Financial Conduct Authority

Research Note

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Employment shocks and financial difficulty: Understanding how leaving paid employment affects ability to meet credit repayments.

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FCA research notes in financial regulation

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Summary

Consumers can become particularly financially vulnerable after they lose a job, as well as due to other employment changes such as retirement or long-term sickness. This is not just because of the resulting loss of income, but because these events can be psychologically draining and stressful. This has become particularly pressing with the ongoing cost-of-living crisis, with many consumers suffering a significant financial squeeze.

At the FCA, we are particularly concerned with how firms can support consumers in changing life circumstances. This is part of our commitment in the Consumer Duty. However, this requires an understanding of how these changes affect consumers, which is not well understood. Do consumers fall behind on their payments for loans or credit cards or do they choose to take out more credit products to maintain levels of spending?

We find that consumers fall behind on credit payments (in industry, this is termed 'going into arrears') significantly more when they lose their job or become long-term sick or disabled. The increases are very large. Respectively, falling behind on a credit payment is 1.9x more likely after a job loss and 2.7x more likely after leaving work due to long-term sickness or disability.

Going into arrears is more persistent, meaning it lasts longer, for those who lose a job than for those who leave work due to long-term sickness or disability.

By contrast, we do not find significant shifts in the number of consumers who use credit cards or overdrafts or increase their debt levels with these products.

We did this work using a unique dataset as part of the FCA's mission to be a more evidence- and data-led regulator. This data comes from 2 sources. The first is credit file data, which readers might be familiar with from credit scores. This gives information on how many credit products (like loans or credit cards) a person has, together with their payments on those products and how much debt they have. The second is survey data, which gives information on the person themselves, for example their age, gender, income, and employment status (notably if they are employed or unemployed and when).

As a result, credit providers could consider whether providing forbearance or other support is appropriate if a consumer loses their job loss or has another change in their employment status.

1 Overview

Background

As part of the Consumer Duty, we require relevant firms to tailor support to the needs of consumers. To support this process, we conduct research on what happens to consumers in different life circumstances where they might need firm support.

This research examined when consumers transition (change) out of employment. These transitions can occur because of, for example, losing a job, becoming long-term sick, or disabled, retiring, entering education or from caring responsibilities. We focus on how those transitions might change how consumers use consumer credit; interest-charging products like credit cards, personal loans, or payday loans. We look at 2 sets of outcomes for consumers: their ability to make payments on those products, and whether they take out new consumer credit products to maintain existing levels of spending.

Why focus on this area? Household debt is a significant area of concern, especially when it is not affordable. In general, the UK saw household debt rise steadily following the 2007 crash for the following decade. While some households saved more money during the pandemic, it also left a significant number of people with high levels of outstanding debt. This has now become a serious squeeze on these households, with rising interest rates on debt, and reduced money for paying back debt due to cost-of-living pressures and inflation.

Non-technical readers could read section 1, 2, and 5 for the key findings and context, and skim or skip sections 3, 4, and 6.

Key findings

We find that:

- On average, consumers who become unemployed or leave employment due to long-term sickness or disability are more likely to fall behind on their credit payments. In particular:
    - Those who become unemployed are 1.9x more likely to miss a payment in the months after losing their job than similar consumers who do not.
    - Those who leave work due to long-term sickness or disability are 2.7x as likely to fall behind on credit payments than similar consumers who do not.
- Arrears do not increase for those who retire, which is likely to be because retirees can usually access pensions or state benefits.
- They also do not increase for those who leave work due to family or caring responsibilities, or for those who leave work to take up full-time education.
- Except for those entering retirement, we do not see a significant change in the use of unsecured credit products including credit cards and overdrafts following leaving full-time employment.

Equality and diversity considerations

We have considered the equality and diversity issues that may arise from the analysis in this Research Note.

Overall, we do not consider that the analysis in this Research Note adversely impacts any of the groups with protected characteristics i.e., age, disability, sex, marriage or civil partnership, pregnancy and maternity, race, religion and belief, sexual orientation, and gender reassignment.

2 Research context

Research objectives

We examine how changes in an individual's employment status affect the likelihood of falling behind on credit payments. We are interested in how much change occurs and how long the effect lasts. We also explore how people's debt situations change when employment changes. We carry out a *descriptive* analysis of the average impact of these changes, rather than being able to definitively attribute changes to the life event itself (sometimes called a *causal* analysis).

Literature review

We now briefly summarise previous work done on related topics. We focus on why people get into problem debt, why they fall behind on credit payments and other research into changes to employment status.

Problem debt

Previously, researchers have focused on 2 key factors that drive debt to become unmanageable for consumers: having a high level of accumulated debt and a change in circumstances (FCA 2014).

On the first point, our earlier research illustrated that those who become financially distressed tend to hold more expensive debt and have a higher proportion of debt relative to their income (Belgibayeva et al. 2020).

On changes in circumstances, Grant (2008) shows that falling behind on debt payments is often preceded by illness or a change in income like a job loss. They also find that there are large national differences in how households react to these events. Those differences can partly be explained by how local financial and legal systems work.

Falling behind on credit payments

Whether a consumer falls behind on payments partly depends on the kind of credit they take out. The crucial factor here is whether the credit is secured, meaning that if the borrower fails to pay back the loan, the bank will repossess an asset, such as a house for a mortgage. Consumer credit products such as personal loans, overdrafts and credit cards are often unsecured lending, meaning the loan that is not backed by an asset, such as a car or a house.

From the borrower's viewpoint, the costs of missing scheduled repayments and/or defaulting on this form of credit are limited compared to secured lending, such as a mortgage. Yet missed payments for unsecured lending may still lead to reduced access to credit in the future, reduced credit scores and potentially legal action.

However, the impact of missed payments and default for mortgage lending can come with the legal right for the lender to repossess a property, bringing emotional distress as well as financial hardship.

There are also other, different, considerations for mortgages, including that house process can fall and so borrowers can't sell a property if they get into financial trouble (Garriga and Hedlund 2020).

Previous studies estimating the impact of employment shocks.

Previous studies have looked at whether people with different employment statuses, like being employed or unemployed, are more or less likely to tend to fall behind on credit payments. For example, Caju, Rycx, and Tojerow (2016) look at whether consumers are over-indebted or not in different employment statuses.

However, previous research has not examined whether the *transition* from being employed to unemployed, or employed to retired, alters whether a person falls behind on credit payments. It also has not examined the timing of these changes and how long they persist for.

3 Data

Matched survey and credit file data

Where then, does the data come from to allow us to draw our conclusions? We conducted this analysis using UK household survey data which is longitudinal (measuring the same people over time) which we then matched (with the same individuals) with monthly data on credit files.

The survey component of the data is the Understanding Society survey which represents the largest longitudinal household survey in the UK. It contained survey responses of the members of approximately 40,000 households when it began (Wave 1). Trained interviewers visit households recruited for the first round of data collection each year to collect information on changes to their household and individual circumstances. Interviews are carried out face-to-face in respondents' homes or through a self-completion online survey. The survey captures wide and varied data on number of individual and household variables, including demographic characteristics, income, finances, health and wellbeing, life satisfaction, and social and political attitudes/participation.

This annual survey data is then matched at the individual level with monthly credit file data from 1 of the 3 largest credit reference agencies (CRAs) operating in the UK. This CRA data contains very rich and granular data on the liabilities side of an individual's personal balance sheet.

The data contains account-level information on credit products owned, their type (e.g., revolving, mortgage, personal loan etc) as well as data on balances outstanding and scheduled repayment amounts. Crucially, the data also contains factors documenting the monthly performance of individuals credit files, indicating any missed payments. There is also borrower-level information on county court judgements (CCJs) or bankruptcy declarations by borrowers.

Overall, the matched survey sample consists of 17,560 adults in the UK survey data (annual) and credit file data (monthly) tracked over the period June 2009 – April 2021. Note that the matched sample does not consist of entire sample surveyed as part of the Understanding Society survey.

We had to ask permission to do the matching between the 2 sources of data. About 53% of respondents gave their consent, which is why the sample became smaller.

Defining financial distress and employment transitions

The primary purpose of this research is to estimate the impact of different employment state transitions on probability of financial distress. Here we outline how these variables are constructed in the data and how to interpret them.

Firstly, the household survey component of the data allows us to construct a complete employment history of each individual up to the point of their latest survey response. Using Wright's methodology (2020), we accurately identify month-level changes in employment 'spells'. This step is crucial in determining with accuracy the timing of any effects. By doing this, the periodic frequency of the survey data (collected annually) can be aligned with the monthly frequency of the credit file data.

Wright (2020) defines 'spells' here as being the single 'main activities' for each individual in the survey, uninterrupted from date of birth to their last interview. Requiring that each individual at a point in time is defined as having one single activity is inevitably a simplification. For example, activities are not always mutually exclusive (for instance working full-time while also being in full-time education). However, due to the limitations of the data, it is only possible to assign a single 'main activity' to each period for an individual. Spells are then defined as the period encompassing the start date of a main activity and the start date of the subsequent main activity.

The full list of activities one can in at any point in time is as follows: self-employed, paid employment, unemployed, retired, on maternity leave, family care or home, full-time student, LT sick/disabled, Govt training scheme, Unpaid, family business, On apprenticeship, On furlough, Temporarily laid off/short-term working, doing something else. We do not construct individual flags for Govt training scheme, Unpaid, family business and on apprenticeship due to a limited number of observations for these individuals.

We define an aggregate flag that denotes an individual Transitioning from Employment (TFE) based on the following logic: a person is defined as TFE in time $\boldsymbol{t}$ ($\boldsymbol{t}$ being calendar month time periods) if they move from any of the following employed states:

- Self-employed,
- Paid employment,
- On maternity leave,
- On furlough,
- Temporarily laid off/short-term working.

In period $\boldsymbol{t-1}$, to any of following *not in employment* states:

- Unemployed,
- Retired,
- Family or home caring responsibilities,
- Full-time student,
- Long-term sick/disabled,
- Govt training scheme,
- Unpaid, family business,
- On apprenticeship,
- Doing something else

in period $\boldsymbol{t}$.

We also construct individual flags for transitions from any of the 5 employed states above into: unemployed, retired, family or home caring responsibilities, full-time student, long-term sick/disabled, doing something else. We do not construct individual flags for Govt training scheme, Unpaid, family business and on apprenticeship due to a limited number of observations for these individuals.

When defining arrears, we can directly observe this at the account level for each individual in the sample by looking at their monthly credit report. Corresponding to each account is a flag showing the account payment status as either being current on all payments, behind scheduled payments (in 30-day increments) or in default in each month. We aggregate this account-level view to the level of the individual for each month to identify borrowers in arrears/default on any of their outstanding credit products.

We then define 3 metrics which we use to identify borrower financial distress, based on different levels of observed severity.

The first is being at least 30 days past due (hereafter 30 DPD) on any scheduled repayment in each month. This can be interpreted at the lower bound for observed financial distress – as it is the first objective indication that a borrower is facing difficulties with making repayments. However, this may be quite a sensitive measure of distress as it may, for instance, reflect a very short-term liquidity shock resulting in a missed payment. It may also include instances where a borrower forgot to make a scheduled payment, despite having the financial capacity to do so (for example failing to pay off a minimum monthly credit card amount where a direct debit is not set up).

The second is a flag for borrowers who enter at least 60 days' worth of arrears (60 DPD) on any credit product.

Finally, we define a broader definition of financial distress on a measure of 'delinquency' (missing a payment on a loan) used by the US Federal Reserve and by Belgibayeva et. al (2020), who also work with CRA data. Here an individual is deemed to enter distress in a given month if at least 1 of the following events occurs:

- they reach arrears of 90 days (or a default) on any credit product,
- they have a county court judgement (CCJ) issued against them,
- they are declared bankrupt,
- or one of their credit accounts is passed to a debt collector.

Hereafter we refer to borrowers who meet this definition as 'financially distressed'.

Data processing

The full panel consists of 17,560 UK adults surveyed between June 2009 and April 2021. We limit our panel to individuals who experience no TFE or at most 1 TFE during our sample period, decreasing our sample to 16,356. The rationale for removing individuals with multiple TFEs is to allow us to accurately differentiate between the likely opposite effects of TFE and the effect of re-entering employment following a period of being unemployed/not in the workforce. Supporting our decision to do this, we observe that the median length of time outside of employment following a TFE is 7 months with an inter-quartile range of 2 to 12 months. As our model does not control for re-entry to employment the estimates of our coefficients in the months following an initial TFE may be biased by subsequent TFE in the following periods.

Given the survey's sampling structure, our sample consists of an unbalanced panel (a dataset where entities are observed a different number of times). This is driven primarily due to additional households being recruited to the survey and younger household members entering the survey. Only household members 16 years or older are surveyed as part of the main questionnaire. Credit reference agencies only capture data on those persons aged 18 or over. As individuals' consent to be matched is taken at the time of the last survey response, we observe all individuals until this point.

How representative the survey sample is, is affected by the fact that individuals must give consent to be matched to their credit file data. While the full unlinked panel of survey data is sampled and weighted in a way that ensures it is nationally representative, the consent and linkage process could potentially lead to non-random selection of individuals for whom linked data is available. However, on reviewing the differences between the matched and unmatched samples, we do not observe significant differences in the compositions of the groups amongst several demographic variables.

A review of the literature on studies with a similar empirical approach to ours shows that no weighting procedure is used (Myrskylä & Margolis, 2014). One argument for not using weighting is that it is difficult to generalise effects of fixed effects models as it is unclear to which population one can generalise them to, as only individuals who experience the treatment contribute to the effect. We explore this in more detail in the Limitations section.

Descriptive statistics

4,118 (25.2%) individuals observed experience a TFE at some point during the sample period. Table 1 shows the breakdown of the status that individuals transition to following employment. Retirement makes up the plurality of TFE, with transitioning to unemployment being the second largest TFE observed.

Table 1: Frequency of TFE

Type of job loss	N
No job loss	12,195
Retired	1,606
Unemployed	1,036
Family care or home	533
Doing something else	360
Full-time student	325
LT sick/disabled	258
On apprenticeship	27
Govt training scheme	9
Unpaid, family business	6

Table 2: Descriptive statistics of sample

Type of TFE	No TFE	Retired	Unemployed	Family care or home	Doing something else	Full-time student	LT sick/disabled
Age	47 (47)	62 (62)	41 (43)	40 (40)	43 (44)	31 (28)	48 (50)

Female	54%	48%	47%	88%	55%	64%	62%
Male	46%	52%	53%	12%	45%	36%	38%
Net annual household income	£39,191 (£36,562)	£38,860 (£36,344)	£38,333 (£35,583)	£39,930 (£36,204)	£46,017 (£41,833)	£42,172 (£38,250)	£32,822 (£30,347)
Mortgage holder	37%	23%	42%	44%	43%	32%	28%
Number of consumer credit accounts	2.42 (2)	2.71 (2)	2.4 (2)	2.55 (2)	2.55 (2)	2.27 (2)	2.57 (2)
Debt-to-income (excl. mortgage)	16.13% (5%)	15.01% (6%)	26.99% (8%)	44.13% (8%)	27.01% (7%)	22% (8%)	19.5% (8%)
Total debt (Excl. mortgage)	£2,813 (£815)	£2,443 (£911)	£3,066 (£1,110)	£2,018 (£744)	£2,849 (£1,011)	£2,909 (£1,112)	£2,696 (£1,008)
High-cost credit user	1%	0%	3%	3%	1%	0%	4%
60 days past due	1%	0%	3%	3%	1%	1%	5%

Note: Numeric values represent mean values, median values are in parenthesis. In instances where no TFE occurs for each individual we take the mean value over the course of the sample period as their representative value. For individuals who experience a TFE, values are taken from the period 3 months prior to the TFE occurring.

From Table 2 we can observe several differences across the groups. Many of these differences are expected, for example, people who transition to retirement being older than those transitioning to full time education.

In terms of income, we observe no large differences across those who do not experience a TFE, who retire or who become unemployed. However, those who leave employment because they are long term sick or disabled tend to have significantly lower income, even before transitioning out of employment.

4 Methodology

Empirical approach

The empirical approach taken here is informed by methodology described in Ludwig & Brüderl (2021). Here the authors make the case for the use of impact functions in measuring time-varying causal effect of a dichotomous treatment (for example, marriage, divorce, parenthood – or in our case change in employment status) on outcomes. This estimation strategy is widely used across research in economics and sociology.

There are many advantages of taking this approach. Firstly, to make unbiased estimates of treatment effects using cross-sectional data requires the strong assumption that all time-constant and time-varying variables that affect both the treatment and the outcome are controlled for in the analysis (Andreß et al. (2013) defines an impact function as a function of $\boldsymbol{t}$ that measures the trend of a dependant variable $\boldsymbol{Y}$ before and after an event of interest). If some confounders are unobserved and cannot be controlled for, inferences will be biased.

Panel data allows us to implement within-person designs, which can identify causal effects. The main advantage of within-person designs is that they are not biased by time-invariant confounders. This means that identifying a treatment effect relies on the much weaker assumption that all time-varying confounders are controlled for in the analysis. Here we use within-individual designs using fixed-effects regressions. Furthermore, given the large number of time periods in the panel used for this study it is possible to observe many treated individuals for many time periods pre and post treatment. This allows us to estimate time-varying treatment effects, which is the time-path of a causal effect (Andreß et al. 2013). By capturing this time varying effect of transitions from employment on propensity to enter arrears this Note represents a significant contribution to the literature.

Estimating model

The estimating model we apply is like that employed by Myrskylä and Margolis (2014). We estimate a linear probability model (LPM) of the form:

$$\boldsymbol{Y_{it}} = \sum_{k=t}^{K} \mathrm{B}_k \boldsymbol{D_{it}^k} + \boldsymbol{a_i} + \boldsymbol{\lambda_t} + \boldsymbol{\epsilon_{it}}$$

Where:

- $\boldsymbol{Y_{it}}$ is a binary flag indicating arrears/distress (i.e., 30 DPD, 60 DPD or Financially Distressed as defined in the Data section).

- $\boldsymbol{D_{it}}$ is a set of dummy variables for $\boldsymbol{K_{it}}$, where $k = 0$ is the period in which the transition from employment occurs.
- $\boldsymbol{a_i}$ are individual specific fixed effects.
- $\boldsymbol{\lambda_t}$ are period specific fixed effects.
- $\boldsymbol{\epsilon_{it}}$ is the error term for unit i at time t.

We use this model framework to test 3 of our outcome variables related to financial distress (30 DPD, 60 DPD and Financially Distressed), as well as other variables related to an individual's debt profile (credit card balance, outstanding overdraft, credit card utilisation, i.e., total credit card balance/total credit card limit). We also subset the data based on type of transition from employment experienced and run separate regressions for each group (see Holgersson et al, 2014). Finally, to understand heterogeneous effects based on consumers with different income levels and debt burdens (as measured by their debt to income (DTI) ratio), we interact each $\boldsymbol{D_{it}}$ with a binary flag indicating the income and DTI tertile (the division into groups of three: upper third, medium, or lower third) of individual $\boldsymbol{i}$.

Here $\boldsymbol{D_{it}}$ can be thought of an interaction term between being treated (experiencing a TFE) and the number of periods to/from treatment. Ludwig & Brüderl (2021) note the flexibility this approach offers, by allowing the inclusion of pre-treatment dummies to capture any pre-treatment of anticipation effects.

5 Results

Full model

Our first model looks at the impact of any Transition From Employment (TFE) on probability of arrears/financial distress.

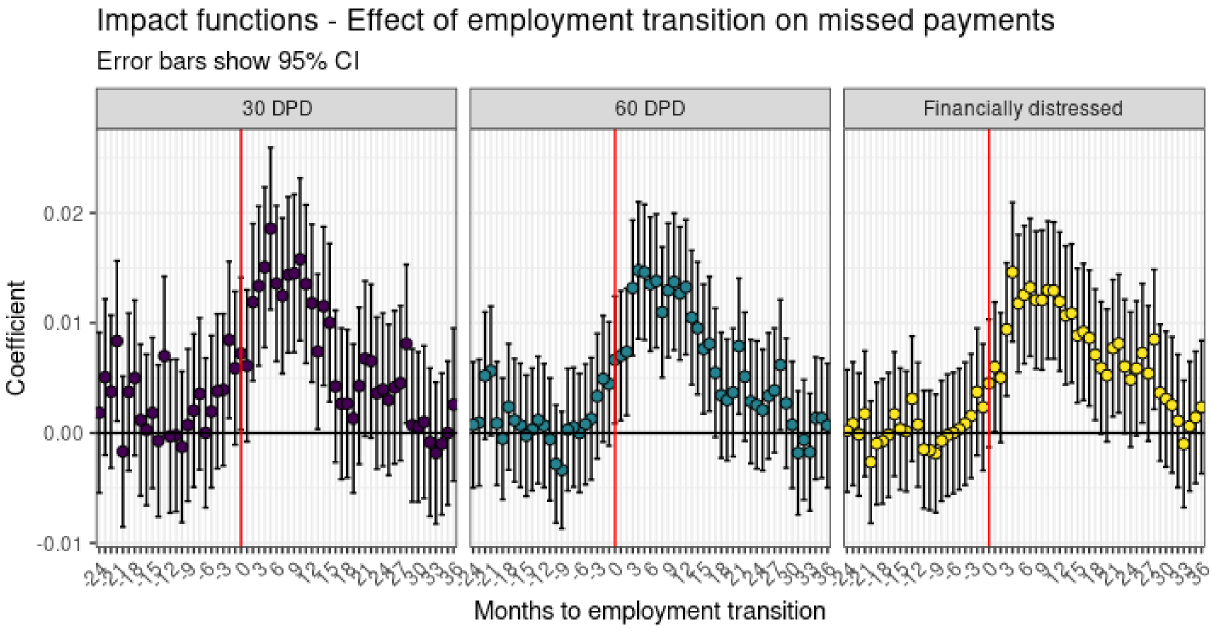
Figure 1 illustrates these results and demonstrates an immediate and significant effect of a TFE on the probability of arrears. Across all three of our outcomes, we see the probability of arrears rise around the TFE event and persisting over a year afterward. Looking at 30 days past due as an outcome, we see an increase in the probability of arrears as rising around the time of the TFE – indicating the timing of the effect treatment is close to immediate. The size of the effect rises in each successive month to peak at 0.019 (or 1.9 percentage points) 5 months post treatment.[1] This is equivalent to approximately 45% increase in the probability of 30 days' worth of arrears.[2] The effect remains persistent for up to a year post TFE.

A similar effect is seen for the 60 DPD and the Financially Distressed outcomes, but the effect is delayed. This delayed effect is most likely by construction, as it takes at least 30 days longer to accrue 2 months of arrears compared to 1 month. Interestingly, the persistence and magnitude of the effect across all three of our outcomes is similar. This indicates that there is likely a high transition rate from 30 DPD to 60 DPD and to being financially distressed.

[1] Throughout this note coefficients are normalised to reflect changes relative to $t-6$. In other words, changes noted here are all relative to average changes compared to 6 months prior to the employment transition occurring.

[2] Over our sample period, the percentage of borrowers who are 30 DPD, 60 DPD or financially distressed is 4.2%, 2.6% and 2.6% respectively. We calculate percentage change (as distinct from percentage point change – which is read directly from the coefficient estimates) as being the $\frac{percentage\ point\ change}{refeence\ value}$ where 4.2%, 2.6% and 2.6% are the reference values for are 30 DPD, 60 DPD and Financially Distressed respectively.

Figure 1

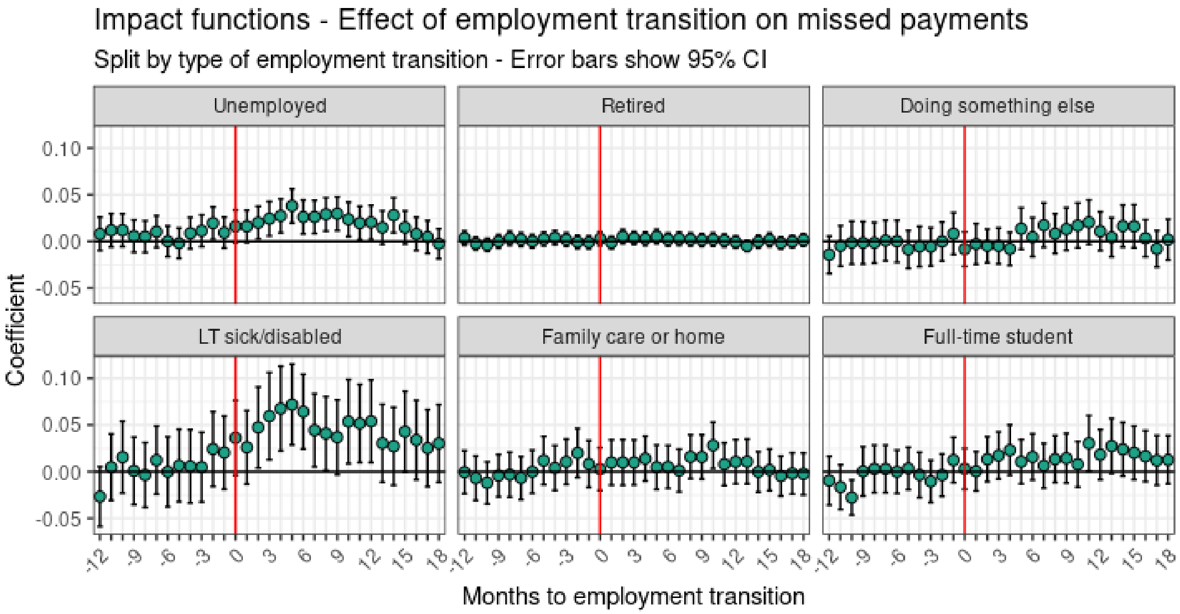


Note: Points represent coefficient estimates normalized relative to t-6. Error bars represent 95% confidence intervals. The red line denotes the period at which the transition from employment occurs. Periods that do not show errors bars intersecting with the horizontal line indicate a statistically significant difference relative to 6 months prior to a job loss.

Decomposing the effect of different transitions from employment

The full model includes several types of transitions which we may impact borrowers differently. For instance, transitioning from employment to retirement is not economically comparable to becoming unemployed or leaving the workforce to take on caring responsibilities. To understand these differences, we evaluate the impact of moving from employment to each of the following states individually: Unemployed, Retired, Family or home caring responsibilities, Full-time student, LT sick/disabled, doing something else. Figure 2 shows the results of this for the 30 DPD outcome.

<u>Figure 2</u>



Statistically significant impacts are only observed for individuals who move from being in employment to either unemployed or out of the workforce due to long-term sickness or disability. Notably, no statistically significant change is observed for people moving to retirement, caring responsibilities, Full-time study or doing something else.

For unemployment transitions, we observe a statistically significant effect as soon as the second month post job loss, suggesting an immediate impact on probability of arrears. This effect peaks at 5 months post job loss at 0.038 (3.8 percentage points), or approximately a 1.9x increase in the probability of a missed payment. Again, the effect remains persistent for up to a year post-job loss.

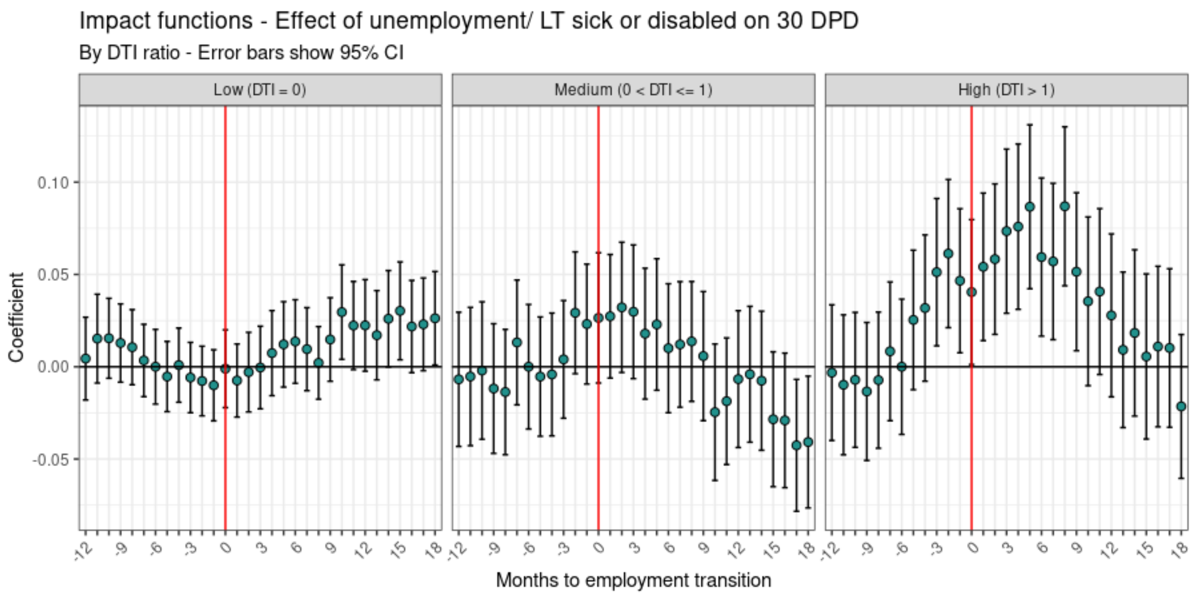
For transitions into long term illness or disability, we see a different effect in terms of size and persistence. The effect size peaks at 0.072 (7.2 percentage points) or a 2.7x increase in the probability of a missed payment. Like unemployment, the effect peaks 5 months after the transition and remains persistent for approximately 1 year.

Differences in Impacts by Household Wealth and Debt Levels

It is likely that effects will differ based off individual household factors such as household wealth and total household indebtedness. For example, households with large levels of liquid savings are likely to be in a better position to service debt after any income shock from transitioning from employment. Similarly, Caju, Rycx and Tojerow (2016) note that households facing the prospect of arrears due to liquidity shocks could be buffered by asset sales. While we cannot observe household wealth in our data, we can observe household income which serve as a very loose proxy for wealth. Similarly, to measure a household's debt burden, we can construct a debt-to-income ratio based off a household's total non-mortgage debt relative to their income.[3][4]

Debt-to-income

Figure 3



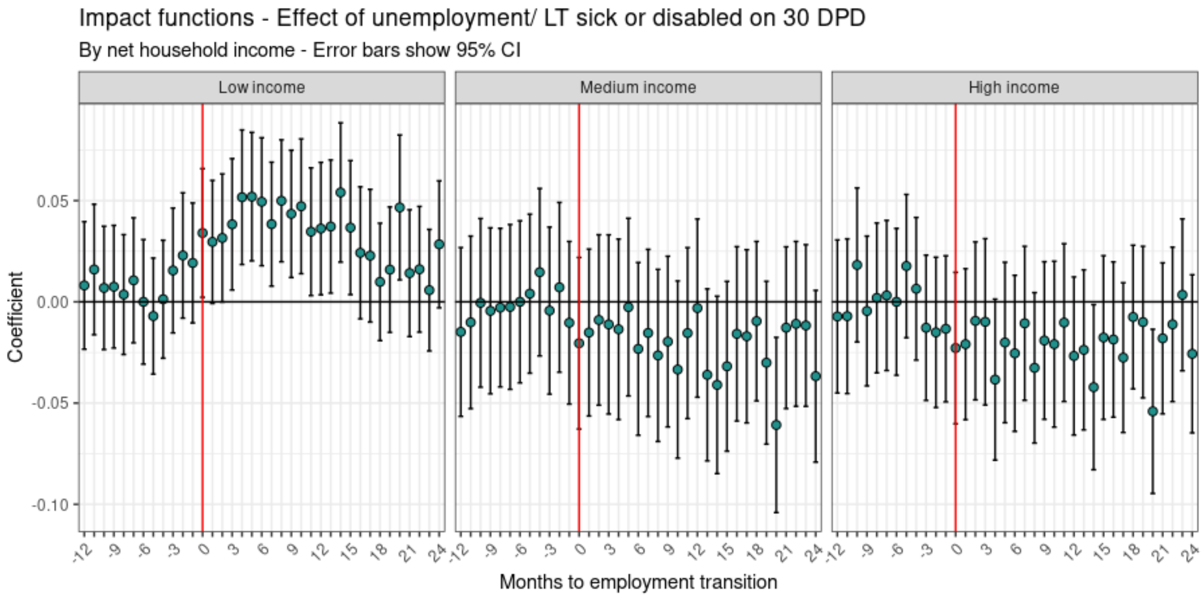
We observe that the effect of job losses on a person's probability of a missed payment is greater for those with larger debt burdens. This makes intuitive sense as those with higher debt burdens ('High DTI' in Figure 3) relative to their income are less likely to be able to meet repayments on their debt given an employment shock. Those with no debt originally ('Low DTI' in Figure 3) see no shift in the short-term because they start with no debt. Finally, those with 'Medium DTI' (some debt but less than their net monthly income) see some modest increases in falling behind on debt payments, but these are easier to service and so the effect of an employment shock is smaller.

Household income

Figure 4

[3] Here we define DTI as $\frac{Total\ non\text{-}mortgage\ debt}{Net\ monthly\ income}$.

[4] To identify different effects of employment transitions in instances where we do observe significant effects (i.e., unemployment and long-term illness/disability) we interact our employment shock dummies with binary flags indicating 3 income terciles (low, medium, high). With respect to debt-burden we split DTI into 3 buckets, low (0), medium (0-1), high (>1).



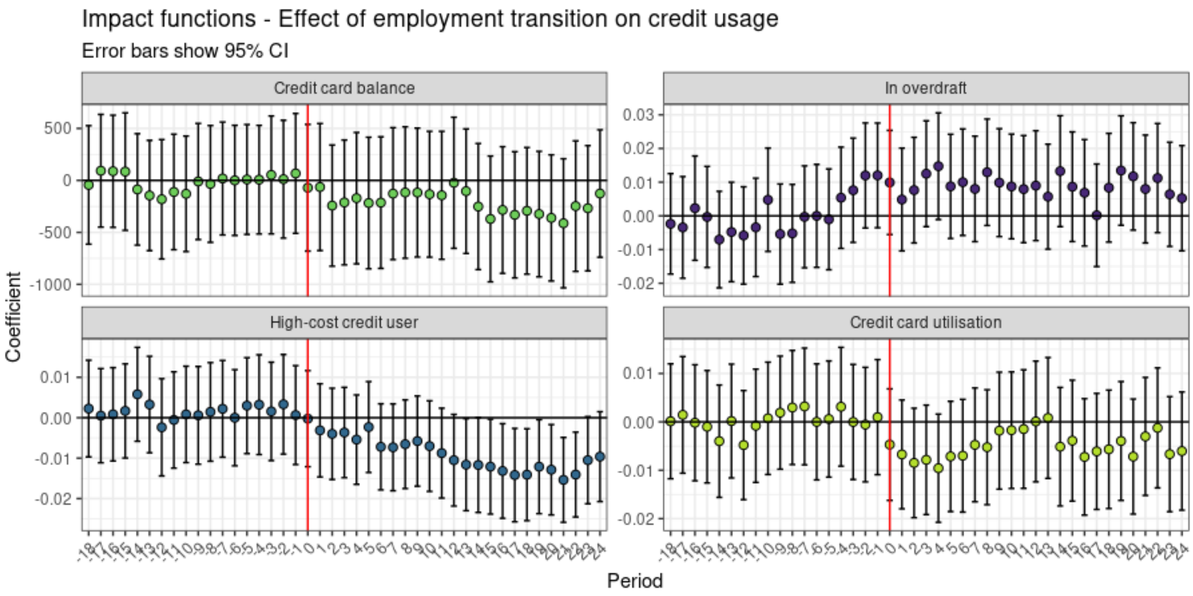
We observe that the effect of job losses on a person's probability of a missed payment is greater for those with lower income. This makes intuitive sense, as those with lower incomes are less likely to have saving 'cushions' to draw on in if they lose their job or are forced to leave employment. They are more likely to live paycheck to paycheck. They may also be using more expensive forms of credit, for example high-cost credit, which could make repayments less affordable during a TFE. For those with medium or high incomes, the amount of missed payments if anything decreases, though most of the per-period effects are not statistically significant. The explanation for the modest decreases we see here is less obvious. It could plausibly be because these households take out less new credit after an employment shock, or that it improves their budgeting slightly during these periods. In any case, on average, the larger savings and/or partner income of medium- and high-income households tends to see them through.

Other outcomes

As well as testing credit arrears outcomes, we also test outcomes of how individuals take on and use credit in response to employment shocks. By doing this we can better understand what may be driving arrears among those who become unemployed or leave work due to illness or disability. For instance, greater reliance on credit post-job loss may indicate that individuals are using credit to maintain existing consumption levels. This may result in incurring unsustainable debt which may eventually lead to credit arrears. Alternatively, if we observe individuals do not take on additional credit in response to employment shocks, it is likely the case that falling income because of the employment shock results in difficulty in meeting existing commitments.

For those transitions from paid employment that result in a higher probability of arrears (I.e., unemployment and long-term illness/disability) we do not observe any significant change in credit use, suggesting that arrears are driven primarily by the income shock channel, rather than consumers taking on unsustainable debt in response to an employment shock.

Figure 4


Impact functions - Effect of employment transition on credit usage
Error bars show 95% CI
Credit card balance
In overdraft
High-cost credit user
Credit card utilisation
Coefficient
Period

6 Discussion

Limitations

The findings of this note have several important limitations which we outline here.

First, our research examines the effects on individuals who have personally undergone changes, such as losing their job. However, consider a scenario where the profile of individuals affected by such changes shifts, like widespread job loss due to a large economic downturn. In this situation our findings might not hold true, as the effects of those transitions on missed payments or taking out new loans might change as different kinds of people would be unemployed and so would respond differently to unemployment.[5] Similarly, the results represent the macroeconomic and wider environment, including risk profiles of firms, during the time period in which the data was collected, and so may not apply to future situations.

Second, we are only able to describe what happens on average to borrowers around a TFE, we cannot infer causal impacts of TFEs. Indeed, we see increasing probabilities of arrears just before the job loss event. This observation weakens any claim to causality, as these unexpected exogenous shocks should not be anticipated. Several reasons might explain these pre-treatment effects. First, some job losses may coincide with other life events that could affect a person's likelihood of credit arrears. These events may even precipitate or cause unemployment shocks. Moreover, in cases where employment ceases due to long-term illness or disability, other factors associated with ill health might lead to an increased probability of default, even before one must leave the workforce for health reasons.

Another explanation for noticing trends before the treatment could be due to errors in how employment transitions in our data. This information comes from what survey participants say about their own work history. Most participants would only need to remember changes in their employment over the past 12 months, assuming they take the survey every year. However, those who skip survey rounds might have to think back to the exact month when their job status changed, which could be several years ago. This gap in time could lead to inaccuracies in reporting their employment history. Nonetheless, our approach still allows

[5] Fixed effects estimation like that applied in this study allow us to estimate the average treatment effect on the treated (ATT). The ATT is the difference in the average outcome of treated units and the average outcome of untreated units, after controlling for all time-invariant differences between units. This is distinct from the average treatment effect (ATE) – the average treatment effect of all units in the population, regardless of whether they were treated or not. This makes generalization of effects difficult, as individuals who did not experience the treatment might also react in different ways if for example difficult macroeconomic conditions made different kinds of workers unemployed from previously.

us to measure the persistence and timing of arrears associated with several types of employment shocks.

Lastly, we believe that a household's wealth could significantly affect their chances of facing financial difficulties after a shock like job loss. But, since we did not have data on household wealth, we could not explore this in our study. This could be a critical area for future research if such data becomes available.

Implications for policy

Better understanding the drivers of financial distress is crucial for the FCA in ensuring we can deliver on our objective of protecting consumers. This research offers an evidence base by which we can regulate firms conduct effectively.

One of the most significant findings is that having to leave the workforce due to long term sickness or disability is associated with the largest increase in probability of arrears – with the likelihood of missing a payment more than doubling in the months after leaving employment. This is an important finding and stresses the need for targeted support for this already vulnerable group. We have extensive guidance on how firms should treat vulnerable customers. Indeed, this requirement for firms to act in the best interests of their consumers and place their customer needs first has been set out in a comprehensive set of rules introduced by the FCA under the Consumer Duty rules introduced in summer of 2023.

By identifying the timing associated with transitioning to unemployment and heightened probability of arrears, we demonstrate the need for firms to act quickly in response to these events to put in place support. This could include forbearance and financial guidance to prevent bad debts mounting and accruing over time. The same need to act quickly in response to these events applies to borrowers in constructively engaging with their lender and seeking support. The FCA is currently consulting on changes to its rules to help in strengthening protections for borrowers in financial difficulty.

The findings also show that the effect of job loss on arrears is persistent for up to 1 year following job loss. This suggests that policies should focus on early interventions to help consumers avoid getting into financial difficulty and distress to help them in the medium-to-long run. We have made it clear that lenders are expected to work constructively with those who fall behind on payments, or are at risk of doing so, ensuring tailored support can be put in place and that when communicating with customers in financial difficulties, consideration should be given to whether it’s appropriate to reduce, waive or cancel fees and charges.

Finally, we use horizon scanning and stress testing to identify and manage future risks to consumers. Horizon scanning involves identifying and assessing emerging risks, while stress testing involves simulating the impact of adverse events on financial institutions. This research provides an empirical evidence base for analysts to use for both horizon scanning and stress testing modelling. For example, by having estimates of the effect different transitions from employment have on the probability of arrears we can make projections (based off forecasted macroeconomic input variables such as unemployment, labor force participation rate, etc.) on the extent of overall credit risk of household credit markets.

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