Can we predict which consumer credit users will suffer financial distress?

August 2016

Occasional Paper 20

Encouraging debate among academics, practitioners and policymakers in all aspects of financial regulation.

Financial Conduct Authority
www.fca.org.uk

FCA Occasional Papers in financial regulation

The Financial Conduct Authority (FCA) Occasional Papers

The FCA is committed to encouraging debate on all aspects of financial regulation and to creating rigorous evidence to support its decision-making. To facilitate this, we publish a series of Occasional Papers, extending across economics and other disciplines.

Occasional Papers contribute to the debate on specific issues relevant to the FCA's work. The main factor in accepting papers is that they should make substantial contributions to knowledge and understanding of financial regulation. If you want to contribute to this series or comment on these papers, please contact Peter Andrews or Kevin James at peter.andrews@fca.org.uk and kevin.james@fca.org.uk

Disclaimer

Occasional Papers contribute to the work of the FCA by providing rigorous research results and stimulating debate. While they may not necessarily represent the position of the FCA, they are one source of evidence that the FCA may use while discharging its functions and to inform its views. The FCA endeavours to ensure that research outputs are correct, through checks including independent referee reports, but the nature of such research and choice of research methods is a matter for the authors using their expert judgement. To the extent that Occasional Papers contain any errors or omissions, they should be attributed to the individual authors, rather than to the FCA.

Authors

John Gathergood & Benedict Guttman-Kenney

John Gathergood (john.gathergood *at* nottingham.ac.uk) is Associate Professor of Economics at the University of Nottingham. Benedict Guttman-Kenney (benedict.guttman-kenney *at* fca.org.uk) works in the Behavioural Economics & Data Science Unit of the Financial Conduct Authority.

Acknowledgements

We would especially like to thank Stefan Hunt, Gianandrea Staffiero and numerous FCA colleagues for providing detailed comments. We would like to thank Bernardo Fonseca Nunes for his excellent research assistance. We are extremely grateful to Professors Richard Disney of the University of Sussex and Tom Crossley of the University of Essex for providing feedback on this research. We are grateful to the Office for National Statistics for providing early access to the microdata of the Wealth and Assets Survey. John Gathergood's research is supported by the Economic and Social Research Council under grant number ES/K002201/1.

All our publications are available to download from www.fca.org.uk. If you would like to receive this paper in an alternative format, please call 020 706 60790, email publications_graphics @fca.org.uk or write to Editorial and Digital Department, Financial Conduct Authority, 25 The North Colonnade, Canary Wharf, London E14 5HS.

Contents

Summary

People suffer financial distress when they face financial and non-financial difficulties from repaying their outstanding debts. This paper analyses the prevalence of financial distress, how this distress is related to consumer credit use, and whether financial distress can be predicted. We aim to inform discussion about how consumer credit lenders should evaluate whether lending to an individual is likely to lead to financial distress (i.e. is “unaffordable”). Using data from the Wealth and Assets Survey, we find the majority (61%) of individuals in Great Britain have at least one consumer credit product and that at any time roughly one in four people hold outstanding debt. Ordering individuals by their consumer credit debt-to-income (DTI) ratio we find the top 10% of individuals hold roughly a third of the total debt and have debt levels in excess of 2.5 months of household income before tax. Using a narrow definition of financial distress based on arrears, 2% of individuals with outstanding consumer credit debt are in financial distress. Using a broader measure of financial distress we estimate that 17% of individuals with outstanding consumer credit debt, or 7% of those holding a consumer credit product, face moderate or severe financial distress. This is a large number of individuals, approximately 2.2 million. Compared to other individuals, those in financial distress are typically younger, with lower income and higher DTI ratios. They also have noticeably worse self-reported measures of well-being. DTI ratio is a strong predictor of future financial distress, even after controlling for ‘life events’ that may cause financial distress, such as becoming unemployed. The top 10% of individuals by DTI ratio are much more likely to suffer financial distress than other individuals. And those who hold the majority of their debts in higher-cost products are substantially more likely to experience financial distress than holders of other forms of credit, such as personal loans. Our findings support the use of DTI ratio over other measures in affordability assessments, especially for higher-cost products.

1. Overview

Purpose

FCA rules require consumer credit lenders to assess the creditworthiness of loan applicants. The FCA is considering whether changes are needed to existing rules and guidance. This Occasional Paper is intended to inform discussion ahead of a future consultation paper on this topic.

This research is authored by Professor John Gathergood (University of Nottingham) and Benedict Guttman-Kenney (FCA) and analyses data from the Wealth and Assets Survey (WAS), produced by the Office for National Statistics (ONS). This is an independent piece of research and should not be interpreted as implying an FCA view on the issues.

The research:

- describes the distribution of consumer credit debts in Great Britain
- estimates financial distress in Great Britain
- analyses the relationship between financial distress and well-being, and
- examines whether financial distress can be predicted

Key findings

Distribution of consumer credit debts

The majority (61%) of individuals in Great Britain hold at least one consumer credit product, but at any time about a quarter (26%) of all individuals hold outstanding debt (43% of individuals with a consumer credit product).[1]

Of those individuals who hold outstanding consumer credit debt, the average consumer credit debts are £3,800. Borrowing is unevenly distributed among individuals with the median consumer credit debt being £1,900 and the top 10% of individuals (ranked by outstanding consumer credit debts) holding at least £10,300 in consumer credit debts.

Individuals with outstanding consumer credit debts hold, on average, consumer credit debts equivalent to 14% of their gross annual individual income or 12% of their household income. Ranking individuals by the ratio of their consumer credit debts relative to income (DTI ratio) we find that the top 10% of individuals with outstanding consumer credit debts, who hold approximately a third of total debt balances, have consumer credit debts that are over 38% of

[1] Figures from wave 4 of the ONS Wealth and Assets Survey (WAS) which were collected between 2012 and 2014. This analysis is of consumer credit debts and therefore excludes mortgages, student loans and other household debts. Note that outstanding debt does not include credit card transactions paid off at the next statement.

their gross annual individual income or 31% of their annual household income. These debts are equivalent to over 3.1 months of individual income or 2.5 months of household income before tax.

Estimating financial distress

People suffer financial distress when they face financial and non-financial difficulties from repaying their outstanding debts. Financial distress may mean that individuals file for bankruptcy or increase working hours, take on additional jobs, or reduce spending in order to meet repayments. Financial distress may also have wider non-financial effects, such as stress, along with other forms of mental and physical distress or social stigma. Through missing repayments or persistently maintaining debt financial distress may also impede an individual's future ability to access credit.

Financial distress can be assessed using objective measures such as whether an individual has missed payments or alternatively using subjective measures which capture an individual's self-reported ability to manage their finances.

Using a narrow, objective measure of financial distress, whether an individual is two or more payments in arrears on at least one credit product, we find 2% of those with outstanding consumer credit debts are in financial distress. The prevalence of financial distress as measured this way varies significantly by product type, with higher-cost credit products such as high-cost, short-term credit (payday loans) and home-collected credit having higher arrears rates than other products such as credit cards or personal loans.

Examining subjective measures of financial distress we find approximately half (49%) of individuals with outstanding consumer credit debts do not regard keeping up with those to be a burden at all, while approximately a third (34%) regard keeping up with repayments to be somewhat of a burden.

Using a broader measure of financial distress which combines objective and subjective measures we estimate that 17% of individuals with outstanding consumer credit debts (or 7% of all individuals holding a consumer credit debt product) appear to face moderate or severe financial distress. This measure is constructed from individuals who are two or more payments in arrears on at least one credit product and/or regard their debts as a heavy burden and/or are falling behind on some or many financial commitments. Given the scale of the consumer credit market this is a large numbers of individuals – approximately 2.2 million - although as this is estimated from survey data the exact figure should be treated with caution. Of course, estimates of financial distress are expected to fluctuate with the economic cycle, rising in periods when unemployment is increasing and real disposable incomes are being squeezed.

Individuals in financial distress are typically younger, with lower income, less likely to be employed and exhibit higher debt-to-income ratios than individuals who are not in financial distress but do have consumer credit debts. They are also more likely to hold higher-cost credit products.

Relationship between financial distress and well-being

The closest we are able to get to understanding the relationship between financial distress and consumer welfare in this dataset is through self-reported measures of subjective well-being. Two standard measures are used – life satisfaction and anxiety – which can be considered observable proxies for the welfare impacts of consumer credit use on consumption and mental health respectively.

This analysis finds that individuals in financial distress exhibit substantially lower average life satisfaction and higher anxiety than other individuals with consumer credit debts. This relationship between financial distress and self-reported well-being remains after having accounted for other socio-economic variables (e.g. income, age).

Predicting financial distress

Individuals may experience financial distress for a variety of reasons. Financial distress may, in part, be predictable where individuals take on an unaffordable amount of credit relative to their ability to repay it. However, financial distress may be somewhat unpredictable as individuals may suffer from unforeseeable 'life events', such as becoming divorced or unemployed, which result in changes to their economic circumstances. This distinction is important as firms have to make lending decisions that consider whether borrowing will be affordable for an individual on the basis of the predictable component which is the information available to them at the time of making the creditworthiness assessment.

This research finds the ratio of consumer credit debts relative to either gross annual individual or household income (known as the debt-to-income or DTI ratio) to be a strong predictor of future financial distress. Individuals with higher DTI ratios are at much higher risk of suffering from financial distress.

Other measures - the number of credit products held, total outstanding debts and measures of income - do not improve our ability to predict financial distress beyond the ability of the DTI ratio. Using gross annual individual income as opposed to gross annual household income in a DTI ratio is a slightly stronger predictor of future financial distress. 'Life events' appear to also predict financial distress but noticeably less so than DTI ratios.[2]

Our ability to predict financial distress is much stronger for individuals in the top 10% of DTI ratio than those with lower DTI ratios. Individuals with higher DTI ratios who have the majority of their debts in higher-cost products are much more likely to experience financial distress than other users of credit.

This research shows the risks of financial distress vary predictably depending on an individual's circumstances. It suggests that affordability policies should be tailored to the products that people apply for and to applicants' circumstances, especially their DTI ratio.

[2] This section of the analysis uses waves 1-4 of the ONS Wealth and Assets Survey (WAS) containing data collected between 2006 and 2014. Fieldwork for each wave of the survey takes two years to collect.

2. Economic theory on consumer credit use and financial distress

Why use consumer credit products?

Consumer credit debt performs a variety of critical roles in the economy. It enables individuals to manage temporary cash-flow shortfalls that may occur within a monthly pay cycle due to incomes being received at a different point to expenditures such as rent payments. Such temporary shortfalls are well-suited to individuals using revolving credit products, such as overdrafts and credit cards, or non-revolving credit products, such as payday loans.

There are also longer-term needs for individuals to use consumer credit in order to smooth the repayment of larger, indivisible purchases: for example, buying a car or household appliances or financing special events such as Christmas, holidays or weddings. Credit products such as personal loans and hire purchase agreements enable individuals to purchase and utilise large, indivisible items and affordably repay them in set repayments over months or years. Consumer credit has an especially important role for individuals who do not own property (with or without a mortgage) as they have no large asset to secure debt against. The economics of consumer credit are summarised in a series of papers in Bertola et al. (2006).

Why do consumers borrow over their lives?

Standard economic theory is useful for understanding how and why households use credit and debt. In economic models of household saving and borrowing, households use financial products in order to smooth the marginal benefit (utility) of consumption over time (Ando and Modigliani, 1963; Browning and Crossley, 2001, Friedman, 1957). When faced with volatile incomes over their lifetimes, the ability to borrow and save allows the household to maintain a steady level of consumption spending by borrowing through periods of reduced income and saving through periods of higher income.

As most households face rising incomes during working lives followed by a period of zero income during retirement, a rational behaviour is to borrow when young (e.g. to fund house purchase or education) and save through the working lifetime to build up a stock of assets that can be used to fund retirement expenditure. Conversely, households who take on high levels of debt close to retirement are unlikely to experience future income growth with which to meet their debt repayment obligations – this is a behaviour not predicted by a life-cycle model. Therefore in a life-cycle model the debt position of a household can only be understood relative to its current and future income.

The life-cycle model of consumption, saving and debt provides a framework for understanding how household characteristics relate to debt usage and levels. First, it tells us that household characteristics associated with income growth are likely to correlate with higher level of indebtedness. Income growth is typically strongest when young among households who are more educated and face steeper age-income profiles over their working lives. We should therefore expect to find a positive relationship between these characteristics and the level of debt. To the extent that more sophisticated households are more educated and perform more strongly in the labour market we should observe these households with the highest levels of debt.

Second, the life-cycle model implies that the level of debt taken on by a household is related to the household's current and future consumption needs. Over the course of their lifetimes households experience varying consumption needs that depend on factors such as work-related expenses, the costs of raising children or the costs of purchasing and refurbishing property. For households in these circumstances, future consumption needs are likely to be lower e.g. when children have grown up and the household's financial obligations are consequentially reduced. Therefore the socio-economic characteristics of households are important to consider as they drive and determine consumption and debt needs over the life-cycle.

It is therefore possible, and economically rational, for a household to have debts that may appear to be 'high' relative to their current income as they are borrowing in anticipation of future income growth and as a consequence their level of debt but is actually moderate relative to their lifetime income (much of which is in the future).

When we refer to the household in the above we mean the economic unit who shares the burden of financial obligations. For assessing mortgage debt the relevant unit is the household income as the total income to finance this asset. Whereas for consumer credit debts the relevant unit of income is less clear. This is because some households regard consumer credit debts as shared obligations (like a mortgage) and the relevant income to maintain repayments is therefore 'household income'. However, other households may not share some (or all) of their consumer credit debts and regard them as individual liabilities – in which case the relevant unit is 'individual income'.

Is using consumer credit debt bad?

In some areas of debate, a view is often expressed that any debt is in some sense a 'bad' economic choice which exposes the individual to financial distress. This view tends to see saving as 'good' and debt as 'bad', and asserts that individuals who use credit and debt are acting irrationally. However, such thinking neglects the useful functions of consumer credit debts - outlined at the start of this chapter – in relation to the management of cash flows and smoothing the consumption of purchases over time.

A second view that is commonly expressed is that 'a lot' of debt must represent a poor economic position for an individual. Having £20,000 of consumer credit debt is seen as 'worse' than having £10,000 of consumer credit debt. While this is true in a simple accounting sense, it is not necessarily true in the context of an individual's economic position. The optimal level of debt for an individual depends on their income, both now and in the future.

A £10,000 consumer credit debt held by an individual when young and faced with future promotion at work and income growth is very different in economic terms to the same level of debt held by a pensioner on a fixed real income. Indeed, individuals with the steepest income growth will hold higher levels of debt in the current period in order to smooth their consumption in anticipation of their higher future income.

There are some individuals who will purposefully borrow with no intention of repaying their loan – these are strategic defaulters and may often be the result of companies fraudulently pretending to be other individuals in order to access credit. Firms work closely to find ways to reduce the potential for this as it results in the cost of credit being inefficiently high for the non-fraudulent users and also results in at the least inconvenience and potentially severe distress or financial loss for the victims of such fraud.

Of the non-fraudulent users of consumer credit, some may face difficulties now or in the future repaying their outstanding debts over a certain period of time. In such a circumstance outstanding debts may be considered 'unaffordable' and the individual may be described as being in 'financial distress'. We expand on the impacts of such 'financial distress' in the next paragraph.

Financial distress may mean that individuals file for bankruptcy or increase working hours, take on additional jobs, or reduce spending in order to meet repayments. Financial distress may also have wider non-financial effects, such as stress, along with other forms of mental and physical distress or social stigma. Through missing repayments or persistently maintaining debt financial distress may also impede an individual's future ability to access credit. For such individuals consumer credit may be associated with financial distress and it may therefore be an attractive option (and welfare-improving) to forgive debts. However, while this may sometimes be necessary and welfare-improving, it is tricky but important to find a balance in order to ensure that it does not give rise to 'moral hazard', whereby individuals feign financial distress in order to freeze interest or clear debts, resulting in an inefficient market outcome.

Why may individuals end up in financial distress?

Standard economic models also provide a framework for understanding affordability and financial distress. If consumers behave rationally and make optimal choices based on their expected income and rational expectations over aspects of the economic environment (e.g. interest rates, credit availability) then they will not choose to take on 'unaffordable' debts ('ex ante'). In other words, if households make optimal plans for the level of debt based on reasonable predictions of the future then they will not plan for unaffordable debts.

However, in the real world which is full of risks and uncertainty rational expectations may not match actual, realized events. Subsequent shocks to income and expenditure, or the regional, national or global macroeconomic environment may result in debt positions becoming unaffordable ('ex post'). Households with relatively secure incomes may, for example, take on levels of borrowing consistent with their expected income but suffer sudden and unlucky 'life events', such as redundancy or ill health, which reduce income. Such shocks may leave an individual unable to maintain their debts and shift them into financial distress. In this framework, unaffordable debt arises due to the underlying riskiness of incomes and the economic environment and not due to planned or poor choice on the part of consumers. Other 'life events' may be more predictable but not fully anticipated or budgeted for such as as having a child.

In contrast with the prediction of the standard model of consumption, saving and debt, alternative modern behaviourally-informed theories focus on the psychological and cognitive aspects of consumer behaviour suggest that households can make poor plans in relation to their saving and borrowing choices, taking on unaffordable debts 'ex ante'. Modern theories of consumer behaviour emphasise that consumers may make sub-optimal choices due to time inconsistent preferences or 'self-control' problems (Laibson, 1997) or a lack of financial sophistication (Agarwal et al, 2009). These behavioural factors may cause consumers to take on levels of debt that are predictably unaffordable. Recent research based on British data has shown that lack of self-control and poor financial sophistication are important drivers of over-indebtedness and financial distress (Gathergood, 2012; Disney and Gathergood, 2013). Taken together, standard consumer theory and modern alternatives suggest that both unpredictable shocks and predictable traits are important at the individual level for understanding unaffordable debt and financial distress.

Finally, it is important to consider the role of firms. Even with behavioural biases firms would not lend to individuals expected to suffer financial distress if incentives were aligned between an individual and lender to act in individual's best interests. However, there are some individuals applying for consumer credit whom firms expect to be profitable to lend to (and would lend to), but it is not in the individual's best interests as they have a very high risk of experiencing financial distress and may not be able to assess this for themselves. One example of firms' incentives not being aligned with consumers was in the UK high-cost, short-term credit (HCSTC) market before FCA intervention.[3] Given the above there is a clear role for consumer protection regulation to prevent high risk consumers from suffering financial distress[4].

[3] See FCA's detailed analysis for setting a price cap on this market in FCA CP14/10 (and accompanying technical annexes) and PS14/16.

3. Distribution of consumer credit debts

61% of individuals hold a credit product.

26% of individuals hold a credit product with outstanding debt.

Top 10% of individuals holding a credit product with outstanding debt have consumer credit debts worth **over £10,300.**

Top 10% of individuals holding a credit product with outstanding debt have consumer credit debts that are **over 31%** of their gross annual household income.

The Wealth and Assets Survey (WAS)

In order to reliably analyse financial distress it is crucial to have data that can show which individuals are suffering from financial distress as opposed to simply whether the ‘average’ holder of consumer credit debt is suffering financial distress. Such analysis requires the use of ‘microdata’, which can display not only the average consumer credit debts but their distribution, measures of financial distress and other socio-economic characteristics (e.g. income and age).

When formulating this research a variety of potential data sources were considered and we chose to use the Wealth and Assets Survey (WAS) produced by the Office for National Statistics (ONS). WAS has been chosen due to its variety of useful features. Firstly (and most importantly) it includes a rich array of variables on the composition of consumer credit debts, measures that can be used to estimate financial distress and well-being, as well as socio-economic characteristics. Secondly, it is a large survey which enables us to have a reasonably large sample of individuals who have experienced relatively rare events such as missing credit repayments or borrowing from more niche high cost credit products. Thirdly, it surveys the same individuals over-time enabling us to track how relationships between consumer credit debts and financial distress change over time and may be affected by changes in individual’s socio-economic circumstances such as ‘life events’. Finally, it is a nationally -representative survey which ensures the analysis is not of a potentially misleading unrepresentative sub-sample of the population[5]. Annex 1 explains this data choice in greater detail.

This paper uses data from all four available waves of WAS. The fieldwork for the first of these, wave 1, was carried out over the period 2006–2008 and the latest wave, wave 4, was carried out during 2012–2014. It should be noted that this survey covers a particularly turbulent period in the economic business cycle and household debts were very high by historical standards at the start

[4] An example of previous regulatory intervention on affordability can be found in the FSA’s mortgage market review (MMR) and Responsible Lending Review of how it has changed firms’ practices.

http://www.fsa.gov.uk/library/policy/cp/2011/11_31.shtml

https://www.fca.org.uk/static/fca/documents/occasional-papers/mortgage_op11_final.pdf

http://www.fca.org.uk/static/fca/article-type/thematic%20reviews/tr16-04.pdf

[5] WAS surveys individuals in Great Britain (excluding the Isles of Scilly and Scotland north of the Caledonian Canal) and does not include individuals in Northern Ireland.

of the survey[6]. The sample size is notably higher in wave 1 compared to subsequent waves as a result of the survey design. Some individuals are not observed in every wave of the survey (an 'unbalanced panel').

The analysis in this paper is carried out at the individual–level, combining survey responses from the individual survey with household components containing information such as homeownership status. More details regarding WAS can be found in Annex 1, the public documentation provided by ONS on its own website and that of the UK Data Service[7].

The sample used for this analysis only keeps observations for respondents to the survey where we observe a minimum set of information (age, marital and family status, employment, education, homeownership and household income). Different parts of the analysis use sub-samples of this population such as restricting it to individuals who hold positive consumer credit debts and focusing on the latest wave of data. Later on in the analysis we restrict the sample to a 'balanced panel' only including individuals we observe across multiple waves.

Table 1 provides summary statistics on the four waves of the survey and displays how characteristics are fairly stable across the four waves. In all waves approximately half of respondents are male and a little more than two-thirds are married or co-habiting. A little less than 70% of individuals are employed (full-time or part-time) with approximately an additional 10% self-employed. Most respondents are educated to A-level (or equivalent for older respondents). More than half of respondents are home owners with a mortgage, with the proportion falling across waves.

Table 2 describes estimates of gross annual individual and household income constructed from the survey. These measures are displayed since alternative measures of income, such as net of tax or rent cannot be reliably constructed across all four waves. Mean and median values are displayed among non-missing observations. Average individual income is reported for approximately 85% of respondents who state they are in employment, self-employed or receive some form of benefit income. Average household annual income is between £36,000 and £41,000, increasing across waves. Average individual income is approximately £20,000, also increasing across waves.

We define household income as the relevant unit of income in this research for a variety of reasons. Firstly, we are unable to reliably distinguish whether individuals in the survey regard their consumer credit debts as individual or household-level obligations (an issue discussed in chapter two). Secondly, using household-level income ensures that we do not underestimate the income available to individuals who have no or low individual income as a result of being unemployed, working for low pay or part-time but who have access to other household income. Lastly, measures of individual and household income are highly correlated (see Annex 2 'Comparison of measures of income' for more details) and there are fewer missing observations for household income than individual income. However, at certain points in this analysis we also display individual income (and measures derived from it) for comparison.

[6] See chapter on UK household indebtedness http://www.bankofengland.co.uk/publications/Documents/fsr/2016/fsrjul16.pdf

[7] http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/was/wealth-in-great-britain-wave-4/2012-2014/index.html

https://discover.ukdataservice.ac.uk/catalogue/?sn=6415#documentation

Table 1: Summary statistics on individuals in WAS waves 1–4 (percent of individuals within wave unless otherwise specified)

	Survey wave			
	1 (2006–2008)	**2 (2008–2010)**	**3 (2010–2012)**	**4 (2012–2014)**
Age				
16–24	15%	14%	15%	15%
25–34	18%	16%	15%	15%
35–44	24%	23%	22%	20%
45–54	22%	23%	23%	24%
55–64	16%	18%	18%	19%
Over 65	5%	6%	7%	8%
Demographics				
Male	50%	50%	50%	50%
Married / co-habiting	69%	69%	68%	68%
Divorced / separated	6%	6%	6%	6%
Average number of children	0.74	0.78	0.75	0.74
Employment				
Employed (full-time or part-time)	68%	68%	68%	66%
Self-employed	10%	9%	10%	9%
Unemployed	1%	2%	2%	1%
Education				
Degree education	26%	28%	30%	20%
A-level education	55%	56%	55%	56%
Home ownership				
Outright home owner	23%	26%	27%	28%
Mortgage home owner	57%	57%	54%	52%
Average mortgage value (£)[8]	£40,100	£42,300	£40,800	£41,400
Number of individuals	36,077	22,121	25,248	23,913

Notes: This table shows all individuals in WAS who report at a minimum their age and gender.

[8] Of those with outstanding mortgage debt.

Table 2: Average (mean and median) gross annual income in survey waves 1-4

	Survey wave			
	1 (2006–2008)	**2 (2008–2010)**	**3 (2010–2012)**	**4 (2012–2014)**
Individual mean income (median income)	£19,800 (£15,600)	£20,800 (£16,500)	£21,500 (£16,800)	£21,900 (£17,200)
Household mean income (median income)	£36,200 (£30,000)	£36,900 (£30,900)	£40,600 (£34,000)	£41,400 (£34,700)
Number of individuals	36,100	22,100	25,200	23,900

Notes: All non-missing observations for individuals who appear in at least one survey wave. Income includes labour income (from employment and self-employment), capital income and pension income.

Consumer credit product holdings

We begin by defining an individual as holding a credit product irrespective of whether they currently use the product. This distinction is most important for credit cards as individuals commonly hold these products but use them for transactions repaying balances each month or having zero outstanding balances and do not hold credit card debt (we examine this distinction in the following section).

Table 3 reports the average (mean) number of consumer credit products held by survey. In the latest wave of the survey (wave 4) 61% of individuals held at least one credit product. By far the most commonly held product is a credit card, which is held by 57% of individuals in wave 4. The next most common product is a store card, which is held by 11% of individuals in wave 4 and has been declining over the course of the survey waves. Approximately 9% of individuals hold a personal loan (inclusive of hire purchase loans) and between 3% and 4% hold an account with a mail order catalogue. Other forms of credit are much less common. In each wave less than 1% of the sample held a home credit, payday loan or pawnbroker loan. Note that overdraft use is unobserved.

It appears as though there may be some under-reporting of some of these forms of credit. Administrative data that the FCA previously collected, found that in 2013, 1.6 million individuals took out high-cost, short-term credit loans (HCSTC, some of which are commonly referred to as payday loans) approximately 4% of the UK's working-age adult population.[9] However, the proportion holding a payday loan debts at any point in time (as asked in the survey) would be less than this and the survey term 'payday loan' may only capture a subset of credit agreements legally defined as HCSTC which captures both single repayment payday loans as well as high cost credit with multiple instalments. US research indicates that unsecured debts may be more prone to being under-reported in surveys than secured debts (Zinman, 2009; Brown et al., 2015).

Table 4 displays the number of consumer credit products held by individuals in survey wave 4 who hold at least one product. On average, these individuals hold approximately two products. It is noticeably more common for individuals to hold at least two credit cards than two or more of any other type of consumer credit product.

[9] HCSTC figures from the FCA's CP14/10, p.16. Working-age population from ONS annual mid-year population estimates.

Table 3: Percent of individuals holding consumer credit products in survey waves 1–4

	Survey wave			
	1 (2006–2008)	2 (2008–2010)	3 (2010–2012)	4 (2012–2014)
Holds at least one credit product	*63.8%*	*66.2%*	*63.6%*	*61.0%*
Credit card	*58.8%*	*61.7%*	*59.4%*	*56.8%*
Store card	*16.6%*	*16.4%*	*12.9%*	*11.2%*
Personal loan	*9.9%*	*9.1%*	*8.8%*	*9.5%*
Mail order catalogue	*4.5%*	*3.9%*	*3.3%*	*2.6%*
Home credit	*0.4%*	*0.4%*	*0.3%*	*0.3%*
Pawnbroker	*<0.1%*	*<0.1%*	*<0.1%*	*<0.1%*
Payday loan	*<0.1%*	*0.1%*	*0.1%*	*0.1%*
Informal loan	*0.8%*	*0.8%*	*0.9%*	*0.6%*
Number of individuals	*36,077*	*22,121*	*25,248*	*23,913*

Notes: 'Personal loan' category includes hire purchase loans. 'Informal loan' category includes loans from family, friends and employers.

Table 4: Number of consumer credit products held (conditional upon holding at least one) from survey wave 4

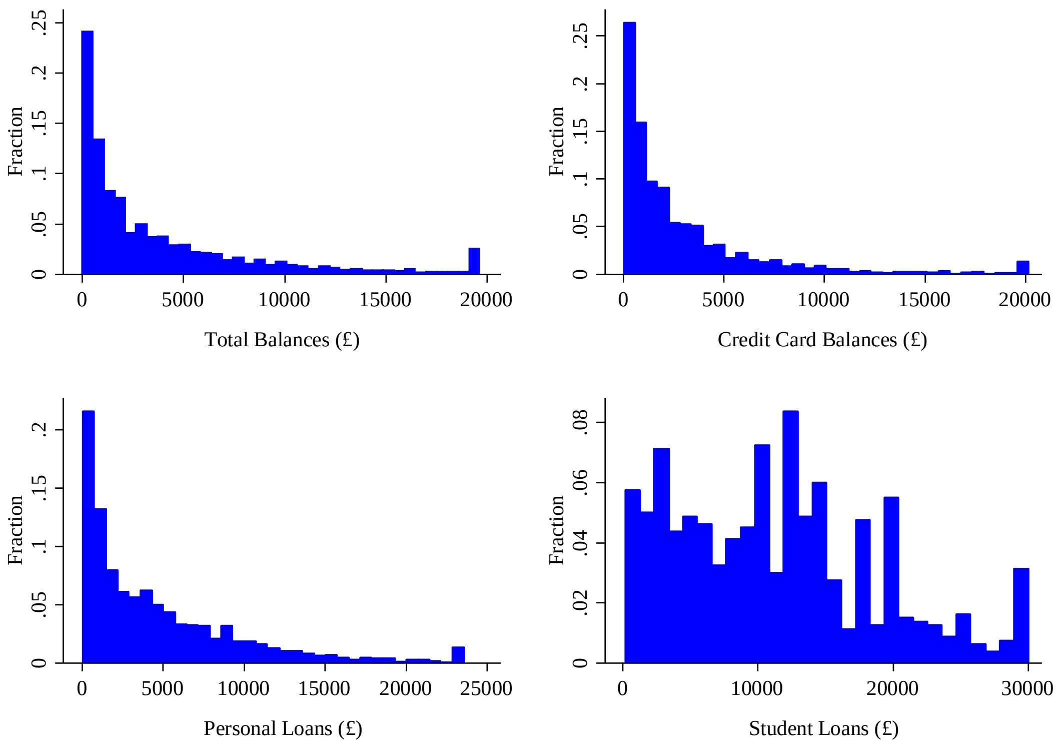
	Mean	Minimum	Percentile			Maximum
			25th	50th	75th	
Total products held	1.9	1	1	2	2	25
Credit card	1.6	1	1	1	2	25
Store card	1.3					11
Personal loan	1.1					11
Mail order catalogue	1.2					6
Home credit	1.2		1			4
Pawnbroker	1.1					2
Payday loan	1.4					4
Informal loan	1.1					2
Number of individuals	14,587					

Distribution of consumer credit debts

While the majority of individuals in Great Britain hold at least one consumer credit product (61%), at any time only about a quarter (26%) of all individuals – 43% of individuals with a consumer credit product – hold outstanding debts (have a non-zero outstanding balance).[10]

The outstanding value of consumer credit debts held by individuals is highly uneven because credit products come in a wide range of amounts and individuals are at different stages of repaying these debts. Figure 1 shows this uneven distribution of balances for individuals with outstanding debts (i.e. excluding individuals with balances equal to zero) split by types of products. A balance is defined as the debt outstanding, which for revolving credit (credit cards, store cards and mail order accounts) includes only revolving balance that incur interest. Balances are top-coded to reduce the potential for outliers, which are likely to be reporting errors, skewing the analysis. As illustrated in Figure 1, there is a long right-tail of individuals with very high balances for total balances, credit card balances and personal loan debts: for comparison, this distribution contrasts with the distribution of student loan debt.

Figure 1: Distribution of outstanding debt balances from survey wave 4



Notes: This figure includes all individuals holding outstanding debt on at least one product in survey wave 4.

Table 5 provides a more detailed description of the distribution of debts by product type. This shows that average (mean) debt among individuals with outstanding debt is £3,800 (which implies average debt among the whole sample is less than £1,000). This average value is substantially above the median value of approximately £1,900 and indicates the sample includes

[10] Figures from wave 4 of the ONS Wealth and Assets Survey (WAS) which was collected in the period 2012–2014. This analysis is of consumer credit debts and therefore excludes mortgages and student loans and other household debts.

a small number of individuals with high debts. Indeed, the top 10% and 5% of individuals with outstanding consumer credit debts respectively hold at least £10,300 and £14,800 in these debts. The average and distribution of consumer credit debts varies noticeably by types of products. For example. those with outstanding debts on informal loans hold on average £5,600 (though less than 1% of the sample is in this group): this is compared to store cards, for which average debts are £400. Given our knowledge of the payday loan market the average balance of £2,100 appears much higher than observed in the FCA's administrative data.

Compared with the whole sample, individuals with outstanding consumer credit debts are typically younger, more likely to be married or cohabiting, more likely to be employed and more likely to own a home via mortgage. This suggests usage of debt is concentrated among individuals with life-cycle characteristics consistent with those predicted by basic economic models. Tables A2:1, A2:2 and A2:3 in Annex 2 provide a more detailed description of the socio-economic characteristics of individuals compared to the whole sample and split by their use of different types of products.

Table 5: Distribution of non-zero balances by product type in survey wave 4

	Mean	Percentile			
		25th	50th	75th	95th
Total balances, £	3,800	600	1,900	5,100	14,800
Credit card	3,000	600	1,600	3,800	10,700
Store card	400	100	200	500	1,100
Personal loan	4,600	900	3,000	6,800	14,900
Mail order catalogue	400	100	200	500	1,700
Home credit	1,300	200	500	1,200	4,000
Pawnbroker	400	100	100	400	1,500
Payday loan	2,100	100	400	1,400	2,200
Informal loan	5,600	900	2,000	6,900	20,900
Number of individuals	6,179				

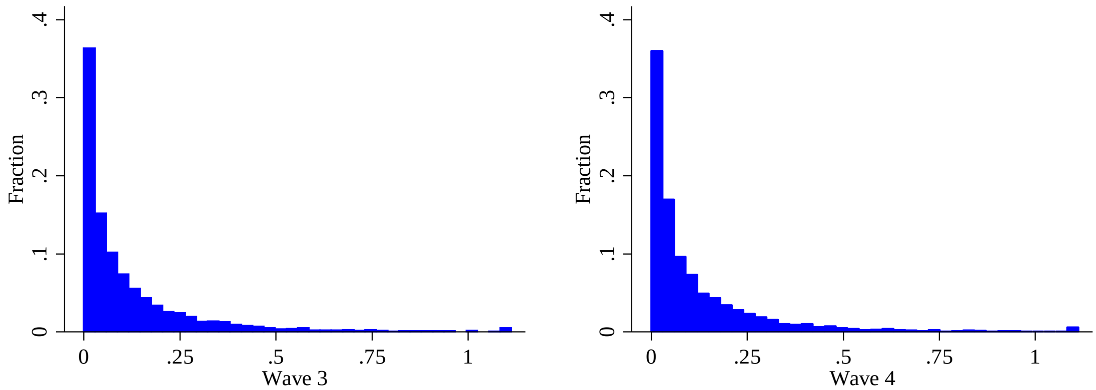
Notes: The table shows summary statistics for non-zero debt balances by credit type among all individuals with non-debt debts of that type in Wave 4 of the WAS sample. Credit card and store card debts are defined as revolving balances (balances not cleared at the end of the payment cycle).

Debt-to-Income (DTI) ratios

In order to understand an individual's ability the repay debts, it is important to consider the value of debts relative to an individual's current and future income. We do not observe future income, and neither do lenders making creditworthiness assessments, but can calculate the level of debt relative to current income through a debt-to-income (DTI) ratio. The DTI ratio is the total level of consumer credit debt held by the individual divided by a measure of total income. Given uncertainty in the degree to which households share the repayment costs of consumer credit debts between adults, we display results for DTI ratios calculated using two alternative income estimates: gross annual individual income and gross annual household income. Observations with a DTI ratio above 1.2 (120% of income) are restricted to this value in order to account for potential data errors.

Individuals with outstanding consumer credit debts hold, on average, consumer credit debts equivalent to 14% of their gross annual individual income or 12% of their gross annual household income. At 6.1% of individual income and 5.3% of household income, the median DTI ratios are significantly below mean DTI ratios. As Figure 2 displays the distribution of the DTI ratio is heavily right-skewed and is fairly stable across survey waves.

Figure 2: Distribution of DTI ratio (using household income) for survey waves 3 and 4



Notes: These figures show all individuals with outstanding consumer credit debt in wave 3 or wave 4 and reporting non-zero individual income.

Ordering individuals by their DTI ratio, we find the top 10% of individuals with outstanding consumer credit debts, who hold approximately a third of total debt balances, have consumer credit debts that are over 38% of their gross annual individual income or 31% of their gross annual household income. These debts are equivalent to over 3.1 months of individual income or 2.5 months of household income before tax. Table 6 displays how the DTI ratio increases non-linearly by decile of individuals with the share of total debts unevenly distributed. Over half of total consumer credit debts are held by individuals in the top 20% ordered by DTI ratio.

Individuals with the highest DTI ratios show higher rates of divorce or marital separation, unemployment and self-employment, more commonly hold informal loans and personal loans, and are less likely to hold credit cards. Further details of the socio-economic characteristics of individuals by DTI ratio can be found in Annex 2 Tables A3:1 and A3:2.

Table 6: Distribution of DTI ratio (using household income) for survey waves 1–4

	Deciles in order of increasing Debt to Income (DTI)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lower DTI threshold	0%	0%	1%	2%	3%	5%	8%	12%	18%	31%
Share of total consumer credit balances	0%	1%	2%	3%	5%	7%	11%	15%	22%	33%

Notes: Each decile has between 3,026 and 3,028 individuals. Only includes individuals with outstanding consumer credit debt.

4. Estimating financial distress

2% of individuals holding a credit product with outstanding debt have missed two or more payments

17% of individuals holding a credit product with outstanding debt (or 7% of all individuals holding a consumer credit product) are in moderate to severe financial distress.

How should financial distress be measured?

This section of the analysis examines alternative measures for estimating financial distress. One of the key benefits of the Wealth and Assets Survey (WAS) used for this analysis is that it captures both objective and subjective measures of financial distress.

An objective measure of financial distress visible in the survey is whether an individual is two or more payments behind (in arrears) on their contractual payments on a consumer credit product. For credit cards and store cards arrears is defined in the survey as not meeting the contractual minimum payments. Two or more payments is the threshold used in WAS in order to not include individuals who have missed one payment by accident. Using this measure approximately 2% of individuals with outstanding consumer credit debts are in financial distress. This proportion remains at this level across all waves of the survey. It is important to note that this measure is based on whether an individual is two or more payments behind at the time of being interviewed and therefore does not capture individuals who have recently been two or more payments behind but have since recovered to be up-to-date with payments (or only one payment behind). It is also important to highlight that while arrears is an objective measure the survey responses given by consumers may be subject to some (intentional or unintentional) mis-reporting by consumers.

This objective arrears measure varies significantly by type of consumer credit product as displayed in Table 7. Across the four waves of data, approximately 2.5% of individuals with outstanding credit card debt (and a similar proportion of store cards) are in arrears on those products. By comparison, a lower proportion of individuals with personal loans are in arrears on those products (less than 0.5% in waves 2–4). The objective measure of financial distress for informal loans is reported, but at these loans are informal the interpretation of being ‘at least two months late on payments’ is unclear.

Compared to other credit products, noticeably higher proportions of individuals with outstanding debts on home credit, pawnbroker loans and payday loans are in financial distress on those products. Higher arrears rates on these products appears plausible given they are higher cost lending to more sub-prime individuals. However, the sample sizes for these credit products are much lower and therefore the exact arrears rates should be treated very cautiously. For example, the payday loan financial distress measure in wave 4 appears lower than the FCA’s administrative data on high-cost, short-term credit (HCSTC) which showed 17% of loans recording late payments in 2013 (at this time few payday loans had more than one instalment and therefore consumers could not go more than one payment behind).[11]

[11] FCA Technical annexes: Supplement to CP14/10, proposals for a price cap on high-cost, short-term credit, p.26.

Table 7: Percent of individuals with outstanding consumer credit debts in financial distress as measured by objective arrears measure (two or more payments behind) disaggregated by product type for survey waves 1–4

	Survey wave			
	1 (2006–2008)	**2 (2008–2010)**	**3 (2010–2012)**	**4 (2012–2014)**
Arrears (any consumer credit products)	0.7%	2.2%	2.4%	1.9%
Credit card	n/a	2.4%	2.8%	2.2%
Store card	n/a	3.3%	1.9%	2.9%
Personal loan	0.9%	0.4%	0.5%	0.3%
Mail order catalogue	1.8%	1.8%	2.6%	1.3%
Home credit	10.2%	17.7%	12.2%	25.0%
Pawnbroker	0.0%	20.0%	25.0%	14.3%
Payday loan	0.0%	25.0%	5.9%	10.5%
Informal loan	5.6%	4.6%	4.3%	2.4%
Number of individuals	5,241	5,891	6,988	6,179

Notes: This table shows arrears rates by product type among all consumers with outstanding debt. Arrears is defined as being at least two months behind on a contractual payment (for credit cards and store cards this is the minimum payment due and only observed in waves 2-4). Sample sizes of home credit, pawnbroker and payday loans are very small and therefore arrears rates should be interpreted with caution.

Objective measures of financial distress examining arrears/delinquencies or defaults are useful as these are clearly observable to lenders through their own credit performance data and on an individual's portfolio of debts as shared through credit reference agencies. However, objective measures may underestimate the proportion of individuals experiencing financial distress. For example, it does not capture individuals who are not currently two or more payments behind on a credit product but are severely struggling to maintain repayments on these items alongside other essential obligations such as household bills. To examine this aspect we turn to more subjective measures of financial distress.

Three subjective measures of financial distress are in the survey with all of these recording how an individual perceives their financial distress with responses being categorical variables, which use 'Likert' scales to enable us to assess the strength of an individual's attitude rather than a simple binary yes/no for whether they agree with a statement.

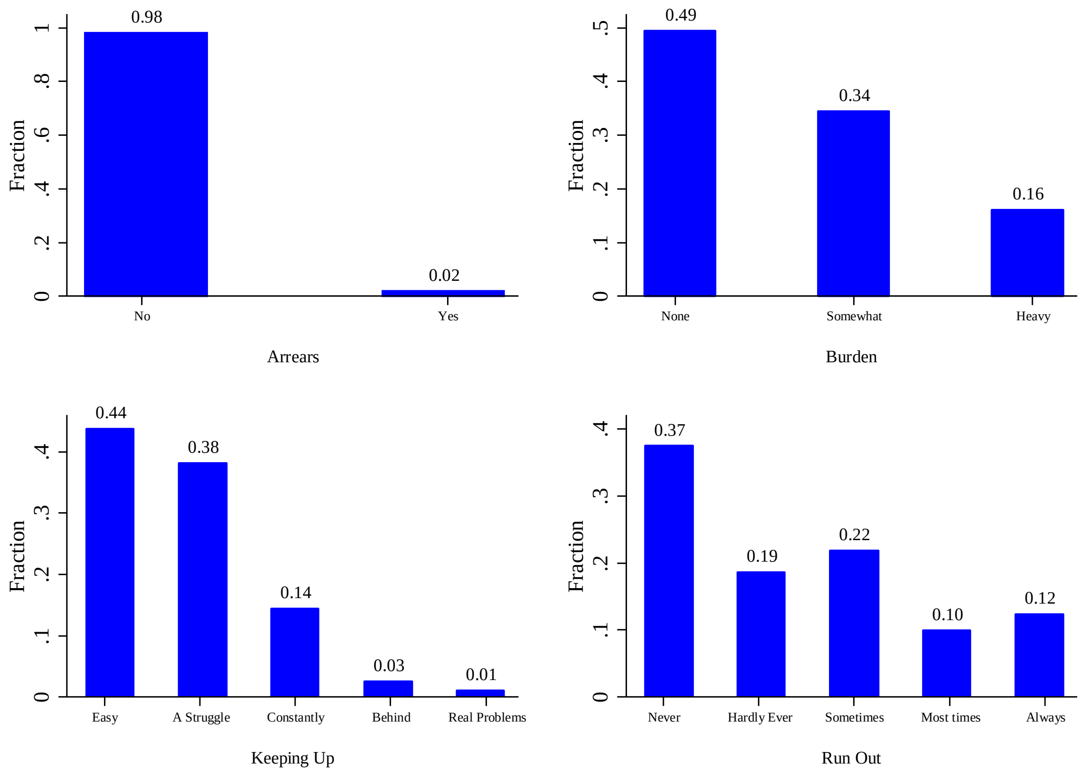
The first of these subjective measures is 'Burden' which has a three point scale where an individual can report whether they regard keeping up with repaying their non-mortgage debts (the consumer credit debts held) to be a financial burden. Response options include: (1) Not a problem (2) somewhat of a burden (3) a heavy burden. This question is separate to a similar question which asking consumers specifically about the burden of their mortgage debts.

The second subjective measure 'Keeping Up' asks how well an individual is keeping up with their bills and credit commitments. Response options are offered on a five point scale ranging from (1) keeping up with all of them without any difficulties to (5) having real financial problems and having fallen behind on many of them.[12] The final subjective measure 'Run Out' asks how often an individual runs out of money at the end of the week or month or needs to use a credit card or overdraft to get by with a five point response option ranging from (1) never to (5) always.

Examining the mean and median values of these subjective measures of financial distress shows the average individual with outstanding consumer credit debts is under half-way through the scales and therefore does not appear to be in financial distress. It is somewhat interesting to consider the 'average' as if the average individual was observed to be in severe financial distress it would result in substantial concerns over the ability of the majority of individuals with consumer credit debts to be able to repay their debts without suffering severe distress. Our results do not support such a conclusion. The median, mean, and standard deviation for the three subjective measures alongside the objective measure can be found in Annex 2 Table A4:1.

In order to understand the scale and severity of financial distress, it is necessary to examine the distribution of these subjective measures rather than focus on the average individual. The distribution of three subjective measures of financial distress is displayed in Figure 3, alongside the objective measure using data from survey wave 4.[13] Examining the distributions of these measures shows that under none of these do the majority of individuals appear to be in the most severe degree of financial distress. Using the 'Burden' measure in survey wave 4, approximately half (49%) of individuals with outstanding consumer credit debts do not regard keeping up with these commitments to be a financial burden at all, while a further third (34%) regard keeping up with repayments to be somewhat of a financial burden.

Figure 3: Distribution of responses to financial distress questions in survey wave 4 (percent of individuals with outstanding consumer credit debt)



Notes: All individuals with outstanding consumer credit debt in survey wave.4.

[12] An additional option is offered for not having any bill or credit commitments.

[13] While the exact proportions change over time, the distribution of these variables follows a similar pattern in earlier waves.

Using the 'Keeping Up' measure we find 82% of individuals with outstanding consumer credit debts are able to keep up with all their bills and credit commitments without any difficulties or are only struggling from time to time. Of those with outstanding consumer credit debts, 56% never, or hardly ever, run out of money, as assessed by the 'Run Out' measure of financial distress.

However, there are a not trivial minority of individuals who appear to be experiencing some financial distress. Using the 'Burden' measure, 16% of individuals with outstanding consumer credit debts regard these to be a 'heavy burden'.[14] The 'Keeping Up' measure shows us that, 14% regard keeping up with repayments a constant struggle with a further 4% falling behind with some commitments or having real financial problems (behind on many commitments). The 'Run Out' measure reveals that 12% report that they always run out of money, while an additional 10% run out of money most times. The distribution of these variables remains similar across earlier survey waves.

There is a very high correlation between different measures of financial distress and there is a logical natural ordering for the severity of distress. The vast majority of those experiencing more severe financial distress would also be captured by less severe measures of financial distress: for example, 85% of individuals in arrears and 92% of individuals constantly struggling are in the group of individuals reporting their non-mortgage debts to be a 'heavy burden'. There is stronger correlation between more severe financial distress states: being in arrears correlates with the measure of 'constantly behind' and 'always' running out with correlation coefficients above 0.5. The broader measures of distress – such as facing a 'heavy burden' of debt, correlate less strongly with the more severe measures. These correlations are displayed in Annex 2 Table A4:2.

This analysis shows that there appears to be a minority of individuals with outstanding consumer credit debts – 2% by an objective arrears measure or 4% by an alternative subjective measure – who are suffering the most severe degree of financial distress.

There is a broader group of individuals suffering moderate or severe financial distress. Producing a composite measure of financial distress, it is estimated that 17% of individuals with outstanding consumer credit debts (or 7% of all individuals holding a consumer credit debt product) appear to face moderate or severe financial distress. This measure is constructed from individuals who are two or more payments in arrears and/or regard their debts as a heavy burden and/or are falling behind on some or many financial commitments. Given the scale of the consumer credit market this is a large numbers of individuals – approximately 2.2 million - although as this is estimated from survey data the exact figure should be treated with caution.[15] Of course, estimates of financial distress are expected to fluctuate with the economic cycle, rising in periods of increasing unemployment and when real disposable incomes are being squeezed.

Characteristics of individuals in financial distress

What are the characteristics of consumers in financial distress? To assess this we allocate individuals with outstanding consumer credit debts into two groups depending upon whether they are included in our composite measure of financial distress constructed in the previous section which comprises 17% of those with debt. Doing so provides us with a suitable comparator group to individuals in financial distress. This section of the analysis pools observations across the four survey waves in order to increase sample sizes.

As shown in greater detail in Table 8, individuals in financial distress are statistically significantly more likely to be younger, more likely to have children, and slightly less likely to be employed (and more likely to be unemployed) than individuals with outstanding consumer credit debts who are not in financial distress. On average, individuals in financial distress have lower incomes and a higher debt-to income (DTI) ratios.

[14] Categories in 'Burden' measure does not sum to 100% due to rounding.

[15] Calculated using average of ONS population estimates during 2012, 2013 and 2014 for individuals in Great Britain aged 16+.

Table 8: Socio-economic characteristics by financial distress for survey waves 1–4 (percent of individuals unless otherwise specified)

	(1) Not in financial distress		(2) In financial distress		Significance test
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**T-statistic**
Age					
16-24	6%	24%	6%	24%	0.3041
25-34	21%	41%	23%	42%	0.1829
35-44	29%	45%	33%	47%	0.0928
45-54	26%	44%	26%	44%	0.6673
55-64	15%	36%	10%	30%	0.0051
Over 65	3%	17%	2%	13%	0.8279
Demographics					
Male	51%	50%	42%	49%	0.0000
Married / co-habiting	75%	43%	69%	46%	0.0000
Divorced / separated	8%	27%	14%	35%	0.0000
Average number of children	0.78	1.01	1.03	1.13	0.0000
Employment					
Employed	73%	44%	69%	46%	0.0000
Unemployed	1%	10%	3%	17%	0.0000
Education					
Degree education	27%	44%	20%	40%	0.0000
A-level education	58%	49%	64%	48%	0.0000
Income and Debt					
Gross annual household income	£38,500	£23,600	£28,700	£17,500	0.0000
DTI ratio	10%	15%	21%	24%	0.0000
Number of individuals	25,889		4,419		

Notes: All individuals with outstanding consumer credit debt in survey waves 1–4.

Individuals experiencing financial distress, compared to other individuals with outstanding consumer credit debts who are not in financial distress, have noticeably different consumer credit product holdings (as shown in Table 9). On average, individuals in financial distress are less likely to hold credit cards and personal loans and more likely to hold higher cost credit items such as mail order catalogues, payday loans and home credit.

Table 9: Proportion of individuals with outstanding consumer credit debts holding credit products split by financial distress for survey waves 1–4

	(1) Not in financial distress		(2) In financial distress		Significance test
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**T-statistic**
Credit card	0.82	0.39	0.80	0.40	0.0567
Store card	0.21	0.41	0.23	0.42	0.0559
Mail order catalogue	0.12	0.33	0.18	0.38	0.0000
Personal loan	0.34	0.47	0.26	0.44	0.0000
Informal loan	0.02	0.15	0.04	0.20	0.1283
Home credit	0.01	0.09	0.04	0.20	0.0000
Pawnbroker	0.00	0.02	0.00	0.06	0.8219
Payday loan	0.00	0.03	0.01	0.09	0.7829
Number of individuals	*25,889*		*4,419*		

Notes: The table reports summary statistics for credit product holdings among individuals separated for those with and without financial distress. The sample comprises all individuals with non-zero outstanding debt in waves 1–4 of WAS.

5. Relationship between financial distress and well-being

Compared to individuals with outstanding consumer credit debts who are not in financial distress, individuals in moderate or severe financial ditress have:

14% lower average measure of life satisfaction.

37% higher average measure of anxiety.

How does financial distress relate to consumer welfare?

Financial distress might not necessarily reduce consumer welfare if financial distress is temporary (e.g. resulting from a transient, negative shock to household finances) or if there are low-cost avenues for individuals to clear their debts and start afresh (e.g. through lenient bankruptcy regime). Alternatively, financial distress may reduce consumer welfare by harming mental or physical health, reducing life satisfaction arising from consumption, attaching the individual with a social stigma or reducing their ability to access to credit in the future.

Attempting to causally identify the impact of financial distress on consumer welfare is not possible from this survey and there is not an alternative data source available which would enable us to do this along with the other needs of this research. Instead, this research carries out descriptive and detailed econometric analysis to inform the interaction between financial distress and well-being.

There may therefore be important omitted, unobservable factors not included in the analysis which cause both financial distress and low welfare. There may also be two-way causality (financial distress may causes lower welfare or lower welfare may cause financial distress). Prior research by Gathergood (2012) econometrically overcomes these potential problems. Although our research is not, and does not claim to be, causally identified the results are broadly consistent with prior academic research linking financial distress and worse health outcomes as summarized in Fitch et al. (2011) and Richardson et al. (2013). The findings are also consistent with the FCA's previous research of 'problem debt' individuals who used HCSTC.[16] The link between financial distress and lower consumer welfare also appears to be broadly consistent with the feedback received by organisations such as citizens advice and money and mental health policy institute who directly interact with financially distressed individuals.[17]

In this survey the closest we are able to get to understanding the relationship between financial distress and welfare is through self-reported measures of subjective well-being. Two standard measures are used – life satisfaction and anxiety – which can be considered observable proxies for the welfare impacts of consumer credit use on consumption and mental health respectively (robustness checks are also shown using other measures). Life satisfaction and anxiety are both recorded on a 0–10 scale, where 0 is an individual who is not at all satisfied / anxious and 10 is

[16] FCA (2014) Technical annexes Supplement to CP14/10 , pp. 274-275

[17] www.citizensadvice.org.uk/about-us/how-citizens-advice-works/media/press-releases/money-worries-have-impact-on-physical-and-mental-health/

http://www.moneyandmentalhealth.org.uk/moneyonyourmind/

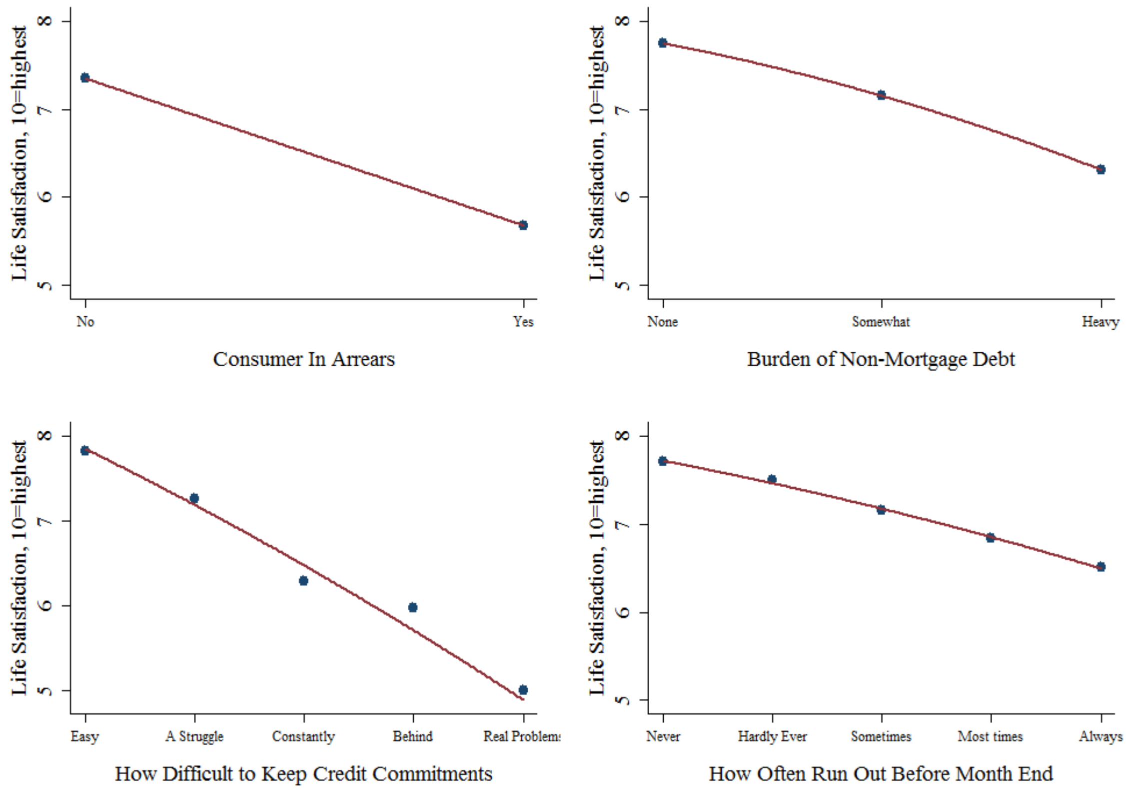
an individual who is completely satisfied / anxious. Measures of well-being are only observed in wave 4 and (some) wave 3 observations. Greater detail regarding these survey questions can be found in Annex 1.

Life satisfaction and financial distress

Examining the (unconditional) relationship between financial distress and average (mean) life satisfaction, as displayed in Figure 4, shows a consistent pattern of individuals in greater financial distress reporting lower life satisfaction.

Across all individuals with outstanding consumer credit debts who were asked the life satisfaction question, the mean is 7.3 (out of 10) with a standard deviation of 1.8. Individuals in arrears show life satisfaction scores which are, on average 1.6 points lower than those not in arrears (a little less than 1 standard deviation). A similar difference in life satisfaction exists for individuals in the 'heavy burden' group compared with those who report no burden of debt.

Figure 4: Relationship between life satisfaction and financial distress from survey waves 3–4



Notes: Binned scatter plots from all individuals with outstanding debts in survey waves 3 and 4 who were asked the life satisfaction question. Y-axis values binned by single units of the x-axis variable. Line of best fit is a quadratic fit through the underlying data.

However, the above relationship may be due to the observable differences in socio-economic characteristics between individuals in financial distress to other holders of consumer credit debts (described in the previous chapter). In order to account for this we estimate Ordinary Least

Squares (OLS) regressions with a set of control variables. Control variables are included for age, marital and family status, education status, employment status, household income, regional and wave dummies. Each potential financial distress measure displayed is a dummy variable.

Table 10 displays the outputs of these regressions (control variables are omitted from the table for brevity) which examine the ability of different measures of financial distress to explain differences in life satisfaction. By the composite measure of financial distress (constructed in the preceding chapter), individuals in financial distress are associated with having 14.1% lower average measure of life satisfaction than other individuals who also hold outstanding consumer credit debts and the similar observable socio-economic characteristics (OLS 1). By the arrears measure of financial distress displays that arrears is associated with a little less than a 1 standard deviation reduction in life satisfaction (OLS 2). Table A5:1 in Annex 2 displays OLS regressions for other measures of financial distress and finds negative relationship between different financial distress and life satisfaction that is statistically significant (at the 0.1% level).

Table 10: OLS Regressions for life satisfaction against financial distress

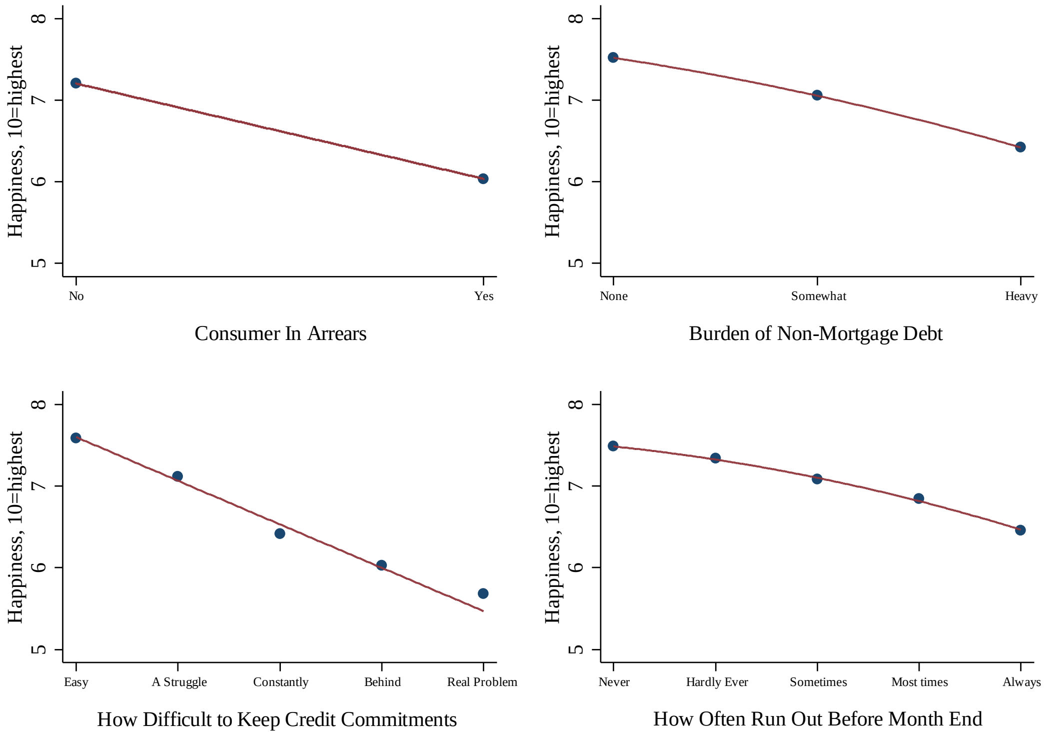
	Life-satisfaction (scale 0-10)	
	OLS 1	**OLS 2**
Financial distress	-1.026***	
['Composite' measure]	(-16.23)	
Arrears		-1.523***
		(-7.25)
Number of individuals	4,898	4,898

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. The table reports coefficient estimates (t statistics) from OLS regressions. Dependent variable is in each case the measure of life-satisfaction on a 0-10 scale. Additional regressors included in the model are described above. Includes all individuals with outstanding debts in survey waves 3 and 4 who were asked the life satisfaction question.*

As the distribution of life satisfaction is highly skewed we also carried out robustness checks of these results by dichotomising the life satisfaction, cutting the variable into a dummy variable at the value taken at the 75th percentile. Other robustness checks are carried out using linear probability models, probit models and poisson (count) models. The robustness checks produce the same qualitative results and are shown in Annex 2 (Tables A5:2, 3, 4).

We also carried out robustness checks examining the relationship between self-reported happiness and financial distress. The results are similar to those found for life satisfaction as displayed in Figure 5.

Figure 5: Relationship between happiness and financial distress from survey waves 3–4



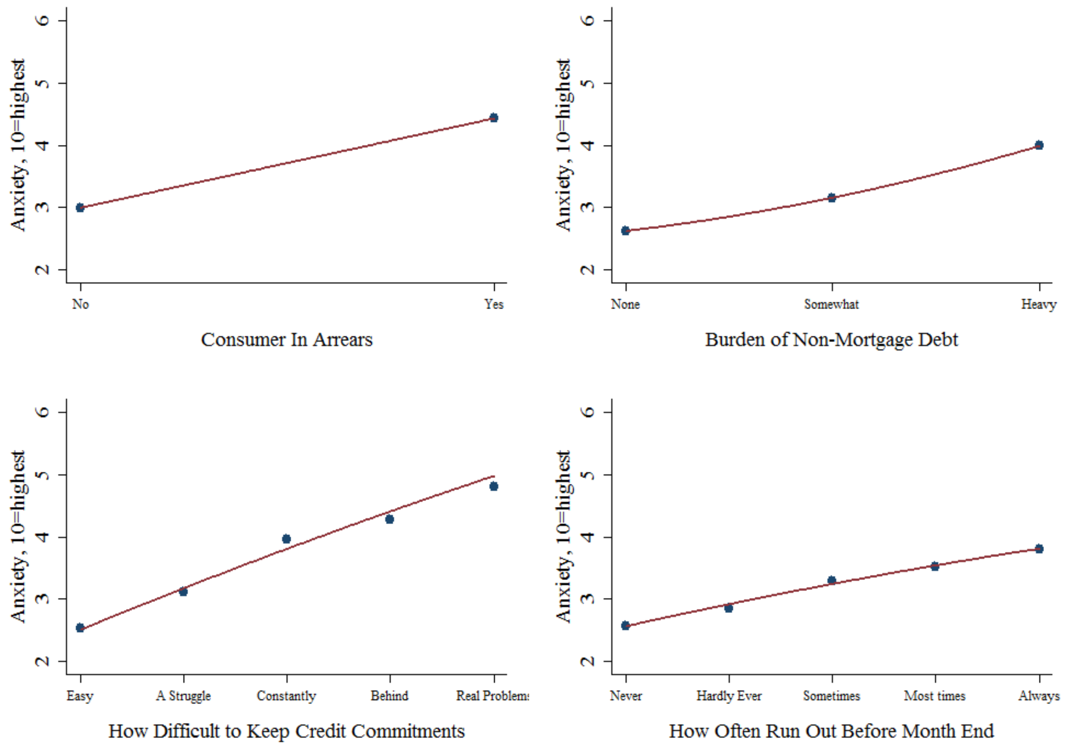
Notes: Binned scatter plots from all individuals with outstanding debts in survey waves 3 and 4 who were asked the happiness question. Y-axis values binned by single units of the x-axis variable. Line of best fit is a quadratic fit through the underlying data.

Anxiety and financial distress

Examination of the (unconditional) relationship between financial distress and average (mean) anxiety, as displayed in Figure 6, shows a consistent pattern of individuals in greater financial distress reporting higher anxiety.

Across all individuals with outstanding consumer credit debts who were asked the anxiety question, the mean is 3.3 (out of 10) with a standard deviation of 2.8. Individuals in arrears show anxiety levels which are, on average, 1.33 points higher than those not in arrears (0.56 of a standard deviation). A similar difference in anxiety (0.67 of a standard deviation) exists for individuals in the ‘heavy burden’ group compared with those who report no burden of debt.

Figure 6: Relationship between anxiety and financial distress



Notes: Binned scatter plots from all individuals with outstanding debts in survey waves 3 and 4 who were asked the anxiety question. Y-axis values binned by single units of the x-axis variable. Line of best fit is a quadratic fit through the underlying data.

Following the same structure of analysis for anxiety as carried out for life satisfaction we model OLS regressions controlling for observable socio-economic characteristics. Table 11 displays the outputs of these regressions (control variables omitted from the table for brevity) which examine the ability of different measures of financial distress to explain differences in anxiety. OLS regressions numbered 1-5, which examine each of these financial distress measures in isolation, find a positive relationship between financial distress and increased anxiety – a relationship significant at the 0.1% statistical significance level.

By the composite measure of financial distress, individuals in financial distress are associated with having 37.4% higher average measure of anxiety than other individuals who also hold outstanding consumer credit debts with similar observable socio-economic characteristics (OLS 1). Arrears is associated with approximately half a standard deviation increase in anxiety relative to the base value of anxiety (OLS 2). Table A5:5 in Annex 2 displays OLS regressions for other measures of financial distress and finds negative relationship between different financial distress and anxiety that is statistically significant (at the 0.1% level). Interestingly the arrears measure becomes statistically insignificant when included alongside subjective measures of financial distress.

As with life satisfaction, the distribution of self-reported anxiety is highly skewed and therefore the same robustness checks are carried out for this outcome variable and are displayed in Annex 2 (Tables A5:6 ,7 ,8) – the results from these are consistent with our findings here.

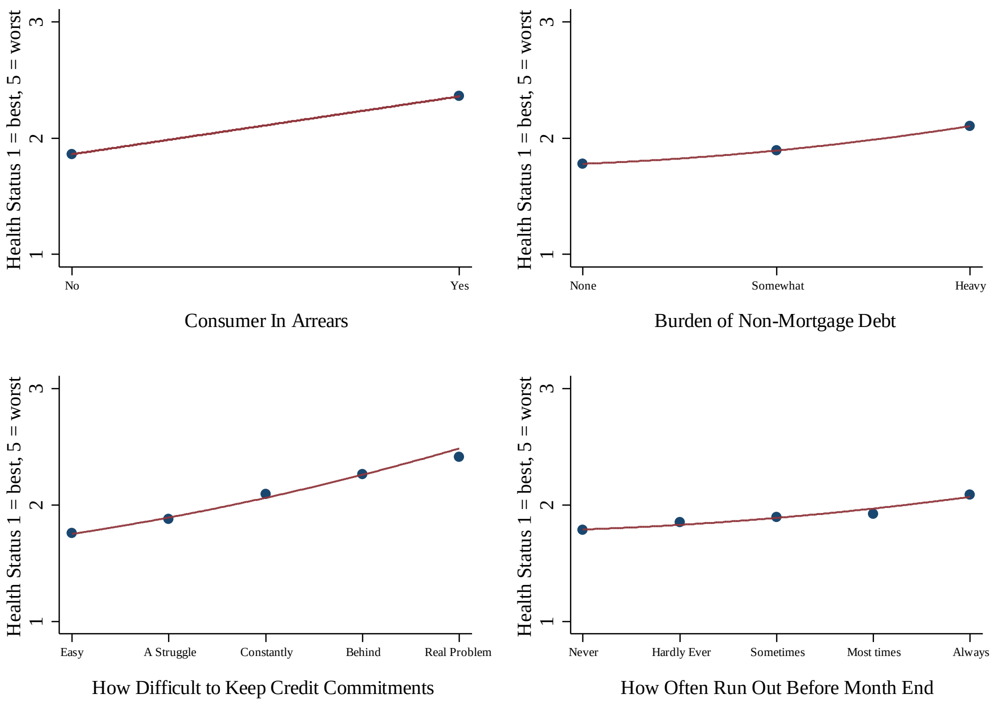
Table 11: OLS regressions of anxiety against financial distress

	Anxiety (scale 0-10)	
	OLS 1	**OLS 2**
Financial distress	1.141***	
['Composite' measure]	(10.07)	
Arrears		1.386***
		(3.76)
Number of individuals	4,898	4898

*Notes: Statistical significance is denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from OLS regressions. Includes all individuals with outstanding debts in survey waves 3 and 4 who were asked the life satisfaction question.*

We also carried out robustness checks examining the relationship between self-reported health and financial distress. The results are similar to those found for life satisfaction as displayed in Figure 7.

Figure 7: Relationship between self-reported health and financial distress



Notes: Figures show binned scatter plots from sample of all individuals with debt in survey waves 3 and 4. Y-axis values binned by single units of the x-axis variable. Survey questions on self-reported health use age-adjusted health evaluation 'compared to people of your own age, would you say your health is 1 'very good', 2 'good', 3 'fair', 4 'bad', 5 'very. Line of best fit is a quadratic fit through the underlying data

Socio-economic characteristics

This final sub-section of this chapter reports regression estimates that show the relationship between socio-economic characteristics and measures of financial distress. The relationship between financial distress and welfare may in part reflect the relationship between factors that contribute to financial distress and welfare. It is therefore important to be cautious regarding whether the statistically significant relationships between life satisfaction/anxiety and financial distress reflect causal effects or are correlations arising from selection effects of consumers into financial distress for other, unobserved reasons.

Table 13 reports estimates from a series of OLS regression models where the dependent variables are the financial distress measures used previously. The set of covariates includes a broad set of socio-economic characteristics and observations where individuals held outstanding consumer credit debts (pooled across all survey waves to increase sample size).

Results show a range of covariates are statistically significant in these models. Gender, marital and family status, employment, education, homeownership and the level of income are each related to one or more of the measures of financial distress. Overall, these socio-economic characteristics can explain approximately 4% of the variation in financial distress by an R-squared statistical measure, though the models only explain approximately 1% of the variation in arrears and the ‘keeping up’ measure of distress. The degree of explanatory power varies for different measures of financial distress, as displayed in Table 12.

Table 12: Proportion of variation in measures of financial distress explained by socio-economic variables (measured using R squared statistic)

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
R squared	0.3816	0.0086	0.0371	0.0097	0.0202
Number of individuals	23,844	23,844	23,844	23,844	23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (t stats) from OLS regressions. See next table for description of regressors.*

Table 13: OLS output regressing financial distress against socio-economic variables

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
Demographics					
Male	-0.0211***	0.00121	-0.0204***	-0.00235	-0.0247***
	(-4.95)	(0.92)	(-4.91)	(-1.53)	(-6.95)
Married / co-habiting	-0.00693	-0.00212	-0.00554	-0.0000371	-0.0132*
	(-1.01)	(-1.00)	(-0.82)	(-0.01)	(-2.29)
Divorced / separated	0.0638***	0.00825**	0.0612***	0.00830*	0.0220**
	(6.41)	(2.69)	(6.30)	(2.31)	(2.64)
Number of children	0.0250***	0.00106	0.0242***	0.00223*	0.0180***
	(10.36)	(1.43)	(10.29)	(2.57)	(8.96)
Employment status					
Employed	-0.0203***	-0.00890***	-0.0161**	-0.00879***	-0.0110*
	(-3.34)	(-4.75)	(-2.71)	(-4.02)	(-2.17)
Self-employed	0.00845	-0.00241	0.00936	-0.00510	-0.0146*
	(0.97)	(-0.90)	(1.10)	(-1.63)	(-2.01)
Unemployed	0.137***	0.0539***	0.120***	0.0608***	0.0928***
	(6.46)	(8.26)	(5.81)	(7.96)	(5.24)
Home ownership					
Home owner	-0.180***	-0.000499	-0.188***	-0.0216*	-0.0690**
	(-6.93)	(-0.06)	(-7.43)	(-2.30)	(-3.18)
Mortgaged homeowner	-0.118***	0.000557	-0.126***	-0.0130	-0.0308
	(-4.63)	(0.07)	(-5.08)	(-1.42)	(-1.45)
House value	-5.47e-08***	-1.56e-08**	-5.13e-08**	-4.41e-09	-2.73e-09
	(-3.36)	(-3.10)	(-3.23)	(-0.75)	(-0.20)
Household income					
Household income	-0.00547***	-0.00110***	-0.0137***	-0.00251***	-0.00862***
(divided by £10,000)	(-3.36)	(-3.45)	(-13.62)	(-6.74)	(-10.00)
Number of individuals	23,844	23,844	23,844	23,844	23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t stats) from OLS regressions. Additional regressors not shown are: dummy variables for age brackets, educational achievements, regional and wave dummies.*

6. Predicting financial distress

The top decile of individuals with outstanding consumer credit debts relative to their household income are **three times** more likley to suffer future financial distress compared with individuals in the median decile.

Individuals with higher proportions of debts in high cost credit items are **80%** more likely to suffer future financial distress compared those in debt a a whole (for a given level of consumer credit debts relative to household income).

Can financial distress be predicted?

Lenders have strong business incentives to accurately assess credit risk – the likelihood of an individual not repaying debts – as lending to individuals who do not repay loans is typically unprofitable. Lenders have clearly observable outcome data on arrears and defaults to be able to construct highly accurate credit scoring and profitability models for this purpose. In some credit markets it may still be profitable to lend to individuals who have a high probability of defaulting on the basis that the high credit risk individuals who do not default generate large enough profits to compensate for the losses from defaulters (as was the case in the HCSTC market before FCA regulatory interventions). However, it is likely that there are some individuals for whom it is profitable for firms to lend to but for whom it is not good to borrow as they may be at high risk of suffering moderate or severe financial distress after increasing borrowing.

Individuals may experience financial distress for a variety of reasons. Financial distress may be in part predictable ('ex-ante') where individuals take on an unaffordable amount of credit relative to their ability to repay it. However, financial distress may be somewhat unpredictable arising from individuals suffering from unforeseeable ('ex-post') 'life events', such as becoming divorced or unemployed, which result in changes to their economic circumstances. This distinction is important as firms have to make lending decisions that consider whether borrowing will be affordable for an individual on the basis of the predictable component which is information available to them at the time of making the creditworthiness assessment.

This chapter does not try to establish whether particular characteristics cause financial distress as characteristics are not randomly assigned and suffer from omitted variable or selection bias. Instead this chapter carries out cross-sectional and panel data econometrics to examine whether financial distress can be predicted, at least on average, for individuals with some characteristics. The ability of a variety of potential predictors of financial distress is evaluated, all of which could potentially be observed by lenders at the time of making a creditworthiness assessment.

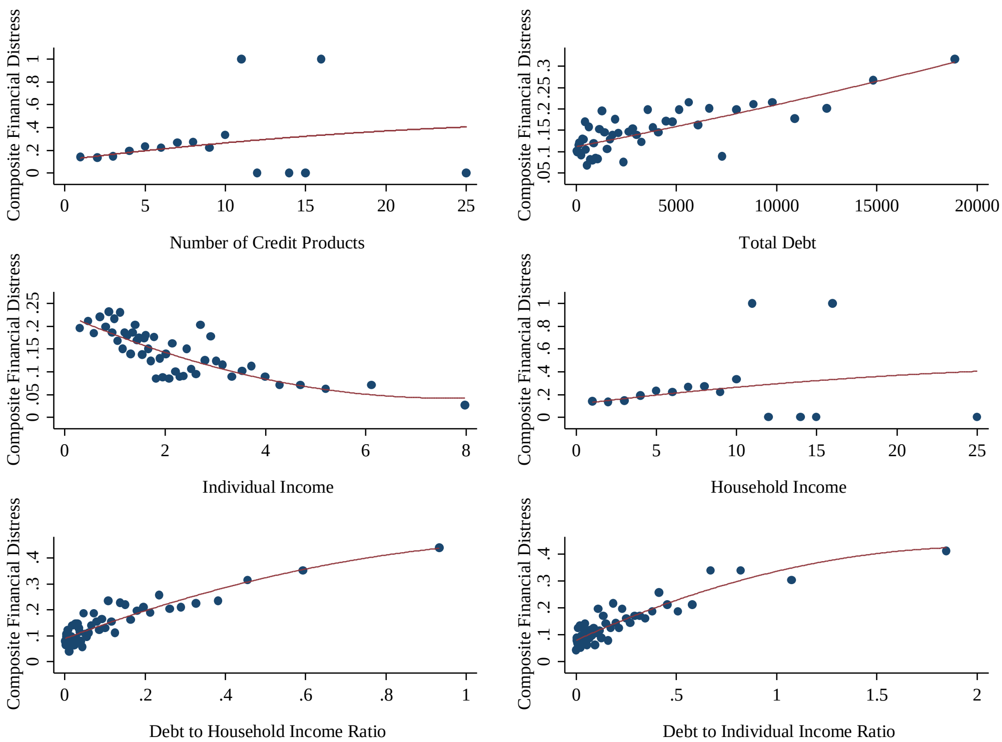
Evaluating potential predictors of financial distress

Analysis presented earlier in this research showed that individuals in financial distress are more likely to use higher cost credit items such as mail order catalogues, home credit and payday loans and are less likely to use lower-cost credit items such as personal loans. This is unsurprising, as higher cost forms of credit are priced higher because they are typically used by individuals with higher risk of default (a segment of individuals sometimes described as being subprime).

The analysis in this section focuses on whether other aspects of the consumer's credit portfolio, aside from the riskiness of the credit products they use, are related to financial distress. The potential predictors examined are: the number of consumer credit products held, the total outstanding value of consumer credit debts, the levels of individual and household income and debt-to-income (DTI) ratios as measured by individual or household income.

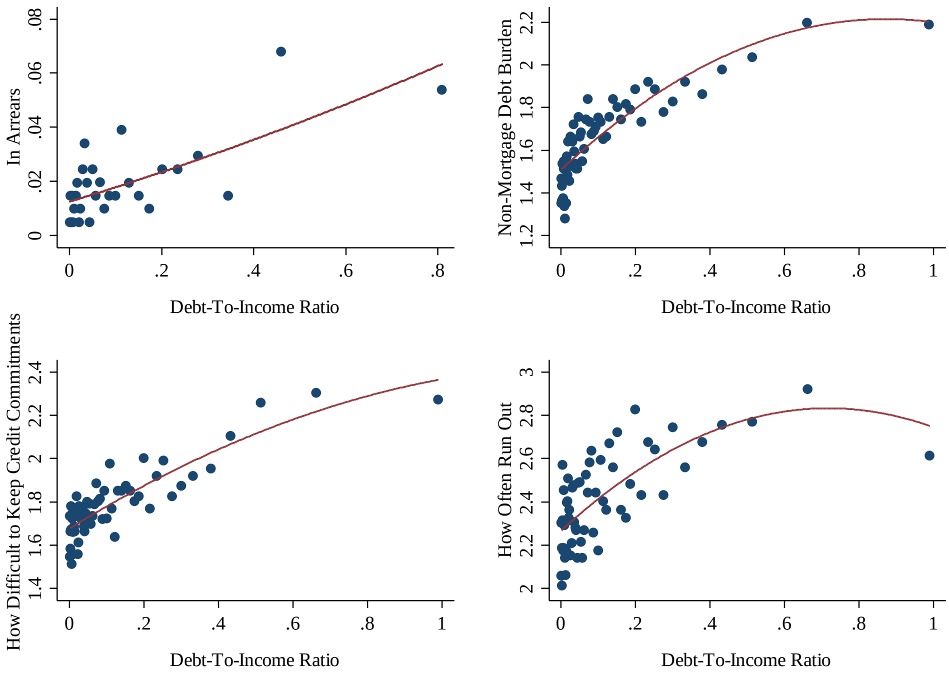
To begin the evaluation of these potential predictors we begin by plotting the cross-sectional (unconditional) relationship between these potential predictors of financial distress and the composite measure of financial distress. Figure 8 displays these scatter plots with regression lines of best fit. These figures show that the number of credit products and the total outstanding value of consumer credit debts only exhibit a weak positive relationship with financial distress. However, robustness checks displayed in Annex 2 (Figures A6:1,2) using alternative measures of financial distress find this relationship to be varied by different measures of financial distress rather than following a consistent, logical ordering.

Figure 8: Relationship between potential predictors and financial distress, waves 1 – 4



Notes: Figure shows binned scatterplots with means of the y-axis variable (measures of financial distress) plotted for 30 equally sized bins of the x-axis variable. Line of best fit is a quadratic fit through the underlying data. Sample comprises all individuals answering financial distress questions in survey waves 1 - 4.

Figure 9: Relationship between debt-to-Income (DTI) ratio (measured using household income) and financial distress, waves 1 – 4



Notes: See preceding figure.

An OLS regression model is used to estimate the relationship between potential predictors and measures of financial distress. All these regressions include the same set of other socio-economic control variables used previously in Table 8. Regressions confirm the earlier (unconditional) finding that the DTI ratio has a much stronger correlation with financial distress than other potential predictors such as the total outstanding value of debt or measures of income.

The regression results in Table 14 show that when DTI ratio is included alongside other potential predictors, the number of products held, total debts and measures of income, it is the only variable which has a statistically significant relationship with measures of financial distress. Most interestingly income is statistically insignificant controlling for the DTI ratio. The results display a higher DTI ratio is associated with greater financial distress after controlling for other observable socio-economic variables. DTI ratio has a very slightly weaker relationship with the composite measure of financial distress (OLS 1a) than the arrears measure (OLS 2a). Table A6:1 and A6:2 displays this result holds for alternative measures of financial distress calculating the DTI ratio household and individual income respectively. The exception to this is the ‘Run Out’ measure of financial distress where no statistically significant relationship is found with the DTI ratio or other potential predictors.

Table 14: OLS regressions for potential predictors of financial distress, waves 1 – 4

	OLS 1a Financial Distress	OLS 1b Financial Distress	OLS 2a Arrears	OLS 2b Arrears
DTI ratio (using household income)	0.136*** (5.18)		0.145*** (4.16)	
DTI ratio (using individual income)		0.168*** (4.15)		0.179*** (4.00)
Number of credit products held	0.0071 (1.05)	0.00467 (1.43)	0.00470 (1.67)	0.00450 (1.66)
Total value of consumer credit debt	0.00164 (0.78)	0.00216 (0.25)	0.00247 (0.37)	0.00286 (0.345)
Income / £10,000 (using household income)	-0.00516 (-0.46)		-0.00801 (-0.29)	
Income / £10,000 (using individual income)		0.00716 (1.58)		0.00416 (0.37)
Number of individuals	23,844	21,924	23,844	21,924

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummies. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Debt-to-income (DTI) ratios and financial distress

Results in the previous sub-section display the DTI ratio is stronger related with financial distress – much more so than alternative potential predictors. This sub-section analyses how this relationship varies within the distribution of DTI ratio and exploits the time dimension of the survey in order to examine whether DTI ratios at a point in time can predict future financial distress.

To estimate the ability of DTI ratios to predict future financial distress we estimate a series of fixed effects regression models. The outcome variables in these regressions are dummy variables for whether an individual is in financial distress (as measured by composite measure in FE 1 and arrears in FE 2 in Table 15 with other measures displayed in Annex 2, Figure A6:3a). The input variables of interest are the DTI ratio (using household income) one wave previous (approximately two years) and the DTI ratio two years previous (approximately four years).[18] The model also includes the full set of control variables from Table 8. The model is estimated over a sample of individuals who are present in three successive waves (i.e. waves 1-3 or 2-4) and who

[18] Contemporaneous DTI is also included in this regression. When this is excluded, lagged DTI more strongly predicts future financial distress.

have outstanding consumer credit debt in each wave (along with positive values of household income) and hence a value of the DTI ratio.

Results show the coefficient on the one-period lag DTI ratio is positive and statistically significant at the 0.1% level. The coefficient on the two-period lag DTI ratio is statistically insignificant. These results can be interpreted as a higher DTI ratio being predictive of future financial distress. There is a much weaker relationship, approximately a quarter of the size, between financial distress and prior DTI compared to when current DTI was as found in earlier results (Table 14). This is understandable given that a lot can change in an individual's circumstances over a two year period. Constructing a DTI ratio using individual rather than household income finds a stronger predictive relationship as displayed in Annex 2 (Figure A6:3b).

Table 15: Fixed effects regressions of DTI ratio against financial distress, waves 1 – 4

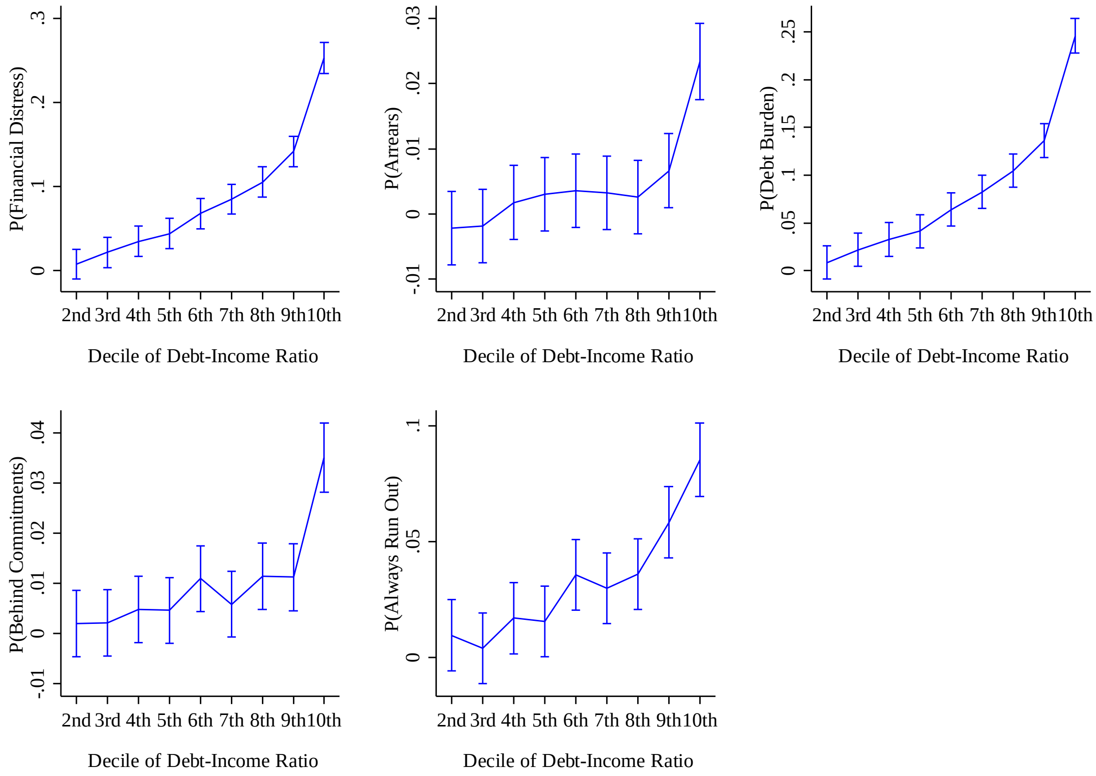
	FE 1 **Financial Distress**	**FE 2** **Arrears**
DTI ratio	0.0516^{***} (50.1)	0.0715^{***} (4.16)
DTI ratio $_{lag\_1}$	0.0431^{***} (30.6)	0.0413^{***} (2.94)
DTI ratio $_{lag\_2}$	0.0102 (0.98)	0.0302 (1.44)
Number of individuals	2,595	2,595

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. The regressions also include household income, regional dummy variables, wave dummy variables and individual fixed effects. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Next we estimate the relationship between different deciles of DTI and future financial distress to examine whether the relationship becomes more predictive (and non-linear) at points in the distribution of the DTI ratio. For this analysis we group individuals into deciles of the DTI ratio (using household income). We then estimate the relationship between the dummy variables for each of these DTI ratio deciles and future financial distress (one survey wave later). The results of this are displayed across a range of measures in Figure 10 (coefficient estimates with 95% confidence intervals) with coefficient estimates for the composite measure of financial distress in Table 16 These results show a positive relationship between financial distress and the lagged DTI ratio across different measures of financial distress. This relationship is non-linear with a noticeably stronger predictive relationship for individuals in the top decile of DTI ratio). More detailed robustness analysis is displayed in Annex 2 using different measures of financial distress and calculating the DTI ratio using individual and household income (Tables A6:5,6), repeating Figure 10 for individuals holding different product types (Figures A6:5a,b,c) and estimating the earlier regressions using 20 quantiles (rather than the 10 quantiles displayed in this section) of DTI ratio (Table A6:9).

These results demonstrate that the DTI ratio is able to predict future financial distress. It should be noted that this estimation is possible only on a subset of individuals who are present in the survey for three successive waves of data and have outstanding debt and positive household income in each wave, so the results may not generalise to all individuals. However, considering that the time lag between waves of WAS is two years, the significance of lagged DTI in predicting current financial distress is notable.

Figure 10: Regression output for deciles of lagged DTI ratio against measures of financial distress, coefficients and 95% confidence intervals, waves 1 – 4



Notes: See Annex 2, Table 6:4a for full specification of regressions. Figure A6:4 shows a similar pattern of results where DTI ratio is constructed using individual income.

Table 16: OLS regressions of deciles of DTI ratio against financial distress, waves 1–4

	OLS 1a Financial Distress		OLS 1a Financial Distress
DTI ratio decile=2	0.00742 (0.81)	DTI ratio decile =7	0.0846*** (9.25)
DTI ratio decile=3	0.0213* (2.33)	DTI ratio decile =8	0.105*** (11.46)
DTI ratio decile =4	0.0347*** (3.77)	DTI ratio decile =9	0.142*** (15.32)
DTI ratio decile =5	0.0438*** (4.80)	DTI ratio decile =10	0.253*** (26.54)
DTI ratio decile =6	0.0676*** (7.41)		
Number of individuals			23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from OLS regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummy variables. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

‘Life events’ and financial distress

In this section we analyse the relationship between shocks to household finances, known as ‘life events’, and financial distress. Such ‘life events’ may be important predictors of financial distress that are unexpected by households. If individuals with higher DTI ratios are more at risk of shocks, for example, then the estimated effect of a DTI ratio on financial distress without accounting for these may be statistically biased. Life events may also be important for understanding the relationship between credit portfolio characteristics and financial distress.

The full range of survey data allows for the construction of ‘life events’ for unemployment, income reductions, becoming divorced, becoming a parent and worsening health. One limitation of the survey data is that information is provided on the status of the respondent only at the point of interview (e.g. employment status at point of interview) and not in the period between interviews (e.g. employment history since last interview). As such we can only construct shock variables for the current status of the individual and not for shocks experienced over a period of time, which may contribute to current financial distress.

We construct the following set of ‘life event’ variables as dummy variables for: becoming unemployed since the last wave, spouse or partner becoming unemployed since the last wave, household income having fallen by 25% or more since the last wave, becoming divorced, having additional children or experiencing a reduction in health. Worsened health is recorded as individuals who report worsening health on a self-assessment health scale of 1 – 5. Not all of these events should be considered ‘shocks’ as some are choices by the household and some are predictable. However, it is likely that some share of the experiences of these changes represent shocks to individuals in the data.

Table 17 summarises the occurrence of these ‘life events’ in the panel. Between waves 1 and 2, 31% of respondents experience at least one ‘life event’ with the most common life events being an income fall and worsening health (the period between waves 1 and 2 includes the period of the onset of the Great Recession). The prevalence of ‘life events’ is one-third lower in subsequent waves, with 7-9% of individuals experiencing an income fall and around 12-13% experiencing a decline in health.

Next, we compare the frequency of ‘life events’ among those in financial distress (using our composite measure) with those not in financial distress who have outstanding consumer credit debts. Table 18 separates the sample into those not in financial distress (column 1) and those in financial distress (column 2) in waves 2 – 4 using the definition from the previous analyses. As can be seen from the table, the occurrence of ‘life events’ is higher among those in financial distress – 28% of the sample compared with 23% – with nearly all of this difference attributable to worsening health. Other life events are comparable across the two groups.

Table 17: Proportion of individuals with outstanding consumer credit debts experiencing ‘life events’, survey waves 1 – 4

	(1) Waves 1–2	(2) Waves 2–3	(3) Wave 3–4
Any ‘life event’	31%	19%	22%
Became unemployed	1%	<1%	<1%
Partner became unemployed	<1%	<1%	<1%
Income fallen by at least 25%	15%	7%	9%
Became divorced	1%	1%	1%
Became a parent	3%	2%	3%
Worsened health	16%	12%	13%
Number of individuals	6,386	6,952	6,179

Notes: This table reports individuals with outstanding consumer credit debts visible in two survey waves.

Table 18: Proportion of individuals with outstanding consumer credit debts experiencing 'life events' split by whether in financial distress, waves 1 – 4

	(1) Not in Financial Distress	(2) In Financial Distress
Any 'life event'	23%	28%
Became unemployed	<1%	1%
Partner became unemployed	<1%	1%
Income fell by at least 25%	10%	11%
Became divorced	1%	1%
Became a parent	2%	2%
Worsened health	12%	18%
Number of individuals	16,532	2,985

Notes: This table reports individuals with outstanding consumer credit debts visible in two survey waves.

To estimate the conditional effects of life events upon financial distress, Table 19 presents OLS estimates from models in which estimate how well 'life events' (measured by a range of 'life event' dummy variables) explain outcome measures of financial distress (additional measures are displayed in Annex 2, Table A6:5). The models also include the full set of covariates from Table 8, plus individual fixed effects.

Results indicate a variety of life events are important for explaining financial distress. The coefficients on the unemployment, partner unemployment, divorce and worsening health events are all statistically significant in models for at least one outcome, with significant coefficients in each case showing positive values. The coefficient on the unemployment dummy is particular large in the model for arrears – with mean arrears among those in debt at 2% the coefficient of 0.038 implies that becoming unemployed increases the likelihood of arrears by close to 200%. This is an effect which is four times larger than that arising from worsening health. The worsening health variable should be interpreted with caution as although this may be a 'life event' it may also partially be due to financial distress worsening health.

Other life events appear to have much weaker effects upon subsequent financial distress. Income falls, for example, have only small effects on the arrears and 'keeping up' outcome, though his is conditional on becoming unemployed (which is associated with reductions in both current and future income).

Table 19 OLS Regressions socio-economic characteristics and financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears
Became unemployed	-0.00204	0.0380**
	(-0.05)	(2.75)
Partner became unemployed	0.147**	0.0721***
	(2.78)	(4.43)
Income fallen 25pc	-0.00203	0.00831**
	(-0.23)	(3.09)
Became divorced	-0.00573	0.00683
	(-0.18)	(0.70)
Became a parent	-0.0234	0.000402
	(-1.38)	(0.08)
Worsened health	0.0561***	0.00901***
	(7.43)	(3.88)
R-squared	0.0404	0.0114
Number of individuals	23,844	23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (t statistics) from OLS regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummy variables. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

One implication of the significance of life events in predicting financial distress may be that life events explain the relationship between DTI ratios and financial distress. As discussed above, to the extent that DTI ratios correlate with life events, the previous model estimates which excluded life events as covariates may suffer from omitted variable bias. To explore this, Table 20 presents results from OLS models with the same set of dependent variables and covariates as those shown in Table 15 except now we also include the first lag of the DTI ratio (the DTI ratio from the previous survey wave). The sample size is substantially reduced due to a smaller number of households holding outstanding debt in both waves.

Results show that the coefficients on the lag of the DTI ratio are positive and statistically significant at the 1% level. However, compared with the model estimates in which life event controls were omitted (Table 15.), the estimates in Table 20 are much smaller in magnitude, by up to one-half of the value of the Table 14 coefficients. This indicates that while DTI remains an important predictor of future financial distress, experiencing ‘life events’, especially worsening health, also correlate with subsequent financial distress. These results are robust to using other measures of financial distress as displayed in Annex 2, Table A6:6. Including life events as lags reduces the number of observations significantly. Including these events as lags reduces the size of the relationship for some measures of financial distress, however, it remains statistically significant as shown in Annex 2, Table A6:7.

Table 20: OLS Regressions lag DTI ratio, 'life events' and financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears
DTI ratio	0.0513***	0.0495***
	(5.01)	(4.51)
DTI ratio $_{lag\ 1}$	0.0167***	0.0105**
	(5.01)	(2.16)
Became unemployed	-0.0164	-0.0322
	(-0.15)	(-0.05)
Partner became unemployed	0.164	0.107***
	(1.67)	(4.04)
Income fallen 25pc	0.00274	0.012
	(0.21)	(0.23)
Became divorced	-0.0235	0.000353
	(-0.55)	(0.02)
Became a parent	-0.0313	-0.000174
	(-1.30)	(-0.46)
Worsened health	0.0419***	0.00903*
	(3.88)	(2.75)
R-Squared	0.0773	0.0205
Number of individuals	16,857	16,857

Interaction between credit product type, DTI ratio & financial distress

For a given DTI ratio, an individual can have very different financing costs. For example, a consumer with a DTI ratio of 0.5 with debt held at an APR of 10% faces half the debt service costs of a consumer with the same level of income and debt, but with debt held at an APR of 20%. In this sense, a DTI ratio comprising higher cost debt is less sustainable than one comprising lower cost debt. Such higher financing costs may be expected to affect an individual's ability to repay and likelihood of experiencing financial distress. To explore this issue, we interact the DTI ratio, a measure of the level of debt relative to the ability to pay, with types of credit product, to approximate for the differing debt-service costs of types of credit product (the survey does not include cost information on different consumer credit debts held).

To implement the analysis, we segment our sample into non-mutually exclusive groups by the type of debt items held in their portfolio. We formulate three groups. The first group comprises all individuals with debt. The second group comprises all individuals with the majority of their debt held as a personal loan debt (which is typically the cheapest form of consumer credit debt). The third group comprises all individuals with the majority of the debt held as high cost debt (where high-cost credit products are defined as : pawnbroker loans, home credit, payday loans and, mail order catalogue accounts). The regression model, which is based on the models shown in Table 20, then includes the non-interacted DTI ratio, the DTI ratio interacted with a dummy for individuals in the personal loan group and the DTI ratio interacted with a dummy for individuals in the high cost group.

Results presented in Table 21 indicate that non-interacted DTI term and the interaction terms are all statistically significant at the 0.1% level in regressions for each of the financial distress outcomes (additional measures of financial distress are displayed in Annex 2, Table A6:8). The coefficients on the personal loan interactions are negative in all specifications, whereas the coefficients on the high-cost debt interactions are positive in all interactions.

The magnitude of the coefficients indicate difference in credit portfolio costs have large mediating effects on the relationship between DTI ratios and financial distress. The personal loan interaction coefficients are between half to two-thirds the magnitude of the non-interaction coefficients, indicating that, for a given DTI ratio value, personal loan dominated portfolios are much less likely to result in financial distress. The interaction terms on the high cost dummy indicate that for a given DTI ratio, higher-cost credit dominated portfolios are between one-and-a-half to two times more likely to result in financial distress.

Taken together, therefore, results indicate that lags of the DTI ratio are important predictors of future financial distress. This is true controlling for life events and other time-varying coefficients, and to the inclusion of individual fixed effects. Moreover, the likelihood that a given level of DTI ratio results in subsequent financial distress is dependent on the cost of the portfolio of debt held by the consumer. Therefore there are important interaction effects between debt levels (relative to income) and debt gearing (relative to income).

Table 21 OLS regressions of interactions between DTI ratio and credit product types against measures of financial distress, waves 1 – 4

	OLS 1	**OLS 2**
	Financial Distress	**Arrears**
Lag DTI ratio	0.580***	0.0692***
	(21.08)	(12.96)
Lag DTI * Personal loan	-0.315***	-0.0558***
	(-12.06)	(-8.81)
Lag DTI * High cost	0.469***	0.311***
	(21.46)	(12.79)
Number of individuals	13,844	13,844

Notes: indicates interaction between Lag DTI and credit product type.

7. Conclusions

This research provides a detailed description of individuals using consumer credit products which will be useful in informing the FCA's regulation of this market. This analysis displays the distribution of consumer credit debts and the variety of individuals and products in this market.

The nature of lending in the real-world, which is full of uncertainty will inevitably mean there will be some individuals who miss payments due, and this can be expected to fluctuate over the course of the economic cycle. Our analysis finds there are a group of individuals who use consumer credit who experience moderate or severe financial distress beyond a narrow, objective definition based on arrears. It should be noted this research does not examine whether the consumer credit sector is functioning competitively in the sense of the cost of credit being efficiently priced and individual consumers effectively selecting products most suitable for their needs.

We find strong, though non-causal, evidence that individuals in financial distress experience lower average life satisfaction, higher anxiety. These individuals are typically younger, less likely to be employed are also more likely to hold higher-cost credit items.

One of the key aspects of this research is whether financial distress can be predicted in order to be informative for lenders' assessments of an individual's ability to borrow affordably. Our analysis shows that debt-to-income (DTI) ratios can be a strong predictor of future financial distress whereas other potential predictors, such as total outstanding debts and measures of income, do not improve the ability to predict financial distress.

We also find that individuals at the top of the distribution of DTI ratio, the top decile, are much more likely to suffer financial distress in the future than those with lower DTI ratios. It is possible that other measures available to lenders but not observable in this survey may fulfil a similar (and potentially be more efficient) predictors of future financial distress. It should also be noted that socio-economic characteristics and 'life events' can help to explain future financial distress.

We observe important interactive effects between the DTI ratio and the composition of consumer credit debts at predicting future financial distress. In particular, consumers with debts dominated by higher-cost credit products are at significantly higher risk of experiencing financial distress than those with lower cost credit products.

The ability to predict financial distress is important in the context of lending decisions by firms. There appears to be a role for interventions, such as debt management plans and insolvency arrangements, to deal with financial distress arising from the inability to predict the exact individual who will suffer financial distress without encouraging moral hazard. Such unpredictable financial distress may arise from unpredictable shocks to individual circumstances such as 'life events' or macroeconomic shocks.

While firms cannot estimate which exact individual will suffer financial distress in the future, it appears possible to consider, on average, whether cohorts of individuals with a set of characteristics are especially vulnerable to future financial distress and therefore whether lending to them may be predictably unaffordable. Our research suggests that affordability policies should be tailored to the products that people apply for and to applicants' circumstances, especially their DTI ratio.

Annex 1: Details of the Wealth and Assets Survey (WAS)

Choice of microdata

The analysis presented in this paper is based on microdata at the individual level. Microdata is crucial for understanding the uneven distribution of debt and financial distress across the population. Aggregate data measures of the total amount of household debt are available for Great Britain and are regularly published by the Bank of England. However, the aggregate level of debt in the economy is not insightful towards understanding the distribution of unaffordable debt and financial distress. For example, aggregate indebtedness may be concentrated among a small subset of households, or alternatively thinly spread across a broad spectrum of households.

While it is possible to construct an aggregate DTI ratio for the economy as a whole, this is also unlikely to be useful for understanding the level of unaffordable debt. For example, growth in income and growth in debt may be concentrated among different groups of households. An aggregate ratio masks this heterogeneity across household types. As shown below, household debt is highly concentrated among a subset of households, so aggregate data is not appropriate for this analysis.

Various different microdata sources are available covering household indebtedness in Great Britain, including administrative data held by Credit Reference Agencies, datasets held by bank and debt charities and survey data administered through official surveys and/or by market research organisations. Here we briefly consider the merits and drawbacks of different sources of microdata before explaining the choice of the Wealth and Assets Survey for this study

In the United Kingdom Credit Reference Agencies (CRA) hold administrative data at the individual level in the form of ‘credit files’. Credit files contain records of usage of consumer credit, mortgage and other credit items involving credit agreements (such as mobile telephone contracts and some insurance contracts). Credit files are very detailed, typically providing monthly records for each credit items for up to six years.

The principle advantage of CRA credit files is that the data is objectively verifiable by banks and credit providers who submit the data to the CRA. Credit file data is therefore not subject to the types of consumer reporting biases that may arise due to under-reporting and mis-reporting in survey data. However, CRA credit files also have certain limitations. In the United Kingdom context, there are multiple CRAs with individual banks and credit providers reporting to only a subset of all CRAs. Hence credit files from individual CRAs may be incomplete records.

Microdatasets of individual and household indebtedness are also held by banks, credit providers and third-sector organisations including debt charities. These datasets can contain very detailed information on particular credit products – for example a dataset held by a credit card provider will include information on each individual transaction undertaken on a credit card. This data is highly detailed but necessarily restrictive to one particular type of credit product or relationship between an individual and their main bank, and do not allow researchers to gain a view of the broader financial situation of the individual or household.

Third-sector organisation datasets, such as those held by debt charities including Stepchange and Citizen’s Advice are a valuable source of individual data that combine records on the full range of individual credit and debt obligations (together with information on assets and income) as well as information on life-events and experiences. However, such datasets necessarily comprise selected samples of individuals in debt who have chosen to use the services offered by the debt charity or organisation. Datasets from such selected samples are therefore not appropriate for drawing reliable inferences about the dynamics of debt and financial distress in the population.

Survey data, which is used for this study, has a number of advantages over administrative data and data held in commercial or third sector datasets. A first key advantage is that samples can be constructed that are representative of the population of interest and, subject to sample sign and sampling design, samples can be used to draw inference to the population-level. A second key advantage is that the scope of a survey can be extremely broad, incorporating questions on credit and debt usage but also labour market participation and experience, health and wellbeing and other outcomes of interest.

There are two main disadvantages to using survey data. The first is that respondents may systematically under-report or mis-report in a non-random fashion. For example, one might expect survey respondents to under-report their level of debt and extent of debt problems due to social stigma effects (even in settings where a survey dataset is constructed to be anonymous). A recent study by the New York Federal Reserve (Brown et al, 2015) in which researchers matched data provided by survey respondents to objective data shows that the level of under-reporting of debt is very low in a sample of US households, however, may be larger for unsecured debts such as credit cards compared to secured debts.

A second disadvantage of survey data is that there is typically a lengthy time delay between the collection of survey data and the release of data for research. This is particularly the case with large scale, official surveys that are extensively cleaned and subject to data imputation before general release. On balance, the most appropriate form of microdata for this particular piece of research is survey data, which allows analysis of a representative sample of individuals incorporating a broad range of outcomes for analysis.

Overview of the Wealth and Assets Survey (WAS)

Multiple official and unofficial surveys are available for the United Kingdom that incorporates data on credit and debt. Official surveys are those used to contribute to the calculation of national statistics by the Office for National Statistics. Among the large government-funded surveys are WAS, Understanding Society (USoc) and the Family and Children Study (FACS). FACS contains the most detailed information on credit and debt (the Family Resources Survey contains information on student debt only and The Family Expenditure Survey contains information on interest servicing costs only). Bridges et al (2008) use FACS and the British Household Panel Survey (the forerunner of USoc) to analyse drivers of over-indebtedness in Great Britain.

WAS, USoc and FACS are each panel surveys which run through multiple waves. For analysis of credit and debt, the data coverage in USoc is the least comprehensive, though USoc incorporates a broad range of measure of life-satisfaction, wellbeing and mental health which may be important outcomes related to financial distress. FACS contains very detailed information on debt and debt payments (the most detailed of any official data), but is limited in coverage to households with families containing dependent children and the data sample ends in 2008. WAS contains detailed information on credit and debt, draws a representative sample of households and currently runs through four waves of panel data.

An alternative source of survey data would be smaller-scale commissioned survey data such as the YouGov Debt Tracker panel or Bank of England / NMG survey. These surveys are specialised in topics relating to credit and debt and the data typically becomes available faster than that from official surveys. However, the sample sizes of these survey are much smaller (a few thousand respondents compared with 10,000+ respondents for the larger official surveys) and so their usefulness for examining the concentration and credit and debt in the population is limited.

WAS is a longitudinal (panel) survey of households in Great Britain which began with Wave 1 in July 2006. Wave 1 comprised interviews with 53,300 adult respondents (aged 16 or over) across 30,500 British households. Due to the sample size and length of interview (90 minutes per respondent, on average) respondents were interviewed over a two-year period. Each household was then re-interviewed two years after the wave 1 interview. The most recent wave, wave 4, covers the period July 2012 – June 2014.

WAS is designed to be representative of households in Great Britain. A representative sample is achieved by applying a probability proportional to size method of sampling cases, which are stratified from the Postcode Address File in 2 x 13 address clusters within each postcode sector. Due to the highly skewed distribution of household wealth and higher non-response among wealthier households, high-wealth households were over-sampled from wave 1 onwards (a high wealth household was 2.5 times more likely to be sampled compared with other households in wave 1). The wave 1 response rate was 55%, which increased to 68% for wave 2 and 73% for wave 3. Throughout the analysis which follows sample weights are applied to compensate for the different probabilities of response across household types.

WAS comprises two components. The first is a ‘household-level’ interview questions set which is asked of the household reference person (household ‘head’) only and asks about household-level information such as details of household members, housing and mortgage details. The second is a ‘person-level’ interview questions set which is asked of each adult (aged over 16) member of the household and covers person specific details, including the person-specific assets and debts of each member of the household.

Major topics covered in WAS include households assets – in particular personal and private pension coverage, financial and non-financial assets and housing wealth, and household debts including mortgage and non-mortgage debts. WAS also includes information on personal insolvency, including bankruptcy filings. Data on household wealth is used to inform the official wealth estimates produced by the ONS in its publication ‘Wealth in Great Britain’[19].

Consumer credit data in WAS

Information on consumer credit and debt is collected within the person interview of WAS. Each adult respondent is asked a series of questions relating to revolving credit (credit cards and store cards) and instalment credit (e.g. personal loans). First, detailed questions are asked about credit and store cards. Respondents are asked about i) the number of cards they hold, ii) their most recent repayment (in full, partial, not applicable i.e. no balance), iii) whether the card is singly or jointly held, iv) starting balance, payment and ending balance in the most recent month and debt outstanding on the card. This question cycle is repeated for up to five credit cards and five store cards, with values for cards numbering over five aggregated into a single set of extra responses.

Second, respondents are asked about a series of instalment credit items comprising mail order catalogues, hire purchase agreements, personal loans, home collected credit (‘cash loans’), pawnbroker loans, payday loans, the respondent’s employer and loans from ‘friends, relatives or others’. In each case the respondent is asked to state whether the loan s active, the outstanding balance and the level of instalment payment. The question cycle is again repeated for up to five items of each credit type.

For tractability, information is aggregated to the product type level and person-level aggregates are calculated in each wave of data. For example, for each respondent to the survey, the number

[19] http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/was/wealth-in-great-britain-wave-4/2012-2014/index.html

of credit cards held by the individual and the current balance and minimum payment across all cards is calculated. Further details of how are the data is used are provided in the next chapter.

Measures of financial distress in WAS

WAS provides measures of financial distress that can be classified into objective and subjective measures. Objective measures are based on objective definitions of a financial situation (e.g. behind on repayments) whereas subjective measures are based on subjective reports of the severity of a financial situation (e.g. ‘how far behind are you?’ type questions). Due to the fact that all survey data in WAS is self-reported, the distinction between objective and subjective measures refers to the inherent objectivity of the definition of financial distress and not its interpretation by the survey respondent.

The objective measures of financial distress relates to whether the respondent is behind with contractual repayments on their credit and debt items. For each credit and debt item the respondent is asked whether they are two or more payments behind. For credit and store cards the question refers to being two or more minimum payments behind. For other forms of credit the question refers to being two or more instalments behind. Respondents are also asked to provide the value of arrears on their account (or the value of minimum payments by which they are in arrears in the case of credit and store cards).

The subjective measures of financial distress are based upon a series of Likert-scale response questions relating to the burden of credit and debt and the ability of the respondent to meet repayments. The first question, which is labelled here as the ‘debt burden’ question is:

‘*Thinking about the [name consumer debts] you have just told me about, to what extent is keeping up with the repayment of them and any interest payments a financial burden to you? Would you say it was:*

A heavy burden

Somewhat of a burden

Or, not a problem at all?

This question is asked to all respondents with at least one consumer debt, and refers specifically to the debt types the respondent stated they held (which are inserted into the [ ] clause within the question). A separate question in the survey relates to the burden of mortgage debt. The second question, which is labelled here as the ‘keeping up’ question, is:

‘Which one of the following statements best describes how well you are keeping up with your bills and credit commitments at the moment? Are you:

Keeping up with all of them without any difficulties;

Keeping up with all of them, but it is a struggle from time to time;

Keeping up with all of them, but it is a constant struggle;

Falling behind with some of them;

Having real financial problems and have fallen behind with many of them;

Don't have any commitments’

This question is asked to all respondents in the survey (whether or not they report holding any consumer credit products or balances) and refers to ‘keeping up’ with repayments on ‘bills’ as well as credit commitments. Hence this question may capture responses from respondents with their broader financial situation in mind than that specifically related to consumer credit and debt. The third question, which is labelled her as the 'run out' question is:

In the past 12 months, how often have you run out of money before the end of the week or month or needed to use a credit card or overdraft to get by? Would you say it was ...

Always,

Most of the time,

Sometimes,

Hardly ever,

Or, never?'

This question is also asked to all respondents in the survey. The question refers to the respondent's general experience of money management, not just management consumer credit, and asks about any experiences of running out of money over the past 12 months.

Measures of well-being in WAS

Alongside the measures of financial distress, WAS has also incorporated measures of subjective wellbeing (SWB). SWB measures can be particularly insightful for measuring the effects of economic circumstances on a range of outcomes as they have been shown to be robust measures of welfare in a variety of domains. WAS incorporates three questions on SWB from the end part of wave 3 onwards. The SWB questions are:

Life satisfaction:'Overall, how satisfied are you with your life nowadays?

	Where nought is "not at all satisfied "and 10 is" completely satisfied"'
Worthwhile:	*Overall, to what extent do you feel that the things you do in your life are worthwhile?*
	Where nought is "not at all worthwhile" and 10 is "completely worthwhile"
Happy:	*'Overall, how happy did you feel yesterday?*
	Where nought is" not at all happy" and 10 is "completely happy"
Anxious:	*On a scale where nought is "not at all anxious" and 10 is "completely anxious", overall, how anxious did you feel yesterday?*

Data collection and survey response rates in WAS

This annex provides additional information on data collection methods and survey response rates in WAS. The information here can also be found in Chapter 8: wealth and Assets Technical Details, 2012-2014.[20]

WAS interviews take place two years after the previous wave, and generally within the same calendar month. Interviewers were given an allocation of addresses on a monthly basis and were instructed to make contact and gain an interview at all of these addresses using best practice in terms of varying calling times and days. Where it was not possible to attempt contact within the month, addresses were carried forward for reissue in the following month.

[20] http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/guide-method/method-quality/specific/economy/wealth-and-assets-survey/chapter-8--wealth-and-assets-technical-details--2012-to-2014.pdf

Where information was unlikely to have changed, or earlier responses were likely to provide a useful aide memoire, answers from the previous wave were rolled forward and made available, in the computer assisted interviewing programme to the interviewer during the interviewing process. For instance, the type of tenure of the household's accommodation from wave 1 would be available to the interviewer at wave 2. However, value information, such as the value of the property, was not rolled forward.

The wave 2 questionnaire covered the same topics as wave 1, however as a result of the longitudinal nature of the survey and specifically the experience gained during wave 1, it was slightly longer. The flow of questions was also improved, the types and nomenclature of some assets and debts were changed, and certain new requirements of stakeholders were included. The content of the wave 4 questionnaire was broadly comparable with wave 3. Improvements were made to the conditional routing of some questions, but generally questions were unchanged so as to preserve consistency in data collection over time.

Questionnaire changes made between waves were tested both cognitively and via a quantative pilot. This ensured the new questions were both likely to be understood by respondents and were suitable for collecting the information needed.

The mean interview length varied for each wave of the survey. The wave 1 mean interview length was 79 minutes; wave 2 was 85 minutes, wave 3 was 82 minutes and wave 4 72 minutes.

An initial sample of 62,800 addresses were selected and sampled at wave 1. Of these, 30,511 took part in the survey, or 55% of the eligible sample. Approximately 10% of sampled addresses were found to be ineligible, and were therefore not interviewed at e.g. non-residential addresses.

For wave 2, the cooperating wave 1 households, along with non-contacts and circumstantial refusals from wave 1 were issued for a wave 2 follow up interview. The eligible sample for wave 2 of the survey was 29,341 households and of these 19,925 either fully or partially responded, giving a household response rate of 68%. This figure is not comparable with the household response rate of 55% achieved in wave 1 since the wave 2 figure is calculated as a proportion of the sample brought forward from wave 1. As a proportion of the original wave 1 sample, the response rate is 36%, which illustrates both the scale of non-response at wave 1 and subsequent attrition between waves 1 and 2. Thus, of the eligible households in wave 2, an interview was achieved with over two-thirds while no interview took place with just under one-third. The non-contact rate at wave 2 (9%) was slightly above that observed at wave 1 (7%). However, the refusal rate was considerably higher in wave 1 than in wave 2, in part because hard refusals from wave 1 were not followed up for wave 2.

For wave 3, cooperating households, non-contacts and circumstantial refusals from wave 2 were followed up. In addition, a new panel of households was selected for wave 3 in order to achieve a target of at least 20,000 household interviews. These new panel cases are included in the total figures for wave 3 in Table 1. The wave 3 response rate was 64%; 51% for the new cohort and 72% for the old cohort.

For wave 4, cooperating households, non-contacts and circumstantial refusals from wave 3 were followed up. In addition, a new panel of households was selected for wave 4 in order to achieve a target of at least 20,000 household interviews. These new panel cases are included in the total figures for wave 4 in Table 1. The wave 4 response rate was 66%; 53% for the new cohort and 70% for the old cohort.

Annex 2: Additional tables and figures

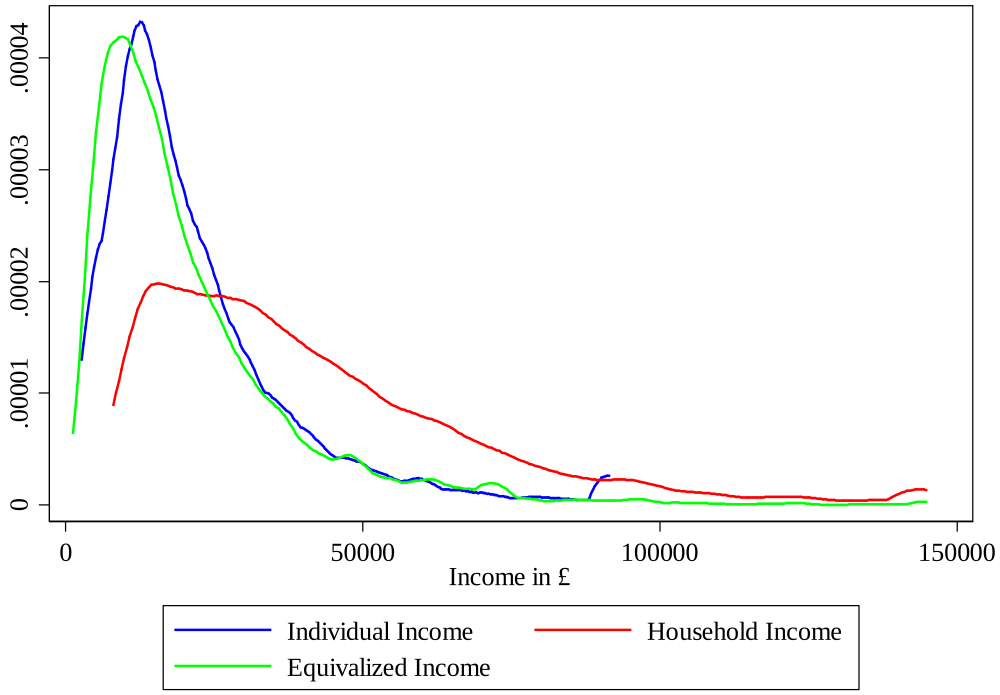
Comparison of measures of income

Table A1:1 Distribution of alternative measures of gross annual income in survey wave 4

	Mean	Minimum	Percentile			Maximum
			25th	50th	75th	
Individual	£21,900	£2,700	£11,100	£17,200	£27,500	£91,400
Equivalised household	£21,000	£1,300	£9,300	£15,600	£26,500	£140,900
Household net of mortgage repayment	£17,200	£6,200	£14,700	£28,800	£46,900	£140,900
Household	£41,400	£8,000	£21,000	£34,700	£54,000	£144,900

Notes: The sample sizes are 19,154 for individual income, 23,913 for household income and 19.170 for household income net of mortgage service cost.

Figure A1:1 Distribution of individual, household and equivalised household income, survey wave 4



Notes: See previous table.

Figure A1:2 Scatterplot of individual income compared with household income, survey waves 1-4

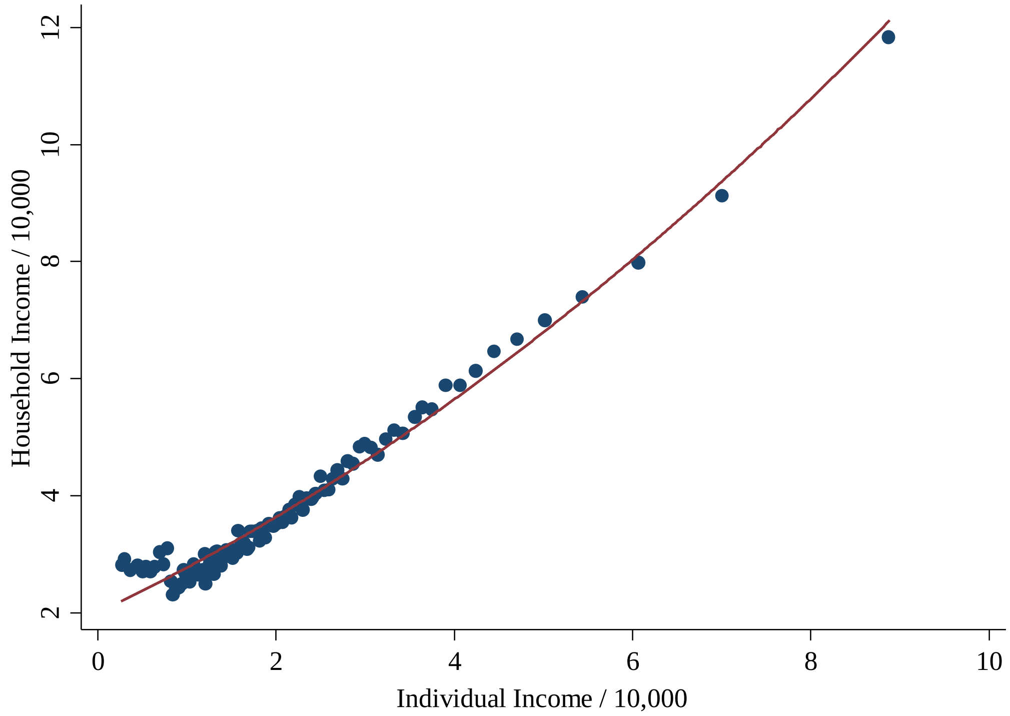
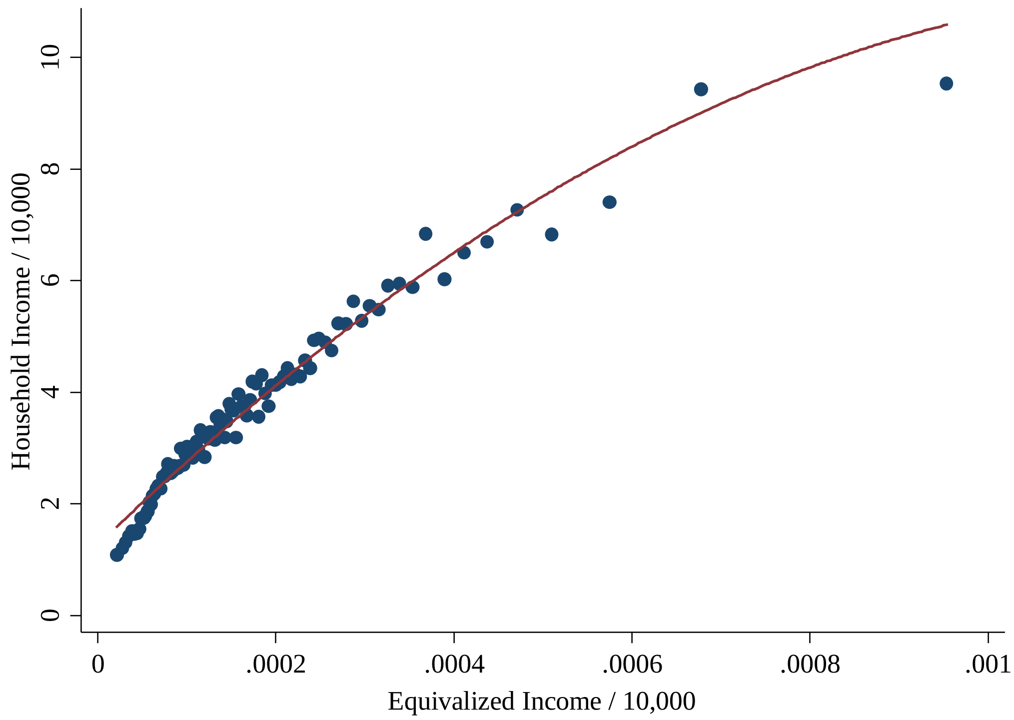


Figure A1:3 Scatterplot of household income compared with equivalised household income, survey waves 1-4



Socio-economic summary statistics

Table A2:1 Percent of individuals with socio-economic characteristics split by type of use of consumer credit products, waves 1–4

	(1) Whole sample	(2) Has credit product	(3) Has credit product with outstanding debt	(4) In arrears on credit product with outstanding debt
Age				
16-24	14%	4%	6%	10%
25-34	17%	12%	21%	26%
35-44	16%	23%	30%	28%
45-54	15%	27%	26%	26%
55-64	12%	25%	14%	9%
Over 65	26%	9%	3%	1%
Demographics				
Male	51%	50%	50%	44%
Married / co-habiting	51%	81%	74%	58%
Divorced / separated	4%	5%	9%	16%
Has children	71%	65%	56%	50%
Average number of children	0.82	0.64	0.81	1.01
Employment				
Employed (full-time or part-time)	47%	64%	73%	59%
Self-employed	11%	16%	18%	24%
Unemployed	3%	1%	1%	8%
Education				
Degree education	13%	38%	26%	14%
A-level education	47%	48%	59%	66%
Home ownership				
Home owner	24%	38%	12%	6%
Outright home owner	21%	24%	9%	2%

Mortgage home owner	49%	53%	66%	40%
Income				
Average household income	£34,649	£43,148	£37,313	£24,054
Below median household income (£32,100)	58%	43%	50%	78%
Household income share				
1st Quintile (Under £17,400)	25%	17%	18%	46%
2nd Quintile	23%	17%	21%	22%
3rd Quintile	20%	19%	22%	17%
4th Quintile	17%	22%	22%	9%
5th Quintile (Over £54,600)	16%	26%	18%	5%
Number of individuals	107,359	70,367	30,037	512
Percent of total individuals	100%	65.5%	34.7%	0.005%

Table A2:2 Percent of individuals with socio-economic characteristics split by category of consumer credit product used, waves 1–4

	(1) Has Revolving Credit	(2) Has Personal Loan	(3) Has High Cost Credit
Age			
16-24	5%	7%	11%
25-34	22%	20%	27%
35-44	31%	29%	25%
45-54	26%	27%	28%
55-64	13%	15%	8%
Over 65	2%	3%	1%
Demographics			
Male	50%	57%	41%
Married / co-habiting	74%	77%	63%
Divorced / separated	9%	8%	14%
Has children	55%	55%	49%
Average number of children	0.82	0.81	1.05
Employment			
Employed	74%	0.72	65%
Unemployed	1%	0.01	4%
Education			
Degree education	27%	28%	9%
A-level education	59%	58%	64%
Homeownership			
Home owner	10%	15%	7%
Mortgaged owner	70%	66%	27%
Income			
Average household income	£37,041	£40,174	£23,766
Below median household income (£32,100)	50%	45%	79%
Number of individuals	21,198	10,105	574

Table A2:3 Percent of individuals with socio-economic characteristics split by more granular type of consumer credit product used, waves 1–4

	(1) Credit card debt	(2) Store card debt	(4) Personal loan debt	(3) Mail order debt	(5) Informal loan debt
Age					
16-24	5%	7%	7%	7%	17%
25-34	22%	22%	20%	21%	38%
35-44	31%	33%	29%	31%	28%
45-54	27%	24%	27%	25%	13%
55-64	13%	11%	15%	13%	4%
Over 65	2%	2%	3%	3%	1%
Demographics					
Male	52%	24%	0.57%	19%	52%
Married / co-habiting	74%	74%	0.77%	74%	62%
Divorced / separated	10%	10%	0.08%	10%	7%
Has children	55%	46%	0.55%	49%	58%
Number of children	0.81	1.01	0.81	0.98	0.83
Employment					
Employed	74%	76%	0.72%	71%	73%
Unemployed	1%	1%	0.01%	2%	1%
Education					
Degree education	28%	20%	28%	11%	34%
A-level education	59%	66%	58%	69%	54%
Homeownership					
Home owner	10%	10%	15%	10%	11%
Mortgaged owner	70%	66%	66%	53%	58%
Income					
Average household income	£37,235	£34,064	£40,174	£28,997	£34,514
Below median household income (£32,100)	49%	55%	67%	45%	56%
Number of individuals	19,814	3,025	10,105	3,865	849

Socio-economic summary statistics by DTI ratio

Table A3:1 Percent of individuals with socio-economic characteristics split by decile of DTI ratio using household income, waves 1–4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Debts										
Total debt (£)	110	320	640	1,070	1,730	2,570	3,690	5,420	7,850	11,620
Share of total debt	<1%	1%	2%	3%	5%	7%	11%	15%	22%	33%
DTI ratios within deciles										
Min	0%	<1%	1%	2%	3%	5%	8%	12%	18%	31%
Median	<1%	1%	2%	3%	4%	7%	10%	15%	24%	45%
Max	<1%	1%	2%	3%	5%	8%	12%	18%	31%	111%
Mean	<1%	1%	2%	3%	4%	7%	10%	15%	24%	53%
Age										
16-24	11%	10%	7%	7%	6%	6%	5%	5%	4%	3%
25-34	20%	22%	22%	22%	23%	21%	21%	20%	21%	19%
35-44	28%	27%	29%	29%	30%	29%	30%	32%	31%	30%
45-54	25%	25%	26%	25%	26%	28%	27%	27%	27%	25%
55-64	13%	14%	14%	14%	14%	13%	15%	14%	15%	18%
Over 65	2%	2%	2%	3%	2%	2%	2%	3%	3%	5%
Demographics										
Male	35%	41%	46%	49%	50%	52%	50%	55%	58%	58%
Married / co-habiting	75%	71%	77%	75%	77%	75%	75%	75%	72%	67%
Divorced / separated	6%	8%	7%	8%	8%	9%	9%	10%	11%	14%
Number of children	0.79	0.77	0.86	0.79	0.81	0.80	0.83	0.84	0.88	0.82
Employment										
Employed	73%	74%	73%	73%	74%	76%	74%	74%	71%	66%
Self-employed	7%	6%	8%	8%	8%	8%	9%	11%	12%	15%

Unemployed	1%	1%	1%	2%	1%	1%	1%	1%	1%	2%
Education										
Degree education	24%	25%	26%	26%	27%	27%	28%	27%	27%	23%
A-level education	60%	59%	60%	58%	58%	59%	60%	59%	59%	62%
Homeowner ship										
Home owner	14%	13%	12%	13%	12%	12%	12%	11%	11%	14%
Mortgaged owner	67%	64%	65%	64%	67%	68%	67%	68%	68%	62%
Income										
Household income (£1,000s)	44.1	39.8	39.9	38.8	39.6	38.6	37.0	36.2	33.2	23.6
Number of individuals	3,028	3,027	3,027	3,027	3,027	3,027	3,028	3,026	3,027	3,027

Table A3:2 Shares of consumer credit debts in product types by decile of DTI ratio constructed from household income, waves 1–4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Credit card	41%	55%	60%	63%	64%	64%	60%	56%	52%	50%
Store card	14%	11%	7%	4%	3%	2%	2%	1%	1%	1%
Personal loan	12%	16%	20%	22%	25%	27%	32%	37%	42%	44%
Mail order catalogue	31%	15%	10%	7%	5%	4%	2%	2%	1%	1%
Pawnbroker	<1%	<1%	1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%
Payday loan	<1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%	<1%
Informal loan	1%	2%	2%	2%	2%	2%	2%	2%	3%	6%
Number of individuals	3,028	3,027	3,027	3,027	3,027	3,027	3,028	3,026	3,027	3,027

Summary statistics on measures of financial distress

Table A4:1 Distribution of measures of financial distress, wave 4

	Mean	Standard deviation	50^{th} percentile
Arrears (binary variable)	0.019	0.138	0.000
Burden (scale 1-3)	1.667	0.738	2.000
Keeping Up (scale 1-5)	1.792	0.862	2.000
Run Out (scale 1-5)	2.412	1.389	2.000
Number of individuals	6,179		

Notes: All individuals with outstanding consumer credit debt in wave 4.

Table A4:2 Correlation matrix of measures of financial distress, wave 4

	Arrears	Heavy burden ('Burden' measure)	Behind on some or real problems ('Keeping Up' measure)	Constantly behind, behind on some or real problems ('Keeping Up' measure)	Run out of money most of the time or always ('Run Out' measure)
Arrears	1.00				
Heavy burden	0.17	1.00			
Behind on some or real problems	0.19	0.28	1.00		
Constantly behind, behind on some or real problems	0.68	0.48	n/a	1.00	
Run out of money most of the time or always	0.11	0.30	0.19	0.58	1.00
Number of individuals	6,179				

Notes: All individuals with outstanding consumer credit debt in survey wave 4.

Regressions of well-being against measures of financial distress

Table A5:1 OLS regressions for life satisfaction against measures of financial distress

	Life-satisfaction (scale 0-10)				
	OLS 2	**OLS 3**	**OLS 4**	**OLS 5**	**OLS 6**
Arrears	-1.523^{***} (-7.25)				-0.546^{**} (-2.67)
Heavy burden ['Burden' measure]		-0.617^{***} (-19.40)			-0.290^{***} (-7.20)
Behind on some or real problems ['Keeping Up' measure]			-0.638^{***} (-22.36)		-0.430^{***} (-11.07)
Run out of money most of the time or always ['Run Out' measure]				-0.232^{***} (-13.68)	-0.0321 (-1.65)
Number of individuals	4,898	4,877	4,868	4,874	4,838

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001.*

Table A5:2 OLS regressions for life satisfaction (dichotomised at 75th percentile) against measures of financial distress

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Arrears	-0.118^{*} (-2.11)				0.0511 (0.91)
Burden		-0.0867^{***} (-13.51)			-0.0394^{***} (-4.84)
Keeping Up			-0.0914^{***} (-18.55)		-0.0646^{***} (-8.73)
Run Out				-0.0336^{***} (-11.67)	-0.00573 (-1.50)
Number of observations	16,726	13,387	16,348	16,637	13,171

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Life satisfaction as a binary variable.*

Table A5:3 Probit Regressions for life satisfaction (dichotomised at 75th percentile) against measures of financial distress

	(1)	(2)	(3)	(4)	(5)
Arrears	-0.562*				-0.000463
	(-2.35)				(-0.00)
Burden		-0.336***			-0.157***
		(-14.09)			(-5.34)
Keeping Up			-0.364***		-0.265***
			(-19.12)		(-9.73)
Run Out				-0.121***	-0.0189
				(-12.01)	(-1.42)
Number of observations	16,726	13,387	16,348	16,637	13,171

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Life satisfaction as a binary variable.*

Table A5:4 Poisson (count) models for life satisfaction (dichotomised at 75th percentile) against measures of financial distress

	(1)	(2)	(3)	(4)	(5)
Arrears	-0.253***				-0.0997
	(-4.58)				(-1.78)
Burden		-0.0811***			-0.0315***
		(-14.13)			(-4.36)
Keeping Up			-0.0883***		-0.0659***
			(-19.73)		(-9.93)
Run Out				-0.0323***	-0.00554
				(-12.69)	(-1.65)
Number of observations	16,726	13,387	16,348	16,637	13,171

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Life satisfaction as a binary variable.*

Table A5:5 OLS regressions for anxiety against measures of financial distress

	Anxiety (scale 0-10)					
	OLS 1	**OLS 2**	**OLS 3**	**OLS 4**	**OLS 5**	**OLS 6**
Arrears		1.386***				0.296
		(3.76)				(0.80)
Heavy burden ['Burden' measure]			0.662***			0.265***
			(11.52)			(3.60)
Behind on some or real problems ['Keeping Up' measure]				0.699***		0.445***
				(13.47)		(6.27)
Run out of money most of the time or always ['Run Out' measure]					0.312***	0.114**
					(10.35)	(3.19)
Number of individuals	4,898	4898	4877	4868	4874	4838

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001.*

Table A5:6 OLS Regressions for anxiety (dichotomised at 75th percentile) against measures of financial distress

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Arrears	0.179***				0.0397
	(3.57)				(0.78)
Burden		0.0666***			0.0248***
		(11.38)			(3.35)
Keeping Up			0.0706***		0.0534***
			(15.83)		(7.91)
Run Out				0.0290***	0.00722*
				(11.13)	(2.07)
Number of observations	16,718	13,385	16,343	16,631	13,169

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Life satisfaction as a binary variable.*

Table A5:7 Probit regressions for anxiety (dichotomised at 75th percentile) against measures of financial distress

	(1)	(2)	(3)	(4)	(5)
Arrears	0.542**				0.0665
	(3.24)				(0.38)
Burden		0.229***			0.0847**
		(10.86)			(3.13)
Keeping Up			0.243***		0.181***
			(14.99)		(7.36)
Run Out				0.102***	0.0260*
				(10.72)	(2.02)
Number of observations	16,718	13,385	16,343	16,631	13,169

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Anxiety as a binary variable.*

Table A5:8 Poisson (count) models for anxiety (dichotomised at 75th percentile) against measures of financial distress

	(1)	(2)	(3)	(4)	(5)
Arrears	0.435***				0.0220
	(7.04)				(0.35)
Burden		0.195***			0.0632***
		(23.47)			(5.86)
Keeping Up			0.206***		0.137***
			(32.79)		(14.17)
Run Out				0.101***	0.0415***
				(26.77)	(8.14)
Number of observations	16,718	13,385	16,343	16,631	13,169

*Notes: t statistics in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Anxiety as a binary variable.*

Relationships between measures of financial distress and potential predictors

Figure A6:1: Relationship between number of credit products and measures of financial distress

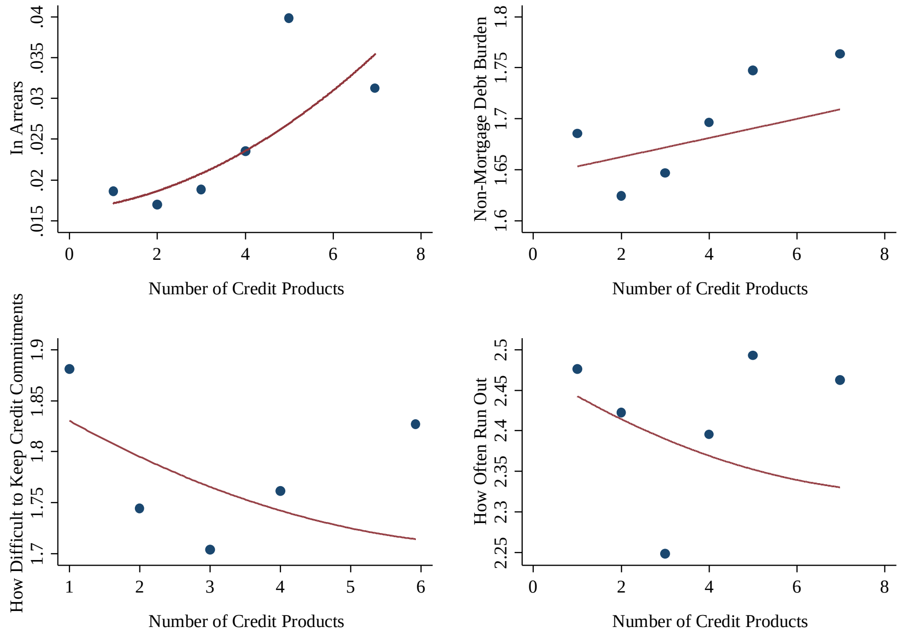


Figure A6:2: Relationship between total consumer credit debt and measures of financial distress

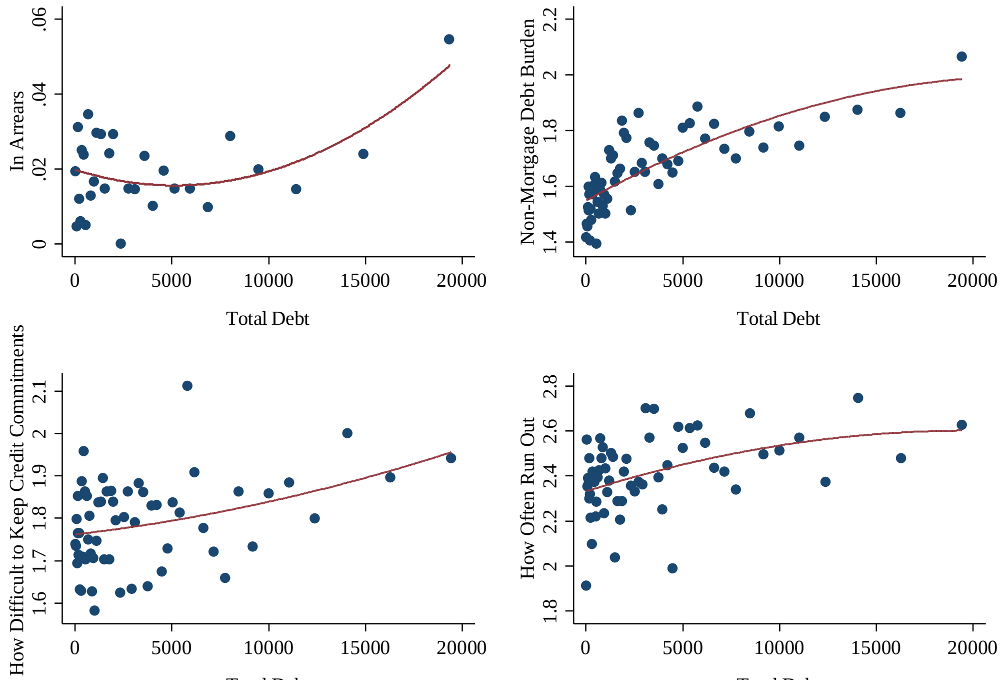


Figure A6:3 Relationship between household income and financial distress

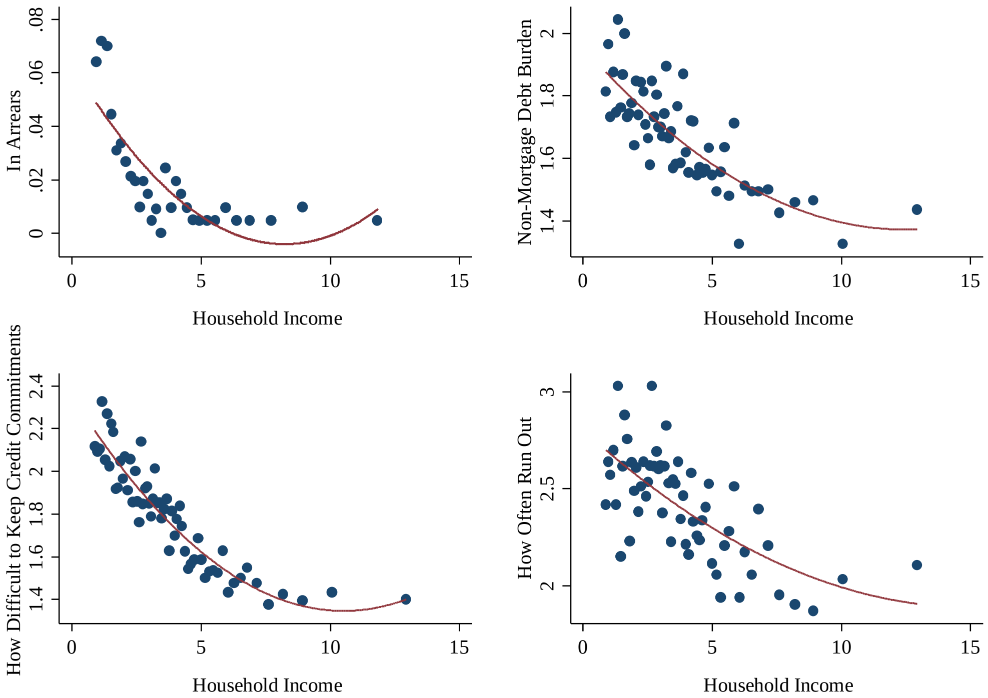


Table A6:1 OLS regressions for potential predictors of financial distress (using household income) against measures of financial distress

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI ratio	0.136*** (5.18)	0.145*** (4.16)	0.167** (2.63)	0.152*** (4.03)	0.00710 (0.07)
Number of credit products held	0.0071 (1.05)	0.00470 (1.67)	0.0116 (1.40)	0.00282 (0.93)	0.00439 (0.51)
Total value of consumer credit debt	0.00164 (0.78)	0.00247 (0.37)	0.0651 (0.30)	0.00187 (0.26)	0.0187 (0.91)
Household Income / £10,000	-0.00516 (-0.46)	-0.00801 (-0.29)	-0.00646 (-1.14)	-0.00473 (-1.57)	-0.00116 (-0.72)
Number of individuals	23,844				

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummies. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Table A6:2 OLS regressions for potential predictors of financial distress (using individual income) against measures of financial distress

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI ratio	0.168***	0.179***	0.183**	0.198***	0.00701
	(4.15)	(4.00)	(2.60)	(4.14)	(0.09)
Number of credit products held	0.00467	0.00450	0.0136	0.00288	0.00375
	(1.43)	(1.66)	(1.75)	(0.35)	(0.65)
Total value of Consumer credit debt	0.00216	0.00286	0.0697	0.00325	0.0826
	(0.25)	(0.345)	(0.31)	(0.23)	(0.96)
Individual Income / £10,000	0.00716	0.00416	0.00678	0.00546	0.00461
	(1.58)	(0.37)	(1.03)	(1.00)	(0.67)
Number of individuals	21,924	21,924	21,924	21,924	21,924

Notes: See previous.

Table A6:3a Fixed effects regressions for lags of DTI ratio (using household income) against measures of financial distress

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI ratio	0.0516***	0.0715***	0.613***	0.123***	0.316***
	(50.1)	(4.16)	(8.11)	(6.48)	(9.13)
DTI ratio $_{lag\_1}$	0.0431***	0.0413***	0.498***	0.619***	0.203***
	(30.6)	(2.94)	(6.13)	(3.16)	(6.01)
DTI ratio $_{lag\_2}$	0.0102	0.0302	0.102**	0.0201	0.142*
	(0.98)	(1.44)	(2.56)	(0.87)	(2.00)
Number of individuals	2,595	2,595	2,595	2,595	2,595

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. The regressions also include household income, regional dummy variables, wave dummy variables and individual fixed effects. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Table A6:3b Fixed effects regressions for lags of DTI ratio (using individual income) against measures of financial distress

	(1) Composite Measure	(2) Arrears	(3) Burden	(4) Keeping Up	(5) Run Out
DTI	0.0612***	0.0537***	0.240***	0.0541***	0.129***
	(10.26)	(6.85)	(11.48)	(6.75)	(6.65)
DTI Ratio $_{lag\_1}$	0.0384***	0.0214***	0.318***	0.0319**	0.0685***
	(24.16)	(30.5)	(4.60)	(20.1)	(3.36)
DTI Ratio $_{lag\_2}$	-0.00498	-0.00298	0.0436*	-0.00379	0.0591**
	(-0.78)	(-0.40)	(2.21)	(-0.50)	(3.23)
Number of individuals	2,350	2,350	2,350	2,350	2,350

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. The regressions also include household income, regional dummy variables, wave dummy variables and individual fixed effects. Includes all individuals with outstanding consumer credit debts in at least one survey wave where individual income observed.*

Table A6:4a OLS regressions of deciles of DTI ratio (household income) against financial distress, waves 1–4

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI ratio decile=2	0.00742	-0.00222	0.00766	0.00150	0.00923
	(0.81)	(-0.77)	(0.86)	(0.45)	(1.18)
DTI ratio decile=3	0.0213*	-0.00183	0.0213*	0.00174	0.00341
	(2.33)	(-0.63)	(2.38)	(0.52)	(0.44)
DTI ratio decile =4	0.0347***	0.00228	0.0327***	0.00439	0.0164*
	(3.77)	(0.79)	(3.64)	(1.30)	(2.10)
DTI ratio decile =5	0.0438***	0.00308	0.0406***	0.00416	0.0147
	(4.80)	(1.07)	(4.55)	(1.24)	(1.89)
DTI ratio decile =6	0.0676***	0.00365	0.0629***	0.0105**	0.0342***
	(7.41)	(1.27)	(7.06)	(3.14)	(4.40)
DTI ratio decile =7	0.0846***	0.00332	0.0820***	0.00541	0.0299***
	(9.25)	(1.16)	(9.19)	(1.61)	(3.84)
DTI ratio decile =8	0.105***	0.00265	0.104***	0.0111**	0.0353***
	(11.46)	(0.92)	(11.60)	(3.28)	(4.52)
DTI ratio decile =9	0.142***	0.00665*	0.136***	0.0108**	0.0575***
	(15.32)	(2.29)	(15.07)	(3.17)	(7.30)
DTI ratio decile =10	0.253***	0.0234***	0.244***	0.0346***	0.0846***
	(26.54)	(7.82)	(26.29)	(9.89)	(10.43)
Number of individuals	23,844	23,844	23,844	23,844	23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. This table reports coefficient estimates (t statistics) from fixed effects regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. The regressions also include household income, regional dummy variables, wave dummy variables and individual fixed effects. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Table A6:4b OLS regressions of deciles of DTI ratio (individual income) against financial distress, waves 1–4

	(1) Composite	(2) Arrears	(3) Burden	(4) Keeping Up	(5) Run Out
DTI ratio decile = 2	0.0160	0.000886	0.0166	0.00183	0.00946
	(1.69)	(0.32)	(1.80)	(0.55)	(1.17)
DTI ratio decile = 3	0.0142	-0.00133	0.0148	0.00419	0.0150
	(1.50)	(-0.48)	(1.61)	(1.25)	(1.85)
DTI ratio decile = 4	0.0274**	0.00117	0.0262**	0.00485	0.0182*
	(2.90)	(0.42)	(2.85)	(1.45)	(2.26)
DTI ratio decile = 5	0.0496***	0.00158	0.0465***	0.00644	0.00751
	(5.26)	(0.57)	(5.06)	(1.94)	(0.93)
DTI ratio decile = 6	0.0539***	0.00228	0.0536***	0.00474	0.0279***
	(5.74)	(0.83)	(5.86)	(1.43)	(3.49)
DTI ratio decile = 7	0.0766***	0.00520	0.0734***	0.00589	0.0383***
	(8.17)	(1.88)	(8.01)	(1.78)	(4.79)
DTI ratio decile = 8	0.112***	0.00465	0.111***	0.00704*	0.0479***
	(11.89)	(1.68)	(12.13)	(2.12)	(5.98)
DTI ratio decile = 9	0.147***	0.00469	0.144***	0.0118***	0.0573***
	(15.70)	(1.70)	(15.75)	(3.56)	(7.17)
DTI ratio decile = 10	0.221***	0.0208***	0.215***	0.0338***	0.0790***
	(23.18)	(7.39)	(23.10)	(10.03)	(9.71)
Number of observations	22,063	22,063	22,063	22,063	22,063

*Notes: t statistics in parentheses. Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (standard errors) from Ordinary Least Squares regressions. Dependent variables are measures of financial distress as described in the text. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regression also includes regional dummy variables and wave dummy variables. Sample comprises all individuals with non-zero outstanding debts present in at least one wave of the WAS sample.*

Table A6:4c OLS regressions of deciles of DTI ratio (equivalized income) against financial distress, waves 1–4

	(1) Composite	(2) Arrears	(3) Burden	(4) Keeping Up	(5) Run Out
DTI ratio decile = 2	0.0123	0.00112	0.0109	0.00507	-0.000738
	(1.29)	(0.40)	(1.17)	(1.50)	(-0.09)
DTI ratio decile = 3	0.0170	0.000427	0.0153	0.00479	0.00345
	(1.77)	(0.15)	(1.64)	(1.42)	(0.42)
DTI ratio decile = 4	0.0360***	-0.00234	0.0363***	0.00561	0.0200*
	(3.79)	(-0.84)	(3.91)	(1.67)	(2.47)
DTI ratio decile = 5	0.0415***	0.00130	0.0371***	0.00831*	0.00581
	(4.36)	(0.46)	(3.99)	(2.47)	(0.72)
DTI ratio decile = 6	0.0742***	0.00767**	0.0694***	0.00872**	0.0196*
	(7.78)	(2.73)	(7.46)	(2.59)	(2.41)
DTI ratio decile = 7	0.0869***	0.00192	0.0833***	0.00950**	0.0312***
	(9.13)	(0.68)	(8.96)	(2.82)	(3.84)
DTI ratio decile = 8	0.111***	0.00631*	0.106***	0.0121***	0.0415***
	(11.53)	(2.22)	(11.31)	(3.57)	(5.06)
DTI ratio decile = 9	0.154***	0.00956***	0.150***	0.0170***	0.0577***
	(15.85)	(3.34)	(15.74)	(4.93)	(6.95)
DTI ratio decile = 10	0.240***	0.0191***	0.233***	0.0305***	0.0827***
	(23.74)	(6.43)	(23.67)	(8.56)	(9.60)
Number of observations	22,063	22,063	22,063	22,063	22,063

*Notes: t statistics in parentheses. Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (standard errors) from Ordinary Least Squares regressions. Dependent variables are measures of financial distress as described in the text. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regression also includes regional dummy variables and wave dummy variables. Sample comprises all individuals with non-zero outstanding debts present in at least one wave of the WAS sample.*

Figure A6:4 Regression output for deciles of lagged DTI ratio (individual income) against measures of financial distress, coefficients and 95% confidence intervals, waves 1 – 4

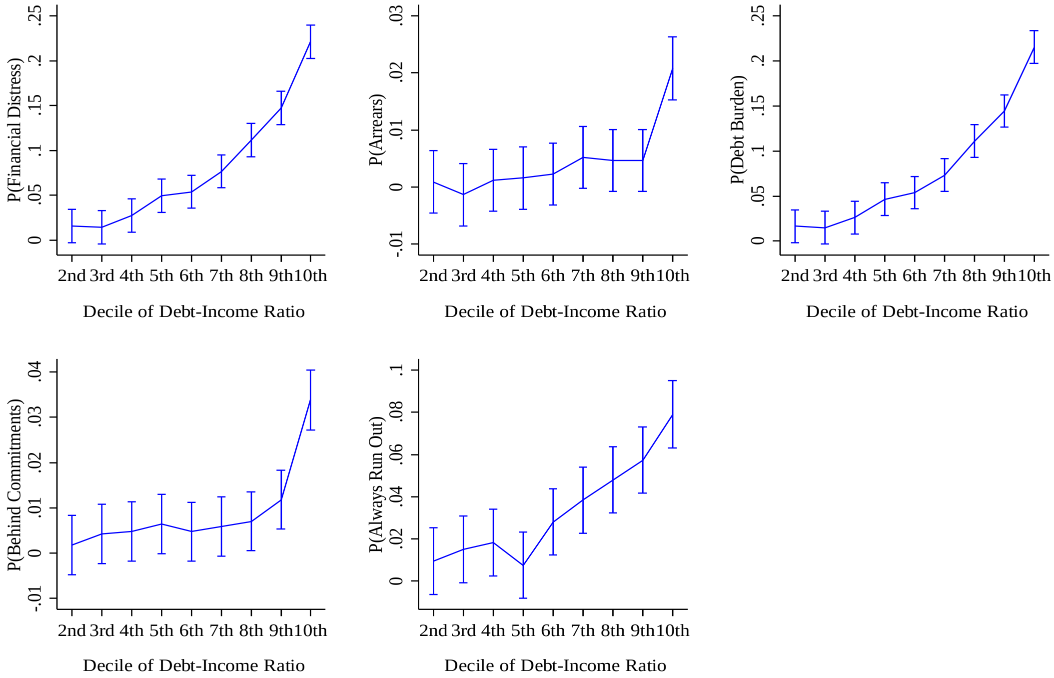


Figure A6:5a Regression output for deciles of lagged DTI ratio (household income) interacted with holding revolving credit product against measures of financial distress, coefficients and 95% confidence intervals, waves 1 – 4

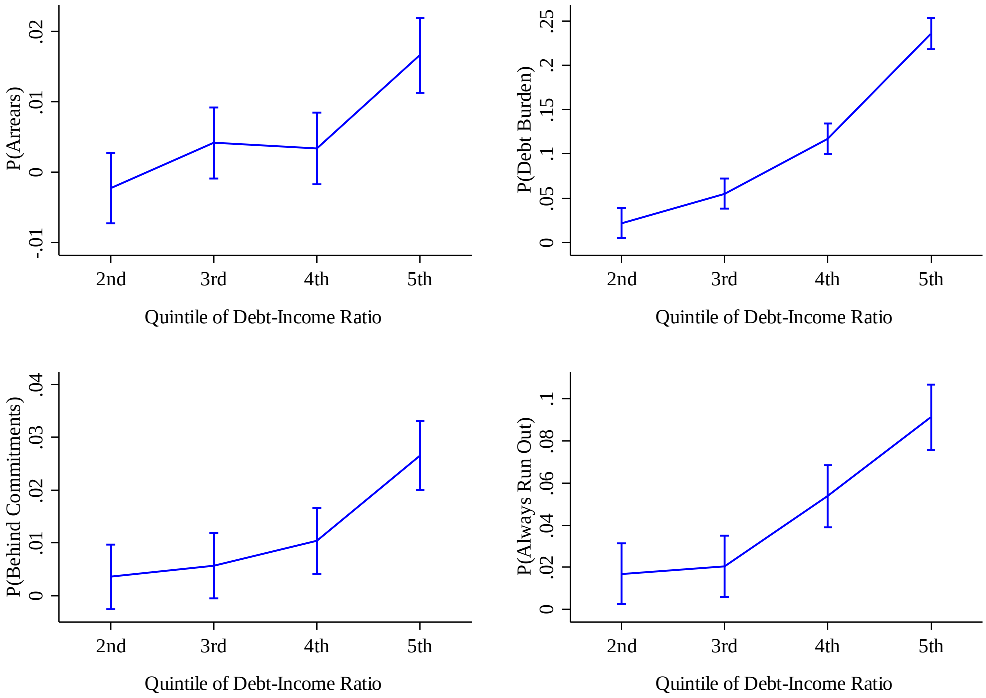


Figure A6:5b Regression output for deciles of lagged DTI ratio (household income) interacted with holding personal loan credit product against measures of financial distress, coefficients and 95% confidence intervals, waves 1 – 4

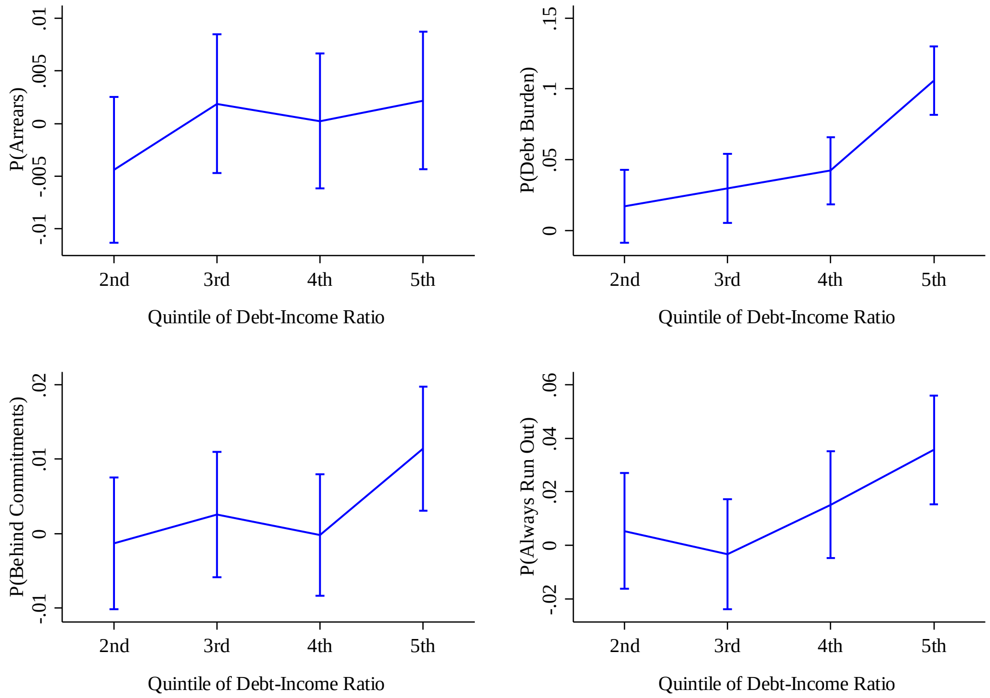


Figure A6:5c Regression output for deciles of lagged DTI ratio (household income) interacted with holding high cost credit product against measures of financial distress, coefficients and 95% confidence intervals, waves 1 – 4

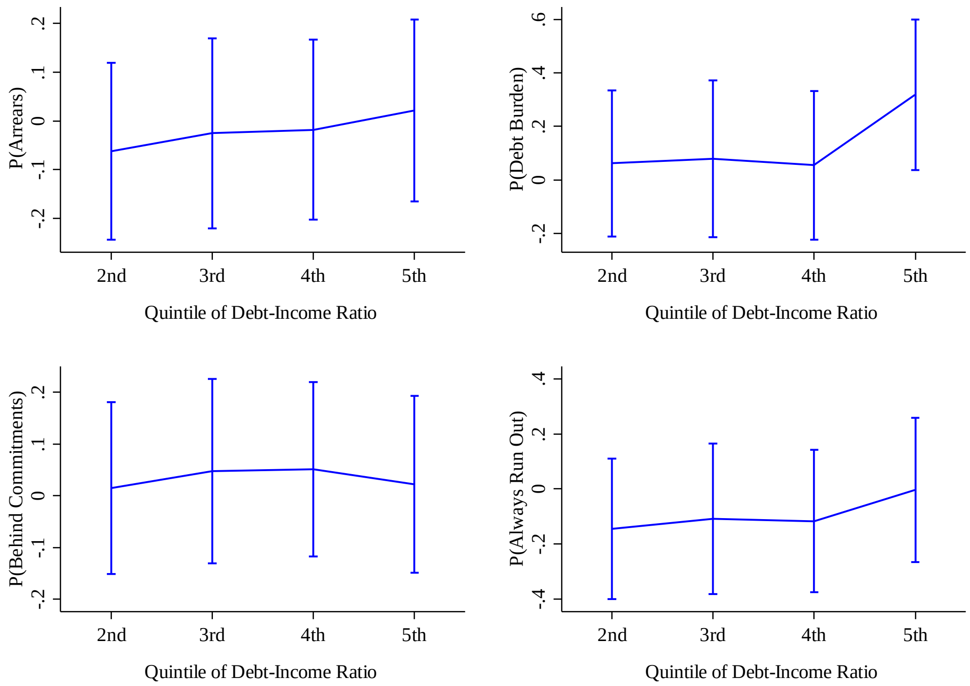


Table A6:5 OLS regressions for socio-economic characteristics against measures of financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
Became unemployed	-0.00204	0.0380**	-0.0235	0.0428**	-0.0565
	(-0.05)	(2.75)	(-0.54)	(2.65)	(-1.50)
Partner became unemployed	0.147**	0.0721***	0.124*	0.0356	0.0559
	(2.78)	(4.43)	(2.41)	(1.87)	(1.27)
Income fallen 25pc	-0.00203	0.00831**	-0.00954	0.00709*	-0.00996
	(-0.23)	(3.09)	(-1.12)	(2.26)	(-1.37)
Became divorced	-0.00573	0.00683	-0.0128	0.0302**	-0.0427
	(-0.18)	(0.70)	(-0.41)	(2.63)	(-1.60)
Became a parent	-0.0234	0.000402	-0.0306	-0.00274	-0.00896
	(-1.38)	(0.08)	(-1.84)	(-0.45)	(-0.63)
Worsened health	0.0561***	0.00901***	0.0527***	0.0206***	0.0463***
	(7.43)	(3.88)	(7.16)	(7.59)	(7.34)
R-squared	0.0404	0.0114	0.0395	0.0135	0.0226
Number of individuals	23,844	23,844	23,844	23,844	23,844

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (t statistics) from OLS regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummy variables. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Table A6:6 OLS regressions for lagged DTI ratio (household income) and 'life events' against measures of financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI ratio	0.0513***	0.0495***	0.0516***	0.0513***	0.110***
	(5.01)	(4.51)	(8.16)	(5.01)	(6.13)
DTI ratio $_{lag\ 1}$	0.0167***	0.0105**	0.0301***	0.0216***	0.0711**
	(5.01)	(2.16)	(7.16)	(3.22)	(2.52)
Became unemployed	-0.0164	-0.0322	-0.154	0.0465	-0.0961
	(-0.15)	(-0.05)	(-104)	(1.59)	(-1.41)
Partner became unemployed	0.164	0.107***	0.194*	0.0576	0.0392
	(1.67)	(4.04)	(2.25)	(1.39)	(1.07)
Income fallen 25pc	0.00274	0.012	0.002	0.00357	-0.0155
	(0.21)	(0.23)	(0.16)	(0.67)	(-1.46)
Became divorced	-0.0235	0.000353	-0.0243	0.0190	-0.0340
	(-0.55)	(0.02)	(-0.56)	(1.10)	(-1.35)
Became a parent	-0.0313	-0.000174	-0.0366	-0.0105	-0.0522
	(-1.30)	(-0.46)	(-1.57)	(-1.02)	(-0.63)
Worsened health	0.0419***	0.00903*	0.0423***	0.0141**	0.0463***
	(3.88)	(2.75)	(3.24)	(3.15)	(5.20)
R-Squared	0.0773	0.0205	0.0743	0.0201	0.0351
Number of individuals	16,857	16,857	16,857	16,857	16,857

*Notes: Statistical significance denoted by * p < 0.05, ** p < 0.01, *** p < 0.001. Table reports coefficient estimates (t statistics) from OLS regressions. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regressions also include household income, regional dummy variables and wave dummy variables. Includes all individuals with outstanding consumer credit debts in at least one survey wave.*

Table A6:7 OLS regressions for lagged DTI ratio (household income) and lagged 'life events' against measures of financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
DTI Ratio $_{lag\_1}$	0.405***	0.0336	0.385***	0.0671***	0.0886*
	(8.54)	(1.89)	(8.27)	(3.56)	(2.05)
DTI Ratio $_{lag\_2}$	-0.00643	0.0101	-0.00331	-0.0206	-0.00566
	(-0.13)	(0.55)	(-0.07)	(-1.06)	(-0.13)
Became unemployed $_{lag\_1}$	0.0261	0.0218	0.0527	0.0329	0.199*
	(0.27)	(0.60)	(0.56)	(0.86)	(2.26)
Partner became unemployed $_{lag\_1}$	-0.0143	-0.0374	-0.0165	-0.00474	-0.188
	(-0.07)	(-0.47)	(-0.08)	(-0.06)	(-0.98)
Income fell by at least 25% $_{lag\_1}$	-0.0145	0.0143	-0.0264	-0.0110	-0.00337
	(-0.63)	(1.66)	(-1.18)	(-1.21)	(-0.16)
Became divorced $_{lag\_1}$	0.129	0.0416	0.107	0.00267	0.0229
	(1.80)	(1.55)	(1.53)	(0.09)	(0.35)
Became a parent $_{lag\_1}$	-0.0152	-0.0168	-0.00869	-0.0146	0.0249
	(-0.37)	(-1.08)	(-0.21)	(-0.88)	(0.66)
Worsened health $_{lag\_1}$	0.0112	-0.00491	0.0125	-0.00146	0.00856
	(0.59)	(-0.69)	(0.68)	(-0.19)	(0.50)
R-Squared	0.0979	0.0259	0.0936	0.0298	0.0527
Number of individuals	2,236	2,236	2,236	2,236	2,236

*Notes: t statistics in parentheses. Statistical significance denoted by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Table reports coefficient estimates (standard errors) from Ordinary Least Squares regressions. Dependent variables are measures of financial distress as described in the text. Additional regressors included in the model not shown in the table are: dummy variables for age brackets, demographics (gender, marital status, whether has children), educational achievements, employment status. Regression also includes household income, regional dummy variables and wave dummy variables. Sample comprises all individuals with non-zero outstanding debts present in at least one wave of the WAS sample.*

Table A6:8 OLS regressions for lagged DTI ratio (household income) interacted with category of credit product against measures of financial distress, waves 1 – 4

	OLS 1 Financial Distress	OLS 2 Arrears	OLS 3 Burden	OLS 4 Keeping Up	OLS 5 Run Out
Lag DTI ratio	0.580***	0.0692***	0.659***	0.0906***	0.252***
	(21.08)	(12.96)	(40.03)	(14.48)	(17.40)
Lag DTI * Personal loan	-0.315***	-0.0558***	-0.442***	-0.0616***	-0.199***
	(-12.06)	(-8.81)	(-22.63)	(-8.31)	(-11.59)
Lag DTI * High cost	0.469***	0.311***	0.370***	0.127***	0.312***
	(21.46)	(12.79)	(4.93)	(4.45)	(4.73)
Number of individuals	13,844	13,844	13,844	13,844	13,844

Table A6:9 Predicted average financial distress within 20 quantiles of DTI ratio (household income)

	Minimum DTI ratio within quantile	Composite financial distress measure	Arrears	Burden	Keeping Up	Run Out
1	<0.1%	0.06	0.01	0.05	0.01	0.05
2	0.1%	0.06	0.01	0.05	0.01	0.07
3	1.1%	0.08	0.01	0.07	0.02	0.08
4	1.2%	0.07	0.01	0.06	0.01	0.06
5	1.4%	0.08	0.01	0.07	0.02	0.07
6	1.7%	0.10	0.01	0.09	0.01	0.07
7	2.2%	0.10	0.01	0.09	0.02	0.08
8	2.6%	0.11	0.02	0.09	0.02	0.08
9	2.8%	0.10	0.01	0.09	0.01	0.07
10	3.6%	0.13	0.02	0.11	0.02	0.07
11	4.8%	0.12	0.02	0.11	0.02	0.09
12	5.7%	0.14	0.01	0.13	0.02	0.09
13	7.6%	0.15	0.02	0.14	0.02	0.08
14	8.9%	0.16	0.02	0.15	0.02	0.09
15	11.6%	0.17	0.02	0.16	0.02	0.09
16	14.4%	0.20	0.02	0.19	0.03	0.10
17	17.8%	0.19	0.01	0.18	0.02	0.10
18	24.6%	0.23	0.03	0.22	0.03	0.12
19	31.5%	0.28	0.03	0.27	0.03	0.13
20	58.3%	0.38	0.05	0.36	0.06	0.17

Notes: 1,513-1,514 observations in each DTI band.

Annex 3: References

Agarwal, S., Driscoll, J., Gabaix, X., and Laibson, D. (2009). The Age of Reason: Financial Decisions over the Life Cycle and Implications for Regulation. *Brookings Papers on Economic Activity*, Fall 2009.

Ando, A and Modigliani, F. (1963) The "Life-Cycle" Hypothesis of Saving: Aggregate Implications and Tests. *American Economic Review*, 53: 55-84.

Bertola, G, Disney, R. and Grant, C. (2006) The economics of consumer credit. Massachusetts Institute of Technology.

Bridges, S., Disney, R. and Gathergood, J. (2008). Drivers of Over-Indebtedness. Department for Business, Enterprise and Regulatory Reform.

Brown, M, Haughwout, A., Lee, D and van der Klaauw, W. (2015) Do We Know What We Owe? Consumer Debt as Reported by Borrowers and Lenders. Federal Reserve Bank of New York Economic Policy Review, October 2015.

Browning, M. and Crossley, T. (2001) The Life-cycle model of consumption and saving. *The Journal of Economic Perspectives,* 15(3): 3-22.

Bryan, M, Taylor, M. and Veliziotis, M. (2010) Over-indebtedness in Great Britain: An analysis using the Wealth and Assets Survey and Household Annual Debtors Survey. Department for Business, Innovation and Skills.

Disney, R. and Gathergood, J. (2009). Understanding Consumer Over-Indebtedness Using Counselling Sector Data: Scoping Study. Department for Business, Innovation and Skills (BIS).

Disney, R. and Gathergood, J. (2013). Financial literacy and consumer credit portfolios. *Journal of Banking & Finance*, 37(7), 2246–2254.

Chamberlin, E. (2015) Wealth in Great Britain Wave 4, 2012 to 2014. 17 December 2015, Office for National Statistics Available from:

http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/was/wealth-in-great-britain-wave-4/2012-2014/index.html

Financial Conduct Authority (2014a) CP14/10 Proposals for a price cap on high-cost, short-term credit. July 2014.

Financial Conduct Authority (2014b) Technical Annexes Supplement to CP14/10 Proposals for a price cap on high-cost, short-term credit. July 2014.

Financial Conduct Authority (2014c) PS14/16 Detailed rules for the price cap on high-cost, short-term credit. Including feedback on CP14/10 and final rules, November 2014.

Fitch, C. and Hamilton, S. & Basset, P. & Davey, R. (2011) The Relationship Between Personal Debt and Mental Health: A Systematic Rreview. *Mental Health Review Journal,* 16: 153-166.

Friedman, M. (1957) The Permanent Income Hypothesis, NBER Working Paper.

Gathergood, J. (2012a) Debt and Depression: Causal Links and Social Norm Effects. *Economic Journal* 122: 1094-1114.

Gathergood, J. (2012b) Self-control, Financial Literacy and Consumer Over-indebtedness. *Journal of Economic Psychology,* 33(3): 590-602.

Gathergood, J. (2014) Personal Debt and Psychological Health. *New Palgrave Dictionary of Economics Online Edition.*

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *The Quarterly Journal of Economics*, 112(2), 443–478.

Richardson, T. and Elliot, P. and Roberts, R. (2013) The Relationship Between Personal Unsecured Debt and Mental and Physical Health: A Systematic Review and Meta-Analysis. *Clinical Psychology Review,* 33: 1148-1162.

Office for National Statistics. Social Survey Division. (2016) Wealth and Assets Survey, Waves 1-4, 2006-2014: *Special Licence Access* [data collection]. *14th Edition.* UK Data Service. SN: 6415.

Zinman, J. (2009) Where is the Missing Credit Card Debt? *Review of Income and Wealth,* 55, no.2 (June): 249-65.

25 The North Colonnade Canary Wharf
London E14 5HS
Telephone: +44 (0)20 7066 1000
Website: www.fca.org.uk