



EDUCATION, JOB QUALITY, AND TRAINING AS DETERMINANTS OF HOUSEHOLD INCOME RANK IN EUROPE

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Abstract: This article examines how education, recent training, and job quality shape household income rank across 30 European countries by using microdata from the European Social Survey. The study estimates a survey-weighted ordered logistic regression model in which household income decile is explained by years of education, training participation, employment contract type, supervisory responsibility, weekly working hours, and employment relation. Robustness is assessed through proportional-odds checks, alternative income groupings, and trimming of extreme working-hour values. The findings show that more years of education, recent training, permanent contracts, and supervisory responsibility are consistently associated with higher household income deciles, while temporary or no-contract arrangements are linked with lower income ranks. Contracted working hours show a small negative association with household income rank. By jointly examining human capital and job-quality factors in a comparative European framework, the study provides evidence relevant for policies aimed at inequality reduction, better access to training, and more secure employment. The results highlight that continuous skill development and stable, higher-quality jobs remain central channels through which households improve their relative economic position.

Keywords: household income, income decile, ordered logistic regression, human capital, job quality, training, labour market inequality, Europe.

JEL classification: J24, J31, D31, C25

1. Introduction

Household income is a fundamental indicator of economic well-being, and understanding its determinants is crucial for addressing inequality and promoting social welfare, as it can have an impact on poverty alleviation and economic growth (Cheng et al., 2021). In Europe, as elsewhere, policymakers and researchers have long examined why some households occupy higher positions in the income distribution while others remain at the bottom. Prior studies identify a complex interplay of individual attributes, job-related factors, and broader socio-economic conditions, including household income (Prayitno et al., 2024; Perugini & Martino, 2008). On the personal level, human capital theory suggests that education and skills enhance productivity and earnings potential, thereby raising household income (Prayitno et al., 2024). Similarly, stable and high-quality employment can secure better pay and a stable income, contributing to higher household income levels (Fritsch & Liedl, 2023). This article aims to investigate how education, job quality, and training jointly influence a household's income rank (measured by decile) across European countries.

We focus on several key determinants suggested by economic theory and prior empirical research. First, educational attainment is expected to positively influence income. More years of schooling generally improve skills and productivity, leading to higher wages for individuals and thereby higher total income for their households. We therefore hypothesise that individuals with more years of formal education will tend to live in households placed higher in the national income distribution. Second, we consider on-the-job training and skill development. Ongoing training can update and increase a worker's human capital beyond formal education, potentially leading to wage growth or improved job security (Albert et al., 2010; Bassanini, 2006). We hypothesise that recent participation in job-related training in the last 12 months is associated with a higher household income decile, reflecting either direct wage premiums or indirect benefits such as greater employability and career advancement for those who continually upgrade their skills.

Third, we examine job quality and employment conditions, in particular, the type of employment contract and supervisory responsibilities. These factors capture aspects of job stability, responsibility, and status, which are often linked to earnings. Secure, permanent employment contracts typically offer higher wages and better career prospects compared to temporary or informal job arrangements, which are frequently lower-paid and less stable. Likewise, having a supervisory role usually signals a higher position in the workplace hierarchy and often comes with a wage premium. We hypothesise that holding a permanent contract and having supervisory duties will correlate with a higher household income rank, whereas being on a temporary or no contract and lacking supervisory responsibility will correspond to a lower income decile position. Finally, we consider work hours as an aspect of job input. While working more hours might increase individual earnings, its relationship

with household income rank is ambiguous, since high-income households often benefit from multiple earners or higher hourly wages, rather than longer hours by a single earner. This analysis will explore whether longer working hours are associated with higher or lower household income positions after accounting for other factors.

The research builds on diverse labour market conditions across Europe. The European Social Survey (ESS) data (ESS ERIC, 2025) allow a comparative perspective, covering 30 countries with varied institutional contexts. This is important because prior evidence shows that both individual-level factors and contextual factors play a role in income outcomes. For instance, macro-level analyses have found that higher aggregate education levels can, in general, lead to more equal income distributions (Bucevska, 2019) and that labour market conditions, such as unemployment rates and the prevalence of precarious work, significantly affect inequality between and within countries (Perugini & Martino, 2008; Varlamova & Larionova, 2015). At the same time, micro-level research consistently demonstrates the centrality of education, skills, and occupation in determining a person's earnings and, by extension, their household's income. Our research bridges these perspectives by using individual-level data across multiple countries, thereby identifying universal patterns while acknowledging cross-country heterogeneity.

The article is structured in such a way as to firstly give a review of relevant literature on how education, training, and job quality influence income and inequality. We then describe the methodology used, including the data, variables, and modelling strategy. Next, we present the empirical results, beginning with descriptive findings and then the results of the ordered logistic regression and robustness checks. We subsequently discuss the implications of these findings and note the study's limitations. Finally, we conclude with reflections on what the results imply for policy and future research on household incomes and reducing inequality in Europe.

2. Literature Overview

Research in economics and sociology suggests that education strongly predicts income at both individual and household levels. Numerous studies across different contexts have found that individuals with higher educational attainment tend to earn more, which in turn raises their household's total income (Prayitno et al., 2024). Education enhances a person's skills and productivity, aligning with the classic human capital theory that such investments yield higher wages over a lifetime. In a systematic review of household welfare determinants, education was identified as a key driver of economic well-being, consistently linked to higher income and better ability to meet living standards (Prayitno et al., 2024). Tasseva (2021) provides a compelling macro-level example: in Great Britain, the early 21st-century expansion of higher education led to overall income growth, especially through higher wages

for those gaining additional qualifications. However, Tasseva (2021) also found that this expansion, while lifting average incomes, had unequal effects across the distribution. The largest income gains accrued to the middle and upper portions of the distribution, with relatively limited gains at the bottom. The result was a modest increase in income inequality because the wage premium for higher education remained high and did not compress even as more people obtained degrees (Tasseva, 2021). This highlights that education's impact on inequality can be complex: raising education levels improves living standards, but if returns to education are disproportional or if low-educated groups do not benefit proportionately, the gap between top and bottom incomes may widen.

At the household level, not only one's own education matters, but also the educational attainment of other household members. Jolliffe (2002) demonstrated this point in a study of households in Ghana. He tested multiple models and found that household income was best explained by the education of the most educated household member, rather than by the household head's education or the average education in the household. In other words, a household tends to earn more when at least one member has a high level of education, as this can enhance the household's overall earning capacity (Jolliffe, 2002). While Jolliffe's (2002) context was a developing country, the general implication is that household income is a function of the combined human capital of its members. In European dual-earner households, for instance, a highly educated second earner can substantially increase total household income. Our research, focusing on a single respondent per household, uses that individual's education as a proxy for the household's human capital. Nonetheless, prior research, such as Jolliffe's (2002), suggests caution in interpretation since a partner's education could also contribute significantly to household income.

Beyond formal education, continuous skill acquisition through on-the-job training or adult learning is another important determinant of income. Training can enhance workers' productivity and adaptability, leading to wage increases or improved career prospects. However, the literature reveals some additional layers. Albert et al. (2010) conducted a multi-country study in Europe. They found wage returns to on-the-job training in nearly all countries examined, suggesting that workers who underwent training earned higher wages on average. This aligns with the expectation that training adds to human capital and should be rewarded in the labour market. Yet, when authors applied fixed-effects models to control for unobserved worker characteristics, the wage benefits of training often diminished to statistically insignificant levels. This indicates that the positive association between training and wages may partly reflect selection bias: those who receive training might be inherently more motivated, skilled, or employed in firms that pay higher wages, rather than training alone causing higher pay. Despite this caution about causal interpretation, training remains correlated with better wage outcomes and is often seen as a means for workers to keep up with technological and organisational

changes (Albert et al., 2010). Notably, the study argued that if training opportunities are extended to lower-skilled workers, it could improve their earnings and narrow income disparities, thereby benefiting the overall income distribution.

Other research highlights that the payoff from training can depend on worker characteristics. Bassanini (2006) analysed European data and found that wage gains from employer-provided training were concentrated among specific groups, namely younger workers and those who were highly educated to begin with. In his analysis, these groups enjoyed a clear wage premium after training, whereas older or less-educated workers did not see significant immediate wage boosts from training (Bassanini, 2006). Additionally, the research discovered that training had a strong positive impact on employment security across the board. Workers who participated in training were significantly less likely to become unemployed subsequently, implying that training enhances employability and job retention. In effect, even if training doesn't always translate into instant wage hikes for every worker, it can stabilise employment. From a household perspective, this means that a member's training can reduce the risk of income loss due to unemployment, an important aspect of sustaining one's income rank over time. All things considered, we anticipate that individuals who invested in their skills through recent training are more likely to be in higher-income households than those who did not, both because of potential wage increments and because training is associated with steadier employment.

Another dimension of employment stability to be accounted for is the type of employment contract. Labour market research often distinguishes between permanent contracts, which generally offer open-ended employment with greater security and benefits, and temporary or fixed-term contracts, which are time-limited and often lower paid. European economies vary in how prevalent temporary contracts are, but evidence shows that temporary workers earn less on average than comparable permanent workers and face more income volatility. An analysis of middle-class stratification by Fritsch and Liedl (2023) found that occupational attributes tied to job quality, such as the prevalence of part-time work in one's occupation, significantly affect income class membership. They showed that individuals, especially women, working in occupations with a high part-time rate were more likely to fall into the lower income class, indicating that jobs characterised by reduced hours and often lower security lead to lower household incomes (Fritsch & Liedl, 2023). By contrast, those in full-time, stable employment have a better chance of attaining middle-income or higher status.

Another job-quality indicator is supervisory responsibility. Holding a supervisory or managerial role usually reflects higher authority and skill level, which tends to be accompanied by higher pay. While not many studies explicitly isolate supervisory status as a determinant of household income, it is implicitly related to occupation and career level, which Baláková et al. (2023) examine in their work on income determinants in the EU. They found that the occupation sector and role matter. For example, people employed in traditionally low-paying sectors, like

agriculture, tend to have lower individual incomes, whereas those in higher-skilled sectors fare better (Baláková et al., 2023). Occupations that involve managing others often come with skill and sector advantages that incur higher earnings. Moreover, Baláková et al. (2023) emphasised that household composition also affects income, in the sense that single-parent households in Europe often have significantly lower incomes, reflecting the difficulty of earning with a limited labour supply and the need for social support for those households. The household composition is not directly measured in the article, but these insights show that factors like being the sole earner or having additional earners can influence a household's income rank.

The broader economic environment also shapes household incomes and their distribution. Cross-country panel analyses show that macroeconomic conditions, including the unemployment rate, GDP per capita, and investment rates, have significant effects on income inequality (Bucevska, 2019). In her study of three EU candidate countries (North Macedonia, Serbia, and Türkiye), higher unemployment was associated with greater income disparities, while a more educated population was linked to a more equal income distribution (Bucevska, 2019). Varlamova & Larionova (2015) similarly examined European countries and highlighted that macroeconomic and labour market factors, such as employment rates and economic development, are important determinants of average household incomes across countries. Perugini & Martino (2008), looking at European regions, reinforce this by demonstrating that regional inequality is strongly tied to labour market characteristics, where regions with more high-quality jobs and favourable institutional settings exhibit lower internal inequality. These macro findings contextualise the micro-level focus of the analysis as they suggest that individual households' chances of prosperity are partly conditioned by the economic and policy context of their country or region.

In sum, the literature suggests a layered set of influences on household income. Human capital factors, such as education and training, emerge consistently as positive forces for income growth, though their effect on inequality can vary depending on who accesses these opportunities. Job quality factors, including secure contracts, full-time work, supervisory roles, and productive sectors, are crucial in differentiating higher-income households from lower-income ones in Europe's stratified labour markets. Additionally, credit access and social capital have been identified as supporting factors for household welfare (Prayitno et al., 2024), though these are beyond the scope of the analysis in this article. Guided by these insights, the analysis will focus on education, training, and job-quality variables as likely determinants of a household's income rank. The aim is to explore whether the general patterns reported in prior research hold across a broad set of European countries using recent survey data, and how strong each factor's association is when considered together in a multivariate framework.

3. Methodology

3.1. Data Collection and Sample

The study uses individual-level microdata from the European Social Survey, Round 11, Edition 4 (ESS ERIC, 2025). Post-stratification weights (*pweight*), given in the ESS dataset, are applied to account for differential selection and to improve representativeness of the target populations by adjusting for sampling design and non-response.

From the full ESS Round 11 sample, we restricted the dataset to cases with complete information on all variables of interest for our analysis. Specifically, we observed complete cases for household income decile, years of education, training participation, employment contract type, supervisory status, weekly working hours, and employment relation. Respondents who did not provide a valid household income or who had missing responses on these key variables were excluded. After this listwise deletion of missing or non-substantive answers, the analytical sample comprises $N = 29.942$ individuals across the 30 countries. By focusing on complete cases, we avoid issues of imputation or differing sample bases across analyses, though we acknowledge this could introduce some degree of bias if those who refused income questions, for example, are systematically the very rich or very poor. The use of survey weights in all analyses helps maintain representativeness despite the excluded cases.

3.2. Variables

The dependent variable is the respondent's household income decile, a rank measure of the household's total net income position within their country. In the ESS, respondents are shown a card explaining national income ranges corresponding to ten deciles of the income distribution $j \in \{1, \dots, 10\}$, from the lowest 10% to the highest 10% in their country. Each respondent selects which decile band their household's total net income falls into, after taxes and transfers. This yields an ordinal variable *hinctnta*, coded 1 through 10, where 1 indicates the household is in the lowest income decile of their country and 10 indicates the highest decile. The decile thresholds were tailored to each country's income distribution, as ESS uses country-specific showcards, making the measure nationally relative. While this method sacrifices absolute income comparisons across countries, it appropriately accounts for cross-national differences in living standards by focusing on relative standing. We treat this decile rank as an ordered categorical outcome, and the modelling approach is later chosen to respect this ordinal nature.

The primary human capital indicator is years of full-time education (*eduyrs*). This variable measures the total number of years the respondent spent in formal full-time education, as reported in the survey. It is treated as a continuous variable in the

analysis. The distribution of education in our sample ranges widely, reflecting diverse educational backgrounds, with some respondents having as few as 0–5 years, while others have 20+ years, though the majority of the sample centres around secondary and tertiary education completion. Education years are expected to positively influence income decile, as discussed beforehand, and including it allows us to estimate the income rank premium per additional year of schooling.

We include a measure of recent training or skill development. ESS asks whether the respondent has taken any course, lecture, or conference in the last 12 months to improve knowledge or skills (*atncrse*). We use this as a binary indicator of recent training investment. It is coded 1 for respondents who attended any educational or training event in the past year and 0 for those who did not. This encompasses formal job training, adult education classes, workshops, or other skill-improving activities. As previously hypothesised, the population that underwent training is expected to be in the higher income decile than those who did not, controlling for other factors, since training could enhance their earnings or job stability.

To capture job security and quality, we use the respondent's type of employment contract (*wrkctra*). It distinguishes whether the person's main job has a permanent contract, a temporary contract, or no contract. We code this as a categorical variable with three levels: permanent contract (reference category), temporary contract, and no contract. We expect negative coefficients for *Temporary* and *No contract* levels, relative to the permanent contract reference, meaning those on less secure terms likely have lower odds of being in a higher income decile.

We include a binary variable indicating whether the respondent has supervisory responsibilities at work (*jbspv*). This variable equals 1 if in their main job the respondent supervises other employees, and 0 if they do not supervise anyone. We anticipate that not being a supervisor will be associated with a lower income rank. In the regression model, we will interpret the coefficient for lack of supervision (when 0 is contrasted to 1) to assess the penalty of not holding a supervisory post.

Work effort is measured by weekly working hours. The ESS provides two related measures: total hours normally worked per week including overtime, and contracted hours per week excluding overtime (*wkhct*). For our analysis, we focus on contracted weekly hours in the main job as the more consistent measure of the job's standard workload. Contracted hours reflect whether someone is full-time or part-time and their basic work schedule. We treat weekly hours as a continuous predictor. Typically, one might expect working more hours to increase individual earnings, and part-time work is a known contributor to lower income (Fritsch & Liedl, 2023). However, because our outcome is household income rank, the relationship might be non-linear or even inverted. For instance, some high-income households have multiple earners, each working moderate hours, rather than one person working very long hours. In preliminary analysis, we will check the correlation between hours and income decile. We include hours to control for and explore this dynamic, with an

open expectation: while part-time status likely correlates with lower income, extremely long hours might appear in lower deciles if they reflect single breadwinners trying to compensate for lower hourly wages.

The ESS differentiates employment relations (*emplrel*) such as being an employee, self-employed, or working in a family business. In our sample, the vast majority are employees. Because there were very few self-employed or family business respondents once filtering for income data and our other variables, we simplified this variable. We create an indicator for employee status, coded 1 for working as an employee for an employer, and 0 for being self-employed or in a family business. This was done to avoid instability due to small sample sizes in the last two categories. The expectation was that being a non-employee might have different income dynamics, and we include this primarily as a control. Given the small number of non-employees in the analytic sample, we do not have a strong hypothesis on its effect, but we allow the model to adjust for any systematic income rank differences between employees and the self-employed.

Table 1 gives an overview of the variables we use in the analysis.

Table 1: Variables Included in the Analysis

Variable	Description
hinctnta	Household's total net income, all sources
eduyrs	Years of full-time education completed
atncrse	Improve knowledge/skills: course/lecture/conference, last 12 months
wrkctra	Employment contract unlimited or limited duration
emplrel	Employment relation
jbspv	Responsible for supervising other employees

Source: European Social Survey

3.3. Analyses

We first compute univariate descriptive statistics for all key variables, using survey weights to obtain representative estimates. For continuous variables like education years and hours, we report the mean and standard deviation. For categorical variables, we examine weighted proportions. We pay particular attention to the distribution of education and the breakdown of contract types and supervisory status, since these help characterise the sample's human capital and job quality profile. We also look at the weighted distribution of the income decile outcome to confirm it is roughly uniform (each decile category containing about 10% of households in a given country by design), with small deviations occurring due to sampling and exclusion of non-response.

Next, we explore bivariate relationships to motivate the modelling. We discretise education into quartiles (Low, Medium-Low, Medium-High, High) and cross-tabulate these against income decile categories. This allows us to see how income ranks improve with higher education. Similarly, we examine the distribution of contract types among employees and self-employed, and the prevalence of supervisory roles by contract type, to understand how these job quality measures interrelate. This is done using contingency tables and a Rao–Scott chi-square test for association. We then compute the Spearman rank correlation between years of education and income decile. A positive correlation would quantitatively confirm that higher education is associated with higher income ranks.

Although normality tests are not strictly required for logistic regression (Efron, 1975), we examined the distribution of continuous variables (education and hours) with Shapiro–Wilk tests on a subsample to see if they deviate strongly from normal. As expected, given the large sample, these variables do reject normality. For instance, the variable measuring education years has a right-skewed distribution with many clustered values at typical graduation ages. This simply informs us that using non-linear modelling, such as logistic regression, is sensible.

We compare mean contracted hours between permanent and non-permanent contract workers using a design-based weighted t-test. This helps us understand if, for example, temporary workers are generally part-time. In fact, we find a significant difference: those without permanent contracts work on average about 3.9 fewer hours per week than permanent contract holders ($p < 0.01$), confirming that the non-permanent group contains more part-timers.

The main econometric analysis estimates a survey-weighted ordered logistic regression model for the income decile. Let Y_i denote the income decile of the individual i , with ordered categories $1 < 2 < \dots < 10$. The ordered logit model can be written using a latent index formulation:

$$Y_i^* = \mathbf{x}_i' \boldsymbol{\beta} + \varepsilon_i,$$

where Y_i^* is an unobserved continuous propensity for a higher income position, $\mathbf{x}_i$ is a vector of independent variables for the individual i (years of full-time education, training indicator, contract type dummies, supervisory status, weekly hours, and employee status), $\boldsymbol{\beta}$ is the parameter vector, and ε_i is a random error assumed to follow a standard logistic distribution. Observed categories are determined by thresholds $\kappa_1 < \kappa_2 < \dots < \kappa_9$ with $\kappa_0 = -\infty$ and $\kappa_{10} = +\infty$. The observed ordinal outcome can be defined in the following way using the threshold cut-off points:

$$\begin{aligned} y_i &= 1 \text{ if } y_i^* \leq \kappa_1, \\ y_i &= j \text{ if } \kappa_{j-1} < y_i^* \leq \kappa_j, j = 2, \dots, 9, \end{aligned}$$

$$y_i = 10 \text{ if } y_i^* > \kappa_9.$$

Using the proportional odds assumption, the cumulative logit representation is:

$$\log\left(\frac{\Pr(Y_i \leq j)}{\Pr(Y_i > j)}\right) = \kappa_j - \mathbf{x}_i' \boldsymbol{\beta}, j = 1, \dots, 9.$$

The ordered logit model estimates these κ_j along with $\boldsymbol{\beta}$ coefficients. The interpretation of coefficients $\boldsymbol{\beta}$ in ordered logit is in terms of odds ratios (OR) for being in a higher versus a lower category of the outcome. We will present our results both as log-odds (logit coefficients) and as odds ratios for ease of interpretation. For a continuous predictor like years of education, the OR represents the factor by which the odds of being in a higher income decile multiply for each additional year of education. For a binary predictor, it represents the odds ratio of being in a higher decile for one group versus the reference group. We incorporate the survey weights (*pweight*) in estimation so that each country's contribution is weighted according to its sample design and size. The weighted ordered logit is estimated via maximum likelihood, adjusting standard errors for the weight-induced heteroskedasticity.

Model adequacy is first assessed using the proportional-odds robustness checks via survey-weighted binary logits at thresholds $y \geq 6$ and $y \geq 8$. The two binary logit models use two cumulative splits of the income decile to assess if their coefficients differ significantly from the coefficients in the main ordered logit model. Next, we re-estimate the model using aggregated outcomes with quintiles (5 categories) instead of deciles. This tests whether our results are sensitive to the granularity of the outcome. We additionally exclude the outlier influence in the working hours by trimming the 1st percentile and the 99th percentile of hours. The ordered logit model is then re-estimated on the trimmed sample to see if the coefficients change significantly. Finally, for each decile, we compute the weighted proportion of the sample actually in that decile and compare it with the average predicted probability of being in that decile as given by our model. Significant differences between the observed and the predicted distribution might signal misspecification of the model.

All analyses were conducted using R statistical software. Significance is evaluated at the conventional levels ($p < 0.05$, $p < 0.01$, $p < 0.001$), and we report confidence intervals at 95% confidence levels for odds ratios to show the precision of estimates.

4. Results

4.1. Descriptive Results

In the complete-case sample $N = 29,942$, the mean years of full-time education is 13.7 (SD 3.90). The unweighted mean contracted weekly hours is 37.8 (SD = 13.2), as shown in Table 2.

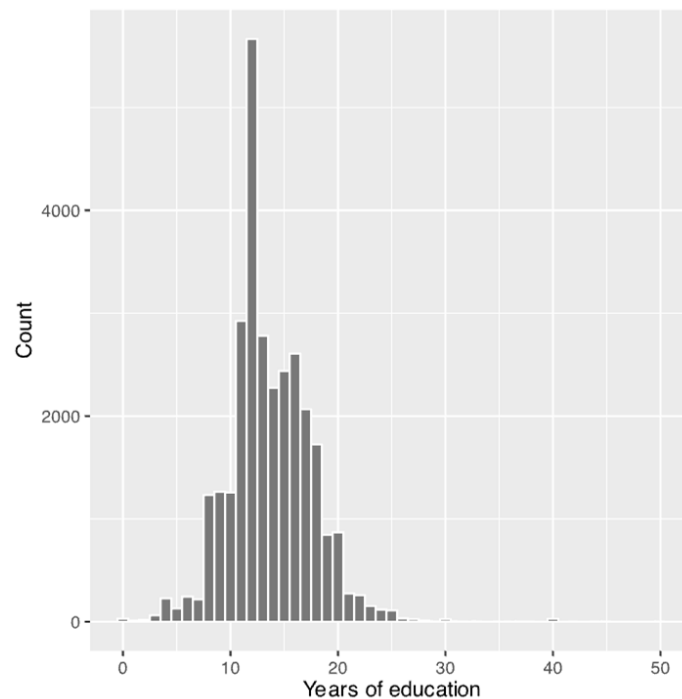
Table 2: Descriptive Statistics

Measure	Mean	Standard Deviation
Years of full-time education completed (in years)	13.7	3.90
Total contracted hours per week in main job overtime excluded	37.8	13.2

Source: author's calculation

Survey-weighted estimates produced a mean of 14.269 years of full-time education ($SE=0.05$) and a mean of 36.97 contracted weekly hours ($SE=0.17$), suggesting that weighting modestly shifts the sample toward more educated respondents with somewhat lower contractual hours.

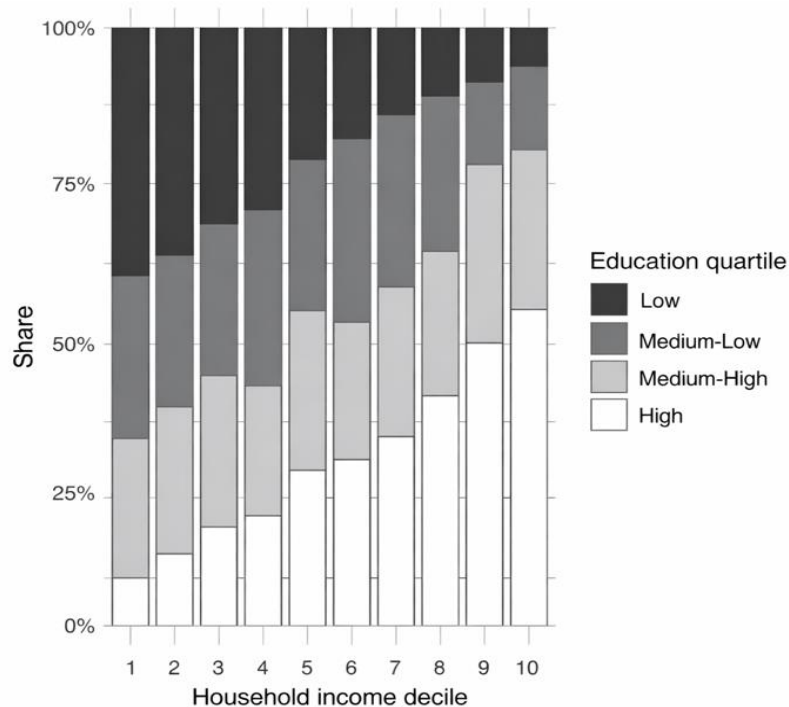
The education distribution is concentrated around approximately thirteen to fourteen years and exhibits a right tail, consistent with heaping at common schooling durations and a smaller share of individuals with very high educational attainment. The distribution of years of full-time education can be observed in Figure 1:

Figure 1: Distribution of Years of Full-time Education

Source: authors' calculation

The weighted cross-tabulation between education quartiles and income deciles shows a pronounced gradient: the high-education quartile constitutes a substantially larger share of the upper deciles, while the low-education quartile is concentrated in the bottom deciles. This pattern is consistent with a human-capital interpretation where schooling shifts individuals toward higher income positions. The graphical representation of the cross-tabulation is given in Figure 2:

Figure 2: Education Composition Within Income Deciles



Source: authors' calculation

We additionally explore the employment status by contract type (Permanent, Temporary, and No Contract). The dominant feature is the prevalence of employees on permanent contracts. The employee category accounts for the vast majority of observations in every contract type, and it is especially concentrated in the permanent contract group. Temporary contracts and no-contract arrangements are much smaller groups overall, suggesting that the subsequent analysis will primarily reflect the variation within employees, rather than between employees and the self-employed.

4.2 Normality and Inference

Shapiro–Wilk tests strongly reject normality for both years of education ($W = 0.968$, $p < 2.2 \times 10^{-16}$) and contracted hours ($W = 0.538$, $p < 2.2 \times 10^{-16}$) in the subsample used for testing. With this sample size, even mild departures from normality tend to become statistically significant (Shatz, 2024). Therefore, the implication is not that parametric modelling is infeasible, but that design-based inference and robustness checks are appropriate, and that distribution-sensitive claims should be made cautiously.

The design-based t-test indicates a statistically significant difference in contracted working hours between permanent and non-permanent contracts. The estimated mean difference is 4.46 hours per week (95% CI: 3.47 to 5.45, $p < 2.2 \times 10^{-16}$), suggesting that permanent contracts are associated with systematically different standard hours.

The Rao–Scott adjusted chi-square test shows a statistically significant association between supervisory responsibility and contract type ($F = 54.99$, $p < 2.2 \times 10^{-16}$), consistent with hierarchical job roles being distributed unevenly across contract arrangements.

The Spearman correlation between education and income decile is $\rho = 0.354$, indicating a moderate positive monotonic association between education and income position in the sample.

4.3 Ordered logit model for income decile

The ordered logistic regression estimated with survey weights provides clear evidence that both human capital and several job-quality and training indicators are systematically related to household income rank.

The education coefficient is positive and highly significant. In odds-ratio terms, each additional year of education increases the odds of being in a higher income decile by approximately 12.1% (OR = 1.1205, 95% CI: 1.1066 to 1.1346), holding other variables constant. This is strong support for the first hypothesis, stating that individuals with more years of formal education tend to live in households placed higher in the national income distribution.

Employment relation is also significant, where being a non-employee (self-employed or working in own family business) is associated with a higher income rank (OR = 1.986, 95% CI: 1.200 to 3.287). This indicates nearly doubled odds of being in a higher income decile, conditional on education, contract characteristics, hours, and training. While the results suggest a premium for non-employee status, it should be interpreted cautiously, given the very small number of self-employed in the sample and potential heterogeneity within the non-employee group.

Table 3: Ordered Logit Odds Ratios

Predictor	β	Std. Error	p-value	Odds Ratio [95% CI]	
Years of education	0.114	0.006	<0.001	1.121 [1.107, 1.135]	***
Not employee (ref: employee)	0.686	0.257	<0.01	1.986 [1.200, 3.287]	**
Temporary contract (ref: permanent)	-0.394	0.0684	<0.001	0.674 [0.590, 0.771]	***
No contract (ref: permanent)	-0.825	0.1302	<0.001	0.438 [0.340, 0.566]	***
No supervisory responsibility (ref: supervisory)	-0.461	0.0495	<0.001	0.631 [0.573, 0.695]	***
Contracted weekly hours	-0.0095	0.0012	<0.001	0.991 [0.988, 0.993]	***
No training last 12 months (ref: yes)	-0.786	0.0538	<0.001	0.456 [0.410, 0.506]	***

Source: authors' calculation

Contract type is strongly associated with income rank. Compared to permanent contracts, temporary contracts reduce the odds of being in a higher income decile (OR = 0.674, 95% CI: 0.590 to 0.771). Having no contract shows an even stronger negative association (OR = 0.438, 95% CI: 0.340 to 0.566). These results align with labour-market segmentation arguments: weaker contractual arrangements are linked with lower household income rank. These estimates imply materially lower odds of a higher household income rank for non-standard employment arrangements. Supervisory responsibility is also positively associated with income rank. Relative to having supervisory responsibility, lacking it is associated with lower income deciles (OR = 0.6310, 95% CI: 0.5727 to 0.6952), suggesting that non-supervisory roles are systematically concentrated in lower income ranks. These findings support the third hypothesis, claiming that holding a permanent contract and having supervisory duties correlates with a higher household income rank, whereas being on a temporary or no contract and lacking supervisory responsibility will correspond to a lower income decile position.

Contracted hours have a statistically significant but negative association (OR = 0.9905, 95% CI: 0.9882 to 0.9928). Substantively, this implies that an additional contracted hour is associated with a small decrease in the odds of being in a higher income decile, conditional on other variables. Given that the dependent variable is household income rank rather than personal earnings, this pattern may reflect compositional mechanisms such as higher hourly wages among those working fewer contracted hours, multi-earner household structures, or occupational differences not explicitly controlled in the model.

Training participation is strongly associated with higher income rank. Not attending training reduces the odds of being in a higher income decile (OR = 0.456, 95% CI: 0.410 to 0.506). Equivalently, training attendance is linked with substantially higher income rank, consistent with a human-capital investment mechanism and supporting the hypothesis stating that participation in job-related training in the last 12 months is associated with a higher household income decile.

4.4 Diagnostics and robustness

The proportional-odds structure was examined using survey-weighted binary logits for thresholds $y \geq 6$ and $y \geq 8$. Across both thresholds, education, contract type, supervisory status, contracted hours, and training retain the same signs and remain statistically significant, indicating substantial robustness. Employment relation is not significant at the $y \geq 6$ threshold but becomes significant at $y \geq 8$, suggesting that non-employee status may matter more for reaching the top part of the income distribution than for moving from low to middle income ranks. This pattern does not invalidate the ordered model, but it indicates that some effects may be stronger at higher cutpoints.

Table 4: Proportional-odds Robustness Check Using Binary Logits

Binary threshold	Predictor	β	Std. Error	p-value	
$\Pr(hinctnta \geq 6)$	Intercept	-0.462	0.170	<0.05	**
$\Pr(hinctnta \geq 6)$	Years of education	0.119	0.009	<0.01	***
$\Pr(hinctnta \geq 6)$	Not employee (ref: employee)	0.455	0.294	0.12	
$\Pr(hinctnta \geq 6)$	Temporary contract (ref: permanent)	-0.504	0.092	<0.01	***
$\Pr(hinctnta \geq 6)$	No contract (ref: permanent)	-0.943	0.165	<0.01	***
$\Pr(hinctnta \geq 6)$	No supervisory responsibility (ref: supervisor)	-0.439	0.06	<0.01	***
$\Pr(hinctnta \geq 6)$	Contracted weekly hours	-0.012	0.002	<0.01	***
$\Pr(hinctnta \geq 6)$	No training last 12 months (ref: yes)	-0.728	0.064	<0.01	***
$\Pr(hinctnta \geq 8)$	Intercept	-1.711	0.190	<0.01	***
$\Pr(hinctnta \geq 8)$	Years of education	0.127	0.009	<0.01	***
$\Pr(hinctnta \geq 8)$	Not employee (ref: employee)	0.630	0.291	<0.10	*
$\Pr(hinctnta \geq 8)$	Temporary contract (ref: permanent)	-0.478	0.111	<0.01	***
$\Pr(hinctnta \geq 8)$	No contract (ref: permanent)	-0.637	0.187	<0.01	***
$\Pr(hinctnta \geq 8)$	No supervisory responsibility (ref: supervisor)	-0.475	0.065	<0.01	***
$\Pr(hinctnta \geq 8)$	Contracted weekly hours	-0.008	0.002	<0.01	***
$\Pr(hinctnta \geq 8)$	No training last 12 months (ref: yes)	-0.729	0.069	<0.01	***
Significance: † * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					

Source: authors' calculation

When income deciles were collapsed into quintiles (categories from 1 to 5) and the ordered model was re-estimated, coefficient signs and significance were essentially unchanged, strengthening confidence that the results are not a consequence of using a 10-category outcome.

Table 5: Binary Logits for Quintiles

Predictor	β	Std. Error	P-value	Odds Ratio [95% CI]	
Years of education	0.120	0.007	<0.001	1.127 [1.113, 1.142]	***
Not employee (ref: employee)	0.572	0.251	<0.05	1.772 [1.084, 2.896]	*
Temporary contract (ref: permanent)	-0.450	0.073	<0.001	0.638 [0.553, 0.735]	***
No contract (ref: permanent)	-0.840	0.140	<0.001	0.432 [0.328, 0.568]	***
No supervisory responsibility (ref: supervisory)	-0.429	0.051	<0.001	0.651 [0.589, 0.719]	***
Contracted weekly hours	-0.010	0.001	<0.001	0.990 [0.988, 0.993]	***
No training last 12 months (ref: yes)	-0.803	0.055	<0.001	0.448 [0.402, 0.499]	***

Significance: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Source: authors' calculation

A descriptive fit check comparing observed weighted decile shares to mean predicted shares indicates broadly similar distributions. The model slightly overpredicts the lowest decile (observed 11.32% vs predicted 12.06%) and underpredicts the top decile (observed 9.52% vs predicted 8.78%), suggesting some compression at the extremes but no major mismatch overall.

Table 6: Observed vs Predicted Shares

Income decile	Observed share (%)	Predicted share (%)	Absolute difference (pp)
1	11.319586	12.060942	0.74135549
2	10.303591	10.772025	0.46843369
3	10.990440	11.371563	0.38112347
4	10.246804	10.508372	0.26156754
5	9.590638	9.690921	0.10028308
6	9.127359	9.033408	0.09395055
7	10.495918	10.227528	0.26838978
8	10.719090	10.304860	0.41422956
9	7.681772	7.253811	0.42796153
10	9.524802	8.776571	0.74823184

Source: authors' calculation

Collinearity diagnostics indicate a full-rank design matrix (rank = 8) with a condition number of approximately 300.8, suggesting non-trivial collinearity. This implies that coefficient estimates remain identifiable, but standard errors and inference for correlated predictors should be interpreted with caution.

Finally, trimming contracted hours to the 1st–99th percentile and refitting the ordered model produced nearly identical coefficients and significance. This indicates that the main conclusions are not driven by extreme values of contracted hours.

Table 7: Trimmed Data Results

Predictor	β	Std. Error	p-value	OR [95% CI]	
Years of education	0.113	0.006	<0.001	1.120 [1.106, 1.134]	***
Not employee (ref: employee)	0.742	0.267	<0.01	2.101 [1.244, 3.548]	**
Temporary contract (ref: permanent)	-0.387	0.070	<0.001	0.679 [0.593, 0.779]	***
No contract (ref: permanent)	-0.850	0.137	<0.001	0.427 [0.326, 0.560]	***
No supervisory responsibility (ref: supervisory)	-0.459	0.050	<0.001	0.632 [0.573, 0.697]	***
Contracted weekly hours	-0.009	0.003	<0.01	0.991 [0.985, 0.996]	**
No training last 12 months (ref: yes)	-0.791	0.054	<0.001	0.453 [0.408, 0.504]	***

Significance: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Source: authors' calculation

5. Discussion and Limitations

The empirical findings from this analysis reinforce and extend our understanding of how human capital and job quality relate to household economic outcomes in Europe. We find that education is a major determinant of income position, where every additional year of schooling is associated with noticeably higher odds of climbing the income ladder. This micro-level evidence resonates with macro-level observations by Bucevska (2019) that raising the education level of the population can improve overall income levels and potentially reduce inequality. Our results highlight that in contemporary Europe, individuals with higher education are far more likely to secure the kinds of jobs or economic opportunities that place their households in the upper segments of the income distribution.

One implication of this education finding is the importance of educational access and quality for social mobility. If higher education has such a strong advantage in income rank, then unequal access to education could produce income disparities across generations. Tasseva (2021) showed that as education expanded in Britain, overall living standards rose, but inequality did not fall because the less-educated still lagged. This suggests that simply having more people educated is not a remedy for inequality unless lower-skilled individuals also see improvements in their incomes. In our analysis, we see that those with less education are disproportionately in lower-income deciles. Over time, if European countries continue to increase educational attainment, we could hope that those currently in low education groups would become a smaller share of society. Yet, the persistent income gap per year of education hints that the returns to education remain steep. Policies such as adult education and training for those who missed out on formal schooling could help uplift incomes at the bottom, as could strategies to boost the earnings of jobs that do not require higher education.

Our analysis also provides clear evidence that job characteristics, especially employment stability and role seniority, are tightly linked to household income prospects. The difference in income rank outcomes between permanent and temporary contract workers is big, which speaks to the duality in many European labour markets. Workers in stable, long-term employment not only have more secure incomes but also significantly higher incomes, whereas temporary workers and those in informal arrangements struggle to attain high income ranks. This finding supports Perugini & Martino's (2008) emphasis on labour market institutions, where countries or regions that allow large pools of precarious employment often see greater income inequality. Our evidence shows that an individual on a temporary contract has a markedly lower probability of reaching the top income ranks than if that same individual were on a permanent contract. It suggests a penalty for non-permanent work that is not solely explained by the worker's education or skills. Part of this may be due to temporary jobs often paying less and having fewer raises or promotion opportunities. Part may also be due to intermittent employment, a situation in which a temporary worker might have periods of unemployment, reducing total household income over time.

From a policy standpoint, this raises the question of whether encouraging more secure employment could contribute to reducing income inequality. If temporary workers remain a necessary feature of modern economies, improving their pay and continuity would likely help their households move up the income ranks. The strong negative coefficient for no contract workers suggests that those in the informal economy are at a severe disadvantage. Formalising work and extending social protections to the currently informal sectors could not only improve equity but also lift many households out of the bottom deciles.

Supervisory status serving as a proxy for job seniority or skill was found to be highly significant. This aligns with the intuition that managers earn more than

subordinate workers, and thus households with a manager in them have higher incomes. What's notable is that even after controlling for education, training, and hours, being a supervisor had a big effect. This implies that part of the return to being in a supervisory role is not just because supervisors have more education or training, but possibly also because of soft skills or networks that got them into leadership, or structural pay premiums for leadership positions. It underscores the value of career progression and climbing the career ladder as a key to higher household income. This might reflect both individual initiative and structural opportunities. From a gender perspective, it's worth recalling Fritsch & Liedl's (2023) finding that women in female-dominated occupations often have lower income prospects. One reason could be that fewer women get into top supervisory positions in some fields. Promoting equal opportunities for advancement and breaking glass ceilings could have tangible effects on household incomes, especially for women and minorities who might be underrepresented in supervisory ranks currently.

The training effect we found is interesting in the context of lifelong learning. Our result that recent training participation is associated with higher income rank lends support to the argument that continuous skill development is important for maintaining and improving one's economic status. This correlation could be partly causal, as training might lead to raises or promotions, or partly selection, as those in better jobs have better access to training. Regardless, it implies that lack of training is a common feature among those in lower-income positions. Bassanini's (2006) work would add that training has a strong effect on keeping people employed. Hence, one can argue that training likely helped some individuals in our data stay in jobs or move to better jobs, thereby contributing to higher household income. It also might reflect that high-income professionals simply make more use of training to continually upgrade. This points to a potential inequality in access to training, since those who might benefit most from training are often the ones not receiving it, while high-skilled professionals get top training opportunities. Policymakers concerned with inequality might consider interventions like training vouchers, subsidised adult education, or employer incentives to train low-wage workers, to spread the gains of training more broadly. As Albert et al. (2010) suggested, if on-the-job training can reach lower-skilled workers, it has the dual benefit of raising productivity and potentially reducing income disparities by lifting those workers' wages.

One result that calls for discussion is the negative association of working hours with income rank. This initially counterintuitive finding actually aligns with some sociological observations: in wealthy households, work-life balance might be easier to attain, whereas in poorer households, the breadwinner might be forced to work overtime or multiple jobs, manifesting as long hours, just to make ends meet. It reminds us of the concept of the time poverty trap, where low-income individuals often trade time for money (Qi & Dong, 2018) and yet do not substantially improve their income position, while higher-income individuals might earn more in less time or have multiple earners each contributing fewer hours. Another interpretation is that

dual-earner households can achieve a high combined income with each person working a moderate full-time schedule, whereas a single-earner household might have one person working more hours but still not reach the same income if the wage rate is low. For policy, this could mean focusing on raising wages for low-income workers rather than expecting them to work ever longer hours.

The insignificance of employment relation (employee vs self-employed) suggests that, within our sample, being self-employed wasn't systematically better or worse after controlling for other factors. It's a reminder that policies around entrepreneurship and small businesses could have mixed impacts on income inequality, in the sense that supporting small businesses might help some grow into high income, but many will remain low-income. Social safety nets for the self-employed and training might help those in self-employment achieve more stable and higher incomes.

Several limitations must be acknowledged in the analysis. First, the data are observational and cross-sectional. We have identified associations, but we cannot conclusively prove causal relationships, as we may encounter reverse causality or omitted variable bias. We did include many relevant controls to mitigate omitted variables, but not all factors are captured. Longitudinal data would be needed to better establish the direction of influence. Secondly, our analysis takes one individual (the respondent) and uses their attributes to explain the household's income rank. In reality, household income could come from multiple members. We have not explicitly included, for instance, the spouse's education or the number of earners in the household due to data limitations. Jolliffe's (2002) point about "whose education matters" is relevant for our analysis: if a respondent had low education but their spouse had higher education and a high-paying job, the household could be high-income even though our model would predict low based on the respondent. Thirdly, the income measure is based on self-reported deciles, which, while useful for comparability, are relatively coarse and subject to reporting error. The ordinal nature also means we cannot account for the nominal width of the deciles, which may vary depending on inequality in that country.

Finally, there is a potential bias due to non-random missingness: approximately 20% of the ESS sample did not report their household income decile, which were excluded from the analysis. Income non-response could be non-random, and higher-income respondents may be more likely to refuse disclosure, or sometimes the very lowest income levels may also drop out. This could result in data missing not at random (MNAR), which may be difficult to model (Rubin, 1976).

Despite these limitations, we derive several recommendations based on the results of our analysis. The first is to invest in human capital and ensure widespread access to quality education and lifelong learning, especially targeting those at risk of being left behind, since education and training prove crucial for income mobility. The second is to enhance job quality by improving conditions and pay for temporary

and informal workers, and creating pathways for those workers into permanent, more secure positions. The third recommendation is to support working families and introduce policies, such as affordable childcare, that can support dual-earner households.

6. Conclusion

This article investigates why some European households occupy higher income ranks while others are lower, focusing on the role of individual education, job-related training, and employment quality. Using recent data from 30 countries and applying an ordered logistic regression approach, we found evidence that human capital and job quality factors are key determinants of a household's income rank within its country's distribution. In particular, higher educational attainment and recent skills training significantly increase the likelihood of a household being in a higher income decile, confirming the enduring importance of investments in knowledge. Secure and high-quality employment also emerged as critical, where having a permanent contract and a supervisory position are associated with substantially better income outcomes, whereas those stuck in temporary or non-contractual jobs with no managerial authority face a marked income disadvantage. These findings held even after accounting for working hours and other controls, and were robust across multiple checks.

The results highlight several points of convergence with the broader literature. They reinforce the notion from prior research that boosting education and skills is not only beneficial for individuals' earnings but is also likely to promote greater household economic welfare (Prayitno et al., 2024; Albert et al., 2010; Bucevska, 2019). At the same time, our analysis underlines the structural side of income inequality. Job features, such as stability, security, and progression opportunities, critically shape how incomes are distributed. This supports the findings of Fritsch & Liedl (2023) and Baláková et al. (2023) that what you do for work, and under what conditions, is as important as your personal attributes in determining whether you are middle class or struggling.

One novel insight from our study is the inverse relationship between individual work hours and household income rank, suggesting that simply working more is not the pathway to prosperity. Rather, working in higher-productivity jobs and having multiple contributions in households appear to matter more. This finding provides a human angle on what macro studies like those of Perugini & Martino (2008) imply, and that is that labour market quality, not just the quantity of labour, drives inequality outcomes.

Our research has policy relevance for the European socio-economic strategy. To foster upward mobility and reduce the number of households stuck at the bottom of the income distribution, policymakers should simultaneously pursue education and training policies and labour market policies that improve job security and quality.

Encouraging lifelong learning could help more workers gain the credentials and skills needed for advancement (Albert et al., 2010; Bassanini, 2006). On the labour side, reducing the two-tier nature of many labour markets by limiting abuses of temporary contracts or by mandating more equal pay and benefits for temporary workers could mitigate the income penalty we observed for those workers.

In conclusion, the determinants of household income rank in Europe are multifaceted but not unpredictable. By examining microdata across countries, we have demonstrated that well-educated, well-trained individuals in secure, higher-level jobs are the most likely to populate the top of the income distribution. Those who lack in any one of these areas, either education, skills, or job quality, face compounded challenges that often relegate them to lower income tiers. The clear policy message is to break these chains of disadvantage by providing opportunities for education and skill development at all stages of life, and by improving job quality for those in the lower rungs of the labour market. Doing so would not only enhance individual households' prospects but could also contribute to a more equitable income distribution across Europe, strengthening the middle class and reducing poverty.

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