Preventing financial distress by predicting unaffordable consumer credit agreements: An applied framework

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Summary

Approximately one in six people with consumer credit debt suffer moderate to severe ‘financial distress’, experiencing financial difficulties or other issues such as mental health problems from the strain of repaying their debts. A challenge for regulators (and firms) is how to design affordability rules which minimise financial distress by limiting access to credit to those who cannot afford to repay, without such rules excessively restricting affordable credit access or imposing processes which unnecessarily increase the costs of borrowing.

This paper provides theoretical and practical evidence to help develop more effective affordability rules. We find it is possible to detect particular groups of consumers who have a high risk of suffering forms of financial distress. There are, however, some important limitations to these rules.

In the absence of adequate affordability rules, consumers can suffer potentially avoidable financial distress. There are strong, economic reasons for this. Lenders are incentivised to offer credit to applicants where it is expected to be profitable, irrespective of the risk of financial distress to the applicant. Consumers may take out such credit if they do not realise they are at a high risk of financial distress. The greater the ability to accurately discriminate between high and low risk applicants, the higher the likelihood that firms’ affordability rules will prevent financial distress by avoiding lending to those at high risk.

Using data on 2.4 million applications for high-cost short-term credit (payday) loans, we examine the ability to predict financial distress. We construct measures of financial distress from detailed credit reference agency (CRA) data. While much financial distress cannot be predicted, high credit risk applicants are at a substantially higher risk of the observable, objective measures of financial distress we measure in this paper, relative to other applicants. Applicants who have outstanding consumer credit debts near or above their annual net individual income (known as the DTI ratio) also have a significantly higher risk of suffering financial distress.

We find substantial differences in the total value of outstanding debts recorded on two different CRAs for the same individuals, at the same points-in-time. We also conclude that data used by lenders for predicting financial distress are unlikely to accurately estimate incomes and expenditures for some applicants. This limits the ability of lenders to predict financial distress and decide which consumers not to lend to.

1 Overview

Purpose

When a consumer applies to take out a consumer credit product, FCA rules require that the lender must consider (i) the potential for the commitments under the agreement to adversely affect the consumer's financial situation and (ii) the consumer's ability to make payments as they fall due (or within a reasonable period in the case of open-ended credit). This is known as undertaking a 'creditworthiness assessment'. These rules are designed to prevent firms lending to individuals who would be expected to be at high risk of suffering detriment from borrowing ('unaffordable debt').

At the time of publishing this research, the FCA is consulting on proposed changes to its existing rules and guidance. This research paper is intended to inform discussion of that consultation and the topic more generally.

This research is the companion paper to FCA Occasional Paper No. 20 which[1]:

- summarised economic theory on consumer credit use and financial distress,
- described the distribution of consumer credit debts and estimated the scale of financial distress in Great Britain, and
- analysed the relationship between well-being and financial distress and whether the latter can be predicted.

Having established a detailed understanding of financial distress in previous research, this paper evaluates the predictability of some forms of financial distress using data that lenders could potentially use when taking a decision whether to grant credit to an applicant. In this paper we:

- present an economic framework for understanding unaffordable consumer credit debt,
- apply our framework to data from real lending decisions in the high-cost short-term credit (HCSTC) market, and
- evaluate data used in creditworthiness assessments.

[1] Gathergood & Guttman-Kenney (2016) Can we predict which consumer credit users will suffer financial distress?

Key findings

Economics of unaffordability in consumer credit

Over 27 million adults in the UK have outstanding debt on consumer credit agreements (or utility bill debt).[2] Such consumer credit debt often performs a critically important function in our economy, as it enables people to manage temporary cash flow shortfalls and purchase goods such as cars and household appliances.

However, some people suffer 'financial distress'; they experience financial or non-financial difficulties from repaying their outstanding debts. Examples of such financial distress include filing for bankruptcy, defaulting on financial commitments, forgoing essential living expenses in order to meet repayments, having to borrow to meet repayments, and suffering mental health issues. We found in previous work that an estimated one in six people with outstanding consumer credit debt are suffering moderate to severe financial distress.[3] When a person is described as being in 'financial distress' prior research has suggested their debts may referred to as being 'unaffordable' – though there are a variety of regulatory and economic definitions.

A challenge for regulators and firms is how to design affordability rules – restricting access to unaffordable credit - to minimise this financial distress, without such rules excessively restricting affordable credit access or imposing processes which unnecessarily increase the costs of borrowing. The economic framework presented here explains the theory that provides the rationale for affordability rules and guides us towards how to solve this challenge. This framework is summarised in Figure 1.

This paper defines a ***'credit agreement with a high risk of unaffordability'*** as one which, at the time of the decision to grant credit, has a high risk that the consumer will face financial distress if the credit application is granted. If lenders decline such applications then the financial distress of these people could be prevented. This definition focuses on the ability to predict financial distress and discriminate between consumers at high and low risks. It recognises that it is inevitable that some people experience financial distress due to subsequent unpredictable changes to their circumstances such as losing their job. It also recognises that some financial distress may be temporary with little adverse impact on the individual. Finally, the definition considers how the risk of financial distress that a person faces changes depending upon whether a credit application is approved.

Such predictably unaffordable credit agreements can only exist if both lenders are willing to offer such agreements and consumers are willing to accept them. The potential role for regulatory intervention to prevent predictably unaffordable credit agreements depends upon how significantly financial distress to the borrower is likely to adversely impact the lender (and therefore in their interest to prevent). The most direct potential adverse impact to the lender is primarily the credit risk they are exposed to - i.e. likelihood of repaying debts on-time which is a key input into lender's overall profitability. If the potential adverse impacts on borrowers and lenders are highly correlated then, even without regulatory intervention, lenders would decline applications from borrowers at high risk of financial distress. There are a variety of economic reasons why we do not expect this to be the case.

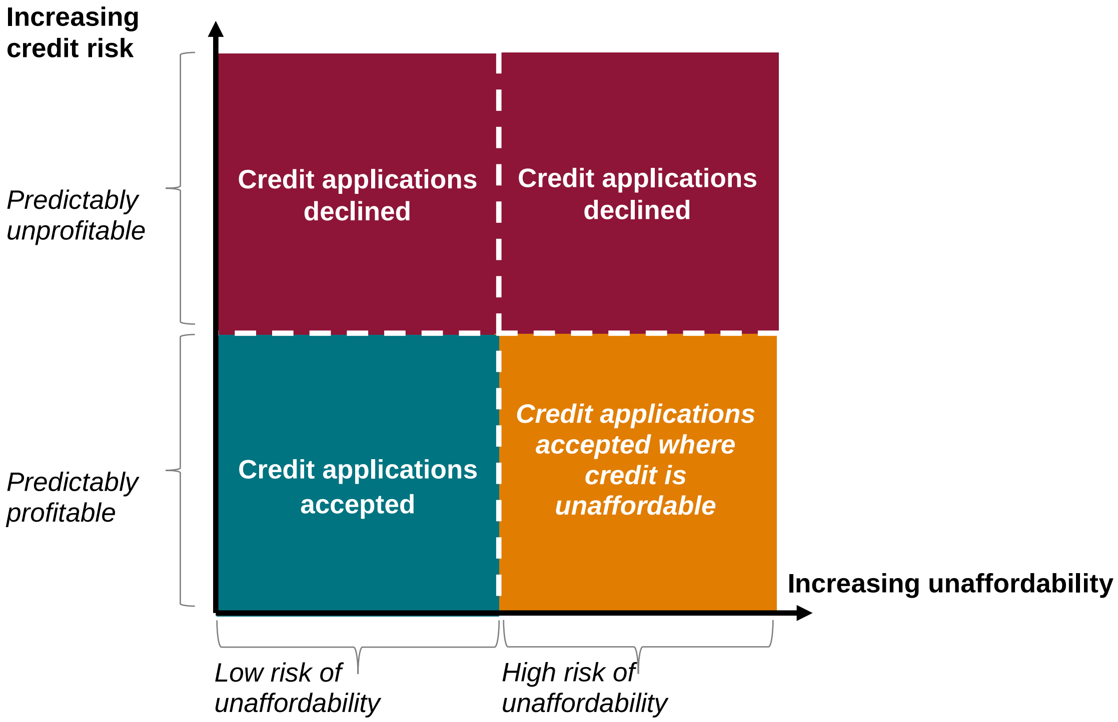
Lenders typically seek to maximise profits and therefore, without regulatory intervention, make lending decisions based on expected profitability. Such lending decisions only focus on narrow aspects of financial distress suffered by individuals that affect the firm – primarily the 'credit risk' to the lender arising from non-repayment, default or late payment of the credit agreement the lender is directly exposed to.

[2] Estimated as of November 2016. FCA High-cost credit FS17/2 Technical Annex 1: Credit reference agency (CRA) data analysis of UK personal debt, July 2017

[3] Gathergood & Guttman-Kenney (2016) includes a variety of estimates using ONS data. Other estimates of people with debt problems have been produced by a variety of organisations such as the Citizen's Advice (Lane, 2016), Department for Business, Innovation and Skills (2013) and the Money Advice Service (2016)

Without affordability rules, firms may be incentivised to offer predictably unaffordable credit agreements to applicants who are expected to be profitable even if these people have a high risk of suffering financial distress which can be predicted – these are the group of consumers in the bottom right quadrant of Figure 1. The extent of such a misalignment between lenders and credit applicants would be expected to vary with different product structures.

Figure 1: Illustration of lending decisions without consideration of whether lending is at high risk of unaffordability



Consumers may take out credit agreements with a high risk of unaffordability because they find it difficult to evaluate the uncertain costs and benefits of borrowing. It may result from consumers exhibiting 'behavioural biases' – in particular making decisions to seek gratificaiton 'now' and postpone costs and making choices they later regret. Consumers who are less financially sophisticated may be especially vulnerable and may struggle to make informed choices. In addition, consumers may take out loans with a high risk of financial distress if they judge (accurately or not) that they will be in even greater distress without borrowing.

Given the above we conclude that there is a role for regulation to require firms to decline applications with a high risk of financial distress at the time of credit application. Such regulation needs to be applied consistently across lenders in order to prevent adverse effects on competition where an applicant considered to have a high risk of financial distress is declined by one lender but then accesses similarly risky credit elsewhere thus not reducing consumer harm.

There could be other reasons why credit agreements with a high risk of unaffordability occur or why unduly restrictive lending practices prevent predictably affordable lending. One possibility is that while financial distress could be predicted in theory, in practice lenders may not have access to the information required in order to accurately make such predictions about which credit applicants are at a high risk of financial distress. For example, survey-based subjective measures of financial distress (e.g. do you consider your debts a burden?) are not observable on a credit application. It is also possible that while some lenders may want to avoid predictably unaffordable credit agreements (which potentially harm their reputation) or unduly restrict lending (which would reduce their revenues) they are unclear of what constitutes having a high risk of unaffordability.

The structure for an assessment by lenders for deciding which applications to decline is therefore a prediction problem built off this economic framework – what factors most effectively predict the risk of financial distress and discriminate between consumers at high or low risk (given the data available to lenders)?

As lenders typically already assess the credit risk of applicants it is possible that measures of credit risk are good predictors of financial distress and no additional factors are needed in an assessment. The highest credit risk a lender *is willing* to lend to from their credit risk perspective may be higher than the highest credit risk they *should* lend to in order to prevent predictably unaffordable credit agreements.

Alternatively, it may be other factors – such as measures of debt relative to income based on economic theory – are good predictors of a high risk of unaffordability as well as (or potentially instead of) credit risk. This would indicate a role for an assessment that measures factors beyond credit risk in order to assess whether granting credit would result in a predictably unaffordable credit agreement. Irrespective of whether it is credit risk or other variables which predict financial distress this process enables an informed assessment for where the predictable risk of consumers applying for credit suffering financial distress become unacceptably high (where lenders decide to decline applications).

Prediction of unaffordability in the high-cost short-term credit (HCSTC) market

We apply the economic framework to data on real lending decisions. This application is designed to offer one practical example of a method to assess credit agreements with a high risk of unaffordability. This is by no means the only method possible. Given the diversity of products in the consumer credit market, the appropriate method for one product may not be the same as for other products.

Our dataset is collected from lenders and covers the successful and unsuccessful high-cost short-term credit (HCSTC) loan applications made by 2.4 million people between January 2014 and June 2015. These HCSTC applications are then matched to the applicant's credit reference agency (CRA) data – sometimes called their credit file. CRA data are the bedrock of credit risk assessments. They contain very detailed information on a credit applicant's current and past debts including whether they repaid their debts late. We use these data to construct a variety of objective measures of financial distress observable to lenders (and regulators). The HCSTC market was chosen for this research primarily because the short-term borrowing duration enables such measures of financial distress to be observed soon after taking out these products.

We also chose to examine this issue in the HCSTC market because we expect the high cost of the product to result in a larger divergence between credit risk to the lender and unaffordability to the customer. We investigate whether this was the case by comparing a measure of credit risk – credit score predicting the likelihood of repaying an HCSTC loan – to a predictor of financial distress – the total value of outstanding non-mortgage debts relative to annual individual net income (DTI ratio).[4] We find that, among HCSTC consumers, the DTI ratio has little correlation with measures of credit risk. Firms' credit risk ranks individuals differently to the DTI ratio. This indicates these may be alternative ways to assess affordability depending upon how effectively they predict financial distress.

We compare these potential predictors to a variety of objective measures of financial distress constructed from CRA data. Some measures of financial distress reflect individuals experiencing payment difficulties, such as missing one or more payments on any of their outstanding debts. Other measures of financial distress reflect individuals' cash flows being under strain, such as exceeding the limit on their personal current account and using unarranged overdraft. We find that the prevalence of financial distress by these measures varies by both credit risk and DTI ratio. There appear to be independent effects from these two factors: consumers who either are a

[4] We measured credit risk using 'credit risk scores' which are used by lenders to predict the likelihood of an individual repaying a particular credit agreement (if granted). Gathergood & Guttman-Kenney (2016) found DTI ratio to be strongly predictive of objective and subjective measures of financial distress.

high credit risk or have a high DTI ratio are at increased risk of financial distress compared to other consumers.

When we examine the ability of these measures to predict financial distress (only using measures available at the time of making a credit application) we find that credit risk is a strong predictor of financial distress. Consumers with high credit risk applying for a HCSTC loan are at significantly higher risk of suffering financial distress than other HCSTC loan applicants. While some applicants with low credit risk may suffer financial distress (based on the observable, objective measures we use) there is not a predictably, high risk of this occurring at the time of taking a decision to grant credit.

In addition to credit risk we find, to a lesser extent, the DTI ratio is able to improve the ability to predict financial distress. We find a 'tipping point' where the likelihood of a consumer experiencing predictable financial distress is noticeably higher. This is at the point where an individual has a DTI ratio that is close to or above 100% – i.e. the total value of outstanding, non-mortgage debts is near or above the value of their annual individual net income. On average, we find that taking out a HCSTC loan makes a limited difference to the risk of an individual suffering financial distress beyond these factors. This work is not able to isolate the causal effect of taking out HCSTC and evaluate whether the welfare of these borrowers is worsened. Instead we take the assumption that, on average, for consumers at high risk of financial distress taking out more debt is unlikely to be welfare improving given prior evidence.[5]

These findings imply HCSTC applications could be assessed as to whether lending is likely to be predictably unaffordable by first considering the credit risk of the applicant. This could be used to estimate whether lending is likely to be predictably unaffordable. If the applicant is a low credit risk they are typically very likely to be at low risk of suffering financial distress (using the measures we observe). Whereas if a credit applicant is a high credit risk there may be sufficient information to conclude that there is a high risk of financial distress (and not grant credit) or there may be a need to consider other factors such as the DTI ratio before assessing the customer's ability to afford the credit and hence whether or not to grant credit.

The assessment approach may vary for other credit products where there are different relationships between credit risk, DTI ratio (or other metrics) and measures of financial distress. The DTI ratio threshold used to judge whether or not lending is predictably unaffordable may also need to change over the course of the economic cycle. For example, with higher interest rates, debt-servicing costs are higher and therefore may warrant a more restrictive DTI ratio being used.

Evaluation of data used for creditworthiness assessments

A variety of data sources are used by different lenders as part of their creditworthiness assessments. Most lenders use CRA data to inform their decision about who to lend to. These data contain a rich array of information such as the credit items held by an individual and whether they have defaulted on past agreements. By collecting this information, CRAs play a valuable role in consumer credit markets as this information helps lenders to evaluate the risks of lending.

Over many decades, CRAs have innovated (and continue to do so) by bringing new products and data sources to the market. For example, CRA data now increasingly record information on mobile phone and utility repayments. This particularly enriches data on younger borrowers who have little or no other credit items - helping these borrowers to demonstrate to lenders their ability to repay debts.

Given the importance of CRA data in creditworthiness assessments, we examine them in detail. In particular, we evaluate whether data for the same individuals held by different CRAs are consistent. If CRA data significantly differ, it would be expected to produce different lending decisions depending on which CRAs a lender uses – this is likely to be an inefficient market outcome both for the functioning of the lender and CRA markets.

[5] In particular, causal evidence from FCA(2014b) and non-causal evidence of Gathergood & Guttman-Kenney (2016)

We examine this by comparing the data held by two CRAs for over one million individuals who had recently taken out at least one HCSTC loan. We find substantial differences in the contents of data between CRAs. For example, we find an average (mean) difference of 24%, in total outstanding, non-mortgage debts, recorded for these individuals in July 2015 by different CRAs. This is £1,200 of unrecorded debt for the median consumer.

These differences are large and could be the difference between an application being accepted or declined depending upon which CRA a lender used for its assessment. This incomplete picture of a credit applicant's debts could result in both unduly restrictive lending and unaffordable lending. One explanation for such differences occurring is that it is the result of some lenders not reporting all credit agreements to all CRAs but only doing so to one or two (or none). We would expect such differences to be smaller (or non-existent) for lower credit risk customers using mainstream products from banks which typically report to all three CRAs. Two other hypotheses for explaining the observed differences are that they arise as result of errors in data submitted by lenders to CRAs or, alternatively, CRAs matching individuals to the incorrect credit files.

If CRA data are not up to date, then assessments carried out by lenders may not accurately reflect the credit risk or risk of financial distress at the time lenders are assessing applications. To investigate this, we also examine how up-to-date CRA data are. We find that current reporting arrangements mean that the data lenders are using for creditworthiness assessments can regularly be one or more months behind in displaying the current position of a borrower.

Current data-sharing practices restrict the information that non-bank lenders can access for their creditworthiness assessments. This means that, compared to banks, non-bank lenders may find it more difficult to assess the risk of financial distress and be exposed to increased credit risk.

Finally, while incomes and expenditures may be important inputs for assessing affordability from a theoretical perspective is difficult to accurately estimate these in practice for some groups of consumers - such as renters with unstable incomes - with the information currently available. Addressing these issues would be expected to help improve the ability of firms to price credit risk and ability to predict financial distress.

2 Economics of unaffordability in consumer credit

Introduction

Over 27 million adults in the UK are estimated to have outstanding consumer credit debt (or utility bill debt).[6] Consumer credit debt covers a variety of products including credit cards, unsecured personal loans, motor finance agreements and payday loans. This consumer credit debt has a critically important function in our economy. It enables people to borrow money to manage temporary cash-flow shortfalls: for example, those that may occur within a pay cycle due to expenditures, such as rent payments, arriving before income is received on payday, or where such payments are indivisible and unexpected, such as car repairs. Consumer credit debt also enables people to spread repayments over months or years for larger purchases, such as buying a car or household appliances, or financing special events, such as holidays or weddings. The use of credit changes over the course of people's lives, based on changes in their current income and expectations of how this will change as they age.[7]

While borrowing has useful purposes, some people suffer financial distress – financial or non-financial difficulties from repaying their outstanding debts. Financial distress may mean that individuals file for bankruptcy or increase working hours, take on additional jobs, reduce spending, default on other financial commitments (e.g. debts, rent and utility bills) – potentially with additional charges - in order to meet repayments. Financial distress may also be in the form of wider non-financial effects, such as stress, along with other forms of mental and physical distress or social stigma. Missing repayments or persistently maintaining debt may also impede an individual's future ability to access credit.[8]

By one estimate 17% of people with outstanding consumer credit debts are in moderate or severe financial distress.[9] A range of research finds that people in financial distress experience significantly worse self-reported measures of well-being, such as life satisfaction and anxiety, than other comparable groups of individuals not in financial distress.[10] Mental health issues are especially important to consider as they can be even more harmful to an individual's well-being than factors such as income losses, unemployment or poor physical health.[11] Therefore preventing financial distress – especially through reducing mental health difficulties – could help to improve the well-being of society.

When a person is described as being in 'financial distress' prior research has suggested their debts may referred to as being 'unaffordable' – though there are a variety of regulatory and economic definitions. How can we assess when debts become unaffordable? Economic theory guides us towards measures that assess debts relative to income in order to evaluate what level of borrowing an individual can reasonably be expected to be able to sustain.[12] The ratio of total outstanding consumer credit debts relative to their individual income (DTI ratio) has been found to be a strong predictor of future financial distress using survey data.[13] In practice, there may be a

[6] FCA High-cost credit FS17/2 Technical Annex 1: Credit reference agency (CRA) data analysis of UK personal debt, July 2017

[7] Ando & Modigliani (1963); Bertola, Disney & Grant (2006); Bijak et al. (2015); Browning & Crossley (2001); Friedman (1957); Fulford & Shuh (2015) Gathergood & Guttman-Kenney (2016).

[8] Gathergood & Guttman-Kenney (2016).

[9] Gathergood & Guttman-Kenney (2016) includes a variety of estimates using ONS data. Other estimates of people with debt problems have been produced by a variety of organisations such as the Citizen's Advice (Lane, 2016), Department for Business, Innovation and Skills (2013) and the Money Advice Service (2016)

[10] Acton (2016); Fitch et al. (2011); Gathergood (2012a); Gathergood & Guttman-Kenney (2016); Holkar & Mackenzie (2016); Lane (2016); Richardson et al. (2013).

[11] Clark, Fleche, Layard, Powdthavee & Ward (2016)

[12] Bertola, Disney & Grant (2006); Gathergood & Guttman-Kenney (2016).

[13] Gathergood & Guttman-Kenney (2016).

variety of ways for lenders to assess the risk of unaffordable debt, which may vary with the diverse range of products in the UK consumer credit market.

But what role is there (if any) for regulation of unaffordable lending? And is it reasonable to expect firms to make such decisions that consider the risk of financial distress?

Concept of unaffordable credit agreements

There is not a single, agreed quantitative measure to determine an 'unaffordable' quantity of consumer credit (or other) debts for an individual. There is no clear historical evidence of a 'tipping point' beyond which the amount of borrowing goes from being affordable to unaffordable. The lack of a 'tipping point' may partially arise from the wide diversity in the socioeconomic characteristics of users of consumer credit products, the variety of financial products in consumer portfolios, and the various reasons for, and uses of, consumer credit debt with attitudes to making payments.

For the purpose of this research, we formulate a conceptual economic definition of '**credit agreements with a high risk of unaffordability'** to provide a framework for considering this issue.

Conceptual definition of credit agreements with a high risk of unaffordability

A credit agreement is at a high risk of unaffordability if, at the time of decision to grant credit, given the information potentially available, there is a high risk that the consumer will face financial distress as a result of the credit application being granted.

This definition has three important components:

- First, the emphasis is on 'financial distress' as the focus is on preventing consumer detriment. People suffer financial distress when they face financial or non-financial difficulties from repaying their outstanding debts.
- Second, it is focused on considering what is *'high risk of unaffordability'* at the time of the decision to grant credit'. This is because lending decisions are subject to uncertainty. This means that some consumers may unavoidably enter financial distress following shocks that lenders could not anticipate for individual consumers. Consumers can still end up being in financial distress for reasons other than the affordability at the time of a credit application – we term this *'unexpected financial distress'*. These reasons can be due to 'life events', such as redundancy, ill health, or other changes in individual circumstances.
- Third, the definition focusses on consumer detriment arising 'as a result of the credit application being granted'. This is important, as some consumers may suffer financial distress irrespective of whether credit is granted. From the perspective of creditworthiness assessments, the focus is on how granting credit would be expected to change the balance of risks faced by consumers.

Considering this conceptual definition, ideal creditworthiness assessments would efficiently prevent lending to consumers who are at predictably high risk of suffering financial distress as a result of the loan without unduly restricting lending to other consumers who would be expected to be better-off from borrowing. Ideally, for the majority of individuals who have low risk of suffering predictable financial distress, creditworthiness assessments would not be very costly or time-consuming. This would avoid increased costs to lenders which could potentially feed through to restricted lending or increase the costs of credit.[14] What is considered a 'high risk' is ultimately a

[14] DeFusco et al. (2017) find significant impacts of US ability to pay mortgage rules on the quantities and costs of lending

judgement after considering the available evidence on the expected best interests of consumers applying for credit given their risk of suffering financial distress.

Creditworthiness assessments may be complemented where a customer nonetheless experiences financial distress through interventions such as insolvency arrangements and forbearance options targeted at people who develop arrears or default difficulties. Forbearance can come in a variety of forms such as not charging arrears or default interest and charges, freezing interest and charges, extending repayments or reducing or cancelling debts. Such measures to address 'unexpected financial distress' have to be carefully designed in order to minimize 'moral hazard' whereby borrowers have reduced incentives to repay their debts on-time, in full – this would be expected to increase the cost of credit to borrowers who do repay.[15]

Potential reasons for unaffordable credit agreements

Having defined an economic concept of credit agreements with a high risk of unaffordability, we now consider the role of consumer behaviour and firm incentives as potential reasons for such credit agreements occurring. We also examine how informational asymmetries and regulatory uncertainty potentially affect these.

Consumer behaviours driving unaffordable borrowing from lenders

If consumers were 'economically rational' (making decisions after accurately assessing all relevant current and future costs and benefits to their welfare) and had 'full information' (having all the information they needed available to make such assessments), they would only take out additional consumer credit products if it were optimal for them to do so. If this were the case, no credit agreements would be unaffordable.

Unexpected financial distress may occur, as we do not perfectly know what the future holds. The real world is full of risks and uncertain events. As such, even if consumers behave rationally, they can only take decisions based on expected rather than actual costs and benefits. Consumers may therefore borrow unaffordable amounts of credit, which they would not have done if they had more accurate information on the actual costs and benefits of borrowing.

However, as set out in FCA Occasional Paper No. 1, consumers do not always make choices in a rational and calculated way.[16] Academic studies explain these departures from rational behaviour through 'behavioural biases' or a lack of financial sophistication.[17] Behavioural biases of particular relevance in the context of borrowing decisions are 'present bias' and 'myopia' (sometimes incorporated into models of consumer decisions as 'hyperbolic discounting'), which occur when people overvalue the present over the future, potentially leading them to make choices that they may later regret.[18] Similarly, 'overconfidence' and 'projection bias' can mean consumers are over-confident in their ability to repay debts without considering the potential for shocks. Consumers may therefore apply for, and take out, credit on the basis of increasing their ability to spend in the present, instead of rationally evaluating current consumption against the expected costs of repaying in the future over the full lifetime of the credit agreement.

Consumer decisions are often influenced by the decisions of their peers, who set social norms that may vary significantly between consumers with different backgrounds. These social norms

[15] Dobbie & Song (2016) find that offering distressed credit card borrowers debt write-downs increased debt repayment, decreased bankruptcy filing and formal sector employment for the most financially distressed borrowers whereas increasing the time a consumer has to repay their debt (reducing the minimum repayment) had little effect on outcomes for consumers. Clara & Cocco (2016) model how a variety of forbearance practices could be built into contracts and how this would be expected to affect welfare. Hundtofte (2016) finds some distressed mortgage holders are worse off after taking up offers to modify their mortgage – this is hypothesised to be due to a lack of financial sophistication. Collins & Schmeiser (2012) find that counselling troubled mortgage borrowers reduces the likelihood of those individuals losing their home due to foreclosure. However, they are more likely to miss loan payments after counselling. Custers (2015) found that highly indebted consumers are very likely to avoid receiving contact from their loan providers (despite it offering forbearance).

[16] Erta et al. (2013).

[17] Laibson (1997); Agarwal et al. (2009); FCA (2016b); Gathergood (2012); Disney & Gathergood (2013); Zinman (2013, 2014).

[18] Campbell (2016); Financial Conduct Authority (2014b) research previously found a high proportion of consumers using HCSTC regretted using this product.

may be a combination of informal attitudes and different legal frameworks that evolve over many generations, based on factors such as the past historical experiences of countries defaulting on debts. For example, arguably it has historically been more socially acceptable for individuals to hold debt in the United Kingdom than other parts of the world, such as parts of Europe.[19] Another example is that it is more socially acceptable to become bankrupt among individuals in USA than the UK (and therefore less costly to take on unaffordable quantities of debt) with large differences in legal frameworks. At one extreme, pressure on consumers to keep up spending levels with their peers may encourage unaffordable lending through unsustainable debt-fuelled consumption.[20] At the other extreme, strong social stigma against borrowing may mean that consumers who would be expected to benefit from borrowing are deterred from doing so.

Consumer demand for unaffordable borrowing may also change over the course of the economic cycle and with changes in social policy. If groups of consumers do not experience rises in their real, disposable income and do not have other social insurance mechanisms available to them, they may take out credit to try to help them 'get by'. Doing so may not solve the underlying problem – a lack of income to meet their expenditures – as opposed to cash flow problems.

Finally, it is important to recognise the diversity across individuals using products in the consumer credit market. Individuals have a broad range of socioeconomic circumstances, meaning that some individuals may be more able to manage the risk of financial distress than other applicants in different circumstances, and therefore avoid suffering financial distress. Some individuals will inevitably end up in unexpected financial distress due to how they manage their finances.

Firm incentives for unaffordable lending to consumers

If the incentives of firms were aligned with those of rational consumers, then we would expect there to be no unaffordable lending. However, the (typical) incentives of firms differ from those of consumers – firms aim to maximise profits subject to regulatory constraints. Hence, firms have an incentive to act in the interests of consumers only insofar as this contributes to their profit maximisation objective.

However, in consumer credit markets one of the largest costs firms incur are financial losses due to default (i.e. non-repayment). It is therefore strongly in the interests of lenders to identify the risk of credit applicants defaulting before they decide whether to approve a credit application – a process known as a credit risk assessment, which typically involves the construction of one or more credit scores. Credit scores are constructed using a variety of statistical methods targeting different outcomes. The output of these are typically a score which estimate the probability of a group of credit applicants experiencing a specific outcome, such as defaulting on a credit obligation, or estimate the relative risks of one group of consumers relative to another.[21]

In the absence of regulation, firms are likely to make lending decisions based on the marginal profitability of lending. A lender assesses the profitability of lending to each potential borrower and lends to all those individual credit applicants who would be profitable to the firm, at the limit restricting lending to the consumer whose marginal profitability is just below zero (i.e. the firm can only expect to break even on lending to that consumer). In practice, firms do this by estimating the optimal minimum credit score (highest credit risk) at which to lend. This is the credit score value at which a loan to a consumer is adjudged to be just profitable. Lenders will lend to customers with a credit score at or above that threshold.[22]

In this environment, firms internalise the risk of unaffordable debt to the consumer only insofar as the risk of unaffordable debt is captured by the lenders' profitability-based credit score. A loan

[19] Anecdotal evidence. We are not aware of economic research analysing this issue.

[20] Bertrand & Morse (2013).

[21] For example, a simple credit score may range from 0 to 100 where a score of 0 estimates that the individual applying for credit has a 100% probability of defaulting on a loan (if granted) within 12 months of issuing with the loan. A higher score indicates a lower probability of defaulting on a loan (if granted) and therefore those individuals with a score of 100 are estimated to have a 0% probability of defaulting on a loan (if granted).

[22] Financial Conduct Authority (2014b) research built models recreating the lending decisions of HCSTC lenders based on expected customer profitability.

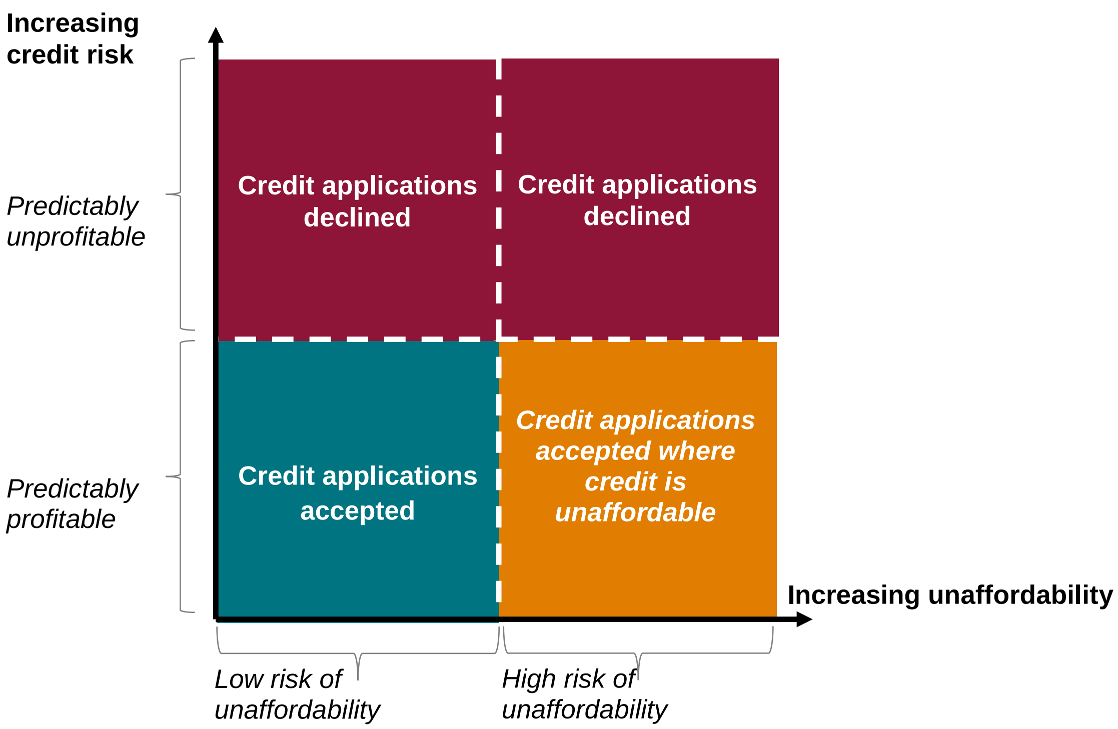
may prove to be a predictably high risk of unaffordability to the consumer, but if this is not reflected in the expected profitability of the loan to the firm, then the loan decision of the firm is unaffected. The risk of financial distress (beyond affecting the probability of defaulting on this loan) can therefore potentially be borne by consumers instead of the lender, with the lender not facing a commercial incentive to internalise these risks (as restricting lending to such individuals will reduce profit).

Figure 1 displays a summary of this framework. It illustrates the relationship between the incentives of borrower and lenders. This shows the partial overlap between expected profitability and unaffordability in lending decisions. In Figure 1, unregulated lending decisions would mean lending to consumers in Zones C and D as, based on credit risk, they are expected to be profitable customers.[23] Consumers in zones A and B are declined as they are expected to be unprofitable irrespective of regulation.

On this basis, it may be considered that there is a need for regulation of lending to protect consumers from unaffordable lending. This is because, in the absence of regulation, firms have commercial incentives to lend to consumers via loans that are expected to be profitable but create a high risk of being unaffordable for the consumer. With effective affordability regulation, lending is reduced to applicants in zone D in Figure 1, for whom borrowing would have been at high risk of being unaffordable.

A potentially helpful way to consider this issue is to view credit risk assessments as being lender-focused, and affordability assessments as customer-focused. The notion of 'creditworthiness assessments' incorporates both forms of risk screening into the lending decisions.

Figure 1: Illustration of lending decisions without consideration of whether lending is at high risk of unaffordability



The simplified framework presented so far is that firms have limited incentives to consider the unaffordability of, and to limit, credit to consumers who are likely to suffer harm from borrowing over and above that internalised in firm lending credit scores. However, it is possible that some

[23] Some consumers who are profitable in expectations will turn out to be unprofitable. One example of this is consumers who take out loans and choose not to repay them despite ability to do so. These are known as strategic defaulters.

mechanisms may help to partially align incentives such that firms consider the affordability of loans to these consumers. For example, adverse reputational impacts may follow from unaffordable lending, which may reduce a firm's profitability, thereby encouraging it not to lend unaffordable amounts of credit

The degree of this incentive misalignment between firms and consumers is expected to vary depending upon the characteristics of the consumer credit product being sold. Below, we highlight features which, holding all else constant, we hypothesise would be expected to change the alignment of incentives between borrower and lender:

- **Distribution mechanisms:** If credit is being sold face-to-face (e.g. through an sales agent in a store or at the applicant's home), then there is expected to be greater social pressure on the individual to take out credit 'now' (or in larger quantities) than if there is no human interaction (.e.g. through online sales) where the individual can more easily walk away from the application (entirely or taking time to consider it further). If lenders heavily financially incentivise their sales agents to sell credit (e.g. if a high percentage of call centre staff remuneration is based on sales volume targets) then it would be expected to be more likely for those agents to engage in pressured or even deceptive mis-selling tactics that encourage consumers to take out unaffordable debt.
- **Asset-backed:** Linking a credit product to an asset enables lenders to lend to higher credit risk customers than they could if the lending was unsecured. This is because borrowers may prioritise repayment of secured debt to avoid the loss of the collateral while lenders can potentially recover the asset in case of late or non-payment. Therefore, credit products linked to assets can be expected to result in increased risk of unaffordable lending when compared to non-asset based credit products. Consumer credit products that are directly linked to an asset, which may be secured or simply credit taken out at the same time to purchase a specific good, are also expected to result in consumers being more focused on the asset being bought than the financial cost of borrowing.
- **Charging structures:** If firms are able to vary the price at which they lend, and are able to recover monies due, even if the prices charged to consumers are very high, it is possible for them to lend profitably to even high credit risk consumers. This may be because with very high prices it can be, on average, profitable to lend to high credit risk consumers if those who do not default repeatedly return for business. It may not merely be higher headline prices which exacerbate this incentive misalignment; products that generate much of their revenue from add-ons, insurance products, opaque or back-end pricing mechanisms or especially customers in arrears, default or refinancing their debts would also be expected to produce similar outcomes.[24] With revolving credit products (e.g. credit and store cards) it can be profitable for groups of consumers to be at low risk of missing their contractual minimum payment but, as a result of only making low payments, be persistently in debt and be unlikely to clear their debt.[25]

Given such diversity in consumer credit products, it appears beneficial to allow some flexibility in how lenders carry out creditworthiness assessments. An approach could be for the expected burden of proof to assess whether lending is affordable to be proportional to the risks a product poses to an individual credit applicant based on their existing circumstances. In particular, the higher the price of credit, the higher the expected burden of proof for a creditworthiness assessment. Such an approach would try to limit the number of cases where a low-cost lender declines a credit applicant and, as a result of this, the denied applicant then applies for and successfully takes out high-cost credit from another lender. This logic is supported by the findings in FCA Occasional Paper No. 20 that consumers with high-cost credit are at significantly higher predictable risk of suffering financial distress than consumers with low-cost credit.[26]

[24] Also if consumers are unable to easily prepay their credit without large penalties.

[25] Keys & Wang (2016)

[26] Gathergood & Guttman-Kenney (2016)

Informational asymmetries affecting credit decisions

The nature of lending is that there will be some 'information asymmetry' – where the lender may have incomplete information on the circumstances of applicants for credit.[27] The scale of this asymmetry could be somewhat reduced by lenders having access to timely and granular data about applicants to understand their financial situation and assess their likelihood to repay debts. This incomplete information can be (partially) solved through lenders co-ordinating to share information on borrowers, such as through reporting to credit reference agencies.[28]

Unaffordable lending may occur as a result of firms not having access to information which could allow them to improve their assessments of credit risk and affordability. For example, even in cases where firms' credit risk decisions internalise the likelihood of consumers suffering distress from unaffordable lending they are only based on the information available to that lender. This could therefore result in lending decisions taken in error. Including other information, known by the consumer or other lenders, could reduce the potential for such errors and assist at reducing the . likelihood of unaffordable debts.

Firms do not have access to all the input data that they would ideally want to make an assessment of the ability of consumers to repay their loans. This could mean that there is a measurement error, meaning more or fewer consumers are in Zone D in Figure 1 than a firm had expected. This measurement error could be due to a credit file not providing a comprehensive view of an individual customer's entire debts or being unable to accurately verify income.

Objective measures of whether applicants for credit are in financial distress – which include arrears, default, debt management plans or bankruptcy – are observable to firms using data from CRAs or other data sources. Subjective measures of financial distress – such as whether consumers regard keeping up with their consumer credit repayments as a heavy burden – are not typically observed by lenders. Given this, lenders make creditworthiness assessments based on observable factors – such as credit risk score and debt to income ratios – to try to predict the risk of future financial distress.

Issues with information can be expected to result in both unaffordable lending and unduly restrictive lending practices. More broadly, such information inefficiencies can also be expected to result in higher lending costs as a result of less efficient credit risk and pricing models.

Regulatory uncertainty affecting credit decisions

In addition to all of the above factors, it may be that there is a gap between the regulatory requirements and firms' interpretation of these. This is known as 'regulatory uncertainty'. Such a mismatch in expectations can mean the regulator evaluates the quantity of loans in Zone D in Figure 1 to be different from the quantity identified by lenders.

The overall effect of regulatory uncertainty on consumer credit markets is ambiguous. Regulatory uncertainty may mean that firms are overly cautious in their lending decisions and therefore unduly restrict lending to customers who would be expected to be able to affordably borrow.[29] It may also result in firms implementing unnecessarily complex creditworthiness assessments that worsen the customer experiences of applying for credit (e.g. more time-consuming form-filling and finding pieces of paperwork). In turn, these cause lenders to incur costs, which raise the overall cost of credit, reduce lender profits, and prevent firms from easily explaining to declined applicants the reasons behind their decisions.

With uncertainty, lenders may use a variety of different products offered by compliance vendors to assess unaffordability (e.g. scores or indicators of unaffordability). Unlike credit risk products, it

[27] Agarwal et al. (2015); Akerlof (1970); Grossman & Stiglitz (1980); Stiglitz & Weiss (1981). In other contexts asymmetry can also mean that firms have more information than individuals.

[28] https://www.brookings.edu/wp-content/uploads/2016/07/1214_financialservices_fellowes_presentation.pdf

[29] Gissler et al. (2016) find evidence of this in the US mortgage market. Broader work such as Bloom (2009) and Baker et al. (2016) and Di Maggio et al. (2017) highlight the real economic costs of uncertainty.

is much more difficult for lenders to establish whether affordability products being used offer them value for money and are effectively preventing unaffordable lending. Credit risk products are used to increase the profitability of lending. The effectiveness of a given credit score model upon default rates and profitability is clearly observable to the lender. By contrast, it is less clear to lenders how to assess the risk of 'financial distress' – given that this is less easily measured – and therefore be able to evaluate the effectiveness of products to prevent unaffordable lending. From the point of view of lenders, it may be rational to regard an effective assessment as one which declines few applications and does not result in complaints from consumers or regulators.

Alternatively, such regulatory uncertainty may result in some firms carrying out insufficiently rigorous creditworthiness assessments, exploiting uncertainty in the regulator's expectations. This may occur through firms 'window-dressing' their creditworthiness assessments – applying tick-box criteria to enable them to say they have considered affordability but which have limited, if any, effect on lending decisions. In such a scenario, unaffordable lending may occur with firms focusing on whether consumers are profitable rather than appropriately assessing the risks of consumer financial distress. Given this, prescriptive approaches on how to carry out creditworthiness assessments may potentially reduce regulatory uncertainty but not reduce consumer detriment.

Comparison with mortgage unaffordability

When considering how to assess consumer credit unaffordability, it is natural to compare the decisions made by lenders in the consumer credit market with creditworthiness assessments undertaken in the mortgage market. While the focus of this paper is on consumer credit affordability, the same underlying conceptual framework could be applied to mortgages following on from previous research carried out by the Financial Services Authority (FSA) and the FCA.[30] While some of the approaches undertaken for assessing mortgage applications may also be applicable to consumer credit applications, these markets are different in a variety of ways that include different legal frameworks. As such, the risks consumers face and the nature of the creditworthiness assessment required to assess those risks can differ between these different markets. Some examples for how mortgage products differ from consumer credit products are:

- **Speed and cost:** As mortgage applications are often linked to house purchases or refinances, they typically do not have a consumer need for the credit application (including the affordability assessment) to be completed within minutes.[31] By contrast, some consumer credit lenders compete on the basis of providing credit within minutes. Mortgage lenders typically take considerable time to carry out more detailed assessments of individual affordability than would be acceptable to applicants or feasible under the business models of consumer credit lenders or necessary given the price, loan size and duration of borrowing. Mortgages produce larger values of revenue than consumer credit products and therefore lenders can more easily absorb a more costly creditworthiness assessment.
- **Uncertainty:** Mortgages are typically of a much larger size and held over longer time-horizons than consumer credit debts. This means that when assessing mortgage affordability, there is much greater uncertainty over the possible changes in circumstances that could emerge during the course of the mortgage. For example, over a longer time-horizon, there is greater uncertainty surrounding what could happen to factors such as an individual's income and expenditure, household composition (e.g. the addition of children, transitions through marrying or separating), and macroeconomic conditions (e.g. the path for real wage growth, inflation and unemployment). UK mortgage contracts adjust very quickly to changes in interest rates and, given the size of mortgage balances, such changes have a large impact on monthly repayments. As the implications of these may be large for the borrower, there may be a rationale to include such shocks in the affordability assessment.
- **Consumption smoothing:** The long-term nature of mortgage obligations means it is difficult for consumers to make short-term changes to their incomes and expenditure to meet

[30] FSA (2010, 2011, 2012); Butterworth et al. (2015); FCA (2016a).

[31] Some forms of mortgage lending, such as bridging loans, may need faster decisions.

repayments sustainably. By contrast, instalment-based consumer credit products are shorter in duration and credit cards is the dominant consumer product which is structured to enable consumers to make short-term flexible changes in their repayments. This flexibility in repayments means debt serving ratios appear less suitable for considering the affordability of consumer credit debts (such as credit card) than in the case of mortgage debts.

- **Negative equity:** One of the largest risks associated with mortgage lending is that of negative equity, where a household's secured debts exceed the value of their property, as this is associated with higher defaults among other harmful effects.[32] As most consumer credit products are unsecured debts, there is no risk of negative equity from this consumer credit lending. Unlike property, nearly all other durables decline in financial value over time (for example, new cars depreciate in value rapidly from the point of purchase) which means that the value of outstanding debt can often exceed the current sales value of the asset.

[32] Hellebrandt & Katwar (2009); Foote et al. (2008); Fuster et al. (2016).

3 Prediction of unaffordability in the high-cost short-term credit (HCSTC) market

Introduction

Now that we have a conceptual framework for considering the issue of unaffordable consumer credit agreements, we seek to apply this by examining the relationship between credit risk, the measure of unaffordability we use in this paper, and subsequent consumer outcomes in real lending decisions using data lenders could have access to.

The application in this chapter offers a practical example of a method to assess the unaffordability risk of consumer credit debt and identify customers who should be subject to a more extensive affordability assessment. This is by no means the only method possible and, given the diversity of the consumer credit market, the appropriate method for one lender and product type may not be the same as the appropriate method for other lenders offering alternative products. The appropriate method and relationships between variables may also change over the course of the business cycle. In the same way as some lenders adjust their credit score thresholds over time to calibrate the optimal value to set these at, lenders could also vary thresholds for assessing unaffordable consumer credit debt and calibrate these accordingly.

We construct our example by analysing lending decisions of HCSTC lenders. We examine how related credit risk is to a potential predictor of financial distress, the total value of outstanding non-mortgage credit debts relative to their income – known as the DTI ratio. The DTI ratio is used due to its link with economic theory and strong ability to predict financial distress in FCA Occasional Paper No. 20.[33]

Following this, we analyse which consumers appear to be at high risk of suffering financial distress – measured by defining a range of outcomes – based on their credit risk and DTI ratio calculated prior to the decision to grant credit.

Finally, we examine how the decision to grant credit affects the predictable risk of financial distress faced by consumers.

Data description

We analyse data on HCSTC loans, often colloquially described as 'payday loans', as the short-term duration of these products enables consumer outcome measures of unaffordability to be observed soon after the use of these products. This market is also useful to examine as, based on the conceptual framework, we would expect higher cost credit products to have a larger misalignment between credit risk to the lender and customer unaffordability. The final reasons for focusing on HCSTC is that we have a detailed understanding of consumers and how firms operate in this market from the previous detailed FCA analysis which informed the setting of a price cap. This is especially topical given the Call for Input into how this market has evolved.[34]

Our dataset consists of 7.2 million HCSTC loans and 7.7 million unsuccessful HCSTC loan applications between January 2014 and June 2015.[35] We observe an individual borrower across

[33] Gathergood & Guttman-Kenney (2016)

[34] FCA (2014a, 2014b, 2014c).

[35] These are all HCSTC loans lent by a sample of lenders (who represent the majority of the market) and all unsuccessful applications for HCSTC made to the largest lenders between January 2014 and June 2015.

their use of multiple lenders using CRA identifiers.[36] These data are then matched to the credit files of all individuals identified by CRAs, including measures of credit risk and affordability.[37]

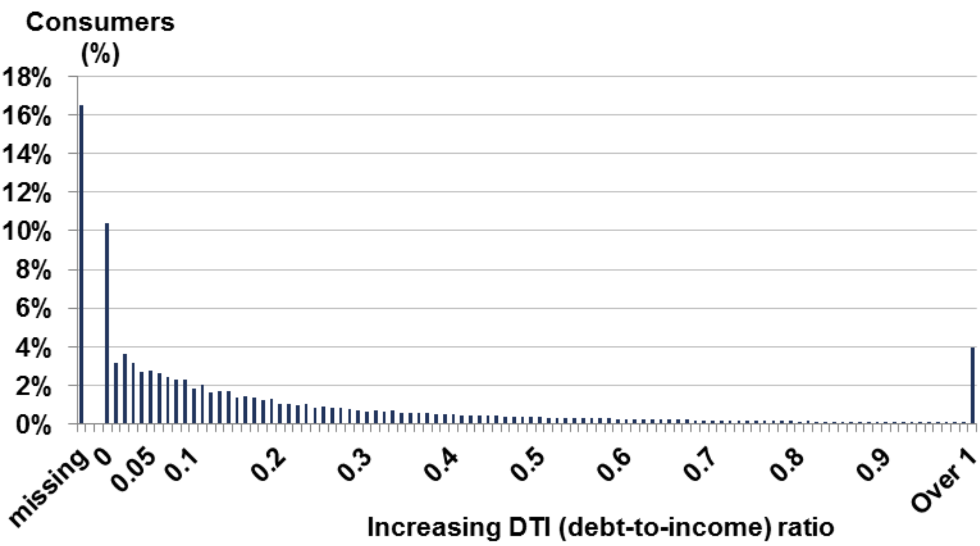
This dataset therefore enables us to observe data potentially available to lenders to use at the time of making creditworthiness assessments, alongside a variety of objective, outcome measures of consumer financial distress firms (and regulators) could observe.

We begin by focusing on the first time in our dataset where a consumer has taken out an HCSTC – a total of 1.3 million individuals (and loans). This approach is used to isolate consumer outcomes relative to a particular HCSTC application and ensure that the results are not driven by a small number of individuals who repeatedly take out a large number of loans.[38]

These individuals typically have total outstanding non-mortgage debts of approximately £4,300 in the month of taking out an HCSTC loan. On average, these debts are increasing over time, from £3,400 12 months before taking out HCSTC to £5,000 12 months after taking HCSTC.[39] The non-mortgage debts of these individuals contain a variety of products – with the majority of balances being in personal loans and revolving credit products (credit or store cards).[40]

On average, before applying for HCSTC, consumers' total outstanding non-mortgage debts are 26% of their estimated annual individual net income calculated from credit file data.[41] The distribution of DTI ratio is shown in Figure 1. It is relatively common for these consumers to have a DTI ratio of 0 (where consumers have no outstanding debts on their credit file) or for the DTI ratio to be missing, indicating a lack of information in credit file data to produce reliable income estimate.

Figure 1: Distribution of consumers by debt-to-income (DTI) ratio



The calculated DTI ratio may be underestimated because not all consumer debts are reported to CRAs. The calculation of the DTI ratio may also be subject to some measurement error, as income is estimated from a combination of application data and monthly data on funds into and

[36] Where we do not observe this, individuals are not included in the analysis, affecting a small percentage of loans.

[37] These data were gathered using the FCA's statutory powers to collect information from lenders and credit reference agencies. See pages 171–174 for description of CRA data:www.fca.org.uk/publication/consultation/cp-14-10-technical-annexes.pdf.

[38] Figure 11 in Annex 1 displays the distribution of individuals across 18 monthly cohorts. Some parts of the analysis drop observations for the latter cohorts, as insufficient time had passed to observe consumer outcomes: e.g. if the outcome is 12 months after HCSTC application, the credit file data finishes in November 2015 and we therefore drop observations from cohorts after November 2014.

[39] Figure 12 in Annex 2 displays the distribution of these debt balances relative to the time HCSTC loan is taken out and split by monthly cohorts.

[40] See Figure 13 in Annex 1 for further details.

[41] DTI ratio is top-coded at a value of 2.

out of personal current accounts. It is expected the general ordering of consumers by DTI ratio is reasonably accurate; however, we treat the precise values of the DTI ratio with some caution.

Consumers using HCSTC are often high credit risks. This can be because they have little or no credit history, or one which is impaired. It is common for consumers applying for HCSTC to have experienced bad credit events (missing one or more payments or being classified as in default) and this is increasingly common over time. On average, 43% of these consumers have missed at least one payment 12 months prior to applying for a HCSTC loan. This increases to 53% and 67% in the month of applying for a HCSTC loan and 12 months after application, respectively.

Other metrics of financial distress based on credit risk events display a similar pattern; for example, the percentage of outstanding debts that are classified as being in default increases from 20% to 25% to 34% over the same period of time. There is a steadily increasing likelihood of these consumers exceeding their overdraft limit – rising from 16% to 19% to 25% in the 12 months before, at and 12 months after application, respectively.

Is high credit risk the same as unaffordability?

Previous research found that the DTI ratio is a strong predictor of future financial distress in survey data, and this will be the metric that we evaluate for use in a possible assessment.[42] If credit risk is highly correlated with the DTI ratio, it may be that a lender's assessment of credit risk can function as part of an affordability assessment. Even if this were the case, however, there may still be a mismatch between the level of credit risk that is profitable for a firm to lend at and the level which puts the credit applicant at high risk of financial distress. If there is little correlation between credit risk and the DTI ratio, it suggests a role for an assessment that examines customer affordability separately to the credit risk assessment.[43] Therefore, using data to examining these concepts is important for considering the potential structure of creditworthiness assessments.

We examine this in our data by looking at the correlation between credit risk scores used predicting the likelihood of repaying an HCSTC loan, an overall credit risk score reflecting the likelihood of consumer repaying debts, and the DTI ratio.[44] As displayed in Table 1, we find little correlation between credit risk measures and the DTI ratio.[45] An alternative measure of affordability, the ratio of debt payments to income, known as the debt servicing ratio or DSR, is highly correlated to the DTI ratio.[46] It is clear that credit risk ranks individuals differently to the DTI ratio, which indicates a potential role for an affordability assessment considering both credit risk and the DTI ratio.

Table 1: Unconditional correlations between DTI ratio and credit risk

All non-missing values	DTI ratio	Overall credit risk	Credit risk of repaying HCSTC loan
DTI ratio	1		
Overall credit risk	0.1	1	
Credit risk of repaying HCSTC loan	-0.1	0.3	1

[42] Gathergood & Guttman-Kenney (2016).

[43] If this occurs, the DTI ratio may still be an input into credit risk scores but it may have limited predictive power.

[44] These measures are constructed only using data before the date of the loan application. We do not observe income before the time of application for all individuals which is required to construct a DTI ratio. Some individuals also do not have a credit risk score. Where these data are missing, we drop observations from these correlations.

[45] Results robust to using quantiles of the DTI ratio to account for potential measurement error in the exact DTI ratio.

[46] By construction, a higher DTI ratio shows a higher strain of debt relative to ability to repay. A higher DSR may not necessarily show this because revolving credit items do not have a fixed monthly repayment amount and it is common for consumers to pay more than their contractual minimum. This means that a higher DSR can give the impression someone is more credit constrained than they actually are (having voluntarily made higher payments).

How does financial distress vary with credit risk and the DTI ratio?

Given that credit risk scores and the DTI ratio rank individuals differently, we now consider how observable measures of financial distress from credit file data vary with these variables. One possibility is that consumers who suffer financial distress are mainly high credit risk. Another possibility is that is consumers who have both a high credit risk and high DTI ratio, or that it is mainly those with high DTI ratios, regardless of their credit risk, who suffer financial distress. Each of these possibilities has different implications for how lenders evaluate which individuals applying for credit face high predictable risk of financial distress, and therefore decline their applications. For example, if financial distress only varies by the DTI ratio it could indicate credit risk is unnecessary when considering the ability of consider whether lending is affordable for an individual credit applicant.

To examine how the relationship between credit risk and DTI ratio relates to overall consumer outcomes, we construct buckets of 20 quantiles of a credit risk score (CR) of the likelihood of repaying an HCSTC loan: bucket 1 is the lowest credit risk and bucket 20 the highest credit risk.[47] We also construct 20 buckets of the DTI ratio: bucket 1 consists of individuals without a DTI ratio, bucket 2 is individuals with a DTI ratio of 0, and the remaining buckets 3 to 20 are quantiles of increasing DTI ratio. The DTI ratio is missing when income data are not observed in credit file data before the time of an HCSTC loan application. The values of CR and DTI are both constructed using data before the time of the HCSTC loan application to reflect how lending decisions have to be taken based on information available to lenders at the time.

Twenty buckets are chosen in order to ensure that each bucket has a reasonable number of observations and to reduce the potential for over-interpreting differences in results between buckets, which may be driven by small sample size or measurement error in the DTI ratio. Table 2 displays the minimum and maximum values of DTI ratio in each of these buckets.

All individuals in our data are allocated to a bucket of CR and DTI, resulting in one of 400 potential CR–DTI bucket combinations.[48] The distribution of individuals across CR–DTI buckets is fairly even with a few exceptions highlighted here: 2.7% of individuals have a missing DTI ratio (DTI bucket 1) and have the default credit risk score assigned to an individual if no positive or negative information is observed in credit files about that person (which is contained within CR group 11); 16.5% of individuals do not have a DTI ratio (DTI bucket 1); and a further 10.4% have no debts recorded and therefore have a DTI ratio of 0 (DTI bucket 2). The smallest CR–DTI bucket combination contains 1,100 individuals, whereas the largest contains over 36,300 individuals.

[47] The number of individuals in each CR bucket is slightly uneven - ranging from 4.7%-5.8% in each bucket - as credit risk score takes integer values and therefore is not a continuous variable. Individuals without credit files are assigned to a default starting value of credit score (e.g. scores typically assign new individuals to the middle of the distribution and move them up or down based on positive or negative information about that individual's credit risk).

[48] Figure 14 in Annex 2 displays the distribution of individuals across these bucket combinations. Buckets of CR and DTI are purposefully created independently given that we are seeking to understand how these variables interact – by contrast if we were constructing buckets to use as sampling weights it would make sense to construct these buckets jointly.

Table 2: DTI Buckets

Bucket number	Minimum DTI in bucket	Bucket number	Minimum DTI in bucket
1	Missing	11	14%
2	0%	12	17%
3	1%	13	20%
4	2%	14	24%
5	3%	15	28%
6	5%	16	34%
7	6%	17	42%
8	8%	18	53%
9	10%	19	69%
10	12%	20	98%

Having allocated each individual to a CR–DTI bucket combination, we now examine the relationship between these buckets and the prevalence of measures of consumer financial distress. Unlike in FCA Occasional Paper No. 20, we do not observe subjective, self-reported measures of financial distress; however, we observe a richer set of objective measures of financial distress.[49] A variety of objective measures of financial distress are constructed from credit file data examining consumer outcomes at different points in time after using HCSTC (defined in Annex 2, Table 4). Credit file data show the details of a consumer's current and past debts including whether they repaid their debts late.

These objective financial distress measures are chosen as they are potentially available to lenders (and regulators) and reflect a mixture of financial distress in themselves and longer-term financial distress through negatively impacting an individual's ability to access credit in the future (through not being able to access credit at all or only at higher prices). Some constructed measures of financial distress reflect individuals experiencing payment difficulties such as missing one or more payments on any of their outstanding debts.[50] Other measures of financial distress reflect individuals' cash flows being under strain such as exceeding the limit on their personal current account and using an unarranged overdraft. It is important to emphasise that these are descriptive statistics showing the incidence of financial distress in different CR–DTI bucket combinations without controlling for other factors and should not be interpreted as CR–DTI bucket combinations (or HCSTC use) causing financial distress.

The first measure of financial distress we examine is whether an individual missed one or more payments on any item in their credit file six months after taking out HCSTC. Figure 2 plots the proportion of consumers in each of the CR–DTI bucket combination who exhibit this measure of financial distress. The proportion of consumers in a CR–DTI bucket combination who have missed one or more payment on any item in their credit file six months after applying for HCSTC varies from 17% to 99%.

If the credit risk score and the DTI ratio were targeting the same financial distress, Figure 3 would be an even plane with the prevalence of bad consumer outcomes for a given credit risk score bucket being the same for different DTI ratios (and increasing by CR). This is not the case – financial distress, by this measure, varies by both credit risk and the DTI ratio. For example,

[49] Gathergood & Guttman-Kenney (2016).

[50] Note that when credit items are repaid by direct debit then payments are only missed if there are insufficient funds in a current account to meet this payment. Such factors are at the extreme end of financial distress. For such individuals this measure can therefore potentially miss early signs of financial distress where an individual has sufficient funds in their current account to meet a credit payment but results in financial difficulties meeting other expenditures. By contrast, when we observe individuals without a direct debit missing a credit payment it may simply reflect the individual forgetting to make a payment as opposed to being unable to do – this explanation is less likely to be the reason if an individual misses multiple payments.

within the highest DTI bucket, the proportion of consumers who have missed one or more payments on any item in their credit file six months after applying for HCSTC increases from 53% to 99% as the CR bucket increases.

Figure 2: Proportion of consumers experiencing any bad credit events six months after HCSTC loan, by CR-DTI buckets

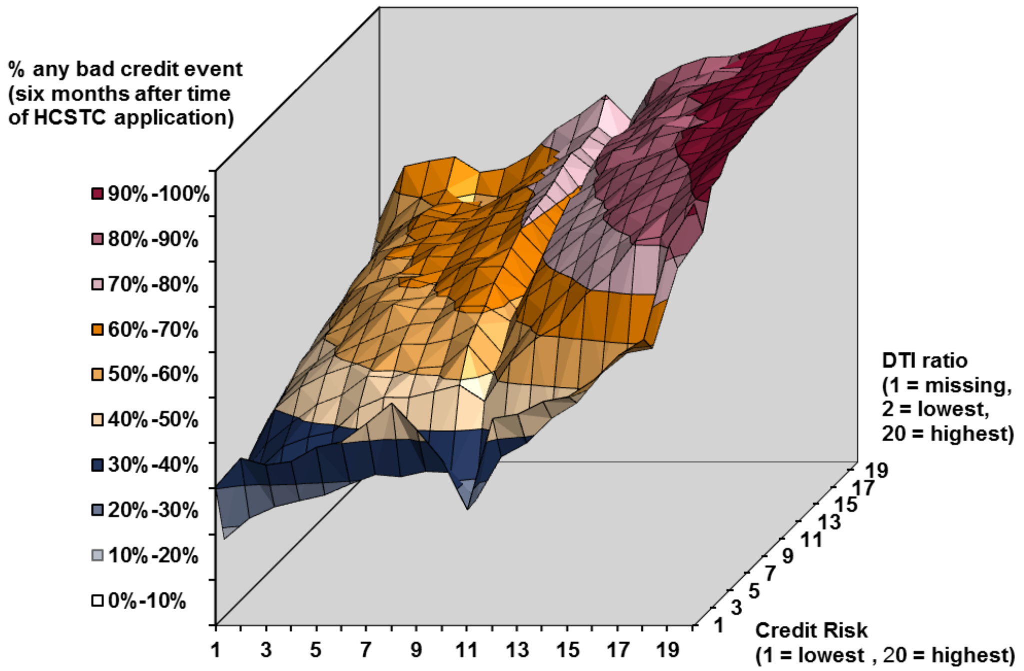


Figure 3 and Figure 4 display similar findings using alternative measures of financial distress: the proportion of an individual's total debt balances in default and the proportion exceeding their personal current account limit six months after taking out HCSTC, respectively. By both these measures, the incidence of financial distress is higher among consumers in buckets of higher credit risk (lower credit score) or DTI ratio.

Some measures of financial distress, such as whether an individual is over their credit card limit (Figure 5), vary little by credit risk score, but do vary a lot by the DTI ratio. Across a variety of measures, the prevalence of financial distress rises when examining consumer outcomes at longer time horizons, such as 12 months rather than six months after HCSTC borrowing, reflecting how consumers using HCSTC typically have a general worsening financial situation over time.

In the context of our conceptual framework, this is evidence that unaffordability is more than just credit risk. The prevalence of financial distress varies independently by both credit risk and DTI ratio. There appears to be independent effects between these two factors: consumers who are either a high credit risk or have a high DTI ratio are at elevated risk of financial distress compared to other consumers. When we order consumers by credit risk and the DTI ratio we find that the prevalence of financial distress after using HCSTC is not random. Instead it appears to increase in a logical direction (higher credit risk, higher DTI ratio) which could be predicted. It therefore appears possible to isolate consumers who are at high risk of suffering financial distress as part of a creditworthiness assessment.

Figure 3: Percentage of consumers' debt balances in default six months after HCSTC loan, by CR-DTI buckets

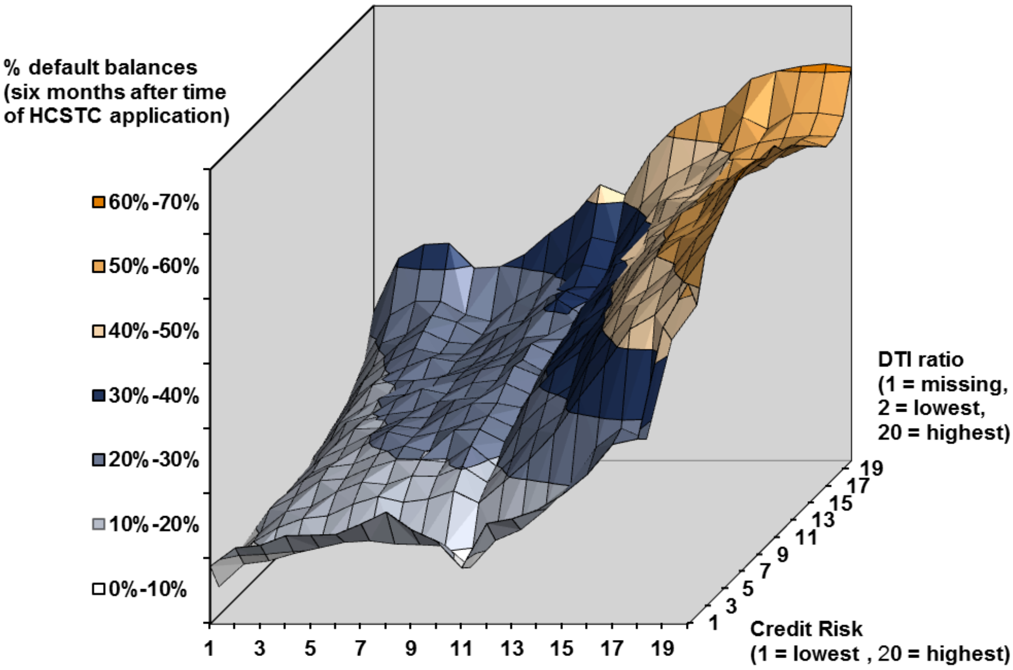


Figure 4: Proportion of consumers over personal current account (PCA) borrowing limit six months after HCSTC loan, by CR-DTI buckets

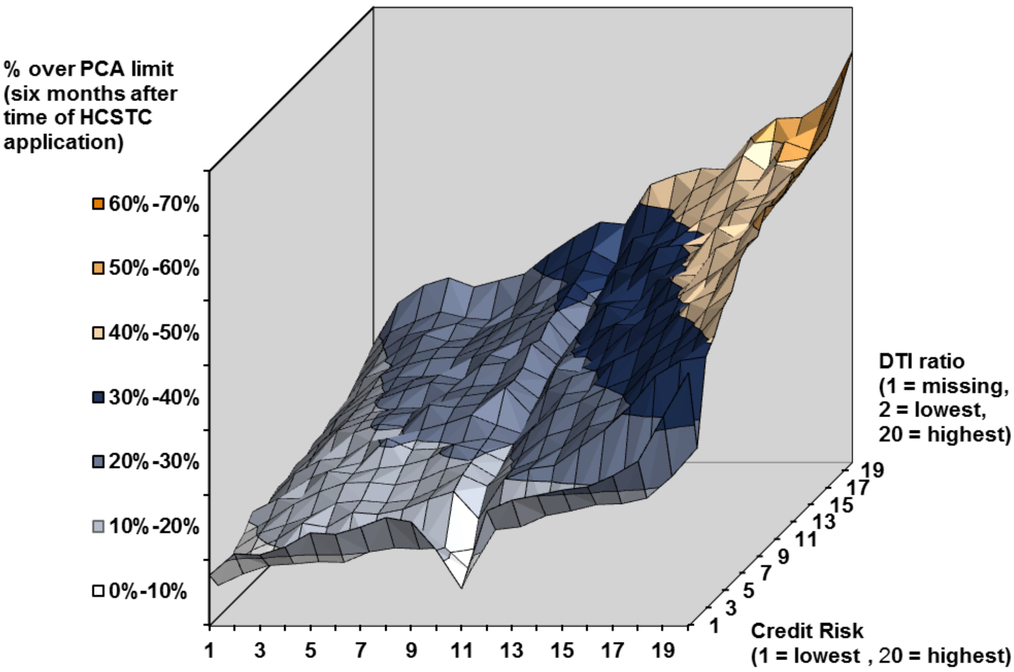
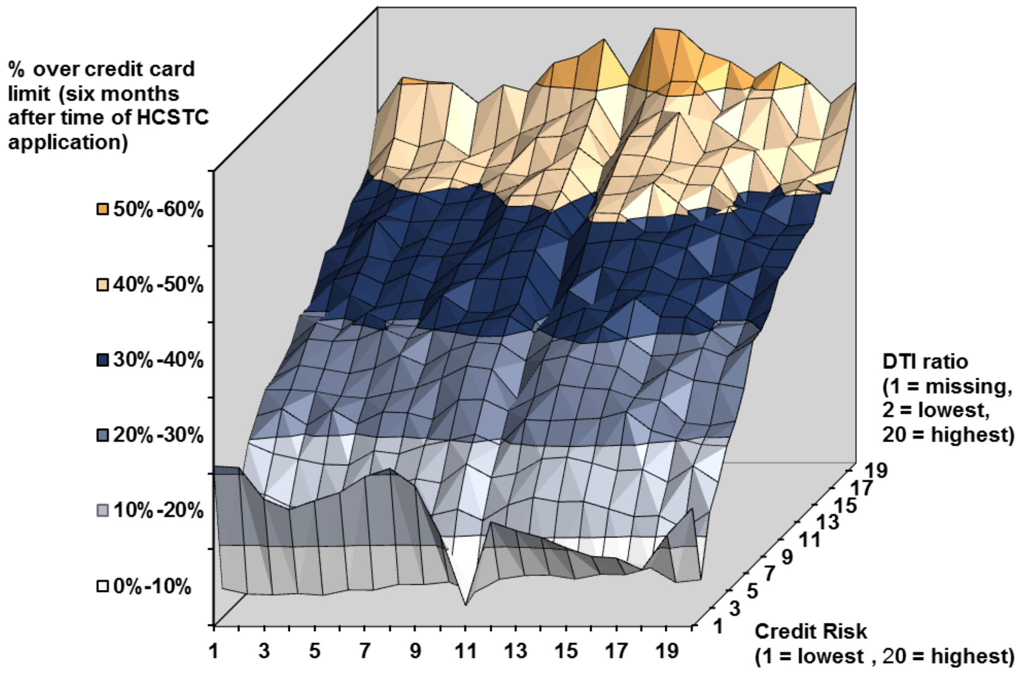


Figure 5: Proportion of consumers over credit card borrowing limit six months after HCSTC loan, by CR-DTI buckets



Predicting high risk of financial distress

It is possible that, despite the relationship between credit risk, the DTI ratio and measures of financial distress, the DTI ratio offers no improvement in the ability to statistically predict financial distress beyond a prediction model which uses credit risk scores and not the DTI ratio. If this were the case, it may imply that only credit risk alone is sufficient for isolating consumers facing a high risk of financial distress.

In order to evaluate this aspect, we use a logistic regression-based approach starting with a basic predictive modelling approach (Annex 3 contains further detail for the regression specifications). This uses the same CR–DTI buckets as previously used – constructed before the time HCSTC loan was taken out – as inputs to potentially predict the likelihood of an individual suffering financial distress (using a variety of measures) in the future.[51]

The result of this is that consumers in higher credit risk buckets are statistically significantly much more likely to be in financial distress in the future. After accounting for credit risk, the buckets of DTI ratio independently have additional statistically significant power at identifying the consumers who are more likely to suffer future financial distress. Consumers with higher credit risks or DTI ratios are predictably more likely to be in financial distress in the future. Credit risk strongly predicts financial distress – especially those in the two highest risk buckets. This logistic regression approach has a reasonable predictive power.[52]

There is a noticeable tipping point in the DTI ratio with consumers who are in the highest DTI bucket – whose outstanding debts are at least 97% of their annual individual net income – having a much higher risk of suffering financial distress in the future than consumers in other DTI buckets. An example of this relationship is shown in Figure 6, which displays the results of this regression for buckets of credit risk, and Figure 7 for buckets of DTI for the same regression where the outcome is experiencing any bad credit event six months after an HCSTC loan application. The results are displayed in odds ratios (an expression commonly used to explain

[51] See Equation 1 in Annex 3 for regression specification.

[52] Pseudo R-squared of 0.19.

relative likelihoods in betting markets) – a value of 1 indicates no more or less likely ('even' odds) and a value above 1 indicates an event is more likely. For example, a value of 2 indicates that by being in that bucket, an individual is twice as likely to suffer financial distress than other individuals (after controlling for other factors). In these and subsequent graphs the blue dots are the odds ratios and vertical lines display confidence intervals within which the odd ratios would be expected to be 95% of the time if the analysis was repeated multiple times. For example, in Figure 7 the blue dot on bucket 20 displays that, compared to an individual in the bottom bucket of DTI (bucket 1 with a DTI ratio of zero), an individual in the top bucket (20) of DTI is just over eight times more likely to suffer a bad credit event six months after taking out HCSTC after controlling for credit risk.

Figure 6: Odds ratios of suffering any bad credit event six months after taking out HCSTC by CR buckets (logistic predictive model)

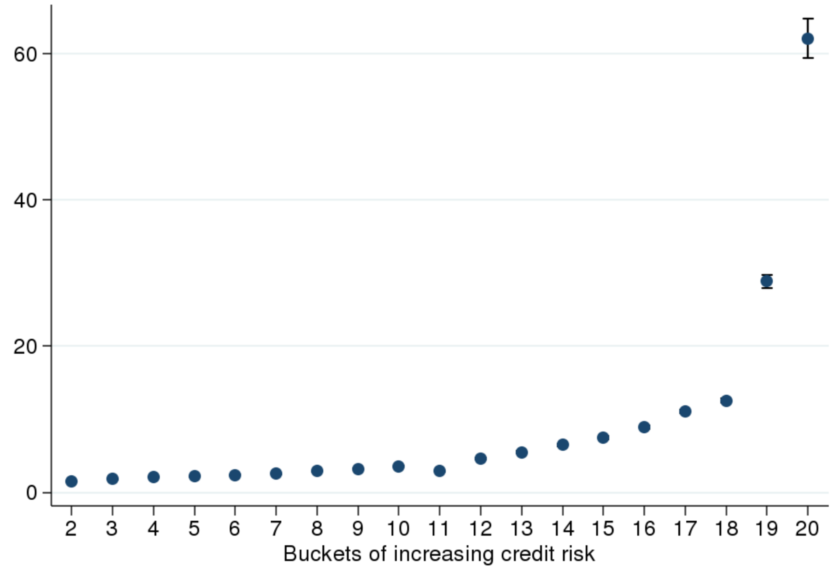
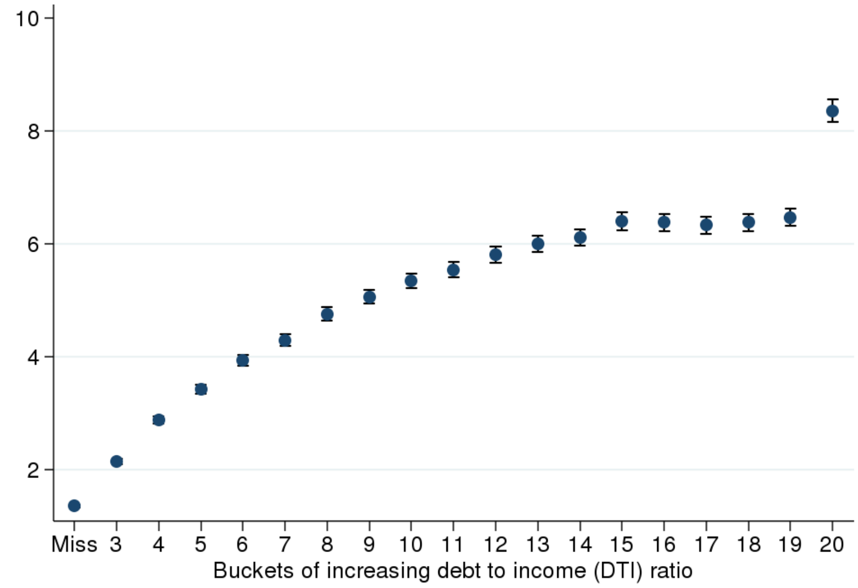


Figure 7: Odds ratios of suffering any bad credit event six months after taking out HCSTC by DTI buckets (logistic predictive model)



Using whether an individual went seven (or 30) days or more into arrears on their HCSTC loan as an outcome measure does not show this pattern of results – consumers in some higher DTI buckets are actually more likely to repay their HCSTC loan than some consumers with lower DTIs.[53] This finding indicates that the metrics lenders are targeting from a credit risk perspective can differ to those which affect overall customer affordability.

The predictive model used for the above results is parsimonious and, as such, it is possible that other variables which are not included could highly correlate with DTI, explaining the ability of DTI to predict financial distress. We therefore include a variety of additional variables to examine whether these initial results are robust to controls.[54] As measures of financial distress are highly path dependent – if a consumer is in default today, it is very likely they will remain so in the next month – we include variables for values of whether the individual was in financial distress in each of the 12 months before taking out HCTSC. Given our sample comes from a variety of points in time, we also include controls for the cohort month a customer is from to account for potential seasonality in our data.

The findings from this model with additional variables remain the same as previously found. The model with controls is better at predicting financial distress – primarily because being in financial distress at the time of applying for a loan is a strong predictor of being in financial distress in the future.[55] Including whether an individual was in financial distress in each of the 12 months before taking out HCSTC reduces the explanatory power of the credit risk buckets elements, as can be seen by comparing the results in Figure 8 from those shown previously in Figure 6. Compared to the earlier results, the odds ratios in from DTI buckets in Figure 9 barely change with the addition of these controls to those displayed from the simpler model shown in Figure 7.

The key findings are that an individual is at higher predicted risk of suffering future financial distress if, at the time of making a credit application, they are already in financial distress, have a high credit risk score, or high DTI ratio (especially if they have a DTI ratio close to or above 1). Inevitably, not all financial distress can be predicted based on information at the time of making a lending decision and therefore some individuals may end up experiencing unexpected financial distress. These results are robust to a variety of measures of financial distress and regression specifications.[56] Unsurprisingly, the ability to predict financial distress is highest for outcomes at shorter time horizons of a few months since HCSTC application and decreases as the outcome duration extends.[57]

[53] See ***Figure 17*** and ***Figure 18*** in Annex 3.

[54] See Equation 2 in Annex 3 for regression specification.

[55] These additional controls increase the predictive power of the model to a pseudo R-squared of 0.40.

[56] Results are robust to alternative regression specifications (OLS and probit). Using a larger number of buckets of credit risk and DTI results in the same pattern of coefficient estimates, however, the standard errors become larger as the number of observations in each bucket decreases. Including additional interactions between CR–DTI buckets do not alter the key conclusions.

[57] For example, the pseudo R-squared decreases from 0.61 to 0.32 when predicting the likelihood of the individual experiencing any bad credit event in the month after taking out HCSTC to 12 months after this time.

Figure 8: Odds ratios of suffering any bad credit event six months after taking out HCSTC by CR buckets (logistic predictive model with additional controls)

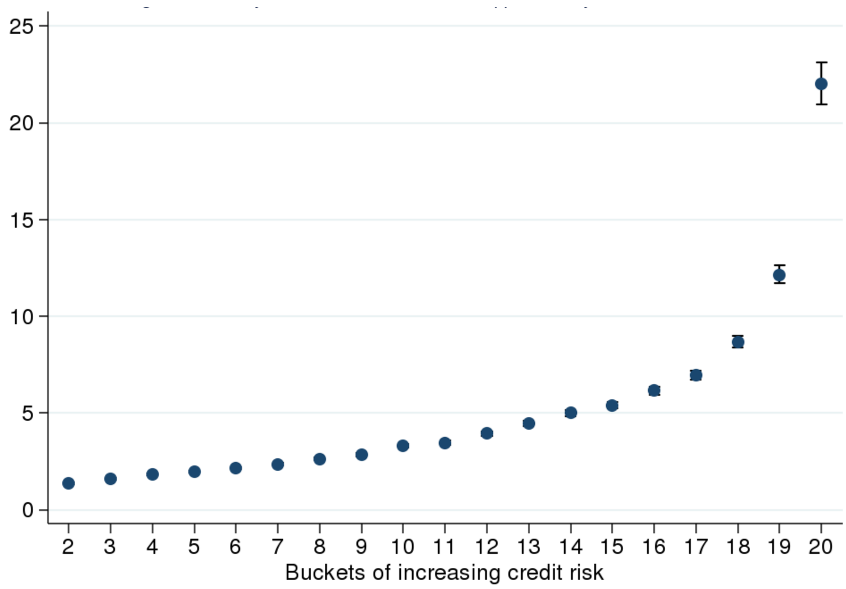
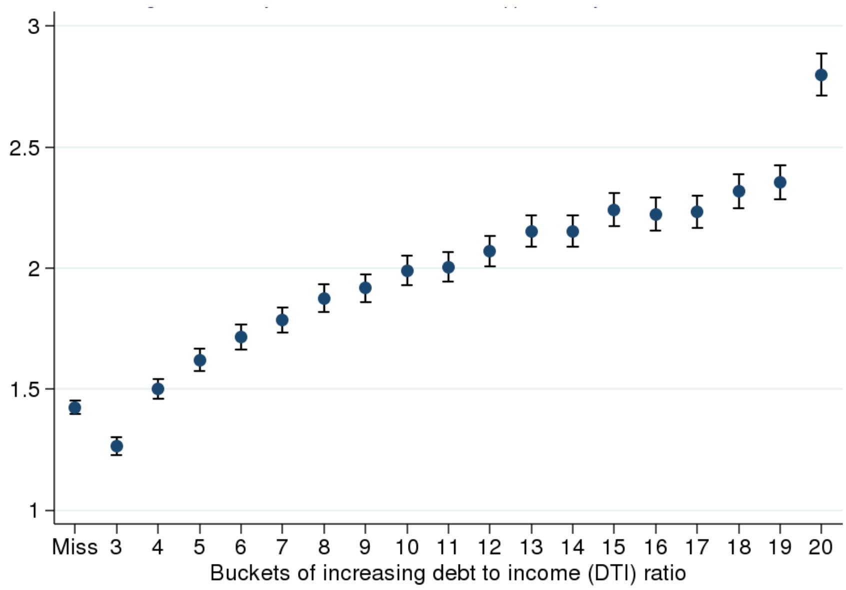


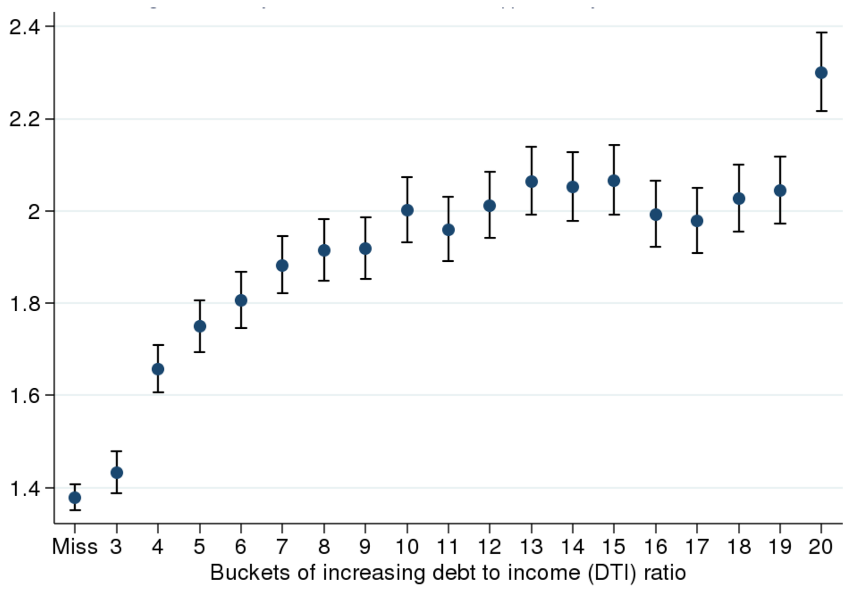
Figure 9: Odds ratios of suffering any bad credit event six months after taking out HCSTC by DTI buckets (logistic predictive model with additional controls)



Given that once consumers are experiencing financial distress, it is relatively common for them to remain in this situation, a group of individuals who are of particular interest are those who are not in observable financial distress at the time of a credit application but suffer financial distress at a later date. Are we able to predict which of these individuals are likely to suffer distress? To do so, we focus only on consumers who are not in financial distress in the month preceding their HCSTC loan application and examine the predictability of entering financial distress in the future.

This approach reduces the sample size of observations and, unsurprisingly, also reduces the predictive power of our model.[58] For this group of consumers we do not find a steadily, consistently increasing relationship between financial distress and DTI found in previous results. However, as displayed in Figure 10, DTI buckets remain statistically significant predictors of future financial distress with a clear non-linearity in the top DTI bucket showing an elevated, predictable risk of future financial distress (as found in earlier results). It should be noted that our data cover a couple of years and therefore the nature of this relationship may change over the course of the economic cycle as incomes change.

Figure 10: Odds ratios of suffering any bad credit event six months after taking out HCSTC by DTI buckets for consumers not suffering bad credit event in month preceeding HCSTC loan taken out (equation 2 logistic regression)



Changing predictable risk as a result of credit applications being granted

Now that we have established the factors that predict the likelihood of suffering financial distress, how does the decision to approve an HCSTC loan application affect the risk of consumers facing financial distress? As consumers using HCSTC are typically facing an increase in financial distress over time, it may be that this is the path their finances are on irrespective of whether an HCSTC loan application is approved – especially as an HCSTC loan is typically a small proportion of consumers' debts.[59]

One reason for individuals using credit, such as HCSTC, is to manage sudden unexpected changes to their incomes or expenditures. If this is the reason for borrowing, it is possible that consumers with the highest risk of detriment are also those for whom the benefits of borrowing are expected to be the greatest. Prior research of HCSTC does not appear to show this as consumers who are denied credit did not appear to be any worse off as measured by self-reported measures of well-being (and worse-off by other measures) than a comparable group of consumers granted credit.[60]

[58] Regression specification is the same as the model with controls used previously, but on a sample of individuals not in financial distress a month before taking out HCTSC. Pseudo R squared reduces to 0.06.

[59] See 'data description' at start of this chapter and Figure 13 in Annex 1 for further details.

[60] Technical annex 3 in FCA (2014b)

It is possible that using HCSTC alleviates a temporary cash flow shortfall among some financially distressed consumers and therefore be beneficial at reducing the risk of individuals suffering increasing financial distress now or in the future. However, it is also possible that, for some consumers, the cost of repaying this debt puts too much of a burden on their already strained financial situation and contributes to making it worse.[61]

We attempted to analyse this issue using a methodology called Regression Discontinuity Design (RDD), which exploits variations in lender creditworthiness assessments over time to analyse the causal effects of borrowing among a variety of consumers denied borrowing under different types of assessments.[62] This method requires confidence in the precise reason for consumers being declined loans and stability in the proportion of individuals accepted day-to-day (or week-to-week) when a creditworthiness assessment process is unchanged. Unfortunately, these criteria were not met in this case, with large fluctuations in daily acceptance rates and data issues meaning we were insufficiently confident in the reasons for consumers being denied loans.

Therefore, we take an alternative approach using a 'Difference-in-Difference' methodology including unsuccessful HCSTC loan applications alongside successful loan applications. We use the same model as in the previous section and take one observation per individual based on the first HCSTC application or loan transaction present in our data.[63] This provides us with a mix of 2.4 million individual consumers who did and did not use HCSTC at the time of this observation. We include an additional variable to measure how taking out an HCSTC loan affects the likelihood of suffering financial distress.[64] This does not show the causal effects of taking out HCSTC on consumer welfare unless strong assumptions are taken. However, we take the less strong assumption that, on average, for people at high risk of suffering financial distress taking out more debt is unlikely to be welfare improving given prior research findings.[65]

Our findings including unsuccessful applicants are consistent with earlier analysis of successful applicants. Consumers in higher CR or higher DTI buckets are at increased risk of suffering financial distress (using a variety of measures) and those in the top DTI bucket are at noticeably increased risk. We find, on average, taking out an HCSTC loan makes little difference to the predictable risk of financial distress in the future. If anything, the consumers who take out HCTSC have a very slight decrease in the likelihood of missing repayments on non-HCSTC loans in future months compared to consumers who were denied HCSTC.

Given the odds ratio on HCSTC loan use being close to 1 (even odds), it remains possible that the difference we observe is affected by other ways in which unsuccessful and successful HCSTC applicants differ from one another (as a result of the credit granting process not being a random process) and not captured in our predictive model (despite controlling for factors).

[61] As found in previous FCA research (see technical annex 3 in FCA, 2014b, as well as FCA, 2014a; 2014c); Morse (2016) discusses this topic in the context of the US payday lending market.

[62] This analysis is explained more in Annex 3. See pages 180–184 in FCA (2014b) for a summary of the RDD methodology.

[63] See Equation 3 in Annex 3 for regression specification.

[64] As individuals may have an application declined but take out an HCSTC loan at a later date from the same or other lenders in the market, we use whether the individual took out an HCSTC loan from any lender within the next 30 or up to 180 days of this loan application.

[65] In particular, causal evidence from FCA(2014b) and non-causal evidence of Gathergood & Guttman-Kenney (2016)

Table 3: Odds ratios of taking out HCSTC on liklihood of suffering bad credit event on non-HCSTC products six months after HCSTC application (logistic regression with additional controls for HCSTC applications)

	(1) **Any bad credit event on non-HCSTC products six months after HCSTC application**	**(2)** **Any bad credit event on non-HCSTC products six months after HCSTC application**
Took out HCSTC loan anywhere within 30 days of application	0.867*** (0.00381)	
Took out HCSTC loan anywhere within 180 days of application		0.903*** (0.00406)
N	2,185,073	2,185,073
Pseudo-R squared	0.46	0.46

4 Evaluation of data used in creditworthiness assessments

Introduction

CRA data are often the fundamental input lenders use when assessing credit risk as part of a creditworthiness assessments as it helps lenders to solve a classic informational asymmetry between credit applicants and lenders. There is also evidence that lenders are increasingly using CRA data for their affordability assessments, following the introduction of a variety of new product offerings over the last few years.

Given the importance of these data to lending decisions and the informational asymmetries present in lending, this chapter evaluates CRA data, as well as other sources available to lenders and their limitations.

Market innovations

One area where CRAs are regarded as adding substantial value is the identification of credit applicants in order to verify whether the applicant appears to be a real person (as opposed to a fraudulent application) and, if so, to match them to the correct credit file. This can be a difficult task as the same individual may use different versions of their name or address, and these can change over time. While the matching process is unlikely to be 100% accurate, it is strongly in the incentives of the lender and CRAs to accurately identify whether an individual is a real person or if the application is fraudulent and isolate the correct credit file.

CRAs have also innovated by bringing new products and data sources to the market. Monthly current account turnover data are now regularly being shared via CRA products, assisting lenders to verify income. Credit files increasingly record information on mobile phone, utility and telecommunication payments, which particularly helps to thicken the credit files of younger borrowers.[66] CRAs have also developed products, such as credit risk scores and indebtedness indicators, and real-time data sharing solutions in the HCSTC area.

However, there are other potential data sources currently not shared via CRAs, or where data sharing is limited. For example, CRA data have good coverage of mortgage payments but not rental payments (although there are innovations to try to address this). Additionally, non-bank lenders do not have access to transaction-level personal current account data. This means that they cannot use such transaction data to verify the level and stability of income or obtain more granular detail regarding an individual’s cash assets, daily arranged and unarranged overdraft use, rental payments and other expenditure.

Open-source application programming interfaces (APIs) in banking are expected to help enable sharing of transaction-level personal current account data and similarly detailed data on other financial products. In turn, this is expected to facilitate innovation in financial services more broadly and competition in banking. However, open APIs rely upon an individual sharing details of their accounts and therefore may be subject to ‘adverse selection’ – whereby individuals do not share details of accounts that they believe could harm their ability to access credit.

[66] Such alternative data sources are not contained in credit files in other countries, for example, the United States https://www.consumerfinance.gov/about-us/blog/using-alternative-data-evaluate-creditworthiness/

Debt coverage

Consumer credit lenders – with the exception of large home collected credit (HCC) providers - are not required to report credit agreements or other data to a CRA.[67] However, many lenders still choose to do so, as lenders have a shared incentive to use and reciprocate information. The value of CRA data in improving the accuracy and discriminatory power of credit risk assessments means that it is very rare for lenders not to use data held by at least one CRA as part of their creditworthiness assessments.[68] CRAs only allow lenders that report their own data (of the same kind) to access CRA data.[69] The purpose of this reciprocity is to ensure that there is no 'free-riding' by individual firms and that there are incentives for firms to contribute to the common goal of more accurate data about individuals. More accurate data assists all firms in making more accurate assessments and monitoring the exposures of their lending portfolio.

In the UK, there are three large CRAs – Callcredit, Equifax and Experian – in addition to niche providers with specialities in different markets.

Firms are not required to share data with all of these CRAs unless they want to use data from each of them. CRAs do not share data reported with each other. While retail banks (and other large firms) typically share data with all three CRAs, smaller lenders may only report to one or two CRAs. This means that each CRA has an incomplete picture of an individual's total debts. While many lenders report to multiple CRAs, they may not use data from multiple CRAs for their assessments but instead have one CRA as a 'backup' provider in case of infrastructure problems.

Incomplete coverage means using data from a single CRA can understate current debt levels and repayments, as well as miss historical data relevant to an individual's ability to repay their debts. Note that using data from a single CRA cannot overstate a consumer's debt levels (unless there are data errors). Even if lenders collected data from all three CRAs – which would increase the costs of credit assessments – firms may not have access to the granularity of data required to accurately de-duplicate credit items reported to multiple CRAs in order to assess actual debts.

Given the importance of CRA data as inputs to credit risk scoring models, such incomplete coverage may reduce the efficiency of credit scoring, increase the cost of credit, and contribute to both unduly restrictive lending and unaffordable lending. Differences in coverage are likely to be greatest for higher credit risk consumers who use less mainstream consumer credit products across multiple providers.

To explore this issue, we examined the credit files of the same individuals from two CRAs.[70] We compared 1.2 million individuals who had taken out an HCSTC loan between January 2014 and June 2015 and examined their credit file debts in July 2015 based on data collected at the end of 2015.[71] The differences observed are substantial: between the two CRAs, there is a difference of 24% or £1.6bn in total outstanding non-mortgage debts for these individuals. The differences in the median debts are similarly large at £1,200 per consumer, indicating that the aggregate result is not merely driven by outliers. Similar differences are observed for the numbers of products – there is a difference of 21%, or 1.6 million credit items, in the total number of active non-mortgage and non-HCSTC credit items appearing on different credit files. While the exact figures vary when

[67] Any home credit lender with over 60 agents or £2 million in annual home credit-related turnover is required to report debts at least two CRAs under the Competition Commission's Home Credit Market Investigation Orders.

www.gov.uk/government/publications/home-credit-market-investigation-orders.

[68] While we refer to 'CRA data', these firms are the custodians of lender or customer data. The term 'discrimination' is used in the statistical sense – effectively separating credit applicants into groups who are or are not likely to default.

[69] The Steering Committee on Reciprocity (SCOR), a cross-industry forum made up of representatives from credit industry trade associations, credit industry bodies and CRAs, administers and develops the Principles of Reciprocity, which set out the administration and development of data sharing agreements: www.scoronline.co.uk.

[70] While the same information was used to collect data from CRAs on these individuals, we cannot be 100% certain that the credit files provided were for the same individuals.We are reasonably confident in the ability of CRAs to identify the correct individual in their databases, but providing a report on the incorrect invididual could be another source of inaccuracy.

[71] These individuals were those who were matched to one profile between the two CRA datasets. This sub-sample was selected to try to ensure comparison of data coverage of the same individuals, rather than being driven by individuals being matched to the incorrect credit files. July 2015 was chosen in order to ensure this comparison is of coverage, rather than picking up the effects which could be due to reporting lags rather than data coverage. We focused on individuals who were granted loans as these were less likely to be fraudulent applications and therefore have higher quality application data to be able to match the individual to their correct credit file.

examining different historic points in time, the differences remain substantial. It should be noted that we would expect such differences to be smaller (or non-existent) for prime customers as such individuals are likely to only borrow from large banks who report to all three CRAs. In our data, for example, we found little difference in the number of first mortgages reported to different CRAs (although holding a mortgage is relatively rare among the consumers we observe).

Different lenders reporting to different CRAs is at least part of the explanation for the observed differences in the number and value of credit products. There are two other hypotheses for the differences which are more difficult to evaluate. One hypothesis is that some of the differences are the result of errors in the data that lenders are submitting to one or more of the CRAs.[72] Each CRA does not observe the data a lender reports to other CRAs in order to be able to evaluate this. Another hypothesis is that some of the differences are the result of CRAs matching credit products held to the incorrect individual. This is difficult to evaluate without showing consumers their credit files and asking them directly if they are correct. We expect it to be harder to identify the correct credit file for new borrowers – especially if they are moving addresses but not updating all of their credit obligations of these details.[73] Under these hypotheses, the amount of debt observed by each CRA could either be higher or lower than the true amount. In the USA in 2013, it was estimated that five percent of consumers had errors on at least one of their three credit reports (for a variety of reasons).[74] In the UK, the Information Commissioner's Office (ICO) carried out a review in 2014 and concluded that each of the three CRAs had robust controls in place to mitigate the risk of data not being accurate.[75]

Some credit accounts – known as unconsented files – do not appear on CRA credit records. This is because these accounts were not allowed to be reported without the individual consumer's consent. This is a historical issue applying to old accounts (often bank or credit card accounts opened before the late 1990s).

Timeliness of data

We also examined the timeliness of CRA data. Current reporting arrangements can mean that the data that lenders are using for creditworthiness assessments and monitoring their lending portfolio are one or two months out of date.

When a lender approves an individual's application for credit, it is not typically reported straight away. The credit application search data are updated in real time, but do not show whether the search led to a credit product being taken out (at all or the details of that agreement). Lenders typically report new credit items after the individual has been due to make their first payment, or when they are doing a batch update for their lending portfolio. As a consequence, any subsequent credit assessments that occur between the time of credit approval and lender reporting would not have information about this new obligation.

Similar reporting lags occur for updating existing debts. Because lenders may report once every month at different points in the month, it can take one to two months until debts from all lenders are updated. When estimating the total debts of an individual borrower, this time lag matters less for loan products that follow a set amortisation schedule than revolving credit products where individual borrowing and repayment patterns are more unpredictable. Irrespective of credit

[72] If the error is submitted to all CRAs then it would not show up at all by comparing data held by different CRAs

[73] Unlike opening ISAs, there is no tax reason for individuals to submit a national insurance number when submitting a credit application - doing so may improve the accurately of matching individuals in some cases. In the USA, social security numbers are typically reported on credit applications, however, similar issues are reported to exist.

[74] Federal Trade Commission (2013)

https://www.ftc.gov/news-events/press-releases/2013/02/ftc-study-five-percent-consumers-had-errors-their-credit-reports

U.S. PIRG (2013)

http://www.uspirgedfund.org/news/usf/new-report-analyzes-complaints-about-credit-bureaus

U.S. PIRG (1998)

http://www.uspirg.org/reports/usp/mistakes-do-happen-1998

[75] ICO (2014)

https://ico.org.uk/media/action-weve-taken/audits-and-advisory-visits/1042574/outcomes-report-credit-reference-agencies.pdf product, this difference is likely to matter from the perspective of arrears and default data. These reporting lags may mean lenders do not observe recent changes, such as an individual going into the early stages of arrears (or recovering from more severe arrears). In the credit file data we collected at the end of 2015, we observe noticeably lower coverage of debts at the end of our dataset, which is explained by such lags in reporting.

Due to the short-term nature of the product, lenders offering HCSTC agreements have increasingly shifted towards using real-time data sharing over the last few years. Real-time data-sharing databases either provide updates at the end of each day, or instantaneously after an event has occurred (e.g. HCSTC account opened, closed or fallen into arrears). However, such reporting comes at additional costs to lenders and it only makes sense for one lender to use a particular database if a large proportion of other market participants are also using the same system.

Data content

It is in the interests of lenders to submit accurate data to CRAs, as inaccurate data submissions can lead to customer complaints and potential regulatory action.

There are different levels of data firms can report to CRAs. Some firms only use and report adverse credit information ('negative data') that records defaults but not loans repaid in line with their contractual agreement. Doing so may be appropriate for their lending businesses (adverse credit information may provide enough predictive power for their credit scoring models), but it has a negative externality in that other firms do not observe data about the credit agreements that consumers did repay without impairment. This limits the ability of firms to carry out assessments of consumers' debts. It also limits the ability of individual consumers to demonstrate their ability to repay debts, which could improve their credit scores helping to increase their access to credit, potentially at a lower cost.

Credit file data are typically held at a monthly frequency. This may not present problems for products that have a monthly repayment schedule, but may be more problematic for other products that have more frequent repayments where aggregating information at a monthly level loses potentially valuable information.

There appear to be differences in how firms report credit items to CRAs, as each CRA has different product categorisations. These are not all mutually exclusive and therefore not all firms report products in exactly the same product categories. For example, some firms use categories such as 'personal loan' only for unsecured personal loans, whereas others may include motor finance agreements, and there is no separate category for HCSTC agreements. These differences in categorisation may be expected to reduce the credit scoring accuracy of products produced from CRA data. Lenders also have some flexibility regarding when they report credit items as being in arrears or default, within parameters laid down by SCOR guidelines.[76] CRA data also does not display the pricing levels or structures of different credit, which may be important to assess the sensitivity of a consumer's portfolio of debt to changes in interest rates.

Income assessment

There are a variety of ways in which lenders may attempt to establish or verify the income of credit applicants. Which of these methods is appropriate for a lender to use is likely to depend upon how likely an individual is to mis-report their income on an application form. It is also likely to depend upon the extent to which this increases the credit risk faced by a lender and risk of financial distress to the consumer. In cases where the credit risk to the lender is high, it would be commercially worthwhile for the lender to incur higher costs to more rigorously assess income; conversely where the risk is low, this may be commercially unnecessary to do. In some case

[76] SCOR Principles for the Reporting of Arrears, Arrangements and Defaults at Credit Reference Agencies: www.scoronline.co.uk/key-documents.

where it may be commercially unnecessary to incur such costs firms may need to incur such costs as part of a creditworthiness assessment as the applicant has a high risk of financial distress.

Consumers have incentives to over-state their income on their credit application as doing so gives the lender an impression that they are wealthier than they are, as this makes it more likley that their application will be approved.[77] The process of finding out that an individual over-stated their income would be expected to be very useful to lenders to enable them to update their assessment of the credit risk of the individual. Such income mis-reporting is fraudulent activity and therefore should not be encouraged. One of the factors attributed to causing the financial crisis in the UK, USA and other countries was the large increase in fraudulent over-reporting of income in mortgage applications.[78]

A traditional way to verify income is through collecting physical payslips and current account statements. However, these can be subject to fraud, and it can be costly and slow for consumer credit lenders to gather and assess this information – particularly if the credit application occurs online (although more generally there are innovations by fintech companies to improve the ability to verify documents efficiently). Aside from the costs of the assessment, lenders may also be reluctant to use this method as the additional time it adds to the credit application process may deter potential customers who instead go to a competitor with a faster application process that does not require them to provide such documentation.

Given this, consumer credit lenders commonly match data from other sources to profile consumers into income groups. Some lenders benchmark income estimates against other estimates derived from public data (e.g. Office for National Statistics, ONS) based on an individual's socioeconomic profile (considering factors such as age, occupation and postcode). Some lenders also use ONS data to assist with estimating an individual's expenditures in order to calculate income net of essential expenditures such as housing and utility payments. Survey data contains very detailed information on household composition and the components of income and expenditures, however, there are concerns regarding the accuracy of reported income and expenditures for some individuals – particularly at the low end of the income distribution.[79]

Other socio-economic characteristics may allow lenders to distinguish between credit applications, where the risk of financial distress is low from those where it is high and require a more detailed creditworthiness assessment (e.g. through a more detailed attempt to establish or verify income net of essential expenditure). FCA Occasional Paper No. 20 found that individuals in financial distress are more likely to be younger, have children, be unemployed and have lower education than a comparable group of consumers not in financial distress.[80] This information may be captured on an individual's application form but, with the exception of age, lenders do not have access to an administrative data to crosscheck such information.

Some firms verify income using CRA data – corroborating the value of income an individual self-reports on their application form with what that customer has reported on previous credit applications, which is reported in CRA data. This approach may accurately verify income if an individual has recently applied for a number of credit products (and therefore the income estimates being assessed against are reasonably up to date) and they have truthfully reported their income on previous application forms (otherwise, it may 'verify' income that is consistently over-reported).

[77] However, this incentive structure is conditional upon the lender being unable to isolate which individuals are over-stating their income and if the lender does not charge higher prices to higher income individuals who pose the same credit risk of those with a lower income.

[78] Mian & Sufi (2016) and Financial Services Authority (2010, 2011, 2012)

[79] Annex 1 of Gathergood & Guttman-Kenney (2016) discuss the advantages and disadvantages of survey data. See Browning, Crossley and Winter (2014) for more details on difficulties of measuring household expenditure. The Institute for Social and Economic Research (ISER) are carrying out research examining ways to improve the measurement of survey data on income and expenditure and FCA staff are advising on this.

https://www.iser.essex.ac.uk/misoc/strands/understanding-household-finance-through-better-measurement

[80] Gathergood & Guttman-Kenney (2016)

Due to the issues with using credit application data to verify income, personal current account providers now report current account turnover (referred to as CATO) data to CRAs. This records monthly data on balances and flows in and out of current accounts. CRAs combine CATO data with credit file data to produce estimates of income. Non-bank lenders do not have access to CATO data, but are able to access CRA products which use CATO data to verify whether an income figure provided by an applicant is within a set range. CATO data are likely to work well for individuals who have a regular salary and a single bank account. When an individual has joint accounts it is difficult to use this to assess the income of an individual person. Estimating income from CATO flow data becomes more complicated when an individual actively uses multiple bank accounts or has irregular sources of income, which could lead to large fluctuations in account turnover (or where elements of income do not pass through a bank account). These same issues occur when using CATO data to estimate expenditure. Examining CATO data among HCSTC customers, we find that the number of individuals covered by these data has noticeably increased over time.

Banks have access to current account transaction data that enables them to isolate the transactions that are expected to be sources of income from other transactions that are not (e.g. funds from transfers or new credit agreements). This enables these firms to assess both the level and stability of incomes and expenditures more accurately. Such data may enable these firms to categorise expenditures for calculating income net of essential expenditure items, which are not observed in CRA data. Arguably the most important expenditure not observed in CRA data are rent but also other household bills such as council tax (these matter in terms of estimating non-discretionary expenditure as well as whether individuals are meeting these payments which could potentially be important inputs for considering both credit risk and affordable lending).[81] Where non-bank lenders compete with banks, it appears that they are put at an informational disadvantage from not having access to such data. This potentially exposes these firms to greater credit risks from less accurate income assessments. However, as previously discussed, the development of open APIs standards is expected to help level the data banks and non-bank lenders have available in this regard.

Income data appear potentially useful for preventing unaffordable lending and may be welfare-improving by increasing the accuracy of risk-based pricing of credit products. However, income data also comes with risks if it is used beyond purely verifying income. For example, income data could be used in a welfare-reducing way by lenders extracting rent from consumers through price discriminating between applicants of equal credit risk and affordability based on their income.[82]

Credit scoring

Assessing the credit risk of new credit applications and existing portfolios is fundamental to lending businesses. Credit risk affects the prices offered on credit, the amount of provisioning required for bad debts and, ultimately, the profitability of lenders. The assessment of credit risk is normally undertaken through the production of credit scores which predict the likelihood of individuals defaulting on obligations.[83]

Credit scores are produced by both CRAs and individual lenders; different scorecards are typically used for different types of product. A high-quality scorecard accurately predicts the probability of an outcome (e.g. defaulting on a loan in the next 24 months) and effectively discriminates between individuals who would and would not be expected to default. These

[81] The ease of mapping transactions to non-discretionary expenditure categories depends upon how these are categorised. This data may also assist with isolating the proportion of property expenditures an individual pays. For example, council tax payments can be calculated from the property address, however, these do not show what proportion of this an individual who rents a room in a house contributes to this where they have no relationship or shared financial link to other individuals in the property.

While current account data shows payments to credit cards it does not reveal the composition of an individual's credit card expenditure which contains both discretionary and non-discretionary purchases.

[82] For a more detailed discussion of price discrimination, see Lukacs et al. (2016) and OECD (2016).

[83] There is variation in which measure of arrears or default firms target as an outcome in these models. Some scorecards model expected profitability directly.

predictions are made on a – potentially quite narrowly defined – cohort basis, given the potential for particular individuals to suffer subsequent shocks, such as becoming unemployed.

Credit scorecards are constructed using a variety of statistical modelling approaches of varying sophistication. The variables that are chosen as inputs are those which are considered effective predictors of default, rather than factors that cause an individual to default.

The Equalities Act 2010 specifies protected characteristics that cannot be used to discriminate between individuals – these include race, sexual orientation and religion. However, there is an exclusion to allow financial service decisions to discriminate based on age, given the importance of this variable for credit risk.[84]

The variables that appear to have most predictive power in existing credit scorecards have a clear link with credit risk without the potential for unintended consequences: for example, factors such as whether an individual has defaulted on any credit agreement in the last few years. However, credit-scoring models include other variables which improve the ability of the model to accurately predict default and discriminate between applicants but can have broader unintended consequences.

An issue of concern raised in previous FCA publications is the use of credit searches. Credit searches occur when an individual applies for a credit product or mobile phone contract. This leaves a 'footprint' on their credit file (unless the search is a 'quotation search' where a full credit assessment is not completed).[85]

Consumers who are aware that applying for credit products harms their credit score could be deterred from applying for credit products, or potentially only apply for a product for which they are more likely to be accepted (but this may not be the lowest cost or most suitable product they could access). Consumers who are not aware of the relationship between credit searches and credit scores may repeatedly apply for credit products, harming their credit score and restricting access to lower cost credit. Some scorecards include variables such as the average age of credit accounts, the age of the oldest account or the number of accounts opened in the last few months. The use of these measures may mean that if consumers switch accounts, it could harm their credit score (and therefore reduce access to credit or increase the price charged). If consumers are aware of this relationship, it could deter them from switching as it may reduce the potential benefits from doing so – especially if they are planning to take out a large credit item or a mortgage where small changes in interest rates may make a large difference to the value of repayments.

The oldest product on individuals' credit files are typically personal current accounts. This is of particular concern, given attempts to encourage consumers to switch current accounts to drive increased competition in retail banking. It should be noted that these measures are not purely affected by switching regulated credit agreements; other accounts reported to CRAs, such as mobile phone contracts or utility providers, can have the same impact.

A broad array of innovative data sources (e.g. social media interactions) is potentially available to lenders which could help predict credit risk and unaffordable lending. Currently, social media data are generally not used in credit scoring but may offer the potential to assist individuals without a credit file accessing credit. The use of social media data in credit scoring models may need further consideration of whether doing so would have adverse consequences for how consumers use social media, as well as data protection implications and ethical considerations (particularly with regards to the implications for consumers who refuse to provide consent).[86]

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[84] www.equalityadvisoryservice.com/ci/fattach/get/588/1354033540/redirect/1/session/L2F2LzEvdGltZS8xNDczNDE0MzkxL3NpZC9jY1YtNWItbQ==/filename/financial-services.pdf

[85] *Feedback on CP15/33, Consumer credit: proposals in response to the CMA's recommendations on high-cost short-term credit* (PS16/15), May 2016; see also *Credit card market study: Final findings report* (MS14/6.3), July 2016.

[86] In 2016 Facebook blocked plans by an insurer to use data to set car insurance premiums: www.bbc.co.uk/news/business-37847647.

Psychometric tests may also greatly assist with predicting credit risk as well as being able to isolate less financially sophisticated consumers, who are expected to be at the highest risk of borrowing an unaffordable amount of credit (and suffering financial distress), more effectively.[87] However, in practice such tests may be difficult to use as some of them can take a relatively long time for consumers to complete. Tests may also be especially vulnerable to being gamed by consumers working out what answers they need to give to increase their chances of their credit application being accepted as opposed to what their true response would be. It may be that, through trialling approaches such as these, lenders can find other, less gameable characteristics which correlate with the psychometric factors and can therefore use this information instead of asking credit applicants to carry out psychometric tests.

[87] https://www.usaid.gov/div/portfolio/settling-score-psychometric
https://www.fomin.org/Portals/0/impact%20evaluation/Brief_psychometrics.pdf

5 Conclusions

This paper provides theoretical and practical evidence to help regulators (and firms) develop more effective affordability rules. It presents an economic framework for analysing the issue of affordable lending within consumer credit. This framework, when applied to the HCSTC market, shows that objective measures of financial distress appear strongly related to a combination of credit risk to the individual lender and the DTI ratio. We find lenders' incentives are imperfectly aligned with those of consumers applying for credit. For instance, consumers may borrow unaffordable amounts of credit, because they struggle to make complex financial decisions or have behavioural biases. Other factors may also contribute to unaffordable or overly-restrictive lending. For example, firms may not have access to accurate information or possess unclear regulatory expectations.

It is important to note that we are not able to isolate the causal effect of taking out HCSTC in this paper. We do not evaluate whether the welfare of borrowers has worsened, but assume that taking out more debt is unlikely to improve welfare, on average, for consumers at high risk of financial distress. We take this assumption based on our knowledge of behavioural economic theory and previous empirical research findings.[88] Our model instead focuses on the likelihood of whether people will be in financial distress in the future.

We find certain consumers can benefit from access to credit. Many have no outstanding debts, low DTI ratios or low credit risks. They, therefore, appear to be at limited risk of financial distress. Unexpected financial distress among such individuals may be mitigated by lenders offering forbearance. However, applicants who are higher credit risks are at a much higher risk of suffering financial distress than other consumers. Applicants with higher DTI ratios, in particular those at the top of the distribution, are also at high risk of suffering financial distress than others, based on information available at the time of a decision to grant credit. Together, the evidence suggests that regulation should require firms to decline credit applicants with a high risk of financial distress.

The substantial differences in debt balances recorded between CRAs for the same individuals, the reporting time lags and the data-sharing restrictions on non-bank lenders all harm the accurate construction of the DTI ratios of individuals. Therefore, the measures used by lenders, and by us in this research, may be subject to some measurement error that inaccurately estimates income and total debts. Reducing this could improve the accuracy of predicting financial distress. Our model may miss some consumers who are in financial difficulty. For instance, we do not observe consumers who report being in financial distress based on subjective, self-reported measures, but who have no impairments in the CRA data that we use to construct objective measures of financial distress. Prior research using subjective measures has shown that the risk of financial distress increases with DTI ratio.[89]

This paper finds that creditworthiness assessments can evaluate risks of unaffordable consumer credit debt through the use of a credit score and DTI ratio as a predictor of financial distress. The income component of a DTI ratio may be calculated in a variety of methods, but it is not the only possible way for predicting financial distress and effectively discriminating between consumers. Other methods may offer more effective and proportionate ways to assess affordability for different consumer credit products, which may be used by different groups of consumers. In particular, more sophisticated machine-learning methods, as used in credit risk modelling, may be able to discriminate between consumers more efficiently. However, such methods are also less

[88] In particular, causal evidence from FCA(2014b) and non-causal evidence of Gathergood & Guttman-Kenney (2016)

[89] Gathergood & Guttman-Kenney (2016)

easily interpretable as they combine a large number of inputs they provide less clarity over which factors influencing lenders' assessments of individual unaffordability.

Annex 1: Summary statistics

Figure 11: Number of individuals by date of cohort

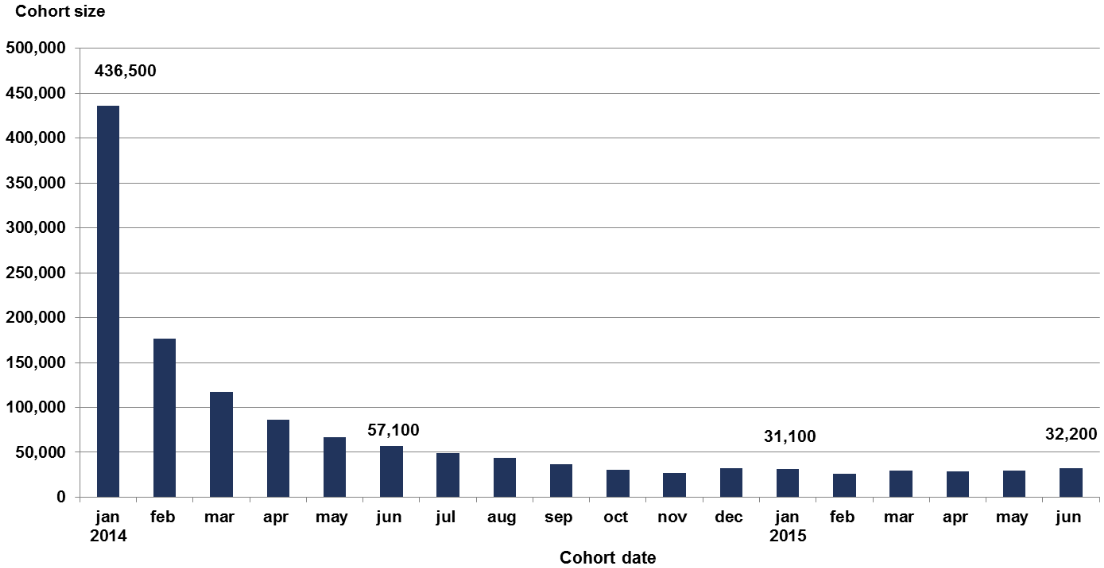


Figure 12: Debt balances relative to time of first HCSTC loan observed in dataset, split by date of cohort

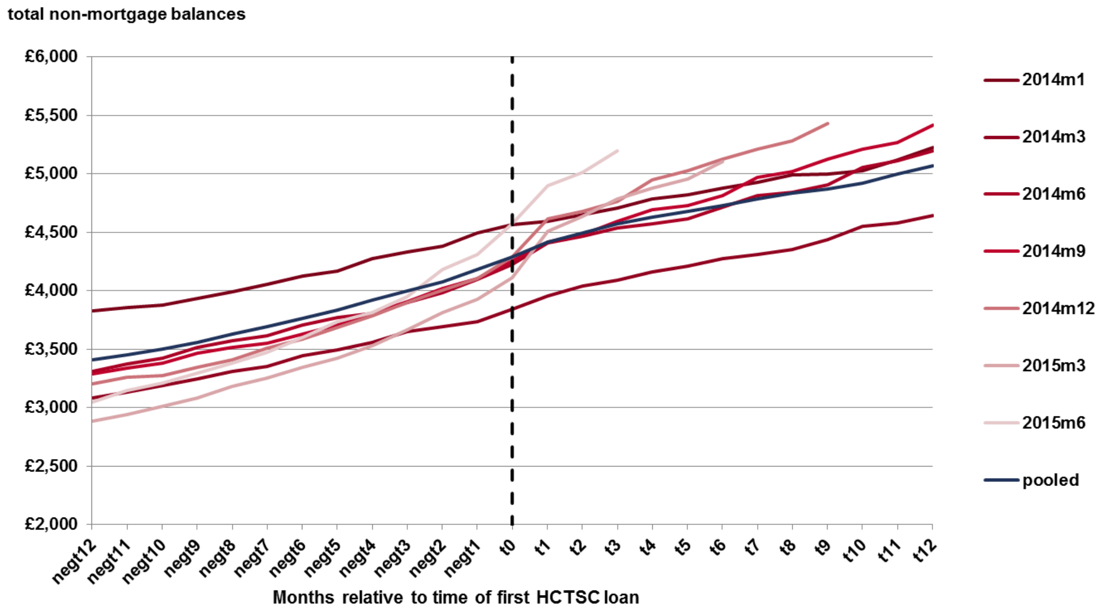
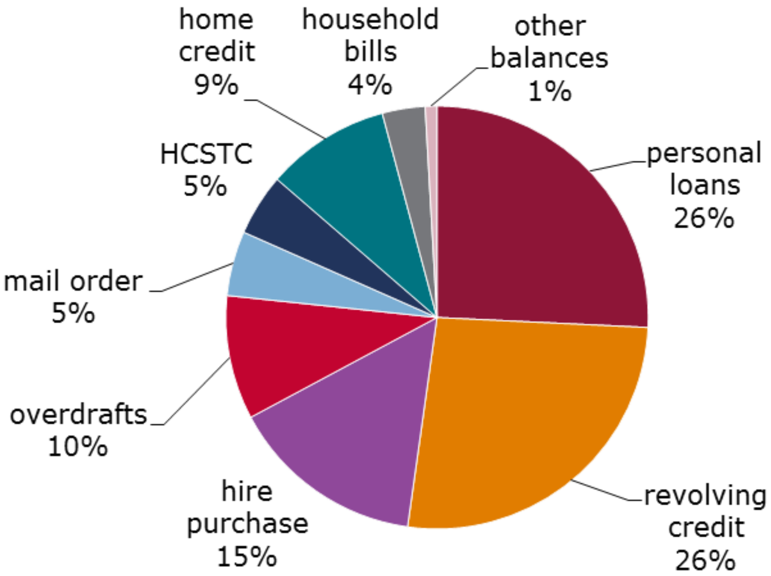


Figure 13: Distribution of non-mortgage total debt balances of HCSTC customers at the month of HCSTC application



Annex 2: Descriptive output

Figure 14: Distribution of consumers, by CR-DTI buckets

	DTI bucket																				
CR bucket	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**Subtotal**
1	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.3%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	4.7%
2	0.2%	0.4%	0.2%	0.2%	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.2%	0.3%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	5.2%
3	0.3%	0.4%	0.2%	0.2%	0.3%	0.1%	0.3%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	5.0%
4	0.3%	0.4%	0.2%	0.2%	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	5.0%
5	0.3%	0.4%	0.2%	0.2%	0.3%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	4.8%
6	0.3%	0.4%	0.2%	0.2%	0.3%	0.1%	0.3%	0.2%	0.2%	0.2%	0.3%	0.2%	0.3%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	5.2%
7	0.3%	0.4%	0.1%	0.2%	0.3%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	4.6%
8	0.4%	0.4%	0.2%	0.2%	0.3%	0.1%	0.3%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	5.0%
9	0.4%	0.4%	0.1%	0.2%	0.3%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	4.3%
10	0.8%	0.5%	0.2%	0.2%	0.3%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	5.0%
11	2.7%	0.5%	0.1%	0.1%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	5.4%
12	0.8%	0.7%	0.2%	0.2%	0.3%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	5.1%
13	1.0%	0.7%	0.2%	0.2%	0.3%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	5.4%
14	0.9%	0.6%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	4.1%
15	1.4%	0.8%	0.2%	0.2%	0.3%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	5.8%
16	1.2%	0.7%	0.1%	0.2%	0.3%	0.1%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	4.5%
17	1.5%	0.8%	0.2%	0.2%	0.3%	0.1%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	5.4%
18	1.6%	0.7%	0.1%	0.2%	0.3%	0.1%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	5.0%
19	1.2%	0.6%	0.2%	0.2%	0.4%	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	5.5%
20	0.8%	0.4%	0.2%	0.2%	0.4%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	5.2%
Subtotal	16.5%	10.4%	3.2%	3.6%	5.8%	2.8%	5.0%	4.6%	3.9%	3.3%	4.5%	3.9%	4.1%	3.4%	4.2%	4.2%	4.3%	4.2%	4.1%	4.1%	100.0%

Table 4: Outcome measures of financial distress

Outcome name	Outcome description
anybce	Any missed payment (delinquent or in default) in credit file
anynpdlbce	Any missed payment (delinquent or in default) in credit file excluding HCSTC (high-cost short-term credit)
anywce	Any credit event in credit file worse than in previous month
badbal	Percentage of total balances in credit file where accounts have missed payment (delinquent or in default)
defbal	Percentage of total balances in credit file where accounts are delinquent
delbal	Percentage of total balances in credit file where accounts are in default
nonpdlbadbal	Percentage of total balances in credit file where accounts have missed payment (delinquent or in default) excluding HCSTC
nonpdldefbal	Percentage of total balances in credit file where accounts have delinquent payments excluding HCSTC
nonpdldelbal	Percentage of total balances in credit file where accounts are in default excluding HCSTC
oPCAlim	Any personal current account in credit file over limit (arranged overdraft or £0 if no arranged overdraft)
oCClim	Any credit card in credit file over credit limit
wrstac	Worst credit event recorded in credit file (1 if 1–2 payments behind, 2 if more than 2 payments behind, 3 if in default)
arr7	HCSTC loan transaction ended 7+ days in arrears
arr30	HCSTC loan transaction ended 30+ days in arrears

All of these variables are observed at one to twelve months after the time of HCTSC loan transaction except for ‘arr7’ and ‘arr30’, which are the outcome of the HCSTC loan transaction itself. Observations from later monthly cohorts are dropped for variables at longer time horizons, as insufficient time has passed to observe these in credit file data.

Figure 15: Proportion of consumers experiencing any bad credit events three months after HCSTC loan, by CR-DTI buckets

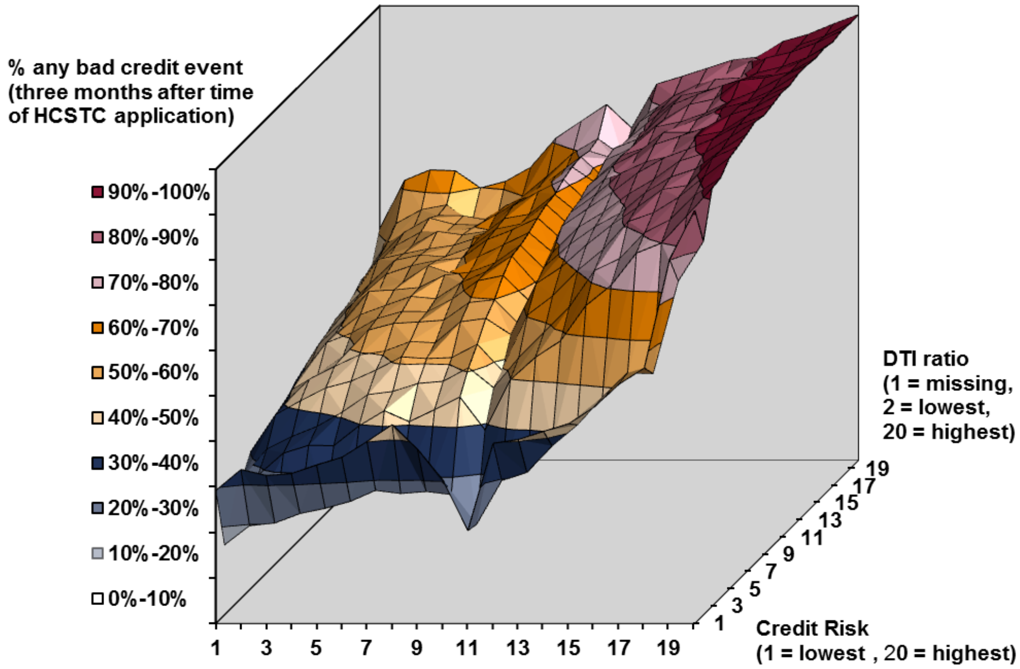
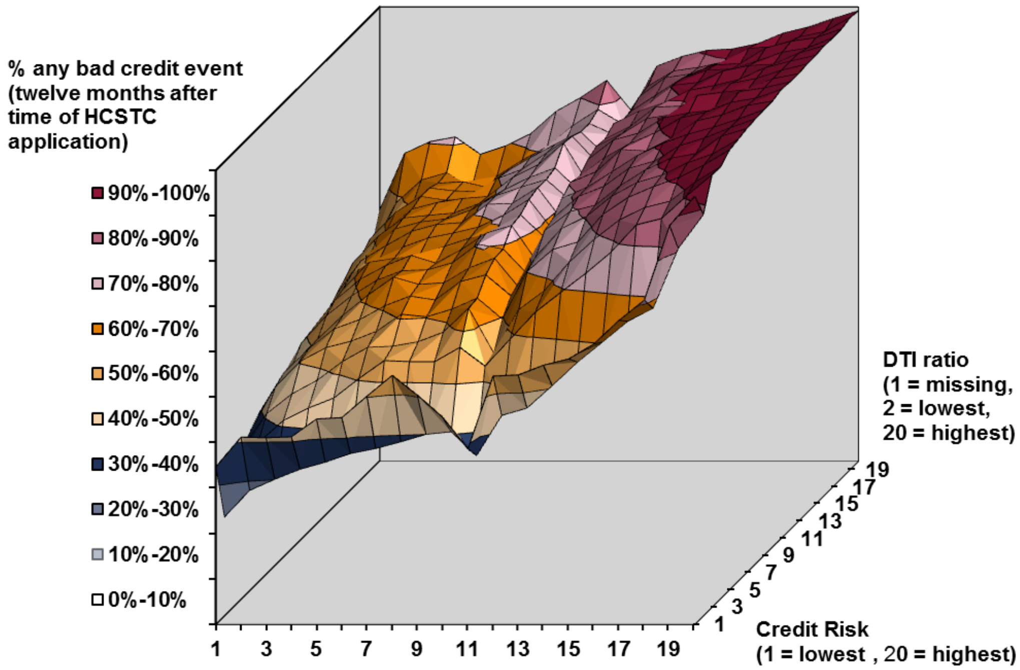


Figure 16: Proportion of consumers experiencing any bad credit events 12 months after HCSTC loan, by CR-DTI buckets



Annex 3: Output from predictive models

We analyse this using a logistic regression-based approach described in Equation 1 below, which predicts the probability of individual, i, experiencing a measure of financial distress, y, at, j, months after the time, t, of taking out HCSTC. The probability of financial distress is predicted by including for buckets of credit risk, CR, and DTI ratio, DTI, before the time of taking out HCSTC, as well as a constant, α.[90] Regression results are evaluated relative to the base group who have a DTI ratio of 0 and in the lowest credit risk bucket.

Equation 1: Predictive model

$$\Pr(y_{i,t+j} = 1) = \alpha_{i,t} + \sum_{c=1}^{C} CR_{i,t}^{c}\,\beta_c + \sum_{d=1}^{D} DTI_{i,t}^{d}\,\delta_d + \varepsilon_{i,t+j}$$

The output from logistic regressions are odds ratios, which display the probability of financial distress divided by the probability of not being in financial distress. To illustrate an example of how to interpret coefficient estimates from a logistic regression, if the coefficient on a DTI bucket 20 has an odds ratio of 1, this can be interpreted as there being a 50/50 likelihood of an individual being in financial distress depending on whether that individual was in DTI bucket 2. A higher odds ratio, such as 2, means that individuals in DTI bucket 1 are twice as likely to experience financial distress than those not in that bucket.

Equation 2 includes additional controls for the monthly cohort dummies (January 2014 to June 2015) and dummy variables for lags of whether an individual was in in the outcome measure of financial distress in each of the 12 months before taking out HCSTC.

Equation 2: Predictive model with additional controls

$$\Pr(y_{i,t+j} = 1) = \alpha_{i,t} + \sum_{c=1}^{C} CR_{i,t}^{c}\,\beta_c + \sum_{d=1}^{D} DTI_{i,t}^{d}\,\delta_d + + \sum_{x=1}^{X} CONTROLS_{i,t}\,\theta + \varepsilon i,\ t+j$$

Equation 3 is Equation 2 with an additional variable, ‘gotloan’, to measure how taking out HCSTC affects the likelihood of suffering financial distress. As individuals may have an application declined but take out an HCSTC loan at a later date from the same or other lenders in the market, we carry out robustness checks for whether the individual took out an HCSTC loan a variety of time periods after the initial application – i.e. whether they took out an HCSTC loan within the next 30 or up to 180 days of the loan application.

Equation 3: Predictive model with additional controls applied to applications

$$\Pr(y_{i,t+j} = 1) = \alpha_{i,t} + \sum_{c=1}^{C} CR_{i,t}^{c}\,\beta_c + \sum_{d=1}^{D} DTI_{i,t}^{d}\,\delta_d + + \sum_{x=1}^{X} CONTROLS_{i,t}\,\theta + gotloan_{i,t}\mu + \varepsilon_{i,t+j}$$

[90] Logistic regression is a monotonic transformation of the data using on the logistic function: $f(z) = \frac{e^z}{1-e^z}$.

Figure 17: Odds ratios of going seven or more days into arrears on HCSTC loan by DTI buckets (logistic predictive model)

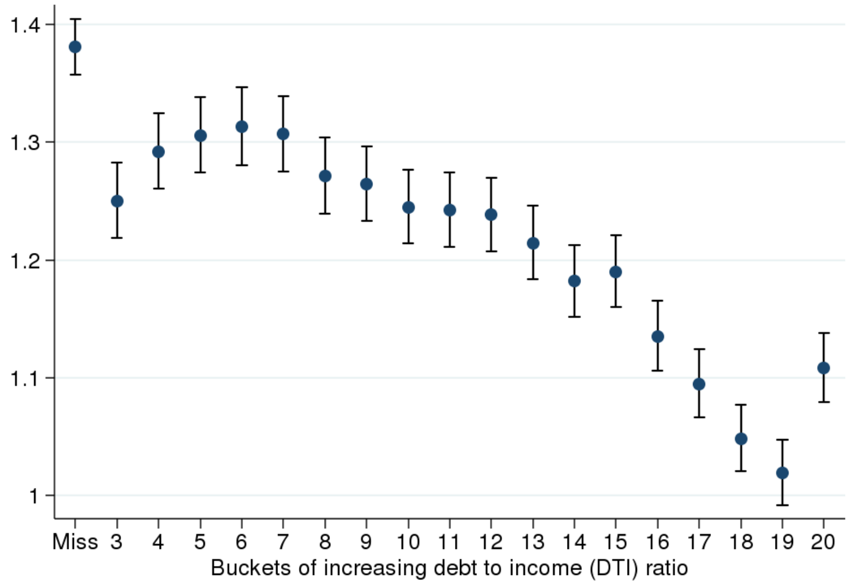


Figure 18: Odds ratios of going 30 or more days into arrears on HCSTC loan by DTI buckets (logistic predictive model)

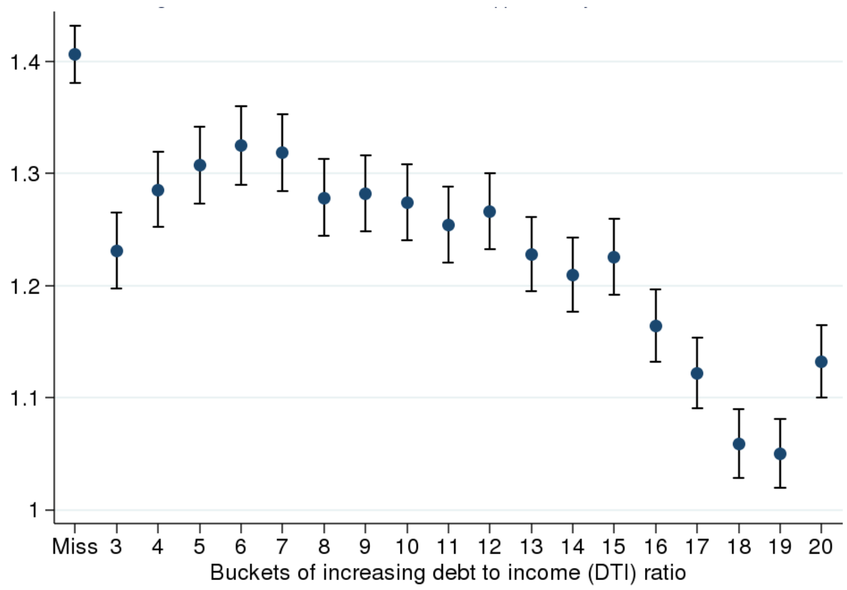


Figure 19: Odds ratios of any debt balances in default six months after taking out HCSTC by DTI buckets (logistic predictive model with additional controls)

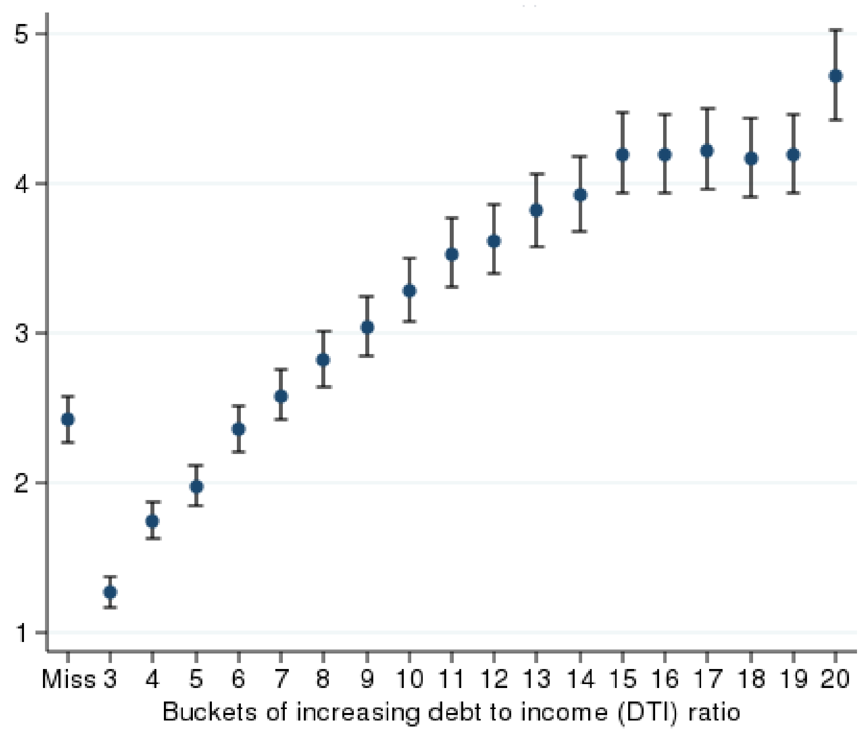


Figure 20: Odds ratios of proportion of consumers exceeding personal current account limit six months after taking out HCSTC by DTI buckets (logistic predictive model with additional controls)

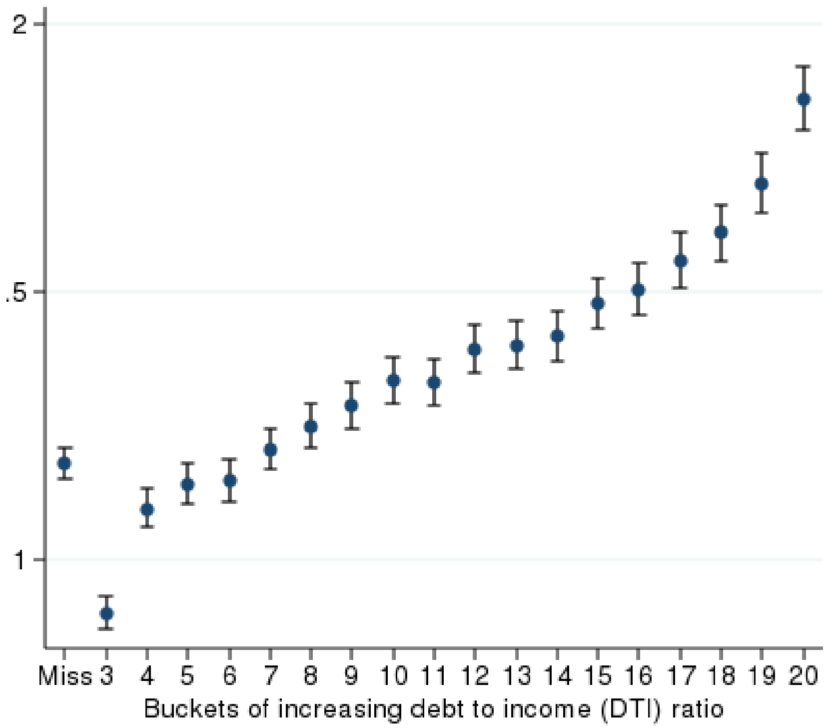


Figure 21: Odds ratios of proportion of consumers exceeding credit card limit six months after taking out HCSTC by DTI buckets (logistic predictive model with additional controls)

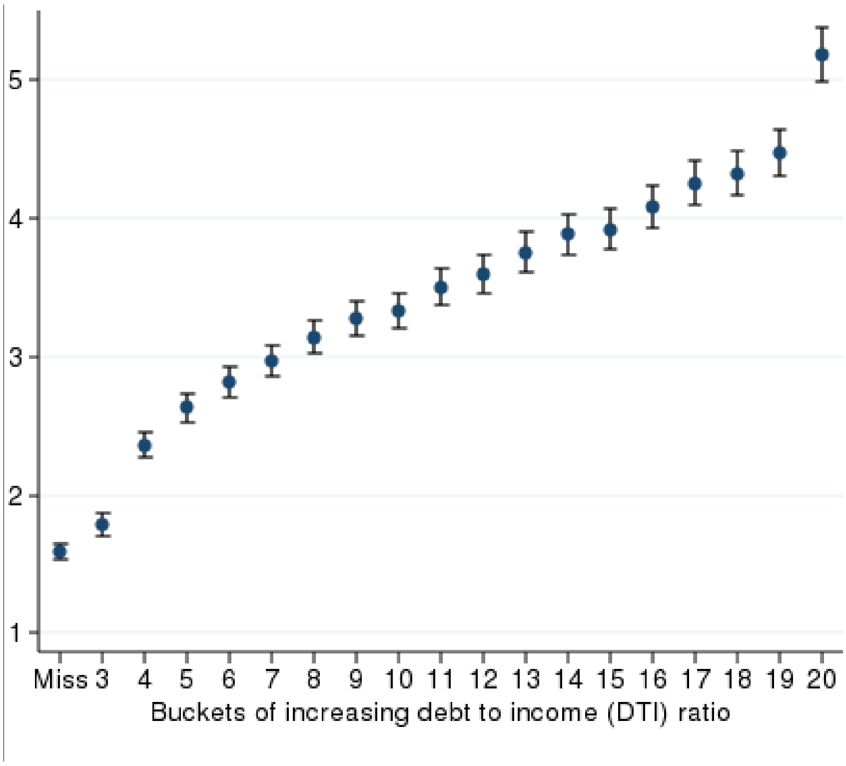


Figure 22: Odds ratios of any debt balances in default six months later by DTI buckets for consumers not suffering bad credit event in month preceeding HCSTC loan taken out (logistic predictive model with additional controls)

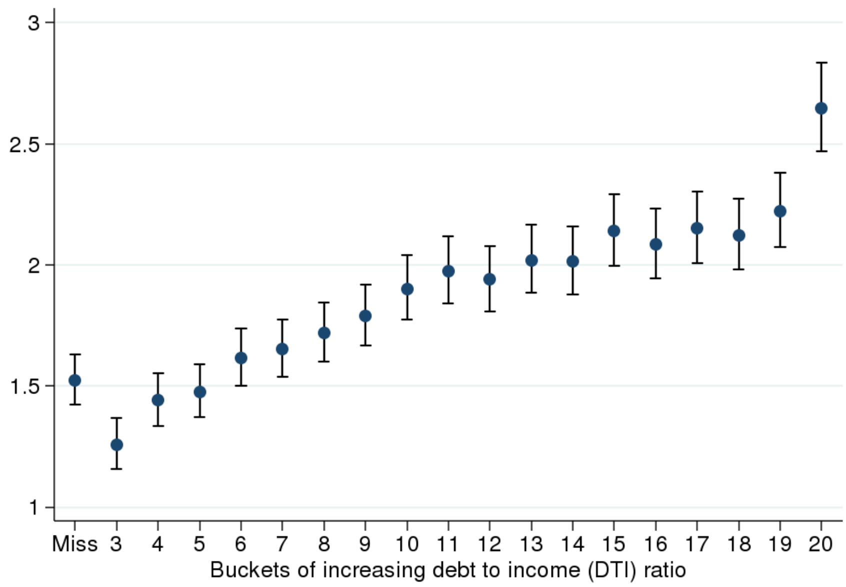


Figure 23: Odds ratios of proportion of consumers exceeding current account limit six months later by DTI buckets for consumers not suffering bad credit event in month preceeding HCSTC loan taken out (logistic predictive model with additional controls)

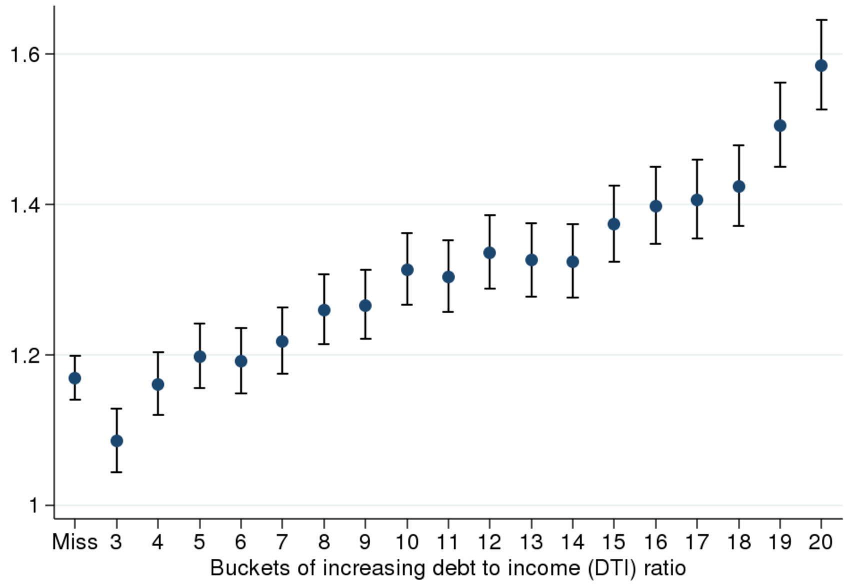


Figure 24: Odds ratios of proportion of consumers exceeding credit card limit six months later by DTI buckets for consumers not suffering bad credit event in month preceeding HCSTC loan taken out (logistic predictive model with additional controls)

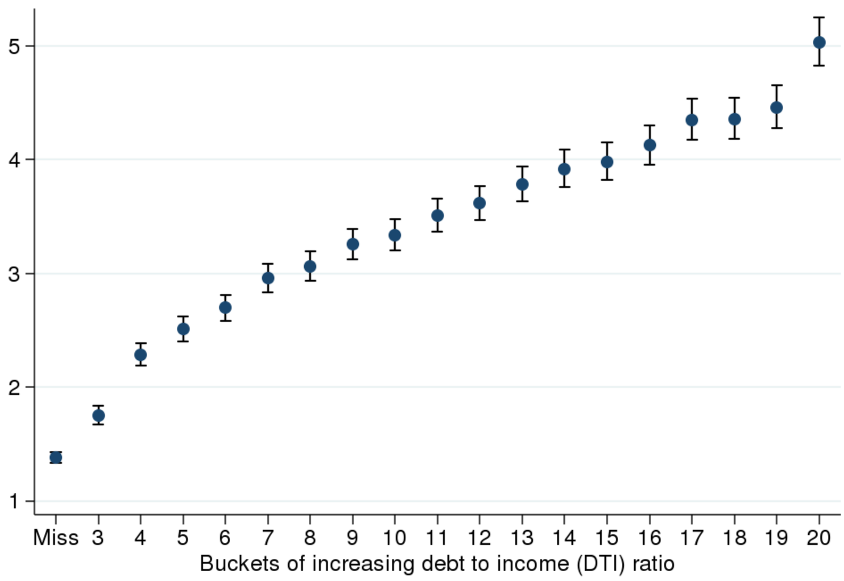
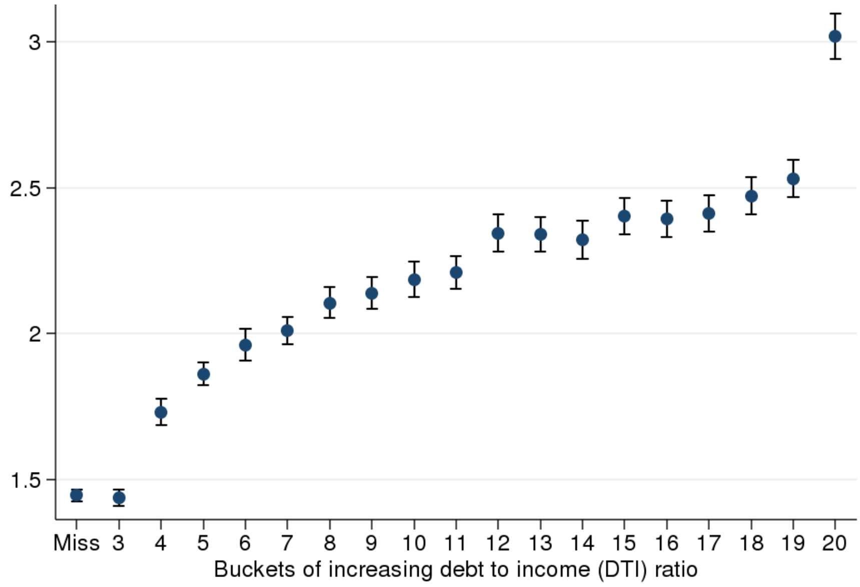


Figure 25: Odds ratios of suffering any bad credit event six months after applying for HCSTC (sucessfully or unsucesfully) by DTI buckets (logistic predictive model with additional controls)



Annex 4: Description and analysis of assessments carried out by HCSTC lenders

Introduction

This annex describes the types of assessments HCSTC lenders undertook between 2014 and 2015 and analysis of these.

The data used for this analysis is millions of HCSTC loan applications (as previously described in the chapter three of this paper). For this part of the research we also used variables in these data which detailed each creditworthiness check an application went through, the result of these checks and the boundary threshold that individual needed to pass (including whether that was manual or automated) in order for an application to be approved.

For other, smaller HCSTC lenders we did not collect application-level data but descriptions of their creditworthiness assessments without application-level details.

Generic journey to taking a decision to lend

This section describes the generic journey to taking a decision to lend from acquiring a customer to apply for credit to when a lender makes a decision to lend. The creditworthiness assessment is part of this process. Firms differ considerably in these practices and this is a simplified description primarily based on detailed data on HCSTC lending practices (but considering data on other consumer credit products).

We think of there being two broad categories of decisions to offer credit. First, for lenders which offer fixed price loans, there is a single decision – whether or not to grant credit. This is the most common approach among HCSTC lenders – some may also consider whether they are willing to lend a lower amount of credit rather than decline an application. For lenders which offer variable price credit the lender has to decide whether to offer credit and at what price (i.e. interest rate) – the amount of credit offered typically being related to the price.

We describe below a generic journey an applicant goes through in order for a decision to lend to be made. Except for stage 1 of this process, the other stages 2 to 5 may occur in any order or simultaneously (and in particular cases may not involve all five stages).

Stage 1: Customer acquisition

The first stage involves acquiring people to apply for credit. Lenders may acquire applications or 'leads' from a variety of sources. Or they may be 'organic' from a firm's existing customer base. High-street lenders receive applications from customers in store, online lenders receive applications via their websites and some lenders use other technology interfaces, such as smartphone apps. Acquisition channels include affiliate websites, credit brokers and lead generators.

The source of acquisition may itself contain information relevant to the riskiness of applications. Lenders take two approaches to internalising this information in their lending decisions. Some lenders treat application routes as different channels within the same lending decision approach – subjecting applications to different checks and threshold values depending upon the channel. Other lenders incorporate information on the acquisition channel into a single lending decision approach. The former may apply, for example, where a firm has grown through acquisition or merger and so there are a variety of systems running in parallel, or where leads are acquired pre-qualified (i.e. with some pre-checks before the lead reaches the lender).

Stage 2: Data completeness checking

Once a lender receives an application or acquires a lead, they will typically undertake basic checks to establish whether the application is sufficiently complete to enable a lending decision or whether further information is needed. Many online applications are submitted only partially complete and may be automatically rejected. Some purchased leads are pre-qualified ensuring they have some basic information, others are not and may be automatically rejected.

Lenders will then typically match the application form data provided by the applicant or lead generator to CRA data. In practice, this occurs via the lender sending identifying information on the individual to the CRA electronically, the CRA attempting to match the information to their data and the CRA returning data to the lender. Some applications fail at this stage if no match can be found, while others fail if the credit file is extremely thin or empty. This stage may also detect primitive forms of fraud, such as an applicant applying for a loan and stating a home address at which they are not the recorded resident. For returning customers lenders will typically also draw in data from previous loan applications and loan performance.

Stage 3: Credit risk assessment

If it is deemed that an application together with matched CRA data (where used) contains sufficient basic information for the lender to make a credit decision then the application will typically reach the credit risk assessment stage. This often involves the calculation of a statistical score which is used to decide whether a loan should be granted. At this stage a credit score is calculated for the individual application and evaluated against a threshold value. Not all lenders (or applications for a particular lender) involve the construction of credit scores.

The calculation of credit scores is typically undertaken within the firm using proprietary credit scoring technology. CRAs provide credit score products but these typically do not discriminate with statistical power at the non-prime segment of the consumer credit market. Therefore, lenders have tended to develop their own models. A credit score model is normally constructed from the back book of data by estimating the relationship between characteristics of loan applications and the subsequent performance of the loan. These estimates are then used to predict the performance of future credit agreements.

When first setting up a lending business, firms have limited information on which to score individuals. However, over time the lender builds a data asset relating application data to loan performance. The firm can then use statistical regression models or other statistical approaches to estimate models from which they can obtain parameters for calculating the credit score of new applicants.

Lenders typically use large sets of data as inputs to their credit scoring models. However, the addition of data does not necessarily improve the performance of the model. Most of the explanatory power of a credit scoring model may be found in a few key variables which predict performance of the loan, with additional information potentially offering little or nothing in terms of explaining outcomes.

Once a credit score has been calculated for the loan application, the score is evaluated against a threshold value for loan approval/decline. A typical convention might be to score applications on a scale of 0 to 1000, where a score of 0 represents non-repayment with certainty and 1000 represents repayment with certainty. The lender will then set a threshold for loan acceptance. For example, 700 points implies the lender will grant loans to applications with a 70%+ likelihood of repayment.

The threshold is chosen to maximise the profits of the firm. If the threshold is set too high then the firm will see low rates of default but low loan volumes. If the threshold is set too low the firm will see high loan volumes but high rates of default. Firms typically attempt to lend to the marginally profitable loan applicant.

Some firms may not subject repeat applicants to credit scoring if the applicant has a history of repaying their past credit agreements on time and there are no adverse indications – although they may calculate a new credit score if the most recent loan is not within a certain period of the new application.

Stage 4: Affordability assessment

The affordability assessment stage may be an additional stage in the application decision process or may be combined with credit risk assessment as a single integrated process.

Firms use a variety of data sources in their affordability assessments. The type of data source they use depends on the type of affordability checks. Some lenders decline applications if the applicant recently failed to repay a past credit agreement to that firm, or recently made multiple applications which had been declined. Such data are typically held within the firm. Other screening metrics are provided by CRAs. Examples of these include metrics based upon the number of loans with other lenders active at the same point in time, the overall level of debt held by the individual and the individual’s income.

CRAs have developed products aimed at meeting the needs of lender’s affordability assessments. These products evaluate, among other metrics, debt-to-income ratios, minimum income limits and limits on the number of active loans. These products typically work in practice by the lender submitting an application to the CRA for automatic checking. The CRA does not always provide the underlying information, e.g. the individual’s debt-to-income ratio, to the lender directly but may tell them if they are above or below a value set by the lender or within a set range of values.

Stage 5: Fraud checks

The fifth stage is typically a check relating to fraud. Some applications are attempted fraud – for example, applying for credit using another individual’s details.

In such cases the applicant will provide information about the third party as their own, while providing their own bank account information in the hope of receiving a transfer of funds. Fraud detection tools check the application details against bank account details, identifying anomalies and potentially flagging these as fraud indicators to the firm. Other types of fraud may also include individuals providing false information on their application form such as over-stating their income.

Where sequential assessments care carried out, the ordering of checks will depend upon i) the information required at each stage and ii) the cost of each check. Historically the fraud check has tended to be the final stage within the model as it can be the most expensive. A data completeness check is typically the first stage as, without this check, the application cannot be meaningfully evaluated by a credit score model.

Each stage may be subject to manual checking for a subset of cases. In markets such as HCSTC, lenders typically aim to process most applications automatically as this increases speed and reduces cost. Such processes then typically identify marginal and/or complex cases where human intervention may be required to complete a decision. This might be the case, for example, if the applicant has a non-standard form of income or income verification.

HCSTC lenders differ greatly in the degree of automation of their decision models. Some use automated decision models with little or no manual underwriting. Other, smaller firms use no automation at all, with staff undertaking manual decision-making.

HCSTC lenders typically use approaches with the potential to update their credit scoring and affordability thresholds at high frequency. HCSTC agreements are typically short duration, hence the lender receives rapid feedback on loan performance. Some lenders exhibit periods of multiple innovations in their credit scoring and affordability data sourcing, model design and threshold setting.

The predictive power of the credit scoring models used by HCSTC lenders appears to differ greatly. Some use very reliable models which distinguish good risks from bad with high degrees of accuracy. Others use models which generate decisions on loans which only poorly correlate with actual loan outcomes but may be more effective in screening out unaffordable loans which are liable to cause financial distress.

In analysing the data we also came across variables which do not appear to serve any function or whose utility (in assessing credit risk or affordability) may be limited.

Affordability assessments by type

HCSTC lenders have introduced a growing variety of assessments over the period since January 2014. These typically fall into three broad types: assessments based on income verification or minimum income limits; assessments based on debt-to-income limits; and assessments based on current and past loan performance.

Income assessments

Many HCSTC lenders have introduced or refined checks which limit credit to applicants based on the level of and/or verifiability of their income. Minimum income criteria for the grant of a loan are typically based on some measure of net income and/or disposable income, such as income after housing costs, other credit commitments and other non-discretionary (or total) expenditure. The lender requires the applicant to provide information about this on the application form and the details may be supplemented by other data, e.g. CRA or ONS data.

Some lenders use minimum income screening services provided by a CRA. These use CRA-collated information relating to income estimates from previous loan applications and/or current account turnover measures.

Debt-to-income assessments

These are based on the ratio of existing debts held by the individual (either HCSTC debt or all consumer credit debt) to the individual's gross or net income. In some cases this may also be assessed at the household level.

Debt-to-income (DTI) ratio assessments primarily take two forms. The first is based on the level of existing debt held by the individual, with the lender declining applications if the individual has existing debts which are too high relative to their current income. The second form is based on the level of the loan applied for relative to the applicant's income. This measure seeks to identify individuals who have applied to borrow large amounts of money relative to their income.

The accurate calculation of a DTI ratio requires complete information on the level of debts held by the applicant. There are practical difficulties in a single CRA accurately estimating both income and debts.

Other assessments

These include limits on the number of existing HCSTC loans the applicant can hold; limits on the time period since the last unsuccessful loan; and limits on the number of times an individual can have been in arrears on previous loans or the duration of such arrears. These criteria can be based upon data recording the history of the applicant with the HCSTC provider to which the applicant is applying, and/or CRA information on loan histories more generally.

Changes in affordability assessments over time

Our analysis found a broad diversity in how HCSTC lenders assessed creditworthiness and that their processes changed during between 2014 and 2015.

The changes to assessments took a variety of forms, but were most commonly changes to credit risk score thresholds or limiting lending based on the value of outstanding debts or loan application amount relative to income. It was common for firms to make changes to multiple aspects of their creditworthiness assessments at the same time.

Lenders both tightened and relaxed their credit score and affordability screening thresholds over time. Over the data period the tendency was towards tightening, but this did not occur on all occasions when elements were changed. There is some evidence of firms testing changes in their scores and screening, such as implementing changes for a few days and then reverting to their previous set of thresholds and screening values.

Effects of creditworthiness assessments on consumer outcomes

Given the variety of creditworthiness assessments HCSTC lenders have carried out and as these have changed over time it potentially provided a good opportunity to test the relationship between these different assessments related to consumer outcomes. Unfortunately, when doing this we encountered problems with the data submitted by lenders. It was not always clear why a particular credit application had gone through a particular creditworthiness assessment, while other applications had not, and why it was concluded that the applicant satisfied the relevant criteria to offer credit to.

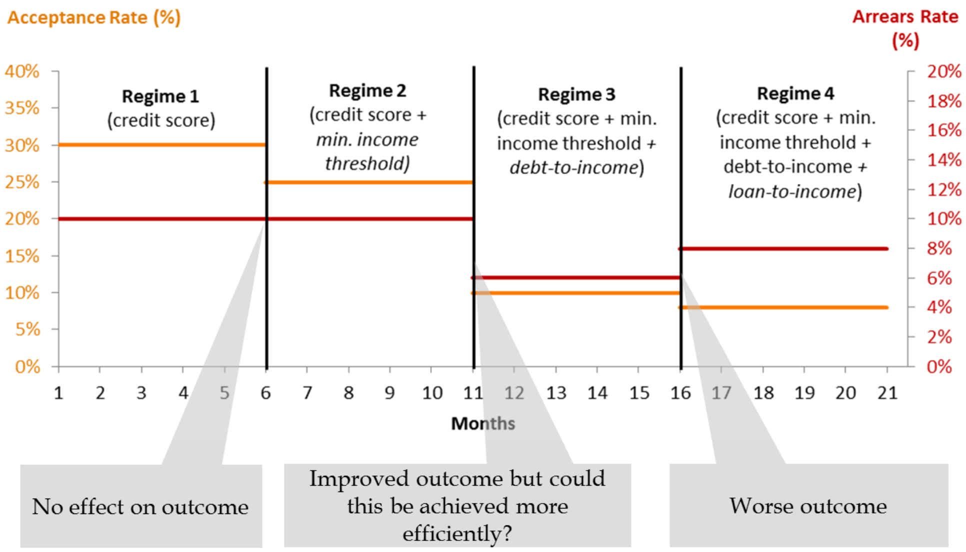
Subject to these caveats regarding the data, we found that additional checks beyond assessing credit risk typically resulted in very few credit applications being declined.

Lenders had changed their lending practices over time in multiple ways and we wanted to use this variation to evaluate:

- How changes in creditworthiness assessments affect outcomes for lenders (e.g. loan acceptance rates, arrears rates) in order to assess whether they are merely 'window dressing' or actually improve lending decisions;
- How changes in creditworthiness assessments affect broader consumer outcomes (e.g. measures of creditworthiness constructed from CRA data);
- Whether changes in particular elements appear to be more effective than others at reducing consumer detriment without unduly restricting lending.

An illustrative example is shown in Figure 26 below. This shows a hypothetical example in which a lender had a creditworthiness assessment which changed over time from regime 1 (a credit score check) to regime 4 (the credit score check is accompanied by a minimum income threshold and restrictions on DTI and loan-to-income). We observe as the lender moved from regime 1 to regime 2 the acceptance rate (orange line, left-hand axis) reduced but there was no reduction in customer arrears rates. Moving from regime 2 to regime 3 caused large reductions in acceptance rates and arrears rates and moving from regime 3 to regime 4 reduced acceptance rates but increased arrears rates.

Figure 26: Illustrative example of changes in creditworthiness regimes



To analyse the effects of changing creditworthiness assessments we planned to exploit variation in the changes in assessment by firms over time – focussing on credit applications around the time of the change. The method used was a regression discontinuity design (RDD), where the discontinuity is the date upon which the changes are implemented by the firm. We denote this form of RDD analysis as 'RDtime'.

The RDtime methodology is a version of RDD which is a technique that, under certain assumptions, provides a way to causally identify effects of 'treatments' (e.g. receiving a HCSTC loan) upon outcomes (e.g. default rates). RDD has been used in a variety of policy contexts, including to inform setting the price cap on HCSTC.[91]

This methodology is reliant upon ensuring we are able to effectively isolate, before a relevant change, which regime each applicant would have gone through if their application had occurred after the change (and vice-versa). If this is not the case, then it could mean that changes observed are due to factors other than the creditworthiness assessment (e.g. changes in the socio-economic characteristics of credit applicants). Issues with data meant we were insufficiently confident in our ability to isolate the effect of changes in assessments on consumer outcomes.

In addition, the methodology needs stability in the acceptance rates within a regime in order to accurately attribute changes in consumer outcomes between regimes to a shift in regime as opposed to other factors. Unfortunately within the HCSTC market during this period this did not hold true. A variety of methods (e.g. restricting the sample, using different time periods, constructing predictive values of outcomes, weighting observations) were attempted. However, none proved to be reliable enough to use.

Given these issues, we took a simple description of acceptance rates on credit applications before and after a change of creditworthiness regime. This analysis does not show the causal effects of the change, and therefore changes observed could be due to a variety of other factors which had nothing to do with changes in credit supply.

[91] PS14/17 Detailed rules for the price cap on high-cost short-term credit (November 2014).

This found some changes in acceptance rates around the time of regime changes, but these typically did not translate into changes in consumer outcomes (and when they did there was no consistent pattern). However, the magnitudes of these changes in acceptance rates were sensitive to the size of window specified for comparing credit applications around the time of a change in creditworthiness regime (e.g. whether we were comparing 1, 7, 14, 30 days or entire regime).

Overall, given the fluctuations in the characteristics of credit applicants we were not confident that the results were informative of a change in creditworthiness assessment as opposed to changing socio-economic characteristics of customers (or other factors).

When we examined some of the changes to non-credit score creditworthiness assessments in greater detail, it appeared as though very few applicants would have been declined. However, this conclusion should be interpreted with caution due to the earlier mentioned concerns over the data.

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