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TÍTOL: Exploring Intergenerational Educational Mobility: The Role of Personal and National Factors Across Europe

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Abstract

This paper aims at contributing to understand the interplay of personal and structural determinants of educational mobility. This study examines intergenerational educational mobility across 21 European countries, focusing on the role of individual and national factors in fostering upward mobility. Using data from the European Social Survey (2008–2020), the research begins by estimating absolute and relative mobility rates and continues analyzing the impact of individual attributes such as gender, ethnicity, and parental occupation, as well as macroeconomic variables, like income inequality and inflation, on upward educational mobility. The results obtained through regression analysis reveal that upward mobility is more likely among women and those from lower parental occupational backgrounds, whereas the effects of ethnic and immigrant status vary by context. At the national level, higher government education expenditure and household savings prove to be positively associated with mobility, while inflation serves as a barrier. Notably, income inequality's effect on mobility highlights complex regional dynamics.

Keywords: Education, Intergenerational mobility, Inequality, Europe

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1. Introduction: Overview of intergenerational educational mobility (IGM) and its relevance

Intergenerational educational mobility—the extent to which educational attainment changes from one generation to the next—is a critical indicator of equality and opportunity within societies (Engzell & Tropf, 2019). It measures how much an individual's educational achievement depends on their parents' education, providing a lens to assess the fairness of social systems. High mobility indicates a society where educational opportunities are broadly accessible, regardless of family background. In contrast, low mobility points to deeply rooted inequalities that limit generational progress.

Understanding the factors that drive upward and downward mobility is essential not only for addressing social inequality but also for informing policies that foster equal opportunities in education. The importance of such research is underscored by evidence that higher levels of education are strongly associated with higher income, greater well-being, and even longer life expectancy (World Health Organization [WHO], 2016). However, despite these benefits, significant disparities in intergenerational mobility persist across Europe, with Nordic countries consistently achieving higher mobility while Central and Eastern European nations often lag behind (Hertz et al., 2007; OECD, 2018). These regional differences highlight the need to investigate the structural, cultural, and economic factors that influence mobility patterns.

This essay seeks to analyze the main determinants of intergenerational educational mobility across 21 European countries. It begins by estimating absolute and relative mobility for the target nations, followed by an investigation into the roles of factors such as parental occupation, ethnicity, income inequality, institutional quality, and other macroeconomic variables in shaping these mobility patterns. By exploring these dynamics, the study aims to contribute to the academic discourse on social inequality and provide insights on the structural and contextual influences that contribute to educational inequalities.

2. Literature Review

While the concept of intergenerational income mobility has been extensively explored in academic research, the transmission of academic capital remains a more recent and comparatively underdeveloped area of study. Nevertheless, educational mobility has been closely associated with income mobility (Breen & Jonsson, 2005), and it also presents distinct advantages for academic research. This is because data on individuals' educational attainment is more easily available than data on households income and, as a stock variable, it tends to remain stable beyond a certain age, facilitating longitudinal and cross-sectional analyses.

In this section, I will review some of the existing literature on the subject, focusing on key findings and theoretical frameworks that contribute to the understanding of intergenerational educational mobility. Previous to this discussion, it is important to differentiate the key concepts of “absolute mobility” and “relative mobility,” for which I have adopted the definition provided in the working paper by van der Weide et al. (2021). Absolute mobility refers to the proportion of individuals in a country who attain a higher level of education than their parents, reflecting the overall prevalence of upward educational movement within a society. In contrast, relative mobility measures the strength of the relationship between parents' and children's educational levels, indicating how much a child's educational attainment is independent of their parents'. While absolute mobility focuses on upward progress across generations, relative mobility assesses the fairness of opportunity by examining the extent to which family background determines educational outcomes.

One of the most influential studies on intergenerational mobility is the work by Chetty et al. (2014), titled “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States”, in which they examined intergenerational income mobility across the U.S. While the study primarily focuses on income mobility, it laid the groundwork for understanding intergenerational persistence and mobility across various socio-economic dimensions, including education.

In this paper they employed a rank-rank methodology to quantify intergenerational income mobility, finding that a 10-percentile increase in parental income corresponded, on average, to a 3.4-percentile increase in a child’s income rank. Their analysis revealed significant geographic variation within the U.S.: in San Jose, children from low-income families had a 12.9% chance of reaching the top income quintile, compared to just 4.4% in Charlotte. This variation underscored the profound influence of local socio-economic conditions on economic mobility.

Moreover, the study identified five key factors associated with high upward income mobility areas: less residential segregation, lower income inequality, better-quality education, stronger social capital, and greater family stability. These findings suggest that policies fostering cohesion, equitable resource distribution, and supportive social environments could play a critical role in enhancing mobility. Interestingly, areas with larger African-American populations exhibited lower upward mobility, yet this effect extended across racial groups within these communities, indicating that structural factors such as segregation and family structure are more impactful than race alone. On the other hand, Chetty et al. also highlighted the limited impact of factors like local tax policies or labor market conditions on mobility.

Although they did not delve into the underlying factors that allow certain regions within the United States to achieve higher rates of mobility than others, the main conclusion of their research was that intergenerational mobility is a local issue that could potentially be addressed through place-based policies.

For studies specifically on educational mobility, the book “Persistent Inequality: Changing Educational Attainment in Thirteen Countries” by Shavit and Blossfeld (1993) is considered a landmark contribution. The authors found that since the early twentieth century educational inequality remained remarkably persistent across generations in most of the 13 countries studied, despite significant expansions in educational systems during the 20th century. Children from higher socio-economic backgrounds continued to have better access to education and were more likely to achieve higher educational levels than those from disadvantaged backgrounds. Although the expansion of education systems increased access to schooling overall, the advantages enjoyed by students from privileged backgrounds tended to shift to new forms, such as access to higher education. Nevertheless, Sweden and The Netherlands showed lower levels of inequality compared to other countries, which were partially attributed to stronger social welfare policies. Additionally, while socio-economic inequalities in education persisted, the gender gap appeared to have narrowed across all nations, with women even surpassing men in average educational attainment in some cases.

Another cornerstone of research in this field is the work of Torul and Öztunali (2021). In their study, “Intergenerational Educational Mobility in Europe”, they analyzed the influence of parental education on the educational attainment of their children across 34 European countries, grouped into four distinct regions: Mediterranean, Nordic, Post-Socialist, and the rest of Europe. Using ordered logistic regressions with individuals' educational attainment as the dependent variable and a latent measure of maximum parental education as the independent variable, the authors examined intergenerational educational persistence [1]for cohorts born between 1940 and 1985. Their findings reveal significant variations in educational mobility both across countries and over time, highlighting distinct trends in persistence for each European country group.

The study observed that intergenerational persistence has declined sharply in Mediterranean countries, which is attributed to a reduction in low-type educational persistence among later-born cohorts. In contrast, Nordic countries exhibit a U-shaped trend, reflecting an initial decline in low-type persistence, followed by a sharp increase in high-type persistence in later cohorts. In Post-Socialist countries, educational persistence decreased moderately for cohorts born in the 1940s but increased monotonically thereafter, driven by rising medium- and high-type persistence over time. Meanwhile, countries in the rest of Europe display a more stable trajectory. Additionally, the study also highlights gender dynamics, showing that female descendants were historically more disadvantaged in terms of educational attainment but have increasingly caught up to or surpassed male counterparts in more recent cohorts.

The role of parental characteristics is further explored, demonstrating that both the most- and less-educated parent's education positively influence descendants' outcomes, particularly in the Mediterranean region. Furthermore, parental financial well-being during a descendant's formative years has a significant, albeit varying, impact across gender and regions. Finally, the research confirms that intergenerational educational elasticity positively correlates with educational inequality, consistent with the "Educational Great Gatsby" hypothesis. It also finds that mobility measures are linked to returns to education, with lower mobility associated with a higher college premium, suggesting that educational and economic inequalities reinforce each other across Europe.

[1] Educational persistence refers to the extent to which individuals' educational attainment mirrors their parents'. Low-type persistence indicates limited mobility for those from less-educated backgrounds (secondary and lower education); medium-type persistence denotes low levels of mobility among the descendents of parents with medium-education (upper secondary and post-secondary); lastly, high-type persistence reflects the strong transmission of high education (tertiary) from parents to children.

3. Presentation of the Data and Methodology

To carry out this research I have resorted to the data provided by the European Social Survey (ESS)[2], a cross-national survey that has been gathering data across more than 30 different countries since 2001. For this project, I have looked at the answers obtained during 7 rounds of the survey (ESS4, ESS5, ESS6, ESS7, ESS8, ESS9 and ESS10), from year 2008 to 2020, and, in particular, I have focused on the following 21 countries: Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom.

The main variables of interest in this study are the respondents' highest level of educational attainment at the time of the survey, as well as the highest levels attained by both of their parents.This analysis focuses on comparing educational levels—such as primary, secondary, and tertiary—rather than years of schooling for several reasons. First,educational levels provide a more standardized measure of attainment, facilitating meaningful comparisons across countries and generations (Chetty et al., 2014). Second, educational levels account for variations in educational systems, where the duration required to complete a specific level can differ regionally. Finally, educational attainment represents key societal milestones, such as completing secondary education or earning a university degree, which are closely tied to socioeconomic outcomes (Behrman & Rosenzweig, 2002).

Given the diversity of countries and education systems included in the research, a categorical measure of educational attainment provided by the ESS is employed. This measure, based on the ISCED standard developed by UNESCO, harmonizes education levels across nations.The variable *eisced* represents the respondent's highest level of education and categorizes attainment into seven groups: (1) ISCED I - less than lower secondary; (2) ISCED II - lower secondary; (3) ISCED IIIb - lower tier upper secondary; (4) ISCED IIIa - upper tier upper secondary; (5) ISCED IV - advanced vocational, sub-degree; (6) ISCED V1 - lower tertiary education, bachelor level; and (7) ISCED V2 - higher tertiary education, master level and

[2] The European Social Survey (ESS) is a biennial, cross-national survey designed to monitor and analyze social attitudes, behaviors, and changing trends across Europe. It is coordinated by the European Social Survey European Research Infrastructure Consortium (ESS ERIC), headquartered at City, University of London. The survey adheres to rigorous methodological standards to ensure high-quality and comparable data. For more information, see www.europeansocialsurvey.org.

above. Additionally, the variables *eiscedf* and *eiscedm* capture the educational levels of the respondent's father and mother, respectively.

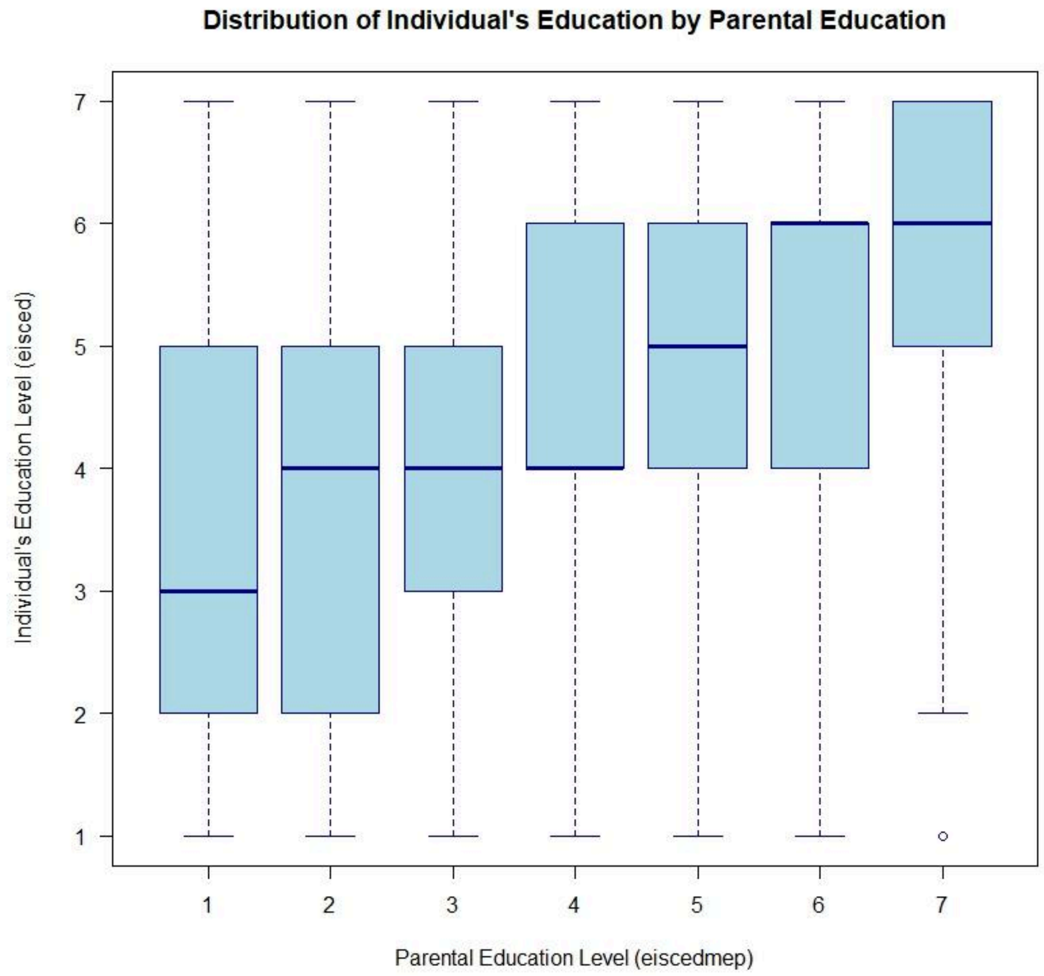
Prior to conducting the analysis, the sample was stratified by generation and age, resulting in a subset of individuals born between 1977 and 1997 who were between 23 and 45 years old at the time of the survey. This age threshold was applied to ensure that only individuals who had likely completed their formal education were included, as 23 years is the average age in which we can expect individuals to have finished their studies. While some previous studies have excluded individuals born in foreign countries, as they may have participated in different education systems, and their educational attainment could have been influenced by external factors not related to the country under study (Strömberg & Engzell, 2023). In this case, foreign-born respondents were kept in the sample group, provided they had moved to their current country of residence before the age of 6, which is the average age when mandatory schooling starts in these states. After this data cleaning process, the sample size was reduced to 50,794 observations.

Table 1 indicates that individuals in this cohort, on average, have achieved higher levels of education (mean: 4.64) compared to their parents (mean: 3.59 for both fathers and mothers). Among the countries analyzed, Finland, Sweden, Belgium, and Norway exhibit the highest average educational levels (above level 5) for respondents, whereas Portugal, Hungary, and Italy report the lowest averages (slightly above level 4). In terms of parental education, Estonia and Norway record the highest mean levels for both fathers and mothers, while Portugal, Spain, and Italy show the lowest parental education levels. Furthermore, the data reveal that educational attainment among respondents exhibits lower variability compared to that of their parents, suggesting a trend towards greater uniformity in educational outcomes among the younger generation.

Table 1: Descriptive Statistics by Country

Country	No of Obs.	Level of Education		Father's Level of Education		Mother's Level of Education	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Belgium	2203	5,08	1,60	4,04	2,05	3,91	1,98
Czech Republic	3723	4,39	1,41	4,04	1,45	3,95	1,32
Denmark	1164	4,68	1,66	3,87	1,91	4,11	1,84
Estonia	2858	4,79	1,52	4,57	1,58	4,86	1,46
Finland	2572	5,14	1,35	4,14	1,86	4,45	1,64
France	2524	4,72	1,58	3,32	1,95	3,16	1,79
Germany	4676	4,73	1,62	4,10	1,63	3,62	1,56
Hungary	2604	4,14	1,43	3,40	1,29	3,38	1,33
Ireland	2928	4,73	1,63	2,98	1,83	3,15	1,72
Italy	1921	4,30	1,61	2,80	1,68	2,72	1,58
Lithuania	2305	4,96	1,48	3,98	1,62	4,40	1,57
Netherlands	2171	4,58	1,92	3,62	2,10	3,20	1,83
Norway	1937	5,02	1,58	4,46	1,82	4,50	1,73
Poland	3072	4,75	1,85	3,00	1,62	3,33	1,66
Portugal	1927	4,08	2,06	2,01	1,76	2,01	1,76
Slovakia	1404	4,57	1,53	3,75	1,48	3,65	1,36
Slovenia	1847	4,62	1,30	3,57	1,32	3,63	1,36
Spain	2752	4,33	2,06	2,44	2,00	2,21	1,77
Sweden	2220	5,10	1,31	4,14	1,93	4,33	1,76
Switzerland	1701	4,33	1,63	3,78	1,64	3,25	1,35
United Kingdom	2285	4,45	1,84	3,27	2,10	3,27	2,00
All	50794	4,64	1,66	3,59	1,86	3,59	1,79

Figure 1. Distribution of Individual's Education by Parental Education



*This boxplot shows how individual educational attainment (y-axis) varies across different levels of parental education (x-axis). Each box represents the distribution of individual education levels for a specific parental education category: The horizontal line inside the box indicates the median (middle value) of individual education for that parental level; The box shows the interquartile range (IQR), which contains the middle 50% of individuals; The whiskers extend to the smallest and largest values within 1.5 times the IQR, while any outliers beyond this range are marked as individual points.

4. Measures of Intergenerational Educational Mobility across European Countries

4.1. Absolute mobility

An important metric for analyzing the intergenerational transmission of educational status in the aforementioned countries is Absolute Mobility.

In studies of educational equality, relative mobility is often prioritized over absolute mobility because it focuses on the degree of "equal opportunity" within a society (Breen & Jonsson, 2005; OECD, 2018). This is because high levels of absolute mobility could coexist with persistent inequalities[3]. Nevertheless, as Chetty et al. (2014) suggest, increases in relative mobility can be complex to interpret as well. These increases do not always reflect gains for disadvantaged groups; they may instead result from declining outcomes for wealthier (or more educated) individuals. This ambiguity makes absolute mobility a valuable complementary measure, as it captures broader trends in educational advancement across socioeconomic groups, offering a more comprehensive view of overall mobility patterns.

To calculate this measure, the data from the European Social Survey (ESS) on the educational levels of respondents' mothers and fathers was used. From this dataset, an additional variable was created to capture the highest level of education among the two parents, referred to as *eiscedmep*. Using this variable, a new indicator, *mobility*, was constructed to compare an individual's educational attainment with that of their most educated parent. This indicator categorizes individuals into three groups: "Up," indicating that the individual's education surpasses that of their most educated parent; "Down," if it falls below; and "No," if it remains the same. Subsequently, the percentages of individuals in each category were calculated for each country. The results are presented in Table 2.

[3] For example, even if educational levels rise across all socioeconomic groups (indicating high absolute mobility), an individual's position relative to others will still depend on their family background, which means that social inequality remains largely unaddressed.

Table 2. Absolute Intergenerational Mobility across European Countries

	Up (%)	Down (%)	No (%)
All (average)	46,19	22,05	31,75
Belgium	45,86	21,70	32,43
Czech Republic	30,38	28,69	40,93
Denmark	36,24	34,41	29,35
Estonia	27,95	38,91	33,14
Finland	39,17	28,22	32,61
France	59,77	15,84	24,39
Germany	32,49	29,24	38,27
Hungary	43,24	15,85	40,91
Ireland	62,01	11,43	26,57
Italy	61,01	10,34	28,65
Lithuania	43,80	25,31	30,89
Netherlands	48,56	22,44	29,00
Norway	35,34	34,98	29,68
Poland	54,05	13,31	32,63
Portugal	69,00	6,67	24,33
Slovakia	44,80	13,02	42,18
Slovenia	50,58	18,73	30,70
Spain	64,84	13,47	21,69
Sweden	41,99	31,26	26,75
Switzerland	36,99	23,56	39,45
United Kingdom	50,55	23,88	25,57

The findings reveal significant cross-country variation in levels of absolute educational mobility. Ireland, Spain, Portugal, and Italy exhibit the highest levels, with over 60% of individuals attaining a higher level of education than their parents. In contrast, Estonia, the Czech Republic, and Germany report considerably lower levels of upward mobility, with fewer than 35% of individuals surpassing their parents' educational attainment. The Nordic countries also fall into this latter category of nations with lower upward mobility. One of the main explanations for this trend is the relatively high average level of parental education in these countries, which may limit the opportunities for children to exceed their parents' educational achievements.

Relating to this, one of the conclusions extracted from the World's Bank paper (2021), is that absolute mobility displays lowest values in both the world's poorest and richest nations. The cause of this is that although in the poorest nations there is a greater chance for children to surpass their parents' educational attainment, because it tends to be quite low, the lack of resources to ensure higher education for children living in these regions plays a more important role. On the opposite side, in countries with very high income levels, children may find it more difficult to exceed their parents' level of education, which is usually very high, despite having a much greater financial capacity to invest in education.

Returning to Table 2, it is noteworthy that among the countries with lower levels of upward mobility, there are distinct patterns regarding the distribution of intergenerational mobility. In certain nations, such as the Czech Republic, Germany, and Finland, the proportion of individuals who attain the same level of education as their parents exceeds the proportion who achieve a lower level. In contrast, other countries, including Estonia, Norway, and Denmark, display a higher prevalence of downward mobility, with a larger share of the population attaining an educational level below that of their parents.

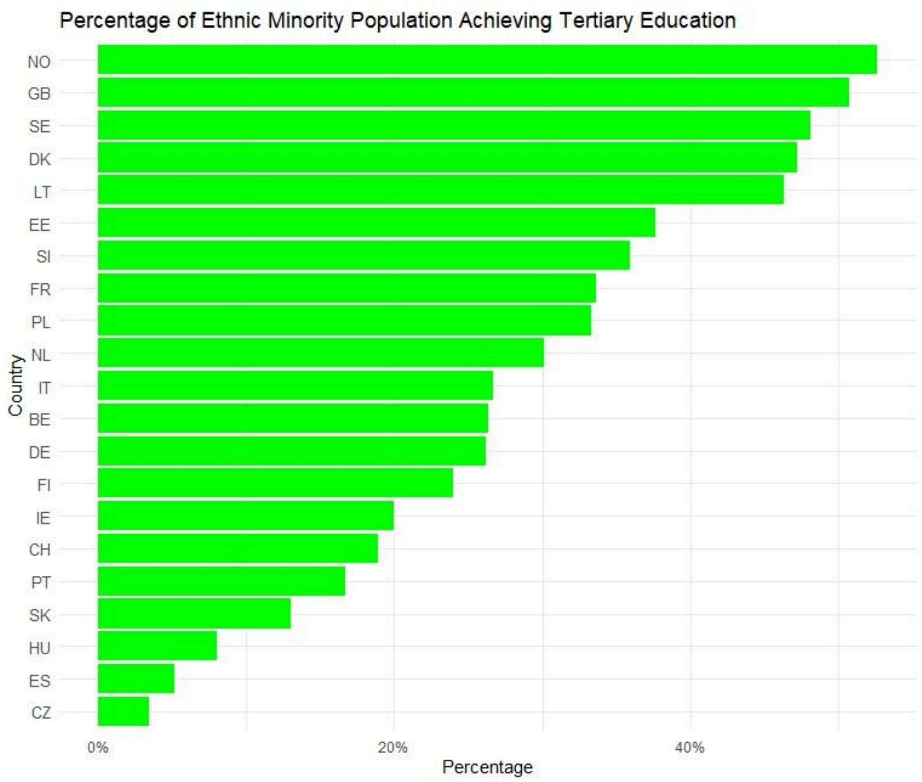
Since very high levels of parental education can create the illusion that some countries are less mobile than others, an additional question worth exploring is the proportion of individuals whose parents did not obtain a university degree end up going to university. This way we can assess the likelihood of an individual completing university when neither of their parents had done so while addressing the discrepancies in average parental educational attainment across countries. For that purpose, another subset was generated which only contained data for those respondents whose most educated parent had an education level of ISCED 5 or lower. Following the nomenclature used by Adamecz et al. (2021), children born to parents without a university degree will be referred to as "potential first-generation students" and, if they end up becoming university graduates, we will use the term "first-generation students".

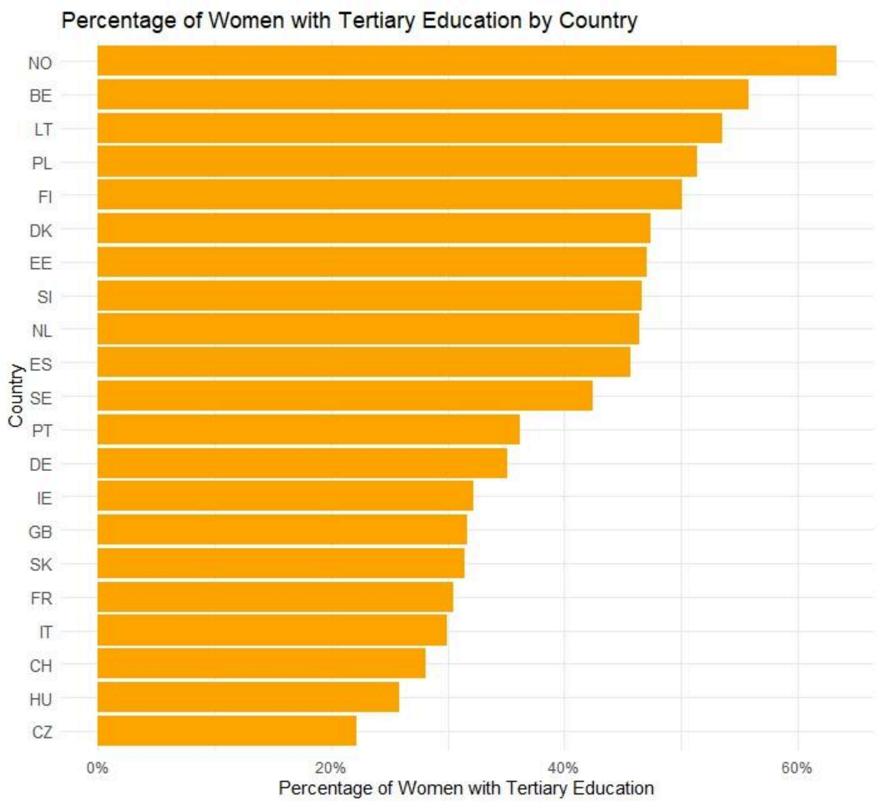
A comparison between Table 3 and Table 2 reveals substantial differences in the rankings of countries with the highest overall upward mobility and those with the largest proportion of first-generation university students. Notably, while the Mediterranean countries, along with Ireland, rank among the top five in terms of overall upward mobility in the first chart, they fall below or only slightly above the average when considering the share of first-generation university students. The opposite trend is observed for the Nordic countries, which rank at the top of the second chart, despite displaying below-average values in the first one.

Table 3. Proportion of 'Potential First-Generation Students' Who Attain a University-Level Education

	Nº of Obs.	First-generation Students (%)
All (average)	33016	27,05
Belgium	1274	32,15
Czech Republic	2991	13,94
Denmark	626	29,95
Estonia	1582	28,35
Finland	1447	40,98
France	1932	23,94
Germany	1881	19,95
Hungary	1886	15,71
Ireland	2216	28,36
Italy	1649	22,06
Lithuania	1560	39,41
Netherlands	1411	35,41
Norway	969	38,47
Poland	1979	33,65
Portugal	1656	27,63
Slovakia	1146	20,84
Slovenia	1484	32,16
Spain	1790	27,33
Sweden	879	27,69
Switzerland	1363	20,40
United Kingdom	1295	31,85

Figure 2. Proportion of Ethnic Minority Population and Women Attaining Advanced Education Across Countries





4.2. Relative mobility

After examining absolute mobility across the selected nations, we turn our attention to another key indicator: relative mobility.

As it has been already mentioned, relative mobility is often used as an indicator of the extent to which a person's educational attainment is influenced by the educational level of their most educated parent. Although there are different ways in which we can measure relative educational mobility, one of the most widely used methods is through correlation coefficients, which quantify the linear relationship between two variables, in this case: parents' education and children's education. Despite presenting some drawbacks, like not being able to capture nonlinear dynamics and contextual factors, correlation coefficients can be useful for initial analyses to provide a quick, straightforward indication of the degree of association between generations.

Therefore, I computed the correlation coefficient between individuals' level of education and that of their most educated parent (COR), from which I then derived the relative intergenerational mobility, which is usually described through formula (1).

$$1 - COR \qquad (1)$$

Simultaneously, I also estimated the correlation between children's educational attainment with that of their mothers and fathers separately, as well as the correlation between these two. The results for each country can be found in Table 4, where *eisced* is the respondent's educational level, and *eiscedmep*, *eiscedm* and *eiscedf* correspond to the educational level of their most educated parent, mother and father, respectively.

As it can be observed, the country with the greatest relative mobility is Finland (0.7379), followed by Slovenia and Norway, which means they demonstrate a strong degree of educational equality between generations. On the other extreme we have Belgium, Czechia, Ireland and Hungary (0,4189), presenting the lowest estimate. Therefore, we might infer that while the educational attainment of a child living in Finland is less dependent on their parents' educational level, family background in Hungary plays a larger role in determining educational outcomes.

Table 4: Relative Educational Mobility measured as Correlation Coefficients by Country

Country	Correlation Coefficient eisced/eiscedmep	eisced/eiscedf	eisced/eiscedm	eiscedf/eiscedm	Relative Mobility (1-COR)	Rank Positi
All (Average)	0,4123	0,3756	0,3709	0,5861	0,5877	
Belgium	0,4833	0,4452	0,4614	0,6055	0,5167	17
Czech Republic	0,4893	0,4708	0,4132	0,5725	0,5107	18
Denmark	0,3134	0,3164	0,2408	0,4776	0,6866	4
Estonia	0,3981	0,3706	0,3860	0,5679	0,6019	10
Finland	0,2621	0,2323	0,2148	0,5420	0,7379	1
France	0,4396	0,3945	0,4139	0,6157	0,5604	14
Germany	0,3840	0,3436	0,3059	0,4998	0,6160	8
Hungary	0,5811	0,5654	0,5434	0,7099	0,4189	21
Ireland	0,4997	0,4163	0,4490	0,5683	0,5003	19
Italy	0,4711	0,4474	0,4473	0,6991	0,5289	16
Lithuania	0,4160	0,3522	0,3962	0,5963	0,5840	12
Netherlands	0,3769	0,3395	0,3022	0,5345	0,6231	7
Norway	0,3101	0,2919	0,2697	0,5311	0,6899	3
Poland	0,4710	0,3971	0,4451	0,6351	0,5290	15
Portugal	0,4234	0,3861	0,4027	0,7169	0,5766	13
Slovakia	0,5271	0,4985	0,4970	0,6802	0,4729	20
Slovenia	0,2925	0,2730	0,2626	0,5625	0,7075	2
Spain	0,4067	0,3773	0,3574	0,6472	0,5933	11
Sweden	0,3438	0,2782	0,3269	0,5532	0,6562	5
Switzerland	0,3928	0,3601	0,3329	0,5192	0,6072	9
United Kingdom	0,3756	0,3322	0,3210	0,4736	0,6244	6

Furthermore, the data reveals that, for this age group, the correlation between an individual's level of education and that of their father's is very similar to the correlation with their mother's. The only noticeable deviations can be found in Czechia, where there seems to be a stronger association between fathers and children education levels compared to the association with their mothers', or in Sweden, Poland and Lithuania, where the opposite happens. It is also interesting to observe the correlation between mothers' and fathers' educational background across countries. This relationship is relatively subtle in nations such as the United Kingdom (0.4736) and Germany (0.4998), yet it is significantly stronger in Portugal (0.7169) and Hungary (0.7099). Overall, these findings suggest a clear presence of assortative mating[4].

[4] Assortative mating refers to the phenomenon where individuals select partners with characteristics similar to their own, particularly in terms of education and socio-economic status. This pattern has been widely documented in sociological and economic studies (see Blossfeld & Timm, 2003).

Another method to estimate relative educational mobility across generations is through regression analysis. In this case, we use an Ordered Logistic Regression Model (also known as a proportional odds model) as it accounts for the ordinal nature of the dependent variable while estimating the relative odds of a child achieving a higher or lower level of education compared to their parents. Given that *eisced* has 7 ordered levels, with higher numbers representing higher levels of education, this model assumes that the relationship between the independent variable (*eiscedmep*, the parents' education level) and the log-odds of being in a higher versus lower category is constant across categories (proportional odds assumption).

This model with *eisced* (individual's education level) as the dependent variable and *eiscedmep* (parent's education level) as the independent variable takes the following form:

$$log(\frac{P(eisced \leq j)}{P(eisced > j)}) = \alpha_j - \beta \cdot eiscedmep$$

Where:

- $j = 1, 2, ..., J - 1$. In this case, $J = 7$ as there are seven categories of *eisced* (e.g., $j = 1$ corresponds to the log-odds of being in category 1 - less than lower secondary education - or lower versus higher categories)
- α_j is the intercept for category j, representing the cumulative log-odds of being in or below category j when $eiscedmep = 0$.
- β is the coefficient for the independent variable *eiscedmep*, representing the effect of parental education on the log-odds of being in a higher category of education for the individual.
- $P(eisced \leq j)$ is the cumulative probability of *eisced* being in category j or lower.
- $P(eisced > j)$ is the cumulative probability of *eisced* being in a category higher than j.

Since the model assumes that the effect of parental education on the log-odds is constant across all thresholds, the coefficient β will be the same regardless of which threshold j is being evaluated. Moreover, there are six thresholds in this model (one less than the number of categories in *eisced*), each defining the boundary between adjacent cumulative probabilities. They capture the difficulty of transitioning from one category to a higher category, independent of the explanatory variable.

Table 5. Ordered Logistic Regression Output

Ordered Logistic Regression Results

Summary of Coefficients and Model Fit

Variable	Coefficient	Std. Error	t-Value
eiscedmep	0.470	0.005	91.550
1|2	−2.498	0.040	−61.936
2|3	−0.399	0.023	−17.311
3|4	0.723	0.022	32.937
4|5	1.944	0.023	82.939
5|6	2.581	0.025	104.312
6|7	3.721	0.028	134.020
Residual Deviance	149,378.987	NA	NA
AIC	149,392.987	NA	NA

The resulting coefficient for *eiscedmep* indicates a strong positive relationship between parental education and individual education, which implies low relative mobility. Specifically, for every one-unit increase in *eiscedmep* (e.g., moving from ISCED 4 to ISCED 5), the log-odds of the child attaining a higher educational category increase by 0.47. This translates into an odds ratio of $e^{0.47} \approx 1.60$, which means that for every additional level of parental education the odds of the child being in a higher educational category increase by 60%. Also, the very large t-value (91.55) suggests that the effect of the independent variable is indeed highly statistically significant, confirming the robustness of the result.

Regarding the thresholds, the increasing intercept values show that transitioning to higher education levels becomes progressively more difficult, particularly for higher categories (e.g., from ISCED 6 to ISCED 7). For the goodness-of-fit of the model we should look at the residual deviance, a lower value indicates a better fit, but it is only interpretable when compared across models.

After replicating the same regression model for each nation separately, we end up with a ranking based on the values the independent variable estimate takes for each one of them. At the upper end of the spectrum are countries where the relationship between an individual's academic qualifications and parental educational background is particularly strong. Notably, Hungary stands out, where for each one-unit increase in the educational level of the most educated parent (eiscedmep), the log-odds of the individual (eisced) attaining a higher educational level increase by 1.021, holding all other variables constant. The Czech Republic and Ireland are also among the nations with lower levels of relative mobility, with log-odds of 0,729 and 0,579, respectively.

Table 6. Relative Educational Mobility measured as Ordered Logistic Regression Coefficient by Country

Ordered Logistic Regression (eisced ~ eiscedmep)

Country	Estimate	Rank Position
All (average)	0,470	
HU	1,021	1
CZ	0,729	2
IE	0,579	3
EE	0,556	4
LT	0,556	5
PL	0,532	6
BE	0,507	7
CH	0,482	8
FR	0,464	9
PT	0,450	10
SI	0,446	11
DE	0,441	12
SE	0,391	13
ES	0,370	14
NO	0,365	15
NL	0,348	16
GB	0,346	17
FI	0,308	18

Conversely, at the lower end of the hierarchy are the Nordic countries (Norway, Sweden, and Finland), the United Kingdom, the Netherlands, and Spain, where the relationship between parental education and individual academic performance seems to be comparatively weaker. In these countries, a one-unit increase in parental education results in a log-odds of less than 0,4. This means that for every extra level of parental education, the odds of an individual to attain a higher level of education increase by a factor of, approximately, $e^{0.4} \approx 1.49$.

5. Variables Definitions

This section outlines the key variables that are expected to shape intergenerational educational mobility for the studied cohort, all of which are incorporated into the regression analysis. First, the individual-level variables are defined, all of which are derived from the European Social Survey (ESS) database[5].

Gender. Gender (*gndr*) is recorded as a binary variable, identifying respondents as either male or female. This variable is particularly relevant given extensive evidence of gender disparities in educational access and mobility. Historically, women have faced structural barriers, such as limited access to education and labor market discrimination, which constrained their ability to achieve higher levels of education than their parents (Hertz et al., 2007). However, more recent research highlights a narrowing of these gaps in many regions, with women in younger cohorts often achieving higher levels of education than their male counterparts (Buchmann & DiPrete, 2006). Including gender in the analysis is crucial for understanding whether these patterns persist in the studied cohort.

Ethnicity. Another of the explanatory variables is *blgetmg*, which differentiates between individuals belonging to the majority ethnic group in the country of reference and those who do not. Thus, this binary variable accounts for differences in ethnicity and can be used as a proxy for the social and structural disadvantages often experienced by minority groups. Ethnicity is a well-documented factor influencing access to education, as minority groups often face systemic barriers such as discrimination, limited access to resources, and social exclusion (Heath & Cheung, 2007).

Parental Immigrant Status. The variable *immpts* captures parental immigrant status by indicating whether at least one parent was born outside the reference country (value = 1) or if both parents were born within the country (value = 0). Similarly to *blgetmg*, this variable intends to account for the structural and social disadvantages that may arise from belonging to a group with limited access to resources or exposure to structural obstacles, such as discrimination, cultural adaptation challenges, or limited social networks, which can influence educational mobility.

[5] For more information about the European Social Survey (ESS) database and the variables included, see https://www.europeansocialsurvey.org.

Parental occupation. One of the conclusions from the study by Chetty et al. (2014) was that, in the United States, a 10-percentile increase in parental income was linked to a 6.7 percentage point (pp) rise in college attendance rates (and a 3 pp decline in teenage birth rates among women). Although the ESS does not provide direct data on household income during respondents' formative years, it does offer information on parents' occupation categories at that time (e.g., when the respondent was 14 years old). The categorical variables *occf14b* (father's occupation) and *occm14b* [6] (mother's occupation) classify parental jobs into nine categories based on the complexity and skill level of the tasks performed. Since the top categories, like "1. Professional and technical occupations" or "2. Higher administrator occupations", are typically associated with greater responsibilities and more complex tasks and, therefore, higher earnings, we could expect that children born to these parents may enjoy greater opportunities to pursue advanced education. Table 7 presents the classification of parental occupations according to the ESS variables, along with their ISCO-08 equivalents and descriptions.

Next, we turn our attention to the country-level variables, which are hypothesized to influence patterns of upward educational mobility by capturing structural, economic, and social factors. Data on the following indicators is sourced from the World Bank and the OECD databases[7].

Inflation. The variable *CPI* (Consumer Price Index) captures the impact of inflation on intergenerational educational mobility. The CPI (2010 = 100) is an indicator that measures annual changes in the cost of acquiring a standardized basket of goods and services, reflecting the cost of living in each country and year. Previous research has suggested that higher inflation exacerbates educational inequalities by disproportionately burdening disadvantaged households (Hanushek & Woessmann, 2015). By Including this variable we can explore how the changes in the cost of living influence educational mobility across the target nations and over time.

Table 7. Mapping of ESS Occupational Categories to ISCO-08 Framework

[6] These variables are based on the International Standard Classification of Occupations 2008 (ISCO-08), a framework developed by the International Labour Organization (ILO) for organizing jobs into standardized categories based on tasks and duties. See https://www.ilo.org/public/english/bureau/stat/isco/ for more details.

[7] The World Bank and OECD databases provide comprehensive, high-quality datasets on macroeconomic, social, and educational indicators. For more information, visit World Bank and OECD.

ESS Category	ISCO-08	Description
1. Professional and technical occupations	**2. Professionals** (e.g., engineers, teachers, medical doctors) **3. Technicians and Associate Professionals** (e.g., laboratory technicians, nursing associates).	These jobs require high skill levels and specialized knowledge.
2. Higher administrator occupations	**1. Managers** (e.g., directors, chief executives).	These roles involve decision-making and policy implementation, often at senior levels.
3. Clerical occupations	**4. Clerical Support Workers** (e.g., secretaries, office clerks).	Focused on administrative and support tasks in office environments.
4. Sales occupations	**5. Service and Sales Workers, specifically sales roles** (e.g., shop sales assistants, cashiers).	These involve direct interaction with customers in commercial contexts.
5. Service occupations	**5. Service and Sales Workers, specifically service roles** (e.g., waiters, personal care workers).	Includes jobs providing services to individuals and communities.
6. Skilled Worker	**7. Craft and Related Trades Workers** (e.g., carpenters, electricians).	These jobs require specialized training or apprenticeships.
7. Semi-skilled worker	**8. Plant and Machine Operators, and Assemblers** (e.g., machine operators, drivers).	Involves jobs with moderate skill levels, often requiring short training periods.
8. Unskilled worker	**9. Elementary Occupations** (e.g., cleaners, laborers).	Includes tasks requiring minimal skill or training.
9. Farm worker	**6. Skilled Agricultural, Forestry, and Fishery Workers.**	Focused on occupations related to farming, forestry, and fishing activities.

Household Savings. The variable *hshldsavings* measures household savings as a percentage of household disposable income, thus reflecting the capacity of families to save after consumption and taxes. This variable provides insights into the financial health and resilience of individuals, which are crucial for funding education, particularly in contexts where access to quality education requires more private financial resources.

Income Inequality. The Gini coefficient (*Gini*) is another critical variable in this analysis, representing the level of income inequality within each country. This measure ranges from 0, indicating perfect equality, to 1, representing perfect inequality[8], and it is particularly relevant

[8] The Gini Coefficient is calculated by comparing the cumulative percentages of the population to the cumulative percentages of income they receive, typically represented as the area between the Lorenz curve (which plots income distribution) and the line of perfect equality, divided by the total area beneath the line of

in the context of intergenerational educational mobility as previous research has shown that higher levels of income inequality are associated with lower mobility. The "Great Gatsby Curve," introduced by Corak (2013), illustrates this relationship, suggesting that countries with greater income disparities tend to experience stronger intergenerational persistence in education and income.

Government expenditure on education. Public investment in education, measured as a percentage of GDP, can be used to assess the relative importance of education in a government's economic priorities while normalizing differences in country size for cross-national comparisons. In 2023, education expenditure across European Union (EU) countries averaged approximately 4.9% of GDP, illustrating stable investment trends in recent years. Leading the region, Denmark and Sweden allocated over 6% of GDP to education, while other nations like Ireland spent less than 4%, pointing to disparities in educational investment that may correlate with differing levels of intergenerational mobility. Certainly, findings from existing literature suggest that public education expenditure is often associated with reduced inequality and enhanced opportunities for upward mobility, particularly in countries with strong welfare systems (Blanden, 2013; OECD, 2023).

Unemployment with Advanced Education. The variable *Unemployadv* measures the percentage of the total labor force with advanced education (tertiary or higher) that is unemployed. High unemployment rates among the highly educated can influence the perceived value of education, potentially discouraging investments in higher education or shaping career aspirations. Conversely, such conditions may incentivize younger generations to pursue further education as a strategy to enhance employability.

Pupil-Teacher Ratio. The variable *Pupteachp* (*Pupteachs*) measures the average number of students per teacher in primary (secondary) schools, capturing the allocation of educational resources during the foundational years of schooling. A higher pupil-teacher ratio may indicate stretched resources and larger class sizes, which could impact the quality of education and individual student outcomes. Previous research suggests that smaller class sizes, particularly in primary education, are associated with improved academic performance and long-term benefits in educational attainment (Hanushek & Woessmann, 2015). Through

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perfect equality. This measure offers a clear insight into income distribution within a country, where a coefficient of 0 represents perfect equality, and a coefficient of 1 signifies complete inequality.

the inclusion of this variable, the analysis considers how differing levels of educational resources influence mobility outcomes.

6. Regression Analysis: Factors Influencing Upward Educational Mobility

6.1. Logistic Regression Model

To analyze the factors influencing upward intergenerational educational mobility, one of the most suitable methods is the Logistic Regression model. This model estimates the relationship between a binary dependent variable and multiple independent variables by modeling the log-odds of the outcome as a linear combination of the predictors, thus predicting the probability of the outcome occurring. In this context, the logistic regression model examines how variables such as gender, belonging to the major ethnic group, having immigrant parents, etc. relate to upward educational mobility. The dependent variable, *mobilityup*, indicates whether an individual has achieved a higher educational level than their most educated parent (value "1") or not (value "0").

A Logistic Regression Model, which expresses the relationship between a set of independent variables $(X_1, X_2, \ldots, X_K)$ and the log-odds of a binary dependent variable (Y), can be written in the following form:

$$log\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

Where:

- The left-hand side represents the log-odds of the probability of the outcome $Y = 1$ (*mobilityup* = 1) occurring.
- β_0 is the intercept, and $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients corresponding to the independent variables.
- $X_1, X_2, \ldots, X_n$ are the independent variables.

Unlike linear regression, logistic regression models do not explicitly include an error term ϵ. Instead, the logistic function inherently accounts for the variability in the dependent variable.

6.2. Assumptions

To ensure the validity of the analysis assessing the influence of various factors on upward educational mobility, the logistic regression model relies on several key assumptions. First, the dependent variable, *mobilityup*, must be binary, as the model predicts the probability of upward mobility occurring (value "1") or not (value "0"). Second, the independent variables—such as gender, ethnicity, immigrant background, parents' occupations, and economic indicators—should be linearly related to the log-odds of the dependent variable, rather than directly to the outcome itself. Third, the model assumes no multicollinearity among predictors, ensuring that variables are not highly correlated with one another. Fourth,the model requires that the observations are independent of each other. Lastly, while logistic regression does not assume normally distributed errors or homoscedasticity, it assumes that the sample size is large enough to provide reliable estimates and ensure the robustness of the model.

6.3. Results

Prior to conducting the regression analysis, all the undefined values were removed and categorical variables - like parental occupation and reference country - were converted into multiple dummy variables. This step is essential, as dummy (binary) variables allow the model to effectively handle non-numeric data while enabling category-specific effects to be interpreted with more clarity.

Subsequently, a refined subset of the original dataset was constructed, including only individuals whose parents had not attained tertiary education (defined as a bachelor's degree or higher). This restriction was applied to focus the analysis on individuals with the potential for upward educational mobility, as those whose parents have already achieved the highest level of education cannot surpass them in this regard. As a result, this second subset consists of those individuals with parental educational levels ranging from ISCED 1 to ISCED 5, yielding a dataset with 33,016 observations.
Both the original dataset and the restricted subset will be used in the study to facilitate a comparative analysis of results.

6.3.1 Influence of Individual-Level Variables on Upward Educational Mobility

For the first model, I aimed to assess the influence of individual-level factors on upward intergenerational educational mobility, using *mobilityup* (1 = achieved a higher educational level than parents, 0 = otherwise) as the dependent variable. The explanatory variables include gender (*gndr*), being born to an immigrant parent (*immpts*), belonging to the minority ethnic group in the reference country (*blgetmg*), and the mother's and father's occupations when the respondent was 14 years old (*occmf14b* and *occf14b*, respectively).

Table 8 shows the results for the sample containing all individuals. As presented, gender (*gndr*) emerged as a significant predictor of upward educational mobility (highly significant coefficient, $\rho < 2e^{-16}$), with females being more likely to achieve upward mobility than males. More specifically, being female (*gndr* = 1) increases the log-odds of achieving upward mobility by 0.458, holding all other variables constant. In terms of odds, it suggests women are approximately $e^{0.45850} \approx 1.58$ times more likely to achieve upward mobility than men. Similarly, belonging to the majority ethnic group (*blgetmg*) positively impacts mobility (significant coefficient, $\rho = 0.004679$), with an odds ratio of approximately $e^{0.2351} \approx 1.27$. This indicates that individuals that are part of the dominant ethnic group in the country are 1.27 times more likely to achieve upward mobility compared to those from minority populations. Parental immigrant status (*immpts*), however, does not show a statistically significant effect on upward mobility ($\rho = 0.726025$), suggesting that this factor does not strongly influence the outcome after accounting for other predictors.

Table 8. Logistic Regression: Effects of Individual-Level Variables on Upward Educational Mobility

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−2.840	0.102	0.0000	***
gndr	0.458	0.028	0.0000	***
immpts	0.012	0.035	0.7260	
blgetmg	0.235	0.083	0.0047	**
occf14b_2	0.556	0.077	0.0000	***
occf14b_3	1.119	0.073	0.0000	***
occf14b_4	1.225	0.073	0.0000	***
occf14b_5	1.161	0.069	0.0000	***
occf14b_6	1.241	0.058	0.0000	***
occf14b_7	1.318	0.061	0.0000	***
occf14b_8	1.428	0.078	0.0000	***
occf14b_9	1.346	0.084	0.0000	***
occm14b_2	0.408	0.107	0.0001	***
occm14b_3	1.044	0.055	0.0000	***
occm14b_4	1.223	0.064	0.0000	***
occm14b_5	1.002	0.057	0.0000	***
occm14b_6	1.007	0.067	0.0000	***
occm14b_7	1.191	0.066	0.0000	***
occm14b_8	1.542	0.064	0.0000	***
occm14b_9	1.485	0.092	0.0000	***
Null Deviance	32,217.547	NA	NA	NA
Residual Deviance	29,286.407	NA	NA	NA
AIC	29,326.407	NA	NA	NA
Number of Observations	23,643.000	NA	NA	NA

Table 9. Logistic Regression: Effects of Individual-Level Variables on Upward Educational Mobility (non-graduate parents)

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−0.465	0.136	0.0006	***
gndr	0.519	0.032	0.0000	***
immpts	0.057	0.040	0.1504	
blgetmg	0.215	0.093	0.0210	*
occf14b_2	0.263	0.123	0.0328	*
occf14b_3	0.149	0.105	0.1578	
occf14b_4	0.173	0.104	0.0952	.
occf14b_5	0.020	0.099	0.8383	
occf14b_6	−0.081	0.088	0.3605	
occf14b_7	0.011	0.091	0.8998	
occf14b_8	0.148	0.104	0.1549	
occf14b_9	0.059	0.110	0.5909	
occm14b_2	0.150	0.167	0.3719	
occm14b_3	0.209	0.082	0.0108	*
occm14b_4	0.276	0.089	0.0019	**
occm14b_5	0.102	0.083	0.2215	
occm14b_6	0.064	0.091	0.4831	
occm14b_7	0.167	0.089	0.0623	.
occm14b_8	0.477	0.088	0.0000	***
occm14b_9	0.452	0.111	0.0000	***
Null Deviance	22,806.827	NA	NA	NA
Residual Deviance	22,392.433	NA	NA	NA
AIC	22,432.433	NA	NA	NA
Number of Observations	16,653.000	NA	NA	NA

In contrast, parental occupations, represented by dummy variables, significantly affect mobility with low ρ-values across all variables. For example, the coefficient for *occf14b_8* is 1.428, which suggests that having a father in a category 8 occupation ("Unskilled workers") increases the log-odds of upward mobility by 1.428 compared to the baseline category (*occf14b_1*). In terms of odds, this means that individuals with fathers in this kind of occupation are approximately $e^{1.428} \approx 4.17$ times more likely to achieve upward mobility than those in the baseline category. A similar trend is observed for mother's occupation, where the coefficient for *occm14b_9* is 1.485, meaning that having a mother in occupation category 9 ("Farm worker") increases the log-odds of upward mobility by 1.485 compared to the baseline. This translates to an odds ratio of $e^{1.485} = 4.41$. These findings likely reflect the lower educational attainment commonly associated with these occupational groups, reducing the threshold for children to exceed their parents' level of education.

Lastly, the model shows a significant reduction in deviance (from 32218 to 29286), indicating an improvement in fit over the null model. The AIC value of 29326 also suggests a reasonably good model fit.

The output for the regression run on the restricted subset is presented in Table 9, from which we may notice a few differences with respect to the first model in both the significance and magnitude of the predictors. To start with, the coefficient for gender (gndr) increases slightly to 0.519 in the second model, while remaining statistically significant in both models. This means that, for children whose parents do not have tertiary education, being a female makes them approximately $e^{0.519} \approx 1.68$ times more likely to achieve upward mobility compared to men. The variable *immpts* remains not significant ($\rho = 0.1504$), implying that immigrant status may not play a critical role in determining mobility within these datasets. However, belonging to the majority ethnic group (*blgetmg*=1) positively impacts mobility (significant coefficient, $\rho = 0.0210$) in this case as well. In particular, individuals that are part of the dominant ethnic group in the country are $e^{0.215} \approx 1.24$ times more likely to achieve upward mobility compared to those from minority populations.

Mothers and fathers' occupational categories show varying significance between the two models. In the first one, most occupational categories exhibit strong significance, reflecting their broad relevance across the entire population. Nonetheless, in the second model, most categories, such as *occf14b_6* and *occf14b_7*, lose significance, possibly due to the more restricted sample. In spite of this, there are some exceptions, like *occm14b_8* and *occm14b_9*, which exhibit low p-values and indicate that having a mother in category 8 ("Unskilled workers") or category 9 ("farm worker") occupations increases the odds of upward mobility by $e^{0.477} \approx 1.61$ and $e^{0.452} \approx 1.57$ times with respect to the baseline category (*occm14b_1*), respectively. Lastly, the null and residual deviances, along with the AIC values, are lower in the model for the restricted subset, indicating a more refined fit to the data.

To continue, and in order to account for the influence of living in a specific country on upward mobility, the model can be extended by incorporating dummy variables representing the country of reference. This change yields the results displayed in Table 10 and Table 11.

For the model in Table 10 the residual deviance is 28,274, which indicates an improved model fit compared to the one without country controls, and the Akaike Information Criterion (AIC) is 28,354. A lower AIC also suggests that the model with country dummies provides a better fit compared to the previous one.

Regarding the coefficients, the one for gender (0.468) does not experience a substantial change. In the same way, the coefficient for having foreign-born parents, *immpts*, (0.01972) continues to not be statistically significant ($\rho = 0.59$). However, in this case, belonging to the majority ethnic group, *blgetmg*, (0.08429) is also not statistically significant ($\rho = 0.33$), indicating no substantial influence.

The coefficients for the country dummy variables reflect deviations from the baseline country's effect on upward mobility. Countries such as the Czech Republic (*cntry_CZ*: -0.750) and Estonia *(cntry_EE*: -0.713) show negative and significant coefficients, suggesting lower odds of upward mobility compared to the baseline country (*cntry_BE*). In contrast, countries like Ireland (*cntry_IE*: 0.581) and Spain (*cntry_ES*: 0.626) exhibit positive and significant effects, indicating higher odds of upward mobility for respondents from these nations. Other countries, such as Norway (*cntry_NO*) and Slovakia (*cntry_SK*), show non-significant effects due to their high ρ-values, suggesting no substantial difference from the baseline.

Table 10. Logistic Regression: Effects of individual-level variables and Country of Residence on upward educational mobility

Logistic Regression Results (1)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−2.734	0.125	0.0000	***
gndr	0.468	0.029	0.0000	***
immpts	0.020	0.037	0.5913	
blgetmg	0.082	0.086	0.3356	
occf14b_2	0.536	0.079	0.0000	***
occf14b_3	1.098	0.074	0.0000	***
occf14b_4	1.180	0.075	0.0000	***
occf14b_5	1.153	0.071	0.0000	***
occf14b_6	1.338	0.059	0.0000	***
occf14b_7	1.400	0.063	0.0000	***
occf14b_8	1.371	0.080	0.0000	***
occf14b_9	1.378	0.086	0.0000	***
occm14b_2	0.404	0.109	0.0002	***
occm14b_3	1.091	0.056	0.0000	***
occm14b_4	1.258	0.065	0.0000	***
occm14b_5	1.050	0.059	0.0000	***
occm14b_6	1.127	0.069	0.0000	***
occm14b_7	1.321	0.069	0.0000	***
occm14b_8	1.484	0.066	0.0000	***
occm14b_9	1.436	0.095	0.0000	***
cntry_IT	0.380	0.114	0.0009	***
cntry_CZ	−0.750	0.082	0.0000	***

Logistic Regression Results (2)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
cntry_EE	−0.713	0.091	0.0000	***
cntry_FI	−0.319	0.087	0.0003	***
cntry_FR	0.716	0.091	0.0000	***
cntry_DE	−0.495	0.087	0.0000	***
cntry_HU	−0.396	0.093	0.0000	***
cntry_IE	0.581	0.102	0.0000	***
cntry_LT	−0.109	0.094	0.2499	
cntry_NL	0.135	0.097	0.1626	
cntry_NO	−0.066	0.092	0.4770	
cntry_PL	0.217	0.086	0.0119	*
cntry_PT	0.803	0.100	0.0000	***
cntry_SI	0.124	0.093	0.1809	
cntry_ES	0.626	0.096	0.0000	***
cntry_SE	0.173	0.093	0.0621	.
cntry_CH	−0.303	0.103	0.0034	**
cntry_GB	0.464	0.097	0.0000	***
cntry_SK	−0.055	0.100	0.5808	
cntry_DK	−0.267	0.098	0.0067	**
Null Deviance	32,217.547	NA	NA	NA
Residual Deviance	28,274.223	NA	NA	NA
AIC	28,354.223	NA	NA	NA
Number of Observations	23,643.000	NA	NA	NA

Table 11. Logistic Regression: Effects of Individual-Level Variables and Country of Residence on Upward Educational Mobility (non-graduate parents)

Logistic Regression Results (1)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−0.076	0.167	0.6482	
gndr	0.545	0.033	0.0000	***
immpts	0.117	0.043	0.0061	**
blgetmg	0.086	0.097	0.3734	
occf14b_2	0.213	0.127	0.0938	.
occf14b_3	0.162	0.110	0.1408	
occf14b_4	0.103	0.108	0.3407	
occf14b_5	0.037	0.103	0.7168	
occf14b_6	0.024	0.092	0.7931	
occf14b_7	0.067	0.095	0.4816	
occf14b_8	0.079	0.108	0.4650	
occf14b_9	0.071	0.114	0.5320	
occm14b_2	0.090	0.172	0.5994	
occm14b_3	0.188	0.085	0.0270	*
occm14b_4	0.237	0.092	0.0099	**
occm14b_5	0.056	0.087	0.5165	
occm14b_6	0.119	0.094	0.2035	
occm14b_7	0.215	0.093	0.0212	*
occm14b_8	0.344	0.091	0.0002	***
occm14b_9	0.290	0.116	0.0123	*
cntry_IT	−0.037	0.133	0.7829	
cntry_CZ	−1.145	0.100	0.0000	***

Logistic Regression Results (2)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
cntry_EE	−0.881	0.112	0.0000	***
cntry_FI	−0.283	0.111	0.0107	*
cntry_FR	0.389	0.113	0.0006	***
cntry_DE	−0.831	0.106	0.0000	***
cntry_HU	−0.696	0.111	0.0000	***
cntry_IE	0.220	0.124	0.0759	.
cntry_LT	−0.148	0.117	0.2071	
cntry_NL	0.085	0.125	0.4965	
cntry_NO	−0.124	0.122	0.3086	
cntry_PL	0.077	0.107	0.4728	
cntry_PT	0.560	0.123	0.0000	***
cntry_SI	−0.254	0.112	0.0227	*
cntry_ES	0.478	0.120	0.0001	***
cntry_SE	0.019	0.118	0.8704	
cntry_CH	−0.915	0.120	0.0000	***
cntry_GB	0.054	0.120	0.6546	
cntry_SK	−0.377	0.118	0.0013	**
cntry_DK	−0.240	0.127	0.0600	.
Null Deviance	22,806.827	NA	NA	NA
Residual Deviance	21,430.036	NA	NA	NA
AIC	21,510.036	NA	NA	NA
Number of Observations	16,653.000	NA	NA	NA

Following this, we assess the changes in the model for the narrowed subset once the country variables are added. Regarding the coefficients, the one for gender (0.545) does not experience a substantial change with respect to the first model, with an odds ratio of approximately 1.72. However, the coefficient for having immigrant parents (0.117) seems to be statistically significant now that the model also accounts for the respondents' country of residence (ρ = 0.0061), indicating a $e^{0.117} = 1.12$ times higher chance of surpassing parental education for these individuals. As in the case of parental occupation, there could be several reasons behind these results, like overall lower levels of education among immigrant parents. However, to confirm this further research would be required. Conversely, being part of the dominant ethnic group in the country, seems not to be a significant predictor of upward mobility upon introducing country-level controls in the model (ρ = 0.3734).

As in the case for the larger subset, the coefficients for some of the countries highlight disparities in upward mobility relative to the country of reference. Notably, countries such as the Czech Republic (*cntry_CZ*: -1.145) and Switzerland (*cntry_CH*: -0.915) show negative and significant coefficients, suggesting lower odds of upward mobility. In contrast, countries like France (*cntry_FR*: 0.389), Portugal (*cntry_PT*: 0.560) and Spain (*cntry_ES*: 0.478) exhibit positive and significant effects, indicating higher odds of upward mobility. Meanwhile, countries like Italy (*cntry_IT*) and the Netherlands (*cntry_NL*) show non-significant effects due to their high ρ-values, suggesting no substantial difference from the baseline.

6.3.2. Influence of Country-Level Variables on Upward Educational Mobility

In order to better understand the influence of macroeconomic and structural factors on upward educational mobility,the analysis was extended by incorporating country-level variables into the model.

In the following analysis, the previous models are replicated, substituting individual-level independent variables with country-level factors. These factors include Consumer Price Index (*CPI*), household savings (*Hshldsavings*), Gini index (*Gini*), total government expenditure on education as a percentage of GDP (*Govexp*), unemployment rate among individuals with advanced education as a percentage of the total labor force with advanced education (*Unemployadv*), and the pupil-teacher ratio in primary education (*Pupteachp*). For all variables except for the pupil-teacher ratio, data corresponding to the year individuals turned 18 was used, reflecting the critical age range of 16 to 18 years when decisions about continuing education or entering the labor force are typically made in European countries (European Commission, n.d.; Eurydice, 2022). For *Pupteachp*, the value used corresponds to the year individuals were 8 years old, as primary education generally begins between ages 6 and 7 across the studied countries.

Table 12. Logistic Regression: Effects of Country-level variables on upward educational mobility

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−3.808	0.327	0.0000	***
CPI	−0.008	0.002	0.0000	***
Hshldsavings	0.015	0.004	0.0002	***
Gini	0.091	0.006	0.0000	***
Govexp	0.094	0.022	0.0000	***
Unemployadv	0.032	0.007	0.0000	***
Pupteachp	0.039	0.005	0.0000	***
Null Deviance	18,311.658	NA	NA	NA
Residual Deviance	17,653.096	NA	NA	NA
AIC	17,667.096	NA	NA	NA
Number of Observations	13,334.000	NA	NA	NA

Table 13. Logistic Regression: Effects of Country-Level Variables on Upward Educational Mobility (non-graduate parents)

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−4.153	0.375	0.0000	***
CPI	−0.006	0.002	0.0056	**
Hshldsavings	0.010	0.005	0.0411	*
Gini	0.098	0.006	0.0000	***
Govexp	0.214	0.026	0.0000	***
Unemployadv	0.037	0.008	0.0000	***
Pupteachp	0.033	0.005	0.0000	***
Null Deviance	13,685.988	NA	NA	NA
Residual Deviance	13,183.418	NA	NA	NA
AIC	13,197.418	NA	NA	NA
Number of Observations	9,993.000	NA	NA	NA

Several conclusions can be derived from these models. To begin with, in Table 12, we see that the intercept in the model is highly significant ($p < 0.001$) with a coefficient of -3.808, indicating that the baseline probability of upward mobility is quite low when all predictors are held at zero.

Among the predictors, *CPI* (Consumer Price Index) has a negative and significant coefficient (-0.008, p = 4.09e-05), and an odds ratio of $e^{-0.008} \approx 0.9925$. This means that for each one-unit increase in CPI, the odds of upward mobility decrease by approximately 0.75%[9]. This finding suggests that rising inflation likely creates financial barriers for families to invest in education, and emphasizes the importance of economic stability in enabling upward mobility. Conversely, *Hshldsavings* (household savings) positively influences mobility (0.015, p = 0.00023) with an odds ratio of 1.015. That is, a one-unit increase in household savings raises the odds of upward mobility by approximately 1.52%. This result highlights the role of financial security in facilitating access to higher education and improving long-term socioeconomic outcomes.

Income inequality, as measured by the Gini coefficient, exhibits a positive and highly significant effect (0.0914, p < 2.16e-16), and an odds ratio of 1.0958. This implies that a one-unit increase in income inequality increases the odds of upward mobility by approximately 9.6%. While this finding may appear counterintuitive, several explanations would account for this relationship. One possibility could be that greater inequality generates stronger incentives for upward mobility, as education may be perceived as a pathway to economic security in more unequal societies. Alternatively, the result may reflect regional variations or the influence of redistributive policies that reduce barriers to education and promote advancement, despite income disparities. Another plausible explanation is that parents in more unequal societies tend to have lower levels of educational attainment, effectively lowering the threshold for their children to surpass them educationally, thus inflating relative mobility rates. Nevertheless, It is worth noting that while the relationship between income inequality (measured by the Gini coefficient) and upward mobility is statistically significant, its practical impact is modest. For example, given that the Gini

[9] The coefficient for CPI (-0.0075) represents the change in log-odds of upward mobility for a one-unit increase in CPI. Converting this to an odds ratio (OR) using the formula OR=e^-0.0075 yields 0.9925. This implies that the odds of upward mobility decrease by approximately 0.75% ((1−0.9925)×100) for each unit increase in CPI, holding other variables constant.

coefficient ranges from 0 to 1, a 0.01 increase would correspond to only a 0.09% increase in the odds of upward mobility, and a 0.10 increase would yield a 0.96% rise.

Interestingly, another unexpected result is that the pupil-teacher ratio in primary education has a positive effect (0.039, $p = 1.20e\text{-}15$) and an odds ratio of 1.0395. Therefore, a one-unit increase in the pupil-teacher ratio (one more student per teacher) is associated with approximately a 3.95% increase in the odds of upward mobility. While this result is unexpected, this relationship might be influenced by contextual factors such as regional disparities in educational resources or differences in the efficiency of education systems[10]. For instance, higher pupil-teacher ratios might coincide with regions that prioritize other aspects of education quality, such as curriculum rigor or extracurricular support, which could mitigate the negative effects of larger class sizes. Additionally, the result could reflect underlying socioeconomic conditions, where areas with stretched resources may simultaneously experience higher upward mobility due to targeted government interventions.

Similarly, government expenditure on education (as % of GDP) shows a positive impact (0.094, $\rho = 2.91e\text{-}05$) with an odds ratio of 1.0992. This indicates that a one-unit increase in government spending is associated with approximately a 9.92% increase in the odds of upward mobility, thus underscoring the critical role of public investment in enhancing educational access and fostering opportunities for higher educational attainment. Labor market dynamics are also important predictors. Higher unemployment rates among those with advanced education (*Unemployadv*) are associated with greater educational mobility (0.032, $\rho = 3.99e\text{-}06$) and an odds ratio of 1.032. This translates into a one-unit increase in advanced education unemployment raising the odds of upward mobility by approximately 3.2%. This relationship might reflect individuals' strategic decisions to invest in education as a way to remain competitive and avoid unemployment.

[10]The relationship between pupil-teacher ratios and educational outcomes has been extensively studied, particularly in developing countries. Research suggests that in resource-constrained settings, prioritizing access to education—even with larger class sizes—can lead to improved educational attainment and mobility (UNESCO, 2020; AfDB, 2014). In developed nations, studies have primarily focused on the effects of pupil-teacher ratios on student performance and academic achievement, often finding that smaller class sizes are associated with better outcomes, especially in early education (OECD, 2022). However, the specific impact of pupil-teacher ratios on educational mobility in developed contexts remains underexplored and warrants further investigation.

As for the overall model fit, the AIC value of 17667 indicates a good balance between model complexity and predictive performance. Additionally, the reduction in deviance from 18312 to 17653 demonstrates the model's ability to explain a substantial portion of the variability in the dependent variable compared to the baseline model.

Concerning the restricted subset (Table 13), the results obtained from the analysis with country-level variables are similar to the ones for the whole sample with a few disparities. To begin with, the coefficient for government expenditure (*Govexp*) is higher for this group, with an odds ratio of 1.214, suggesting a stronger positive association with upward mobility. Similarly, the coefficients for income inequality (*Gini*) and for unemployment among the highly educated (*Unemployadv*) increase slightly to 0.098 and 0.037, respectively, maintaining their positive and highly significant effect. In addition, the coefficients for *CPI* and household savings (*Hshldsavings*) present a slight decrease with respect to the other subset, with *CPI* remaining significant, while *Hshldsavings* having a weaker marginal effect.

Lastly, this second model demonstrates an improved model fit, as evidenced by the lower AIC (13,197) and reduced residual deviance, which indicates a better explanation of variance in upward mobility within the refined dataset.

6.3.3. Joint Effects of Individual- and Country-Level Variables on Upward Educational Mobility

After examining the effects of personal characteristics and national context on mobility, the next step involved evaluating their interaction by conducting a regression analysis that incorporated variables from both categories. For this regression, variables that exhibited a low level of significance in previous analyses were excluded to enhance the model's parsimony and robustness. Consequently, the variables used to conduct the regression are different for the original sample and for the restricted subset; for example, parental occupations are not assessed in the latter. Additionally, in order to reduce the amount of deleted observations due to data missingness, the variable *Pupteachp* was also excluded from the analysis[11].

[11] See the regression model with the variable *Pupteachp* in the appendix.

Table 14. Logistic Regression Model: Joint Effects of Individual- and Country-Level Variables on Upward Educational Mobility

Logistic Regression Results (1)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−4.788	0.289	0.0000	***
gndr	0.447	0.036	0.0000	***
occf14b_2	0.543	0.096	0.0000	***
occf14b_3	1.138	0.093	0.0000	***
occf14b_4	1.205	0.091	0.0000	***
occf14b_5	1.244	0.087	0.0000	***
occf14b_6	1.252	0.074	0.0000	***
occf14b_7	1.300	0.079	0.0000	***
occf14b_8	1.440	0.102	0.0000	***
occf14b_9	1.480	0.109	0.0000	***
occm14b_2	0.361	0.134	0.0071	**
occm14b_3	1.160	0.071	0.0000	***
occm14b_4	1.165	0.082	0.0000	***

Logistic Regression Results (2)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
occm14b_5	1.029	0.072	0.0000	***
occm14b_6	0.996	0.087	0.0000	***
occm14b_7	1.258	0.087	0.0000	***
occm14b_8	1.522	0.085	0.0000	***
occm14b_9	1.372	0.125	0.0000	***
CPI	−0.014	0.002	0.0000	***
Hshldsavings	0.026	0.004	0.0000	***
Gini	0.073	0.006	0.0000	***
Govexp	0.126	0.020	0.0000	***
Unemployadv	0.060	0.008	0.0000	***
Null Deviance	20,024.472	NA	NA	NA
Residual Deviance	17,804.956	NA	NA	NA
AIC	17,850.956	NA	NA	NA

Table 15. Logistic Regression Model: Joint Effects of Individual- and Country-Level Variables on Upward Educational Mobility (non-graduate parents)

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−2.494	0.287	0.0000	***
gndr	0.419	0.035	0.0000	***
immpts_2	0.592	0.093	0.0000	***
blgetmg	0.234	0.093	0.0118	*
CPI	−0.014	0.002	0.0000	***
Hshldsavings	0.001	0.004	0.8795	
Gini	0.069	0.005	0.0000	***
Govexp	0.196	0.020	0.0000	***
Unemployadv	0.073	0.007	0.0000	***
Null Deviance	19,159.574	NA	NA	NA
Residual Deviance	18,430.529	NA	NA	NA
AIC	18,448.529	NA	NA	NA
Number of Observations	14,007.000	NA	NA	NA

The results from the regression analysis conducted on the original sample, incorporating the most significant variables from the previous models, are presented in Table 14. Consistent with prior findings, gender (*gndr*) remains highly significant, with a coefficient of 0.447. This translates into an odds ratio of $e^{0.447} \approx 1.564$, indicating that females are 1.56 times more likely than males to surpass their parents' educational attainment.This finding reinforces the robust role of gender as a key determinant in upward educational mobility.

Parental occupation categories (*occf14b* and *occm14b*) also keep displaying strong and significant effects. For instance, the coefficient for *occf14b_9* is 1.480 ($\rho < 0.001$), with an odds ratio of $e^{1.480} \approx 4.39$. This implies that individuals with parents in this occupation category have odds of upward mobility that are more than four times higher than those in the baseline category. Similarly, the variable *occm14b_8* demonstrates a coefficient of 1.522, translating into an odds ratio of approximately 4.58. As previously mentioned, the higher coefficients for lower parental occupational categories likely reflect the fact that these professions are typically associated with lower levels of education. Consequently, it is easier for children in these contexts to surpass their parents' educational attainment

National-level factors continue to demonstrate significant relationships with the log-odds of the dependent variable, *mobilityup*. For instance, the Gini coefficient (0.073, $\rho < 0.001$) has an odds ratio of $e^{0.073} \approx 1.076$. In contrast, the Consumer Price Index (*CPI*) shows an odds ratio of $e^{-0.014} \approx 0.9861$, implying that a one-unit increase in inflation reduces the odds of upward mobility by about 1.39%. Household savings and government expenditure on education also show positive effects on upward mobility. The odds ratio for *hshldsavings* is $e^{0.026} \approx 1.026$, suggesting that a one-unit increase in savings is associated with a 2.6% increase in the odds of surpassing parental educational attainment. Similarly, government expenditure on education has a log-odds coefficient of 0.126, translating to an odds ratio of $e^{0.126} \approx 1.134$. Lastly, the unemployment rate among individuals with advanced education exhibits a log-odds of $e^{0.060} \approx 1.062$, meaning a one-unit increase in this variable raises the odds of upward mobility by 6.2%.

6.3.4. Test of Multicollinearity

Multicollinearity tests were conducted as a robustness check to evaluate the potential influence of highly correlated independent variables on the regression models.This involved calculating the Variance Inflation Factor (VIF) for all variables in the models using R Studio. Multicollinearity occurs when independent variables are highly correlated, complicating the model's ability to estimate the distinct effect of each predictor on the dependent variable. Such correlation can lead to instability in the regression coefficients and an inflation of their standard errors, reducing the reliability of statistical inferences such as p-values and confidence intervals.

The Variance Inflation Factor (VIF) analysis conducted across all regression models confirmed that multicollinearity is not a significant concern in these regressions[12]. Table X displays the VIF values for the Logistic Regression Model (X).

Table 16. Multicollinearity Test

Variance Inflation Factor (VIF) Results Multicollinearity Assessment	
Predictor	Variance Inflation Factor
gndr	1.007
occf14b_2	1.723
occf14b_3	1.789
occf14b_4	1.902
occf14b_5	2.102
occf14b_6	3.480
occf14b_7	3.018
occf14b_8	1.781
occf14b_9	1.996
occm14b_2	1.229
occm14b_3	2.736

Variance Inflation Factor (VIF) Results Multicollinearity Assessment	
Predictor	Variance Inflation Factor
occm14b_4	2.013
occm14b_5	2.729
occm14b_6	1.868
occm14b_7	2.007
occm14b_8	2.105
occm14b_9	1.688
CPI	1.069
Hshldsavings	1.136
Gini	1.330
Govexp	1.279
Unemployadv	1.127

6. Regression Analysis: Factors Influencing University Education Attainment for Potential First-Generation Students

For individuals whose parents did not attend university, achieving upward educational mobility often entails becoming the first in their families to pursue higher education—a milestone that carries significant implications for breaking cycles of socioeconomic disadvantage (Hout, 2012; Reardon, 2011).

[12] See all Variance Inflation Factor tests performed in the appendix.

While not the primary focus of this study, additional analyses were conducted to provide valuable complementary insights into the factors influencing university attainment among individuals whose parents lack higher education. This specific group, referred to as "Potential First-Generation Students," was examined using a newly created dependent variable, *universityg*. This variable is binary, with a value of "1" assigned to individuals who have completed a tertiary education degree or higher and "0" to those who have not. The results of this analysis are presented below, accompanied by a brief discussion.

6.1. **Influence of Individual-Level Variables on University Education Attainment**

The logistic regression results in Table 17 highlight which of the variables used along this study influence university attainment among potential first-generation students. At the individual level, it can be seen how gender is a strong predictor, just as in the case of general upward mobility. Parental occupational background also plays a crucial role, with children from lower-skilled occupational groups showing lower odds of attaining tertiary education compared to those from higher-skilled parental occupations. Interestingly, neither immigrant parental status nor ethnicity demonstrates significant effects.

At the country level, notable disparities emerge across Europe. Countries such as France, Hungary, and the Czech Republic exhibit significantly lower odds of university attainment compared to the reference country, pointing at potential structural barriers or inequalities that impede mobility. In contrast, Lithuania is the only nation to stand out for their positive and statistically significant effects on university attainment. Countries like Norway and the Netherlands show no significant deviations.

Table 17. Logistic Regression: Effects of Individual-Level Variables and Country of Residence on University Education Attainment

Logistic Regression Results (1)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	0.391	0.176	0.0265	*
gndr	0.641	0.037	0.0000	***
immpts	0.044	0.048	0.3542	
blgetmg	−0.144	0.108	0.1818	
occf14b_2	0.020	0.127	0.8726	
occf14b_3	0.017	0.111	0.8812	
occf14b_4	−0.251	0.109	0.0212	*
occf14b_5	−0.443	0.106	0.0000	***
occf14b_6	−0.528	0.093	0.0000	***
occf14b_7	−0.811	0.098	0.0000	***
occf14b_8	−1.071	0.117	0.0000	***
occf14b_9	−0.629	0.121	0.0000	***
occm14b_2	−0.090	0.173	0.6022	
occm14b_3	−0.102	0.087	0.2411	
occm14b_4	−0.483	0.095	0.0000	***
occm14b_5	−0.641	0.090	0.0000	***
occm14b_6	−0.696	0.100	0.0000	***
occm14b_7	−0.844	0.100	0.0000	***
occm14b_8	−1.026	0.098	0.0000	***
occm14b_9	−1.002	0.127	0.0000	***
cntry_IT	−0.740	0.147	0.0000	***
cntry_CZ	−1.576	0.115	0.0000	***

Logistic Regression Results (2)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
cntry_EE	−0.383	0.119	0.0012	**
cntry_FI	0.223	0.115	0.0516	.
cntry_FR	−0.721	0.117	0.0000	***
cntry_DE	−0.931	0.116	0.0000	***
cntry_HU	−0.873	0.129	0.0000	***
cntry_IE	−0.084	0.125	0.5012	
cntry_LT	0.526	0.120	0.0000	***
cntry_NL	−0.193	0.128	0.1305	
cntry_NO	0.098	0.126	0.4360	
cntry_PL	0.100	0.110	0.3623	
cntry_PT	−0.220	0.122	0.0720	.
cntry_SI	−0.309	0.117	0.0086	**
cntry_ES	−0.357	0.123	0.0037	**
cntry_SE	−0.447	0.124	0.0003	***
cntry_CH	−1.084	0.135	0.0000	***
cntry_GB	−0.313	0.124	0.0114	*
cntry_SK	−0.790	0.132	0.0000	***
cntry_DK	−0.276	0.136	0.0415	*
Null Deviance	20,051.018	NA	NA	NA
Residual Deviance	18,268.441	NA	NA	NA
AIC	18,348.441	NA	NA	NA
Number of Observations	16,653.000	NA	NA	NA

6.2. Influence of Country-Level Variables on University Education Attainment

Table 18. Logistic Regression: Effects of Country-Level Variables on University Education Attainment

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−3.283	0.397	0.0000	***
CPI	0.002	0.002	0.3703	
Hshldsavings	−0.034	0.006	0.0000	***
Gini	0.036	0.007	0.0000	***
Govexp	0.127	0.028	0.0000	***
Unemployadv	0.003	0.007	0.6355	
Pupteachs	0.036	0.011	0.0009	***
Null Deviance	13,134.635	NA	NA	NA
Residual Deviance	13,002.944	NA	NA	NA
AIC	13,016.944	NA	NA	NA
Number of Observations	11,632.000	NA	NA	NA

By replacing the explanatory variables in the previous model with country-level factors, such as the Consumer Price Index (CPI) and the Gini coefficient, this analysis shifts focus to the influence of macroeconomic and structural determinants on university attainment among potential first-generation students. As shown in Table 18, the most significant predictors include government expenditure on education (*Govexp*), the Gini coefficient (*Gini*), and the pupil-teacher ratio in secondary school (*Pupteach*), with coefficients of 0.127, 0.036, and 0.036, respectively.

Although the positive effects of *Gini* and *Pupteach* are less intuitive and warrant further examination. The significant association of the Gini coefficient with university attainment could reflect incentives in more unequal societies, where education is perceived as a pathway to economic advancement and social mobility. Similarly, the positive relationship with the pupil-teacher ratio might suggest contextual factors, such as regions where larger class sizes coexist with stronger education systems or complementary support structures. These results align with earlier discussions in the essay, which highlight that these seemingly counterintuitive effects could arise from complex socio-economic dynamics.

The analysis also shows the significant negative effect of household savings (*Hshldsavings*), with a coefficient of -0.034. This suggests that lower levels of household savings may correlate with higher university attainment among first-generation students. This could maybe reflect a prioritization of education as an investment in future earnings over immediate financial security. Conversely, *CPI* and *Unemployadv* are not statistically significant.

6.3. Joint Effects of Individual- and Country-Level Variables on University Education Attainment

Finally, this last regression model (Table 19) highlights the influence of individual and structural factors on university attainment among potential first-generation students. Gender (*gndr*) is a significant positive predictor (coefficient: 0.584, $\rho < 0.001$), with women more likely to attain higher education than men. Parental occupation, particularly lower-skilled roles such as semi-skilled or unskilled work (*occf14b_6*, *occf14b_7*, *occm14b_6*), shows a significant negative association with attainment.

Structural factors also play a crucial role. Lower household savings (*Hshldsavings*) negatively impact university attainment (coefficient: -0.032, $\rho < 0.001$), while government expenditure on education (*Govexp*) is strongly positive (coefficient: 0.209, $\rho < 0.001$), highlighting the importance of public investment.

Table 19. Logistic Regression Model: Joint Effects of Individual- and Country-Level Variables on Upward Educational Mobility

Logistic Regression Results

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−2.594	0.312	0.0000	***
gndr	0.584	0.045	0.0000	***
occf14b_2	0.045	0.150	0.7660	
occf14b_3	0.067	0.132	0.6088	
occf14b_4	−0.115	0.131	0.3821	
occf14b_5	−0.299	0.127	0.0186	*
occf14b_6	−0.520	0.115	0.0000	***
occf14b_7	−0.759	0.121	0.0000	***
occf14b_8	−0.953	0.145	0.0000	***
occf14b_9	−0.305	0.148	0.0399	*
occm14b_2	−0.009	0.213	0.9649	
occm14b_3	0.055	0.107	0.6075	
occm14b_4	−0.306	0.117	0.0090	**
occm14b_5	−0.455	0.110	0.0000	***
occm14b_6	−0.659	0.127	0.0000	***
occm14b_7	−0.607	0.125	0.0000	***
occm14b_8	−0.795	0.122	0.0000	***
occm14b_9	−0.815	0.162	0.0000	***
Hshldsavings	−0.032	0.005	0.0000	***
Gini	0.041	0.006	0.0000	***
Govexp	0.209	0.024	0.0000	***
Null Deviance	12,700.664	NA	NA	NA
Residual Deviance	11,927.359	NA	NA	NA
AIC	11,969.359	NA	NA	NA
Number of Observations	10,611.000	NA	NA	NA

Conclusions

This study has delved into intergenerational educational mobility across 21 European countries, shedding light on how personal characteristics and broader national contexts interact to influence educational opportunities. The findings make it clear that gender and parental occupation are key factors in shaping upward mobility. Women consistently appear to be more likely than men to achieve upward mobility, reflecting progress in closing the gender gap in education. However, the study also reveals that ethnic minorities often face significant systemic barriers, which continue to limit their opportunities for educational mobility.

On a national level, the research emphasizes the critical role of government investment in education and broader economic conditions. Countries that allocate a higher percentage of their GDP to education demonstrate higher levels of upward mobility, underscoring the importance of well-funded and accessible education systems. Conversely, economic challenges such as inflation and low household savings rates act as significant obstacles. The relationship between income inequality and mobility is complex, and presents an unexpected divergence from previous research, highlighting the need for further investigation. While income inequality can serve as a motivator for some, it also exacerbates the challenges faced by individuals from the most disadvantaged backgrounds, reinforcing the cycle of limited opportunity. These findings also reveal important regional patterns, with some countries standing out as leaders in fostering upward mobility, while others lag behind due to structural challenges.

In conclusion, this study highlights the need for a comprehensive approach to fostering intergenerational educational mobility. Policies that aim to reduce socio-economic disparities, promote gender and ethnic equality, and invest in education systems are essential for creating a more inclusive and equitable society.

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Appendix

Table 14. Logistic Regression Model: Joint Effects of Individual- and Country-Level Variables on Upward Educational Mobility (with *Pupteachp*)

Logistic Regression Results (1)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
(Intercept)	−6.741	0.461	0.0000	***
gndr	0.419	0.048	0.0000	***
occf14b_2	0.512	0.134	0.0001	***
occf14b_3	1.074	0.128	0.0000	***
occf14b_4	1.265	0.125	0.0000	***
occf14b_5	1.300	0.119	0.0000	***
occf14b_6	1.285	0.101	0.0000	***
occf14b_7	1.223	0.108	0.0000	***
occf14b_8	1.380	0.136	0.0000	***
occf14b_9	1.611	0.148	0.0000	***
occm14b_2	0.594	0.173	0.0006	***
occm14b_3	1.194	0.096	0.0000	***
occm14b_4	1.195	0.112	0.0000	***
occm14b_5	1.104	0.099	0.0000	***

Logistic Regression Results (2)

Summary of Coefficients and Model Statistics

Variable	Coefficient	Std. Error	p-Value	Significance
occm14b_6	1.061	0.118	0.0000	***
occm14b_7	1.332	0.115	0.0000	***
occm14b_8	1.565	0.114	0.0000	***
occm14b_9	1.250	0.172	0.0000	***
CPI	−0.008	0.002	0.0009	***
Hshldsavings	0.031	0.006	0.0000	***
Gini	0.099	0.007	0.0000	***
Govexp	0.166	0.029	0.0000	***
Unemployadv	0.031	0.010	0.0023	**
Pupteachp	0.030	0.007	0.0000	***
Null Deviance	11,350.567	NA	NA	NA
Residual Deviance	10,043.657	NA	NA	NA
AIC	10,091.657	NA	NA	NA
Number of Observations	8,421.000	NA	NA	NA

Table 8. Logistic Regression: Effects of Individual-Level Variables on Upward Educational Mobility (VIF Test)

Variance Inflation Factor (VIF) Results Multicollinearity Assessment	
Predictor	Variance Inflation Factor
gndr	1.004
immpts	1.145
blgetmg	1.139
occf14b_2	1.638
occf14b_3	1.794
occf14b_4	1.833
occf14b_5	2.027
occf14b_6	3.511
occf14b_7	3.135
occf14b_8	1.859
occf14b_9	2.188
occm14b_2	1.216
occm14b_3	2.690
occm14b_4	2.000
occm14b_5	2.593
occm14b_6	1.909
occm14b_7	2.073
occm14b_8	2.247
occm14b_9	1.878

Table 10. Logistic Regression: Effects of individual-level variables and Country of Residence on upward educational mobility (VIF Test)

Variance Inflation Factor (VIF) Results

Multicollinearity Assessment

Predictor	Variance Inflation Factor
gndr	1.011
immpts	1.213
blgetmg	1.164
occf14b_2	1.645
occf14b_3	1.808
occf14b_4	1.825
occf14b_5	2.023
occf14b_6	3.534
occf14b_7	3.212
occf14b_8	1.868
occf14b_9	2.217
occm14b_2	1.219
occm14b_3	2.695
occm14b_4	2.001
occm14b_5	2.634
occm14b_6	1.917
occm14b_7	2.126
occm14b_8	2.263
occm14b_9	1.923

Variance Inflation Factor (VIF) Results

Multicollinearity Assessment

Predictor	Variance Inflation Factor
cntry_IT	1.449
cntry_CZ	2.593
cntry_EE	2.087
cntry_FI	2.212
cntry_FR	1.956
cntry_DE	2.186
cntry_HU	2.104
cntry_IE	1.655
cntry_LT	1.941
cntry_NL	1.759
cntry_NO	1.909
cntry_PL	2.342
cntry_PT	1.672
cntry_SI	1.903
cntry_ES	1.792
cntry_SE	1.903
cntry_CH	1.636
cntry_GB	1.772
cntry_SK	1.715
cntry_DK	1.728

Table 12. Logistic Regression: Effects of Country-level variables on upward educational mobility (VIF Test)

Variance Inflation Factor (VIF) Results

Multicollinearity Assessment

Predictor	Variance Inflation Factor
CPI	1.293
Hshldsavings	1.139
Gini	1.292
Govexp	1.444
Unemployadv	1.173
Pupteachp	1.615

Figure X. Percentage of Upward Mobility by Country with Breakdown by Category