FICO Decisions

WHITE PAPER

# A New Challenge for Risk Management: Understanding Consumer Affordability Risk

## Driven by increasing consumer debt and new regulations

### By Dr. Andrew Jennings

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Access to credit plays a vital role supporting consumer expenditure, which makes up around 70% of the economic activity in a modern consumer-driven economy. By just about any measurement, the modern consumer finance business can be seen as a success, but that success has come with the consequence of rising levels of consumer indebtedness.

This paper describes important new research by FICO into an area of growing concern for the industry and regulators referred to as "affordability risk." We will show that this risk is not adequately covered by today's risk tools, and will present a new type of predictive analytics to address the problem. We can envisage two variations of affordability risk:

1. The situation where simple data on the current situation indicates a high risk of lack of affordability
2. The situation where the proposed action or the behaviour of the consumer will induce financial stress

In the latter, we will show that the profile of a consumer likely to "increase balance and experience financial stress" looks a lot like a good profitable prospect to a lender. Profits come from interest margins and fees, and so consumers that appear to have the potential for additional borrowing are where profits are made. Current credit policies encourage lending to this type of consumer.

# A New Challenge for Risk Management: Understanding Consumer Affordability Risk

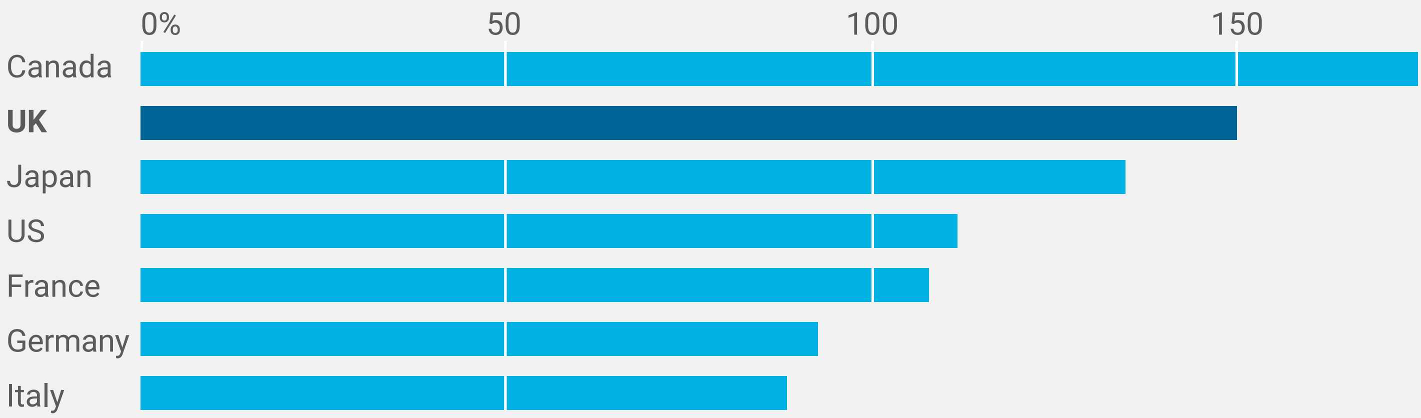
Not all such consumers represent an affordability risk, and so the "trick" is to be able to separate those that do and act accordingly. High-affordability risk would naturally be associated with reduced limit-increase offers or even reductions of limit to reduce exposure.

Three of the most consumer-indebted countries in the world are the UK, Canada and the US. In the UK, it was reported that the current overall household debt (secured and unsecured) to income ratio is running at over 150%.

In Canada, the figure stands at 167.7% debt to disposable income[1], and in the US, the New York Federal Reserve Board reports that "aggregate household debt balances increased in the third quarter of 2107 for the 13th consecutive quarter, and are now $280 billion higher than the previous (2008 Q3) peak of $12.68 trillion."

"As of September 2017, total household indebtedness was $12.96 trillion, a $116 billion (0.9%) increase from the second quarter of 2017. Overall household debt is now 16.2% above the 2013 Q2 trough." [2]

**Figure 1: Household total debt to disposable income: G8 countries**




Guardian graphic | Source: OECD figures on household debt as % of net disposable income, 2015. No figures available for Russia.

Of course, the picture is more complicated than these figures would imply. For one thing, they ignore asset values and household wealth, but equally we know that in all these countries middle-income wage growth has been slow. So even if the aggregate is sustainable, the worry exists that there is a class of consumer that is getting deeper into debt, and that the industry has a responsibility to act.

[1] "Canadian household debt hits another record in fourth quarter": The Star.com March 15, 2017

[2] Quarterly Report on Household Debt and Credit 2017: Q3 Released November 2017

## The United Kingdom

## Regulatory Reaction

The regulatory reaction has been most pronounced in the UK.[3] After the 2007–2008 recession, consumer debt fell as economic pressure restricted earnings and spending, and also caused "forced" reductions in debt due to increased write-downs. A post-recession policy of lower interest rates deliberately made credit cheap in an effort to stimulate the economy. The UK was not alone, as similar policies played out in many other western countries. Central banks kept rates low and purchased assets to take them off banks' balance sheets and on to their own, releasing funds which they in turn hoped the banks would lend.

Prior to the financial crisis in 2007, unsecured lending in the UK reached a peak of £245 billion, representing 45% of household income.[4] Between 2008 and 2012, in the aftermath of the recession, consumers deleveraged with the total level of unsecured debt falling from 47% to 35%. However, since then, fuelled by low-interest rates, there has been a significant upward trend. The Office of Budget Responsibility expects the ratio of household debt-to-income to rise to 47% by 2021. Even between July 2016 and July 2017, there was a 4.9% increase in total unsecured debt in the UK, from £192 billion to £201.5 billion.

Recent trends in utility arrears bring the current and future state of unsecured lending sharply into focus. Utilities are a major leading indicator of financial stress because the consequences of non-payment are not immediate to the consumer. Council Tax arrears have risen by 12% between 2012 and 2017, Water arrears are up over 17% in four years to be in excess of £2.2 billion, and Gas and Electricity arrears exceed £1.3 billion.[5] There is significant evidence that consumers are starting to hurt, which is a trend that is expected to continue.

Governments have started to recognise this situation and no more so than in the United Kingdom.

By way of multiple consultations, such as the Credit Card Market Review (MS14.6.3 -FCA) and the Review and Consultation of Assessing Creditworthiness in consumer lending (CP17-27), the Financial Conduct Authority is taking steps to ensure that lenders take more effective action to understand the financial situation of both existing borrowers and new applicants, going as far as stating: "A challenge for regulators and firms is how to design affordability rules — restricting access to unaffordable credit — to minimise this financial stress…."

The clear implication is that bad lending decisions are being made and the industry needs to do more to identify those consumers "who cannot afford to repay."

The obvious questions are "what do these people look like and how do I find them?"

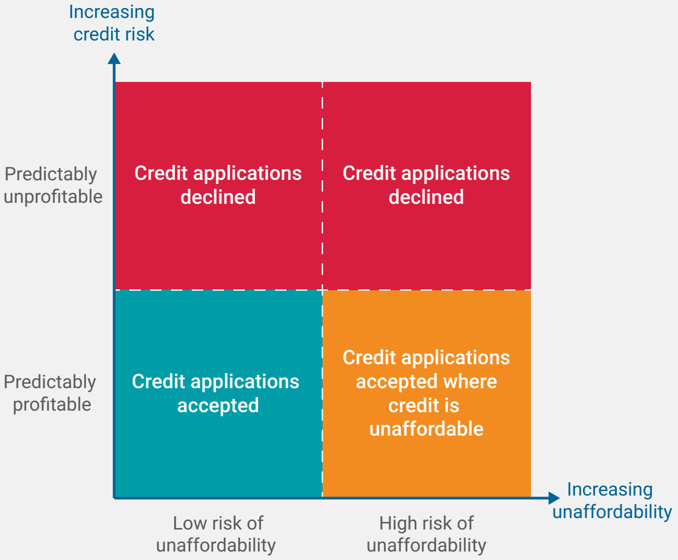
[3] While other countries such as Australia have introduced responsible lending rules, the UK is going beyond defining consumer situations such as "persistent debt" and requiring lenders to act in a way to both avoid and recognise if a consumer is in such a situation, essentially placing a fiduciary responsibility toward borrowers on the lender.

[4] Bank of England UK Bankstats, also numerous media publications reporting on credit data crisis https://www.theguardian.com/business/2017/sep/18/uk-debt-crisis-credit-cards-car-loans.

[5] Department of Communities and Local Government statistics and data.

**Figure 2: FCA Consultation Paper CP17-27 characterises the situation in the following graphic**




The identified issue of "unaffordability" is the accounts that get accepted from the bottom right quadrant. The credit granted can result from new applications and equally can arise from extending credit on an existing product for which a credit limit increase would be the most common. The implication of the table is clear: The issue raised applies to both new and existing credit agreements.

The division between profitable and unprofitable can be thought of as passing or failing the lender's credit risk evaluation and says that there will be a higher level of credit risk in this group. This could lead lenders to be willing to make lending decisions because they meet some "profitability" criterion, but the alternative question is: Should they lend? Because the downside of increased financial stress imposed both on some consumers and societal structures outweighs any benefit that is reaped by this group as a whole.

This is a judgement, but it is increasingly one that the UK regulators are prepared to make.

## The Difference Between Credit Risk and Affordability Risk

Credit risk is a well-developed concept which measures the likelihood that an obligation will not be repaid in full within the agreed terms. In modern consumer credit, credit risk is summarised by a credit score.

Credit risk models take the data known at the time from the application or the behaviour of the account or customer as applicable, to predict the known payment performance. The model creates a probability of non-payment — known as probability of default (pD). This probability is often expressed on an odds scale using a score, where, for example, a score of 600 represents odds of 10:1. This means that for any 11 borrowers 10 will be good, and one will be bad. This is not new.

Affordability is a very different, but clearly related concept. If we knew that a loan were "unaffordable," a lender would be unlikely to make it. Just as if a consumer is already severely delinquent, I don't need a credit score. It should also be the case that we would expect high credit risk to be positively correlated with lack of affordability. However, it is not that simple.

Credit risk is made up of ability — which is more like affordability — as well as willingness. Willingness is the trait that captures a consumer's desire to stick with the commitment. Two individuals with the same affordability may have very different willingness. Neither of these concepts is explicit in a credit score; they are both implicit in that either could be the reason for non-payment. The score only predicts the odds for that consumer. If the emphasis is on separating out affordability risk, it will require new tools.

"Affordability" left to one's imagination is more like an accounting calculation. In a perfect world, a lender would be aware of income and outgoings, they would be stable and predictable, and a determination could be made of the affordability of a new loan based on a calculated debt-to-income ratio.

This is not the real world because such data is not readily available and verifiable. And consumers are not always fully aware of their own current financial situation.

Income and outgoings are not stable and predictable over the life of a credit obligation.

The modern consumer credit world makes, and consumers now expect, near instant decisions. The implication being that all data used to underwrite a credit decision needs to be available to an origination system at the time of application.

And because the same level of affordability can result in different outcomes depending on the credit risk, it is clear that however affordability risk is measured it needs to work hand in hand with a credit risk metric.

FCA Occasional Paper 28 defines “a credit agreement with a high risk of unaffordability” as “a credit agreement (that) if at the time of the decision to grant credit, given the information potentially available, there is a high risk that the consumer will face financial distress as a result of the credit application being granted.”

The key word is “if.” Thinking about the concept this way makes the concept of affordability a conditional one. It is not something that can be a simple (or complex) calculation that results in a yes or no answer. By extension, neither can it be a simple variation of the observance of severe delinquency, because this becomes circular, and we end up with something that looks very much like the risk score we are trying to complement.

*To assess affordability, we need a different construct to ask a different question and to apply new techniques.*

There are two variations of affordability risk:

1. The situation where simple data on the current situation indicate a high risk of lack of affordability
2. The situation where the proposed action or the behaviour of the consumer will induce financial stress

Any solution needs to address both aspects of the problem. A lender needs simple current metrics of the consumer’s situation as well as a more complex summarisation of the overall consumer profile. This is why we need analytics to help answer the question. Just like a credit risk score, we need a model that will allow us to select and organise the important data and express the output as an easily used metric.

## Conditional Models: How Do We Structure the Question of Affordability Risk?

One of the underappreciated characteristics of a credit risk model is that it is conditional on the situation of the consumer prior to a decision being taken. This is interesting because the model is invariably used to make conditional decisions. The limit is raised or a loan is approved conditionally on the score. The inputs to the score are ex ante to the decision, not ex post. Thus, the implication is such that the action will not have an appreciable impact on the ex post risk.

Taking into account the ex post behaviour of the consumer is clearly more complicated. However, the need is to anticipate if an action will induce stress, either directly or by allowing the consumer to mismanage their own situation; we need to reformulate the problem to take account of the possible action that a consumer might take. In other words, we need to understand if a consumer were to increase balance what implication that would have for the probability of default. With that understanding a lender can calibrate their actions away from such individuals and toward those where a balance increase is less likely to induce stress.

Like a credit score, where we are indifferent to ability and willingness as the reasons for the risk, the same is true here. We are only interested in the likelihood of future affordability risk; it could be induced by the lender action extending credit or the result of a consumer action taken within the bounds of their existing available credit.[6]

Thought of this way, we can define affordability risk as the extra risk associated with a sizeable future increase in customers' balances.

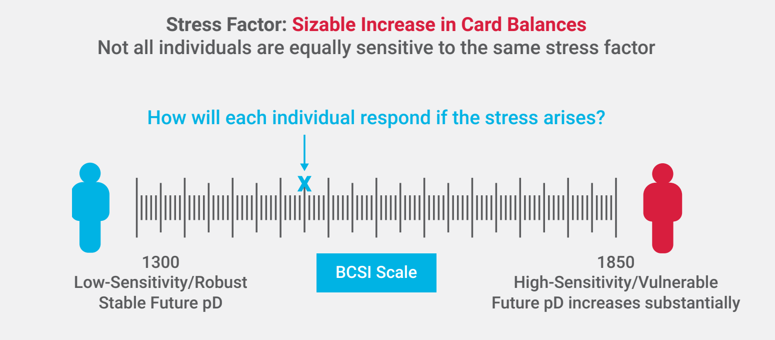
The resulting model of this behaviour is what FICO calls the "Balance Change Sensitivity Index" (BCSI).

## Balance Change Sensitivity Index for Affordability Risk Measurement

The goal of Balance Change Sensitivity Index (BCSI) is to inform a lender of an individual's sensitivities to potential future increases in balances given their current situation. Figure 3 depicts the concept and scale of BCSI.

Imagine an experiment where two individuals are exposed to the same financial stress factor, defined as a sizeable increase in their total credit card balance[7]:

**Figure 3: Conceptual depiction of BCSI**




The individual on the left side can easily afford the additional debt and his/her default likelihood remains unchanged whether the stress factor is present or absent.

The individual on the right side can ill-afford the additional debt and his/her pD increases substantially when exposed to the stress.

BCSI rank-orders individuals with respect to their pD sensitivity to a sizeable future increase in total credit card balances, such that low-sensitivity individuals receive a BCSI value near the bottom of the scale (1300), and highly sensitive individuals receive a BCSI value near the top of the scale (1850).[8]

Unlike traditional credit risk scores which are designed as associative[9] predictive models, this conditional approach to estimation of balance change sensitivities requires a concept called causal modelling. We consider balance increase stress as a possible cause and subsequent increase in default likelihood as a possible effect that follows the cause.

[6] Clearly the borrower is ultimately responsible in the sense that they make the application or they spend on their card. However, the distinction between the lender and the borrower is still useful because we need to alert the lender to those with a higher latent sensitivity to higher balances. Sensitivity is a "conditional risk." It only becomes a real risk if (i) the lender provides the opportunity, and (ii) the consumer behaves irresponsibly. The former is what the lender can control, and the latter is what's hard to predict.

[7] As discussed below, we use credit cards because there is a far greater extent to natural variation in behaviour by which a consumer can choose to increase balance.

[8] The BCSI scale was chosen to reflect the FICO® Score scale +1000. Note that while higher FICO® Scores are associated with lower risk, higher BCSI values are associated with higher affordability risk.

The scientific gold standard to infer causality is to perform randomized experiments. While practically impossible, it is nevertheless instructive to imagine an experiment that would allow us to learn about individuals' sensitivities to additional balances.

- Divide the portfolio randomly into a treatment and a control group.
- Force the treatment group to run up additional balances over some exposure window, and force the control group not to run up additional balances over the exposure window.
- Follow the exposure window, compare default rates between the treatment and the control group during a subsequent performance window.
- The comparison yields the portfolio average sensitivity to the balance increase.
- Drill down into smaller sub-populations (e.g., by risk score band, by utilization, by maturity, by number of searches, etc.) to learn which types of customers may be more or less sensitive to the balance increase.

Because such an experimentation is unethical and impractical, we resort instead to natural experiments that happen in many credit card portfolios syndicated into credit bureau data. Whereby some consumers self-select and are allowed by some lenders to run up their card balances, others keep their balances flat or pay them down.

Clearly, one must be careful to mitigate possible selection biases when replacing randomised experiments with natural experiments — the natural treatment group could be composed of very different types of consumers than the natural control group. There can also be slices of the population who are tightly credit constrained by all lenders, and hence no natural experiments can occur for them. Due to these possible biases and data limitations, a direct comparison of default rates between the two groups could be confounded with substantial differences between the groups. FICO analysis found that this is indeed the case. To understand and to mitigate these selection biases we therefore use a matching approach following the Rubin Causal Model.

## The Rubin Causal Model

FICO defines an entity's sensitivity in the framework of the Rubin causal model[10] as the difference between potential payment performances when the entity is subjected to alternative conditions ("stressed" and "unstressed"). For the purpose of the model development, we used an increase of £900 over six months to define "stressed."[11] As such, an entity's sensitivity is an individual-level causal effect of a binary condition on future payment performance. Normal and stressed conditions appear as two arms of two mutually exclusive paths (see Figure 4). In reality, an entity can only travel along one arm of the experiment for which the entity's performance is observed.

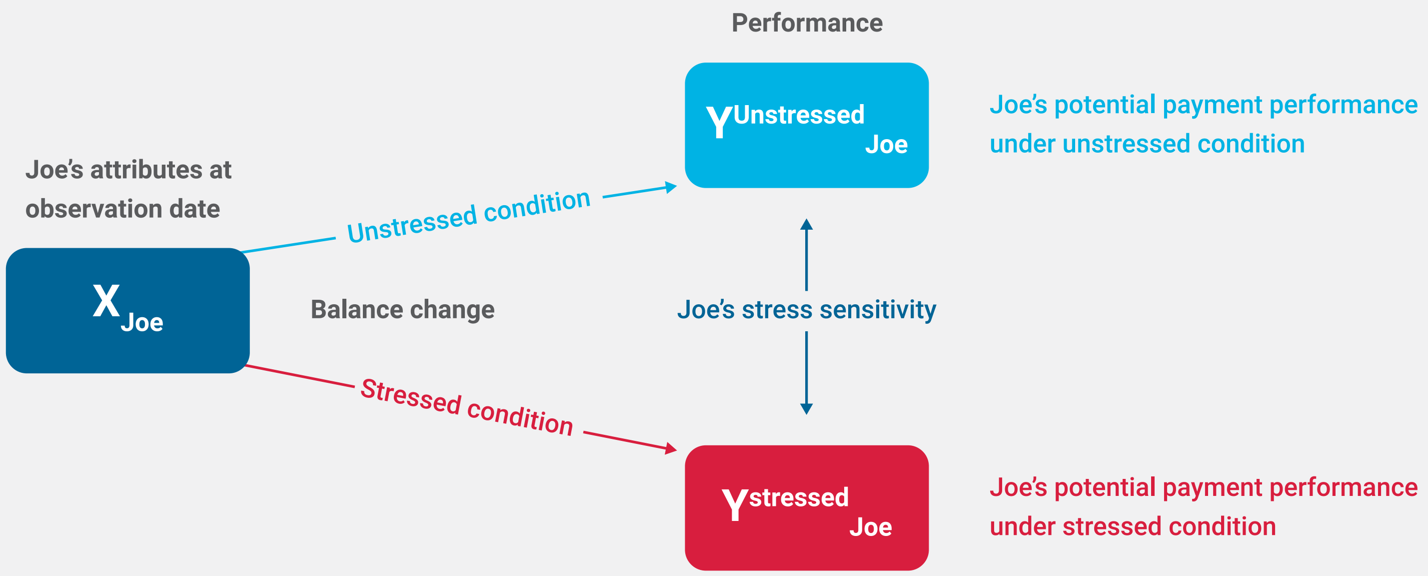
[9] The included variables are based on correlation rather than any underlying theory of consumer behaviour and credit risk.

[10] Holland, P. (1986). Statistics and causal inference. Journal of the American Statistical Association, 81(396), 945–960.

[11] The amount while not arbitrary might change from one situation to another. It needs to be large enough to be considered as a stress event but be frequent enough that it supports the observation of sufficient accounts that make that change with good and bad outcomes.

**Figure 4: Rubin Causal Model to define individual balance change sensitivity**




Rubin causal model to define individual balance change sensitivity as the difference between two potential outcomes for the same individual subject to two conditions.

Subject to statistical and econometric conditions on a sample of development data, it is possible to estimate individual-specific causal effects.[12] FICO's method to estimate sensitivities leverages hundreds of thousands of natural experiments occurring in large credit bureau data samples, in a transparent and fail-safe manner as described in a recent patent application.[13] There will be like consumers making decisions to increase balance and like profiles can be matched and their performance observed, so that statistically we can simulate a close approximation to the scientific experiment.

The matching techniques are used to sample pairs of customers — think of them as twins in a twin experiment — who have similar values of their credit bureau attributes at an observation date (outset of the experiment) and subsequently, during an exposure window, travel along different arms of our experiment.

Following this exposure window where we monitor stress levels, we define a performance window where we classify payment performance as "Good" or "Bad."

The matched-pair approach is an effective tool to mitigate the aforementioned selection biases created by natural experiments, because the twins who are exposed to stress have very similar attribute distributions to the twins unexposed to stress — just like in a randomised experiment. While each twin experiment is very noisy by itself, sampling a large number of twin experiments enables us to discern attribute profiles of sensitive twins (where the stressed twins tend to have substantially worse performance than the unstressed twins), from attribute profiles of robust twins (where performances of stressed and unstressed twins remain comparable). The BCSI model captures the association structure between attribute profiles and sensitivity.

[12] Fahner, G. (2012). Estimating causal effects of credit decisions. International Journal of Forecasting, Vol. 28, Issue 1, 248–260.

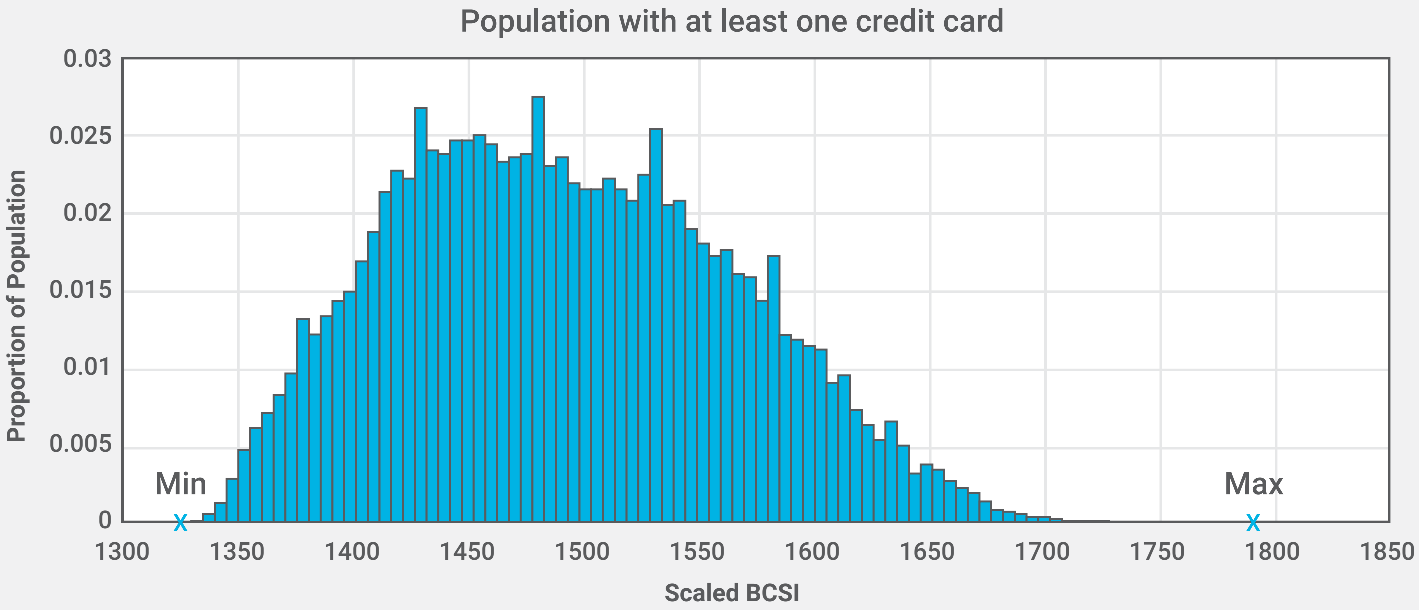
[13] Fahner, G., Vancho, B. (2017). Entity segmentation for analysis of sensitivities to potential disruptions. Patent Application, Serial No. 15/801,265.

## Affordability Risk, BCSI and BCSI Lending Decisions: Results from a UK Model

The following results are generated on a validation sample of consumers randomly drawn from the UK population. The validation sample was not used for BCSI development. Figure 5 shows the BCSI distribution for consumers who have at least one credit card. It is approximately bell-shaped with a slight skew to the right, which is the lower-sensitivity consumer. The important thing is that the distribution is broad, meaning there is a large spread in the range of BCSI among the population.

**Figure 5: BCSI distribution**




The graph shows the BCSI distribution for consumers who have at least one credit card. It is approximately bell-shaped with a slight skew to the right which is the lower-sensitivity consumer.

To understand the overlap with a risk score, Table 1 shows the joint distribution between the FICO® Score[14] and BCSI. The table is factored to approximate the joint distribution to the number of credit cards in the UK (59 million).

**Table 1: Number of cards (in millions) within bivariate cells defined approximately by crosses of FICO® Score quartiles and BCSI quartiles.**

| No Card Accounts | FICO® Score Q1 300–581 | FICO® Score Q2 582–652 | FICO® Score Q3 653–724 | FICO® Score Q4 725–850 |
|---|---|---|---|---|
| BCSI Q1: 1325–1467 | 0.42 | 1.28 | 5.83 | 17.24 |
| BCSI Q2: 1468–1533 | 1.86 | 3.98 | 6.66 | 4.33 |
| BCSI Q3: 1534–1592 | 3.34 | 4.39 | 2.80 | 0.84 |
| BCSI Q4: 1593–1784 | 3.36 | 2.01 | 0.61 | 0.06 |

[14] FICO® Score is the UK FICO® Customer Management Score available from Equifax.

There is a tendency for the numbers to concentrate in the bottom left and top right corners, meaning that higher sensitivity is weakly linked to higher risk and vice versa. This is not surprising; however, there are substantial counts toward the centre of the table and within credit risk score segments, there tends to be additional, strategically actionable heterogeneity in the BCSI distribution that enables further treatment refinement.

BCSI can be used to segment customers according to their affordability risks and to treat the resulting segments strategically different. For example, a credit card lender might refine a limit increase strategy by lowering increase levels (or by foregoing increases) for high-BCSI customers, and/or by upping increase levels for low-BCSI customers. Or a lender may target line decreases towards high-BCSI customers.

Other analytic tasks where BCSI can add value include what-if analysis, prescriptive and decision modelling, and optimization. For example, a card lender could develop or improve a pD calibration model to estimate and to simulate the effect of balance increases on pD while accounting for customers' BCSI. Such a model could yield more accurate decision modelling results and hence better decisions, than a pD model that ignores individuals' sensitivities to balance changes.

To a lender and for the effective incorporation into lending strategies, we need to examine the difference in pD across the joint distribution.

**Table 2: Consumer-level delinquency rates and differential delinquency rates by crosses of FICO® Score quartiles and BCSI quartiles.**

| Stressed pD | FICO® Score Q1 300–581 | FICO® Score Q2 582–652 | FICO® Score Q3 653–724 | FICO® Score Q4 725–850 |
|---|---|---|---|---|
| BCSI Q1: 1325–1467 | 11.51 | 5.06 | 1.57 | 0.38 |
| BCSI Q2: 1468–1533 | 20.55 | 5.70 | 2.69 | 1.13 |
| BCSI Q3: 1534–1592 | 23.65 | 8.27 | 3.81 | 1.95 |
| BCSI Q4: 1593–1784 | 28.68 | 11.48 | 5.37 | 5.19 |

| Unstressed pD | FICO® Score Q1 300–581 | FICO® Score Q2 582–652 | FICO® Score Q3 653–724 | FICO® Score Q4 725–850 |
|---|---|---|---|---|
| BCSI Q1: 1325–1467 | 16.28 | 2.74 | 0.75 | 0.24 |
| BCSI Q2: 1468–1533 | 19.49 | 3.02 | 1.00 | 0.46 |
| BCSI Q3: 1534–1592 | 22.92 | 3.31 | 1.06 | 0.54 |
| BCSI Q4: 1593–1784 | 25.41 | 4.45 | 1.75 | 0.73 |

| Differential pD | FICO® Score Q1 300–581 | FICO® Score Q2 582–652 | FICO® Score Q3 653–724 | FICO® Score Q4 725–850 |
|---|---|---|---|---|
| BCSI Q1: 1325–1467 | -4.77 | 2.32 | 0.82 | 0.14 |
| BCSI Q2: 1468–1533 | 1.06 | 2.68 | 1.69 | 0.67 |
| BCSI Q3: 1534–1592 | 0.73 | 4.96 | 2.75 | 1.41 |
| BCSI Q4: 1593–1784 | 3.37 | 7.03 | 3.62 | 4.46 |

Note: Table 2: Top table ("Stressed pD") reports subsequent delinquency rates (in %) for consumers who increase their credit card balances by a substantial amount during an exposure window. Middle table ("Unstressed pD") reports subsequent delinquency rates for consumers who do not increase their credit card balances by a substantial amount during the exposure window. Bottom table ("Differential pD Stressed – Unstressed") subtracts respective cell pDs of top and middle table.

The top table shows that pD for stressed consumers substantially increases as we move down the columns for each FICO® Score band towards higher BCSI values. This finding is promising, but it does not yet constitute a validation that BCSI rank-orders sensitivities (the pD increase observed down the columns could be a result of higher BCSI values being mildly correlated with lower FICO® Scores). To check against this possibility, consider the middle table: pD for unstressed consumers remains rather flat as we move down the columns (while there is an increasing tendency, it is far weaker than observed in the top table).

The bottom table provides evidence that BCSI works as expected. For consumers with higher BCSI values, we see a larger differential in their pDs between stressed and unstressed conditions, even after controlling for the FICO® Score.

This is important, because it demonstrates the complementarity as well as showing that lower-sensitivity consumers exist in lower-risk score bands. Whereas the spirit of the regulatory pressure naturally tends to restrict lending, the spread of the conditional risks indicates that we get some insight into a consumer profile that has lower sensitivity, and so creates opportunities for lenders. Clearly, if a solution can create opportunities, it has a greater chance for being adopted rather than some blunt regulatory rule being imposed with greater costs to lenders and borrowers.

The leftmost column in the bottom table of Table 2 (first quartile of FICO® Score between 300 and 581): Firstly, pDs are not strictly increasing down this column, and secondly, we find a surprising negative value (-4.77%). The latter owes to the fact that stressed pD for this cell is lower than unstressed pD. These peculiar results are presumably due to the scarcity of natural experiments happening within the lowest FICO® Score range. Lenders very rarely permit these credit-damaged consumers to substantially increase their credit card balances, and when they give permissions, the associated individuals can be severely cherry-picked. The upshot is that we see limited opportunity for BCSI to refine credit decisions for the lowest FICO® Score segment, and lenders should continue treating the worst risks in the most conservative ways.

This is precisely the distinction made above. In these cases, it is possible to discern affordability risk in a more straightforward way by bringing the right currently observed data items to the decision.

In the other situations, the profile of affordability risk is more complex and requires the use of analytics.

## A Profile of High- and Low-Balance Sensitivity Consumers

An obvious question is: What distinguishes low- and high-sensitivity consumers? The answer starts to provide an intuitive understanding of the behaviour that underlies the consumer's ability to induce financial stress and also demonstrates that it would be very hard to represent this profile in a set of rules.

First, we look at the profile of a high- and low-sensitivity consumer independent of a risk score, i.e., we ignore the variation in risk that naturally occurs within each group.

**Table 3: Profile of high- and low-sensitivity consumers independent of credit risk score**

| Dimensions of behavior | Least sensitive 20% bottom-ranking | Most sensitive 20% top-ranking |
|---|---|---|
| What percent of total balances have been repaid over the last 12 months on all cards? | 93.7 | 19.8 |
| When was the oldest credit card opened? | 14 years ago | 4 years ago |
| Total credit card balances? | €1,280 | €2,140 |
| What percent have no credit card balance at all? | 9.9 | 22 |
| How many active credit card accounts? | 2.2 | 1.6 |
| How many settled accounts? | 4.2 | 2.6 |
| How many mortgages? | 1.4 | 0.1 |
| How long since last incidence of missed payment? | 26 months | 13 months |
| What percent have never been delinquent? | 69.5 | 44.7 |
| How many credit searches last year? | 0.2 | 1.0 |

The immediate impression from Table 3 is that the more sensitive have many of the attributes that are associated with higher risk. They have paid down a lower percentage of their card balances, and they have shorter time on books, more recent delinquency, and so on.

Clearly, there is a positive correlation, and not surprisingly, higher sensitivity is higher credit risk and that comes across as the predominate feature. However, from the tables above we have seen that once you control for credit risk more interesting patterns emerge.

For illustrative purpose Table 4 describes a summary of the profile of the bottom (least sensitive) and top (most sensitive) consumers at a FICO® Risk Score of 680. For context, on the FICO® Customer Management Score, 40% of the UK population have a score at or above 680 and the bad rate in the 680–700 group is around 1.5%.

**Table 4: Profile of high- and low-sensitivity consumers controlling for credit risk score**

| Dimensions of behavior | Least sensitive 20% bottom-ranking | Most sensitive 20% top-ranking |
|---|---|---|
| What percent of total balances have been repaid over the last 12 months on all cards? | 72.3 | 40.7 |
| When was the oldest credit card opened? | 11 years ago | 6 years ago |
| Total credit card balances? | €2,480 | €1,350 |
| What percent have no credit card balance at all? | 11.2 | 57.2 |
| How many active credit card accounts? | 2.1 | 1.4 |
| How many settled accounts? | 4.3 | 2.3 |
| How many mortgages? | 1.2 | 0.2 |
| How long since last incidence of missed payment? | 18 months | 34 months |
| What percent have never been delinquent? | 35.0 | 62.4 |
| How many credit searches last year? | 0.3 | 0.5 |

The first thing that strikes the reader is that the profile of the high sensitivity does not fit that of the chronically over-indebted. We are seeing something different from the accounting DTI approach. We are separating a profile that has a greater risk of using "the available rope to hang themselves." These are the over-indebted consumers of tomorrow, and if the problem is to be tackled it is precisely these consumers that need to be identified.

One of the features of any risk model is that it allows different features and behaviours to compensate for each other. Thus, for example, two individuals can have a similar score where one has a higher utilisation and a longer credit history, and the other has a shorter history and perhaps fewer missed payments. The lack of delinquency "compensates" for the shorter history creating a similar risk.

Something similar emerges in Table 4. What becomes evident is that there are variations which become important when we formulate the problem in the format of BCSI. Two of the most striking are total card balances and time since last missed payment. Both are favourable for the most-sensitive group, and both of these are factors that would tend to increase a risk score. The implication is these are the same profile that a lender might target with a credit limit increase as they have balance, and they have a superior payment record.

A counter argument can be made that because the most-sensitive group has lower credit card balances, then a balance increase will have a significantly greater impact on their financials than the least-sensitive group with higher credit card balances. Basically, if the balance increase makes up a larger percentage of their current debt, then it is more of a "shock" to that customer.

It is also important to keep in mind variables such as "percentage of balance repaid last 12 months on all cards," which consistently show (whether holding risk constant or not) the least sensitive consumers paying off a higher percentage of their recent card balances. With that information in mind, it gives a different perspective on the higher total balances that this least-sensitive group is showing; they have higher balances, but they also show that in the recent past they have had a greater ability to pay off those high balances than the most-sensitive group does on their lower balances.

So just like with a risk score, we find these compensating features. This would be hard for a lender to distinguish from the behaviours directly, because just as in a risk score you don't know how to trade off one against another. And it's likely that the trade-off varies depending on which slice of the risk profile is being considered.

If you are a lender and all you are doing is looking at how much debt the person currently has to make a decision on whether or not to increase their card limit, then the BCSI score can help give you a fuller picture of their ability to pay.

It's important to stress that the high sensitivity is not saying that these people will be bad. The whole concept is a conditional one, and there will be individuals for which increased balances are perfectly fine. The issue, though, is that the lender does not know. They know that this group had a higher pD conditional on balance increases, and so BCSI provides the ability to navigate away from them.

## In Summary

The creditworthiness of any individual lies at the heart of all lending decisions. Affordability risk is a new dimension that is being added to the list of requirements for responsible risk management. We have seen that there are two aspects to understanding affordability risk: data required to identify persistent debt and systematic minimum repayments (for example), and new tools required to identify those consumers most sensitive to balance changes and ensuing financial stress.

Market-ready solutions need to combine data and innovative analytics to measure the new concepts being demanded by regulators and be able to present opportunities as well as restrictions.

In this paper, FICO has presented a summary of the pressure at play, offered a new definition of affordability risk, and described an analytic approach that is designed to predict the conditional risks that occur because of increases in balance.

From a regulatory point of view, we already have evidence of the impact of failing to take affordability issues into account when setting strategies, with penalties and provisions for remedial action looking likely to cost billions to lenders in the UK who fail to address the issue. It is likely that others will follow suit.

Additionally, from IFRS9, capital provisioning and stress testing, the impact of the failing customer is likely to cause a major impact. This impact is set to increase as and when interest rates return to normal levels.

Lenders of course need to improve productivity and the profitability of their portfolios, and having this same understanding of consumers who are less likely to suffer from future stress, even if their balances are increased, presents opportunities to provide additional products and obtain increased share of wallet from the more stable customers in the portfolio. The combination of credit and affordability risk presents an ideal opportunity to create tailored solutions to each customer which are fit for purpose and less likely to lead to default — whilst not placing unnecessary financial strain on the customer.

**FICO is continually analysing trends and practices in the credit market to help lenders apply analytics most effectively in their decision processes. To learn more, contact us at globalscoreservice@fico.com.**

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