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RESEARCH PAPER

Forecasting human capital of EU member countries accounting for sociocultural determinants

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Abstract
Inclusion of additional dimensions to population projections can lead to an improvement in the overall quality of the projections and to an enhanced analytical potential of derived projections such as literacy skills and labor force participation. This paper describes the modeling of educational attainment of a microsimulation projection model of the European Union countries. Using ordered logistic regressions on five waves of the European Social Survey, we estimate the impact of mother's education and other sociocultural characteristics on educational attainment and implement them into the microsimulation model. Results of the different projection scenarios are contrasted to understand how the education of the mother and sociocultural variables may affect projection outcomes. We show that a change in the impact of mother's education on children's educational attainment may have a big effect on future trends. Moreover, the proposed approach yields more consistent population projection outputs for specific subpopulations.

Key words: Education; Europe; European Union; human capital; microsimulation; population; projection; sociocultural

JEL classification: C00; C15; C53; J1; J24; I24; J15

1. Introduction

Traditional demographic projections are based on age–sex differentials in demographic behaviors. Recently, the importance of education as an additional dimension in population projection models has been highlighted [Lutz et al. (1998), Lutz (2010)]. Indeed, education has been shown to influence fertility and mortality levels, as well as migration rates [Martin and Juarez (1995), Docquier and Marfouk (2004), Valkonen (2006), Kravdal and Rindfuss (2008), Skirbekk (2008)]. Education will likely have a significant impact on population growth and structure and should be included as a dimension in projection models, in addition to age and sex [Lutz and KC (2011)]. Changes in future educational pathways could affect significantly the future world population in terms of size and age structure [Lutz et al. (2014)]. Furthermore, educational attainment is in itself an output relevant for public policies as well as for other analytical issues [Crespo et al. (2014), Loichinger (2015), Loichinger and Prskawetz (2017)]. In most economies, education is a strong and positive determinant of labor force participation, earnings, and productivity: as a matter of fact, the anticipated increase in the highly educated population is expected to curb some of the negative economic impacts of population aging [Loichinger (2015)]. Finally, including education in population projections can provide insights into the relationship between education and population dynamics, thus proving a useful tool in the implementation of education or population policies by decision-makers [Lutz et al. (2008)].

In this paper, we describe the modeling of educational attainment for a microsimulation projection model of the EU28 member states developed within the framework of a larger project called CEPAM.[1] The CEPAM microsimulation model (CEPAM-Mic) includes—in addition to age, sex, and education—mother's education and sociocultural variables that are themselves determinants of educational attainment. These additional variables allow for a more refined modeling of education, and can lead to an improvement in the overall quality of the projections and to an increase in the value of derived factors such as literacy skills, labor force participation, or employment. They also provide more flexibility in the generation of policy relevant alternative projection scenarios, notably in terms of the intensity and composition of future migration flows and of the future evolution of educational attainment. Furthermore, results are enriched by these additional variables, as multistate projections usually do not account for demographic differentials related to immigration and sociocultural variables. Since demographic behaviors and socio-economic outcomes of immigrants differ from those of natives, and since the immigrant population is growing fast, taking these differentials into account becomes more and more important.

On the one hand, conventional multistate models are poorly adapted to the simultaneous projection of a large number of dimensions, because the number of cells increases exponentially with the number of individual characteristics and in consequence, the computational effort quickly becomes unmanageable [Van Imhoff and Post (1998)]. Microsimulation, on the other hand, is a powerful tool that can be used to make population projections when the number of dimensions becomes large [Van Imhoff and Post (1998)], because various statistical models can be used to derive life-course transitions and events. There is also a growing consensus on the usefulness of this type of model for population projections in general [Asghar et al. (2009)]. In microsimulation models, individuals are simulated one by one and their characteristics are modified through scheduled events whose timing is determined by the values of their specific parameters at any given time during the projection period. Since the simulation is performed at the individual level, individual records over the life course and across generations can be stored and retrieved. Characteristics of mothers, such as education, can be stored and used as determinants of further events.

The power and flexibility of microsimulation allow for the inclusion of 11 dimensions to the CEPAM-Mic model: region of residence, age, sex, educational

[1]The Centre for Expertise on Population and Migration (CEPAM) is a joint research project between IIASA and the Joint Research Centre of the European Commission aiming at studying the consequences of alternative future population and migration trends in Europe.

attainment, mother's educational attainment, immigrant status, age at arrival in host country, religion, language spoken, and labor force participation.

This paper presents the argumentative and empirical basis for the projection of education. First, we discuss the necessity of inclusion of additional sources of heterogeneity in order to model the future evolution of educational attainment. Second, we describe the education module of the microsimulation model and estimate its parameters using an ordered logit regression model. The results of this analysis show the importance of mother's education and of sociocultural variables in explaining the educational attainment of EU28 residents. In the last section, we implement these parameters in the CEPAM-Mic microsimulation model and show the results of a sensitivity analysis obtained by comparing five scenarios of population projection, one using only gross cohort trends and the others using different sets of parameters for sociocultural variables and mother's education.

2. Empirical and past evidence on the importance of parental education and socio-cultural characteristics in determining educational attainment

Over the 20th century, the massification of education has been a worldwide phenomenon, resulting in the rapid growth of tertiary education [Altbach et al. (2009)]. Although there exists no scientific consensus on the link between countries' broad characteristics and the expansion of higher education, Schofer and Meyer (2005) stress the positive role of democratization, human rights, scientization, and development planning. This evolution in educational attainment was made possible by cultural and institutional changes that took place after the Second World War, as expansion in higher education was increasingly seen as a source of progress that benefits both individuals and society rather than a source of inefficiency and anomie [Schofer and Meyer (2005)]. Since then, developed nations have seen, along with the emergence of the welfare-state and social security, a strong decline in the cost of education [Breen et al. (2009)]. As more schools were built and travel conditions improved, living conditions also increased for working classes, resulting in universal access to primary and secondary education [Breen et al. (2009), Barakat and Durham (2014)]. Through a domino effect, this improvement in primary and secondary education also increased the postsecondary enrolment [Altbach et al. (2009)].

Figure 1 shows trends in educational attainment in European countries for cohorts born between 1940 and 1979. As a general trend, we note that the proportion of low-educated population has continuously declined for most countries.[2] The decline has occurred at a stronger pace for females when compared to males, and in countries lagging behind in terms of educational attainment, such as Greece. Overall, a convergence of all countries to a small proportion of low-educated population is clearly observed. Indeed, the arithmetic mean of low-educated population for EU28 countries decreased for females from 58.6% [standard deviation (SD) = 18.8%] for the cohorts of 1940–1944 to 14.5% (SD = 10.1%) for the cohorts of 1975–1979, and for males from 45.4% (SD = 19.2%) to 16.9% (SD = 12.8%). Despite this general decline in low education, significant gaps remain among EU28 countries. For instance, the range in the proportion of low-educated population varies from 3.3%

[2]In this paper, low education is defined as less than high school (ISCED 1 and 2), medium education corresponds to completed secondary education (ISCED = 3), and high education corresponds to post-secondary education (ISCED 4 or higher).

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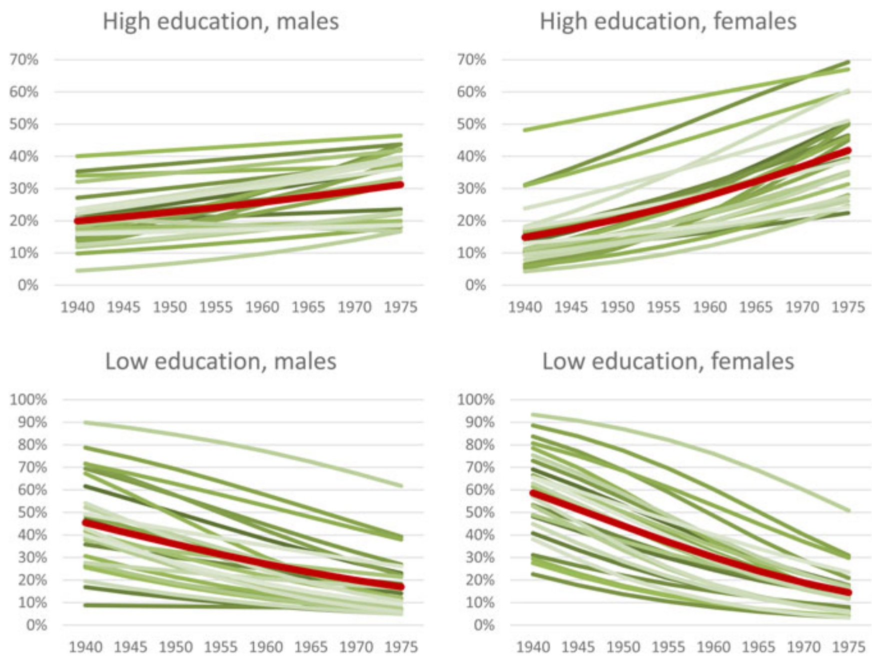

Figure 1. Evolution of educational attainment across cohorts (%) for European-born and immigrants arrived before age 25, by country (red line = arithmetic average).
Source: Pooled data of ESS (2006 to 2014). See data section for details on variables and categories.

(females born in Sweden) to 61.8% (males born in Portugal) for cohorts born between 1975 and 1979.

Conversely, most countries have seen a general increase in the proportion of high education across cohorts. In general, the rate of change was greater for females than for males, so much so that females born between 1975 and 1979 were more likely to get a post-secondary degree than males of the same cohorts [Van Bavel et al. (2018)]. The opposite had been true for cohorts born 30 years earlier. Some countries, such as the Czech Republic and Romania, even saw their proportion of high-educated males stagnate at moderate or low levels. Overall, the arithmetic mean for the proportion of the high-educated population increased from 14.8% (SD = 9.3%) to 41.9% (SD = 12.7%) for females, and from 19.9% (SD = 8.1%) to 31.2% (SD = 9.7%) for males. Interestingly, and contrary to what was observed for low education, Figure 1 shows that there is no evidence of convergence between countries in post-secondary educational attainment.

It is known since many decades that the socioeconomic status of the family influences the educational attainment [Sewell and Shah (1967), Sewell et al. (1969), Lin (2001)]. Among socioeconomic characteristics, the education of parents proves to be an even better determinant of a child's educational attainment than the occupation [Shavit et al. (2007)]. Past research has consistently shown a strong correlation between a parent's and his/her children's educational attainment: individuals whose parents have a high level of education have a better chance of getting a high level of education themselves [Bowles and Gintis (1976), Hertz et al.

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(2008), Kogan et al. (2012)]. Evidence shows that this type of intergenerational transfer occurs consistently in all developed nations and has remained stable since the Second World War [Erikson and Goldthorpe (1992), Shavit and Blossfeld (1993), Pfeffer (2008)]. Moreover, commenting a journal special issue on ethnic differences in educational attainment, Heath and Brimbaum (2007) conclude that the socioeconomic status of parents, which is captured in part by their education level, has about the same effect for every ethnic group, since very few interaction variables were found to be significant.

Researchers have identified several mechanisms by which a child's education might be linked to the education of its parents: economic and cultural resources, the influence of other family members, track placement, and incentives to make more ambitious educational choices [Shavit et al. (2007)]. In short, the parents' education is an important part of a child's social capital [Bourdieu (1986)]. In addition, the educational attainment may also be linked to inherited abilities which are correlated between family members [Black et al. (2005)].

Along with parents' education, other sociocultural variables may have an impact on educational attainment. Many studies in Europe and in the USA have found that some groups such as foreign-born children or racial minorities are at a disadvantage with respect to their educational trajectory [Hirschman (2001), Riphahn (2003), Heath and Brinbaum (2007)] or on the contrary performs better than natives following the segmented assimilation hypothesis [Portes and Zhou (1993), Alba and Foner (2016)].

Global expansion in higher education in the USA was shown to have been depressed by compositional effects, the expansion having been slower for Blacks and Hispanics than for Whites [Barakat and Durham (2014)]. In Germany, Gang and Zimmermann (2000) showed that children of immigrants meet a disadvantage in educational attainment that resists statistical controlling of several factors such as parents' education. Moreover, the educational experience differs following the ethnic origin of children of immigrants, suggesting a persistence of cultural differences in a multicultural society. According to Heath and Brindaum's (2007) review on ethnic inequalities, this persistent disadvantage affects mainly immigrants from low-developed countries. Among contextual factors explaining these differences, some researchers observed that minority groups are often concentrated in economically deprived neighborhoods, where the poorer quality of schools together with unequal access to resources and other contextual effects are likely to reduce their opportunities [Gronqvist (2006), Heath and Brinbaum (2007), Pong and Hao (2007), Zhou (2009)].

3. Projecting the education

3.1 The multistate approach and the need of a new paradigm

Previous projections of education used a multistate approach in a dynamic model of all countries of the world [Lutz et al. (2014)]. Assumptions concerning future educational attainment were set by extrapolating previous cohort trends by sex and country, and different scenarios were constructed for prospective analyses.

Looking at the observed educational attainment by cohorts, it might appear reasonable to assume that past trends would extend to future generations. This would be called a *gross cohort trend*, as it does not account for population heterogeneity. However, as was shown in the previous section, educational attainment varies according to the individual's sociocultural characteristics and parental education, so that observed trends across cohorts may vary depending on changes in population composition.

As a matter of fact, population composition has changed across cohorts due to education-related fertility differentials, immigration flows and past changes in educational attainment of mothers. Thus, some of the observed changes at the aggregate level can be explained by changes in the composition of the population rather than by behavioral changes at the micro level [Orcutt (1957)]. Since cohorts' educational attainment is inextricably linked to the evolution of sociocultural variables and to the education level of parents, we may expect that part of the observed changes in educational attainment is explained by changes in population composition, rather than by a *net cohort trend*, or changes affecting all subgroups of a cohort. Given the high transmission of education from parents to children, an observed increase in the proportion of the highly educated population could be explained by an increase in the education level of parents, even as the net cohort trend within education levels stagnate or decrease. Thus, explicitly considering the relationship between parental education and one's education level in the forecasting model should improve its predictive capacity.

Additionally, if the net effect on the educational attainment of ethnocultural characteristics remains statistically significant, it becomes necessary to take these characteristics into account as well. This is particularly necessary in a context where increasing immigration is increasing sociocultural diversity. However, multistate population projection models can hardly project simultaneously several dimensions, because the number of cells grows exponentially with the number of characteristics included. The microsimulation can overpass these challenges [Van Imhoff and Post (1998)]. Therefore, a change in the methodological paradigm is required.

3.2 The CEPAM-Mic microsimulation model

In a continuous time dynamic microsimulation model, individuals from the base population are simulated one by one and their characteristics are modified through scheduled events whose timing is stochastically (Monte-Carlo) determined using the values of their specific input parameters at any given time during the projection period [Van Imhoff and Post (1998), Bélanger and Sabourin (2017)]. Rules for intergenerational transfers of characteristics from mother to child determine the base characteristics of newborns, which can then change during the life-course following assumptions set in inputs. The parameters used as inputs are themselves derived through various statistical methods, using available data sources.

The objective of this paper is to describe the modeling of educational attainment for a microsimulation projection model of the EU28 countries called CEPAM-Mic. The framework of the model is based on the Canadian LSD model [Bélanger and Sabourin (2017), Bélanger et al. (2018a, 2018b)]. CEPAM-Mic is a dynamic, continuous time, event-based, open, and spatial microsimulation projection model of the EU28 population programed in the Modgen language.[3] The model aims at investigating the impact of immigration on the future European population. It simultaneously projects demographic (age, sex, place of residence, and immigrant

[3]Modgen is developed and maintained by Statistics Canada. For more details, see http://www.statcan.gc.ca/eng/microsimulation/modgen/modgen.

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status), ethno-cultural (country of birth, language, and religion), and socioeconomic (education, labor force participation, and employment) characteristics of the EU28 population. It allows for changes in individual characteristics over the life course, as well as for intergenerational transfers of some characteristics from the mother to her child.

The starting population of CEPAM-Mic is derived from pooled data of the LFS 2014–2015 calibrated to the 2011 Census by age (5-year age groups from 0 to 95+), sex, country, education, and immigrant status. Religion and language are imputed from pooled data of the European Social Survey (ESS), following statistical procedures described in Sabourin et al. (2017). There is no theoretical limit for the time range of the projection, although for the purpose of this paper, we set it at 2060. Fertility differentials for region of birth, age at immigration, duration of stay, and student status are estimated from logit regressions applied to the EU-LFS controlling for, age, education, and country of residence. These differentials are assumed to remain constant during the projection period. The education variable used in the modeling of fertility included the category "is student" in order to avoid attributing the fertility level of low educated females to individuals who will complete their education later in life. These differentials are applied to country, age, and education fertility base rates which follow the trend estimated following a worldwide experts survey used in Lutz et al. (2014). Mortality assumptions by age, sex, and educational attainment are also taken from the projection model used in Lutz et al. (2014).

To obtain out-migration rates by sex and country of residence, the average number of out-migrants from 2014 to 2016 (Eurostat table: migr_emi2) is divided by the average population aged 20–34 during the same period. Age-specific outmigration rates are then derived within the microsimulation model as follows. First, the Eurostat derived outmigration rates are applied to the 20–34 population to obtain the expected number of out-migrants in a given year. The number of out-migrants are then distributed according to age using a Rogers-Castro schedule [Rogers and Castro (1981)]. Finally, age-specific outmigration rates are obtained by taking the ratio of out-migrants to the population, by age, sex, and country of residence. Out-migration rates in the simulation are recalculated every 5 years. During the simulation, out-migrants may either move within the EU, and are assigned a new country of residence, or they can leave the EU, in which case their simulation is terminated. The proportion of out-migrants leaving the EU is derived from Eurostat tables on emigration according to region of destination (table: migr_emi3nxt). Origin-destination matrix for intra-European mobility was derived using an update for the period 2009–2016 of Raymer et al.'s (2013) Bayesian estimates of European migration.[4]

The number of international immigrants is assumed to remain constant at the average level observed for the period 2014–2016 [Eurostat (2018)]. Furthermore, future immigrants in the baseline scenario are assumed to have the same characteristics as recent immigrants. Although the origin and composition of immigrants are not likely to remain constant, it is not possible to predict migration for the long run [Sander et al. (2014), Azose et al. (2016)]. This is particularly true when we need to make assumptions on migration composition along several

[4]The authors would like to acknowledge Erofili Grapsa for the update of Bayesian estimates of migration flows.

dimensions. In consequence, the demographic scenario presented in this paper should be interpreted as being a continuation of current trends rather than a forecast. As stated above, the objective of this paper is to describe the modeling of the education module of the microsimulation model and for this purpose, a single set of assumptions for demographic events is sufficient.

The microsimulation model also includes intragenerational transmission of religion and language. At birth, religion and language are probabilistically attributed to the child according to their mother's characteristics, and are then allowed to change during the life course. Life course transition rates for language spoken at home are estimated from the ESS using a cross-section approach [Sabourin and Bélanger (2015)], whereas rates for religion are taken directly from the PEW projections by religion [Hackett et al. (2015)].

3.3 The CEPAM-Mic educational module

3.3.1 Data and variables

Because CEPAM-Mic aims at implementing sociocultural factors and the education of the parents as determinants of individual's educational attainment, it requires a microdata set that includes all or most of the theoretically relevant determinants of education for all countries, on which statistical models will be built to estimate the needed parameters.

Although the EU-LFS has a large sample covering all EU28 countries, it contains limited information on sociocultural characteristics. Moreover, education of the mother is only available for individuals living in the same household as their mother.[5] Despite its smaller sample size, the ESS was thus preferred to the EU-LFS for the analysis of educational attainment. Five cycles of the ESS (2006–2014) were pooled and reweighed in order to match the base population of the projection model (according to country/age/sex/region of birth/education).[6] Of the 28 EU countries, 13 participated in all five cycles, 13 were missing from at least one cycle, and two were completely missing (Luxemburg and Malta). These two latter countries are thus excluded from the analysis presented in this paper.

From this merged database, people born between 1940 and 1979[7] and immigrants arrived in their host country before the age of 25 were selected. Individuals were then classified according to their country of birth (if born in the EU) or country of residence (if born abroad). A description of the sample size for all countries can be found in Appendix Table A1.

Educational attainment is the dependent variable and is divided into three broad categories based on ISCED classification either:

(1) Low: lower secondary or less (ISCED 1 and 2);
(2) Medium: upper secondary completed (ISCED 3);
(3) High: postsecondary (ISCED 4+).

[5]In the microsimulation model, since the education is only imputed for newborns and younger individuals, this limitation of the EU-LFS has no consequence: the education of the mother is known for the quasi-totality of the relevant sample.

[6]Before calibration, age is adjusted to what it was in 2011 using subtraction of years. For some countries, no data on immigrant status are provided in the 2011 Census Data Hub: only age, sex, and education are then used for reweighting.

[7]Individuals below 30 years old at the time of the survey are excluded in order to avoid analysis on incomplete education paths.

The independent variables used for the analysis are the following:

- Education of the mother: categories are the same as for the dependent variable.
- Country of birth (natives) or country of residence (immigrants): EU28 countries.
- Region of birth[8]: Native, North America or Oceania/Other Europe/North Africa/ Latin America/East, South, and South-East Asia/Near and Middle East.
- Religion: Christian/Muslim/Other religions/No religion.
- Language spoken at home: Country's official language(s)/Other official languages in the EU28/Other languages. Language has to be official at the national or federal level.

3.3.2 The education module

In the CEPAM-Mic model, educational attainment is modeled in three steps:

Step 1. Determining educational attainment

This first step is at the core of the education module and requires parameters from ordered logit regressions (or cumulative logit with non-proportional odds) at the education level. When an individual is born, a variable indicates the highest level of education that will be reached in his/her lifetime. This is also done for immigrants who arrived before their twentieth birthday and for individuals aged less than 30 in the base population.

The ordered logit regression analysis has two purposes. The first is to estimate the net effect of relevant individual characteristics on educational attainment. The second purpose is to estimate country-specific cohort effects in order to make assumptions on the educational attainment of future cohorts. Because the sample size is insufficient to build stratified country-specific models, countries are grouped into two large regions, EU15/NMS13, corresponding approximately to former historical division of Europe during the second half of the 20th century, which still shapes the immigration patterns in terms of number, origin, and socioeconomic integration [Kahanec and Zaiceva (2009)]. The country-specific effect is captured by an interaction variable between the cohort and the country. The model equation is thus formulated as follows:

$$\ln\left(\frac{E_{ij}}{1-E_{ij}}\right) = \beta_{0j} + \beta_{1j}Ct_i + \beta_{2j}Cr_i + \beta_{3j}(Ct_i \times Cr_i) + \beta_{4j}X_i + \beta_{5j}Z_i \qquad ((1))$$

Where

- E_{ij} is the probability that an individual i reaches level of education j, where j equals high or medium;
- Ct is the country;
- Cr is a discrete variable for cohorts (1940–44 = 1; 1945–49 = 2, …, 1975–1979 = 8);
- X is a set of sociocultural variables;
- and Z is the education of the mother.

The ordered logit model provides distinct parameters for high and medium education, low education being the reference. Detailed parameters for all categories and variables are presented in Appendix Table A2. For the sake of simplicity, we

[8]Due to low sample size and low number of international immigrants arrived during the childhood in New Member States (NMS13), this variable cannot be used for models of this region.

focus our analysis on the odds of getting a post-secondary degree (high) compared to the odds of getting a lower degree (low and medium combined).

Note that the attribution of a highest educational attainment only concerns individuals with incomplete education paths: newborn, immigrants arrived before age 20 and members of the base population under 30 years old. For immigrants arrived in adulthood and older members of the base population, the highest degree is the one at the arrival in the host country or at the time of the survey. In the reference scenario, it is assumed to remain the same for the rest of the simulation, although other assumptions may be set in alternative scenarios.

Step 2. Graduation schedule

For those reaching at least the upper secondary level, the age at graduation is determined for all degrees using Eurostat distributions by ISCED levels for the latest graduated cohorts (2013–2014). For those scheduled to complete a post-secondary level, the education module first establishes age at graduation for the post-secondary degree, and then finds a coherent age at graduation for the upper secondary level.

For the three countries with missing data (France for high education; Croatia and UK for medium education), the average distribution of comparable countries was used as an approximation.

Unfortunately, no data exist on education schedules according to sociocultural characteristics or education of mothers and data quality sometimes appears questionable for certain countries. Nevertheless, we assume that variations due to these sources of heterogeneity occur within the age resolution of the model (5 years).

Step 3. Simulation of life course

The last step involves the actual simulation of individual educational events at the age at graduation that was predetermined. At birth, the education level is set to low for everyone. If the individual survives until graduation, the education state variable changes to reflect the appropriate educational attainment. As long as the highest level set at birth is not reached, the individual is tagged as being a student, along with his/her current educational attainment. Since the education variable is used for the modeling of other demographic events, a change in education immediately affects mortality and fertility rates as well as labor force participation.

3.3.3 Limitations

Due to both data and methodological limitations, a large part of the social determinants of educational attainment are discarded in the modeling. For instance, although the literature suggests that father's education is probably more important than the mother's in the prediction of the educational attainment of their children [Gang and Zimmermann (2000)], CEPAM-Mic is a female-dominant model, that is fertility rates are applied to women, and thus, it is not possible to create a link between the father and the child within the current microsimulation model. It is technically possible to model union formations and dissolutions by pairing individuals to form households and thus access to the characteristics of a potential father, but there are no data covering all EU member countries that would allow consistent statistical estimates of the parameters of these events without generating several major inconsistencies in the projection. Moreover, such addition would necessitate computer power that is actually out of range of most institutions. However, educational homogamy is important as shown by the high correlation between the education of the mother and the education of the father (0.61 in this sample). For these reasons, using education of the mother appears as a good proxy in this context.

Additionally, other sociocultural variables would empirically be relevant, but are not included in the projection model and some heterogeneity remains even when controlling for religion, language, and region of birth. As an example, Muslim or those speaking a non-European language include people from different socio-cultural backgrounds. However, as the sample size is relatively small, it was necessary to create some broad categories, especially for minority groups, to reduce the variance of the estimated parameters. In new member states (NMS13) specifically, the small sample size along with the small number of immigrants do not allow for a distinction of immigrants by region of origin. For the same reason, it is not possible to obtain reliable and coherent parameters from an interaction between the region of birth and religion or with language spoken at home to capture patterns for specific ethno-cultural groups such as Roma.

Similarly, contextual and environmental factors could not be accounted in the modeling of education. Organizational properties of schools (classroom effectiveness, teaching quality, etc.) have a major impact on student achievement [Heck (2009)]. Including this dimension in country-level projection of education would be very hazardous, as it would require to build a standardized indicator for all EU countries that is internationally comparable, and to set assumptions on how this indicator would involve in the future. Summing up, we can nevertheless assume that some of those missing factors are implicitly taken into account in the country-specific parameter of equation (1).

4. Estimation of parameters for the education module

Table 1 shows Max-rescaled R^2 and concordance levels for partial and full models. On average, adding mother's education (Z) and sociocultural variables (X) to cohort trends by country ($Ct \times Cr$) increases the concordance by 5–10 points compared to models including cohort trends by country alone. The two performance indicators also show that mother's education is a better predictor of educational attainment than are sociocultural variables: models including Z alone perform better than those including X alone. Moreover, Max-rescaled R^2 scores show that mother's education and cohort/country have a similar effect on the explained variance. Performance indicators also show that models perform slightly better for the EU15 region when compared to NMS13, as well as for females compared to males.

In order to assess the effect of the education of the mother and sociocultural variables, we compare their net and gross effect in Figure 2. Gross effects correspond to observed differences (translated into logit), which do not take account the effect of other variables. Net effects are obtained from the full model (country, sex, cohort, sociocultural variables, and mother's education).

The importance of mother's education stands out from all other variables as the main determinant of educational attainment. In both regions, the odds of getting a post-secondary degree compared to getting other lower educational levels fall below 0.2 for both males and females with low-educated mothers (reference is high-educated mother), meaning that individuals with a low-educated mother are approximately five times less likely to complete a post-secondary level than individuals with a high-educated mother. Results for individuals whose mother has a medium level of education are similar, although a little less pronounced (odds ratio: approximately 0.3).

Table 1. Performance indicators for partial and full models

	Parameter	EU15—M	EU15—F	NMS13—M	NMS13—F
Max-rescaled R^2	$Ct \times Cr$	0.236	0.231	0.106	0.183
	X	0.014	0.017	0.029	0.034
	Z	0.162	0.183	0.139	0.171
	$X + Z$	0.169	0.191	0.152	0.191
	$Ct \times Cr + X$	0.244	0.241	0.124	0.208
	$Ct \times Cr + Z$	0.295	0.309	0.206	0.286
	$Ct \times Cr + X + Z$	0.300	0.316	0.217	0.303
% of concordance	$Ct \times Cr$	64.8	68.7	59.4	64.7
	X	30.9	31.3	35.7	33.5
	Z	36.6	37.6	45.4	45.6
	$X + Z$	53.0	53.9	58.9	58.2
	$Ct \times Cr + X$	65.1	69.1	60.9	66.5
	$Ct \times Cr + Z$	70.1	73.6	68.8	72.3
	$Ct \times Cr + X + Z$	70.3	73.8	69.3	73.1

Preliminary models also included interaction terms between the education of the mother and the country or cohort, but most of the resulting parameters turned out not to be significant. Although the absence of a significant interaction could be a consequence of a relatively small sample size, this suggests that the effect of mother's education is roughly the same in all countries and didn't change across cohorts (at least since 1940). This result supports many other empirical analyses showing that differentials in intergenerational mobility rates do not vary much over time and across countries [Piketty (2000)]. As stated earlier, including mother's education explicitly in the projection model should improve predictive capacity.

Parameters for the region of birth show that cultural background is an important driver of educational attainment, and its effect differs according to sex. Indeed, a strong heterogeneity is observed with respect to the region of birth of immigrants arrived in their host country during childhood, as differences between some immigrant groups are larger than between immigrants and natives. For males in EU15, being born in other European countries (non-member of EU28) significantly reduces the odds of getting a high education level, while the odds increase strongly for those born in African countries (excluding North Africa). Females born in Near and Middle East have a significant disadvantage compared to others. Interestingly, the net effect is even larger than the gross one. By contrast, females born in East, South, and South-East Asia are about twice more likely to get a post-secondary degree than native-born females. Note that due to small sample size and low number of immigrants arrived during childhood in NMS13, this variable could not be included in models for this region.

Another significant result can be observed for the educational attainment of individuals according to their religious affiliation. Compared to being Christian, being Muslim significantly reduces the odds of obtaining a post-secondary degree in both regions and for both sexes and the effect remains significant even when controlling for the other

* Statistically significant at p<0.05

Figure 2. Odds of getting high level of education over odds of getting a low or medium level of education.

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variables. Since the education of the father could be a better explanatory variable than the education of the mother for Muslims [Gang and Zimmermann (2000)], it is possible that part of the Muslim effect is due to the use of this later variable rather than the former.

With the exception of females in the NMS13 region, a significant and positive effect of religion also remains for the category "Other religions," which mainly comprises Jews. Having no religion has a small positive effect on education in the gross models, but when controlling for the other variables this effect completely disappears, except for females in NMS13. In general, we can also conclude that the observed differences between religious groups are in part explained by their different composition in terms of mother's education or other variables, as the net effect of religion is always smaller than the gross effect.

Concerning the language spoken at home, the effect of speaking a non-European language on the odds of completing a post-secondary degree is generally reduced after a statistical control, but still remains negative and significant. Social issues underlying these differentials are distinct between EU15 and NMS13. In Eastern Europe, the non-official languages group comprises mainly Romani, whose educational pathways are well documented [Forray (2002)]. In the EU15, this group mostly comprises first and second generations of international immigrants.

Our results have shown that the net effect of the education of the mother on educational attainment is particularly strong, but that other sociocultural variables such as religion, language spoken at home, and in the case of EU15, the region of birth are also playing a significant role. Cohort composition has changed significantly along these dimensions in the course of the 20th century, and so we must aim to disentangle changes that occurred from the evolution of cohort composition and changes that affected the whole population. The second part of the analysis thus concerns the net cohort effect, which is the trend over cohorts once changes in population composition in terms of sociocultural variables and mother's education are factored out.

Figure 3 summarizes the net and gross cohort trends for males and females. For a simplified overview of the analysis, the graphs show the arithmetic average of cohort trend parameters across EU15 and NMS13 countries, and only provide odds for high education compared to the two lower categories.

When population composition in terms of sociocultural variables and mother's education is taken into account, cohort trends shift down significantly, in one case even changing the direction of the cohort trend from positive to negative. For males in the NMS13 region, gross odds ratios for high education followed a slightly increasing trend (Figure 3, NMS13, solid blue line). However, taking sociocultural variables and mother's education into account, the trend is reversed and becomes slightly negative (Figure 3, NMS13, dashed blue line). This result means that, *ceteris paribus*, a boy born in the 1970s from a mother with high education has less chance of obtaining a post-secondary level than a similar boy born in the 1940s. As a corollary, this shows that the observed improvement in the gross trends for NMS13 boys is more than completely explained by changes in population composition: there were more educated mothers in the 1970s than in the 1940s and consequently, children born in the 1970s are more likely to get a post-secondary degree. So the observed improvement in educational attainment of men in NMS13 among cohorts born between 1940 and 1979 is an echo of a past net cohort effect affecting previous cohorts of women. Because intergenerational transmission of education is high, a general increase in the level of education in a cohort reverberates in the following generations.

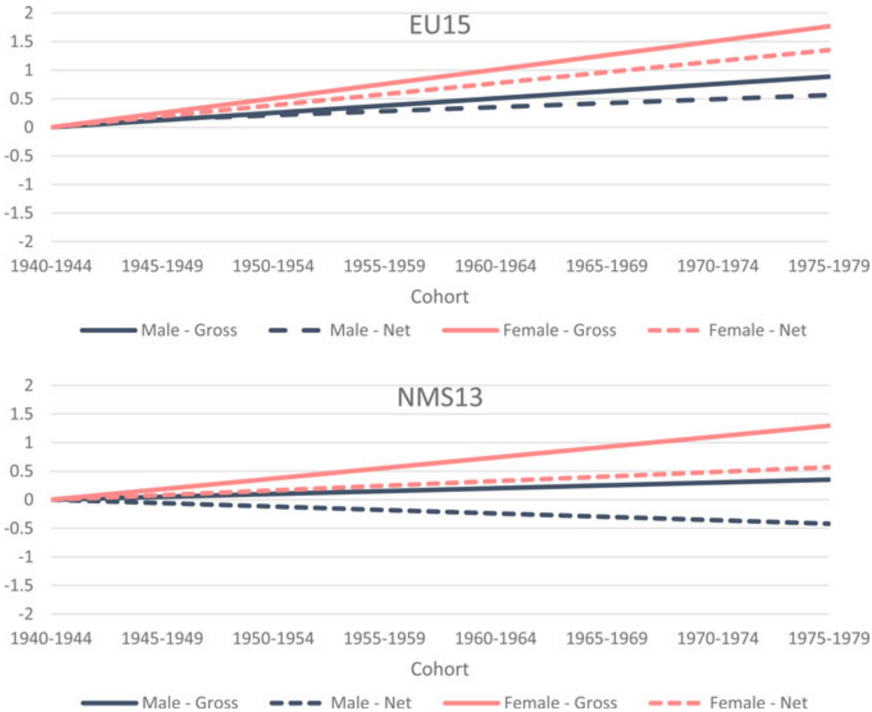

Figure 3. Comparison of gross and net cohort trends for the odds (logarithm) of getting a high level of education compared to medium or low levels.

For females in both EU15 and NMS13 and for males in EU15, Figure 3 shows that population composition alone does not fully explain the observed improvement in educational attainment, since net cohort trends (dashed lines) still show improvements across cohorts. Nevertheless, the amplitude is reduced compared to gross trends (solid lines), meaning that a significant part of the improvement across cohorts is explained by sociocultural characteristics and by mother's education.

5. Implementing education of mothers and sociocultural variables in a microsimulation projection model of education

Given the results presented in Section 4, how does population composition in terms of mother's education and sociocultural characteristics affect the outcome of projections? Different forces will work in different directions.

On the one hand, international migration flows are likely to increase the proportion of people speaking a foreign language at home and of Muslims [Coleman (2006)], which will likely have a negative impact on the average educational attainment. On the other hand, women are more educated than ever before, which is expected to positively affect their children's educational attainment. Moreover, the global increase in educational attainment, net of population composition effects, has been observed to level off or even decline in many countries.

To investigate how these dynamics could affect demographic projections of human capital, we designed five scenarios. First, we built two main scenarios to assess how

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taking into account sociocultural variables and the education of the mother impact projections of educational attainment:

(1) Gross cohort trend in education (GCTE)

In this scenario, educational attainment of future cohorts is extrapolated based on countries and cohort parameters for each sex (without controlling for sociocultural variables and mother's education). Because universal postsecondary attainment is unlikely to happen, the probability of getting a high degree of education is capped at 90% [Barakat and Durham (2014)]. This type of scenario can be used in common cohort-components or multistate demographic projections, where future trends are a function of past trends by age and sex only [Lutz et al. (2014)].

(2) Multivariate determinants of education (MDE)

In this scenario, all parameters from equation (1) are used and cohort trends are extrapolated over the time span of the projection (postsecondary is capped at 90%, as in the first scenario). This second scenario allows isolating the effect of the different components of the model on the future evolution of educational attainment. As explained previously, taking many dimensions into account is best realized in a microsimulation model.

In short, scenario GCTE is closer to the reference scenario of the projection model used in Lutz et al. (2014), although without the specific convergence assumptions [Barakat and Durham (2014)] and with different hypotheses in terms of immigration. Scenario MDE adds differentials according to sociocultural characteristics and education of the mother, so that the evolution of educational attainment can be decomposed into changes due to net cohort trends and changes due to the evolution of population composition.

In addition to these two main scenarios, we built three scenarios, taking the MDE scenario as a basis, but changing only a specific set of parameters. These scenarios allow analyzing how sensitive the modeling of education is to its different drivers of changes.

(3) Equality in education for Muslims (MDE-MuslimEq)

In this scenario, we set to 0 parameter for Muslims. In other words, this scenario assumes that there is no differential between Muslims and Christians in terms of educational attainment. Remember that the negative parameter associated with the mother's Muslim religion only describes a statistical relationship. It does not come from a causal analysis of the dynamics that could explain this observed relationship. The objective of this scenario is to test the sensitivity of the projection to this sociocultural variable, but additionally, it can also serve as an example of the potential impact of policies aimed at equal opportunities in education. Indeed, this statistical disadvantage to Muslim children may result from contextual factors associated with inequalities between neighborhoods and schools [Gronqvist (2006), Pong and Hao (2007)], as well as unequal access to resources [Zhou (2009)].

(4) Equality in education for children from low- and medium-educated mothers (MDE-EduM)

This scenario is set to 0 parameter for children from low- and medium-educated mothers and test how projection outputs are sensitive to this component of the equation. It thus assumes that these children have the same probability of getting the highest level of education than children from a high-educated mother. It may thus serve as an illustration of how policies improving the access to post-secondary education of children from less educated families may affect future education trends.

(5) Twice more Muslims among new immigrants (MDE-MuslimX2)
This scenario doubles the proportion of Muslims among new international immigrants (passing from about 30% to 60%). It tests how outcomes are sensitive to the migration composition in terms of religion.

In this paper, scenarios are built with the purpose of assessing how different models of education would affect projection results in the context of continued current demographic trends. Consequently, all scenarios assume continuation of recent trends for other demographic components of change, such as fertility, mortality, and domestic mobility.

Figure 4 shows the projected proportion of high education in the population aged 25–54 years old. First, concerning scenario GCTE and MDE, because of demographic inertia, the trends for high education are also very similar for the first decades of the projection. This occurs because educational attainment does not change for middle- and old-age adults: adults from the base population are only gradually replaced by new cohorts through a process of demographic metabolism [Ryder (1965)]. At the end of the projection, however, results from the two scenarios differ by about five points, the proportion of post-secondary education being higher in scenario GCTE (52% vs. 48%). To a certain degree, in a scenario such as the GCTE in which no change in trends is explicitly modeled for major factors that are likely to change population composition, we can assume that gross cohort trends implicitly take population composition into account. The usefulness of microsimulation is that it makes it possible to explicitly model both the effects of a change in behavior and the effects of a change in population composition over time and to present the consequences of each on specific results pertaining to different population subgroups.

Different assumptions concerning parameters for the education of the mother may result into very different projection outcomes. The scenario MDE-EduM yields a much higher proportion of high-educated population in 2060 (62%). As shown by the scenario MDE-EduM, giving to children from low-educated mothers the same chance to get a post-secondary degree than those from a high-educated mother is likely to double the expected increase in the proportion of high-educated adults by 2060 compared to the MDE scenario. This outcome highlights the importance of the education of the mother as a driver of future educational trends and the potential gains in terms of future educational trends that can generate a policy aimed at increasing access to high education for children from less educated families. Scenarios MDE-MuslimEq and MDE-MuslimX2 yield about the same trend as MDE. The proportion of high educated is only slightly higher for MDE-MuslimEq and slightly lower for MDE-MuslimX2. Removing the parameter for the Muslim population is indeed unlikely to have a large effect on to whole European population because it only concerns a very small proportion of the population. For similar reasons, doubling the proportion of Muslims among immigrants cannot drastically change general educational trends among the whole population.

Integrating additional variables in the microsimulation model also allows for outputs that go beyond age, sex, and education, and that may thus provide valuable insights to European policy makers. Figure 5, for instance, contrasts the evolution of the proportion of Muslims in the total population and in the population with low

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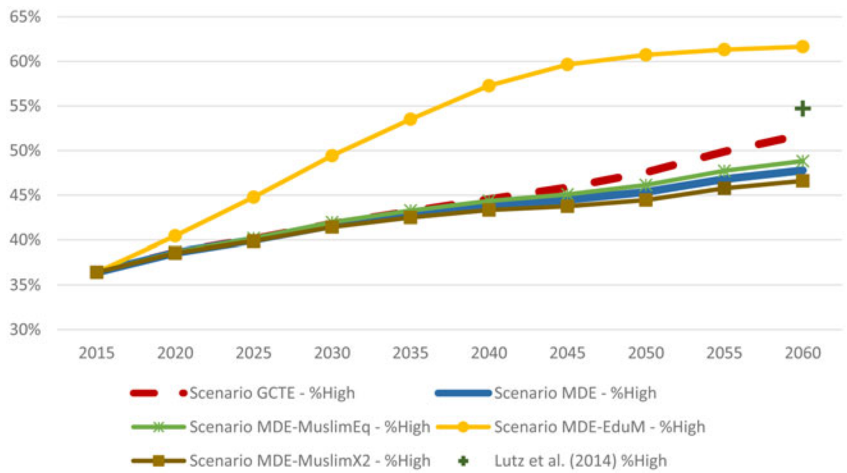

Figure 4. Projected proportion of high education, 25–54 years old, 2015–2060, EU26 (Luxemburg and Malta are excluded).

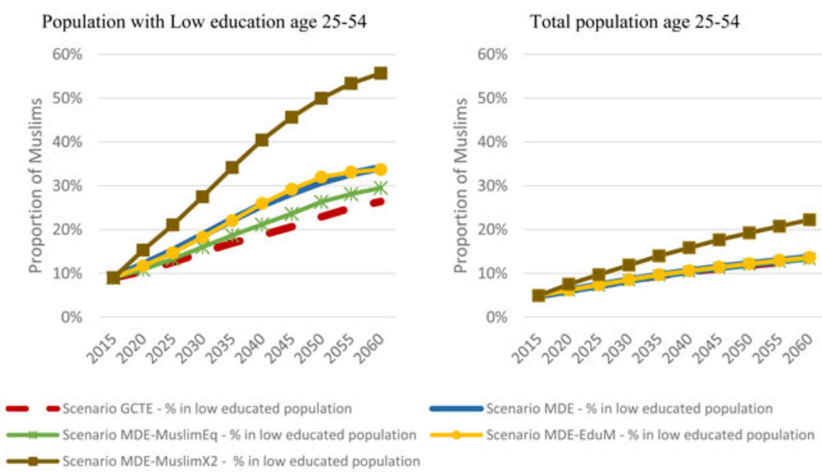

Figure 5. Projected proportion of Muslims in the total population and in the population with low education, age group 25–54, 2015–2060, EU26 (Luxemburg and Malta are excluded).

education (age group 25–54).[9] It also illustrates the analytical possibilities provided by the microsimulation model which can generate outputs with much more dimensions.

Figure 5 shows that for all scenarios, the proportion of Muslims is higher in the starting population and grows faster among the low-educated population than in the total population. In the population with low education, the growth of the proportion

[9]Assumptions concerning shifts in religions, and demographic events are the same in all scenarios. The only difference remains in the modeling of education for new births and immigrants arrived during childhood, and for the immigration composition (in the case of scenario MDE-MuslimX2).

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of Muslims increases about 50% faster in scenario MDE (blue line, left graph) when compared to scenario GCTE (red line, left graph). The proportion of Muslims in the population with low education increases from 9% in 2015 to 34% in 2060 in scenario MDE, compared to 26% in scenario GCTE. In scenario GCTE, the proportion of Muslims in the population with low education grows faster than in the total population solely because of assumptions on the intensity and composition of future immigration flows. In scenario MDE, the proportion of Muslims in the population with low education is also driven up by the religion-specific regression coefficient used in the derivation of educational attainment as well as by parameters for characteristics correlated with Muslims that affect negatively educational attainment (mother's education, region of birth, and language). The difference between scenarios GCTE and MDE in this specific output illustrates the importance of taking sociocultural variables into account in order to measure the impact of immigration on future educational attainment or on social cohesion and inequalities. Given that low-educated women, Muslims, and speakers of non-European languages will likely continue to be overrepresented in future cohorts of international immigrants compared to the native population, the outcome from the model variant MDE appears more plausible than the outcome from GCTE.

We saw that scenarios MDE-MuslimEq and MDE-MuslimX2 only slightly affected the EU28 trend in education. However, when looking at the Muslim population specifically, the effect of these alternative scenarios is much more evident. In 2060, the proportion of Muslims among the low educated is about five points of percent lower in the scenario MDE-MuslimEq compared to the scenario MDE. In opposite, the scenario MDE-MuslimX2 strongly increases the proportion of Muslims not only in the total population (brown line, right graph) (about 22% in 2060 vs. 13%–14% for other scenarios), but particularly among the low educated population (brown line, left graph) (about 55% in 2060 vs. 26%–34% for other scenarios).

In addition to testing how the model reacts to changes in parameters, scenarios MDE-MuslimEq and MDE-MuslimX2 are also examples of the potential of microsimulation in the generation of alternative scenarios to help understanding the interaction among different variables and the potential impact of public policies on education trends. While the scenario MDE-MuslimX2 showed that a change of the composition in immigration might lead into more disparities in education among sociocultural groups, the scenario MDE-MuslimEq revealed that a better access to post-secondary education for Muslim children is likely to reduce significantly those disparities. Such results, moreover, highlight important social fragmentation issues that could emerge from increasing immigration flows to Europe and rising inequalities in education without implementing programs facilitating better integration of the second generation for some population groups at risk of experiencing lower upward social mobility.

6. Conclusion

This paper makes several contributions to the modeling and projection of educational attainment. First, using ordered logistic regressions on ESS data, we have confirmed what had been already demonstrated in the scientific literature, namely that the education of the mother and sociocultural characteristics have a significant impact on educational attainment. In EU countries, mother's education has emerged as the main predictor of children's future educational attainment. Other sociocultural variables, such as being Muslim (especially for women) or speaking a non-European language at home, were also shown to decrease the odds of getting postsecondary education. It is important to stress that these results do not provide hints on the mechanisms involved or on normative actions to be taken. Those issues must be the object of further investigations.

Second, we described the design and structure of the education module in the CEPAM microsimulation model. The module uses a three step process. First, for individuals with incomplete educational paths, a final level of education is stochastically selected based on individual characteristics and parameters obtained from ordered logit regressions. The attributed level of education is then stored in a variable and age at graduation is determined in a second step based on graduation schedules provided by Eurostat. Finally, the life course of the individual is simulated and its education level is updated according to the provided schedule.

Third, the education module was used to further investigate the impact of using a multivariate approach in the modeling of educational attainment instead of using simple assumptions based on gross cohort trends in EU countries. The use of gross cohort trends or MDE in the projection of educational attainment leads to similar projection outcomes for the total population. However, when outputs on specific subpopulations are required, multivariate modeling of educational attainment is preferable because gross cohort trends tend to underestimate the impact of changes in the composition of the future population. The CEPAM microsimulation model can provide a more refined and richer set of outputs than a macro model including only age, sex, and education as dimensions. For instance, based on the assumptions of the model, we have shown that the share of Muslims grows faster in the population with low education than in the general population, possibly raising issues of segmented assimilation and increasing inequalities.

Fourth, different scenarios have been built to analyze how sensitive the modeling of education is to its different drivers of changes. A microsimulation model such as the one developed for the CEPAM project can be useful for policy makers as it can measure the effect of changes along several dimensions, thus allowing for a wide array of "What if" scenarios. For instance, the model can assess the effect of a scenario in which children from mothers with low education have the same probability of getting a post-secondary education as other children. We have shown that a change in the impact of mother's education on children's educational attainment may have a big effect on future trends. It could also investigate the impact of immigration selection, considering that immigrants' characteristics would also affect the education of the second generation.

This paper presented the basic structure of the education module in the CEPAM microsimulation model. In many ways, this is a first iteration and further developments are still required. First, Malta and Luxembourg, which were missing from the pooled data of the ESS, should be modeled properly using other sources of data. Second, because post-secondary education is becoming increasingly relevant in knowledge-based economies, the high level of education should be broken down into three subcategories: postsecondary below bachelor's degree, bachelor's degree, and master's degree or above. To model these additional levels, other sources of data will be necessary, as the sample size of the ESS is too small to make robust estimations. Third, projections presented in this paper are based on a logit extrapolation of net observed cohort trends by sex and country. Other extrapolation assumptions should be explored to identify the best strategy for projecting cohort trends. Finally, with a policy-oriented focus, CEPAM-Mic will further be used to assess the impact on the population of different migration scenarios (in terms of size and composition), as well as scenarios related to changes in inequalities in education.

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Appendix

Table A1. Description of the sample

Country	ISO-code	ESS 2006	ESS 2008	ESS 2010	ESS 2012	ESS 2014	Male	Female	Total
Austria	AT	x		x		x	1,754	1,967	3,721
Belgium	BE	x	x	x	x	x	2,333	2,445	4,778
Germany	DE	x	x	x	x	x	4,256	4,182	8,438
Denmark	DK	x	x	x	x	x	2,482	2,441	4,923
Spain	ES	x	x	x	x	x	2,881	2,966	5,847
Finland	FI	x	x	x	x	x	3,217	3,222	6,439
France	FR	x	x	x	x	x	2,537	2,867	5,404
UK	UK	x	x	x	x	x	2,666	3,291	5,957
Greece	GR		x	x			1,329	1,770	3,099
Ireland	IE	x	x	x	x	x	2,674	3,359	6,033
Italy	IT				x		294	292	586
Luxemburg	LU						0	0	0
Netherland	NL	x	x	x	x	x	2,618	3,016	5,634
Portugal	PT	x	x	x	x	x	2,302	3,518	5,820
Sweden	SE	x	x	x	x	x	2,364	2,424	4,788
Total—EU15							33,707	37,760	71,467
Bulgaria	BG	x	x	x	x		2,306	3,152	5,458
Cyprus	CY	x	x	x	x		1,166	1,422	2,588
Czech Republic	CZ		x	x	x	x	2,771	2,896	5,667

Estonia	EE	x	x	x	x	x	1,890	2,623	4,513
Croatia	HR		x	x			822	1,022	1,844
Hungary	HU	x	x	x	x		1,833	2,204	4,037
Lithuania	LT			x	x	x	1,342	2,124	3,466
Latvia	LV		x				412	672	1,084
Malta	MT						0	0	0
Poland	PL	x	x	x	x	x	2,420	2,728	5,148
Romania	RO		x				635	802	1,437
Slovenia	SI	x	x	x	x	x	1,668	2,018	3,686
Slovakia	SK	x	x	x	x		1,951	2,722	4,673
Total—NMS13							19,216	24,385	43,601

Table A2. Parameters from ordered logit regression on educational attainment

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
NMS13	Male	Intercept		H	0.8927	0.1694	<0.0001
NMS13	Male	Intercept		M	1.9569	0.1767	<0.0001
NMS13	Male	Country	CZ	H	−0.7866	0.2088	0.0002
NMS13	Male	Country	CZ	M	0.8543	0.207	<0.0001
NMS13	Male	Country	EE	H	0.2986	0.451	0.5079
NMS13	Male	Country	EE	M	0.9276	0.5141	0.0712
NMS13	Male	Country	CY	H	−0.5963	0.4928	0.2263
NMS13	Male	Country	CY	M	−1.2656	0.4398	0.004
NMS13	Male	Country	LV	H	0.4572	0.3418	0.181
NMS13	Male	Country	LV	M	0.278	0.3621	0.4427
NMS13	Male	Country	LT	H	0.7791	0.2951	0.0083
NMS13	Male	Country	LT	M	0.5826	0.3205	0.069
NMS13	Male	Country	HU	H	−0.1821	0.2297	0.4279
NMS13	Male	Country	HU	M	−0.0417	0.1941	0.83
NMS13	Male	Country	PL	H	−0.6469	0.1785	0.0003
NMS13	Male	Country	PL	M	0.0242	0.1549	0.876
NMS13	Male	Country	RO	H	−0.163	0.1938	0.4001
NMS13	Male	Country	RO	M	−0.7724	0.1643	<0.0001
NMS13	Male	Country	SI	H	−0.8286	0.3779	0.0283
NMS13	Male	Country	SI	M	0.6991	0.3237	0.0308

NMS13	Male	Country	SK	H	−0.4149	0.2661	0.1189
NMS13	Male	Country	SK	M	1.0233	0.2721	0.0002
NMS13	Male	Country	HR	H	−0.1571	0.2856	0.5823
NMS13	Male	Country	HR	M	0.4694	0.2485	0.0589
NMS13	Male	Cohort		H	−0.1004	0.0323	0.0019
NMS13	Male	Cohort		M	0.2136	0.0324	<0.0001
NMS13	Male	Cohort × country	CZ	H	0.0329	0.0414	0.4279
NMS13	Male	Cohort × country	CZ	M	−0.0975	0.0471	0.0383
NMS13	Male	Cohort × country	EE	H	−0.0194	0.0859	0.8214
NMS13	Male	Cohort × country	EE	M	−0.1723	0.1112	0.1215
NMS13	Male	Cohort × country	CY	H	0.2566	0.0963	0.0077
NMS13	Male	Cohort × country	CY	M	0.1663	0.1006	0.0984
NMS13	Male	Cohort × country	LV	H	−0.00873	0.0677	0.8975
NMS13	Male	Cohort × country	LV	M	−0.0744	0.0826	0.3673
NMS13	Male	Cohort × country	LT	H	0.00665	0.0576	0.9082
NMS13	Male	Cohort × country	LT	M	−0.0743	0.0719	0.3014
NMS13	Male	Cohort × country	HU	H	−0.00223	0.0457	0.961
NMS13	Male	Cohort × country	HU	M	−0.056	0.0442	0.2046
NMS13	Male	Cohort × country	PL	H	0.0785	0.0356	0.0276
NMS13	Male	Cohort × country	PL	M	0.00442	0.0361	0.9025
NMS13	Male	Cohort × country	RO	H	−0.0306	0.0387	0.4281
NMS13	Male	Cohort × country	RO	M	0.00256	0.037	0.9448

(*Continued*)

Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
NMS13	Male	Cohort × country	SI	H	0.1134	0.0727	0.1187
NMS13	Male	Cohort × country	SI	M	−0.1875	0.0693	0.0068
NMS13	Male	Cohort × country	SK	H	0.0103	0.0527	0.8455
NMS13	Male	Cohort × country	SK	M	−0.084	0.0624	0.1784
NMS13	Male	Cohort × country	HR	H	0.047	0.0559	0.4008
NMS13	Male	Cohort × country	HR	M	0.0168	0.0562	0.7653
NMS13	Male	Language	Other EU	H	0.1085	0.0968	0.2624
NMS13	Male	Language	Other EU	M	−0.3562	0.0926	0.0001
NMS13	Male	Language	Non EU	H	−0.4386	0.1599	0.0061
NMS13	Male	Language	Non EU	M	−1.1064	0.1131	<0.0001
NMS13	Male	Religion	Muslim	H	−0.9037	0.3369	0.0073
NMS13	Male	Religion	Muslim	M	−0.8373	0.1778	<0.0001
NMS13	Male	Religion	No religion	H	0.0526	0.0541	0.3309
NMS13	Male	Religion	No religion	M	−0.0618	0.0563	0.2727
NMS13	Male	Religion	Other	H	0.3403	0.1318	0.0098
NMS13	Male	Religion	Other	M	−0.3363	0.1299	0.0096
NMS13	Male	Edu. of the mother	L	H	−2.2466	0.0617	<0.0001
NMS13	Male	Edu. of the mother	L	M	−1.7287	0.1096	<0.0001
NMS13	Male	Edu. of the mother	M	H	−1.3217	0.06	<0.0001
NMS13	Male	Edu. of the mother	M	M	−0.5909	0.1164	<0.0001
NMS13	Female	Intercept		H	0.7411	0.1417	<0.0001

NMS13	Female	Intercept		M	2.0762	0.1562	<0.0001
NMS13	Female	Country	CZ	H	−1.3418	0.1989	<0.0001
NMS13	Female	Country	CZ	M	−0.4824	0.1661	0.0037
NMS13	Female	Country	EE	H	0.273	0.3401	0.4221
NMS13	Female	Country	EE	M	0.7589	0.4297	0.0773
NMS13	Female	Country	CY	H	−1.0799	0.5323	0.0425
NMS13	Female	Country	CY	M	−1.8475	0.4322	<0.0001
NMS13	Female	Country	LV	H	0.3138	0.2543	0.2171
NMS13	Female	Country	LV	M	0.1853	0.2769	0.5035
NMS13	Female	Country	LT	H	1.5018	0.2274	<0.0001
NMS13	Female	Country	LT	M	0.5622	0.2536	0.0266
NMS13	Female	Country	HU	H	−0.9702	0.209	<0.0001
NMS13	Female	Country	HU	M	−0.9909	0.1655	<0.0001
NMS13	Female	Country	PL	H	−0.6516	0.1479	<0.0001
NMS13	Female	Country	PL	M	−0.6505	0.1321	<0.0001
NMS13	Female	Country	RO	H	−1.0118	0.173	<0.0001
NMS13	Female	Country	RO	M	−1.9181	0.146	<0.0001
NMS13	Female	Country	SI	H	−1.2384	0.3459	0.0003
NMS13	Female	Country	SI	M	−1.0502	0.2565	<0.0001
NMS13	Female	Country	SK	H	−1.0006	0.2347	<0.0001
NMS13	Female	Country	SK	M	−0.3613	0.1919	0.0598
NMS13	Female	Country	HR	H	−0.3594	0.2625	0.1711

(*Continued*)

Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
NMS13	Female	Country	HR	M	−0.7448	0.2078	0.0003
NMS13	Female	Cohort		H	0.00771	0.0256	0.7633
NMS13	Female	Cohort		M	0.2214	0.0282	<0.0001
NMS13	Female	Cohort × country	CZ	H	0.0234	0.0371	0.5275
NMS13	Female	Cohort × country	CZ	M	−0.00745	0.0386	0.8469
NMS13	Female	Cohort × country	EE	H	0.0908	0.0661	0.169
NMS13	Female	Cohort × country	EE	M	−0.059	0.1033	0.5678
NMS13	Female	Cohort × country	CY	H	0.2937	0.0983	0.0028
NMS13	Female	Cohort × country	CY	M	0.1978	0.0915	0.0307
NMS13	Female	Cohort × country	LV	H	0.0368	0.05	0.4621
NMS13	Female	Cohort × country	LV	M	−0.00329	0.0698	0.9625
NMS13	Female	Cohort × country	LT	H	−0.07	0.0447	0.1172
NMS13	Female	Cohort × country	LT	M	−0.03	0.0603	0.619
NMS13	Female	Cohort × country	HU	H	0.0844	0.0393	0.0318
NMS13	Female	Cohort × country	HU	M	0.0475	0.0386	0.2183
NMS13	Female	Cohort × country	PL	H	0.0985	0.0286	0.0006
NMS13	Female	Cohort × country	PL	M	0.1206	0.0318	0.0001
NMS13	Female	Cohort × country	RO	H	0.0763	0.0321	0.0174
NMS13	Female	Cohort × country	RO	M	0.146	0.0324	<0.0001
NMS13	Female	Cohort × country	SI	H	0.1558	0.0636	0.0143
NMS13	Female	Cohort × country	SI	M	0.0688	0.0588	0.2417

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NMS13	Female	Cohort × country	SK	H	0.0554	0.0438	0.2061
NMS13	Female	Cohort × country	SK	M	0.0634	0.0464	0.1719
NMS13	Female	Cohort × country	HR	H	0.0379	0.0472	0.4219
NMS13	Female	Cohort × country	HR	M	0.1378	0.0454	0.0024
NMS13	Female	Language	Other EU	H	−0.1811	0.0757	0.0167
NMS13	Female	Language	Other EU	M	−0.5994	0.0648	<0.0001
NMS13	Female	Language	Non EU	H	−0.5045	0.1424	0.0004
NMS13	Female	Language	Non EU	M	−1.3627	0.0994	<0.0001
NMS13	Female	Religion	Muslim	H	−0.8617	0.2436	0.0004
NMS13	Female	Religion	Muslim	M	−1.4238	0.1564	<0.0001
NMS13	Female	Religion	No religion	H	0.127	0.0489	0.0093
NMS13	Female	Religion	No religion	M	−0.00239	0.0504	0.9621
NMS13	Female	Religion	Other	H	0.00982	0.1114	0.9297
NMS13	Female	Religion	Other	M	−0.3836	0.1046	0.0002
NMS13	Female	Edu. of the mother	L	H	−2.2952	0.0588	<0.0001
NMS13	Female	Edu. of the mother	L	M	−1.8836	0.1021	<0.0001
NMS13	Female	Edu. of the mother	M	H	−1.2133	0.0581	<0.0001
NMS13	Female	Edu. of the mother	M	M	−0.4468	0.1079	<0.0001
EU15	Male	Intercept		H	0.3625	0.192	0.0591
EU15	Male	Intercept		M	0.9193	0.1787	<0.0001
EU15	Male	Country	DK	H	0.0861	0.2922	0.7683
EU15	Male	Country	DK	M	1.2727	0.2618	<0.0001

(*Continued*)

Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
EU15	Male	Country	DE	H	0.4623	0.1937	0.017
EU15	Male	Country	DE	M	2.7868	0.1883	<0.0001
EU15	Male	Country	IE	H	−0.5715	0.3521	0.1045
EU15	Male	Country	IE	M	−0.3518	0.2992	0.2397
EU15	Male	Country	GR	H	−0.3365	0.2624	0.1998
EU15	Male	Country	GR	M	−0.4268	0.2246	0.0574
EU15	Male	Country	ES	H	−0.6796	0.2112	0.0013
EU15	Male	Country	ES	M	−0.7926	0.1827	<0.0001
EU15	Male	Country	FR	H	−0.4812	0.2051	0.019
EU15	Male	Country	FR	M	0.6187	0.1767	0.0005
EU15	Male	Country	IT	H	−0.9199	0.214	<0.0001
EU15	Male	Country	IT	M	−0.4134	0.1772	0.0197
EU15	Male	Country	NL	H	0.6612	0.2227	0.003
EU15	Male	Country	NL	M	1.1749	0.2038	<0.0001
EU15	Male	Country	AT	H	−0.3365	0.2771	0.2247
EU15	Male	Country	AT	M	1.3118	0.2722	<0.0001
EU15	Male	Country	PT	H	−1.8146	0.3673	<0.0001
EU15	Male	Country	PT	M	−1.6591	0.2715	<0.0001
EU15	Male	Country	FI	H	0.3297	0.2858	0.2486
EU15	Male	Country	FI	M	0.3685	0.2625	0.1604
EU15	Male	Country	SE	H	0.2233	0.2565	0.3838

EU15	Male	Country	SE	M	0.8157	0.2376	0.0006
EU15	Male	Country	UK	H	0.1798	0.2015	0.3722
EU15	Male	Country	UK	M	0.7467	0.1768	<0.0001
EU15	Male	Cohort		H	0.0424	0.0356	0.2336
EU15	Male	Cohort		M	0.2068	0.0336	<0.0001
EU15	Male	Cohort × country	DK	H	−0.0757	0.0581	0.1927
EU15	Male	Cohort × country	DK	M	−0.1619	0.0568	0.0044
EU15	Male	Cohort × country	DE	H	−0.0476	0.0374	0.2025
EU15	Male	Cohort × country	DE	M	−0.2309	0.0391	<0.0001
EU15	Male	Cohort × country	IE	H	0.1145	0.0668	0.0866
EU15	Male	Cohort × country	IE	M	0.0231	0.0615	0.7077
EU15	Male	Cohort × country	GR	H	0.1	0.049	0.0415
EU15	Male	Cohort × country	GR	M	0.0901	0.0454	0.0471
EU15	Male	Cohort × country	ES	H	0.1468	0.0399	0.0002
EU15	Male	Cohort × country	ES	M	0.0288	0.0369	0.4357
EU15	Male	Cohort × country	FR	H	0.0427	0.0392	0.276
EU15	Male	Cohort × country	FR	M	−0.0222	0.0368	0.5465
EU15	Male	Cohort × country	IT	H	0.0506	0.0412	0.2196
EU15	Male	Cohort × country	IT	M	−0.0024	0.0365	0.9475
EU15	Male	Cohort × country	NL	H	−0.0185	0.0439	0.6735
EU15	Male	Cohort × country	NL	M	−0.1164	0.043	0.0068
EU15	Male	Cohort × country	AT	H	0.0194	0.0536	0.7167

(*Continued*)

Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
EU15	Male	Cohort × country	AT	M	0.0192	0.0619	0.7559
EU15	Male	Cohort × country	PT	H	0.1491	0.0681	0.0285
EU15	Male	Cohort × country	PT	M	0.0244	0.0524	0.642
EU15	Male	Cohort × country	FI	H	−0.0488	0.0573	0.3938
EU15	Male	Cohort × country	FI	M	0.0412	0.0601	0.4936
EU15	Male	Cohort × country	SE	H	−0.0476	0.0502	0.3432
EU15	Male	Cohort × country	SE	M	0.0698	0.0557	0.2102
EU15	Male	Cohort × country	UK	H	−0.0184	0.039	0.6365
EU15	Male	Cohort × country	UK	M	−0.1122	0.0368	0.0023
EU15	Male	Language	Other EU	H	0.1702	0.1145	0.137
EU15	Male	Language	Other EU	M	0.1811	0.1026	0.0776
EU15	Male	Language	Non EU	H	−0.0924	0.1519	0.543
EU15	Male	Language	Non EU	M	−0.1306	0.1212	0.281
EU15	Male	Region of birth	Other Europe	H	−0.9449	0.2294	<0.0001
EU15	Male	Region of birth	Other Europe	M	−0.376	0.1771	0.0337
EU15	Male	Region of birth	North Africa	H	0.3322	0.2251	0.14
EU15	Male	Region of birth	North Africa	M	0.3617	0.1784	0.0426
EU15	Male	Region of birth	Other Africa	H	0.6317	0.2174	0.0037
EU15	Male	Region of birth	Other Africa	M	0.1444	0.2252	0.5215
EU15	Male	Region of birth	Latin America	H	0.1393	0.2263	0.538
EU15	Male	Region of birth	Latin America	M	0.7335	0.2458	0.0028

EU15	Male	Region of birth	East, South, and South-East Asia	H	0.00767	0.2449	0.975
EU15	Male	Region of birth	East, South, and South-East Asia	M	−0.1623	0.2217	0.4643
EU15	Male	Region of birth	Near and Middle East	H	−0.1819	0.2385	0.4458
EU15	Male	Region of birth	Near and Middle East	M	−0.6343	0.2429	0.009
EU15	Male	Religion	Muslim	H	−0.4974	0.1486	0.0008
EU15	Male	Religion	Muslim	M	−0.7792	0.1246	<0.0001
EU15	Male	Religion	No religion	H	−0.0251	0.0275	0.3622
EU15	Male	Religion	No religion	M	−0.0502	0.0278	0.0705
EU15	Male	Religion	Other	H	0.2543	0.0897	0.0046
EU15	Male	Religion	Other	M	−0.5068	0.0865	<0.0001
EU15	Male	Edu. of the mother	L	H	−1.8587	0.0493	<0.0001
EU15	Male	Edu. of the mother	L	M	−1.6995	0.0735	<0.0001
EU15	Male	Edu. of the mother	M	H	−0.937	0.0531	<0.0001
EU15	Male	Edu. of the mother	M	M	−0.5507	0.085	<0.0001
EU15	Female	Intercept		H	−0.211	0.2121	0.3199
EU15	Female	Intercept		M	0.5818	0.1832	0.0015
EU15	Female	Country	DK	H	0.4645	0.3149	0.1401
EU15	Female	Country	DK	M	0.8557	0.2654	0.0013
EU15	Female	Country	DE	H	−0.024	0.2187	0.9127
EU15	Female	Country	DE	M	1.4386	0.1832	<0.0001
EU15	Female	Country	IE	H	−0.2017	0.3683	0.5839
EU15	Female	Country	IE	M	−0.1273	0.3009	0.6722

(*Continued*)

Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
EU15	Female	Country	GR	H	−0.5977	0.2941	0.0421
EU15	Female	Country	GR	M	−0.7036	0.235	0.0028
EU15	Female	Country	ES	H	−1.0165	0.2393	<0.0001
EU15	Female	Country	ES	M	−1.1661	0.1948	<0.0001
EU15	Female	Country	FR	H	−0.1859	0.2259	0.4106
EU15	Female	Country	FR	M	0.2342	0.1835	0.2018
EU15	Female	Country	IT	H	−0.6168	0.2409	0.0105
EU15	Female	Country	IT	M	−0.3964	0.1892	0.0362
EU15	Female	Country	NL	H	0.4966	0.2521	0.0488
EU15	Female	Country	NL	M	0.2896	0.2106	0.169
EU15	Female	Country	AT	H	−0.3143	0.3141	0.317
EU15	Female	Country	AT	M	0.8638	0.2492	0.0005
EU15	Female	Country	PT	H	−1.0886	0.3212	0.0007
EU15	Female	Country	PT	M	−1.7161	0.2598	<0.0001
EU15	Female	Country	FI	H	0.6687	0.2977	0.0247
EU15	Female	Country	FI	M	0.6869	0.266	0.0098
EU15	Female	Country	SE	H	1.0379	0.2709	0.0001
EU15	Female	Country	SE	M	1.3758	0.2524	<0.0001
EU15	Female	Country	UK	H	0.422	0.2221	0.0574
EU15	Female	Country	UK	M	0.3293	0.1833	0.0723
EU15	Female	Cohort		H	0.2133	0.0378	<0.0001

EU15	Female	Cohort		M	0.3108	0.0352	<0.0001
EU15	Female	Cohort × country	DK	H	−0.1159	0.0595	0.0514
EU15	Female	Cohort × country	DK	M	−0.0895	0.0585	0.1261
EU15	Female	Cohort × country	DE	H	−0.0569	0.04	0.1549
EU15	Female	Cohort × country	DE	M	−0.1172	0.0384	0.0023
EU15	Female	Cohort × country	IE	H	0.0421	0.0663	0.5255
EU15	Female	Cohort × country	IE	M	0.0312	0.0615	0.6113
EU15	Female	Cohort × country	GR	H	0.0909	0.0515	0.0777
EU15	Female	Cohort × country	GR	M	0.0942	0.0462	0.0417
EU15	Female	Cohort × country	ES	H	0.1824	0.0428	<0.0001
EU15	Female	Cohort × country	ES	M	0.0837	0.0391	0.0321
EU15	Female	Cohort × country	FR	H	−0.0106	0.0409	0.7959
EU15	Female	Cohort × country	FR	M	0.0192	0.0379	0.6128
EU15	Female	Cohort × country	IT	H	−0.00654	0.0432	0.8796
EU15	Female	Cohort × country	IT	M	−0.0146	0.0383	0.7028
EU15	Female	Cohort × country	NL	H	−0.0747	0.0465	0.1082
EU15	Female	Cohort × country	NL	M	−0.0119	0.0435	0.7837
EU15	Female	Cohort × country	AT	H	−0.0523	0.0566	0.3551
EU15	Female	Cohort × country	AT	M	−0.0954	0.0517	0.0649
EU15	Female	Cohort × country	PT	H	0.0467	0.0578	0.4189
EU15	Female	Cohort × country	PT	M	0.0484	0.0497	0.3308
EU15	Female	Cohort × country	FI	H	−0.0593	0.0576	0.3035

(*Continued*)

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Table A2. (*Continued.*)

Region	Sex	Variable	ClassVal0	Response	Estimate	StdErr	ProbChiSq
EU15	Female	Cohort × country	FI	M	0.0414	0.0644	0.5202
EU15	Female	Cohort × country	SE	H	−0.1603	0.0512	0.0018
EU15	Female	Cohort × country	SE	M	0.0409	0.0617	0.5076
EU15	Female	Cohort × country	UK	H	−0.1095	0.0407	0.0072
EU15	Female	Cohort × country	UK	M	−0.0867	0.0378	0.022
EU15	Female	Language	Other EU	H	0.2085	0.0936	0.0259
EU15	Female	Language	Other EU	M	0.2357	0.0888	0.008
EU15	Female	Language	Non EU	H	−0.4621	0.1682	0.006
EU15	Female	Language	Non EU	M	−0.0724	0.1445	0.6164
EU15	Female	Region of birth	Other Europe	H	0.0564	0.1766	0.7494
EU15	Female	Region of birth	Other Europe	M	−0.5159	0.1655	0.0018
EU15	Female	Region of birth	North Africa	H	−0.395	0.3314	0.2333
EU15	Female	Region of birth	North Africa	M	0.5554	0.2287	0.0152
EU15	Female	Region of birth	Other Africa	H	−0.042	0.2432	0.863
EU15	Female	Region of birth	Other Africa	M	−0.5557	0.2267	0.0142
EU15	Female	Region of birth	Latin America	H	0.2794	0.1615	0.0836
EU15	Female	Region of birth	Latin America	M	0.6633	0.1713	0.0001
EU15	Female	Region of birth	East, South, and South-East Asia	H	0.6507	0.2355	0.0057
EU15	Female	Region of birth	East, South, and South-East Asia	M	−0.1314	0.2372	0.5796
EU15	Female	Region of birth	Near and Middle East	H	−0.904	0.2657	0.0007
EU15	Female	Region of birth	Near and Middle East	M	−0.9921	0.2188	<0.0001

EU15	Female	Religion	Muslim	H	−0.4236	0.1469	0.0039
EU15	Female	Religion	Muslim	M	−1.3191	0.1217	<0.0001
EU15	Female	Religion	No religion	H	−0.0432	0.028	0.1225
EU15	Female	Religion	No religion	M	−0.0352	0.027	0.1918
EU15	Female	Religion	Other	H	0.3246	0.0843	0.0001
EU15	Female	Religion	Other	M	−0.1478	0.0806	0.0665
EU15	Female	Edu. of the mother	L	H	−2.1112	0.0474	<0.0001
EU15	Female	Edu. of the mother	L	M	−1.9026	0.068	<0.0001
EU15	Female	Edu. of the mother	M	H	−1.0908	0.0516	<0.0001
EU15	Female	Edu. of the mother	M	M	−0.5006	0.0785	<0.0001

Source: Pooled data of ESS (2006 to 2014); authors' calculations.