Credit Card Market Literature Review: Affordability and Repayment

Katarzyna Bijak

Christophe Mues

Mee-Chi So

Lyn Thomas

Southampton Business School, University of Southampton

22 October 2015

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Executive Summary

1. Introduction

The review summarises the academic literature on affordability and consumer repayment behaviour as it relates to credit cards. It gives insights into the features affecting unaffordable credit card debt, the third area in the terms of reference of FCA's UK Credit Card Market Survey. The review identifies the way in which the concepts of 1) affordability, 2) creditworthiness, 3) over-indebtedness and 4) responsible lending are defined in the literature and provides an overview of how they are assessed and measured. Different aspects of consumers' credit card usage and lenders' policy impact the likelihood of a consumer defaulting. The former include consumers' repayment behaviour and their use of other credit products; the latter include firms' marketing strategies and the use of variable pricing. The review looked at over 150 papers, more than half being published since 2009.

2. Results in Brief

2.1 Affordability and over-indebtedness

Different definitions of affordability have been proposed for consumer credit in general but they all focus on the ability to repay the loan without financial distress. They vary over whether they take into account only the current situation of the borrower or seek also to forecast any future changes in the borrower's finances (cf. the current debate over mortgages extending into retirement). There has been no credit card specific definition of affordability but given the unlimited horizon on a credit card's borrowing, the issue of what time horizon to use is particularly pertinent. The literature on affordability assessment is sparse. There is little information available in the public domain on how firms assess affordability in practice and the strength of the models they use. What there is suggests affordability is typically assessed using application data (including income), credit bureau reports and estimated expenditure. A common problem is that consumers may exaggerate their income in the application process. Commonly used affordability measures are debt to income, or debt service to income ratios, which are then compared with a predetermined threshold in making affordability decisions. Some credit bureaus have developed affordability indices based on socio-demographic characteristics, income, credit commitments and estimated expenditure.

There is an emphasis in the literature on not estimating the affordability of any credit product (including a credit card) in isolation but to find whether, when added to the other credit commitments, the borrower is able to repay without incurring financial difficulties. In particular, adding new credit products may lead to a consumer becoming over-indebted. Over-indebtedness also has a number of definitions in the literature, but most of them use the household rather than the individual as the unit. Typical is one which says that over-indebtedness is when a household's income is "insufficient to meet its financial commitments without lowering its living standards". Such a definition can be interpreted subjectively (repayments are a "heavy burden") or quantitatively (e.g. repayments on unsecured loans being at least 25% of gross income). The literature recommends using several indicators since the overlap between them is often very small. It also suggests that current approaches tend to be static in nature and should include the consumer's stage of life and long run expected income. This though is more difficult to accurately estimate and more open to abuse.

2.2 Credit Worthiness

Credit worthiness is the ability and willingness of a consumer to repay what is borrowed within the terms agreed. The definition of default, i.e. not doing this, varies by product and by lender.

Scorecards which use data on previous borrowers to relate characteristics of the borrower and the loan to the probability of subsequent default have been used in the industry for 50 years. Although there is a large literature on alternative ways of building scorecards and now how Big Data might be used, most scorecards are built using logistic regression. There are two types of scorecards: application scorecards, used to assess new credit card applicants and relying on socio-economic data, financial indicators and external customer data (including credit bureau information); behavioural scorecards, used to assess existing credit card holders and relying on observed usage and repayment behaviour as well as the bureau information of their current position on other credit products. Credit bureaus also build their own credit scores, but in the UK most lenders seem to build their own scorecards, as opposed to the U.S., where lenders often use the FICO bureau scores.

2.3 Consumer repayment behaviour

There are two main categories of repayment behaviour: transactors, who pay off their balance every month, and revolvers, who hold interest bearing balances. Although only revolvers can default, the literature on the respective characteristics of transactors and revolvers is limited. US data showed transactors to be richer and older on average than revolvers, while education level, real assets and income all increased the outstanding balance before repayment.

Monitoring repayment behaviour can help lenders predict whether a borrower is likely to default, as data on arrears are powerful characteristics in a behavioural scorecard. Similarly, usage behaviour, like number of times the card is used for cash withdrawals, is also relevant. Some papers divide defaulters into two groups, the "can't pays" and the "won't pays", i.e. those who do not have the capacity to repay and those who do not have the willingness to repay. The literature suggests loss of income is the main driver of the former group, while a dispute with the lender could be an example reason for the latter group. Some of the UK data on this is somewhat questionable because it involves the "poll tax" period.

2.4 Responsible lending

The literature definition of responsible lending is ensuring consumers can afford repayments and are aware of the consequences. The literature emphasises that it should continue through the entire period a consumer has the credit card and so involves the initial marketing and acceptance decision, the subsequent operating and marketing decisions, and even the collections strategy if the consumer defaults. The literature also states that assessing affordability is a main component of responsible lending. Although some marketing strategies such as balance transfers and low initial teaser rates have been considered problematic, there is little evidence in the literature that they increase default rates. Similarly, unsolicited credit limit increases do encourage consumers to spend more, but there is limited literature on to what extent they increase default rates. Some research results suggest that there may be links between balance transfers or credit limit increases and financial difficulties. Nevertheless, the available evidence on what lending practices are associated with financial difficulties is limited (and often mixed). A large-scale data analysis could help to further identify potentially problematic practices.

2.5 Switching between credit cards and marketing strategies.

There are two separate decisions a consumer makes: whether to acquire a particular credit card and whether to then use it. Common acquisition strategies by lenders identified in the literature are pre-approved solicitation, balance transfer deals and reward programmes. The latter, as well as credit limit increases, also increase usage. Studies on whether pre-approved solicitation and balance transfer increase the risk of default are limited. A recent U.S. report showed that the traditional

channel for acquisition has declined by 35% between 2008 and 2013 mainly because lenders find it up to 60% cheaper to use on-line acquisition. A number of studies show that credit limit increases do increase spending, one suggesting a 23% rise in usage after a credit limit increase. Another though showed it was associated with a significant rise in debt.

There are a number of studies of credit card churn, i.e. consumers moving to another credit card issuer or at least ceasing to actually use their existing card. This is linked to the "front of the wallet" effect, in that consumers often have a preferred credit card. As with the credit scorecard literature, the research effort is more on what techniques to use to build churn models than on establishing the important characteristics that predict churn.

2.6 Switching between credit cards and other financial products

For a consumer who uses a credit card as a credit facility, the main alternatives are store cards, personal loans, payday loans, overdrafts or occasionally or occasionally increasing the level of a first charge mortgage loan. For those who use a credit card as a payment mechanism, the alternatives are debit cards, cash, cheques and electronic methods. There is more of a literature on switching between those products in the latter case than in the former. There is evidence that consumers swap to store cards and payday loans when they cannot get a credit card or are up against their credit card limit. The literature thus suggests these are ways of obtaining extra credit. The switch between credit cards and other forms of payment mechanisms is found to be driven by the cost and ease of use of the method, the value of the transaction and the age of the consumer.

Two anomalies in switching between credit cards and other financial credit instruments have attracted considerable attention in the literature. One is why some consumers with debit cards and the capacity to service them continue to pay interest on their credit card balances. The literature suggests this may be due to transaction costs, the value of maintaining liquidity or problems of self-control. The second anomaly was that, in the U.S., during the financial crisis some consumers continued to repay their credit cards while defaulting on their mortgages. Again, the explanation suggested concerns about conserving liquidity. In general though, the literature notes that, since the financial crisis, consumers have become more aware of their commitments and more are paying off their credit card balances in full.

2.7 Variable pricing

Risk based pricing at an individual level is often impractical and so firms use multi-level pricing regimes where the population is segmented based on default risk and each segment is charged a different interest rate (the price). The literature suggests this price depends on a consumer's credit rating, the levels of previous and current outstanding debt, features of the credit card and the market power of the lender. In the U.S., lenders used rate-jacking to increase their profit from existing customers by increasing the rate they charged, until this was stopped by the 2009 CARD Act.

For the last 25 years, the literature has investigated why credit card rates have remained "sticky", i.e. why they remained high despite the competition in the market. As well as the searching and switching costs involved in changing credit cards, both adverse selection and winner's curse have been given as explanation. Adverse selection suggests that dropping interest rates attracts more revolvers who have higher default risk than transactors. Winner's curse implies that if a lender offers a borrower a lower rate than the competition, it is because they have underestimated the default risk of that borrower.

The literature is beginning to develop models to optimise the profitability of a credit card by adjusting the interest rate offered so that profitability, not default risk, becomes the acceptance criterion for credit card customers.

3. Conclusions and Recommendations

This review has concentrated on the literature on affordability assessment, credit worthiness and responsible lending in the credit card context. This has also led to why and how consumers switch between and out of credit cards and the marketing strategies including variable pricing that lenders use to attract and profit from their customers.

The review's main recommendations for the FCA's affordability assessment exercise reflect the areas where the existing literature is very limited. One such recommendation is to collect evidence from lenders on how they undertake affordability assessment both at application and when considering credit limit increases and interest rate changes. In particular, are their models static ones or do they reflect future possible changes in the borrower's situation, and how are these estimated?

Secondly, there could be an investigation using UK bank data of which lending and marketing practices, particularly balance transfer acquisition, credit limit increases and interest rate changes are associated with subsequent default or financial difficulties for the borrower.

It could also be worth conducting an up to date survey of those who have defaulted on their credit cards to identify the current reasons why this happens.

Finally, the review also needs to take note of the impact in the U.S. of practices like rate-jacking and changes in minimum repayment levels.

1 Introduction

This is a review of the relevant empirical and theoretical literature on assessing credit card affordability and borrowers' willingness to repay. It is one of three literature reviews commissioned by the FCA as part of their Credit Card Market Study. Since the market study also explores whether there is effective competition in lending to consumers, the review includes examining whether and why consumers switch between different credit cards and between credit cards and other consumer credit products. Another objective of the study is how lenders recover their costs from different types of borrowers so the review also looks at consumer repayment behaviour. A significant part of the review addresses the literature on the major objectives of affordability, credit worthiness and responsible lending on credit cards.

A clear theme throughout this review is the limited data available to academic researchers until recently. For many years, there was little incentive for lenders to share their data with external researchers. With the advent of the Basel Accord, financial institutions have been more willing to do so, so that they have examples of externally built systems against which they can benchmark theirs. Previously, some data was obtained by regulatory authorities but this tended to be at the industry level. There were also some government annual or triennial surveys of general consumer purchase behaviour that had some credit card information. However, publically available data sets were few and atypical. This review found parts of the existing literature to be more theoretical and model based than empirical and consumer characteristic based.

The key terms of the review are defined in the literature as follows:

Affordability is "the ability to do something without causing financial distress, or other undesirable consequences" (Anderson, 2007, p. 664) or "the measure of a customer's financial capacity to fund new and outstanding debts, now and in the future" (Experian, 2014).

There are many definitions of consumer **overindebtedness**. For example, overindebtedness can be defined as "the circumstance where the household's credit-financed spending plans are inconsistent with its potential income stream" (Disney et al., 2008).

Responsible lending can be defined as "acceptable practices that ensure borrowers can afford the repayments and know the consequences, and still try to accommodate as many people as possible" (Anderson, 2007, p. 627).

Creditworthiness is typically defined in terms of the (current and future) ability and willingness of the borrower to pay back a loan or other credit obligation in accordance with all the terms agreed upon. In other words, it is directly linked to the likelihood that a borrower will default on their repayment obligations.

The review is split into seven topic sections. The first three of these topics concentrate on lenders' actions and information; the next three on the borrower's behaviour and decisions; the last looks at the impact of variable and risk based pricing in credit cards. The remainder of this introduction section outlines the objectives of each of these seven sections.

Section 2: Creditworthiness and its drivers

This section looks at the literature on credit-worthiness and how lenders determine a borrower's credit worthiness. For five decades, industry practice has been to estimate this via credit scorecards (application and behavioural). Despite the length of time scorecards have been in use and the fact that individuals can check their bureau credit score online, it is seemingly only since the inception of

Basel II that lenders have become more willing to allow external researchers access to the data on which they build their scorecards; hence, the literature in this area still heavily relies on a relatively small number of available datasets.

Section 3: Affordability and consumer overindebtedness

This section provides definitions of affordability and overindebtedness offered in different literature sources. Affordability and overindebtedness models are then presented that are used in banking practice. Subsequently, theoretical models are described that are proposed in the literature. Where possible, the focus is on solutions for credit cards.

Section 4: Responsible lending

This section provides a definition of responsible lending. Subsequently, it discusses what responsibility means at the different stages of the lending lifecycle (especially in the case of credit cards).

Section 5: Credit card payment behaviour

This section looks at the literature on the repayment behaviour of credit card account holders. Such behaviour produces the extra characteristics that make behavioural scorecards more predictive than application scorecards. More recently, the advantages have been recognised of building models for segmenting transactors (i.e. those who pay off their credit card balance every month) from revolvers (who carry over a balance). A second division appearing in the literature is that between consumers who won't pay and those who can't pay.

Section 6: Choice between credit cards/"front of wallet" and their risk implications

This section investigates why consumers choose one credit card over another, that is, which one is at the "front of the wallet", the different acquisition strategies used by credit card lenders and a marketing strategy that is uniquely suited for current customers – increasing the credit limit of current cardholders.

Section 7: Choice between different consumer credit products

This section looks at how and why consumers choose between different loan products, such as credit cards, store cards, overdrafts, personal loans, payday loans and even mortgages. It also investigates why consumers use credit cards as a payment mechanism as opposed to debit cards or cash and cheques.

Section 8: Risk based pricing and variable pricing and the connection to creditworthiness

This section looks at the impact of variable and risk-based pricing of credit cards and why credit card rates have remained high despite the competition between lenders.

2   Creditworthiness and its drivers

2.1   Definitions of creditworthiness

In both the academic literature as well credit risk practice, creditworthiness is typically defined in terms of the (current and future) ability and willingness of the borrower to pay back a loan or other credit obligation in accordance with all the terms agreed upon. In other words, it is directly linked to the likelihood that a borrower will default on their repayment obligations. Creditworthiness is assessed by the lender itself, and/or by external organisations such as credit bureaus (who provide scores for retail customers) or rating agencies (who provide ratings to wholesale obligors). For the lender, it is a key factor in driving other decisions, e.g. whether to grant credit or issue a certain type of credit card to an applicant, its pricing, etc. For the borrower, it has a direct impact on his/her access to (additional) sources of credit and the rate that they are offered.

Creditworthiness as such is unobservable (at least not prior to an actual default) but retail lenders use scoring systems as a surrogate (Thomas, 2009). Provided that sufficient historical data about individual borrowers' repayment behaviour is available, those scoring systems are typically based on a statistical model that is trained to estimate the probability of default given loan account level or customer level characteristics (or in the case of secured lending, also the type and value of any collateral).

The event of default itself and how to define it may vary depending on the product, the bank's own policies, local industry practices, and whether the model is used for Basel II and III regulatory capital calculations. For example, Basel II suggests the following triggers for default (par. 452): (1) the lender recognises that the obligor is unlikely to meet its credit obligations in full without having to revert to actions such as realising security; (2) the borrower is "*past due more than 90 days on any material credit obligation*". However, national supervisors have the discretion to allow the retail credit default trigger to be set at up to 180 days past due, in order to better reflect local industry practices – this is true for credit cards both in the UK (FCA, BIPRU 4.6.20 R) and the U.S. (Fed. Reg., 2007, p.69306). The counter for days past due on credit cards normally starts at the minimum payment due date (see e.g. BIPRU 4.3.57 R); inability to meet minimum agreed repayment terms over a specified period of time thus forms the main trigger.

To assess the risk of default (and hence creditworthiness), two types of scorecards are in common use by those who issue credit cards or other forms of retail loans, depending on whether they are to be applied to new applications or existing accounts – application and behavioural scorecards.

2.2   Application scorecards and characteristics used

Application scorecards are used by creditors to assess the creditworthiness of new loan or credit card applicants. They are used to risk rank potential borrowers with the help of data that is available or collected at the time of application, which may include both data entered on an application form or external bureau data.

By far the most common technique to build either application or behavioural scoring systems is logistic regression. This is probably due to a number of reasons: logistic regression performs relatively well on real-life data, whilst other, more recent classifiers (e.g. neural networks, ensemble classifiers, etc.) may provide a small improvement in predictive accuracy but do not provide an as straightforward explanation as logistic regression of how characteristics contribute positively or negatively to a score. Arguably, this has so far held back a wider adoption of these techniques

amongst practitioners, particularly if the lender is legally required to provide an explanation of why an application was rejected or for models used in a regulatory setting (e.g. scoring models used as part of a Basel II or III Internal Rating Based (IRB) implementation). Nonetheless, a substantial body of academic literature has investigated alternative methods to produce default prediction models; for a recent benchmarking study comparing a wide selection of techniques over a suite of real-life datasets, we refer to Lessmann et al. (2013).

Prior to the introduction of application scorecards, common qualitative criteria to assess credit worthiness were the 5 Cs (character, capital, collateral, capacity and condition); with the advent of scorecards, this judgmental approach has largely been replaced by a statistical one that uses a range of measurable explanatory variables or characteristics. This process towards using what is a largely empiricist approach to quantifying credit worthiness has not been without its critics; e.g. a critical stance with regards to the absence of a true explanatory model is expressed as early as in Capon (1982), who also lists (and questions) some of the variables in common use at the time.

The switch to a scoring approach was inevitable certainly for credit cards, as the volume of applications and 24-hour coverage quickly called for an automated scoring approach (Thomas et al, 2002, p.10). The variables that end up in an in-house application scorecard will inevitably vary, but, as categorised in Van Gestel & Baesens (2009, p.249), could include socio-demographic data (subject to whichever local regulatory constraints may apply to the lender), financial indicators, product characteristics, and other internal or external customer-level data (see Table 2.1). The latter may also include behavioural data for customers that already have other credit products with the bank, similar to those used in behavioural scoring systems (see next section). Similarly, banks have found that using credit reference bureau data in application scorecards considerably enhanced their power. In the UK, credit card organisations tend to use the characteristics available in the bureau data while in the U.S. they tend to use the bureau score. In reality, these characteristics and behavioural data on the consumer's other loan products are usually more predictive of default than socio-demographic data.

Table 2.1. Commonly used variables for application scoring (e.g. Van Gestel & Baesens (2009), p.249; Siddiqi (2006), p.93; Anderson (2007), p.277)

Type	Example variables
Socio-demographic	Age, marital status, number of dependents, employment status, industry sector, time with employer or in industry, residential status, time at address, geographical region, etc.
Financial indicators	Income, debt, debt-to-income ratio, savings, etc.
Product information	Type and purpose of the loan or card type, collateral type/value (if any), insurance, loan amount or credit limit, loan term, instalment amount, payment frequency/method, interest rate/APR, source of business (channel), etc.
Customer information	Tenure (length of relationship with bank/issuer), behavioural data (existing customers only), external data (credit bureau score, past credit record, credit lines available, recent searches, recent delinquency, etc.)

Note that, in the credit scoring literature, many methodology-oriented studies for some time tended to use a small set of (relatively small) publicly available credit scoring datasets, i.e. Australian and German Credit, which are available in the UCI Machine Learning Repository (Lichman, 2013). Hence,

the characteristics reported in much of this strand of the literature are heavily biased towards those and should not be taken as fully representative of the characteristics used in the financial services sector. Table 2.2 provides an overview of publicly available data including two more recent additions. Other papers may use individual banks' or bureau data sets, which, although often richer and more representative, tend to be subject to data exchange agreements restricting access.

Table 2.2. Publicly available credit scoring datasets

Data set	Cases	Inputs	Loan type	URL
German Credit	1,000	20	Personal loans	http://archive.ics.uci.edu/ml/
Australian Credit	690	14	Credit card applications (approval/reject)	http://archive.ics.uci.edu/ml/
PAKDD 2010 Competition	50,000	37	Credit cards	sede.neurotech.com.br/PAKDD2010/ (currently unavailable)
"Give me some credit" Kaggle competition	15,000	10	Unspecified	https://www.kaggle.com/c/GiveMeSomeCredit/

2.3   Behavioural scorecards and characteristics used

Behavioural scorecards are used by creditors to assess the creditworthiness of existing loans or credit card accounts. Such scorecards are particularly important in the context of credit card portfolios as the scores produced by them might drive other decisions, e.g. whether to extend a customer's credit limit.

Behavioural scorecards would typically include characteristics summarising the observed repayment or usage behaviour for that account, e.g. in a 6- or 12-month period prior to the observation point. With instalment loans, one would typically consider variables such as the number of payments missed in the last 3, 6, or 12 months, number of consecutive payments missed, minimum/average/maximum amount in arrears, etc. For credit cards, in addition to past delinquency (here: failure to pay off at least the minimum amount), another main driver would normally be utilisation rate or credit usage, i.e. the ratio of drawn amount (or amount carried forward) over the credit limit, as measured either at the observation point or aggregated over a certain time period prior to it. Some application variables (e.g. socio-demographic ones) may still be useful but tend to lose their predictiveness and are not always reliably updated over time, although in some cases proxies may be available; e.g. Avery et al. (2004) give the example of using changes in account (co-)ownership as a proxy for changes in marital status (note that their paper considers consumer credit in general, not just credit card data). Furthermore, where available, external data and/or data about the behaviour of the customer with regards to other products (s)he holds with the bank could again be incorporated into the behavioural scorecard.

Van Gestel and Baesens (2009, p.249) distinguish between what they call: flow variables, which measure the number and GBP amount of credit and debit operations; interval measures, which look at the length of a certain time period (e.g. payment delays); customer relation measures (e.g. age of account); product status management (e.g. blocked yes/no); flash volume variables (e.g. account

and/or card balances, debt levels, etc.); debt level and burden (e.g. total debt to income or savings); and demographic customer information.

Several studies have confirmed the importance of these variables for explaining or predicting credit card default. For example, although not using a traditional scoring approach but a hazard model fitted to an Equifax panel data sample, Canals-Cerdá and Kerr (2014) found that account-specific characteristics like delinquency history, account age (seasoning effect), line (i.e. limit) and utilization, as well as a proprietary Equifax risk score, were strongly related to probability of default. Interestingly, they also found that unemployment rate and house price index had a significant relationship with probability of default, but that the effect varies with the risk score of the borrower: subprime borrowers appeared much less affected by the macro-economic environment than prime ones. Note that there is little evidence, however, that lenders would effectively include such economic variables into their own scorecards, in part because account-level models are often built using a fairly short, recent timespan of data, where the economy is not changing much. Similarly, in an application scorecard, every applicant in a given cohort would have the same value for a macro-economic characteristic; therefore, it cannot change the relative ranking of the applicants. Economic covariates do, however, have a major impact on the probability of default estimation (see e.g. Zhang and Thomas, 2015). Also, local rather than national economic data could be considered here where available, as suggested e.g. by Avery et al. (2004), or by Agarwal and Liu (2003), who found that U.S. county-level unemployment rates significantly influenced credit card delinquencies. Note that the latter is an example paper of a larger body of literature that has empirically investigated the relationship between the economy and credit card default rates.

Another empirical study by Dunn and Kim (1999) used household-level survey data to investigate the determinants of credit card default. The three most significant variables identified in their study were: the ratio of total minimum required payment from all credit cards to household income; (2) utilisation (measured over the total credit line); (3) the number of credit cards on which the borrower has reached the credit limit (i.e. has "maxed out"). Based on their results, the authors make a case for the first ratio having minimum repayment in the numerator rather than using the conventional debt-to-income ratio as a predictor for imminent (as opposed to longer-run) default. However, a potential limitation in their work, apart from the sample size, is a lack of clarity of the respective time horizons for measuring the explanatory and outcome variables, so it was uncertain whether certain variables are acting as (early) predictors or as symptoms of default.

More recently, more papers seem to be emerging that analyse much richer bank data sets. For example, Khandani et al. (2010) used customer-level data to predict credit card holders' delinquencies (more specifically, being delinquent for 90 days or more) which included not just account-balance and credit bureau data, but also account-level transactions data including each transaction's amount and direction (inflow or outflow), channel and category (there were reportedly 138 categories ranging from food expenses to mortgage payments).

This is just one example of a number of large data sources (e.g. online ones) that are starting to become more readily available for analysis (often coined as "big data" in the analytics industry), several of which would require further scrutiny as to their appropriateness for scoring purposes.

2.4   Bureau scorecards

The credit bureaus and Fair Isaac Company have developed their own scorecards both at a customer level and for specific products. These scores are arguably more important in the U.S. where the FICO score produced by Fair Isaac Company using respectively Experian, Equifax and TransUnion data is

one used by all lenders and known by most consumers. Since 2006, the bureaus have built their own score, the Vantage Score, each built on their own bureau's data. The FICO score is used by the vast majority of lenders, with Vantage Score having a smaller market share, selling 1 billion scores compared to FICO's 11 billion in 2014, and other non-FICO scores having even less (Sullivan, 2015).

This is in contrast to what happens in the UK, where the major lenders tend to build their own scorecards using their own and bureau data. The three main bureaus in the UK are Experian, Equifax and Call Credit. The former two produce their own bureau scores – Experian Credit Score and Equifax Credit Score – while the last produces a five-level credit rating.

It is important to realise that there are several different types of bureau scores depending on the lending product and the bureau data being used. It is claimed that, in the U.S., an individual can have up to 47 different FICO scores for this reason. Moreover each score can have up to twenty different scorecards, each scoring a segment of the population. Typical segmentation would be between "thick" and "thin" files (which reflect the amount of data available on the individual), home ownership, and type of product (Fico 2014a, 2014b).

Obviously the details of the scorecards are confidential but the general importance of the various aspects is publically available. Table 2.3 describes these for the classic FICO score, the Vantage Score and Score Plus which Experian has produced for educational purposes, where importance is the percentage of the average score attributable to those variables. For a further report on credit reporting in the U.S., we refer to Avery et al. (2003).

Table 2.3. Relative importance of bureau score drivers (% of score attributable to those factors)

Score	FICO	Vantage Score	Score Plus
Reference	www.myfico.com	www.experian.com	www.freecreditscore.com
Payment history	35	28	31
Length of credit history	15	9	15
Type of credit in use	10	0	14
Amount owed	30	9	0
New credit accounts recently	10	30	0
Utilization of accounts	0	23	30
Available credit	0	1	0
Number of enquiries	0	0	10

2.5   Other empirical work on creditworthiness

In addition to the work discussed above, it is important to note that other methodologies have been proposed to estimate probability of repayment and hence creditworthiness.

First, Markov-chain analysis allows one to distinguish not just between a "good" and "bad" state but model the risk of moving to progressively worse delinquency bands or rolling back to being on time. One such example can be found in Till & Hand (2003).

Second, survival analysis techniques are what seems an increasingly popular alternative to the scoring approach that does not require the output window for the event(s) of interest (i.e. default or its competing event: early prepayment of an instalment loan or credit card churn) to be fixed to a certain time interval (e.g. one year). As such, these methods allow one to estimate not just whether but when borrowers are more likely to default. The case for using survival analysis as a compelling alternative to application and later on behavioural scoring was made by e.g. Banasik et al. (1999). Later on, survival analysis with time-dependent covariates has also regularly been used to incorporate changing economic circumstances into the models, or the analysis was extended to model transitions between different delinquency bands (which may also be referred to as "intensity models"). For example, Leow and Crook (2014) combine both application variables (including type of employment, tenure, time at address and age) and time-dependent behavioural variables (including monthly spending and repayment amounts, credit limit and outstanding balance) into the intensity models they built for a large bank dataset containing 49,000 credit card accounts; note that, for the purpose of making predictions, this does require lagging those behavioural variables.

Third, as mentioned earlier, algorithms emerging from other research disciplines (e.g. machine learning) have been regularly proposed as being able to produce more accurate account-level predictions. However the problems with an arguable lack of transparency and as yet unproven robustness over time still seem barriers to their wider adoption in practice.

3 Affordability and consumer overindebtedness

This section provides definitions of affordability and overindebtedness offered in different literature sources. Affordability and overindebtedness models are then presented that are used in banking practice. Subsequently, theoretical models are described that are proposed in the literature. Where possible, the focus is on solutions for credit cards.

3.1 Definitions of affordability

Speaking generally, both assessing affordability and estimating the probability of default (PD) focus on a possible loan repayment (or lack thereof). However, affordability assessment only concentrates on the lack of repayment resulting from the customer's inability to repay, whereas PD estimation focuses on default, regardless of its reason. Furthermore, when assessing affordability, it should be checked whether the customer can meet the credit commitment 'in a sustainable manner' (in particular, without difficulties in the context of their other commitments and normal expenditure). When estimating PD, credit sustainability is not taken into account. This difference is fundamental from a responsible lending point of view.

Credit scoring assesses the customer's creditworthiness, i.e. their propensity to repay a loan. This assessment is based on the comparison with similar customers who were granted loans in the past. Nevertheless, the propensity to repay is separate from the ability to repay (Curtis, 2013). As a result, some customers may be classified as low risk based on their credit scores, although they may be unable to repay their loans. Hence, it is crucial to assess affordability. Moreover, affordability assessment may help identify those customers who remain affluent (North, 2012).

As far as it can be ascertained, no definition of affordability has been proposed specifically for credit cards. Anderson (2007) defined affordability as "ability to do something without causing financial distress, or other undesirable consequences" (page 664). According to Experian (2014), affordability is "the measure of a customer's financial capacity to fund new and outstanding debts, now and in the future". The Financial Services Authority (2010) suggested that a (mortgage) loan can be deemed affordable "if its level and terms allow the consumer to meet current and future payment obligations in full, without recourse to further debt relief or rescheduling, avoiding accumulation of arrears while allowing an acceptable level of consumption" (paragraph 2.16).

Anderson (2007) simply described affordability assessment as "evaluation of a borrower's ability to repay" (page 664). The Office of Fair Trading (2011) defined affordability assessment as "a 'borrower-focussed test' which involves a creditor assessing a borrower's ability to undertake a specific credit commitment, or specific additional credit commitment, in a sustainable manner, without the borrower incurring (further) financial difficulties and/or experiencing adverse consequences" (paragraph 4.1). The literature does not recommend assessing affordability for credit cards (or any other loans) in isolation; all the customer's existing debts should ideally be taken into account in this process (Lucas, 2005; Dell, 2007; Brooksby, 2009; Maydon, 2011; Curtis, 2013).

According to the FCA Handbook, "before entering into a regulated credit agreement […], a firm must carry out an assessment of the potential for the commitments under the agreement to adversely impact the customer's financial situation, taking into account the information of which the firm is aware at the time the agreement is to be made" (CONC 5.2.2R (1)). Moreover, "the creditworthiness assessment and the assessment required by CONC 5.2.2R (1) should include the firm taking reasonable steps to assess the customer's ability to meet repayments under a regulated credit

agreement in a sustainable manner without the customer incurring financial difficulties or experiencing significant adverse consequences" (CONC 5.3.1G (2)).

Affordability assessment is closely related to the consumer overindebtedness and responsible lending concepts. The relationship between affordability assessment and responsible lending is explored in Section 4.2.3.

3.2   Definitions of overindebtedness

It is suspected that irresponsible lending practices exacerbate excessive indebtedness/ overindebtedness (Kempson, 2002). For example, increasing the credit limit or granting credit without reasonable affordability assessment may lead to the customer being overindebted, which in turn may lead to default. The consumer overindebtedness phenomenon, including its scale and drivers, has been intensively studied at both the national level (Kempson, 2002; Oxera, 2004; Disney et al., 2008; Bryan et al., 2010) and the European Union level (Fondeville et al., 2010). Selected reports are summarised in Table 3.1.

Overindebtedness is analysed at the individual or household level (although the latter level is generally preferred and recommended e.g. by Disney et al. (2008)), and a number of definitions have been proposed. Oxera (2004) assumed that overindebted are "those households or individuals who are in arrears on a structural basis, or are at a significant risk of getting into arrears on a structural basis". The households which are in arrears "on a structural basis" do not include those that are in arrears temporarily and those that are able but not willing to repay (Oxera, 2004). Haas (2006) cited a German definition according to which a household is overindebted "when its income, in spite of a reduction of the living standard, is insufficient to discharge all payment obligations over a longer period of time". Disney et al. (2008) suggested that overindebtedness is "the circumstance where the household's credit-financed spending plans are inconsistent with its potential income stream". Fondeville et al. (2010) defined an overindebted household as "one whose existing and foreseeable resources are insufficient to meet its financial commitments without lowering its living standards". Murray (1997) described an overburden of debt as "a level of debt that imposes obligations for the payment of interest and principal that force a household to trim its spending below what its members had been accustomed to and/or had expected to spend". Finally, a large number of definitions from different European countries can be found in Davydoff et al. (2008). For example, in the Netherlands "individuals are considered to be over-indebted if they meet the conditions to benefit from the debt settlement scheme Schuldsanering – for that it is sufficient that an individual, in good faith, is unable to meet his/her debt commitments" (Davydoff et al., 2008). Similarly, in Norway "a person can be regarded as over-indebted if he meets the first condition to obtain debt settlement. This is the case if the debtor is permanently incapable of meeting [his] obligations" (Davydoff et al., 2008).

Betti et al. (2001) classified definitions of overindebtedness into three models (types): administrative, subjective and objective (quantitative). For overindebtedness to occur in the administrative model, it must be declared before the court and/or registered by an official authority. In the subjective model, it is sufficient to self-define oneself as overindebted, whereas in the objective model, overindebtedness is measured e.g. using debt to income or debt to assets ratios. The Department of Trade and Industry (2005) used a mix of the objective and subjective models to specify the five indicators of overindebtedness: spending more than 25 per cent of gross income on repayments of unsecured loans, spending more than 50 per cent of gross income on repayments of both secured and unsecured loans, having four or more credit commitments, being in arrears for more than three months and considering repayments a 'heavy burden'. On a similar note, Tudela

and Young (2003) analysed data on unsecured debt and whether it was a burden. However, their analysis excluded any debt that was going to be paid in full at the end of the month as temporary borrowing and "a convenient way of making transactions" (using credit cards).

The subjective model may be preferred over the objective one, as it is simple (Betti et al., 2001) and provides a direct measure of overindebtedness (Oxera, 2004). However, it depends on the individual interpretation and perception of a 'heavy burden', etc. (Fondeville et al., 2010; Betti et al., 2001). The objective model may also be useful, but only because there is a relationship between the objective indicators and overindebtedness. According to the Department of Trade and Industry (2005), the overlap between the overindebtedness indicators is surprisingly small. For example, only 22 per cent of those who were spending more than 25 per cent of their income on repayments of unsecured loans found the repayments a heavy burden (Department of Trade and Industry, 2005). Possible explanations include having savings and other or expected future incomes. Nevertheless, this is a strong argument for the use of several indicators instead of a single one. The number of indicators could possibly be reduced, at the risk of losing information, using such methods as Principal Component Analysis, as suggested by Disney et al. (2008).

Many reports use several indicators, both objective and subjective (e.g. Bryan et al., 2010; Department of Trade and Industry, 2005; Kempson, 2002; Oxera, 2004). However, it may sometimes be helpful to adopt a simplified working definition of overindebtedness, such as "consumers are over-indebted when they fall into arrears on at least one credit commitment" (Disney et al., 2008). Understandably, using simplified definitions affects the analysis results. For example, the above-mentioned working definition leads to the overestimation of the overindebtedness scale, since most household who miss one payment will get back on track on their own (Disney et al., 2008). On the other hand, using a definition based on a single indicator may result in the underestimation of the overindebtedness scale, as e.g. debt to income ratios only provide information on a part of the picture.

It is often assumed that increasing unsecured indebtedness may cause financial difficulties, but Del-Rio and Young (2005) suggested that this depends on the type of customers. In particular, increasing unsecured indebtedness may be less of a problem if it reflects positive changes in customers' financial situation, i.e. such changes that make them more optimistic about their future income and feel more confident about their ability to repay. It may also be a substitution from personal loans (Fortin and Préfontaine, 2008; Zywicki, 2008). The substitution is when customers switch from personal loans to credit cards but maintain the same levels of borrowing (see Section 4.2.3).

Applying the same overindebtedness thresholds to all customers was criticised by Betti et al. (2001), since such an approach does not take into account the customer's stage of life. For example, young people can often expect their income to increase over time, and thus they may be able to manage higher debt to income ratios. Betti et al. (2001) proposed analysing not only the customer's current income but also their permanent income, i.e. expected income over a long period of time (Friedman, 1957). The Permanent Income Hypothesis assumes that current consumption depends on permanent rather than current income and is sensitive to permanent but not transitory income shocks (Snowdon and Vane, 2005). Moreover, Betti et al. (2001) suggested considering the Life-Cycle Theory (Modigliani and Brumberg, 1954), which states that consumers smooth their consumption over time and e.g. young people may borrow against their expected future incomes. Betti's suggestions were later repeated by Disney et al. (2008). Applying them when accepting/rejecting credit card applicants and/or changing credit limits would mean adopting a dynamic approach to affordability assessment.

Table 3.1. Selected reports on consumer indebtedness and overindebtedness

Report	Brief summary	Data
Betti et al. (2001)	This study focuses on the definitions and measures of consumer indebtedness and overindebtedness. It is illustrated with the analysis of data collected among households in European countries.	Household surveys carried out in the EU member states in the 1990s: • The European Community Household Panel Survey • The (European) Household Budget Surveys
Bryan et al. (2010)	This report analyses the results of two surveys conducted among British households. The second survey only targeted those who were in financial difficulties according to the first survey.	Surveys conducted among British households between 2006 and 2009: • Wealth and Assets Survey • Household Annual Debtors survey
Department of Trade and Industry (2005)	This reports studies the results of a large survey that was carried out among British consumers. The survey focused on overindebtedness, but unlike other surveys, it does not targeted households.	Survey carried out by MORI among British consumers in 2004
Disney et al. (2008)	This report examines trends in overindebtedness among the UK households between the late 1990s and 2008. It includes the analysis of both quantitative data and qualitative information (interviews).	The UK household panel datasets: • Family and Children Survey • British Household Panel Survey
Fondeville et al. (2010)	This study focuses on consumer indebtedness and its relationship with overindebtedness in European countries. It also analyses the relationship between overindebtedness and household characteristics	Household surveys carried out in the EU member states between 1995 and 2008: • The European Community Household Panel Survey • The European Union Statistics on Income and Living Conditions

Kempson (2002)	This report analyses the results of a survey that was conducted among British households. The survey was designed to offer an insight into the causes, scale and consequences of overindebtedness.	Survey conducted by MORI among British households in 2002
Oxera (2004)	This report investigates the extent of consumer indebtedness and overindebtedness in the UK. It analyses information provided in other reports as well as data from the ONS and the Bank of England.	Sources of information/data: • Other reports[1] • ONS • Bank of England
Tudela and Young (2003)	This article studies the results of a survey that was carried out among consumers in the UK. The survey focused on the types and amounts of consumers' unsecured debt and whether the debt was a burden to their households.	Survey carried out by NMG among the UK consumers in 2003

3.3 Affordability/overindebtedness models used in practice

First of all, it must be noted that this section is limited to what has been available in the public domain.

Affordability assessment is often based on information from the three sources: application data (including income), credit reports and estimation of expenditure (Lucas, 2005; Dell, 2007; Brooksby, 2009; Maydon, 2011; Curtis, 2013). This enables calculating a disposable income that can be then taken into consideration in the credit decision making process (Dell, 2007; Maydon, 2011). In particular, a disposable income can be used to decide on credit limit increases/decreases (Maydon, 2011). However, the most commonly used affordability measures are debt to income and debt service to income ratios (these measures can also be used to assess overindebtedness). The ratios can also be computed using application data, information on credit commitments from credit bureaus and expenditure estimates (e.g. Lucas, 2005). The expenditure estimate is often modelled on public data such as the ONS Living Costs and Food Survey (formerly known as the Expenditure and Food Survey). To assess affordability, the calculated ratio can be compared with a predetermined threshold. A common problem is that some customers exaggerate their income in the application process, which affects all income-based assessments. Self-certified income can be

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[1] The Oxera report includes the summaries and assessments of 10 earlier reports.

verified to some extent by comparing it with incomes stated in previous credit applications and income estimates offered by credit bureaus (Curtis, 2013; Brooksby, 2009).

Affordability models are another approach. In particular, an affordability model can be used to assess the impact of changes in credit limit on the credit card customer's risk profile. Somers (2009) developed a stepwise regression model to estimate the probability of the customer defaulting that takes into account the forecasted credit limit. The forecasted limit is estimated using another model that contains only one independent variable, a risk score. The affordability model includes a risk score as well as the log ratio of the actual limit and the forecasted limit. It also contains a number of characteristics multiplied by the log ratio to adjust the model outcome for those customers for whom the forecasted limit differs from the actual one. Somers' model is part of a solution designed to determine new credit limits that was developed for one of the UK banks.

Furthermore, credit bureaus have been offering solutions to help assess affordability. For example, Experian developed the Affordability Index (Experian, 2011). For this purpose, a multi-scorecard model was built, where the customer's status definition was based not only on delinquencies but also on the Consumer Indebtedness Index. A high indebtedness level was indicated by such factors as high utilisation of credit cards and excessive credit activity. To assess affordability, Experian was analysing (among other things) the customer's socio-demographic characteristics, income and credit commitments as well as expenditure estimated using the Expenditure and Food Survey data (Russell, 2005; Brooksby, 2009).

Apart from the Consumer Indebtedness Index, Experian currently offers income estimation and Current Account Turnover data-based income verification as well as disposable income assessment (Experian, 2014). The income models which are developed by credit bureaus are mostly based on geo-demographic characteristics, mortgage loan amounts and credit card limits (Curtis, 2013). However, according to Curtis (2013), their performance may not always be satisfactory, especially in case of low and high incomes. Nevertheless, such models enable monitoring the customer's financial situation and may possibly help make decisions about increasing the credit limit.

Another example of the credit bureaus' solutions is Callcredit's Affordability Suite (Callcredit, n.d.). Among other things, there are indicators based on debt to income ratios as well as indication of income accuracy. This solution also includes a score to estimate probability of default as a result of overindebtedness.

Finally, Curtis (2013) suggested adding debt to income ratios to risk scorecards to improve the model performance for those customers who are heavily indebted and on low incomes. The proposed characteristics include: revolving credit commitments as a percentage of net monthly income, mortgage payment as a percentage of net monthly income, total credit limit as a percentage of gross annual income and total unsecured balance as a percentage of gross annual income (Curtis, 2013).

Affordability and overindebtedness are usually assessed as of the date of the loan application or the interview/survey. They are difficult to predict for the future, since there are so many factors that may affect them. Nevertheless, some models offer an insight into the future, e.g. by estimating probability of default as a result of overindebtedness (Callcredit, n.d.) or taking into account the forecasted credit limit (Somers, 2009).

3.4 Theoretical affordability/overindebtedness models

Currently, there is sparse literature on affordability and overindebtedness models. Finlay (2006) suggested using linear regression to estimate expenditure to income ratio for affordability

assessment. He also proposed applying logistic regression to estimate probability of overindebtedness at the time of application. Both regressions were based on application data and credit reports. Nevertheless, Finley mentioned that these models do not reflect the dynamic nature of income and expenditure. Bijak et al. (2014) noted that static approaches to affordability have a number of drawbacks. For example, ignoring possible increase in consumption may lead to granting too much credit, overindebtedness and default. On the other hand, ignoring possible increase in income may lead to offering less credit than the customer would be able to repay and, in consequence, losing potential profits.

Thomas (2009) suggested using structural models based on affordability to model the credit risk of portfolios of consumer loans. In this approach, the customer's asset process is modelled, and defaults result from cash flow problems. The realizable assets are increased by income and reduced by both expenditure and loan repayment on the monthly basis. The customer defaults when the realizable assets become negative or fall below a percentage of the total debts. Income and expenditure could be treated as functions of economic conditions to model the dynamics of the asset process. Although this approach was proposed with a different view, it could be applied for assessing affordability.

Bijak et al. (2014) suggested a theoretical framework for dynamic affordability assessment. It was assumed that income and consumption vary over time, and their changes are modelled with random effects models for panel data, i.e. time-series cross-sections. Panel data analysis was proposed to allow for the introduction of dynamics. The models were derived from the economic literature, including the Euler equation of consumption. In this approach, the estimated models are applied in a simulation that is run for the customer. In each iteration, the predicted income and consumption time series are generated, and the customer's ability to repay is assessed over the life of the loan, for all possible instalment amounts. As a result, a probability of default is assigned to each amount. In this framework, a loan is affordable if the customer is able to repay it while also meeting consumption costs and repayments of all other debts month after month until the loan is paid in full. This approach takes a long term perspective and considers the dynamic nature of the customer's financial situation. It is designed for instalment loans, but could be modified to accommodate credit cards.

Adopting a dynamic approach to affordability assessment would allow for the prediction of the customer's ability to repay and overindebtedness in the future.

3.5   Conclusions

There are a number of definitions of affordability and overindebtedness. As far as it can be ascertained, no definitions have been proposed specifically for credit cards. However, spending more than 25 per cent of income on repayments of unsecured loans is one of the commonly used indicators of overindebtedness. When assessing overindebtedness, it is recommended to use several different indicators, though.

Since numerous factors may have an impact on affordability and overindebtedness, it is challenging to make predictions for the future. Affordability assessment is often based on application data, credit reports and estimation of expenditure. Little information on the implemented affordability models is available in the public domain, except for the solutions offered by credit bureaus. There is even less information on models for credit cards. The existing literature on affordability and overindebtedness models is also sparse. Nevertheless, a dynamic approach to affordability

assessment may be preferred that takes into account possible changes in both income and expenditure and enables predicting for the future.

4 Responsible lending

This section provides a definition of responsible lending. Subsequently, it discusses what responsibility means at the different stages of the lending lifecycle (especially in the case of credit cards): when advertising credit, explaining credit agreements, assessing affordability, managing repayments, credit limits and interest rates, and handling arrears and defaults.

4.1 Definition and nature of responsible lending

Anderson (2007) defined responsible lending as "acceptable practices that ensure borrowers can afford the repayments and know the consequences, and still try to accommodate as many people as possible" (p. 627). Affordability assessment is the crucial component of responsible lending, whereas poor affordability assessment is typical for irresponsible (reckless) lending (Anderson, 2007).

At the EU level, the Consumer Credit Directive states that "it is important that creditors should not engage in irresponsible lending" (Council Directive 2008/48/EC, point 26). At the national level, the OFT (2011) listed numerous possible irresponsible lending practices[2]. Irresponsible lending practices may even be a reason for a consumer credit licence being revoked. According to the Consumer Credit Act 2006, the practices which involve, in the view of the OFT (now FCA), irresponsible lending are examined when considering the lender's fitness to hold the licence (section 29, subsection (2)).

4.2 Responsibility at the different stages of the lending lifecycle

In response to a consultation by the Department for Business, Innovation and Skills, The UK Cards Association (2010)[3] declared that "it is imperative to recognise that responsible lending does not end with an initial underwriting decision, but continues throughout the entire period that a customer has a credit card account".

4.2.1 Advertising credit

There are a number of guidelines and requirements related to credit advertisements. For example, credit cannot be advertised in the way that suggests its availability irrespective of the borrower's financial situation or obfuscate the information about the associated risks (OFT, 2011). Following the implementation of the Consumer Credit Directive, if an interest rate or an amount related to the associated costs is mentioned in the advertisement, there must be a representative example of the credit (Department for Business, Innovation and Skills, 2010a, Chapter 6).

One of the potentially problematic marketing strategies is offering low initial interest rates and high credit limits to encourage borrowers to transfer balances on credit cards (Kempson, 2002). According to Kempson (2002), there is no evidence that it can cause financial difficulties, but it is especially attractive to those who are already experiencing such problems, and can make the difficulties even greater. It is argued that some people who are having financial problems transfer balances but do not intend to pay the interest charges after the initial low interest rate period. They may even be unaware of the initial period length and what will happen next. Among the households

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[2] See Section 4.2.

[3] Both the consultation document and the response focused on four areas: the allocation of payments, unsolicited credit limit increases, minimum payments and risk-based pricing. Generally, the response was in favour of the current practices, and the scope of changes proposed by the industry was fairly limited.

whose data were analysed by Kempson (2002), half of those who transferred balances were in financial difficulties.

Nevertheless, Disney et al. (2008) found that lenders did not associate balance transfer customers with financial difficulties. They rather viewed such customers as "a low-risk group of consumers who are typically more literate and sophisticated in their financial management than the broader consumer base" (Disney et al., 2008). The difference in findings between Disney et al. (2008) and Kempson (2002) may be due to differences in research approaches (qualitative/quantitative), participants (lenders/households) and timeframes as well as asymmetric information between households and lenders.

4.2.2 Explaining credit agreements

Many requirements related to credit agreements were specified in Part V of the Consumer Credit Act 1974. Some of them were additionally repeated by the OFT (2011) and the FCA Handbook. In particular, lenders are required to disclose specified information to borrowers and provide them with adequate explanation (CONC 4.2.5R). The provided explanation should allow the borrower a reasonable assessment of their ability to repay: after receiving the explanation the borrower should be able to judge on their own whether they can afford the credit (CONC 4.2.6G). The explanation should cover the associated risks and costs to the borrower. The level and type of the explanation should be adjusted to the borrower's needs. The borrower should have an opportunity to ask questions about the credit agreement, even if the credit transaction is made remotely (over the Internet, etc.).

Among other things, the most important elements of the explanation include: the features of the agreement making the credit unsuitable for certain use, the amounts the borrower will need to pay, the consequences of failure to meet the credit commitment and the right of withdrawal (CONC 4.2.5R (2)). As far as credit cards are concerned, the borrower should be informed about: different rates and/or charges associated with different components of the credit, the consequences of only making minimum payments, possible increases of interest rates charged, the limitations of introductory offers and the conditions of balance transfers (CONC 4.2.15R (1)).

According to The UK Cards Association (2011), "card issuers will give customers the information they require to make informed decisions. Information should be clear, concise, consistent and customer-friendly" (Section 2.5).

4.2.3 Assessing affordability

Assessing affordability is considered the main component of responsible lending. In line with the Guide to Credit Scoring (the document which set out some best practice principles related to scoring of consumer credit applications), creditors should make it clear to borrowers that "as responsible lenders, we take into account your personal circumstances to establish the appropriate level of credit to grant to you" (Association for Payment Clearing Services et al., 2000, Appendix 2). According to the standards of good practice set out in the Lending Code, "before lending any money, granting or increasing an overdraft or other borrowing, subscribers should assess whether the customer will be able to repay it in a sustainable manner" (British Bankers' Association et al., 2014, Section 4, paragraph 50). As far as credit cards are specifically concerned, "before giving a customer a credit limit, or increasing an existing limit, subscribers should assess whether they feel the customer will be able to repay it" (Section 6, paragraph 115). Furthermore, "issuers should

undertake appropriate checks to assess a customer's ability to repay […] before increasing a credit limit" (The UK Cards Association, 2011, Section 2.4).

When considering an unsolicited (i.e. not requested by the customer) credit limit increase, lenders are advised to take into account such indicators of financial difficulties as: "regular late and/or missed payments; paying the minimum payment over an extended period, and possibly across multiple credit/store cards, particularly with high balance/limit utilisation; changes in repayment behaviour, which could potentially point to a change in the customer's circumstances; a significant increase in overall outstanding balances over time; instances of exceeding credit limits, making frequent use of cash advances; problems in respect of other accounts held across a group relationship, such as a current account, or a mortgage; sudden reductions in income and/or high debt to income ratios" (The UK Cards Association, 2011, Section 2.4). Nevertheless, unsolicited credit limit increases raise concerns with regard to responsible lending (Kempson, 2002). Furthermore, Kempson's analysis suggested that there is a link between credit limit increases and financial difficulties: those who were experiencing financial difficulties were found to be more likely to have had their credit limits increased within the last 12 months than others. Interestingly, The UK Cards Association (2010) claimed that unsolicited credit limit increases are "a cornerstone of responsible lending". It must be emphasised that nowadays, according to the FCA Handbook, "a firm under a regulated credit agreement for a credit card or store card must notify the customer of a proposed increase in the credit limit under the agreement at least 30 days before the increase comes into effect" (CONC 6.7.9R). Customers have right to reject unsolicited credit limit increases. In line with the Lending Code, they "may at any time: request a reduction in their existing credit limit; reject an unsolicited credit limit increase; inform the subscriber that they do not want to be given a credit limit increase at all in the future; and request an increase in their credit limit" (British Bankers' Association et al., 2014, Section 6, paragraph 156). Although customers can now prevent their credit limits from being increased if they wish to do so, it can still be argued that unsolicited credit limit increases may encourage them to borrow more than they have originally planned (Department for Business, Innovation and Skills, 2010b).

It is sometimes claimed that the greater availability of credit cards leads to increased indebtedness, which in turn leads to financial distress/overindebtedness that ends up in more bankruptcies. However, according to Zywicki (2008), there is no evidence that there is a relationship between easier access to credit cards and increased indebtedness or overindebtedness, at least in the U.S. Instead, both Zywicki (2008) and Fortin and Préfontaine (2008) suggested that there may be a substitution from other types of consumer credit, in particular personal loans. In the U.S., the non-mortgage debt service ratio remained stable between 1980 and 2007 (Zywicki, 2008). Simultaneously, the non-mortgage non-revolving debt service ratio decreased and the revolving debt service ratio increased, which supports the substitution hypothesis (the increase was mostly related to credit cards). A similar analysis for the 1970-1999 period in the U.S. can be found in Fortin and Préfontaine (2008). In addition, there may be a substitution from informal types of credit such as pawn shops and payday lenders, but this is difficult to measure (Zywicki, 2008). The substitution is likely to result from the advantages of credit cards over the alternatives: most importantly lower interest rates and more flexibility.

Examples of irresponsible lending practices include: lack of policies and procedures for reasonable affordability assessment, lack of affordability assessment in individual cases, failure to assess whether a borrower is likely to be able to repay in a sustainable manner, granting credit without having assessed affordability and granting credit when the affordability assessment results suggest that it is likely to be unsustainable (OFT, 2011).

To assess affordability lenders should use various sources of information, such as evidence of income and expenditure and/or credit reports provided by credit bureaus (OFT, 2011). When analysing income or expenditure, creditors should not limit the analysis to the borrower's current situation, but they should also take into account the expected changes over time. In general, the OFT (2011) suggested that lenders consider credit sustainability in a long term perspective: creditors could even accept occasional missing of a payment on a due date or – in some circumstances – a temporary (initial) inability to repay. Similarly, the FSA (2010) proposed that lenders should assess the borrower's ability to repay (mortgages), considering variability of income over time. They should take into account the borrower's income, expenditure and debts, and use statistical data to estimate expenditure (FSA, 2010). Nevertheless, neither the FCA Handbook nor other guidelines/codes of practice advocate any specific statistical models or methods for affordability assessment.

Obviously, in other countries the problem of irresponsible lending has also been recognised and tackled through legislation on assessing affordability:

- In the U.S., (mortgage) lenders are expected to carry out a reasonable verification process to confirm that "the consumer has a reasonable ability to repay the loan, according to its terms, and all applicable taxes, insurance (including mortgage guarantee insurance), and assessments" (Dodd-Frank Wall Street Reform and Consumer Protection Act, 2010, section 1411(a)(2)). The verification process must cover "the consumer's credit history, current income, expected income the consumer is reasonably assured of receiving, current obligations, debt-to-income ratio or the residual income the consumer will have after paying non-mortgage debt and mortgage-related obligations, employment status, and other financial resources" (section 1411(a)(2)).
- In Australia, lenders are required to assess "whether the credit contract will be unsuitable for the consumer if the contract is entered or the credit limit is increased in that period" (National Consumer Credit Protection Act 2009, paragraph 129(1)(b)). The credit contract will be unsuitable if there is a high probability that "the consumer will be unable to comply with the consumer's financial obligations under the contract, or could only comply with substantial hardship" (paragraph 131(2)(a)).
- In South Africa, lenders are expected to take reasonable actions to make the assessment of "the proposed consumer's existing financial means, prospects and obligations" (National Credit Act 2005, section 81(2)(a)(iii)). Prior to increasing a credit limit, they "must complete a fresh assessment of the consumer's ability to meet the obligations that could arise under that credit facility" (section 119(3)). Lenders "must not enter into a reckless credit agreement with a prospective consumer" (sections 81(3)). An example of a reckless credit agreement is one that "would make the consumer over-indebted", i.e. "unable to satisfy in a timely manner all the obligations under all the credit agreements to which the consumer is a party" (sections 80(1)(b)(ii) and 79(1), respectively).

Understandably, the above-mentioned acts do not provide any details of possible affordability models or statistical methods that could be used for the assessment purpose. The models used in banking practice and proposed in the literature are discussed in Sections 3.3 and 3.4, respectively.

4.2.4 Managing repayments, credit limits and interest rates

Lenders should monitor the borrower's repayments (CONC 6.7.2R). With regard to credit cards, a number of specific guidelines can also be found in the FCA Handbook. In particular, lenders should allocate repayments against an outstanding balance to the most expensive debt first (CONC 6.7.4R). (It is worth noting that The UK Cards Association (2010) argued that the reverse allocation of

payments was a trade-off for the zero per cent balance transfer deals.) According to the FCA Handbook, lenders should not increase the credit limit (and should not even suggest to do so) if the borrower is at risk of financial difficulties (CONC 6.7.7R). Borrowers should always be allowed to reduce their credit limits and not to accept the suggested increases (CONC 6.7.8R). Lenders should not increase the interest rate if the borrower is at risk of financial difficulties (CONC 6.7.10R), and should never change the interest rate without a valid reason (CONC 6.7.14R).

In line with the Lending Code, the minimum payment must cover at least interest and one per cent of the credit card balance as well as any fees and charges (British Bankers' Association et al., 2014, Section 6, paragraph 160). However, as recently as in 2002 the minimum payment for most credit cards was five per cent, and those lenders who were reducing it to three or two per cent were criticised for making borrowers pay for decades (Kempson, 2002). In 2005 the typical minimum payment was between two and two and a half per cent (Department for Business, Innovation and Skills, 2010b), but in 2009 some lenders started reducing it to one and a half per cent, which raised the same concerns as previously. One of the lenders claimed that this would help struggling customers, who would be able to use the saved money to meet other commitments (The Money Stop, 2009). Nevertheless, reducing the minimum payment is a lending practice that is associated with borrowers' financial difficulties (Kempson, 2002). The UK Cards Association (2010) argued, though, that increasing the minimum payment would now cause financial difficulties for the existing customers who cannot afford higher payments. According to The UK Cards Association (2010), if the minimum payment were increased to five per cent, almost 40 per cent of accounts would be affected and an average borrower would need to pay ca. £100 more each month.

If the borrower has made a number of minimum payments or low repayments, they should be sent an advice communication according to the industry agreement (British Bankers' Association et al., 2014, Section 6, paragraph 161). If the borrower has made repayments using another credit card, it is recommended to send them a similar warning (OFT, 2011).

4.2.5   Handling arrears and defaults

Understandably, responsible lending does not end with default. Lenders should have appropriate procedures and policies for dealing with those who are in arrears. Borrowers in arears and defaulters should be treated with due consideration and forbearance (CONC 7.3.4R). Other, more specific guidelines related to handling arrears and defaults can also be found in the FCA Handbook.

As far as treating customers in financial difficulties is concerned, several examples of good practice were described by the Lending Standards Board (2014). In particular, it is recommended to contact customers who had a returned direct debit on their account, even if they are not in arrears. The contacted customers should be offered help if needed (Lending Standards Board, 2014). This is a preventive approach to customer support.

4.3   Conclusions

Responsibility should be demonstrated at each stage of the lending lifecycle: when advertising credit, explaining credit agreements, assessing affordability, managing repayments, credit limits and interest rates, and handling arrears and defaults. The OFT (2011) provided a detailed, yet not exhaustive, list of possible irresponsible lending practices (both general and specific to credit cards). Nevertheless, the evidence (if any) is sometimes mixed. Hence, it would be helpful to perform a large-scale data analysis to confirm which lending practices are indeed associated with financial

difficulties. The analysis could focus on such areas as unsolicited credit limit increases, balance transfers, minimum payments, risk-based pricing and the allocation of payments.

5   Credit card payment behaviour

Various approaches have been used by researchers or practitioners to model credit card holders' payment behaviour, which will be discussed in this section. We will also discuss some relevant work on different categorisations of customer behaviour (i.e. revolvers vs. transactors and can't pay vs. won't pay) that are linked to the modelling of payment patterns. One risk-related aspect of modelling credit card repayment behaviour is to predict whether a card owner is likely to default. Alongside this probability of default, the Basel Accords also require lenders to estimate the potential loss in the event of default. The idea of modelling this loss by looking at the underlying payment and repayment patterns is briefly considered at the end of this section. An even more challenging objective when modelling credit card payment behaviour is to build models for the profitability of the account to the lender. As well as estimating the default risk and loss given default of the account, this also requires estimation of card usage and likely interest accrued.

5.1   Payment patterns: empirical studies and models

One of the most popular approaches to model repayment behaviour is to build behavioural scorecards, which are set up to classify credit card accounts into one of two classes: those likely to default and those that will not (see also section 2.3). Classification techniques used by practitioners for this purpose most often involve logistic regression, which produces account-level estimates of the probability of default, possibly combined with decision trees, which first segment the accounts into a small number of distinct risk profiles to which different regression models are then applied (see the reviews by Thomas et al. (2001) and Thomas (2009)). Instead of just estimating the propensity of default vs. non-default, Kou et al. (2005) used multiple criteria linear programming to build a four-class model that distinguishes between four classes: bankrupt charge-off, non-bankrupt charge-off, delinquent or standard account.

The actual characteristics used in a bank's behavioural scorecard are rarely or never published openly. Although the examples used in the literature to describe new scorecard development techniques concentrate on socio-economic variables like age, marital status, number of dependents, etc., the reality is that the most powerful characteristics in a behavioural scorecard for a credit card product are a credit bureau's information about the current credit position of the borrower on other accounts and the lender's information of the borrower's arrears performance on the account itself (see also section 2.3). Examples of the two types of information could be the number of other accounts where the balance is more than 75% of the credit limit, time since last County Court Judgment, time since last arrears letter on this account and number of times this account has been one month in arrears. Although individual lenders' scorecard characteristics are not openly available, the general characteristic types used in bureau scorecards (which are typically behavioural scorecards) are in the open literature. More details of these are found in section 2.4, where payment history, length of credit history, amount owed and new credit accounts opened are cited as relevant examples (FICO, 2014a; Vantage Score, 2014).

The aforementioned techniques are essentially static, in that they make predictions about the risk of defaulting in a fixed subsequent time window. What they do not do is explicitly model the dynamics of a cardholder's repayment behaviour over time. Alternative models have therefore been proposed. The Markov chain model is by far the best-known approach to capture and model the movements between repayment states over a period of time. Cyert, Davidson and Thompson (CDT) (1962) were pioneers in this area. In their study, accounts were classified into *N* different states based on the number of payments in arrears, the transitions between which they then modelled by

a Markov chain. A number of studies have since used CDT models to understand customer's repayment behaviour (Corcoran, 1978; Kallberg and Saunders, 1983). The aims of these studies are to estimate the expected number of defaulted accounts and to estimate the receivable from the different accounts. However, the stationarity assumption of Markov chains is usually difficult to justify. Frydman et al. (1985, 2004) looked at how to tackle this problem in order to improve the estimations when modelling the account repayment behaviour using Markov chain models.

Another approach to understand credit card payment behaviour is to use longitudinal data to model the payment patterns of credit card holders. A recent study by Jiang and Dunn (2013) looked at the relationship between 15 different age cohorts in the U.S and their corresponding debt and balance pay-off rates. As one might expect, the results show that younger cohorts tend to borrow more from their credit cards and pay back at a lower rate. Another key finding in their study is that "one additional percentage point increase in the minimum payoff rate on credit cards will increase the average payoff rate by 1.9 percentage points" (Jiang and Dunn, 2013, p.404).

To our knowledge, loan repayment patterns have been used to rank borrowers in terms of their likelihood to default on personal loans, but not so for credit cards. Schwarz (2011) evaluated observed payment patterns for instalment loans to introduce new variables, namely the ratio of actual instalment payments made over those required. A payment pattern approach could also be used in modelling the account receivable to be paid to a retail organisation (Stone, 1976). However, in this paper, the whole cost must be paid off in one repayment. Stanford (1995) instead developed an analytic solution to the accounts receivable forecast problem based on the CDT model.

Similarly, models based on the idea that previous payment affects the probability of the next payment have received some attention in consumer credit modelling but mostly for fixed term loans or corporate credit and not for credit cards. The idea of using such a Bayesian approach to estimating the probability of a payment in the next period was begun by Bierman and Hausman (1970); although subsequently there had been a number of developments, it was only with Thomas et al. (2001) that it was introduced into the credit card context.

5.2   Transactor/revolver behaviour

Among all those with active credit accounts, card holders are usually referred to by credit lenders as being either "transactors" or "revolvers". Transactors are those paying back their full balance every month and revolvers are those who carry some balance on their credit cards. As mentioned by Field and Walker (2004), revolvers are card issuers' preferred customers because they pay interest on the balance carried forward. Traditionally, the transactor/revolver classification could be done on existing card holders only, because lenders do not yet have any (in-house) usage or repayment records for new credit card applicants. Until recently, credit bureaus in the U.S. have included the time series payment data in consumers' credit reports, which show a consumer's monthly credit balance, amount due, amount paid and amount past due (Ulzheimer, 2014). Lenders therefore would be able to work out whether the credit applicant has been a revolver or transactor elsewhere.

What characterises a card holder to be a revolver or transactor? The Federal Reserve Bank of Philadelphia (Herbst-Murphy, 2010) studied the characteristics of revolvers and transactors and unsurprisingly found transactors to be older and richer on average than revolvers. Kim and DeVaney (2001) applied a Heckman two-stage model to identify the important characteristics in a dataset from the U.S. Survey of Consumer Finances. They found that education level, income, real assets, number of credit cards and positive attitude toward credit all tend to increase the amount of the outstanding balance. Zinman (2009) built a neoclassical choice model to understand why some

consumers use debit cards while others decide to be credit card transactors. The paper looks at reasons why it might be rational for a consumer to prefer the former to the latter. Further work on this problem was undertaken by Sprenger and Stavins (2008). Again using data from the Survey of Consumer Finances, they showed that credit card revolvers are more likely to use debit cards if they can. Simon et al. (2010), using an Australian survey data set with 662 respondents, also found some similar results. In their paper, a series of probit regression models were built to better understand the impact of loyalty programmes, transactor/revolver status, gender, use of cheques, age, transaction amount, income level and some lifestyle variables on cardholders' use of different payment instruments. The "Debit Card Use" model indicated that revolvers are more likely to use a debit card whereas the "Credit Card Use" model showed the opposite result. However, in the above study, no clear definition seems to be provided for what constitutes a transactor or revolver. For example, should a borrower repay fully every month for half a year, one year or the whole lifetime in order to be regarded as a transactor?

Another way to understand the characteristics of revolvers is to build a classification model with individual-level credit card usage and repayment data to predict whether a card holder will be a future transactor or revolver. Hamilton and Kahn (2001) thus applied logistic regression and linear discriminant analysis on a UK credit card dataset consisting of credit card holders' monthly transaction records to estimate the probability that a card holder would become a revolver. The most predictive input variables in the study were: age, minimum payment, amount of cash advanced, whether the cardholder has a loan, years on book and the APR. The sampling period of Hamilton and Kahn (2001)'s study is relatively short: the dataset only covers a fourteen-month period. They selected a group of transactors who were not carrying a balance from month 8-11 as the sample dataset. Next, they observed these card holders during month 12 to 14 to see if they had a carrying balance then. In other words, the performance period is four months and the outcome window is three months. Instead of predicting whether current transactors will become revolvers, So et al. (2014) used a Hong Kong credit card dataset to predict if a new card applicant would turn out to be a transactor or revolver. The study defined revolvers as those who did not pay back their full balance for at least one month within a one-year period. The chosen predictive variables were occupation, education level, citizenship, residential type, employment status, months with bank, annual income and age. Apart from these personal characteristics, So and Thomas (2010) looked at the different ways changes in economic conditions affected the default risk of revolvers and transactors in the same data set. For example, the default risk of revolvers was shown to react much more to changes in the unemployment rate than that of transactors.

The transactor/revolver split has also led to research on how the costs of credit card systems should be split between the parties involved. This involves modelling the situation as a game; an approach pioneered by Shubik (1962) and Young (1985) in other contexts. Thomas (1992) used a game with revolvers, transactors, merchants and credit card organisation, to look at the appropriate level of interest rates charged, annual fees and merchant service charges. Others like Gau et al. (2012), Bolt and Chakravorti (2008) and Rysman and Wright (2012) developed three-player games involving issuing banks, acquiring banks and merchants to determine appropriate levels of interchange fees and merchant discounts.

5.3   Won't pay/can't pay

One area of investigation is why consumers default on their credit cards or other loan products. Two main reasons are identified. Either the consumer is capital constrained and so is unable to repay (the "can't pays") or they wilfully refuse to pay (the "won't pays"). There are two main streams of

research which look at why consumers exhibit such behaviour and the characteristics of the defaulters in the two groups. One is to collect and analyse surveys of defaulters and the other is to build models of rational economic behaviour of the defaulters based on the characteristics of the defaulter and the loan.

One UK-based survey was that by Dominy and Kempson (2003), who interviewed and analysed previous interviews with 64 debtors. Among the can't pays, they found that loss of income accounted for 42% of the cases, with redundancy (18%), relationship breakdown (6%) and sickness (6%) being the other main factors. Low income accounted for 18% of the cases, with overlooked payments 12%, and unexpected expenses causing another 6% of the cases. Among the won't pays, there were four typical types of defaulters – those not paying on principle or because of disputes with the lender; ex-partners withholding payment; debtors working the system with long delays; and those lacking responsibility or intending to be fraudulent. One reason for the default on principle group was that the previous interviews included some from the poll tax controversy era. Dunn and Kim (1999) used a telephone survey conducted by Ohio State University to investigate credit card usage and debt (see also section 2.3). They looked at what defaulters were doing rather than why they were doing it and so identified variables like minimum payment to income ratio rather than balance to income ratios as being significant indicators of likely default. Similarly, percentage of total credit used and number of cards with balances at credit limit were significant. These seem more indicative of can't pay behaviour than won't pay behaviour.

The other strand on building economic models of why consumers default assumes that most consumers in the won't pay category are behaving rationally. Block-Lied and Janger (2006) found this was true for some but not all segments of the won't pay category. Bravo et al. (2014) built a game theory model to identify the won't pays for whom it is rational to default and then used clustering procedures to identify the clusters. They were able to show that building different scorecards on the two clusters gave better default estimates than just using one scorecard for the whole population. Bravo et al. (2015) extended this idea by using the clustering approach to identify two groups of can't and won't pays. They then used mixture models and competing risk ideas from survival analysis to build risk assessment systems which were superior to the standard approach. This showed that the won't pays tend to default earlier in the loan repayment period than the can't pays. These models were built on consumers requiring micro-finance loans but a similar approach can be used on credit card data.

5.4   Loss-given-default

A number of approaches could be considered for modelling the loss-given-default (LGD) for credit cards, the most attractive of which arguably is to model the collections process. Little work has been done on this until recently when the idea of modelling repayment patterns has been considered. Note that, unlike in the previous subsections, the patterns considered here all related to post-default behaviour, which is likely to be substantially different from that prior to default. Specifically, Thomas et al. (2014) suggested that, in the post-default repayment process, there is an initial non-payment sequence, followed by a sequence of monthly payments. Once that stops, a new non-payment/repayment cycle can begin. This succession of cycles continues until either the debt is paid off or the repayments have been so infrequent or of so small an amount that the debt is written off. Such a pattern can be modelled in two ways. Firstly as a Markov chain with four states – non-payment sequence, payment sequence, write-off and cured. Alternatively, one can use survival analysis to model the durations of the payment and non-payment sequences. The parameters of these models are either set using orthodox statistics based on historic data or by thinking of them as

functions of the borrower and economy. This latter approach has connections with the idea of a collections score which some organisations use to determine their collections strategy. This is akin to a behavioural score but the probability being estimated is whether the collections process will recover a pre-specified fraction of the debt (Anderson, 2007).

6 Choice between credit cards/"front of wallet" and their risk implications

Many consumers have more than one credit card. In this section, we are going to first look at some studies that examine if a particular type of credit card would be the preferred choice by consumers for their daily consumption (i.e. "front of wallet"). The second and third topic deal with the acquisition/retention strategies used to attract new and to keep current card holders. Although we are particularly interested here in whether there are any studies that investigate the relationship between these strategies and the associated default risk, the literature on this relationship appears fairly limited so far. As part of the strategies to keep current credit card customers, lenders may introduce a retention programme to enhance the relationship with some customers who have a high propensity to churn. The last part of this section is to look at what variables have been used by lenders and/or in the research literature to build those churn models.

To start with, we need to have a closer look at how to further categorise credit cards. According to The UK Cards Association (2014a)[4], one of the possible categorisations for credit cards is to divide them into four groups: basic credit cards, standard credit cards, premium credit cards and charity/affinity credit cards (see Table 6.1):

Table 6.1. Types of credit cards (The UK Cards Association (2014a))

Type	Key characteristics
Basic credit cards	Lower annual percentage rate (APR)
	Interests incurred immediately after each transaction
Standard credit cards	Most common type
	Provide an interest-free period
Premium credit cards	Higher APR and credit limit
	Annual fee are required
	With additional benefits (e.g. travel insurance, product guarantees, etc.)
Charity/affinity credit cards	Similar to standard credit cards
	Card issuer would donate a fraction of the credit card holder's transaction amount to a charity/affinity group

6.1 Credit card selection and "front-of-wallet"

Credit card holders need to make two types of credit card selection decisions: (a) which card(s) to acquire? (b) which of these cards to use when they make a certain transaction. In a survey dataset of 1,937 UK consumers, the Office of Fair Trading (2010) found that Lloyds Banking Group (29%) had the largest share of credit card holders (with 29% of respondents). More importantly, according to the results, a sizable share of respondents held more than one credit card. Each time they make a

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[4] Although some may include store cards and charge cards as credit cards, for the purpose of this study, we will regard these two as other payment mechanisms, in accordance with their treatment in FCA (2014).

purchase, those consumers thus need to make a choice among these credit cards. What do we know about either the factors that drive card acquisition decisions, or the process through which credit card holders decide which of their credit cards to use? Most studies looked at the former. An early study by Kara et al. (1996) tried to answer this question by examining various credit card characteristics. These include the brand (e.g. visa, master, AMEX, etc.), credit limit, card type (i.e. platinum, gold, classic), annual fee, APR and payment type (i.e. full amount, deferred). Kara et al. (1996) collected their data by asking respondents to evaluate 25 different credit cards (which have different characteristics) in terms of 'likelihood of consideration'. The analysis showed that, when choosing which credit cards they are most likely to obtain consumers appeared to pay the most attention to whether the card would charge an annual fee and the interest rate. A similar study had been done by Kara et al. (1994) before, but that study focused on the credit card market of college students. The results showed that interest rate and payment types were the two key factors for students. Kara et al. (1994, 1996) however did not explicitly look at actual usage or the potential relationship between usage behaviour and the payment history of credit card holders. For example, could it be the case that revolvers (i.e. those who tend to pay off only part of the monthly balance and hence incur interest charges) are more sensitive to APR, whilst transactors (i.e. those who tend to pay off their entire balance at the end of the month) could be more reluctant to use (or even subscribe to) a credit card with an annual fee?

6.2 Card issuers' acquisition strategies

In many developed financial markets, there is keen competition in the credit card sector. Card issuers have used different strategies to acquire new customers. Here, we will first provide an overview of the channels being used by card issuers to attract customers. We will then look at the literature about three popular acquisition strategies: pre-approved solicitation, balance transfers and reward programmes.

6.2.1 Channels

A study conducted by the Federal Deposit Insurance Corporation (FDIC) looked into the acquisition channels in the U.S. (FDIC, 2007). They found that traditional mail shots remained a key acquisition avenue, widely used by practitioners (see also Palmer, 2011). Apart from this traditional channel, online acquisition, including the use of companies' websites, banner advertisements, emails, etc., has become popular in recent years. According to a report by McKinsey (Bollard et al., 2013), direct mail acquisition had declined thirty-five percent from 2008 to 2013. This is partly due to the fact that many banks seem to have shifted to online acquisition because it could be up to sixty percent cheaper than the postal mail approach. In the U.S., the third popular channel for credit card acquisition appears to be tele-marketing, which is regulated by the Federal Communications Commission. Other common marketing approaches for credit card lenders are television advertisement and print advertisement.

6.2.2 Pre-approved solicitation

According to FDIC (2007), pre-approved solicitation is a popular acquisition method in the credit card industry. This involves credit issuers collecting a target population list from internal information, lists acquired from third parties or affiliates, or sometimes from a general credit bureau search. After some pre-processing to remove certain customers from the list (e.g. existing customers, address associated with criminal records, etc.), those left in the list may be selected to undergo a credit bureau check. This credit screening process would exclude a further pool of potential customers who do not meet the issuer's requirements. The rest in the list will then often be allocated to different

segments, and a credit line can be designed per credit segment. These potential credit card customers (or "prospects") will then be contacted by mail or email about their pre-approved credit card offer.

6.2.3   Balance transfers

Another common approach to target new customers is by providing incentives for balance transfers (Jones, 2014). This entails that a reduced APR will be introduced for those transferring their carrying balance (or even bad debt) from other credit cards. In most situations, this reduced rate does depend on some other criteria (e.g. a limit on the transferred balance, a limited time frame, application fees may apply, etc.). The attraction of this approach to the issuer lies in its ability to quickly acquire profitable customers, as these new customers may generate a high level of receivables in a relatively short time. However, poor management of this acquisition strategy would result in a high level of bad debts for the issuers. Interestingly, there seems to have been limited academic research so far on the relationship between balance transfers and cardholders' behaviour.

6.2.4   Reward programmes

Introducing a reward programme is another well-documented approach to attract new (as well as better retain current) customers (Lewis, 2004; Palmer, 2011; Wirtz, et. al, 2007). When signed up for a reward programme, the card holder will be awarded a certain amount of cash or loyalty points for every pound spent with the credit card. A study conducted by Steffes et al. (2008) showed that the return of introducing a reward programme, however, might be over-rated. Using a credit card dataset provided by a US bank with 9,000 accounts including variables such as customer demographics, acquisition channels and transaction behaviour for a three-year period, a Tobit model was built with the objective of understanding the impact of acquisition channels, reward/affinity programmes and credit limit on profit. The profit was derived from the discounted monthly interest charges, interchange fees, customers' repayments and the cost of running the reward/affinity programme. They found that, on average, customers joining the programs generated less profit than those who did not. Another interesting finding in their study is that direct mail and online marketing were able to attract more profitable customers. Working with a credit card issuer in Central America, Tsai et al. (2005) used their credit card customer database to understand the characteristics of those using the reward programmes and whether reward programmes do lead to higher spending. Not surprisingly, the group using the reward programme the most were elderly cardholders. Their results show that frequent reward programme redeemers provide the card issuer with higher revenue, which is different from the results by Steffes et al. (2008). These studies, however, did not give a clear indication of whether the profit or revenue included the estimation of potential losses due to default and so the results might be biased.

6.3   Card issuers' incentives to promote existing card usage

Many acquisition strategies discussed in the previous section have also been used to promote existing customers' card usage. For example, current customers might receive an interest-free period for transferring balance from another credit card; or a reward programme may be used to increase transactions.

Among these strategies, the one that is most studied is the impact of reward programmes on customer card usage behaviour. Using the Consumer Payment Preferences survey dataset in the U.S., Ching and Hayashi (2010) used a set of multinomial logit models to examine the impact of payment card reward programmes on consumers' choice of various payment methods (including

credit cards, debit cards, cash and cheque). Participants were asked about their views on loyalty reward programmes and their use of different types of payment mechanisms at different retail establishments (e.g. supermarket, restaurants, etc.). The results show that the probability of choosing a credit card for such transactions would be reduced if the reward programme associated with the card were removed. The same impact on credit card usage was also apparent in the study by Carbó-Valverde and Linares-Zegarra (2011), who used a survey dataset in Spain to conduct a similar study. A further study by Simon et al. (2010) (discussed in Section 5) looked at the same topic in Australia. They found that having a reward programme does increase the probability of credit card use by 23 percent. All of these studies therefore show that the lender's use of a reward programme tends to be associated with higher credit card usage by the consumer.

Increasing the credit limit of current card holders is a marketing strategy that is uniquely suited for current customers. A study by Soman and Cheema (2002) found that granting a credit limit increase does appear to encourage some card holders to increase their spending. They conducted a series of surveys and experiments to understand consumers' perceptions of credit limit increases. The results indicate that some people may regard their credit limit as an indicator of future potential income. The study suggests credit limit increments will trigger this group of consumers to increase their spending; from the credit card lender's perspective, this implies that actively managing the credit limit could make a positive impact on profitability. Using a data set containing the time series data of credit card accounts provided by several card issuers, Gross and Souleles (2002) studied whether any changes in credit limit and interest rates could change the behaviour of a consumer. The dataset consists of around 200,000 accounts and has information about consumers' application records, monthly statements, and credit bureau reports. Some key variables included in the study are the changes in credit card balance, a change of APR and credit limit changes. They found that increases in credit limits are indeed associated with an immediate and significant rise in debt. The results of this study hence suggest that any policy of increasing credit limits would also need to take into account the risks to the lender. So and Thomas (2011) therefore proposed the use of a Markov Decision Process to derive optimal credit limit policies, which take into account both spending as well as the increased risk of losses due to default.

As an excessive increase in the credit limit may well increase default risk, the UK Cards Association (2011) has introduced a best practice guideline on credit limit increases. The guideline clearly states: "Issuers should undertake appropriate checks to assess a customer's ability to repay and overall creditworthiness before increasing a credit limit."

6.4   Credit card churn and model characteristics

Just like many other businesses, the last thing a credit issuer would like to see is high churn (or attrition) rates amongst their card holders. In 2014, 20% of consumers switched their credit card issuer which is high compared to the churn rate of electricity, gas or mobile (The UK Cards Association, 2014b; McEwen and Krikorian-Slade, 2014). In order to lower the number of customers lost to their competitors, card issuers may introduce retention campaigns designed to "win over" those customers that are at risk of churning (i.e. incentivising them to stay). To better target limited resources, a churn model may first be fitted to a sample of past churners and non-churners to pick up the early-warning indicators of churn. This statistical model will then typically be used to select the highest-churn risk segments among their customer base; those may be sent an offer or be contacted as part of the retention campaign.

In a contractual service setting (e.g. mortgages, insurance, mobile phone services, etc.), the definition of churn is often fairly clear: a customer who has moved from one service provider to

another. For credit cards, the definition of churn could be wider. Certainly, if a customer asks to terminate the card service, s/he can be labelled as a churner. However, in the case that a customer has not used the credit card for a long enough period of time, s/he could also be classified as a churner. This could happen fairly often since customers usually have multiple credit cards.

There are a number of studies looking at customer churn and how to build churn prediction models. In Table 6.2, we only review those related to churn models for credit cards or other financial products.

Table 6.2. Previous studies about churn analysis on financial products

Reference	Products and Country	Definition of Churn	Characteristics	Techniques
Glady (2009)	Debit accounts at customer level; Belgium	Customers are classified as churners if their customer lifetime value (CLV) decreases	1. Number of debit transactions by month 2. Total amount debited by month	Logistic regression, neural networks (MLP), decision trees, cost-sensitive decision trees, AdaCost boosting
Van den Poel (2004)	Customer level; European financial service company	Customers who closed all their accounts, i.e. with no activity	1. Customer behaviour (e.g. credit card ownership, current/saving accounts ownership, use of phone banking) 2. Demographic variables 3. Macroeconomic variables	Survival Analysis
Nie (2011)	Credit card; China	No transaction during the observation period	Details not provided. The variables are broadly classified into five groups: 1. Customer information 2. Basic card information 3. Transaction information 4. Risk related information	Logistic regression, Decision trees
Kim (2005)	Credit card; Korea	Terminate credit card account	1. Month to renewal* 2. Average credit limit 3. Age	Support Vector Machines

			4. Gender	
			5. Average usage	
			6. Instalment period*	
			7. Average interest	

*No further explanation.

7 Choice between different consumer credit products

The literature on the choice between credit cards and other consumer financial products splits into whether the credit card is being used as a payment facility or a credit facility. If used as a payment facility, then the choice is between it and debit cards, cash, cheques and electronic forms of payments. If it is considered as a credit facility, then the comparison is with store cards, personal loans, overdrafts, payday loans and even with mortgages. There is much more of a literature on the former of these than the latter.

The current position in the UK on the usage of consumer credit benefits greatly from the research contracted out by the FCA last year. There is some research on the relationship between credit cards and store cards, and the review by the Competition Commission outlined some of the relationship between credit card and payday lending. The relationship between credit cards and other credit products and payment mechanisms is almost non-existent, apart from two issues which have received significant attention. The first is the surprising reverse in the priority consumers gave to credit card repayments compared to mortgage repayments during the U.S. mortgage crisis. The second is why consumers who have both debit cards and credit cards would keep interest-bearing balances on their credit card despite having the ability to pay it off.

7.1 Distribution of consumer credit products and other forms of borrowing

The most comprehensive and current description of the types and distribution of consumer credit products in the UK are the series of surveys of consumer credit products authorised by the FCA in 2014 as preparation for the market study. As well as looking at the consumer credit products such as credit cards, unauthorised overdrafts, personal loans, payday loans, and logbook loans, the research identified who uses which product and why and how they swap between them. This research consists of three papers (Jigsaw Research (2014), ESRO (2014), FCA (2014a)) and two overview articles (FCA (2014b), FCA (2014d)).

The main findings are as follows:

- There are 30 million cardholders in the UK.
- Credit card holders owe £57 billion and spend nearly £14billion per month using their cards.
- 60% of card holders claim to pay off their balance each month (and older customers are mainly in this group).
- The remaining 40% of accounts have 60% of the total balance (£34 billion) on which interest is being paid. This is a lower percentage than that in the U.S. data in Section 8.1, p.46.
- 8% of card holders had swapped their balance between one card and another in the previous year.
- Vulnerable customers belong mainly to four types: the hard pressed; those starting out; surviving and supporting; and those living for now.
- In general, 75% of consumers use credit cards; but of those with incomes below £25K, only 25% use credit/store cards.
- The trigger for acquiring a credit card was often an offer in the mail or email.
- Store cards were considered less threatening than credit cards, mainly because they tended to have much lower balances and so it seemed easier to pay off the balance.

7.2   Comparison with other credit facilities

7.2.1   Credit cards vs. store cards

Store cards have many of the features of credit cards – they are a source of revolving credit and they offer easy payment mechanisms. The differences are in the limited locations where they can be used and that it is reportedly easier to get credit with them (Stavins, 2000). Of course some retailers are introducing their own credit cards and these made up 14% of the credit card market in 2010 (Office of Fair Trading, 2010). Lee and Kwon (2002) found that store cards were used both as a payment mechanism and a method of financing purchases. For users who were using it for finance, a low credit limit and a high balance on their credit card were linked to an increased use of a store card, while their income, age and education affected their use of it as a payment mechanism. Ramona and Heck (1987) also found that high instalment debt encouraged store card usage. So consumers tended to use store cards either when they cannot get a credit card or to supplement the credit they can get on their credit card.

7.2.2   Payday loans vs. credit cards

One of the most comprehensive discussions currently on payday lending is the Working Paper by the Competition Commission (2014) that formed part of their investigation into that type of lending. The interaction between payday lending and credit cards is described in a survey of those using payday lending. 18% said they could have used a credit card, 31% said they had used a credit card in the last 12 months and of those 33% said they were still able to use it. The review made the comparison of payday loans with credit cards. They found similarities in terms of loan amount (though credit card amounts could be higher), speed, rollovers and top-up facilities but differences in terms of payment and repayment method, payback period and time to acquire first credit. In answer to the query what they would have done if they had not been able to get a payday loan, only 2% said they would use a credit card, but as only 6% said they would use any alternative credit, this was nonetheless the most common alternative. Asking similar questions about other forms of borrowing by those who use credit cards would be informative in future research.

Agarwal et al. (2009) looked at why credit card owners with unused liquidity on their credit card used payday lenders. They found in their survey of payday users that 61% of those with cards did not want to use their card in case they exceeded their credit limit. They found such consumers had a gradual drop in the available credit on their card in the year before using a payday lender, rather than a significant drop in available credit just before becoming a payday borrower. The latter might indicate a change in financial circumstances and so the evidence suggests a gradual fall in available credit before using payday lenders. As to lenders, they felt it was the small fees that credit bureaus charge for releasing information that meant credit card companies did not get information on their customers' payday lending activity and what stopped payday lenders regularly using customers' bureau credit scores.

7.2.3   Credit cards vs. other consumer credit facilities

Although there is some literature on the substitution of personal loans for overdrafts and vice versa there is little academic literature on the substitution of credit cards for these types of loans or the reverse. There are many articles by lenders describing the advantages and disadvantages of such substitution but it is difficult to find evidence of these claims. Similarly, peer-to-peer lending is relatively new and so there does not appear to be any academic literature yet looking at why consumers would swap between it and credit cards.

7.2.4 Ordering of repayments before/during and after the financial crisis

The global financial crisis had several significant impacts on consumers' credit behaviour. One of the most surprising was that U.S. borrowers started to pay off their credit cards before their mortgages. TransUnion (2010, 2011) conducted surveys looking at those who had defaulted on their mortgage but were up to date on their credit card, compared with those who had defaulted on their credit card but were up to date on their mortgage. The percentage of the former first exceeded the percentage of the latter in Q1 2008 and was 7.24% as against 3.0% by Q4 2010. Timiraos (2014) reported this unexpected ordering had been reversed by December 2013, but the mortgage and credit card default rates had remained higher than the car loan default rates for the whole period. The drivers of the reversal in the importance of repaying credit cards rather than mortgages were suggested to be the depressed house prices and the rising unemployment rate. Yet when adults were asked if they could only make one repayment next month what would it be, 79% said mortgage, 9% said credit card and 5% car loan (TransUnion 2010). This contradicted the real default pattern where among all defaulters in Q4 2010, 52% defaulted on their mortgage but kept up their credit card payments, while only 22% defaulted on their credit card but kept up the mortgage payments.

There have been a number of papers using survey information collected before and during the subprime mortgage crisis to understand and explain consumers' default behaviour between mortgage and credit cards. This relates to the discussion on whether strategic default on mortgage is driven by net equity or ability to pay (Jackson and Kasserman, 1980). Andersson et al. (2013) looked at data over the period 2001 to 2009. They found the ratio of rates of default between credit cards and mortgages changed from 8:1 in 2001 to 1:1 in 2009. They explained this was because consumers could not afford the mortgage repayment amounts but still wanted to preserve liquidity. Cohen-Cole and Morse (2009) looked at over 2.2 million consumers in 2006-7 and also saw this preference to pay off the credit card first, then their mortgage, concluding this was to preserve liquidity. Elul et al. (2010) found that homeowners with more than 80% utilisation on their credit cards increased their mortgage default risk by over 1% per quarter. It seemed that householders with multiple debt obligations preserved liquidity by defaulting on their mortgage so as to keep their credit card or home equity line up to date and so maintain their essential goods. Wang and Dunn (2012) also looked at the interconnection between strategically defaulting on mortgages and other forms of consumer credit using the Consumer Finance Monthly surveys from 2006 to 2011. They found high loan-to-value (LTV) increased the probability of default on a mortgage but surprisingly also on other types of consumer loans. As LTV approached 1, mortgage default increased rapidly but for higher LTVs, the mortgage default rate flattens and also has no further effect on the default rate on credit cards. As credit card utilisation increases, they found the default risk for mortgage loans and all other forms of consumer loans are also likely to increase.

O'Neill and Xiao (2012) showed that a second result of the global financial crisis for consumers was that they paid more attention to their financial management, including increased financial awareness which resulted in them paying off credit card balances fully. This is an obvious outcome of financial awareness as is shown by Allgood and Walstad (2011). They reported it is the self-perception of one's financial knowledge that is as important as the financial knowledge itself. Consumers with perceived and actual financial knowledge are 12% more likely to fully pay off their credit cards than those with low perceived views of their knowledge but high actual knowledge. So what is important for consumers to make rational economic decisions is not that they understand the financial implications but that they believe they understand what the implications are.

7.2.5 Other aspects of mortgage vs. credit card

There is little attention to other aspects of the relationship between mortgages and credit cards. Scholinck et al. (2008) looked at what consumers did with the extra free income that occurs when they finish paying off their mortgage. If the mortgage payments were relatively low, then they felt the extra liquidity allowed them to reward themselves by increasing their credit card activity to fund consumption. Specifically, the credit card balance tended to stay the same or increase. If the mortgage repayments were large though, the subsequent extra income was used to pay off the credit card debt, as it was "too large" to be wasted.

7.3 Credit cards as payment mechanisms

7.3.1 Credit and debit cards vs. cash

In the U.S., the triennial Federal Reserve Payment Study and the Diary of Consumer payment Choice have provided much material for research on consumer preferences with regards to payment methods. From this, Bennett (2014) showed in 2014 that cash payments, at 40%, had the largest share of consumer transactions, followed by debit cards (25%), credit cards (17%) and electronic methods (7%). O'Brien (2014) showed that the preference depends on the value of the transaction, the age of the user and the type of purchase. Cash is often preferred if the transactions are for small amounts, the user is older and if it is for food or personal supplies. If under $20, Schuh and Stavins, in a pair of papers (2010, 2012), show that it is the features of the method rather than the user that most affects the choice of payment method. It is the obvious features like cost, setup effort and ease of use that encouraged the adoption and use of a particular payment method.

7.3.2 Why credit card revolvers do not move to debit cards

The issue about consumer choice between payment methods that has probably attracted the greatest amount of literature is why revolvers with credit cards who also have debit cards continue to hold interest-bearing balances on their credit cards. Brito and Hartley (1995) suggest that the transaction costs associated with arranging loans from banks is higher than the interest rate charged on the credit card. Calem et al. (2005) also showed that credit card debt may actually be lower-cost than other options. Gross and Soules (2002) supported this by showing the cost of credit card debt is negatively correlated with interest rate changes. Telyukova and Wight (2008) and Zinman (2009) claim that the liquidity and safety of having balances in their current account outweigh the interest rate charges on their credit cards. An alternative explanation, first suggested by Laibson et al. (2000), is that that credit card spending is susceptible to problems of self-control. So borrowers with such problems seek to use other payment instruments as an act of will to keep some control of their credit card spending. Ausubel (1991) and Shu and Ausubel (2004) suggested that these self-control problems are a driver of credit card profits and the success of teaser rates in the credit card market. Sprenger and Stavins (2008), using data from the 2005 Study of Consumer Preferences, argued that the evidence supported the self-control hypothesis since revolvers with credit cards consumers are more likely to acquire and use debit cards than transactor credit card users.

8 Risk based pricing and variable pricing and the connection to creditworthiness

The price of a credit card is essentially the interest rate charged on outstanding balances, though there are other aspects like annual fees, reward programmes, and non-payment penalties that are relevant (see Furletti, 2003). Surprisingly, for many years, credit cards charged a fixed interest rate to all borrowers (Knittel and Stango, 2003). However, in the last twenty years (the detailed survey by Staten (2014) put this as starting in the credit card market at around 1988), the advent of private application channels such as the Internet and the telephone have led to risk based pricing. These are variable pricing regimes, either with each individual receiving their own risk based price or multi-level pricing regimes (Phillips, 2005). The former involves setting a different interest rate for each individual card holder depending on their default risk. Although this optimises profit in theory, it often proves impractical in reality. The latter involves segmenting the population and charging different interest rates to each segment. Often the lower rate is offered as a discount due to good behaviour or length of history with the card. That approach has the disadvantage that the initial rate advertised is the highest rate. An alternative is to advertise the interest rate as 'from x%' where x% is the lowest rate.

This section initially looks at existing surveys of credit card pricing. These are mostly U.S. based, using the triennial Survey of Consumer Finance. One particular issue of interest was rate-jacking where customers' interest rates were increased suddenly. This was used as evidence before and after the U.S. CARD Act of 2009/10, which outlawed this practice.

The theoretical literature on risk based pricing has focused on why credit card rates were "sticky", that is, stayed high despite competition. Suggested reasons for this included adverse selection, high switching and search costs and even the winner's curse (see section 8.2).

The final section looks at risk based pricing models for optimising the profit to the lender. Such models require the estimation of the take rates; i.e., what proportion of borrowers with a given default risk would accept a credit card at a particular interest rate. It was only since Phillips' book (2005) that such models have been openly discussed and, in practice, it is recognised that estimating such take rates will involve experimentation by offering different interest rates to many potential credit card holders.

8.1 Surveys of drivers in risk based pricing

The wide ranging literature survey by Scholnick et al. (2008) identified a number of factors affecting credit card pricing. These included a consumer's credit rating, level of current and previous outstanding debt, market power of the credit card organisation and the other features of the credit card. Much of this came from work on credit card pricing based on U.S. data. One of the first was Calem and Mester (1995) who used the 1989 Survey of Consumer Finance (SCF, 1989) to identify that households with large credit card balances were more likely to be denied credit or given lower limits when switching accounts. They repeated the exercise using 1998 and 2001 SCF data (Calem et al, 2006) with similar results. Edelberg looked at the SCF surveys from 1983 to 1998 to confirm that for credit cards the risk premium, i.e. the extra rate charged for default risk, doubled over this period. This is in contradiction to educational and other consumer loans which remained relatively unchanged. Zegarra and Wilson (2012) used a 2008-09 survey to look at the factors affecting credit card pricing. Some of their results are reasonable – e.g., nationwide banks have APRs 7% lower than local banks –, but others need considering – cards with reward programmes charge 0.6%APR less

than those without and consumers with low credit scores (high risk) pay 0.39% lower APR than those with high scores (low risk). Zegarra and Wilson (2012) also found that high previous balances increase average APR by 1.9%, which contradicts the results of Kim et al. (2005). Other research involves data samples from a few banks. Stango (2002) find APRs charged are related to the outstanding balance of the issuer bank, and its market share. Two studies on whether the bank's market power impacted the interest rate charged disagree. Akin et al. (2011) find it is the case for Turkish banks, while Massoud et al. (2011) do not find a significant effect using U.S. data. Amess et al. (2010) used UK data to show that low-risk reward card customers pay lower rates than high-risk standard card customers.

Massoud et al. (2011) is one of the few papers to look at the determinants of credit card penalty fees. The results suggested that penalty fees charged do reflect the charge-off ratios in the banks' balance sheets but that the banks with larger market share charged higher penalties than others.

One consequence of variable pricing is that credit card organisations will start to change their rates over time, including rate-jacking. This is where interest rates and fees are raised suddenly. Stengo (2000) looked at what was happening in the U.S. in the 1990s when there were both "fixed rate" and "variable rate" cards available. In the former, the rates only changed infrequently, say every three years, while in the latter they were changing every quarter. They showed, not surprisingly, that the latter were more profitable, particularly for large firms. Leviton (2011) analysed why rate-jacking was happening and what impact the Credit CARD Act of 2009, which among other changes made it difficult for credit card organisations to change their terms and conditions, had on borrowers. They showed that since, in their sample, 70% of credit card holders consistently revolved their balances, and so were more likely to be affected by rate-jacking, the positive effect on them more than compensated for any increase in the original rate charged to the other 30%. Note that this proportion of revolvers is comparable with Ausubel (1991)'s, who found 75% of cardholders paid finance charges on their credit card, but seems much higher than in UK data, where transactors (who always pay off balances) reportedly are three times the level of revolvers (UK Card Association, 2014c). The CARD Act supported the need for card organisations to undertake affordability calculations before cards were issued or credit limits extended. Jambulapati and Stavins (2013) examined what happened while the Act was being discussed. The likely rules were announced in December 2008; the Act passed in May 2009 and was implemented in February 2010. Jambulapati and Stavins (2013) found that there was a significant increase in the fraction of card accounts closed in the first of these periods but little change in the second.

8.2   Stickiness of interest rates, adverse selection and winner's curse

As well as on the drivers of credit card prices, there has been a substantial literature on distortions in the pricing of credit cards. These involve the "stickiness" of credit card prices (which remain high despite competition) and the mispricing of risk and are often explained by general economic phenomena like adverse selection and winner's curse.

Ausubel (1991) was one of the first papers to recognise the distortions in credit card pricing and how they could be explained. He suggested that cutting a card's APR would attract more revolvers than transactors and so increase the default rate. Hence, banks would be reluctant to cut rates because of this form of adverse selection. However, this hypothesis was not supported by Park (1991) and Stavins (2000), who found that high APRs led to lower default rates, suggesting that low-APR card lenders tend to control default risk more carefully. Ausubel (1991) had also suggested that, apart from adverse selection, search costs and switching costs for borrowers may act as deterrents to borrowers switching and so may keep interest rates high. Calem and Mester (1995) expanded

Ausubel's ideas and, by testing them on data from the 1989 Survey of Consumer Finance, found evidence for all three deterrents. Stango (2002) suggested that large outstanding balance increased the switching and search costs since such borrowers are seen as riskier by other lenders, Berlin and Mester (2004) used a search theory model with some borrowers searching for a better credit card rate and others not bothering to look in more detail, and searching and switching costs. However, the empirical results did not support this thesis.

Considering the issue of risk based prices underestimating the risk of default. Huang and Thomas (2014) considered this as an example of winner's curse. Given the ease of assessing credit card rates on the Internet, acquiring a borrower can be thought of as an auction by the credit card lenders rather than a search by the borrower. The "winner" who offers the lowest APR is the one who has most underestimated the default risk of the borrower. Broeker (1990) had looked at another winner's curse where banks only offer a fixed rate but there are two types of borrowers – high and low risk ones. Offering a low rate to get the low-risk customers increases the chance of getting too many high-risk customers. Ausubel (1999) performed experimentations with risk based pricing varying the introductory rate, the duration of the introductory rate and the post introductory rate. The analysis confirmed adverse selection occurred both between those who accepted and rejected offers and between those who accepted offers of different interest rates. The winner's curse led to underestimating the default risk for each type of offer.

8.3   Models for optimising risk based pricing

Most of the literature on variable credit card pricing has looked at the drivers of price and the anomalies like adverse selection that occur. It is only since the publication of Phillips' book (Phillips 2005) that models which seek to optimise the profitability of a credit card portfolio by choice of a risk based pricing strategy have started to appear in the open literature. The move from using risk based pricing to minimise default risk to using it to increase profitability or other business measures requires estimation of the price-demand relationship via the take probability. This is the chance of a borrower with certain characteristics taking the offer of a credit card with a given interest rate. Estimating such probabilities is the major challenge of such modelling. Phillips (2005) suggested that simple versions of this relationship could be represented by a linear function, a logit function or a reverse S-shaped function. However, as Karlan and Zinman (2005) explain, despite lots of studies, there is little consensus on the shape of this curve, which reflects consumers' elasticity for credit.

Using such price-demand curves and a hazard rate approach to default risk, Phillips (2013) built a model to optimise the interest rate for a fixed-period loan. Tereblanche and de la Rey (2014) extended the model by allowing the price-demand curve to change from period to period. Thomas (209) used a static model to investigate three pricing strategies for consumer loans – a fixed interest rate for all borrowers, a two-price strategy with a lower rate for low-risk borrowers and a higher rate for high-risk borrowers, and one where the interest rate varies according to the individual borrower's default risk. Huang and Thomas (2014) extended these models to allow for the impact of the Basel Accord capital requirement. They showed there is a decrease in profitability and an increase in the optimal interest rate in all these cases when the Accords are introduced. This effect is most noticeable under the Basel III regulations. Dey (2010) uses an influence diagram to sketch out a model that would optimise both the interest rate charged and the credit limit. This involves modelling adverse selection in that those who want high credit limits also tend to have high credit risk. A more practically based paper is that by Trench et al. (2003) who used data from Capital One credit cards. They built a Markov decision process model to find the optimal interest rate to charge

and the optimal credit limit to impose. Both the Dey and Trench models did not consider the take rate in their modelling.

9   Conclusions and recommendations

The literature on credit cards has two strands. The first is borrower-focused: who uses credit cards; how do they use them and who defaults when using them? The second is lender-focused: how do they decide whom to accept for credit cards and what actions do they subsequently use to make the borrowers more profitable? The depth of literature is very uneven over the different aspects of these two strands but the highlights are as follows:

- There is a large body of literature on how to improve the building of credit scorecards, i.e. the tool lenders use to estimate the default risk of potential borrowers, yet far less on what they do to estimate the possible overindebtedness of the borrower, which would be one of the significant reasons for defaulting.

- The academic credit scoring literature has concentrated on new scorecard building methods rather than on the information that is most powerful in identifying likely default. Until the advent of the Basel Accord, lenders seemed more reluctant to share their data with outside researchers and so credit scoring models are often built on one or two publically available but small and atypical datasets.

- There are a number of definitions of affordability and overindebtedness. As far as it can be ascertained, no definitions have been proposed specifically for credit cards.

- When assessing overindebtedness it is recommended that several different indicators be used. Spending more than 25 % of gross income on repayments of unsecured loans is one of the commonly used indicators of overindebtedness.

- Affordability assessment is often based on application data, credit reports and estimation of expenditure.

- A dynamic approach to affordability assessment may be preferred that takes into account possible changes in both income and expenditure and enables predicting for the future.

- It has been recognized that responsible lending is required at each stage of the lending lifecycle: when advertising credit, explaining credit agreements, assessing affordability, managing repayments, credit limits and interest rates, and handling arrears and defaults.

- As to borrowers' usage of credit cards, surveys of borrowers and especially defaulters are quite limited until the work preparing for this market survey.

- The literature has to some extent concentrated on anomalies rather than standard credit card usage.
  - Why did consumers started paying off their credit card debt and defaulting on their mortgages in the U.S. during the global financial crisis;
  - Why do consumers hold interest-bearing balances on their credit cards, when they have the resources and the ability to fund the purchases by debit card;
  - Does adverse selection occur when risk-based pricing is used to set credit card interest rates.

- It may be interesting to compare the literature concerning the previous points with the limited literature on whether it is feasible at acquisition to distinguish transactors from revolvers and whether lenders should deal with the two groups differently.

There are actions which the literature suggests have proved useful in acquiring information on credit cards, and some actions could be needed to cover lacunae in the literature. These could include the following:

- Evidence from lenders on their acceptance decision processes:
  What scorecards do they use (credit, usage, churn)? What affordability tests are used and how do these fit into the acceptance process? What information do they use and what are their data sources? How do they deal with "thin" files (i.e., those applications for which little or no credit history is available)?

- The evidence on the impact of irresponsible lending practices is mixed. Hence, it would be helpful to perform a large-scale data analysis to confirm which lending practices are indeed associated with financial difficulties. The analysis could focus on such areas as unsolicited credit limit increases, balance transfers, minimum payments, risk-based pricing and the allocation of payments.

- Evidence from lenders on the decision processes they use for credit limit increases and interest rate adjustments.

- Surveys of those who defaulted on credit cards:
  Why did they default? How did they default (No payment, below minimum level; all credit cards or only one)? What interaction was there with the lender at acquisition, before default and after default?

- Credit bureau information on other credit cards of those rejected on one card and reason from lender for rejection.

- More work could be done to look at the relationship between acquisition strategies and the associated default risk.

- Investigate whether the Living Costs and Food Survey (formerly known as the Expenditure and Food Survey) data can be used to estimate consumption (as in the industry).

- Investigate evidence from the U.S. of the impact of changes in minimum level of credit card repayments.

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