Good Practice Lending Guide

RM04 Credit Risk Lending Policy

May 2024

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1 Introduction

1.1 Why is an assessment of credit risk important?

When deciding if to lend to a customer, a lender must undertake an assessment of the customer's creditworthiness. Under UK regulations, as defined in the FCA's Handbook[1], lenders should consider the following aspects of creditworthiness:

- **Credit Risk.** This is the risk of financial loss resulting from granting a loan. Credit risk is usually associated with customers who don't keep to their contractual repayment terms and fall into arrears, default and are eventually written-off. This is sometimes referred to as default risk or loss risk
- **Affordability.** This is the customer's ability to make repayments. More precisely, in taking out a loan the customer is not borrowing beyond their means, resulting in financial difficulty and a poor outcome for the customer

It can be easy to think that these two things are the same. If a loan is affordable then the credit risk is also acceptable and vice-versa. However, while there is some overlap between credit risk and affordability there are also significant differences.

- Consider a customer with the means to make their repayments but simply decides not to and spends the money on something else instead. This is an example of unacceptable credit risk.
- Another example of credit risk is a customer who can easily afford a loan when they originally applied for it, but who unexpectedly loses their job a few months later leaving them unable to make their repayments.
- Now, consider a customer whose only means of making loan repayments is to use their credit card. This customer is an acceptable credit risk because they make all loan repayments. However, their behaviour demonstrates a lack of affordability due to the customer having to increase their borrowing elsewhere to do so

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[1] CONC 5.2A Creditworthiness Assessment. For core credit union lending not classified as regulated consumer credit, then technically this specific regulation does not apply. However, the FCA and PRA both require credit unions to lend responsibly and prudently, as demonstrated by the outcome of several Financial Services Ombudsman cases and PRA publications respectively.

Another way to think about this is that credit risk provides a business orientated view of the customer. It's about assessing the expected financial impact on the business of a customer's repayment behaviour. If an organisation does not have a suitable process in place to accurately assess the credit risk of each loan application it considers, then that creates a risk that the business will be loss making and potentially unviable in the long term.

Affordability on the other hand, is very much customer focused and how they will be impacted by the loan. Consequently, making accurate assessments of both credit risk and affordability demonstrates that a lender is acting prudently and responsibly, which supports good outcomes for the customer and the lender.

The remainder of this document covers the credit risk element of lending policy. Therefore, when lending policy is discussed in this document, we are specifically referring the credit risk part of the policy. The affordability part of lending policy is dealt with as a separate topic in the Lending Policy (Affordability) component. Both should be considered together when formulating your organisation's lending policy and making lending decisions.

1.2 Why has Fair4All Finance commissioned this guide?

In our work with community finance lenders, those we have made significant investments into, and those we have funded through grants and capability support, we have come across a range of approaches to credit risk and provided consulting support to enhance them in some instances. This guide reflects our intention to document what good practice looks like on credit risk to share the insight that has been developed for specific lenders more broadly.

1.3 Purpose of this document

This document is intended to support Community Finance lenders in making accurate assessments of their customers' credit risk, effectively and in line with UK regulatory requirements.

Specifically, this covers the different approaches that can be adopted to assessing the likelihood of customer default (and hence write-off and loss). This is so that a lender can formulate an appropriate lending policy, and hence, make sound lending decisions based on the credit risk profile that each customer represents.

Every lender has their own approach to assessing credit risk. However, it is important that firms clearly define, and comprehensively document, their credit risk policy and set up appropriate governance and oversight processes to ensure that they are optimising their stated business objectives in line with their risk appetite.

This guide to assessing credit risk is not prescriptive. It is not intended to provide the definitive view as to how organisations should credit risk-assess their customers. However, it describes industry standard good practice approaches that are widely used across the credit industry.

The approach to assessing credit risk described here is generally applicable to all UK lenders, but it is primarily intended for small to medium sized organisations who are working to provide fair and affordable credit to sectors of the community who may otherwise struggle to obtain it. For example, not-for-profit lenders and credit unions. Therefore, it adopts a proportionate approach suitable for these types of organisations.

Organisations can use the Guide in one of two ways:

1. As a reference manual, to help them enhance their own lending policies and to provide assurance that there are no gaps or shortcoming
2. To support new organisations in setting up appropriate credit risk based lending policies

The focus of this document is Credit Risk. However, there are clear overlaps with other areas of lending, such as Risk Appetite, Affordability, Management Information, Governance etc. These are signposted within the relevant sections throughout this guide.

2 Scope

The scope of this document is the methods for undertaking credit risk assessments of loan applicants, as part of a lender's overall assessment of creditworthiness, as captured in their lending policy.

Given that:

- The end-to-end application process, covering the customer journey from initial enquiry through to disbursement of funds is covered in Module 3
- Assessing customers' affordability, ie ensuring customers have sufficient funds to meet their loan repayments, is covered Module 5
- Identifying Fraud and Customer Verification that supports to Know Your Customer (KYC) requirements are covered in Module 6

These elements won't be specifically covered in this module. However, reference will be made to these topics where appropriate.

The document focuses on unsecured personal loans, but the principles described are generally applicable across other types of consumer lending.

2.1 Legislation and regulatory guidance

There is little regulatory guidance or legislation that explicitly defines how organisations should assess credit risk, other than the FCA's requirement that an assessment should be made as part of a lender's overall assessment of creditworthiness and that this process should be documented, approved and periodically reviewed by the lender's governing body. This includes keeping accurate records of each agreement entered and establishing suitable procedures and oversight to ensure that the approved lending policy is adhered to [2].

As the Information Commissioner's office has stated, no one has an automatic right to credit, and lenders want to be confident that their customers will repay what they borrow[3]. Therefore, lenders have a high degree of latitude in deciding how they assess customers' credit risk, what types of customer data they use in this process and which customers they accept. However, they must still comply with UK legislation

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[2] FCA Handbook. CONC 5.2A Creditworthiness Assessment.
[3] Credit Explained (ICO). P.4. Credit explained (ico.org.uk)

and regulatory principles more generally when making lending decisions and we discuss these in the following sections.

2.1.1 FCA's Principles of Business

The FCA's Principles of Business[4] describe the principles under with FCA regulated firms are expected to conduct their business. Often, the focus when assessing credit risk is that this needs to be done in a fair way that supports good customer outcomes in line with principles 6 and 12. However, lenders should also be mindful of principles 3 and 4.

Principle 3 requires firms to have adequate risk management processes in place (which includes the management of credit risk) and to display financial prudence (Principle 4). This can be taken to mean that lenders should always have their customers best interests at heart, but this does not override their requirement to make sound financial decisions about who they lend to and under what terms, in line with their business objectives and risk appetite.

2.1.2 General Data Protection Regulation (GDPR)

The GDPR is best known for ensuring that organisations only collect and use data for purposes that individuals have consented to and that this data is maintained securely and accurately. If you think about the data protection stories that appear frequently in the press, the vast majority of these relate to data breaches and customer information either being stolen or inadvertently released into the public domain. However, the GDPR's remit is far wider than this. In particular, the use of data must be:

1 **Fair.** Data must not be processed in a way that is unduly detrimental, unexpected or misleading to the individual concerned. Organisations must be clear with people at the outset about how their personal data will be used. This is complementary to the FCAs principles of treating customer fairly and consumer duty

2 **Transparent and explicable**. This means being able to explain to someone, in simple terms, why a decision was taken to treat them in that way

Practically, this means that to carryout credit risk assessments lenders must:

- Clearly inform customers about the types of personal data and processes that are going to be used to make decisions about them when they apply for a loan[5]
- Have accurate and up to date lending policy guides that describe how customer decisions

[4] FCA Handbook. PRIN 2.1. The Principles.
[5] Or at any stage of the customer lifecycle.

are made using the data that is held about people

- Have strong oversight to ensure the policies are adhered to.
- Clear documentation and audit trails to be able to unpick how individual decisions were made

In consumer lending, many lenders use a fully automated decision-making process for some, or even most, loan applications. This is either via policy rules to decline applications with certain features (such as the applicant is under 18 or bankrupt) or credit scoring[6], where those with a low credit score are declined. In these cases, the GDPR requires there to be a separate manual process to assess a loan application if a customer challenges the original automated decision.

The manual review process must be completely independent of the automated decision-making process. It can't be just a case of rubber stamping the original decision. This means that even lenders who have automated their entire decision-making process still need to maintain a standalone underwriting function to enable independent manual reviews to be undertaken when required.

2.1.3 Equal Opportunities Act 2010

The Equal Opportunities Act makes it illegal to discriminate against people based on "protected characteristics." Protected characteristics are defined as: Age, Disability, Gender Reassignment, Marriage and Civil Partnership, Race, Religion or belief, Sex and Sexual Orientation. Therefore, there is considerable overlap between these and GDPR special category data.

Note that the act makes a specific exemption for age, allowing age to be considered for financial services. This includes for assessing creditworthiness and making lending decisions based on someone's age.

For lenders, most of the Act's requirements relating to a lender's treatment of customers are covered by the FCA's principles of business and/or the GDPR.

Customer insight

Some of the work Fair4All Finance has commissioned has focussed on lending to hard to serve groups and monitoring who we are and are not helping is a vital part of understanding whom our products are serving, or not. We've heard from many lenders that they're concerned about asking customers for their characteristics during a lending journey, or even in an evaluation survey, because of GDPR or Equal Opportunity Act concerns. Not asking these questions may appear like an easy way out – but it can mean that lenders are unsighted on who they are inadvertently not serving, or whom they are over-indexed on (a kind of concentration risk). Although it is not discussed in this document the use of privacy notices to

[6] Credit scoring is explained in more detail later in this document.

given customers context for why their data is sought and to gain their consent to how it is then processed, are valid and useful ways to overcome these considerations.

2.2 The rest of this document

In the remainder of this document, we start by discussing the credit risk assessment process, and good practice in defining and measuring credit risk when formulating a lending policy. Then, we describe the statistical and expert led approaches used to identify customer features that are indicative of credit risk that should be incorporated into the lending policy.

Following this, the various sources of customer data that can be used to create a lending policy are presented. We conclude with an example of a lending policy that covers the various aspects of credit risk that should be included in a complete and well-rounded lending policy document.

3 The credit risk assessment process

In this section we describe the key elements of the credit risk assessment process.

3.1 Building a credit risk lending policy

An organisation's lending policy captures all the rules that an organisation applies in assessing a loan application. The policy should incorporate all the credit risk elements shown in Table 1

Table 1 credit risk requirements for a lending policy

Area	Description
Policy Decline Rules	• These are "hard" rules that must be followed as part of the standard underwriting process. This is to enforce risk appetite and/or based on the losses customers with these features tend to generate. For example, "Decline all applications from bankrupts" • These types of policy rules are often hard coded into IT systems, allowing fast tracking of cases and supports automated decision-making • Policy decline rules are rarely overridden and overriding can only be undertaken following referral to a senior decision maker within the organisation, such as the Head of Credit

Area	Description
Policy Referral Rules	• These are rules where the case must be reviewed by an experienced loan assessor to come to a final decision. The two main reasons for referral for manual review are: 1 **Marginal cases.** These are just above or just below the threshold for acceptability. Where credit scoring is employed, there will often be a range of scores representing marginal cases that lead to the majority of referrals 2 **Missing information.** For example, the CRA is unable to provide a credit report for the customer. Therefore, this needs further investigation before a final decision can be arrived at • Sometimes referral rules may be further segmented into: 1 **Refer to decline.** The general view is that these cases should be declined, but a human assessor makes the final decision, checking that there are not any additional criteria that might support a loan being granted 2 **Refer to accept.** The general view is that these cases should be granted a loan, but a human assessor makes the final decision, checking that there are not any additional criteria that might prevent a loan being granted
Auto-Accept Rules	• These rules lead to automatic approval (of the customer's credit risk). Usually, these are exception-driven, firing only at the end of the process if no decline or refer rules are hit
Underwriting Guidelines	• This part of the policy provides details loan features assessors should consider if a case is referred to them. This will usually incorporate a more holistic assessment of the customers' situation and risk profile, rather than following specific rules (otherwise, you don't really need an underwriter to be involved). Often this type of assessment is viewed in the context of the five Cs of credit: The customer's Character, Capacity (affordability), Capital (deposit for secured lending) and Collateral (assets secured against the loan) and Conditions (personal and macroeconomic considerations). For unsecured lending, Character, Capacity and Conditions are the primary considerations • The underwriting policy should contain details of approval limits for underwriters and the conditions under which a case should be referred to a more senior person (such as the head of credit)

Area	Description
Appeals Process (For a decision that the customer has contested)	• Lending policy should contain a section on appeals, describing how the company reviews declined applications where the customer has challenged the decision

In terms of priority, decline rules always take precedence over refer rules, which in turn take preference over auto-accept rules.

3.2 How many rules should there be?

There are no hard and fast requirements, but it is important that the lending policy is sufficiently detailed to cover the full range of customer behaviours that indicate an unacceptable level of credit risk. However, the rules defined in the policy should also be as concise as possible. This is to avoid creating an overly complex solution that is difficult to understand and maintain[7].

This is one reason why credit scoring can be so useful, in that a single credit scoring based rule can replace many individual rules based on lots of different data items. Credit scoring is discussed in more detail in Section 5.3

When designing a lending policy, good practice is to undertake analysis to make sure that there is no duplication or redundancy. For example, one policy decline rule is to decline a customer if there are any CCJs on their credit report. There is another policy rule to decline customers if the value of any CCJs is >£0. These two rules are effectively the same and hence only one is required. Likewise, if very few customers hit a rule, then the value of that rule is questionable. Consider a refer rule to refer loan applications from customers aged >110. Sure, there could be the odd customer that is this old, but they will be so rare as not to be significant enough to justify their own rule.

As a very rough rule of thumb, if a loan provider has more than about 30 credit risk related rules, then that is probably too many, regardless of the size of the loan book.

3.3 Where in the application process to apply the lending policy?

In terms of where in the application process a credit risk assessment occurs, credit risk is usually addressed after customer verification (Know Your Customer) and fraud checks have been undertaken[8] but

[7] This is a particular problem if there are many overlapping or interacting rules, making it difficult to determine the primary reason why an application was declined.
[8] See the Customer Verification and Fraud Prevention Component (RM3) of the Guide for more details

before the customer's affordability has been assessed[9]. This is because:

- There is no point spending time, effort and cost continuing with an application if the customer is believed to be fraudulent or whose personal details cannot be verified.
- The affordability element of a creditworthiness assessment is the point where the most questions / discussions with customers tend to arise. Therefore, a customer may feel their time has been wasted if they spend a lot of time discussing their income and expenditure only to be told that they were rejected on the grounds of credit risk.

There is no legal requirement to assess credit risk at this point in the application process, but it is generally the most efficient place to do so and produces the best customer outcomes.

3.4 Automation of lending policy

From a cost, efficiency, accuracy and audit perspective, it makes sense to automate as much of the underwriting process as possible via decision rules. This is because it is a repeatable process[10], that results in clear and unambiguous reasons for why decisions were taken. These decisions are then easily audited and supports the production of management information far more easily than the case notes that must be captured for manual decision making approaches.

Having said this, the strength of a manual underwriting process is that it allows for a more nuanced approach. It provides greater flexibility, allowing better treatment of marginal customers and customers whose circumstances are unusual or non-standard in some way. Similarly, any lenders who use automated decision making must also maintain a manual underwriting capability to be able to review cases where a customer appeals a previous decision.

Determining the balance between automation and manually based decision making should be a key consideration when designing and maintaining the lending policy. As a guide, if an organisation is granting several hundred loans or more a month and has several years' worth of customer data available for analysis, then a reasonable expectation is that it should be possible to automate most lending decisions and possibly 90% or more.

3.5 Recording and monitoring

Regardless of how automated or manual the application of lending policy is, the loan application processing system should maintain a record of all key data and decisions made about the customer during

[9] See the Lending Policy (Affordability) component (RM5) for more details.
[10] ie when presented with the same data, it will always deliver the same decision. This cannot be said to be true for all manually based risk assessments.

the application process. This should be in sufficient details that it allows an independent assessor / auditor to be able to fully understand the customer's journey and why the eventual decision to accept or decline the application was made.

This data will also support monitoring and refinement of the lending policy over time. This is by being able to determine which customers met which rules, which cases were referred for manual review, and how well loans that hit different conditions performed[11].

3.6 Treatment of vulnerable customers

If a customer is identified as being vulnerable, this does not directly impact the assessment of the customer's credit risk (or affordability). A customer should not be treated more favourably or receive credit on better (or worse) terms than other customers just because they are vulnerable.

However, appropriate consideration needs to be given to *how* a vulnerable customer is communicated and dealt with throughout the loan application process, taking the nature of their vulnerability into account. For instance, having alternative ways to provide customers with information about the loan to ensure they fully understand the information they are provided with.

Some lenders provide funds specifically to support for customers who are financially struggling or have other vulnerabilities. If an organisation takes this into account as part of their lending policy, then this still needs to comply with FCA Consumer Duty principles to ensure that good outcomes result for the customer. For example, consider a lender who specifically grants loans to vulnerable customers who would otherwise be declined due to their credit risk, to help them with short term financial difficulties. If the lender then adopts a very aggressive collections process involving DCAs and Bailiffs when these customers enter arrears, granting them the loan was probably not in their best interest and has not resulted in a good outcome for the customer.

[11] This won't apply to policy declines because there will be no repayment performance for these cases. However, where cases are referred, or policy decline rules have been overridden then the performance of these cases can be assessed.

4 What is acceptable credit risk for your business?

4.1 General principles

In the introduction, credit risk was defined as the "risk of financial loss." Consequently, a key goal of an organisation's lending policy is to assess, for each loan application, the potential for financial loss against the revenues that it expects to receive. Therefore, in deciding which rules to incorporate into lending policy, a lender needs to understand the following 2 things:

1. **What it defines as acceptable credit risk**. As we shall discuss, there are several ways this can be defined.
2. **The risk associated with each customer feature.** For example, how risky someone is who is not in permanent employment, or who defaulted on a credit agreement a few months ago.

Note that when assessing an individual customer, the acceptable credit risk is not the same this as the overall portfolio risk appetite. A lender's risk appetite may, for example, state a maximum portfolio arrears rate of 12.5% However, there may be customer groups where higher arrears rates are permitted (and profitable), which are offset by lower arrears rates in others customer segments.

Net Present Value (NPV) approach to acceptable risk

Maximising profit is not every lender's goal, but every lender needs to consider the profitability of the loans they grant to be able to continue operating on an ongoing basis. Therefore, let's start by considering a lender who decides that its strategy is to lend only to customers where it expects to at least break even on the loan.

One way the lender can assess customers is to calculate the profit/loss that each customer is *expected* to generate when they apply for a loan. All those where the expected profit is positive[12] are considered "good" customers and granted a loan. "Bad" loans that are expected to generate a loss are declined.

To be able make this assessment of expected profitability for each loan application, the lender needs to consider, amongst other things, the amount, term and APR of the loan, the costs of servicing the loan as well as the probability of the loan being written off each reporting period[13] over the term of the loan. In accounting terms, the lender assesses the expected Net Present Value (NPV)[14] of each loan, and only grants the loan if the NPV is positive.

4.1.1 Pricing for risk approach to acceptable risk

Another avenue for lenders is "pricing for risk." Pricing for risk can be seen as the flip side of the NPV approach. With the NPV approach, the lender seeks to determine if a customer is likely to generate a sufficient return, given the product on offer. For example:

We offer loans of between £2,000 and £7,500, with terms of between 12 and 36 months, at an APR of 14.9% Given this customer's risk profile, will I make a sufficient return if I grant them a loan with these terms?

With pricing for risk, the product's APR is not determined by the product, but is set to reflect the risk profile of the customer and the loan they are applying for. The question becomes:

The customer has applied for a £5,000 loan over a 24 month term. Given this customer's risk profile and the loan they are applying for, what APR do I need to charge to make a sufficient return?

In theory, if the APR is high enough, then almost any customer can be offered credit profitably. This is because the interest revenue from the few that repay will offset the costs of those that default. Historically, this is a practice was adopted by some sub-prime lenders who offered loans with APRs of hundreds and sometimes thousands of percent.

Today, maximum APRs are now limited by law. For credit unions the maximum APR is the 42% figure specified by the Consumer Credit Act. For other lenders, the interest rate cap is set by the FCA at 0.8% per day and the total costs of loans must not exceed the value of the original loan[15]. Lenders must also be mindful of Consumer Duty, and make sure that whatever interest or other charges apply, the customer is getting good value from the agreement.

[12] Or above a minimum expected level, ie zero profit is not the ideal decision point but something slightly above zero. This because a profit orientated lender knows that they could invest their funds in things like a deposit account, which would generate a profit. Therefore, the minimum acceptable profit from granting a loan needs to exceed this value.
[13] ie the expected loss is dependent upon the repayments made before default occurs and the balance at the point of default.
[14] NPV is a standard accounting practice, used to represent the decreasing value of money over time, ie a loan repayment of say, £200 received this month has greater intrinsic value than a payment of £200 received in 2 years' time.
[15] High-cost short-term credit | FCA

When considering a pricing for risk strategy, credit unions are in a unique position in that they can also consider the savings that a member holds, as well as the loans they have. In effect, it is possible to net-off the savings against the loans when assessing potential credit losses. To put it another way, they only need to consider the losses from the customer's net position, ie the loan balance less savings (shareholding) in the credit union. If a customer borrower £10K but has £8K in savings, the net exposure is only £2,000[16]. However, relatively few credit unions currently apply this type of approach to its full potential when assessing loan applications.

4.2 Practical limitations of NPV and pricing for risk approaches

Some (mainly larger) organisations do take a full NPV view of individual customer profitability when making lending decisions and/or apply pricing for risk strategies. There is no reason why other organisations should not adopt NPV and/or pricing for risk-based approaches. However, this isn't always practical (even for some quite large lenders) for the following reasons:

- **Complexity.** Coming to a precise and accurate view of the expected profitability for each loan at the point of application is difficult. Not least, due to the requirement to estimate all the expected cash flows over the lifetime of the agreement, considering expected losses at each reporting period and changing economic conditions over the term of the agreement
- **Business goals.** Most organisations need to be profit making to remain viable. However maximising profit is not the primary goal of every lending organisation, particularly in the credit union and community finance sectors of the financial services industry
- **Credit risk appetite.** An organisation's credit risk appetite[17] is a set of constraints which act to limit the level of credit losses that a business is willing to accept. As discussed, in theory, almost any customer segment can be profitable if the cost of credit is high enough, but responsible lenders won't lend to customers if the risk of them defaulting exceeds certain thresholds. This is both to protect the business and to ensure that good customers outcomes result
- **Quantitative estimates of default and loss.** To be able to estimate NPV or apply pricing for risk, a lender needs an accurate estimate of how likely a customer is to default, and the and the losses the result from that default.

[16] This is somewhat simplistic, because until default occurs, the customer can draw down their savings. The shareholding at the time a loan is granted is not an accurate representation of the shareholding should default occur. This is a somewhat like the problem faced by credit card providers when trying to assess how much of a customer's credit limit will be used before, they default.
[17] See the Credit Risk Appetite component of the Guide for more details.

4.3 A good and bad perspective of acceptable risk

Given the complexities of applying a pure NPV / pricing for risk strategy, organisations will, when designing their lending policy, focus on risk measures that are highly correlated with profitability and loss, but which are easier to calculate, evaluate and manage. In particular arrears rates and default rates. This is one reason why these measures feature so prominently in lenders' management reporting.

Lending policy is designed to deliver to these metrics: ie to only lend where the arrears and/or default rates are acceptable. Take the case of a lender that has determined (via suitable analysis of their book) that they make a loss where the default rate is more than 10%. Therefore, the company's lending policy is designed around a 10% default rate strategy. Lending rules are designed to reject customers where the attributes of those customers indicate the default rate will be greater than 10% if the loan is granted.

For unsecured personal loans, perhaps the most common credit risk metric used *during the application process* are the odds of a customer becoming 3+ months in arrears (ie the likelihood of defaulting[18]) during the first X months of a loan. To put it another way, someone who defaults within X months of being granted a loan represents a "***bad***" credit risk that will likely result in a loss. Likewise, a customer who makes it through this period without entering default is considered to represent a "***good***" lending decision that is expected (but not guaranteed) to deliver a positive return on investment.

The value of X is lender specific. However, measuring default over the first 12 months of a loan to define the good/bad outcome on a loan is common. This is because:

- It provides a good compromise between allowing repayment performance to be observed over a reasonably long period, and not being so long as to require the business to wait years before it can decide if it made the right lending decision or not
- It has been widely observed across the credit industry that customers most likely to display repayment difficulties tend to do so earlier rather than later, ie if a customer makes all their repayments over the first 12 months of a loan, that is a strong indicator that they are low risk when it comes to meeting their remaining loan repayments, despite whether or not that lender encounters a greater level of risk with longer term products
- Using a standard fixed period provides consistency when measuring loan performance and simplifies reporting ie each loan is measured using the same metric

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[18] For the purposes of this document, we take the backstop view adopted by the IFRS9 impairment reporting standard as our definition of default, ie 90 days (3 months) in contractual arrears. In practice, most organisations include additional default criteria in their definition of default, but the 90 day definition usually accounts for most default cases.

- Measuring default over 12 months is specifically required for elements of the IFRS9 accounting standards and PRA (CRR) capital requirements for measuring default[19]

Using 12 months to measure loan performance is common and is a good place to start if you are unsure what period to use. However, using 12 months is not universal. Every lender needs to come to their own view as to what constitutes a good or bad outcome for its business model and over what period to assess this outcome. For example, for low value short term lending, an outcome as short as 6 months may be appropriate because most loans don't run to 12 months. For large unsecured lending and mortgages, an outcome period of 24-36 months is not uncommon. Likewise, loan performance can be assessed as "bad" at an earlier or later arrears stage in some cases.

However, this general approach of **assessing credit risk based on the principal amount and repayment performance over a defined outcome period** is widely adopted across the credit industry.

It is also common for lenders to consider more than just one measure of loss when designing their lending policy. As well as looking at bad rates over 12 months, a lender may for example, also consider 1+ months arrears rates and write-off rates.

4.4 Lending policy based on good / bad performance

Lenders use their definitions of "good" and "bad" to derive a view of the acceptable bad rate (default rate) from a profitability perspective and in terms of their wider business objectives.

The bad rate is defined as:

Bad rate = (Number of Bads) / (Number of Bads + Number of Goods)

Let's take a simple example. Consider a lender who uses the likelihood of customers becoming bad (ie (becoming 3+ months in arrears and in default[20]) over a 12 month period to make lending decisions. Their strategy is to only accept those customers who are likely to make a positive contribution to profits and decline the rest.

The lender has done some analysis of loans granted in the past. This shows that:

- For good loans, where customers didn't default within 12 months of being granted a loan, this resulted in an average return (profit) of £100 over the entire loan term
- For bad loans, where customers defaulted within 12 months of being granted a loan, this

[19] These financial standards and regulations are not directly relevant to most credit unions and other community lenders but are worth bearing in mind given that they are a standard used across many parts of the financial services industry including all banks and building societies.
[20] Going forward we shall use the term default and bad interchangeably.

resulted in an average loss of £400 over the entire loan term

What this analysis tells the lender is that, on average, it takes the profit from four good loans to offset the loss from one bad loan. To put it another way, for customers group to generate a positive contribution to profit the bad rate in that group must be below 20% (odds of at least 4:1)[21].

In this example, a lender could incorporate this information into their lending policy in one of two ways.

1. Where data exists, analyse the historic performance of customers' features (characteristics). Where customers with specific features have bad rates of more than 20%, this leads to the creation of a decline rule within the lending policy. For example, customers with County Court Judgements (CCJs) of more than £1,000 within the last 6 months had average bad rates of 23% This is greater than the breakeven point of 20% Therefore, the lending policy includes a rule to decline all customers with a CCJ of >£1,000 within the last 6 months
2. Use expert opinion to define decline rules where it is believed that the bad rate will exceed 20% If the business has no historic experience of lending to customers aged <21 then no analysis can be performed to understand how well under 21s repaid their loans. However, the Head of Credit Risk's wider industry experience is that young customers in this market segment typically have bad rates of around 30% Therefore, a decline rule will be applied to reject all applications from those aged <21

In practice lenders use a combination of these approaches to define and refine their lending policies on an on-going basis. Some lenders may also operate different products to consider the expectations of their historical analyses and to reflect as possible the risk within the APR.

We'll explore this further in the next section.

[21] The good:bad odds are defined as the number of goods divided by the number of bads. Default rate is the number of Bads/(Goods+Bads). Odds and default rate are interchangeable. Odds = 1/(Default Rate)+1.

5 Defining lending policy

This section describes how lenders identify the credit risk-related criteria that should be included in their lending policy. Each rule in the lending policy will be determined based on the following principles

- **Deterministic rules.** These are rules that are clear cut. A lender must have these rules in place to comply with legislation, regulatory guidance or their own risk appetite. These rules are almost always policy decline type rules.
- **Analytically based rules**. Statistical analysis is undertaken to establish the relationships between customer attributes and default risk (or other metrics). Lending policy is then formulated based on the results of the statistical analysis. For example, analysis of historic loans indicates that the bad rates associated with a gambling spend is unacceptably high. Therefore, a rule is defined to decline these cases.
- **Credit scoring-based rules.** These are similar to the previous point, defining rules based on the credit scores that someone receives, and how the credit score relates to the bad rate.
- **Expert derived rules.** Subject matter experts define the rules for lending policy based on their industry knowledge and experience. This is particularly useful in cases where the lender has no historical arrears/default data to analyse.

We explore each of these in more detail in the following sections.

5.1 Deterministic rules

Where specific factors are clearly stated as unacceptable in a lender's credit risk appetite statement or not aligned with business objectives, then it's a straightforward process to include matching statements in lending policy. For instance, if there is no appetite to lend to bankrupts and the business does not lend to people who are not resident in the UK, then no further analysis is required. Rules for bankruptcy and residency status just need to be stated in the lending policy as a reason to decline.

There are also rules that may be required for legal reasons. The rule: "Do not lend to people aged under 18" aligns with legislation making any loans to under 18s uncollectable.

5.2 Analytically based rules

When a risk appetite statement refers to more general portfolio measures, such as having an overall 12 month default rate of eg x%, then further consideration and analysis is required to ensure that the risk appetite is not breached. Similarly, if certain customers don't align with business objectives (for example, they are unlikely to be profitable) then the features that define these customers also need to be established and incorporated into lending policy so that loans are not advanced to them or are advanced consistent with an exceptions policy.

As an example, consider a Credit Union offering a loan product of between £2,500 and £5000, over terms of between 12 and 36 months, with an APR of 14.9% The credit union has calculated that:

- On average, customers are likely to be loss making if their predicted 12-month bad rate (default rate) is greater than 7.5% Therefore, if the predicted bad rate is greater than 7.5% these customers should be declined from a profitability perspective, although there may be exceptions to this in special cases
- The risk appetite is that the maximum 12-month bad rate across the portfolio should be no more than 5.0% This does not mean that each individual loan must have a default risk of less than 5.0% but that the average across all loans is less than 5.0%

To address these two requirements within lending policy, the lender needs to identify the relationships between customers' characteristic and the default rate.

As an example, let's take the characteristic: **Credit Limit Utilisation (CLU)**. This is a common piece of information that a credit reference agency will supply as part of a credit report and is usually very predictive of default risk. The CLU represents how much of a customer's credit limit has been used on their credit cards and other revolving credit facilities. A value of zero means that they have zero balances on any cards, a value of 100%+ that they are maxed out with no remaining spare credit.

The lender has examined a sample of several hundred loans that were made between 12 and 24 months ago and their default status 12 months later, as shown in Table 2.

Table 2. Relationship Between Credit Limit Utilisation and Bad Rate (Default Rate)

A		B	C	D	E
Credit limit Utilisation		**Volume of loans (%)**	**Cumulative volume of loans (%)**	**Bad Rate @ 12 months**	**Cumulative bad rate (%)**
From %	**to %**				
<0	**0**	11.0%	11.0%	3.2%	3.2%
1	**10**	15.0%	26.0%	3.4%	3.3%
11	**20**	21.0%	47.0%	3.9%	3.6%
21	**30**	8.4%	55.4%	3.7%	3.6%
31	**40**	6.3%	61.7%	**7.3%**	4.0%
41	**50**	9.0%	70.7%	7.9%	4.5%
51	**60**	6.0%	76.7%	8.7%	**4.8%**
61	**70**	5.0%	81.7%	15.4%	5.5%
71	**80**	4.9%	86.6%	19.4%	6.2%
81	**90**	3.0%	89.6%	20.0%	6.7%
91	**100**	4.0%	93.6%	22.6%	7.4%
101	**999**	6.4%	100.0%	25.0%	8.5%

In Table 2, Column D shows the bad rate for each range of credit limit utilisation. This is sometimes referred to as the marginal bad rate. For example. Customers with a CLU of 1-10% have a bad rate of 3.4% Those with a CLU of 101% or more have a bad rate of 25.0% There is a clear trend in rising bad rates with higher utilisation. Based on the information in Column D, the average default rate of customers exceeds 7.5% if their CLU exceeds 40% Therefore, customers with a CLU of greater than 40% are likely to be unprofitable.

If we now look at things from the **credit risk appetite perspective**, then column E shows the cumulative default rate for all customers up to a given CLU. To put it another way, the average bad rate across the whole portfolio for customers with CLU's up to and including that range of values. Based on the information in Column E, it's safe to lend to customers with a CLU of up to 60% before the 5% portfolio level risk appetite is likely to be breached.

So, the lender has some options:

1. If they want to lend as much as they can within risk appetite, then lending policy will include a rule to decline customers where the CLU is greater than 60%
2. If they want to maximise profitability, then the rule will be set at 40%

They could of course choose something between these two options to cater for other business objectives that are not profitability based and remain within risk appetite.

This type of analysis can be very useful in identifying relationships between borrower characteristics and credit risk. However, it does have its limitations:

- It can require a lot of analytical effort. This is because there are usually dozens, and sometimes thousands, of different data items to consider.
- Often, it makes sense to consider some variables in combination. For example, the previous analysis of Credit Limit Utilisation could be crosscut (cross tabulated) by someone's income, their current arrears status, their time in employment and so on. However, an organisation would need to have large amounts of data about defaults to do this effectively
- If there are many different tables like this, leading to many different rules, it can result in confusing and overlapping credit strategy that makes it difficult to come to a holistic understanding of customers and the specific reasons why they were declined

The main way that lenders overcome these problems is to:

1. Have relatively few rules (no more than about 20-30) that focus only on the most important features.
2. Use methods that allow the information contained across many different customer features to be condensed into much simpler summarised view of default risk. The most common way this is done is via credit scoring, which is discussed in the next section.

5.3 Credit scoring based rules

These days, organisations tend to know a lot about their customers. When open banking and credit reference data are included, then there can be thousands of individual data items available for consideration for each customer.

Practically, this makes it almost impossible to be able to fully analyse all that data and to condense it into an optimal set of decision rules that are incorporated into lending policy. These days, even the largest organisations struggle to fully analyse all their data in a feature by feature way, as discussed earlier in Section 5.2 in relation to Credit Limit Utilisation. Likewise, it is impossible for a human loan assessor to be able to fully evaluate all that data as part of a holistic assessment of someone's creditworthiness without there being some clear guidelines being established as to which say, 20-30, data items, are the most important ones that they should focus on. To help overcome these problems, most lenders utilise credit scoring as a key component of their lending policy.

A credit score provides a holistic view of a customer's credit risk as a single number. The score provides a measure of the customers expected repayment behaviour, ie how likely they are to repay their loan vs the likelihood of serious arrears or default. The general convention used across the industry is that a high credit score equates to very low risk of default, while low scores are associated with very high risks of default. A customer with a very high credit score may be predicted to have less than a 1% chance of defaulting, while someone with a very low credit score could be predicted to have a 50% or higher chance of default[22].

Once the relationship between the score and default rates is known, it then becomes a relatively simple task of selecting the score that aligns with your business objectives and risk appetite.

One way to think about a credit score is as a "super feature" of the customer. It's just another piece of information about customers, but an immensely useful one. The way to use it is to formulate decision rules as part of your lending policy. This is in a similar manner to the way that Credit Limit Utilisation was considered in section 4.2.

Let's continue with our previous example, where profitability aligns with a marginal 7.5% default rate, and risk appetite is set at an overall portfolio default rate of 5.0%, Table 3 shows how the default rate relates to the score.

Table 3. Score Distribution Showing the Relationship between Credit Score and Bad Rate (Default Rate)

A		B	C	D	E
Credit Score		**Volume of loans (%)**	**Descending cumulative volume of loans (%)**	**(Marginal) Bad rate @ 12 months**	**Descending cumulative bad rate (%)**
From %	**to %**				
<0	**405**	10.0%	100.0%	20.0%	8.5%
406	**490**	10.0%	90.0%	15.4%	7.3%
491	**558**	10.0%	80.0%	13.1%	6.3%
559	**592**	10.0%	70.0%	10.6%	5.3%
593	**667**	10.0%	60.0%	9.2%	**4.4%**

[22] When we say a customer with a given credit score has a predicted default rate of say, 1% what we mean is that, on average, out of every 100 customers with this score one customer will default. Likewise for a 50% default rate, then on average 50 out of every 100 customers with this score will default.

668	**722**	10.0%	50.0%	**7.4%**	3.4%
723	**768**	10.0%	40.0%	4.9%	2.4%
769	**808**	10.0%	30.0%	2.1%	1.6%
809	**883**	10.0%	20.0%	1.6%	1.4%
884	**999+**	10.0%	10.0%	1.1%	1.1%

Table 3 shows a similar example to Table 1 but **using a credit score instead of utilisation**. The table has been produced by examining the repayment performance of several hundred loan applications that were booked 12-24 months ago. Column A shows the range of scores that where calculated when the loan was applied for. In this example, the ranges have been chosen to contain 10% of the new loan population within each range. In practice, there may be more or fewer ranges depending on the volume and nature of the data.

Column D shows the 12 month bad rate for each range; based on the arrears status 12 months after the loan was granted. For example, for loans that scored between 769 and 808 had an average bad rate of 2.1% There is a clear trend of reducing bad rates with increasing score.

Based on the information in Table 3, the average default rate of customers exceeds 7.5% (Column D) if their credit score is below 668. The portfolio default rate exceeds 5.0% (Column E) if the score is below 593. This means that:

- The lender can remain within risk appetite if they only grant loans to customers with a credit score of 593 or more
- The lender can expect to maximise profitability by only granting loans to customers with a credit score of 668 or more
- If the lender decides to lend to customers with scores between 593 and 668, then these will be unprofitable, but overall lending will remain within risk appetite. For community and not for profit lenders, this represents a group of customers who can't be lent to profitability, but as they are within risk appetite may be suitable customers to lend to on a social benefit basis

In practice, lenders need to monitor score distributions and adapt their credit scoring-based decision rules (cut-off strategies) to account for changes in both the score distribution and changes to the relationship between score and default rate. These can shift for a variety of reasons such as changes to the economy or marketing activity targeting new types of customers. Further information about good practice for monitoring the credit scores provided by credit reference agencies is contained in Appendix B.

For organisations that build and maintain their own credit scoring models, additional and more detailed information is provided in the Model Monitoring component of the Guide (RM9).

5.3.1 Different providers, different credit scores

The precise credit score someone receives depends on how the underlying credit scoring model has been constructed. In particular, the type of algorithm that has been applied (there are dozens of variants), the data sample used in the analysis and the logic that defines how the different weights are combined. Credit scoring providers also scale their scores to different ranges. Consequently, if a lender obtains more than one credit score for a customer, each score will equate to a somewhat different estimate of the customers likelihood of default. Usually, the predictions from different scores are similar and closely correlated, but this is not always the case.

In terms of where a lender can obtain a credit score from, there are two main sources:

- **Generic Scores.** These are generated using credit scoring models developed by the credit reference agencies, using the vast databases that they maintain about most of the adult population in the UK. The agencies do not provide lenders with the underlying credit scoring model, just the score their models generate as part of a credit search, ie they will provide a credit score as part of a standard credit report. Examples of these scores are Experian's Delphi Score, Equifax's Risk Navigator and TransUnion's VantageScore
- **Bespoke Scores.** These are generated using a credit scoring model developed specifically for the lender using only data about the lender's customers. The lender then owns the credit scoring model and generates the scores themselves by implementing the model within their loan application processing system.

As a rule, if a lender has access to ~1,500-2,000+ default cases over the last ~2-3 years, then a bespoke scoring solution will deliver more accurate credit scores than those available from a credit reference agency. This is because the resulting credit scoring model will be optimised for that lender's customers, compared to CRA's credit scores that have been developed on a broader and more general population[23].

This is particularly true for lenders operating outside of the mainstream lending environment. This is because their types of customers will be only a very small sub-set of the wider population used by the CRAs to construct their models, which focus mainly on mainstream mass market high street lenders, using data from people who have well established credit records. Consequently, those with thin credit files such as young people and those who only recent moved to the UK, will not score very highly and may therefore struggle to obtain credit due.

[23] This is why all high street lenders maintain their own suites of credit scoring models tailored to the range of products they offer (loans, cards, mortgages, auto-finance etc).

A further benefit of bespoke credit scoring models is that they can incorporate additional information that the lender has, that is not considered by the credit scoring model supplied by the CRA. For example, most CRA supplied credit scores don't reference open banking data. However, a credit scoring model developed by a lender who uses open banking could incorporate this data. Likewise, addition information provided on an application form, such as residential status, type of employment, number of dependents and income can also add value. For credit unions considering developing their own credit scoring models, customers' savings behaviour with the credit union should be a key additional factor considered within the model.

The only major downside of the bespoke approach is that it requires more resources from the lender to develop and implement. For small but growing lenders, good practice is to start by using a generic score supplied by a CRA, but then move to consider bespoke scoring when the customer base is large enough to justify it on a cost / benefit basis. There may be a cost/benefit gain for a smaller lender to move to more quickly to bespoke credit scoring, in cases where there is a clear path to reducing risk quicker and more effectively in their target customer segments, or using a generic score increases the number of cases that require expert/second review, increasing the resource required.

In addition to the upfront development and implementation costs, lenders who use credit scoring also need to consider on-going monitoring requirements. This is because there can be shifts in the underlying relationships between score and default rate over time, requiring changes to the range of scores used in decision rules, new credit scoring models to be developed or a combination of these.

5.3.2 Why not define lending policy just using credit scores?

If credit scoring is so good, then a sensible question to ask is: why not just have a single rule in your lending policy based on customers' credit scores?

Credit scoring can be very powerful and is a good way to evaluate the credit risk of customers accurately, objectively and efficiently. However, like most things, credit scoring is not perfect and there can be small pockets of customers that are not treated optimally even by the best credit scoring models. There still needs to be other credit risk-related rules included within lending policy even when the very best credit scoring models are deployed. The reasons for this are:

- **Enforcing risk appetite**. A credit score provides a general measure of risk. It can be expected that high risk cases will generally receive low scores and be declined, but this is not guaranteed. Therefore, rules are also employed to provide a "belt and braces" approach for these cases. For example, always decline bankrupts no matter how high their credit score.
- **Lack of data / missing information / Thin credit file.** Sometimes, the information required to accurately calculate a credit score will be missing. A credit search may return no information about someone who has recently moved address or become a UK resident. In this case, it is

prudent to refer the case to an experienced person and make the assessment based on what information is available, or to contact the customer to find out more about them

- **Exception cases.** There may be certain cases where credit risk is not the over-riding consideration. For example, if the lender is committed to providing a certain amount of lending to vulnerable customers or financially excluded groups, it may ignore or override credit scoring (and other decision rules) to meet this objective
- **Marginal cases**. If applicants' credit scores are only just below the acceptable minimum, then these cases may be referred to an experienced person to review. The aim of the review is to establish if there are any additional circumstances that support lending in these cases. This should consider additional information that may not be incorporated into the credit score, but which may provide additional evidence that the customer is likely to repay the loan. The same logic can also be applied to cases scoring just above the minimum, with a view of ensuring there are no additional negative factors that should lead to the loan being declined, despite their credit score being above the minimum

However, one should be careful not to diminish the power of credit scoring by introducing too many rules that lead to the score being overridden or disregarded. If there is evidence that a rule is redundant due to the credit score, ie use of the score always leads to the right outcome for these cases, then that rule should be removed. For example, if all applications with recent high value County Court Judgements (CCJ's) receive very low credit scores, then there is no reason to also have a rule to specifically decline these cases – the credit score will deal with them.

Given the above considerations, in practice, a common way that lenders employ credit scoring is as follows.

- **Define a minimum acceptable cut-off score.** All cases below the cut-off are declined. There may be some cases that are over-ridden and accepted based on the above criteria, but these are unusual or exceptional cases that require some degree of senior management approval
- **Define a "fast track" approval cut-off score.** Cases scoring above the cut-off are deemed to be acceptable from a credit risk perspective. These cases are normally only declined if they fail other lending criteria (such as KYC or affordability checks)
- **For anyone in the middle (between the minimum and approval cut-offs)** these are subject to a fuller assessment by a suitably trained loan assessor who makes the final decision

Over time, as familiarity with credit scoring improves, and new and more predictive credit scoring models become available[24], then the cut-off scores used to define the above groups are refined with a view of increasing the proportion of automated declines and/or fast-tracked applications.

5.4 Expert based rules

If a lender has access to large amounts of historical data as discussed in the previous sections, using this to help define and maintain lending policy based on statistical analysis and/or credit scoring is good practice. However, not all lenders have a large customer database to draw upon, and even for those that do, there are always circumstances where data is insufficient or unavailable. In these circumstances, it is appropriate to use expert judgement to define lending policy, which can then be reviewed and refined as and when more data becomes available.

The main reason why loan performance (outcome) data is unavailable is because customers with those characteristics have historically been declined. Most lenders will not advance funds to people aged under 18[25]. Therefore, they have no experience of lending to under 18s to draw upon in terms of their repayment and default profiles. However, most credit professionals know that lending to under 18s is a risk to be avoided. Therefore, it makes sense to include this as a decline rule within lending policy. A similar situation often exists for where customers have serious arrears or recent court action against them (CCJs).

The other reason for a lack of data is often due to a new product launch meaning that there is no history to examine, or new data sources coming online. In both these cases it is standard practice for the head of credit risk, or another suitably experienced credit professional, to create the lending policy based on their past industry experience initially, and then refine the policy as performance information becomes available. If the lender is already providing credit, then the lending policy for that product is often a good starting point that can be copied and tweaked to fit the requirements of the new product.

When to comes to deciding whether to use a statistical or judgemental based approach – it's not a case of either or. A lender should use whatever data they have available to inform the formulation of their lending policy, but this should be combined with the view of experts who often have broader industry experience that they can contribute.

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[24] For example, when moving from using a generic CRA supplied score to one developed in house.
[25] It is not illegal to lend to people under 18, but for most forms of credit a customer has no obligation to repay a loan if they are not an adult. Therefore, there are no recovery options if they don't make their repayments.

6 Data for credit risk-based decision making

In this section we describe the types of data that are available to be used to develop the credit risk elements of lending policy. This applies to both automated rule-based decision-making and manual loan assessments.

6.1 Applicant supplied data / application form

This covers the information that an applicant provides as part of their application for a loan. Most application forms will contain four types of information that may be useful in assessing credit risk.

- **Geo-demographics.** This covers information about the customer. Typically, this includes information about their location, age, income, employment, number of dependents, residential status and so on.
- **Eligibility Checks.** Many lenders will ask customers to self-certify that they meet basic lending criteria. Typically, that they are **not:** bankrupt, have recent high value CCJs or are currently in serious arrears with other debts
- **Expenditure details**. This covers key expenditure categories such as rent/mortgage, utility bills, council tax, general household expenditure, transport costs and existing credit commitments. This type of information is primarily used to assess affordability but can also be used to assess credit risk
- **Loan details.** The amount and term of the loan that the customer is asking for, as well as the purpose of the loan

Most lenders will gather all available information before undertaking a credit risk assessment a single step in the application process. However, some lenders have a preliminary set of lending rules that they apply as soon the application form is complete. Any customers who don't satisfy residence rules (eg not resident in the UK), who are too young/old or who fail other eligibility checks are declined at this point. The benefit of doing this is that it reduces costs downstream. There is no point paying for a credit search from a CRA if you already know that you are going to decline them. However, the counter argument is that if all customer data is obtained for every application, this allows for detailed analysis of those customers later and this analysis can be useful for informing changes to lending policy.

6.2 Internal data (previous customer history)

If a customer already has a relationship with a lender, this information is often useful in setting lending policy. The most relevant information relates to previous loans that customers have had with the lender and how they repaid these. As a rule, if a recent loan was not fully repaid, then that is a strong reason to decline a new loan application and is a common policy decline rule included in lending policy.

Savings history and current account behaviour can also prove useful, particularly in terms of assessing the character and capability of a customer. Specifically, a long term pattern of regular saving is indicative of someone that is financially stable and has additional resource to draw upon.

6.3 Credit Reference Agency (CRA) data

The most important source of external data used to define lending policy is a credit report provided by a Credit Reference Agency (CRA).

All three of the UK's main CRAs (Equifax, Experian and TransUnion) supply the following types of information as part of a credit report.

- **Public information.** This is information that is accessible to the general public[26]. This covers details of Insolvencies (Bankruptcies, IVAs and Debt Relief Orders) and County Court Judgements (CCJs) over the last 6 years. A credit report will also include confirmation of the person being registered on the electoral roll at their current address
- **(Private) account performance and search data.** This information is not publicly available and is shared by financial services companies, utility suppliers and other organisations under the principles of reciprocity[27]. It provides details of balances and arrears status for each loan (and other credit commitments) that a customer has, or had, with other lenders over the last 6 years. Details of previous credit searches that other lenders have undertaken is also provided[28]
- **Derived information**. This is new data that the CRAs have created from a variety of public and private sources. As well as credit scores and measures of credit limit utilisation, these provide

[26] For example, via records maintained by local courts or the records maintained by the Government Insolvency Service (GIS). Lenders obtain this information from CRAs rather than gathering it themselves because the CRAs have done the hard work of collating all the information from all the different courts and other data providers.
[27] The principles of reciprocity is a UK wide industry data sharing agreements between lenders and the CRAs, overseen by the Standing Committee on Reciprocity (SCOR).
[28] This is useful because applying for lots of new credit in a short period of time is often indicative of increased credit risk.

customer profiling at individual, household and postcode levels. For example, average number of CCJs by postcode

Further details about the information CRAs hold and the products and services they supply is provided in the Credit Agency Reporting (RM8) component of the Good Practice Lending Guide.

6.4 Open banking data

Open Banking is a mechanism whereby an individual gives an organisation permission to view details of their current accounts electronically. This covers money paid into accounts such as salary, pensions, and benefits, as well as payments made from accounts such as utility bills, grocery shopping and cash withdrawals. This is the same information that a customer sees on their bank statements each month.

Open banking data is predominately used to verify and/or calculate a customer's income and expenditure as part of assessing the affordability of a loan. However, some elements of open banking are also useful for assessing credit risk and there is no barrier to using affordability information in credit risk assessments. For example, certain types of expenditure such as gambling or crypto is often associated with higher credit risk. Another example is where open banking data is used to calculate risk relevant ratios such as expenditure as % income. Open Banking can also be a useful source of information for those with no or thin CRA files eg recent immigrants may show a stable pattern of paying rent over time.

More details of open banking are provided in the Lending Policy (Affordability) component of the Guide.

6.5 Data that should not be used to assess credit risk

In general, if a customer has given consent for certain types of data to be used to make lending decisions about them it is acceptable to use that data within lending policy, provided it complies with the FCA and ICO (GDPR) principles discussed earlier. However, there are certain types of personal data that should never contribute to a lending policy or be considered by a human loan assessor when making a lending decision. These are:

- **Special category and protected data**. This is data, defined within the GDPR and equal opportunities Act 2010, relating to racial or ethnic origin, political opinions, religious beliefs, marital status, trade union membership, genetic data, biometric data, health data and data concerning a person's sex life and sexual orientation
- **Data about other people.** Data about third parties, such as someone's parent or partner, should never be used to assess credit risk. The exception to this is if there is a proven financial link between the applicant and the third party, which classifies them as an "Associated Individual". A proven financial link means that two people took out a joint credit agreement together such as a

joint mortgage or a joint loan. Details about associated individuals is usually provided as part of a credit report provided by a credit reference agency[29]

In considering the above, it is important that proxies data items are not used. For example, using the number of syllables in peoples' surnames is illegal because it can be a proxy for ethnic origin. Likewise, treating people differently because of how they type when completing an application form (speed and patterns in their use of a keyboard and mouse) could be viewed as discriminatory against people with a physical disability.

[29] The lender does not need to obtain permission from the associated individual to have this information about them supplied as part of a credit report.

7 Data for credit risk-based decision making

7.1 Setting the scene

A lending policy is designed to support the delivery of an organisation's business objectives in line with their risk appetite. For this example, we shall consider the lending policy for the fictional All Welcome Credit Union (AWCU).

7.1.1 The business and its objectives

As a credit union, AWCU is a not for profit organisation. This means its main business objective is to provide its members with good quality saving and loan products that serves their needs and delivers good outcomes for them. The credit union currently has 20,000 members and a £25m loan book.

Although AWCU is not profit orientated, it still needs to generate profits to enable it to continue as an on-going concern and to support its capital base (reserves) in line with regulatory (PRA) requirements. Therefore, it's products are designed to be as cheap and accessible as possible while still making a positive contribution to profits.

To this end, the credit union offers unsecured loans to members of between £1,000 and £15,000. Repayment terms are between 6 months and 5 years with APRs ranging from 6.9% to 29.9% The APR charged to members is determined by the overheads in arranging and running the loan, plus the term and value of the loan. This is to ensures that each loan generates a similar margin overall and proportionally, all customers are charged a similar amount.

Risk appetite

AWCU defines its appetite for credit risk as low-medium, as detailed in the extract from its risk appetite statement in Figure 1.

Figure 1. Extract from AWCU's Credit Risk Appetite Statement.

Our members typically have good credit histories, although some have a history of moderate financial difficulty. Consequently, we have a low-medium risk appetite for credit risk.

This means that we will advance credit to customers with some history of arrears within the last 24 months or who have a history of more serious arrears further in the past, ie CCJs (>£1,000) or discharged bankruptcies that are more than 3 years old. However, we do not believe that it would be responsible, or meet our wider business objectives, to offer loans to higher risk customers with a recent history of CCJs or delinquency (3+ months in contractual arrears) within the last 6 months, or who are currently 2+ months arrears with any existing credit agreements with us or any other lenders.

Based on our target market, we will accept a portfolio default rate (3+ months in arrears) of up to 5.0%, and we will design our underwriting procedures in line with this target.

Taking its business objectives and risk appetite into account, AWCU has undertaken analysis of its historic customer base and determined that it can lend profitably, and within risk appetite, if the 12 month predicted default rate on a new loan application is below 10% ie it is willing to lend to customers where it believes that the chance of the customer defaulting within the first 12 months is <10%. It therefore declines customers where the probability of them defaulting is greater than or equal to 10%

7.1.2 The application process

AWCU has purchased an application processing system purchased from an IT vendor that it maintains in-house. This allows lending policy to be implemented automatically as a set of rules, which incorporates referral rules to pass cases for manual review when required. The system supports the capture of notes/files/screenshots from customer interactions and underwriting decisions. The policy rules are maintained as a set of parameters that allow AWCU to easily update the rules when they need to.

Most new loan applications are made on-line via AWCUs website. However, customers can arrange to come into head office and make a loan with the support of AWCU staff.

Once an application is submitted, and after customer verification and initial fraud checks have been completed, a credit report is requested from a CRA which includes the CRAs credit score. Permission to use open banking data is a mandatory requirement for a loan, which is supported by bank statements if necessary.

Applications are also matched to AWCUs customer management system, to provide information about the customers other savings and loans products that customers have with AWCU.

Once the full set of customer data is available, the system applies the policy rules as detailed in the next section. This is augmented by additional information and decisions supplied by the underwriting team where they are required.

Following a final decision to lend, the customer signs a credit agreement, funds are disbursed, and the customer's account is created on the account management system.

Where a loan is declined, the customer is informed and provided with an explanation of the decision. The customer can contest the decision if they wish, which is then passed to a senior underwriter to independently review.

7.2 The policy

7.2.1 Policy rules

The rule based elements of AWCU's lending policy, as implemented in their application processing system, is detailed in Table 4.

Table 4 AWCU Policy Rule Implementation

Ref	Rule	Rule type	Data source to drive the rule	Action / Outcome	Rationale
1	Age < 18	Policy Decline	Application form.	Decline	Expert rule. It is not illegal to lend to under 18s, but no legal recourse to recover debts in arrears cases.
2	Loan requested >£15,000	Policy Decline	Application form.	Decline	Expert rule. Outside of product range / risk appetite
3	Loan requested / Income ratio >50%	Policy Decline	Application form.	Decline	A customer may technically be able to meet AWCU's affordability criteria, but analysis shows that borrowing a very large proportion of income correlates with default rates >10%
4	Default on previous AWCU loan within the last 3 years, or currently in arrears with existing AWCU loan.	Policy Decline	Account Management System	Decline	Expert rule. If a customer has been unable to demonstrate consistent up to date repayment behaviour on previous AWCU loans, then it is not responsible lending to give them another.
5	Customer is currently bankrupt/IVA or DRO	Policy Decline	Credit Report	Decline	Expert rule to enforce risk appetite. Also, standard industry practice due to high risk and legal limitations
6	Customer has been bankrupt within the last 3 years.	Policy Decline	Credit Report	Decline	Expert rule to enforce risk appetite.

Ref	Rule	Rule type	Data source to drive the rule	Action / Outcome	Rationale
7	Customer has had CCJs of more than £1,000 in the last 3 years	Policy Decline	Credit Report	Decline	Expert rule to enforce risk appetite.
8	Value of outstanding CCJs > £500	Policy Decline	Credit Report	Decline	Analysis of previous lending suggests that default rates for customers with this characteristic will average >10% which will not be profitable
9	Time since most recent CCJ < 6m	Policy Decline	Credit Report	Decline	Expert rule to enforce Risk Appetite. Analysis of previous loans that were granted suggests that default rates for customers with this characteristic will average >10% which will not be profitable.
10	Currently 2+ months arrears with existing credit agreements with other lenders	Policy Decline	Credit Report	Decline	Expert rule to enforce Risk Appetite
11	Worst arrears status on any credit agreement within the last 12 months 3+ months	Policy Decline	Credit Report	Decline	Analysis of previous loans indicates that the default rate >10% for customers with this characteristic which would not be profitable.
12	2+ months in arrears with any credit agreement within the last 3 months.	Policy Refer	Credit Report	Refer for manual review	Analysis has shown that the default rates on loans with this characteristic are marginal, and we would also like to understand the reasons for the arrears. Therefore, manual underwriting employed to investigate and make the final decision.
13	CRA supplied credit Score <550	Policy Decline	Credit Report	Decline	Analysis of previous loans indicates that the default rate >11% for customers with these credit scores.

Ref	Rule	Rule type	Data source to drive the rule	Action / Outcome	Rationale
14	CRA supplied credit Score 551 – 625	Policy Refer	Credit Report	Refer for manual review	Analysis has shown that the default rates on loans with these scores are marginal at between 9% and 11%. Therefore, manual underwriting employed to make the final decision.
15	CIFAS Indicator	Policy Refer	Credit Report	Refer for manual review by senior manager	The CIFAS indicator suggest that this customer could be fraudulent, but the case requires fuller review to ensure that any fraudulent behaviour is confirmed before being declined.
16	Credit Limit Utilisation on revolving credit products >100%	Policy Decline	Credit Report	Decline	Analysis of previous loans indicates that the default rate >10% for customers with this characteristic
17	Credit Limit Utilisation on revolving credit products 81-100%	Policy Refer	Credit Report	Refer for manual review	Expert rule. Although analysis of previous loan customers suggests that default rates are <10% for customers with this characteristic, a manual review is undertaken to ensure that it is a responsible thing to do, even if the borrower meets AWCU's affordability criteria.
18	No credit report available (No Trace)	Policy Refer	Credit Report	Refer for manual review	There is insufficient information to make a decision. Therefore, further investigation required eg check correct name and address and DOB supplied.
19	Gambling spend >10% gross income	Refer	Open Banking Data	Refer for manual review	Expert rule. There may be reasons for the high gambling expenditure, but this should be investigated further before a decision is made. Previous analysis has shown a marked increase in arrears for customers with gambling more than this.

Ref	Rule	Rule type	Data source to drive the rule	Action / Outcome	Rationale
20	Cash withdrawals >50% gross income	Refer	Open Banking Data	Refer for manual review	As above, investigation required to understand why the customer is withdrawing this amount of cash (eg check it is not for gambling).
21	Accept	Auto-accept	N/A	Accept	Default outcome if no previous rules met.

7.3 Underwriting guidelines

When lending policy (As per Table 4) determines that a case should be manually reviewed by an under-writer, then AWCU directs the underwriter to review the case in line with the following guidelines.

- **Where "no credit report available (No Trace)" is the reason for referral**. Check that the details provided by the customer, provided to the CRA to undertake the search, are correct. Verify the spelling of the customer's name, their date of birth and that address details (flat numbers/letters in particular) are correct. If an error is found, manually request another credit report using the corrected information and apply the policy rules (from Table 4) to arrive at a decision. If no errors are found, then seek further verification from the customer of their home address before making a decision.
- **When the referral is for high gambling spend.** Contact the customer to gain an understanding of why the spend is so high. Where gambling spend exceeds 25% of income then these cases should generally be declined unless there is a very good explanation eg customer has submitted single bet on behalf of a club or syndicate.
- **Where high credit limit utilisation is the reason for referral.** Contact the customer to gain an understanding of why they are so indebted and the expected trajectory going forward. For example, if the customer can evidence recent credit card payment that will result in their utilisation dropping, this may lead to accepting the loan. Alternatively, if they have bought a single high value item such as a car, then this is probably less risky than where their utilisation has been steadily rising for a long period of time. If they have substantial savings (with the credit union or elsewhere) this may allow the loan to be accepted despite a high utilisation.
- **For cases where there are large cash withdrawals,** seek an explanation from the customer, and ask for supporting evidence if required (eg receipts of the spending).
- **Where the credit score is marginal**, review the customer's full credit report, considering the recency and value of any arrears or court judgements. Also consider any internal AWCU data, such as evidence of regular savings or previous good loan repayment behaviour.
- **Where a CIFAS indicator exists on the credit report**. Determine the reason for the CIFAS indicator and contact the customer to confirm their status and identity if required.

Where an underwriter requires further information or confirmation from the customer, they should always contact the customer to seek explanations or provide further details.

If the value of the requested loan is for between £7,500 and £12,500 then the case should be reviewed by one of AWCU's senior underwriters.

If the value of the requested loan is for more than £12,500, then the decision should be approved by the Head of Credit.

7.4 Appeals process

Where a customer has appealed a case, AWCU refers the case to a senior underwriter (Which could be the head of credit risk or another senior manager) to undertake an independent review of the case. The elements of this review should include:

- Confirming if the borrower was declined correctly based on specific lending policy criteria (policy rules) such as being bankrupt or having high a high credit limit utilisation
- Where the decline was based on credit scoring, to review the customer's credit report, along with the other information available, to come to a final decision based on the underwriting policy
- Where a human underwriter made the decline decision, independently assess the case again using the underwriting policy

The result of the appeal shall be communicated to the customer and is deemed final. No subsequent appeals are allowed.

7.5 Example credit risk assessments

In this section we consider four loan applications and assess these against AWCU's lending policy as described in the previous sections.

7.5.1 Example 1: A perfect credit record

In this example, the key pieces of customer information are:

- The customer has an income of £38,000
- They have applied for a £3,000 loan
- The customer's credit report has been provided and indicates no CCJ's arrears or bankruptcy
- Their credit score is 766
- The customer is currently up to date with their 3 other loan agreements
- The customer has a credit limit utilisation of 12%

In this example, the customer displays exemplary behaviours. There is no information that causes any of the policy decline rules or policy refer rules to be hit. Therefore, the loan is deemed acceptable from a credit risk perspective. Consequently, if their affordability is deemed to be acceptable too, they will be granted the loan.

7.5.2 Example 2: Multiple credit risks

In this example, the key pieces of customer information are:

- The customer has an income of £28,000
- They have applied for a £15,000 loan
- The customer's credit report indicates a CCJ for £1750 18 months ago
- The customer's credit score is 553
- The customer is currently up to date with 2 other loan agreements
- The customer previously fully repaid a loan to AWCU 3 years ago
- The customer has a credit limit utilisation of 84%

In this example, the customer displays both positive and negative behaviours. On the plus side, they are up to date with their current credit agreements and have previously repaid an AWCU loan without any problems.

However, because of the high loan to income ratio and the CCJ recorded against them, they will be declined as these characteristics 1) do not align with risk appetite 2) Indicate that the chance of them defaulting is greater than the minimum acceptable threshold of 10%

The customer also hits two policy referral rules due to their credit limit utilisation and their credit score. However, because they have already hit the two policy decline rules, these take preference, and the case is not referred for manual review.

7.5.3 Example 3: A poor credit score

In this example, the key pieces of customer information are:

- The customer has an income of £33,000
- They have applied for a £5,000 loan
- The customer's credit report is good but not perfect. They were 1 month in arrears 11, 7 and 5 months ago.
- The customer's credit score is 478
- The customer has 3 other current credit agreements.
- The customer is not confirmed as being on the Electoral Roll at their address
- The customer has applied for 9 other credit products in the last 3 months (9 credit searches reported on their credit report).

- The customer has a credit limit utilisation of 78%

In this example, the only reason that the customer has been declined is due to their credit score. There is no one item of information that has caused them to have a low credit score, but there are several pieces of information that collectively are the reason why they are a risk. This includes some previously arrears, not being confirmed on the electoral roll, having sought a large amount of credit in a short period of time and having a relatively high credit limit utilisation.

7.5.4 Example 4: A case for manual review

In this example, the key pieces of customer information are:

- The customer has an income of £47,000
- They have applied for a £4,500 loan
- The customer's credit report is pretty good. They missed a payment on their mortgage 8 months ago but have not had any other arrears before or since then.
- The customer's credit score is 670
- The customer has 3 other current credit agreements. All of these are up to date currently.
- The customer has a credit limit utilisation of 96%

This case is referred for manual review due to the high credit limit utilisation reported on their credit report. Apart from this, there are no other warning signs that the customer might be a poor credit risk.

The underwriter decides to discuss the issue with the customer. The customer says that they have spent a lot on their credit card in recent months, to support the building of an extension on a rental property that they own, and that the loan they are applying for will pay for the final works. Once the extension is completed next month, the customer expects spending on their card to decline and their rental income to increase due to the increased space provided by the rental property.

To evidence that this is the case, the underwriter asks to see evidence of ownership of the rental property and evidence that the extension is nearing completion. The customer provides a copy of land registry documentation proving ownership, plus a picture of the nearly completed extension. On this basis, the underwriter decides to grant the loan.

8 Appendices

8.1 Appendix A. The history and rationale for credit scoring

The ability to represent many different customer attributes as a single score, which predicts their risk of default more accurately than a trained underwriter can, may be difficult to believe, but credit scoring has a proven track record. Credit scoring was first introduced in the 1950s in the USA and has been the primary decision making took used in consumer credit markets in the UK since the mid-1990s. As a method of predicting default risk, it has been demonstrated many times that, *on average*, a well-designed credit scoring model outperforms experienced human assessors across all types of consumer credit. To put it another way, automated credit scoring can lead to wrong decisions sometimes when an experienced loan assessor would have made a better one but overall, the use of credit scoring leads to better decision making than a purely manually based approach.

A good question to ask is: how is it to possible represent a customer's behaviour using just a single score? Without going too far into the technical details, credit scores are created using complex mathematical algorithms[30]. These are the same types of algorithms that are used in many "artificial intelligence"[31] applications, tailored to the specific requirements of credit risk prediction. These algorithms analyse large samples of historical data to establish how all the different features of loan applications relate to how those loans were repaid. Based on its analysis of the data, the algorithm allocates each item of information a weight. The weights are then combined to create the credit score. The set of weights, and logic that defines how to combine them, is called a "credit scoring model."

When a credit score is required, the customer's information is fed into the credit scoring model. The model combines all the relevant weights to generate the customer's score. A key feature of this process is consistency. If the same customer information is provided to the same credit scoring model again, then the same score will result each time, which supports explicability in decision making[32]. This cannot be said to be universally true of human underwriting, where different loan assessors[33], when provided with identical information, can come to very different views of a customer's creditworthiness.

[30] An algorithm is a set of rules that one follows to carry out a given task.
[31] The terms "Artificial Intelligence" and "Machine Learning" are often used interchangeable in common parlance -although technically they are not the same thing.
[32] If the customer's circumstances change, ie different data is provided to the credit scoring model, then a different score will be generated.
[33] Or even the same underwriter a short while later.

8.1.1 AI and Machine Learning and their use in credit scoring.

Over the last few years, the terms "AI" and "Machine Learning"[34] have become increasing used to describe complex computer systems that "learn from data." It seems that almost every supplier of IT and consultancy services now has some sort of "AI tool" or "Machine learning-based system" that can be used to support customer assessment and the automation of loan decisioning.

It is important not to forget that traditional credit scoring, that has been used for decades, is a form of machine learning[35]. However, in the last few years some more advanced methods for analysing data and creating credit scoring models have become available, and these methods are also used for a wide variety of AI applications. For example, "Deep Neural Networks" that underpin chatbots such as Bard and ChatGPT can also be used to create credit scoring models. The evidence is that these advanced "AI" methods typically outperform older credit scoring models by ~10-15% ie are 10-15% more accurate when it comes to identify which customers will default. From a usage perspective AI/Machine learning based credit scoring is no different from a traditional credit scoring model. Data about the customer is supplied into the model and a credit score is produced, that is used exactly as described previously.

The main drawback with these newer approaches to credit scoring is that they are generally far more complex and far less explicable. This means that it is more difficult (although not impossible) to understand why a certain customer received the score that they did. This potentially has ramifications under GDPR, in terms of transparency and explicability.

8.2 Appendix B. Monitoring credit scores

Many lenders use the credit scores provided by a credit reference agency as part of a credit report as an important part of their underwriting policy. These scores are designed to rank customers from "best" to "worst" in terms of their likelihood of defaulting on a credit agreement. High scoring cases have a very low chance of defaulting, lower scoring cases a much higher chance of defaulting.

To use the scores appropriately, each lender needs to calibrate the credit score to the default rates observed in their portfolio. This is so that suitable cut-offs can be defined based on the default risk (bad debt rates) estimated by the credit score. Given the differences in the customer population, product terms and customer management approaches employed by each lender, the credit score calibration will be different for every lender. A credit score of say, 600 may equate to a default rate of 10% for one lender and 15% for another.

[34] Technically AI and Machine learning are not the same thing. Practically, everything that is described as "AI" has machine learning at its heart. Therefore, it's reasonable to use these two terms interchangeably in general parlance.
[35] Typically based on multi-variate regression methods such as linear or logistic regression.

Credit reference agencies do provide a "Vanilla" calibration that organisations can use if they don't have sufficient information to perform their own calibration. However, these are often inaccurate having been based on a typical high street lending population rather than the community finance sector. Consequently, lenders should look to perform their own calibration at the earliest opportunity.

To perform a calibration, a lender ranks a historic sample of their customers by their credit score and calculates the default rates associated each score grade; that is, each range of scores. An example of a score distribution to establish the calibration is shown in Table 5 (which is adapted from Table 3).

Table 5. A Score Distribution Table

Credit Score Range (Grade)		Volume of loans (%)	"Good" (non-defaulted) loans @ 12m	"Bad" (defaulted) loans @12m	(Marginal) Bad rate @ 12 months
From %	**to %**				
<0	**405**	10.0%	424	106	20.0%
406	**490**	9.9%	444	81	15.4%
491	**558**	10.0%	461	69	13.1%
559	**592**	10.1%	479	57	10.6%
593	**667**	10.1%	488	49	9.2%
668	**722**	10.0%	490	39	7.4%
723	**768**	10.0%	506	26	4.9%
769	**808**	10.1%	517	19	3.6%
809	**883**	10.0%	520	11	2.1%
884	**999+**	9.9%	522	6	1.1%
Total		100.0%	4,851	464	8.7%

To produce Table 5 for this example, the lender took the credit scores for all accepted loan applications in Q2 202x and then classified them as "good" or "bad" performing loans based on their repayment performance over the next 12 months. If they were in default (3+ months in arrears) after 12 month's they were classified as "bad" loans and "good" loans otherwise. If the loan term was <12 months, then the performance at the end of the loan was used to define the good/bad status.

For this example, the lender has reviewed the revenues and losses associated with good and bad performing loans in each grade. They have used this to calculate that they can lend profitably and in line with risk appetite if the default rate is below 7.5% Therefore, they create a rule in their lending policy to decline any loans where the credit scores indicates that the default will be higher than this, ie decline any applications where the credit score is less than 668.

If nothing ever changes, then that is all the lender needs to do. The credit score can be used on this basis forevermore. However, in real-world situations the calibration tends to change over time, driven by both macro and micro economic factors. At a macro level, default rates associated with a given credit score tend to increase when the economy enters a downturn and decrease in an upturn. At a micro-economic level, if there is a shift in the customer profile of loan applications then this can also result in changes in the calibration. Likewise, changes to a lenders' customers management processes can also have an impact. As well as the default rates associated with each grade, the overall distribution of cases can also change. In a downturn, there tends to be an increase in the number of lower scoring cases and in an upturn the reverse.

What this means is, the calibration needs to be reviewed on a regular basis. If the calibration has changed, then it may be necessary to modify the lending rules to cater for the new calibration. If we continue with the example relating to Table 5, Table 6 shows the situation a couple of years later.

Table 6. A Score Distribution Table 12 Months Later

Credit Score Range		Volume of loans (%)	"Good" (non-defaulted) loans @ 12m	"Bad" (defaulted) loans @12m	(Marginal) Bad rate @ 12 months
From %	**to %**				
<0	**405**		N/A	N/A	N/A
406	**490**		N/A	N/A	N/A
491	**558**		N/A	N/A	N/A
559	**592**		N/A	N/A	N/A
593	**667**		N/A	N/A	N/A
668	**722**	20.1%	735	83	10.1%
723	**768**	20.1%	759	60	**7.3%**
769	**808**	20.3%	776	51	6.2%
809	**883**	19.9%	780	31	3.8%
884	**999+**	19.5%	783	11	1.4%
Total		100.0%	3,833	236	5.8%

The first thing to note about Table 6 is that many of the rows are marked "N/A." This is because the lending policy was set to decline cases scoring below 668. Consequently, the lender no longer has any cases scoring below 668 to report upon[36].

The next important item is that that defaults have risen for each score grade. For example, the default rate in the 668-722 grade has risen to from 7.4% to 10.1% This is above the target maximum of 7.5% Therefore, the lender needs to raise the cut-off to 723; ie Reject cases that score less than 723 to continue accepting cases with expected default rates below 7.5%.

If things had gone the other way, with the default rates now being lower, then the lender may decide to reduce the score cut-off to below 668.

A couple of years is quite a long time. In the above example, the changes seen over the two year period quite dramatic. Consequently, most lenders monitor the calibration of their credit scores more frequently, typically monthly, or quarterly. This monitoring then becomes a regular item of discussion at board or credit risk governance forums. An example showing a typical report of this type, showing the long term trend in default rates by Grade is shown in Figure 2.

[36] In practice there will be some cases with lower scores due to overrides decisions taken in special/exceptional cases.

Figure 2. Long run default rates by score grade

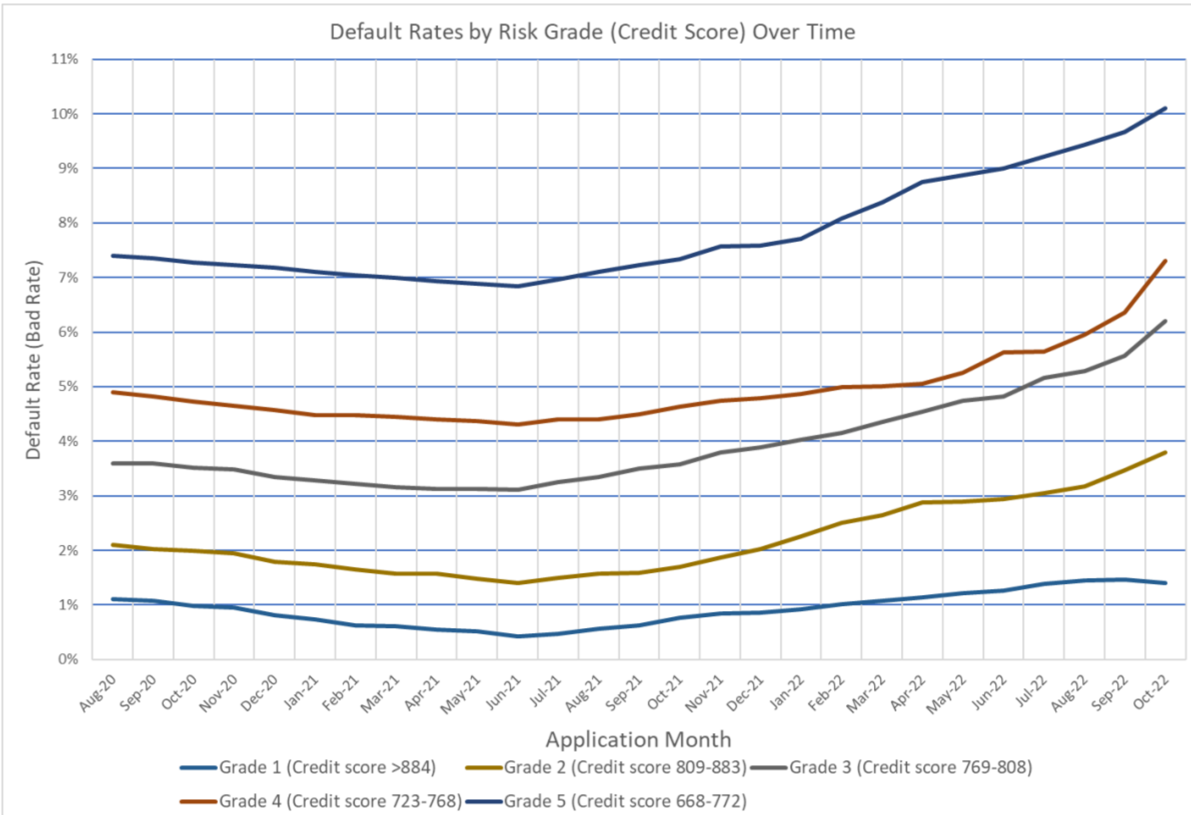

Figure 2 shows the 12 month default rates for applications made each month, that were subsequently granted a loan. For example, the left most point shows the default rates in August 2021 for applications made in August 2020.

Figure 2 shows that initially, the default rates in each score grade were marginally improving month on month, but this trend reversed in July-21, with the default rates in Grade 5 exceeding the 7.5% threshold in November-21. Therefore at this point it would have been prudent for the lender to have taken action to tighten their lending policy, by rejecting applications from customers in Grade 5.

A good question to ask at this point is what is driving the increase in default rates? Given the timing, it is probably the case that this was due to the "cost of living crisis" that occurred at about this time, which saw large increases in utility bills, inflation, and mortgage rates, all within a relatively short period of time. This undoubtedly put stress on many household budgets.

8.3 Appendix C: Glossary of terms used in this document

Term	Description
“Bad”	A common, informal term, used across the credit industry to define customers whose repayment behaviour is undesirable. Bad usually used to mean the same or very similar thing to “default” or a case of “bad debt.” However, lenders will sometimes define alternative definitions of “Bad” for specific analytical of risk modelling purposes
Bad rate	Broadly similar in meaning to “default rate” but based on the lenders definition of “Bad.” The bad rate is defined as the number of Bads/

Term	Description
	(number of goods + number of bads)
CIFAS	CIFAS is a not-for-profit fraud prevention membership organisation
Credit Reference Agency (also known as a Credit Bureau)	An organisation, licensed under the Consumer Credit Act 1974, to hold information about individuals' repayment behaviour when using credit products such as mortgages, loans, and credit cards. Nearly all UK-based Lending institutions provide details of the balances and arrears status of their customer accounts to one or more of the UK credit reference agencies each month When a new customer applies for a loan, a lender will purchase a copy of the customer's credit report from the CRA, which details the balances and arrears status of the customers current and previous loan agreements with other lenders. The 3 main credit reference agencies in the UK are Experian, Equifax, and TransUnion (formally CallCredit)
Credit Score	A credit score is a number which provides a holistic view of a customer's creditworthiness based on several different features (characteristics). Typically, these are a mixture of geo-demographics (eg age, occupation, residential status) and financial history (eg number of existing credit agreements, credit card utilisation, defaults, and court judgements) Credit Reference Agencies each provide their own credit scores and the scores differ between agencies due to the different data and methodologies used to create them. Individual lenders often develop their own Credit Score(s), which are tailored to their customer base and may incorporate additional data sources that they have available
Credit Scoring	An algorithm (mathematical formula) that creates a credit score for an individual by assigning weights to the different pieces of information that is known about them
Financial Conduct Authority (FCA)	This is the regulatory body responsible for the functioning of the UK financial markets. This includes the regulation of firms providing consumer credit products and services

Term	Description
"Good"	The opposite of "Bad" see above
IVA (Individual Voluntary Arrangement)	An IVA is a statutory insolvency agreement where a borrower agrees a formal repayment plan to repay their debts. This will usually involve a borrower agreeing what they can afford to pay each month, and then agreeing with creditors the proportion of their debts and over what timeframe (usually several years) they will repay those debts Having an IVA will usually restrict an individual's ability to take out new borrowing and will adversely impact their credit rating for several years
Open Banking	Open Banking refers to customers who have given permission for lenders to review the transactions that occur in relation to their bank account(s). This enables the lender to verify the customer's income and expenditure patterns
Policy Rule	A clear statement of a lenders criteria for lending. Usually, a set of clear Policy decline rules are used within the lending policy to identify specific high risk cases, such as bankrupts of those with serious arrears, that should never normally be granted a loan
Principles of Reciprocity	These are the rules that are determined by the Standing Committee on Reciprocity (SCOR) as to how lenders share and use data via a credit reference agency
Prudential Regulatory Authority (PRA)	The PRA is a part of the Bank of England and is regulatory body responsible for ensuring the soundness of the UK financial system. For example, ensuring that companies hold enough capital reserves and have sufficient liquidity to remain solvent
Risk Appetite	An organisations expression of the risk profile of their customers. What type of risks they will or won't accept in line with their business model
Thin Credit File	This refers to cases where a person's credit report contains no or very little credit reference data. There is no standard UK definition of a thin credit file, but the FCA in its 2022 market survey defined a thin credit file as: "i) has 2 or fewer credit accounts (eg a credit card and a personal current account) and ii) those accounts were opened

Term	Description
	in the last 6 months." (MS19/1.2 Credit Information Market Study Interim Report Annex 1: Data quality, p.5)