Financial Conduct Authority

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# Methods for analysing mortgage markets

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# Contents

# Summary

The core element of the 2012 Mortgage Market Review (MMR) recommendations – the responsible lending rules – aimed to ensure that borrowers would in future only be able to take out 'affordable' mortgages. During the development of the new policy and to explore its likely impact, a method was needed to measure and judge mortgage affordability, using the data available at the time.

This paper presents research undertaken for the MMR into three potential mortgage affordability metrics. These were based on: the debt service ratio (DSR), an expenditure-adjusted DSR and a quality of underwriting (QoU) score. The DSR measures evaluated affordability by looking at causal factors (household income, expenditure and mortgage characteristics), whereas the QoU score focused on mortgage outcomes (whether the borrower subsequently went into arrears or the home was repossessed).

This report sets out the theoretical and practical advantages and limitations of these approaches. To assess the impacts of the proposed affordability rules, we also developed a methodology for exploring changes in the well-being of borrowers. This enabled us to compare the gains in well-being when borrowers were stopped from taking out unaffordable loans, with the loss in well-being caused if the same rules blocked mortgages that in reality would not have become impaired.

For the MMR analysis, given data constraints at the time, a hybrid affordability metric was preferred, based on the QoU methodology but also using the DSR. An important finding, however, was that the expenditure-adjusted DSR is likely to offer the most valuable method for informing future mortgage policy development, as improved expenditure data becomes available in 2015.

Overall, it is hoped that the methodological insights offered here will be valuable to other researchers working in the highly topical area of mortgage affordability.

# 1 Overview

## Purpose

The Mortgage Market Review (MMR) was set up by the Financial Services Authority (FSA) following the 2008 financial crisis as a comprehensive review of the mortgage market. It culminated in a Policy Statement and final rules in October 2012, with the majority of the MMR reforms coming into effect in April 2014. The core element – the responsible lending rules – made lenders fully responsible for assessing whether a customer could afford a loan and set out principles for assessing affordability (section 2). The aim was to prevent consumers from taking out mortgages that were beyond their financial means or where the risks were high that the loans would become unaffordable as a result of reasonable, foreseeable developments, including increases in interest rates.

The MMR did not precisely define what was meant by 'affordable' or how affordability should be measured. Instead, the affordability requirements reflected a qualitative principle. However, during the development of the new policy and to explore its likely impact on consumers, a method was needed to measure and judge mortgage affordability, using the data available at the time. Our task was to provide a quantitative estimate of the impact of the new rules on mortgage lending, by constructing and using an affordability metric that:

- captured affordability in a way that applied the affordability assessment rules;
- was able to determine whether a particular mortgage granted in the past would have been affordable; and
- was feasible to construct, given data constraints, which included a very low rate of default caused by the length of the 'great moderation' and later a degree of forbearance.

This paper presents the research undertaken for the review into three potential mortgage affordability metrics and their use in the cost benefit analysis of the mortgage lending reforms. It offers a more detailed discussion of the methodologies than was possible in the consultation documents. Given the continuing interest in mortgage and housing affordability, it is hoped that the insights offered will be valuable to other researchers working in this area.

The consideration of well-being and how best to measure whether regulation is effective is also important given that the Financial Conduct Authority (FCA) is now mandated to quantify not only the costs but also the benefits of its rules.

## Key findings

We assessed three different affordability metrics that were constructed for the cost benefit analysis of the MMR affordability assessment rules:

- The **debt service ratio (DSR)** was a simple affordability ratio that measured the mortgage payment as a proportion of household net income (after tax and

national insurance) at the time the mortgage was taken out. While its simplicity was attractive, the DSR was not able to capture important determinants of mortgage affordability – particularly household expenditure (page 24).

- The **expenditure-adjusted DSR** adapted the basic DSR to take into account the proportion of net income devoted to household expenditure. It did this by measuring the combined cost of the mortgage payment plus household expenditure as a proportion of household net income (after tax and national insurance) at the time the mortgage was taken out. Two measures of household expenditure were explored: essential expenditure and total expenditure. This type of adjusted DSR metric was an improvement over the basic DSR. However, the lack of good expenditure data and the subjectivity of deciding which expenditures to class as 'essential' made it unacceptable for use in policy-related analysis (page 28).
- The **quality of underwriting (QoU)** approach was based on an underwriting risk score. This worked in a different way, by using the risk of mortgage impairment[1] from poor underwriting to measure mortgage affordability. The results showed that a key determinant of whether a mortgage became impaired was which lender had originated the loan. Other factors that increased the risk of impairment were high loan-to-value (LTV) and/or high personal debt, self-certification of mortgages, self-employment, interest-only mortgages, right-to-buy loans, mortgages used for debt consolidation, loans that extended into retirement, low income, remortgaging with low equity, high DSR and increased deprivation. The underwriting risk score provided a usable metric, albeit with some important limitations (page 38).

For the MMR itself, we chose a hybrid metric, based on the underwriting risk score but incorporating the DSR for some elements of the analysis (page 47). However, a natural question – when looking beyond the MMR – is which affordability metric could be the most useful for future work on mortgage affordability. On this, our view is that an expenditure-adjusted DSR could provide a very useful measure for regulation, given that from 2015 onwards the Financial Conduct Authority (FCA) has started to collect actual data on household composition and expenditure when a mortgage is agreed. A key advantage of an expenditure-adjusted DSR is that it has a natural affordability threshold, defined by the point at which income is insufficient to cover mortgage payments plus essential expenditure.

Well-being analysis was used with the preferred metric to measure the impact of the MMR proposals (page 48). The main finding was that the reduction in borrowers' distress from successfully avoiding impairment was significantly greater than the lost satisfaction associated with wrongly turning down a mortgage and thereby preventing a would-be borrower from becoming a homeowner (or owning a more expensive property). We thus demonstrated that the MMR proposals could still produce a net well-being benefit even if the majority of borrowers affected by the affordability rules would not in reality have experienced payment difficulties.

[1] By impairment we mean that the borrower has either been in arrears or defaulted (property was repossessed).

## Background

Prior to the 2008 financial crisis, household debt as a share of GDP had risen from 73% in 2001 to 100% by the end of 2007.[2] This rapid increase was primarily due to residential mortgage borrowing, fuelled in part by rising house prices and irresponsible mortgage lending practices by some firms. The regulatory framework in place at the time failed to constrain risky mortgage lending by some companies and unaffordable borrowing, although the position might have been far worse had the framework not been in place. There was a marked rise in the share of mortgages taken out by borrowers who had not previously had access to long-term credit and high-risk lending by specialist non-banks came to account for a significant share of the market. This was coupled with the emergence of business models that specifically targeted borrowers with impaired credit histories (page 11).

The onset of the financial crisis led to a significant decline in the availability of mortgage credit, a large fall in house prices, worsening economic conditions and a rise in both mortgage arrears and home repossessions. With the benefit of hindsight, a key reason for failures in the mortgage market was the lack of proper affordability assessments when some borrowers took out mortgages. It was in this context that the MMR proposed a package of far-reaching responsible lending reforms, including rules for assessing affordability.

Up until the MMR, most of the work on measuring housing affordability related to the provision of social housing rather than mortgages. These metrics were nevertheless relevant to mortgage lending and we started our work by reviewing the pre-existing common approaches to measuring affordability (page 15). For us, the most relevant were point-in-time methods that constructed affordability metrics from household income and expenditure data at one point in time, and then used pre-specified thresholds to determine affordability. However, these approaches all suffer from at least two main shortcomings. First, they do not explicitly take account of household wealth, which can provide a buffer when mortgage payment difficulties arise. Second, as point-in-time estimates they ignore how household circumstances change over time and what impact this has on affordability.

The other area of particular interest was the literature on mortgage default. Existing research provided a useful starting point for identifying the key drivers of mortgage arrears and repossessions so that we could then isolate the drivers related to poor underwriting. As well as academic research, we drew on work by credit rating agencies on the types of borrowers and mortgages that were most at risk of impairment. The material showed it was feasible to construct a model of the drivers of mortgage impairment that could be used to construct a metric of mortgage affordability.

## Data and methodology

Under the responsible lending reforms, lenders must verify a borrower's income and be able to demonstrate that the mortgage is affordable, taking into account the net income and, as a minimum, the borrower's committed expenditure and basic household expenditure. They must also take account of the impact of

[2] See FSA's Financial Risk Outlook (2010c).

expected future interest rate increases on affordability, with reference to market expectations for interest rates over the next five year[3] and assess the affordability on a capital and interest basis, unless there is a credible repayment strategy. Our affordability metric had to allow us to estimate the impacts of these affordability rules (page 11).

As mentioned, we assessed three potential mortgage affordability metrics: the debt service ratio (DSR), an expenditure-adjusted DSR and a quality of underwriting (QoU) approach based on an underwriting risk score. The analysis was undertaken using mortgage transactions from the Product Sales Data (PSD) for the period April 2005 to September 2010[4], combined with impairment information from the Council of Mortgage Lenders on these particular mortgages. We built a microsimulation model to simulate how mortgages taken out over this period would have been affected if the proposed affordability rules had been in place when the loans were taken out. The model identified which mortgages would have passed the affordability rules and those that would have been classified as unaffordable. This classification was then compared against actual subsequent mortgage impairment to assess its predictive accuracy (page 24).

## Affordability metric 1: Debt service ratio (DSR)

In our dataset, the average DSR was 25%, which indicated that the average mortgage holder spent approximately a quarter of their net income on mortgage payments at the time the loan was taken out (page 24). There was a positive relationship between DSR and the probability of mortgage impairment in the future. However, somewhat counter intuitively, the rate of increase in the probability of mortgage impairment was less steep for DSRs above 25% (i.e. for borrowers whose mortgage payments represented a higher proportion of net income) than for those with DSRs below 25%. This meant there was no convincing way to set a DSR threshold above which mortgages should be deemed unaffordable. In addition, by not taking household expenditure and other factors into account, this metric could not capture affordability as understood in the affordability rules.

## Affordability metric 2: Expenditure-adjusted DSR

An expenditure-adjusted DSR takes into account non-housing expenditure and furthermore can distinguish between 'non-essential' spending that could be reduced to make a mortgage payment and 'essential' expenditure that cannot easily be curtailed (page 28). If a borrower is pushed to a point where their expenditure is purely essential then any shock that reduces income or increases essential expenditure will cause them to miss a mortgage payment (ignoring any savings or wealth the borrower may have). To construct an expenditure-adjusted DSR metric required data on household expenditure, which was not included in the PSD. We therefore used data from the Living Cost and Food (LCF) survey[5] to estimate total and essential household expenditures (net of mortgage costs) for different types of households and mapped these onto the PSD sample. We could then obtain an expenditure-adjusted DSR for each borrower.

[3] There is now also a requirement to have regard to any prevailing Financial Policy Committee (FPC) recommendation on appropriate interest rate stress tests. The FPC has also introduced a prudential recommendation on loan-to-income ratios.

[4] See Annex 1

[5] See Annex 3

When using the affordability measure based on essential expenditure, 3.2% of mortgages were identified as unaffordable, although this differed greatly by type of household, with mortgages to the least affluent households being almost seven times more likely (6.1%) to be unaffordable than those to the most affluent households (0.9%). By incorporating expenditure, the adjusted DSR was more closely aligned with the concept of affordability targeted in the responsible lending rules. However, the imperfect modelling of expenditure and, as mentioned, the subjectivity regarding which expenditures to classify as essential meant we did not use this type of metric for the cost benefit analysis.

## Affordability metric 3: Quality of underwriting score

The quality of underwriting approach required more complex multi-stage modelling (page 38). Our aim was to isolate the portion of risk at origination that was due to poor underwriting and to differentiate it from other sources of risk which lead to mortgage default. In brief, we first modelled the risk of impairment and then isolated the part of this impairment risk that was due to factors that represented poor underwriting. This made it possible to calculate an underwriting risk score for each mortgage transaction in our PSD dataset. Mortgages with a higher underwriting risk score indicated poorer underwriting; mortgages with a lower underwriting risk score indicated better underwriting. The next step was to determine a threshold for the underwriting score above which mortgages would likely have been deemed unaffordable. This was done by looking at the underwriting risk score profile for all the lenders in our sample, and identifying points at which there was a marked acceleration in the score. In practice, to allow for uncertainty, a range was chosen for the threshold, which also allowed us to estimate ranges for the impacts.

Of the three affordability metrics we considered, the underwriting risk score was the only one that met all three of the requirements (page 5) so it was used in our cost benefit analysis to measure the impacts of the affordability rules. However, it also required that some judgement be exercised: first in the choice of which impairment risk factors were indicators of poor underwriting; and second in the choice of a threshold at which mortgages became unaffordable. In addition, the underwriting risk score was in large part driven by the lender variable, which was probably acting as a proxy for many factors relevant to underwriting but for which no data were available. As a result, the underwriting risk score was less sensitive to changes in the other underwriting factors, which made it difficult to model the impact of some of the responsible lending proposals, particularly related to interest rate rises. As a result, for this aspect of the analysis for the MMR, we used a hybrid approach that combined the underwriting risk score with a DSR measure (page 47).

## Well-being cost benefit analysis

In practice it is difficult to implement a set of rules that can perfectly exclude borrowers who would have been granted unaffordable mortgages due to poor quality lending. So a 'well-being methodology' was devised to determine the relative costs and benefits of the impact on borrowers who were affected by the rules – the 'winners and losers'. The well-being data were from the General Health Questionnaire, which is an index of household psychological well-being reported in the British Household Panel Survey. Reduced well-being arose when

the rules wrongly constrained affordable borrowing, while increased well-being was achieved when the same rules blocked unaffordable mortgages. Using the hybrid affordability metric we found that only around 30% of the borrowers affected by the rules would in reality have gone into impairment, other things equal:

- Around 200,000 borrowers who in the sample period experienced impairment would have been protected from the associated distress had the responsible lending proposals been in place.
- Around 530,000 borrowers would have been impacted by the responsible lending proposals even though they did not experience impairment. These borrowers would have experienced distress from not getting the mortgages they wanted but they might have benefited from increased financial stability in the UK generally.

As mentioned, the estimated overall net impact on well-being was still positive. That said, deciding the relative importance to attach to borrowers experiencing well-being gains versus well-being losses is inherently subjective as our only data are subjective, self-reported estimates of well-being. In addition, there were a number of caveats attached to our well-being analysis. Its results, therefore, are best interpreted as indications of the relative positive and negative effects of the detailed policy options.

Overall, the findings of our research show that the modelling approaches described in this paper have a valuable contribution to make in assessing mortgage affordability and, generally, the effectiveness of regulation.

# 2 Introduction

## A consensus for regulatory change

The Mortgage Market Review (MMR) was a comprehensive review of the UK mortgage market, which started with a Discussion Paper in 2009 and culminated in a Policy Statement and final rules in October 2012. The majority of the MMR changes came into effect on 26 April 2014, including the responsible lending rules which made lenders fully responsible for assessing whether the customer can afford a loan. The run-up to implementation of the rules coincided with a revival in the UK housing market, bringing the issue of mortgage affordability – and how it can best be measured – sharply back into focus. This paper specifically looks at how affordability can be assessed in practice and compares the merits of three different approaches.

Momentum in the UK housing market poses potential risks to the FCA's statutory objectives and can also undermine wider public policy objectives. These risks emerge if significant increases in house prices fuel inappropriate mortgage lending, weaker loan underwriting standards and an increase in household indebtedness.

Prior to the 2008 financial crisis, there had been a significant increase in household indebtedness in the UK, primarily due to residential mortgage borrowing. Household debt as a share of GDP rose from 73% in 2001 to 100% by the end of 2007.[6] This rapid increase was characterised by declining credit standards, which contributed to a marked rise in the share of mortgages taken out by high-risk groups of borrowers who had not previously had access to long-term credit. High-risk lending by specialist non-banks – often using securitisation and other forms of wholesale funding – came to account for a significant share of the market. This was coupled with the emergence of business models that specifically targeted borrowers with impaired credit histories.

For some years rising property prices masked the impact of these lower credit standards. But ultimately this proved unsustainable. The onset of the financial crisis and irresponsible mortgage lending practices undermined confidence in the mortgage market. This led to a significant decline in the availability of mortgage credit, a large fall in house prices, worsening economic conditions and a rise in both arrears and home repossessions.[7]

The regulatory framework that had been in place ahead of the crisis had clearly failed to constrain a significant amount of risky lending and unaffordable mortgage borrowing. A key reason was the lack of a proper affordability assessment, with considerable evidence of imprudent lending practices. There

6 See the FSA's Financial Risk Outlook (2010c), p 9.

7 We note, though, that mortgage impairment was mitigated by very low interest rates and by the forbearance measures adopted by lenders following the 2008 financial crisis. By historical standards, therefore, mortgage impairment rates in this post-2008 data may have been unrepresentatively low.

was a general consensus that important regulatory reforms were needed to create a more sustainable mortgage market which would work better for consumers and reduce the risks to financial stability.

## Principles of good mortgage underwriting

Mortgage affordability is intuitively desirable. When enforced, it should prevent consumers from taking out mortgages that are clearly beyond their financial means or where the risks are high that loans will become unaffordable as a result of foreseeable developments (including increases in interest rates).

The affordability rules introduced through the MMR are designed to ensure that mortgages are only taken out if the borrower will be able, other things equal, to keep up the payments. In particular, they seek to prevent a return to the high-risk lending observed before the 2008 crisis, when lenders offered self-certified mortgages, interest-only mortgages with no verifiable source of capital repayment, and high loan-to-value (LTV) loans to borrowers with poor credit records.

The key elements of the responsible lending reforms (the affordability rules) capture the three principles of good mortgage underwriting:

- **The affordability assessment:** the lender must verify income and be able to demonstrate that the mortgage is affordable, taking into account the borrower's net income and, as a minimum, the borrower's committed expenditure and basic essential expenditure and quality of living costs of the customer's household.
- **The interest rate stress test:** the lender must also take account of the impact of expected future interest rate increases on affordability, with reference to market expectations for interest rates over the next five years.[8]
- **Interest-only mortgages:** the lender must assess affordability on a capital and interest basis, unless there is a clearly credible repayment strategy.

In addition to these affordability requirements, further protection was provided to borrowers through the introduction of new standards on selling. Advice is now mandatory for interactive sales (e.g. face-to-face and telephone sales)[9], and for mortgages that involve debt consolidation or equity release. Therefore the vast majority of sales – especially to financially vulnerable borrowers – must include advice.

It is important to remember that the affordability requirements reflect a qualitative principle – that loans should only be granted where they are affordable based on an identifiable income and expenditure, and where no reliance is placed on assumed property price appreciation – and not a specific quantitative measure. The rules are therefore not prescriptive about the affordability metrics that lenders should use. In practice, lenders employ a range of metrics to assess mortgage affordability, taking into account an applicant's income and

[8] There is now also a requirement to have regard to any prevailing Financial Policy Committee (FPC) recommendation on appropriate interest rate stress tests. The FPC has also introduced a prudential recommendation on loan-to-income ratios.

[9] Exemptions apply in cases where the customer is a mortgage professional, high net worth individual or business customer. Execution-only sales are allowed only in very limited circumstances.

expenditure, with the final decision subject to each lender's specific risk appetite.[10]

## Quantifying affordability: three metrics

The fact that the responsible lending requirements did not precisely define what was meant by 'affordable' posed a serious methodological challenge to our research to inform the cost benefit analysis of the MMR package of proposals. The task was to provide a quantitative estimate of the impact[11] of the new rules on mortgage lending, by constructing and using an affordability metric that:

- captured affordability in the sense likely to eventuate from the affordability assessment rules;
- was able to determine whether a particular mortgage granted in the past would have been affordable; and
- was feasible for us to construct given data constraints.

This paper discusses the three methods we considered to create such a metric to measure affordability:

- The debt service ratio (DSR) approach.
- An expenditure-adjusted DSR approach.
- A quality of underwriting (QoU) measure.

Once constructed, each affordability metric was used in our simulation model. This model was the main tool for the cost benefit analysis and was designed to estimate the key effects of the package of affordability proposals. A standardised set of inputs captured the relevant policy parameters – such as affordability rules, thresholds and stress tests – thereby enabling us to investigate the three alternative approaches for measuring affordability. This type of microsimulation modelling was extremely valuable for the policy analysis and policy advice.

The key data for the modelling were Product Sales Data (PSD)[12] – individual mortgage transaction data that the Financial Services Authority (FSA) collected as part of its regulatory returns from firms – and mortgage impairment[13] information collected on our behalf by the Council of Mortgage Lenders (CML). These data were used with the model to estimate the impact of the proposed affordability rules. For each metric, unaffordable mortgages were those reduced or prevented by the proposals, while affordable mortgages were assumed to be granted unchanged.

The rules sought to exclude borrowers who would have been granted an unaffordable mortgage due to poor quality underwriting, i.e. a mortgage which at the point of origination[14] would be expected to become impaired. However, in practice it is difficult to implement a set of rules than can perfectly identify such

[10] The risk appetite (or tolerance) refers to what level of impairment the lender estimates is an acceptable level for it to achieve the required level of profitability. Lenders with different business models will have different risk appetites.

[11] The paper is a technical guide to the methodology used in the MMR CBA. It does not focus on the borrower impacts of the policy which are well documented in the various consultation papers published as part of the consultation process.

[12] See Annex 1 for details on the mortgage transactions and impairment data used in the analysis.

[13] By impairment we mean that the borrower has either been in arrears or defaulted (property was repossessed).

[14] The term 'origination' refers to when a mortgage has been successful granted (i.e. when the transaction has legally completed).

lending, and some borrowers who should be prevented from borrowing (or constrained to borrow less) will not be, while other borrowers who should not be constrained by a rule will be.

To assess the overall effectiveness of the proposed rules a 'well-being methodology' was devised. This was used to capture the impact on those borrowers who were affected by the rules, by determining their relative costs and benefits. Changes in well-being arising from the proposed affordability rules were calculated by comparing:

- increased well-being under the proposed rules (for those households whose borrowing was constrained and who *would* have faced mortgage impairment without them), with
- reduced well-being under the proposed rules (for those households whose borrowing was constrained but who *would not* have faced any form of mortgage impairment without the rules).

The net benefits of the proposed rules will be reduced by any mis-targeting of borrowers. It is a matter of judgement, but a judgement usefully informed by reported well-being data, to decide on the relative importance to attach to borrowers who accrue well-being gains compared to those who suffer well-being losses, along with the appropriate threshold to use to calibrate the affordability metric.

This paper presents our work on the measurement of mortgage affordability and shows how the effectiveness of policy can be assessed in terms of changes in consumer well-being. The analysis was undertaken in 2010-11 as part of the review of the mortgage market, but the methodology and findings remain relevant. The consideration of well-being and how best to measure whether regulation is effective is also important given that the FCA is now mandated to quantify not only the costs but also the benefits of its rules.

The paper is structured as follows: section 3 provides some necessary context by presenting a brief review of recent academic and policy work on housing and mortgage affordability. This review brings out some of the different ways of measuring affordability, including some points of contention, and shows how affordability is a difficult concept that is not straightforward to define in a clear-cut manner. Section 4 discusses the three methods we considered to measure affordability: the DSR approach, an expenditure-adjusted DSR approach and the 'Quality of Underwriting' measure. Section 5 considers how the effectiveness of the responsible lending rules can be assessed, and reviews the well-being analysis that we carried out. Finally, Section 6 draws some conclusions from our work.

# 3 Common approaches to housing and mortgage affordability

Considerable research has been undertaken into the issue of measuring affordability and is reported in the housing policy literature. Although much of this work has largely been in relation to the provision of social housing rather than mortgage affordability, the metrics developed for housing affordability provide useful lessons for measuring mortgage affordability.

Mortgage affordability refers to the ease with which a household is able to meet its mortgage payments. Affordability problems arise when a household's income is insufficient to cover mortgage payments and other living expenses. These affordability problems are often due to:

- 'facts of life' (e.g. unemployment, divorce etc.) that are unrelated to the functioning of the mortgage market
- personal factors (e.g. excessive borrowing or poor financial planning by the household), or
- systemic factors (e.g. changes in interest rate or house prices) that are related to the proper functioning of the mortgage market.

Whether or not a mortgage is affordable depends on the characteristics of the mortgage chosen. However, selecting an optimal mortgage is complex. As illustrated by Campbell and Cocco (2003) and Campbell (2006), households must consider interest rate risk, inflation risk, current and future borrowing constraints, their level of risk aversion, the probability of moving home and their ability to refinance.[15]

A measure of mortgage affordability would ideally take all of these factors into account. In practice, of course, this is simply not feasible. Borrowers may not have the knowledge or the time to make a fully informed decision. Also, they tend to put more emphasis on the current reward of their actions (e.g. buying the house they want) than the future consequences (e.g. going into arrears). Attempts to measure affordability have tended instead to focus on core indicators (household income, expenditures, rent or mortgage payments) at the point of the origination of the mortgage plus personal expectations about the future. This leads to an inevitable loss in precision in the affordability metric for some households.

Figure 1 provides an overview of the different approaches to measuring affordability and how they relate to each other.

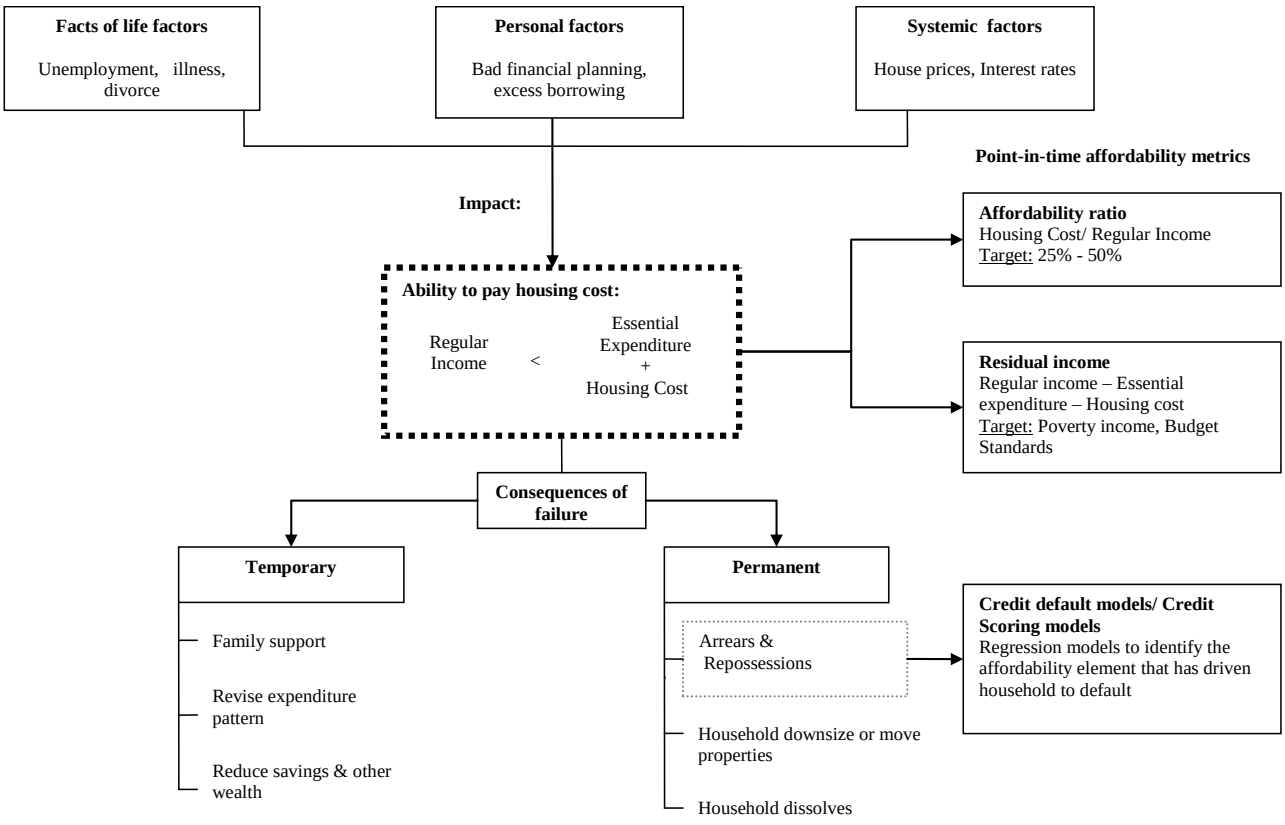
## Point-in-time methods

In the housing policy literature, there are two main approaches to measuring affordability. The affordability ratio approach assesses affordability using ratios of

[15] Although credit and interest rate risk are expected to decline over the life of the mortgage.

income to housing costs, while the residual income approach does so in terms of net income after expenditure. Both approaches are point-in-time approaches: they both construct affordability metrics from household income and expenditure data at one point in time. This is then compared to a pre-specified threshold in order to determine affordability (see Hulchanski (1995) and Stone (2006a)).

**Figure 1: Alternative ways of measuring mortgage affordability**



Affordability ratios normally compare current household expenditure to current household income. However, in reality there should be more focus on expected affordability, as the values for the numerator and denominator change over time. In the literature, the thresholds used with the housing affordability ratio vary from about 25% to 50% of income (Stone (2006a), Struyk (2005), Chen et al (2010)). Despite the widespread acceptance of the ratio approach itself, there appears to be no clear theoretical foundation for choosing a particular threshold. Apart from the apparent subjectivity of any preferred threshold, the application of the same standard across all households is also problematic. It ignores the particularities (e.g. composition of the household, essential expenditure), which can affect mortgage affordability (Brownill et al (1990), Sharp et al (1990)). For example, households with children may have higher daily expenses, leading to affordability problems even if their housing cost to income ratio is below the set threshold. On the other hand, households with higher levels of income may be in a position to afford housing costs to income ratios in excess of a threshold without facing affordability problems (Whitehead (1991)).

The residual income approach was developed to address some of the deficiencies of affordability ratios. The approach arises from the recognition that each household has a set of essential expenditures that puts rigid demands on a household's income and hence should not be ignored in the calculation of affordability. The residual income is calculated as the difference between income and housing cost and this is compared with a standard set of essential expenditure items to assess housing affordability. The approach assumes that a household has affordability problems if it is unable to pay for all essential expenditures after paying for housing. Stone (2006a) argues in favour of the conceptual soundness of the residual income approach. However, he also recognises the practical difficulties of setting an evidence-based residual income standard (i.e. deciding the minimum acceptable income after housing costs).

In the empirical literature two strands have developed to address this challenge. The first adopts a fraction of the national poverty threshold as a standard (e.g. Kutty (2005)) while the other uses a family budget standard based on a basic basket of necessities (e.g. Stone (2006a)). However, as Stone notes, none of these standards is without its problems. The standard based on the poverty threshold is conceptually simple but inherits the problems of the poverty threshold more generally.[16] For the family budget standard, it is difficult to select and cost the items that should be included in a basket of necessities. Moreover, it is important that any residual income metric be specific to family size and composition. A key problem is that data are not always available to meet all of these criteria.

A great advantage that affordability ratios and residual income metrics share is that they are both easy and quick to calculate, as they only require estimates of household income and expenditure at one point in time. However, there are at least two main shortcomings to both affordability ratios and residual income metrics. First, they do not explicitly take account of household wealth, as wealth is only inferred

[16] In the UK the most widely quoted measure of income poverty classifies households with incomes less than 60% of the contemporary median (IFS (2012)) as poor. However, this measure is subject to criticism as to why 60% of median income is the appropriate poverty threshold (e.g. Bradshaw (2001)). For a discussion of the limitations of poverty thresholds see Bernstein et al (2000) and Ruggles (1990).

from reported household income. This provides only a partial picture of a household's assets and its choices when financial difficulties arise. Second, as they are point-in-time estimates the measures ignore how household circumstances change over time and what impact this has on affordability.

## Statistical techniques

Another branch of the literature attempts to go beyond the limits of point-in-time estimates by using more complex statistical techniques. Using a micro dataset, Calhoun and Stark (1996) present two approaches for assessing affordability. In the first approach, they develop an optimisation model to estimate the optimal house price for each household. This is used to determine how much a household can afford. In the second approach, an underwriting simulation is carried out to assess whether each household qualifies for a particular mortgage given the associated underwriting criteria.

As Struyk (2005) notes, a great advantage of using micro datasets is that the results produced can be disaggregated in a variety of ways, such as into household composition and wealth. These models also address the problem of point-in-time estimates by looking at the long-term ability of a household to repay a mortgage. However, this comes at the expense of simplicity. They require more data than the simple affordability metrics and they still ignore the choices that a household can make to avoid affordability problems.

Read et al (2014) use micro-level data to investigate mortgage impairment in Australia. Their household-level analysis indicates that high debt-servicing ratio (above 50%) increase the probability of mortgage payment problems.

## Composite indicators

More recent work by Bramley (2011) calls for composite indicators that combine affordability ratios with subjective evidence of payment problems and material financial hardship. Bramley developed this approach after trying to validate the ability of the affordability ratios and residual income metrics to predict payment problems. He used the British Household Panel Survey (BHPS)[17] dataset to identify households in financial difficulties and concluded that the affordability ratios have better predictive power than residual income measures. However, affordability ratios still do not fully predict problems, as only a minority of households with adverse ratios reported difficulties, while some with acceptable ratios reported difficulties.

Based on these shortcomings, he suggested a composite indicator which also brings in evidence of payment problems or financial hardship. An appealing feature of Bramley's approach is that it takes into account the consequences of affordability problems in addition to the key elements that caused those problems in the first place. This is helpful because it connects the affordability standard to affordability-related consequences, which the more subjective thresholds of the point-in-time approaches are not able to do. While this is conceptually attractive, it is also a difficult approach to operate because the necessary data are hard to obtain. One

[17] For further details on the British Household Panel Survey, see www.iser.essex.ac.uk/bhps .

reason is that households tend to guard their financial privacy when they face difficulties and do not like to reveal their financial status and the actions they are taking. In addition, the actions households take to tackle financial difficulties vary widely and are very difficult to capture.

## The impact of unaffordability

When a household has affordability problems and does not have enough income to cover its mortgage payments, it has to find ways to increase its income or reduce its expenditures, or both. The coping method and eventual outcome depend on whether the problem is temporary or permanent (Figure 1).

If affordability problems arise due to a temporary mismatch of income and expenditure, for example if a member of the household is a seasonal worker, then the household may be able to use its savings to cover immediate needs. In some cases, the household may be able to make up for some missed housing payments after the temporary problem ends. If the problem is more persistent, the household needs to consider ways to alter its 'balance sheet composition'. One option is to make cost savings by reducing non-essential expenditures and cutting-down on (the price of) essential expenditure. Which expenditures will be stopped or reduced depends on the household's preferences. Households will also vary in their judgment of what types of expenditure are essential or not. However, one would expect some commonality here: for example, expenditures that cover basic needs such as food, clothes and health would be expected to be the last affected when households reduce their expenditure.

Longer-term unaffordability leads to more permanent consequences. Households in financial difficulty may have to consider changing their accommodation by moving to a smaller property ('downsizing') or to a cheaper area, or by applying for social housing. In practice, though, households face a variety of constraints (including their creditworthiness) with respect to their mobility. For example, serious arrears can lead to repossession of a home by the mortgage lender. Households may also break up in the fall-out from mortgage unaffordability.

## Drivers of mortgage default

Affordability problems that cannot be managed lead to mortgage impairment. So another alternative is to construct a measure of affordability based on the drivers of arrears and repossessions. The extensive academic literature on mortgage default is a useful starting point for identifying the key drivers for mortgage arrears and to isolate the drivers that are related to unaffordable lending. At a theoretical level, a number of papers[18] have considered the drivers of default and have developed two theories: the ability to pay and the equity theory.

The ability to pay theory takes into account the liquidity constraints that borrowers face. It argues that borrowers do not default if their income is sufficient to pay their

[18] See Jackson and Kaserman (1980), Quercia and Stemgan (1992), Vandell (1995), Boheim and Taylor (2000) and Whitley et al (2004).

mortgage obligations without undue financial burden. Under this theory the factors that exhibit a significant relationship with arrears can be categorised into:

- Mortgage characteristics: e.g. self-certification and fast-track.
- Household characteristics: e.g. age of household heads, number and age of dependents, household expenditure, household savings, other debt, income shocks due to illness, divorce or death.
- Macroeconomic characteristics: e.g. increases in interest rates (with impacts depending on the duration, type and size of the mortgage) and income shocks leading to a rise in unemployment.

The equity theory is based on borrowers' willingness to pay and assumes that they decide to default if the market value of the property is less than the outstanding mortgage. Breedon and Joyce (1992) argue that a fall in nominal house prices reduces the amount of unwithdrawn equity in a property, and under certain circumstances provides the incentive for borrowers to accumulate arrears and for lenders to repossess. This theory contradicts the ability to pay theory which states that households will keep making payments as long as possible. According to the equity theory a key driver of default is the current LTV. However, it is unclear to what extent the theory is transferable across countries, as the recourse a lender has to a borrower's assets varies widely. In the UK, mortgages are 'non-recourse mortgages', which means borrowers are personally liable for making payments on the secured debt. If a borrower gets into difficulty and their property is repossessed and sold at a price lower than the outstanding mortgage, the borrower is still liable to cover the outstanding amount from future earnings. Therefore, it may not be rational behaviour for a UK borrower to default when their property moves into negative equity. This may depend on a borrower's earning prospects, any other assets and ability to access social housing. Behavioural (psychological) factors may also be relevant. Lambrecht et al (1997) examined the equity theory using UK household level data. They found that ability to pay variables were more important determinants of default than equity variables and that the likelihood of default peaks within the first year after origination, and then falls over the life of the mortgage.

Aron and Muellbauer (2010) cut across the equity theory and the ability to pay theory, arguing that default and repossessions are driven by three variables: the debt service ratio (DSR), the proportion of mortgages with negative equity, and the rate of unemployment. They report that recent incidence of impairment in the UK would have been almost a quarter higher had the government not encouraged forbearance and income support measures.

Detailed research undertaken by credit rating agencies gives consistent results to the academic work on mortgage default. A report by Moody's (2009) analysed the determinants of mortgage default rates. According to Moody's, high LTV loans, buy-to-let loans, loans to the self-employed and self-certified, remortgages and interest-only mortgages exhibited higher default rates than other mortgages. In addition, loans to borrowers close to retirement, loans without full property valuations or backed by high value properties exhibited marginally higher default rates than other mortgages. Loans to first time buyers, and loans with high income multiples did not exhibit higher rates of default. Fitch (2010) carried out an analysis of the drivers of default risk for UK mortgages. Fitch reached similar conclusions to those of Moody,

finding that the main drivers of default were LTV, debt to income ratio, interest-only loans and self-employment.

The academic literature on the drivers of mortgage default, particularly the ability to pay models and the reports by the credit ratings agencies, show that it is in principle feasible to build a model of the drivers of mortgage arrears and default that could be used in constructing a metric of mortgage affordability.

# 4 Three approaches to measuring mortgage affordability

As explained in section 2, our goal was to construct an affordability metric that would allow us to estimate the impacts of the affordability rules. Our literature review informed the approaches we considered for constructing an appropriate metric.

- The first approach we present to measure mortgage affordability – the debt service ratio (DSR) – is an affordability ratio (page 24).
- The second approach – the expenditure adjusted DSR measure – attempts to construct a more sophisticated point-in-time affordability measure by also using expenditure data to measure residual income (page 28).
- The third measure is the quality of underwriting metric (page 38). This metric is constructed by modelling the probability of arrears and default in terms of their key drivers. The metric is then used to construct a measure of affordability. This approach drew on the ability to pay models of mortgage default discussed on page 35.

The analysis was undertaken using a sample of mortgage transactions (and corresponding impairment information) originated over the period April 2005 to September 2010. [19] To apply each of the affordability metrics, we built a microsimulation model to simulate how mortgages originated over this period would have been impacted if the proposed affordability rules had been in place at this time. The simulation model captured all the relevant policy parameters, such as affordability rules, thresholds and stress tests within a standardised set of inputs. This made the use of microsimulation extremely valuable for policy analysis and policy advice.

For each affordability rule, the model simulated the impacts of the rule on each borrower in the sample. It identified which borrowers would pass the affordability rules and be awarded a mortgage, and which mortgages would be classified as unaffordable, having failed to pass a particular affordability rule. This classification was then compared against actual subsequent mortgage impairment to assess its predictive performance

## Debt service ratio (DSR)

The DSR was discussed in section 3 and is an often-used summary of household debt (Dynan et al (2003) and Aron and Muellbauer (2010)). The ratio is intended to capture the share of a household's after-tax income committed to mortgage debt repayment. A key advantage of this ratio is its simplicity. It requires little data and is easy to calculate. The only data we needed for calculating the ratio was the size of

[19] See Annex 1

the mortgage debt payments and the household's income after tax. This information could be constructed from the Product Sales Data (PSD) dataset.

Under this approach, we calculated the DSR for each individual mortgage transaction in our dataset, where DSR measures the cost of funding the mortgage as a proportion of household net income at origination (equation 1). A higher DSR represents a mortgage which costs the borrower more as a proportion of post-tax income, and is thus less affordable.[20]

$$DSR = \frac{Mortgage\ Payment}{Net\ Income\ (i.e. Gross\ Income - (Tax + National\ Insurance))} \quad (1)$$

A key part of the MMR proposals was to consider the impact of expected future interest rate increases, and whether a borrower would still be able to afford the mortgage if interest rates were to rise. While interest servicing costs are currently at an historic low, thus mitigating the effects of higher house prices on mortgage affordability, households are vulnerable to future increases in rates. The MMR stipulated that the interest rate stress test (IRST) should be a minimum of a 1% rise or set according to market expectations for interest rates over the next five years.[21]

In our dataset, the average DSR was 25%, which indicated that the average mortgage holder spent approximately a quarter of their net income on mortgage payments at the time of origination. To explore whether DSR could be used to model affordability, we analysed how it was associated with subsequent mortgage impairment. Figure 2 shows there was a positive relationship between DSR and the probability of impairment in the future, where impairment was also analysed in terms of the duration of the arrears and whether a possession order or repossession had taken place.[22] Segmenting arrears by duration is important because it allows us to differentiate between the arrears that are likely to be of a temporary nature (such as when arrears are less than three months) and therefore less likely to be indicative of serious affordability problems, and the longer-term arrears (such as arrears over

[20] The mortgage payment is based on the annuity formula, and is calculated as a function of the interest rate (r), term (n) and principal advanced (P), following the equation:

$$Mortgage\ \ Payment\ = \frac{rP}{1-(1+r)^{-n}}$$

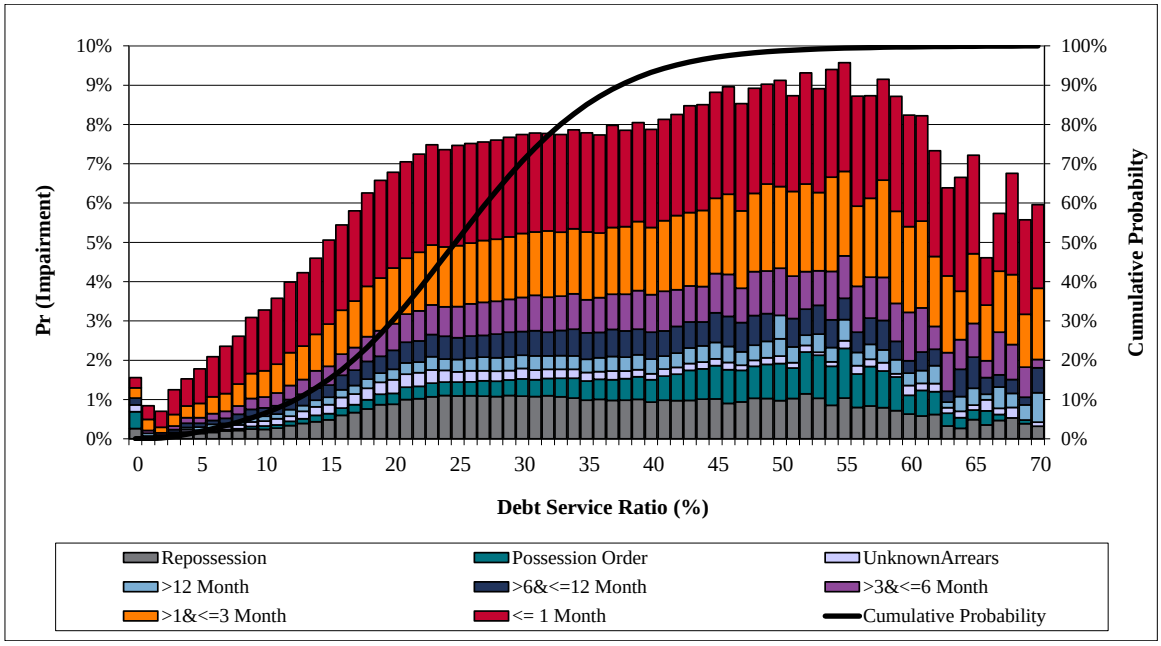
The interaction of the principal, interest rate and term variables, combined with the borrower's net income, is used to determine the affordability. Note that in the case of interest-only mortgages, the mortgage payment is equal to rP, since the borrower repays the principal separately.

[21] More recently the FPC recommended that lenders should have due regard to any prevailing FPC recommendation on interest rate stress tests when assessing affordability. The current recommendation, made in June 2014, is that lenders should consider whether borrowers can still afford the mortgage if interest rates were to rise by 3% in the five years after origination.

[22] The duration of arrears variable is calculated by the FSA from arrears information provided by the Council of Mortgage Lenders (CML). For instance, if an account was in arrears, then the duration of arrears was estimated by dividing the outstanding value of arrears by the imputed monthly mortgage payment. This method does not include historical impairment, and therefore underestimates both the true level of impairment and the total benefits from a policy which targets arrears.

three months) which are more likely to indicate affordability problems that are harder to resolve.

***Figure 2: DSR and probability of mortgage impairment (using PSD data 2005 Q2 - 2010 Q3)***




For DSRs between 0% and 25% (which covered more than half the borrowers in the dataset), the probability of impairment (left-hand scale in Figure 2) rose at an almost constant rate. This was in line with what one might have expected (i.e. impairment increases steadily as indebtedness increases), reflecting the fact that the more leveraged a borrower is at the time of mortgage origination, the less likely they will be able to meet the mortgage payments in the face of subsequent economic shocks and life events. We also observed from Figure 2, that over much of this DSR range, arrears tended to be of a lower duration and temporary, and that cases of repossession were extremely rare.

DSRs between 25% and 45% are in a range where leverage might be high enough to indicate unaffordability. About 45% of the mortgages lay in this DSR range. However, in this region, impairment risk did not significantly increase with DSR, which is counterintuitive. Also, the relative proportions of arrears by duration were relatively stable across this range of DSRs. These features suggest that confounding factors were at play. For example, borrowers in this DSR range are typically home-movers on their second or third move, have stable jobs, high levels of income relative to their ongoing commitments, and savings and experience of managing credit and debt (so that for them a higher DSR is positively correlated with a greater ability to manage the risk of payment problems).

The region where DSR is above 45% contains a small proportion of the borrowers (less than 5%) but is likely to contain a significant amount of the unaffordable

borrowing. However, for DSR values in this range, the risk of payment problems remained flat and the proportions of arrears durations were stable. This was due to the region being dominated by higher wealth and higher income individuals who could borrow affordably at high DSRs. The PSD does not provide estimates of household wealth. The insensitivity of impairment to DSR for high DSRs may also be a consequence of the abnormally low interest rates that were prevalent during the sample period. Interest rates fell rapidly following the onset of the 2008 financial crisis and this – along with the forbearance measures that many lenders introduced – may have helped to cushion borrowers from economic shocks that would otherwise have led them into mortgage impairment. It may be that during normal interest rate environments, or in a buoyant housing market when lenders' incentives to forebear are reduced, we would observe a greater sensitivity of impairment risk to DSR at high DSR levels.

### Limitations

Overall, while its simplicity is welcome, the DSR has some important limitations as an affordability metric. In order for the DSR to be useful for modelling the impact of an affordability assessment rule, that rule requires a threshold at which mortgages would be considered unaffordable. This requires a method for determining an appropriate threshold. One way to do this would be to look for a point beyond which the DSR is associated with much higher levels of impairment. In other words one would look at Figure 2 to find a point on the curve where there is a strong upward kink in impairment and use this to calibrate a DSR limit for affordability. However, there are three problems with this:

- First, as already mentioned, there is an empirical problem. Figure 2 shows a steady increase in probability of impairment for low DSRs (where mortgages would mostly be affordable). However, the rate of increase for DSRs above 25% is relatively gentle with no point of upward acceleration that could be used convincingly to calibrate the DSR as a measure of when mortgages become unaffordable.
- Second, the DSR does not take a borrower's expenditure into account. As a result, it is not satisfactory for assessing the impacts of affordability rules that require lenders to use expenditure data in their lending decisions.
- Third, as with other affordability ratios, other factors (besides expenditure) that are relevant to affordability are not adequately taken into account by the DSR. For example, borrowers with higher levels of income are likely to be able to afford a mortgage with a higher DSR than lower income borrowers. This is because they will have larger proportions of free disposable discretionary income to divert to their mortgage if they need to.

Taken together, these issues mean the DSR fails as a usable metric because it is not sufficiently discriminating to capture affordability as understood in the affordability rules and because there is no convincing way to set a DSR threshold below which mortgages should be deemed to be affordable. However, the insights from this analysis while not incorporated in the detailed affordability rules can be considered good practice, and something which we might expect supervisors to monitor.

To overcome these limitations, we explored other ways to improve this type of measure of affordability. In particular, we considered incorporating expenditure data into a DSR.

## Expenditure-adjusted DSR

As mentioned, a key problem with the DSR-based measure is that it is not informed by household expenditure. Borrowers have 'non-essential' expenditure they can reduce in order to make a mortgage payment and 'essential' expenditure they will not reduce, or possibly cannot reduce without suffering financial penalties for breach of contract. If a borrower is pushed to a point where their expenditure is purely essential then any shock that reduces income or increases essential expenditure will cause them to miss a mortgage payment (ignoring any savings or wealth the borrower may have).[23]

As discussed on page 16, the residual income approach was developed to improve affordability ratios by taking account of household expenditure. This suggested to us that it might be fruitful similarly to adjust the DSR. We hoped this would lead to a measure of affordability that was better able to discriminate between affordable and unaffordable mortgages in the DSR region from 25% to 45%, in a way that fitted well with the affordability rules.

The expenditure-adjusted DSR (or affordability ratio) is shown as equation 2. It is identical to the DSR in equation 1, except that an estimate of household expenditure is included in the numerator.

$$Expenditure\ adjusted\ DSR = \frac{Mortgage\ \ payment + \ \ Household\ \ \text{exp}\ enditure}{Net\ income\ \ \ (i.e.\ after\ tax\ and\ \ NI)} \qquad 2)$$

We considered two different measures of household expenditure. Both adjusted the basic DSR (equation 1) to take into account the proportion of income devoted to expenditure (as shown in equation 2):

- ***Essential expenditure ratio***: This is the ratio of essential net expenditure plus mortgage payments to net income.
- ***Total expenditure ratio****:* This is the ratio of total net expenditure (i.e. net of mortgage costs)[24] plus mortgage payments, to net income (i.e. income after tax and national insurance).

These measures naturally require expenditure data. Unfortunately, the PSD does not include data on borrowers' household expenditure.[25] We therefore explored how far it was possible to estimate robust and reliable measures of expenditure for households in the PSD using available survey data.

[23] Household wealth is an important factor but we have not incorporated it into our attempts to construct a measure of affordability because we did not have appropriate data available to us. One potential way of addressing this shortcoming would be to use the Wealth and Assets survey from the ONS to impute estimates.

[24] Estimates of essential expenditure and total net expenditure both exclude mortgage costs, so as to avoid double counting.

[25] To correct for this shortcoming in the PSD, from April 2015 the submissions which mortgage lenders report to the Financial Conduct Authority will include fields to capture household expenditure (along with mortgage performance data). See Financial Conduct Authority (2013), "Mortgage Market Review – Data Reporting", Policy Statement, PS 13/12.

Our approach followed two stages:

**Stage 1**: Supplementing the PSD with estimates of borrower household expenditure, i.e. construct essential net expenditure and household total net expenditure estimates using survey data for the households undertaking the mortgage transactions in the PSD.

**Stage 2**: Construct the affordability ratios and evaluate the resulting measures.

## Stage 1: Estimating household expenditure for mortgage borrowers

Incorporating estimates of borrower expenditure into the PSD involved several modelling steps. First, we needed to source expenditure data. After some consideration, we decided to use the Living Cost and Food (LCF) survey – collected by the Office for National Statistics – to construct estimates of household expenditure for the households in the PSD.[26] In the LCF, respondents are asked to report their expenditure in detail. Total expenditure in the survey is organised into 13 broad expenditure categories, which in turn contain 484 detailed expenditure categories. The LCF thus provides a comprehensive breakdown of total expenditure and does this for a representative sample of approximately 6,000 UK households every year. It includes housing costs (mortgage or rental costs). The highly detailed breakdown of expenditure in the LCF was attractive, as it lent itself well to categorising expenditure into non-essential and essential components.

We next constructed estimates for total net and essential household expenditure for each household – net of direct housing costs (i.e. mortgage payments or rent) – that reported in the LCF. Total net expenditure was calculated for mortgage holders as the sum of all expenditure items minus mortgage costs. Essential net expenditure required a judgment as to whether each component of household expenditure was essential or non-essential. Components considered essential were then summed to construct the essential expenditure estimate. We recognised that this method might be considered somewhat arbitrary, because of the subjective element.[27] However, it also had the advantage of flexibility and transparency: if any included or excluded items were considered controversial, the measure could be quickly and easily revised.

To illustrate the mechanics of this method we report the figures for 2008. Table 1 gives the average breakdown of expenditure from the LCF and the corresponding breakdown into essential net expenditure and total net expenditure, and consumption expenditure is split between 12 high level categories. From the LCF survey we found that the average household owning a mortgaged property has a total net monthly income of £3,155 and a total monthly expenditure of £2,934, including average mortgage payments of £576 a month. (Rental costs are not

[26] The Living Costs and Food (LCF) survey, formerly the Family Expenditure Survey, collects information on both expenditure patterns and the cost of living for households in the UK. The primary use of the survey is to provide information about patterns of expenditure for the Consumer Price Indices (CPI). Use of the survey for measuring household expenditure was recommended by the Institute of Fiscal Studies (IFS).

[27] In the case of our estimate of household essential expenditure we considered 279 expenditure items as essential and 205 as discretionary. It has to be noted that some expenditure items contain essential and discretionary parts. Therefore the estimates might have been improved by considering fractions of expenditure items, rather than items in full. However, we decided against this as it would have come at the expense of clarity and transparency of the expenditure estimate.

included in Table 1 because we were only looking at households with a mortgage.) Therefore, average household:

- essential net expenditure was estimated as £1,241 a month (39% of net income).
- total net expenditure (net of mortgage costs) was estimated as £2,358 per month (or 75% of net income), and

***Table 1: Breakdown of average monthly expenditure for owner-occupiers of households with a mortgage (£: 2008)***

| | Total | Essential Net* | % | Total Net* | % |
|---|---|---|---|---|---|
| Net Income (after tax and NI) | 3,155 | | | | |
| Total Expenditure | 2,934 | 1,241 | 39% | 2,358 | 75% |
| | | | | | |
| Consumption Expenditure | 2,105 | 1,090 | 35% | 2,105 | 67% |
| *Food and non-alcoholic beverage* | 263 | 245 | 8% | 263 | 8% |
| *Alcoholic Beverages, Tobacco* | 55 | 13 | 0% | 55 | 2% |
| *Clothing and Footwear* | 129 | 59 | 2% | 129 | 4% |
| *Other Housing**,Water, Electricity* | 173 | 172 | 5% | 173 | 5% |
| *Furnishings, HH Equipment,* | 170 | 65 | 2% | 170 | 5% |
| *Health Expenditure* | 27 | 27 | 1% | 27 | 1% |
| *Transport Costs* | 410 | 241 | 8% | 410 | 13% |
| *Communication* | 64 | 46 | 1% | 64 | 2% |
| *Recreation* | 328 | 29 | 1% | 328 | 10% |
| *Education* | 40 | 0 | 0% | 40 | 1% |
| *Restaurants and Hotels* | 227 | 36 | 1% | 227 | 7% |
| *Miscellaneous Goods and Services* | 219 | 158 | 5% | 219 | 7% |
| | | | | | |
| Non Consumption Expenditure | 829*** | 151 | 5% | 253 | 8% |

* Net of mortgage payment costs
** Other housing costs include items such as housing maintenance and repair costs.
*** Includes average monthly mortgage payments of £576

*Source: Living Cost and Food Survey, ONS*

A key difficulty with this approach to estimating household expenditure – and specifically the use of the output to assess affordability – is the problem that important components of expenditure are not explicitly captured in the explanatory variables. Expenditure items such as changes in transport costs (for commuting to work, school runs, shopping, etc.), council tax, energy costs and insurance costs are

all part of any house purchase decision. For example, property close to the workplace or good state schools cost more (and therefore the mortgage appears to be less affordable). They are also likely to be in higher council tax bands. On the other hand, transport or schooling costs are likely to be lower. Therefore an affordability assessment that is based on estimated rather than the actual household expenditure (i.e. measurement error) that will arise when living in the new property may lead to an incorrect assessment of whether or not a mortgage is affordable.

At this stage, we had essential net expenditure and total net expenditure estimates for households surveyed in the LCF. The next step in constructing expenditure estimates was to use regression analysis[28] to explain the value and variations in these essential and total expenditure estimates in terms of household characteristics and other determinants of household expenditure covered by the LCF. This was needed so that these variables could be mapped onto the PSD. The choice of possible determinants was limited – with the important exception of household size which we discuss below – to those variables in the LCF that could reasonably be matched with characteristics included in the PSD. This was done so that (if successful) we would be able to construct values for essential and total net expenditure relating to each borrower in the PSD, by applying the predicted values from the regression equation to these characteristics in the PSD.

The expenditure regression analysis identified the following significant drivers of household expenditure: disposable income, household size, age of the head of the household and geographical region. Overall, this simple expenditure regression model based on the LCF variables fits the measures of expenditure well, explaining more than 56% of the cross-sectional variation in both essential and total net expenditure The expenditure regression analysis suggested the following were the main drivers of household expenditure: disposable income, household size (i.e. expenditure is strongly related to the presence of children), the age of the head of the household (expenditure is greatest for households with a middle-aged household head) and overall geographical region. Apart from household size, these were all variables which we could map onto the PSD and therefore use to estimate essential household and total expenditure for borrowers covered by our PSD. However, we did not have data on household size in the PSD. This was a significant problem as household size is a crucial driver of household expenditure.[29] We could have decided not to include household size in the regression model above. However, removing it would have significantly weakened the precision of any resulting expenditure estimates. Instead, we decided to try to estimate household size for borrowers in the PSD using another data modelling step.

In this additional step we used Experian data on household segmentation, the Financial Strategy Segments (FSS) [30] behavioural consumer classification, which

[28] See Annex 3 for more details on estimating household expenditure using regression analysis.

[29] Strictly speaking the PSD does contain information as to whether there are one or two income earners in the household. However, this information was too limited to explain expenditure due to household size.

[30] The Financial Strategy Segments (FSS) categorisation developed by Experian seeks to accurately describe the financial behaviour of UK households. The FSS segmentation characterises financial behaviour around key dimensions such as demographics, investments, equity, borrowings and debt, and household attitude and aspiration. FSS classifies all adults in the UK into one of 82 individual types, which are the aggregated into 45 household types and 13 groups. See Experian (2010) for further details on the FSS segmentation and descriptions of the particular segments.

classifies UK households into 45 types on the basis of their financial behaviour and characteristics. The rationale for using this data on consumer types is that it is postcode-specific and FSS provides information on the probability that a particular household segment has children. The postcode information was important because the borrower postcode is also reported in the PSD, allowing us to match Experian estimates to actual mortgage transactions. This enabled us to construct an estimate of household size, from which we were then able to construct estimates for total and net expenditure for the PSD borrowers.

With all of these steps completed, we used the predicted values from the LCF regression analysis to construct estimates of essential net expenditure and total net expenditure for borrowers in our PSD sample. Summary results are shown in Table 2, where the table is organised on the basis of the FSS categorisation.

***Table 2: Monthly net Income and estimates of expenditure for borrowers (£: 2005-2010)***

| | Net Income | Essential Expenditure | %* | Net Total Expenditure | %* |
|---|---|---|---|---|---|
| | | | | | |
| Average Household | 3,163 | 960 | 37% | 2,234 | 76% |
| | | | | | |
| On the Breadline | 1,890 | 748 | 44% | 1,483 | 81% |
| Ageing Workers | 2,111 | 797 | 43% | 1,629 | 80% |
| Happy Housemates | 3,120 | 949 | 36% | 2,111 | 71% |
| Elderly Deprivation | 2,212 | 817 | 42% | 1,658 | 77% |
| Credit-hungry Families | 2,244 | 817 | 40% | 1,802 | 83% |
| Modest Mid-years | 2,561 | 881 | 39% | 1,959 | 79% |
| Surviving Singles | 2,532 | 875 | 39% | 1,900 | 78% |
| Successful Start | 3,916 | 1,063 | 32% | 2,553 | 70% |
| Advancing Status | 3,039 | 961 | 36% | 2,202 | 76% |
| Wealthy Retirement | 3,461 | 1,029 | 35% | 2,401 | 74% |
| Mid-life Affluence | 4,143 | 1,127 | 32% | 2,811 | 73% |
| Flourishing Families | 3,496 | 1,016 | 33% | 2,559 | 77% |
| Gilt-edged Lifestyles | 7,806 | 1,622 | 26% | 4,368 | 65% |
| Other | 3,318 | 965 | 34% | 2,306 | 73% |

* The expenditure estimates (in percentage terms) are calculated as the *mean of the individual ratios*. For instance, in the case of the average household, the reported estimate of 76% is higher than the ratio of average total expenditure to average net income (£2,234 / £3,163 = 71%). Given that we are most concerned about financially vulnerable households, using the mean of the individual ratios avoids the estimates being skewed by the inclusion of very high income borrowers, and provides more representative measures.

Sample: PSD borrowers, 2005-10

Reporting expenditure estimates by FSS group segmentation, as presented in Table 2, allows us to differentiate between the expenditure patterns of different household types. Segments are chosen for their ability to accurately describe differences in financial behaviour.[31] In table 2, the least affluent households are found to have much lower levels of essential expenditure than affluent households, but for these households essential expenditure unsurprisingly represents a much larger proportion of the household net income. In the case of the least affluent Experian household segment, essential expenditure represents 44% of net income, compared to only 26% in the case of the most affluent segment. This has important implications for household affordability and indebtedness, and would indicate that on average more affluent households are able to manage relatively higher levels of mortgage indebtedness because more of their money can be diverted to mortgage payments if necessary.

## Stage 2: Constructing and evaluating an expenditure-adjusted DSR

Having constructed estimates of household expenditure for mortgage borrowers in our PSD dataset, the next step was to investigate the impact of expenditure (essential or total net) when included in the household affordability ratio (equation 2). One obvious advantage of including expenditure in the affordability metric is that it makes the measure easier to calibrate. Unlike the basic DSR, which requires the analyst to select a threshold to define unaffordability, by taking account of expenditure, one can define a straightforward affordability threshold by considering a borrower's budget constraint (albeit ignoring wealth, savings etc.). Provided the mortgage payment and other expenditures (however defined) can be funded out of net income, then the mortgage is affordable.

In the case of expenditure-adjusted measures the key threshold is 100% i.e. where the mortgage payment plus the chosen measure of net expenditure is equal to the net income of the borrower. These measures can be thought of as representing limits on a spectrum of affordability. The essential expenditure measure represents a 'hard' measure of affordability, where expenditure has already been constrained and any mortgages identified as unaffordable are genuinely so. The total expenditure measure is a 'softer' measure of mortgage affordability and indicates cases where a household could cut back on non-essential items in their household budget to meet their mortgage payments.

Table 3 shows the estimated average affordability ratios for the base DSR (equation 1) along with the DSR adjusted for essential and total expenditure (equation 2). These represent 25.7%, 62.2% and 101.9% of net income respectively. In the case of the affordability measure based on essential expenditure, we observed that 3.2% of mortgages were identified as unaffordable, although this differed greatly by type of household, with mortgages originated to the least affluent households being almost seven times more likely to be unaffordable than those to the most affluent households.

[31] In 2013 the FCA launched its own Consumer Segmentation model – the Consumer Spotlight (http://www.fca.org.uk/news/consumer-spotlight) which differentiates between UK consumers based on their financial needs and vulnerability to risk. As the Consumer Spotlight was introduced after the affordability research was completed it was not available for use in the expenditure analysis described here.

In the case of total expenditure, the indicated levels of unaffordability were much higher, with half of all households being identified as having potentially unaffordable mortgages. While this number would seem high, it is important to put it into context. First, this reflected the way net expenditure was estimated and imputed for PSD households. We observe from Table 1 that, using the LCF data, total net expenditure is on average 76% of net income, and from an analysis of the PSD we know that the average DSR is 26%. Therefore we should not be surprised that the mean affordability ratio for net expenditure is 102% and that half the sample is in excess of the 100% threshold. From the detailed expenditure regression results reported in Annex 3, we observe that on average the expenditure regressions marginally over-predict actual total and essential expenditure, and this is particularly so for low income households.

There are obvious shortcomings when using the total expenditure measure. First, it is only really meaningful if households are truly unable to reduce their non-essential expenditure, while in reality most households have the potential to tighten their budgets. Second, the measure takes no account of accumulated wealth and savings in expenditure decisions. This would provide households with a buffer against temporary affordability problems.

It is also interesting to examine the estimates summarised using the FSS segmentation of the population as reported in Table 3. While financial overstretch is experienced by all types of households – almost a quarter (23.8%) of the most affluent households have total net expenditure exceeding net income – evidence of financial overstretch is particularly noticeable among the poorest families and particularly those that have been identified as having most difficulty managing credit i.e. the 'credit hungry'.[32] In this latter segment, 66.5% of households were estimated to have insufficient income to meet their mortgage payments once their total net expenditure is accounted for (i.e. where the affordability metric in equation 2 is estimated to be more than 100%).

[32] Credit-hungry families are identified as households who "have spent beyond their means, becoming dependent on credit to fund their lifestyles. Their incomes are below average and a good proportion of the money that comes in each month is required to fund their existing debt". See Experian (2010), p11.

***Table 3: Impact of adjusting for expenditure on mortgage affordability (2005-10)***

| | DSR | DSR adjusted for Essential Net Expenditure | | DSR adjusted for Total Net Expenditure | |
|---|---|---|---|---|---|
| | A.R.* | A.R. | P(Unaffordable)** | A.R. | P(Unaffordable)* |
| Average Household | 26% | 62% | 3.2% | 102% | 50.2% |
| On the Breadline | 25% | 70% | 6.1% | 106% | 58.6% |
| Ageing Workers | 25% | 68% | 5.7% | 105% | 56.3% |
| Happy Housemates | 27% | 62% | 2.8% | 97% | 38.3% |
| Elderly Deprivation | 25% | 67% | 5.5% | 103% | 51.6% |
| Credit-hungry Families | 26% | 66% | 4.3% | 109% | 66.5% |
| Modest Mid-years | 26% | 64% | 3.7% | 105% | 57.7% |
| Surviving Singles | 27% | 66% | 4.0% | 105% | 56.8% |
| Successful Start | 27% | 59% | 1.9% | 96% | 35.6% |
| Advancing Status | 25% | 61% | 3.0% | 101% | 49.2% |
| Wealthy Retirement | 25% | 60% | 2.9% | 99% | 43.9% |
| Mid-life Affluence | 25% | 57% | 1.8% | 98% | 39.2% |
| Flourishing Families | 26% | 59% | 1.8% | 103% | 54.4% |
| Gilt-edged Lifestyles | 24% | 50% | 0.9% | 90% | 23.8% |
| Other | 26% | 60% | 1.6% | 99% | 44.7% |

* The average affordability ratio summarised by Experian's FSS segmentation.
** Proportion of households with mortgages where the monthly net income after deducting expenditure is not sufficient to meet monthly mortgage payments.

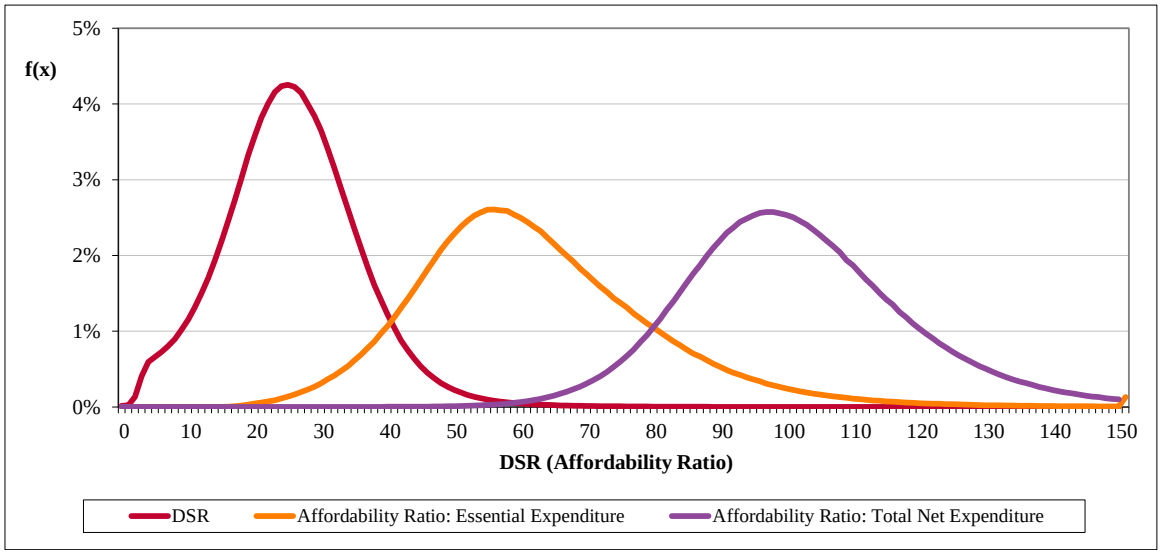
Sample: PSD borrowers, 2005-10

Figure 3 illustrates the impact on the distribution of mortgage affordability of including household expenditure in the affordability metric. This shows the marginal and cumulative distributions for the basic DSR, the essential net expenditure-adjusted DSR and the total net expenditure-adjusted DSR. We can see that, compared to the basic DSR distribution, the main impact of adjusting for expenditure is that the distributions shift to the right and become flatter and dispersed over a greater range. While there is evidence that the expenditure-based distributions are more positively skewed compared to the DSR, indicating that expenditure measures better capture an increase in relative indebtedness, there is no strong evidence to

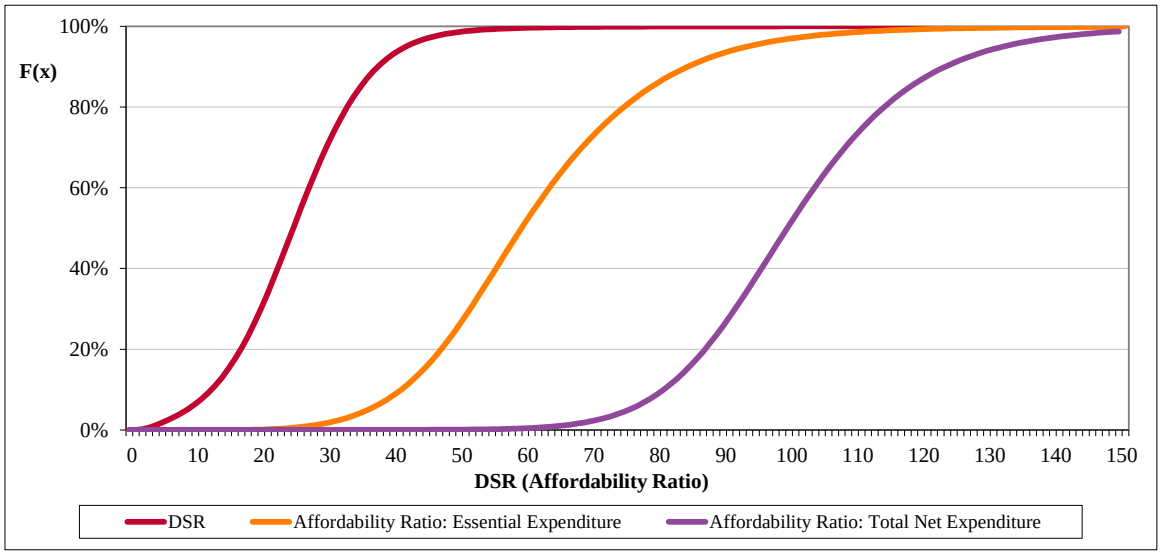
indicate a greater concentration of indebtedness across any particular segments of the distribution.

***Figure 3: Distribution of affordability ratios (2005-10): Marginal and cumulative effects***

**a. Marginal distribution**




**b. Cumulative distribution**




## Limitations

Owing to the lack of good expenditure data, the methodology has to impute estimates for the specific different types of households in our PSD dataset. So it important to remember that there are shortcomings with this approach because the expenditure estimates used are only approximate. Specifically:

- There are important differences in the two samples – LCF and PSD – we have used. These arise not only in terms of the samples' composition and coverage, but also in terms of the underlying purposes of the two datasets and the way the variables have been constructed. There is also the issue of potential sample selection bias since the PSD refer to borrowers' mortgage accounts at the point of mortgage origination. For these reasons, inferences drawn from one sample and imputed to another are going to be imperfect.
- The mapping of household composition from the LCF dataset to the PSD was approximate. This was achieved using the 45 FSS Experian household types and predicting their average household size. As explained, household size is a key determinant of actual expenditure. Inferring household size from 45 FSS household categories and using the postcode data to produce estimates of household composition in the PSD is imperfect.
- The affordability measures make no allowance for wealth (e.g. savings and other non-housing assets). These may be significant for some households and can be run down to smooth the impact of household expenditure and act as a buffer against any adverse income or funding shocks.[33] For these households, the figures in Table 3 are likely to overstate affordability problems.

Constructing an affordability measure based on expenditure is theoretically more attractive than using a basic DSR approach. By incorporating expenditure and not relying on wealth, the affordability ratios here are aligned more closely with the affordability assessment rules. This suggested these ratios were possibly better suited as affordability ratios for the cost benefit analysis. However, as the discussion above shows, creating these ratios also introduces significant data challenges, particularly when linking the LCF and PSD datasets.

Perhaps most important for us when we evaluated this approach was our reliance on subjective judgments when determining at an early stage which expenditures to classify as essential. We were concerned that the dependence of affordability ratios on such a step could be interpreted as stipulating how borrowers should and should not spend their money.

For all these reasons, we decided not to use the expenditure-adjusted DSR ratios for the cost benefit analysis. Instead, we developed an alternative approach based on the quality of the underwriting to estimate the impacts of the affordability assessment.

## Quality of underwriting

The Quality of Underwriting (QoU) approach differs from the DSR and expenditure-adjusted DSR approaches by using the risk of impairment from poor underwriting to measure mortgage affordability[34], rather than working from information on the

[33] Estimates from the ONS's Wealth and Assets survey shows that holdings of financial wealth vary significantly across UK households. For instance, in 2008 the median value of financial assets held by the least deprived decile of households was £56,000, compared with £750 in the case of the most deprived decile.

[34] For a review of mortgage underwriting standards and origination practices, along with a discussion of the impact of lowering of underwriting standards on the patterns of mortgage lending, house prices and impairment, see Van Dijk and Garga (2006), Sherlund (2008), Wilcox (2009), Bhardwaj and Sengupta (2009), FSB (2011), Demyanyk and Van Hemert (2011), Quercia (2012).

borrower's income and expenditure at the time the mortgage was originated. The rationale is that mortgages that are poorly underwritten (i.e. based on weak assessments of credit and other factors) are the mortgages that are most likely to be affected by the affordability assessment rules.

In general terms, the difference in approach is one of measuring affordability through effects (impairment) rather than causes (insufficient income, expenditure, mortgage characteristics), as was done with the DSR methods. The background to this approach, discussed on page 21, is research on the drivers of mortgage default, particularly the ability to pay and credit ratings agencies' models of the drivers of mortgage arrears and default.

Our method constructed a metric by first modelling the risk of mortgage impairment and then constructing an affordability measure based on isolating the part of impairment risk that was due to poor underwriting. As outlined on page 12, standards of good underwriting are related to a proper assessment of affordability. In other words, an adequate underwriting standard implies that a mortgage is granted only if it passes the affordability assessment rules.

Separating out the part of impairment risk related to affordability is necessary because impairment risk has many drivers and not all are related to poor underwriting. For example, life events (e.g. divorce, having children, illness, unemployment etc. – as illustrated in Figure 1) can lead borrowers to struggle with a mortgage that was originally affordable.[35]

The QoU approach therefore comprised several modelling steps:

- Estimate a measure of impairment risk of a mortgage using a logistic regression model.
- Decompose the impairment risk score using an ordinary-least-squares (OLS) regression (i.e. the impairment risk measure is regressed on the explanatory variables used in the logistic regression).
- Determine which variables are relevant for underwriting and then judge the QoU by calculating an underwriting risk score for each mortgage transaction.
- Having obtained an underwriting risk score, identify a threshold for calibrating the score.
- Using this threshold, identify the higher risk mortgages that have a sufficient probability of going into impairment that they would be deemed unaffordable.

## Stage 1: Estimating the risk of impairment

First, a logistic regression was used to estimate the probability at origination that the mortgage would become impaired in the future. A logistic regression is a standard approach for estimating probabilities of categorical events such as impairment in terms of various risk factors. Logistic models have been used in other studies for identifying the factors that drive a mortgage into arrears and repossession. In our model, the relevant factors included borrower and loan characteristics, the lender that provided the mortgage, and macroeconomic factors following origination of the

[35] Some life events can also prevent impairment even when lender underwriting is poor. Examples are promotions at work, inheritances or inflation driving wages but not interest rates higher.

mortgage. The macroeconomic factors were included to avoid erroneously associating impairment with factors at origination when they were actually associated with subsequent macroeconomic events. In our actual model, including the leading values of macroeconomic variables[36] helped to filter out their influence on subsequent mortgage impairment, which improved our measure of underwriting quality at origination. Table 4 reports a full list of the variables included in the logistic regression.

***Table 4: Variables in the logistic regression model***

| | Variable | Type | Comments |
|---|---|---|---|
| Dependent variable | Impaired mortgage | 0/1 | For the purpose of the regression, a mortgage is in impairment if: it is in arrears ≥ 3 months; reported an arrears letter date but is not currently in arrears, or; is in forbearance[37] |
| Independent variables - PSD | Lender | 0/1 for each lender | Lender who originated mortgage. |
| | LTV | continuous | |
| | Low LTV (<40%) mortgage | 0/1 | Used to capture different impairment relationship for high and low LTV borrowers. |
| | High LTV (>80%) mortgage | 0/1 | |
| | Fast track | 0/1 | Non-income verified mortgages that went through the fast track process. |
| | Self-certified | 0/1 | Non-income verified mortgages that were self-certified. |
| | Self-employed | 0/1 | Borrowers who are self-employed. |
| | Interest-only (not Mixed) | 0/1 | |
| | Mixed interest-only mortgage | 0/1 | Mortgages that are part interest-only, part repayment. |
| | First time buyer | 0/1 | |
| | Right-to-buy borrower | 0/1 | Bought through the right-to-buy scheme |
| | Remortgage for Debt Consolidation | 0/1 | |
| | Credit-impaired borrower | 0/1 | Borrowers with historical impairments. |
| | Mortgage term extends into retirement | 0/1 | |
| | Borrower household with low real income (<£18k) | 0/1 | Real income is measured using household income after tax scaled by RPI in 2010 (RPI = retail price index, a general measure of prices which provides a measure of inflation). |
| | Borrower household with high real income (>£68k) | 0/1 | |

[36] To capture the impact which changes in the economic outlook might be expected to have on impairment, lead values for key macroeconomic variables – i.e. 18 months after the origination date - were included in the regression.

[37] Alternative definitions of impairment were considered. There is a trade-off between introducing 'noise' with less restrictive definitions of arrears and limiting the number of observations for impairment with more restrictive definitions of arrears. In the end we chose cases where the mortgage was at least 3 months in arrears as a measure of impairment. This definition satisfied this statistical trade-off well.

| | Variable | Type | Comments |
|---|---|---|---|
| | Remortgage with low equity (< 30%) | 0/1 | Remortgages where the borrower had equity below 30%; this allows the model to capture differences in impairment of these borrowers. |
| | DSR for borrowers with low leverage | continuous | Used to capture different impairment relationships for high and low DSR borrowers. |
| | DSR for borrowers with high leverage | continuous | |
| Independent Variables -- Macro Variables[38] | Regional poverty[39] | continuous | This is the Index of Multiple Deprivation which can be interpreted as an index of regional poverty |
| | Regional unemployment 18 months post origination | continuous | Regional claimant counts, which measures the number of people claiming unemployment related benefits. We tested different leads and we have used 6 quarters (18 months) forward. |
| | Change in equity 18 months post origination | continuous | Calculated the change in house equity 18 months post-origination using change in house prices over that period. |
| | 6 month LIBOR 18 months post origination | continuous | |
| | Regional gross value added | continuous | Regional economic growth in value added. |

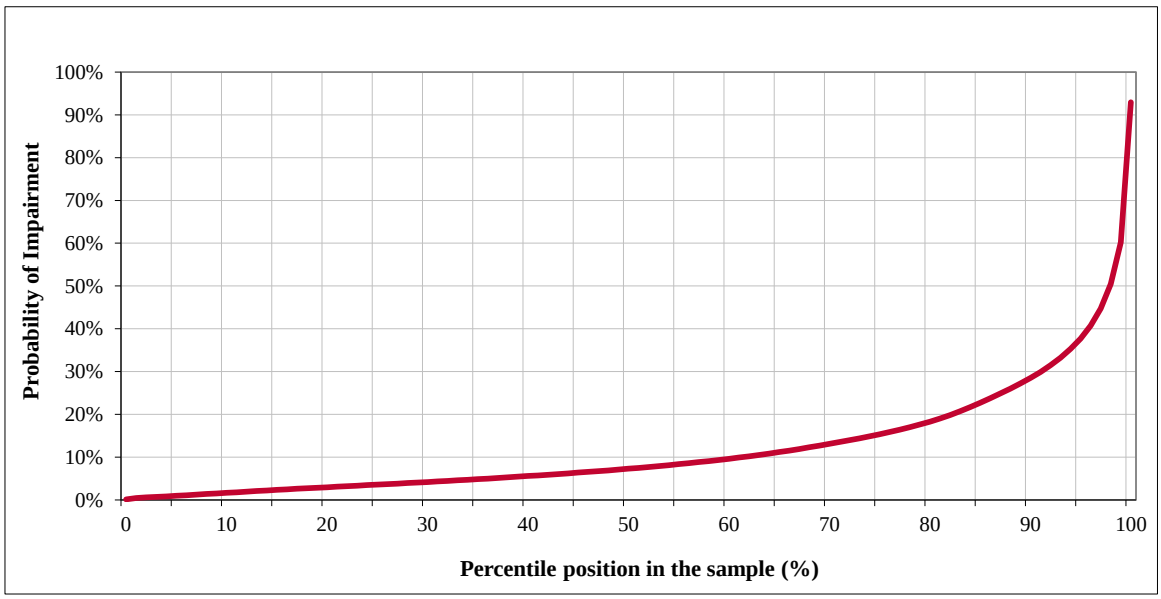
In our logistic model we also restricted the sample in various ways. First, for the regression we restricted the estimation sample to transactions originated over the period 2005-2008, and then used the estimated regression results to predict the probability of arrears for mortgages over the full period of the dataset (2005-2010). This is because we only had short-run impairment data for the later period (2009-2010) lending and while some borrowers develop arrears soon after they take out a mortgage, it typically takes longer for arrears to develop. Also, over the later period, mortgage impairment was mitigated by very low interest rates and by the forbearance measures adopted by lenders following the 2008 financial crisis. By historical standards, therefore, mortgage impairment rates in this post-2008 data may have been unrepresentatively low. For these reasons we concluded that including mortgages issued after 2009 would understate impairment and weaken the ability of the logistic regression model to identify relationships between risk factors and mortgage impairment. We also restricted the sample used for the logistic regression to open accounts as many lenders were unable to provide reliable records of arrears for historic closed accounts.

[38] Using the NOMIS service provided by the ONS, regional data is used to measure the impact of future changes in the economic landscape on repayment behaviour. NOMIS collects a range of economic and labour market statistics at the regional level. It geographically decomposes the UK into 133 segments (i.e. NUTS3 regional administrative level). By doing this we can take account of the impact of local labour market conditions on repayment behaviour. These regional economic measures are merged into the PSD using each borrower's postcode. See www.nomisweb.co.uk

[39] Regional poverty is proxied by the Index of Multiple Deprivation (IMD). The IMD is a measure of deprivation at the small area level and is based on distinct dimensions of deprivation such as income, employment, health, education and crime, which can be recognised and measured separately. See www.data.gov.uk/dataset/index-of-multiple-deprivation .

The results of the logistic regression are reported in Table A2 in Annex 4. The logistic regression has test-statistics within acceptable ranges and most variables[40] are statistically significant (P-values < 0.001). The output of the logistic regression is a risk scoring variable which provides a measure of the probability of a particular mortgage going into impairment, based on its underlying characteristics at origination and controlling for subsequent changes in the macroeconomic environment. This distribution of the risk of impairment is presented in Figure 4. For example, an individual at the 60th percentile of the distribution has an estimated probability of around 10% of their mortgage going into impairment.

***Figure 4: Impairment risk score from logistic regression model***




Sample: PSD borrowers, 2005-10

## Stage 2: Identifying impairment risk due to poor underwriting

The second step of our modelling approach was to isolate the portion of impairment risk which arises directly from poor underwriting. Unfortunately, the logistic regression did not allow us to do this because it jointly estimates impairment risk as a non-linear function of the drivers of risk. Non-linearity means that the residuals from the logistic regression will not be normally distributed and therefore the effect of a regressor having a particular impact on impairment will not be constant. The contribution of one factor to impairment risk depends on the value of the other factors and so does not allow one to separate out the influence of different factors. To overcome this difficulty, we used an ordinary-least-squares (OLS) model to regress our impairment risk score (probability of impairment) from the first regression on all the impairment risk factors. As an OLS regression uses a linear function, it assigns to each risk factor a constant marginal impact on impairment risk. This provided the needed decomposition of the impairment risk score into the

[40] A few lender dummy variables were insignificant because of idiosyncratic properties of those lenders (e.g. they had very few mortgages, or were extremely low risk with essentially no defaults). This does not undermine the quality of the model.

individual contribution associated with different risk factors.[41] The results from the OLS regression are reported in Table A3 in Annex 4. Unsurprisingly (since the OLS model regresses an impairment risk measure which is a function of the risk factors in the logistic regression on the same risk factors), all the 68 variables are statistically significant and the goodness-of-fit of the OLS regression is very high, with an $R^2$ of 0.95. This shows that the decomposition of the impairment risk measure using the OLS explains almost all (95%) of the variation in the logistic impairment risk score.

Interestingly, the results show that the key determinant of impairment risk arose from which lender originated the loan. In the case of the riskiest lenders – those with the largest coefficients – this was the largest source of risk. For these mortgage providers, the coefficients are capturing the various risk characteristics that were prevalent in mortgages originated by specialist lenders over the sample period. For instance, specialist lenders tended to provide funding to credit-impaired borrowers who were using the loans to remortgage and consolidate debt. The inclusion of the lender variables in the regression modelling meant that the economic significance of the other variables was much diminished. Had the lender variables been excluded from the regression, much of this other variation would have been captured by the other variables. However, it was important for policy to explore these lender-specific fixed effects.[42]

From the other factors, we observed that mortgages that had:

- *an increased* risk of going into impairment (i.e. positive coefficients) were characterised by high leverage (captured by the LTV ratio and high leverage dummy), self-certification, self-employment, interest-only, right-to-buy, used for debt consolidation, term extends into the retirement period, low income, remortgaging with low equity, high debt service ratio and increased deprivation; and
- *a decreased* risk of going into impairment (i.e. negative coefficients) were characterised by low leverage, fast-tracked, mixed repayment and high income.

Although much weaker than the observed borrower and loan characteristics, macroeconomic effects were also found to be relevant in explaining the risk of impairment. For instance, households living in areas that experienced higher levels of regional unemployment and lower levels of regional economic growth were found to have a higher risk of mortgage impairment.

## Constructing the underwriting risk score

Having decomposed the impairment risk into the individual elements associated with different risk factors, the final step in constructing a measure of QoU was to select the risk factors that were thought to be relevant to underwriting and to use these to construct an underwriting risk score. This required us to exercise some judgement because the affordability rules set out good underwriting standards partly in qualitative terms. The variables identified in Table 4 which we considered to be

[41] The OLS model calculates an average constant marginal impact on impairment risk for each risk factor in the logistic regression.

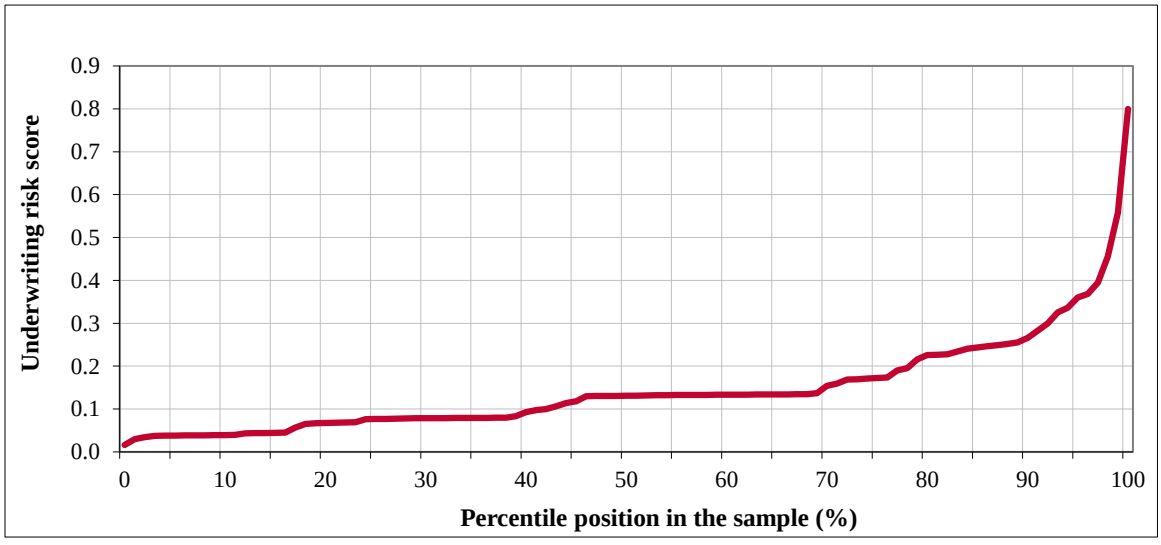
[42] The lender-specific fixed effects capture the incremental effect of a mortgage being originated by a particular lender, once all other variables in the regression have been conditioned for.

directly relevant to underwriting were the individual lender effects, self-certification, self-employed, credit-impaired, debt-consolidation and the debt service ratio (DSR).

The individual lender effects were included in order to capture the many factors in a lender's underwriting process for which we did not have data (e.g. a lenders risk appetite[43]). The other factors are all clearly relevant to a lending underwriting process: one would expect a lender to take these factors into account when deciding if a borrower can afford a mortgage. Based on the factors relevant to underwriting, we defined our mortgage affordability measure – the underwriting risk score – as the combined impact of the included factors on impairment risk. The underwriting risk score was calculated as the sum product of each risk factor multiplied by its coefficient from the OLS regression.

Mortgages with a higher underwriting risk score indicated poorer underwriting; mortgages with a lower underwriting risk score indicated better underwriting. The distribution of the underwriting risk scores is illustrated in Figure 5 for the mortgages in our dataset, starting with the mortgage with the best quality underwriting and finishing with the worst. This shows that, as measured using our score, a significant majority of mortgages (90%) have a relatively low underwriting risk score (with scores between 0 and 0.25). Beyond this point (i.e. for the remaining 10% of mortgages), the underwriting risk score begins to increase more and more steeply, indicating sharply increasing risk of impairment from poor underwriting.

***Figure 5: Underwriting risk score for mortgage population****




* Higher risk score indicates poorer underwriting.

Sample: PSD borrowers, 2005-10

## Stage 3: Setting a threshold for affordability

Having constructed an underwriting risk score, the next step was to determine a threshold for the underwriting score above which mortgages would likely have been

[43] As mentioned earlier, the risk appetite (or tolerance) refers to what level of impairment the lender estimates is an acceptable level for it to achieve the required level of profitability. Lenders with different business models will have different risk appetites.

deemed unaffordable. This is a variant of the problem faced with the first affordability measure, the DSR. In that instance we needed to determine a DSR threshold beyond which mortgages would be plausibly considered unaffordable for the purposes of modelling the affordability assessment. As with the DSR measure, the aim here was to find a point in the graph beyond which the affordability measure clearly deteriorated. However, unlike the DSR graph in Figure 2, for the underwriting risk score there is a marked steepening in the line in Figure 5 at various points, for example, around the 90% and 95% percentiles.

To help find a clear point of acceleration in the underwriting risk score, we also looked at the average underwriting risk score by lender. The identity of the lender was chosen as it was the risk factor with the strongest association with impairment risk. It also provided a separate justification for the choice of a threshold, since the identities of the worst-performing lenders could be checked to see that this matched other information (e.g. anecdotal evidence) about these lenders i.e. whether they were the organisations that had granted mortgages in the least responsible way. The average underwriting risk score by lender is shown in Figure 6.

***Figure 6: Average underwriting risk score by lender (2005-10)***

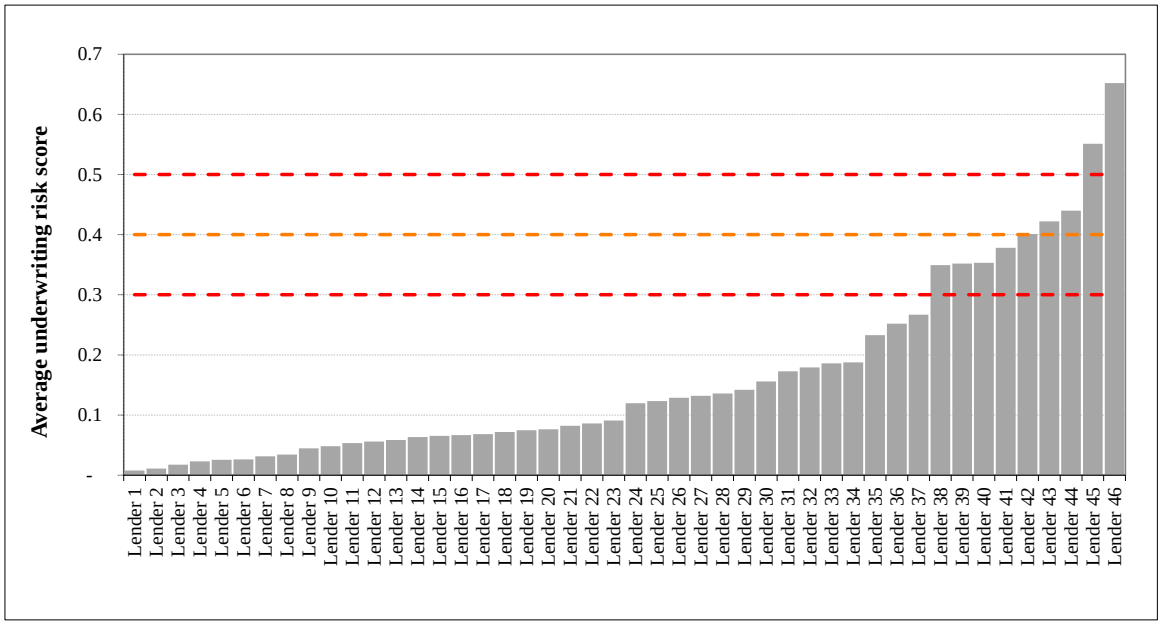



Figure 6 shows that up to lender 37 there is a rather gradual increase in the impairment risk from poor underwriting. From lender 38 to lender 46 the average underwriting risk score increases much more rapidly. We think it likely therefore that a quality of underwriting affordability metric would have predominantly affected lenders 38 to 46.

As a specific threshold, we chose lender 42's average underwriting risk score as our central estimate of the point beyond which the affordability assessment would have affected the granting of a mortgage. Lender 42 was chosen because it is the median lender between lender 38 (where the poor lending begins to be visible) and lender 46 (the worst lender). Lender 42's average underwriting score of 0.4 provided us with a

central threshold beyond which we believed mortgages would have been affected by the affordability assessment.

To capture the uncertainty in this process we also chose lower and higher unaffordability thresholds for the mortgages that might have been affected by the rule. We did this by choosing more extreme points at which a mortgage would no longer be considered affordable, at underwriting risk scores of 0.3 and 0.5 respectively. Having a range for the threshold allowed us to estimate ranges for the impacts, reflecting the uncertainty in the impacts the affordability assessment would have had.

## The preferred metric and limitations

As discussed in the MMR's consultation document, we used the underwriting risk score in our cost benefit analysis to measure the impacts of the affordability rules. Of the three affordability metrics we considered, the underwriting risk score was the only one that met all three of the requirements:

- It captured affordability as understood in the proposed affordability assessment rule.
- It could be used to classify whether or not a particular mortgage transaction in the PSD dataset would have been affordable.
- It was feasible for the FSA (and now the FCA) to carry out.

However, as the discussion above makes clear, the underwriting risk score approach was not without limitations. It required that some judgement be exercised: first in the choice of which impairment risk factors were indicators of poor underwriting, as understood by the affordability assessment; and second in the choice of a threshold at which mortgages became unaffordable.

A further difficulty was that, as constructed, the underwriting risk score was in a large part driven by the lender. We suspect that this was due to the lender variable acting as a proxy for many factors relevant to underwriting for which no data were available. As a result, the underwriting risk score was not very sensitive to changes in the other underwriting factors, which made it difficult to model the impact of some of the responsible lending proposals. For example, if one were to ask how much the underwriting risk score of a mortgage would increase if the interest rate at origination were to increase by 1%, this is not adequately answered just by changing the DSR variable in the URS equation. This is because some of the impact of higher rates was captured by the fact that some lenders issued mortgages with higher rates than others and this was incorporated in the model through the lender factor. As a result, for this aspect of the analysis for the MMR, we used a hybrid approach that combined the underwriting risk score with a DSR measure that was incorporated to illustrate the incremental impacts of the interest-only proposals and the interest rate stress test (IRST).[44,45]

[44] First, we checked if a loan was affordable using the underwriting risk score. Loans that had an underwriting risk score greater than 0.40 were considered unaffordable and were not originated. Second, for the affordable loans (i.e. with underwriting score less than 0.40) we calculated the DSR after the implementation of the IRST and interest-only rules (i.e. stressed DSR). If the stressed DSR was greater than 45% the loan was not offered.

[45] More generally, it is important to be open to some of potential shortcomings of building policy metrics based on historically observed relationships. For instance, Lucas (1976) cautions against drawing strong policy conclusions

# 5 Winners and losers

The proposed affordability rules (as enforced using the metrics described in section 4) aim to prevent borrowers being granted unaffordable mortgages due to poor quality underwriting i.e. mortgages that at the point of origination can be expected to become impaired. However, in practice no rules will be able perfectly to identify such mortgages, and some borrowers who should be prevented from borrowing (or constrained to borrow less) will not be, while other borrowers who should not be constrained by the rules will be. It is therefore important to find ways to assess the likely net impact of enforcing the affordability rules – or in other words, to explore who are the winners and losers.

## Well-being analysis

One way of assessing the potential impacts of the proposed affordability rules and their associated cost and benefits was through a well-being analysis. Well-being analysis is concerned with measuring changes in consumers' psychological states as a result of experiencing particular events. It uses self-reported measures of consumer well-being from survey data as proxies for utility, welfare or happiness.[46] For example, consumers who have a mortgage that they can easily afford are likely to experience greater well-being than consumers who are in arrears with their mortgage payments.

Regression analysis was used to estimate changes in life satisfaction resulting from experiencing certain non-market goods or events (such as home ownership or mortgage impairment), with the coefficients in the well-being regression equation measuring the changes in well-being (gains and losses) that consumers experience from these particular goods or events. These estimated changes are referred to as the well-being weights.

To measure the expected impacts of the proposed affordability rules, we first identified the borrowers (from April 2005 to September 2010) who would have been affected if the rules had been in place over this period. We then compared the expected costs and benefits experienced by these borrowers, measured in terms of changes in well-being. The aggregate net well-being impact arising from enforcement of the responsible lending requirements can be shown as:

based purely on past data, noting that once an empirical relationship observed in one period is targeted for policy-making, its effectiveness often declines. To counter this, it is important to model the micro foundations which are assumed to govern individual behaviour.

[46] The approach is based on the methodology of Taylor et al. (2006). Other academic works, focusing on different determinants of reported well-being, share the same econometric framework.

$$Net\ wellbeing = \sum_{i=1}^{n} \Delta WB_i = \sum_{i=1}^{n} \left[ (B_{Gi}\ x\ WBW^G) + (B_{Li}\ x\ WBW^L) \right] \quad (3)$$

Equation 3 shows the relationship between net well-being and:

- well-being gains – measured by well-being weight $WBW^G$ – for borrowers ($B_{Gi}$) whose borrowing is constrained by the MMR and who would have faced mortgage impairment without the MMR proposals, and
- well-being losses – measured by well-being weight $WBW^L$ – for borrowers ($B_{Li}$) whose borrowing is constrained by the MMR but who would not have faced any form of mortgage impairment without the MMR proposals.

The number of borrowers ($B_{Gi}$ and $B_{Li}$) whose borrowing decisions would have been affected by the responsible lending rules was identified by using the microsimulation model and applying the affordability metrics – as described in section 4 – to the 2005-10 PSD dataset. The well-being gains and losses ($WBW^G$ and $WBW^L$) we expected these borrowers to experience were imputed from levels of well-being[47] reported by households in the British Household Panel Survey (BHPS).

## Findings and implications

An important key finding of our well-being analysis was that only around 30% of the borrowers affected by the rules (about 200,000 out of 730,000) would have gone into impairment. This means:

- Around 200,000 borrowers who in the sample period experienced different degrees of impairment would have been protected from the associated distress had the responsible lending proposals been in place.
- Around 530,000 borrowers would have been impacted by the responsible lending proposals even though they did not experience impairment. These borrowers would have experienced distress from not getting the mortgages they wanted. Of these about 75,000 would have obtained a smaller mortgage; the rest would be forced (at least) to delay their borrowing.

This type of analysis was included as part of the MMR consultation, and was based on using the hybrid metric for affordability that combined the underwriting risk score with a DSR measure (as described on page 47).[48]

Deciding on the relative importance to attach to borrowers experiencing well-being gains versus well-being losses is inherently subjective and could ultimately be based on political or social considerations. However, it is possible to use the impacts on

[47] Individual well-being is measured using the General Health Questionnaire (GHQ), which is an index of household psychological well-being reported in the British Households Panel Survey (BHPS), over the period 1991-2008. One of the major advantages of the BHPS is that the annual questionnaire contains a wide range of information on reported psychological well-being, household income and finances, savings behaviour, job and employer characteristics, housing tenure and conditions, household composition, education profiles and other relevant factors.

[48] The estimated impacts from the responsible lending rules (i.e. combining the affordability assessment, interest rate stress test (IRST) and interest-only rules) were modelled using the hybrid affordability metric. This combined the underwriting risk score and the DSR (see footnote 38). Further details on the MMR well-being analysis can be found in FSA CP 11/31 (section A4H).

well-being to obtain an idea of the scale of the trade-off and to obtain some insights into the costs and benefits. We do this by measuring borrowers' psychological well-being with respect to:

- the benefit arising from the responsible lending proposals in preventing the emotional distress from unaffordable lending
- the cost to those borrowers whose home-ownership will be delayed, and
- the cost to those borrowers who will be granted smaller mortgages and are therefore constrained in their housing choices.

The main finding was that the distress avoided by households who suffered from payment problems and impairment was considerably greater than the lost satisfaction from not becoming a homeowner or not being able to buy a more expensive property. This suggested that the proposed affordability rules could still be beneficial in terms of net well-being even if the majority of people affected would not have experienced payment difficulties, arrears or repossession.

It is important to note that the well-being analysis was undertaken in a live policy environment, and time pressure necessitated that the methodology developed to support this element of the cost benefit analysis adopted a number of simplifying assumptions. For instance, our approach assumed that there were only positive outcomes from preventing impairment and only negative outcomes from not preventing impairment.

However, as Coates (2014) argues, the assumption that all affordable loans produce only social gains and all unaffordable loans produce only social losses is debatable. Coates argues: 'Some loans that turn out to be unaffordable represent gambles by borrowers that turn out bad, but which ex ante, even on a fully informed basis, the borrowers would take again. The new rules will likely prevent those gambles, and while one can make good arguments in favour of preventing such gambling, at least some normative approaches to welfare analysis would treat preventing informed consumers from making knowing gambles as a welfare harm'(p. 81). A counter-argument to Coates stems from growing evidence in behavioural economics of the widespread irrationality of consumer choice behaviour, including in probabilistic contexts. This growing evidence from the behavioural economics literature challenges the view that consumer gambling choices are informed and rational and that to constrain such choices would necessarily harm welfare (see Erta et al (2013)).

Owing to data constraints, our analysis provided only a partial view of the well-being effects, as it only considered the impact of the MMR proposals on the ability of borrowers to buy houses with mortgages. The well-being impacts of the MMR on other parties in the housing market – such as the impact on house sellers, the private rental market and other housing market intermediaries – were not addressed in the analysis. Our work also makes no explicit allowance for the impact of repossessions on well-being, or the effects of resale of repossessed homes. Had it been possible to take account of all these elements, then we would have been able to arrive at a more complete measure of the true net impact on well-being.

No amount of quantification could remove the need to make a judgement on these trade-offs. The well-being approach is imperfect and the estimates are approximate – they involve isolating the impact of an individual policy by looking at how an individual feels about their whole life, rather than their direct responses to a specific policy. Gathering survey data that are sufficiently detailed to link actual policy proposals with individual assessments of self-reported well-being is a particular challenge. There is also the question of how best to link estimates of consumer behaviour imputed from one survey and matched to individuals in a completely different dataset. Overall, therefore, the approach should not be interpreted as providing definite measures of well-being effects. Rather it supports some reasonable assumptions about the relative importance to attach to different positive and negative effects, and illustrates how different relative weights might support different judgements about preferred policy options.

## Alternative approaches for assessing well-being impacts

In addition to using the well-being approach outlined, alternative methods exists for estimating the welfare impacts of non-marketed goods, which might be relevant in the context of valuing the costs and benefits of the responsible lending proposals.[49]

The standard model traditionally used to evaluate policy decisions has been the classic welfare approach. Classical welfare economics uses a preference-based approach to valuation in which consumers are assumed to have well-defined, pre-existing preferences and values for goods and services. Welfare benefits arise when consumers obtain a more-preferred option; welfare costs arise when consumers are constrained to accept a less-preferred option. A well-functioning mortgage market should ensure that consumers obtain what they prefer, typically loans that they can afford. Welfare benefits will arise from the responsible lending requirements to the extent that they reduce market failures.[50]

In a competitive residential mortgage market, where borrowers act in their informed own self-interest, the mortgage that a borrower chooses will maximise their welfare. If the responsible lending proposals were to constrain such a borrower's choice it would reduce their welfare. For borrowers who do not act in their informed own self-interest and who take out unaffordable mortgages, there is scope for the proposals to improve welfare.

Regulation can improve consumer welfare by providing important information that consumers otherwise lack, enabling them to make choices more in line with their preferences. For instance, the new sales standards which were introduced, which placed much stricter requirements on lenders to ensure borrowers received

[49] Fujiwara and Campbell (2011) provide a useful survey of the alternative valuation techniques which can be used in the valuation of non-market goods, and the measurement of well-being.

[50] The responsible lending rules should be welfare-enhancing insofar as they help borrowers who, because of information asymmetries (e.g. being less informed than lenders about their true risk of impairment) or behavioural biases (e.g. over-optimism, overly discounting the future), borrow more than they (on reflection) would ideally like to. A discussion of the market failures present in the mortgage market can be found in FSA 11/31 (section A3), and a discussion of the behavioural biases to which consumers are susceptible can be found in the review of Erta et al (2013).

professional advice. Redressing the previous market failure in this area and reducing the consumer detriment it brought were important aims of the review.

However, the practicalities of estimating the welfare impacts of the MMR proposals would have been extremely difficult. This approach would have required estimating changes in consumer and producer surpluses, as derived from the demand and supply curves for mortgages. As different borrowers may behave differently, aggregating the welfare impacts would require that borrowers were adequately distinguished from each other and modelled. This would involve estimating an agent-based model for the mortgage demand of different borrowers. This approach was not feasible, since it would have required highly complex modelling and data that was not available.

An alternative approach which could have been used to complement (and supplement) our well-being analysis and to improve the robustness of the overall analysis appraisal would have been to use stated preference valuation. As the name suggests, stated preference methods estimate utility functions by using statements from individual respondents about their preferences. Specially constructed questionnaires are devised to uncover estimates of consumers' willingness to pay or willingness to accept a good. A hypothetical market is constructed and respondents are presented with a set of alternative descriptions of the good and are asked to express their preferences by ranking the options or by giving a rating value for each one. This approach is well-suited to capturing the trade-off between a good's attributes and the costs.

In the context of the MMR, stated preference could be used to measure an individual's willingness to accept the lower risk of impairment from stricter affordability requirements, relative to the costs they expected to incur from being prevented from taking out their preferred mortgage (or receiving a smaller mortgage). This could be used to provide a utility-based valuation. However, while stated preference analysis is more established and much more closely related to classical welfare analysis than well-being analysis, it has significant well-known problems of its own. A key problem is that respondents may not necessarily do what they say and tend to overstate their responses under experimental conditions.[51] For instance, previous studies using stated preference have produced results which were inconsistent with utility-based predictions, and the approach is also potentially expensive and time-consuming (requiring focus groups, interviews to gauge respondents' understanding and pre-tests).

## Looking ahead

Although well-being analysis is still evolving, its measures are cheap and quick to collect and produce relatively consistent results. As O'Donnell et al (2014) argue, the demand for measures of subjective well-being can be expected to grow given the increasing appetite within government to use analyses of well-being and social impact when making policy decisions.

[51] Establishing true preferences in the context of consumer behavioural biases is extremely difficult. See the survey by Huck et al (2011).

Well-being can help in understanding consumer behaviour and decision making where non-market outcomes are involved, and to provide inputs for other analyses, such as cost-benefit analysis. The OECD (2013) recommends that all national statistical agencies include well-being measures in annual household surveys. In the UK, well-being (or life-satisfaction) measures are found in many panel survey datasets – including the BHPS, the Wealth and Assets survey, the Integrated Household survey and the Annual Population survey. These surveys have large sample sizes and include a rich variety of economic, demographic and social factors that are important for identifying the main drivers for non-market valuations. These datasets can provide unique insights into the financial attitudes, behaviour and experiences of a wide range of households, along with their financial assets and liabilities, and can be used to support future FCA policy analysis.

# 6 Summary and conclusions

This paper has discussed three different affordability metrics that were constructed as part of the cost benefit analysis of the MMR affordability assessment rules. The first metric, the debt service ratio (DSR), was a simple affordability ratio that was not able to capture important determinants of mortgage affordability – particularly expenditure. The second metric, an expenditure-adjusted DSR, followed a residual income approach and was an improvement over the basic DSR. However, data difficulties and the need to stipulate a basket of essential expenditures made it unacceptable for us to use in policy-related analysis. The final quality of underwriting metric, the underwriting risk score, worked in a different way, being constructed from a model of impairment risk rather than from the borrower's income and expenditure at the time the mortgage was taken out. It provided a usable metric, albeit with some important limitations.

Table 5 summarises the advantages and disadvantages of the three metrics in respect of our requirements for an affordability measure. It also sets out some of the considerations that are relevant when choosing an affordability metric to be used in formulating policy.

***Table 5: Summary of strengths and weaknesses of three affordability metrics***

| | Three requirements | | | |
|---|---|---|---|---|
| **Affordability Metric** | **Captures affordability as in the assessment rules** | **Can determine whether individual PSD mortgages were affordable** | **Feasible** | **Other comments** |
| DSR | **No,** ignores expenditure | **Yes** | **Yes** | Judgement used in deciding threshold for affordability |
| Expenditure-adjusted DSR | **Yes,** since based on income and expenditure, ignoring property appreciation | **Yes** once expenditure data added | **No**, mapping income to expenditure is difficult | Avoids threshold judgement of other measures<br><br>Involves controversial stipulation of which expenditures are essential |

| Affordability | Three requirements | | | Other comments |
|---|---|---|---|---|
| Underwriting risk score | **Yes,** since the risk factors included are those judged relevant for the rules | **Yes** | **Yes** | Judgement used both in deciding which factors are relevant to the rule, and in selecting on the threshold<br><br>Not usable for measuring incremental impacts of the other proposals, i.e. interest-only and the interest rate stress test |

For the cost benefit analysis we opted for a hybrid metric, combining the underwriting risk score and the DSR. A natural question – when looking beyond the work we carried out for the MMR – is which affordability metric could be the most useful for future work on mortgage affordability. On this question, our view is that the expenditure-adjusted DSR could provide a very useful measure for regulation, if the data difficulties were overcome.

A key advantage is that it has a natural affordability threshold, defined by the point where income is insufficient to cover mortgage payments plus essential expenditure. From 2015, as part of its revised PSD submissions, the FCA will start to collect actual data on household composition and expenditure at the time of mortgage origination. These data will eliminate the need to impute household expenditure when constructing this type of expenditure affordability metric, and therefore result in a much more robust and reliable method for assessing affordability.

The difficulty in stipulating the basket of essential expenditures would remain, but several baskets could be chosen and the choices could be made explicit and open to debate. To calibrate the affordability measure properly to a household's particular funding circumstances, consideration should also be given to wealth, which may be significant for some households and is available to smooth expenditure and act as a buffer against temporary affordability problems.

Well-being analysis was used to measure the effect of the responsible lending proposals, by estimating the expected costs and benefits – measured in terms of changes in life satisfaction – that were experienced by borrowers for whom the proposed affordability rules had an impact. The main finding from this analysis was that the reduction in distress from successfully avoiding future payment problems and impairment for some households was significantly greater than the lost satisfaction associated with wrongly turning down a mortgage and preventing a would-be borrower from becoming a homeowner or owning a more expensive property. This demonstrated the proposals could still produce a net benefit even if the majority of borrowers affected by the affordability rules would not have experienced payment difficulties.

The findings show that the modelling approaches described in this paper have a valuable contribution to make in assessing the effectiveness of regulation. Although well-being analysis is still evolving, there is increasing appetite within government to use it alongside other more established methods to assess the welfare impacts of policy choices.

# Annex 1: Information on mortgages in the Product Sales Data (PSD)

The main source of data for the statistical analysis undertaken for the cost benefit analysis was the Product Sales Data (PSD). The PSD covers all regulated first-charge mortgage transactions. Our analysis focused on mortgage transactions originated over the period April 2005 to September 2010. The dataset covers information collected at the point of origination, including mortgage details (e.g. mortgage amount, date originated, initial interest rate, loan-to-value (LTV), mortgage type: fixed vs. variable rate, repayment vs. interest-only), borrower details (e.g. age, gross income, employment status) and lender details (e.g. type of lender, authorisation status). The raw dataset covers more than 9.1 million mortgages with submissions from more than 200 lenders.

Unfortunately, the dataset contained no post-sale information about the mortgages, e.g. which mortgages subsequently became impaired.[52] The link between origination characteristics and impairment is an important indicator that the mortgage was unaffordable at origination. To analyse this link, the PSD was matched with impairment data (arrears and repossessions) collected on our behalf by the Council of Mortgage Lenders (CML). In 2009, the CML obtained a one-off transactional arrears and possessions data report from a cross-section of banks, building societies and specialist lenders, covering April 2005 to August 2009. In 2010, they repeated this data collection and obtained data on the performance of mortgages sold in the period April 2005 to September 2010, which also included some data on historic payment problems and on forbearance.

Jointly these datasets provided a snapshot of the repayment state of the UK mortgage book at two points in time, and allowed us to assess mortgage non-performance at an individual transaction level. We calculated the duration of arrears by dividing the value of the individual arrears reported by the CML, by the imputed monthly mortgage payment to estimate how many months in arrears a particular account had been impaired. Although these estimates are only approximate they did allow us to differentiate between accounts which were experiencing moderate and severe impairment.

The resulting matched dataset comprised 7 million transactions, covering the lending activities of 46 mortgage providers (a selection of banks, building societies and specialist lenders of different size and market focus). Matching mortgages with their subsequent impairment outcomes provided a rich dataset that was extremely useful in our construction of affordability metrics.

[52] To correct for this shortcoming in the PSD, from April 2015 the submissions which mortgage lenders report to the Financial Conduct Authority includes information on mortgage performance. See Financial Conduct Authority (2013), "Mortgage Market Review – Data Reporting", Policy Statement, PS 13/12

# Annex 2: Using a microsimulation model to support policy development

We built a microsimulation model to simulate how the proposed affordability rules (if they had been in place) would have affected mortgages originated in the period April 2005 to September 2010. The model supported the development of policy and the cost benefit analysis for the MMR.

Microsimulation models are an excellent tool for policy analysis. However, in the past their widespread use has been limited through the lack of suitable data.[53] The PSD is a dataset that is suitable for a microsimulation model. Using the PSD allowed us to focus on distributional questions: we were able to analyse the affordability distribution of all mortgages and systematically to investigate the heterogeneity in affordability and repayment behaviour among different types of borrowers.

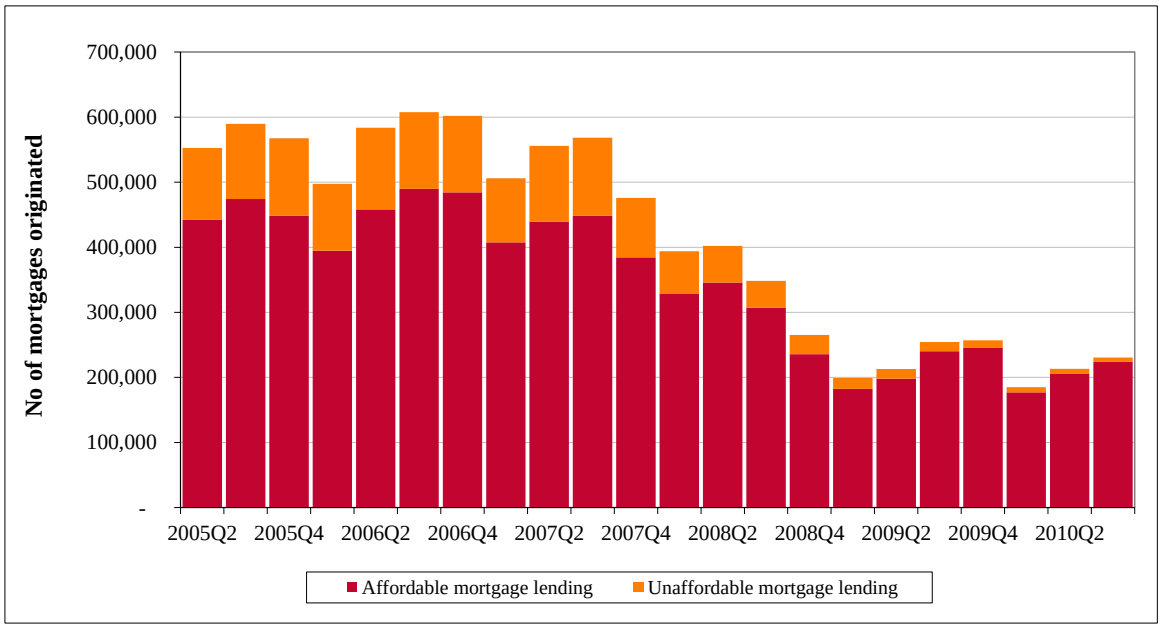
We specifically developed the microsimulation model to investigate three alternative metrics for modelling affordability – the debt service ratio (DSR), expenditure-adjusted DSR and a quality of underwriting measure. We did this by capturing all the relevant policy parameters, such as affordability rules, thresholds and stress tests within a standardised set of inputs. The approach made the use of microsimulation extremely valuable for policy analysis and policy advice.

For each affordability rule (and its many variants), the model simulated the impacts of the rule on each borrower in the sample. It identified which borrowers would pass the rule and be awarded a mortgage, and which mortgages would be classified as unaffordable, having failed to pass the particular affordability rule. This classification was then compared against actual subsequent mortgage impairments, and any costs or detriments that the borrowing household was expected to incur were estimated. We were also able to identify how the impacts changed at different points in the lending cycle. This is illustrated with a hypothetical example in Figure A1.

At an aggregated level the model allowed us to estimate the reduction of mortgage lending that would have resulted from the implementation of the proposals over the sample period. As we can see from illustration in Figure A1, when the MMR affordability rules were applied retrospectively across the period, the greatest impacts (measured in terms of a reduction in mortgage lending) are observed over the boom period when underwriting standards had been relaxed. Over the subdued period (from the start of 2009 onwards), when credit was severely rationed and underwriting standards tightened, the effect of the proposed affordability rules is minimal.

[53] Microsimulation models were initially developed for use in the tax and social security fields. The improved availability of better data means that they are now a valuable tool in the area of policy and regulatory evaluation. See Mitton et al (2000) and O'Donoghue (2014) for surveys of the microsimulation literature.

***Figure A1: Illustrative impact of the MMR proposed affordability rules on mortgage lending***




Along with the impacts on mortgage lending, the model outputs were also used to assess the well-being of borrowers and the macroeconomic costs and benefits of the proposals. To calculate the macroeconomic impacts of the responsible lending proposals, the National Institute for Economic and Social Research's NiGEM[54] model was calibrated using the quarterly impacts from the responsible lending simulation model and used to forecast future macroeconomic impacts arising from a reduction in mortgage lending (inter alia on GDP, consumer expenditure and inflation). This was an example of where micro effects are used to quantify macroeconomic changes.

The model was designed to be flexible, making it suitable for analysing the effects of different policy proposals and for quickly quantifying their impact under different policy configurations (for example, different interest rate stress tests, variations in the interest-only proposals, and affordability thresholds). For instance, to isolate the effect of a particular interest rate stress, we only needed to change the relevant parameter(s), re-run the model and compare the results with earlier outputs. In this way it was possible to analyse the incremental impacts of changes in policy design. The model was also able to investigate the effects of a particular set of policies at the level of particular groups, such as credit-impaired borrowers or first time buyers.

The microsimulation model provided a rich set of analyses which gave us a strong evidence base for the detailed cost benefit analysis for the review. It identified which groups of borrowers were most likely to be affected by the proposed changes and by how much. This was an important step in estimating the main costs and benefits of the proposed responsible lending rules.

[54] Further details on the MMR macroeconomic impacts can be found in FSA CP 11/31 (section A4G).

# Annex 3: Using the Living Cost and Food survey to estimate measures of expenditure

On page 28 we described how we implemented an expenditure-adjusted debt service ratio (DSR) approach. The first step was to construct measures of total and essential expenditure from the Living Cost and Food Survey (LCF). This annex provides more detail on the regression analysis that was used to estimate essential and total expenditure for borrowers in the PSD dataset.

On the basis of our LCF expenditure measures, we fitted a regression model to each of these LCF expenditure measures using five years of LCF data from 2004 to 2008. We used variables contained within the LCF, which could also be matched to information in the PSD. To normalise across measures of expenditure and income in the regression analysis, all financial time series data were rebased[55] and expressed in real rather than nominal terms. Doing so removed the effect of any time trend, and allowed us to generate estimates which were time-neutral.

In fitting a regression model to our measure of household expenditure, we opted to run the regression on all households rather than restricting the sample to households who owned property with a mortgage. Our reasoning for doing so was that essential expenditure for similar types of households will be comparable, irrespective of whether they are in the private rental or owner-occupier market. Differences that are specific to households who own a property with a mortgage can be captured using a fixed effect model. To explain the variation in the cross-section over time we deliberately opted for a simple model, where the variables could be relatively easily replicated using the PSD. Our base regression model specification is shown in equations A1 and A2 for total and essential expenditure measures respectively. We regressed the log of real expenditure on the explanatory variables that appear on the right-hand side of each equation.

$$TotExp_{it} = \alpha + \beta_1 DispInc_{it} + \beta_2 Age_{it} + \beta_3 Age_{it}^2 + \beta_4 NoAdults_{it} + \beta_5 DumSingle_{it} + \beta_5 DumOM_{it} + \sum_{j=1}^{3} \gamma_j DumChild_{it}^j + \sum_{k=1}^{10} \theta_j Dum\,\mathrm{Re}\,gion_{it}^k + \varepsilon_{it} \quad \text{(A1)}$$

[55] Measures of household expenditure and income were rebased as of 2010 and expressed in real terms using the UK RPI index.

$$EssExp_{it} = \alpha + \beta_1 DispInc_{it} + \beta_2 Age_{it} + \beta_3 Age_{it}^2 + \beta_4 NoAdults_{it} + \beta_5 DumSingle_{it} + \beta_5 DumOM_{it} + \sum_{j=1}^{3} \gamma_j DumChild_{it}^{j} + \sum_{k=1}^{10} \theta_j Dum\,\mathrm{Re}\,gion_{it}^{k} + \varepsilon_{it} \quad \text{(A2)}$$

$TotExp_{it}$ is the log of real total net[56] expenditure; $EssExp_{it}$ is the log of real essential net expenditure; $DispInc_{it}$ is the log of real household net income; $Age_{it}$ is age of the head of household; $Age^2_{it}$ is age-squared; $NoAdults_{it}$ is number of adults in the household; $DumSingle_{it}$ is a dummy which is 1 if there is a single head of household and 0 otherwise; $DumOM_{it}$ is a dummy which is 1 if the tenure is owned with a mortgage; and $DumChild^j_{it}$ is a dummy which is 1 if number of children in the household equals j (where j assumes value of 1, 2 and 3 or more children); $DumRegion^k_{it}$ includes categorical dummy variables to capture any regional differences in expenditure.

The results from the regression of both total net and essential net expenditure are reported in Table A1. Overall, this simple model based on LCF variables fitted the measures of expenditure well. It explained over 56% of the variation. The regression analysis suggested the following were the main drivers of household expenditure: disposable income, household size (i.e. expenditure is strongly related to the presence of children), the age of the head of the household (expenditure is greatest for households with a middle-aged household head) and overall geographical region.

***Table A1: Regression results – Forecasting real expenditure***

| | Total Net Expenditure | | | | Essential Expenditure | | |
|---|---|---|---|---|---|---|---|
| **Variables** | **Coefficients** | **S.E.** | **P> \| t \|** | | **Coefficients** | **S.E.** | **P> \| t \|** |
| Constant | 1.616 | 0.0425 | 0.000 | | 1.975 | 0.0353 | 0.000 |
| Real DispIncome | 0.553 | 0.0052 | 0.000 | | 0.391 | 0.0043 | 0.000 |
| Age | 0.034 | 0.0012 | 0.000 | | 0.027 | 0.0010 | 0.000 |
| $Age^2$ | 0.000 | 0.0000 | 0.000 | | 0.000 | 0.0000 | 0.000 |
| No. Adults | 0.078 | 0.0064 | 0.000 | | 0.099 | 0.0053 | 0.000 |
| DumSingleHH | -0.239 | 0.0103 | 0.000 | | -0.237 | 0.0086 | 0.000 |
| DumOwnMortg | 0.018 | 0.0072 | 0.011 | | 0.091 | 0.0060 | 0.000 |
| DumChild1 | 0.051 | 0.0094 | 0.000 | | 0.131 | 0.0078 | 0.000 |
| DumChild2 | 0.122 | 0.0098 | 0.000 | | 0.211 | 0.0081 | 0.000 |
| DumChild3 | 0.130 | 0.0135 | 0.000 | | 0.262 | 0.0112 | 0.000 |
| DumReg_NE | -0.046 | 0.0163 | 0.004 | | -0.084 | 0.0135 | 0.000 |
| DumReg_NW | -0.006 | 0.0117 | 0.595 | | -0.026 | 0.0097 | 0.007 |

[56] Both total and essential expenditures were net of direct housing costs (i.e. mortgage or rental payments).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DumReg_YH | 0.027 | 0.0125 | 0.030 | | -0.014 | 0.0104 | 0.182 |
| DumReg_EE | 0.090 | 0.0123 | 0.000 | | 0.089 | 0.0102 | 0.000 |
| DumReg_GL | -0.015 | 0.0124 | 0.214 | | 0.020 | 0.0103 | 0.049 |
| DumReg_SE | 0.085 | 0.0109 | 0.000 | | 0.078 | 0.0090 | 0.000 |
| DumReg_SW | 0.086 | 0.0123 | 0.000 | | 0.076 | 0.0103 | 0.000 |
| DumReg_WA | 0.001 | 0.0153 | 0.973 | | 0.013 | 0.0127 | 0.306 |
| DumReg_SC | 0.049 | 0.0124 | 0.000 | | -0.033 | 0.0103 | 0.001 |
| DumReg_NI | 0.069 | 0.0123 | 0.000 | | 0.016 | 0.0103 | 0.125 |
| | | | | | | | |
| No Obs. | 32,143 | | | | 32,151 | | |
| $R^2$ | 0.561 | | | | 0.566 | | |

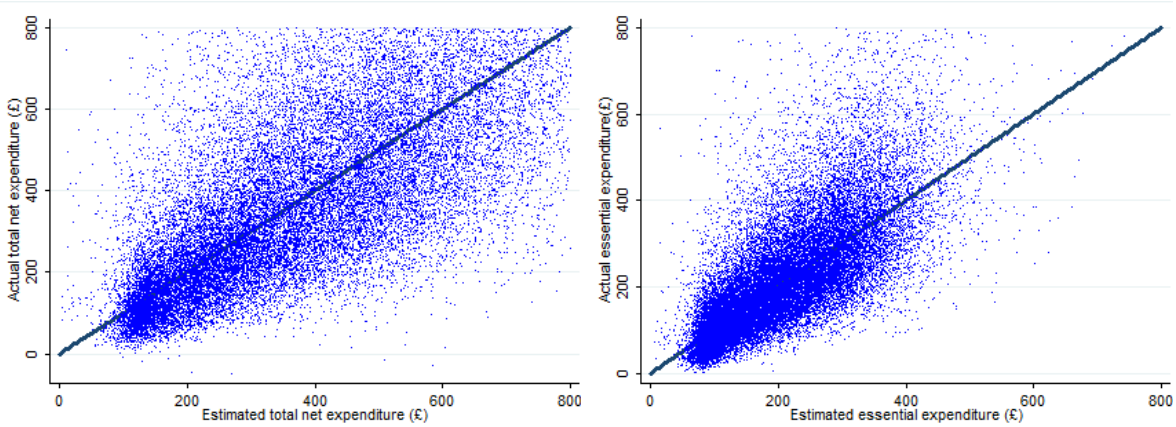
One has to bear in mind that these are rather simple estimates of expenditure. They only include drivers of expenditure that can be reasonably – if imperfectly – identified within the PSD. Such misspecification often leads to an *omitted variable bias*. This bias can arise when a model seeks to compensate for a missing variable by over (or under) estimating one of the other variables. We know that omitted variables lead to biased and inconsistent estimates of the coefficients, and can cause the error term in certain cases to be so large as to make the analysis meaningless. Estimates based on predicted values are only useful where the average values predicted by the model (based on the LCF) are representative of similar types of households within the relevant population. Applying these estimates to 'atypical' households will lead to expenditure estimates that are very different from the actual expenditure of the household.

With this in mind, a comparison of actual and estimated household expenditure was an important check of the goodness of fit of the model and the suitability of using of our approach for imputing estimates of household expenditure within the PSD. Taking the exponent of the log of expenditure to obtain real expenditure, Figure A2[57] shows actual household expenditure plotted against the predicted values.

[57] To improve the readability of the plots only cases of reported household total net expenditure and essential expenditure of less than £800 a week are illustrated.

***Figure A2: Actual versus predicted real weekly household expenditure (LCF)****

**a. Total (net) expenditure** **b. Essential expenditure**




* A scatter plot of household actual and estimated expenditures, with the 45-degree line.
** Estimates of household expenditure were calculated net of mortgage payments and rental charges

Source: Analysis using the LCF

Figure A2a plots actual vs. predicted total expenditure and Figure A2b plots actual vs. predicted essential expenditure, in all cases net of housing costs. At an aggregate level, both models seem to predict the measures of expenditure reasonably well, particularly essential expenditure, with evidence of clustering around the 45-degree line. (A 45-degree line occurs when observed actual expenditure is equal to predicted expenditure). Comparing the differences between the actual and estimated expenditure measures, we found that 50% of total expenditure (42% of essential expenditure) estimates were found to be within 25% of their actual values. However, Figure A2 also indicates that for low income households, on average both models over predict actual total and essential expenditure. For instance, for households with real disposable income of less than £300 a week, the model over predicts actual total expenditure on 54% of occasions, and essential expenditure on 53% of occasions. This indicates that the expenditure-adjusted DSR measure is likely to understate mortgage affordability for these types of households.

# Annex 4: Modelling the quality of underwriting

This annex sets out the methodology underpinning the construction of the quality of underwriting (QoU) measure. It also provides more technical details on the logistic model that was used to estimate impairment risk, and how this risk score was transformed to produce a QoU measure. Specifically, the statistical analysis carried out in modelling the impacts of the affordability rules comprised the following steps:

- Estimate a measure of impairment risk of a mortgage using a logistic regression. The regression generated an econometric model of impairment risk. We found a number of important determinants of impairment risk: the lender, the LTV, borrower characteristics (self-employed or credit-impaired) and mortgage characteristics (interest-only, self-certified or fast-tracked). Macroeconomic factors also played a role.
- Decompose the impairment risk score using an ordinary-least-squares (OLS) regression (i.e. the impairment risk measure was regressed on the variables in the logistic regression). This allowed us to express impairment risk as a linear function, so we could isolate the marginal effect of each variable.
- Determine which variables were relevant for underwriting and estimate the QoU by calculating the underwriting risk score for each mortgage. This score is a linear function of the relevant underwriting variables, weighted by their marginal effects.

## Logistic regression to construct a measure of impairment risk

To construct our measure of impairment (our impairment risk score), we used data only from 2005-2008 in our dataset. While some borrowers develop arrears soon after they take out a mortgage, sometimes it takes longer for borrowers to go into arrears. Including mortgages issued between 2009 and 2010 would therefore have understated impairment and weakened the ability of the regression model to identify relationships between the various risk factors and mortgage impairment. We also restricted the sample used for the logistic regression to only accounts which were open since some lenders could only provide reliable estimates of the duration of arrears for active accounts.

Logistic regression is a standard approach for estimating probabilities of categorical events (here whether a mortgage goes into impairment or not) in terms of risk factors. The dependent variable is actual observed impairment, which takes a value of 1 if the mortgage becomes impaired and zero otherwise.[58] We regressed observed

[58] Alternative definitions of impairment were considered. There is a trade-off between introducing 'noise' with less restrictive definitions of arrears and limiting the number of observations for impairment with more restrictive definitions of arrears. In the end we chose as our measure of impairment cases where the mortgage was at least 3 months in arrears, as this definition satisfied the statistical trade-off well.

impairment on a large set of possible relevant risk factors. The relevant factors included borrower and mortgage characteristics, the lender and macroeconomic factors after mortgage origination. Economic factors were included to avoid erroneously associating impairment from subsequent macroeconomic events to factors at origination. Including lead values of macroeconomic data helped to filter out their influence on later mortgage impairment, which helped to improve our measure of underwriting quality at origination. Since the aim of the modelling of the affordability rule was to identify underwriting quality, when constructing our logistic regression model we kept the lender identity variable(s) ('the lender dummies') in the regression. The results from the logistic model are reported in Table A2. This reports the impact of the individual lender dummies on the left-hand side of the table, and the impact of all the other variables on the right-hand side of the table.

Most of these variables[59] are statistically significant (P-values < 0.001). However, a key diagnostic test of a regression model of the type reported in Table A2 is how well it fits the data. Typically, in the case of linear estimation the goodness-of-fit is measured using the $R^2$ statistic, which represents the proportion of variation in the dependent variable explained by the explanatory variables in the regression. However, because the logistic regression is non-linear, $R^2$ is not an appropriate indicator here. For logistic regressions, the convention is to assess goodness of fit, measured in terms of the predictive performance of the model, by comparing the values predicted by the model to actual observed events in the sample, using contingency tables.

Contingency tables present the 'hit rate' of the model by assessing how well the model predicts – using the probabilities it estimates – the actual occurrences of events in the sample. Calibrating the contingency tables requires choosing a threshold for the probability e.g. observations with a probability above the threshold are classified as a prediction of the event by the model, observations with a probability below the threshold are classified as predictions of the event not occurring. The threshold is selected in relation to an objective function, where the proportion of events that are correctly identified is measured in terms of the non-events that are incorrectly identified. The predictions that follow from this rule are then compared to the actual observed events in the sample in order to calculate the hit rate. A graphical illustration of the predictive performance of the model can be made by comparing the model's sensitivity and specificity to the cut-off threshold, where:

- *Sensitivity* is the probability of correctly predicting that the event occurs (i.e. true positives).
- *Specificity* is the probability of correctly predicting that the event does not occur (i.e. true negatives).

Sensitivity and specificity vary with the threshold. The predictive performance of the logistic model of impairment is summarised in Table A2 and illustrated in Figure A3.

[59] A few lender dummies are insignificant because of idiosyncratic properties of those lenders (e.g. they have very few mortgages, or are extremely low risk with essentially no defaults). This does not undermine the quality of the model.

***Table A2: Measure of Impairment: Logistic model estimates***

| Variables | Coefficients | S.E. | P> \| t \| | * | Variables | Coefficients | S.E. | P> \| t \| |
|---|---|---|---|---|---|---|---|---|
| Lender Dummies: All 43 lenders | 1.904 | 0.086 | 0.000 | * | Constant | -6.012 | 0.084 | 0.000 |
| | 2.968 | 0.082 | 0.000 | * | Loan-to-Value | 0.009 | 0.000 | 0.000 |
| | 2.196 | 0.083 | 0.000 | * | LTV:0 - 40%[d] | -0.038 | 0.010 | 0.000 |
| | 3.777 | 0.083 | 0.000 | * | LTV: >80%[d] | -0.006 | 0.007 | 0.403 |
| | 2.090 | 0.086 | 0.000 | * | Fast-Tracked [d] | -0.243 | 0.005 | 0.000 |
| | 2.130 | 0.083 | 0.000 | * | Self-Certified [d] | 0.538 | 0.009 | 0.000 |
| | 1.544 | 0.129 | 0.000 | * | Self-Employed [d] | 0.414 | 0.005 | 0.000 |
| | 0.547 | 0.085 | 0.000 | * | Interest-Only [d] | 0.106 | 0.004 | 0.000 |
| | 1.953 | 0.084 | 0.000 | * | Mixed payment [d] | -0.147 | 0.010 | 0.000 |
| | 1.978 | 0.092 | 0.000 | * | First Time Buyer [d] | -0.088 | 0.006 | 0.000 |
| | 1.553 | 0.085 | 0.000 | * | Right-To-Buy [d] | 0.070 | 0.014 | 0.000 |
| | 3.023 | 0.083 | 0.000 | * | Rem-LowEquity [d] | 0.274 | 0.005 | 0.000 |
| | 2.556 | 0.084 | 0.000 | * | Rem-DebtCons [d] | 0.299 | 0.007 | 0.000 |
| | 2.353 | 0.089 | 0.000 | * | Rem-TermRetire [d] | 0.124 | 0.005 | 0.000 |
| | 2.392 | 0.102 | 0.000 | * | Low Dsr [id] | 0.137 | 0.028 | 0.000 |
| | 3.468 | 0.084 | 0.000 | * | High Dsr [id] | 0.282 | 0.025 | 0.000 |
| | 0.218 | 0.225 | 0.332 | * | Low Income [d] | 0.082 | 0.005 | 0.000 |
| | 3.021 | 0.083 | 0.000 | * | High Income [d] | -0.060 | 0.005 | 0.000 |
| | 2.350 | 0.098 | 0.000 | * | Credit-Impaired [d] | 0.650 | 0.008 | 0.000 |
| | 1.858 | 0.087 | 0.000 | * | I.M.D. | 0.001 | 1.001 | 0.000 |
| | 2.524 | 0.176 | 0.000 | * | F6Q_ClaimCount | 0.268 | 0.004 | 0.000 |
| | 3.227 | 0.084 | 0.000 | * | F6Q_dEquity | 0.000 | 0.000 | 0.000 |
| | 3.434 | 0.084 | 0.000 | * | F6Q_dLibor6mth | 0.000 | 0.000 | 0.000 |
| | 3.888 | 0.084 | 0.000 | * | F6_GVA | 0.001 | 0.089 | 0.987 |
| | 2.436 | 0.101 | 0.000 | * | | | | |
| | 3.385 | 0.390 | 0.000 | * | | | | |
| | 2.228 | 0.092 | 0.000 | * | | | | |
| | 2.552 | 0.132 | 0.000 | * | | | | |
| | 3.389 | 0.084 | 0.000 | * | | | | |
| | 2.037 | 0.096 | 0.000 | * | | | | |
| | 1.145 | 0.226 | 0.000 | * | | | | |
| | 3.231 | 0.084 | 0.000 | * | | | | |

| Variables | Coefficients | S.E. | P> \| t \| | * | Variables | Coefficients | S.E. | P> \| t \| |
|---|---|---|---|---|---|---|---|---|
| | 3.701 | 0.083 | 0.000 | * | | | | |
| | 4.531 | 0.085 | 0.000 | * | | | | |
| | 1.743 | 0.085 | 0.000 | * | | | | |
| | 3.353 | 0.083 | 0.000 | * | | | | |
| | 2.611 | 0.089 | 0.000 | * | | | | |
| | 4.257 | 0.106 | 0.000 | * | | | | |
| | 3.732 | 0.084 | 0.000 | * | | | | |
| | 3.401 | 0.085 | 0.000 | * | | | | |
| | 1.425 | 0.084 | 0.000 | * | | | | |
| | 4.402 | 0.112 | 0.000 | * | | | | |
| | 3.604 | 0.119 | 0.000 | * | | | | |
| | | | | * | | | | |
| | | | | * | | | | |
| No. of Obs | 3,519,359 | | | | | | | |
| Log-likelihood | -1,024,169 | | | | | | | |
| Chi-squared | 416,460 | (0.000) | | | | | | |

[d] Denotes the use of categorical dummy variables that assume a value of 1 when the condition holds and zero otherwise.
[id] Denotes the use of interactive dummy variables that assume the value of the underlying variable when the condition holds and zero otherwise.

***Figure A3: Sensitivity and specificity trade-off: impairment vs. non-impairment***

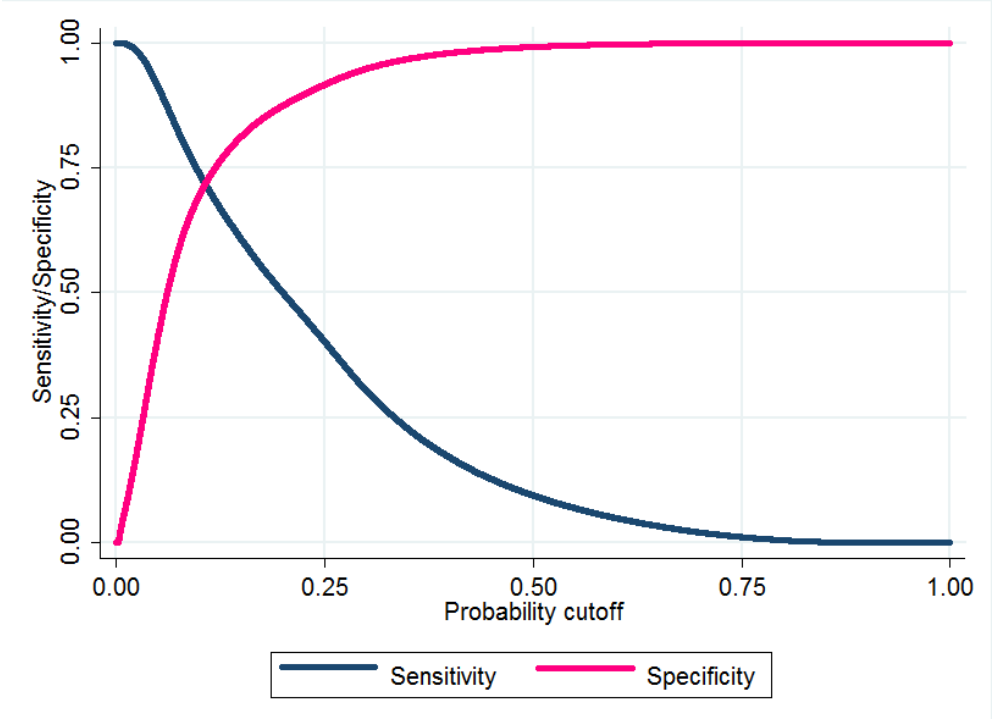



Figure A3 demonstrates the trade-off between 'correctly predicting an event' and 'failure to predict an event not occurring' for different modelling probability cut-offs. For instance, if we select a threshold close to zero it is possible to identify correctly all impaired accounts – since we would predict all mortgages go into impairment – but this would come at the cost of a complete failure to identify accounts that do not go into impairment. In regards to the appropriate choice of probability cut-off threshold:

- When the selected cut-off threshold is 0.3, the model correctly predicts 95% of observations that did not go into impairment, although it only correctly identifies 30% of accounts that did actually go into impairment. Overall, it correctly predicts 88% of the observations.
- By lowering the threshold to 0.15, the proportion of accounts correctly identified as not going into impairment falls to 81%, while the proportion of accounts correctly identified as going into impairment increases to 61%. Overall, it correctly predicts 79% of the observations.

On average, by chance alone we would expect to achieve a successful prediction 50% of the time. Therefore, taken together, these findings indicate that the goodness-of-fit of the model is very strong. There are inevitable limits, however. While the risk at the time of mortgage origination has been shown to be a strong indicator of future repayment behaviour, life events – which are unrelated to the risk at origination – are also important. In particular, mortgages that are extremely low risk at origination – and therefore not predicted by the risk score as an impaired account – may still go into arrears due to unforeseen and unexpected life events.

The output of the logistic analysis is a risk scoring variable, which measures the probability of a mortgage going into impairment based on its underlying characteristics and subsequent macroeconomic events

## Decomposing the impairment risk score

The second step of our modelling approach allowed us to decompose the impairment risk score (equation A3) in order to isolate the effects of the individual components of risk that were relevant for estimating the QoU. The logistic regression did not allow us to do this because it is a non-linear function of the drivers of risk. Non-linearity implies that the contribution of one factor to the impairment risk depends on the value of the other factors. To resolve this, we used an ordinary-least-squares (OLS) model which regressed our impairment risk score on all the impairment risk factors. The linear decomposition allowed us to assign to each individual risk factor its constant, marginal contribution to impairment risk.[60]

The results from the OLS regression are reported in Table A3. All variables were statistically significant ($P<0.001$). The OLS model regressed an impairment risk measure which was a function of the risk factors in the logistic regression on the same risk factors, so it was not surprising that the goodness-of-fit of the OLS regression was very high, with an R2 of 0.95. This showed that the decomposition of the impairment risk measure using the OLS explained almost all (95%) of the variation in the impairment risk measure.

## Calculating the underwriting risk score

Having decomposed the impairment risk from different factors, the final step in constructing a measure of quality of underwriting was to identify the risk factors that were relevant to underwriting and to use these to construct the affordability measure. This categorisation was informed by the affordability assessment rules. This helped to ensure that our resulting underwriting risk score measured affordability as understood in the affordability assessment rule.

[60] One consequence of using OLS to fit the impairment risk score to the underlying variables is that without a non-negativity constraint a small proportion of extremely low risk mortgages were predicted a negative risk score. To deal with this, we rescaled all these records to zero.

***Table A3: Decomposing the impairment risk score: OLS estimates***

| Variables | Coefficients | S.E. | P> \| t \| | * | Variables | Coefficients | S.E. | P> \| t \| |
|---|---|---|---|---|---|---|---|---|
| | 0.044 | 0.000 | 0.000 | * | Constant | -0.059 | 0.000 | 0.000 |
| | 0.111 | 0.000 | 0.000 | * | Loan-to-Value | 0.001 | 0.000 | 0.000 |
| | 0.057 | 0.000 | 0.000 | * | LTV:0 - 40%[d] | -0.001 | 0.000 | 0.000 |
| | 0.204 | 0.000 | 0.000 | * | LTV: >80%[d] | 0.010 | 0.000 | 0.000 |
| | 0.046 | 0.000 | 0.000 | * | Fast-Tracked [d] | -0.020 | 0.000 | 0.000 |
| | 0.046 | 0.000 | 0.000 | * | Self-Certified [d] | 0.062 | 0.000 | 0.000 |
| | 0.034 | 0.000 | 0.000 | * | Self-Employed [d] | 0.039 | 0.000 | 0.000 |
| | 0.016 | 0.000 | 0.000 | * | Interest-Only [d] | 0.010 | 0.000 | 0.000 |
| | 0.055 | 0.000 | 0.000 | * | Mixed payment [d] | -0.006 | 0.000 | 0.000 |
| | 0.039 | 0.000 | 0.000 | * | First Time Buyer [d] | -0.010 | 0.000 | 0.000 |
| | 0.022 | 0.000 | 0.000 | * | Right-To-Buy [d] | 0.013 | 0.000 | 0.000 |
| | 0.112 | 0.000 | 0.000 | * | Rem-LowEquity [d] | 0.035 | 0.000 | 0.000 |
| | 0.076 | 0.000 | 0.000 | * | Rem-DebtCons [d] | 0.028 | 0.000 | 0.000 |
| | 0.065 | 0.000 | 0.000 | * | Rem-TermRetire [d] | 0.010 | 0.000 | 0.000 |
| | 0.065 | 0.000 | 0.000 | * | Low Dsr [id] | 0.006 | 0.000 | 0.000 |
| | 0.151 | 0.000 | 0.000 | * | High Dsr [id] | 0.082 | 0.000 | 0.000 |
| | 0.012 | 0.000 | 0.000 | * | Low Income [d] | 0.006 | 0.000 | 0.000 |
| | 0.108 | 0.000 | 0.000 | * | High Income [d] | -0.004 | 0.000 | 0.000 |
| | 0.054 | 0.000 | 0.000 | * | Credit-Impaired [d] | 0.122 | 0.000 | 0.000 |
| | 0.034 | 0.000 | 0.000 | * | I.M.D. | 0.001 | 0.000 | 0.000 |
| | 0.070 | 0.001 | 0.000 | * | F6Q_ClaimCount | 0.016 | 0.000 | 0.000 |
| | 0.131 | 0.000 | 0.000 | * | F6Q_dEquity | 0.000 | 0.000 | 0.000 |
| | 0.224 | 0.000 | 0.000 | * | F6Q_dLibor6mth | 0.067 | 0.000 | 0.000 |
| | 0.354 | 0.000 | 0.000 | * | F6_GVA | -0.042 | 0.000 | 0.000 |
| | 0.042 | 0.000 | 0.000 | * | | | | |
| | 0.153 | 0.001 | 0.000 | * | | | | |
| | 0.031 | 0.000 | 0.000 | * | | | | |
| | 0.044 | 0.001 | 0.000 | * | | | | |
| | 0.219 | 0.000 | 0.000 | * | | | | |
| | 0.032 | 0.000 | 0.000 | * | | | | |
| | 0.009 | 0.000 | 0.000 | * | | | | |

Lender Dummies: All 43 lenders

| Variables | Coefficients | S.E. | P> \| t \| | * | Variables | Coefficients | S.E. | P> \| t \| |
|---|---|---|---|---|---|---|---|---|
| | 0.155 | 0.000 | 0.000 | * | | | | |
| | 0.252 | 0.000 | 0.000 | * | | | | |
| | 0.481 | 0.000 | 0.000 | * | | | | |
| | -0.017 | 0.000 | 0.000 | * | | | | |
| | 0.150 | 0.000 | 0.000 | * | | | | |
| | 0.075 | 0.000 | 0.000 | * | | | | |
| | 0.337 | 0.001 | 0.000 | * | | | | |
| | 0.289 | 0.000 | 0.000 | * | | | | |
| | 0.219 | 0.000 | 0.000 | * | | | | |
| | 0.017 | 0.000 | 0.000 | * | | | | |
| | 0.362 | 0.001 | 0.000 | * | | | | |
| | 0.181 | 0.000 | 0.000 | * | | | | |
| | 0.007 | 0.000 | 0.000 | * | | | | |
| | -0.005 | 0.000 | 0.000 | * | | | | |
| | | | | | | | | |
| N | 6,875,671 | | | | | | | |
| R-squared | 0.951 | | | | | | | |

[d] Denotes the use of a categorical dummy variable that assumes a value of 1 when the condition holds and zero otherwise.
[id] Denotes the use of an interactive dummy variable that assumes the value of the underlying variable when the condition holds and zero otherwise.

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