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A Microsimulation Approach for Modelling the Future Human Capital of EU28 Member Countries

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Working Paper **WP-17-017**

A Microsimulation Approach for Modelling the Future Human Capital of EU28 Member Countries

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Abstract

In knowledge-based economies, human capital is a major determinant of labor force participation and productivity and has received growing interest from researchers and policy makers alike. Recently, the Wittgenstein Centre for Demography and Global Human Capital (WiC) performed macro-level projections by age, sex and education for all countries in the world. Projections of education in this model are computed based on past trends at the macro level by cohort and sex. This working paper uses data from five waves of the European Social Survey and ordered logistic regressions to estimate the impact of additional dimensions on educational attainment in EU28 countries. Variables included in the model are cohort year, sex, religion, language, immigration status and education of the mother. Cohort analysis allowed us to estimate educational trends net of individual characteristics. Analysis showed that the most important determinant of educational attainment was the education of the mother, but that other ethno-cultural factors such as religion and language spoken at home also played a role. Cohort trends net of individual characteristics varied significantly from country to country, with many countries having low or even null improvement in educational attainment for recent cohorts, most notably in Eastern Europe. The parameters derived from this analysis are used as inputs to a European microsimulation model including several dimensions beyond age, sex and education, many of which will be used to assess future immigrant integration in Europe. Preliminary results from the projections show that net and gross trends yield similar results in many countries where net trends are still dominant, but significant differences emerge in other countries in which net trends are low or null. The microsimulation model also allows for a better appreciation of dynamics in population sub-groups, for instance in rising concerns about potentially growing inequalities, notably for Muslims.

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A Microsimulation Approach for Modelling the Future Human Capital of EU28 Member Countries

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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 was highlighted by several researchers (Lutz et al. 1998; Lutz 2010). Indeed, education has been shown to influence fertility and mortality levels, as well as migration rates (Castro Martin & Juarez 1995; Valkonen 2006; Docquier & Marfouk 2004; Skirbekk 2008; Kravdal & Rindfuss 2008). Education will likely have a significant impact on population growth and should be included as a dimension in projection models, in addition to age and sex. The Wittgenstein Centre's worldwide multistate projections showed that 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 Cuaresma et al. 2014; Loichinger 2015; Loichinger & 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 modelling of educational attainment for a microsimulation projection model of the EU-28 countries developed within the framework of a larger project called CEPAM. 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. The CEPAM microsimulation model (CEPAM-Mic) includes – in addition to age, sex and education – education of mothers and sociocultural variables that are themselves determinants of educational attainment. These additional dimensions allow for a more refined modelling of education, and, by extension, can lead to an improvement in the overall quality of the projections and to an increase in the value of derived projections 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.

Accounting for such variables in projection models has been made necessary by the changing composition of the population of several countries due to significant influx of immigrants (Coleman 2006). The resulting diversity is not only a matter of country of birth, but spans many other dimensions (language spoken, religion, etc.), simultaneously, leading Vertovec to call the phenomenon a "diversification of diversity" or superdiversity (Vertovec 2007).

Since demographic behaviors and socio-economic outcomes of immigrants differ from natives, and since the immigrant population is growing fast, taking these differentials into account becomes more and more important. Moreover, new cohorts of migrants and their children contribute to social change through a process that, following Norman Ryder, Lutz has called "demographic metabolism" (Ryder 1965; Lutz 2013).

Conventional multistate models are poorly adapted to the simultaneous projection of a large number of individual characteristics or attributes. A new methodological paradigm had therefore to be adopted: microsimulation. Microsimulation is a powerful tool that can be used to make population projections when the number of dimensions becomes large (Van Imhoff & Post 1998). There is also an emerging consensus about the usefulness of this type of models for population projections in general. In these type of model, individuals from the base population are simulated one by one and their characteristics are modified through scheduled events whose timing are determined by the values of their specific input parameters at any given time during the projection period. Since the simulation is performed at the level of individuals, this method allows keeping individuals records over life course and across generations. For newborns, for example, we can keep track of the mother's characteristics, such as her education, and use these as determinants of further events.

The power and flexibility of microsimulation allows for the inclusion of 11 dimensions to the CEPAM-Mic model: region of residence, age, sex, educational attainment, educational attainment of mother, immigrant status, age at arrival in host country, religion, language spoken, labor force participation and employment.

This paper presents the argumentative and empirical bases for the development of the education module. First, we discuss the necessity of including additional sources of heterogeneity in order to model the future evolution of educational attainment. Second, we describe the education module of the microsimulation model. We show the net effect of the mother's education and sociocultural variables on the educational attainment of EU28 residents and make assumptions on how these variables will affect cohort trends. Finally, we show the results of a sensitivity analysis obtained by comparing two scenarios of population projection, one using only gross cohort trends and the other using specific parameters for all variables.

2 Assumptions on future educational trends: Including the education of the mother and sociocultural determinants

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

& Gintis 1976; Hertz et al. 2008; Kogan et al. 2012). Evidence shows that this type of intergenerational transfers occurs consistently in all developed nations and has remained stable since the Second World War (Shavit & Blossfeld 1993; Erikson & Goldthorpe 1992; Pfeffer 2008). An illustration of this is shown in Figure 1 for EU15 and New Member States (NMS13) countries[1], which differ substantially in terms of global educational attainment. In the EU15, 40% of males whose mother has Low education also have a Low education (below secondary), while this proportion drops below 10% when the mother has Medium (secondary level) or High education (postsecondary)[2]. At the other end of the spectrum, only 21% of males whose mother has a Low education completed a postsecondary degree, while this proportion exceeds 65% when the mother has a High level. This pattern also holds for females and in the NMS13 countries.

Education of parents proves to be an even better determinant of a child's educational attainment than the occupation of the father (Shavit et al. 2007). This transmission of human capital is caused mainly by family characteristics and inherited ability, which are correlated with education level (Black et al. 2003). 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). As described metaphorically by Black et al. (2003), the apple never falls far from the tree.

Along with the education of the parents, 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 (Riphahn 2003; Hirschman 2001). Global expansion in higher education in the USA was shown to have been depressed by compositional effect, the expansion having been slower for Blacks and Hispanics than for Whites (Barakat & Durham 2014). Figure 2 illustrates these differences in the EU15 and NMS13 countries with respect to language spoken at home, religion and immigrants status.

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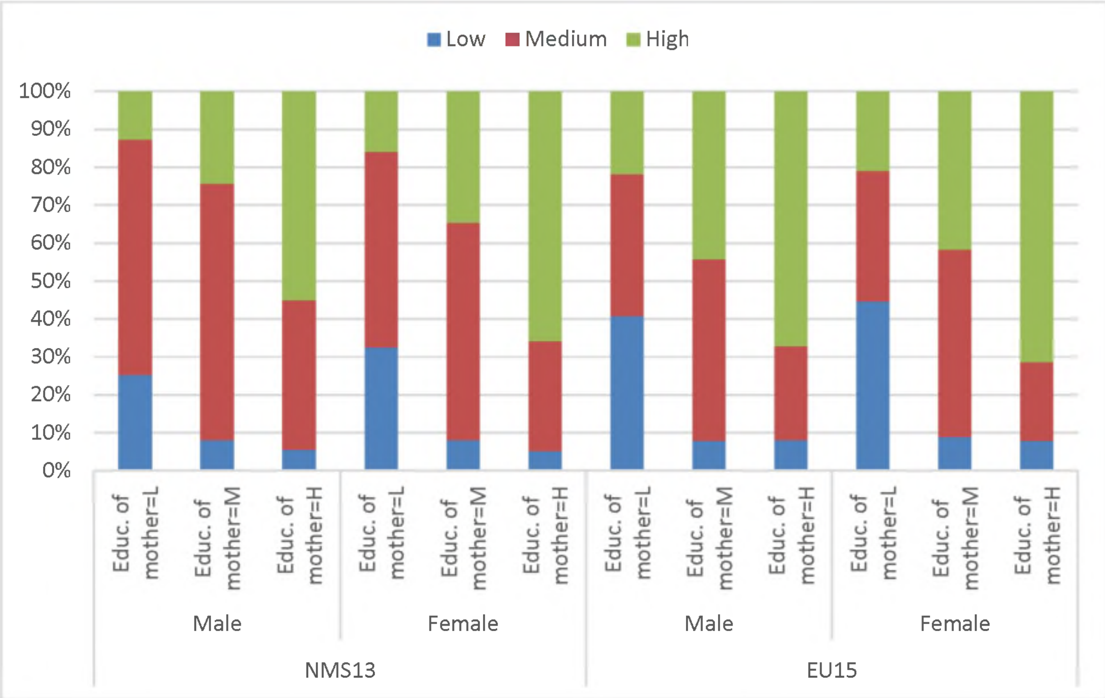
[1] EU15 (European Union 15) includes: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain, Sweden and the United Kingdoms. NMS13 includes: Bulgaria, Cyprus, Czech Republic, Croatia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

[2] For more details, see Section 4.1.

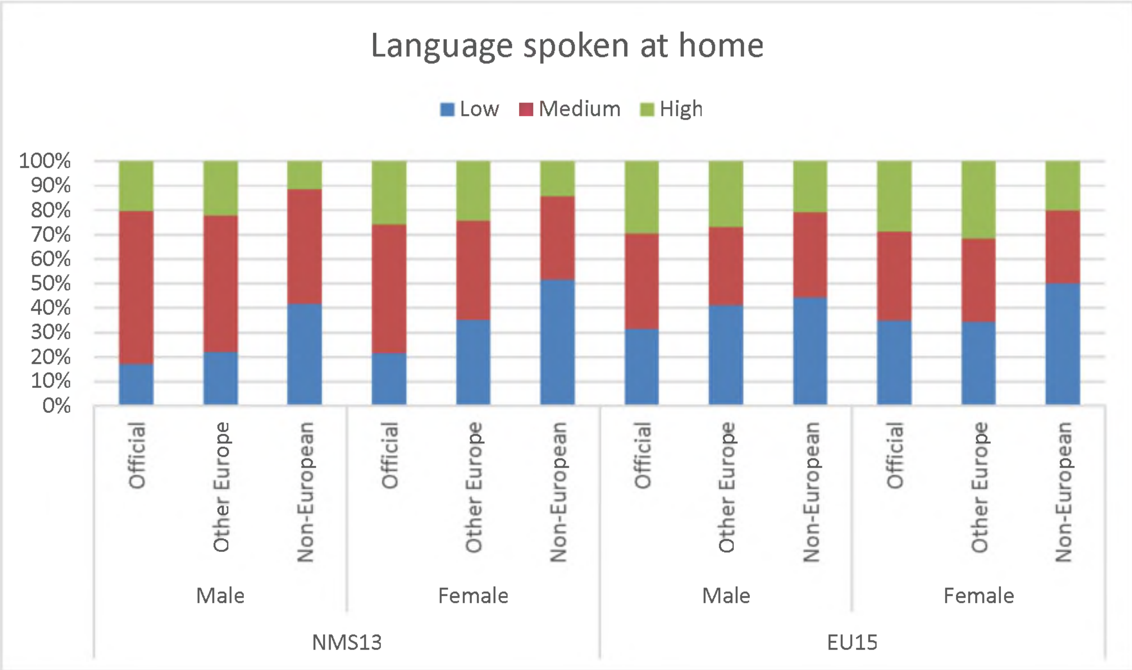
Figure 1: Educational attainment (Low, Medium or High) according to mother's education, birth cohorts 1940-1979

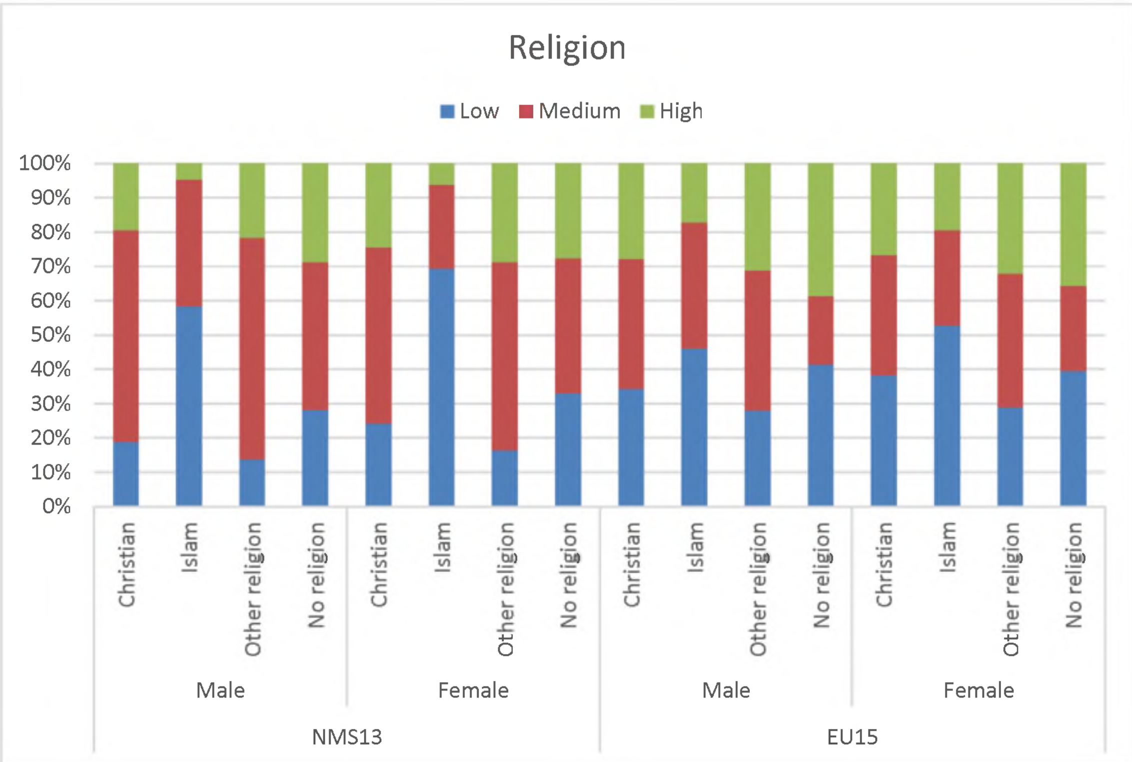


Source: Pooled data of ESS 2006 to 2014. See data section for details on variables and categories.

Figure 2 shows some interesting results. For European-born and immigrants arrived before the age of 25, the proportion of lower education is much higher when a non-European language is spoken at home, compared to when an European language is used, and the proportion of higher education is lower. Another significant result is linked to religion. Compared to other religious groups, Muslims show a higher proportion of lower education and a correspondingly lower proportion of higher education. Few variations are observed among other religious groups. This pattern is observed for both sexes and in both regions, although the gap is wider in NMS13 than in EU15 countries. Among contextual factors explaining these differences, we can state that sociocultural variables are associated with specific issues and inequalities related to neighborhoods and schools conditions (Gronqvist 2006; Pong & Hao 2007), as well as unequal access to resources (Zhou 2009).

Figure 2: Educational attainment according to sociocultural characteristics, European-born and immigrants arrived before age 25, cohorts 1940-1979





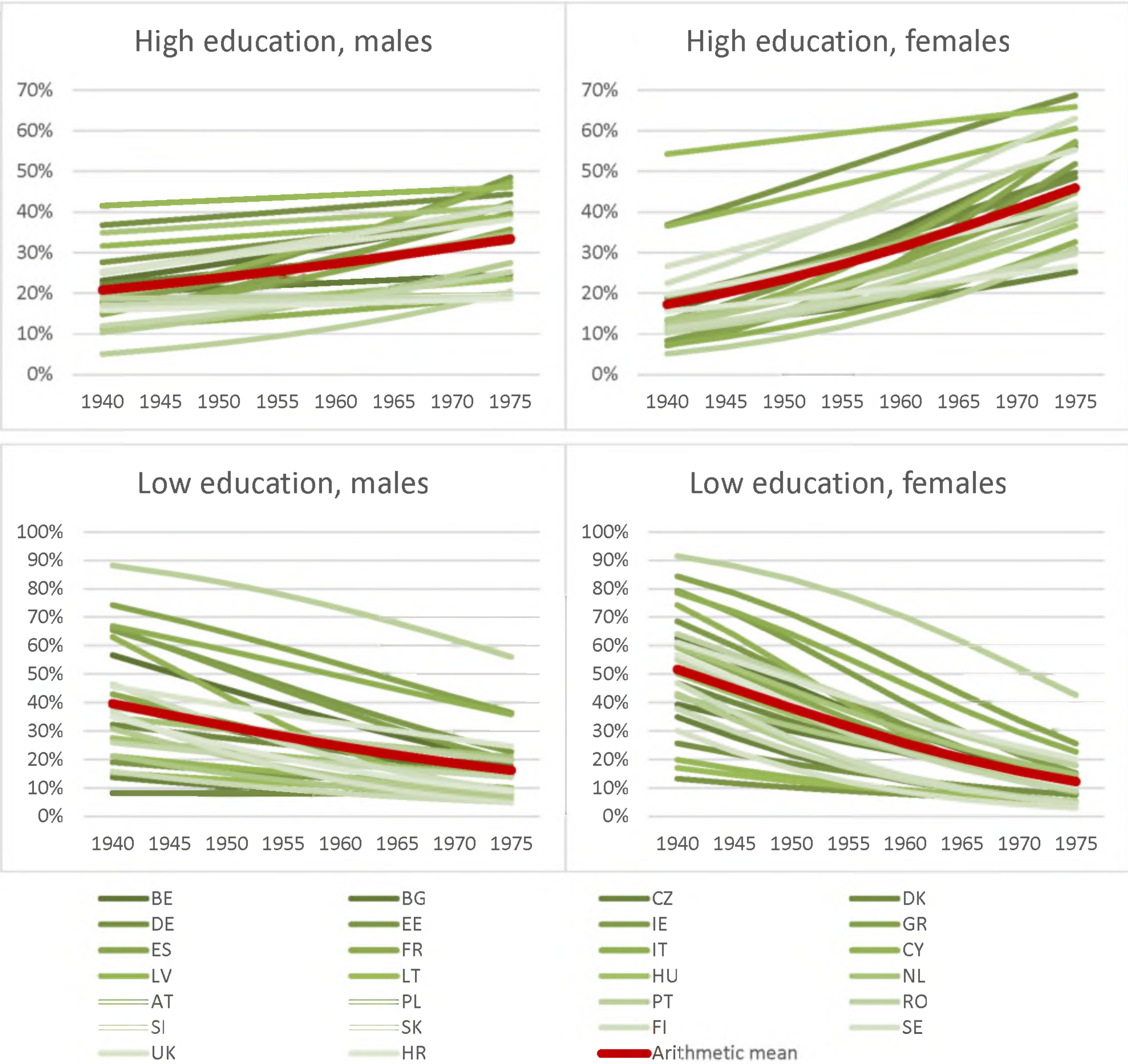
Source: Pooled data of ESS 2006 to 2014. See data section for details on variables and categories.

Over the 20th century, the massification of education has been a worldwide phenomenon, resulting in a rapid growth in 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) underlines the positive impact of increasing 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 & 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 & Durham 2014). Through a domino effect, this improvement in lower levels of education had positive repercussions on postsecondary enrolment (Altbach et al. 2009).

Figure 3 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. The decline has occurred at a stronger pace for females when compared to males, as well as in countries lagging 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 51.6% (standard deviation=20.3%) for the cohort 1940-1944 to 12.2% (s.d.=8.3%) for the cohort 1975-1979, and for males from 39.6% (s.d.= 20.2%) to 16.2% (s.d.=11.4%). Despite this general decline in Low education, significant gaps remain between EU28 countries. For instance, the range in the proportion of low-educated population varies from 2.9% (females born in Sweden) to 56.0% (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 that females born between 1975 and 1979 were more likely to get a postsecondary degree than males of the same cohorts. 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 17.3% (s.d.=10.6%) to 45.9% (s.d.=12.1%) for females, and from 20.8% (s.d.=8.2%) to 33.3% (s.d.=9.8%) for males. Interestingly, and contrary to what was observed for Low education, Figure 3 shows that there is no evidence of convergence between countries in postsecondary educational attainment.

Figure 3: Evolution of educational attainment across cohorts (%) for European-born and immigrants arrived before age 25, by country



Source: Pooled data of ESS 2006 to 2014. See data section for details on variables and categories.

Previous projections of education used a multistate method in a dynamic modeling 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 cohort, it might be reasonable to assume that past trends would continue for further generations. This would be called the *gross cohort trend*. However, as was shown in Figure 1 and 2, educational attainment varies according to the individual's sociocultural characteristics and the education of the mother, so that observed trends across cohorts may change 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. Then, observed changes at the aggregated level can be explained by changes in the composition of the population rather than changes of relationships at the micro level. Since cohorts' educational attainment is inextricably linked to the evolution of sociocultural variables and education of mothers, 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, in other words, by 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 of the parents, even as the net cohort trend stratified by parents' education stagnate or decrease. Then, if stability exists in the main driver of one's education attainment – the relationship between the education level of the parents and one's education level – considering this relationship explicitly in the forecasting model should improve its predictive capacity.

In addition to this, if holding everything else constant, the effects of ethnocultural characteristics, such as religion and language remains statistically significant, on the educational attainment remains, it becomes necessary to take these characteristics into account as well. Increasing sociocultural diversity in developed nations may have a significant impact on future educational attainment, as immigration is becoming the main driver of population growth.

3 The CEPAM-Mic's education module

CEPAM-Mic is a dynamic, continuous time, event-based, open and spatial microsimulation projection model of the EU-28 population programmed in the Modgen language[3]. Its starting population is based on the merged microdata files of the 2014-2015 European Union Labour Force Survey (EU-LFS) and was reweighted to fit the observed distribution by country, age, sex, education level and immigration status according to the Eurostat Census database. The EU-LFS has the advantage of providing several years of consistent and harmonized data for all countries and has a large sample size (typical yearly data files contain between four and five million cases). Projection scenarios are established according to specific sets of assumptions on both the general level of each phenomenon and the characteristic-specific differentials between individuals at risk of experiencing the event. For example, the fertility module allows for both changes in total fertility level over time and in fertility differentials according to the women's characteristics. A detailed description of the microsimulation model is included in other papers (Bélanger et al. Forthcoming; Marois et al. 2017).

Determination of educational attainment in the CEPAM-Mic model is performed in three steps.

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

Step 1. Determining educational attainment

This first step constitutes the core of the education module and requires robust parameters from generalized ordered logit regressions on education level. When an individual is born, a latent variable indicates the highest level of education that will be reached in his lifetime. This is also done for immigrants arrived before their twentieth birthday and for individuals aged less than 30 in the base population. The analysis required for this step are presented in the next section.

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. Schedule of education

For those reaching at least upper secondary level, the age at graduation is determined for all degrees from Eurostat distributions by ISCED levels for the latest graduated cohorts (2013-2014). For those scheduled to complete a postsecondary level, the education module first establishes age at graduation for the postsecondary 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 United Kingdom for Medium education), the average distribution of comparable countries was used as an approximation.

Unfortunately, education schedules are not detailed according to socio-economic characteristics or education of mothers and data quality sometimes appears questionable for certain countries. Nevertheless, we assume that variations due to noise or to individual characteristics 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. Because education is set up as a latent variable, actual changes in education does not occur immediately, but only later at the predetermined age at graduation. If the individual survives until graduation age, the education state variable changes to reflect the appropriate educational attainment. Since the education variable is used for the modeling of other demographic events, a change in education immediately affects internal migration, mortality and fertility rates as well as labor force participation and employment.

4 Trends and determinants of educational attainment

4.1 Data

The first step in the development of the education module involves the exhaustive analysis of trends and determinants of educational attainment. It requires a microdata set that includes variables that are relevant and comparable across countries. Although the EU-LFS has a big 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[4].

Despite its smaller sample, the European Social Survey (EU-ESS) was thus preferred to the EU-LFS for the analysis of educational attainment. Five cycles of the EU-ESS (2006 to 2014) were pooled and reweighted in order to match the base population of the projection model (according to country/age/sex/region of birth/education)[5]. Of the 28 EU countries, 13 participated in all five cycles, 13 were missing from at least one cycle and 2 were completely missing (Luxemburg and Malta)[6].

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). Table 1 presents a synthetic description of the sample size for all countries. Variables included in the analysis are described in Section 4.1.2.

4.1.1 Education

Educational attainment is the dependent variable and is divided in 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+).

4.1.2 Independent variables

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.
- Immigration status; Born in country, Immigrants.
- Religion; Christian, Muslim, Other religion, 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 of federal level.

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[4] 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.
[5] Before calibration, age is adjusted to what it was in 2011 using millesimal difference. For some countries, no data on immigrant status is provided in the 2011 Census Data Hub: Only age, sex and education are then used for reweighting.
[6] These two later countries are thus excluded from the analysis presented in this paper.
[7] Individuals below 30 years old at the time of the survey are excluded in order to avoid analysis on incomplete education paths.

Table 1: 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
United Kingdom	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**

4.2 Multivariate analysis

A generalized ordered logit model incorporating all the variables described Section 4.1 was used for the analysis. Because the sample size was insufficient to build stratified country-specific models, countries were grouped into two large regions (EU15/NMS13).

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. This effect is captured by an interaction variable between the cohort and the country. The model equation is thus formulated as follows:

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

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;

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 the Appendix. For the sake of simplicity, we focus our analysis on the odds of getting a postsecondary degree (High) compared to the odds of getting a lower degree (Low and Medium combined).

Table 2 shows Max-rescaled R-Square 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/Cr) increases the concordance by 5 to 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-Square scores show that mother's education and cohort/country have similar effect on the 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 on Figure 3. Gross effects are obtained by removing all but the variable of interest from the model equation. Net effects are obtained from the full model, controlling for all other variables.

The importance of the mother's education stands out from all other variables as the main determinant of educational attainment. In both regions, the odds of getting a postsecondary 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 postsecondary 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 2: Performance indicators for partial and full models

	Parameter	EU15 – M	EU15 – F	NMS13 – M	NMS13 – F
Max-Rescaled R-Square	Ct/Cr	0.218	0.220	0.079	0.159
	X	0.012	0.015	0.026	0.035
	Z	0.154	0.174	0.130	0.166
	X + Z	0.160	0.181	0.143	0.187
	Ct/Cr + X	0.224	0.229	0.097	0.185
	Ct/Cr + Z	0.278	0.300	0.179	0.266
	Ct/Cr + X + Z	0.282	0.305	0.190	0.284
% of concordance	Ct/Cr	64.7	68.7	59.3	64.7
	X	30.9	31.3	35.6	35.4
	Z	36.6	37.6	45.4	45.6
	X + Z	53.0	53.9	58.9	58.2
	Ct/Cr + X	65.2	69.2	60.6	66.4
	Ct/Cr + Z	70.0	73.6	68.4	72.1
	Ct/Cr + X + Z	70.2	73.8	68.9	73.0

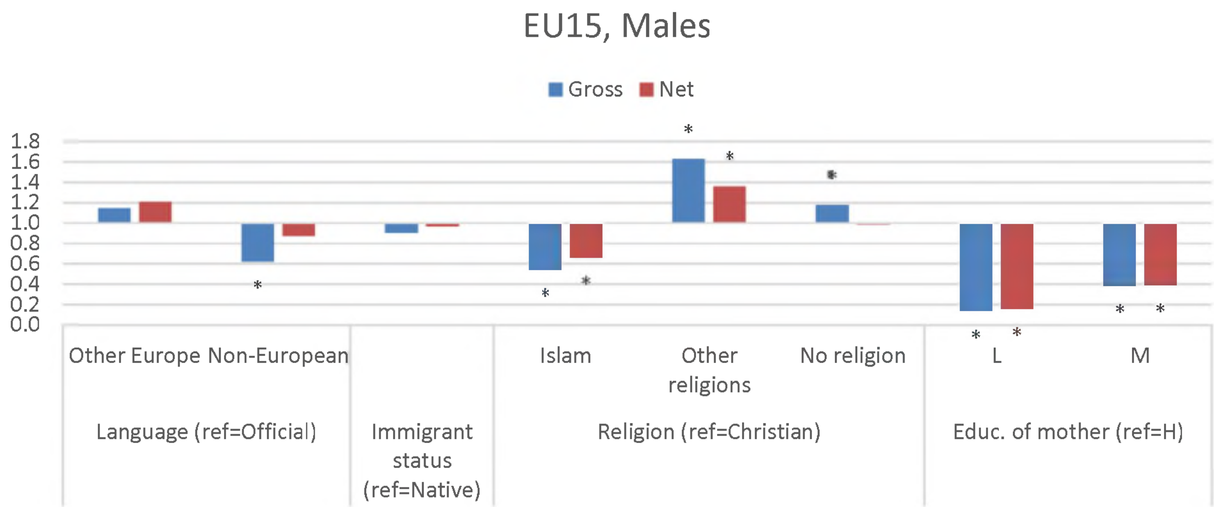
Preliminary models also included interaction terms between the education of the mother and the country or cohort, but most of the resulting parameters were not significant. This means that the effect of the mother's education is roughly the same in all countries and didn't change across cohorts (at least since 1940). This result supports many other empirical analyses showing that intergenerational mobility rates don't vary much over time and across countries (Piketty 2000). As stated earlier, including it explicitly in the projection model should improve its predictive capacity. It also adds a nice feedback effect in the model.

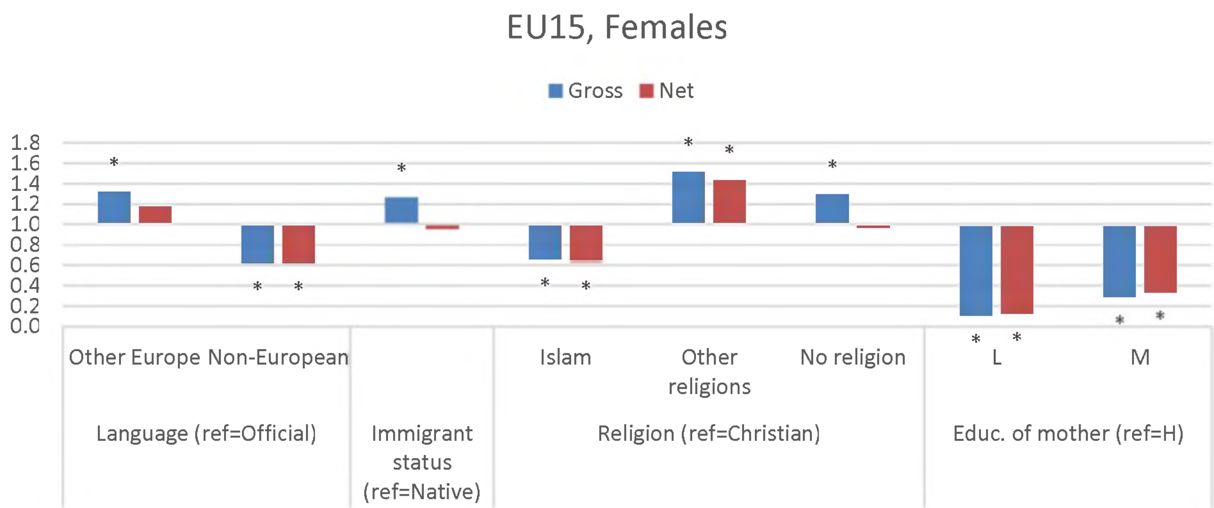
Another significant result can be observed for the educational attainment of individuals according to their religious affiliation. Compared to being Christian, being Muslim significantly and strongly reduces the odds of obtaining a postsecondary degree in both regions and for both sexes and the effect remains significant even when controlling for the other variables. 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 of 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 education of mothers or other variables, as the net effect of religion is almost always smaller than the gross effect.

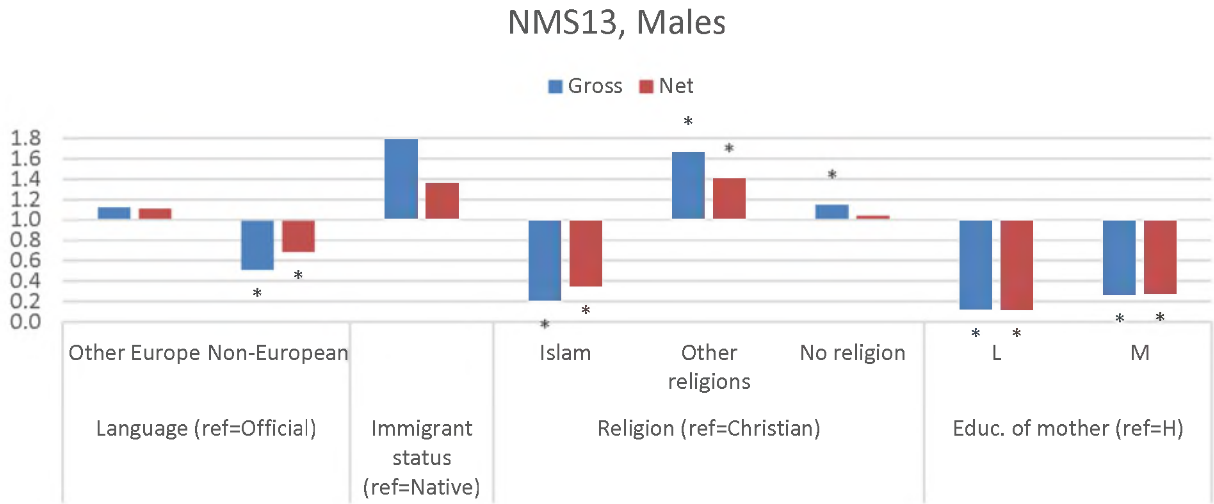
Concerning the language spoken at home, the effect of speaking a non-European language on the odds of completing a postsecondary degree is reduced after a statistical control, but still remains negative and significant, except for males in EU15. Social issues underlying these differentials are distinct 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 is mostly constituted of first and second generations of international immigrants. Interestingly, there are no statistical differences between immigration categories when controlling for the other variables.

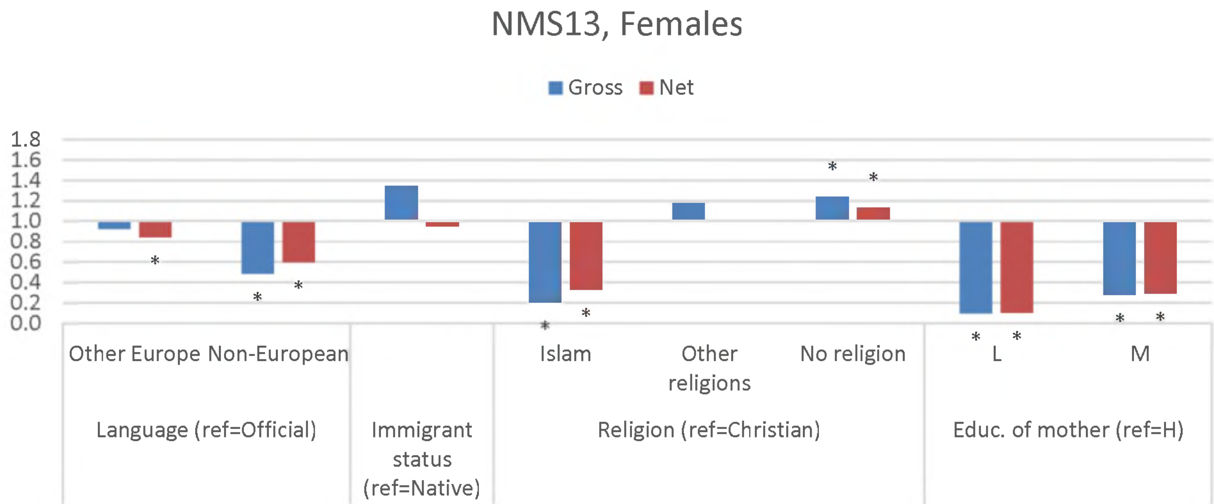
Overall, education of the mother appears to explain a significant part of the observed differentials in the educational attainment of sociocultural groups. However, some of the gross effects still resist the impact of statistical controls. The most important factors that were identified are speaking a non-European language and being Muslim.

Figure 3: Odds of getting High level of education over odds of getting a Low or Medium level of education





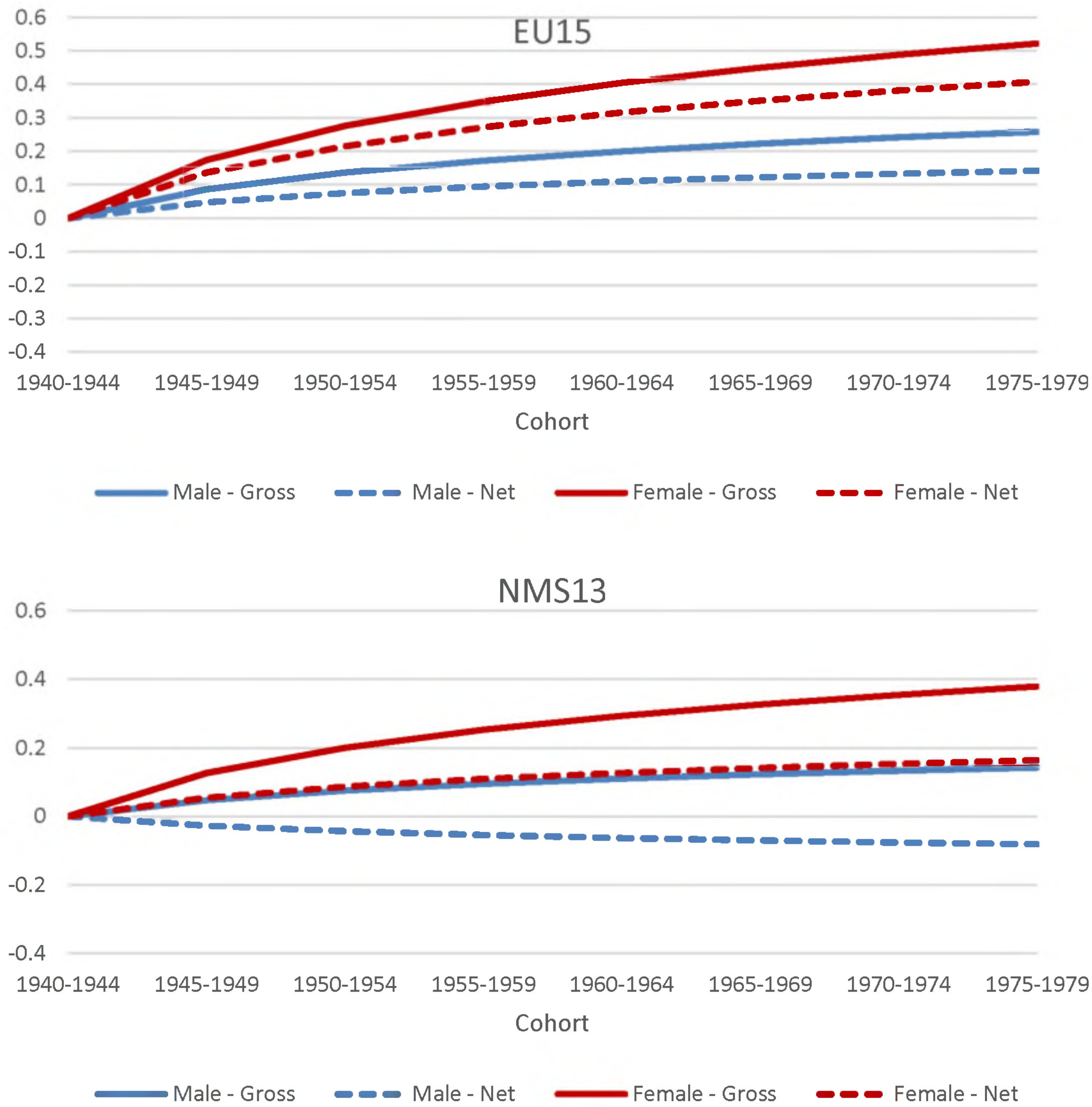




Our results have shown that the net effect of the education of the mother on educational attainment is particularly strong, but that other sociocultural variables such as religion and language spoken at home are also playing a significant role. Cohort composition has changed significantly along these dimensions in the course of the 20th century, and so we must aim to disentangle changes that occurred from evolution of cohort composition from 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 are factored out.

Figure 4 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 provides odds for High education compared to the two lower categories. Detailed results of the generalized ordered regressions are presented in the Appendix.

Figure 4: Comparison of gross and net cohort trends for the odds of getting a High level of education compared to Medium or Low levels



When population composition 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 4, NMS13, solid blue line). However, taking sociocultural variables and mother's education into account, the trend is reversed and becomes slightly negative (Figure 4, NMS13, dashed blue line). This result means that, *ceteris paribus*, a boy born in the 70s from a mother with High education has less chance of attaining a postsecondary level than a similar boy born in the 40's. 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 70's than in the 40's and consequently, children born in the 70's are more likely to get a postsecondary 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 preceding 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.

Table 3: Parameters for net and gross cohort trends (β_2+β_3)

Country	Education=High				Education=Medium			
	Net		Gross		Net		Gross	
	$Trend_M$	$Trend_F$	$Trend_M$	$Trend_F$	$Trend_M$	$Trend_F$	$Trend_M$	$Trend_F$
BE	0.041	0.213	0.108	0.273	0.201	0.324	0.239	0.342
BG	-0.078	0.018	0.039	0.150	0.176	0.168	0.195	0.205
CZ	-0.056	0.042	0.009	0.139	0.073	0.223	0.145	0.334
DK	-0.035	0.097	0.077	0.203	0.025	0.208	0.113	0.284
DE	-0.012	0.146	0.045	0.200	-0.049	0.159	0.009	0.206
EE	-0.109	0.067	0.075	0.190	-0.047	0.009	0.109	0.150
IE	0.165	0.279	0.218	0.307	0.235	0.356	0.267	0.384
GR	0.129	0.306	0.160	0.354	0.275	0.412	0.295	0.439
ES	0.186	0.401	0.205	0.409	0.219	0.383	0.231	0.394
FR	0.100	0.204	0.163	0.252	0.169	0.318	0.211	0.347
IT	0.086	0.217	0.088	0.260	0.189	0.336	0.184	0.362
CY	0.146	0.293	0.196	0.336	0.369	0.464	0.426	0.494
LV	-0.090	0.024	0.045	0.140	0.005	0.090	0.126	0.221
LT	-0.108	-0.099	0.027	0.070	0.005	0.053	0.104	0.186
HU	-0.051	0.109	0.070	0.226	0.041	0.199	0.116	0.295
NL	0.005	0.133	0.040	0.172	0.075	0.290	0.101	0.308
AT	0.056	0.160	0.110	0.197	0.168	0.210	0.208	0.228
PL	0.042	0.133	0.170	0.231	0.173	0.315	0.250	0.382
PT	0.202	0.288	0.226	0.304	0.239	0.370	0.253	0.382
RO	-0.076	0.094	0.008	0.192	0.100	0.271	0.135	0.301
SI	0.048	0.170	0.131	0.248	0.057	0.293	0.112	0.361
SK	-0.087	0.053	0.024	0.170	0.095	0.267	0.185	0.357
FI	-0.007	0.135	0.105	0.253	0.225	0.326	0.306	0.422
SE	-0.011	0.059	0.108	0.175	0.267	0.319	0.349	0.382
UK	0.025	0.107	0.085	0.155	0.083	0.223	0.134	0.262
HR	-0.048	0.044	0.029	0.097	0.205	0.345	0.247	0.340

Note: Betas refer to equation 1. Subscripts $_M$ and $_F$ refer to Male and Female, respectively.

For females in both EU15 and NMS13 and for males in EU15, Figure 4 shows that population composition alone does not fully explain the observed improvement in educational attainment, since net cohort trends (dashed lines) still show improvement across cohorts. Nevertheless, amplitude is reduced compared to gross trends (solid lines), meaning that a significant part of the improvement across cohorts is explained away by sociocultural characteristics and the education of mothers.

The analysis presented above rests on the arithmetic average of regression parameters and hides the heterogeneity in trends across countries. Table 3 shows net parameters for countries and cohort trends for males (M) and females (F). The trend parameter corresponds to $\beta_2+\beta_3$, as presented in Equation 1.

In order to identify groups of countries with similar characteristics, a cluster analysis was performed on the difference between the net and the gross cohort trend parameters, the result of which is presented in Table 4.

Table 4 – Classification of countries according to cluster analysis

Cluster	Name	Trend	Countries	Mean difference between net and gross cohort effect			
				Edu=H, Sex=M	Edu=H, Sex=f	Edu=M, Sex=M	Edu=M, Sex=F
1	Moderate composition effect	Small decrease for males, no variation for females	BE, DE, IE, GR, ES, FR, IT, CY, NL, AT, PT, UK, HR	-0.046	-0.040	-0.033	-0.023
2	Strong composition effect	Strong or moderate increase	BG, CZ, DK, HU, PL, RO, SI, SK, FI, SE	-0.105	-0.108	-0.067	-0.073
3	Very strong composition effect	Moderate decrease for males, no change for females	EE, LT, LV	-0.151	-0.136	-0.126	-0.135

Figure 5 further illustrates net probabilities of obtaining a High level of education for the three clusters and for each sex separately. Probabilities are calculated from Equation 1.

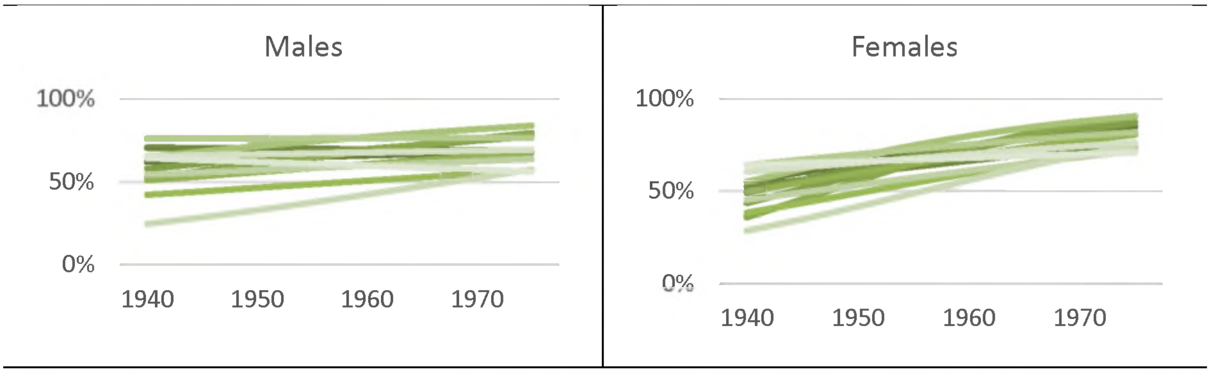
Cluster analysis shows that the effect of population composition on cohort trend is stronger for the attainment of a High level of education than it is for the attainment of a Medium level, as shown by the mean difference between the net and the gross cohort trends in Table 4.

Results further demonstrate that cohort trends in all countries are significantly affected by population composition. The analysis has identified three clusters with respect to this gross-net trend difference.

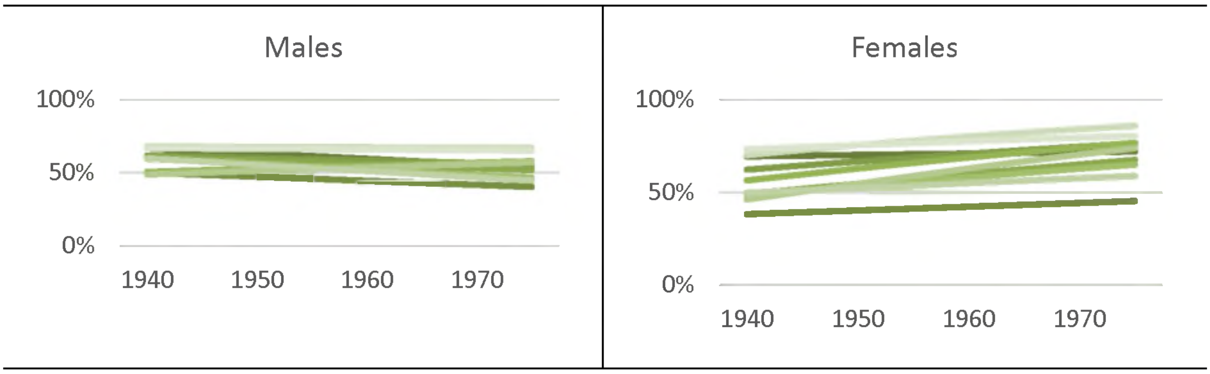
The first identified cluster includes countries where the gross-net trend difference is smallest. Although small in appearance, the compositional effect remains relatively important: For postsecondary education, it corresponds to about a quarter of the gross trend. Nevertheless, a net cohort effect can still be observed for those countries. This is further illustrated in Figure 5, where we can see an increase in the proportion of postsecondary education across cohorts, even after statistical controls have been factored in. This “moderate compositional effect” cluster includes most Western European countries. Some of these countries lagged behind others with respect to postsecondary education, especially for females, but filled in a large part of the gap in the last decades through a net cohort effect.

Figure 5: Net fitted probabilities of getting a postsecondary degree (High) with respect to cohort year (individuals born in the country, Christian, speaking an official language at home and having a mother who has a postsecondary degree)

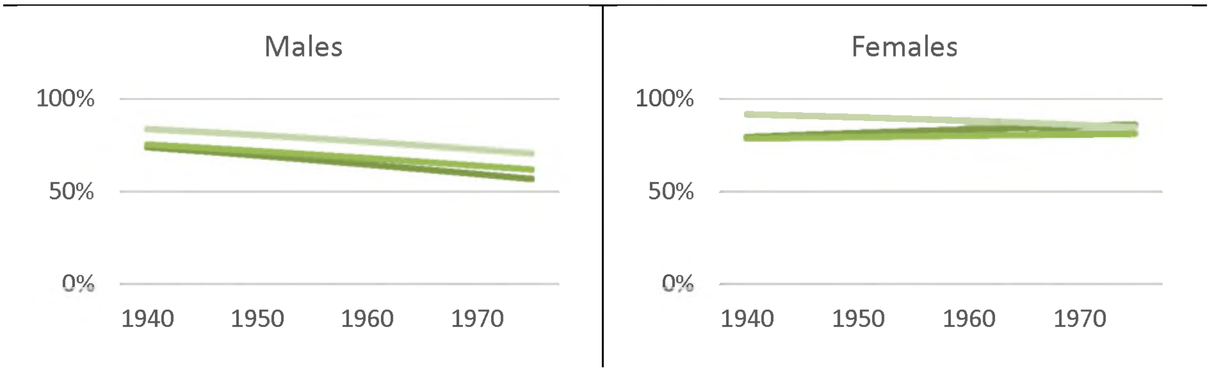
Cluster 1 - Moderate composition effect



Cluster 2 - Strong composition effect



Cluster 3 – Very strong composition effect



The second cluster includes countries where the effect of population composition on cohort trend is strong (mean gross-net difference of about -0.11 for High education and -0.07 for Medium, see Table 4). This cluster includes most Eastern European countries, as well as Scandinavia. For this cluster, the cohort trend becomes almost flat when population composition is taken into account. For postsecondary education, all the observed improvement is explained by a change in population composition, mostly in terms of education of mothers. All other things being equal, an individual born in the 70's has the same chance of getting a postsecondary degree than one born in the 40's.

Finally, the third cluster comprises Baltic countries, a region where the effect of population composition on cohort trends is strongest for both High and Medium education. These countries show a high proportion of postsecondary-educated people in older cohorts, but the net trend for younger cohorts is declining for males or flat for females. *Ceteris paribus*, younger cohorts of males have less chance of getting a postsecondary degree than older ones. This finding could have important policy implications, as general access to tertiary education in the Baltic countries may be degrading.

4.3 Implementing education of mothers and sociocultural variables in a microsimulation projection model of education: a sensitivity analysis

Given the results presented in Section 4.2, how does population composition in terms of education of mothers and sociocultural characteristics affect the outcome of education projections? Different forces will work in different directions.

International migration flows are likely to increase the proportion of both foreign language speakers and of Muslims (Coleman 2006), which should have a negative impact on global educational attainment. Moreover, the global increase in educational attainment, net of population composition effects, is levelling off or even declining in many countries. On the other hand, women are more educated than ever before, which is expected to positively affect their children's educational attainment.

To investigate how these dynamics could affect demographic projections of human capital, we designed two distinct scenarios:

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 (see Equation 1). Because universal postsecondary attainment is unlikely to happen, the probability of getting a High degree of education is capped at 90% (Barakat & 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.

2. *Multivariate determinants of education (MDE)*
   In this scenario, all parameters from Equation 1 were used and cohort trends were extrapolated over the time span of the projection (postsecondary education was capped at 90%, as in the first scenario). This second scenario allows us to isolate 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 with microsimulation.

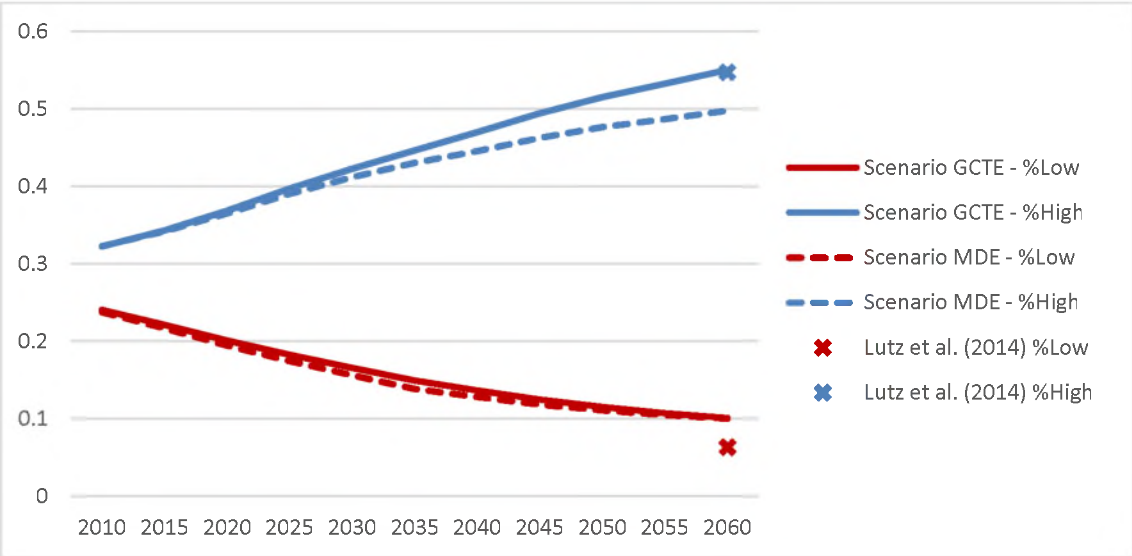
In short, scenario GCTE is closer to the reference scenario of the projection model used in Lutz et al. (2014), although without the specific convergence assumptions (Barakat & Durham 2014) and with different hypotheses in terms of immigration composition. Scenario MDE adds differentials according to 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.

As this paper is mainly focused on education, assumptions for other demographic components are kept simple. Fertility and mortality assumptions by age, sex and educational attainment are taken from the projection model used in Lutz et al. (2014). For international migration, inflows and outflows are taken from these projections as well, but the composition of immigration is derived from the base population, itself built from the 2014-2015 EU-LFS, all rounds of the EU-ESS and Eurostat census data. Furthermore, future immigrants in the model are assumed to have the same characteristics as recent immigrants.

The microsimulation model does not yet include intragenerational or intergenerational transitions in terms of religion and language, so these characteristics are automatically transmitted from mother to child and stay constant throughout the life course. Although somewhat unrealistic, this assumption is unlikely to affect the results of the projection in terms of educational attainment. Religion and language shifts are indeed rare and have limited impact on the population composition in the short and medium term (Sabourin & Bélanger 2016; Hackett et al. 2015).

Figure 5 shows for both scenarios the projected proportion of Low and High education in the population aged 25-54 years old.

Figure 5: Projected proportion of Low and High education, 25-54 years old, 2010-2060, EU26[1]



1. Luxemburg and Malta are excluded

First, we note that the two scenarios produce similar trends, especially for the proportion of Low educated. The proportion of Low education is similar in both scenarios, decreasing from 24% in 2010 to 10% in 2060. Moreover, at the end of the projection (2060), educational attainment in both scenarios comes relatively close to but is still a little higher than the reference scenario of the projection of Lutz et al. (2014).

Because of demographic inertia, the trends for High education are also very similar in both scenarios 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 postsecondary education being higher in scenario GCTE. Scenario GCTE yields the same proportion of High education as the Lutz et al. projection (around 55%), while scenario MDE produces a lower proportion (50%)

Figure 6 shows a comparison of the results from the two projection scenarios for each country and for Low and High education separately. Table 4 further summarizes the results.

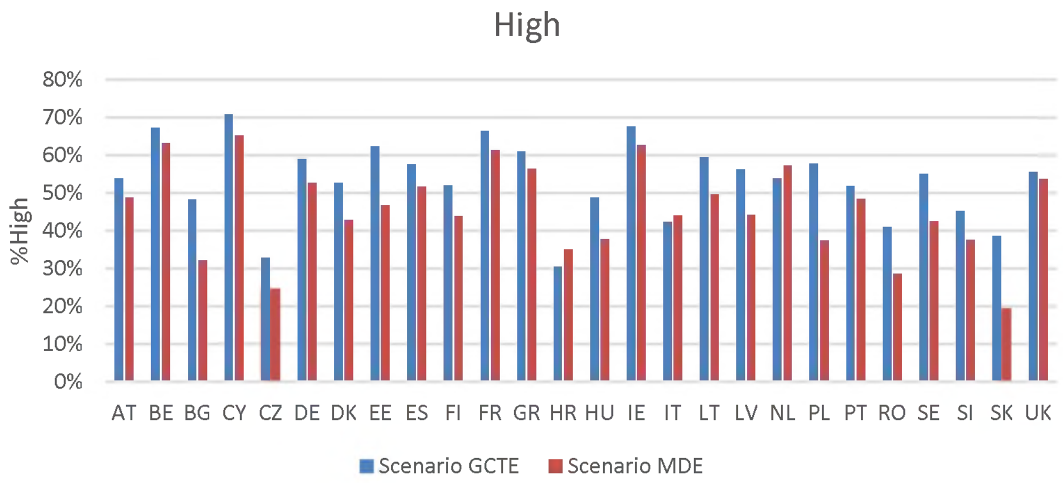
For the proportion of High education, scenario GCTE lies above scenario MDE by 7.7 percentage points (PP), as calculated by the mean difference. For Low education, scenario GCTE lies on average 0.8 PP below scenario MDE. Overall the mean absolute difference between scenarios is 8.4 PP for High education and 1.4 PP for Low education.

Considering the time span of the projections (50 years), these discrepancies are relatively small. In fact, for many countries, the two scenarios yield approximately the same results, especially in countries from the first cluster, for which the mean absolute difference is only 4.4 PP for High education and 0.7 PP for Low education.

To a certain degree, we can conclude that gross cohort trends implicitly take population composition into account. When a net cohort trend may still be observed, there appears to be no clear advantage to projecting educational attainment with microsimulation, at least for the total population, as it closely produces similar the results. The possibility of decomposing the projection results in terms of population groups will however remain.

As countries from the first cluster make up a large part of the European population, it is expected that macro and micro projections will yield similar results at the global level. When looking at specific countries, however, the advantages of microsimulation become more apparent. In countries from cluster 2 and 3, where compositional effects are strong or very strong, taking the mother's education and sociocultural variables into account significantly alter the projection results, especially for High education. Indeed, the resulting proportion of High education is about 10 PP lower for scenario MDE than it is for scenario GCTE in these countries.

Figure 6: Projected proportion of Low and High education for the population aged 25-54 years old, by country, 2060



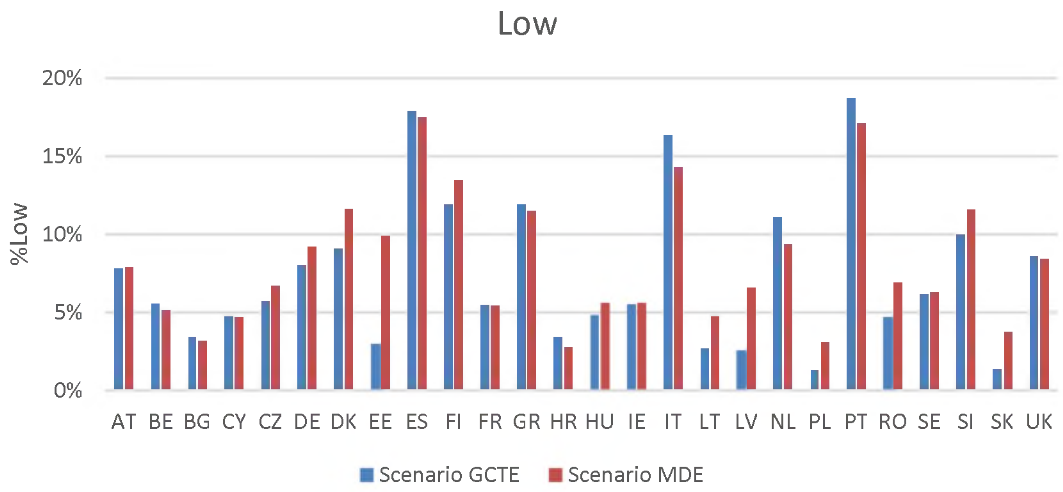
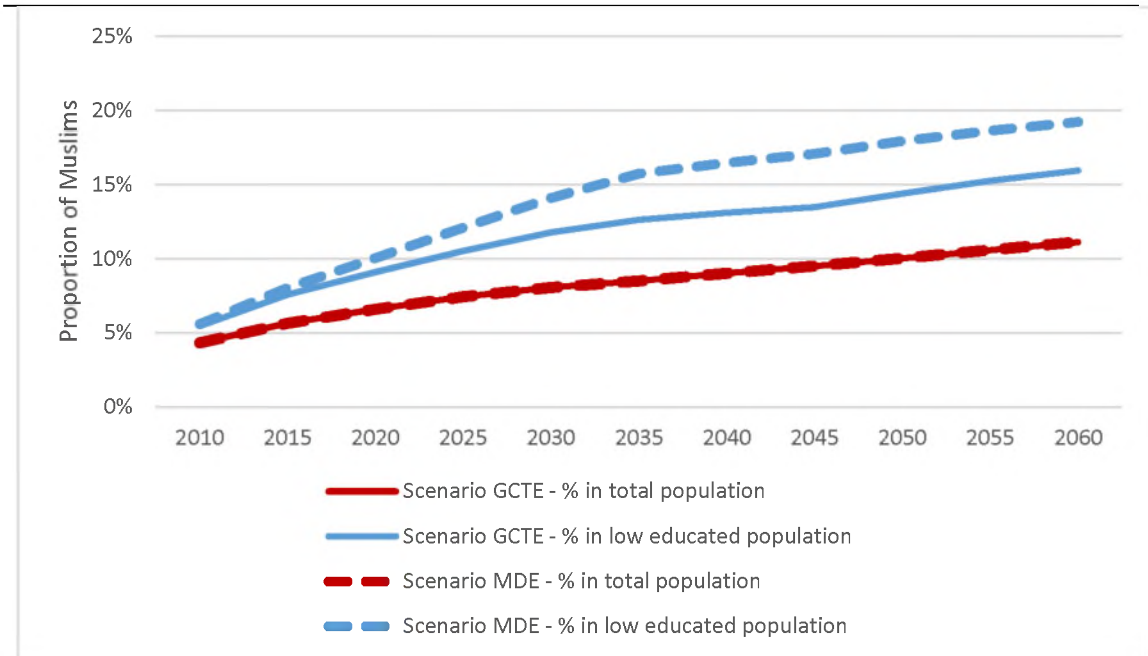


Table 5: Comparison between scenario GCTE and MDE, proportion of High and Low education in population aged 25-54 years old, 2060

	Education level	Mean difference	Mean absolute difference
Total	High	-7.7%	8.4%
	Low	0.8%	1.4%
Cluster 1	High	-2.8%	4.4%
	Low	-0.5%	0.7%
Cluster 2	High	-12.5%	12.5%
	Low	1.4%	1.4%
Cluster 3	High	-12.5%	12.5%
	Low	4.3%	4.3%

Integrating additional heterogeneities in the microsimulation model also allows for the generation of outputs that go beyond age, sex and education, and that may provide valuable insights to European policy makers. Figure 7, for instance, illustrates the proportion of Muslims in the total population and in the population with Low education (age group 25-54). It should be noted that different scenarios with different assumptions on immigration composition might yield different results. Moreover, the microsimulation model does not, as of yet, include shifts in religion. Figure 7 nevertheless illustrates the analytical possibilities provided by the microsimulation model.

Figure 7: Projected proportion of Muslims in the total population and in the population with Low education, age group 25-54 , 2010-2060, EU26[1]



1. Luxemburg and Malta are excluded

Figure 7 shows that in both scenarios, the proportion of Muslims grows faster in the population with Low education than in the total population. Indeed, according to scenario MDE, the growth of the Muslim population is expected to be twice as fast in the population with Low education that in the total population. Moreover, in the population with Low education, the growth of the Muslim population is about 30% faster in scenario MDE when compared to scenario GCTE. The proportion of Muslims in the population with Low education increases from 5.5% in 2010 to 19.2% in 2060 (dashed blue line) in scenario MDE, compared to 15.9% in scenario GCTE (solid blue line).

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 a specific parameter for this population as well as by parameters for characteristics correlated with Muslims that affect negatively educational attainment, namely a higher proportion of mothers with Low education and a higher proportion using a non-European language at home.

The difference between scenario GCTE and scenario MDE in this specific output illustrates the importance of taking the education of the mother and 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 could remain overrepresented in future flows of international immigrants, the outcome from scenario MDE appears more plausible than the outcome from scenario GCTE, as empirical results show that children from these three groups are less likely to reach a Medium level of education. Such results highlight important social fragmentation issues that could emerge from increasing immigration flows to Europe and rising inequalities in education.

5 Conclusion

In this working paper, we have made several contributions to improve 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, even after controlling for other characteristics. In EU countries, the education of the mother emerged as the main predictor of children's future educational attainment, but other sociocultural variables, such as being Muslim (especially for women) or a speaker of 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 make statistical associations between variables and do not provide hints on the mechanisms involved or on normative actions to be taken: Those latter 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 works in 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 latent variable. In a second step, age at graduation is determined based on data provided by Eurostat. For individuals with High education, age at graduation is determined for both Medium and High levels. Finally, the life course of the individual is simulated and its education level is updated according to the predetermined schedule. The education module was used to further investigate the impact of using a multivariate approach in the modelling of educational attainment instead of using simple assumptions based on gross cohort trends in EU countries.

Third, we showed that for some countries, the use of gross cohort trends in the projection of educational attainment leads to an overestimation of postsecondary education. In such cases, many of which are in Eastern Europe, the increase in postsecondary education across cohorts is totally explained by changes in education of mothers and sociocultural characteristics. Once these characteristics are factored in, the net cohort trends turn out to be flat or even slightly negative. In other countries, mostly in Western Europe, a positive net cohort trend leads to a continued better access to postsecondary education in the future, especially for women. In these countries, the projections based on gross trends were similar to the projections based on net trends as well as on the full set of covariates. Thus, gross cohort trends such as those used in multidimensional cohort-component models appear to adequately project education at the European level or in specific countries where net cohort trends are still prominent. However, when outputs on specific subpopulations are required, multivariate modeling of educational attainment is preferable.

Fourth, we showed that 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 population of Muslims grows faster in the population with Low education than in the general population, possibly raising issues of segmentation and inequalities. Moreover, we have shown that taking mother's education and language into account further increased the proportion of Muslims in the population with Low education, as these variables are correlated with religion.

A microsimulation model such as the one used in the CEPAM project can be most 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 could assess the effect of a scenario in which children from mothers with Low education have the same probability of getting a postsecondary education as other children. It could also investigate the impact of immigration selection in terms of educational attainment, considering that immigrants' characteristics would also affect the education of the second generation. Multivariate modeling of education using microsimulation also allows for the generation of detailed and consistent outputs across several dimensions, such as future educational attainment by religious affiliation or immigrant status. A research program seeking to compare the impact of different scenarios of international immigration on future human capital, labor force participation and social cohesion should rely on a projection model using multidimensional modeling of educational attainment.

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 modelled properly using other sources of data. Secondly, because postsecondary 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. Finally, 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.

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Appendix: Parameters from ordered logit regression on educational attainment

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
NMS13	Male	Intercept		H	0.706	0.170	<.0001
NMS13	Male	Intercept		M	2.242	0.181	<.0001
NMS13	Male	country	CZ	H	-0.764	0.210	0.000
NMS13	Male	country	CZ	M	0.791	0.217	0.000
NMS13	Male	country	EE	H	0.441	0.449	0.326
NMS13	Male	country	EE	M	0.937	0.537	0.081
NMS13	Male	country	CY	H	-0.162	0.475	0.733
NMS13	Male	country	CY	M	-1.109	0.439	0.012
NMS13	Male	country	LV	H	0.992	0.335	0.003
NMS13	Male	country	LV	M	1.121	0.450	0.013
NMS13	Male	country	LT	H	0.597	0.296	0.044
NMS13	Male	country	LT	M	0.072	0.311	0.817
NMS13	Male	country	HU	H	-0.235	0.228	0.303
NMS13	Male	country	HU	M	0.317	0.207	0.126
NMS13	Male	country	PL	H	-0.816	0.180	<.0001
NMS13	Male	country	PL	M	0.073	0.162	0.652
NMS13	Male	country	RO	H	-0.197	0.196	0.313
NMS13	Male	country	RO	M	-0.435	0.170	0.011
NMS13	Male	country	SI	H	-0.840	0.381	0.027
NMS13	Male	country	SI	M	0.367	0.334	0.272
NMS13	Male	country	SK	H	-0.315	0.266	0.236
NMS13	Male	country	SK	M	0.917	0.289	0.002
NMS13	Male	country	HR	H	-0.095	0.286	0.739
NMS13	Male	country	HR	M	0.373	0.257	0.147
NMS13	Male	cohort		H	-0.072	0.032	0.025
NMS13	Male	cohort		M	0.186	0.034	<.0001
NMS13	Male	cohort*country	CZ	H	0.034	0.041	0.413
NMS13	Male	cohort*country	CZ	M	-0.108	0.048	0.026
NMS13	Male	cohort*country	EE	H	-0.038	0.086	0.656
NMS13	Male	cohort*country	EE	M	-0.216	0.111	0.052
NMS13	Male	cohort*country	CY	H	0.201	0.094	0.032
NMS13	Male	cohort*country	CY	M	0.164	0.104	0.115
NMS13	Male	cohort*country	LV	H	-0.053	0.066	0.426
NMS13	Male	cohort*country	LV	M	-0.195	0.095	0.041
NMS13	Male	cohort*country	LT	H	0.043	0.058	0.458

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
NMS13	Male	cohort*country	LT	M	-0.081	0.068	0.235
NMS13	Male	cohort*country	HU	H	0.021	0.045	0.638
NMS13	Male	cohort*country	HU	M	-0.123	0.046	0.008
NMS13	Male	cohort*country	PL	H	0.125	0.036	0.000
NMS13	Male	cohort*country	PL	M	-0.003	0.038	0.935
NMS13	Male	cohort*country	RO	H	-0.027	0.039	0.494
NMS13	Male	cohort*country	RO	M	-0.086	0.038	0.024
NMS13	Male	cohort*country	SI	H	0.122	0.072	0.091
NMS13	Male	cohort*country	SI	M	-0.125	0.073	0.087
NMS13	Male	cohort*country	SK	H	-0.006	0.052	0.911
NMS13	Male	cohort*country	SK	M	-0.072	0.066	0.273
NMS13	Male	cohort*country	HR	H	0.017	0.056	0.760
NMS13	Male	cohort*country	HR	M	0.020	0.058	0.732
NMS13	Male	Language	Other_Eu	H	0.081	0.099	0.415
NMS13	Male	Language	Other_Eu	M	-0.447	0.095	<.0001
NMS13	Male	Language	Non_Eu	H	-0.343	0.160	0.032
NMS13	Male	Language	Non_EU	M	-1.086	0.116	<.0001
NMS13	Male	genstat3	Immigrants	H	0.043	0.431	0.920
NMS13	Male	genstat3	Immigrants	M	0.396	0.516	0.443
NMS13	Male	religion	Muslim	H	-1.099	0.365	0.003
NMS13	Male	religion	Muslim	M	-0.890	0.183	<.0001
NMS13	Male	religion	Other	H	0.384	0.133	0.004
NMS13	Male	religion	Other	M	-0.403	0.136	0.003
NMS13	Male	religion	No_religion	H	0.063	0.054	0.238
NMS13	Male	religion	No_religion	M	-0.076	0.059	0.202
NMS13	Male	mother_edu	L	H	-2.175	0.061	<.0001
NMS13	Male	mother_edu	L	M	-1.661	0.110	<.0001
NMS13	Male	mother_edu	M	H	-1.304	0.059	<.0001
NMS13	Male	mother_edu	M	M	-0.572	0.117	<.0001
NMS13	Female	Intercept		H	0.785	0.137	<.0001
NMS13	Female	Intercept		M	2.516	0.164	<.0001
NMS13	Female	country	CZ	H	-1.316	0.192	<.0001
NMS13	Female	country	CZ	M	-0.670	0.174	0.000
NMS13	Female	country	EE	H	0.451	0.332	0.175
NMS13	Female	country	EE	M	1.106	0.488	0.024
NMS13	Female	country	CY	H	-0.689	0.483	0.154
NMS13	Female	country	CY	M	-1.627	0.421	0.000
NMS13	Female	country	LV	H	0.656	0.246	0.008

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
NMS13	Female	country	LV	M	0.529	0.324	0.102
NMS13	Female	country	LT	H	0.986	0.227	<.0001
NMS13	Female	country	LT	M	0.659	0.274	0.016
NMS13	Female	country	HU	H	-0.910	0.198	<.0001
NMS13	Female	country	HU	M	-0.847	0.170	<.0001
NMS13	Female	country	PL	H	-0.714	0.143	<.0001
NMS13	Female	country	PL	M	-0.624	0.138	<.0001
NMS13	Female	country	RO	H	-0.948	0.169	<.0001
NMS13	Female	country	RO	M	-1.696	0.148	<.0001
NMS13	Female	country	SI	H	-1.145	0.326	0.000
NMS13	Female	country	SI	M	-1.159	0.262	<.0001
NMS13	Female	country	SK	H	-0.904	0.224	<.0001
NMS13	Female	country	SK	M	-0.419	0.202	0.038
NMS13	Female	country	HR	H	-0.231	0.253	0.362
NMS13	Female	country	HR	M	-0.684	0.215	0.001
NMS13	Female	cohort		H	0.016	0.025	0.520
NMS13	Female	cohort		M	0.176	0.029	<.0001
NMS13	Female	cohort*country	CZ	H	0.025	0.036	0.488
NMS13	Female	cohort*country	CZ	M	0.039	0.041	0.339
NMS13	Female	cohort*country	EE	H	0.054	0.065	0.406
NMS13	Female	cohort*country	EE	M	-0.164	0.105	0.117
NMS13	Female	cohort*country	CY	H	0.249	0.092	0.007
NMS13	Female	cohort*country	CY	M	0.240	0.097	0.013
NMS13	Female	cohort*country	LV	H	-0.020	0.049	0.679
NMS13	Female	cohort*country	LV	M	-0.038	0.079	0.633
NMS13	Female	cohort*country	LT	H	-0.039	0.045	0.384
NMS13	Female	cohort*country	LT	M	-0.120	0.060	0.046
NMS13	Female	cohort*country	HU	H	0.089	0.038	0.017
NMS13	Female	cohort*country	HU	M	0.024	0.040	0.548
NMS13	Female	cohort*country	PL	H	0.121	0.028	<.0001
NMS13	Female	cohort*country	PL	M	0.138	0.033	<.0001
NMS13	Female	cohort*country	RO	H	0.063	0.032	0.046
NMS13	Female	cohort*country	RO	M	0.105	0.033	0.002
NMS13	Female	cohort*country	SI	H	0.154	0.061	0.011
NMS13	Female	cohort*country	SI	M	0.097	0.061	0.112
NMS13	Female	cohort*country	SK	H	0.038	0.042	0.370
NMS13	Female	cohort*country	SK	M	0.090	0.050	0.069
NMS13	Female	cohort*country	HR	H	0.023	0.046	0.624

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
NMS13	Female	cohort*country	HR	M	0.151	0.047	0.001
NMS13	Female	Language	Other_Eu	H	-0.162	0.075	0.030
NMS13	Female	Language	Other_Eu	M	-0.685	0.066	<.0001
NMS13	Female	Language	Non_Eu	H	-0.546	0.139	<.0001
NMS13	Female	Language	Non_EU	M	-1.414	0.102	<.0001
NMS13	Female	genstat3	Immigrants	H	-0.588	0.437	0.178
NMS13	Female	genstat3	Immigrants	M	-0.451	0.345	0.190
NMS13	Female	religion	Muslim	H	-0.912	0.256	0.000
NMS13	Female	religion	Muslim	M	-1.331	0.162	<.0001
NMS13	Female	religion	Other	H	0.028	0.108	0.793
NMS13	Female	religion	Other	M	-0.486	0.107	<.0001
NMS13	Female	religion	No_religion	H	0.134	0.048	0.005
NMS13	Female	religion	No_religion	M	0.046	0.054	0.386
NMS13	Female	mother_edu	L	H	-2.263	0.058	<.0001
NMS13	Female	mother_edu	L	M	-1.903	0.108	<.0001
NMS13	Female	mother_edu	M	H	-1.230	0.057	<.0001
NMS13	Female	mother_edu	M	M	-0.435	0.114	0.000
EU15	Male	Intercept		H	0.471	0.187	0.012
EU15	Male	Intercept		M	1.206	0.180	<.0001
EU15	Male	country	DK	H	0.032	0.285	0.911
EU15	Male	country	DK	M	1.216	0.267	<.0001
EU15	Male	country	DE	H	0.269	0.189	0.154
EU15	Male	country	DE	M	2.371	0.185	<.0001
EU15	Male	country	IE	H	-0.549	0.336	0.102
EU15	Male	country	IE	M	-0.452	0.299	0.131
EU15	Male	country	GR	H	-0.337	0.255	0.185
EU15	Male	country	GR	M	-0.399	0.223	0.074
EU15	Male	country	ES	H	-0.296	0.202	0.142
EU15	Male	country	ES	M	-0.389	0.181	0.031
EU15	Male	country	FR	H	-0.585	0.200	0.003
EU15	Male	country	FR	M	0.636	0.178	0.000
EU15	Male	country	IT	H	-0.832	0.206	<.0001
EU15	Male	country	IT	M	-0.357	0.177	0.043
EU15	Male	country	NL	H	0.676	0.218	0.002
EU15	Male	country	NL	M	1.146	0.207	<.0001
EU15	Male	country	AT	H	-0.408	0.269	0.129
EU15	Male	country	AT	M	1.358	0.278	<.0001
EU15	Male	country	PT	H	-1.734	0.342	<.0001

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
EU15	Male	country	PT	M	-1.634	0.259	<.0001
EU15	Male	country	FI	H	0.214	0.282	0.448
EU15	Male	country	FI	M	0.412	0.269	0.125
EU15	Male	country	SE	H	0.124	0.252	0.623
EU15	Male	country	SE	M	0.893	0.242	0.000
EU15	Male	country	UK	H	0.094	0.196	0.631
EU15	Male	country	UK	M	0.651	0.178	0.000
EU15	Male	cohort		H	0.036	0.035	0.298
EU15	Male	cohort		M	0.199	0.034	<.0001
EU15	Male	cohort*country	DK	H	-0.070	0.057	0.216
EU15	Male	cohort*country	DK	M	-0.172	0.058	0.003
EU15	Male	cohort*country	DE	H	-0.040	0.037	0.269
EU15	Male	cohort*country	DE	M	-0.236	0.039	<.0001
EU15	Male	cohort*country	IE	H	0.150	0.065	0.021
EU15	Male	cohort*country	IE	M	0.057	0.063	0.366
EU15	Male	cohort*country	GR	H	0.091	0.048	0.056
EU15	Male	cohort*country	GR	M	0.129	0.047	0.006
EU15	Male	cohort*country	ES	H	0.089	0.039	0.020
EU15	Male	cohort*country	ES	M	-0.029	0.037	0.432
EU15	Male	cohort*country	FR	H	0.066	0.038	0.086
EU15	Male	cohort*country	FR	M	-0.033	0.038	0.379
EU15	Male	cohort*country	IT	H	0.031	0.040	0.439
EU15	Male	cohort*country	IT	M	-0.020	0.037	0.588
EU15	Male	cohort*country	NL	H	-0.041	0.043	0.345
EU15	Male	cohort*country	NL	M	-0.129	0.044	0.004
EU15	Male	cohort*country	AT	H	0.020	0.052	0.709
EU15	Male	cohort*country	AT	M	-0.020	0.063	0.755
EU15	Male	cohort*country	PT	H	0.140	0.064	0.029
EU15	Male	cohort*country	PT	M	0.030	0.051	0.556
EU15	Male	cohort*country	FI	H	-0.040	0.057	0.479
EU15	Male	cohort*country	FI	M	0.035	0.063	0.583
EU15	Male	cohort*country	SE	H	-0.027	0.050	0.592
EU15	Male	cohort*country	SE	M	0.009	0.056	0.877
EU15	Male	cohort*country	UK	H	-0.010	0.038	0.795
EU15	Male	cohort*country	UK	M	-0.118	0.038	0.002
EU15	Male	Language	Other_Eu	H	0.324	0.105	0.002
EU15	Male	Language	Other_Eu	M	0.136	0.100	0.173
EU15	Male	Language	Non_Eu	H	-0.334	0.137	0.015

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
EU15	Male	Language	Non_EU	M	-0.492	0.119	<.0001
EU15	Male	genstat3	Immigrants	H	0.005	0.100	0.959
EU15	Male	genstat3	Immigrants	M	-0.120	0.098	0.223
EU15	Male	religion	Muslim	H	-0.180	0.132	0.173
EU15	Male	religion	Muslim	M	-0.588	0.117	<.0001
EU15	Male	religion	Other	H	0.344	0.090	0.000
EU15	Male	religion	Other	M	-0.480	0.089	<.0001
EU15	Male	religion	No_religion	H	-0.009	0.027	0.747
EU15	Male	religion	No_religion	M	-0.055	0.028	0.047
EU15	Male	mother_edu	L	H	-1.837	0.049	<.0001
EU15	Male	mother_edu	L	M	-1.741	0.076	<.0001
EU15	Male	mother_edu	M	H	-0.924	0.053	<.0001
EU15	Male	mother_edu	M	M	-0.574	0.087	<.0001
EU15	Female	Intercept		H	0.080	0.198	0.686
EU15	Female	Intercept		M	0.914	0.184	<.0001
EU15	Female	country	DK	H	0.361	0.298	0.225
EU15	Female	country	DK	M	0.880	0.269	0.001
EU15	Female	country	DE	H	-0.129	0.204	0.526
EU15	Female	country	DE	M	1.350	0.183	<.0001
EU15	Female	country	IE	H	-0.420	0.350	0.230
EU15	Female	country	IE	M	-0.223	0.303	0.463
EU15	Female	country	GR	H	-0.861	0.290	0.003
EU15	Female	country	GR	M	-0.534	0.231	0.021
EU15	Female	country	ES	H	-0.699	0.218	0.001
EU15	Female	country	ES	M	-0.652	0.189	0.001
EU15	Female	country	FR	H	-0.265	0.210	0.208
EU15	Female	country	FR	M	0.237	0.183	0.197
EU15	Female	country	IT	H	-0.668	0.224	0.003
EU15	Female	country	IT	M	-0.426	0.188	0.024
EU15	Female	country	NL	H	0.410	0.238	0.084
EU15	Female	country	NL	M	0.344	0.210	0.102
EU15	Female	country	AT	H	-0.368	0.292	0.207
EU15	Female	country	AT	M	0.862	0.251	0.001
EU15	Female	country	PT	H	-0.976	0.290	0.001
EU15	Female	country	PT	M	-1.506	0.242	<.0001
EU15	Female	country	FI	H	0.618	0.282	0.029
EU15	Female	country	FI	M	0.841	0.271	0.002
EU15	Female	country	SE	H	0.803	0.258	0.002

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
EU15	Female	country	SE	M	1.604	0.257	<.0001
EU15	Female	country	UK	H	0.242	0.208	0.244
EU15	Female	country	UK	M	0.236	0.183	0.198
EU15	Female	cohort		H	0.200	0.036	<.0001
EU15	Female	cohort		M	0.317	0.037	<.0001
EU15	Female	cohort*country	DK	H	-0.116	0.057	0.044
EU15	Female	cohort*country	DK	M	-0.126	0.061	0.038
EU15	Female	cohort*country	DE	H	-0.061	0.038	0.110
EU15	Female	cohort*country	DE	M	-0.188	0.040	<.0001
EU15	Female	cohort*country	IE	H	0.096	0.064	0.135
EU15	Female	cohort*country	IE	M	0.051	0.065	0.433
EU15	Female	cohort*country	GR	H	0.079	0.052	0.125
EU15	Female	cohort*country	GR	M	0.104	0.048	0.031
EU15	Female	cohort*country	ES	H	0.131	0.040	0.001
EU15	Female	cohort*country	ES	M	-0.003	0.040	0.950
EU15	Female	cohort*country	FR	H	0.003	0.039	0.936
EU15	Female	cohort*country	FR	M	-0.003	0.040	0.939
EU15	Female	cohort*country	IT	H	-0.009	0.041	0.826
EU15	Female	cohort*country	IT	M	-0.009	0.040	0.822
EU15	Female	cohort*country	NL	H	-0.085	0.045	0.059
EU15	Female	cohort*country	NL	M	-0.043	0.045	0.341
EU15	Female	cohort*country	AT	H	-0.047	0.054	0.377
EU15	Female	cohort*country	AT	M	-0.130	0.053	0.015
EU15	Female	cohort*country	PT	H	0.029	0.054	0.592
EU15	Female	cohort*country	PT	M	0.017	0.049	0.723
EU15	Female	cohort*country	FI	H	-0.068	0.056	0.226
EU15	Female	cohort*country	FI	M	-0.012	0.068	0.862
EU15	Female	cohort*country	SE	H	-0.135	0.050	0.007
EU15	Female	cohort*country	SE	M	-0.116	0.060	0.055
EU15	Female	cohort*country	UK	H	-0.099	0.039	0.012
EU15	Female	cohort*country	UK	M	-0.102	0.040	0.010
EU15	Female	Language	Other_Eu	H	0.258	0.087	0.003
EU15	Female	Language	Other_Eu	M	0.282	0.088	0.001
EU15	Female	Language	Non_Eu	H	-0.357	0.157	0.023
EU15	Female	Language	Non_EU	M	-0.675	0.140	<.0001
EU15	Female	genstat3	Immigrants	H	0.061	0.087	0.480
EU15	Female	genstat3	Immigrants	M	0.152	0.091	0.096
EU15	Female	religion	Muslim	H	-0.606	0.142	<.0001

EU15	sex	Variables	Classification	Response	Estimate	StdErr	ProbChiSq
EU15	Female	religion	Muslim	M	-1.099	0.120	<.0001
EU15	Female	religion	Other	H	0.368	0.083	<.0001
EU15	Female	religion	Other	M	-0.126	0.081	0.118
EU15	Female	religion	No_religion	H	-0.022	0.027	0.412
EU15	Female	religion	No_religion	M	-0.028	0.027	0.302
EU15	Female	mother_edu	L	H	-2.090	0.046	<.0001
EU15	Female	mother_edu	L	M	-1.927	0.070	<.0001
EU15	Female	mother_edu	M	H	-1.117	0.051	<.0001
EU15	Female	mother_edu	M	M	-0.550	0.081	<.0001

Source: Pooled data of European Social Surveys 2006 to 2014; authors' calculations