Fabri S. et al. (2022). *Xjenza Online*, 10(2):74–85.

Xjenza Online: Science Journal of the Malta Chamber of Scientists
www.xjenza.org
DOI: 10.7423/XJENZA.2022.2.02

Review Article

Understanding the Economic and Sociodemographic Determinants of Early School Leaving: A Configurational Approach

S. Fabri*[1], V. Martinelli[2], J. Spiteri[1], V. Cassar[1]
[1]*Faculty of Economics, Management and Accountancy, Old Humanities Building, University of Malta, Msida, Malta*
[2]*Faculty Of Education, Old Humanities Building, University of Malta, Msida, Malta*

Abstract. Education is at the heart of any nation's social and economic development and certainly within the specific scope of the European Union's strategic development. As a result, early school leaving is a subject of inexorable importance because its effect reverberates in other social and economic realities. This paper examines the macroeconomic and socioeconomic determinants of ESL by adopting a multi-analytical strategy involving a linear regression method and a configurational approach. The outcomes highlight the complexity of ESL involving nonlinearity, equifinality, and asymmetric relations. Inequality and parental education emerge as key determinants of ESL; these relationships are more robust compared to the other determinants, namely Gross Domestic Product per capita, youth unemployment, and parental job status. The practical and theoretical aspects of these outcomes are explained throughout the discussion.

Keywords: Education, Early School Leaving, Configurational Approach, Fuzz-Set Qualitative Comparative Analysis

1 Introduction

Early School Leaving (ESL) is an indisputably important subject because it is a reality that has profound implications not only on the 'early school leaver' but also on societies and economies. Due to these consequential implications, one encounters a wide array of studies focusing on the individual motivators that cause young people to leave schooling early and on the educational circumstances that engender such courses of action (Humphrey et al., 2013; Lamb & Rice, 2008; Thrupp & Lupton, 2006). To a much lesser extent, other studies take a more macro approach to explain the broader context in which ESL happens (De Witte et al., 2013). Our study's contribution is twofold: First, we examine both macroeconomic (Gross Domestic Product (GDP), inequality, and youth unemployment) and socioeconomic (parents' professional and occupational status, and parents' educational background) features that account for the preponderance of ESL. Second, we adopt a multi-analytical strategy involving linear-based regressions and the configurational approach based on fuzzy-set qualitative comparative analysis (fsQCA). These high-level analyses allowed us to explore patterns invisible to similar previous inquiries and shed new light on how school leaving rates manifest themselves in more complex ways than we usually conceive. The rest of this article is planned as follows. We first present a critical review of the macroeconomic and socioeconomic determinants of ESL and highlight a few lacunae that require attention. Then, using EU-level data, we explain the method and present a series of analyses using both regression techniques and fuzzy-set analyses to establish whether socioeconomic patterns are in line with the general understanding of the wider literature or whether patterns require more attention. Finally, we provide an analysis of our results in the discussion section before concluding.

2 The Macroeconomic and Sociodemographic Determinants of ESL

Whilst various studies attempt to understand what causes early school leaving in developed countries, despite the opportunities available for young people, few studies focus on both the macro-economic and sociodemographic determinants.

**Correspondence to*: S. Fabri (stephanie.fabri@um.edu.mt)

2.1 GDP and ESL

There is both a hypothesised and an actual negative correlation between ESL and GDP (De Witte et al., 2013). This is posited at a theoretical level by Calero and Gil-Izquierdo (2014) using economic microsimulation to estimate the monetary costs of early school leaving in Spain. Over a 20-year period, starting in 2007, the recuperation of the wage losses attributable to ESL was estimated to account for anything from 4% to 17% with respect to the GDP of the country if ESL were eliminated. On the other hand, Andrei et al. (2011) established a clear relationship between increased expenditure on education as a share of the GDP and the improved quality of education. Using the EUROSTAT database, they concluded that this increase in education expenditure resulted in lowered ESL rates across the EU. Recent data corroborates this, with negative correlations between state investment in key areas, including education and ESL, across many central and east European countries (Vodă, 2020).

2.2 Inequality and ESL

The impact of socioeconomic backgrounds on school failure tends to move in the same direction as general school failure (Fernández-Mellizo & Martínez-García, 2017). From an economic perspective, unlike as predicted by human capital theory (Becker, 2009), equality of educational opportunity has not led consistently to increased social mobility. Despite improved educational opportunities for all, ESL continues to plague educational systems even in developed European countries, particularly south European ones such as Spain, Malta and Italy, with percentage rates of ESL well above the targeted 10% for 2020 (Eurostat, 2021). From a sociological inequality of educational opportunity perspective, there is an element of persistent inequality based on how sociodemographic and educational characteristics influence ESL and school engagement (Bayon-Calvo et al., 2020). International literature shows that students' socioeconomic background is strongly correlated with ESL (De Witte et al., 2013). Self-system level factors of feeling related, competent and in control in education impacts students' school engagement and students' ESL (Nouwen & Clycq, 2019). This suggests that to counteract ESL, one may consider the possible influence of policies based on equity and management of student diversity within a framework of inclusion and flexibility in educational pathways backed by public funding (Bayon-Calvo et al., 2020).

2.3 Youth Unemployment and ESL

The three concepts of ESL, NEET (not in education, employment or training), and youth unemployment are used to describe youth vulnerability. They are defined using different variables, and all highlight various aspects of problematic transitions from education to employment (Ryan & Lörinc, 2015). While it is understood that they share common characteristics, this section deals specifically with ESL. When one leaves school early, it is implied that the individual lacks the necessary skills for gainful employment. Indeed, it is not just literacy and numeracy that early school leavers lack but critical thinking skills, problem-solving, and knowledge of the STEM subjects. Furthermore, ESLs lack the entrepreneurial skills that broadly contribute to business creation and employability (Ross & Leathwood, 2013). Early school leavers experience a range of disadvantages in their adult life chances and cost society dearly in the form of social welfare expenditure, health services and imprisonment rates (C. R. Belfield & Levin, 2009; Smyth & McCoy, 2009). When economies are in decline, the labour market for young people, particularly for ESLs who typically have no or few qualifications, is unforgiving. These school leavers' employment prospects are bleak, often characterised by low-paid, low-security employment, dependence on government training schemes, and periods of being NEET (Ryan & Lörinc, 2015).

2.4 Adult educational background and ESL

Despite improved retention rates among working-class young people, ESL remains structured by social class background, and the degree of inequality in school completion between social strata has remained relatively stable (Byrne & Smyth, 2010). In terms of parental education, social capital is a significant factor in educational and occupational opportunities for youth (Iannelli et al., 2002). One also needs to consider the primary (Boudon, 1974) and secondary (Breen et al., 2009) effects of social capital and parental educational background on ESL. Primary effects explain how children from different social backgrounds perform differently in school because lower-educated parents are less able to help their children with their school assignments. Additionally, parents' economic constraints may affect their children's educational prospects deleteriously (Lavrijsen & Nicaise, 2015). Secondary effects explain how even students of the same academic performance level make different educational decisions depending on their social background (Breen et al., 2009). Even if Breen et al. (2009) suggest that such inequality is diminishing, they posit that children of better-educated parents are better guided to make more ambitious cost-benefit type decisions supporting higher social mobility and higher earnings in the longer term by virtue of their social capital and access to guidance that lower social background peers may not have. Ultimately individual lives are affected by extraneous circumstances best explained by reproduction theory (Bourdieu et al., 1977) on the one hand and rational action theory (Boudon, 1974) on the other.

2.5 Adult Professional Status and ESL

Lloyd and Mensch (1999) defined the successful transition to adulthood as a critically important aspect of human development through schooling. Conversely, premature exit from schooling affects other inter-related markers in the transition to adulthood (Utomo et al., 2014). Education is the primary mechanism through which opportunity and success are determined and is a vital predictor of a person's level of engagement in lifelong work and study. On the one hand, individuals with higher education levels enjoy higher-paying jobs, better general health, and a lower likelihood of engaging in crime (Lamb & Huo, 2017). On the other hand, being an ESL means disengagement from study and work, and the consequences are private, fiscal and social (C. Belfield, 2008; Psacharopoulos, 2007). One needs to consider the costs of families who are not economically independent, their reliance on resources from non-governmental agencies to support vulnerable individuals, and the intergenerational burdens transferred to their children. This is apart from the loss to society of lost revenue, cost of crime and incarceration, social welfare payments, and poor health (Lamb & Huo, 2017). Individuals who pursue their education through to tertiary level receive significant positive returns in the form of higher earnings and an increased likelihood of being employed full-time (Wilkins, 2015). This amounts to an earning differential of around 40 per cent for adults with a university degree (Forbes et al., 2010; Sinning, 2014). Indeed, all considered, most early school leavers can only look forward to a life on the fringes of society. As can be seen from the analysis in this section, the research available about the outlined determinants is limited and sometimes contradictory. Moreover, research focuses on linear regression methods, which assume the individual impact of these elements on the individual rather than concurrently. Individual analysis is not reflective of real-world settings. Thus, in the next section, we shall conduct a linear regression analysis to understand if the results are in line with previous studies. A configurational analysis will enhance this investigation to reflect real-world settings and analyse the impact of these elements in a concurrent rather than an individual manner.

3 Method and Analysis

3.1 Sample and Data Collection

In this article, we utilise data from 30 European countries, including all European Union (EU) member states (with the exception of Croatia due to lack of data) and Iceland, Norway and Switzerland, spanning the period 2010 to 2017.

3.2 Measures

Table 1 provides details regarding the measurement of each of the variables used in this article, including data sources. While the relationship between our economic variables and early school leaving has been explored at length in the literature (e.g. (Clark, 2011; De Witte et al., 2013; Lavrijsen & Nicaise, 2015), the sociodemographic variables require further unpacking and discussion. It is important to note that in the case of the socioeconomic variables, the age brackets reflect the expected age ranges of parents for youths aged between 18 and 24 within our sample period (i.e. 2010 to 2017). The inclusion of both parental education and professional status in our analysis follows directly from evidence linking these variables to early school leaving (e.g. Chevalier et al. (2013) and Traag and Van der Velden (2011).

3.3 Calibration

In order to be able to conduct the fuzzy-set analysis, all measures have to be calibrated and thus take on a value from 0 to 1 in order to conduct an analysis using fuzzy-sets. The calibration process used is known as the direct method of calibration, a method that is known to lead to precise results, as per previous application in social sciences literature (Ragin, 2000). The direct method of calibration involved identifying the value of full-membership, non-membership and the cross-over point (neither in nor out). The calibration values (table 2) are based on the researchers' theoretical knowledge and statistical distribution of the sample. Thus, following a thorough analysis of the distribution of the data for each variable, the researchers analysed the theoretical meaning of each construct to determine the high (score of 1), low (score of 0), and cross-over (score of 0.5) points (Schneider & Wagemann, 2010). Before identifying the values shown in table 2, different options for the calibration points have been considered to make sure that the calibration points are robust.

The sufficiency analysis involves the analysis of sufficient conditions. Such conditions show configurations relevant to producing an outcome, but they are not the only configurations possible associated with the outcome (Ragin, 2008). The first step of the sufficiency analysis involved the development of a truth table, with each row illustrating the different sufficient combinations. This table is made up of 2k rows, where k is the number of causal conditions used in the analysis (in total, five). The second step involved the analysis of the subset relation through the consistency value, which indicates the extent by which the individual or overall solution differs from being a perfect subset of the outcome. The third

Category	Variable Name	Description	Source
Dependant Variable	Rate of early school leavers	The proportion of the total population aged 18 to 24 who have completed at most a lower secondary level of education and are currently not involved in further education or training	Eurostat (2019)
Economic Explanatory Variable	GDP	Annual Gross Domestic Product (GDP) per person, measured at constant 2010 Euros (€), millions	Eurostat (2019)
Economic Explanatory Variable	Inequality	Gini coefficient denoting the distribution of income in each country. The measure ranges from 0 to 1, with 0 denoting perfect equality and 1 denoting perfect inequality	Eurostat (2019)
Economic Explanatory Variable	Youth unemployment	The proportion of the active population aged 18 to 24 who is currently unemployed	Eurostat (2019)
Sociodemographic Explanatory Variable	Adult educational background	The proportion of population aged 35 to 44 with a level of education equal to or below ISCED level 2	Eurostat (2019)
Sociodemographic Explanatory Variable	Adult professional status	The proportion of active population aged 40 to 59 who are either managers, professionals or technician and associate professionals	Eurostat (2019)

Table 1: Description of Variables and Sources

Variable	Statistical Distributions				Calibration		
	Max.	Mean	Min.	Std. Dev.	Full-Membership	Cross-Over	Non-Membership
ESL	3.11	2.29	1.50	0.42	3.00	2.50	1.50
GDP	11.28	10.04	8.62	0.66	11.28	10.10	8.62
Inequality	3.58	3.38	3.16	0.13	3.58	3.40	3.10
Youth Unemployment	3.86	2.93	2.06	0.46	3.80	3.80	2.00
Parents' Education Level	3.95	2.75	1.50	0.56	3.90	2.80	1.50
Parents' Job Status	-1.28	-1.60	-2.23	0.21	-1.28	-1.60	-2.20

Table 2: Descriptive Statistics and Calibrations

step involves reducing the matrix rows to simplified conditions, which is done by implementing Quine-McCluskey algorithm whereby Boolean algebra is employed (Ragin, 2008). At this stage, the solutions are assessed through their coverage, which measures the extent by which an outcome is explained by a causal condition (Fiss, 2007). The fourth step involves the assessment of the complex solutions, given that the study is based on inductive reasoning. At this stage, the complex solution is used. Unless there is a theoretical justification that supports the use of logical remainders, the complex solution is deemed to be the best solution (Cooper & Glaesser, 2011). The fifth step of the sufficiency analysis involves the assessment of the causal conditions. The analysis consists of 32 (25) possible combinations. The frequency threshold for both high and low ESL outcomes was set at 1, which implies that there is at least one case per configuration. This allowed the analysis to perform on more than 90% of the sample for both outcomes, exceeding the 80% threshold (Ragin, 2008; Rihoux & Lobe, 2009). The consistency cut-off value was set at 0.854 for high ESL outcomes and 0.935 for low performing outcomes, higher than the 0.750 threshold (Campbell et al., 2016). Following the analysis of the sufficiency conditions, the analysis of necessary conditions is undertaken. The analysis is undertaken in order to assess whether the presence (or absence) of any of the variables alone is necessary (has to be present) for the two outcomes to take place. For a condition to be called necessary, there has to be a consistency of at least 0.9, and coverage of at least 0.8 (Ragin et al., 2006).

3.4 Data Analysis

The first part of the analysis includes traditional linear regression modelling using panel data estimation methods given that the sample consists of 30 countries over the period 2010 to 2017. Panel data methods are particularly useful given that they utilise both cross-country and time-varying factors in order to explain variations in ESL, thus resulting in more information being used within the estimation and therefore greater inference accuracy (Hsiao, 1985). The rate of ESL across our sample is expressed as a function of a number of economic and sociodemographic determinants, as identified in the vast empirical literature discussed earlier. Thus, we specify the following linear regression model:

$$\begin{aligned}\ln(\text{Early}_i t) = \beta_0 + \beta_1 \ln(\text{GDP}_{it}) + \beta_2 \ln(\text{Inequality}_{it}) \\ + \beta_3 \ln(\text{Youth}_{it}) + \beta_4 \ln(\text{Educ}_{it}) \\ + \beta_5 \ln(\text{Prof}_{it}) + \alpha_i + u_{it}\end{aligned} \quad (1)$$

Where:
ln = Natural logarithm; $\text{Early}_i t$ = Rate of early school leavers in country i at time t;
GDP_{it} = Real GDP per capita;
Inequality_{it} = Gini coefficient capturing income inequality;
Youth_{it} = Youth unemployment;
Educ_{it} = Proportion of adults aged 35 to 44 with a level of education equal to or below ISCED level 2;
Prof_{it} = Proportion of the working population aged 40 to 59 who are either managers, professionals or technicians and associate professionals;
α_i = Country-specific, time-invariant unobservable factors;
u_{it} = Random disturbance term.

Equation (1) is estimated using three different specifications, namely a Random Effects model (REM), a Fixed Effects model (FEM), and a Panel Data Instrumental Variables model with Fixed Effects (IVFEM). This three-pronged approach is adopted in order to ensure the robustness of our findings. Furthermore, all three methods allow us to control to some degree for a number of additional , time-invariant determinants of ESL that may be unique to each country but which may not be directly observable or measurable from the data. This is extremely important, since it leads to a more parsimonious econometric model with greater efficiency, while also minimising any risks of inconsistency or endogeneity bias. In the REM we account for unobservable country-specific effects across our panel but, for efficiency, assume that they are uncorrelated with our explanatory variables. This assumption of independence is relaxed under the FEM, where we explicitly account for unobservables and assume that they are correlated with our explanatory variables. Finally, the IVFEM expands on the FEM by accounting for potential reverse causality (endogeneity) between our dependent variable (early school leavers) and our economic variables, namely GDP per capita, inequality and youth unemployment, since there is some evidence that the rate of early school leaving is associated with various negative economic outcomes (e.g. Heckman (2011). Pairwise correlations across our explanatory variables indicate that there are moderate levels of correlation between youth unemployment and inequality ($r = 0.5$; $p = 0.00$) and inequality and GDP per capita ($r = 0.5$; $p = 0.00$), and high levels of correlation between professional status and GDP per capita ($r = 0.8$; $p = 0.00$), indicating only a limited potential presence of multicollinearity in our regression estimates. It is important to note that while the panel data analysis proposed above yields various important estimation benefits, it also has a number of shortcomings. Firstly, it does not account for potential non-linearities, particularly between the unobserved country-specific effects and ESL, which may affect the reliability of our parameter estimates (Hsiao, 2007). Secondly, there is the possibility of cross-sectional dependence, i.e. correlations across the unobserved effects across countries, which may result in inconsistent estimators, although the proper treatment of such dependencies is still unclear (Hsiao & Tahmiscioglu, 2008). Following the analysis using linear methods, we analysed the connections between the variables through configurational analysis. Fuzzy-set Qualitative Comparative Analysis (fsQCA) 2.0 is used to conduct this analysis (Ragin et al., 2006). This analysis involves the calibration of each variable as explained in the previous section followed by a sufficiency and necessity analysis (Schneider & Wagemann, 2012). These two forms of analysis have been conducted for both high and low ESL outcomes.

4 Results

4.1 Regression Results

Results from the regression analysis estimate equation (1) under three different specifications (table 3). Each column shows the results for each specification in turn. In each specification, robust standard errors are used, clustered at the country level to account for within-panel serial correlation and heteroscedasticity across panels.[1] The results obtained are somewhat mixed across the three specifications, particularly when it comes to the economic variables. For example, although GDP per capita is negatively-related to early school leaving, it only emerges as marginally significant (at the 10% level) in the FEM. Similarly, income inequality is negatively correlated with ESL, although in this case the coefficients are statistically significant (at the 10% level) in both the REM and FEM specifications. In turn, the coefficients on youth unemployment are not statistically significant across all specifications. Thus, it appears that the relationship between our economic variables and ESL is somewhat unclear across our three specifications. This may be due to several factors, including endogeneity issues between our independent and dependent variables, which may explain the lack of statistically significant coefficients in our IVFEM specification. It is also possible that these results reflect the shortcomings of the methods used, which assume a log-linearised relationship between each economic variable and ESL, which may not reflect reality as captured in the data. Matters are somewhat different when it comes to our sociodemographic determinants of ESL. This is because adult education is positively and significantly correlated with ESL across all three specifications and is the only significant coefficient in the IVFEM specification. In fact, the results indicate that a 1% increase in the proportion of adults aged 35 to 44 with an education level of ISCED level 2 or lower is associated with an increase in the proportion of ESL by around 0.4–0.5%. Thus, it is clear that parental education is an important determinant of ESL, with youths more likely to leave formal schooling or training if parents (and indeed other adults) have low levels of education. Along similar lines, adults' professional status is positively-correlated with ESL, albeit only in the REM and FEM specifications, which tallies somewhat with the previous results on educational background, since the findings suggest that adults in high-level jobs are more likely to be associated with lower levels of ESL. Nonetheless, it is important to note that professional status is not significant in the third IVFEM specification. The results from our regression analysis indicate that while the relationship between our economic variables and ESL is mixed, there is a clear association with sociodemographic variables, with parental education and (to a lesser extent) adult professional status emerging as key determinants of ESL rates.

4.2 Fuzzy-Set Analysis and Results

In essence, the above analysis demonstrates the limitations of using an additive-based method. This form of analysis fails to show whether there is complementarity between practices in reaching the outcome. It also fails to provide potential equifinal solutions. It would be interesting to assess the combinations that are effective in different situations. Regression analysis also has limitations when it comes to analysing higher-order interactions and, therefore, such questions are answered through fsQCA, which provides a more refined insight of the connection between the variables (Fiss, 2011). To this effect, the rest of this section is divided in two parts consistent with other presentations of Qualitative Comparative Analysis (QCA) results (Schneider & Wagemann, 2010).

4.3 Necessity Conditions Results

The results of the necessity analysis for high and low (∼) ESL (log) outcomes are illustrated in table 4. A condition is necessary if the consistency and coverage are at least 0.9 and 0.8, respectively. None of the conditions tested meet these criteria, thus none of the conditions is necessary for any of the outcomes. The analysis will now proceed with the examination of the sufficiency conditions.

[1] In addition to testing for serial correlation and heteroscedasticity, we also conducted unit root tests on each of the variables used in the regression models, utilizing the Harris-Tzavalis test (Harris & Tzavalis, 1999) for panel data variables where the number of panels exceeds the number of time periods. For each variable, we reject the null hypothesis for the existence of a unit root, implying that our variables are stationary.

Coefficients	**POLS** (1)	**REM** (2)	**FEM** (3)	**IVFEM** (4)
Log GDP per capita	-0.2222***	-0.1767	-0.7204*	-0.4057
	(0.0572)	(0.1080)	(0.4143)	(1.5782)
Log Inequality	-0.4193*	-0.8367*	-0.9345*	-1.4734
	(0.2145)	(0.4473)	(0.5059)	(1.9006)
Log Youth Unemployment	-0.0851**	-0.0328	-0.1662	-0.1076
	(0.0405)	(0.0974)	(0.1065)	(0.3505)
Log Adult Education	0.6715***	0.5448***	0.3817*	0.4923**
	(0.0336)	(0.1244)	(0.2100)	(0.2463)
Log Professional Status	-0.0478	-0.4798*	-0.6822**	-0.4454
	(0.1359)	(0.2509)	(0.3101)	(0.4587)
Constant	4.2630***	4.7193**	11.0260**	9.5803
	(1.1939)	(2.2236)	(4.9196)	(15.8607)
N	240	240	240	240
R-Squared	0.6417	0.5925	0.1759	0.4207
F-Statistic	118.48***		6.92***	
Wald Statistic		42.62***		8.86

Table 3: Regression Results

	High ESL		Low ESL	
Condition tested	**Consistency**	**Coverage**	**Consistency**	**Coverage**
High GDP	0.645	0.523	0.674	0.791
Low GDP	0.742	0.612	0.593	0.708
High Inequality	0.782	0.640	0.561	0.663
Low Inequality	0.588	0.481	0.696	0.822
High Youth Unemployment	0.734	0.627	0.606	0.748
Low Youth Unemployment	0.705	0.553	0.698	0.792
High Parents' Education	0.887	0.748	0.548	0.667
Low Parents' Education	0.604	0.481	0.801	0.920
High Parents' Job Status	0.702	0.509	0.734	0.770
Low Parents' Job Status	0.683	0.640	0.531	0.720

Table 4: Necessity Analysis

	High School Leaving Rate				**Low School Leaving Rate**			
Permutation	1	2	3	4	5	6	7	8
Macroeconomic Conditions								
GDP	⊕	⊕	⊕	●	●	●	⊕	●
Inequality	⊕	●	●	●	⊕	⊕	⊕	●
Youth Unemployoemnt	⊕	●	●	●		●	⊕	●
Socio-Economic Conditions								
(Low) Parents Education Level	●	●	⊕	●	⊕		⊕	⊕
(High) Parents' Professional Status	⊕	⊕	●	●	●	●	⊕	⊕
Consistency	0.929	0.898	0.855	0.868	0.945	0.945	0.980	0.698
Raw Coverage	0.354	0.526	0.388	0.430	0.471	0.350	0.283	0.241
Unique Coverage	0.073	0.112	0.020	0.031	0.122	0.022	0.051	0.036
Overall Solution Consistency	**0.789**				**0.936**			
Overall Solution Coverage	**0.687**				**0.583**			

Table 5: Configurations of Macro and Socioeconomic Factors with respect to High and Low ESL Rates across the EU.

4.4 Sufficiency Conditions Results

Table 5 shows the solutions for high and low ESL outcomes among the different EU countries used in the sample. The table includes two symbols under each configuration—"•" illustrates the high presence of a condition, and "⊕" illustrates the low presence. The blank spaces indicate that the specific variable is ineffective within the specific configuration. The analysis shows four configurations for high ESL, and four configurations for low ESL. The overall and individual consistency levels for the two outcomes exceed the 75% threshold, implying that the configurations outlined are strongly associated with the respective outcomes (Campbell et al., 2013). The solution also indicates acceptable overall and individual raw and unique coverage, in line with previous studies (Fiss, 2007; Meuer, 2016). Raw coverage shows the number of cases that are fully part of the conditions of a solution. Unique coverage represents the proportion of cases that are not covered by other solution terms (Schneider & Wagemann, 2012). The results for each configuration are explained in table 6. To examine the robustness of the sufficiency analysis outcomes, further analysis was conducted. First, the calibration points were varied by ±0.5%. Second, the analysis was conducted for the periods 2010–2013 and 2014–2017, separately. The interpretation of the findings with these changes remains unchanged in all of these analyses. Thus, it can be deduced that the results are robust. The sufficiency analysis results show that there are clear signs of complex relations among ESL, macroeconomic conditions, and socioeconomic conditions. These complexities involve nonlinearity, equifinality, and asymmetric relation. Nonlinearity is illustrated through different relations among variables. For example, parents' educational level and job status could have a positive association (configuration 3), or a negative one (configuration 4). Equifinality is shown through the fact that there are alternative configurations of socioeconomic conditions occurring within the same macroeconomic context and outcome (configurations 2 and 3). The results also indicate clear signs of asymmetric relations whereby the factors that lead to low ESL are not the exact inverse of the factors that lead to high ESL. For example, despite the different outcomes, configurations 4 and 8 have the same macroeconomic factors, while configurations 3 and 5 have the same socioeconomic factors.

5 Discussion and Conclusion

This article has sought to understand the relationship between ESL rates and various macroeconomic and social factors. The results from both the panel data regression and fuzzy-set analysis point towards a complex relationship between ESL and the various economic and social determinants specified in the literature. Considering the macroeconomic conditions, inequality emerges as a key correlate of ESL rates under both estimation methods, with the fuzzy-set analysis indicating that high levels of inequality are generally associated with high levels of ESL, although the opposite scenario of low inequality and ESL is somewhat less evident. These findings are broadly consistent with the results of Kearney and Levine (2016), who find that youth from low-income backgrounds may perceive the returns to further schooling and human capital accumulation to be low, thus resulting in higher levels of ESL among these cohorts. Therefore, a key implication of this result is the importance of social and redistributive policy mechanisms to minimise income disparities and promote higher levels of social mobility. This has been explicitly identified by the EU as a priority area in the medium term, with 'Fairness' a key pillar of its 2021 Annual Sustainable Growth Strategy, particularly in light of the economic crisis precipitated by the COVID-19 pandemic (EC, 2020a) In addition, GDP per capita also emerged as an important determinant of ESL, particularly in the fuzzy-set analysis where high GDP levels were associated with low levels of ESL, underscoring the importance of economic prosperity in boosting returns to education via improved job conditions and opportunities (Jensen, 2010). These results further emphasise the need to pursue macroeconomic policies that encourage sustainable economic growth in the post-COVID recovery phase, with mechanisms like Next Generation EU aimed at re-energising growth and investment among EU member states (EC, 2020b). In addition, the fuzzy-set analysis identifies low youth unemployment as a potential correlate of ESL, with high youth unemployment associated with high ESL rates. Although the direction of causality is somewhat of a moot point, the finding underscores the need to ensure growth and investment to create job opportunities across all strata of society, and in particular young people. When it comes to the social factors, low parental education is closely associated with high levels of ESL, across both methods employed in this article. This finding is consistent with the literature on intergenerational educational mobility and, in particular the fact that attainment is highly persistent across parents and children, thus perpetuating inequality and hampering mobility (Checchi et al., 2013). Within this scope, educational policies should be aimed at breaking this cycle of low attainment through widespread reforms and improved learning resources for all students irrespective of background from a young age (Chetty et al., 2011). Against the background of the results obtained, one needs to consider which aspects of the problem to address and the critical time to act. When low parental education co-occurs with

Configuration	ESL Level	Macroeconomic Context	Socio-Economic Context
1	High ESL	Low GDP, Inequality, Youth Unemployment	Low Parents' Education and Professional Status
2		Low GDP, High Inequality and Youth Unemployment	Low Parents' Education and Professional Status
3		Low GDP, High Inequality and Youth Unemployment	High Parents' Education and Professional Status
4		High GDP, Inequality, Youth Unemployment	Low Parents' Education and High Professional Status
5	Low ESL	High GDP, and Low Inequality	High Parents' Education and Professional Status
6		High GDP, Low Inequality, and High Youth Unemployment	High Parents' Professional Status
7		Low GDP, Inequality, Youth Unemployment	High Parents' Education and Low Professional Status
8		High GDP, Inequality, Youth Unemployment	High Parents' Education and Low Professional Status

Table 6: Description of the Configurations

high inequality and high youth unemployment, this creates deficit and necessitousness, associated with intergenerational stability perpetuating inequality and youth unemployment. This calls for supporting families 360-degrees, literally from the moment parents make first contact with hospital at the beginning of the mother's pregnancy, right through early toddlerhood, childcare, early schooling and throughout the child's school life. Such parents may benefit from familial support in preparation for their parenting roles. They would benefit from training to support their children's learning in a proactively participative manner rather than just reactively, or not at all, assisted by family support workers. The diametric opposite has also been indicated in our study where. High professional status is associated with lower levels of ESL, further highlighting the impact of parental attainment on children's educational choices, which in turn influences their future job and earning prospects (Lee & Solon, 2009).

Therefore, the main findings from this article indicate that early school leaving among European youths is a complex and multi-faceted problem that requires a variety of economic and social policy interventions in order to keep it in check. Further research should seek to analyse each individual determinant, in turn, to further understand the underlying relationship in greater detail, with a particular emphasis on teasing out causal linkages, which would further aid the development of effective policies.

References

Andrei, T., Teodorescu, D., & Oancea, B. (2011). Characteristics and causes of school dropout in the countries of the European Union. *Procedia-Social and Behavioral Sciences*, *28*, 328–332.

Bayon-Calvo, S., Corrales-Herrero, H., & De Witte, K. (2020). Assessing regional performance against early school leaving in Spain. *International Journal of Educational Research*, *99*(10151), 5.

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis*. University of Chicago press.

Belfield, C. (2008). *The cost of early school-leaving and school failure*. World Bank.

Belfield, C. R., & Levin, H. M. (2009). High school dropouts and the economic losses from juvenile crime in California. *Center for Benefit-Cost Studies of Education*, *26*.

Boudon, R. (1974). *Education, opportunity, and social inequality: Changing prospects in western society*.

Bourdieu, P., Passeron, J. C., & Nice, R. (1977). *Education, society and culture.* SAGE Pub.

Breen, R., Luijkx, R., Müller, W., & Pollak, R. (2009). Nonpersistent inequality in educational attainment: Evidence from eight European countries. *American journal of sociology*, *114*(5), 1475–1521.

Byrne, D., & Smyth, E. (2010). *No way back? the dynamics of early school leaving.*

Calero, J., & Gil-Izquierdo, M. (2014). Too much to pay: An estimation through microsimulation techniques of the monetary costs of early school leaving in Spain. *Journal of Simulation*, *8*(4), 314–324.

Campbell, J. T., Sirmon, D., & Schijven, M. (2013). *The good, the bad, and the fuzzy: A configurational approach to acquisitions*. Paper presented at the Academy of Management Proceedings.

Campbell, J. T., Sirmon, D. G., & Schijven, M. (2016). Fuzzy logic and the market: A configurational approach to investor perceptions of acquisition announcements. *Academy of Management Journal*, *59*(1), 163–187.

Checchi, D., Fiorio, C. V., & Leonardi, M. (2013). Intergenerational persistence of educational attainment in Italy. *Economics letters*, *118*(1), 229–232.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? evidence from project STAR. *The Quarterly journal of economics*, *126*(4), 1593–1660.

Chevalier, A., Harmon, C., O'Sullivan, V., & Walker, I. (2013). The impact of parental income and education on the schooling of their children. *IZA Journal of Labor Economics*, *2*(1), 1–22.

Clark, D. (2011). Do recessions keep students in school? the impact of youth unemployment on enrolment in post-compulsory education in England. *Economica*, *78*(311), 523–545.

Cooper, B., & Glaesser, J. (2011). Paradoxes and pitfalls in using fuzzy set QCA: Illustrations from a critical review of a study of educational inequality. *Sociological Research Online*, *16*(3), 106–119.

De Witte, K., Nicaise, I., Lavrijsen, J., Van Landeghem, G., Lamote, C., & Van Damme, J. (2013). The impact of institutional context, education and labour market policies on early school leaving: A comparative analysis of EU countries. *European Journal of Education*, *48*(3), 331–345.

EC. (2020a). *Annual sustainable growth strategy 2021. european commission COM(2020) 575.*

EC. (2020b). *Europe's moment: Repair and prepare for the next generation. european commission COM(2020) 456.*

Eurostat. (2019). *Eurostat statistics explained.* http://ec.europa.eu/eurostat/statistics-explained/index.php/Main_Page

Eurostat. (2021). *Early leavers from education and training aged 18–24 by sex and labour status, 2021 (% of population aged 18–24).* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Early_leavers_from_education_and_training_aged_18-24_by_sex_and_labour_status,_2021_(%25_of_population_aged_18-24).png

Fernández-Mellizo, M., & Martínez-García, J. S. (2017). Inequality of educational opportunities: School failure trends in Spain (1977–2012). *International Studies in Sociology of Education*, *26*(3), 267–287.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of management review*, *32*(4), 1180–1198.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420.

Forbes, M., Barker, A., & Turner, S. A. (2010). *The effects of education and health on wages and productivity.*

Harris, R. D., & Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of econometrics*, *91*(2), 201–226.

Heckman, J. J. (2011). The economics of inequality: The value of early childhood education. *American Educator*, *35*(1), 31.

Hsiao, C. (1985). Benefits and limitations of panel data. *Econometric Reviews*, *4*(1), 121–174.

Hsiao, C. (2007). Panel data analysis—advantages and challenges. *Test*, *16*(1), 1–22.

Hsiao, C., & Tahmiscioglu, A. K. (2008). Estimation of dynamic panel data models with both individual and time-specific effects. *Journal of Statistical Planning and Inference*, *138*(9), 2698–2721.

Humphrey, N., Wigelsworth, M., Barlow, A., & Squires, G. (2013). The role of school and individual differences in the academic attainment of learners with special educational needs and disabilities: A multilevel analysis. *International Journal of Inclusive Education*, *17*(9), 909–931.

Iannelli, C., Zentrum, M., Sozialforschung, E., & Cristina, I. (2002). *Parental education and young people's educational and labour market outcomes: A comparison across europe* (tech. rep.). Paper presented at the MZES Working Papers 45, MZES.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly journal of economics*, *125*(2), 515–548.

Kearney, M. S., & Levine, P. B. (2016). *Income inequality, social mobility, and the decision to drop out of high school*.

Lamb, S., & Huo, S. (2017). *Counting the costs of lost opportunity in Australian education*.

Lamb, S., & Rice, S. (2008). *Effective intervention strategies for students at risk of early leaving*. Centre for Post-compulsory Education; Life Long Learning. The university of Melbourne.

Lavrijsen, J., & Nicaise, I. (2015). Social inequalities in early school leaving: The role of educational institutions and the socioeconomic context. *European Education*, *47*(4), 295–310.

Lee, C.-I., & Solon, G. (2009). Trends in intergenerational income mobility. *The Review of Economics and Statistics*, *91*(4), 766–772.

Lloyd, C. B., & Mensch, B. (1999). Implications of formal schooling for girls' transitions to adulthood in developing countries. *Critical perspectives on schooling and fertility in the developing world*, 80–104.

Meuer, J. (2016). Exploring the complementarities within high-performance work systems: A set-theoretic analysis of UK firms. *Human Resource Management*, *56*(4), 651–672.

Nouwen, W., & Clycq, N. (2019). The role of social support in fostering school engagement in urban schools characterised by high risk of early leaving from education and training. *Social Psychology of Education*, *22*(5), 1215–1238.

Psacharopoulos, G. (2007). *The costs of school failure: A feasibility study*. EENEE Brussels.

Ragin, C. C. (2000). *Fuzzy-set social science*. University of Chicago Press.

Ragin, C. C. (2008). Qualitative comparative analysis using fuzzy sets (FsQCA). In B. Rihoux & C. C. Ragin (Eds.), *Configurational comparative methods. qualitative comparative analysis (qca) and related techniques.* (pp. 87–122). Sage.

Ragin, C. C., Drass, K. A., & Davey, S. (2006). Fuzzy-set/qualitative comparative analysis 2.0. *Tucson, Arizona: Department of Sociology, University of Arizona*, *23*(6), 1949–1955.

Rihoux, B., & Lobe, B. (2009). The case for qualitative comparative analysis (QCA): Adding leverage for thick cross-case comparison. *The Sage handbook of case-based methods*, 222–242.

Ross, A., & Leathwood, C. (2013). Problematising early school leaving. *European Journal of Education*, *48*(3), 405–418.

Ryan, L., & Lörinc, M. (2015). Interrogating early school leaving, youth unemployment and NEETs: Understanding local contexts in two English regions. *Educação, Sociedade & Culturas*, *45*, 33–54.

Schneider, C. Q., & Wagemann, C. (2010). Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets. *Comparative Sociology*, *9*(3), 397–418.

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press.

Sinning, M. (2014). *How much is it worth? new estimates of private returns to university education in Australia* (F. Report, Ed.).

Smyth, E., & McCoy, S. (2009). *Investing in education: Combating educational disadvantage* (ESRI).

Thrupp, M., & Lupton, R. (2006). Taking school contexts more seriously: The social justice challenge. *British journal of educational studies*, *54*(3), 308–328.

Traag, T., & Van der Velden, R. K. (2011). Early school-leaving in the netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, *30*(1), 45–62.

Utomo, A., Reimondos, A., Utomo, I., McDonald, P., & Hull, T. H. (2014). What happens after you drop out? transition to adulthood among early school-leavers in urban Indonesia. *Demographic Research*, *30*, 1189–1218.

Vodă, I.-M. (2020). Correlation between school dropout and gross domestic product in the emerging countries of central and Eastern Europe. *Educatia*, *21*(19), 66–72.

Wilkins, R. (2015). Measuring income inequality in Australia. *Australian Economic Review*, *48*(1), 93–102.