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Job polarisation and household borrowing

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Abstract
The last few decades have seen transformative changes to the structure of employment, which have led to a deterioration in demand for middle-skill occupations, a process known as job polarisation. As demand for middle-skill workers shrinks, expectations about households' income through their lifetime horizon must be adjusted. It is possible that these expectations loop back into the credit system and affect the lending behaviour of credit institutions or that they impact households' self-assessment of their opportunities to borrow money. In this paper we study how the process of job polarisation affects credit demand and supply, studying its relationship with credit constraint and credit quality.

Keywords Job polarisation · Job security · Household credit · Employment expectations

1 Introduction

Since access to credit is a key determinant of social inclusion (Trumbull, 2012; Dwyer, 2018), unequal access to credit can reflect and sustain the processes that lead to increasing income and wealth inequality. Borrowers who cannot provide sufficient guarantees and collateral are often unable to obtain credit or can only do so at unfavourable rates, experiencing credit rationing (Stiglitz and Weiss, 1981) and sometimes over-indebtedness (Dynan and Kohn, 2007; Keese, 2019). Rationing may arise because lenders are uncertain about the borrowers' ability or willingness to repay or because of asymmetric information between lenders and borrowers.

For many, access to credit is determined by the characteristics of their occupation, such as income level, tenure, and stability, which are vital for lenders in assessing the creditworthiness of the borrowers. However, these characteristics may change over time due to structural shifts in the labour market, such as job polarisation. Job polarisation, i.e. the erosion of demand

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for middle-skilled occupations relative to high- and low-skilled jobs, has drawn increasing attention in economics and policy discussions. This phenomenon has characterised both the US (Autor et al., 2006; Autor and Dorn, 2013; Autor, 2013, 2019) and the EU alike over recent decades (Goos and Manning, 2007; Goos et al., 2009, 2014; Fernández-Macías and Hurley, 2016), and has often been considered one of the drivers of rising earnings inequality.[1]

This paper studies whether workers who experience job polarisation are more or less likely to experience credit rationing than other individuals. For example, workers in jobs that are being automated may face more credit rationing than workers in non-routine jobs because they have lower and more volatile incomes, and devaluing human capital. If these considerations factor into the lenders' decisions, job polarisation might affect inequality through both earnings and credit channels. Therefore, understanding how job polarisation affects credit access is important in assessing its implications for economic inequality and social welfare.

Job polarisation can affect households' access to credit *indirectly* through changes in income and employment status. In these cases, its effect on credit access is straightforward. Income drops have been known to affect credit records (Birkenmaier and Fu, 2019; Trumbull, 2012) and, similarly, low-income households have been found to experience higher credit prices and reduced access to credit (Coibion et al., 2020). Employment status changes, especially the switch to unemployment, are also causally connected to access to household credit (Keys, 2018; Keese, 2019).[2] Inter-generational effects should also not be excluded. Some authors (Berger and Engzell, 2022; Guo, 2022; García-Peñalosa et al., 2023; Hennig, 2023) have observed that the shrinking range of opportunities for middle-class workers also affects their children's prospects. Polarisation-biased credit constraints might exacerbate these second-order effects by further limiting inter-generational mobility and credit opportunities.

The existence of a *direct* effect of polarisation is less clear. The plausibility of this effect is tied to the permanent income hypothesis (Friedman, 1957). As consumption and, by extension, savings are determined by long-term considerations based on future income, they might be affected by economy-wide transformations in the occupational structure. On the credit demand side, households might then reconsider whether to apply for credit when job uncertainty increases.

On the credit supply side, credit institutions might use this information to understand the creditworthiness of applicants, and the discussion ties in with the issue of information asymmetries between banks and credit applicants (Stiglitz and Weiss, 1981). Occupational information is generally considered "hard" information that loan inspectors routinely collect and use to grant loans (Wang, 2020). This information is often used to assess the probability of default (Munnell et al., 1996) and to proxy and complement information on reported income that lenders cannot always verify (Ambrose et al., 2016). After the Great Recession, changes in regulations and best practices have now made the collection of job titles increasingly

[1] Its causes have been thoroughly discussed, and the consensus is that routine-biased technological changes are the predominant drivers of job polarisation (Goos et al., 2014; Green, 2019). These changes reduce the competitive advantage of human labour in routine-intensive activities (Acemoglu and Restrepo, 2018), leading to a fall in the relative demand for affected occupations, usually middle-skill jobs.

[2] The opposite causal channel (whether poor credit scores affect employment opportunities) has been investigated by Dobbie et al. (2020), who found no significant association.

commonplace (Ambrose et al., 2016).[3] In the light of these phenomena, it is not unreasonable to wonder whether polarisation in the labour market can affect solvency expectations on both the supply and demand side of credit, and whether the borrower's occupation might be used as a proxy for their occupational stability.

Our study focuses on this direct channel. It studies whether polarisation alone, net of variation in income and job status, can affect credit access through changes in expectations about future job prospects and stability. These credit constraints might be self-imposed by the household or derive from the explicit decisions of credit institutions. In other words, are individuals less likely to receive credit or even to apply for it if they have been working in occupations that, *ceteris paribus*, have become less prevalent?

Answering this question requires us to disentangle expectations about creditworthiness arising from aggregate-level and individual-level aspects of expected job security, which will inevitably be correlated. At the individual level, we examine how one's own job security, which may depend on personal characteristics and circumstances, influences the demand for and supply of credit. These conditions, relating to individual characteristics, are clearly endogenous in nature but might also include macro-level expectations.

At the aggregate level, we investigate how the polarisation of jobs in the economy translates into a source of "soft" information about job stability and, by extension, solvency for both lenders and borrowers. This effect might also be endogenous if individuals' ability to anticipate these changes, which led to their current occupations, correlates with credit access. Differences in the effect of job polarisation and security on credit demand and supply can reveal how much individuals internalise these macro-level transformations and provide a measure of information asymmetries between lenders and borrowers, given that households will disclose their occupation status but not their perceived job security when applying for credit.

Finally, we need to understand how these expectations are formed and when past changes in the occupational structure start affecting expectations about future job stability. Expectations might be based on medium-term trends that are less volatile than short-term shocks. Still, when occupations experience sudden shocks, banks and households might quickly react and revise their expectations.

For all these reasons, we study the role impact of job security and job polarisation separately and further divide polarisation into medium-term (15 years) and short-term (5 years) components. We use the European Labour Force Survey (EU-LFS) to measure changes in the occupational structure of Euro-Area countries between 2002 and 2017, and construct short-term and medium-term polarisation indicators, which we then combine with data from the Household Finance and Consumption Survey (HFCS). We then analyse how much job security and job polarisation predict household access to finance, focusing on credit exclusion, self-exclusion, and credit constraint as outcomes. To allay some endogeneity concerns, we also control for unobserved self-selection by controlling for the level of polarisation in the year that the individual obtained their current job.

[3] This academic evidence is also supported by first-hand official accounts from credit reporting agencies, such as this promotional article from the company Experian: "Why Do Lenders Ask Your Job Title?", August 2022 (Link: https://www.experian.com/blogs/ask-experian/why-do-lenders-ask-for-your-job-title/; Last accessed: 27/11/2023). Furthermore, in our informal conversations with banking supervision experts, we were told that banks routinely collect the job titles of applicants, if only for verification of the customer's identity. For example, the proposed EU Regulation COM(2021) 420 (also known as the Anti-money-laundering regulation) sets up the obligation for banks to verify information on "the occupation, profession, or employment status" of prospective borrowers. While the regulation has not been turned into law by the reference frame of our study, is indicative of existing best practices and increasing trends towards collecting and verifying this information.

While we refrain from attributing causal meaning to our results, they are suggestive and indicate that workers' access to credit correlates positively with the growth experienced by their occupation, regardless of their household's income level. Finally, we find that job polarisation and job security affect credit access in different ways, with the former playing a larger role in credit supply and the latter prevailing in terms of credit demand.

Our work contributes to the literature in several ways. On the credit demand side, the idea that expectations regarding the changing nature of jobs can also affect households' long-term plans is not unsubstantiated. Clark and Lepinteur (2022), for example, have found a link between job insecurity and decreasing fertility in France. There is also evidence that job insecurity affects consumption (Benito, 2006), and that individual expectations affect borrowing behaviour in general, as Kløve and Mehlum (2018) find that over-optimistic income and wealth outlooks can lead individuals to accrue unsustainable levels of debt.

On the credit supply side, there is evidence that credit institutions are wary of investing in labour-intensive industries with human capital at risk of substitution. We know that this process already affects credit access at the firm level, as industries experiencing wage and labour growth have easier access to credit (Favilukis et al., 2020), and unproductive, routine-intensive, and offshorable firms are the most strongly affected by buyouts, which trigger further investments in automation and offshoring, and hence further job losses (Olsson and Tåg, 2017).

In looking at personal credit, we have noted that occupational information is used to verify reported income: Ambrose et al. (2016) show that, before the Great Recession, "low-documentation" loans, which were issued without collecting the applicant's job title, featured a higher likelihood of income overreporting and were more likely to default than "high-documentation" loans. There is also evidence that credit institutions try to proxy job security somehow.[4] For example, employment status and history have been known to be highly correlated with credit access (Herkenhoff et al., 2021) and to influence credit scoring (Reichert et al., 1983). It follows that proxies for job security are abundantly used in credit scoring and range from job stability (Reichert et al., 1983) to biological and psychobehavioural factors (Brockett and Golden, 2007). Finally, and most importantly, Gabriel and Rosenthal (1991) find that credit rationing is predicted by the aggregate *level* of employment in the applicant's occupation. However, the relationship between job polarisation or, more simply, the aggregate *change* in employment and access to credit in the household sector remains unexplored.

The paper is organised as follows: Section 2 discusses our empirical model, and details how our polarisation indicator is constructed. Section 3 discusses our data sources, and the results are presented in Section 4. Section 6 concludes.

2 Empirical model

In the short term, it is straightforward that phenomena such as job polarisation occur outside the control of the individual. To account for this, a naive model can take the following form:

$$Y_{ico} = \alpha + X^{'}_{ico}\beta + K^{'}_{co}\gamma + \xi_c + e_{ico} \tag{1}$$

[4] The idea that credit institutions, employers, or insurance firms might proxy unavailable individual information through other observables is not new to the economics literature. In the context of job applications, this form of statistical discrimination has been studied, for example, in Agan and Starr (2017); Doleac and Hansen (2020), and Bartik and Nelson (2019).

where we define, for household i, in country c, and occupation group o, Y as the set of outcome variables of interest (credit constraint, credit refusal, credit self-exclusion, and interest rates over a three-year span). X is a vector of control variables varying at the individual level, and β is a vector of coefficients.

The coefficient vector γ captures the effect of our vector of job polarisation variables $K : \{K_{t,t-15}, K_{t,t-5}\}$. We incorporate polarisation in our model by looking at both short-term (a 5-year timeframe) and medium-term (15-year) polarisation. While these cut-offs are arbitrary in nature, they provide much-needed simplification for purposes of empirical traceability.[5] The time subscript t is omitted from the rest of the equation for clarity since time variation is fixed between the short-term and medium-term periods.

The literature measures polarisation in terms of variation in total hours worked for each occupation in a given country over a specific timeframe (see, for example, Goos et al., 2014, 2009). For example, the polarisation indicator for managerial occupations in a country is usually measured by the change between two specific years in the share of hours worked by managers against the total hours worked in the country. We follow a similar approach in creating our polarisation indicators, aggregating the data at the country and occupation levels.

Our indicator of choice will proxy job polarisation through changes in occupational shares. These changes are related to job polarisation, but it should be noted that these are two separate but closely related phenomena. Job polarisation refers to the simultaneous growth of employment shares in occupations at the high and low ends of the skill or wage distribution while the share of occupations in the middle declines. Changes in occupational shares are more general and can capture other patterns of employment shifts that are not necessarily related to routine-biased occupational changes. While the two concepts often overlap, it is important to remember these limitations.[6]

In formulas, both short- and medium-term indicators are computed as:[7]

$$K_{ico} = \frac{\sum_{i=1}^{N} h_{ico,t}}{\sum_{i=1}^{N} h_{ic,t}} - \frac{\sum_{i=1}^{N} h_{ico,t_0}}{\sum_{i=1}^{N} h_{ic,t_0}} \tag{2}$$

where h is the usual number of hours worked per week by each individual i in country c and occupation o, in years t and t_0. The 15- and 5-year indicators are obtained by setting t_0 at $t-15$ and $t-5$, respectively.[8] In other words, for each country, each term on the right side of the equation gives the percentage of total hours worked in a given occupation relative to the total hours worked in a country, and polarisation is given by the difference between these percentages in t and the baseline year t_0.

[5] While there is no defining year for the beginning of the current polarisation process, a large body of research has placed its beginning at the very end of the last century (Fernández-Macías and Hurley, 2016; Goos et al., 2014), and most studies on job polarisation focus on the transformation of the labour market over a period that can go back 15 years (Fernández-Macías and Hurley, 2016; Goos et al., 2009, 2014; Autor et al., 2006; Autor, 2019). Those that have studied polarisation for a longer period (such as Adermon and Gustavsson, 2015) find that task-biased polarisation has played a large statistical and economic role only since the turn of the century.

[6] Other indicators, such as those from Dauth et al. (2014) and Mahutga et al. (2018), have been considered. In some cases, data requirements often limit the empirical tractability of these indicators in our research. This is the case for the indicators from Mahutga et al. (2018), which do not go up to 2017 or generally do not feature enough time variation to be incorporated into our analysis. In some other cases, such as for Dauth et al. (2014), the model-based nature of the indicators renders their interpretation less clear in the context of our model, hence we opted for the simpler indicator focusing on the change in the share of hours worked in an occupation.

[7] LFS survey weights are omitted from the formula for simplicity.

[8] These values equal 2002 and 2012 when setting t at 2017 for our estimation.

Returning to Eq. 1, as K varies at the level of the country and occupation, country fixed effects ξ_c are identified, and γ will yield the within variation for each state. As the change in working hours should be measured relative to the total working hours in each country, we would like to keep country-idiosyncratic employment levels and credit propensity fixed. This is achieved in two ways. First, idiosyncratic employment levels are used to weight the polarisation indicators, ensuring that the γ coefficient will not be biased by the total employment levels in each country. Secondly, general differences in the credit system between countries are controlled for by the state-level intercept ξ_c without the need to add further controls.

Following Abadie et al. (2017), standard errors are clustered at each occupation cluster (for a total of 50 clusters), as this is where the source of variation in treatment is located after controlling for country effects. Occupation fixed effects (which we will define as ψ_o) can also be included for robustness, but this way γ will yield the within variation for each state and occupation cluster. Occupation categories are based on ISCO-08 two-digit sector codes.

Other individual-level controls included in vector X are age (and its squared term), level of education, gender, nationality, employment status (and temporary/fixed nature of a contract), years of experience in the main occupation, labour income (in logarithmic terms), and hours worked per week. We also include controls for individual risk propensity and for property status of the main household residence (denoting whether the household inherited the residence or is renting it). Household characteristics were also included in X, comprising household total gross income (in logarithmic terms), and information on household components, such as the total number of members, the number of dependent children, and the number of members in employment. The choice of these controls is consistent with the determinants for credit demand studied by the literature on debt attitudes (Almenberg et al., 2021) and earnings stability (Cappellari and Leonardi, 2015).

While it is tempting to include fixed and financial assets as controls, it should be noted that credit access might affect these directly, meaning that they should be considered endogenous and, as such, be omitted from the equation. However, we need to control for the household's financial situation in some way. Other than controlling for the income components and individual risk attitudes, all of which ultimately affect the accumulation of capital, we also add controls for the pre-existing level of indebtedness of the household. More specifically, we control for the outstanding amount of credit (in logarithmic form) for all pre-existing debt. We do so by subtracting the outstanding amount of credit obtained in the last three years from the total outstanding amount of credit a household is holding in its liabilities.

This naive model starts from the implicit assumption that K is exogenous to all individuals in the short to medium terms. While it is true that the process of job polarisation is outside the control of the individual, there are reasons to argue that, if the process of job polarisation was already taking place, an individual might have had some control over their past occupational choices.

In other words, we are interested in looking at the effects of polarisation ex-post an individual taking up a job. If all these changes occurred after the job was taken, the polarisation variable should not suffer from bias. However, some of these changes might have occurred before an individual took up a specific occupation, creating a self-selection issue that needs to be accounted for. This line of reasoning is not new to the literature: as Clark and Postel-Vinay (2008) find, individuals with lower risk propensity usually self-select into more stable jobs, such as permanent public sector positions.

To account for this issue, an alternative strategy can be considered, quantifying the level of job polarisation when the individual enters the labour market. The model can be adjusted to control for sector-specific employment levels during the year the job was taken, adding as a control a variable, the change in employment levels in the respondent's occupation between the long-term baseline year and the year that the job was taken ("Polarisation at t_i"). [9]

$$Y_{ico} = \alpha + X^{'}_{ico}\beta + K_{co}\gamma + L_{ico}\delta + \xi_c + e_{ico} \tag{3}$$

The equation now includes the control L_{ico} (Polarisation at t_i), measuring the economy-wide change in total working hours in a given occupation between the current year and the year that the occupation was taken up by the individual. This indicator is obtained using formula 2, switching t for t_i, the year the individual started their last job, and setting t_0 to the farthest available baseline year (2002, in our case). The indicator will then denote the change in the relative polarisation level between the long-term baseline and t_i, the year the occupation was taken up. We also define this baseline year as the beginning of the polarisation process: if the individual started their current job before the baseline year, we set the change as 0.

We adopt 2002 as our baseline year for this self-selection control. Data availability concerns dictate this choice, as occupational data becomes more unreliable for the years preceding 2002.[10] However, as discussed earlier, most commentators place the beginning of the polarisation process (and of routine-biased technological change in particular) at the end of the last century (around 1980), so our frame of analysis will not cover the entire routine-biased polarisation window.

Nonetheless, while this choice does not completely shield our approach from selection bias caused by career and education decisions taken before the arbitrary baseline year, we feel that it is reasonable to argue that it will cover some important sources of endogeneity. First, the polarisation process has continued until the end of our sample period, and, if anything, the number of occupations at risk of automation has only been growing, so it is reasonable to believe that many of these changes have been unexpected. Second, few workers entering the labour market before 2002 could have predicted labour market developments 15 years into the future and changed occupation before 2002. Controlling for time in the main occupation on top of our self-selection control, as we do, should mitigate the issue. In any case, it is worth keeping these limitations in mind, as some workers might still have been able to anticipate these changes when pursuing further education or training.

Finally, additional selection concerns might arise when studying access to credit from the supply side. As access results from the equilibrium between demand and supply, it is clear that banks will only receive loan applications from individuals who believe that they can repay a loan or, at the very least, that the bank will grant it. If the explanatory variable is affected by this selection issue, we might then have another endogeneity problem.

This problem arises when the outcome variable is only observed for households with access to credit markets. Households with no interest in ever applying for credit should then be disregarded.

In our case, we exploit information on credit demand to overcome this selection problem. We do so by restricting the sample so that only those households which had considered applying for credit within the last three years were retained in the estimation. We identify these households as those which have either applied for credit within the last three years or

[9] Alternatively, instrumental variables (such as the job of the parents of the reference person) can be used to achieve randomisation for the chosen occupation and then exploit this randomisation to predict the assigned degree of polarisation. This is a more complicated strategy with extremely limited empirical tractability for the case at hand, given that only a handful of HFCS countries (Spain, France, and Portugal) have data on parental occupation.

[10] Nonetheless, the polarisation indicator can still be reconstructed for a subset of countries for all years until 1999. See our robustness checks in Appendix A for specifications using wave 2 of the HFCS.

have decided not to apply for credit (within the same timeframe) because of perceived credit constraints.

Under the assumption that this variable is independent of other unobservable factors that affect credit demand, we can proceed with the estimation without worrying about endogenous selection when studying access to credit.[11] Naturally, this is a strong assumption. Still, we argue that controlling for income idiosyncratic risk attitudes and other household characteristics should reasonably ensure that the endogenous components of credit demand are accounted for (for a review of determinants of credit choice, see Guiso and Sodini, 2013).

A serious effort to tackle the endogeneity in credit demand goes beyond the intentions of this paper and is left to future research. Therefore, the job security results might not be robust to endogeneity in credit demand. However, if polarisation is assumed to be an exogenous process, which, as we discussed, is not an unreasonable statement after controlling for the relevant confounders, then its assignment occurs regardless of the demand for credit, and we can claim that the results for job polarisation are robust to selection bias.

3 Data and main variables

The main variables used in the analysis are reported in Table 1. We use the Household Finance and Consumption Survey (HFCS) as our main data source. The survey collects detailed household-level data on various aspects of household balance sheets and related economic and demographic variables, including income, occupational information, and household characteristics. The HFCS is conducted in a decentralised manner by the European Central Bank, using a harmonised blueprint questionnaire. The HFCS is available for Austria, Belgium, Croatia, Cyprus, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Slovakia, Slovenia, and Spain.

We use the latest wave of the HFCS (wave 3, 2017), so our analysis focuses on polarisation in the new millennium and studies credit access during a time window (2014-2017) of stable and extremely low interest rates in the Euro Area.

However, the data structure of the HFCS presents a few challenges for our analysis. In particular, while occupational information is provided for each household member, financial information regarding liabilities is usually nested at the household level. To account for how the occupational composition of a household affects debt, we focus on the specific occupation of the household head, which we assume is the person who will be applying for credit. Nonetheless, we have considered the occupational status of other household members, which we use as a control in our analysis.

Also, we restrict the sample to all households that have applied for (or have considered applying for) credit within the last three years preceding the survey. In this way, the correlations with job security/polarisation can be measured over a relatively small timeframe, potentially increasing the probability that the household characteristics and macroeconomic

[11] Alternatively, Heckman selection models can be used to randomise the credit demand component, exploiting some other source of variation. For example, this variation could be found in the receipt of gifts or inheritances. We have tested these methods with little success: traditional two-step Heckman models do not allow for clustered standard errors, which are a strict requirement for correct inference in our model since the treatment is assigned at the occupation-country level. Maximum likelihood Heckman models allow for clustering but are more computationally intensive and can suffer from collinearity issues (Puhani, 2000), and in our case, convergence could not be obtained precisely for these reasons.

Table 1 Main variables

VARIABLES	Definition	Source	original coding
Outcome variables			
Credit refusal	Household's credit applications have been refused at least once (last 3 years)	HFCS	DOCREDITREFUSAL
Credit self-exclusion	Household has considered applying for credit but has not applied for it (last 3 years)	HFCS†	HC1400
Credit constrained	Household has experienced either credit refusal or self-exclusion (last 3 years)	HFCS	DOCREDITC
Interest rates	Weighted average of the interest rates of all loans received by the household in the last 3 years	HFCS†	–
Control variables			
5-year polarisation	% change in total hours worked between 2012 and 2017	LFS†	–
15-year polarisation	% change in total hours worked between 2002 and 2017	LFS†	–
Polarisation at t_i	% change in total hours worked between 2002 and t_i	LFS-HFCS†	–
Job security	Inverse of perceived likelihood of losing current main job in the last 12 months	HFCS†	PEZ010
Family income	Total family income before taxes, including interest payments (ln)	HFCS	DI2000
Labour income	Sum of received employee and self-employee income (ln)	HFCS†	DI1100, DI1200
Age	Age of reference person, Canberra definition	HFCS	DHAGEH1
Gender	Gender of reference person (female)	HFCS	DHGENDERH1
Work hours	Hours worked per week in main job (average over year)	HFCS	PE0600
Work experience	Years worked in main job	HFCS	PE0700
Outstanding debt	Outstanding amount of all debt received before 2014	HFCS†	–
Hh. size	Household size	HFCS	DH0001
Hh. employment	Number of household members in employment	HFCS	DH0004
Education	Educational attainment of reference person (ISCED)	HFCS	PA0200
Job status	Labour status and status in employment	HFCS†	PE0100, PE0200
Foreign born	Born outside the country of fieldwork	HFCS†	RA0400
HMR acquired before 2014	Household has acquired the main property before 2014	HFCS†	HB0700
Investment attitudes	Self-assessed financial risk aversion	HFCS	HD1800
Occupation	Two-digit ISCO-08 occupation class	HFCS	PE0300

Notes: Outcome and control variables used in the analysis. All variables concern the reference person unless stated otherwise. †Author's re-elaboration using the stated data source. Original variable coding omitted when more than two variables have been used to construct the final variable conditions captured at the time of the survey were still representative at the time of the credit application.

When looking at our main dependent variables, we focus on two aspects of credit access and conditions: credit constraint (including self-exclusion from credit and credit refusal) and interest rates. The first two variables are already included in the HFCS.[12] As credit constraint describes a situation in which the household has applied or considered applying for credit but was refused credit, received less credit than requested, or has not applied due to perceived credit constraints, we intend to disentangle credit supply from credit demand. We do so by studying credit refusal, which describes the same situation but only for households which have applied for credit, omitting the households that self-excluded. Finally, we study self-exclusion by examining how the decision to apply for credit is formed and influenced by changes in occupations among all households who considered applying for credit.

Interest rates are constructed by dividing the sum of all interest payments from all the debt accumulated over the last three years by the total amount of this debt. As the year when the loan was taken is not available for all types of credit (it is missing for consumer credit), the missing year is imputed by looking at the difference between the amount initially borrowed and the outstanding balance of the debt by the yearly repayments. If the distance with the latest loan is greater than three years, this source of credit is not considered in the estimation. Calculating interest rates in this way might subject our results to attenuation bias because of the discounting of debt over the years due to inflation: we feel, however, that by focusing on a short timespan characterised by low inflation, this bias is moderately contained, and that the marginal contribution of adjusting the interest rate calculation for real rates is quite limited.

To measure perceived job security, we use the HFCS variable on the probability of losing one's job: "On a scale of 0 to 100, what do you think is the likelihood that you will lose your current job in the next twelve months [...]?" (*pez010*). We invert this variable and divide it by 100 to harmonise it with the job polarisation variables in terms of comparability of results. As will be discussed later, dummies for the temporary and fixed-term nature of work are also included in the control vector of the regression model so that job security can be studied by holding contract characteristics as fixed.

To ensure that the largest possible period of job polarisation was examined, we focus on the third and latest wave of the survey (2017), but the analysis could be replicated on previous waves from 2011 and 2013.

We measure medium-term polarisation from the baseline year of 2002, combining official Eurostat data on average working hours and on the number of people employed in each occupation to obtain the total amount of hours of work supplied in an occupation for each country in the years 2002 and 2017[13] Thus, polarisation is measured as the difference between the share of hours worked in a given occupation and for a given country within each major occupational group (ISCO-08 one-digit codes) relative to the total occupation level in that same year and the same relationship in 2002.

Short-term polarisation is measured using EU Labour Force Survey data from 2011 onwards. We use a more granular indicator for short-term polarisation than the medium-

[12] Variables *hc1400* "In the last three years, did you (or another member of your household) consider applying for a loan or credit but then decided not to, thinking that the application would be rejected?", and *hc1310* "In the last three years, has any lender or creditor turned down any request you [or someone in your household] made for credit, or not given you as much credit as you applied for?".

[13] These data, based on EU-LFS estimates, are publicly available at https://ec.europa.eu/eurostat/databrowser/view/LFSA_EWHAIS__custom_10689/default/table?lang=en and https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=lfsq_eegais&lang=en. Data for all Euro area countries is only available beginning from 2000.

term one, and measure changes in the country-wide share of two-digit ISCO-08 occupations since 2012 instead. At the one-digit ISCO-08 level, jobs are divided into 10 major occupational groups. These groups are divided into 43 more granular sub-major groups at the two-digit level.

This dichotomy between short and medium-term polarisation and the difference in the granularity of the indicators is linked to changes in the occupational coding conventions used in the surveys. ISCO-08 occupational codes in the LFS are available only from 2011 onwards and are difficult to harmonise at the two-digit level with the ISCO-88 codes used in the previous survey rounds. While harmonisation for two-level codes is challenging (ILO, 2012), two-digit ISCO-88 codes can be converted directly into ISCO-08 at the one-digit level with relative ease: this means that, for the medium term, our polarisation indicator can only be measured for major occupational groups.

These differences between classification schemes do not compromise our methodology but can better accommodate qualitatitive changes within professions. As the nature of occupations changes, so does the demand for them: we need to disentangle the idiosyncrasies born of changes in the quality of occupations from changes in the demand for specific skills and tasks. In other words, over a 15-year period, the same occupation might change its task structure completely or cease to exist altogether.

In the medium to long term, changes in the occupational structure can be expected to be accompanied by non-negligible idiosyncratic transformations in the nature of the occupation. These transformations are less likely to occur in the short term and are reflected in the changing nature of ISCO classification standards, which are updated precisely to reflect the changing nature of occupations. For this reason, our strategy is not compromised by measuring changes in major (one-digit) occupational groups for the medium-term indicator and changes in sub-major (two-digit) groups for the short-term.

As a final note, our data choices are intended to account for the subprime crisis of 2008 and the sovereign debt crisis of 2009. On the credit side, focusing on the latest HFCS wave ensures that credit access occurs post-crisis. The use of country-fixed effects also ensures that country-level credit shocks are taken into account. On the labour side, the labour structure has indeed been affected by both crises, possibly accelerating the polarisation process, which, in turn, can affect expectations regarding trends in the labour market. We expect the long-term polarisation indicator to capture changes in the labour structure attached to these crises. The short-term indicator (and its effect on credit) will also reflect these changes if they persist. Should they not persist, the temporary nature of these changes in labour market expectations would emerge from a lack of significance of the long-term polarisation indicator in our analysis.

Before proceeding with the rest of our analysis, we must evaluate how our security and polarisation variables correlate with the observed regressors. Table A from Appendix A1 displays the correlations between our job security/polarisation variables and the rest of the controls used in our analysis. The job security/polarisation variables are now scaled by a $\times$ 100 factor to better appreciate the correlations with the other controls. As expected, job security appears strongly correlated with most other controls. Its strong correlations with labour income, tenure, and employment status are expected. The correlation with prior debt, household income, and low-risk propensity also indicates that certain environmental factors might lead individuals to worry more about their employment situation.

Interestingly, the job polarisation indicators are not correlated with many variables, confirming their mostly exogenous nature. The short-term polarisation indicator is almost unrelated to any other variable. Some correlations are to be noted: long-term polarisation is connected with education and weekly working hours, as is the job market entry polarisation variable. This evidence confirms our hypotheses regarding the nature of polarisation, as jobs requiring skill and education appear to have a strong influence on medium-term polarisation. The negative relationship with household size, which also characterises job security, indicates that changes in future employment prospects might lead to decreased fertility, supporting recent literature on the topic (De Paola et al., 2021).

Short-term polarisation, before adding occupational fixed effects, appears to be connected mostly with weekly working hours instead, suggesting that these changes in labour demand have mostly translated into a reduction in working hours and have yet to translate into income deterioration, holding hours of work as fixed. The lack of correlation with most other variables suggests that these short-term shocks are mostly exogenous.

4 Results and discussion

In this section, we report the main results from the model presented in Section 2. We present results for the influence of job security, short- and medium-term polarisation over credit constraint, access to credit and self-exclusion, and interest rates. For each outcome, we offer estimates with and without the self-selection control for polarisation (Polarisation at t_i).

Looking at credit constraints in Table 2, Columns 1 to 5 each alternate between the job security and polarisation variables in a stepwise approach. Column 6 presents the joint effect of security and polarisation. Column 1 reports results for job security: we find that perceived job security is negatively and significantly related to credit constraint. The coefficient obtained implies that for every 1% increase in subjective job security, the probability of experiencing credit constraint is reduced by 0.14%.

It is important to recall that these results are robust to the job status of the respondent,[14] meaning that a statistically significant relationship between subjective security and credit constraint can be found regardless of whether the respondent is in a part-time, fixed-term, or temporary employment arrangement, and independently of self-employment status.

How are these results driven by endogenous self-assessed insecurity, and how much are they related to exogenous decaying demand for specific jobs?

Columns 2 to 5 drop the job security variable and investigate the relationship between short- to medium-term job polarisation and credit constraint. Columns 2 and 3 switch between the medium-term and short-term variables, while column 4 shows their joint effect. Finally, column 5 introduces the control for self-selection into occupations experiencing polarisation (Polarisation at t_i). We find a statistically significant effect of short-term polarisation in all columns where the variable appears. Medium-term polarisation is usually not statistically significant and only gains significance once the self-selection control is included.

These findings imply that a 1% shift in the hours worked within a specific occupational group between 2017 and the last five years is linked to a decrease of approximately 0.80% in the probability of the household experiencing credit constraints.

Most importantly, the introduction of the self-selection control indicates that a 1% difference in the relative weight of an occupation between 2017 and the year that the individual started working in their current job leads to an average 0.49% decrease in the probability of experiencing credit constraint. As discussed earlier, this strategy is employed to account for potential self-selection into occupation groups experiencing polarisation within the last 15 years.

[14] The job status group of dummies are omitted from the table because of lack of space, but the full model is available on request.

Table 2 Job polarisation and credit constraint

VARIABLES	(1) Credit constrained OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
Job security	-0.139***					-0.144***	-0.139***
	(0.021)					(0.022)	(0.023)
15-year polarisation		-0.059		-0.023	0.166	0.228*	0.605**
		(0.088)		(0.087)	(0.112)	(0.113)	(0.250)
5-year polarisation			-0.826***	-0.815***	-0.798***	-0.814***	-1.294***
			(0.257)	(0.263)	(0.269)	(0.285)	(0.395)
Polarisation at t_i					-0.487**	-0.494**	-0.519**
					(0.200)	(0.218)	(0.218)
Family income	-0.028***	-0.030***	-0.035***	-0.035***	-0.035***	-0.033***	-0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Labour income	-0.007**	-0.008**	-0.006*	-0.006*	-0.006*	-0.005	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Gender	0.023**	0.022**	0.021*	0.021*	0.021*	0.021*	0.019*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Work hours	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Work experience	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Outstanding debt	-0.015***	-0.016***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	10,378	10,708	9,904	9,904	9,904	9,574	9,574
Adjusted R-squared	0.248	0.245	0.241	0.241	0.241	0.244	0.247
Occupation controls	No	No	No	No	No	No	Yes
Member state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reference person controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS estimates for the effect of job security and job polarisation on credit constraint. Standard errors clustered by occupation in parentheses. Other controls: household size, HMR acquired before 2014, risk attitudes, no prior credit past the three-year mark, nationality, education, and labour status of reference person *p<.05; **p<.01; ***p<.001

Interestingly, the introduction of the self-selection variable only reduces the magnitude of the short-term polarisation coefficient by a negligible margin, meaning that self-selection is only relevant in the context of medium-term polarisation (the coefficient of which indeed gains in magnitude and significance through the introduction of the self-selection variable), and that has no influence on short-term polarisation. These results can be explained by the intuition that, in the medium term, individuals might have time to reconsider their occupational choices given the macroeconomic circumstances, while short-term occupational shocks leave individuals with little leeway. Our findings here are consistent with our hypotheses and show that households with a head who has been employed in an occupation which has experienced a decrease in demand have a higher probability of finding themselves credit-constrained.

The inclusion of controls for individual and family financial characteristics (along with all other controls) rules out this relationship being driven by the income class of a given occupation. Instead, it suggests that expectations regarding income change and employment security do play a role in situations of credit constraint. Job security is reintroduced in Column 6, but has negligible influence on the other coefficients of interest.

The full set of controls is included in all specifications, except for occupational intercepts, which are introduced in Column 7, featuring the same specifications offered in Column 6 plus the fixed occupational effects. The use of occupation controls in column 7 increases the effect of short-term polarisation but is countered by a positive value for the medium-term coefficient. However, it should be recalled that, by adding occupational intercepts, we are only studying the effect of polarisation within each country and occupation group, so these estimates are to be interpreted as the lower bound of polarisation. However, the difference between the two coefficients confirms that, on average, the trend towards credit constraint persists regardless of the idiosyncrasies of individual occupations. Job security is only marginally affected by the use of occupation controls in Column 6, with its coefficient retaining its sign and magnitude.

The models in Table 2 are estimated over the full population of households considering credit, meaning that credit demand and supply are bundled together. However, we might wish to focus on the demand side and supply side of the phenomenon only. We do so in Tables 3 and 4.

Focusing on credit supply, Table 3 shows the relationship between job security and polarisation over the probability of experiencing credit refusal or reduction at least once, estimating our model over the population of households that have applied for credit. Instead, Table 4 focuses on credit demand by studying the decision to apply for credit, estimated over the sample of all households that have considered applying for credit in the last three years.

The results of job polarisation are largely unchanged with regard to credit supply. The short-term coefficient retains significance, and its magnitude is only tempered by a few points. The full specification in column 5 indicates that a one-point increase in the relative importance of a job in a country over the last five years leads to a 0.70% decrease in the probability of having a credit application refused or reduced credit. The self-selection variable also displays a similar -0.45% coefficient. Again, the reintroduction of job security in Column 6 leaves the estimated coefficients largely unaffected, with the larger magnitude of the polarisation coefficients also suggesting that these factors play a much larger role in credit supply than what little information banks could have on the effective security of an applicant's job.

Perceived job security has much less influence on credit refusal than it has over credit constraint. An increase in one percentage point in the perceived security only reduces the probability of rejection by around 0.04%, compared to the -0.14% coefficient when looking at credit constraint in general. Table 4 reveals that job polarisation does not have a statistically significant effect on self-exclusion, but job security does. More specifically, we find that perceived job security affects the probability of applying for credit by around 0.09% for every 1% increase in perceived security. Job polarisation is nearly always statistically insignificant. These results indicate that while job security affects credit access across the board, job polarisation might have a negligible effect on credit demand while strongly influencing credit supply. Finally, the inclusion of occupational intercepts in column 7 does not seem to significantly affect the estimates obtained earlier.

Intuitively, these results suggest that credit institutions do not take subjective job security into account (or are not able to observe it), but that they will take general labour market trends into consideration when making lending decisions. Furthermore, they suggest that perceived

Table 3 Job polarisation and credit refusal

VARIABLES	(1) Credit refusal OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
Job security	-0.052***					-0.045**	-0.043**
	(0.019)					(0.019)	(0.019)
15-year polarisation		-0.087		-0.037	0.121	0.164*	0.205
		(0.082)		(0.076)	(0.089)	(0.089)	(0.247)
5-year polarisation			-0.747***	-0.732***	-0.703***	-0.694***	-0.760**
			(0.204)	(0.212)	(0.214)	(0.212)	(0.372)
Polarisation at t_i					-0.422**	-0.464***	-0.469***
					(0.175)	(0.170)	(0.163)
Family income	-0.018***	-0.018***	-0.023***	-0.023***	-0.023***	-0.023***	-0.020***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Labour income	-0.003	-0.003	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	0.007	0.008	0.003	0.003	0.003	0.003	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Work hours	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Work experience	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Outstanding debt	-0.006***	-0.006***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	9,275	9,538	8,809	8,809	8,809	8,546	8,546
Adjusted R-squared	0.104	0.112	0.113	0.113	0.113	0.104	0.104
Occupation controls	No	No	No	No	No	No	Yes
Member state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reference person controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS estimates for the effect of job security and job polarisation on credit refusal. Standard errors clustered by occupation in parentheses. Other controls: household size, HMR acquired before 2014, risk attitudes, no prior credit past the three-year mark, nationality, education, and labour status of reference person
*p<.05; **p<.01; ***p<.001

security does not necessarily align with job polarisation and that, while households might not take polarisation into account when building expectations about their jobs, credit institutions will.

Focusing on credit constraint and refusal does not necessarily paint the full picture of the relationship between job polarisation and borrowing. Another important facet of credit pertains to the credit quality accessible to a household. In Table 5, we then study the relationship between polarisation and interest rates. The sample is now censored to include only households with access to credit within the last three years.

Table 4 Job polarisation and credit self-exclusion

VARIABLES	(1) Credit self-exclusion OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
Job security	-0.081***					-0.090***	-0.087***
	(0.013)					(0.014)	(0.014)
15-year polarisation		-0.107		-0.121*	-0.111	-0.105	-0.081
		(0.065)		(0.068)	(0.088)	(0.083)	(0.159)
5-year polarisation			-0.004	0.053	0.054	0.010	-0.396
			(0.222)	(0.227)	(0.228)	(0.217)	(0.415)
Polarisation at t_i					-0.025	-0.009	-0.024
					(0.155)	(0.139)	(0.138)
Family income	-0.008**	-0.009**	-0.011***	-0.010***	-0.010***	-0.009***	-0.008**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Labour income	-0.005**	-0.006**	-0.005*	-0.005*	-0.005*	-0.004*	-0.004*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.000	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.012*	0.013*	0.013*	0.014*	0.014*	0.014*	0.014*
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Work hours	0.000	0.000	0.000	0.000	0.000	0.001	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Work experience	-0.001**	-0.001***	-0.001***	-0.001**	-0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Outstanding debt	-0.015***	-0.016***	-0.015***	-0.015***	-0.015***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	10,796	11,138	10,334	10,334	10,334	9,992	9,992
Adjusted R-squared	0.424	0.424	0.429	0.429	0.429	0.430	0.431
Occupation controls	No	No	No	No	No	No	Yes
Member state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reference person controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS estimates for the effect of job security and job polarisation on credit self-exclusion. Standard errors clustered by occupation in parentheses. Other controls: household size, HMR acquired before 2014, risk attitudes, no prior credit past the three-year mark, nationality, education, and labour status of reference person

*p<.05; **p<.01; ***p<.001

In all specifications, we find no significant association between interest rates and either job security or polarisation. These findings suggest that, although households experiencing polarisation find it more difficult to access credit, polarisation alone does not seem to be connected with households experiencing harsher credit conditions. Moreover, they suggest that the relationship between credit constraint and debt quality might not make debt harder to manage. In other words, expectations about employment security and about the change in demand for a given occupation might restrain a household's demand for credit and credit

Table 5 Job polarisation and interest rates

	(1) Interest rates	(2)	(3)	(4)	(5)	(6)	(7)
Job security	-0.046					-0.111	-0.134
	(0.235)					(0.260)	(0.264)
15-year polarisation		-0.897		-1.197	-0.072	-0.239	-7.032*
		(1.057)		(1.085)	(1.288)	(1.331)	(3.992)
5-year polarisation			-4.611	-4.152	-3.915	-3.048	8.402
			(3.235)	(3.513)	(3.502)	(3.381)	(11.500)
Polarisation at t_i					-3.060	-2.481	-1.105
					(2.758)	(2.757)	(2.791)
Family income	-0.497***	-0.483***	-0.481***	-0.479***	-0.478***	-0.493***	-0.460***
	(0.124)	(0.117)	(0.131)	(0.132)	(0.132)	(0.140)	(0.144)
Labour income	0.028	0.038	0.028	0.028	0.028	0.017	0.019
	(0.030)	(0.028)	(0.029)	(0.029)	(0.030)	(0.032)	(0.030)
Age	0.031***	0.031***	0.031***	0.031***	0.031***	0.031***	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Gender	0.210**	0.230**	0.153	0.158	0.155	0.136	0.171
	(0.100)	(0.097)	(0.103)	(0.101)	(0.101)	(0.104)	(0.108)
Work hours	0.009	0.006	0.010	0.010	0.010	0.013*	0.015**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Work experience	-0.022***	-0.022***	-0.021***	-0.021***	-0.022***	-0.021***	-0.019**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Outstanding debt	0.029	0.043	0.046	0.046	0.046	0.031	0.032
	(0.032)	(0.031)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
Observations	7,252	7,426	6,789	6,789	6,789	6,615	6,615
Adjusted R-squared	0.302	0.296	0.301	0.301	0.301	0.308	0.310
Occupation controls	No	No	No	No	No	No	Yes
Member state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reference person controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS estimates for the effect of job security and job polarisation on loan interest rates. Standard errors clustered by occupation in parentheses. Other controls: household size, HMR acquired before 2014, risk attitudes, no prior credit past the three-year mark, nationality, education, and labour status of reference person *p<.05; **p<.01; ***p<.001

institutions' willingness to supply credit, but these limitations, all things considered, are only limited to the credit access phase.

5 Robustness analysis

In this section, we introduce a number of robustness checks. All checks are discussed here, but the corresponding tables containing the full specifications are relegated to Appendix A.

As a first robustness check, we have provided estimated marginal effects from logistic regression estimates for all binary dependent variables (credit refusal, self-exclusion and constraint) in the Appendix, Tables A2, A3 and A4. For clarity of exposition, we have provided marginal effects for the variables of interest only. As a word of caution, logistic regression is not necessarily the ideal tool for this specific analysis: firstly, we are not particularly interested in predicting credit access behaviour but rather in estimating the coefficients of our variables of interest (job security/polarisation), so the fact that predictions from a linear probability model will lie outside of the {0,1} interval is not a cause for concern. Secondly, our empirical setting imposes specific assumptions on the clustering of standard errors, given that our "treatment" is assigned at the occupation level. Linear probability models, which we have adopted for our main estimates, are known to be the better tool for this task.[15] However, logistic regression estimates can still provide a robustness check for our main estimates, and our results from Tables A2, A3 and A4 are comparable to those obtained from our linear probability models. While the coefficients differ slightly, which is expected given the skewed distribution of some variables, the sign, relative magnitude, and statistical significance are preserved in all instances.

Secondly, it could be argued that local factors might influence credit conditions or job displacement. To account for this issue, we perform additional robustness checks in Appendix A, Tables A5, A6, A7 and A8, in which we replace the country fixed effects with regional fixed effects. Unfortunately, data censoring in the LFS limits the empirical tractability of a polarisation indicator based on the regional level. We find little to no variation in terms of coefficient magnitude and significance compared to previous estimates. Arguably, the disappearance of previously significant coefficients would indicate that the relationship between polarisation and credit-taking would have been spurious, but this does not seem to be the case.

Finally, while wave 3 remains an ideal time window for both identification and data reasons, we can replicate our exercise for waves 1 and 2 of the HFCS.

Identification-wise, the stable and low interest rates characterising the time window of wave 3 make it preferable to other waves, but studying other waves might offer some insight into how much our results are affected by period-specific contingencies. Data-wise, some issues complicate this task, as (i) the job security variable is missing from waves 1 and 2, and (ii) the medium-term job polarisation variable cannot be retrieved easily. In fact, while the HFCS uses the ISCO-08 classification in all its waves, ISCO classifications in the LFS have switched between ISCO-88 and ISCO-08 codings after the 2011 wave. Nonetheless, we have been able to convert three-digit ISCO-88 codes in the LFS into two-digit ISCO-08 codes using official ILO crosswalk tables[16] to produce a medium-term polarisation indicator for the years 2009 to 2014, and have updated our long-term indicator to reflect changes from 1999 to 2014. The new medium-term indicator is far from perfect, as the conversion from ISCO-88 to 08 could never be exact.

Estimates for wave 2 are reported in Table A9 in Appendix A. While they feature larger standard errors, these estimates confirm the direction of the effect estimated in wave 3. However, it is difficult to say whether the much lower statistical significance associated with the medium-term polarisation term is to be attributed to monetary policy heterogeneity in bank lending behaviour or, more simply, to the higher statistical noise caused by the conversion from ISCO-88 to ISCO-08. Nonetheless, the effects estimated for the self-selection term remain positive and significant, and suggest that individuals who have self-selected into growing occupations have had easier access to credit, even in 2014.

[15] Using cluster-robust standard errors in logistic regression implies that the model is misspecified.

[16] Available at: https://www.ilo.org/public/english/bureau/stat/isco/isco08/,Lastaccess:15/05/2023.

6 Conclusions

In this paper, we have studied the relationship between job polarisation and access to credit for households, finding evidence that individuals whose occupations have become increasingly less prevalent in the labour market are more likely to experience credit constraints.

Our results indicate that, overall, for every 1% decrease in weekly hours in a given occupation over the last five years, equal (on average) to 25,000 full-time jobs, the probability that a household whose head is employed in that occupation does not apply for credit or sees its loan application refused increases by around 0.8%. Changes in the medium term (i.e. over a 15-year window) have a much smaller effect on credit access, while individuals who self-selected into dwindling occupations also experience an additional 0.5% reduction in the probability of loan success. These results suggest that, at least during our period of study (2014-2017), the success of credit applications was more reliant on sudden occupational shocks rather than on slower, momentous processes of transformation of the employment structure unless individuals chose to take jobs that were already disappearing.

Our results are robust to household characteristics and, most importantly, to the income level attached to an individual's occupation, meaning that these credit constraints are probably generated by expectations on the future income growth of the household. As our results remain unchanged even after controlling for the fixed effects of the occupation, we are able to rule out the effect of occupation-specific biases from the analysis.

Furthermore, we find job polarisation to be largely unrelated to perceived job security, with the former playing a larger role in credit supply and the latter prevailing in terms of credit demand. These results suggest that informational asymmetries between lenders and borrowers cannot be compensated for by proxying idiosyncratic job security with economy-wide polarisation, as job polarisation is a poor predictor of credit demand and, as such, is also uncorrelated with the actual job security perceived by the household. This process is entirely to the detriment of households, as these asymmetries might negatively affect credit access for households with a stable employment situation but whose members are working in occupations experiencing polarisation.

Interestingly, while households experience both (self-imposed) demand-side and supply-side constraints in access to loans because of expectations of shrinking demand for occupations, households experiencing polarisation do not seem to face more difficulties than other households in dealing with repayments, as we find no significant effect of either job security or polarisation on interest rates, indicating that fears about a connection between polarisation and insolvency might also be overstated.

Overall, this process might exacerbate economic inequality by creating a gap between those who can access credit and those who cannot. While our results suggest that occupational growth leads to easier access to capital, regardless of skill level, occupational groups that are already labour-income rich might benefit from even more opportunities to generate property and entrepreneurial income based not only on their current situation but also on general societal expectations on the income and career trajectory of occupations alone.

It is important to recall that the associations we found, while strong, do not necessarily indicate causality. Our approach allows us to control for certain sources of self-selection, as households might find it difficult to predict how the labour market will change in the short to medium term, let alone readjust their skills and qualifications, since human capital notoriously requires long-term investment. However, some individuals might be better than others in anticipating these changes when changing careers or choosing their study paths.

Furthermore, while the relationship between polarisation and credit access is strong enough to persist after several robustness checks, our results do not necessarily imply that banks directly use job polarisation as a proxy for creditworthiness. While the evidence we collected points to the fact that banks often collect job title information, the possibility remains that occupation is proxying for some other researcher-unobserved attribute that is used explicitly by banks to make these decisions and that correlates with the degree of polarisation in an occupation.

The value of our results thus lies in signalling the relationship between job polarisation and debt-taking, and calls for further research into this question, better investigating the causal ramifications and country idiosyncrasies of this relationship.

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Data Availibility Statement The dataset generated during the current study is not publicly available as it contains proprietary information that the authors acquired through a license. Please refer to the Data Transparency Statement (attached as a supplementary file) for instructions on how to access the data.

Declarations

Competing interests Neither author has any relevant or material financial interests that relate to the research described in this paper.

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