United States House of Representatives

Committee on Financial Services

Subcommittee on Oversight and Investigations

Hearing on
"What Borrowers Need to Know About Credit Scoring Models and Credit Scores"

July 29, 2008

Testimony:

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Good afternoon Mr. Chairman and members of the Committee. My name is Michael Staten. I am a Professor in the Norton School of Family and Consumer Sciences at the University of Arizona, and the Director of the Take Charge America Institute for Consumer Financial Education and Research. I've had the privilege of testifying before this committee previously when I was at Georgetown University, and am pleased to be able to join you again this afternoon.

I appreciate the Committee's wish to explore consumer education issues related to the development and use of credit scores and credit scoring models. From the consumer's standpoint, maintaining a good credit score is more important now than it has ever been. The rapid escalation in loan delinquencies and mortgage foreclosures over the past 18 months has caused many lenders to back away from higher risk applicants. A low credit score today can sharply limit credit availability, relative to the borrowing opportunities available as recently as two years ago. The widespread adoption of risk-based pricing in consumer lending means that a low credit score will also cost you money, possibly big money in the case of mortgage and auto loans. In addition, the bar has been raised for qualifying for the best interest rates. Two years ago you might qualify for the best mortgage rates with a FICO score of 720 – 750. Today, you will likely need a score well above 750 to get the best rates. The same is true for auto loans, especially on the subsidized dealer or manufacturer financing deals (heard in radio ads, etc).

Credit scoring impacts consumers outside of loan markets as well. Landlords routinely pull credit reports and may reject apartment rental applications or require a higher deposit or cosigner to compensate for a lower credit score. Cell phone service providers routinely pull credit reports, as do many utility companies. Many insurance companies use credit reports and scores in the decision to approve and price property and casualty insurance policies. Some employers also obtain credit bureau information, including credit scores, in evaluating applicants. In short, a consumer's credit report and the resulting credit scores have become an important dimension of personal financial management.

Consumer awareness of credit reports and the importance of credit scores has improved in recent years, but much education remains to be done. The Consumer Federation of America has partnered with Providian and Washington Mutual Bank to sponsor a series of consumer surveys since 2005 that track consumer knowledge of credit scores. The latest edition of the survey released earlier this month (Consumer Federation of America, 2008) found that only half of U.S. adults had obtained their credit score within the past two years. While this was a distinct improvement from the 42% who answered similarly in the prior year's survey, answers to other questions in the survey indicate a significant gap in knowledge of how scores are used between those who have viewed their scores and those who have not. Overall, the survey indicates that a large portion of the population has yet to focus on management of their credit history and credit score as part of their personal financial affairs.

In my testimony today I'd like to make two main points. First, business reliance on credit reports and credit scoring to make decisions about financial transactions is here to stay. Credit scoring has proved overwhelmingly superior to the manual judgmental loan evaluation systems of a generation ago, for a variety of reasons. Widespread adoption of credit scoring as a decision tool has generated significant benefits for consumers and transformed the U.S. consumer financial markets into the most competitive in the world. Because they are so useful, scoring models have been constantly improving, and will continue to do so as long as financial institutions compete for customers. My second point springs from the first: because the use of scoring is so commonplace in financial transactions, consumers need to develop a better understanding of the importance of their credit histories and credit scores, and better awareness of their power to manage the components to obtain more favorable offers in the financial marketplace.

In the following sections I respond to the committee's request for information about the development of credit scoring models and the use of credit scores in underwriting. Based on this information, I also offer some suggestions regarding the most important things that consumers should know about their credit scores.

The Evolution of Credit Scoring as a Key Decision Tool for Lenders

Possibly the most significant development in consumer lending in the past 25 years has been the widespread adoption of credit scoring as a standard tool for evaluating applicant and account risk. During this period, lenders shifted from manual and judgmental systems for evaluating credit decisions to automated underwriting using statistical scoring, dramatically impacting the supply of consumer and mortgage credit in the U.S. The quantity of available credit has greatly expanded as scoring facilitated better sorting of the pool of potential borrowers according to likelihood of default. Credit decisions are made much faster and at far lower cost. Compared to the manual loan decisions of a generation ago, scoring brings consistency to credit decisions companywide, supports highly accurate estimates of portfolio losses, allows for rapid implementation of company-wide changes to lending policy, and provides greater assurance that lending decisions will comply with regulatory rules regarding fair-lending practices. It is no wonder that lenders have embraced credit scoring across all dimensions of consumer lending, and in other credit-related businesses.

Credit scoring is not the lending decision: it is a tool to assist the lender in making a decision. Through most of the past century in American consumer finance, lenders trying to assess a borrower's creditworthiness have been guided by an industry maxim known as the five "C"s of lending: Character, Capacity, Capital, Collateral, and Conditions. An evaluation of "character" is really an assessment of the borrower's willingness to repay, typically gauged by the borrower's past payment behavior and current use of credit. Capacity refers to the size, source and stability of the borrower's income stream relative to existing (and proposed) debt obligations. Capital refers to the borrower's assets, liquid or otherwise, which could be tapped if income proved insufficient to meet the required payments. The value of Collateral, and the possibility that it might be repossessed by the lender, comes into play on secured loans such as automobile loans or home mortgages both as an incentive to the borrower to continue making payments and as an assurance to the lender that some portion of the loan principal could always be recovered through sale of the repossessed asset. Lastly, an assessment of economic Conditions is prudent because they are likely to affect the borrower's capacity to repay.

Until the late-1960s, consumer lending decisions in the United States were typically made by thousands of loan officers who each exercised their individual judgment with each new application. Loan officers gathered information from and about the applicant in each of the five critical areas and applied lessons from their personal lending experience to decide whether an application should be approved. However, a number of factors combined to push the consumer credit industry away from this "judgmental" model of underwriting. The judgmental approach was too slow and labor intensive in the face of the enormous post-World War II boom in consumer loan applications. More importantly, the inconsistency inherent in a fragmented, judgmental approach rendered a company-wide underwriting policy nearly impossible. Management had no way of expressing a corporate policy of accepting only applicants with a probability of default of, say, 5% or less. Loan officers were left to figure out for themselves the level of risk an applicant represented and whether that risk was acceptable to the company. As Lewis (1992) notes, "In a nationwide loan company with, perhaps, one thousand offices, there might be as many as two to three thousand people defining overall corporate policy."[1]

The advent of statistical credit scoring dramatically changed consumer loan underwriting. The "5 Cs" of lending were no less important for conceptualizing the factors that determined loan risk, but credit scoring gave lenders a powerful tool for rapidly and consistently evaluating a key component of risk (past payment behavior and current credit usage) as well as summarizing it via a numerical score that translated into probability of default. Between 1970 and 2000, judgmental credit decision systems in

[1] Lewis, 1992, p2-3.

consumer and mortgage lending were gradually supplemented or replaced with empirically derived, statistically sound scoring systems. This dramatic change in risk evaluation technology greatly reduced the subjective nature of the lending decision.

The conceptual rationale for statistical credit scoring is essentially the same as for judgmental lending: patterns observed in the past are expected to recur in the future. Borrower and loan attributes that have been observed to be associated with loan defaults in the past become the basis for expecting default on similar loans in the future. Using multivariate statistical methods and data on millions of loans made in the past, credit scoring models today are built to identify predictive relationships between a wide variety of variables and loan performance.

The first credit scoring models were built to guide the loan application process, and application scoring remains an important use of scoring technology. The primary concern in granting a new loan (although not the only concern) is whether the borrower will repay the loan as agreed. Consequently, most new-account application models have been built to predict the likelihood that a loan will default within a given time period, usually 12 – 24 months. Default has been defined in a variety of ways, but often refers to a loan that achieves a level of serious delinquency, e.g., 90 days or more, or generates a repossession or chargeoff loss for the lender. From the outset of scoring and through decades of evolution in commercially available models, discriminant analysis and multivariate regression techniques have been the most common statistical tools used to model loan defaults. These models calculate credit scores for each application in such a way as to rank applications according to their relative risk of a loan default. Typically, scoring systems are scaled so that a lower score signals higher risk. That is, applications that receive lower scores are more likely to default within a specified time period than are applications with higher scores.[2]

During the 1970s and 1980s, many lenders (and most of the large national lenders) invested in the development of proprietary custom application scoring models (Mays, 2004). A custom application scoring model is built for a specific loan product (e.g., general purpose credit card) using a single lender's account data and experience. Custom models typically incorporate both credit bureau data and application data. There are very few published studies of these models, perhaps not surprisingly since an accurate scoring model can confer a distinct competitive advantage on a lender. As scoring developed through this period, new ideas were plentiful, lots of variables were explored, and public discussion of successful model components could quickly dissipate the value of the intellectual capital acquired through scorecard development.

[2] Some applicants with low credit scores will actually pay as agreed and some applicants with high credit scores will default. This fact underscores the probabilistic nature of risk assessment: at the time of the loan application the lender never knows with certainty who will repay and who will not. What the lender wants is a scoring system that will achieve significant separation in the score distributions of good accounts and bad (defaulted) accounts. More separation is better. This gives the lender more confidence that the event of a high-scoring applicant defaulting on a loan will be an anomaly. So, the key to building a good (predictive) application scoring model is to find readily observable borrower and loan characteristics that consistently distinguish consumers who will pay as agreed from those who will not. For an overview of how the typical scoring model is developed see Mays, 2004, pp 63-130.

The Federal Reserve Board recognized the increasing use of application scoring systems when it developed its Regulation B that implemented the Equal Credit Opportunity Act of 1974, and the ECOA amendments of 1976. Both pieces of legislation were intended to prohibit discrimination in lending by prohibiting the use of information on the borrower's gender, marital status, race, nationality, age and certain other attributes from consideration in the underwriting process. Regulation B established criteria that scoring systems must satisfy to be considered methodologically and statistically sound.[3]

By the mid-1980s a clear divergence in processing procedures had emerged across loan products. Larger loan transactions (mortgage and automobile loans) still warranted loan officer scrutiny of paper application forms, credit reports and supporting documents. However, credit card account application processing had become increasingly automated. In large part this was due to improved quality of credit report data and the demonstrated success of statistical scoring models in rapidly and accurately determining applicant risk. The drive to lower processing costs also favored automation, and further pushed the credit card industry toward risk assessment based mostly on credit bureau data. Information from a loan application was time-consuming to code into machine-readable form that could be used by the scoring models. Moreover, application data was costly to verify, which meant that it was subject to exaggeration and outright fraud. Verification would delay an approval decision, a clear negative for a retailer considering a new account application at the point of sale.

For all these reasons the consumer credit industry migrated to the use of statistical scoring of credit applications first for credit cards and only later for automobile loans and virtually every other type of consumer loan by the early 1990s. Last to accept scoring was the mortgage industry, but by mid-1996, credit scoring was endorsed as a valid tool for evaluating mortgage applications by the Federal Reserve (Avery, et al 1996) and by the government-sponsored-enterprises Freddie Mac and Fannie Mae. By the end of the decade automated underwriting of mortgages using credit scoring had become the industry standard (Stracka, 2000).

Components of Scoring Models

What types of information are scored? This, of course, depends on the outcome to be predicted. Credit scoring began as a tool for evaluating new loan applications. In the early days of credit scoring, model builders sought data that would approximate the various factors represented in the "5 Cs" of lending. Models were initially designed to incorporate information that was commonly collected on loan application forms as well as information from credit reports.[4] Credit card application data in the 1980s included attributes such as the applicant's age, time at current/previous residence, time at

[3] Interestingly, Regulation B made the case for using credit scoring to standardize risk evaluation even more compelling than did the economic efficiencies alone. The ECOA created liability for a lender if it could be shown that loan acceptance policies were based on prohibited attributes. Credit scoring gave lenders an easily monitored tool for demonstrating that their loan acceptance decisions were consistently based on ***economic*** factors associated with the borrower and loan that could be shown to impact loan risk.
[4] Eventually, loan application forms were redesigned to reflect the information found to be most useful to scoring models.

current/previous job, housing status, occupation group, income, number of dependents, presence of telephone at residence, banking relationships, outstanding debts and open credit accounts. In addition, the models would also utilize credit bureau variables including the number, type and recency of any delinquencies, balances on open accounts and lines of credit, and the number and type of creditor inquiries (an indicator of credit shopping and new account activity).[5]

Chandler and Parker (1989) demonstrated that U.S. credit bureau data outperformed application data in predicting risk on bank and retail credit card applications. Using models built to score bank card applicants, and data from a period during which credit card issuers still collected detailed application information, the authors found that application data without the credit bureau data yielded the lowest predictive power and fared poorly when compared with predictions based on any level of credit bureau data. The predictive power increased substantially when the models incorporated higher levels of credit bureau detail, with the most detailed model exhibiting predictive power 52% greater than the simplest credit bureau treatment. In fact, a model incorporating the detailed credit bureau data plus application data actually performed worse than a model based on the detailed credit bureau data alone. Perhaps this is not surprising given that most application data on bank card products is not verified because of the cost and consequent delay in the accept/reject decision. The authors noted that for most applicants (those with an established credit history) a detailed examination of credit bureau data alone provided the most accurate assessment of new account risk.[6]

Generic Scoring Models and the FICO Score

By the mid-1980s the predictive power of credit bureau information convinced credit score model developers that effective models could be developed with credit bureau information alone. Fair, Isaac Corp. and other scoring system developers (including the major consumer reporting agencies) created and introduced "generic" credit bureau scoring models that incorporated only information from credit reports. Generic scoring models marked a sharp departure from the custom application models based on data that was unique to a specific creditor's loan product and customer base. In short, generic scoring models opened up credit scoring to the entire credit industry.

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[5] Chandler and Parker (1989), pp 47-48.

[6] Lay observers of the consumer credit industry, including members of Congress, often misinterpret the credit card industry's lack of explicit consideration of income in the application process. Income has much intuitive appeal as an important predictor of repayment risk. But, credit bureau data allow a creditor to infer repayment capacity from the degree to which past and existing lines of credit have been utilized and whether payments were made on time or late. In short, risk assessment based on credit bureau data rewards those consumers who find a way to make their payments. This is why credit bureau data can be more predictive than credit card application data that is unverified. The empirical evidence of the predictive superiority of credit bureau data over application data might change if application data were verified. But, verification is costly. In the mortgage arena, where the stakes are larger (loan size, potential interest income and loss in the event of foreclosure), it pays to measure risk attributes more precisely. But for smaller loans like credit card loans, the number of accounts is much larger (driving up total risk evaluation costs), and the size of the loan is typically much smaller (reducing the potential loss). And, objective credit bureau data is readily available.

The first generic scoring model was brought to market by Fair Isaac Corp. in 1986 to evaluate new applicant risk on credit card solicitations mailed to consumers. In 1987, Management Decision Systems, Inc. (MDS) rolled out the first generic scoring models that used credit bureau data to predict bankruptcy. In 1989, in partnership with Equifax, Fair Isaac introduced the first general purpose credit scoring model that utilized its FICO score, a product that 15 years later would become so ubiquitous as to become nearly a household term. The first model was built using Equifax credit report data. By 1991, Fair Isaac had developed similar models for the other two major U.S. consumer reporting agencies (Experian and Trans Union) using their respective credit report databases so that all three major consumer reporting agencies were selling their equivalent of the FICO score product under each bureau's marketing brand.[7]

The precise composition of commercially available generic scoring models is proprietary.[8] According to the Fair, Isaac website (www.myfico.com) the key determinants of a consumer's FICO score can be divided into the five general categories described below. A consumer's FICO score may vary across the three credit bureaus because the FICO score obtained from each bureau is built on the information in that bureau's database. The content of consumer credit reports varies across the three bureaus. The website hints at the direction of influence of specific attributes and provides, in percentage terms, the approximate influence on the overall FICO score.

1. ***Payment history: Accounts paid as agreed, Late Payments, Delinquencies, Bankruptcies (35%):*** Fair, Isaac advises individuals who seek to improve their FICO score to always pay their accounts before the due date. Simply put, the fewer late payments, the better the score. In the event of a late payment, the more serious is the degree of delinquency, the greater the negative impact on the score. In addition, more recent late payments tend to be more indicative of future default than those that occurred in the past. And, a late payment in a consumer credit report that has relatively few accounts, or accounts that are only recently opened will have a greater negative impact than the same late payment in a credit report with more accounts that have been long established.
2. ***Outstanding Debt (30%):*** Fair, Isaac advises consumers who seek to improve their credit score to keep balances low, especially credit card balances. People who have used a large portion of the credit available to them tend to be higher risks than those who use credit conservatively.

[7] Over the years Fair Isaac has developed several versions of its FICO score products tailored for different market segments (e.g., FICO Classic, NextGen, and Expansion score products). The FICO Classic model is the one most commonly referenced and the one dissected on the firm's website with advice for consumers. The three major consumer reporting agencies collaborated to develop their own generic scoring model which hit the market in 2006 as VantageScore.

[8] For a variety of reasons, commercial generic scoring models such as the FICO score are typically constrained to the 10-20 most predictive variables from the credit report. Also, generic bureau scorecards marketed to date have generally been customer-based rather than loan-based models. That is, the observation unit for the generic bureau scorecard is a consumer, not a loan, and the dependent variable describes whether a consumer with a given credit profile at the start of the observation period becomes seriously delinquent (90+ days) by the end of the period (18-24 months) on at least one account.

3. ***Length Of Credit History (15%):*** Importantly, for a consumer to have a credit score, they must have some history of using credit. In addition, Fair Isaac advises that the longer someone has had credit established, the better is his or her credit score.

4. ***New Applications For Credit, or Inquiries (10%):*** Fair, Isaac advises individuals to apply for new credit sparingly if they seek a better credit score. In particular, they suggest that borrowers should not open lots of new accounts in a short period of time, as multiple new account acquisition can be a sign of financial distress and higher risk.

5. ***Types of Credit in Use (10%):*** The model considers how many types of credit accounts (credit cards, mortgage, auto loans, other installment loans) a consumer has, and how much credit usage falls into one category vs. others. The website notes that a good score doesn't require accounts in all categories, and that opening accounts just to broaden the mix probably won't boost the score.

Generic credit bureau scores (e.g., FICO scores) are now used to evaluate individual credit risk in virtually every sector of the consumer and mortgage credit industry in the United States.[9] The nearly instantaneous availability of rich and comprehensive credit bureau information on a borrower, coupled with the proven predictive power of scoring models has made instant credit at the point of sale commonplace. The industry-wide shift from manual to automated underwriting transformed the competitive landscape in the U.S. by encouraging new entry into the consumer lending business (at much lower cost than would be the case for a new lender in nearly every other country) and bringing a broader range of product offerings, wider credit availability and lower prices to consumers.

In addition, generic credit bureau scores are frequently combined with additional data from existing account activity to give a lender a powerful "behavioral score" decision tool for existing accounts. Behavioral credit scoring is now used to determine when and how much to increase the limit on credit card accounts; approve authorizations of new credit card purchases at the point of sale; monitor credit card account transactions for possible fraudulent activity (including identity theft); predict account attrition so that lenders can take steps to recruit and keep loyal customers; initiate collection strategies on delinquent accounts, set their tone and predict dollar recoveries; select potential new customers for receipt of pre-approved invitations to apply for credit; and identify existing customers who may respond favorably to the cross-selling of other products.

Three Criticisms of Scoring

Debate over the pros and cons of reliance on credit scoring often incorporates one or more of the following criticisms: 1) generic credit scoring models are biased against consumers in certain minority groups because the models include credit-history items that

[9] Chandler (2004) catalogued 70 different generic credit scoring systems containing over 100 different scoring models or scorecards that were available in the market as of 2004 to assist in a wide range of credit decisions.

may have a differential (and negative) impact on certain minority groups; 2) lender decisions based on credit-history scoring models (i.e., generic models) are flawed because of errors in credit reports, and 3) generic scoring models rely on credit report data that is an incomplete picture of a consumer's ability to handle recurring monthly obligations such as rent and utility payments. A thorough discussion of each criticism is well beyond the scope of this testimony, but below I offer some short observations about each.

Regarding the fairness of scoring models toward minority groups, the Federal Reserve Board in 2007 released a major study of the issue as required by the Fair and Accurate Credit Transactions Act of 2003 (FACT Act). In the report, the Fed researchers concluded that generic, credit-history-based scoring models do not have a differential and negative impact on certain racial minority groups. None of the credit characteristics in standard models were found to serve as proxies for race or ethnicity. However, the researchers also noted that recent immigrants have somewhat lower credit scores than would be implied by their actual performance on loans. This is because their credit histories resemble those of young consumers (e.g., fewer accounts and shorter history, relative to general borrower population) who generally perform somewhat worse on credit repayment. The researchers suggested that expanding the information supplied to credit reporting agencies to include rent payments and other recurring bill payments would possibly enhance the credit profile of these consumers.

Credit reporting agencies and scoring model vendors have recognized that conventional credit reports are missing information that could be useful for predicting loan performance. In fact, the industry is breaking new ground in the collection and use of alternative payment history data for consumers with little or no past credit history captured in traditional credit reports. As of 2006, an estimated 35 – 54 million American adults had limited or nonexistent credit files (Turner, et al, 2006). Most of these consumers in what the industry calls the "thin file/unscoreable population" are new to or completely outside of the credit-granting system, either because they are young, or are recent immigrants or have simply operated on a cash basis or through non-traditional sources of credit. Their lack of traditional credit history makes them appear to lenders as high risk when, in fact, they are often not. Data on payments for rent, utilities, insurance premiums, pay day advances, and rental furniture could enhance scoring models. Utility and telecommunications sources of data show the most promise, as studies estimate that 90% or more of the thin file/unscoreable population has one or more such accounts. The major consumer reporting agencies, established scoring vendors (e.g., Fair Isaac) and new entrants to the credit reporting industry are exploring how to collect, store, and score monthly bill payment data that has traditionally not been reported to the major consumer reporting agencies. Success on this front will undoubtedly expand credit availability and open up a large consumer market to competition from major national lenders.

As for the accuracy of information that is utilized by credit-history-based scoring models, this is a decades-old issue that has yet to be definitively resolved through empirical evidence. I only point out here that this is more of a "reporting" problem than a "scoring" problem. The effectiveness of scoring will always depend on the quality of the underlying information being scored. In the absence of credit scoring, lenders would still be basing their decision on the content of credit reports, flawed or otherwise. Erroneous information can lead to bad decisions in both judgmental and automated scoring systems. Recognizing this, Congress included one requirement in the 2003 FACT Act (Section 319) that directs the Federal Trade Commission to study the accuracy and completeness of information in consumers' credit reports and make a series of biennial reports to Congress over a period of 11 years beginning in December 2004. The FTC is currently undertaking a series of pilot studies to determine the feasibility of engaging a nationally representative sample of consumers in a review of their credit reports from the three major consumer reporting agencies. Should the large national study take place, it could provide the first reliable evidence regarding incidence of such "errors of commission" and their impact on consumer credit scores.

In this area, the consumer plays an important but underutilized role. Although participation is improving, too few consumers understand the importance of credit scores, and too few check their credit reports. Under the Fair Credit Reporting Act (FCRA), Congress gave the consumer the role of "quality inspector" with the power to dispute and initiate re-investigation of any piece of information in the credit report. For consumers to find errors, they have to look. Much of the FCRA's effectiveness in promoting accurate credit reporting hinges on consumer willingness to exercise the power to monitor their reports. Given the heightened consumer awareness of credit scoring (especially for mortgages), concerns over identity theft, and the right to one free annual credit report (per bureau) under the FACT Act, it seems likely that consumers will inspect their reports more often than was the case a decade ago, and the problem of "errors of commission" in credit reports will gradually diminish.

What Should Consumers Know About Credit Scores?

Credit scoring is no longer the impenetrable "black box" that it may have appeared to consumers are recently as 2001. Even prior to the FACT Act in 2003, the major consumer reporting agencies and scoring model vendors recognized a marketing opportunity and began to view consumers as customers of scoring information products, including a host of credit score monitoring and ID theft alert services. Today, numerous websites, originating in both the public and private sectors, provide consumers advice on how to understand their credit reports and what goes into determining their credit scores. Managing a FICO score into the "700 club" has gained a bit of a cult following (WSJ, 2008), with advice flying around the internet regarding how to manipulate account balances and manage existing accounts to tweak a score to a higher level.

Yet, according to the Consumer Federation of America surveys, a large proportion of U.S. borrowers still don't understand what a credit score represents or the factors that determine a score. Far more important than coaching to tweak their scores, American borrowers should be aware of the following points:

- Your credit score reflects your decisions. Consumers have the ability to raise and lower their scores. Because credit scores reflect a consumer's own past payment history and current use of credit, consumers can control their own score to a large degree, especially over time. This makes a credit score an important but underappreciated personal financial management tool.

- Failing to properly manage your credit score costs you money: sometimes big money. Fair Isaac's myfico.com website provides ready examples of loan rates that correspond to various score ranges. The cost differential between low scores and higher scores can easily translate into hundreds of dollars per month in additional finance charges for larger loans such as home mortgages

- Knowing your score – and knowing what lenders consider to be a good score and a poor score - helps you shop and recognize a good offer from a bad one

- Your FICO and VantageScore credit scores are based solely on information in your credit report, so check your credit report periodically to see what is there and be sure that what is there is correct.

Thank you for the opportunity to contribute to your discussions.

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