers, and regulators have also been exploring the use of advanced machine learning models in credit underwriting. These models use sophisticated algorithms that can help uncover complex relationships between numerous data points, enabling lenders to leverage massive amounts of alternative consumer data to improve credit risk prediction and access (FinRegLab 2022). Indeed, studies have found that the credit-scoring models of some fintech firms that

leverage both machine learning and alternative data result in higher rates of credit approvals or lower interest rates for underserved consumers compared with models using traditional credit scores (Di Maggio, Ratnadiwakara, and Carmichael 2022; Jagtiani and Lemieux 2019).

Even when using only traditional credit data, most studies agree that sophisticated machine learning models generally outperform logistic models (which are commonly used for credit risk assessments) in predicting default risks of borrowers; however, studies differ on whether these improved predictions benefit underserved consumers. Some studies find that machine learning can help score a larger number of consumers even when using only traditional credit data, which may improve credit access among consumers who are not scoreable with the traditional credit-scoring model (Albanesi and Vamossy 2019; VantageScore 2021). However, other studies find that machine learning may have little to no benefit for populations that tend to have lower traditional credit scores, as it does not eliminate—and may even worsen—disparities in the accuracy of default risk predictions for consumers who are underserved relative to those who are not (Blattner and Nelson 2021; Mersault and others 2021; Wang and Perkins 2019). For example, Fuster and others (2022) find that the use of machine learning marginally improves loan approval rates for Black and Hispanic consumers but substantially increases the range of interest rates these consumers face, which may make them worse off overall. MacCarthy (2019) and Klein (2020) have also warned of machine learning’s potential to perpetuate or worsen existing disparities in credit access or enable discrimination by proxy. More research is needed to examine the implications of using machine learning methods in credit underwriting on credit access for underserved populations and to inform regulation, particularly as the technology continues to evolve.

Conclusion

The lack of a high traditional credit score is a barrier to accessing affordable credit for many consumers in the United States. A lower ability to obtain affordable credit as needed may adversely affect consumers’ financial well-being and impede economic mobility, particularly among economically disadvantaged consumers. In this article, I discuss the barrier traditional credit scores pose to credit access and

highlight that traditional credit scores not only hinder many consumers from obtaining credit, they may also drive disparities in credit access across socioeconomic groups. I then review both public- and private-sector efforts to address this barrier. Earlier efforts largely focused on helping consumers establish or increase their traditional credit scores (for instance, by providing consumers with credit-building products, financial education, and credit counseling), while more recent efforts have concentrated on developing credit-scoring models that can better predict default risks by leveraging alternative data and more advanced machine learning techniques.

Although these efforts may improve consumers' access to affordable credit, they are currently limited by low adoption rates. Consumer adoption of credit-building products has thus far been low due to both a lack of data and lack of awareness. Once more data on the efficacy of credit-building products are available, more consumer outreach and promotion efforts may be needed to boost adoption of the best-performing products. Lenders' adoption of alternative credit-scoring models, too, may be limited due to regulatory uncertainty, resource constraints, and inadequate data and research demonstrating their effectiveness. More research—especially on the use of machine learning methods for credit scoring—is needed to help establish the benefits and risks of alternative credit-scoring models.

Moreover, credit-building products and alternative credit-scoring models mostly serve to improve the accuracy of credit scores in predicting consumers' underlying creditworthiness (or default risks) and do not address consumers' lack of creditworthiness itself (except for credit counseling). These measures will only improve consumers' access to credit to the extent that their repayment behavior and the alternative data on consumers reflect low default risks. Measures to address consumers' lack of creditworthiness will likely be necessary to ensure that all consumers are able to access the credit they need.

Endnotes

¹Lenders may be especially reluctant to lend to subprime borrowers, as subprime lending subjects lenders to stricter lending standards and thus to higher compliance costs and risks. Examples of regulations that impose stricter requirements on subprime lending include the Credit Card Accountability and Disclosure (CARD) Act of 2009 and the Dodd-Frank Act of 2010. Studies have found that the CARD Act and Dodd-Frank Act led, respectively, to a decline in subprime credit card lending and a decline in mortgage lending in the mainstream credit markets (Eliehausen and Hannon 2017; Kramer-Mills, Landau, and Scally 2020).

²The FICO score was created in 1989 by FICO, while VantageScore was jointly created in 2006 by the three main credit bureaus—Equifax, Experian, and Transunion. Of the two scores, the FICO score is used more widely; according to FICO, over 90 percent of top lenders use the FICO score in credit underwriting.

³I assume the first two groups of reasons listed in Table 1 to be credit-score related.

⁴A consumer may also be unscorable if they have stale credit records, with no recent credit activities.

⁵Bach, Campa, and Giorgi (2023) find that consumers' initial credit scores are highly persistent and underpin the evolution of their credit scores. Higher initial credit scores tend to lead to better credit access, higher credit limits, and lower utilization rates, which result in high credit scores.

⁶In contrast, those who apply for credit alone may face a Catch-22 situation, in which they are unable to obtain a loan because they do not have a credit score and are unable to obtain a credit score because they are unable to get their first line of credit. Although most of these consumers eventually become scorable, they may take longer to obtain a credit score and have lower credit scores when they do, both because their accounts are younger and their credit utilization rates are higher (due to lower credit limits).

⁷Traditional credit scores may either under- or over-predict default risks for consumers with noisier credit files, leading to inefficient approval or rejection of credit applications, respectively. Blattner and Nelson (2021) find inefficient rejections (that is, rejections of consumers who are creditworthy) are more common among LMI and minority consumers.

⁸I consider any consumers who did not apply for credit for reasons other than not needing additional credit or preferring not to use credit as having a desire for credit.

⁹Race or ethnicity is time-invariant, and income mobility in the United States is limited, especially over the short term (Congressional Research Service 2021).

¹⁰Although each principal payment that a CBL borrower makes is returned to them in the form of a bank deposit they can withdraw almost immediately, taking out a CBL appears to worsen their ability to manage their other existing

debt obligations. Burke and others (2022) find that borrowers who had a high level of existing debt (in the form of other installment loans) experienced higher non-CBL delinquencies when taking out CBLs.

¹¹Although consumers effectively pre-pay for their loans through the security deposit they post when obtaining a secured credit card, secured credit card lenders are still required to perform the ATP test as stipulated by the CARD Act of 2019. CFPB (2017) finds that about 12 percent of secured card applicants were denied because they did not pass the ATP test.

¹²Examples of such fintech firms include Petal and TomoCredit.

¹³By not requiring consumers to post a security deposit, these fintech credit cards are likely to be more accessible to consumers with cash flow constraints than secured credit cards.

¹⁴I am thankful to Petal's CEO, Jason Rosen, and Petal's vice president of communications, Matt Graves, for sharing this information with me.

¹⁵As of February 2023, Petal had over 350,000 cardholders. No data on the number of Tomo cardholders are available, though TomoCredit's CEO disclosed in 2022 that they have received over 2.5 million applications over time (Azevodo 2022).

¹⁶Some employers have also recognized the importance of employees' financial well-being on their engagement and productivity and have introduced or expanded their employee financial wellness programs, providing services such as financial counseling (CFPB 2014).

¹⁷The share of questions that consumers answered correctly, on average, in the Financial Industry Regulatory Authority Investor Education Foundation's National Financial Capability Study fell from 59.8 percent in 2009 to 51.6 percent in 2021. The share of questions that consumers answered correctly for the TIAA Institute-GFLEC Personal Finance Index has fluctuated at around 50 percent from 2017 to 2022 (Urban and Valdes 2022; Yakoboski, Lusardi, and Hasler 2022).

¹⁸Project REACH's alternative credit assessment workstream has so far collaborated with financial institutions to explore integrating permissioned deposit account data, shared across participating financial institutions, with traditional credit bureau data to assess consumer's creditworthiness. The workstream also plans to further explore the use of other permissioned alternative data, particularly for consumers without a deposit account for credit scoring (OCC 2023).

¹⁹Due in part to additional compliance requirements and data accuracy issues, these products are available to consumers only on an opt-in basis. As of January 2022, nearly 9 million consumers have signed up for Experian Boost (Boundy 2022).

²⁰The 2021 GAO report provides other examples of initiatives and efforts to expand the use of alternative data in mortgage lending, including incorporating rental payment data into Fannie Mae's underwriting model.

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