



THE ECONOMIC BENEFITS OF RISK-BASED PRICING

FOR HISTORICALLY UNDERSERVED
CONSUMERS IN THE UNITED STATES



TABLE OF CONTENTS

Key Findings..... **3**

- 1. Consumers are better off in the risk-based pricing system than in a uniform pricing system.
- 2. Credit scores, credit-based insurance scores, and other risk-based pricing factors are proven to accurately predict risk unbiasedly.
- 3. Minority and low-income households have realized the greatest improvements in assets and access to capital.
- 4. Companies are innovating and using alternative data to reduce the credit-invisible population and improve credit scores for those who currently have them.
- 5. Incorporating more predictive data, not less, into risk-based pricing models generates positive economic benefits.

Foreword..... **5**

Risk-Based Pricing for Consumer Credit and Insurance Products..... **7**

The Positive Impact of Risk-Based Pricing **19**

- The Positive Effect of Risk-Based Pricing on Capital Access and Utilization for U.S. Communities28
- The Positive Effect of Risk-Based Pricing on Minority Groups29
- The Positive Effect of Risk-Based Pricing on Lower-Income Groups35
- The Positive Effect of More Data Versus Less in Risk-Based Pricing Models.....39

Policy Recommendations..... **43**

- ▶ Support the use of more data in risk-based pricing models.
- ▶ Support policies that improve the financial health of all Americans.
- ▶ Support additional research.

References **45**

KEY FINDINGS

The Economic Benefits of Risk-Based Pricing for Historically Underserved Consumers in the United States

The benefits of risk-based pricing are far reaching. Financial companies use analytics to better assess risks to offer innovative products at lower prices for consumers. The use of risk-based pricing has allowed lenders and insurers to better serve consumers across the risk spectrum. Under this system, costs are lowered for the majority of consumers who are deemed low risk, while credit opportunities are expanded for higher-risk consumers. Risk-based pricing also creates a fairer marketplace. The use of objective financial information and other factors proven to correlate with risk allows for increased consistency across each company's lending or insurance underwriting process. Additionally, consumers are not expected to pay for the costs imposed by someone else's dissimilar risk, as is often the case in a uniform pricing system. However, risk-based pricing is currently under scrutiny and is being threatened by proposals that would limit access to data that drives the benefits of risk-based pricing. Limiting risk-based pricing by eliminating predictive data or banning it would have significant negative impacts on consumers, especially minority and low-income households.

The following are several key findings of the report:



1.

Consumers are better off in the risk-based pricing system than in a uniform pricing system.

In the risk-based pricing system, firms offer consumers individual rates based on their risk profile. Two major benefits of this system are the

following: (1) consumers, over time, pay less in the risk-based pricing system than in the uniform pricing system; and (2) unlike in the uniform pricing system, consumers have incentives to improve their financial health (e.g., by paying bills on time, by paying down debt) and, by extension, reduce their risk to enjoy lower-priced financial products in the risk-based pricing system.



2.

Credit scores, credit-based insurance scores, and other risk-based pricing factors are proven to accurately predict risk unbiasedly.

Credit scores predict the probability of default, while credit-based insurance scores, and other factors

such as occupation and education, predict insurance losses. The accuracy and reliability of these variables have been validated repeatedly. Importantly, race, ethnicity, religion, or any other unrelated personal information are not included in risk-based pricing models.



3.

Minority and low-income households have realized the greatest improvements in assets and access to capital.

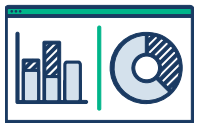
Black and Hispanic households and low-income households had the highest growth rates over the past 30 years across six measures of assets and capital: homeownership, auto ownership, mortgage and line-of-credit loans, auto loans, installment loans, and credit cards. For homeowners and auto insurance policies, participation in the residual market (for those who cannot get approved in the private market) has decreased substantially over time, indicating that more consumers have access to competitive products and rates.



4.

Companies are innovating and using alternative data to reduce the credit-invisible population and improve credit scores for those who currently have them.

At the end of 2018, 60.4 million American adults were unlikely to be able to access credit, including 26.5 million credit-invisible Americans. Alternative data, such as mobile phone bills, cashflow data, and telematics, help companies better determine consumers' risk profiles when traditional information is lacking. Alternative data produces more scorable consumers and can improve rates for those who have traditional credit scores. Companies are using this data to increase access to credit and insurance.



5.

Incorporating more predictive data, not less, into risk-based pricing models generates positive economic benefits.

Consumers have access to more financial products and better rates when alternative data is used in risk-based pricing.

According to the Organisation for Economic Co-operation and Development, "in the aggregate, lending is increased, leading to greater economic growth, rising productivity and greater stocks of capital. Average interest rates drop. Poverty and income inequality are alleviated."

U.S. policymakers should continue strengthening the existing risk-based pricing system. Financial institutions should be allowed and encouraged to utilize predictive data to better assess risk to offer innovative financial products to all consumers. Alternative data will enhance traditional data to assist financial companies to assess risk for consumers, especially the credit invisible. Regulators should encourage the use of alternative data, including risk models that leverage alternative data, and adopt policies to further support alternative data's usage. The more accurately risk can be measured, the more underserved populations will benefit from risk-based pricing, including better access and rates.

FOREWORD

The U.S. Chamber of Commerce Center for Capital Markets

The goal of this report is to evaluate how risk-based pricing and the use of data results in better outcomes for consumers by increasing access to financial services products and enabling the pricing of these products to accurately and appropriately calibrate for borrower or repayment risk.

While the benefits of risk-based pricing are clear, there are undoubtedly opportunities to strengthen the ecosystem. This paper makes policy recommendations to increase equity in the risk-based pricing system while leveraging the aspects that work, but we know that the general economic opportunity and full potential for minorities and underserved communities has yet to be fully embraced and realized in America. All Americans should have a fair chance to earn their success, rise on their merit, and live their own American Dream.

Last year, the U.S. Chamber of Commerce launched the Equality of Opportunity Initiative to develop real, sustainable solutions to help close race-based opportunity gaps in six areas: education, employment, entrepreneurship, criminal justice, health, and wealth. Inequalities in these six areas perpetuate broader inequalities in our society, hold back individual and business success, and hinder economic growth.

Driven by data and informed by conversations with business, government, academics, and civic leaders, we developed the Equality of Opportunity Agenda to advance private sector solutions and best practices, scale impactful programs, and drive policy action at the federal, state, and local level. In early 2021, the U.S. Chamber of Commerce established task forces around six main pillars as well as access to capital and supplier diversity. These conversations are bringing together business, policy experts, and others to share and discuss strategies to advance progress on these issues and solutions in the years to come—including opportunities to strengthen the risk-based pricing system.

THE ECONOMIC BENEFITS OF RISK-BASED PRICING FOR HISTORICALLY UNDERSERVED CONSUMERS IN THE UNITED STATES

NAM D. PHAM, PH.D., AND MARY DONOVAN¹

Over the past few decades, financial companies have refined and improved risk-based pricing models to offer innovative products and improve access to capital and insurance for consumers. Unlike a uniform pricing system in which one price is offered to all consumers, risk-based pricing allows lenders and insurers to offer different rates or other terms to consumers based on their individual risk. In recent years, financial companies have become more sophisticated with their data collection and predictive modeling and, as a result, are able to assess risks more accurately for individuals. These companies compete fiercely through cost reductions realized by risk mitigation. Consequently, more consumers have access to capital to pursue economic opportunity. Under the current risk-based pricing system, in which the cost of obtaining credit or insurance is inversely tied to risk, consumers are incentivized to lower their risk profiles by maintaining accurate credit reports and taking action to improve their credit scores.

However, risk-based pricing is currently under scrutiny and is being threatened by proposals that would limit access to data that drives the benefits of risk-based pricing. Limiting or banning risk-based pricing would have significant negative impacts on consumers, especially, minority and low-income households.

1. Nam D. Pham, Ph.D., is managing partner and Mary Donovan is principal at ndp | analytics. Cassandra Brzenszki, Lauren Korlewitz, and Tamueyn Do provided research assistance. The U.S. Chamber of Commerce Center for Capital Markets provided financial support to conduct this study. The opinions and views expressed in this report are solely those of the authors.

RISK-BASED PRICING FOR CONSUMER CREDIT AND INSURANCE PRODUCTS

The economic rationale of risk-based pricing is simple, straightforward, and proven. Firms offer financial products at different rates for different consumers based on their individual risks. These products, such as loans, credit cards, and insurance, are different from other consumer goods because of the financial risks undertaken by firms. For loans and credit cards, firms advance capital when there is potential for nonpayment and default. For insurance, such as homeowners and auto, firms provide financial protection against an individual's future unknown costs related to insurable losses. These risks are, in part, caused by “asymmetric” information, meaning that the individual applying for credit or insurance knows far more about his or her risk level (e.g., likelihood of making on-time payments, driving behavior, ability to keep a home in good condition) than does the firm (see Box 1).² To address this issue, firms collect, analyze, and verify available information to best assess the applicant's risk profile and determine an appropriate rate.

To mitigate risk and attract customers, firms use risk-based pricing to offer customized rates to individuals based on their risk profile. Both consumers and firms benefit from this system because it provides more consumers with access to capital and insurance at better rates and helps firms accurately predict and account for risk. Lower-risk consumers have lower interest rates and insurance premiums, all else equal; higher-risk consumers have higher rates because the likelihood of nonpayment or potential costs associated with insurable losses are greater.

A key benefit of risk-based pricing is that it is dynamic. When consumers lower their risk, they receive better rates and more access. This risk-based pricing principle is applied across all consumers regardless of race, income, or other demographics. Moreover, as consumers improve their risk profiles, they can request their current rates be reassessed or shop around for better rates from other firms. In this way, financial literacy can play a significant role in improving access to credit for consumers as they learn the financial behaviors that lenders and insurers apply to their decisions.

2. See for instance: Akerlof, George A. 1970. “The Market for “Lemons”: Quality Uncertainty and the Market Mechanism.” *The Quarterly Journal of Economics*, 84(3).

BOX 1.

HOW RISK-BASED PRICING BENEFITS CONSUMERS AND COMPANIES

Illustrating the value of risk-based pricing with “lemons” in the used car market

Using risk-based pricing, consumers receive competitive rates based on their risk level. If a consumer is less likely to default on a loan or incur insured losses, he or she benefits from lower rates. Since companies lack reliable data on a consumer’s behavior, largely due to asymmetric information, they use complex models to predict risk.

To illustrate this concept of “asymmetric information,” consider the used car market and the issue of “lemons.” In this case, the owner knows the true condition of the car, while the buyer has limited information about the car’s quality and likelihood of being a lemon (see George Akerlof’s “Market for Lemons; Quality Uncertainty and the Market Mechanism” for an in-depth look at this issue). The availability and use of data, such as a CARFAX or AutoCheck report, reduces asymmetric information and helps the consumer evaluate potential risks associated with the car to determine if the asking price reflects the value.

Similarly, consumers applying for credit or insurance have more knowledge about their own risk profiles than do lenders and insurers, which makes it difficult to accurately price these products and protect against losses. A company’s ability to access and use data to accurately evaluate risk results in competitive rates and more product offerings for consumers.

Risk-based pricing models vary by industry and company and are subject to strict regulation and government oversight. In addition to adhering to regulatory requirements, companies develop risk-based pricing models using factors that are statistically significant (the factor clearly corresponds to risk) and credible (the relationship is proven and reliable).³ Indeed, insurance rates are required by law to “reflect the actual and expected loss experience” in each individual state, and insurers cannot use profits of one category of insurance (e.g., automobile) to subsidize losses in another category (e.g., homeowners).⁴ In terms of consumer credit, lenders determine their pricing based on the customer’s credit relative to the overall pool of customers. The Truth in Lending Act requires lenders to disclose rates and terms so consumers can easily understand and compare across lenders.⁵

3. CAS and III. 2019. “Insurance Rating Variables: What They Are and Why They Matter.”

4. Insurance Information Institute. 2013. “Financial Reporting in the P/C Insurance Industry.”

5. U.S. Treasury, Office of the Comptroller of the Currency. 2021. “Truth in Lending.”

Lenders' risk-based pricing models are regulated by prudential regulators like the Office of the Comptroller of the Currency (OCC), the Consumer Financial Protection Bureau (CFPB), and Federal Trade Commission (FTC). While proprietary models vary by company, lenders commonly use third-party credit scores, debt-to-income ratios, employment, and other factors, such as the ratio of the value of a house or car, relative to the loan applied for, to assess risk and subsequently determine the appropriate interest rate on a loan or credit card. Under the Fair Housing Act (FHA) and the Equal Credit Opportunity Act (ECOA), it is illegal for a creditor to discriminate against any applicant on the basis of race, ethnicity, sex, marital status, religion, nationality, age, or participation in a government social assistance program (Table 1).⁶

Insurers' risk-based pricing models are regulated by state governments. As a result, the rules can vary significantly by location. In general, insurers commonly use factors such as credit-based insurance scores (CBIS), location, driving experience, education, occupation, and property value and type in their risk models in states where these factors are permitted (Table 1). According to the Insurance Information Institute, "state and federal laws prohibit using rating variables that directly or indirectly impact groups based on characteristics such as race, nationality, religion, or income. Almost every state in the U.S. has the regulatory authority to reject a rating variable that it determines does not meet state requirements."⁷

Importantly, variables like CBIS, education, and occupation that, on the surface, seem unrelated to auto or homeowners insurance are important and valid components of risk-based pricing. From an actuarial perspective, these factors are proven to predict risk and can improve the accuracy of risk-based pricing models.⁸ As a result, insurers can better predict losses and offer consumers more competitive rates. In line with state regulations, these factors meet the actuarial and policy criteria to be included in insurance models and have been reviewed by state agencies and found not be unfairly discriminatory.⁹

6. CFPB. 2016. "What Should I Do If I Think That a Lender or Auto Dealer Discriminated against Me in My Auto Loan Application, such as by Denying My Application or Charging Me a Higher Interest Rate?" November.

7. CAS and III. 2019. "Insurance Rating Variables: What They Are and Why They Matter."

8. Hartwig, Robert O., Ph.D. 2007. "The Use of Education and Occupation as Underwriting Factors in Determining Policyholder Premiums for Private Passenger Auto Insurance." Written Testimony for the Florida Office of Insurance Regulation. February 9.

9. See, for instance, Redmer, Al. 2019. "Use of Occupation and Education Level as Rating Factors in Private Passenger Motor Vehicle Insurance." Maryland Insurance Administration. December 31; Goldman, Steven M. and Jon S. Corzine. 2008. "The Use of Occupation and Education Factors in Automobile Insurance." New Jersey Department of Banking and Insurance. April.

TABLE 1

Risk-based pricing in consumer credit and insurance industries¹⁰

	Consumer Credit Loans and Credit Cards	Insurance Homeowners and Automobile
Landscape	Lenders use risk-based pricing to evaluate credit applications and determine interest rates.	Insurers use risk-based pricing to evaluate policy applications and existing policies to determine premiums.
Primary Regulators	CFPB, FTC, and OCC	State Departments of Insurance
Common Factors Used in Evaluating Credit/ Policy Applications	<i>Factors vary by company, but may include:</i> <ul style="list-style-type: none"> • Ability to repay • Credit score • Debt-to-income ratio • Employment status • Loan-to-value ratio 	<i>Factors vary by company and state, but may include:</i> <ul style="list-style-type: none"> • CBIS • Driving experience (for auto) • Education • Gender • Location • Occupation • Previous losses • Property value and type
Factors Prohibited in Evaluating Credit/Policy Applications	<i>Per FHA and ECOA</i> <ul style="list-style-type: none"> • Nationality • Race • Religion • Familial/marital status • Participation in public assistance programs 	<i>Per a combination of federal and state laws</i> <ul style="list-style-type: none"> • Nationality • Race • Religion

Credit scores and CBIS are pillars of risk-based pricing. These scores predict risk and are calculated using statistical models that rely on credit history data. Neither credit scores nor CBIS are based on personal information such as race, ethnicity, religion, income, or employment.¹¹ The role of credit scores and CBIS in risk-based pricing models varies by industry and company. Lenders can use credit scores as the sole determining factor in credit decisions or can combine the score with additional information (e.g., down payment amount, loan-to-value ratios).¹²

10. U.S. Treasury, Office of the Comptroller of the Currency. 2019. “Fair Lending.” CAS and III. 2019. “Insurance Rating Variables: What They Are and Why They Matter.”

11. Insurance Information Institute. 2019. “Background on: Credit Scoring.” April 8; MyFICO.com. 2021. “What’s Not in My FICO Score.”

12. FDIC. 2008. “Fair Lending Implications of Credit Scoring Systems.” Supervisory Insights. Summer.

Insurers, on the other hand, can use CBIS only as one of a combination of factors in policy determinations, and only in states where CBIS are permitted.¹³ These scoring systems have protections in place for consumers negatively impacted by natural or declared disasters, such as the COVID-19 pandemic (see Box 2).¹⁴ At the federal level, the government implements consumer protections related to credit scores and CBIS through the Fair Credit Reporting Act (FCRA), which helps ensure the accuracy, fairness, and privacy of data in consumer credit files.¹⁵ To provide additional protections for insurance consumers, most states have enacted statutes or regulations that mandate the steps an insurer must take to price insurance risks for applicants with insufficient credit histories.

BOX 2.

COVID-19 AND CREDIT SCORES: PROTECTIONS FOR CONSUMERS

Longstanding guidance minimizes impact of natural and declared disasters on credit standing.

The fact that scoring systems are dynamic allows consumers to improve their scores by reducing their risk; at the same time, extraordinary events have potential to negatively impact a consumer's ability to pay his or her bills and, subsequently, lower his or her score. As a result, credit reporting agencies have tools to protect consumers' credit standing during natural and declared disasters, including the COVID-19 pandemic.

Longstanding guidance allows a special comment to be added to credit reports that acknowledges the disaster and that payments can be deferred as part of a forbearance plan in order to minimize the impact on consumers. Importantly, flagging tradelines to identify a natural or declared disaster, as opposed to simply deleting data during the disaster period, helps consumers maintain accurate and current credit history. Deleting data would create gaps and cause challenges down the road in accessing credit or receiving better interest rates and lower insurance premiums. Consumers can request to have this comment added to their credit report.

Credit scores are used to predict the probability of default using credit history data such as payment history, outstanding debt, length of credit history, application for new lines of credit, and credit mix.¹⁶

13. Insurance Information Institute. 2019. "Background on: Credit Scoring." April 8.

14. CDIA. 2020. "Support Available during Coronavirus Response." March 10.

15. FTC. "Fair Credit Reporting Act." 2021.

16. FTC. 2020. "Consumer Information: Understanding Your Credit." January.

The use of credit scoring in lending benefits consumers. According to the FTC, “properly designed, credit scoring systems generally enable faster, more accurate, and more impartial decisions than individual people can make.”¹⁷ FICO and VantageScore have developed models to produce credit scores for use by credit bureaus, lenders, and insurers. Lenders and credit bureaus also disclose these scores through various free or subscription services as a means of increasing score transparency. Alternatively, lenders can develop their own proprietary models to calculate credit scores. As a result, a consumer’s credit score can vary based on the company and model used. However, credit scores typically range from 300 to 850.¹⁸ Consumers with higher scores have lower predicted risk.

Credit-based insurance scores are used to predict insurance losses. Similar to credit scores, CBIS models utilize credit history data but include only factors shown to statistically correlate with claim costs.¹⁹ While the regulations vary by state, examples of credit history data used in CBIS models include payment history, credit card balances relative to credit limits, and credit inquiries, where permitted.²⁰ CBIS strongly correlate with insurance risk, and their validity and value have been proved repeatedly in independent actuarial and regulatory studies.²¹ One explanation for the link is the behavioral connection: “People who manage their finances well tend to also manage other important aspects of their lives responsibly, such as driving a car. People who manage money carefully may be more likely to have their car serviced at appropriate times and may also more effectively manage the most important financial asset most Americans own—their house—making routine repairs before they become major insurance losses.”²² The models used to calculate CBIS vary by company. FICO, LexisNexis, TransUnion, and other companies have developed scoring models, and many insurers have proprietary models. The CBIS range is often wider than that of credit scores. For example, FICO CBIS range from 100 to 900, LexisNexis CBIS range from 200 to 997, and TransUnion CBIS range from 300 to 900 (Table 2).²³

17. FTC. 2013. “Consumer Information: Credit Scores.” September.

18. DeNicola, Louis. 2019. “The Difference between VantageScore Scores and FICO Scores.” Experian. May 15.

19. Insurance Information Institute. 2019. “Background on: Credit Scoring.” April 8.

20. Ulzheimer, John. 2020. “What Is the Difference between Credit-Based Insurance Scores and Credit Scores.” Experian. June 29.

21. Boyd, Lamont. 2011. “Credit-Based Insurance Scores.” Presentation by FICO for NAIC.

22. Insurance Information Institute. 2019. “Background on: Credit Scoring.” April 8.

23. Ulzheimer, John. 2020. “What Is the Difference between Credit-Based Insurance Scores and Credit Scores.” Experian. June 29; TransUnion. 2021. “Product: TrueRisk.”

TABLE 2.

Credit scores and credit-based insurance scores are pillars of risk-based pricing²⁴

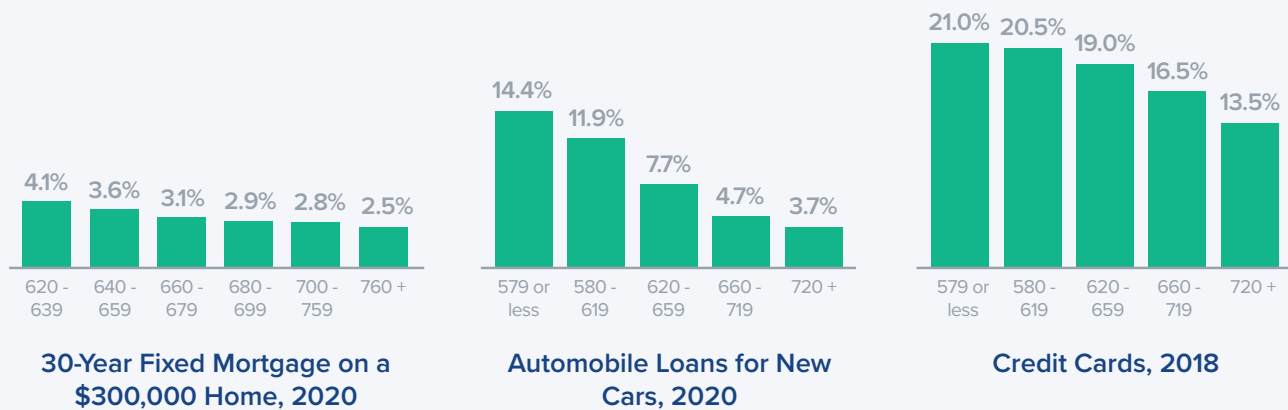
	Credit Scores	CBIS
General Landscape	FICO and VantageScore develop scoring models used by credit bureaus (Equifax, Experian, and TransUnion) and lenders.	LexisNexis, FICO, and insurance companies develop CBIS scoring models and scores.
Role of Score in Risk-Based Pricing	Credit scores can be the sole factor considered in making credit decisions or the score can be combined with other criteria.	CBIS must be used alongside other factors in making policy decisions in states where CBIS are permitted. Applicants cannot be rejected based on CBIS.
Purpose of Score	To predict the probability of default	To predict the likelihood of insurance losses
Factors Included in Credit Score/CBIS Calculations	Credit history data including: <ul style="list-style-type: none"> • Credit mix • Credit utilization vis-à-vis total credit available • Length of credit history • New credit • Payment history 	Credit history data shown to statistically correlate with claim costs and permitted under state regulation. Factors may include: <ul style="list-style-type: none"> • Payment history • Credit card balances relative to limits • Credit inquiries
Factors Excluded in Credit Score/CBIS Calculations	Data not related to credit history, including personal information such as: <ul style="list-style-type: none"> • Gender • Income, occupation, or employment history • Interest rates charged on a credit card or account • Location of residence • Marital status • Participation in credit counseling of any kind • Race, color, or national origin • Religion 	
Typical Score Range	300 to 850 (FICO and VantageScore)	100 to 900 (FICO) 200 to 997 (LexisNexis) 300 to 900 (TransUnion)

24. MyFICO.com. 2021. "What's in My FICO Scores?"; MyFICO.com. 2021."What's Not in My FICO Scores"; NAIC. 2021. "Credit-Based Insurance Scores Aren't the Same as a Credit Score. Understand How Credit and Other Factors Determine Your Premiums."

Individuals with better credit scores and credit-based insurance scores receive better rates when all other factors are equal. In consumer lending, lower-risk borrowers have more access to credit at better rates because they are more likely to make full and on-time payments. For example, comparing two individuals, one with a 720 credit score and one with a 620 credit score, the individual with better credit (720) pays lower interest rates: 2.8% compared with 4.1% for a 30-year fixed mortgage, 3.7% versus 7.7% for a car loan, and 13.5% versus 19.0% for credit cards. The lower interest rate for individuals with higher credit scores reflects the lower likelihood of default (Figure 1).

FIGURE 1

Consumers with higher credit scores receive lower rates²⁵



Insurers use credit-based insurance scores, in addition to other factors, to determine risk and subsequently insurance premiums. According to the FTC, CBIS are effective predictors of risk, and the use of these scores is “likely to make the price of insurance better match the risk of loss posed by the consumer.”²⁶ Thus, lower-risk individuals receive better rates on premiums because they are less likely to incur losses. In 2013, the average annual auto insurance premium in the U.S. was \$841 for drivers with high CBIS. These drivers saved \$232 and \$409 compared with those with median and low CBIS, respectively.²⁷ A similar pattern exists for homeowners insurance. In 2014, the average homeowners insurance annual premium in the U.S. was \$1,132 for those with high CBIS. These homeowners saved \$871 and \$1,292 compared with homeowners with median and low CBIS, respectively.²⁸ (Figure 2).

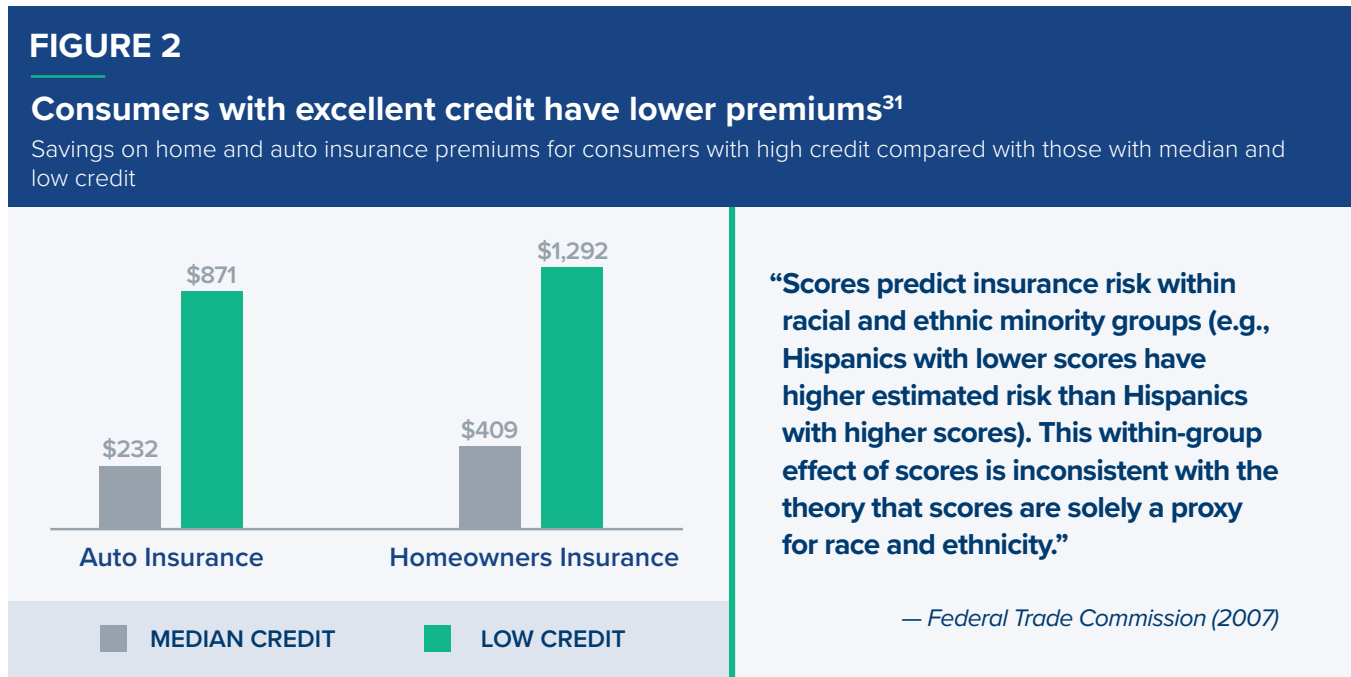
25. Knueven, Liz. 2020. “The Average Credit Card Interest Rate by Credit Score and Card.” Business Insider. September 19; Luthi, Ben. 2020. “What Auto Loan Rate Can You Get with Your Credit Score.” Experian. August 16; Stolba, Stefan Lembo. 2020. “What Kind of Mortgage Interest Rate Can I Get with a 750 Credit Score.” Experian. September 4.

26. FTC. 2007. “Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance A Report to Congress by the Federal Trade Commission.” July.

27. DiUlio, Nick. 2016. “Bad Credit? Expect Higher Auto Insurance Premiums Despite a Good Driving Record.” InsuranceQuotes. October 20.

28. DiUlio, Nick. 2017. “Why Poor Credit Can Triple Your Homeowners Insurance.” InsuranceQuotes. May 3.

The empirical correlation between credit data and insurance loss has been repeatedly validated: people with poorer credit histories on average incur more insured losses than do people with better credit histories.²⁹ Importantly, these scores accurately predict risk and are not tied to race or ethnicity. The FTC found that “[credit-based insurance] scores predict insurance risk within racial and ethnic minority groups (e.g., Hispanics with lower scores have higher estimated risk than Hispanics with higher scores). This within-group effect of scores is inconsistent with the theory that scores are solely a proxy for race and ethnicity” (Figure 2).³⁰



Credit scores and CBIS are dynamic, so consumers can reduce their cost of borrowing and insurance premiums by improving their credit history. Risk-based pricing not only creates efficiencies by adequately pricing products based on consumer risk profiles, but also reduces moral hazard by incentivizing consumers to adopt less-risky behavior.

However, not all consumers are in the formal credit market and therefore do not have a credit score, which makes it more challenging for lenders and insurers to predict their risk. Those with no credit data available are typically referred to as unscored or credit invisible.

29. FICO. 2021. “Using Credit to Predict Insurance Loss.”

30. FTC. 2007. “Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance A Report to Congress by the Federal Trade Commission.” July.

31. DiUlio, Nick. 2016. “Bad Credit? Expect Higher Auto Insurance Premiums Despite a Good Driving Record.” InsuranceQuotes. October 20; DiUlio, Nick. 2017. “Why Poor Credit Can Triple Your Homeowners Insurance.” InsuranceQuotes. May 3; FTC. 2007. “Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance A Report to Congress by the Federal Trade Commission.” July.

The Federal Reserve Bank of New York estimates that, at the end of 2018, 60.4 million American adults, 23.8% of the adult population, were unlikely able to access credit at choice (the ability for adults to obtain credit products at fair terms when they choose). Among those, about 26.5 million American adults, 10.5% of the adult population, were not in the formal credit economy and therefore did not have credit history.³² Historically, these credit-invisible individuals face barriers to accessing credit and reaping the benefits of risk-based pricing in lending.

To address this challenge, companies have begun to incorporate alternative data into risk-based pricing models and scoring algorithms. Alternative data provides the ability to determine a consumer's risk profile when traditional information is lacking (i.e., payment history, length of credit history, consumer indebtedness, acquisition of new credit, and credit mix). Common forms of alternative data include utility and mobile phone bills, and rent payments. Lenders also use cashflow and banking information, while insurers are increasingly using telematics (in-vehicle devices that track mileage and driving behavior). Just like traditional data, alternative data is subject to strict consumer protections and rigorous actuarial requirements (in insurance).

Alternative data offers numerous benefits: (1) It produces more scorable consumers and improves their access to credit. These newly scorable consumers can then potentially qualify for a loan or lower insurance rates. (2) Alternative data can improve rates for consumers who have traditional credit scores; alternative data “thickens” credit files by adding new datapoints related to a consumer's financial history. The inclusion of this data helps consumers build their credit history and helps lenders and insurers improve the accuracy of their risk assessments even further. An Experian study found that even consumers who remain in the same risk segment, transitioning from thin-file to full-file with alternative data, show some improvement in pricing.³³ (3) Alternative data improves additional risk segmentation, making it is easier to distinguish bad risks from the good risks.

In the risk-based pricing ecosystem, all types of companies are actively working to reduce the credit-invisible population, including companies that produce credit scoring models (e.g., FICO, VantageScore), companies that collect credit history data and calculate scores (Equifax, Experian, and TransUnion for credit scores and FICO, LexisNexis, and TransUnion for CBIS), and lenders and insurers that evaluate applications and make credit and policy determinations. These companies are developing and implementing innovative solutions to improve risk-based pricing, especially for the credit invisible. However, regulatory and technical challenges create limitations of the use and inclusion of alternative data (Table 3).

32. Hamdani, Kausar, et al. 2019. “Unequal Access to Credit—The Hidden Impact of Credit Constraints.” Federal Reserve Bank of New York.

33. Experian. 2015. “Let There Be Light: The Impact of Positive Energy-Utility Reporting on Consumers.”

Companies that produce scoring models have made efforts to reduce the credit-invisible population by developing new models that incorporate alternative data into the scoring methodology. For example, FICO recently launched FICO® Score XD and UltraFICO® Score, both of which leverage data not found in the traditional credit file in order to deliver reliable scores for a greater percentage of the total adult population.³⁴ Credit bureaus have developed innovative tools for consumers who lack sufficient information to generate a traditional credit score and to increase the accuracy of credit scores for those who already have them. For example, Experian Boost allows consumers to leverage their financial data by connecting utility, telecom, and video streaming subscription accounts to their Experian credit report, to be incorporated into their credit score.³⁵ This data can bolster the consumer’s qualifications for credit that might be missed in the traditional credit reporting and underwriting processes, particularly among consumers with less-extensive credit histories. Other innovative products that leverage alternative data include Equifax Insight Score (industry specific) and TransUnion CreditVision. Finally, lenders and insurers collect alternative data outside of the credit score/CBIS to better assess risk and offer new products to consumers. Lenders have incorporated alternative data such as utility and mobile phone bill payments and transaction data into underwriting. A TransUnion survey found that nearly 34% of lenders are currently using various types of alternative data to assess both prime and nonprime borrowers.³⁶ Specifically, 66% of surveyed lenders were able to lend to more borrowers in current markets and 56% were able to lend to borrowers in new markets through the use of alternative data.

More widespread use of alternative data can improve risk modeling for individuals with little to no credit report information. While the federal government has generally been supportive of the use of alternative data, regulatory uncertainties hold back broader adoption of these types of data in risk-based pricing. In 2019, the federal government recognized the benefits and encouraged the responsible use of alternative data in underwriting in a joint statement issued by the Federal Reserve Board of Governors, CFPB, FDIC, National Credit Union Administration, and Office of the Comptroller of the Currency. Specifically, the statement read:

“The agencies recognize that use of alternative data may improve the speed and accuracy of credit decisions and may help firms evaluate the creditworthiness of consumers who currently may not obtain credit in the mainstream credit system. Using alternative data may enable consumers to obtain additional products and/or more favorable pricing/terms based on enhanced assessments of repayment capacity. These innovations reflect the continuing evolution of automated underwriting and credit score modeling, offering the potential to lower the cost of credit and increase access to credit.”³⁷

34. FICO. 2019. “UltraFICO Score Fact Sheet”; FICO. 2019. “FICO Score XD.”

35. Long, Emily. 2020. “What Is Experian Boost and How Does It Work?” New York Times. April 21.

36. TransUnion. 2015. “The State of Alternative Data.” TransUnion and Vesta Research.

37. FDIC. 2019. “Interagency Statement on the Use of Alternative Data in Credit Underwriting.”

However, uncertainties about whether regulators will provide additional guidance or take action on the use of alternative data are a concern among financial companies.³⁸ Additionally, companies face challenges obtaining alternative data, in part due to the regulatory environment as well as technical challenges obtaining and validating data.

Data submitted to credit bureaus must comply with federal, state, and local regulations. The regulatory burden creates disincentives for companies from submitting valuable alternative data, such as bill and rent payments. Currently, nationwide credit bureaus have utility data for only 2.6% of consumers and cell phone bill data for 5% of consumers.³⁹ This results in less innovation and reduces the use of these data in risk-based pricing, which, ultimately, most negatively impacts access to capital and insurance for the credit invisible and consumers with thin credit files.

TABLE 3.
Companies are using alternative data to reduce credit invisible population

	Scoring Models	Credit Scores/ CBIS	Credit/Policy Determinations
Proactive Approach	Companies that produce scoring models are incorporating alternative data into their methodologies	Credit bureaus are collecting alternative data from organizations & individuals for scoring	Lenders and insurers are using alternative data in addition to credit scores/CBIS to evaluate applications
Examples of Innovation	FICO XD UltraFICO	Equifax Insight Score (industry-specific) Experian Boost TransUnion CreditVision	Use of telematics by insurers Use of bill payments by lenders
Challenges	<ul style="list-style-type: none"> Utilities, landlords/property managers, and other firms that could provide data must comply with FCRA, state, & local regulations; many of which are not currently set up for compliance Regulatory uncertainties hinder adoption of alternative data Companies face technical challenges obtaining and verifying data 		

38. Aite. 2018. "Alternative Data across the Loan Life Cycle: How FinTech and Other Lenders Use It and Why."

39. Gaskin, Joanne. 2019. "Leveraging Alternative Data to Extend Credit to More Borrowers." FICO. May 22.

THE POSITIVE IMPACT OF RISK-BASED PRICING

Risk-based pricing has evolved over decades and resulted in sophisticated models that use credit scores, CBIS, and other factors to accurately predict risk, where permitted. The ability for companies to use these tools has helped reduce gaps in access to credit and insurance for low-income and minority households in the U.S. Recent calls for removing risk-based pricing in favor of a uniform system will hurt—not help—underserved communities, the credit invisible, and consumers with sub-prime credit.

BOX 3.

RISK-BASED PRICING PROVIDES MORE PROTECTION FOR CONSUMERS

Uniform rates and no barriers to entry have negative financial consequences for high-risk consumers.

Improved consumer financial well-being benefits individuals, companies, and policymakers alike. Individuals benefit from increased financial freedom, companies can attract more customers, and governments realize cost savings. Risk-based pricing positively influences financial health more so than a uniform pricing system. Indeed, risk-based pricing deters high-risk customers who are more likely to be unable to repay. It not only protects the lender from losses, the system importantly protects the consumer from taking on too much unaffordable debt. A uniform pricing system, on the other hand, and especially one that lowers or removes barriers to entry (thus accepting all applications, like the Education Department’s Federal Direct Loan Program), incentivizes consumers to borrow more, even if there is high risk of nonpayment. This approach worsens consumer financial health and exacerbates gaps in economic opportunity.

If policymakers prohibit the use of scoring systems and mandate uniform pricing for financial products, consumers will have less incentive to reduce risky behavior and improve financial health to access lower-priced financial products. Even under a uniform pricing system, lenders and insurers must evaluate applications and determine if an individual’s risk is acceptable under the uniform rate.

Two significant challenges arise under this system: (1) without credit scores, CBIS, or other predictive data, lenders and insurers have fewer datapoints to determine an applicant’s risk; and (2) lenders and insurers must determine if the applicant’s risk is sufficiently covered by the uniform price—if not, the applicant is more likely to be rejected since the company cannot offer a higher rate to compensate for risk. Without dynamic credit scoring, consumers whose applications are rejected under a uniform pricing system would have to change other factors under consideration, such as down payment amount, to reduce risk; such a system would create more barriers to pursue economic opportunity, especially for lower-income and minority households. If lenders and insurers had to approve all loan or policy applications at the uniform rate, there would be significant negative consequences, especially for consumers, who could end up in worse financial situations (see Box 3).

In contrast, risk-based pricing allows lenders and insurers to offer different prices to individuals based on risk. Two major benefits of risk-based pricing for consumers are the following: (1) consumers, over time, pay less in the risk-based pricing system than in the uniform pricing system; and (2) unlike in the uniform pricing system, in the risk-based pricing system, consumers have incentives to improve their behavior (e.g., pay bills on time and pay down debt) and, by extension, their risk scores to enjoy lower-priced financial products (Table 4).

TABLE 4.
Comparison between risk-based and uniform pricing systems

	Risk-based Pricing	Uniform Pricing
Application	Consumer applies for loan/insurance policy	
Review	Lenders/insurers assess risk of default/insurance losses	
Determination	Lenders/insurers evaluate application; offer a competitive rate based on individual risk assessment	Lenders/insurers evaluate application; offer one rate to all applicants that accounts for risk of entire population
Impact	<ul style="list-style-type: none"> • Consumer pays rate based on risk. • Consumer has incentive to improve risk profile for better access to credit and better rates/premiums. • Applications with higher risk profiles more likely to be approved than in a uniform pricing system and offered rates comparable to risk. 	<ul style="list-style-type: none"> • Consumer pays for others’ risks; lower-risk consumers pay more, and overall costs are higher. • Consumer has little incentive to improve risk profile above minimum acceptable score. • Applications with higher-risk profiles more likely to be rejected.

While risk-based pricing has been around for decades, the use of credit scores to determine if a consumer qualified for a mortgage was not widely adopted until the mid-1990s.⁴⁰ To illustrate the benefits of risk-based pricing quantitatively, we analyzed mortgage originations and performance from 1999 to 2020 using Fannie Mae Single-Family Historical Loan Performance Data. Our findings show consumers pay less overall in the risk-based pricing system than in the uniform pricing system.

Lower-risk consumers pay lower interest rates. During 1999-2020, the rate differential was 229 basis points between the highest-risk group (6.73% for borrowers with FICO scores below 620) and the lowest-risk group (4.44% for borrowers with FICO scores of at least 800). During the same period, the higher-risk groups also had higher delinquency rates and higher net loss rates compared with their lower-risk counterparts (Table 5).

TABLE 5.

Higher-risk groups had higher delinquency rates and net loss rates⁴¹

Loan originations and performance for 30-year loans of first-time homebuyers by risk band, 1999-2020

Risk Band (FICO Score)	Average Interest Rate	Origination Loan Count	Origination Unpaid Principal Balances (\$M)	Average Origination Unpaid Principal Balances (\$M)	Share of Unpaid Principal Balances that Were Ever 180 Days Delinquent	Net Loss Rate
620 or less	6.73%	67,529	\$9,130	\$135,206	10.88%	1.93%
620-640	5.73%	123,573	\$20,448	\$165,472		
640-660	5.53%	209,537	\$36,071	\$172,146	2.42%	0.43%
660-680	5.34%	303,568	\$54,574	\$179,776		
680-700	5.02%	459,845	\$90,281	\$196,329	2.36%	0.34%

40. RocketHQ. 2020. "The History of Credit." October 15.

41. Fannie Mae. 2021. "Single-Family Historical Loan Performance Dataset." February 8.

Risk Band (FICO Score)	Average Interest Rate	Origination Loan Count	Origination Unpaid Principal Balances (\$M)	Average Origination Unpaid Principal Balances (\$M)	Share of Unpaid Principal Balances that Were Ever 180 Days Delinquent	Net Loss Rate
700-720	4.85%	570,537	\$118,014	\$206,847		
720-740	4.72%	677,491	\$144,239	\$212,902	1.06%	0.16%
740-760	4.65%	759,878	\$166,575	\$219,213		
760-780	4.60%	775,345	\$176,793	\$228,019	0.54%	0.10%
780-800	4.51%	714,691	\$168,136	\$235,257		
800 or more	4.44%	327,306	\$71,778	\$219,300	0.40%	0.09%

Under the risk-based pricing system, lenders charge higher rates for higher-risk groups to compensate for expected losses. As shown above, the data shows higher delinquency and net loss ratios for higher-risk groups. To account for these losses, we calculated an adjusted interest rate.⁴² After adjusting for losses, the rate differential among higher-risk and lower-risk groups becomes much narrower. During 1999-2020, the rate differential adjusted for net losses was only 45 basis points between the highest-risk group (4.80%) and the lowest-risk group (4.35%) compared with 229 points for the non-adjusted rate differential (Table 6).⁴³

42. During 1999-2020, origination unpaid principal balances totaled nearly \$1.1 trillion. Based on the average interest rate and net loss rate of each risk band, we calculate an average annual interest payment of origination unpaid principal balances and expected losses of origination unpaid principal balances of each risk band. We then calculate expected annual interest payment of each risk band, which equals an average annual interest payment minus expected losses. The average interest rate adjusted for expected losses equals expected annual interest payment divided by original unpaid principal balances.

43. The difference between the highest and lowest risk bands is reduced significantly when the interest rate is adjusted for expected losses. While variation still exists across risk bands, this is, in part, due to limitations of the data and analysis, as well as expected limitations in pricing models which are proven to be accurate but may not be perfect (see Table 3, Figures 20-21, and corresponding text on how alternative data can improve modelling).

TABLE 6.

When adjusted for expected losses, interest rates are similar across risk bands

Average interest rate and average interest rate adjusted for expected losses by risk band, 1999-2020

Risk Band (FICO Score)	Average Interest Rate	Origination Unpaid Principal Balances (\$M)	Net Loss Rate	Average Annual Interest Payment of Origination Unpaid Principal Balances (\$M)	Expected Losses of Origination Unpaid Principal Balances (\$M)	Expected Annual Interest Payment (adjusted for expected losses) (\$M)	Average Interest Rate (adjusted for expected losses)
620 or less	6.73%	\$9,130	1.93%	\$614	\$176	\$438	4.80%
620-640	5.73%	\$20,448		\$1,172	\$395	\$777	3.80%
640-660	5.53%	\$36,071	0.43%	\$1,995	\$156	\$1,839	5.10%
660-680	5.34%	\$54,574		\$2,914	\$236	\$2,678	4.91%
680-700	5.02%	\$90,281	0.34%	\$4,532	\$306	\$4,226	4.68%
700-720	4.85%	\$118,014		\$5,724	\$400	\$5,324	4.51%
720-740	4.72%	\$144,239	0.16%	\$6,808	\$237	\$6,571	4.56%
740-760	4.65%	\$166,575		\$7,746	\$273	\$7,472	4.49%
760-780	4.60%	\$176,793	0.10%	\$8,132	\$180	\$7,953	4.50%
780-800	4.51%	\$168,136		\$7,583	\$171	\$7,412	4.41%
800 or more	4.44%	\$71,778	0.09%	\$3,187	\$63	\$3,124	4.35%
Sum		\$1,056,039		\$50,407	\$2,593	\$47,814	

If uniform pricing were mandatory, lenders would find a rate to charge all borrowers such that the net interest payments would remain unchanged compared with the current risk-based pricing system. Compared with the current risk-based pricing system, borrowers with better credit scores would pay higher interest rates while borrowers with poorer credit scores would pay lower interest rates. Two major negative impacts of the uniform pricing system on consumers are the following: (1) fewer borrowers with high credit scores would be able to borrow money and, therefore, fewer low-risk borrowers would be in the lender portfolio; and (2) borrowers with lower credit scores would have little incentive to change their behavior to improve their credit scores to access lower-cost borrowing.

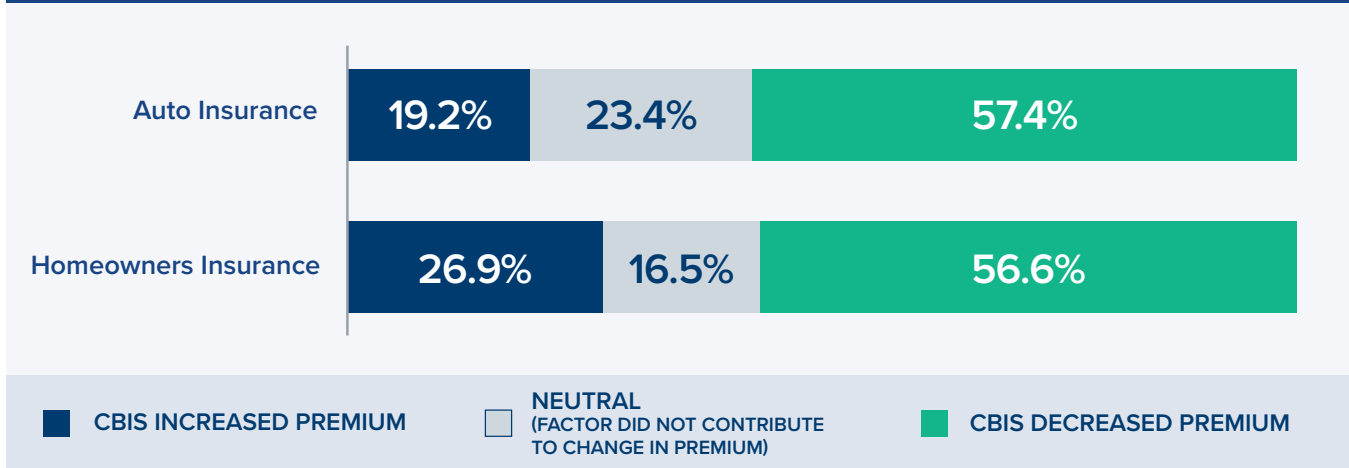
The combination of a reduction in higher-credit borrowers and an increase in lower-credit borrowers produces higher losses for lenders. As a result, lenders will raise rates to cover their costs under a uniform pricing system which, in turn, has substantial negative impacts on the U.S. economy. Consumers will have less access to capital to pursue economic opportunity, such as to obtain a mortgage to buy a home, get a car loan, or borrow money for large purchases. Freddie Mac estimated a 146-basis-point increase in mortgage rates and loan originations reduced by 30%, which is equivalent to a 20.5% reduction in loan originations for every 100-basis-point increase in the interest rate.⁴⁴

Research findings in other areas of consumer finance support the same conclusion that risk-based pricing is more beneficial than is uniform pricing, specifically that consumers have higher access to capital at lower costs in the risk-based pricing system. For example, a 2003 study by the Information Policy Institute found that access and use of credit cards by underserved populations, including low-income and minority groups, increased substantially from 1970 to 2001 and that “competition, credit scoring, and technology have reduced the consumer’s price for credit card credit.” In total, the research found that consumer savings from these efficiencies were about \$30 billion per year.⁴⁵

Similarly, the use of CBIS reduced premiums for the majority of policyholders. A survey conducted by the Arkansas Department of Insurance found that, during 2016, 57.4% of automobile insurance policies that were written or renewed had reduced premiums because credit was included as a factor in the ratemaking decision and 56.6% of homeowner’s insurance policies resulted in premium reductions (Figure 3).

44. Freddie Mac. 2018. “Nowhere to Go but Up? How Increasing Mortgage Rates Could Affect Housing.” Economic & Housing Research Insight.

45. Information Policy Institute. 2003. “The Fair Credit Reporting Act: Access, Efficiency, and Opportunity.” June.

FIGURE 3**CBIS decreased or had no impact on most homeowners and auto insurance premiums⁴⁵**

However, CBIS is only one of many factors used in insurers’ risk-based pricing models. Inclusion of other predictive data, such as education and occupation, contributes to more competition and lower premiums for consumers. According to a 2008 study by New Jersey’s Department of Banking and Insurance, “Allowing insurers to use a wider variety of rating factors has contributed to overall improvement in the marketplace for many kinds of drivers and in all regions of the State.”⁴⁷ This study was prompted by GEICO’s inclusion of education and occupation as rating variables. The department determined, “The use of these factors has not created higher overall premiums for drivers with lesser occupational and educational attainment. Indeed, GEICO’s New Jersey rates for these consumers are often lower than the rates of competing companies where such factors are not used.”⁴⁸ Similar findings on competition and rates have been found by other state insurance agencies. Most recently, in 2019, Maryland’s Insurance Administration determined that prohibiting occupation and education in auto insurance “could result in a smaller range of available rates or stricter eligibility guidelines and reduced risk appetite ... thus limiting price options and competition.”⁴⁹

46. Lacy, William. 2017. “Use and Impact of Credit in Personal Lines Insurance Premiums Pursuant to Ark. Code Ann. § 23-67-415.” Arkansas Insurance Department. June 7.

47. Goldman, Steven M. and Jon S. Corzine. 2008. “The Use of Occupation and Education Factors in Automobile Insurance.” State of New Jersey Department of Banking and Insurance. April.

48. Goldman, Steven M. and Jon S. Corzine. 2008. “The Use of Occupation and Education Factors in Automobile Insurance.” State of New Jersey Department of Banking and Insurance. April.

49. Redmer, Al. 2019. “Use of Occupation and Education Level as Rating Factors in Private Passenger Motor Vehicle Insurance.” Maryland Insurance Administration. December 31.

While many consumers have realized lower premiums through the use of robust risk-based pricing models, three states have banned insurers from using CBIS and other predictive data, including education and occupation. These types of regulations hinder innovation and competition, and ultimately hurt consumers. Insurance companies compete in pricing analytics and, while the ultimate goal is accuracy, variation is a feature of flexible rating laws. Indeed, states that have implemented positive regulatory reforms in the automobile insurance market have realized a number of consumer benefits, including lower premiums, increased availability, and improved underwriting.⁵⁰ Insurers use different sets of variables, and they weigh each factor differently. No single variable can be used as the sole factor to decide their decisions. Rather, credit information, along with other predictive data, such as education and occupation, are only some of the many other factors entered into insurance models to assess risks accurately. In fact, insurers may use up to 20 or more risk factors to determine rates.⁵¹ Simply removing factors from insurance models does not result in lower premiums. According to the Insurance Information Institute, restrictions on actuarially valid underwriting criteria lead to less competition, higher prices, and growth in residual auto insurance markets.⁵²

We disprove the assertion that including predictive data such as CBIS, education, and occupation in risk-based pricing models drives up auto insurance premiums. California, Hawaii, and Massachusetts prohibit the use of CBIS, education level, and occupational data in rate setting and underwriting auto policies.⁵³ We use A.M. Best's auto insurers data and U.S. Census Bureau demographic data to show that states that prohibit this information tend to have lower competition. In 2019, the median number of auto insurers operating in a state was 536 and ranged between 279 in Hawaii and 685 in Texas. Except California, all three states that ban CBIS, education level, and occupational data have fewer auto insurers than the median. To account for market size, we divide the population (16 years old and above) by the number of auto insurers. The median adults per company was 6,368 in the U.S., ranging from 1,099 in Wyoming to 54,702 in California. Except Hawaii, states that prohibit key risk-based pricing factors have a higher number of adults per auto insurer, indicating that there is less competition. Importantly, states that are more competitive tend to be more affordable for consumers (Table 7).⁵⁴

50. Insurance Research Council. 2012. "The Long-Term Effects of Rate Regulatory Reforms in Automobile Insurance Markets." March.

51. Hartwig, Robert O., Ph.D. 2007. "The Use of Education and Occupation as Underwriting Factors in Determining Policyholder Premiums for Private Passenger Auto Insurance." Written Testimony for the Florida Office of Insurance Regulation. February 9.

52. Hartwig, Robert O., Ph.D. 2007. "The Use of Education and Occupation as Underwriting Factors in Determining Policyholder Premiums for Private Passenger Auto Insurance." Written Testimony for the Florida Office of Insurance Regulation. February 9.

53. The Zebra. 2021. "The State of Auto Insurance, 2021."

54. Schmid, Patrick. 2014. "Auto Insurance Affordability." National Association of Insurance Commissioners.

TABLE 7.

States that prohibit CBIS, education level, and occupational data often had less competition than the median across states⁵⁵

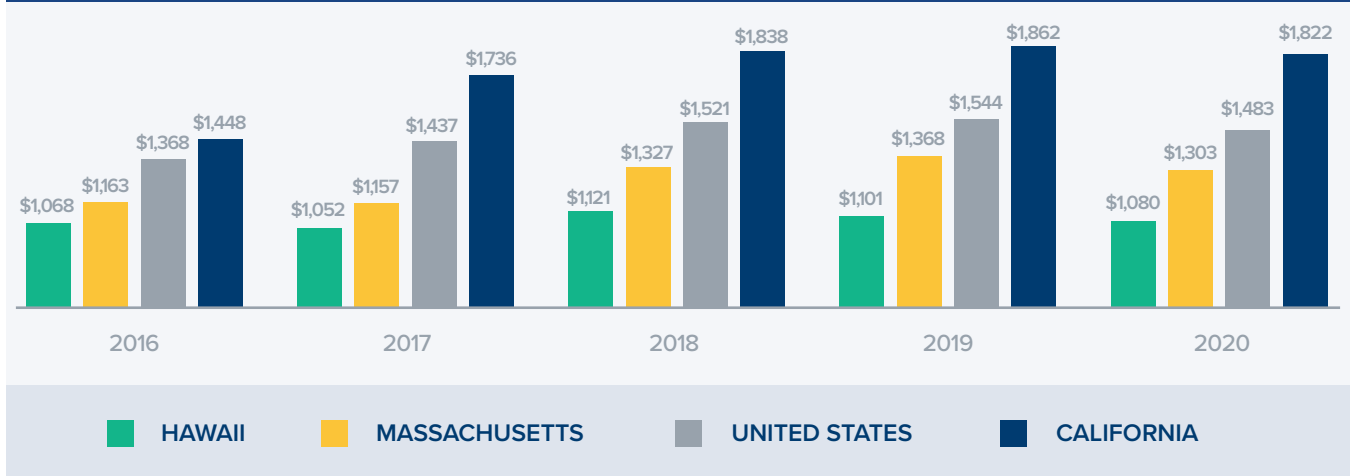
	All States (Median)	California	Hawaii	Massachusetts
Number of companies	536	578	279	387
Adults per company	6,368	54,702	4,113	14,747

States that prohibit CBIS, education level, and occupational data do not necessarily have lower insurance premiums. Indeed, insurance premiums are based on many factors, including individual risk profiles, state regulatory requirements (e.g., financial responsibility minimum limits), and local cost drivers (e.g., tort climate). We use average expenditures for auto insurance by state calculated and published by the Zebra to compare to the national average the average expenditures and growth in states that prohibit CBIS, education level, and occupational data. During 2016-2020, California had higher auto insurance expenditures than the national average. During the same period, auto insurance expenditures in California and Massachusetts grew faster than the national average (26% and 12%, respectively, compared with 8% overall; Figure 4).

FIGURE 4

States that prohibit the use of CBIS, education level, and occupational data were not necessarily cheaper than the national average⁵⁵

Average expenditures for auto insurance by state, 2016-2020



55. A.M. Best Company, Inc. 2020. "U.S. Auto Liability – Top Writers by State, Canada and U.S. Territories - 2019." Best's Review; U.S. Census Bureau. 2020. "American Community Survey, 2019."

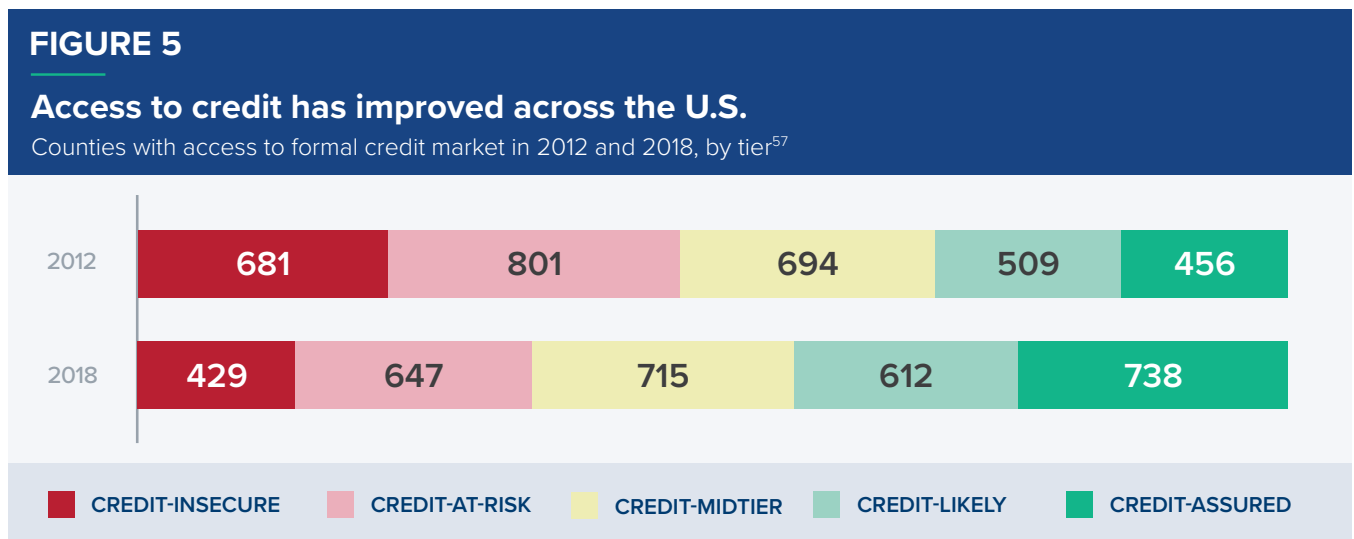
56. The Zebra. 2021. "The State of Auto Insurance, 2021."

All told, consumers in states that restrict predictive data for auto insurance do not have the lowest insurance premiums nor the most choice for auto insurers.

The Positive Effect of Risk-Based Pricing on Capital Access and Utilization for U.S. Communities

Individuals who have access to credit have more economic opportunity and financial security. Under the risk-based pricing system, financial institutions can assess consumer risks accurately and offer loans and insurance products at different rates to individuals based on their risk levels. As a result, more individuals have access to capital at lower costs. The Federal Reserve Bank of New York publishes the Credit Insecurity Index, which measures the financial health of communities at the county level by assessing individual credit scores and ability to access credit, including those who are credit invisible (not in the formal credit economy). The index categorizes counties in five broad tiers: credit-assured, credit-likely, credit-midtier, credit-at-risk, and credit-insecure.⁵⁷

Since 2012, individuals and communities have increased access to credit. The improvement from 2012 to 2018 is attributed to more individuals having access to the traditional credit market and more individuals with better credit scores. In 2012, about half of all counties across the U.S. (1,482 of 3,082 counties) were classified as credit-insecure or credit-at-risk and less than 15% of all counties (456 counties) were considered credit-assured. By the end of 2018, 406 counties were no longer classified as credit-insecure or credit-at-risk and 738 counties were credit-assured (Figure 5).



57. Hamdani, Kausar, et al. 2019. “Unequal Access to Credit—The Hidden Impact of Credit Constraints.” Federal Reserve Bank of New York.

58. Hamdani, Kausar, et al. 2019. “Unequal Access to Credit—The Hidden Impact of Credit Constraints.” Federal Reserve Bank of New York.

The Positive Effect of Risk-Based Pricing on Minority Groups

Historically, Black and Indigenous individuals and other People of Color have had less access to financial products. Although wealth disparities of these economically disadvantaged groups remain an issue, these gaps have narrowed over the past couple decades. Continued innovation in risk-based pricing positively contributes to improved economic opportunity. Over time, risk-based pricing has helped minorities gain better access to credit and insurance. Assertions that risk-based pricing is racially biased against minorities are unmerited. Research by the Board of Governors of the Federal Reserve System concludes that there is little or no evidence of disparate impact by race, ethnicity, or gender resulting from the reliance on credit scoring in risk-based pricing models for underwriting and pricing mortgage and consumer credit markets. While the research found that credit scores, on average, vary across demographic groups, it also found that a credit score is predictive of credit risk regardless of race or ethnicity.⁵⁹ Importantly, credit scores were predictive of risk within racial and ethnic groups, meaning that consumers who present greater risk within a group also have a riskier credit score. The Federal Reserve’s research does not identify any credit characteristics to be the result of correlations with demographic groups. Moreover, credit scores did not lead to individual discriminatory results. These findings dispute concerns about possible discrimination in the credit underwriting process.⁶⁰ Indeed, credit scoring models are prohibited from having a statistical bias with regard to any specific consumer group.⁶¹ A 2020 performance analysis by VantageScore found that, “for both bankcard and first mortgage loans, default curves are statistically aligned among ethnic groups at each credit score value and among the overall population. For all ethnic groups, there is near alignment of default curves, indicating an unbiased model.”⁶²

We combine Census’ American Community Survey demographic and economic statistics with the Federal Reserve Bank of New York’s Credit Insecurity Index to assess the benefits of the risk-based pricing system of minority groups at the county level. From 2012 to 2018, counties whose populations have a high density of minorities experienced a greater increase in credit accessibility than did other communities. The top 10th percentile of counties with Black, Hispanic, and Asian populations in 2012 increased their access to credit more than the national average and the top 10th percentile of counties with predominately White populations. We found similar patterns for the top 25th and 50th percentiles of counties with Black, Hispanic, and Asian populations.

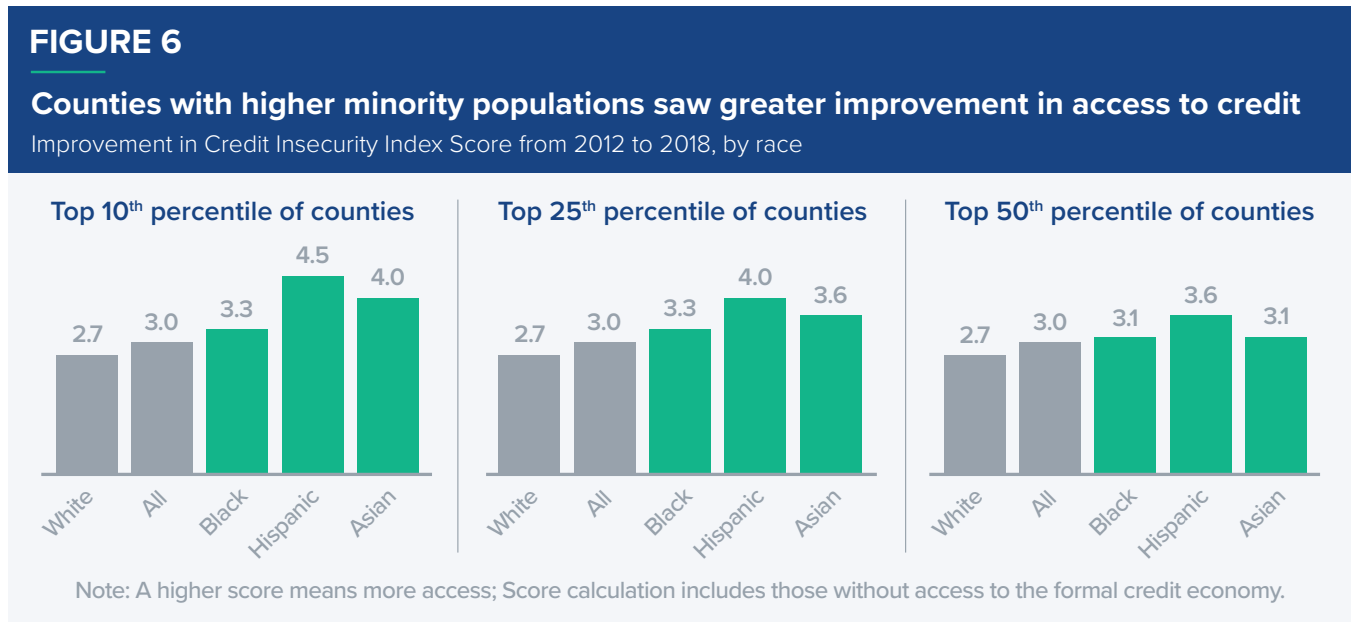
59. Board of Governors of the Federal Reserve System. 2007. “Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit.” August.

60. Avery, Robert B., Kenneth P. Brevoort, and Glenn B. Canner. 2010. “Does Credit Scoring Produce a Disparate Impact?” Federal Reserve Board.

61. VantageScore. 2020. “2020 VantageScore Model Performance Assessment.” April.

62. VantageScore. 2020. “2020 VantageScore Model Performance Assessment.” April.

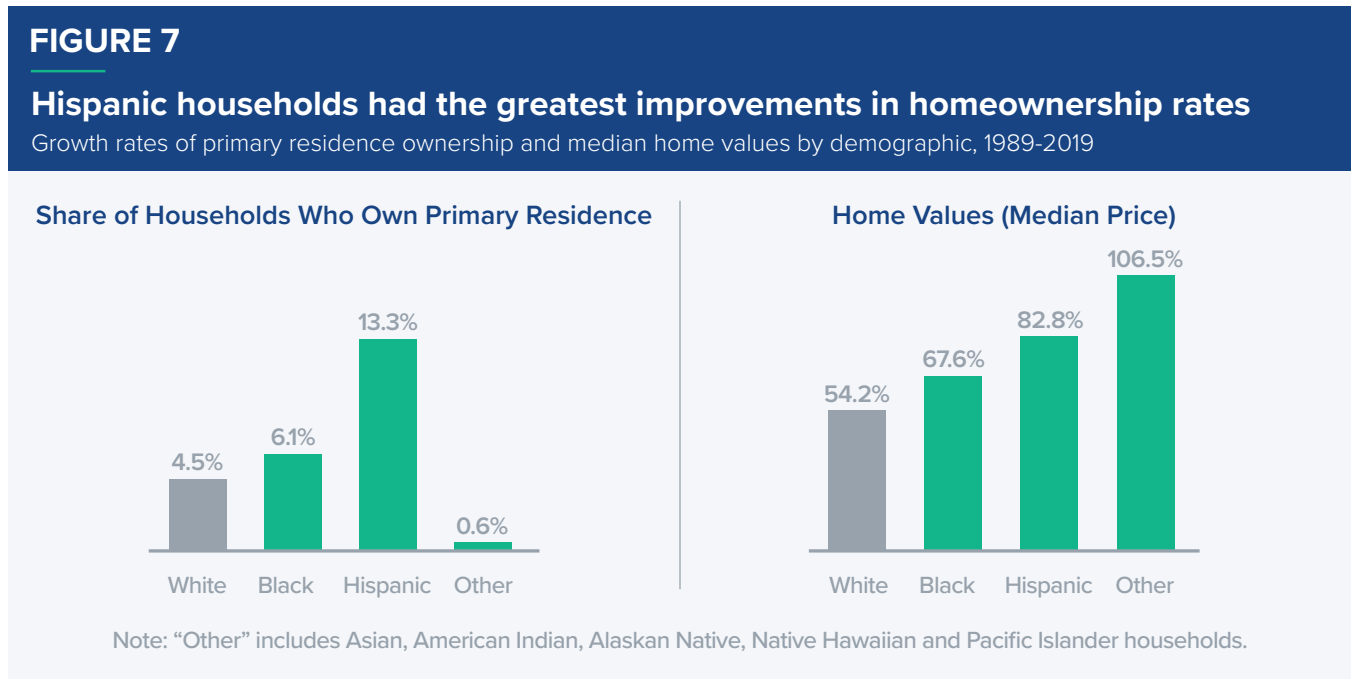
While the national average improvement in Credit Insecurity Index Score during 2012-2018 was 3.0, the index score improvement was 4.5 for counties with the highest share of Hispanic populations, 4.0 for counties with the highest Asian population, 3.3 for counties with the highest Black population, and 2.7 for counties with the highest White population (Figure 6).



Risk-based pricing models are more widely used and more sophisticated and accurate than they were when first put into use decades ago. To examine the impacts of risk-based pricing on minority groups over the past 30 years, we use the Federal Reserve’s Survey of Consumer Finances (SCF) to analyze the following six indicators: (1) primary residence ownership, (2) automobile ownership, (3) mortgage and line of credit loans, (4) automobile loans, (5) installment loans, and (6) credit card balances. The first two indicators measure assets while the latter four indicators measure access to credit. We calculate the 30-year growth rates of (1) the share of households and (2) the dollar amount for each indicator by demographic group. Then we compare the growth rates of each consumer group.

Our findings show that the expanded use of risk-based pricing in underwriting financial products over the past several decades created positive economic opportunities for minority groups, as measured by asset holdings as well as access to capital. Furthermore, the economic opportunity grew faster among minority households compared with their counterparts. Over the past 30 years, an increasing number of minorities have owned their primary residences and purchased higher-priced homes. The share of minority households who own homes and their associated median prices grew faster than their counterpart white households. During 1989-2019, the share of Black and Hispanic households who own primary residence homes grew by 6.1% and 13.3%, respectively, compared with 4.5% growth for white households.

The median home value of Black and Hispanic households, measured by median price, rose 67.6% and 82.8%, respectively, compared with 54.2% for white households (Figure 7).



Households are required to obtain homeowners insurance on properties they own; therefore, the increase in households who own their primary residence is expected to reflect the increase in households with homeowners insurance policies. Importantly, the residual market for property insurance has declined over time, indicating that more homeowners are able to obtain policies through the private marketplace. Over the past decade, the number of policies issued through Fair Access to Insurance Requirements Plans, which serve the residual market, decreased 39% from nearly 2.3 million in 2008 to less than 1.4 million in 2019.⁶³

Automobile ownership is the second asset indicator in our assessment. Over the past 30 years, the share of Black and Hispanic households who own automobiles grew faster compared with white and other minority households. During 1989-2019, the share of Black and Hispanic households who own automobiles grew by 25.7% and 9.7%, respectively, compared with 0.1% growth for white households and -0.4% for other minority groups. The value of the automobiles purchased, measured by median price, rose 101% for Hispanics compared with 24.3% and 22.7% for white and Black households, respectively (Figure 8).

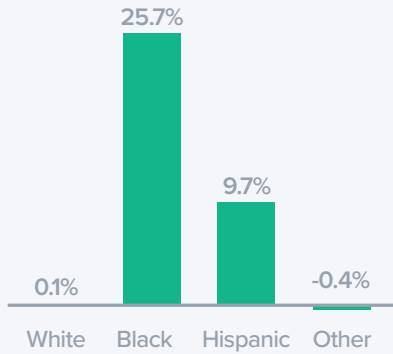
63. Insurance Information Institute. 2021. "Insurance Provided by FAIR Plans by State, Fiscal Years 2019 and 2008."

FIGURE 8

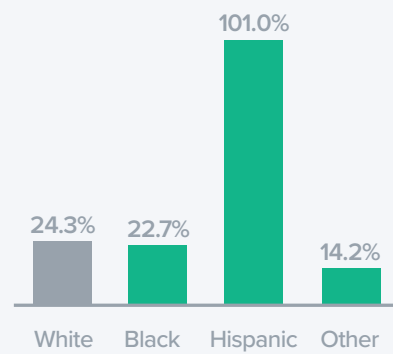
Black households had the greatest improvements in auto ownership rates

Growth rates of auto ownership and median auto values by demographic, 1989-2019

Share of Households Who Own an Automobile



Automobile Values (Median Price)



Note: "Other" includes Asian, American Indian, Alaskan Native, Native Hawaiian and Pacific Islander households.

Since nearly all states require drivers to obtain auto insurance on their vehicles, the increase in households with automobiles likely reflects the increase in households with auto insurance policies. Notably, over time the residual market for auto insurance has declined substantially, so more individuals are able to get competitive policies at lower rates through the private marketplace. In 1989, the residual market accounted for 8.9% of total auto premiums and by 2008 that share had been reduced to 0.8%.⁶⁴ In 2016, the residual market accounted for only 0.2% of total auto liability premiums.⁶⁵

Access to credit has increased over the last few decades, especially for Black and Hispanic households. This is shown not only in the growth rate of households obtaining mortgages, but also in median loan amount. During 1989-2019, the share of Black households who obtained mortgage or home equity loans grew 10.1%, the fastest growth, compared to 6.0% for white households and 3.9% for Hispanic households. The median mortgage obtained by Black households grew nearly 324% compared to 110.2% for white households and only 61% for Hispanic households. (Figure 9)

64. Insure.com. 2010. "Swimming in the Assigned-Risk Pool for Car Insurance." March 21.

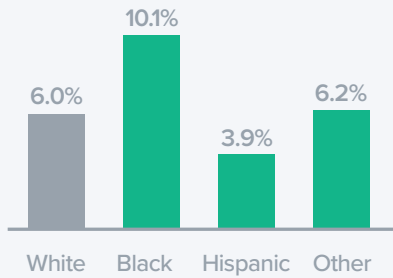
65. NAIC. 2020. "Auto Insurance Database Report 2016/2017." January.

FIGURE 9

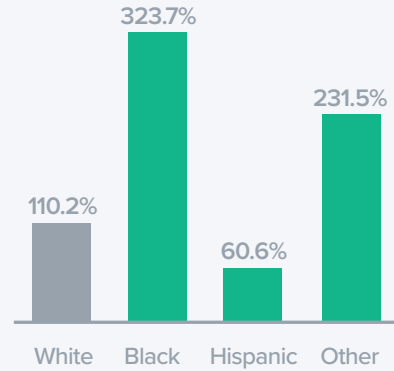
Black households had the greatest improvements in access to mortgages

Growth rates of households obtaining mortgages and median loan amounts by demographic, 1989-2019

Share of Households Obtaining Mortgages



Median Mortgage Loan Amount



Note: "Other" includes Asian, American Indian, Alaskan Native, Native Hawaiian and Pacific Islander households.

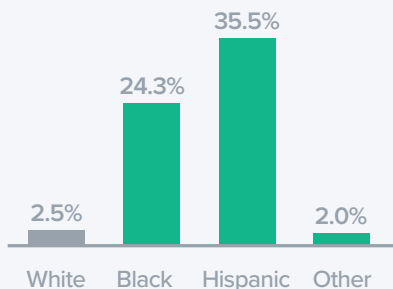
A similar trend is seen in access to auto loans. In 1989-2019, the share of Black and Hispanic households who obtained automobile loans grew 24.3% and 35.5%, respectively, compared with 2.5% for white households. The median automobile loan amount grew 40.8% for Hispanic households compared with 17.4% for white households and 10.7% for Black households (Figure 10).

FIGURE 10

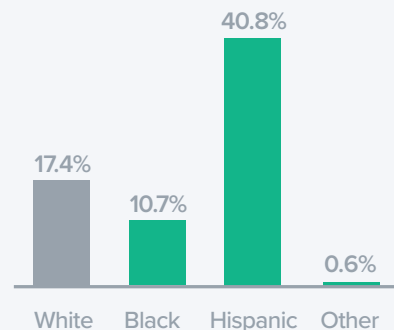
Black and Hispanic households had the greatest improvements in access to auto loans

Growth rates of households with auto loans and median loan amounts by demographic, 1989-2019

Share of Households with Auto Loans



Median Auto Loan Amount



Note: "Other" includes Asian, American Indian, Alaskan Native, Native Hawaiian and Pacific Islander households.

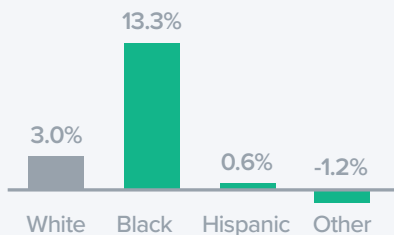
Access to installment loans increased most for Black households. These types of loans are often for major purchases like appliances, furniture, and home improvement costs, which may be difficult to afford in full up front. The share of Black households who obtained installment loans grew 13.3% during 1989-2019, compared with 3.0% for white households and less than 1% for Hispanic households. The median installment loan amount of minority groups grew between 126.1% and 184.8% compared with 51% for white households (Figure 11).

FIGURE 11

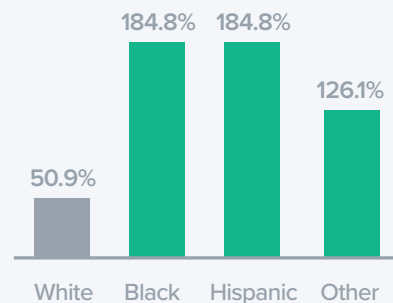
Black households had the greatest improvements in access to installment loans

Growth rates of households with installment loans and median loan amounts, 1989-2019

Share of Households with Installment Loans



Median Installment Loan Amount



Note: "Other" includes Asian, American Indian, Alaskan Native, Native Hawaiian and Pacific Islander households.

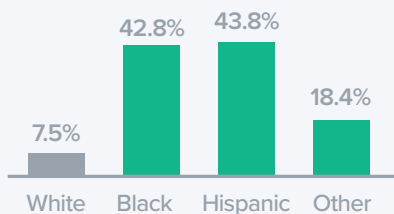
Finally, the shares of minority households with credit cards grew faster compared with white households during 1989-2019. However, the amount of credit card balances for white households grew 69% compared with only 9% for Black households (Figure 12).

FIGURE 12

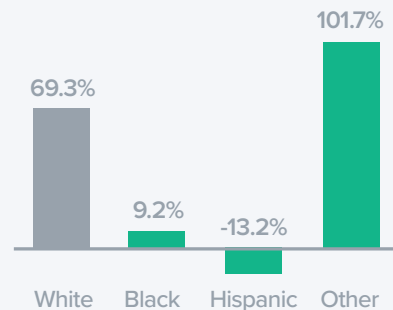
Black and Hispanic households had the greatest improvements in access to credit cards

Growth rates of households with credit card balances and balance amounts by demographic, 1989-2019

Share of Households with Credit Cards



Credit Card Balance Amount



Note: "Other" includes Asian, American Indian, Alaskan Native, Native Hawaiian and Pacific Islander households.

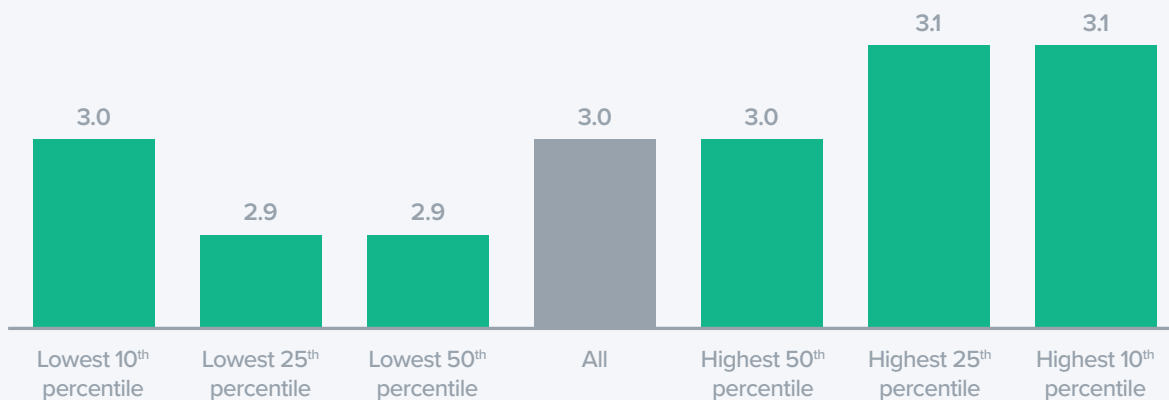
The Positive Effect of Risk-Based Pricing on Lower-Income Groups

Improvements in asset holdings and access to credit have been made across income groups, especially for low-income households. We analyzed the benefits of risk-based pricing for lower-income groups over the past three decades. The Federal Reserve Bank of New York's Credit Insecurity Index shows all income groups improved their access to capital in a similar pattern. From 2012 to 2018, the index scores of the lowest 10th percentile and the highest 10th percentile of counties by income improved by 3.0 points and 3.1 points, respectively, compared with 3.0 points for all counties (Figure 13).

FIGURE 13

Lower-income and higher-income counties had similar improvements in access to credit

Improvements in Credit Insecurity Index Score from 2012 to 2018, by percentile of income



Note: A higher score means more access; Score calculation includes those without access to the formal credit economy.

Similar to our analysis by race and ethnicity, we use the Federal Reserve's SCF to examine growth in assets and access to credit for lower-income groups over the past 30 years for the same six indicators: (1) primary residence homeownership, (2) automobile ownership, (3) mortgage and line of credit loans, (4) automobile loans, (5) installment loans, and (6) credit card balances. We calculate the 30-year growth rates of the household utilization and the dollar amount for each indicator by income group. Our findings demonstrate that the expansion of risk-based pricing for financial products over the past few decades has helped create positive economic opportunities for lower-income groups.

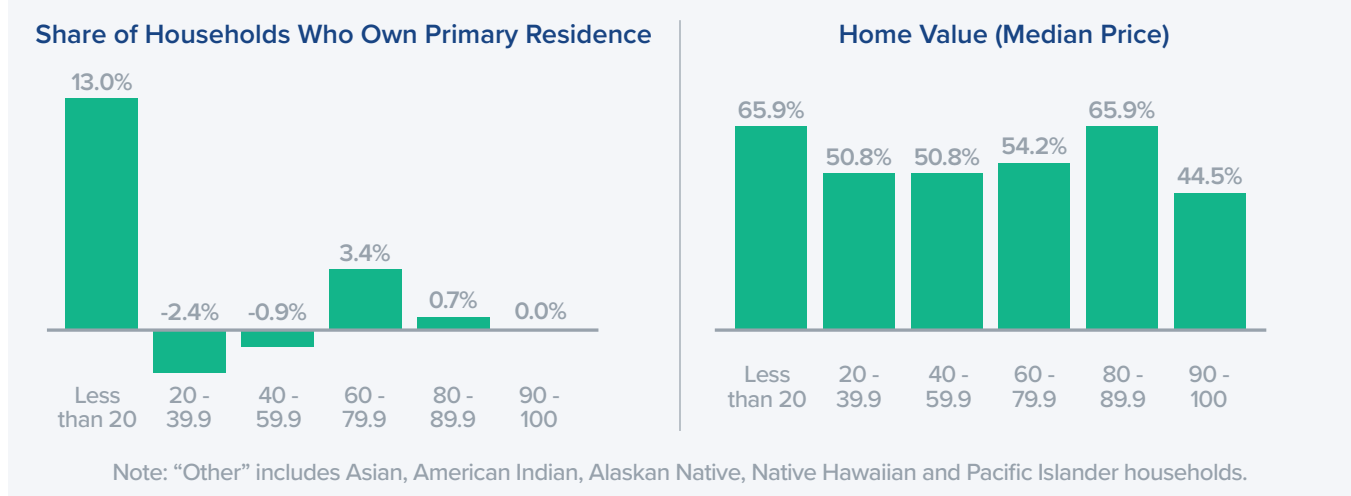
The growth in the share of lowest-income households who are homeowners and the value of these homes has outpaced that of other income groups. During 1989-2019, the share of households in the lowest-income bracket who own their primary residence grew 13%. The median home value for this group also grew faster than for other income groups during this time.

The increase in households who own their primary residence results in an increase in homeowners insurance policies. As aforementioned, the residual market for this type of insurance has declined, signaling that more homeowners are able to access competitive policies at lower rates through the private marketplace (Figure 14).

FIGURE 14

Lowest-income households had the greatest improvements in homeownership rates

Growth rates of primary residence ownership and home values by percentile of income, 1989-2019



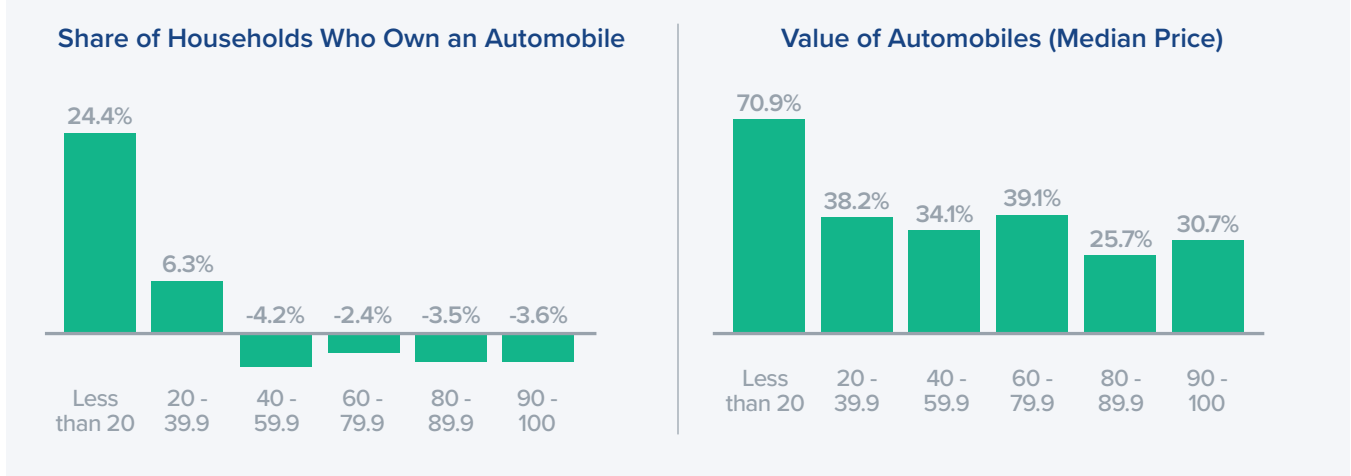
Since 1989, growth in automobile ownership rates has improved among lower-income groups. Additionally, the value of the automobiles owned, as measured by median price, has grown more for the lowest-income group than for all other income groups. Transportation is an important factor in pursuing economic opportunity, especially for low-income households. Access to cars gives individuals more choice in employment and potentially higher-paying jobs because they are not limited by public transit routes.⁶⁶ Again, the increased automobile ownership likely reflects the increase in households with auto insurance policies. With substantial declines in the residual market for auto insurance over the past decades, more individuals are able to obtain insurance through the private marketplace and receive competitive policies at lower rates (Figure 15).

66. Waller, Margy. 2005. "High Cost or High Opportunity Cost? Transportation and Family Economic Success." Brookings Institute. December 2.

FIGURE 15

Lowest-income households had the greatest improvements in auto ownership rates

Growth rates of auto ownership and median auto values by percentile of income, 1989-2019

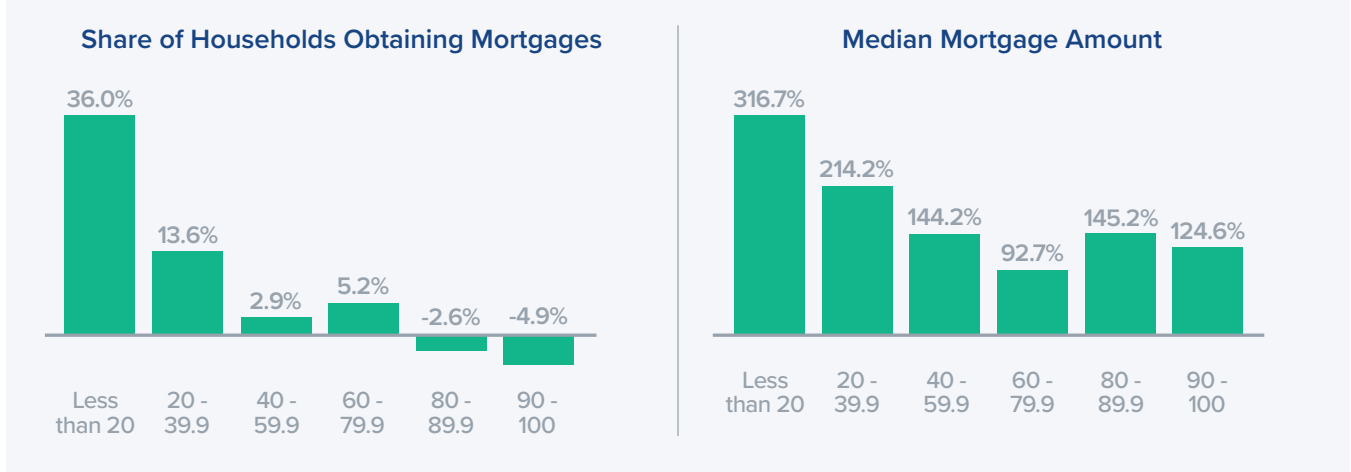


Access to mortgages improved most for lowest-income households. The share of households who obtained a mortgage or home equity loan grew 36% from 1989 to 2019 for the lowest-income group, faster than for any other group. The median mortgage amount also grew fastest for the lowest-income households, increasing nearly 317% during this period (Figure 16).

FIGURE 16

Lowest-income households had the greatest improvements in access to mortgages

Growth rates of households obtaining mortgages and median loan amounts by percentile of income, 1989-2019

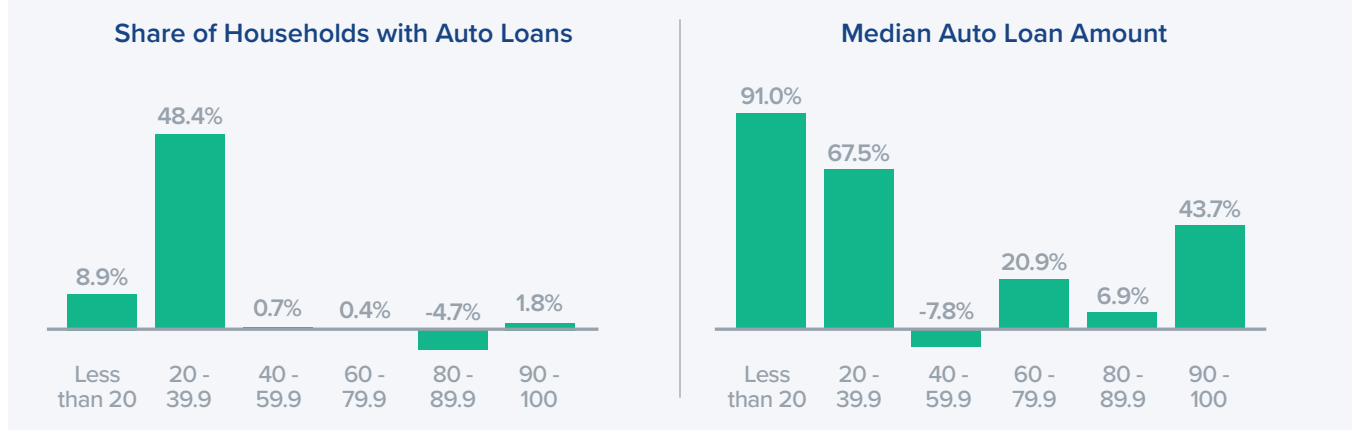


Access to automobile loans has improved for lower-income groups. The share of households who have automobile loans in the lowest- and the second-lowest-income percentiles and their median automobile loan amounts grew faster than for other income groups during 1989-2019 (Figure 17).

FIGURE 17

Second-lowest-income households had the greatest improvements in access to auto loans

Growth rates of households with auto loans and median loan amounts by percentile of income, 1989-2019

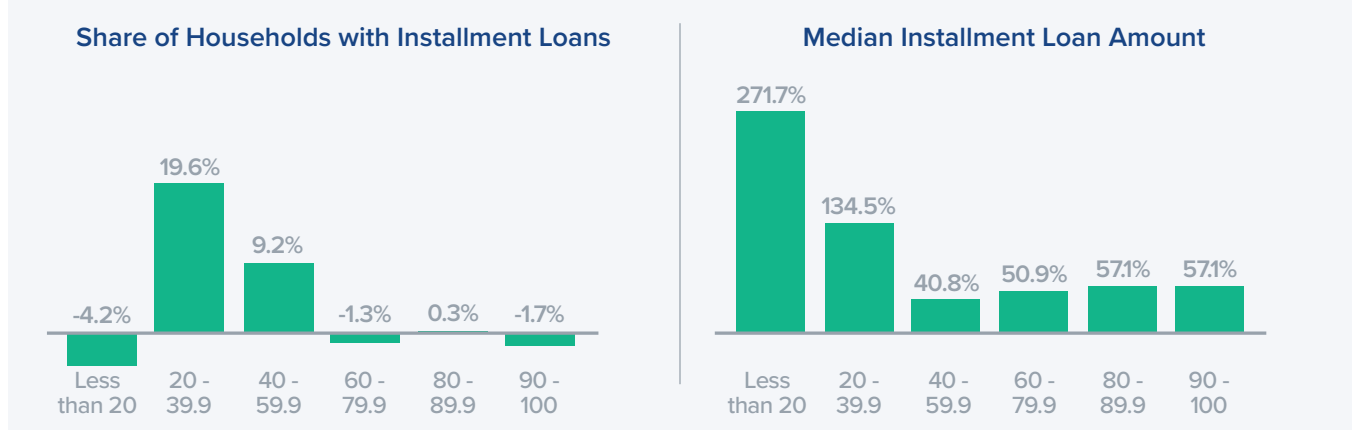


Access to installment loans improved most for the second-lowest-income group. Installment loans help households, especially low-income families, purchase durable goods, such as appliances and furniture. The share of households who had installment loans in the lowest 20th income percentile declined over the past 30 years while their median installment loan amount increased more than for other income groups. During the same period, the share of the households who had installment loans in the second lowest-income group (20th to 40th percentile) grew fastest, however (Figure 18).

FIGURE 18

Second-lowest-income households had the greatest improvements in access to installment loans

Growth rates of households with installment loans and median loan amounts by percentile of income, 1989-2019

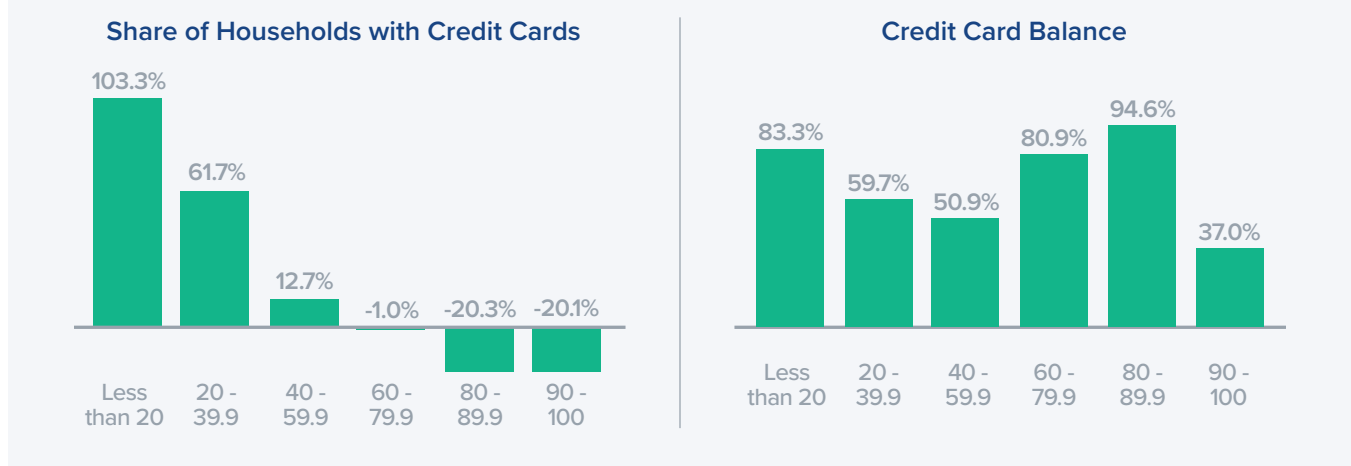


Finally, the share of households with credit cards group grew fastest for the lowest-income group during 1989-2019. The amount of credit card balances grew somewhat similarly among all income groups (Figure 19).

FIGURE 19

Lowest-income households had the greatest improvements in access to credit cards

Growth rates of households with credit cards and balance amount by percentile of income, 1989-2019

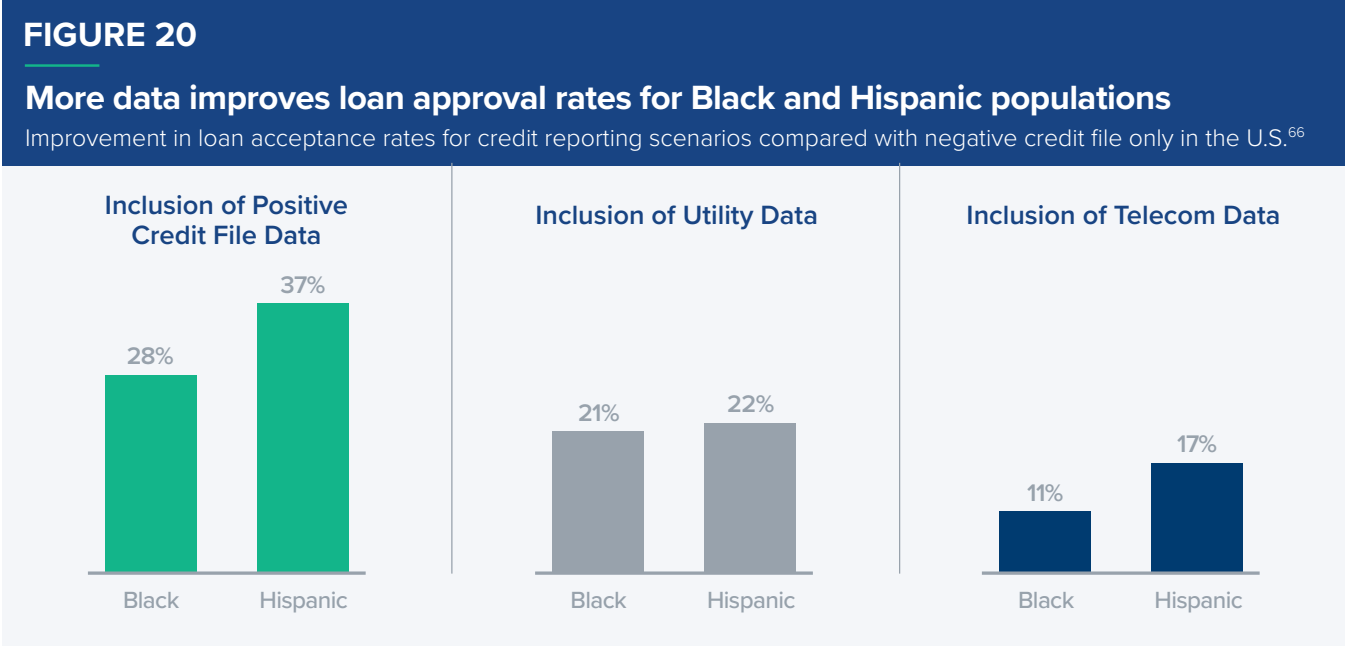


The Positive Effect of More Data Versus Less in Risk-Based Pricing Models

Risk-based pricing helps firms predict the probability of nonpayment or insurance losses. The more accurately these models can predict risk, the more companies can offer lower rates and expand access to insurance, especially for underserved populations. However, accuracy can be improved only by adding more data, not less, to risk-based pricing models. Limiting or prohibiting the use of relevant data in risk-based pricing has negative consequences; firms must rely on less information to predict risk, which reduces accuracy and, ultimately, increases costs and decreases access to competitive credit and insurance products for consumers.

Several types of information can be included in risk-based pricing models: traditional credit file data, which can be negative (e.g., missed payments) or positive (e.g., on-time payments, credit utilization); traditional credit or insurance application data (e.g., down payment amount, car or home value and type); and alternative data (e.g., cashflow data, utility or telecom bill payments, rent payments). An Organisation for Economic Co-operation and Development (OECD) study revealed that underserved populations including minorities and low-income groups in the U.S. benefit from having more information incorporated into credit decisions.

Compared with loan application approvals made using credit reports with negative traditional credit file data only, lenders would approve 28% and 37% more applications for Black and Hispanic populations, respectively, using full-file credit reports with both positive and negative financial data. If lenders use utility data in their risk models, 21% and 22% more Black and Hispanic applications would be approved, respectively, compared with models with negative traditional credit file data only. Finally, if lenders use telecom data in their risk models, 11% and 17% more Black and Hispanic applications would be approved, respectively, compared with models with negative traditional financial data only (Figure 20).



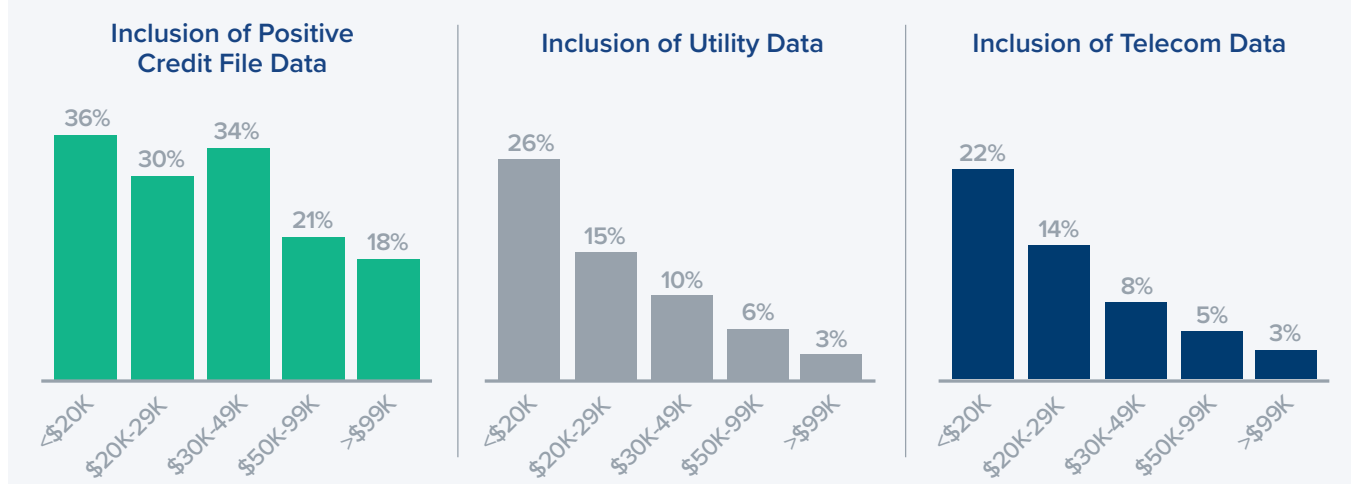
Similarly, lower-income households benefit from additional information included in credit decisions. Compared with loan application approvals made using credit reports with negative traditional credit file data only, lenders would approve 36% more applications of the lowest-income group (less than \$20,000) using full-file credit reports with both positive and negative financial data. If lenders are able to use utility data in their risk models, 26% more applications would be approved for the lowest-income group compared with models with negative data only. Finally, if lenders are able to use telecom data in their risk models, 22% more applications would be approved for the lowest-income group compared with models with negative data only. As discussed earlier, some of the greatest challenges to incorporating alternative data, such as utility and telecom bills, into risk-pricing models are data access and regulatory uncertainty (Figure 21).

67. Compared to negative credit file data only. Turner, Michael and Robin Varghese. 2010. “The Economic Consequences of Consumer Credit Information Sharing: Efficiency, Inclusion, and Privacy.” OECD Policy & Economic Research Council. December 1. Table 4: Change in Acceptance Rate with Reporting Regime Change.

FIGURE 21

More data improves loan approval rates for lower income populations

Improvement in loan acceptance rates for credit reporting scenarios compared with negative credit file only in the U.S.⁶⁷



Incorporating more—not less—data into risk-pricing models to better assess risk generates positive economic benefits. According to an OECD study on the topic, “in the aggregate, lending is increased, leading to greater economic growth, rising productivity and greater stocks of capital. Average interest rates drop. Poverty and income inequality are alleviated.”⁶⁹

Similarly, the better risk-based pricing models can predict risk in the insurance industry, the better off consumers are. Experiences abroad have provided evidence that reducing data increases costs for consumers. According to a 2020 study, “When insurers are prohibited from using an accurate rating variable, or the use of a variable is tempered, the average price for higher-risk policyholders decreases, and that of lower-risk policyholders increases.”⁷⁰

In 2011, the European Union imposed a ban on using gender in risk-based pricing for auto insurance. Before the ban, young men paid more than young women for auto insurance, all else equal, because “young men, on average, make more and larger claims than young women, which has been linked to risk-taking behavior while driving and is common across all EU countries.”⁷¹

68. Compared to negative credit file data only. Turner, Michael and Robin Varghese. 2010. “The Economic Consequences of Consumer Credit Information Sharing: Efficiency, Inclusion, and Privacy.” OECD Policy & Economic Research Council. December 1. Table 4: Change in Acceptance Rate with Reporting Regime Change.

69. Turner, Michael and Robin Varghese. 2010. “The Economic Consequences of Consumer Credit Information Sharing: Efficiency, Inclusion, and Privacy.” OECD Policy & Economic Research Council. December 1.

70. Powell, Lars. 2020. “Risk-Based Pricing of Property and Liability Insurance.” *Journal of Insurance Regulation*, 39(4).

71. Oxera. 2013. “‘Equality’ in Insurance Pricing.” *Oxera Agenda*. April, pp. 2.

The EU gender ban increased insurance premiums for young women across the board, and in some counties, for young men, too. In Italy, premiums for women increased over 40% and premiums for men increased over 20% after the ban was enacted; in the U.K. and Germany, premiums increased for women and decreased for men (Table 8).⁷²

TABLE 8.
The EU gender ban increased insurance premiums for young women across the board
 Impact of gender ban on auto insurance rates in the EU

	Change in Average Premiums for Females	Change in Average Premiums for Males
Germany	Increase	Decrease
Italy	Increase	Increase
United Kingdom	Increase	Decrease

Across financial products, consumers benefit from the inclusion of as many indicators as possible that accurately predict risk. Indeed, the more factors that are included in risk-based pricing models, the less the lender or insurer relies on any one factor for rate determinations. So, individuals applying for a loan or credit card with a poor credit score (or no credit score) will benefit from the inclusion of telecom or utility data in rate determinations. Similarly, individuals applying for an auto insurance policy will benefit from the inclusion of the combination of many factors, such as location, property type and value, age, gender, driving history, credit, education, occupation, and driving behavior (i.e., telematics), in determining premiums.

72. Oxera. 2013. “‘Equality’ in Insurance Pricing.” Oxera Agenda. April.

73. Oxera. 2013. “‘Equality’ in Insurance Pricing.” Oxera Agenda. April.

POLICY RECOMMENDATIONS

The use of risk-based pricing has allowed lenders and insurers to better serve consumers across the risk spectrum in a fair marketplace. The use of objective financial and payment history information for consumers allows for increased consistency across each company's lending or insurance underwriting process. With better understanding of client risks and accurate predictions, firms are able to compete with others to offer innovative products at lower costs that ultimately benefit all consumers. High-risk consumers are able to access credit products and insurance to pursue economic opportunities while low-risk consumers are rewarded with lower costs to access capital. As seen over the past several decades, consumers across economic and demographic groups in the U.S. have improved their risk behavior to enjoy lower costs of capital.

Recognizing the benefits of risk-based pricing, many developed and developing countries have established a formal credit reporting system and have introduced risk-based pricing for financial products. In 2018, Australia implemented its comprehensive credit reporting system. The comprehensive system amounted to large structural changes from its previous credit reporting system, with the creation of a mandate for Australian banks to record consumers' detailed credit information in order to appropriately assess an individual's overall risk. Prior to its implementation, providing information on a consumer's complete credit history was optional for banks, so the information often was not used as a factor in lending decisions. Prior to this change, when information was reported, frequently only negative credit history information was made available. A 2019 University of Sydney study found that, as a result of the new credit reporting, more than two-thirds of consumers saw improved credit scores, often followed by better credit rates.⁷⁴

Kenya recently introduced risk-based pricing as one of the central pillars of its latest Banking Industry Charter, effective as of March 2019. The Central Bank of Kenya introduced the mandate with a goal of increasing both the fairness and transparency of Kenyan lending practices. The Insurance Regulatory of Kenya has continued advocating for increased usage of risk-based pricing since the charter was introduced, not only in Kenya but across the East African region as well. It is expected that the same adaptation trend will occur throughout the region in the coming years, as many regulators in other East African countries have already stated their intentions of moving to a risk-based pricing system.⁷⁵

While these countries have introduced more widespread structural changes with the introduction of risk-based pricing systems, several other countries have begun to adopt risk-based pricing into specific industries. In 2017, Malaysia introduced a risk-based pricing approach in its auto insurance industry, enabling low-risk drivers access to more competitive rates compared with high-risk drivers.⁷⁶

74. Grant, Andrew. 2019. "The Impact of the Introduction of Positive Credit Reporting on the Australian Credit-Seeking Population." The University of Sydney.

75. The Central Bank of Kenya. 2019. "Kenya Banking Sector Charter."

76. The Malaysian Reserve. 2017. "Risk-Based Pricing for Motor Insurance a 'Positive Move.'"

Similarly, India began offering rating-based retail mortgage loans in 2016. This process prices individual loans based on a consumer's credit score, rather than the previous model of offering loans at a uniform rate irrespective of credit quality. Historically, corporate customers in India had been charged for loans based on their credit rating, but until 2016 the policy had not been extended to retail borrowers.⁷⁷

U.S. policymakers should continue strengthening the existing risk-based pricing system. Financial institutions should be encouraged to utilize alternative data to better assess risks and offer innovative financial products to all consumers. Alternative data enhances traditional credit file data to assist financial companies in assessing the risk of consumers, especially underserved populations. At the end of 2018, an estimated 60.4 million American adults, 23.8% of the adult population were unlikely able to access credit. Among those, about 26.5 million American adults, 10.5% of the adult population, were credit invisible. Alternative data provides significant benefits to these consumers. Furthermore, regulators should encourage the use of alternative data, including risk models that leverage alternative data, and adopt policy to further support its usage. The more accurately risk can be measured, the more underserved populations will benefit from risk-based pricing, including better access and rates.

The following are three policy recommendations:

- ▶ **Support the use of more data in risk-based pricing models.** The more predictive data that is included in risk-based pricing models, the more accurately companies can predict risk. Importantly, consumers benefit from improved accuracy through increased access to financial products and better rates. Supporting the use of more data includes two components: (1) policymakers should not restrict the use of predictive data currently used in modeling; and (2) policymakers should support the use of alternative data in risk-based pricing models. Additionally, regulators should provide clear guidance on the permissible uses of alternative data to reduce uncertainty, thus encouraging wider use of alternative data.
- ▶ **Support policies that improve the financial health of all Americans.** In risk-based pricing, consumers' credit scores improve as their financial health improves. With higher credit scores, consumers enjoy increased access to credit at lower costs. Policymakers should support policies that help Americans improve their financial health, which, in turn, will increase economic opportunities for these individuals.
- ▶ **Support additional research.** The use of additional data helps Americans improve their credit scores. However, little research exists on the barriers preventing or discouraging companies from incorporating alternative data into their risk-based pricing models. Government agencies should examine the regulatory and market conditions causing these barriers in order to encourage wider adoption of alternative data in risk-based pricing. For example, the Government Accountability Office (GAO) could conduct a study on the barriers related to reporting of payment data to credit bureaus by large telecom providers.

77. Shukla, Saloni. 2016. "Bank of Baroda Plans Rating-Based Lending." *The Economic Times*.

REFERENCES

- Akerlof, George A. 1970. “The Market for “Lemons”: Quality Uncertainty and the Market Mechanism.” *The Quarterly Journal of Economics*, 84(3).
- A.M. Best Company, Inc. 2020. “U.S. Auto Liability – Top Writers by State, Canada and U.S. Territories - 2019.” *Best’s Review*.
- Avery, Robert B., Kenneth P. Brevoort, and Glenn B. Canner. 2010. “Does Credit Scoring Produce a Disparate Impact?” *Federal Reserve Board*.
- Board of Governors of the Federal Reserve System. 2007. “Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit.” August.
- Carroll, Peter and Saba Rehmani. 2016. “Alternative Data and the Unbanked.” *Oliver Wyman*.
- Carter, Matt. 2020. “Average Student Loan Interest Rates in 2020.” *Credible*. November 10.
- Consumer Financial Protection Bureau. 2016. “What Should I Do If I Think That a Lender or Auto Dealer Discriminated against Me in My Auto Loan Application, such as by Denying My Application or Charging Me a Higher Interest Rate?” November.
- Cox, Natalie. 2017. “The Impact of Risk-Based Pricing in the Student Loan Market: Evidence from Borrower Repayment Decisions.” August 31.
- DiUlio, Nick. 2016. “Bad Credit? Expect Higher Auto Insurance Premiums Despite a Good Driving Record.” *InsuranceQuotes*. October 20.
- DiUlio, Nick. 2017. “Why Poor Credit Can Triple Your Homeowners Insurance.” *InsuranceQuotes*. May 3.
- Experian. 2015. “Let There Be Light: The Impact of Positive Energy-Utility Reporting on Consumers.”
- Fannie Mae. 2021. “Single-Family Historical Loan Performance Dataset.”
- Federal Reserve Bank of St. Louis. “Continuing Education Series: Understanding How a FICO Credit Score Is Determined.” Accessed January 2021.

- Federal Trade Commission. 2007. “Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance: A Report to Congress By the Federal Trade Commission.” July.
- Federal Trade Commission. 2016. “Using Consumer Reports for Credit Decisions: What to Know about Adverse Action and Risk-Based Pricing Notices.” November.
- FICO. 2019. “FICO Score XD.” Fair Isaac Corporation.
- FICO. 2019. “ultraFICO Score Fact-sheet.” Fair Isaac Corporation.
- Freddie Mac. 2018. “Nowhere to Go but Up? How Increasing Mortgage Rates Could Affect Housing.” Economic & Housing Research Insight.
- Goldman, Steven M. and Jon S. Corzine. 2008. “The Use of Occupation and Education Factors in Automobile Insurance.” New Jersey Department of Banking and Insurance. April.
- Hamdani, Kausar, Claire Kramer Mills, Edison Reyes, and Jessica Battisto. 2019. “Unequal Access to Credit—The Hidden Impact of Credit Constraints.” Federal Reserve Bank of New York.
- Hartwig, Robert O., Ph.D. 2007. “The Use of Education and Occupation as Underwriting Factors in Determining Policyholder Premiums for Private Passenger Auto Insurance.” Written Testimony for the Florida Office of Insurance Regulation. February 9.
- Information Policy Institute. 2003. “The Fair Credit Reporting Act: Access, Efficiency, and Opportunity.” June.
- Insurance Information Institute. 2019. “Background on: Credit Scoring.” April 8.
- Insurance Information Institute. 2013. “Financial Reporting in the P/C Insurance Industry.” August 3.
- Insurance Information Institute. 2021. “Insurance Provided by FAIR Plans by State, Fiscal Years 2019 and 2008.”
- Insure.com. 2010. “Swimming in the Assigned-Risk Pool for Car Insurance.” March 21.
- Knueven, Liz. 2020. “The Average Credit Card Interest Rate by Credit Score and Card.” Business Insider. September 19.
- Lacy, William. 2017. “Use and Impact of Credit in Personal Lines Insurance Premiums Pursuant Ark. Code Ann. § 23-67-415.” Arkansas Insurance Department. June 7.

- Luthi, Ben. 2020. “What Auto Loan Rate Can You Get with Your Credit Score.” Experian. August 16.
- National Association of Insurance Commissioners. “Credit-Based Insurance Scores Aren’t the Same as a Credit Score. Understand How Credit and Other Factors Determine Your Premiums.” Accessed January 2021.
- National Association of Insurance Commissioners. 2020. “Auto Insurance Database Report 2016/2017.” January.
- National Conference of Insurance Legislators. 2020. “Model Act Regarding Use of Credit Information in Personal Insurance.”
- Oxera. 2013. “‘Equality’ in Insurance Pricing.” Oxera Agenda. April.
- Powell, Lars. 2020. “Risk-Based Pricing of Property and Liability Insurance.” *Journal of Insurance Regulation*, 39(4).
- Redmer, Al. 2019. “Use of Occupation and Education Level as Rating Factors in Private Passenger Motor Vehicle Insurance.” Maryland Insurance Administration. December 31.
- Stolba, Stefan Lembo. 2020. “What Kind of Mortgage Interest Rate Can I Get with a 750 Credit Score.” Experian. September 4.
- The Zebra. 2021. “The State of Auto Insurance, 2021.”
- TransUnion. 2015. “The State of Alternative Data.” TransUnion and Vesta Research.
- Turner, Michael and Robin Varghese. 2010. “The Economic Consequences of Consumer Credit Information Sharing: Efficiency, Inclusion, and Privacy.” OECD Policy & Economic Research Council. December 1.
- U.S. Census Bureau. 2020. “American Community Survey, 2018 and 2019.”
- VantageScore. 2020. “2020 VantageScore Model Performance Assessment.” April.
- Waller, Margy. 2005. “High Cost or High Opportunity Cost? Transportation and Family Economic Success.” Brookings Institute. December 2.



CENTER FOR CAPITAL MARKETS

COMPETITIVENESS