European Commission

JRC SCIENCE FOR POLICY REPORT

Science career plans of adolescents: patterns, trends and gender divides

Zsuzsa Blasko

Artur Pokropek

Joanna Sikora

2018

Joint Research Centre

EUR 28878 EN

JRC Science Hub
https://ec.europa.eu/jrc

JRC109135

EUR 28878 EN

PDF ISBN 978-92-79-76475-2 ISSN 1831-9424 doi:10.2760/251627

Luxembourg: Publications Office of the European Union, 2018

How to cite this report: Blasko, Zs., Pokropek, A., Sikora, J.: *Science career plans of adolescents: patterns trends and gender divide*, EUR 28878 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-76475-2, doi:10.2760/251627, JRC109135.

Contents

Acknowledgements

The authors would like to thank colleagues from the Directorate-General Joint Research Centre (DG JRC) and the Directorate-General for Education and Culture (DG EAC) for their useful comments on earlier versions of this report. In addition, we would like to say thank you specifically to Clara Centeno Mediavilla for her contribution to identifying relevant policy initiatives related to the topic of this study.

Note

This report is part of the CRELL IX Administrative Agreement between DG EAC and DG JRC. Its content is stipulated under point 2.1 of the Technical Annex accompanying CRELL IX (Section 'Technical report #3').

Authors

Zsuzsa Blasko (European Commission, JRC, Italy)

Artur Pokropek (European Commission, JRC, Italy)

Joanna Sikora (Australian National University, Australia)

Executive summary

Meeting the demand for STEM workers – that is, for employees with a science, technical engineering or mathematics background – has been a high priority across the European Union (EU). There is widespread concern that the potential lack of sufficient STEM labour supply may hinder future economic development and reduce the economic competitiveness of the EU (European Commission et al., 2015). This report looks at adolescents' career plans and their correlates to better understand why men and women end up studying certain subjects and then entering corresponding jobs.

In 2015, on average, 20% of 15-year-old students in Europe planned to pursue a science-related career. However, considerable differences exist across countries, with the country averages ranging between 12% and 27%. The difference between males and females is quite remarkable, with the average gender gap reaching 19 percentage points. This means that, on average, European males are three times more likely to choose a STEM occupation than European females. A gap favouring males was identified in every Member State, varying only in size, and with a minimum of 15 and a maximum of 31 percentage points.

Between 2006 and 2015 no major changes occurred in European students' career orientations towards STEM. The share of 15-year-olds considering such an occupation increased only marginally and rather unevenly across the Member States, while gender segregation remained deep, showing a tendency to persist across European countries. Notably, in most countries that experienced a significant increase in the overall level of students' interest in STEM, a parallel increase in the size of the gender gap occurred. This suggests that, over time, the proportion of males who are interested in STEM is growing faster than that of females.

Several individual characteristics are related to STEM career choices. Science ability (as measured by Programme for International Student Assessment (PISA) scores) is the single most important factor guiding students' career plans in STEM. Interestingly, ability in science does not affect both genders in the same way: more able males tend to look more to STEM while more able females turn rather to medical professions. Attitudes towards science also constitute an important factor, but their significance varies across cultural settings.

Family characteristics, such as parental employment in STEM and migration status, are also significantly related to STEM career choices. Our analysis indicates that males are more influenced by their fathers' STEM employment than females, while maternal models for STEM occupations influence daughters and sons to a similar extent. This may be treated as an indicator that more gender-neutral parental role modelling can help reduce the gender gap in STEM. Migrants show a greater interest in science careers than other students who are comparable with respect to science performance, attitudes, and parental cultural and socio-economic background.

Schools are more or less equipped to teach sciences and they offer different opportunities for engagement with science outside compulsory classes. However, in general, neither the resources available for science teaching nor the provision of science-related activities can be linked directly to students' plans for a STEM career. The differences between educational systems and tracks are more important in accounting for STEM career choices than the differences between schools in the same country.

In a number of countries, students who are on a vocational track at the age of 15 are increasingly interested in choosing a STEM job. Between-country comparisons further reveal that this influence is particularly strong and positive in countries where upper secondary vocational programmes offer a relatively smooth transition to higher education. Finally, we find indications that the share of 15-year-old students on a vocational programme and the existence of a compulsory national examination in mathematics are positively related with STEM career choices.

Extended summary

European labour markets require substantial workforce equipped with upper secondary and tertiary credentials in science, technology, engineering and mathematics (STEM). As STEM workers are employed in the technologically most advanced and potentially most productive sectors of the labour market, meeting the labour force demand for STEM skills is considered a high priority in the European Union (EU). In fact, the prospect of shortages in STEM-skilled labour has been named one of the main barriers to economic growth in the first half of the 21st century. There is widespread concern that lack of sufficient STEM labour supply may hinder future economic development and reduce economic competitiveness across the EU.

To better understand why men and women end up studying certain subjects and then entering corresponding jobs, it is important to look at their early socialisation and education. In particular, when adolescents approach the end of compulsory education their career plans become consequential for their choices of further education. Even though there is no one-to-one correspondence between the subject of higher education studies and the area of later employment, a strong path dependency between education and career exists. Thus much can be gained from understanding why and how young people set their minds on particular career paths.

STEM employment is one of the most gender-segregated areas in the labour market, with a massive underrepresentation of women across Europe and beyond. The situation has changed very little during the past decades, and it has been named not only as a source of labour supply shortages but also as a risk factor for talent loss and gender inequalities. As adolescents' career plans already faithfully reflect this gender divide, analysing these plans also provides a good insight into the early segregative processes.

Therefore, in our report, we systematically explore a range of potential influences on young people's career plans, starting from individual characteristics and moving through school-level factors to interventions at the national level. For the analyses, we use the Programme for International Student Assessment (PISA) data from 2006 and 2015 for each of the EU Member States. Besides exploring the main influencing factors of adolescents' career choices in STEM, as well as of the gender gap identified in these choices, we also attempt to identify and explain changes in science-related occupational expectations that occurred between 2006 and 2015.

In 2015, on average, 20 in every 100 15-year-old students in Europe planned to pursue a science-related career. However considerable differences exist across countries, with the respective country averages ranging between 12% and 27%. The difference between males and females was found to be quite remarkable, with the average gender gap reaching 19 percentage points. This means that, on average, European males are three times more likely to choose a STEM occupation than European females. A gap favouring males was identified in every Member State, varying only in size, and with a minimum of 15 and a maximum of 31 percentage points.

Between 2006 and 2015 no major changes occurred in European students' career orientations towards STEM. The share of 15-year-olds considering such an occupation increased only marginally and rather unevenly across the Member States, while gender segregation remained deep, showing a tendency to persist across European countries. Notably, in most countries that experienced a significant increase in the overall level of students' interest in STEM, an increase in the size of the gender gap also occurred. This suggests that, over time, the proportion of males who are interested in STEM is growing, but not of females.

Besides gender, science ability is the single most important factor in guiding students' career plans in STEM. Consequently, the more a school can promote students' capacity to understand scientific concepts and ideas, the more students will consider entering an occupation in this field. However, males are likely to be more responsive to this approach than females, who – when their understanding improves – are more likely to turn to medical professions.

Alongside cognitive understanding, non-cognitive attitudes towards science, and enjoyment of science learning in particular, are also relevant. Students who enjoy science learning more are also more likely to plan a STEM career. There are however notable cultural variations in the effect of science enjoyment. While in the majority of the post-socialist Member States enjoyment does not matter, or matters only for females, in the rest of Europe, boosting the enjoyment of science is again an approach that can affect males more than females.

Of the students' family background characteristics, the factor that comes across as most influential is parental employment in STEM. Our analysis also indicates that sons are more receptive to modelling the occupational interests in alignment with parental employment in STEM. This is mostly because males are more influenced by their fathers' STEM employment than females. Mothers also serve as role models for STEM occupations and they influence daughters and sons to a similar extent, which may be treated as an indicator that more gender-neutral parental role modelling will be important in the future.

Migrants show a greater interest in science careers than other students who are comparable with respect to science performance, attitudes, and parental cultural and socio-economic background. We also find that the greater interest in STEM in migrant populations comes mostly from males. Although the pattern is not universal, migrant males plan to pursue STEM careers more often than other members of the student population, while migrant females are much more similar to native females.

Schools can be more or less well equipped to teach sciences and they can also offer different opportunities for engagement with science outside compulsory classes. In general, however, neither the resources available for science teaching nor the provision of science clubs in schools can be directly linked to students' plans for a STEM career. Science competitions, however, seem to have some marginal effect on this decision, although more so for males than for females. Thus, again, offering competitions for students to test their science competencies may increase the tendency towards segregation.

As expected, students also develop their career plans differently across the different educational systems in Europe. In most countries, students who are on a vocational track at the age of 15 are increasingly interested in choosing a STEM job. Between-country comparisons further reveal that this influence is particularly strong and positive in countries where upper secondary vocational programmes offer a relatively smooth transition to higher education. School characteristics explain the largest proportion in the variation of students' career plans as well as in the related career plans in those countries where early tracking of students is taking place, with a high share of 15-year-olds already on a vocational track.

Regarding the country-level factors, our findings reveal two important positive influences on students' STEM career plans: the share of 15-year-old students on a vocational programme and the existence of a compulsory national examination in maths. First, we find that the share of 15-year-old students who are enrolled in a programme whose curriculum is pre-vocational or vocational is significantly positively related to the number of students with STEM career expectations. This is not so surprising, given the relative importance of STEM-related subject areas in vocational schooling at the upper secondary level. Assuming that these schools can either directly lead to (non-professional) STEM careers or prepare for entering a science-related higher education path, vocational programmes at the upper secondary level appear to positively influence students' motivations for STEM careers. Our individual-level analysis shows a positive association between attending a vocational programme and developing an interest in a STEM career in Austria, Croatia, the Czech Republic, Slovakia and Slovenia. Our second finding from the country-level analysis suggests a significant positive association between compulsory national examination in maths and students' plans to enter a STEM occupation. A possible mechanism behind the positive association we have identified is that facing a compulsory maths exam at the end of secondary education may force students to continue studying this subject, even if they might have dropped, or at least neglected, this area of study in a less standardised system.

Regarding the main trends between 2006 and 2015 our results have shown that the various Member States have been travelling along different paths in this period. The small increase in the overall number of students interested in STEM was due to the fact that, in a number of countries, a more substantial increase in the level of males' interest was achieved, with or without a small increase in females' STEM aspirations. In fact, gender-neutral growth was more an exception. From the data PISA provides it is hard to identify the processes guiding all these changes, and it is not possible to point to any consistent pattern across the countries related to these changes. The most important finding (again) points to the relevance of vocationality, as it shows that an increase in the share of students interested in STEM occupations was most likely to occur in countries where the number of students in the vocational upper secondary programmes has also increased.

Our results indicate that the interventions capable of positively influencing the overall level of students' interest in STEM occupations are not necessarily the same as those that can be efficient in decreasing gender segregation. This implies that pedagogical approaches and policy tools need to be selected with great care, considering the potential influences not only on STEM labour supply in general but also on gender segregation in STEM in particular. Further, initiatives that aim to influence interest in STEM in a gender-balanced way are possible on various levels of potential policy interventions, beginning at school-level policies and country-level education policies and extending to the collaborative efforts of all Member States.

Clearly, there is still room to creatively design curriculum activities that popularise science and STEM occupations. Up to now most school-level science-promoting programmes and actions have showed rather marginal effect on students' vocational interest in STEM. To increase students' motivation to pursue a STEM career, schools should be supported by educational policies, most importantly in promoting maths and science competencies but also in promoting enjoyment of science and interest in science. As our results suggest, good science curricula should be paired with proper assessment systems for science and maths competencies. Developing the willingness to enter a science occupation and access to good information on individual students' science ability should be supported by a tailored vocational counselling system that will minimise rates of talent loss in science. Parents and their children should receive reliable information about children's achievements through the assessment system, as well as information on realistic vocational perspectives that takes into account both the level of abilities and the personal interests of children.

To achieve more gender balance in students' career choices, science and enjoyment of science need to be promoted in a gender-sensitive way. The initiatives already in existence seem to appeal more to males than to females, so the remaining challenge is to design curriculum activities that are at least as effective for females as for males. There is for example room for educating parents so that they can assist in overcoming gender bias, changing their own perceptions and values but also the environment in which young people grow up. Parents can be effective role models for STEM education and employment, or effective mentors for their science-oriented children – but perhaps also for other parents' children.

1 Introduction

1.1 Background

The importance of achieving balance in the supply and demand for Science, Technology, Engineering and Mathematics (STEM) labour has been recognised by policymakers and researchers as one of the key challenges of recent times (OECD 2006; Caprile et al., 2015; European Commission et al., 2015). The discussion about STEM revolves around two key issues. The first is a potential shortage of STEM workforce and its consequences for global economic competitiveness. The second is the salience of diversity within this workforce. Diversity prevents talent loss and optimises the problem-solving potential of scientific teams. Achieving diversity requires ameliorating the chronic underrepresentation of women and other minority groups in STEM training and employment.

The past 15 years have seen a reinvigoration of interest in horizontal gender segregation, which affects labour markets and education systems across the world (Charles, 2003; Estévez-Abe, 2005; Gerber and Cheung, 2008). This interest is fuelled by persistent concentrations of men and women in different fields of study and occupations, which has been linked to gender inequalities and talent loss. Despite the growing numbers of working women with higher education credentials, horizontal gender segregation continues. While, in most countries, men remain in a minority among teaching or nursing professionals, they account for most professionals working in engineering and computing. In fact, STEM remains one of the most markedly segregated groups of occupations across Europe and in other parts of the world. The massive underrepresentation of women in STEM raises concerns, as vibrant STEM activity is considered necessary to stimulate economic growth. Hence the projections of an increased future labour market demand for advanced STEM skills motivate an interest in popularising STEM among future workers of all genders (Gonzalez and Kuenzi, 2012; Caprile et al., 2015).

Definitions of STEM vary from publication to publication but they often include natural and physical sciences that rely on systematic observation and rigorous testing of hypotheses, namely physics, astronomy, environmental science, chemistry and earth sciences. Moreover, STEM encompasses engineering, mathematics, information and communications technology (ICT) and cognate disciplines. International definitions of STEM education (e.g. Böttcher et al., 2016) often draw on the International Standard Classification of Education (ISCED) (UIS, 2006), while single-country studies rely on country- or context-dependent definitions that vary considerably (e.g. Sadler et al., 2012) (for more elaborate discussion see Koonce et al., 2011). In international studies, STEM occupations are usually defined with reference to the titles of the International Standard Classification of Occupations (ISCO) (ILO, 1990, 2012) that denote jobs involving an extensive use of technology. Technology, in this context, is understood as the application of scientific knowledge to real-life problems to enhance the wellbeing of populations. STEM occupations comprise science and engineering professionals, ICT professionals as well as associate professionals and technicians in these fields. STEM skills involve generic skills such as numeracy (broadly understood) and the ability to solve complex problems (UKCES, 2011) or to use IT. STEM also requires specific competencies, such as lab analysis or software development. Both types of STEM skills – generic and specific – are crucial to innovation, problem-solving, global competitiveness and economic growth (OECD, 2010).

European labour markets require substantial STEM workforce equipped with upper secondary and tertiary credentials. Although not all STEM graduates enter occupations they are trained for, strong pathway dependencies exist between STEM education and employment. In secondary schooling, individual field-of-study specialisation and ability streaming facilitate, if not determine, later entry into tertiary STEM. Therefore, any analysis of the supply and demand factors that affect the availability of STEM skills needs to recognise the implications that early education and vocational orientations of adolescents have for their later opportunities to undertake STEM training and work.

Vocational preferences and orientations of teenagers are of particular importance in comprehensive education systems where capable youth can choose to specialise in fields that appeal to their personal interests and can thus opt out of other fields, even when they have the capacity to study them at advanced levels.

1.2 Objectives of this report

Given the importance of teenage vocational orientation, this research report contains a detailed analysis of STEM-related occupational expectations reported by European teenagers, contrasting two cohorts: those who were 15 years of age in 2006 and their counterparts in 2015.

1. The first objective of this report is to examine the level of interest in STEM occupations by 15-year-old students in all European countries. The main focus is on occupations related to STEM fields grouped in ISCO sub-major categories of Science and engineering professionals as well as ICT professionals. These are also occupations that require training in fields grouped in ISCED under the broad categories of Science (4) and Engineering (5). Additional information is provided for expectations related to ISCO's Health professionals (ILO, 1990, 2012), whose skills are acquired through qualifications grouped in ISCED's field of Health (7.2).
2. The second objective is to examine and explain the gender gap in the STEM-related occupational expectations of European teenagers.
3. The report contains systematic comparisons of males and females in 28 European MSs at two points in time, to identify a comprehensive set of individual student characteristics, characteristics of schools and peer groups, and characteristics of national economies, educational systems, policy initiatives and gender equality indicators that may produce favourable teenage orientations towards STEM, or bridge the gender gap in these orientations.
4. The report contributes to the potential development of policy interventions that are likely to sustain the growth of the STEM workforce, and foster its greater gender diversity across Europe, by highlighting the sources of variation in early orientations towards STEM.

1.3 Organisation of the report

By interrogating the patterns of adolescent interest in STEM careers, the current report describes adolescent career plans as indicators of the future supply of STEM workforce and the future gender diversity within STEM. We undertake this by comparing STEM-related career expectations over time and across genders. Both of these issues have raised substantial interest in the academic community as well as in the sphere of policymaking in Europe and beyond. The resulting debate has generated attempts to alleviate the embedded risks and potential losses. Our approach stems from the assumption that a close interdependency exists between educational and labour market processes. As we have shown, gender segregation in vocational preferences and educational specialisation of young students has the potential to affect the future supply of STEM workforce. Simultaneously, youth preferences and their pathways are shaped by the existing and perceived labour market opportunities.

By providing a detailed analysis of STEM-related career plans of 15-year-olds across Europe we aim to identify the major influences that encourage teenage males and females to plan a STEM career. To achieve this aim we have organised our report into several sections.

In the following part of this introductory chapter, we discuss the motivation of our study, starting with the importance of STEM in contemporary economies and then moving on to the issue of gender segregation in this field. Gender segregation in both STEM education and STEM employment will be discussed. Finally, to contextualise our work, we provide some information on the gender divide in a strongly related sector of employment, health and medicine.

Chapter 2 then summarises empirical evidence demonstrating that career plans of adolescents are good indicators of their later educational and occupational attainments, that career plans differ systematically between males and females, and that they are subject to historical and cross-country variation. This chapter also provides a systematic overview of individual, family, peer group and school factors that contribute to adolescent vocational orientations. Chapter 2 concludes with a comprehensive discussion of country characteristics, including economic factors, differences between education systems, the content of science and mathematics curricula, teaching methods, national policy initiatives to promote science, and cross-country variation in gender inequalities, all of which matter as contexts that affect youth interest in STEM.

In Chapter 3, we turn to the data and the methodology. First, relevant aspects of the Programme for International Student Assessment (PISA) study are described, and the variables are then introduced. We describe student and school-level variables from PISA data and then discuss the 33 country-level indicators that were collected for this study from various sources. Finally, we explain some methodological and statistical considerations relevant to this report.

Chapter 4 provides descriptive findings from the data. The focus of this chapter is on cross-country, cross-time and cross-gender comparisons of career plans of adolescents. This chapter, like the report overall, focuses on STEM occupations but also provides some background information that separates STEM occupations into specific occupations, and makes distinctions between STEM professional occupations and STEM associate professions. We also raise the issue of health occupations here.

Chapter 5 gives some of our main empirical results from the multivariate models – including those that are multilevel– developed to better understand students' interest in STEM occupations in 2015. STEM career choices and the factors associated with them in Europe will be identified on the individual, school and country level, and much attention will be given to how they relate to the gender gap in planning a STEM career.

Trends in STEM career choices between 2006 and 2015 will be introduced in Chapter 6, as well as the identification of country-level factors that correlate with changes either in the level of interest or in the size of the gender-gap.

Finally, Chapter 7 concludes and explains the policy implications of the results presented in this report.

1.4 Why STEM is important

As STEM workers are employed in the technologically advanced and potentially most productive sectors of the labour market, their sufficient supply is considered a high priority in the European Union (EU). The prospect of shortages in STEM labour has been named one of the main barriers to economic growth in the first half of the 21st century (Caprile et al., 2015, p. 12), as insufficient STEM labour supply may hinder future economic development and reduce economic competitiveness across the EU (Gonzalez and Kuenzi, 2012; European Commission et al., 2015). In the EU in 2014, for example, a European Parliament report on creating a competitive European labour market emphasised the need for STEM workforce. The report 'underlines the importance of STEM (Science, Technology, Engineering and Mathematics) studies and highlights the role they have in enabling Europe to play an important part on the global stage with regard to advancing technology developments' and 'highlights the fact that the EU faces a shortage of skills in science, technology, engineering and mathematics (STEM)' (European Parliament, 2014). This coincided with calls to tackle STEM skills shortages: 'supplementary initiatives at European and national level are necessary to respond to the bottlenecks in STEM-related jobs and studies' (European Parliament, 2014). Even more specifically, an earlier Communication of the European Commission noted that, to tackle the problem, 'greater efforts must now be made to highlight STEM as a priority area of education, and increase engagement at all levels. Although broad challenges are well known, such as the need to make it more attractive to females, it is also now important to increase understanding of the career pathways followed by STEM graduates' (European Commission, 2012).

Several indicators signal a high overall demand for STEM professionals and technicians in Europe. Firstly, between 2003 and 2013 the number of professionals and associate professionals in science and engineering ([1]) increased by 12% – that is, by 1.8 million people across Europe (ICF and Cedefop, 2014). Moreover, people qualified to work in STEM occupations enjoy low unemployment rates and high wages, which is considered to be an

([1]) ICT professionals (ISCO/SOC 25) are not included in this figure.

indication of high demand (Goos et al., 2013) ([2]). In particular, STEM professionals and associate professionals across 27 European countries ([3]) enjoyed a 19% average wage premium compared with their counterparts in other occupations. STEM workers' unemployment rates in Europe also remained significantly below overall unemployment levels throughout the 2000s. In the first decade of the 21st century, the average STEM unemployment rate across 22 EU members ([4]) did not exceed 4%, in contrast to the overall unemployment rate of 10% (Goos et al., 2013). Finally, the European Commission listed science and engineering professionals second among the ten occupations that are most difficult to fill, with ICT professionals following in third, and science and engineering associate professionals in seventh place ([5]) for Europe (Attström et al., 2014).

According to Cedefop (the European Centre for the Development of Vocational Training), the current demand is only likely to grow in the future. Part of the expected increase is related to the general demographic changes that also affect STEM workers. Overall ageing of STEM professionals will require replacement of a large number of retiring persons across the EU in the coming years (Caprile et al., 2015; European Commission et al., 2015). At the same time, new job openings are bound to emerge in the 'green' sector, ICT start-ups and other increasingly digitalised sectors of the economy (Cedefop, 2016). All in all, predictions stipulate that the demand for STEM professionals and technicians will increase by 8% between 2013 and 2025, with estimated average growth for other occupations at only 3% (Caprile et al., 2015). On the supply side, however, no similar tendencies are foreseen. During the 2000s the number of STEM graduates in higher education increased, albeit without a growth in the share of STEM graduates among the entire graduate population. Meanwhile, the number of upper secondary-level STEM graduates is no longer increasing. It even fell slightly after 2005 (Caprile et al., 2015).

While many sources predict shortages of qualified STEM workforce, some studies question the validity of this prediction and suggest that future supply is likely to meet expected demand in 2025, without serious problems. Arguably, projections in this area are subject to multiple qualifications and therefore not entirely reliable (European Commission et al., 2015). The existing shortages can be linked partly to worker–location mismatches rather than general shortages (Craig et al., 2011). While predictions of future shortages of STEM labour continue to be debated, there is no doubt that gender diversity within the STEM workforce and in education has not been achieved and remains on the policy agenda.

1.5 Why gender diversity in STEM is important

The shortage of STEM skills can arguably be addressed through increasing STEM participation of groups that are currently underrepresented – predominantly women (Gonzalez and Kuenzi, 2012; Caprile et al., 2015). Attracting more females into STEM education and thus into STEM employment is seen as a suitable response to the challenge of low supply by broadening the pool of applicants and potential recruits (Gonzalez and Kuenzi, 2012; ICF and Cedefop, 2014). For example the EU 'recommends that the Commission and the Member States take measures to enhance the attractiveness and value of STEM subjects and to encourage young people, including women, to take up STEM studies' (European Parliament, 2014). The European Commission, in its latest vision of a European Education Area, also includes this issue among the key challenges European education is facing today: 'An additional problem is that few students choose to study science, technology, engineering and mathematics, especially girls' (European Commission, 2017, p. 7). However, policy interventions need to be based on the

---

([2]) STEM occupations in this study were defined on the basis of three-digit ISCO-88 codes and refer to the following occupations: Physicists, Chemists and Related Professionals (211); Life Science Professionals (221); Life Science Technicians and Related Associate Professionals (321); Mathematicians, Statisticians and Related Professionals (212); Computing Professionals (213); Computer Associate Professionals (312); Architects, Engineers and Related Professionals (214); and Physical and Engineering Science Technicians (311).

([3]) Croatia is not included.

([4]) Data for Bulgaria, France, Malta, Poland and Slovenia was not available and Croatia was not included in the report.

([5]) Bottleneck occupations were identified on the basis of the following criteria: duration of vacancy filling; past/existing bottleneck vacancies (vacancies have been hard to fill); and expected bottleneck vacancies (employers stating they expect vacancies in an occupation will be difficult to fill).

recognition that vocational orientations towards STEM develop early (Osborne et al., 2003; Osborne and Dillon, 2008; Archer et al., 2010) and depend on cultural and structural constraints that foster gender segregation in education and in labour markets. Below, we discuss the nature of this gender segregation in Europe, starting with upper secondary education, moving to tertiary education and finishing with occupational segregation within STEM.

1.5.1 Gender segregation at the (upper) secondary level

European educational systems vary significantly with the greatest variations evident at the upper secondary level. Most 15-year-olds are either already in upper secondary education or are about to commence it. At this stage, many teenagers make their first important educational choices or are streamed into particular types of training, which may have consequences for their ability to pursue STEM-related pathways.

1.5.1.1 Vocational education

Across Europe, at this stage of schooling different proportions of teenagers are already in pre-vocational or vocational training. Vocational education at upper secondary level in Europe is strongly segregated by gender (European Centre for the Development of Vocational Training, 2014) and this segregation persists throughout the later careers of men and women who obtained vocational qualifications at either upper secondary or tertiary levels (Smyth and Steinmetz, 2015).

The extent to which 15-year-olds are already sorted into pre-vocational or vocational education varies from country to country. It practically never occurs in Denmark, Estonia, Finland, Iceland, Ireland, Latvia, Malta, Poland, Romania, Sweden, Spain and the United Kingdom, but accounts for 70% of 15-year-olds in Austria, and nearly as high a proportion in Croatia (OECD, 2016b). Between 17% (Belgium) and 52% (Hungary) of students in vocational education are in a STEM-related programme ([6]).

The absolute and relative numbers of STEM graduates with upper secondary credentials fluctuated in Europe in the past, but has tended to fall in the most recent times (Caprile et al., 2015). Although men generally outnumber women in European upper secondary vocational training, women's share is particularly low in all STEM-related fields in this sector. In 2012, there were only 5 females in every 100 vocational upper secondary graduates in engineering and engineering trades, no more than 10 females in architecture and building, 13 in computing, and 33 in manufacturing and processing across the EU. Yet, in science, mathematics and computing, and in engineering, some improvement in the number of women took place between 2003 and 2010. All in all, gender segregation in upper secondary STEM is more marked than at the higher educational levels.

1.5.1.2 Comprehensive education

Gender segregation, which has the potential to affect young people's ability and motivation to pursue STEM pathways, occurs also in non-vocational education. In most European countries – exceptions include Austria and Croatia – upper secondary students tend to follow a comprehensive educational programme and a general curriculum (OECD, 2016b). In these programmes, science and mathematics are compulsory in every European country (Eurydice, 2011a, 2011b). Nevertheless, in some countries students sort themselves by gender through subject selection, as is the case in the United Kingdom (Noyes and Adkins, 2016). In other countries, students are streamed or tracked, which affects their options for studying specific science curriculum content.

1.5.1.3 Self-sorting

In 2015, and across the whole of Europe, over 85% of 15-year-olds had a minimum of one science class per week, and this ratio exceeded 90% everywhere except Belgium, Hungary, the Netherlands, Portugal, Slovakia and Spain (OECD, 2016b). Despite that, students may

([6]) Own calculations based on 2012 Eurostat data.

have choices about specialising in subject areas, for instance different weekly numbers and curricular contents of mathematics or science classes. They can opt in or out of extracurricular activities related to these subjects and, in some of countries, they can choose whether or not to take a final exam in them. All these options provide opportunities for gendered self-sorting into or out of STEM-oriented educational pathways. Subject-specialisation options vary between countries. In some countries, certain choices made within the comprehensive system dictate what students learn during the rest of their secondary studies. Elsewhere classes within the same school, or in different schools, offer options to specialise in distinct subject areas, e.g. humanities, languages or sciences.

In 2015, science subjects were part of compulsory, standardised examinations at the end of the general upper secondary education only in France, Germany, the Netherlands and Portugal. In other countries, students could opt out of some science study at this level. However, European students have fewer opportunities to opt out of upper secondary mathematics, as in 10 Member States (Austria, Croatia, Estonia, Germany, Hungary, Ireland, Latvia, the Netherlands, Portugal and Slovenia) a successful examination in mathematics is needed for the completion of upper secondary education (OECD, 2016a) ([7]).

1.5.1.4 Institutional sorting

Irrespective of their own preferences, students can be streamed based on their academic achievement and placed into study groups that follow different curricula, receive different number of lessons and are required to complete different types of assessments. Ability grouping can occur between or within classes ([8]). Only in the United Kingdom, Ireland and, to a lesser extent, in the Netherlands are students streamed both between and within classes. Between-class groups affect over 50% of students in Luxembourg and Finland. In many European countries, however, the more dominant approach is ability grouping within classes. In Denmark, the Czech Republic, Hungary, Iceland and Poland, 60% to 90% of students learn in ability-streamed environments (OECD, 2016c).

Ability streaming was a recommended approach to science teaching at the upper secondary level in 2010/2011 in Austria, Cyprus, Denmark, Latvia, Lithuania, Luxembourg, Hungary, Malta Romania, Slovenia, Spain, the United Kingdom and also Iceland (Eurydice, 2011b). A similar approach was recommended for mathematics teaching in Austria, Bulgaria, the Czech Republic, Denmark, Greece, Ireland, Lithuania, Malta, Romania, Slovenia, Slovakia and Spain. In the remaining countries, ability grouping may still occur, at the discretion of the school principal or individual teachers (Eurydice, 2011a).

As a consequence, upper secondary students within the same country or even the same school are likely to experience different STEM education – following either from their own choices, or from institutional sorting, or from a combination of the two. These different experiences lead to the development of different skills, self-beliefs and levels of interest in STEM. To the extent that mathematics achievement varies between genders, ability streaming can have implications for the gender composition of students in basic and advanced science streams. This is consequential, as students' vocational orientations towards STEM and health fields are closely related to their science self-concept (students' beliefs and perceptions about themselves in specific academic situations), choices of science and mathematical subjects, where such choices exist, and the subsequent pathways into specific fields of studies at university level (Sikora, 2015). At this level of education students also form concrete career expectations with respect to STEM, and, in 2006, these were strongly segregated by gender in all European countries (Sikora and Pokropek, 2011). Therefore, the patterns of segregation in STEM-related tertiary education correspond to the patterns evident at the upper secondary level (European Commission et al., 2015; Cedefop, 2016).

([5]) Data from http://dx.doi.org/10.1787/888933286339, Table D6.2c. (web only).

([8]) School systems have different approached to the diversity of children with respect to their abilities and interests. They can offer a single, comprehensive programme and delay sorting until later ages, or they can apply early sorting based on students' interests and abilities. Students with similar characteristics can be grouped either to same schools or to same classes within a school, but grouping can also occur within a class. Grouping is meant to provide better tailored curricula and support to individual students' needs (OECD, 2016c).

1.5.2 Gender segregation in tertiary education and STEM

Tertiary education is segregated by gender throughout Europe, which reflects but also drives occupational segregation. For example, across 17 European countries in 2004–2005, 69% of employed men who graduated from a male-dominated field of study were consequently employed in a male-dominated occupation (Smyth and Steinmetz, 2008).

In 2014, women made up the majority of tertiary graduates in all the Organisation for Economic Co-operation and Development (OECD) countries except Switzerland ([9]) (OECD, 2016a). Women's increased participation in higher education, however, has not led to equal distributions of genders across different fields of studies. In contrast, field-of-study segregation has remained a persistent feature of the higher education system in virtually every country in the world. In a number of Western countries, some desegregation processes had taken place prior to the 1990s. They had slowed and even started to stagnate by the end of the 20th century (Barone, 2011). Although the extent and also the exact pattern of segregation varies between countries, the general trend appears to be universal: across the OECD countries, women outnumber men in gaining qualifications in education, health and welfare, humanities and arts, social sciences, business and law. Yet they remain a minority in science, mathematics, computing and engineering (OECD, 2016a).

Data from Eurostat, available up to 2012, allow for a more detailed overview of European segregation. In 2012, 23% of all tertiary students in the 28 Member States of the EU (EU-28) graduated in the two ISCED fields of 'Science, Mathematics and Computing' and 'Engineering, Manufacturing and Construction' ([10]). The average gender ratio across the EU-28 in Science, Mathematics and Computing in 2012 was 40%, meaning that there were only 4 females for every 10 graduates in these fields. The lowest ratio of women was found in the Netherlands (26%), Malta (29%) and Belgium (30%). In only four countries did women outnumber men in this graduate population: in Bulgaria (51%), Italy (55%), Portugal (56%) and Romania (61%). At the same time, Engineering, Manufacturing and Construction saw the greatest underrepresentation of women. Here, the proportion of females was as low as 27% in 2012, and it did not exceed one third in any of the EU-28 except Italy (34%), Romania (35%), Poland (36%), Denmark (37%), Luxembourg (40%) and Cyprus (50%).

Within the two main STEM-related areas, remarkable differences in the gender gaps within sub-fields can be also observed over time in the EU-28. Among the 'core' STEM fields, only in Life Sciences does the share of women exceed their overall share in the student population (62% in 2012). In other sub-areas, women's share remains well below this level, although to a varying extent. In Mathematics, Manufacturing and Processing, and Physical Sciences, women lag behind men only by a small extent, and in Mathematics and Statistics women's share remains very close to that of male graduates (50% in 2012). After a steady increase and then some fall back between 2008 and 2012, the proportion of women also approached 50% in Manufacturing and Processing (48% – the only Engineering field with only a moderate women's disadvantage) and in Physical Sciences (45%). At the same time in Architecture and Building ([11]) some improvement was also apparent, with women's ratio moving from 33% to 37%. The two subject areas with the greatest gender imbalance are undoubtedly Engineering and Engineering trades – which is also the biggest sub-field within the broad category of Engineering – and Computing. In these two sub-fields, the ratio of female graduates remained below 20% for most of the period described here. In other words, of five graduates in these areas only one was a woman, even in 2012. Instead of some improvement during the decade, in the case of Computing a setback was recorded, as in 2003 the share of women was 6 percentage points higher here than 9 years later.

Given that the described tendencies were coupled by a general expansion in higher education, the stagnation of women's share in STEM fields as these fields expand is both remarkable and concerning. The corresponding patterns in the occupational structure across Europe mirror this stagnation.

([9]) No data on Belgium, Canada, Estonia, France, Greece, Ireland, Israel, Korea and Poland.
([10]) From Eurostat. Own calculations. Data retrieved 20 April 2017. Graduations in ISCED 3 to 6 by field of education and sex [educ_grad5].
([11]) A subject area not always considered as STEM – see European Commission et al., 2015.

1.5.3 Gender segregation in STEM occupations

Notwithstanding the increasing level of female employment, the liberalisation of gender roles and the fact that in several countries women outnumber men in the higher education system, gender segregation remains a persisting characteristic of the European and non-European labour markets. Gender segregation in the workforce occurs when some occupations are dominated either by men or by women. Overall segregation can be considered to have two dimensions: a horizontal and a vertical one. Horizontal segregation refers to the unequal representation of men and women across occupations that are comparable in terms of authority, prestige or pay. Thus horizontal segregation denotes differences and not inequalities. In contrast, vertical gender segregation entails gender inequality by definition, as it concerns women's underrepresentation in occupations that are considered to be more desirable in terms of social prestige, income or other resources (Jarman et al., 2012).

According to a study based on Labour Force Survey data, among the 20 most popular occupations in Europe the most male-dominated professional jobs are those for engineering and computing professionals (where the proportion of women is 18.3%), and engineering and computing technicians (where the proportion of women is 20%). The proportion of women in these occupations varies somewhat across countries, but does not exceed 30% anywhere except Bulgaria (39% in the case of professionals) and Ireland, Romania and Estonia (32%, 33% and 39% for technicians). Moreover, the underrepresentation of women in these areas remained rather stable between 2005 and 2010 (Burchell et al., 2014).

So far in Europe a marked underrepresentation of women in certain STEM occupations as well as in related study areas has persisted over time. The concentration of men in STEM occupations, with women working mostly outside STEM, contributes to talent loss and limits the beneficial effects of social diversity, which has been shown to enhance research excellence and innovation in teamwork (Page, 2008). The persistence of women's underrepresentation in particular fields of STEM also contributes to reproducing economic gender inequalities, as STEM occupations represent some of the best paid and most prestigious jobs in the labour market. As mentioned above, an analysis on 2005–2010 data from 27 EU Member States (Goos et al., p. 17) has revealed a significant wage advantage for STEM workers when a range of other factors (including years of education, experience, gender, marital status, hours worked, industry and country) were controlled for. Compared with the 19% average wage premium in the EU, significantly smaller values were found in Belgium and Denmark (below 10%), but the premium exceeded 20% in Sweden, Slovenia, Spain, Germany and Latvia. In a comparable analysis involving wage regressions in the USA, it was also shown that the wage premium of women in STEM jobs is even higher than the premium of men when compared with wages of women/men in similar non-STEM occupations (Beede et al., 2011). As few women work in STEM, these findings imply that a large number of females are excluded from access to some of the best paid occupations in the labour market. This continues to be the case over and above the gender inequalities that exist within the STEM workforce. As was made evident by an analysis on the Labour Force Survey 2010 data across Europe, in the heavily male-dominated occupations of engineering and computing professionals and engineering and computing technicians, women are further underrepresented in positions entailing supervisory responsibilities (Burchell et al., 2014).

Moreover, women's underrepresentation in STEM careers also reinforces cultural stereotypes, which discourage many young women from seeking entry into STEM. This further restricts the occupational choices of men and women, reinforcing existing gender inequalities (Jarman et al., 2012) and hindering the optimal utilisation of talent, as females with capabilities, skills and interests equal to those of males may abandon their goals of pursuing STEM specialisation.

1.6 Gender diversity in health and medicine

The structural and cultural factors that operate in upper secondary and tertiary education as well as in the labour market, described in previous sections, also affect the level of interest and gender segregation of adolescent vocational orientations and pathways into health and medicine-related occupations. Most literature on PISA data and science-related adolescent expectations juxtaposes STEM, as defined in this report, with health and medicine (Sikora and

Pokropek 2012a, 2012b; Mann et al., 2015; Han 2016a, 2016b, 2017; Mann and DiPrete, 2016; OECD, 2016). The key reason for that is that young women tend to be overrepresented among youth who intended to pursue careers in these fields. Moreover, health and medical studies involve a strong science element, thus for students with a particular interest and good performance in life sciences they constitute a real alternative to STEM occupations that have a similar focus, such as life science professionals and associate professionals (e.g. biologists).

Females outnumber males in medical and healthcare areas both in the labour market and in the education system, although the extent of the female advantage varies greatly depending on the field and type of job, in the USA as well as in Europe. Burchell et al. (2014) list health professionals and associate nurses and healthcare assistants among the top 20 jobs in Europe in 2010, and note that while women accounted for 65.1% of health professionals, they accounted for more than 82.9% of associate nurses and healthcare assistants. Further, in 2012 females constituted as much as 75% of all tertiary graduates of Health and welfare studies across Europe, with the proportion ranging from 60% in Cyprus to 91% in Estonia and Latvia (Eurostat data, educ_grad5). Given that this gender divide is also evident in the career plans of 15-year-olds in 50 countries, including in Europe (Sikora and Pokropek, 2012b), STEM and medical fields remain territories of marked horizontal gender segregation, but with opposite trends. Moreover, studies looking into high school students' career preferences also point to the complementary relation between the two areas. Using a slightly different division of occupational fields, Sikora and Pokropek have found for example that females and males with a similar science profile – that is, with a similar level of science performance and science self-concept – tend to choose diverging paths across 50 OECD countries. In all countries studied, females were more likely to choose employment in biology, agriculture or health, while males were more likely to go into computing, engineering or mathematics, even when their science performance self-confidence is very similar (Sikora and Pokropek, 2012a). Acknowledging all these similarities and differences between core STEM and medical areas, in this report we keep our focus on the former and only briefly discuss medical careers as an alternative path for science-oriented students.

2 The career plans of adolescents

In this chapter, we survey the theoretical and empirical work on students' career plans. First, we focus on three main pillars of the report: (1) the relevance of career plans for future behaviour, (2) the gender differentials and (3) cross-country comparability. After presenting recent findings on these three issues, we systematically review factors that may contribute to choosing a STEM career over other jobs. We concentrate on four sets of factors – that is, student-related variables, school-related variables, country-level factors, and global-cultural trends and characteristics – that may be responsible for shaping career plans of adolescents.

2.1 Career plans have predictive power

To better understand why men and women end up studying certain subjects and then entering corresponding jobs, it is important to look at their early socialisation and education. In particular, when adolescents approach the end of compulsory education their career plans become consequential for their choices of further education. Thus much can be gained from understanding why and how young people set their minds on particular career paths. Students' career preferences may reflect their scholarly achievement, parental encouragement, peer role models, self-concept and social identity, as well as a plethora of other influences. These influences are in a cyclically reinforcing flux: students who do better in science are more likely to consider a career in a related field, and commitment to this career boosts later student achievement. But career plans matter not only because they reinforce scholarly achievement but also because many top students do well in nearly all academic fields, and so their occupational preferences indicate the fields of study in which students take a special interest and make extra effort to do well.

Longitudinal research that estimates the extent to which adolescent career plans predict later educational and occupational attainment is characterised by different measurements of occupations. Some studies focus on occupational prestige or occupational status (Croll, 2008; Ashby and Schoon, 2010); others compare the professions with other occupations (Croll, 2008). Although youth tend to change their detailed occupational plans, aspirations to professional occupations in high school quite accurately predict entry into the professions, irrespective of family background and educational performance. Evidence from the British Household Panel Survey, for example, consistently showed that aspirations identified in terms of broad occupational categories at the age of 15 predicted occupational status attained 5 to 20 years later. This held in various birth cohorts (Schoon et al., 2007; Croll, 2008; Ashby and Schoon, 2010). Similar findings were reported from Australia, for students who were 14 years of age in 1998 and participated in the Longitudinal Surveys of Australian Youth. Occupational expectations of high school students predicted later occupational attainment around the age of 25, even when several characteristics, including parental socio-economic status and student scholarly achievements, were held constant (Sikora et al., 2011).

These studies, however, show that aspiring to managerial or professional jobs is predictive of later attainments, without discerning which specific professions young people aspire to and whether or not they end up in these professions. For instance, few studies demonstrate whether or not youth who plan to enter science professions of a particular type actually enter those professions in adulthood. In contrast, research on the links between early career plans and attainment focuses on the attainment of tertiary education, specifically on educational fields. This provides indirect evidence, as tertiary study specialisation tends to be strongly correlated with the occupational attainment of graduates. The largest number of studies of this type comes from the USA. In one such study, the expectation of eighth grade students in 1988 to pursue a science-related career at the age of 30 doubled the likelihood of eventually earning a science-related baccalaureate and increased by 3.4 times the likelihood of earning an engineering degree (Tai et al., 2006). An early plan to earn a physical science and engineering degree increased the chances of attaining such a degree 3.4 times, after controlling for a range of individual factors including mathematical achievement (Tai et al., 2006). Studies on PISA longitudinal data in Australia found that an occupational plan to work in a science-related area was one of the most important factors that predicted the pursuit of a university qualification in related fields. Adolescent students who reported a plan to work in an occupation linked to computing, engineering or mathematics were more likely than others to choose a degree in these fields, whereas students who expressed an early interest in biology- or health-related occupations were more likely to end up studying these fields, irrespective of their other characteristics (Sikora, 2014).

2.2 Career plans are gendered

Adolescent career plans are not only well aligned with later educational and occupational attainments but are also gender typed, as these later attainments are. Males and females have different career preferences and gender differences in plans show patterns that broadly resemble the patterns of actual gender segregation in the labour market. Already in childhood and even more so in adolescence, females tend to opt for female-dominated occupations while males prefer male-dominated jobs. In a number of studies, males have demonstrated more interest in science jobs, in particular engineering or computing, or in becoming police/fire service mechanics, electricians and builders. In contrast, females are more likely than males to aspire to medical and social science jobs, nursing, teaching, journalism, and art and design. Clerical and secretarial occupations, child care, catering, and work as a hairdresser or beautician are also more attractive to females (Croll, 2008). Considering the entire range of occupations in Australia, it was found that between 13% and 42% of students who were aged 14 in 1998 (depending on the level of detail used for occupational disaggregation) would have had to change their career expectations to achieve a perfectly gender-balanced share of occupational choices (Sikora et al., 2011). Dissimilarity indices of occupational expectations of adolescents in 2000–2006 ([12]) from the European PISA data suggested that between 35% (Luxembourg) and nearly 50% of students (Finland) would need to change their plans to achieve gender-balanced distribution of occupational plans in Europe (Hillmert, 2015).

In PISA-participating countries, studies on males' and females' STEM-related vocational plans demonstrate that adolescent plans are broadly segregated by gender. PISA 2006 data show that, across all the OECD and partner countries, males express an interest in engineering and computing occupations in much higher proportions than females, whereas in health careers there is an opposite trend (Sikora and Pokropek, 2011; Han, 2015, 2017). Using the same data, the probability across a range of OECD countries that a female would expect a STEM occupation, when their individual characteristics but also several school- and country-level factors were held constant, was consistently found to be 58% lower than the probability for males (Han, 2016, 2017). Looking at the occupational expectations of high school students in the USA in the Education Longitudinal Study, Morgan and his colleagues have also identified marked gender differences in the proportion of adolescents who expect to pursue a STEM career at the age of 30. In particular, between 2002 and 2006, for every 100 students in post-secondary education, 18 males but only 4 females expected a STEM occupation ([13]). Also in the USA, gender differences in STEM occupational plans were not only found to be substantial, but they also predicted fairly well the gender gap in field-of-study choices across higher education, even after controlling for family goals, prior coursework uptake, academic performance and family background (Morgan et al., 2013). Students' orientation towards science-related careers is likewise highly gender typed in Australia. Longitudinal PISA data in this country show that males are four to five times more likely to choose a physical science-related occupation ([14]) than females, and that females are significantly more interested in life-science-related occupations ([15]) (Sikora, 2014). Only 26% of Australian females who were planning a career in physical science or related fields at the age of 15 actually studied these fields when they entered higher education, compared with 60% of males (Bytchkova and Salvi del Pero, 2013).

([12]) In this analysis a pooled set of 2000 and 2006 data is used.
([13]) In these numbers, doctoral-level medical, biological, health or clinical science-related occupations are not included.
([14]) Engineering, mathematical and computing occupations.
([15]) Occupations related to biology and health services.

2.3 Cross-country variation and changes in career plans over time

To understand gender segregation of occupational plans, educational choices and occupational attainments, it is helpful to consider global patterns in gender divides. Most popular explanations of youth vocational motivation related to STEM recognise the importance of cultural contexts (Ceci et al., 2009; Charles and Bradley, 2009; Nagy et al., 2010; Barone, 2011; Eccles, 2011). This is the case regardless of whether these arguments originate from social psychology, sociology or cognate disciplines. Few explanations, however, offer concrete hypotheses that propose how and why differences in cultural contexts should affect adolescent occupational expectations related to STEM (for exceptions, see Charles et al., 2014, 2017). As cultural trends, economic phenomena, policies and the flow of digital information become increasingly global in scope and content, traditional accounts of how adolescents come up with plans for the future are often myopic in their focus on individual attributes and local contexts (Helwig, 2008; Cochran et al., 2011).

Macro-cultural theories that aid appreciation of the global picture cannot evolve without international comparisons and understanding the processes that they highlight. One issue discussed in comparative research in recent years is the contrast between youth in the transitioning and the affluent parts of the world (Sjøberg and Schreiner, 2005, 2010). Students in countries experiencing transitions and rapid economic growth take more interest in STEM than their peers in post-industrial societies (i.e. the OECD countries). By and large youth in developing countries are more interested in STEM than youth in post-industrial societies (Sjøberg and Schreiner, 2010). The gender gap in STEM interest is also considerably larger in affluent countries (Charles, 2017). In many developing countries, gender gaps in STEM education are smaller than the corresponding gaps in affluent parts of Europe, North America, Asia and Oceania.

International comparisons of educational choices and vocational preferences have led to the development of macro-cultural theories that call for attention to the global and universal gender stereotypes that flourish under specific structural conditions and are taken for granted as norms (Charles, 2011). In post-industrial societies, youth are more likely to select occupations that fit in with the stereotypical conceptions that all females thrive in communication- and care-oriented careers, while men, in contrast, are bound to succeed and find self-fulfilment in solving abstract mathematical and technological problems (Charles and Bradley, 2009). This stereotypical alignment between specific cultural conceptions of femininity and masculinity and specific occupational activities – commonly referred to as gender essentialism – has been shown to operate as a powerful constraint on the choices of careers among youth.

Moreover, it is possible that the earlier in their lives young men and women get to shape their education pathways, by virtue of having a choice to specialise, the stronger the self-sorting tendencies (Xie and Shauman, 2003; Reisel et al., 2015). This self-sorting is facilitated in affluent post-industrial countries by the widespread acceptance of self-realisation and the legitimacy of matching a choice of vocation with self-perceived gender identity. Such matching is commonly accepted as the typical career choice strategy (Charles and Bradley, 2009). The prominence of these cultural values is further enabled by a progressive shift towards comprehensive education across Europe and elsewhere (Sikora and Pokropek, 2012a). In comprehensive education, youth can and are encouraged to specialise early in areas that they find personally interesting and appealing, even if this means discontinuation of education in other areas, including science. Finally, in post-industrial societies women find plenty of opportunities to work in skilled professions that fit in with the stereotypical conceptions of feminine excellence in communication and care (Charles and Bradley, 2009). In contrast, in developing countries the gender gap in career expectations between youth is significantly less pronounced (Sjøberg and Schreiner, 2010). Young people are more interested in science and young women do not differ much from young men in their aspirations to pursue science-intensive careers, unlike their peers in more affluent parts of the world.

The study of cross-national variation in adolescent occupational expectations thus offers several important contributions. Firstly, the extent of variation in gender segregation in youth vocational goals across countries provides a defining insight into the global and local contours of gender stereotypes. This is directly linked to a realistic assessment of how local policies can succeed in eradicating gender imbalance in STEM. Moreover, cross-national comparisons identify important correlates of global and local stereotypes. More precisely, such comparisons can reveal which country-specific economic conditions, cultural beliefs and institutional arrangements go hand in hand with deep gender divides in STEM. Some examples of such factors include women's participation in the STEM labour force, ability streaming in mathematics and science education, provisions for compulsory testing in mathematics and science on graduation from secondary schools, and other conditions that vary from country to country (Hillmert, 2015). Only systematic and rigorous international comparisons can highlight the role of cultural and policy contexts that are effective in counteracting gender stereotypes and bridging the associated disparities in STEM.

Understanding the historical changes in institutional and cultural triggers behind STEM segregation is important to inform education and labour market policies, be they local or global in scope. As policies are designed to transform outcomes for young people, and to achieve greater equity and talent utilisation, assessing what works in various institutional and cultural contexts is paramount for targeted policy development.

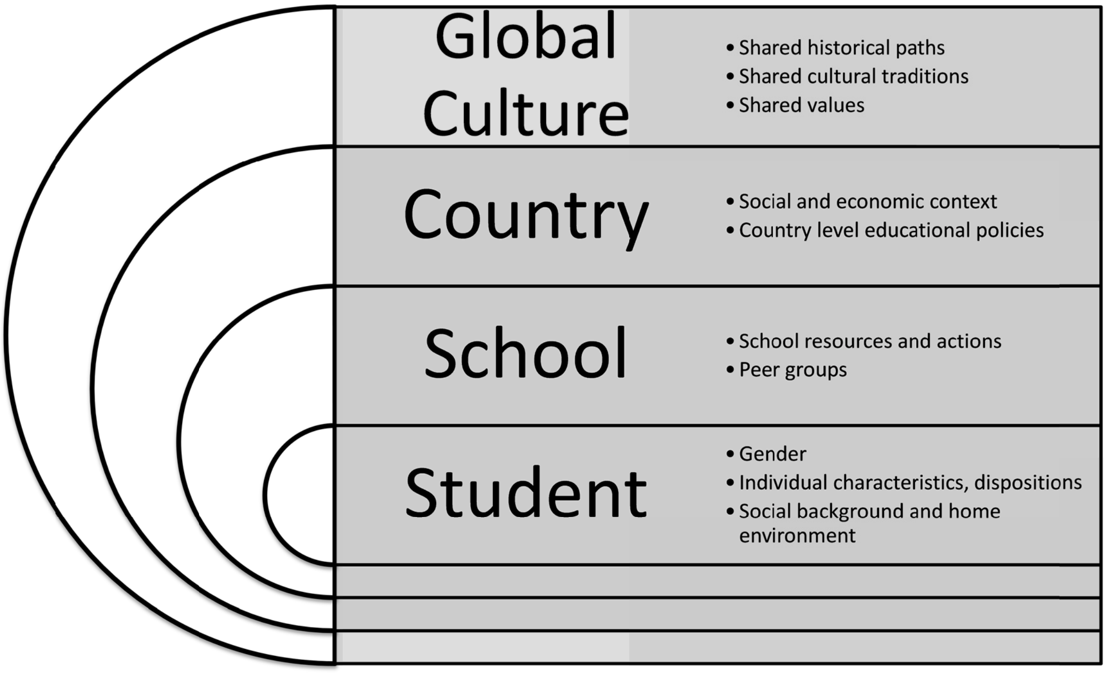
However, to date few comparative studies of change over time in adolescent occupational preferences related to STEM have been possible. The only source of information on this topic suitable for international comparisons has been Trends in International Mathematics and Science Study (TIMSS) (Charles, 2017). An analysis over time of adolescent aspirations to STEM jobs involved eighth graders in 32 countries and territories, including several European countries (Hungary, Italy, Lithuania, Norway, Romania, Slovenia, Sweden and the United Kingdom) and also some societies that have not been involved in the PISA study, e.g. Botswana, Ghana, Iran, Lebanon, Saudi Arabia, South Africa and Syria. Comparing TIMSS data for the period between 2003 and 2011 demonstrated that with higher levels of Human Development Index the male-favouring gap in aspirations to STEM careers was greater. In other words, the gender divide in youth interest in STEM jobs is wider in affluent countries (Charles, 2017). The gender gap in STEM interest was also related to students' at-home internet use. It was reported that wider student access to the internet correlated with stronger stereotyping of STEM career plans among males and females. In contrast, the degree of gender segregation in STEM was unrelated to the difficulty of national mathematics curricula, to cultural gender stereotyping of STEM activities, or to the percentage of women in higher education or in the labour force. This analysis, based on fixed effects models, provides the most rigorous evidence so far of the link between gender segregation and societal development (Charles, 2017). It also suggests that many countries may be on a path towards exacerbated gender segregation in STEM, which is unlikely to abate of its own accord in democratic and affluent settings. This is why understanding the cross-national variation in youth career plans and its historical changes is of value.

2.4 What factors affect the STEM career plans of adolescents, and what makes them gendered?

Within different cultural contexts, educational and career decisions of individuals are anchored in the choices students and their families make prior to the transition into post-compulsory education. Policies and practices that can be adopted in the labour market and in further education and training, to attract diverse genders to counter-stereotypical fields of science, are important. However, exploring factors that shape career expectations of very young students is paramount. In fact, it is commonly argued that to achieve a greater gender balance in STEM occupations, interventions should focus on (early) educational careers and the early divergence of females' and males' career expectations (Archer et al., 2010, 2013). Similarly, to increase the number of students opting for STEM-related careers, early school experiences of children need to be well understood.

Occupational choices are interrelated with a range of individual and structural factors. Individual choices are not made in a vacuum; instead, the processes that shape career plans take place in a socio-cultural environment represented by the family and the school, and also influenced by the broad cultural and economic context at country and global level. Thus various layers at the global cultural, country, school and individual levels interact in complex ways, shaping students' experiences and their vocational choices. Gender in particular affects career plans through a range of mechanisms, as prevailing cultural norms are channelled through institutions and interactions at various levels, resulting in massive differences in males' and females' career plans – as we have seen in the previous chapter.

Figure 2.1. Layers of variables that influence STEM choices.



Hereafter, we discuss the main factors that drive students' occupational choices, emphasising mechanisms that operate differently for males and females and are therefore likely to contribute to gender segregation in interest in STEM careers. In doing so, we will distinguish between individual-, school-level, country-level and cultural characteristics, moving from the lower to the higher levels and noting that they interact in several ways (see Figure 2.1.). Although several individual characteristics, such as gender, family background and ethnicity, cannot be manipulated by policymakers, others may potentially be subjected to educational interventions. Most importantly science achievements but also attitudes towards STEM-related subjects can be considered as areas for intervention. At the school level, we will consider aspects of school composition and also resources invested in science teaching. At the country or system level, characteristics of the education system will be discussed that are likely to contribute to cross-country differences either in overall interest or in the gender segregation in STEM fields. Here we will distinguish between the broad institutional characteristics of the national systems and a set of subject-specific policies. Finally, we will move to the cultural level that incorporates current traditions and values derived from common historical paths. Here we will introduce the notion of gender essentialism – an explanatory framework that has so far been most successful in accounting for the universal patterns of gender differences in STEM choices. Although PISA contains no potential indicators to measure gender essentialism in the individual countries, and although external sources are scarce, we will keep this perspective in mind as a means of better understanding cross-country differences and similarities.

2.4.1 Individual characteristics of students and their career plans

2.4.1.1 Proficiency in science/mathematics

In a fully meritocratic society, educational as well as occupational advances would be based mostly on interest, individual abilities, performance and motivations. Based on meritocratic theory, we should expect occupational expectations to be driven by interest, academic performance and motivation. Indeed, research has shown that abilities play an important role not only in shaping individual academic achievement but also in influencing career plans and ambitions. Generally, more able students have more ambitious occupational plans (Schoon et al., 2007; Ashby and Schoon, 2010). More specifically, we also know that students with better science performance are more likely than others to have science-related occupational plans (Sikora and Pokropek, 2012a; Han, 2015, 2016b, 2017). Notwithstanding the ethos of today's mass education system, which advocates equality for children from every strata of society, abilities account for only a part of career plans. Students with comparable academic achievements still select particular careers more in line with their socio-economic background or prevailing gender stereotypes than their academic capacity.

For a long time, unequal mathematics and scientific skills were the most common explanations of gender differences in STEM (e.g. Mann and DiPrete, 2013; Wang and Degol, 2013). A growing body of research, however, has demonstrated that even if some slight gender differences in mathematical skills persist, males' advantages in mathematical skills are far too small to explain a significant part of gender segregation, either in higher education or in the labour market (Xie et al., 2003; Mann and DiPrete, 2013; Wang and Degol, 2013). Gender divides in STEM expectations remain wide even when students' test scores in maths or in science are held constant (Sikora and Pokropek, 2012a; Han, 2015, 2016b, 2017; Mann et al., 2015; Mann and DiPrete, 2016). Moreover, it was also shown that gender differences in maths performance can themselves be a function of exposure to gender essentialist beliefs, as women show lower performance when gender stereotypes are activated in stereotype threat situations (Steele et al., 2002; Lesko and Corpus, 2006). Finally, learning about positive female role models can positively influence women's mathematical results (Marx and Roman, 2002; McIntyre et al., 2003).

2.4.1.2 Self-belief and motivation

As has been long established in psychology, educational and career-related behaviours and decisions depend not solely on what people achieve but also on how much they think they can achieve, how they evaluate their capabilities and how much they believe in themselves (Bandura, 1977, 1999; Eccles et al., 1990, 1993; Eccles, 1994, 2009). Such self-belief is shaped but not determined by earlier experiences of achievements, and can also reinforce (or weaken) later performance. It is, however, not solely through shaping performance that it influences educational and career decisions; self-belief also has the capacity to independently motivate such choices (Eccles et al., 1998). Students with similar levels of performance can make different academic choices depending on their self-belief in various subjects. Therefore, for the selection of STEM occupations it matters greatly how much self-confidence males and females develop in their scientific and mathematical skills, not only because academic achievements and related self-belief can mutually reinforce each other but also because, with similar achievements, pupils more confident in their maths and science skills are more likely to opt for STEM careers (Wang and Degol, 2013).

Evidence based on the PISA 2006 data and other studies are in agreement that adolescent males are more confident in their STEM-related skills than adolescent females with identical levels of science achievement (Osborne et al., 2003; Sikora and Pokropek, 2012a; Wang and Degol, 2013). PISA data has also shown that males on average have a higher level of mathematical and also scientific self-efficacy than females. (Self-efficacy refers to the extent to which students believe that they can handle given subject-related tasks effectively.) In science, the gap is notably smaller than it is in mathematics, and females even outperform males regarding some of problems (in particular females are more self-confident than males in being able to explain how antibiotics work). In the PISA studies, gender differences were also found in mathematics- and science-related self-concept. In this case, the gap was found to be largely the same in the two subject areas. Very importantly, the gender gap in both self-efficacy and self-concept remained significant independently of the level of actual performance in these areas (OECD, 2015b). These findings are in accordance with earlier ones from the USA that suggest that males are more confident of their mathematical competencies than their female counterparts with comparable mathematical grades and test scores (Correll, 2001).

Besides actual and perceived abilities, personal interest, enjoyment of science, motivations and values attached to certain occupational characteristics are (consciously or unconsciously) considered when educational and occupational choices are made. According to several studies, males in the USA (Eccles, 1994, p. 595; Wang and Degol, 2013, p. 309) and in Germany (Frenzel et al., 2010) reported a higher level of interest in mathematics in elementary school but also as they grew older. The latest PISA study, however, shows no universal pattern in gender differences in students' enjoyment of learning sciences. In Europe, females have markedly less interest in science than males in the most affluent countries, such as Germany, France and the Netherlands, in contrast to the situation in Bulgaria, Lithuania and Poland, where the opposite is the case (OECD, 2016b). As an increased interest in science and maths is associated with a greater interest in making related educational choices (Koller et al., 2001), females' more moderate interest either in maths or science can lead to segregated occupational choices.

2.4.1.3 Role models and socialisation

During early childhood and also later in adolescence, gender essentialist beliefs are transmitted through role models such as parents, peers, teachers and media figures. These key actors in the socialisation process not only provide direct advice and opinions on an individual's educational and career decisions but also shape these choices unconsciously as role models with their reactions and behaviour. The feedback provided by role models also provides information on the gender appropriateness of the choices one might want to make (Yazilitas et al., 2013), Parents' values and expectations towards their daughters and sons often reflect gender stereotypes (Crowley et al., 2001). Research in Switzerland, for instance, has demonstrated that gender beliefs held by the teachers and parents can directly and indirectly shape students' self-belief and can also contribute to gender differences in students' subject-related choices (Keller, 2001). Thus, parents' values may influence not only children's own cultural beliefs but also their academic performance and consequent educational and occupational choices (Wang and Degol, 2013, p. 317). Although the complex interrelationships between parents' stereotypes, their plans for their sons' and daughters' careers, and the expectations students themselves develop are not yet fully known, it has been shown that parents of 15-year-old students were significantly more likely to expect their sons rather than their daughters to enter a job in a STEM field in all the countries participating in the PISA 2012 parent survey ([16]). The gaps remained notable even for males and females with similar results in mathematics, reading and science (OECD, 2015b).

Most social stratification researchers agree that socio-economic background persistently influences various types of educational and occupational outcomes, which is the source of social inequality in contemporary societies. Socio-economic status of the family can affect career choices of pupils in a number of ways. Parents actively create the material and cultural environment of the home, fostering certain interests and activities and imposing expectations on their children, and they also give direct advice on educational and career choices. Parents of high socio-economic status tend to have higher educational and career expectations for their children (e.g. Ashby and Schoon, 2010), but their children have also been shown to have higher academic achievements in general (Shavit and Blossfeld, 1993) and produce higher test scores in science in particular (OECD, 2007). Moreover, students from families with higher socio-economic background tend to have higher aspirations in general, and they are also more likely than others to form science-related occupational plans (Sikora and Pokropek, 2012a). Indirect evidence further suggests that parents' tendency towards gender stereotyping varies according to their level of schooling. As females' – but not males' – persistence in choosing a STEM higher education subject is positively influenced by their parents' level of education, it is

([16]) Participating countries were Belgium (Flemish), Chile, Croatia, Germany, Hong Kong (China), Hungary, Italy, Korea, Macao (China), Mexico and Portugal.

very likely that more educated parents have less gender-stereotyped expectations towards their daughters' career choices (Ware et al., 1985). This is also in line with more general findings that children of highly educated parents are more likely than others to choose gender-atypical educational routes (Dryler, 1998). Nevertheless, some of the more recent social stratification research notes that cognitive abilities play an important role in stratification mechanisms distinct from the impact of socio-economic background. Cognitive abilities must be considered when studying social inequalities, as effects of socio-economic background peter out in contemporary societies (see Marks, 2013) for an overview).

Over and above the complex influence of parental socio-economic status, we also predict a more direct form of intergenerational transmission of occupational preferences, implying that children of parents who themselves work in a STEM occupation are more likely to develop similar orientation. This happens not only because parents in such cases may serve as direct references and role models for their children but also because they are better equipped to support their children's interest in science. In sociology, it is well established that children whose parents work in a specific area are increasingly likely to choose a related educational path or occupation themselves (e.g. Dryler, 1998). Moreover, gender socialisation theory also suggests that children are more likely to mirror the educational/occupational choices of their parents of the same sex. Empirical studies usually find partial support for this suggestion. In a study of Swedish teenagers in the 1970s, for instance, it was shown that males' educational choices mirror their fathers' more than their mothers' career – but females' educational choices did not demonstrate a similar relation to their mothers' occupation (Dryler, 1998). More recently, the gender socialisation theory has also received some support in the area of STEM career plans, and here the male link has also proved to be more influential. Although variations exist across countries, Sikora and Pokropek found that in most of the PISA countries, fathers' occupations in STEM areas do inspire males' choices. At the same time, maternal occupation was only influential for females' career plans in a small number of countries, and only in choosing health-related careers (Sikora and Pokropek, 2012b).

With some exceptions, students with an immigrant background tend on average to perform worse at school than their native counterparts. Moreover, their lower achievement cannot be attributed solely to their socio-economic disadvantages (Buchmann and Parrado, 2006; Fisi et al., 2016). In their science scores, for example, the performance gap between immigrant and non-immigrant students is reduced but does not disappear when their socio-economic background is also taken into account. This general tendency shows major variations, however, not only between the destination countries but also depending on the country of origin and on other characteristics of the immigrants (OECD, 2016b). Taking this performance gap into account, and comparing immigrant and non-immigrant students with similar science scores, immigrant students have a clear preference for science-related careers. In some of the main European destination countries (Belgium, Denmark, the Netherlands, Sweden and the United Kingdom), immigrant students are more than twice as likely to plan such a career as their non-immigrant peers with a similar science performance. This finding is most likely to reflect the strong culture of upward intergenerational mobility prevalent in some immigrant subcultures (Lee and Zhou, 2015). More analyses are needed, however, to better understand the notable variations behind this pattern, the role of ethnic disparities and the intersectionality of different identities – most importantly ethnicity and gender. US research indicates marked variation in the role of individual attitudes in guiding adolescents' aspirations towards science and maths careers, depending on both their gender and ethnicity, and suggesting that there are different mechanisms behind gender segregation in various ethnic/racial groups (Riegle-Crumb et al., 2011).

In addition to the influence of students' academic achievement, self-belief and motivation, exposure to peer and adult role models, family background, and individual ethnic and cultural differences, prior literature has demonstrated that school environments exert considerable influence on adolescent vocational orientations and career plans.

2.4.2 School characteristics and students' career plans

Although comparative research evidence devoted to factors that lead to between-school differences in students' STEM-related career plans amounts to no more than a few studies (e.g. Mann et al., 2015; Mann and DiPrete, 2016), it shows that school and classroom experiences not only influence students' interest in STEM careers but do so differently for males and females – enhancing or bridging gender segregation. For example, widely shared gender beliefs may be strengthened or weakened by specific school environments, so interactions between and within school and out-of-school cultures are likely to occur and affect males and females differently, depending on their prior history of achievement in science.

While some of these school characteristics, most importantly the composition of the student body, are not easy targets for policymaking, other factors, such as the availability of certain science-related resources and facilities within schools, are relatively easy to manipulate. Likewise, the levels of responsibility that various actors have for school-related decisions and grade repetition in particular schools are potential targets for intervention, either at school or at higher levels.

2.4.2.1 School autonomy and grade repetition

School autonomy and grade repetition are considered two school-level factors that – despite the influence of national or local educational policies (e.g. in Germany) – constitute important aspects of a school's practice. School autonomy – the number of areas where decisions are taken by the principal, by teachers or by governing boards, and the level of responsibility they assume – denote the school's level of independence, and the potential it has to tailor education methods and also to some extent curricula to the needs, capacities and interests of the student body. Findings from the latest PISA study reveal positive correlations between higher autonomy of teachers and principals on the one hand and students' science scores on the other. At the same time, higher levels of school autonomy also correlate with more inequality in science performance, with students' background being more strongly related to their performance when school autonomy is higher (OECD, 2016b). The assumption exists that schools with higher levels of autonomy are likely to be more flexible in catering to students' needs and generate more engaging environments for learning. On the one hand, factors associated with school autonomy might generate conditions in which students are steered toward more science-related careers. On the other hand, school autonomy could intensify processes that discourage students from developing deeper interests in STEM.

Grade repetition or retention refers to the practice of making low-achieving students repeat the same grade for an additional school year. This practice is significantly more prevalent in some European countries than in others, with the proportion of PISA students who report that they have repeated a school year at least once ranging from 1.9% in Slovenia to 34% in Belgium (OECD, 2016b). The incidence of grade repetition is significantly correlated with students' academic performance, but also with their behaviour and motivation (OECD, 2016b). Although evidence is mixed, it has been suggested that grade repetition may have negative effects on self-concept, social adjustment and emotional adjustment (Holmes and Matthews, 1984; Hattie, 2008), as well as resulting in disengagement from school (Balfanz et al., 2007)**.** Moreover, grade retention is also associated with a decrease in parents' educational expectations (Hughes et al., 2013). Grade repetition policies that force low-achieving students to repeat a grade for an additional school year may therefore affect students' STEM career choices by lowering their motivation and engagement in science learning. We introduce this variable to check whether or not school retention policies can affect occupational career plans in STEM and non-STEM dimensions.

2.4.2.2 Peer influences

Various aspects of school population compositions have been shown to affect individual students' performance, educational behaviour (Crosnoe et al., 2008; Schneeweis and Zweimüller, 2012) and aspirations (Mann et al., 2015). Teenagers are particularly sensitive to their peers' opinion and judgement, and their development of self-identity is highly dependent on what their friends and classmates think and do. Peer effects within class are dependent on the socio-economic background of the student body, their dispositions to learning in general as well as to specific subjects, the average academic performance in the class, and the share of males and females in the class. Fellow students' behaviour also reflects their parents' views and expectations, and the overall socio-cultural home environment. Moreover, several of these influences vary by gender, potentially shaping males' and females' interest in STEM-related studies and careers in different ways (Frank et al., 2008).

Concerning the gender composition of schools, the widespread assumption exists that single-sex education may reduce females' exposure to gender stereotyping and thus increase their interest and attainments in male-dominated subjects. Although the PISA evidence indicates that the impact of single-sex education varies from country to country (Law and Kim, 2011), in some countries single-sex classroom environments can have a positive impact on females' mathematics and science achievements (Schneeweis and Zweimüller, 2012; Wang and Degol, 2013, p. 312). In some countries, females are more likely to make STEM-related subject and occupational choices if they are educated in a classroom without males (Smyth, 2010). Apart from strictly sex-segregated educational settings, in Austria it was found that an increased share of females in the classroom might make females more likely to choose a male-dominated (technical) school (Schneeweis and Zweimüller, 2012). In the PISA 2006 data, higher shares of females within schools were also associated with a significant decrease in the overall level of interest in pursuing a science-related career (a career in computing, engineering or mathematics) (Sikora and Pokropek, 2012a).

Research has shown that school academic performance influences related career aspirations of high school students independently of their own performance. The big-fish/little-pond effect (Marsh and Hau, 2003) suggests that high-achieving students develop higher self-perceptions in academically weaker environments, which will then encourage them to develop more ambitious career plans. High average school performance, on the other hand, lowers students' self-perceptions, leading to less ambitious career plans at the same level of individual performance. These associations were also found to guide science-related career plans in a number of OECD countries, albeit with substantial variations depending on the level of individual performance, gender and the characteristics of the education system (Mann et al., 2015). Mann and colleagues found in a study of PISA 2006 data in 57 OECD countries that stronger academic environment reduced students' career aspirations towards STEM, particularly among males with higher individual achievements. There are, however, substantial cross-country variations in these patterns, which are partly related to the presence of early tracking in the education system. Peer academic performance lowers individual aspirations more in the absence of early tracking, suggesting that social comparison is a powerful mechanism of adjustment. When track placement occurs, however, strong academic environments do not weaken students' ambitions to pursue STEM-related careers (Mann et al., 2015).

2.4.2.3 Resources and exposure to science and mathematics

While associations between students' STEM expectations and school variables describing school populations have been the subject of several studies, less attention has been paid to the potential influence of the resources that schools devote to teaching and popularising science. However, it is generally expected that a more intense exposure to science and mathematics as well as more resources made available for their teaching will not only improve students' science skills and abilities but will also promote students' willingness to enter STEM careers (Eurydice, 2011b). To promote science outside the school, during the past decade science centres were set up and a range of initiatives were started across a number of European countries (Eurydice, 2011b). Therefore, we can assume that the more schools invest in teaching science and mathematics, through material resources, time spent on formal lessons or related extracurricular activities (e.g. clubs or competitions), the higher the number of students planning a STEM career will be. This could be because extracurricular activities stimulate more interest in science and students, or because students more interested in mathematics and science are selected into schools that emphasise these subject areas.

Interestingly, providing a strong curriculum in mathematics and science has been shown to have promoted females' but not males' orientation towards STEM in US high schools during the 1990s. As a consequence, a gender gap in the likelihood of choosing a STEM subject in higher education was narrower in the context of more intense science and mathematics curricula (as measured by an index of advanced placement, college- or university-level courses offered at school). Using a range of information on students' prior motivation and academic experiences, the authors argue that their analysis comes close to establishing a causal relationship between school characteristics and students' orientation to STEM irrespective of student selectivity into particular schools. They conclude that 'a strong high school curriculum in maths and science provides more opportunities for concrete experiences of interest and competence and thus provides a partial antidote to gender stereotyping' (Legewie and DiPrete, 2014, p. 5).

2.4.3 Country characteristics and students' career plans

While variations in science and mathematics teaching across schools may contribute to within-country variations in STEM aspirations, researchers have started looking into cross-country differences, trying to understand how historical and cultural social differences, in particular in labour markets and education systems, may contribute to the variation in males' and females' aspirations to STEM careers. Social norms and values have repeatedly been found to influence students' career decisions. Prevailing gender essentialist values, i.e. the widely shared conviction that women are naturally suited to occupations involving inter-human communication and caring activities, while men are naturally suited to occupations involving technology and abstract problem-solving, was argued to be the major factor enhancing gender-typical career choices (Sikora and Pokropek, 2012a; Charles, 2017). Essentialist beliefs are more likely to be acted on in affluent, democratic countries with more gender-egalitarian values (Sikora and Pokropek, 2012a), and this is where the gender gap in STEM expectations is wider. Recently, public attitudes towards science and technology have been identified as positive correlates with students' interest in STEM careers across various countries (Han, 2017). This association is similar for males and females but it is stronger for low achievers in science than for high achievers (Han, 2017). Finally, a recent study has argued that more competitive national maths and science performance environments narrow the STEM gender gap, and that the apparent relationship between gender-egalitarian values and the STEM gender gap is due to the differences in national performance environments (Mann and DiPrete, 2016).

Various characteristics of education systems have also been investigated to assess the complex influence they exert on students' interest in STEM careers and the related gender segregation. Research has explored general characteristics that differentiate entire education systems, and curriculum-specific characteristics concerning the differences in mathematics or science teaching. As we will see, research has so far focused on the former, exploring the ways students in different types of educational systems develop an interest in STEM careers, and less attention has been paid to subject-specific policies. In this report, both sets of educational system characteristics will be discussed.

2.4.3.1 Educational systems: stratification, vocational orientation and standardisation

Research on educational systems distinguishes three forms of relevant institutional arrangements: the level of tracking, vocational orientation and standardisation. It is argued and supported by evidence that educational systems that differ with respect to tracking, vocational orientation and degree of standardisation produce different outcomes for students in terms of education achievement, equality of opportunities and labour market placement (Bol and Van de Werfhorst, 2013). A number of studies have demonstrated that these institutional arrangements may affect students' educational and occupational preferences (Buchmann and Dalton, 2002; Sikora & Pokropek, 2012a; Han, 2015, 2016a, 2016b; Hillmert, 2015; Mann et al., 2015).

Stratification or level of tracking refers to the extent to which students of the same age are placed in different educational tracks that lead to different qualifications. In stratified systems, streaming or tracking occurs between different programmes and between schools within the same level of education. By separating students on the basis of ability between different programmes and schools rather than within the same programme, differentiation becomes more pronounced as it relates to the entire curricula for several years, typically with restricted opportunities to move between tracks. Tracking takes place mainly in secondary education. The most widely used indicator of tracking is age at first selection of students into different types of schools or programmes, but the number of school types available at the age of 15 is also commonly applied (Bol and Van de Werfhorst, 2013).

A high level of stratification has been shown to reduce equality of opportunities in education and thus to increase the association between parental socio-economic background and educational achievements (Buchmann and Park, 2009; Bol and Van de Werfhorst, 2013). Parents (and also teachers) have particularly strong influence on the early choices of students, practicing a form of social control over the early decisions taken in education systems with early tracking (Barone, 2011). As academic achievements and consequential educational and occupational choices are strongly linked to the school type or to the educational programme attended, in the stratified systems early choices have far-reaching consequences and early parental impact is less likely to diminish. Interestingly, some research has also shown that systems with intense tracking also intensify the influence of gender. In the more stratified systems, bigger gaps between males' and females' test scores exist in mathematics (van Langen et al., 2006; Bedard and Cho, 2010) and science (van Langen et al., 2006) in both TIMSS and PISA data.

In terms of academic but also occupational expectations, research suggests that in highly differentiated systems, students' expectations depend more on parental background and on students' achievements than they do in the undifferentiated systems (Buchmann and Dalton, 2002). Moreover, occupational plans in the stratified systems were also found to be more realistic in the sense, that on average, fewer students expect to enter highly skilled white-collar jobs. Overall, the distribution of the types of careers planned by students in the stratified systems mirrors more closely the actual situation in the labour market. Clearly, in these systems, students are already aware of the restrictions that the type and level of school they attend place on their future educational and career prospects, and they shape their expectations accordingly. In line with these suggestions, the hypothesis that higher levels of system stratification lead to more realistic and thus more moderate expectations of entering a (professional) STEM career was also corroborated by PISA 2006 data, albeit in a specific group of countries. According to Sikora and Pokropek, for instance, fewer students plan to enter computing, engineering or mathematics occupations in countries with a higher degree of stratification, but only in developing and transforming OECD countries[17], rather than more industrialised settings (Sikora and Pokropek, 2011, 2012a).

Other interesting associations exist between system stratification and gender segregation in adolescent occupational expectations. In a study on PISA data, it was found that level of stratification (as measured by a combined index based on age of first selection, the relative duration of tracking in secondary education and the number of school tracks) across the 22 countries studied was associated with fewer gender-typical career choices ([18]) for males, but with more gender-typical choices for females (Hillmert, 2015). Another more specific, STEM-related analysis suggests that in the more stratified systems females – but not males – are less likely to opt for a professional career in engineering or computing, which widens the gender gap (Han, 2016a). Han's study further suggests that the negative effect of system stratification (as proxied by the number of school types or distinct educational programmes available to 15-year-olds) on female students' interest in computing and engineering careers only occurs among the top science performers, while at lower performance levels there is no significant association between system stratification and students' career plans (Han, 2016a). Other comparable studies, however, have not revealed any significant associations between the size of the gender gap and system stratification (Sikora and Pokropek, 2012a; Han, 2015). Technically speaking, the difference in results may be due to model specification, i.e. the different control variables used by particular researchers. However, the lack of difference in the level of gender segregation between the stratified and the comprehensive systems may also be related to a rather paradoxical phenomenon that may contribute to an increased gender gap in the less stratified systems. As early self-sorting is encouraged in these institutions and the opportunity for early specialisation based on personal interest is offered,

([17]) Also including Bulgaria, the Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia and Slovenia.

([18]) For this measure the relative gender composition of the occupation that the student planned to enter was taken into account in the labour market of the individual countries.

self-perceived gender identity may increasingly guide students' self-selection and encourage females to drop science and mathematics subjects at an early age (Sikora and Pokropek, 2012). Such a mechanism may compensate for the absence of institutional pressures that guide males and females on different tracks in the more stratified systems.

The second characteristic of the education system, level of vocational tracking, refers to the extent to which students are placed or select themselves into vocational programmes that offer specific skills and preparation for a restricted set of jobs. This is in contrast to students in academic tracks, who gain generic skills and have more open options for later educational and career choices. Vocational tracking is not always considered as a separate factor because it relates to the co-existence of several educational paths in the stratified systems. Among these, several vocational paths are also likely to occur (Bol and Van de Werfhorst, 2013). In his aforementioned study, Hillmert finds that the level of vocational enrolment in a country is associated with intensified gender-typical occupation plans for both females and males. This applies mostly to medium-level occupations that do not require a higher education degree. These effects are additional to the system stratification effects discussed earlier (Hillmert, 2015).

Finally, the extent of standardisation denotes the regulation of what and how students are taught, which qualifications are required for teachers, which exams must be sat, and other forms of restricting individual school and teacher autonomy. To achieve a certain level of similarity in terms of content and quality of education provided, every national system is at least to some extent standardised. The level and also the means of standardisation, however, vary between the countries. The two dominant approaches to standardisation include standardisation of inputs (teacher training, curricula, textbooks, etc.) and standardisation of outputs (national exams), and each potentially leads to different consequences as far as students' achievements are concerned. Standardisation has also been shown to relate to STEM career expectations.

Expectations with regards to the relationship between input standardisation and interest in STEM careers vary. One possibility is that, with more standardised curricula, students are exposed to a generally higher level of mathematics and science teaching, which may help in developing an interest in science among students who would otherwise not have pursued these subjects. On the other hand, less tailored teaching content and practices in maths and science may discourage students from following related careers (Han, 2015). Exploring the potential effect of input (curricula) standardisation on interest in STEM occupations, Han finds little supporting evidence. In more standardised systems, females are slightly less likely to develop an interest in health service occupations, but not in other science careers. For males, no significant association was found (Han, 2015, 2016a).

Standardisation of outputs, on the other hand, was shown to be systematically and negatively related to interest in general science careers among 15-year-old students. In particular, students were less likely to opt for an occupation in mathematics, physical and life science, engineering, or computing in countries where standardised examination in science takes place. A standardised examination in this study was defined as an examination enforced by a national institution, measuring performance against relative standards and with consequences for students' educational progression. This finding is most robust for careers in the physical sciences, computing and engineering, and it does not vary by gender (Han, 2016b). A possible explanation for the negative exam effect is that, even though students who are expecting standardised testing with consequences perform better on various subjects (Fuchs and Wössmann, 2004), they may lose intrinsic interest in learning the subject. This can happen if the need to meet rigid standards motivates test-focused classroom practices, a narrowing of the curricular content, and repetitive preparatory exercises and teaching methods (Sheldon and Biddle, 1998). As we have above, intrinsic interest – or enjoyment – is one of the key factors guiding occupational choices. If standardised exams in science reduce this interest, then they may – indirectly – decrease the number of STEM-oriented students. Further, it has also been suggested that in systems with standardised science exams students' science achievements serve as a strong signal regarding their potential failure or success on a related career path, which makes students' career expectations more realistic (Han, 2016b).

2.4.3.2 Science and mathematics curricula and pedagogies

As mentioned above, research on cross-country differences in education systems related to STEM orientation has so far focused mainly on the three key dimensions of institutional systems: stratification, standardisation and – to a lesser extent – level of vocationality. Less attention has been paid to subject-specific educational policies, and those that are aimed at science or mathematics teaching in the school. Nevertheless, from a policy point of view it is important to better understand how the various educational goals and methods supported by national educational policies, and presented either in mathematics and science curricula or in support structures, might be linked either to students' general interest in following a STEM career or to related gender segregation. Therefore, in the following, we briefly discuss four important aspects of science and mathematics teaching that are typically addressed in country-level education policies: (1) the existence of a national strategy to evoke interest in these subjects; (2) an explicit attempt to address the gender imbalance in STEM; (3) some elements of the content of science and mathematics curricula; and (4) the existence of ability grouping in the classroom.

As mentioned above, it is generally assumed that more exposure to mathematics and science will evoke interest in these subjects, which may eventually turn into a higher number of students following a related educational and occupational career. Several countries have developed a national strategy for science and mathematics education, or have at least launched country-level initiatives towards these aims. Initiatives across Europe often involve promoting cooperation between schools and the business sector to organise activities for pupils; workshops, conferences and training for science and maths teachers; network-building among teachers; thematic summer-camps for students; and even the inclusion of media for promotion purposes etc. (Eurydice, 2011a, 2011b). The national programmes vary greatly in terms of scope and content, but they nevertheless seek a very similar result, which is improving students' motivation – females' and males' alike – in mathematics and science learning and consequent career choices.

Besides these general attempts to popularise science (or mathematics), which might – intentionally or unintentionally – either promote or weaken students' relative interest in STEM careers, in certain countries specific measures were purposefully introduced to positively influence females' career plans and reduce the gender gap in STEM-related subjects or careers. In several European countries, the idea of gender sensitivity in mathematics (but also science) teaching has been introduced into pre-service teacher education. Another approach has been to centrally support teaching activities that are meant to reflect gender differences (Eurydice, 2011a). The rationale behind such measures is to reduce the gender gap in interest in mathematics (or science) by improving females' attitudes. Ideally, we would also expect these initiatives to mitigate against the gender differences in STEM career plans.

Further, as gendered identities impose different expectations on females and males, who therefore develop different self-beliefs, males and females may also respond differently to certain elements of the content of the curricula, irrespective of the intentions of the curriculum writer. For example, as gender-essentialist ideologies claim that men are more able than women to solve abstract analytical tasks, we might expect that a more practically oriented mathematics and science curriculum that put greater emphasis on applying theories to real-life situations would encourage females to engage in these subjects and to develop a related career plan. Similarly, as women are more likely to endorse communal goals (which involve helping other people) than men (Diekman et al., 2010), a science curriculum that emphasised science's relevance to such goals and embedded science more deeply into the cultural context might have a positive impact on females' interest in STEM.

Ability grouping with respect to mathematical or science abilities is a common practice in European schools, at both the primary and the secondary level (Eurydice, 2011b, 2011a). Grouping or tracking is usually aimed at creating homogenous student groups between or within classes, in order to increase efficiency of teaching. The controversial effects it has on equity of opportunities in education are well documented (Hattie, 2008). Moreover, doubts have also been raised in terms of how it may influence females' interest in mathematics and science. Early tracking has been suggested to be detrimental to females' STEM motivations, as teachers have a tendency to underestimate females' mathematical ability as compared with that of males, which may lead to disadvantaged tracking of females. Similarly, tracking based on standardised test scores in maths may also be disadvantageous for females (Wang and Degol, 2013), driving them early towards educational paths less supportive of STEM careers.

After discussing a range of country-level factors that may explain some of the cross-country variation in adolescent males' and females' interest in pursuing a STEM career, we now turn to describing gender essentialism, an explanatory framework that may account for the global nature of gender segregation and also improve our understanding of cross-country differences in this area.

2.4.4 World culture: gender essentialism

The most powerful explanation for the non-decreasing, universalistic trend for gender segregation in education as well as in the labour market has been the universal prevalence of gender-essentialist beliefs. Gender-essentialist beliefs are widespread and commonly shared cultural stereotypes suggesting that women are 'naturally' more capable than men in certain areas and vice versa. In particular, gender-essentialist ideologies suggest that women have more potential to succeed in social interactions and nurturing, which gives them an aptitude to engage, for example, in teaching or social services. Men, on the other hand, are assumed to be more competent than women at abstract analytical tasks, problem-solving and reasoning, and also in interacting with objects, and are therefore believed to perform better in occupations where such skills are required (Charles, 2003; Charles and Bradley, 2009).

Gender essentialism is in perfect correspondence with women's underrepresentation and men's overrepresentation in mathematically intensive STEM occupations, as long as these are socially constructed as requiring relatively little social interaction, little possibility of serving communal goals and more abstract thinking. In the same manner, gender-essentialist beliefs also support females' concentration in medical jobs, as these involve more social interaction, nurturing and help (Diekman et al., 2010; Cheryan, 2012).

Gender essentialism is especially perdurable as it is not necessarily incompatible with egalitarian values and can easily be complied with an 'equal but different' standpoint. As differential occupational choices appear as independent, individual decisions that follow from 'natural' gender differences, and as differences entailed in these choices do not (explicitly) involve inequalities, they remain socially acceptable in modern, egalitarian societies (Charles and Bradley, 2002; Barone, 2011). Research suggests that although gender-essentialist beliefs seem to be universally shared, the extent or strength of these stereotypes can vary between the countries. In particular, gender-essentialist beliefs have been found to influence students' occupational choices most markedly in highly developed, post-industrial societies, where ideologies of self-expression and gendered identities gain more dominance in guiding individual choices (Sikora and Pokropek, 2012a). Thus – although part of the global culture, and is likely to contribute to cross-country as well as over-time stability of gender segregation – varying levels of gender essentialism may also explain some of the cross-country variation in these segregatory patterns.

Deeply rooted cultural beliefs about gender roles have the potential to influence students' occupational choices by guiding females' and males' perceptions of what is compatible with prescribed gender norms. Through gender role socialisation, gendered identities are developed as males and females face different expectations from their parents and educators, observe different role models and are provided with different choices (Charles, 2003; Charles and Bradley, 2009). Males and females seek to fulfil expectations internalised through their socialisation process, turning gender-essentialist beliefs into self-fulfilling prophecies and reaffirming gender stereotypes about masculine and feminine career paths (Eccles, 1994).

Gender-essentialist beliefs can operate at each layer of the career plan-shaping process: at the individual, the school and the country level. As mentioned above, at the individual level even students' achievements were shown to be influenced by such beliefs, as women were found to perform less well in mathematics when confronted with relevant gender stereotypes (Tiedmann, 2000; Steele et al., 2002; Lesko and Corpus, 2006). Clearly, such confrontations form part of the everyday experiences of children from a very early age, as gender stereotyping of STEM occupations and subjects is prevalent among parents of young and also older children (Bleeker and Jacobs, 2004). Moreover, parents tend to evaluate their male and female children's maths competencies differently, and their gender-biased perceptions have an impact on children's self-perception (Tiedmann, 2000). Parents' stereotypes have also been shown to influence their children's career choices later in life (Bleeker and Jacobs, 2004). Further, gender stereotypes are expected to be more or less intense in the school environment, depending, for example, on the gender composition of the classroom (Schneeweis and Zweimüller, 2012), or on teachers' personal beliefs (Keller, 2001). Different teaching methods and different education systems may activate prevailing gender stereotypes to varying degrees; for instance, early tracking can strengthen the importance of the stereotypes held by the parents (Barone, 2011), potentially leading to more gender differences in stratified school systems.

As, through all these channels, prevailing gender stereotypes can restrain females from entering STEM occupations, such channels can influence gender segregation in these occupations and, as a consequence, may also reduce overall levels of interest in them.

3 Data and methods

3.1 Programme for International Student Assessment

For this study we use data from PISA collected by the OECD. This survey is the only source of comparable data on occupational expectations of adolescents from countries in Europe and elsewhere in the world. PISA was launched in 2000 and is repeated in 3-year cycles. The main aim of PISA is to assess the cognitive skills of 15-year-old students that are necessary for their adult lives. PISA comprises achievement tests in three core domains: reading literacy, mathematics and science. Each cycle concentrates on a different learning domain. For instance, in 2000 PISA focused on reading, with mathematics and science as minor areas of assessment, while in 2003 mathematics was the main domain.

The assessment component of PISA is complemented by information gathered through a background questionnaire administered to all participating students. The questionnaire collects a range of information on student characteristics, parental and family background, resources available in the home, and the practices and stimuli that may be related to academic success in specific subjects. Information about the school system and the learning environment is collected through principals' questionnaires administered in each school (OECD, 2017).

The question about occupational expectations of adolescents – our main variable of interest – was included in the questionnaires in the 2000, 2006 and 2015 cycles. However, after preliminary analysis we decided to concentrate on PISA 2006 and 2015. The reasons behind this are that only 21 current EU Member States participated in PISA 2000, and that analysis of missing data showed potential problems with comparability of coding students' responses on occupational expectations in PISA 2000 and other waves of this research, as the patterns of missing data differ significantly from those observed in the later waves. Additionally, many individual- and school-level variables in 2000 do not correspond to variables from PISA 2006 and 2015, as the first PISA round was focused on reading while PISA 2006 and 2015 focused on science. Finally, most policy-relevant country-level variables are only available for the period between 2006 and 2015.

PISA is based on two-stage stratified samples of students enrolled in lower secondary or upper secondary institutions and aged between 15 years and 3 months and 16 years and 2 months. The samples are nationally representative of student populations. The two-stage sampling strategy means that schools are sampled first and students are then sampled within sampled schools. Complete documentation of the sampling design, response rates, quality assurance, and weighting procedures is provided in the PISA technical reports (OECD, 2009, 2017). Table 3.1 provides a list of the EU-28 and their sample sizes for 2006 and 2015.

Table 3.1. EU-28 countries participating in PISA 2006 and 2015 cycles, and their sample sizes.

	Number of students		Number of schools	
Country	**2006**	**2015**	**2006**	**2015**
Austria	4,927	7,007	199	269
Belgium	3,733	3,976	107	113
Bulgaria	4,498	5,928	180	180
Croatia	5,213	5,809	161	160
Cyprus	0	5,571	0	126
Czech Republic	5,932	6,894	245	344
Denmark	4,532	7,161	211	333
Estonia	4,865	5,587	169	206
Finland	4,714	5,882	155	168
France	4,716	6,108	182	252
Germany	4,891	6,504	226	256
Greece	4,873	5,532	190	211
Hungary	4,490	5,658	189	245
Ireland	4,585	5,741	165	167
Italy	21,773	11,583	799	474
Latvia	4,719	4,869	176	250
Lithuania	4,744	6,525	197	311
Luxembourg	4,567	5,299	31	44
Malta	0	3,634	0	59
Netherlands	4,871	5,385	185	187
Poland	5,547	4,478	221	169
Portugal	5,109	7,325	173	246
Romania	5,118	4,876	174	182
Slovakia	4,731	6,350	189	290
Slovenia	6,595	6,406	361	333
Spain	19,604	6,736	686	201
Sweden	4,443	5,458	197	202
United Kingdom	13,152	14,157	502	550
Total	**166,942**	**176,439**	**6,270**	**6,528**

3.2 Dependent variable – occupational expectations of adolescents

PISA is the only source of internationally comparable data on teenage career expectations that contains verbatim information about occupational titles nominated by adolescents as their future jobs. It is also the only source of such data collected at different points of time. In this chapter, we commence analysis of the cross-national variation in adolescent career expectations using PISA data from 2006 and 2015 (OECD, 2016b).

The measure of student career expectations was constructed from the following single question:

What kind of job do you expect to have when you are about 30 years old?

Write the job title: ___________________________________

The responses were coded using ISCO. In 2006, the data were coded to ISCO-88 at four-digit level (ILO, 2012). In 2015, the data were coded using the updated ISCO-08 codes at four-digit level. ISCO-08 is an updated version of ISCO-88 created in 2007 by the International Labour Organization (ILO). Not surprisingly, some changes in categorisation have also occurred in the area of scientific and technical (STEM) occupations – a sphere of dynamic change in the labour market. For the purposes of the current study, the definition of STEM occupations will be based on ISCO-08, which means that occupations in the 2006 PISA data have been recoded to ISCO-08. Hereafter, we will explain how STEM occupations were defined in this study and how the conversion from ISCO-88 to ISCO-08 affects the comparisons we conduct here.

To identify STEM occupations for the purposes of this study we have chosen the categorisation of occupations previously applied by e.g. Caprile et al. (2015) and European Commission et al. (2015). Accordingly, the following ISCO subgroups were classified as STEM:

- 21 Science and engineering professionals;
- 25 Information and communications technology professionals;
- 31 Science and engineering associate professionals;
- 35 Information and communication technicians.

Within these major groups, jobs related to STEM are captured at two distinct levels of the occupational hierarchy: at the professional level and at the associate professional level. In professional jobs, skills and knowledge typically obtained as the result of study at a higher educational institution (for a period of 3–6 years, and leading to the award of a first degree or higher qualification) are required. Associate-level jobs, on the other hand, require studies undertaken at a higher educational institution for a period of 1–3 years, following completion of secondary education (ILO, 2012). Further, jobs included in STEM appear in this categorisation in a symmetrical manner: sub-major groups 21 and 31 and also 25 and 35 are similar to each other as far as tasks and activities are concerned, although they have different skill requirements.

An important distinguishing factor between categorisations applied in the different studies is whether or not they include Health professionals (22) and Health associate professionals (32) in STEM (for health occupations included in STEM jobs, see e.g. Hidden Half, 2015). Indeed, occupations in health remain strongly science related and thus they certainly share common features with occupations labelled as STEM. As can be seen from earlier research (e.g. Sikora and Pokropek, 2012a*)*, students choosing health jobs are in many aspects similar to those opting for STEM occupations. For the most part in the present study the narrower definition is chosen, not only because it appears to be the more widely accepted one, but also because occupations in health – although science related – have a very different gender profile and require a different approach. Still, to allow for a better understanding of these relations, in the descriptive part of our study Health Professionals (22) and Health Associate Professionals (32) are differentiated and students' interest in these categories of occupations are looked at separately – even though our main interest remains in the narrowly defined STEM occupations. However it needs to be noted than a substantial part of the work on science career plans includes health occupations (Sikora and Pokropek 2012a, 2012b; Mann et al., 2015; Han, 2016a, 2016b, 2017; Mann and DiPrete, 2016; OECD, 2016a).

In this study, we use ISCO-08 as a baseline for defining student interest in particular occupations. This means that we first recoded ISCO-88 codes from 2006 to ISCO-88 codes using a consistent definitional framework, with all our data expressed in ISCO-88 codes. For the conversion we used the concordance developed by Ganzeboom and Treiman (2015). The conversion from ISCO-88 into ISCO-08 affected no more than 2% of our data in 2006. Specifically, there were three issues that might have affected our definition of STEM (ISCO codes 21, 31, 25 and 35). First, a small number of occupations that would not have been considered STEM in ISCO-88 were included in STEM in ISCO-08. Examples include Decorators and Commercial Designers, Decorators and Commercial Designers at the professional level and a series of machine operators (e.g. Mining-plant Operators; Fibre-preparing, Spinning- and Winding-machine Operators; Chemical-heat-treating-plant Operators; Chemical-filtering- and Separating-equipment Operators; Industrial-robot Operators) as well as some technicians (e.g. Life Science Technicians, Agronomy and Forestry Technicians) on the associate professional level. At the same time, an even smaller number of occupations, previously in a sub-major category under STEM, were not included in ISCO-08 (Industrial Pharmacists; Pharmaceutical Chemists; Medical Equipment Operators; Safety, Health and Quality Inspectors; Sanitarians). Finally, some occupations within the STEM categories were also moved. Essentially, some occupations that were categorised as STEM professions in ISCO-88 coding were moved to associate professionals. This last issue, however, has no impact for most of our results (except where we actually distinguish between professionals and associate professionals in our fine-grained presentation of the statistics). The detailed discrepancies between STEM coded by ISCO-88 and STEM coded by ISCO-08 are presented in Table A3.1 in the appendix. The impact of the conversion is negligible, because many of these occupations do not feature on the list of what teenagers expect. Less than 2% of the data in 2006 were affected.

To understand better the type of tasks and activities described by ISCO codes 21, 25, 31 and 35, it is worth looking at the definitions given by the ILO (quotes taken from ILO, n.d.):

> Science and engineering professionals (21) conduct research; improve or develop concepts, theories and operational methods; or apply scientific knowledge relating to fields such as physics, astronomy, meteorology, chemistry, geophysics, geology, biology, ecology, pharmacology, medicine, mathematics, statistics, architecture, engineering, design and technology. Competent performance in most occupations in this sub-major group requires skills at the fourth ISCO skill level. Occupations in this sub-major group are classified into the following minor groups: 211 Physical and Earth Science Professionals; 212 Mathematicians, Actuaries and Statisticians; 213 Life Science Professionals; 214 Engineering Professionals (excluding Electro-technology); 215 Electro-technology Engineers; 216 Architects, Planners, Surveyors and Designers.

> Information and communications technology professionals (25) conduct research; plan, design, write, test, provide advice and improve information technology systems, hardware, software and related concepts for specific applications; develop associated documentation including principles, policies and procedures; and design, develop, control, maintain and support databases and other information systems to ensure optimal performance and data integrity and security. Occupations in this sub-major group are classified into the following minor groups: 251 Software and Applications Developers and Analysts; 252 Database and Network Professionals.

Associate professionals undertake work similar to professionals, however, the tasks they perform are less complex and require only skills at the third ISCED level:

> Science and engineering associate professionals (31) perform technical tasks connected with research and operational methods in science and engineering. They supervise and control technical and operational aspects of mining, manufacturing, construction and other engineering operations, and operate technical equipment including aircraft and ships. Competent performance in most occupations in this sub-major group requires skills at the third ISCO skill level. Occupations in this sub-major group are classified into the following minor groups: 311 Physical and Engineering Science Technicians; 312 Mining, Manufacturing and Construction Supervisors; 313 Process Control Technicians; 314 Life Science Technicians and Related Associate Professionals; 315 Ship and Aircraft Controllers and Technicians.

> Information and communications technicians (35) provide support for the day-to-day running of computer systems, communications systems and networks, and perform technical tasks related to telecommunications, broadcast image and sound as well as other types of telecommunications signals on land, sea or in aircraft. Competent performance in most occupations in this sub-major group requires skills at the third ISCO skill level. Occupations in this sub-major group are classified into the following minor groups: 351 Information and Communications Technology Operations and User Support Technicians; 352 Telecommunications and Broadcasting Technicians.

The descriptive statistics of the STEM variable by country and for two waves of PISA research in 2006 and 2015 are presented in the appendix (Table A3.2). Like all surveys, PISA is affected by missing data and uncodeable responses to some of the questions. In all tables in the appendix that relate to variables containing missing data, we provide the descriptive statistics of raw, unadjusted data as well as of data after the multiple imputations of all missing data. For more details, see section 3.6 of this report.

3.3 Student-related variables

In this section, we describe student-related variables that are used in our analysis as predictors for STEM career expectations. All of the variables originate from PISA assessment and survey questionnaires that were administered to all participants after cognitive testing. In 2006, the cognitive testing and the questionnaire were paper based, while in 2015 both components of PISA employed a computer-based method of testing and collecting data. The 2015 study was designed to maintain full comparability between two modes of data collection, which was tested and confirmed in empirical studies (OECD, 2017). The questionnaire collects a range of information on students' households, resources available in their home, parental and family circumstances, and attitudes to school, learning and sciences. The predictor variables were chosen based on theoretical evidence availability of the data for EU Member States. Although PISA is designed mainly for comparative purposes, countries are free to choose additional modules to enrich the data. For instance in PISA 2015 most, but not all, of the EU Member States decided to ask additional in-depth questions about ICT usage. As these questions were applied only in some of the countries, we have not used them in our analysis, which relies mostly on cross-country comparisons.

3.3.1 Students' characteristics

3.3.1.1 Science literacy

For measuring student ability, PISA utilises a cognitive assessment lasting 2 hours. In 2006, the assessment was paper based, while in 2015 comparable computer-based testing was applied. In both waves, test items were a mixture of questions requiring students to construct their own responses and multiple-choice items. As PISA uses an incomplete balanced matrix design, which means that students answer a sample of test questions only, plausible values are used as indicators of performance for each student and for each domain in the PISA database. For the purposes of this study, PISA science test scores were used because, in both 2006 and 2015, science literacy was the main testing domain and science literacy items were delivered to all students tested (which is not true for other domains in 2006 and 2015). This makes science literacy scale the most precise and reliable measures of students' achievements. The correlation between PISA mathematic literacy scale and science literacy scale is around 0.9, meaning that both measured constructs are very similar. In fact, when we used mathematic literacy scale instead of science literacy scale for validity checks, the result parameters of the statistical models were virtually the same, and conclusions based on the models with different ability indicators remained unchanged. The scale was standardised to the average value of 0 and the standard deviation of 1 across European countries.

3.3.1.2 Gender

For gender a dummy variable was used, with the value of 1 for females and 0 for males. In the regression models, coefficients for this variable indicate the size of gender gap in selecting a STEM occupation in each country. Together with science literacy scale, gender was one of the few variables without missing data. As such, the multiple imputation procedure was not applied to this variable. Descriptive statistics of science literacy scale and gender is available in Table A3.3 in the appendix.

3.3.1.3 Student family background

Three variables were used to depict students' family background: economic, social and cultural status (ESCS) index; a binary indicator of whether or not at least one parent was working in a STEM occupation; and migration status. Descriptive statistics for those indicators are presented in Tables A3.4–A3.6 in the appendix. More detailed description of these variables can be found in OECD reports (e.g. OECD, 2016b, 2017).

3.3.1.4 Economic, social and cultural status

The parental ESCS index in PISA was created from the following variables: the International Socio-Economic Index of Occupational Status (ISEI); the highest level of education of the student's parents, converted into years of schooling; and a home possession indicator that captures family wealth, possessions, cultural possessions, home educational resources, availability of ICT resources at home and number of books at home. In this way, ESCS is considered a multidimensional indicator of students' family background. In this analysis, the index, as with all continuous variables, was standardised to the average of value of 0 and the standard deviation of 1 across European countries (OECD, 2017).

3.3.1.5 Parents in STEM

ISCO occupational codes for mothers and fathers were recorded in the same way as students' career expectations. ISCO codes 21, 25, 31, and 35 were coded as STEM occupations, and others as non-STEM occupations. Based on those variables a dummy variable was defined. It takes the value of 1 if at least one of the parents works in a STEM occupation, and otherwise is set to 0.

3.3.1.6 Migrant status

Migration status variable is a dummy variable, with 0 indicating native students and 1 migrants. Migrants include first-generation and second-generation migrants as defined by the OECD (2016a). Accordingly, foreign-born students whose parents are also foreign born fall into this category, as do students in the test country whose parents are foreign born (https://www.oecd.org/edu/school/Definitions.pdf).

3.3.2 Student attitudes to science

Two scales developed to measure personal attitudes to science were utilised in the analysis. Both scales were constructed by the PISA consortium using item response theory (IRT) models that map individual responses to items into continuous scale and estimate individual scores (OECD, 2016b, 2017). In this analysis, the indexes were standardised to the average value of 0 and the standard deviation of 1 across European countries. The descriptive statistics are presented in Tables A3.7–A3.8 in the appendix. Short descriptions of the scales are provided below.

3.3.2.1 Self-efficacy

Self-efficacy in science in PISA was measured by asking students about their confidence in being able to solve a series of scientific problems. In the questionnaire, students were asked to report whether they believed they could perform a series of tasks either easily or with a bit of effort. Alternatively they could also indicate that they would struggle to perform the tasks on their own or they could not do them. These tasks included (1) explaining why earthquakes occur more frequently in some areas than in others; (2) recognising the science question that underlies a newspaper report on a health issue; (3) interpreting the scientific information provided on packages of food; (4) predicting how changes to an environment will affect the survival of certain species; (5) identifying the science question associated with the disposal of garbage; (6) describing the role of antibiotics in treating disease; (7) identifying the better of two explanations of how acid rain is formed; and (8) discussing how new evidence can lead to a change of understanding about the possibility of life on Mars. Higher values of the index correspond to higher levels of science self-efficacy. For analysis of PISA 2015 data we used the IRT version of this index provided by the OECD (OECD, 2017). The IRT version was not designed for cross-time comparisons, and therefore we constructed our own cross-time comparable index, constructed as the sum of imputed responses to self-efficacy questions.

3.3.2.2 Enjoyment of science

The enjoyment of science in PISA is a scale based on students' agreement with the following statements: 'I generally have fun when I am learning [broad science] topics'; 'I like reading about [broad science]'; 'I am happy doing [broad science] problems'; 'I enjoy acquiring new knowledge in [broad science]'; 'I am interested in learning about [broad science]'. Possible answer categories were 'strongly agree', 'agree', 'disagree' and 'strongly disagree'. Higher values of the index correspond to higher levels of enjoyment of science (OECD, 2017). Like the self-efficacy scale, the IRT scale for enjoyment of science was not designed for cross-time comparisons, and therefore we constructed our own cross-time comparable index, constructed as the sum of imputed responses to enjoyment of science questions.

3.4 School-related variables

As well as students' characteristics, PISA also collects information about school-related factors that might be categorised into two broad areas. The first reflects school-level variables on school management, resources and student composition, and the second consists of institutional factors shaped by educational policies. In our analysis, we used several indicators from both areas, including school resources, indicators of school actions to promote science, average school performance, female composition of school, students' level of education, programme content, school autonomy and grade repetition. More detailed description of these variables can be found in OECD reports (OECD, 2016b, 2017)

3.4.1 School resources and compositional variables

All variables reflecting school management, resources and student composition were derived from the PISA principals' questionnaire. Descriptive statistics are provided in Tables A3.9–A3.12 in the appendix.

3.4.1.1 Science-specific resources

Science-specific resources indicator is an index that was constructed using principals' responses to a series of statements about science resources in the school. Principals were to evaluate the following aspects: (1) 'Compared to other departments, our school's science department is well equipped'; (2) 'If we ever have extra funding, a big share goes into improvement of science teaching'; (3) 'Science teachers are among our best-educated staff members'; (4) 'Compared to similar schools, we have a well-equipped laboratory'; (5) 'The material for hands-on activities in science is in good shape'; (6) 'We have enough laboratory material that all courses can regularly use'; (7) 'We have extra laboratory staff that help support science teaching'; (8) 'Our school spends extra money on up-to-date science equipment'. The four response options were 'not at all', 'very little', 'to some extent' and 'a lot'. The index was calculated using IRT methodology and in our analysis it was standardised to the average value of 0 and the standard deviation of 1 across European countries. The index is available only for PISA 2015.

3.4.1.2 Science clubs

This is a 0–1 variable that identifies whether or not the school offers science clubs in the current academic year. The indicator is based on the school principal responses. Principals were given a list of activities including participation in science clubs and were asked the question '[This academic year], which of the following activities does your school offer to students in the [national modal grade for 15-year-olds]?'

3.4.1.3 Science competitions

This is a 0–1 variable that identifies whether or not the school offers science competitions in the current academic year. The indicator is based on school principal responses. Principals were given a list of activities including participation in science competitions, listing relevant national examples, and were asked the question '[This academic year], which of the following activities does your school offer to students in the [national modal grade for 15-year-olds]?'

3.4.1.4 Gender composition of school

This variable is the average proportion females within a school. The indicator was re-standardised on the student level to obtain standard deviation of 1 and mean of 0 among EU Member States participating in PISA.

3.4.2 Structure of schooling: organisation and decentralisation

PISA collects information on study programmes and records it using ISCED. We utilise this information to construct two indicators describing students' education level and programme content. An Index of School Autonomy was created using the principal questionnaire, while the student questionnaire was used to obtain information about grade repetition. The descriptive statistics of the variables describing institutional factors are provided in Tables A3.13–A3.15 in the appendix.

3.4.2.1 Educational level

This is a 0–1 variable that identifies students' educational level. It is coded 0 for ISCED level 2 and 1 for ISCED level 3. The indicator has no missing data. In most countries, 15-years-olds are at ISCED level 3, therefore the variable was used only for countries where the share of ISCED 2 students in the PISA sample was greater than 5%.

3.4.2.2 Vocational track

This is a 0–1 variable that identifies student programme orientation. It is coded 0 for general programme orientation and 1 for pre-vocational, vocational and modular programmes (see (OECD, 2016b, 2017) for an explanation of what modular programmes are). The indicator has no missing data. In analyses that include this variable, we use information from countries where vocational programmes involve more than 5% of students.

3.4.2.3 Autonomy

The Index of School Autonomy is the percentage of tasks for which 'principals', 'teachers' and/or 'school governing board' have considerable responsibility. The calculation is based on all 12 tasks included in the school questionnaire: (1) selecting teachers for hire; (2) firing teachers; (3) establishing teachers' starting salaries; (4) determining teachers' salary increases; (5) formulating the school budget; (6) deciding on budget allocations within the school; (7) establishing student disciplinary policies; (8) establishing student assessment policies; (9) approving students for admission to the school; (10) choosing which textbooks are used; (11) determining course content; (12) deciding which courses are offered. On the original metric of this indicator, 0 would indicate that neither the principal, nor the teachers or the school governing board, hold any responsibilities for the listed tasks. Higher values (maximum 100) indicate more autonomy for school principals and/or teachers. In our analysis, the index was standardised to the average value of 0 and the standard deviation of 1 across European countries. This index attests to the decentralisation evident at the school level (OECD, 2016b).

3.4.2.4 Grade repetition

This is a 0–1 variable that identifies whether or not a student had repeated a grade in at least one ISCED level. It is coded 0 for students that had never repeated a grade and 1 for students that had repeated a grade at least once.

3.5 Country-level variables

The analysis of youth career expectations presented in this report involves more than 30 potential correlates depicting country characteristics. Some of these characteristics have been shown to relate to adolescent interest in STEM jobs in previous research based on comparative data (Sikora and Pokropek 2011, 2012b; Mann and DiPrete, 2016; Charles, 2017); others, however, are the original contribution of this report, aimed at assessing the extent to which initiatives that were in place across Europe around 2010 and 2011 correspond to specific levels of STEM-related interest among youth, as well as the gender gap in this interest.

3.5.1 Main features of education systems

Education systems are most commonly characterised by three main factors: stratification (or tracking), level of vocational orientation and standardisation.

3.5.1.1 Age at first selection in the education system (age at first selection) ([19])

The age at which the various education systems start selecting children into different programmes is commonly referred to as age at first selection. In our analysis, we use this as one of the indicators of stratification in the education system. We follow the information from OECD data (OECD, 2016b) and (OECD, 2013), and record the age at which students are first divided or allowed to sort themselves into different educational programmes. A lower age of selection indicates a higher degree of system stratification.

3.5.1.2 Number of education programmes available at age 15 (programmes)

This is our second indicator of stratification in the education system. The indicator was based on OECD data (OECD, 2013, 2016b). A greater number of education programmes available for 15-year-olds indicates a higher degree of stratification.

3.5.1.3 National/central examination at the upper secondary level (national exam/maths exam)

For measuring the level of standardisation of the system we applied a dummy variable showing whether or not a national/central examination at the upper secondary level exists (OECD, 2016a). As most of the EU Member States have some kind of central examination at the end of the secondary education, this variable depicts little variation and thus is not useful for the comparative analysis. Therefore, we decided to focus instead on a compulsory mathematics exam, which is a feature of upper secondary schooling in 9 out of the 28 EU Member States (OECD, 2016a). Altogether, three indicators were created, two referring to the existence of national exams in 2006 and 2015, and one referring to maths exams in 2015.

3.5.1.4 Vocational orientation

The level of vocational orientation was calculated using PISA data as the share of 15-year-old students who are enrolled in a programme whose curriculum is pre-vocationally or vocationally oriented (OECD, 2013, 2016b.)

For all indicators except that on compulsory maths exams we collected data from two time points – 2006 and 2015 – corresponding to the PISA cycles that are analysed in this report. For the last indicator the information was available only for the year 2015. Table 3.2 presents the indicators for each of the EU Member States.

([19]) Short names of indicators provided in brackets are used in the following tables.

Table 3.2. Country-level variables I. Main features of education systems.

Indicator	Age at first selection		Programmes		Vocational orientation		National exam		Maths exam
Year	2006	2015	2006	2015	2006	2015	2006	2015	2015
Austria	10	10	4	4	0.70	0.71	yes	yes	yes
Belgium	12	12	4	4	0.39	0.28	yes	yes	no
Bulgaria	11	13	2	3	0.47	0.46	yes	yes	no
Croatia	14	14	3	1	0.72	0.67	yes	yes	yes
Cyprus	15	15	NA	NA	NA	0.12	yes	yes	no
Czech Republic	11	11	5	6	0.41	0.33	yes	yes	no
Denmark	16	16	1	1	0.00	0.00	yes	yes	no
Estonia	15	16	1	1	0.00	0.00	yes	yes	yes
Finland	16	16	1	1	0.00	0.00	yes	yes	no
France	14	15	3	3	0.09	0.19	yes	yes	no
Germany	10	10	4	4	0.02	0.03	yes	yes	yes
Greece	15	15	2	2	0.14	0.16	yes	no	no
Hungary	11	11	3	3	0.57	0.16	yes	yes	yes
Ireland	15	15	4	4	0.01	0.01	yes	yes	yes
Italy	14	14	3	4	0.56	0.50	yes	yes	no
Latvia	16	16	3	5	0.03	0.01	yes	yes	yes
Lithuania	15	16	3	5	0.00	0.01	yes	yes	no
Luxembourg	13	13	4	4	0.13	0.22	yes	yes	no
Malta	16	16	3	3	NA	0.00	yes	yes	no
Netherlands	16	16	1	1	0.31	0.26	yes	yes	no
Poland	16	16	1	1	0.00	0.00	yes	yes	no
Portugal	15	15	3	3	0.14	0.13	yes	yes	yes
Romania	14	14	3	2	0.23	0.00	yes	yes	no
Slovakia	11	11	5	5	0.43	0.33	yes	yes	no
Slovenia	14	14	3	3	0.52	0.57	yes	yes	yes
Spain	16	16	1	1	0.00	0.01	yes	no	no
Sweden	16	16	1	1	0.01	0.00	no	yes	no
United Kingdom	16	16	1	1	0.00	0.01	yes	no	no

3.5.2 National activities to improve STEM education

Besides the general characteristics of the national educational systems, potential associations between several subject-specific educational measures and students' interest in STEM careers were also considered. In most cases, science and mathematics – the two school subjects most related to the main STEM areas – were considered. Our main sources of information have been two Eurydice reports, presenting data on European national policies in mathematics and science education respectively. The reports describe teaching of these subjects across Europe at ISCED levels 1 and 2 (Eurydice, 2011a, 2011b). Both reports are based predominantly on official documents from central education authorities, including strategy and programme papers. Both reports take 2010/2011 as a reference year. However, the two reports are unfortunately not comparable in the sense that they do not consistently provide information about comparable topics or comparable formats. Further, in some cases we supplemented Eurydice data with information from the OECD. It is important to note that some national indicators could not be derived for the United Kingdom, where different regions follow markedly different education policies. See Table 3.3.

3.5.2.1 National strategies and initiatives to increase student motivation in mathematics learning, 2010/11 (national strategies)

The presence of national-level attempts to motivate students' mathematics learning was assessed on the basis of the Eurydice report. Regarding mathematics, a dummy variable was constructed on whether or not national strategies and initiatives to increase student motivation in mathematics learning exist in the country (Eurydice, 2011a).

3.5.2.2 Number of centrally supported activities to improve attitudes towards learning mathematics (central maths activities)

In the 2011 Eurydice report, country experts identified several activities that formed part of centrally promoted efforts to improve positive attitudes towards learning mathematics in their countries. To construct this (single) indicator, the number of such activities was counted. They were promotion of specific teaching methods to improve engagement; involvement of parents in the learning process; addressing the gender issue in mathematics education; promotion of extra-curricular activities; promotion of partnerships with companies, universities and other organisations; and running awareness-raising campaigns in wider society (Eurydice, 2011a).

3.5.2.3 Existence of national science centres or similar institutions promoting science education, 2010/2011 (national centres)

This is a binary measure, based on information from Eurydice. It is coded 0 in countries without such centres or institutions, and 1 in countries with them (Eurydice, 2011b). These centres are often umbrella organisations led by established higher education institutions, and aim to promote science at the national level.

3.5.2.4 Specific guidance measures to encourage careers in science for pupils and students at ISCED levels 2 and 3, 2010/2011 (careers guidance)

Another binary measure adopted from Eurydice indicates whether or not, in a particular country, specific guidance measures exist to encourage careers in science among students at ISCED levels 2 and 3 levels, 0 indicating no guidance or only general guidance and 1 indicating the existence of specific guidance oriented towards popularising science careers (Eurydice, 2011b, p. 49). Thus in countries with value 1, schools are expected to provide advice and support to students to encourage them to consider options for science-related educational pathways and careers.

3.5.2.5 Overall science/mathematics promotion indicators (science promotion)

To produce an index depicting the above-mentioned aspects of mathematics and science promotion in the various countries, principal component analysis with polychoric correlation matrix was used for combining the information on the existence of national initiatives both on science and mathematics and on the availability of guidance measures for career advice on science careers.

Table 3.3. Country-level variables II. Indicators of national activities to improve STEM education.

Country	National strategies	Central maths activities	National centres	Careers guidance	Science promotion
Austria	yes	5	yes	no	0.55
Belgium	no	1	no	no	−1.22
Bulgaria	yes	0	no	no	−0.18
Croatia	NA	NA	NA	NA	NA
Cyprus	yes	2	no	no	−0.18
Czech Republic	yes	4	yes	no	0.55
Denmark	no	0	no	no	−1.22
Estonia	yes	4	yes	no	0.55
Finland	yes	5	yes	no	0.55
France	no	2	yes	no	−0.49
Germany	no	2	no	no	−1.22
Greece	no	2	yes	no	−0.49
Hungary	no	1	no	no	−1.22
Ireland	no	2	yes	yes	0.54
Italy	yes	1	no	yes	0.85
Latvia	yes	4	no	yes	0.85
Lithuania	no	3	yes	no	−0.49
Luxembourg	no	0	no	no	−1.22
Malta	no	3	yes	no	−0.49
Netherlands	yes	0	yes	yes	1.58
Poland	yes	4	yes	yes	1.58
Portugal	yes	0	yes	yes	1.58
Romania	no	4	no	no	−1.22
Slovakia	no	1	no	no	−1.22
Slovenia	no	3	yes	no	−0.49
Spain	yes	2	yes	yes	1.58
Sweden	yes	1	yes	no	0.55
United Kingdom	yes	NA	yes	NA	NA

3.5.3 Social context of science teaching

3.5.3.1 Binary measures on different contextual themes in science teaching

In the Eurydice report on science education, several topics that can potentially be part of science teaching were listed. Here the countries indicated whether or not these topics were mentioned in the relevant steering documents – including the curriculum, syllabuses and official guidelines – at ISCED levels 1 and 2. Listed topics that we consider relevant for promoting interest for STEM occupations include the following: (1) everyday technology, (2) ethics of science, (3) social/cultural context of science, (4) history of science and (5) philosophy of science (Eurydice, 2011b, p. 67) For each of these topics ([20]), a pair of binary indicators (altogether nine variables) was created, each referring to whether or not the specific topic was included in the countries' steering documents for science teaching at ISCED levels 1 and 2. See Table 3.4 for more information.

3.5.3.2 Contextualisation of science teaching in steering documents (contextualisation)

From the above-mentioned nine binary indicators, a single index was created, based on the aggregations of the individual indicators. The resulting indicator was standardised to the average value of 0 and the standard deviation of 1 across European countries, the highest values indicating that all the listed contextual themes form part of the science teaching guidance at both ISCED 1 and ISCED 2 levels.

([20]) The only exception is 'everyday technology' in ISCED 2, because this topic was mentioned in the steering document of each and every participating country.

Table 3.4. Country-level variables III. Indicators for contextualisation of science teaching.

Indicator	Everyday technology		Ethics		Social/cultural context		History of science		Philosophy of science		Combined
Country/ISCED level	I	II	I	II	I	II	I	II	I	II	
Austria	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	1.22
Belgium	yes	yes	no	no	no	no	yes	yes	no	no	−0.67
Bulgaria	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	1.60
Croatia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Cyprus	yes	yes	no	yes	no	no	no	no	no	no	−1.05
Czech Republic	yes	yes	yes	yes	no	no	no	no	no	no	−0.67
Denmark	yes	yes	yes	yes	no	yes	no	yes	yes	yes	0.84
Estonia	yes	yes	no	yes	no	yes	no	yes	no	no	−0.29
Finland	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	1.60
France	yes	yes	yes	yes	no	yes	no	yes	no	no	0.09
Germany	yes	yes	no	yes	no	yes	no	yes	no	yes	0.09
Greece	no	yes	no	no	yes	yes	no	yes	no	no	−0.67
Hungary	yes	yes	no	no	no	yes	no	yes	no	no	−0.67
Ireland	yes	yes	no	no	no	no	no	no	no	no	−1.43
Italy	no	yes	yes	yes	yes	yes	no	no	no	yes	0.09
Latvia	yes	yes	no	yes	no	yes	no	yes	yes	yes	0.47
Lithuania	yes	yes	yes	yes	yes	yes	no	yes	no	yes	0.84
Luxembourg	yes	yes	no	no	yes	yes	yes	yes	no	no	0.09
Malta	yes	yes	no	no	no	no	no	yes	no	no	−1.05
Netherlands	no	yes	no	yes	no	yes	no	no	no	no	−1.05
Poland	yes	yes	no	no	no	no	no	no	no	no	−1.43
Portugal	yes	yes	no	yes	yes	yes	yes	yes	no	yes	0.84
Romania	yes	yes	yes	yes	yes	yes	no	yes	no	no	0.47
Slovakia	yes	yes	no	no	yes	yes	no	no	no	no	−0.67
Slovenia	yes	yes	no	no	no	no	no	no	no	no	−1.43
Spain	yes	yes	no	yes	yes	yes	yes	yes	yes	yes	1.22
Sweden	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	1.60
United Kingdom	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

3.5.4 Ability grouping in mathematics

3.5.4.1 Differentiation of maths curriculum content according to ability

These indicators measure if differentiation of maths curriculum content according to ability is recommended in steering documents at ISCED levels 1 or 2 (one indicator per level) (Eurydice, 2011a, p. 89). The binary measures take the value of 1 if the same content is taught at different levels of difficulty, or if different content is taught to students of different abilities.

3.5.4.2 Ability grouping within class in science subjects is recommended

In science, two dummy variables are available, indicating if ability grouping within class in science subjects is recommended in steering documents at ISCED levels 1 and 2 (given separately) (Eurydice, 2011b, p. 77).

3.5.4.3 Ability grouping combined

The combined index was derived, by simple aggregation, from the four separate binary measures of ability grouping in mathematics and science at ISCED levels 1 and 2. The values were standardised to the average value of 0 and the standard deviation of 1 across European countries, with highest values indicating ability grouping to be recommended across both subjects and at both levels of schooling. (Information on ability grouping in each country is given in Table 3.5)

Table 3.5. Country-level variables IV. Differentiation of STEM curriculum content according to ability, as recommended in steering documents 2011.

Countries/ISCED level	Mathematics I	Mathematics II	Science I	Science II	Combined (Differentiation in at least one category)
Austria	no	no	yes	yes	yes
Belgium	no	no	no	no	no
Bulgaria	no	yes	NA	NA	yes
Croatia	NA	NA	NA	NA	NA
Cyprus	no	no	no	yes	yes
Czech Republic	no	no	no	no	no
Denmark	yes	yes	yes	yes	yes
Estonia	no	no	no	no	no
Finland	no	no	no	no	no
France	no	yes	no	no	yes
Germany	no	no	no	no	no
Greece	yes	yes	no	no	yes
Hungary	no	no	yes	yes	yes
Ireland	no	yes	no	no	yes
Italy	no	no	no	no	no
Latvia	no	no	no	no	no
Lithuania	yes	yes	yes	yes	yes
Luxembourg	yes	yes	yes	yes	yes
Malta	yes	yes	no	yes	yes
Netherlands	no	no	no	no	no
Poland	no	no	no	no	no
Portugal	no	no	no	no	no
Romania	no	no	no	no	no
Slovakia	no	no	yes	yes	yes
Slovenia	no	no	yes	yes	yes
Spain	yes	yes	yes	yes	yes
Sweden	no	no	no	no	no
United Kingdom	NA	NA	yes	yes	yes

3.5.5 Addressing gender in mathematics education

In the case of mathematics, data on centrally promoted attempts to specifically increase females' interest in the field were also available. Accordingly, in our models we included an indicator of whether or not the country had a central policy for addressing the gender issue in mathematics education among the centrally supported activities, to improve attitudes towards learning mathematics (Eurydice, 2011a). Another indicator shows whether or not 'teaching maths in a gender sensitive way' was mentioned in the regulations/guidance among the areas of knowledge and skills for mathematics teaching to be covered in initial teacher education in the country (Eurydice, 2011a).

Table 3.6. Country-level variables V. Addressing the gender issue in mathematics education.

Countries	Centrally supported activities to improve attitudes towards learning mathematics		
	Addressing the gender issue	Teaching in a gender sensitive way	Combined (at least one activity)
Austria	yes	yes	yes
Belgium	no	no	no
Bulgaria	no	no	no
Croatia	NA	NA	NA
Cyprus	no	yes	yes
Czech Republic	no	no	no
Denmark	no	no	no
Estonia	no	yes	yes
Finland	no	no	no
France	yes	yes	yes
Germany	no	no	no
Greece	no	no	no
Hungary	no	no	no
Ireland	no	no	no
Italy	no	no	no
Latvia	no	no	no
Lithuania	no	no	no
Luxembourg	no	no	no
Malta	no	yes	yes
Netherlands	no	yes	yes
Poland	yes	no	yes
Portugal	no	no	no
Romania	no	no	no
Slovakia	no	no	no
Slovenia	no	no	no
Spain	no	yes	yes
Sweden	no	no	no
United Kingdom	NA	yes	yes

3.5.6 Gender inequality and social development

3.5.6.1 Human Development Index (HDI)

The Human Development Index (HDI) was developed by the United Nations Development Programme and is widely used to characterise a country's level of development in a multidimensional manner, rather than solely by taking economic growth into account. In HDI, three aspects of development are considered: health (assessed by life expectancy at birth), education (assessed by average years of schooling of the population aged 25 or more) and standard of living (assessed by gross national income per capita).

3.5.6.2 Gender Inequality Index (GII)

The Gender Inequality Index (GII) is an inequality index, also created by the United Nations Development Programme. It incorporates three aspects of women's status in society. Firstly, reproductive health is measured by maternal mortality rate and birth rate among adolescents. Secondly, empowerment is measured by the percentage of female members in the relevant national legislature, and by the proportion of females with at least secondary education compared with the same proportion of males. Thirdly, economic status is measured by labour force participation rates. The higher the GII, the more gender disparities exist in the country.

3.5.6.3 Gender Pay Gap (GPG)

We use Eurostat's Gender Pay Gap (GPG) in unadjusted form to account for gender inequalities in the labour market. This provides the difference in average gross hourly earnings of male employees and female employees as a percentage of average gross hourly earnings of male employees in a country ([21]).

3.5.6.4 Female employment rate

Employment rate is calculated by Eurostat and is the ratio of employed females aged 20 to 64 to all females of this age ([22]).

([21]) http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=tsdsc340
([22]) http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=t2020_10

Table 3.7. Country-level variables VI. Contextual country-related variables.

	HDI		GII		GPG		Female employment	
	2006	2015	GII05	GII16	2006	2015	2006	2015
Austria	0.86	0.89	0.12	0.08	25.50	21.70	65.20	70.20
Belgium	0.87	0.90	0.10	0.07	9.50	6.50	58.80	63.00
Bulgaria	0.76	0.79	0.25	0.22	12.40	15.40	60.40	63.80
Croatia	0.79	0.83	0.16	0.14	NA	2.90	53.60	55.80
Cyprus	0.84	0.86	0.14	0.12	21.80	14.00	65.90	64.00
Czech Republic	0.85	0.88	0.15	0.13	23.40	22.50	61.80	66.40
Denmark	0.90	0.92	NA	0.04	17.60	15.10	74.80	72.60
Estonia	0.83	0.87	0.21	0.13	29.80	26.90	72.50	72.60
Finland	0.87	0.89	0.09	0.06	21.30	17.30	71.50	71.80
France	0.87	0.90	0.16	0.10	15.40	15.80	NA	66.00
Germany	0.90	0.93	0.12	0.07	22.70	22.00	65.00	73.60
Greece	0.85	0.87	0.18	0.12	20.70	NA	51.30	46.00
Hungary	0.81	0.84	0.26	0.25	14.40	14.00	55.60	62.10
Ireland	0.90	0.92	0.19	0.13	17.20	12.20	63.30	62.60
Italy	0.86	0.89	0.17	0.09	4.40	5.50	49.60	50.60
Latvia	0.81	0.83	0.22	0.19	15.10	17.00	68.40	70.50
Lithuania	0.81	0.85	0.19	0.12	17.10	14.20	68.00	72.20
Luxembourg	0.88	0.90	0.16	0.07	10.70	5.50	59.40	65.00
Malta	0.81	NA	0.31	0.22	5.20	9.50	35.70	53.60
Netherlands	0.90	0.92	0.08	0.04	23.60	16.10	69.00	70.80
Poland	0.81	0.86	0.16	0.14	7.50	7.70	53.10	60.90
Portugal	0.80	0.84	0.18	0.09	8.40	17.80	66.30	65.90
Romania	0.77	0.80	0.35	0.34	7.80	5.80	58.50	57.20
Slovakia	0.80	0.84	0.19	0.18	25.80	19.60	57.50	60.30
Slovenia	0.86	0.89	0.14	0.05	8.00	8.10	66.50	64.70
Spain	0.85	0.88	0.12	0.08	17.90	14.90	57.10	56.40
Sweden	0.90	0.91	0.05	0.05	16.50	14.00	75.80	78.30
United Kingdom	0.89	0.91	0.26	0.20	24.30	20.80	68.60	71.30

3.6 Methods

3.6.1 Missing data and imputation techniques

The first issue we briefly consider is the quality of the PISA data and the degree of difficulty that the question about occupational expectations might have caused adolescent respondents. This is important because the extent to which respondents find a survey question easy or difficult to answer is indicated by the proportion of missing data, or the share of respondents who did not give a valid answer to the question posed. The patterns of missing and invalid data and the methods chosen to deal with them can have important consequences for data quality and influence conclusions based on international comparisons. Furthermore, the quality of the data for the purpose of international comparisons is indicated not only by the proportion of missing data but also by the reasons behind particular types of missing data. Both the extent and type of non-response ought to be considered in any analysis of cross-national surveys. However, existing publications on adolescent career expectations that originated from the PISA 2006 dataset are often silent on handling missing observations on this variable (for example, see Sikora and Saha, 2009; Han, 2016a, 2017). This is a frequent practice even though different methods of dealing with missing data could lead to different estimates regarding the popularity of STEM occupations and the gender gap in youth preferences.

The PISA question about adolescent career expectations has an open-ended format. This kind of question is more difficult to answer than a closed-ended question with a precoded set of answer categories. Nevertheless the majority of respondents – an average of 74% of males and 79% of females in Europe – provided valid answers in 2006, as seen in Figure 3.1. Generally, males are less certain about their future career destinations, while females are more likely to provide a valid answer.

In 2006, the lowest proportions of males who knew what specific career they would like to pursue were in the Czech Republic (63%), Croatia (64%), Austria (65%) and Hungary (65%). In contrast, Romania (89%), the Netherlands (85%), Italy (85%), the United Kingdom (84%) and Ireland (82%) had the largest proportions of males who had no difficulty in naming their future occupation (Figure 3.1).

In 2006, the same countries also had low proportions of females who were able to name their future career destination. In Croatia, only 67% of females knew what job they wanted to work in once they turned 30. In Austria, this proportion was 69%. In Hungary and the Czech Republic, it was 71% and in Germany 72%. In contrast, 90% of females in Romania, 88% of females in the Netherlands, 87% of females in the United Kingdom, 86% of females in Ireland and 85% of females in Italy were able to articulate their occupational expectations.

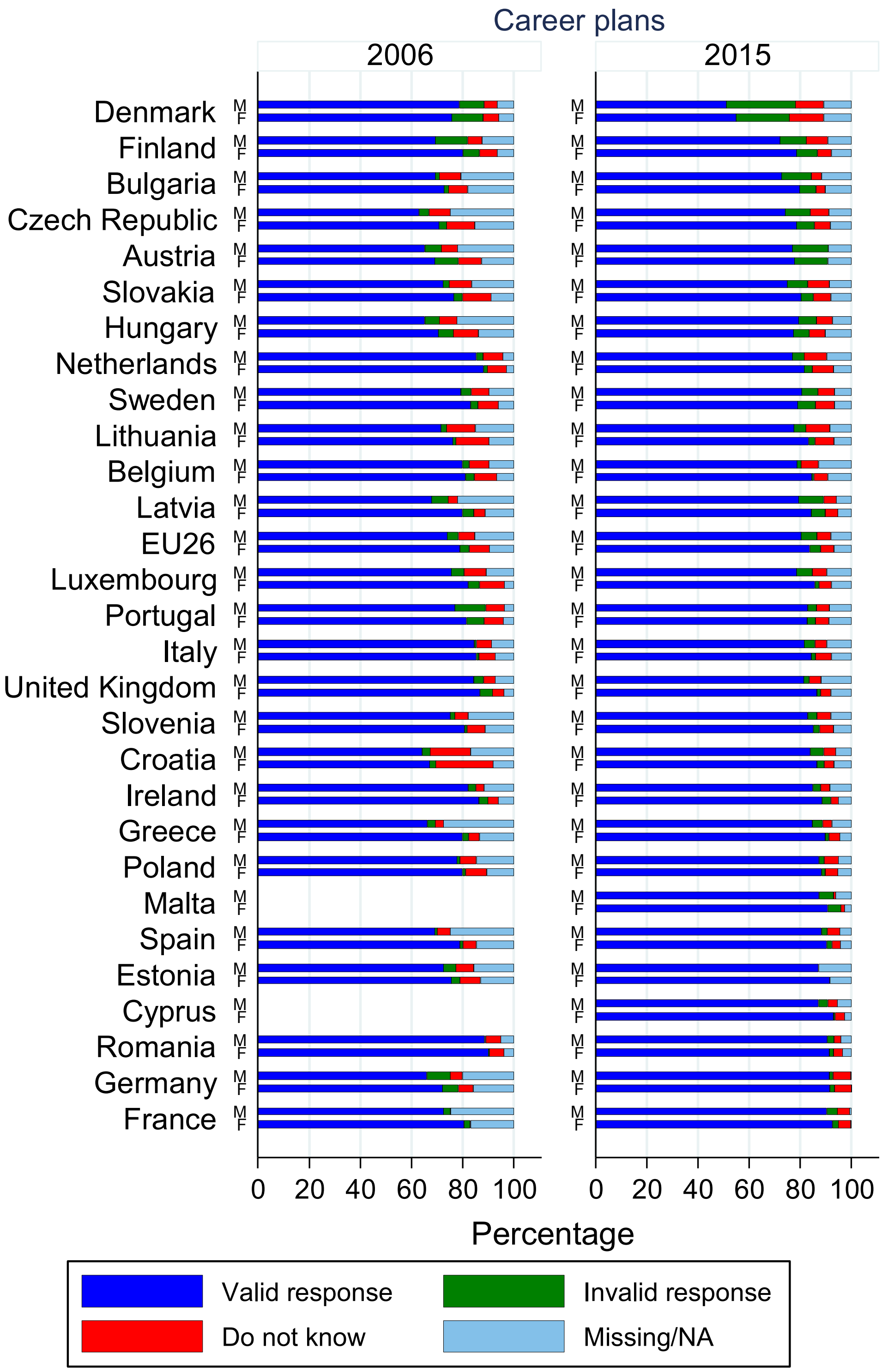
By 2015, the numbers of adolescents unable to answer the question about occupational destinations typically fell across countries. Across Europe 80% of males and 84% of females provided valid data. However, in Denmark in 2015 only 51% of males reported their future career plan, which seems anomalous. This is followed by 72% of males in Finland, 73% in Bulgaria, 74% in the Czech Republic and 75% in Slovakia. At the high end of the spectrum, 91% of German and Romanian males, 90% of males in France, 88% of males in Spain and 87% of males in Poland were able to meaningfully answer the question about their future careers (Figure 3.1).

The lowest proportion of adolescent females who answered the question about future careers were also in Denmark (55%). The second lowest figure was from Hungary (77%), followed by Austria and Finland (78%), with 79% of females in the Czech Republic. In contrast, 93% of females in Cyprus and France provided information about their occupational expectations, followed by 92% of females in Estonia and Germany, and 91% females in Malta and Romania (Figure 3.1).

The proportion of missing data so defined in 2006 is 12% (15% males and 10% females), and only a little more than 7% in 2015, with a greater contribution from males (8%) than females (7%). The share of invalid responses was around 4% in 2006 and went up to about 5% in 2015. All in all, with average valid response rates of approximately 75% in 2006 and 84% in 2015, this data collection provides data of the highest available quality.

Generally, the proportion of students who reported their career plans rose over time while the proportion of missing data decreased slightly between 2006 and 2015. It is not clear, however, whether this should be treated as a time trend or as a method effect attributable to the change from a paper and pencil questionnaire in PISA 2006 to a computer-based survey in PISA 2015.

Figure 3.1. Valid and missing responses for the career expectation question, sorted by number of valid responses in 2015 (see Table A3.16 in the Appendix for details).



Examination of the missing data patterns in Figure 3.1 indicates that the PISA data is of high quality. Most students in most European countries have given codeable responses to the question about future careers in both surveys. Nevertheless, it must be borne in mind that the quality of 2015 data in Denmark is below the benchmark typical for other countries. Specifically invalid responses amounted to 20% in Denmark, while in other countries they did not exceed 6%. This captures the extent to which the quality of the data varies across participating countries.

The methodological literature suggests that when more than 10% of data are missing, multiple imputation techniques (or maximum likelihood techniques) with auxiliary variables are the best strategy for proceeding with analysis (Newman, 2014). As the proportions of missing data on career expectations exceed this limit, averaging around 20% across countries, we use multiple imputations to infer career destinations for students who failed to answer this question.

Multiple imputations substantially outperform other methods of handling missing data in terms of potential bias and estimation precision (Schafer and Graham, 2002; Enders, 2010) and have the advantage of being easily integrated into complex analyses of datasets, such as PISA, that contain achievement scores expressed as plausible values.

For generating multiple imputation, we used a procedure known as imputations by chained equations (ICE) (Royston, 2004). The imputation model included all the variables from the analysis. The generation of multiple imputations was performed separately for each country to account for country-specific effects. We generated 10 multiple imputed datasets matching the 10 plausible values in PISA 2015, and five multiple imputed datasets matching the 5 plausible values in PISA 2006.

Because of our use of imputations and plausible values, all estimates have been obtained using multiple imputation methodology. This involved fitting 10 (or five) sets of models, each with one plausible value, and then combining these values using the Rubin rule (Little and Rubin, 1987).

3.6.2 Cross-country modelling strategy

The key dependent variable in this report is a student's expectation of working in a STEM occupation at age 30, coded 1 for science occupations and 0 for non-science occupations. Two widely used approaches exist for modelling binary outcomes. The first is the linear probability model (LPM), which is simply the ordinary least squares (OLS) regression with a binary dependent variable. The second is the logistic regression modelling. Neither of those approaches is perfect. On the one hand, the OLS approach results in non-normal and heteroskedastic error terms that may bias the estimation of standard error. Moreover, in some situations OLS may provide an invalid prediction that is outside the bounds of 0 and 1, which set the probability boundary (Scott Long, 1997). On the other hand, logistic models are not tailored to the comparability analysis, as for valid comparison of the logistic coefficients between the groups, the assumption about equal unobserved heterogeneity among the groups (variation in the dependent variable that is caused by non-observed variables) must be fulfilled (Scott Long, 1997; Mood, 2010). Moreover, the logistic models create problems of interpretation. While an LPM parameter value of 0.1 means that a one-unit increase in independent variable is associated with a 10 percentage point increase in the probability that the dependent variable is 1 in logistic models, the parameters are expressed on non-intuitive log odds scale or odds ratio scale. The problem of interpretability in logit models is even bigger in terms of interactions. A review of the 13 economics journals listed on JSTOR, performed by Ai and Norton (2003), found 72 articles published between 1980 and 1999 that used interaction terms in nonlinear models. According to the authors of the review, none of the studies interpreted the coefficient on the interaction term correctly.

We have chosen the LPM over the logistic model, for the following reasons. Simulation studies showed that the problem of biased standard errors in LPM seems to be of little practical importance (Hellevik, 2009). Our analysis focuses on cross-country comparisons, where LPM requires less restrictive assumptions (Scott Long, 1997; Mood, 2010). We are investigating both main effects and interaction terms, and in this context LPM is less exposed to errors of interpretation (Ai and Norton, 2003). We back up these reports with visual representations of adjusted predicted probabilities derived from logic models based on the same predictors as our OLS models. Adjusted predicted probabilities are free of cross-group comparability problems and interpretational problems of logistic regression, although they require graphical representation for correct interpretation, at least for continuous predictors. Keeping this in mind, we use them mostly for summarising the results or checking specific hypothesis about selected countries.

All continuous predictors presented here have been standardised to a mean of 0 and a standard deviation of 1 across European countries. We rely on estimations with balanced replication weights that account for the clustering of students within schools. In pooled sample estimations, countries are treated as fixed effects and Tylor's linearisation is used to account for the clustering of students within schools (Demnati and Rao, 2004; Fuller, 2011) .

3.6.3 Multilevel modelling

For the analysis of the country-level indicators we used two-level logistic models using maximum likelihood estimation with robust standard errors (Raudenbush and Bryk, 2001). In fact, our analysis might be defined by three empirical structures: students, schools and countries. We simplified the analysis by combining individual and school levels. The rationale for doing this is as follows. First, we used multilevel modelling only for analysing the country-level effects, and treat other variables in this analysis as controls (the effects of those variables were analysed separately). Second, the limited number of countries motivate us to simplify models as much as possible (other than on country level), to be able to detect country-level effects with the highest possible statistical power. Third, the application of three-level logistic models for survey data is still under development (Carle, 2009; Rozi et al., 2017). The most critical issue for the three-level logistic models, still not satisfactorily solved, is the use of the sampling weights that are necessary for unbiased estimation using PISA data.

3.6.4 Explaining changes over time: Blinder–Oaxaca decomposition

To explain the changes between 2006 and 2015, we used Blinder–Oaxaca decomposition, also known as Oaxaca decomposition. The aim of this decomposition is to explain how much of the difference in mean outcomes across two groups may be attributed to group differences in the levels of the various explanatory variables. The method also takes into account the differences in the relations between outcome variables and explanatory variables across the two groups (Blinder, 1973; Oaxaca, 1973; Jann, 2008). Using Blinder–Oaxaca decomposition we divide the differences in STEM career expectations between 2006 and 2015 into the 'explained' part, i.e. the part accounted for by student- and school-related variables, and the 'unexplained' part. This 'unexplained' part includes the effects of group differences in unobserved predictors as well as measurement error. This technique allows for decomposing the explained part of the changes over time into the effects of particular variables. Although there is a specific version of this method suitable for logistic regression (Jann, 2008), we chose OLS regression over the logistic for ease of interpretability and computational stability.

4 Career plans of European adolescents in 2006 and in 2015

We begin this chapter by considering what proportions of adolescents have concrete career expectations. This is crucial for the validity of the investigated variable. In our data, most adolescents could articulate a specific occupational expectation, but some youth either could not name their future occupation at all, or else gave information that could not be coded into the categories of ISCO-08. We consider the patterns of answers in both groups of adolescents, paying special attention to the preferences for professional occupations – which include most STEM jobs. Professional occupations are the most popular career choice among adolescents in all PISA-participating countries (Sikora and Pokropek, 2011).

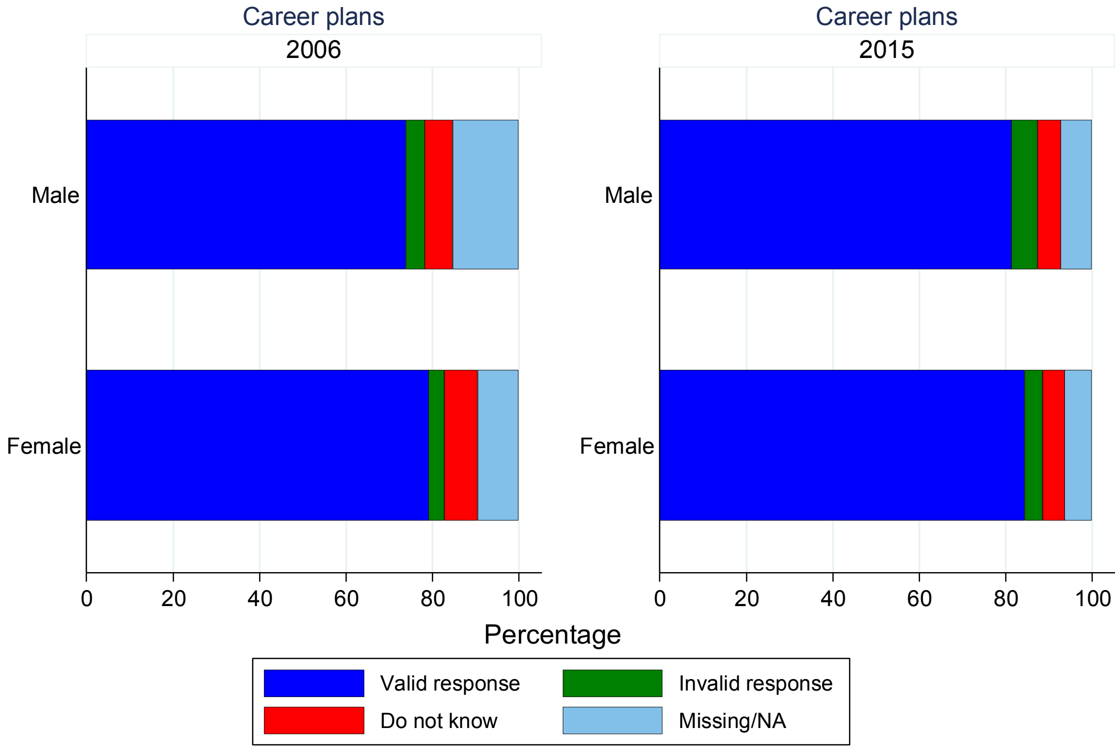
In relation to preferences for professional careers, concerns have been raised, predominantly in the USA, about unrealistic occupational expectations among youth (Schneider and Stevenson, 2000; Reynolds et al. 2006; Baird et al., 2008). Apparently, too many teenagers expect to work in highly skilled professional occupations. Even if a significant expansion should occur in the service sector in the future, it is unlikely that as many professionals as there are interested teenagers could be accommodated. Nevertheless, it is possible to argue that a large number of teenagers keen to enter the professions is a positive phenomenon, so the discussion of adolescent career plans involves not only the potentially negative but also the positive consequences of this interest (Alexander et al., 2008; Hardie, 2014). The latter include the motivation to study for higher level educational credentials, with positive effects on the overall amount of human capital in the economy. We start by comparing the level of interest in the professions and the associate professions over time and between genders. To this end we compare the proportions of young people who are interested in pursuing occupations that fall in the top three major (i.e. one-digit) categories of ISCO-08. The professionalisation of youth ambition is relevant because STEM occupations require either professional or associate professional credentials at entry, so if youth take more interest in the professions this could potentially widen the supply of STEM workers. Conversely, however, it is possible that while overall interest in the professions is on the rise, across countries the younger cohorts of adolescents tend to steer their career preferences away from science professions toward non-science occupations.

The key issue we address in this chapter is the gender gap in career expectations. First, we consider whether or not the proportions of males and females who are unable to name their future career destination are similar in different parts of Europe. Next, we compare males and females with respect to their interest in professional careers in general, and in STEM careers in particular.

4.1 Do all adolescents have career expectations?

In chapter 3, we discussed in detail some missing data issues from statistical and data quality perspectives. In this chapter, we supplement that discussion with more considerations on the missing data. The PISA question about adolescent career expectations has an open-ended format. This means that if a respondent does not have a specific occupational expectation, he or she can leave the question blank and move on to the next part of the questionnaire. Nevertheless, the majority of respondents in 2006, on average 74% of males and 79% of females across Europe, provided valid answers. By 2015, the numbers of adolescents unable to answer the question about occupational destinations had typically fallen across countries. Across Europe, 80% of males and 84% of females provided valid data (see Figure 4.1 for the overview). Generally, males are less certain about their future career destinations, while females are more likely to provide a valid answer.

Figure 4.1. Missing data on occupational expectations across Europe, by gender.



The non-response summarised in Figure 4.1 comprises three categories. It is worth noting that overall the percentage of explicit 'don't knows' is very low – 7% in 2006 and only 5% in 2009. The 'Missing/non-Applicable' category describes the situation where the respondents did not answer the question at all, either for administrative or for non-administrative reasons. Either the question could not be delivered to them (for instance because of computer failure), or they did not reach the relevant part of the questionnaire, or they left a blank space for unknown reasons. Only some of this non-response may be attributed to the fact that a teenager has no occupational plans. All in all, the share of missing data in this category remains small (10% in 2006 and 6% in 2015).

As well as 'Missing/non-Applicable' and 'Don't know', there is 'Invalid response', which covers responses that were impossible to code to the categories of ISCO-08, for instance 'Housewife', 'Student' and 'Social beneficiary', but also 'King', 'Billionaire' and 'Dictator'. 'Invalid' includes also responses that were indicative of occupational pursuits but not specific enough to be coded to ISCO categories, such as 'Work in my father's ITC company', 'Work with medicine and technology', 'Work on a cruise ship', etc. Finally, 'Invalid' also involves responses that combined two or more occupational choices, such as 'Veterinarian or Veterinary Nurse' or 'Diplomat or Journalist or researcher', given that these combinations were also classified as invalid.

Invalid responses can arise from two sources. First, the student might not provide a codeable answer, and, second, the coder might be unable to code the answer provided and thus classify it as invalid. For instance, the response 'Designer or architect' might be considered invalid because it involves two occupations, or the coder might elect to categorise it as a three-digit ISCO minor group 'Architects, Planners, Surveyors and Designers'. Therefore, it is impossible to determine exactly how to interpret invalid responses, as their sources may not be equivalent between countries. Some countries, such as Austria and Estonia in 2015, did not use the 'Don't know' category and instead coded such responses as invalid. The overall share of this category was 4% in 2006 and 5% in 2015.

Examination of the missing data patterns in Figure 4.1 indicates that the PISA data is of reasonably high quality. Most students in European countries have given codeable responses to the question about their future careers. This attests to the validity of our analysis.

4.2 What types of careers appeal to adolescent males and females?

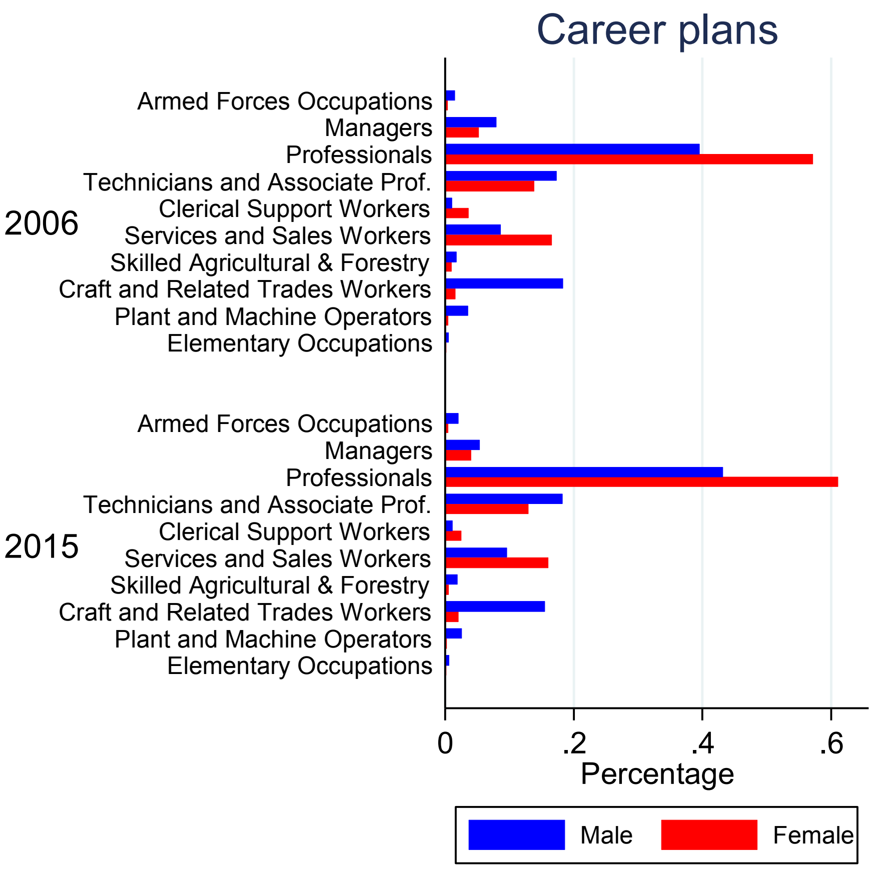
The preferences of males and females are at this stage very heavily oriented towards working in highly skilled professional occupations. One reason for this might be that the PISA survey is answered by most respondents towards the end of their compulsory schooling, and in many countries this is before students are segregated into vocational or university-oriented pathways of further education. It is not yet evident to some students that they will soon enter vocational education and no longer have an opportunity to enter a professional career. However, this pattern is by no means specific to the PISA surveys, and has been found in a number of studies based on various data sources in the affluent and developed countries as well as the developing or transitioning countries (Little, 1978; Saha, 1982; Patton and Creed, 2007; Sikora and Saha, 2009). In the latter group, student aspirations to professional employment are even more widespread than similar aspirations in the post-industrial developed world.

Figure 4.2 presents an overview of students' plans grouped into the major categories of ISCO-08. Professional occupations (which also include STEM professional jobs) are decidedly the most popular labour market destinations in the minds of young people, and the trend is only getting stronger over time. In 2006, 48% of all students indicated their expectations to enter one of the professional occupations. By 2015, this proportion across European countries had risen to 52%.

The professionalisation of occupational expectations is stronger among females. In the decade 2006–2015, the proportion of females who hoped to become professionals increased from 57% to 61%, while the corresponding figures for males were 39% and 43% (Figure 4.2). This gap can be interpreted as female advantage in the sense that it projects future upskilling of females in the labour force. In other words, it suggests that highly skilled professional employment in the future will involve greater numbers of females. At the same time, however, this gender gap might be interpreted as arising from a relative lack of attractive employment options for young women outside of the professions. In many countries, it has been highlighted that females are heavily underrepresented in vocational education and associated employment in trades (Reisel et al., 2015).

The pattern of career expectations presented in Figure 4.2 is consistent with the prognosis that females will continue to be underrepresented among trade workers in the future. Conversely, more females than males expect to enter employment in services and sales. This seems to be the expected, if not preferred, career pathway for adolescent females who do not envisage obtaining a university degree. By definition, professional occupations require a university degree on entry and this is usually known to students at this stage of their schooling. Males are more attracted than females to occupations in defence and law enforcement agencies. They also outnumber their female peers among students with expectations to become managers, technicians or associate professionals as well as plant and machine operators (Figure 4.2).

Figure 4.2. Career plans of adolescents in broad categories (ISCO-08 main groups).

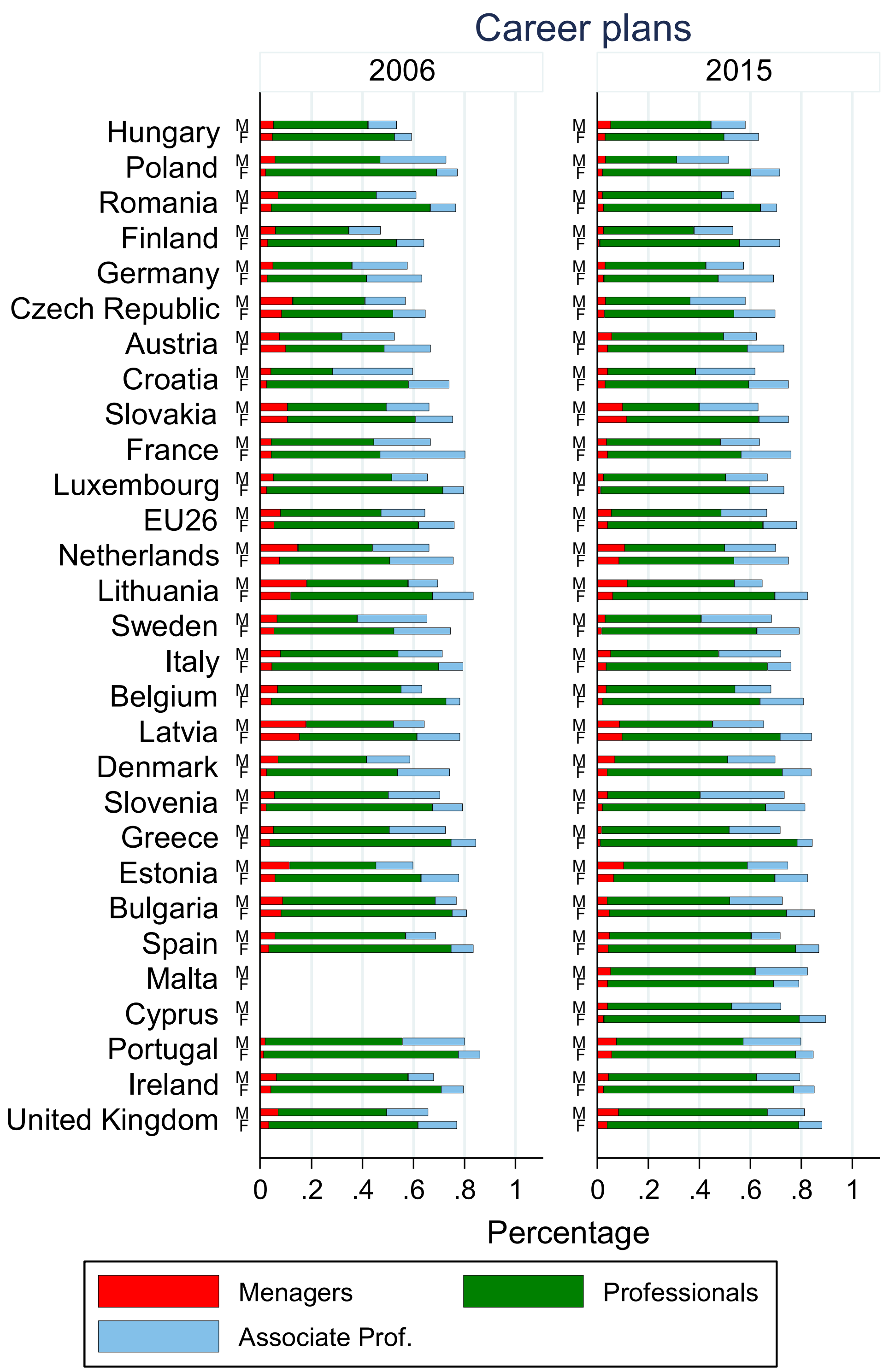


As illustrated in Figure 4.2 and as found in prior studies (Little, 1978; Rindfuss et al., 1999; Looker and Magee, 2000; Sikora and Saha 2009; Marks, 2010), the dominant expectation among adolescents in Europe is that they will enter one of the professional occupations. These are jobs defined as major group 2 in ISCO-08, which typically require a university degree at entry. Figure 4.3 shows the breakdown by country in the proportions of youth who expect to work in the professions (ISCO-08 major group 2), as well as those who expect to become managers (ISCO-08 major group 1) or associate professionals (ISCO-08 major group 3). It is worth noting that these three major occupational groups account for a vast majority of adolescent occupational expectations. In 2006, on average, 70% of European students expected to work in one of these occupations. By 2015 this proportion had risen slightly to 73%. Without exception, in each country greater proportions of females than males were drawn to professional and managerial occupations: on average this was 76% of females versus 65% of males in 2006, with the divide remaining similar in 2015, when 78% of females and 67% of males expected to become a manager, a professional or an associate professional in adulthood.

The lowest proportions of students with plans to pursue professional occupations in 2006 resided in Austria (32%), Germany (35%), the Czech Republic (35%), the Netherlands (36%) and Sweden (39%). In comparison, the highest proportions are found in Ireland (59%), Spain (62%), Bulgaria (63%) and Portugal (66%).

In 2015, the smallest shares of students who plan to work in professional occupations live in Slovakia (41%), the Czech Republic, the Netherlands and Denmark (42%), and in Poland (43%). The highest proportions, in comparison, are found in Cyprus and also Greece (63%), Spain (65%), Ireland (66%) and the United Kingdom (67%).

Figure 4.3. Cross-country differences in career plans of adolescents in broad categories (ISCO-08 major groups 1, 2 and 3), sorted by the total proportion of students who expected to become either a manager, a professional or an associate professional in 2015 (see Table A4.1 in the appendix for details).



The typicality of the gender gap in the combined preferences for managerial and professional occupations (also including associate professionals) can be visually appreciated in Figure 4.3, as the bars for females tend to be longer than the bars for males in every country. In particular, the proportions of females who prefer professional occupations are consistently higher than the proportions of males in all the European countries, in both 2006 and 2015.

4.3 Science career plans of adolescents

Table 4.1 presents a summary of the most popular occupational choices for males and females in 2006 and 2015. The table comprises four panels, one for each sex, for 2006 and 2015. The far left of each panel shows the two most popular occupational destinations at the level of ISCO-08 major categories (one digit). As in 2006, working in the professions was by far the most popular choice for females in 2015, followed by service and sales work, which attracts 16% of females. Moving to the right, those females who would like to become professionals are most interested in the Legal, Social and Cultural Professions (34% of the 60% of females), while the second choice is Health Professions (30% of the 60% of females) – an occupational preference that, as we will see in the next section, shows the opposite of the patterns seen in STEM careers. Both Legal, Social or Cultural Professions and Health Professions are ISCO-08 two-digit sub-major groups. Within the Legal, Social and Cultural Professions the breakdown at the minor three-digit ISCO-08 group level, further to the right, shows that the two most popular destinations among the 34% females who want to work in Legal, Social and Cultural Professions are Creative Performing Artists (33%) and Legal Professionals (28%). STEM occupations did not appear among the most popular female choices, either in 2006 or in 2015.

The expectations of males are similarly organised and presented in the right hand panel of Table 4.1. STEM occupations are highlighted in grey at the top and appear on the list of the most popular occupations among males (the relevant percentages are higher in 2015 than in 2006). In 2015, only 44% of males want to be professionals but in this group the most popular destination at the two-digit ISCO-08 level is Science and Engineering Professions, where more than one third of males interested in professional employment plan to work. Table 4.1 is just a snapshot of the most popular occupational choices, but it clearly illustrates the deep gender divide in adolescent occupational expectations related to STEM.

Table 4.1. Specific career choices of adolescents in PISA 2015 and 2006. Conditional distributions.

2006

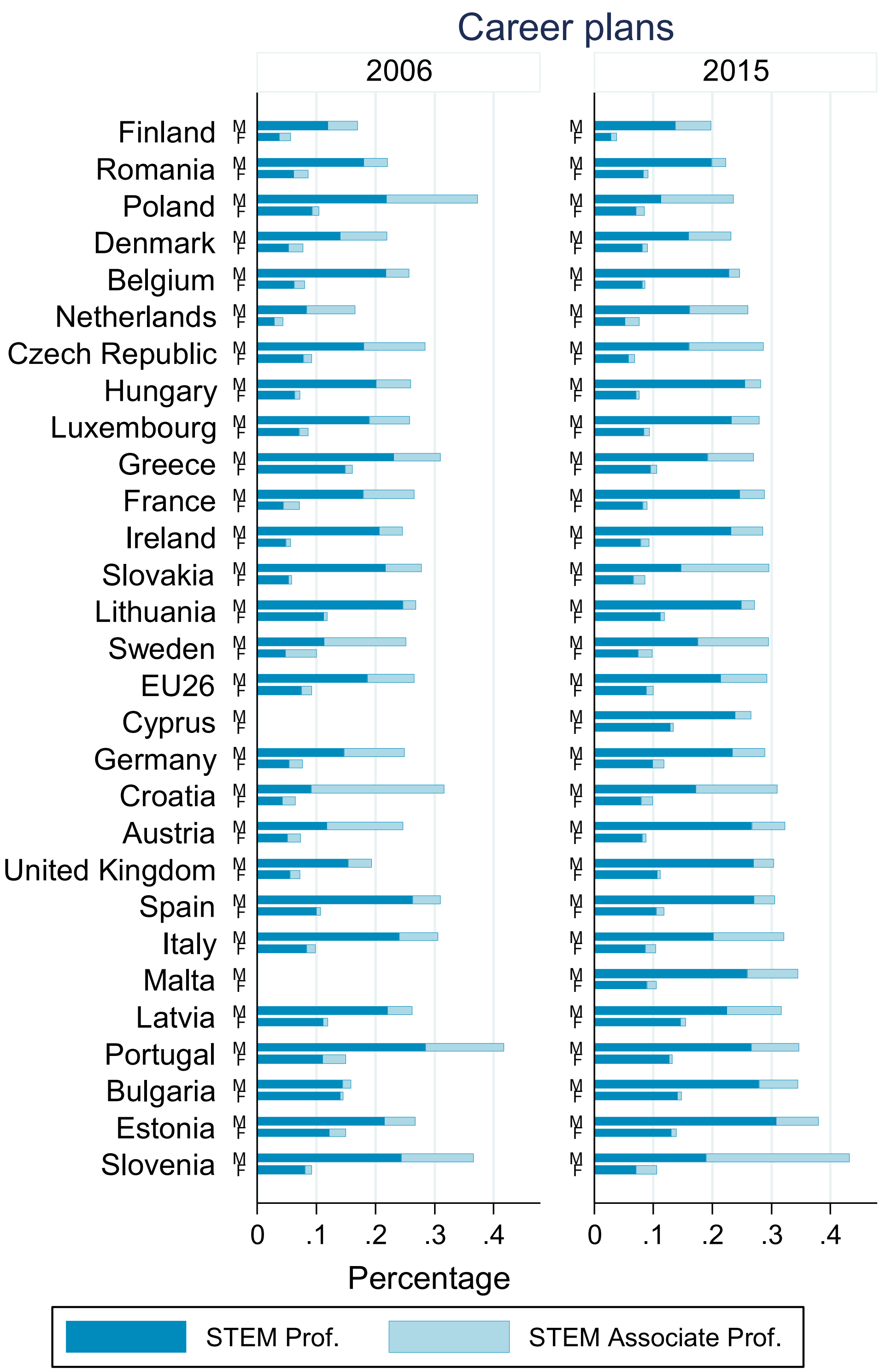
Female			Male		
Professionals (57%)	Legal, Social and Cultural Professionals (38%)	Social and Religious Professionals (31%)	Professionals (39%)	Science and Engineering Professionals (30%)	Engineering Professionals (44%)
		Legal Professionals (27%)			Architects, Planners, Surveyors and Designers (20%)
	Health Professionals (24%)	Medical Doctors (48%)		Legal, Social and Cultural Professionals (24%)	Legal Professionals (31%)
		Other Health Professionals (25%)			Creative and Performing Artists (29%)
Services and Sales Workers (17%)	Personal Services Workers (65%)	Hairdressers, Beauticians and Related Workers (62%)	Craft and Related Trades Workers (18%)	Building and Related Trades Workers (37%)	Building Frame and Related Trades Workers (69%)
		Cooks (14%)			Building Finishers and Related Trades Workers (22%)
	Sales Workers (13%)	Shop Salespersons (85%)		Metal, Machinery and Related Trades Workers (34%)	Machinery Mechanics and Repairers (77%)
		Other Sales Workers (7%)			Sheet and Structural Mental Workers, Modulers and Welders (14%)

2015

Female			Male		
Professionals (60%)	Legal, Social and Cultural Professionals (34%)	Creative and Performing Artists (33%)	Professionals (44%)	Science and Engineering Professionals (36%)	Architects, Planners, Surveyors and Designers (52%)
		Legal Professionals (28%)			Life Science Professionals (15%)
	Health Professionals (30%)	Medical Doctors (60%)		Legal, Social and Cultural Professionals (21%)	Social and Religious Professionals (33%)
		Other Health Professionals (24%)			Legal Professionals (26%)
Services and Sales Workers (16%)	Personal Services Workers (55%)	Hairdressers, Beauticians and Related Workers (51%)	Technicians and Associate Professionals (17%)	Legal, Social, Cultural and Related Associate Professionals (35%)	Sports and Fitness Workers (81%)
		Travel Attendants, Conductors and Guides (16%)			Artistic, Cultural and Culinary Associate Professionals (17%)
	Personal Care Workers (17%)	Child Care Workers and Teachers' Aides (61%)		Science and Engineering Associate Professionals (25%)	Ship and Aircraft Controllers and Technicians (41%)
		Personal Care Workers in Health Services (38%)			Physical and Engineering Science Technicians (38%)

A more comprehensive overview of gender differences in adolescent expectations of STEM-related employment is shown in Figure 4.4.

Figure 4.4. Cross-country, cross-time and cross-gender differences in STEM career plans among associate professionals and professionals, ordered by the overall total percentage of students planning a STEM career in 2015 (see Table A4.2 in the appendix for details).



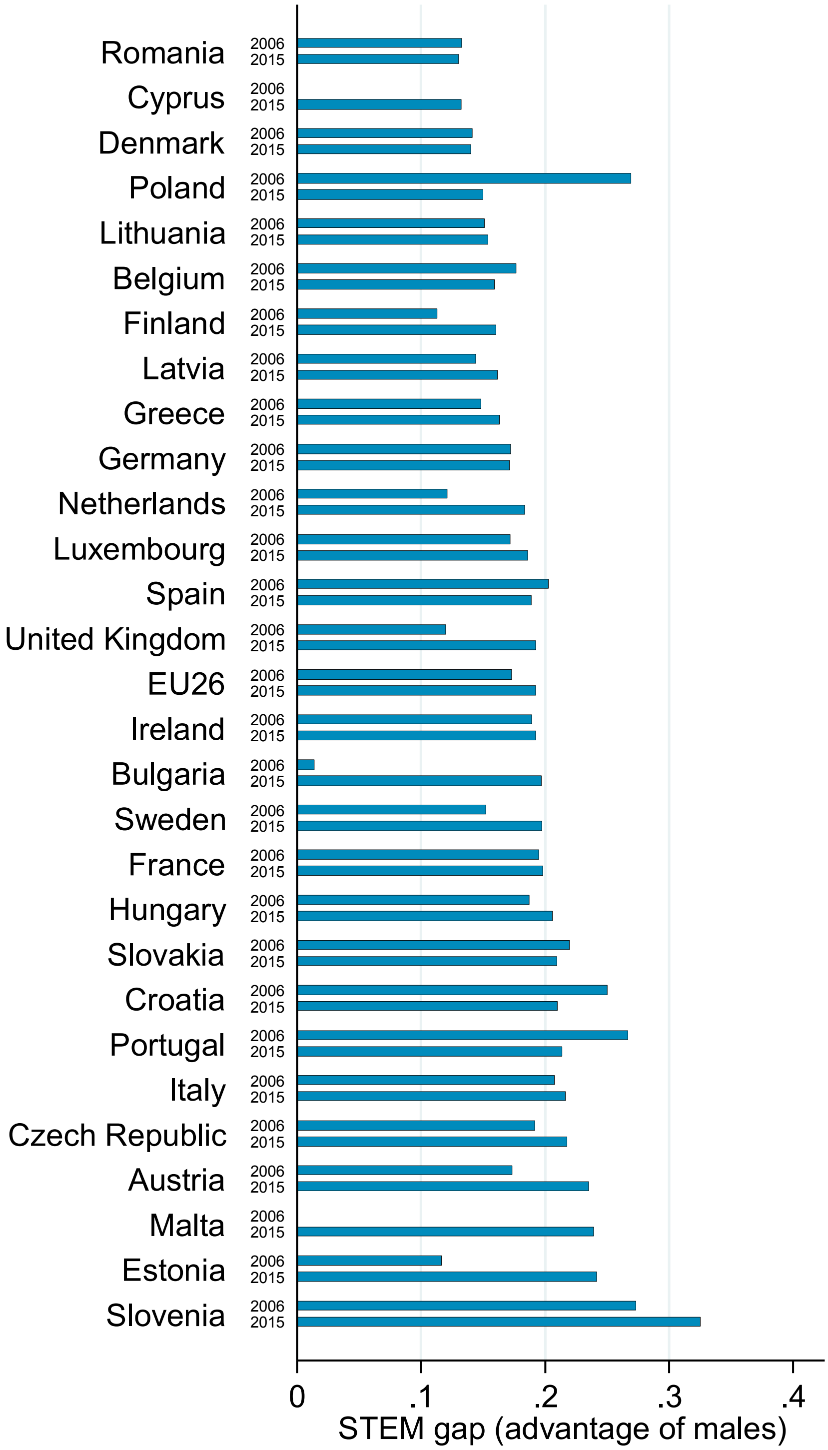
Across European countries, on average, 27% of males but only 9% of females expected to work in STEM-related occupations in 2006. This level of vocational interest in STEM rose to 29% of males in 2015, while for females the figure was 10%. Figure 4.4 shows a breakdown of these occupations by professionals and associate professionals. Typically, adolescents are interested in STEM-related professions rather than associate professions, but in some countries (for instance Croatia and Poland in 2006, and Slovenia and Sweden in 2015) the proportions of students who expected to work in STEM associate professions accounted for about one third of all teenage preferences for STEM employment.

The most systematic pattern in Figure 4.4 is a clearly pronounced gap between males and females in each of the European countries. In 2006, the countries with the largest proportions of teenagers interested in pursuing STEM-related occupations were Portugal (28%), Poland (24%), Greece (23%), Slovenia (22%) and Spain, Italy and the Czech Republic (20%). With no exception, males outnumbered females in all of these countries. For instance, in Poland 37% of males but only 10% of females planned on working in science-related occupations. In Portugal, the corresponding breakdown was 42% of males and 15% of females, while in Greece these proportions were 31% of males and only 16% of females.

The countries with the lowest interest in STEM careers in 2006 were the Netherlands and Finland, with only 11% of students, and the United Kingdom, with 13% of students. In the Netherlands, at that time, 18% of males and only 4% of females were interested in entering a STEM career; in Finland, it was 6% of females and 17% of males, while in the United Kingdom it was 7% of females and 19% of males. So it appears that largely regardless of whether the overall level of interest in STEM occupations is high or low, the gender gap tends to be wide everywhere.

In 2015, the largest proportions of students interested in science-related occupations resided in Slovenia (27%), Estonia (26%), Bulgaria (25%), Portugal (24%), and Malta and Latvia (23%) (Figure 4.4). At the low end of the spectrum, Finnish students reported the lowest interest in STEM occupations (11%), followed by students from Romania (16%), Denmark (16%) and Poland (15%). In Romania, the gender gap in 2015 was lower than elsewhere, at 13%, i.e. the difference between 9% of females and 22% of males. In Cyprus, the ratio of females to males was similar, as 13% of females and 27% of males expected to work in an STEM job. In Denmark in 2015, 23% of males and 9% of females had science-oriented vocational interests.

Figure 4.5. Cross-country differences in gender gap of STEM career plans of adolescents (see Table A4.3 in the appendix for details).



Except in Poland, the size of the gender gap in 2015 had changed little from 2006, marginally increasing or decreasing in particular countries; the overall pattern remained as it was a decade ago, as is evident from Figure 4.5. A remarkably small gender gap was recorded in 2006 in Bulgaria, with only a 1% difference between males and females. Other countries with small gaps in 2006 included Finland (11%) and Denmark, Estonia and the United Kingdom as well as Denmark (12%). In contrast, the largest gender gap a decade ago was found in Slovenia, Poland and Portugal, with a difference of 27% between males and females, followed by Croatia with 25%, Slovakia with 22%, and Estonia and France with 20%.

By 2015, the average gender gap in STEM vocational interest amongst teenagers had increased across Europe (Figure 4.5). In 2015, it was largest in Slovenia, at 32%, followed by Estonia, Malta and Austria (24%), and the Czech Republic and Italy (22%). At the other end of the spectrum, the smallest gender gap in 2015 was recorded in Romania and Poland (13%), in Denmark (14%), and in Poland and Latvia (15%).

Overall, PISA data show that over time the gender gap favouring males has increased slightly. A decrease occurred in few countries. However, in Poland the recorded decrease of 12% is so large that it raises questions over data quality. In Portugal, the gap decreased by 5%, in Croatia by 4% and in Belgium by 2%. The largest shift in the opposite direction (18%) occurred in Bulgaria, followed by 12% in Estonia, 7% in the United Kingdom, and 6% in the Netherlands and Austria. Slovenia and Finland also recorded a growing gender gap in teenage vocational expectations related to STEM, with growth of about 5% in both countries.

4.4 Health-related occupations

Figures 4.6. and 4.7. show that teenage interest in health professional and health associate careers is greater among females than males, which is the opposite of the gender patterns affecting preferences for jobs in STEM occupations. All over Europe, females are significantly more likely to plan a health-related career than males are – producing a reverse gender gap compared with the STEM occupations. Both of these gender disparities are comparable in size. Indeed, if we aggregate teenage expectations of STEM and health occupations for males and females, we find that the overall number of females planning either career is almost as high as the overall number of males (Figure 5.7).

Similarly to STEM, professional occupations are significantly more popular than associate professional ones in the area of health. Across Europe, in 2006 14% of female students planned a professional career in health, but only 4% a non-professional one, while the respective figures among males were 6% and 1%. By 2015 females' interest in entering a professional health career had increased to 19%, while the other categories remained largely the same.

The overall interest in medical careers in 2015 varied from 17% in Hungary to 40% in Finland. Other countries with a lower level of interest included Estonia, Latvia and Malta, while countries similar to Finland were Slovenia, Denmark and Belgium. Variations in the size of the gender gap – in the favour of males in each case – are also remarkable. The smallest gap can be observed in Malta (7%), followed by Greece (9%), Hungary (10%), Italy (11%), then Cyprus, Estonia, France and Luxembourg (12%). Quite often, countries that attract the most students to health careers also produce the biggest gender gap in students' interest in these careers. Thus the greatest gaps were observed in Finland and Denmark (21%), Slovenia (20%), and Portugal, Poland and Lithuania (19%).

Figure 4.6. Cross-country, cross-time and cross-gender differences in health career plans among associate professionals and professionals, ordered by the overall health expectations in 2015 (see Table A4.4 in the appendix for details).

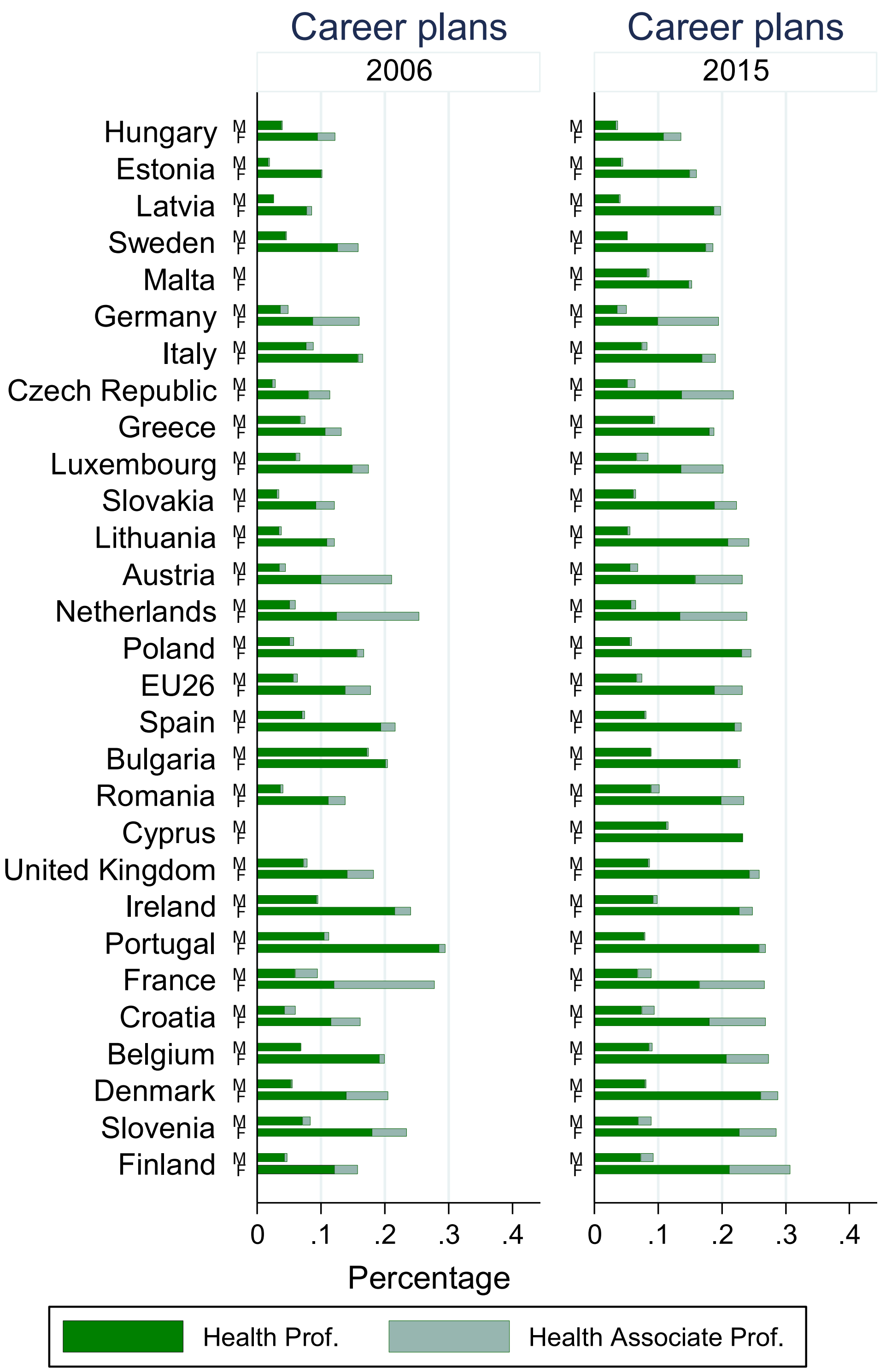
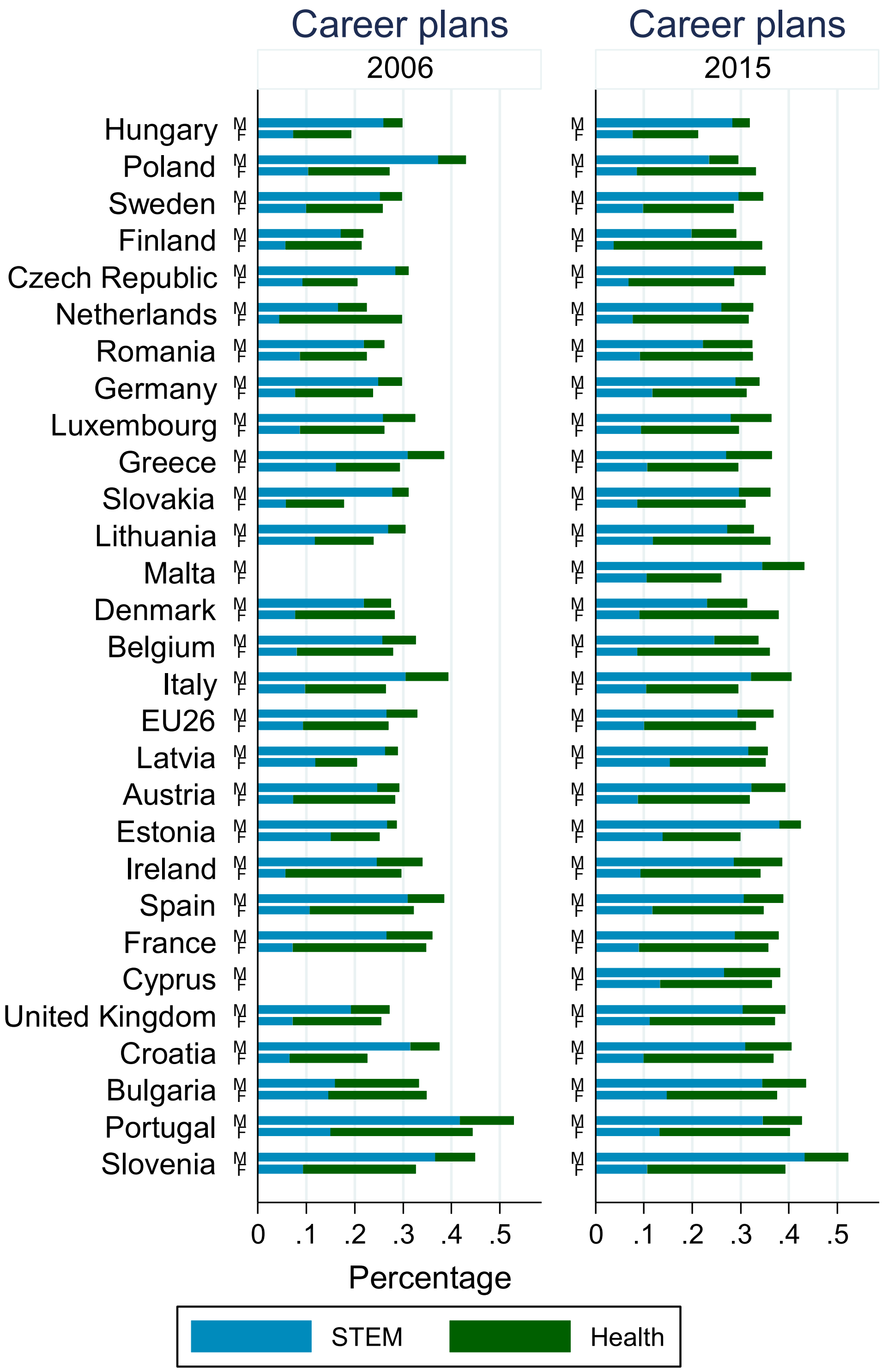


Figure 4.7. Cross-country, cross-time and cross-gender differences in combined STEM and health career plans among associate professionals and professionals, ordered by the overall STEM and health expectations in 2015 (see Table A4.5 in the appendix for details).



4.5 Summary

Not all teenagers are able to answer the question about the occupation they expect to be in once they reach the age of 30. In some countries, as few as 10% of respondents leave this question blank, and in other countries about 20%, 30% or even (in Denmark in 2015) 50% of respondents did not provide a valid answer to this question. Notwithstanding that, because PISA is the only source of internationally comparable information on adolescents' occupational plans that uses an open-ended question format, PISA surveys remain the best available source of data on this topic for cross-national comparisons and comparisons over time.

Overall, European teenagers are strongly oriented towards working in professional occupations. This is particularly the case among females. In 2006, 57% of females planned to work as professionals. By 2015 this proportion had risen to 60%. The corresponding proportions of males were 39% in 2006 and 44% in 2015. Although it is unlikely that all of these teenagers will be able to realise their adolescent expectations, the dominant tendency to aspire to professional employment can be seen as a positive phenomenon in that it may encourage young people to engage in post-compulsory education, given that the professionals usually require a university degree at the start of their career. Conversely, in countries where there are shortages of youth available for vocational training to fill vacancies in trades and related occupations, this strong focus on professions may be undesirable.

Two key features of the gender gap in teenage expectations have been identified in this chapter. First, females are significantly more oriented towards working in professional jobs than males. Second, despite their stronger tendency to aspire to professional jobs, they are significantly less oriented towards working in STEM occupations than males. These divides not only correspond with what was found in previous studies, but the examination of changes over time also confirms this trend to be stable and even becoming slightly stronger over time. The size of the gender gap varies from country to country and also over time, but these variations are all within a broader tendency for more females than males in each country to expect professional employment in the future, while significantly fewer females than males expect to work in STEM occupations.

5 STEM career plans in Europe 2015

This chapter presents evidence on the factors that affect adolescent STEM career choices. We approach the task of explaining these choices sequentially using a bottom-up strategy. We investigate various hierarchical layers of factors, beginning at individual level and finishing with country-level characteristics. Using this strategy we consider various potential explanations concerning STEM career choices (which were discussed in chapter 2). Our special focus is on gender differences. We also focus on possible determinants of students' choices, which can be targeted by policy interventions designed to encourage adolescents to pursue STEM careers. Firstly, we examine individual characteristics that differ between students and their families. Secondly, we examine school-related variables. Finally, we turn our attention to country-level correlates.

5.1 Overview of STEM career plans

Chapter 4 provided an overview of students' responses to the question about expected career at age 30. We also showed the distribution of missing data for these questions. In this chapter, we report the distribution of students' occupational expectations with missing data replaced by estimates based on the information about students' individual characteristics. Imputed data are effectively more accurate and less affected by non-response bias. However, the imputed data do not distinguish between STEM professional occupations and STEM associate professional occupations, and so the two categories have been combined in this chapter. The main reason for that is the fact that in some countries the numbers of STEM associate professionals are not large enough for the category to be imputed separately. This gives us more accurate estimates, at the cost of not being able to distinguish between professionals and associate professionals in STEM.

Table 5.1 shows the proportions of students expecting a career in STEM in total and by gender. The table provides similar information to those presented in chapter 4, however here the results are obtained using multiple imputed data, which give more precision at the cost of losing the distinction between professionals and associate professionals. We also show the gender gap, which is the difference between the proportions of males and females interested in pursuing a science occupation in the future. The cross-national patterns in the imputed data closely correspond to those seen in the original data. The largest gender gap in adolescent plans is evident in Slovenia (31%), then in Estonia (24%), Austria (23%), Malta (23%) and Croatia (21%). In contrast, the smallest gap is in Cyprus (13%), Romania (13%), Denmark (15%), Poland (15%) and Lithuania (15%).

Slovenia (42%), Estonia (38%), Bulgaria (33%), Portugal (34%) and Latvia (32%) are the five countries with the largest proportions of males interested in STEM occupations. In contrast, the lowest proportions of males with vocational science interests are in Finland (20%), Romania (22%), and Denmark and Poland (24%). So the differences between countries in the average interest of adolescents are also significant.

Latvia leads European countries with respect to the proportion of females interested in pursuing a career in STEM occupations (16%), as defined in this report. Bulgaria also has about 15% of females with similar interests, and is followed by Estonia (14%), Cyprus (13%) and Portugal (13%). At the other end of the spectrum, Finland has under 4% of females who plan to work in these occupations, while in the Czech Republic the proportion is about 7%, in Hungary about 8% and Slovakia about 9%. So the ratio between the European country that has most males interested in STEM occupations and the one that has least males is about two males in the former to one male in the latter, while the ratio for females is higher, as the share of STEM-oriented females in Latvia is four times the respective share in Finland. In other words, there is more inequality in expectations among females than males.

Table 5.1. STEM career plans and gender gap. Proportions of students after multiple imputations.

Country	STEM plans	St.Error	Female plans	St.Error	Male plans	St. Error	Gap	Standard Error
Austria	**0.207**	(0.010)	**0.091**	(0.006)	**0.321**	(0.018)	**0.231**	(0.019)
Belgium	**0.164**	(0.008)	**0.087**	(0.009)	**0.238**	(0.014)	**0.150**	(0.017)
Bulgaria	**0.244**	(0.014)	**0.148**	(0.012)	**0.330**	(0.018)	**0.182**	(0.022)
Cyprus	**0.195**	(0.006)	**0.133**	(0.007)	**0.259**	(0.009)	**0.126**	(0.012)
Czech Republic	**0.178**	(0.008)	**0.069**	(0.005)	**0.281**	(0.013)	**0.211**	(0.014)
Germany	**0.194**	(0.006)	**0.114**	(0.006)	**0.271**	(0.010)	**0.158**	(0.012)
Denmark	**0.163**	(0.006)	**0.089**	(0.008)	**0.237**	(0.010)	**0.148**	(0.012)
Estonia	**0.261**	(0.007)	**0.140**	(0.008)	**0.377**	(0.010)	**0.237**	(0.013)
Greece	**0.191**	(0.007)	**0.108**	(0.007)	**0.268**	(0.011)	**0.160**	(0.013)
Spain	**0.211**	(0.006)	**0.120**	(0.007)	**0.303**	(0.009)	**0.183**	(0.011)
Finland	**0.121**	(0.006)	**0.039**	(0.005)	**0.197**	(0.010)	**0.158**	(0.011)
France	**0.185**	(0.007)	**0.091**	(0.007)	**0.279**	(0.011)	**0.188**	(0.013)
Croatia	**0.204**	(0.012)	**0.101**	(0.010)	**0.314**	(0.018)	**0.213**	(0.020)
Hungary	**0.178**	(0.009)	**0.077**	(0.006)	**0.279**	(0.016)	**0.201**	(0.017)
Ireland	**0.191**	(0.005)	**0.095**	(0.006)	**0.282**	(0.009)	**0.187**	(0.011)
Italy	**0.208**	(0.012)	**0.103**	(0.008)	**0.314**	(0.015)	**0.210**	(0.017)
Lithuania	**0.195**	(0.006)	**0.119**	(0.006)	**0.269**	(0.010)	**0.150**	(0.012)
Luxembourg	**0.185**	(0.006)	**0.095**	(0.006)	**0.276**	(0.009)	**0.181**	(0.011)
Latvia	**0.237**	(0.007)	**0.156**	(0.008)	**0.317**	(0.011)	**0.161**	(0.014)
Malta	**0.223**	(0.007)	**0.104**	(0.007)	**0.339**	(0.013)	**0.234**	(0.015)
Netherlands	**0.167**	(0.006)	**0.078**	(0.005)	**0.257**	(0.011)	**0.178**	(0.012)
Poland	**0.164**	(0.006)	**0.087**	(0.007)	**0.238**	(0.010)	**0.150**	(0.012)
Portugal	**0.239**	(0.007)	**0.132**	(0.008)	**0.344**	(0.012)	**0.212**	(0.014)
Romania	**0.157**	(0.009)	**0.092**	(0.008)	**0.222**	(0.015)	**0.131**	(0.017)
Sweden	**0.198**	(0.007)	**0.101**	(0.007)	**0.293**	(0.011)	**0.193**	(0.013)
Slovenia	**0.269**	(0.006)	**0.108**	(0.007)	**0.420**	(0.010)	**0.311**	(0.012)
Slovakia	**0.190**	(0.009)	**0.087**	(0.008)	**0.287**	(0.012)	**0.201**	(0.015)
United Kingdom	**0.209**	(0.006)	**0.112**	(0.006)	**0.303**	(0.009)	**0.191**	(0.011)
EU-28	**0.197**	(0.001)	**0.103**	(0.001)	**0.290**	(0.002)	**0.187**	(0.000)

Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

Historically, the differences between adolescent males and females in science-related vocational interests were attributed to the differentials in school performance (Steinkamp and Maehr, 1984). Prior to the 1990s females tended to lag behind males in mathematics but also in science (Benbow and Stanley, 1980; Fensham, 1988). This was the case in many countries, although the main evidence available in English comes from English-speaking countries (Becker, 1989). At the turn of the century, however, more and more evidence emerged that the gap in school mathematics and science performance between males and females was shrinking (OECD, 2007). Even in places where it did not entirely disappear, it was suggested that the gender gap in performance was not large enough to have significant implications for students' career expectations (Riegle-Crumb et al., 2012). Rather, the concern for the past 20 years has been that females whose mathematical and science ability often matches, and at times exceeds, the ability demonstrated by males (OECD, 2007), turn away from mathematically intensive careers for reasons unrelated to their aptitudes or histories of school performance (Osborne et al., 2003; Osborne and Dillon, 2008).

5.2 Which students make plans to enter STEM as a career?

In this section, student-level correlates of STEM careers are investigated. We do this by estimating a series of regression models for each country. In the models, we focus on two aspects of STEM career plans: the proportion of students interested in pursuing a science career and the gender gap in STEM career choices. To investigate the first aspect, we concentrate on the percentage of variance explained in STEM choices by particular sets of variables, as well as regression coefficients that describe the relation between career choices and explanatory variables. For the second aspect, we evaluate the size of the gender gap in each country before and after controlling for different sets of variables. If the gender gap decreases after introducing the sets of controls, it will be plausible to assume that some part of the gender gap is due to the differences in students' characteristics. To explore the factors that affect the gender gap more deeply, we develop additional models with the interaction effects of gender and other explanatory variables. The description of the models used in this section is depicted in Table 5.2.

Table 5.2. Description of models predicting interest in STEM using student-level variables.

Model	Independent variables	Description
M0	Gender	Baseline
M1	M0 + science literacy	+ Abilities
M2	M1 + ESCS, parents in STEM, migrant status	+ Background
M3	M2 + science self-efficacy, enjoyment of science	+ Attitudes
M3i	M3 + gender interactions with all explanatory variables	+Interactions

We begin with the model that includes only gender as a predictor of planning STEM careers. That is our baseline model (M0). Next, we consider the effect of school science achievement on students' STEM career plans (M1).

Apart from science achievement and cognitive attributes of youth, prior literature suggests that students' cultural and socio-economic background may be conducive to greater interest in science careers. It has been suggested that middle-class parents are more effective in facilitating their offspring's interest in science, and more often the interest of sons than daughters. Similarly, arguments and empirical research on within-family socialisation point out that youth who grow up with parents who work as science professionals are more likely than other young people to follow a corresponding career path. From a completely different angle, some literature suggests that migrant students, both first- and second-generation migrants, are more motivated to engage in certain science-related occupations, including engineering, irrespective of their science performance (OECD, 2007).

Model M2 accounts for the effects of students' social background and home environment. Social background includes parental economic and socio-cultural status, their employment in science (employed in science coded as 1 and other occupations coded as 0), and students' migration status. Students' economic and social/cultural family background includes information about parental education, occupation and various home possessions, as well as cultural resources and the resources specific to ICT.

The growing literature supplemented by common sense indicates that attitudes towards science may be an important factor in determining teenage choices. Model M3 also includes students' aptitudes towards science measured by two indicators: science self-efficacy and enjoyment of science.

Model M3i additionally includes interaction terms between each of the explanatory variables and gender, which are helpful in understanding the gender gap. Should some of these individual factors influence males' and females' career plans in different ways, the interaction terms in model M3i will be significant.

The overview of the results from the presented models, including the percentage of the variance explained and size of the gender gap after controlling for different sets of variables, is presented in Table 5.3.

Table 5.3. Percentage of the variance explained and size of the gender gap after controlling for different sets of variables.

	% of variance explained (R2)				Gender gap (Female coefficient)			
Country	M0	M1	M2	M3	M0	M1	M2	M3
Austria	0.081	0.113	0.114	0.117	**−0.231**	**−0.217**	**−0.217**	**−0.216**
Belgium	0.041	0.089	0.093	0.099	**−0.150**	**−0.141**	**−0.141**	**−0.137**
Bulgaria	0.045	0.098	0.110	0.112	**−0.182**	**−0.197**	**−0.198**	**−0.197**
Croatia	0.070	0.115	0.120	0.121	**−0.213**	**−0.208**	**−0.208**	**−0.208**
Cyprus	0.025	0.056	0.061	0.065	**−0.126**	**−0.139**	**−0.137**	**−0.134**
Czech Republic	0.076	0.125	0.127	0.130	**−0.211**	**−0.204**	**−0.203**	**−0.205**
Denmark	0.040	0.061	0.071	0.079	**−0.148**	**−0.144**	**−0.145**	**−0.141**
Estonia	0.073	0.094	0.099	0.100	**−0.237**	**−0.235**	**−0.235**	**−0.235**
Finland	0.058	0.085	0.090	0.092	**−0.158**	**−0.168**	**−0.168**	**−0.166**
France	0.059	0.108	0.118	0.135	**−0.188**	**−0.187**	**−0.188**	**−0.176**
Germany	0.040	0.097	0.111	0.123	**−0.158**	**−0.148**	**−0.147**	**−0.136**
Greece	0.041	0.053	0.061	0.076	**−0.160**	**−0.164**	**−0.165**	**−0.158**
Hungary	0.069	0.139	0.149	0.152	**−0.201**	**−0.198**	**−0.199**	**−0.200**
Ireland	0.057	0.090	0.102	0.108	**−0.187**	**−0.178**	**−0.180**	**−0.179**
Italy	0.067	0.092	0.094	0.107	**−0.210**	**−0.198**	**−0.199**	**−0.190**
Latvia	0.036	0.066	0.071	0.071	**−0.161**	**−0.171**	**−0.170**	**−0.170**
Lithuania	0.036	0.077	0.081	0.082	**−0.150**	**−0.157**	**−0.156**	**−0.157**
Luxembourg	0.054	0.099	0.104	0.108	**−0.181**	**−0.175**	**−0.174**	**−0.171**
Malta	0.079	0.111	0.116	0.131	**−0.234**	**−0.241**	**−0.242**	**−0.239**
Netherlands	0.057	0.090	0.096	0.115	**−0.178**	**−0.175**	**−0.177**	**−0.165**
Poland	0.041	0.088	0.090	0.090	**−0.150**	**−0.145**	**−0.145**	**−0.146**
Portugal	0.062	0.107	0.109	0.114	**−0.212**	**−0.202**	**−0.202**	**−0.201**
Romania	0.032	0.088	0.103	0.103	**−0.131**	**−0.137**	**−0.135**	**−0.135**
Slovakia	0.065	0.107	0.109	0.109	**−0.201**	**−0.201**	**−0.203**	**−0.203**
Slovenia	0.123	0.142	0.148	0.148	**−0.311**	**−0.315**	**−0.314**	**−0.314**
Spain	0.050	0.116	0.122	0.129	**−0.183**	**−0.175**	**−0.176**	**−0.174**
Sweden	0.058	0.102	0.108	0.115	**−0.193**	**−0.196**	**−0.197**	**−0.190**
United Kingdom	0.055	0.083	0.086	0.095	**−0.191**	**−0.190**	**−0.189**	**−0.182**
EU-28	0.057	0.096	0.102	0.108	**−0.187**	**−0.186**	**−0.185**	**−0.182**

Note: gender gap results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

On average, around 6% of variation in STEM choices in the EU-28 may be explained by gender. Adding science literacy to the model almost doubles the explained variation, to 10%. Adding the additional home background variables results in a small increase of 0.5% and adding additional attitudes in another 1%, making it clear that the two most important predictors for choosing STEM careers are gender and science literacy. A similar conclusion is suggested by LPM coefficients, presented in Table 5.4. In all countries, controlling for all other factors, females choose STEM careers less often than males, and students with higher science literacy choose STEM career more often than other students. These are the two key effects; the third is having parents who work in STEM. Detailed description of what is included in the measurement of these variables was provided in chapter 3.

Table 5.4. Coefficients of the M3 LPM. Main effects.

Country	Female	Science	ESCS	Parents STEM	Migrant	Self-efficacy	Enjoyment of science
Austria	**−0.216**	**0.075**	−0.011	–	0.026	−0.008	**0.021**
Belgium	**−0.137**	**0.077**	−0.005	0.034	**0.042**	0.004	**0.030**
Bulgaria	**−0.197**	**0.086**	0.011	**0.132**	**−0.108**	0.009	**−0.016**
Croatia	**−0.208**	**0.081**	**0.016**	**0.062**	−0.013	−0.002	**0.015**
Cyprus	**−0.134**	**0.062**	−0.004	**0.086**	−0.030	0.005	**0.026**
Czech Republic	**−0.205**	**0.079**	−0.007	**0.048**	−0.024	0.005	**0.024**
Denmark	**−0.141**	**0.043**	−0.011	**0.113**	0.003	0.007	**0.031**
Estonia	**−0.235**	**0.063**	−0.002	**0.094**	0.010	−0.001	**0.017**
Finland	**−0.166**	**0.048**	0.000	**0.042**	**0.084**	0.002	**0.020**
France	**−0.176**	**0.063**	0.006	**0.087**	**0.065**	−0.004	**0.055**
Germany	**−0.136**	**0.073**	**0.016**	**0.101**	**0.060**	−0.010	**0.046**
Greece	**−0.158**	**0.023**	0.000	**0.121**	−0.003	0.005	**0.049**
Hungary	**−0.200**	**0.094**	−0.006	**0.123**	−0.014	−0.001	**0.025**
Ireland	**−0.179**	**0.066**	−0.011	**0.073**	**0.097**	0.001	**0.034**
Italy	**−0.190**	**0.059**	**−0.014**	**0.052**	0.017	0.005	**0.052**
Latvia	**−0.170**	**0.080**	0.011	**0.098**	−0.015	−0.004	0.008
Lithuania	**−0.157**	**0.076**	**0.018**	**0.077**	−0.019	−0.006	0.010
Luxembourg	**−0.171**	**0.069**	0.003	**0.074**	0.022	**0.013**	**0.016**
Malta	**−0.239**	**0.043**	0.001	**0.107**	0.009	**−0.022**	**0.060**
Netherlands	**−0.165**	**0.045**	0.008	**0.068**	0.019	0.001	**0.057**
Poland	**−0.146**	**0.078**	0.012	0.049	0.023	0.008	0.004
Portugal	**−0.201**	**0.083**	**0.012**	**0.045**	0.009	−0.010	**0.038**
Romania	**−0.135**	**0.085**	**0.038**	**0.084**	0.006	0.012	0.001
Slovakia	**−0.203**	**0.074**	0.004	**0.055**	−0.020	0.001	0.007
Slovenia	**−0.314**	**0.061**	**−0.025**	**0.085**	−0.031	0.009	0.011
Spain	**−0.174**	**0.098**	0.007	**0.074**	**0.056**	0.001	**0.035**
Sweden	**−0.190**	**0.066**	0.000	**0.069**	**0.039**	0.005	**0.029**
United Kingdom	**−0.182**	**0.053**	−0.003	**0.054**	**0.032**	0.009	**0.038**
EU-28	**−0.182**	**0.068**	**0.003**	**0.078**	0.012	0.001	**0.027**

Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

Investigating the female coefficients in Table 5.3 leads to the conclusion that controlling for student-related variables does not reduce the average gender gap significantly, although the interaction results presented in the figures that follow (and Table A5.1 in appendix) clearly show that the relationships between some explanatory variables – science literacy and parents in STEM in particular – differ significantly for males and females.

5.2.1 Gender and science performance

In this section, we will focus on two basic students' characteristics: gender and scientific literacy. In line with the pattern evident from our descriptive statistics, females are less interested in STEM careers in every European country. The only aspect of this pattern that differs internationally is the size of the gender gap.

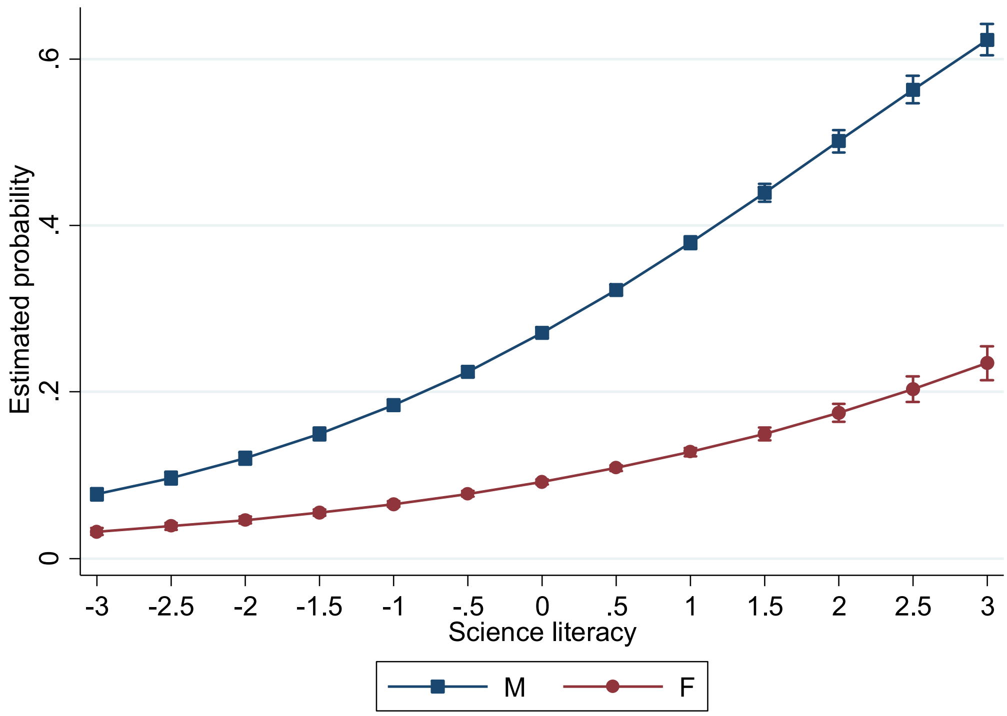
Students' science performance is positively associated with the intention to work in STEM occupations. This association is comparable in strength across all European countries.

Controlling for students’ school performance in science reduces the gender gap only to a very small extent in each country. On average, in Europe the gender gap does not really decrease, as −0.187 in model M0 is effectively identical to −0.186 in model M1. Within particular countries the gender coefficient (or, to be exact, its point estimate) is marginally smaller in model M1, but in some cases it is identical or even marginally larger after school science performance is controlled for. This provides very strong evidence that the marked difference between females’ and males’ interest in STEM occupations cannot be related to gaps in their science performance. In fact (as can be seen in Table A6.6. in the appendix), data reveal no statistically significant differences between males’ and females’ average science performance across the EU Member States.

Moreover, the extent to which success in science is conducive to a plan to work in science in the future is different for males and females. This can be seen from the statistically significant interaction terms in model M3i across almost all the countries (see Table A5.1 in the appendix). The interaction effects indicate that females’ expectations to work in STEM are not as strongly related to science performance as those of males. The only exceptions to this pattern are Denmark, Greece and Ireland, where the effect of school science performance on students’ expectations of a career in science is similar for equally capable males and females.

The same pattern is visually represented in Figure 5.1., which depicts the estimated probabilities of opting for a STEM career for males and females at different levels of science literacy for the pooled sample of European countries. If lack of readiness to plan an entry into STEM careers among high-performing female students is to be interpreted as talent loss from the perspective of STEM, Figure 5.1 provides a summary of the extent to which this talent loss occurs across Europe. In this figure, the typical probability of planning a science career is shown for students with different results on their science tests. To the far left are probabilities for students who performed three standard deviations below the mean, and these students are unlikely to expect that they will work in science when they are 30 years of age. But even among them, the gender gap somewhat favours males. For students who perform at an above-average level in science, the probability of planning a science career for those males who performed at one standard deviation above the mean is close to 38%, while for females it is well below 13%. Among the most successful students, those who perform three standard deviations above the mean, typically over 62% of males have a plan to pursue a science career, whereas the proportion of equally capable females with similar occupational plans is just above 23%. These gender differences among above-average-performing students could be seen as indicators of a potential talent loss for STEM employment. Moreover, the comparison also shows that the absolute gender gap is increasing, as we move from the low-performing students to the high-performing ones – reinforcing the conclusion from the negative interaction effects discussed above.

Figure 5.1. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the EU.



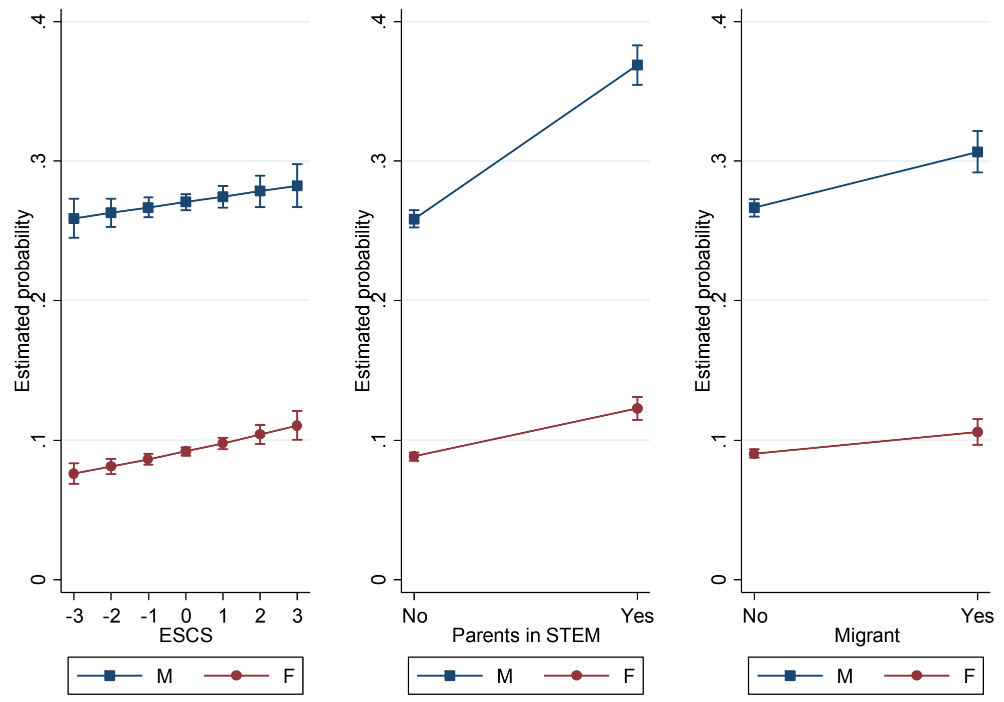
5.2.2 Social background and home environment

Students' background effects are estimated after school science performance has been taken into account. In other words, these are the net effects (regardless of how well a student is doing in science) that contribute directly to students' interest in science careers (once we control for students' science performance at school, which in turn increases their interest in science occupations).

5.2.2.1 Parental influences

Of student background variables, the factor that comes across as most influential is parental employment in STEM. While an estimate of this effect is unavailable for Austria because of lack of detailed information on parental occupation, and the coefficients are not significant in Belgium and Poland, in the remaining 25 countries, parental employment in STEM is positively related to students' expectations of pursuing a similar occupation. This finding is regardless of students' gender, success in school science and other characteristics (see Table 5.2) and supports earlier analysis on PISA 2006 data (Sikora and Pokropek, 2011, 2012b; Han, 2015, 2016a, 2016b, 2017). All in all, parental influence in the form of providing role models contributes to adolescent vocational goal forming. This effect does not negate the possibility that parents employed in non-science occupations can actively encourage science orientation in their children. Rather, it suggests that parents who work in the science sector are more successful in influencing their children than other parents, regardless of whether or not they make a conscious effort in this direction. With parents working in STEM occupations controlled for, higher economic and socio-economic status of the family matters little in most countries, and in Italy and Slovenia it actually decreases by a small margin the probability that an adolescent will consider science as a future career. Exceptions are Croatia, Germany, Lithuania, Portugal and Romania, where higher parental status is associated with a somewhat higher probability that a young person will want to become a science professional even after controlling for parental employment in STEM.

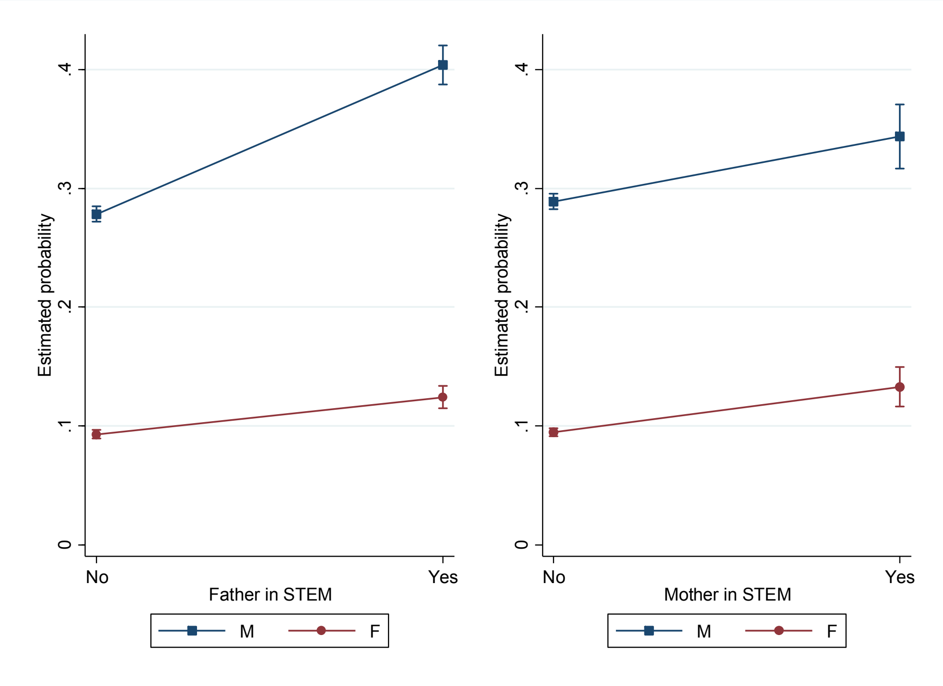
Figure 5.2. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the EU.



The interaction effects added to the model – together with the predicted probabilities from the logit models in Figure 5.2 – show that the gender gap between males and females does not vary by socio-economic background. On the other hand, parental role models rather consistently appear to be more influential on males' than on females' STEM choices. With a parent working in STEM, the probability of females making a similar choice increases from 9% to 12%, while for males a more substantial increase from 26% to 37% occurs (Figure 5.2). Our country results show that males are more influenced than females by having a parent with a STEM career to a statistically significant extent in Cyprus, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Luxembourg and the Netherlands (see Table A5.1 in the appendix).

Figure 5.3 shows the impact of parental role models separately by sex of parent. Males are more influenced by their fathers' STEM employment than females. The estimated probabilities of modelling one's teenage career preference on mother's versus father's STEM occupation in the pooled sample reveals that while mothers' STEM occupation similarly inspires males and females, fathers have a greater influence on their sons' choices. (In country regressions, this distinction could not be made because of the low numbers of mothers who work in STEM in several countries.)

Figure 5.3. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the pooled EU sample.



5.2.2.2 Migration status

We next turn to investigating the potential influence of students' migration background. In several locations, migrant students indeed show a greater interest in science careers than other students who are comparable with respect to their science performance, attitudes, and parental cultural and socio-economic background. Similar patterns have already been found with the 2006 pooled PISA data (Han, 2015, 2016b, 2016a). Our country-wise comparison suggests that migrant students are more interested in science careers in particular in Belgium, Finland, France, Germany, Ireland, Spain, Sweden and the United Kingdom.

A closer look at migrant career choices provides further insights, revealing that the greater interest in STEM in migrant populations comes mostly from males (see Figure 5.2). Although the pattern is not universal, migrant males pursue STEM careers more than rest of the population in Finland, France, Germany, Ireland, Spain and Sweden, while migrant females are much closer to native females (for details see Table A5.1 in the appendix). Migrant students' STEM choices are country dependent and also conditioned by type of migration inflow, which can not be examined fully in this analysis because of sample size restrictions.

The literature on the differences between migrant and non-migrant students in PISA studies indicates that, besides the circumstances in the destination countries, a key factor is the composition of the migrant population. In other words, it matters a lot which countries migrants come from, what the overall economic and cultural resources available to citizens in these countries are, whether migrants tend to represent upper, middle or lower classes in the country of origin, and similar characteristics (Dronkers et al., 2014). However, the general characteristics of the immigrant populations of the above-mentioned countries show rather mixed profiles. For example, Belgium, Germany, France and the United Kingdom are all long-standing destination countries, the first three mainly with low-educated migrants, while the United Kingdom has recently received many highly educated migrants. Sweden, Finland, Portugal, Spain and Ireland, on the other hand, are more recent targets of immigration – some with highly educated immigrants. Finally, Slovakia and Estonia are mostly influenced by immigration related to border changes (OECD, 2015a). The migrant populations of these countries also show a very mixed picture in terms of their origins, with, for example, France receiving over half of its immigrants from Africa, Germany and Ireland receiving three quarters of their migrant populations from other European countries (OECD, 2015a). Nevertheless these patterns are in line with prior literature on migrant optimism (Kao and Tienda, 1995; Lee and

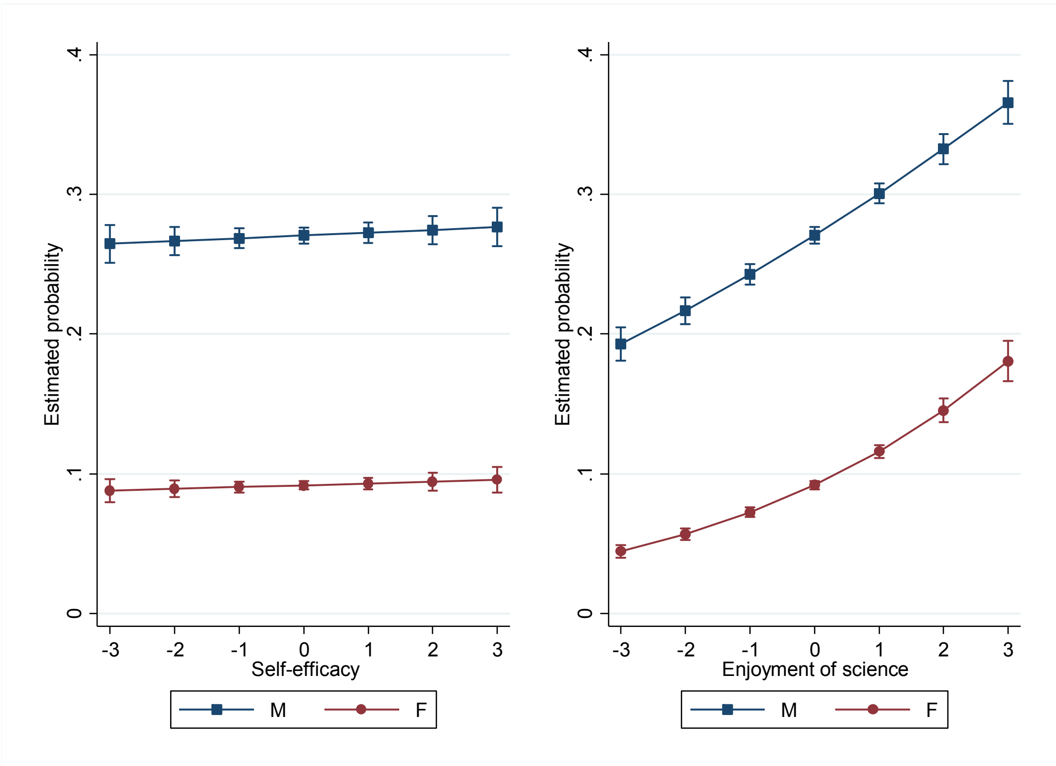
Zhou, 2015), which suggests that migrant youth desire to enter the most coveted and prestigious occupations that span the areas of medicine, law and engineering.

5.2.3 Students' attitudes

Attitudes towards science can make a notable difference in children's occupational expectations: students who enjoy science more are also more likely to expect a STEM occupation in most European countries (Table 5.4.). The effect is the same for males and females: an increase in enjoyment of sciences raises the probability of choosing a STEM career by a similar gradient. The expected probability of choosing a STEM career for females with an average level of science enjoyment is 9%, while for females with a very high level of enjoyment of science (three standard deviations above the mean) it is 18%. At the same time the expected probability of choosing a STEM career for males with an average level of enjoyment of science is 27%, while for males with a very high level of enjoyment of science it is 36%, as presented in the right-hand panel of Figure 5.4.

According to the results in the pooled sample presented in Figure 5.4, science self-efficacy is not strongly related to STEM expectations when enjoyment is also controlled for. We found a statistically significant association between science self-efficacy and expectations for a STEM career only in Luxembourg and Malta (for males only), and the correlation is positive in the first case and negative in the second (Table 5.4). Confidence in one's own science ability plays a moderate role in determining STEM career plans, when enjoyment of science and other characteristics discussed above are held constant.

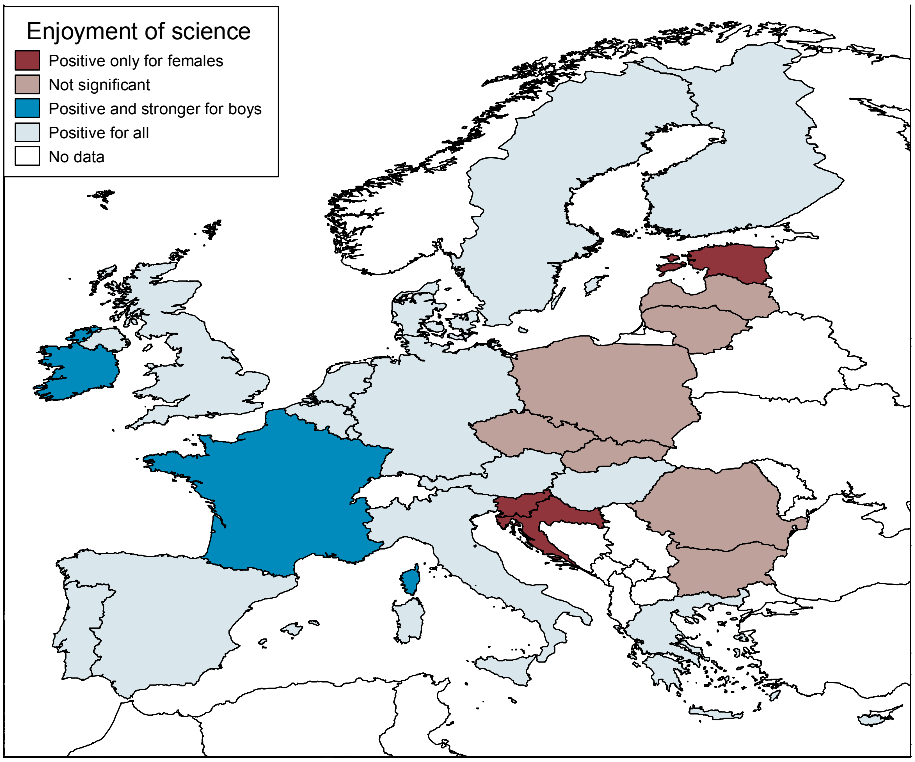
Figure 5.4. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the pooled EU sample.



Differences between countries in the effect of science enjoyment provide some interesting insights. Enjoyment of science is consistently positively related to the choice of STEM, but only in the countries without a recent socialist past. In the majority of the former socialist countries – Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia – enjoyment of science is not statistically related to STEM career choices. (Moreover, in Bulgaria even a statistically significant negative correlation was found – see Table 5.4). Further, as is evident from model

M3i (see Table A5.1 in the appendix), males are in general more positively influenced by enjoyment of science than females, but again, the average patterns hold only in the ‘western’ part of Europe. In fact, country-specific patterns in the interactions add interesting details to the picture of the divide between post-socialist countries and other countries. In particular, we find that in the second group of countries, the relevance of enjoyment is either consistently positive across genders (Austria, Belgium, Cyprus, Denmark, Finland, Germany, Greece, Italy, Luxembourg, Malta, Portugal, Spain, Sweden and the United Kingdom), or more pronounced for males (France, Ireland, the Netherlands). In the post-socialist countries, on the other hand, the models with the interaction terms included either reveal no significant enjoyment effect at all (Bulgaria, the Czech Republic, Latvia, Poland, Romania, Slovakia), or show a significant positive effect for females only (Croatia, Estonia, Slovenia). The two exceptions to this pattern in the post-Soviet bloc are Lithuania and Hungary. This is depicted in Figure 5.5. The lack of relevance of this individual attitudinal variable either for both genders or for males in several post-socialist countries is an interesting phenomenon. We can only speculate about its roots, but it is very likely to be a part of the heritage of the industrialised socialist economies, where becoming an engineer was a popular choice, often a path of social mobility for males, and not necessarily linked with individual interests or internal motivations.

Figure 5.5. Significance of conditional relation between enjoyment of science and STEM career choices in PISA 2015 data.



5.3 STEM career plans and school-related variables

Examining school-related variables, we follow the logic presented in the section concerning student-related variables. Table 5.5 describes the models used in this section. In model M4, we add variables that describe school-related characteristics closely related to within-school policies and conditions – school science resources, existence of science clubs and science competitions – and also gender composition and average science performance in school. In models M5 and M6, we add variables that are related to country-level or regional educational policies but operate at the level of the school: school autonomy, grade repetition, students' vocational orientation and ISCED level. We needed to use different sets of variables in different sets of models, as in a large number of countries 15-year-old students share the same vocational orientation and ISCED level. Therefore, in these countries we could not compare students participating in different programmes or students at different ISCED levels. For model M6, we present results only for the countries where at least 5% of students in the PISA sample were in different educational programmes and/or at least 5% of students were at different ISCED levels. Similarly to the analysis in the previous section, we introduce interaction terms in models M5i and M6i.

Table 5.5. Description of student-level-related models predicting interest in STEM.

Model	Independent variables	Description
M4	Individual level variables + school science resources, science clubs, science competitions, % of females + school performance	+ Within-school policies
M5	M4 + school autonomy, grade repetition	+ Between-school educational policies
M6	M5 + vocational orientation, ISCED level	+ Additional educational policies
M5i	M5 + female interactions with all explanatory variables	M5 + Interactions
M6i	M6 + female interactions with all explanatory variables	M6 + Interactions

The results presented in Table 5.6 indicate that, on average, the ratio of explained variance increases only to a very small extent – from 0.108 to 0.119 – when all the school characteristics are added to the models. This change is attributable to between-school educational policies – but the additional educational policy variables make practically no difference in the variance explained. However, there are some notable variations across countries: while in most of the countries practically no change can be detected even when moving from model M3 to model M5, school factors seem to have considerable importance in influencing students' interest in STEM careers in Austria, Croatia, Italy and Slovenia – and to a lesser extent also in Bulgaria and Slovakia.

Larger variations between countries can be found for the role that school factors play in shaping the STEM-related gender gap. On average, school characteristics slightly reduce the difference between females' and males' expectations for STEM: the average gender gap decreases from 0.182 to 0.166 when school factors are added to the models. Accordingly, if males and females attended schools with similar characteristics, females would be somewhat less different from males in their level of interest in such careers. This pattern is apparent and rather strong in Austria and Slovenia, where the size of the gender gap is reduced by over 50% when school characteristics are added to the models, but also to a somewhat lesser extent in Croatia and Italy, and (even less) in Bulgaria and Slovakia – the same countries where school characteristics contribute to students' STEM interest to a considerable extent. In Malta, Ireland and – less markedly – in Belgium, however, a very different pattern emerges, which indicates that in these countries, the gender gap in STEM would increase even more if males and females attended similar schools. In other words, in these countries selection (and self-selection) into particular schools contributes to the mitigation of gender segregation in STEM.

Table 5.6. Percentage of the variance explained and size of the gender gap after controlling for different sets of variables.

	% of variance explained (R2)				Gender gap (Female coefficient)			
Country	M3	M4	M5	M6	M3	M4	M5	M6
Austria	0.117	0.173	0.174	0.201	**−0.216**	**−0.094**	**−0.092**	**−0.089**
Belgium	0.099	0.108	0.108	0.112	**−0.137**	**−0.151**	**−0.150**	**−0.150**
Bulgaria	0.112	0.134	0.135	0.135	**−0.197**	**−0.148**	**−0.150**	**−0.150**
Croatia	0.121	0.174	0.177	0.179	**−0.208**	**−0.119**	**−0.119**	**−0.114**
Cyprus	0.065	0.066	0.066	0.066	**−0.134**	**−0.137**	**−0.137**	**−0.137**
Czech Republic	0.130	0.138	0.139	0.146	**−0.205**	**−0.178**	**−0.179**	**−0.178**
Denmark	0.079	0.080	0.080	-	**−0.141**	**−0.139**	**−0.139**	-
Estonia	0.100	0.102	0.103	-	**−0.235**	**−0.240**	**−0.242**	-
Finland	0.092	0.094	0.095	-	**−0.166**	**−0.161**	**−0.162**	-
France	0.135	0.136	0.136	0.137	**−0.176**	**−0.167**	**−0.166**	**−0.167**
Germany	0.123	0.125	0.126	-	**−0.136**	**−0.136**	**−0.134**	**-**
Greece	0.076	0.083	0.083	0.084	**−0.158**	**−0.138**	**−0.138**	**−0.138**
Hungary	0.152	0.171	0.171	0.179	**−0.200**	**−0.176**	**−0.176**	**−0.176**
Ireland	0.108	0.110	0.110	0.110	**−0.179**	**−0.206**	**−0.206**	**−0.207**
Italy	0.107	0.146	0.146	-	**−0.190**	**−0.104**	**−0.106**	-
Latvia	0.071	0.071	0.072	-	**−0.170**	**−0.168**	**−0.169**	-
Lithuania	0.082	0.082	0.082	-	**−0.157**	**−0.159**	**−0.159**	-
Luxembourg	0.108	0.108	0.110	0.109	**−0.171**	**−0.172**	**−0.173**	**−0.171**
Malta	0.131	0.132	0.133	-	**−0.239**	**−0.276**	**−0.275**	-
Netherlands	0.115	0.116	0.117	0.118	**−0.165**	**−0.168**	**−0.169**	**−0.169**
Poland	0.090	0.091	0.091	-	**−0.146**	**−0.142**	**−0.144**	-
Portugal	0.114	0.115	0.116	0.117	**−0.201**	**−0.202**	**−0.204**	**−0.201**
Romania	0.103	0.105	0.106	-	**−0.135**	**−0.135**	**−0.135**	-
Slovakia	0.109	0.122	0.124	0.127	**−0.203**	**−0.159**	**−0.161**	**−0.160**
Slovenia	0.148	0.240	0.240	0.253	**−0.314**	**−0.129**	**−0.129**	**−0.126**
Spain	0.129	0.128	0.129	-	**−0.174**	**−0.175**	**−0.178**	**-**
Sweden	0.115	0.116	0.116	-	**−0.190**	**−0.186**	**−0.186**	**-**
United Kingdom	0.095	0.097	0.097	0.097	**−0.182**	**−0.184**	**−0.184**	**−0.184**
EU-28	0.108	0.118	0.119	0.114	**−0.182**	**−0.165**	**−0.166**	**−0.169**

Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

Looking at each of the school characteristics in turn in Table 5.8 further confirms that the school-level factors explored in these models have moderate and somewhat inconsistent effects on students' interest in STEM careers.

Table 5.7. Coefficients of the M5 LPM. Main effects.

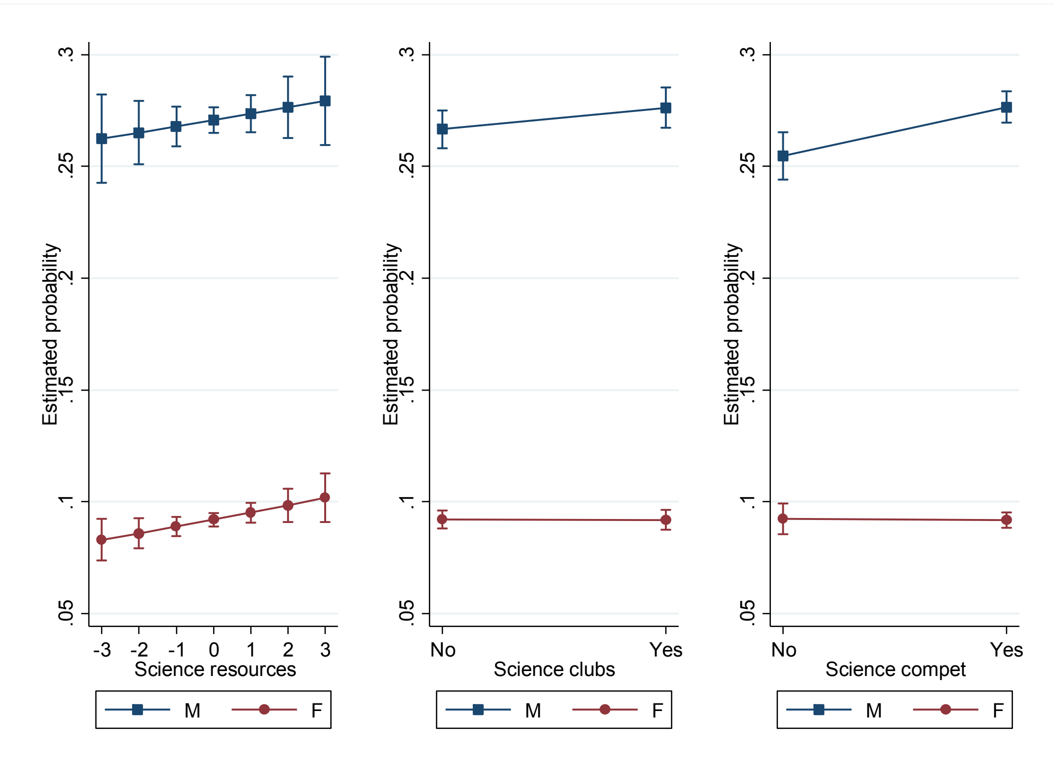
Country	Female	Science resources	Science clubs	Science compete-tions	% of females	School autonomy	Grade repetition	School performance
Austria	**−0.092**	**0.027**	−0.058	0.021	**−0.063**	−0.007	**0.036**	**0.046**
Belgium	**−0.150**	**−0.035**	0.001	0.027	**0.022**	0.007	0.003	0.001
Bulgaria	**−0.150**	−0.017	0.010	0.015	**−0.072**	−0.006	**−0.065**	**0.046**
Croatia	**−0.119**	0.023	0.012	**0.061**	**−0.070**	**0.041**	0.045	0.009
Cyprus	**−0.137**	−0.003	0.011	−0.022	0.013	−0.009	0.006	−0.021
Czech Republic	**−0.179**	−0.014	0.028	0.035	**−0.029**	0.019	−0.044	0.001
Denmark	**−0.139**	−0.006	0.005	−0.003	−0.006	−0.002	0.035	−0.013
Estonia	**−0.242**	**0.015**	0.004	−0.007	0.025	−0.004	−0.058	**−0.044**
Finland	**−0.162**	−0.006	−0.005	0.009	−0.034	0.007	−0.018	−0.017
France	**−0.166**	0.005	−0.007	−0.009	−0.015	−0.010	−0.012	−0.019
Germany	**−0.134**	**−0.013**	−0.023	0.026	−0.007	0.000	**0.036**	0.017
Greece	**−0.138**	−0.003	0.020	−0.002	**−0.042**	−0.012	−0.004	−0.024
Hungary	**−0.176**	0.011	0.020	**−0.070**	**−0.034**	−0.006	0.005	**0.071**
Ireland	**−0.206**	0.005	0.012	−0.007	**0.012**	0.003	−0.010	−0.024
Italy	**−0.106**	0.014	−0.006	0.016	**−0.071**	−0.001	−0.015	0.020
Latvia	**−0.169**	−0.002	−0.002	0.024	−0.004	−0.004	**−0.058**	−0.013
Lithuania	**−0.159**	−0.005	0.017	−0.001	0.005	−0.023	0.009	0.011
Luxembourg	**−0.173**	0.008	−0.010	0.013	−0.002	**0.033**	−0.001	0.002
Malta	**−0.275**	0.014	**0.040**	−0.022	0.008	−0.002	−0.038	0.002
Netherlands	**−0.169**	−0.006	−0.001	0.009	0.031	0.008	−0.003	−0.012
Poland	**−0.144**	0.010	0.007	−0.019	−0.020	−0.008	−0.030	−0.008
Portugal	**−0.204**	−0.009	0.018	0.025	0.020	0.021	−0.013	−0.006
Romania	**−0.135**	0.010	−0.027	−0.009	−0.006	−0.019	−0.016	0.035
Slovakia	**−0.161**	−0.004	0.010	**0.052**	**−0.040**	−0.009	**−0.061**	−0.019
Slovenia	**−0.129**	**0.016**	**−0.046**	**0.039**	**−0.110**	**0.016**	0.015	**0.051**
Spain	**−0.178**	0.001	0.003	0.002	0.004	0.002	**−0.034**	−0.011
Sweden	**−0.186**	0.000	0.001	−0.010	−0.017	−0.009	−0.010	−0.030
United Kingdom	**−0.184**	−0.004	0.009	0.008	0.002	−0.003	−0.015	**−0.036**
EU-28	**−0.166**	0.000	0.004	0.007	**−0.016**	0.001	**−0.013**	−0.001

Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

5.3.1 School resources, actions and compositional variables

The overall amount of resources available for science teaching in the school and the provision of science clubs both have very little, and mostly mixed, effects on teenagers' STEM career plans (see Figure 5.6 for an overview). Analysis of the regression coefficients from Table 5.7 and the related interaction effects (see appendix A5.3) has not revealed any significant patterns in either of the cases, and only a few statistically significant coefficients could be identified. In particular, the presence of science clubs shows a significant positive association with STEM career choices only in Malta and Romania (females only), and a negative association in Slovenia. Further, the more science resources are available in the school in general, the more students want to obtain a career in STEM in Austria (males only), Estonia and Slovenia, while in Belgium and Germany more resources at the school level are associated with fewer STEM-oriented students in general, and in Italy and Romania with fewer female students in particular.

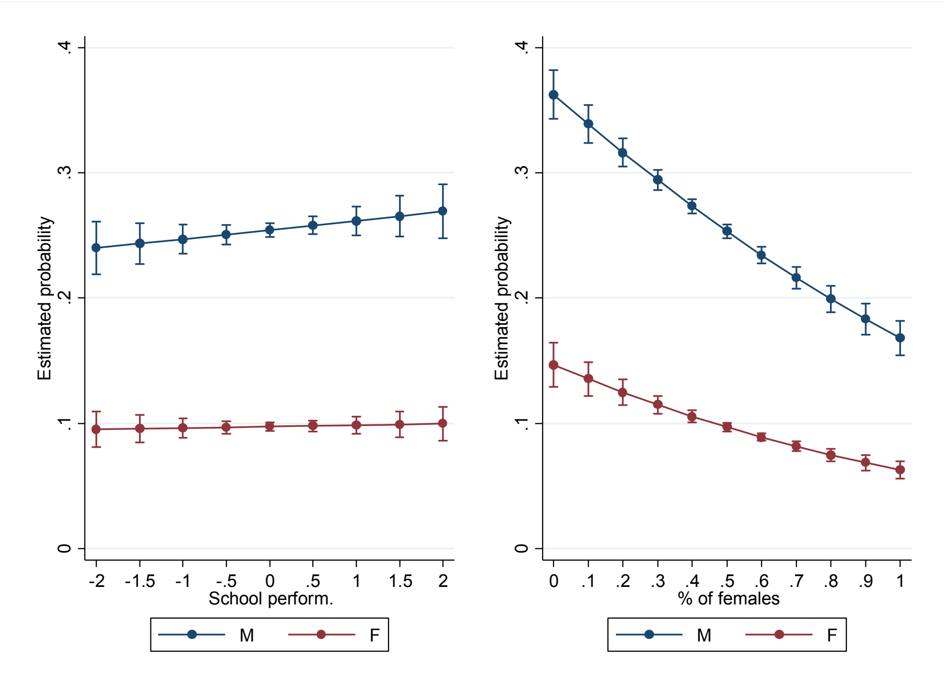
Figure 5.6. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the pooled EU sample.



Organising science competitions in the school is positively correlated with the number of students who would choose a related career only in Croatia, Slovakia and Slovenia, but it is negatively linked to such plans in Hungary. In this case, however, the estimated probabilities from the logistic regression models presented in Figure 5.6 reveal some interesting patterns. In particular, they suggest that science competitions motivate males somewhat more than females to choose a science career. The estimated probability of females choosing a STEM career is unaffected by the opportunity to participate in competitions, while for males it moves up slightly from 25% to 28%. Accordingly, by running science competitions in the school, it might be possible to gain a slight increase in the overall number of applicants for STEM positions, but this might be at the price of increasing the gender gap. This tendency is particularly marked in Croatia, the Czech Republic and Slovakia (for more details see Tables A5.2 and A5.3 in the appendix).

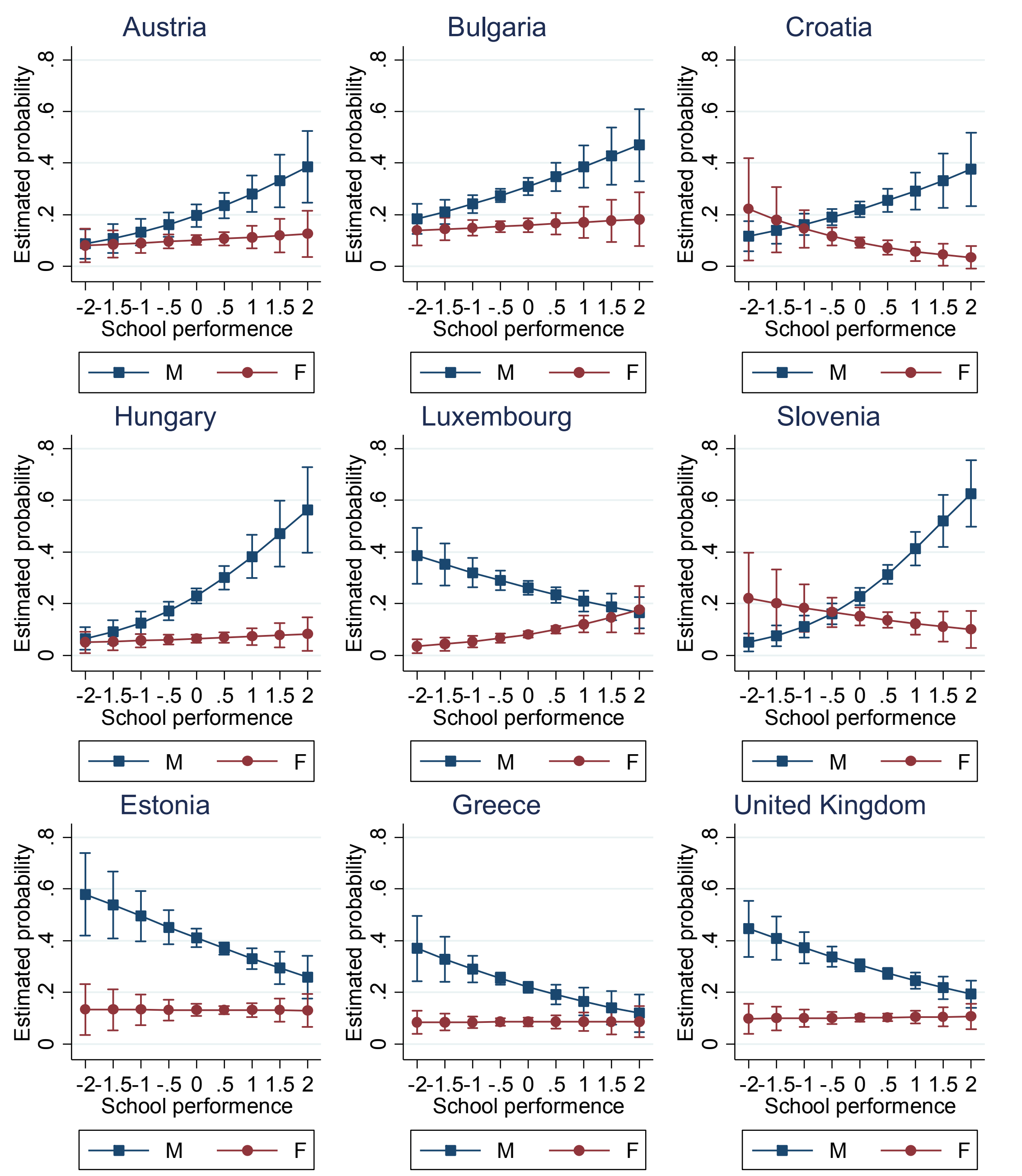
The last two school-level variables capture the composition of the student body in terms of average science performance and gender composition, and thus represent peer effects. Our results suggest no general tendency in the relationship between average school (science) performance and students' interest in STEM careers. The respective regression coefficient in the EU-28 model practically equates to 0, and only in a handful of countries do we find any significant association (see Table 5.7). Conversely, gender composition shows a strong relation with STEM career choices. In short, the more female dominated the school, the lower the probability of choosing STEM career, and this effect is stronger for males than for females. See Figure 5.7 for the relation between probability of choosing STEM career and the level of compositional variables.

Figure 5.7. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the pooled EU sample.



When we look into the results in more detail, cross-country comparison draws a more interesting picture. In particular, average school performance in science is significantly positively related to the number of students who would follow a STEM career in Austria, Bulgaria, Hungary and Slovenia – suggesting that, in these countries, a strong academic school environment further inspires students to develop an interest in STEM-related employment (Table 5.7). In Estonia and the United Kingdom, however, an opposite trend is evident: here a stronger average performance has a negative association with the expectations of students. Adding interaction effects to the models, we can further differentiate between males and females. In Figure 5.8, we plot the relation between STEM career expectations and average school performance for all countries where, for at least one gender, the relations captured by the LPM were significant.

Figure 5.8. Predicted probability for selected countries (logit models) of expecting a STEM career.



The first, obvious, conclusion that can be drawn from Figure 5.8 is that, in most cases, the average school performance is related to STEM career choice for males but not for females (with rare exceptions). Predicted probabilities suggest that in Austria, Bulgaria, Croatia, Hungary and Slovenia the effect is positive while for Luxembourg, Estonia, Greece and the United Kingdom the effect is negative. Although these results are not precisely in line with earlier findings from PISA 2006 data (Mann et al., 2015), the general tendencies are correspond with the conclusions of that study. Although we do not have formal statistical confirmation because of the limited number of countries, it seems that high average school performance is likely to enhance students' expectations in education systems with early tracking, but have an adverse effect in the less selective systems. Indeed, track placement takes place early in Austria (age 10), in Hungary (age 11), Luxembourg (age 13) and Slovenia (age 14). (For ages at first selection by country, see Table 3.2 in chapter 3.) In these countries with early tracking – with the exception of Luxembourg – a strong academic environment improves males' vocational interest in STEM, but it has no or slight negative association with females' occupational plans. In Estonia and the United Kingdom, on the other hand, first selection only happens at the age of 16 – meaning that students in the PISA sample have not yet been placed on tracks. Figure 5.8. reveals that in these two countries males are significantly and negatively affected by an academically strong environment, while for females, again, no systematic influence is present. Finally, two countries where first tracking takes place when children are 15 years old seem to be in an intermediate position: the patterns found in Croatia more resemble those in the first, early-tracking group of countries, while the patterns in Greece are closer to the patterns associated with the second group. Thus the explanation provided by Mann and his colleagues (Mann et al., 2015) also seems to hold for the findings from the 2015 data. Accordingly, in countries where early tracking takes place, high-performing environments tend to reinforce STEM aspirations. However, where no early tracking occurs and PISA students have not yet been placed on specific tracks, students tend to interpret their own performance relative to their peers' performance, and a social comparison effect occurs – decreasing students' motivation to pursue a STEM career in strong academic environments – holding their own abilities constant.

Further systematic patterns emerge from measuring the other compositional variable, the proportion of female students in the school. Overall, the higher the ratio of females in the school, the less likely males and females are to name a STEM occupation as their preference. This association is statistically significant in Austria, Bulgaria, Croatia, the Czech Republic, Greece, Hungary, Italy, Slovakia and Slovenia. Figure 5.7 depicts the relation between gender composition and STEM career choices for the pooled sample.

As explained in chapter 2, it is widely assumed that female dominance in the classroom can promote gender-atypical occupational choices, as it reduces gender stereotyping. Such a comparison, however. is most likely to hold across similar educational programmes, i.e. when classrooms with the same curricula but with different proportions of females are compared. With the PISA sample, this is not the case: in all of the nine countries except Greece, where a high proportion of females negatively affects interest in STEM, early placement or at least a placement before the age of 15 takes place. Table 5.8 divides the countries according to age of first selection in the education system, and highlights the fact that in countries with an early tracking system female dominance tends to be negatively associated with students' vocational interest in STEM, and that this association is in most cases also statistically significant. The main exception is Belgium, where a significant positive impact is evident. On the other hand, Greece is the only country with a late selection where a significant negative association appears between the percentage of females and STEM career plans. In the other countries with a similar institutional system, the ratio of females is either not significantly or positively (in Ireland only) related to vocational interest in STEM.

Education systems with early selection tend to offer the opportunity to specialise in traditionally female-dominated areas. If females at the age of 15 are already overrepresented in programmes that do not prepare them for science-related occupations, than a high proportion of females is likely to be associated with less interest in STEM careers. This suggests that the negative coefficients in the models are due to females' early selection into secondary schools that do not particularly promote STEM careers. (Unfortunately, in our models we cannot precisely control for the types of educational programmes attended by students. The only factor for which we can control, to be added to the models later, is a distinction between vocational and non-vocational programmes. But this in itself does not systematically influence the associations between the proportion of females in the class and STEM choices.)

Table 5.8. Age of first tracking and coefficients for percentage of females (gender composition of school) in the M5 LPM.

Education systems with early tracking (age 14 or earlier)		Education systems with first tracking after age 14	
Austria	**−0.063**	Cyprus	0.013
Belgium	**0.022**	Denmark	−0.006
Bulgaria	**−0.072**	Estonia	0.025
Croatia	**−0.07**	Finland	−0.034
Czech Republic	**−0.029**	France	−0.015
Germany	−0.007	Greece	**−0.042**
Hungary	**−0.034**	Ireland	**0.012**
Italy	**−0.071**	Latvia	−0.004
Luxembourg	−0.002	Lithuania	0.005
Netherlands	0.031	Malta	0.008
Romania	−0.006	Poland	−0.02
Slovakia	**−0.04**	Portugal	0.02
Slovenia	**−0.11**	Spain	0.004
		Sweden	−0.017
		United Kingdom	0.002

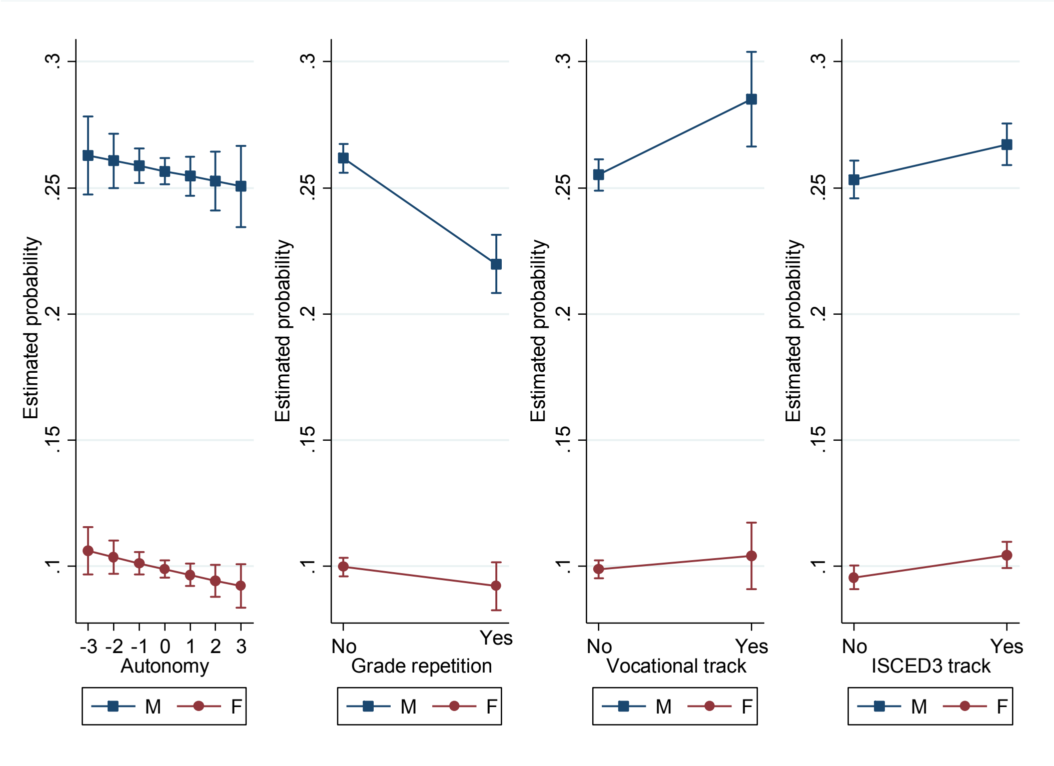
Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$.

Moreover, female dominance in the classroom can have different impacts on females' and males' expectations for STEM. In this respect, the interaction effects added to our models suggest no general tendency (see Tables A5.2 and A5.3 in the appendix). Instead, the individual European countries have distinct characteristics, suggesting that in some countries with early tracking, female dominance has similarly negative effects on both males' and females' interest (Bulgaria, the Czech Republic, Hungary and Slovakia), while in other places males are more strongly influenced (Austria, Croatia, Italy and Slovenia). As for Romania, the negative coefficients are statistically significant for females only. In countries with later selection, a high share of females in the classroom seems to facilitate interest in STEM in France (females only) and in Ireland and Cyprus (males only), while it negatively affects males in France and females in Cyprus. See Tables A5.2 and A5.3 in the appendix for details.

5.3.2 School-policy-related variables

In this section, we will focus on school-policy-related variables, i.e. the variables that are directly associated with either local or country-wide educational policies that regulate the level of school autonomy, grade repetition policy, and the type and ISCED level of education for 15-year-old students. As these policies create variations at the school level, the variables need to be considered at the same level. The visual representation of these policy-related variables are depicted in Figure 5.9. The pooled results for school autonomy and grade repetition were obtained using all countries, while when we consider the type of education (vocational versus non-vocational) and ISCED level we used only countries where at least 5% of students occupied one category (see Table 5.9 for details).

Figure 5.9. Predicted probability (logit model on the pooled sample with countries as fixed effects) of expecting a STEM career in the EU.



School autonomy appears to have no general association with overall interest in STEM, and only in a small number of countries is the association between school autonomy and STEM career plans statistically significant. In particular, small positive associations were found only in Croatia, Luxembourg and in Slovenia, and in none of the countries did our analysis reveal any gender difference.

Grade repetition, on the other hand, was found to be somewhat more systematically and negatively linked to overall interest in STEM occupations: this association is statistically significant in Bulgaria, Latvia, Slovakia and Spain. The two exceptions, with a statistically significant positive correlation between grade repetition and choice of STEM, are Austria and Germany. Grade repetition affects males and females differently: on average, females seem to be less negatively affected, while the estimated probability of males choosing a STEM career is 26% in schools with little grade repetition, and only 22% in schools with frequent grade repetition. From this it also follows that the gender gap in STEM is slightly smaller in education systems with a higher frequency of grade repetition. This pattern is most evident in Lithuania and the Netherlands. In Hungary, however, more frequent occurrence of grade repetition is associated with a reduced level of STEM aspiration among females – and thus also with a bigger gender gap (see Tables A5.2 and A5.3 in the appendix for details).

As mentioned above, and depending on the age of first selection in the education system, in several countries we cannot separate 15-year-old students based on whether or not they are on a vocational track and on their ISCED level. For these reasons, in the models presented in Table 5.9 only a subset of the EU Member States is shown.

Table 5.9. Coefficients of the M5 and M5i LPMs.

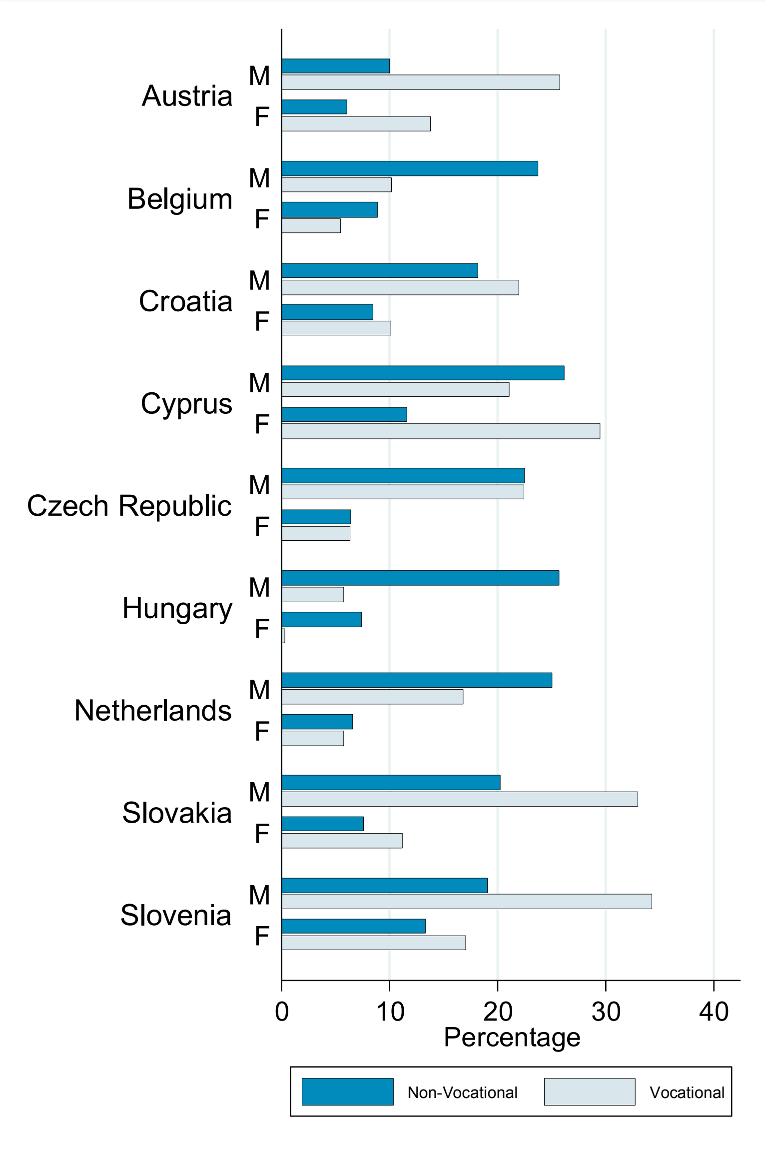
Country	Model M5			Model M5i (with interactions)				
	Female	Voc.[(a)]	ISCED 3	Female	Voc.[(a)]	ISCED 3	F X Voc.[(b)]	F X ISCED 3[(c)]
Austria	**−0.089**	**0.189**	-	0.036	**0.232**	-	**−0.137**	-
Belgium	**−0.150**	**−0.066**	−0.010	**−0.124**	**−0.120**	0.010	**0.099**	−0.040
Bulgaria	**−0.150**	0.012	-	**−0.133**	−0.004	-	0.022	-
Croatia	**−0.114**	**0.066**	-	0.039	0.055	-	−0.033	-
Cyprus	**−0.137**	0.007	−0.012	−0.137	−0.027	−0.001	**0.179**	−0.003
Czech Republic	**−0.178**	**0.118**	**−0.122**	−0.064	**0.172**	**−0.194**	**−0.144**	**0.161**
France	**−0.167**	−0.024	0.061	**−0.138**	−0.042	0.037	0.026	0.023
Greece	**−0.138**	0.052	-	−0.068	0.047	-	0.011	-
Hungary	**−0.176**	**−0.119**	-	**−0.141**	**−0.146**	-	**0.101**	-
Ireland	**−0.207**	-	0.019	**−0.203**	-	0.021	-	−0.002
Italy	**−0.106**	−0.003	-	−0.063	0.006	-	−0.030	-
Luxembourg	**−0.171**	0.016	−0.013	**−0.163**	0.038	−0.011	−0.039	0.003
Netherlands	**−0.169**	**−0.039**	0.002	**−0.218**	**−0.071**	0.021	**0.074**	−0.027
Portugal	**−0.201**	0.038	0.029	−0.145	0.065	0.029	−0.058	0.001
Slovakia	**−0.160**	**0.084**	**−0.077**	**−0.158**	**0.119**	**−0.123**	−0.076	**0.107**
Slovenia	**−0.126**	**0.143**	-	**0.107**	**0.173**	-	**−0.138**	-
Average	**−0.152**	**0.032**	**−0.014**	**−0.098**	**0.033**	−0.023	−0.010	0.025

Note: results in **bold** are statistically significant (different from zero) at $p \leq 0.05$, controlled for individual-level variables.[(a)] Voc. = in vocational school [(b)] F X Voc. = Females in vocational school (interaction); [(c)] F * ISCED3 = Females at ISCED 3 level.

For vocational school attendance, statistically significant coefficients were found in several countries where such programmes are provided, although the nature of the association varies. Attending a vocational school is positively linked to interest in STEM careers in several countries, as well as in the pooled dataset. In particular, students – males and females alike – in vocational secondary schools are increasingly interested in such careers in Slovakia and also in the United Kingdom. Males, however, are more positively affected than females in Austria, the Czech Republic and Slovenia, while vocational schooling has a positive influence only for females in Cyprus. At the same time, however, in Belgium, Hungary and the Netherlands males who attend a vocational school are less interested in STEM occupations than are similar students in more general schools. See Figure 5.10 for an overview of the significant effects. According to Cedefop data from 2014 ([23]), in the EU-28 Hungary has the lowest and Belgium the second lowest proportion of higher secondary-level vocational students who are enrolled in a programme that provides direct access to tertiary education. The share of such students in Hungary was as low as 2%, while in Belgium it was 21% – both values were far below the EU average of 69% in that year. These are interesting facts that may explain the negative associations between being on a vocational track and aspiring to a STEM career in these two countries, given that the majority of STEM jobs require a higher education degree. (The relevant information was not available in the Netherlands.)

([23]) http://www.cedefop.europa.eu/en/publications-and-resources/statistics-and-indicators/statistics-and-graphs/03-how-many-ivet-students#_ftn1

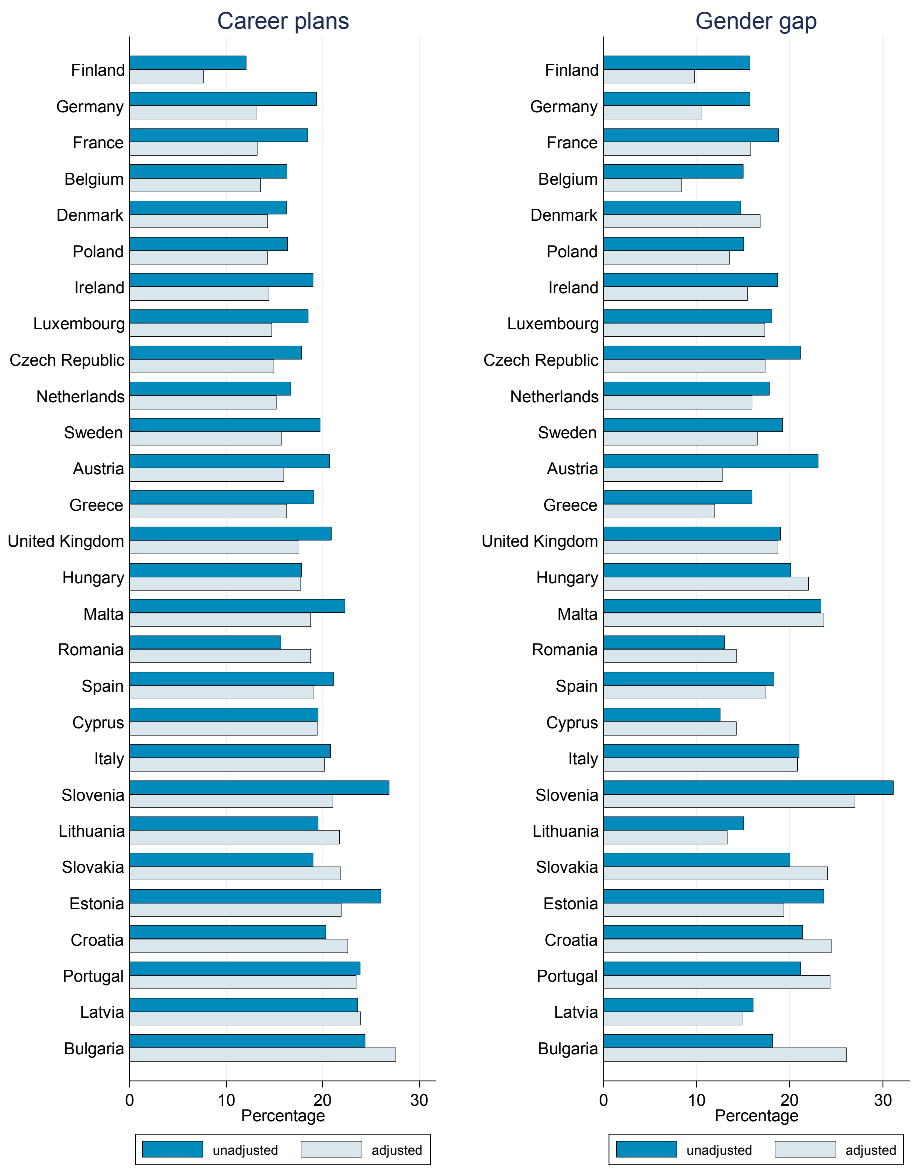
Figure 5.10. Predicted probability of choosing STEM career for selected countries on vocational and non-vocational track (logit model on the pooled sample with countries as fixed effects)



5.4 STEM career plans and country-level variables

In the previous sections, we examined regression coefficients and marginal effects, investigating the effects of particular variables or sets of variables. Those variables together were able to explain between 10% and 20% of the variance in STEM choices. Beyond that, we have seen considerable differences between countries that have been qualitatively described. In this section, we look more closely at cross-country differences. These are depicted in Figure 5.11. The dark blue bars represent actual levels (precisely corresponding with those in Table 5.1), while light blue bars denote the adjusted indicators. Adjusted indicators are predicted levels of overall STEM career plans and gender gap, assuming that the level of all explanatory variables introduced so far (science performance, home background, attitudes to science and school-related variables) are equal across the countries and equal to the current EU-28 average.

Figure 5.11. Unadjusted and adjusted level of STEM career expectations and gender gap. Adjusted estimates were computed under the assumption that variables correspond with current EU average levels.



This exercise informs us that, by equalising the individual variables, we do not reduce the cross-country variation either in overall STEM choices or in the gender gap. This means that the individual- and school-level variables we used cannot explain the large differences between countries. Differences between countries are not fully driven by the fact that science performance, enjoyment of science, family background, science resources available and the other variables we have used vary across countries. This clearly raises the possibility that other factors, probably those that are embedded in cultural, economic and political circumstances as well as in countries' educational systems, play a role in shaping males' and females' vocational interest.

5.4.1 Selection of country-level variables and modelling

In this part of the chapter, we test the effects of country-level variables described in chapter 3. The variables are grouped into six blocks addressing:

1. main features of the education system;
2. national activities to improve STEM education;
3. content of science curricula;
4. ability-grouping policies;
5. national activities addressing the gender issue in mathematics education;
6. macro-economic variables.

Altogether, we have collected 33 country-level indicators (minus one that has no variation: everyday technology is mentioned in the relevant steering documents at ISCED level 2 in all countries) that, from a theoretical point of view, may be relevant for STEM career choices and for gender differences in those choices. From a statistical point of view, having 32 country-level indicators that could potentially explain the level and the gender gap in STEM expectations (in total, 2 × 32 parameters) makes it impossible to conduct analysis in a single statistical model. To overcome this problem we adopted a stepwise procedure that consists of two general steps: (1) initial screening and (2) backward stepwise selection of multilevel models. This results in a modelling strategy in which the initial inclusion of country-level predictors is based on prior research as well as the need to demonstrate the extent to which educational and STEM-promoting policies correlate with STEM-related youth career expectations. The second step isolates the relevant country characteristics based on substantive as well as statistical criteria, leading to the most efficient and informative model specification.

In the first step, we looked at simple bivariate correlations between country-level variables and the overall levels of STEM and the gender gap in STEM choices. We used two indicators for both STEM career choices and for the gender gap in these choices: the unadjusted and the adjusted versions that are depicted in Figure 5.11. The analysis with the unadjusted version simply reveals observed correlations, while the adjusted version rules out the individual- and school-level characteristics, resulting in a counterfactual situation where the distribution of the individual- and school-level variables are the same in each country. This adjustment allows analysis of the direct effects of country-level variables without interference from individual and school characteristics. This brings some additional costs, however. The statistical adjustment introduces some additional measurement error that may hide small country effects. This is an acceptable situation, as we would rather minimise false detection than pursue, at any cost, all of the country effects. For binary country-level variables correlated with continuous STEM level and the STEM gender gap we used polyserial correlation, while in the other cases Pearsons's correlation was used. In this initial screening, we excluded variables that show no empirical relation with STEM interests and the gender gap. This step was designed to filter out variables that show no empirical relevance. Therefore, we preferred to search for strong proof to reject the hypothesis about the association, rather than to find some evidence on the variable's relevance. For exclusions we followed the threshold of the significant level greater than 0.1 and effect sizes smaller than 0.3 – although the borderline cases were not excluded, as we wanted to ensure that all potentially relevant variables would go to the next step (see Table 5.10 for details). In this first step, we also considered the correlation between country-level variables and excluded variables that were too highly correlated (more than 0.3) because they could not be used together in one model. The correlations between country-level variables are depicted in Table A5.4 in the appendix. The exclusion procedure was conducted separately for overall STEM interest and gender gap.

After the first screening exercise, to explain overall STEM interest, nine variables were chosen: vocational orientation; maths exam; national initiatives for mathematics motivation; promoting science education; socio-cultural context in steering documents at ISCED level 1 and ISCED level 2; addressing the gender issue (centrally supported); and HDI and GII (see Table 5.11). To explain the gender gap, 10 variables passed the initial screening: vocational orientation; maths exam; mathematics attitudes (centrally supported activities); ethics in steering documents at ISCED level 1; history of science in steering documents at ISCED level 2; addressing the gender issue (centrally supported); ability grouping in science at ISCED level 1; ability grouping in science at ISCED level 2); and HDI and GII.

In the second step of the analysis, we tested the effects of country-level variables using a backward selection procedure that consists of specifying the initial model with the full set of covariates and removing variables that have a significant level above 0.157. We then re-estimated the model with a new set of covariates, removing variables with a significance level above 0.157 and re-estimating the model again and again – repeating the procedure until all country-level effects had a level of significance below 0.157. Among many procedures for model selection, this approach has been proven to be one of the most robust while retaining simplicity (Royston and Sauerbrei, 2008). The threshold value of 0.157 is a standard choice, as it provides asymptotically similar results that would be obtained with model selection based on Akaike Information Criterion (AIC) measures (Royston and Sauerbrei, 2008, p. 33).

Table 5.10. Country-level correlations between STEM expectations, gender gap in STEM expectations and country-level variables.

	STEM level expectations				Gender gap			
	Unadjusted		Adjusted		Unadjusted		Adjusted	
Variable	Cor.	*P*-value	Cor.	*P*-value	Cor.	*P*-value	Cor.	*P*-value
A1) Selection age	0.092	0.630	0.013	0.947	−0.157	0.332	−0.054	0.783
A2) Programme availability	−0.011	0.959	0.100	0.629	0.015	0.925	−0.058	0.713
A3) Vocational orientation	**0.253**	**0.194**	**0.295**	**0.126**	**0.519**	**0.005**	**0.421**	**0.026**
A4) National exam	−0.005	0.912	0.209	0.000	−0.067	0.198	0.030	0.509
A5) Maths exam	**0.521**	**0.005**	**0.268**	**0.267**	**0.570**	**0.001**	**0.231**	**0.337**
B1) National initiatives for mathematics motivation	**0.217**	**0.396**	**0.207**	**0.398**	0.045	0.864	0.036	0.891
B2) Mathematics attitudes (centrally supported activities)	−0.073	0.773	−0.214	0.381	**0.087**	**0.574**	**−0.400**	**0.027**
B3) Existence of institutions promoting science education	**0.162**	**0.503**	**−0.288**	**0.201**	0.573	0.002	−0.049	0.853
B4) Specific guidance measures to encourage careers in science	0.141	0.574	0.153	0.556	−0.062	0.785	0.016	0.950
B5) Overall science/mathematics promotion indicator	0.181	0.280	0.010	0.953	0.186	0.269	0.089	0.611
C1) Everyday technology in steering documents at ISCED level 1	0.158	0.450	0.108	0.625	0.056	0.798	0.076	0.765
C2) Ethics in steering documents at ISCED level 1	−0.345	0.109	−0.123	0.651	**−0.153**	**0.516**	**−0.139**	**0.594**
C3) Socio-cultural context in steering documents at ISCED level 1	**−0.041**	**0.866**	**0.281**	**0.269**	−0.098	0.679	0.119	0.641
C4) History of science in steering documents at ISCED level 1	−0.016	0.954	−0.050	0.866	0.008	0.972	−0.069	0.812
C5) Philosophy of science in steering documents at ISCED level 1	−0.022	0.941	0.037	0.912	−0.363	0.111	−0.033	0.911
C6) Ethics in steering documents at ISCED level 2	0.048	0.850	0.158	0.499	−0.260	0.233	−0.192	0.470
C7) Socio-cultural context in steering documents at ISCED level 2	**−0.023**	**0.931**	**0.247**	**0.277**	−0.171	0.531	0.032	0.914
C8) History of science in steering documents at ISCED level 2	0.038	0.882	0.037	0.878	**−0.221**	**0.369**	**−0.251**	**0.274**
C9)Philosophy of science in steering documents at ISCED level 2	0.150	0.569	0.189	0.473	−0.154	0.511	−0.093	0.721
C10) Contextualisation of science teaching in steering documents	−0.052	0.841	0.119	0.663	−0.215	0.330	−0.087	0.743
D1) Ability grouping in maths at ISCED level 1	−0.043	0.850	−0.113	0.647	−0.210	0.441	−0.076	0.759
D2) Ability grouping in maths at ISCED level 2	0.060	0.801	−0.018	0.947	−0.170	0.469	0.076	0.763
D3) Ability grouping in science at ISCED level 1	0.174	0.472	0.245	0.352	**0.319**	**0.132**	**0.425**	**0.047**
D4) Ability grouping in science at ISCED level 2	0.251	0.290	0.291	0.259	**0.272**	**0.237**	**0.486**	**0.016**
D5) Ability grouping combined	0.225	0.360	0.149	0.549	0.217	0.350	0.388	0.065
E1) Addressing the gender issue (centrally supported)	**−0.232**	**0.352**	**−0.492**	**0.039**	**0.063**	**0.829**	**−0.468**	**0.042**
E2) Teaching in a gender sensitive way (centrally supported)	0.274	0.234	−0.079	0.739	0.215	0.418	−0.030	0.899
E3) Centrally supported activities for gender (combined)	0.149	0.539	−0.197	0.391	0.094	0.718	−0.159	0.482
F1) HDI	**−0.240**	**0.228**	**−0.738**	**0.000**	**0.088**	**0.664**	**−0.404**	**0.036**
F2) GII	**0.067**	**0.734**	**0.438**	**0.020**	**−0.118**	**0.549**	**0.251**	**0.197**
F3) GPG	0.175	0.384	−0.036	0.859	0.077	0.702	−0.117	0.562
F4) Female Employment	−0.020	0.921	−0.193	0.326	−0.053	0.790	−0.241	0.215

Note: values in bold indicate that the variable was selected for the multilevel modelling.

The model selection procedure was first applied to the random intercept model, i.e. the model that was utilised for exploring the effects on overall levels of STEM expectations. Among the explanatory variables two pairs were found to be too highly correlated and could not be included in a single model. The first pair consists of two binary indicators of whether or not steering educational documents include a reference to social and cultural context to be addressed in sciences education at ISCED levels 1 and 2. The second pair of variables with a particularly high correlation is HDI and GII. As we wanted to test the effects of each of these variables we needed to specify four models (ML1a, ML2b, ML3c, ML4d). All those models follow the same specification, being two-level logistic multilevel models with random intercept, where at level one we control for all variables from model M5, except the indicator of parents in STEM occupations (as we want to include Austria in the multilevel modelling). Country-level variables were then introduced at the second level of the analysis ([24]). The first two models (ML1a and ML2a) control for HDI and not for highly correlated GII, which is in turn tested in models (ML3a and ML4a). Models ML1a and ML3a test the effects of socio-cultural context in steering documents at ISCED level 1 but not at ISCED level 2, which is tested in models ML2a and ML4a.

Table 5.11. Initial and final sets of country-level variables explaining the level of STEM career choices (random intercept model).

Model	ML1a		ML2a		ML3a		ML4a	
Step	i	f	i	f	i	f	i	f
Vocational orientation	×	✓	×	✓	×	✓	×	✓
Maths exam	×	✓	×	r	×	r	×	r
National initiatives for mathematics motivation	×	r	×	r	×	r	×	r
Promoting science education	×	r	×	r	×	r	×	r
Socio-cultural context in steering documents at ISCED level 1	×	r	-	-	×	r	-	-
Socio-cultural context in steering documents at ISCED level 2	-	-	×	r	-	-	×	r
Addressing the gender issue (centrally supported)	×	r	×	r	×	✓	×	✓
HDI	×	✓	×	✓	-	-	-	-
GII	-	-	-	-	×	✓	×	✓

Note: i, initial model; f, final model; ×, variable included in first step; ✓, variable included in last step; -, not included in the model; r, removed from the model as did not reach a level of significance below 0.157

The final sets of variables presented in Table 5.11 differ in the various specifications. In all specifications, vocational orientation appears to be related to overall level of STEM. In all specifications including HDI, this variable also shows relevance. In models where GII was used as a substitute for HDI, it also shows considerable relation to overall STEM level. Additionally, the presence of a maths exam was detected as a potential predictor in model ML1a, and centrally supported activities addressing gender issues was selected in model ML3a.

The same procedure of model selection was performed for gender gap (random slope of female coefficient), also building on previous random intercept models. This means that the initial step of model ML1b incorporates all predictors from the final step of model ML1a, plus variables selected in the first screening exercise. The variables are specified in Table 5.12. Similarly to the overall level of STEM, we wanted to test the effects of both HDI and GII, which forced us to use two model specifications: one with HDI (ML1b–ML2b) and one with GII (ML3b–ML4b). Again, we had a second set of two correlated variables, which are ability grouping in science at ISCED level 1 (ML1b and ML3b) and ISCED level 2 (ML2b and ML3b), introduced in two different sets of models.

Table 5.12. Initial and final sets of country-level variables explaining the gender gap of STEM career choices (random intercept models).

	ML1b		ML2b		ML3b		ML4b	
Step	i	f	i	f	i	f	i	f
Vocational orientation	×	r	×	r	×	r	×	r
Maths exam	×	r	×	r	×	r	×	r
Mathematics attitudes (centrally supported activity)	×	r	×	r	×	r	×	r
Ethics in steering documents at ISCED level 1	×	r	-	-	×	r	-	-
History of science in steering documents at ISCED level 2	-	-	×	r	-	-	×	r
Addressing the gender issue (centrally supported)	×	r	×	r	×	r	×	r
Ability grouping in science at ISCED level 1	×	r	-	-	×	r	-	-
Ability grouping in science at ISCED level 2	-	-	×	r	-	-	×	r
HDI	×	r	×	r	-	-	-	-
GII	-	-	-	-	×	r	×	✓

Note: i, initial model; f, final model; ×, variable included in first step; ✓, variable included in last step; -, not included in the model; r, removed from the model as did not reach a level of significance below 0.157

These exercises showed that among our country-level variables, and after controlling for individual- and school-level characteristics, only GII is considerably related to gender gap.

The effects of country-level variables on overall STEM level and gender gap from the final multilevel models are presented in Table 5.13. We present two sets of results. In the first, HDI was used as a country-level explanatory variable; in the second, GII was used.

Table 5.13. Country-level effects of final logistic multilevel specification.

	Final model 1		Final model 2	
	Estimate	*P*-value	Estimate	*P*-value
Level of STEM (intercept) on				
Vocational orientation	0.361	0.030	0.556	0.001
Maths exam	0.097	0.153	-	-
HDI	−2.206	0.072	-	-
Addressing the gender issue (centrally supported)	-	-	−0.148	0.010
GII	-	-	1.000	0.041
Gender gap (female slope)				
GII	-	-	1.142	0.110

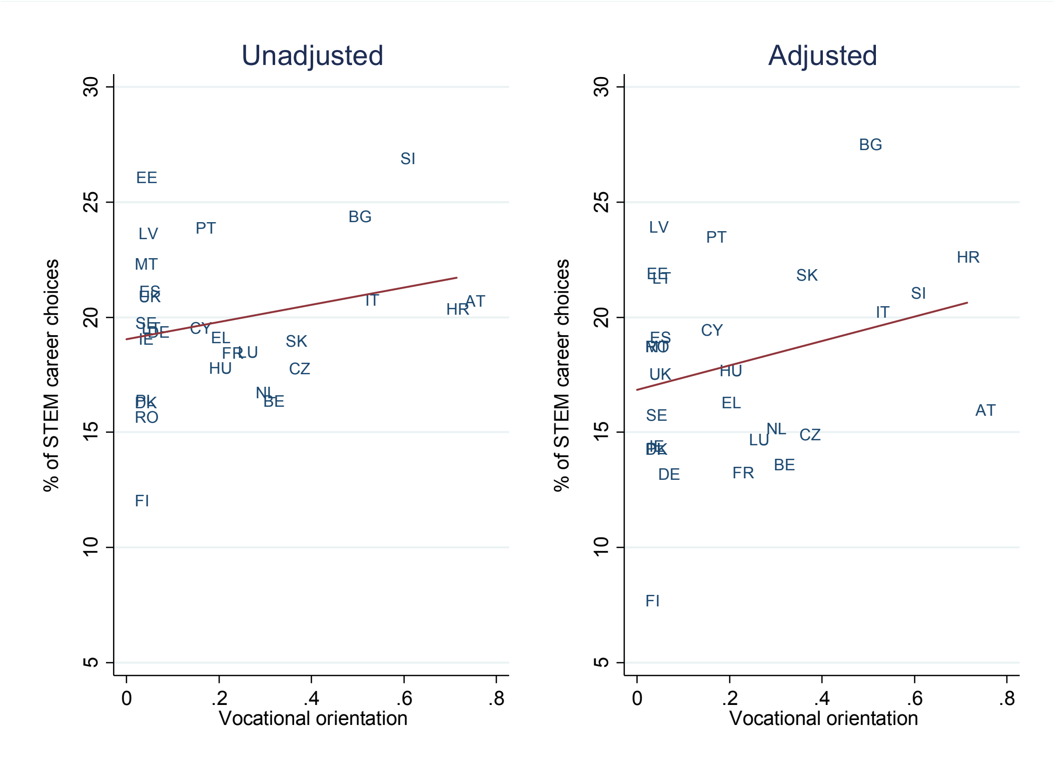
5.5 Discussion

5.5.1 Main features of education systems

At the country level, the vocational orientation of the education system appears to be the single most significant educational factor affecting students' overall interest in pursuing a STEM career, no matter how our final model is specified (Table 5.13). In particular, the share of 15-year-old students who are enrolled in a programme whose curriculum is pre-vocational or vocational is significantly positively related to the number of students with STEM career expectations. (See also Figure 5.12) This finding is generally in line with our school-level results (Table 5.9), which also showed that in most of the countries, students in vocational schools tend to have an increased interest in entering a STEM occupation. This is not surprising, given the relative importance of STEM-related subject areas in vocational schooling at the upper secondary level. For instance, in 2012, within upper secondary education, graduates in science, mathematics and computing together with graduates in engineering, manufacturing and construction accounted for between 17% (Belgium) and 58% (Estonia) of all the graduates in Europe ([25]). Assuming that these schools can either directly lead to (non-professional) STEM careers or prepare students for entering a science-related higher education path, vocational programmes at the upper secondary level appear to positively influence students' motivations for STEM careers. However, there is also some indication that this might happen at the cost of increasing the gender gap in STEM employment. Although the level of system vocationality does not remain statistically significant in the final models for gender gap, it still has a significant positive correlation with both the unadjusted and the adjusted level of this gap (Table 5.10). Considering that the share of males among science and engineering vocational graduates at the upper secondary level exceeded 90% in almost all of these countries in 2012, we can conclude that vocational programmes can serve as early tracks that direct students towards gender-typed educational careers. Hence a high level of student participation in upper secondary vocational programmes may be an effective way to increase students' participation in STEM, as much of vocational education is STEM-oriented. But, as upper secondary vocational training is strongly differentiated by gender, i.e. males are more likely to enter these programmes, a growth in student numbers in this sector of education may widen the gender gap in STEM. This result also corresponds with the more general finding of Hillmert's study, which shows that the level of vocational enrolment is associated with more gender-typical career plans of students (Hillmert, 2015). Further, we also have to keep in mind that, besides the overall positive association between system vocationality and students' interest in STEM, in some countries we have observed that – at the individual level – studying in a vocational programme may reduce the probability of opting for a STEM career. This implies that our findings about system-level vocationality will not hold for professional STEM occupations in countries where upper secondary vocational schooling does not allow students to transition into the tertiary education system.

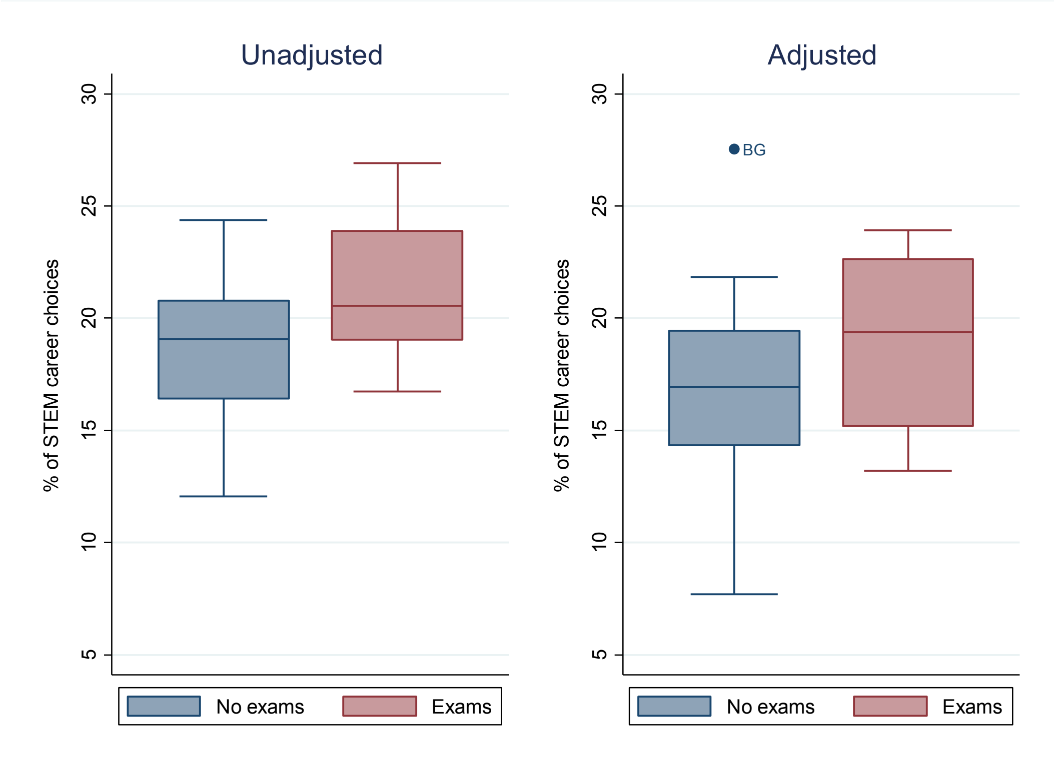
([25]) Own calculations based on Eurostat data. Latest reported data is from 2012 and information was not available for Croatia, Cyprus, Denmark, Ireland, Italy, Luxembourg, Poland, Romania, Slovakia and the UK. (Graduations in ISCED levels 3 to 6 by field of education and sex [educ_grad5].)

Figure 5.12. Relation between STEM career choices and vocational orientation of the system.



The level of vocationality and the level of stratification of the system (as often measured by the age of first selection or the number of educational programmes available at age 15) are empirically and also conceptually interrelated, as more stratified systems are more likely to direct more students towards vocational tracks. Earlier studies have revealed some significant negative associations between stratification and students' interest in STEM careers (Sikora and Pokropek, 2011, 2012a), and one study has also revealed some positive association between system stratification and gender segregation of these plans (Han, 2016a). Our analysis, however, is more in line with studies that could not justify the relevance of system stratification – age at first selection and number of educational programmes available – for students' career plans in computing and engineering fields (Han, 2015). As can be seen from Table 5.10, proxies of system stratification were not included in our multilevel models, as they appear not to be strongly and significantly related to STEM career choices.

Figure 5.13. Relation between STEM career choices and presence of maths exam in country (boxplots).



Although the existence of standardised examinations in the system is sometimes considered a proxy for the standardisation of outputs in the education system as a whole (and could therefore be linked to students' careers plans through the more general associations between output standardisation and students' achievements (Bol and Van de Werfhorst, 2013)), the existence of specific, STEM-related examinations (either in maths or in science) may also have a more direct relation with students' expectations for a related career. So far, research on the topic has been limited to one study (Han, 2016b), which revealed a significant negative relationship between the existence of standards-based external exams in science and students' plans to work in STEM across 55 PISA countries in 2006. The association explored was consistent across gender and also students' level of science performance. The interpretations offered referred to the negative influence that focused, possibly over-standardised, exam-preparatory teaching practice can have on students' attitudes towards the subject studied, but also to the possibility that preparing for standardised external testing may make students' career expectations more realistic, and more strongly associated with their school performance. As this second hypothesis could not be justified in her study, Han concluded that more attention needed to be paid to the potential negative non-cognitive outcomes of the standardised exams, which might also manifest themselves in a reduced interest for certain career path, including STEM careers (Han, 2016b). Interestingly enough, our findings suggest a significant positive association between maths results and students' plans to enter a STEM occupation. In model ML1a, maths exams were included in the final specification of the model, with a positive coefficient of 0.097 at a *p*-value of 0.153. The boxplots presented in Figure 5.13 suggest that the correlation between students' STEM career plans and the existence of maths exams decreases only very slightly after we adjust to the individual- and school-level variables. However, the size of association in the not statistically significant results provides a strong indication that the existence of standardised maths tests at the end of upper secondary education may even promote students' STEM career expectations. A mechanism that may explain the positive association is that facing a compulsory maths exam at the end of secondary education may force students to continue studying this subject even if, in a less standardised system, they might have dropped or at least neglected this area of study.

5.5.2 National activities to improve STEM education

Attempting to explore possible relationships between centrally supported activities directly aimed at raising students' – and the wider publics' – interest in either science or math, we tested the associations between a series of policy indicators and students' STEM-related career plans, and the gender gap in that association. With only cross-sectional data, and policy indicators from several years before the survey, we could not of course conduct a proper impact evaluation. Still, we were interested in seeing possible associations between national attempts and STEM-related outcomes. However, as is revealed in Table 5.10, none of our four indicators (plus one aggregate indicator) on national initiatives have proved to be significantly related to the overall levels of students' plans to enter a STEM career. Two of them – national initiatives for mathematics education and promoting science education – were tested in the final models (selected on the basis of lowest *p*-values, and highest correlations with the adjusted values), but they did not reach the required level of significance and were therefore excluded from the final models. Concerning gender segregation, it appears that a higher number of centrally supported activities ([26]) aiming to improve students' attitudes towards mathematics is negatively related to the size of the adjusted gender gap. In other words, it seems that, holding the students' individual characteristics as well as school factors at a constant level, the more these activities are present in a country, the smaller the difference is between males' and females' STEM-related career plans. However, even this indicator has not reached the expected level of significance in the multilevel model, and it was therefore excluded from the final model.

The lack of success in establishing any systematic, significant association between centrally supported science- and maths-promoting activities in the Member States and desirable outcomes related to students' STEM career plans might have several reasons. Most importantly, the reliability of the measures of national activities is a matter of concern, as the information collected in the Eurydice exercise often covers a rather wide range of activities compressed in a single indicator. For example, 'national activities for mathematics motivation' can be both national strategies or centrally supported initiatives. Although the main target group is the student body in all cases, there are significant variations in the specific age groups in focus, as well as in the education methods supported. In addition, the definition applied in the study is not indicative of the scope of the activity, either in terms of money spent or in number of students reached. Moreover, information on the national initiatives refer to 2010/2011, and it is unclear whether or not the programmes that were in effect in that year were still running 4 years later, when the PISA study took place. Of course, it is equally possible that some countries that had no maths- or science-supporting initiatives in 2010/2011 had successfully launched them by 2015. For all these reasons, our results by no means indicate that none of the listed activities can have any positive influence either on students' STEM-related career plans or on the perceived gender segregation. The association is certainly not obvious, and more precise measurements as well as more tailored data collection would be needed to establish the potential influence of these country-level initiatives.

([26]) Activities were selected from the following list: promotion of specific teaching methods to improve engagement; involvement of parents in the learning process; addressing the gender issue in mathematics education; promotion of extra-curricular activities; promotion of partnerships with companies, universities and other organisations; and running awareness-raising campaigns in wider society (Eurydice, 2011a).

5.5.3 Social context of science teaching

As suggested in chapter 2, in this study we attempt to explore associations between curriculum content and students' – particularly females' – plans for STEM occupations. Our expectations were based on earlier studies suggesting that females are more interested in communal goals and social aspects of life than men (Diekman et al., 2010). Therefore, we tested whether or not science teaching that pays more attention to the various social aspects of science can more successfully motivate female students to follow a career in STEM. Our empirical findings provided little support to these expectations, and they were excluded from the final specification.

Again, it would be premature to claim on the basis of our findings that embedding various aspects of the social context into science teaching has no consequence for students' – either male or female – career plans in the related fields. As our measures were based on country experts' reports on whether or not certain topics were mentioned in the national steering documents as contextual issues recommended for coverage in the teaching process, they provide no information on what actually happens in the classroom. These recommendations may be more influential on teachers' practice in one country than in another, and contextualising may also happen in schools where the relevant national documents include no reference to these issues.

5.5.4 Ability grouping in maths and science

Ability grouping is expected to accommodate heterogeneous student needs and abilities, and hence to promote higher student achievement. Ability grouping with respect to student ability in maths and science is quite common in European classrooms, at the primary as well as the secondary level. Although research typically concludes by identifying some positive impact of grouping as far as student academic achievement is concerned, ability grouping seems to have more controversial effects on equal opportunities. The main concerns relate to the lack of positive influence of more able students on less able ones, the unequal quality of teaching in the different groups, and also to the selection process. In relation to gender inequalities, both teachers' judgement and standardised test scores can be affected by negative gender bias in the masculine fields of maths and science (Wang and Degol, 2013, p. 312).

Indeed, our empirical results give some indication of such mechanisms, as in the 11 countries (nine in the case of ISCED level 1) where ability grouping is recommended in science classes for pupils with different ability levels, either with the same content or with different content, the size of the adjusted gap tends to be significantly higher than in countries without such recommendations. Although the two factors accounting for ability grouping are ultimately excluded from the final models, the finding is still noteworthy and requires further investigation. In this case, again, further tests would be needed that relate actual classroom practices – rather than steering document contents – to what careers students envisage for themselves.

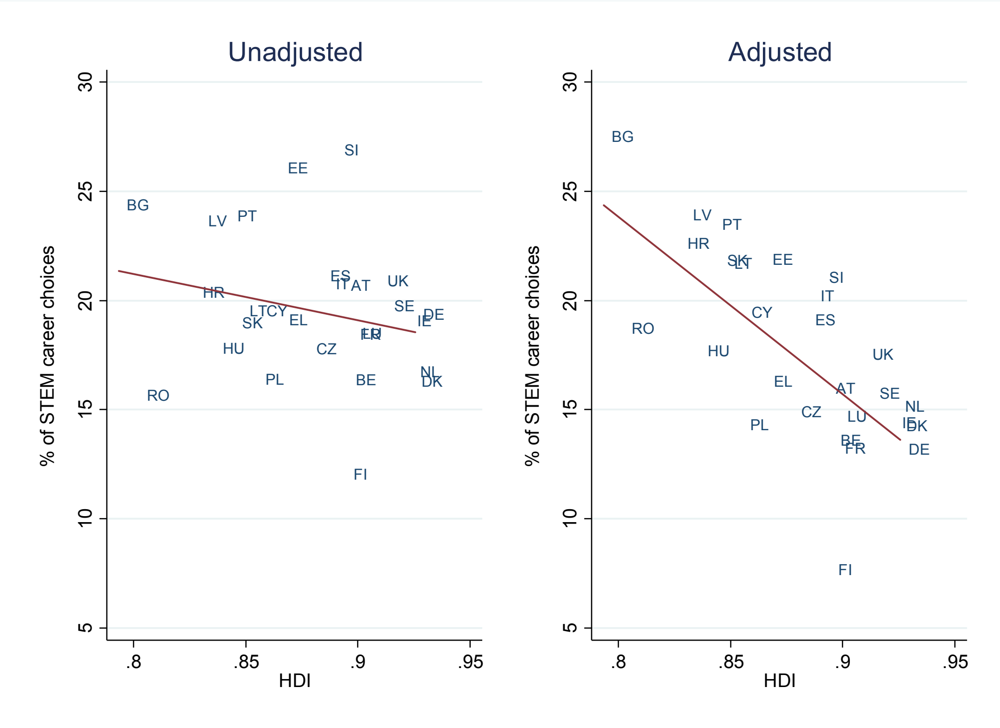
5.5.5 Addressing the gender issue in mathematics education

In a small number of Member States, gender imbalance in the field of mathematics is targeted by centrally supported activities, the aims of which range from 'addressing the gender issue in mathematics education' to 'teaching maths in a gender sensitive way'. The first approach was taken in only three countries (Austria, Greece and Poland), and the second in eight (Austria, Cyprus, Estonia, France, Malta, the Netherlands, Spain and the United Kingdom). Our results show some rather unexpected patterns, as addressing gender issues in mathematics education appears to be significantly negatively correlated to the size of the adjusted gender gap. At the same time it also shows a significant negative association with the overall level of STEM career expectations. Moreover, when included in the models, it only maintains its statistical significance in the STEM interest-level model, suggesting that students in countries where attention is paid to the gender issue in mathematics education are less likely to plan a STEM career. Given the small number of countries that explicitly focus on this issue in maths teaching, we suspect a spurious correlation caused by some other characteristic shared by Austria, Greece and Poland that is linked to reduced student interest in STEM careers.

3.5.6 Additional country-level correlates

Besides various characteristics of the education system, we also tested the relevance of some more general country-level indicators, including the HDI, as well as three indicators related to gender equality in the countries. Firstly, societal affluence – as measured by HDI – was found to be consistently and negatively related to the level of student interest in STEM careers across all the specifications. In this way, our findings confirm earlier results that also revealed young people’s reduced interest in STEM in more affluent countries (Sjøberg and Schreiner, 2005, 2010; Charles, 2017). Our results contribute to this finding by confirming this association for a more limited and more homogenous set of countries: Member States of the EU. Entering a career in the field of sciences and technology in Europe is accordingly a more appealing option in transitioning countries, with a recent industrial past, than in countries that are further on in the post-industrialisation process.

Figure 5.14. Relation between STEM charier choices and HDI.



However, the negative, statistically significant correlation between the adjusted level of gender gap and HDI contradicts earlier research findings, which typically point to an increased gender gap in more affluent settings (Sikora and Pokropek, 2012a; Charles, 2017). Such findings typically relate to a more diverse set of countries, also including developing and transforming non-European countries (e.g. Lebanon and Syria), as well as some highly developed non-European economies such as Japan and the USA. Although the pattern is clear (see Figure 5.14), one should keep in mind that the negative effect was not confirmed by multilevel modelling strategy.

However, the GII of United Nations Development Programme, which is closely related to HDI (negative correlation of −0.7), was significantly and positively related to the level of interest in STEM careers in its unadjusted form, and also in the final model. In fact, GII was the only country-level factor that reached the required level of significance to be retained in the final version of the multilevel models for gender gap in STEM career plans (see Figures 5.15-5.17 for details).

Figure 5.15. Relation between STEM gender gap and HDI.

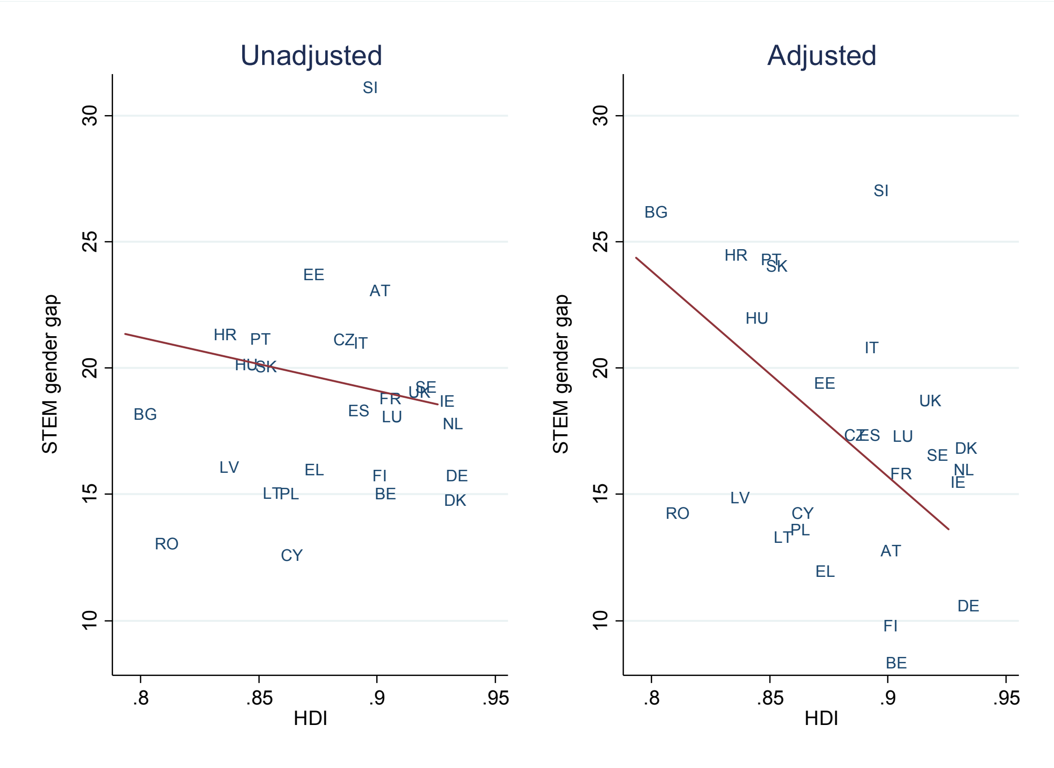


Figure 5.16. Relation between STEM level and GII (note that Slovenia is excluded as an outlier).

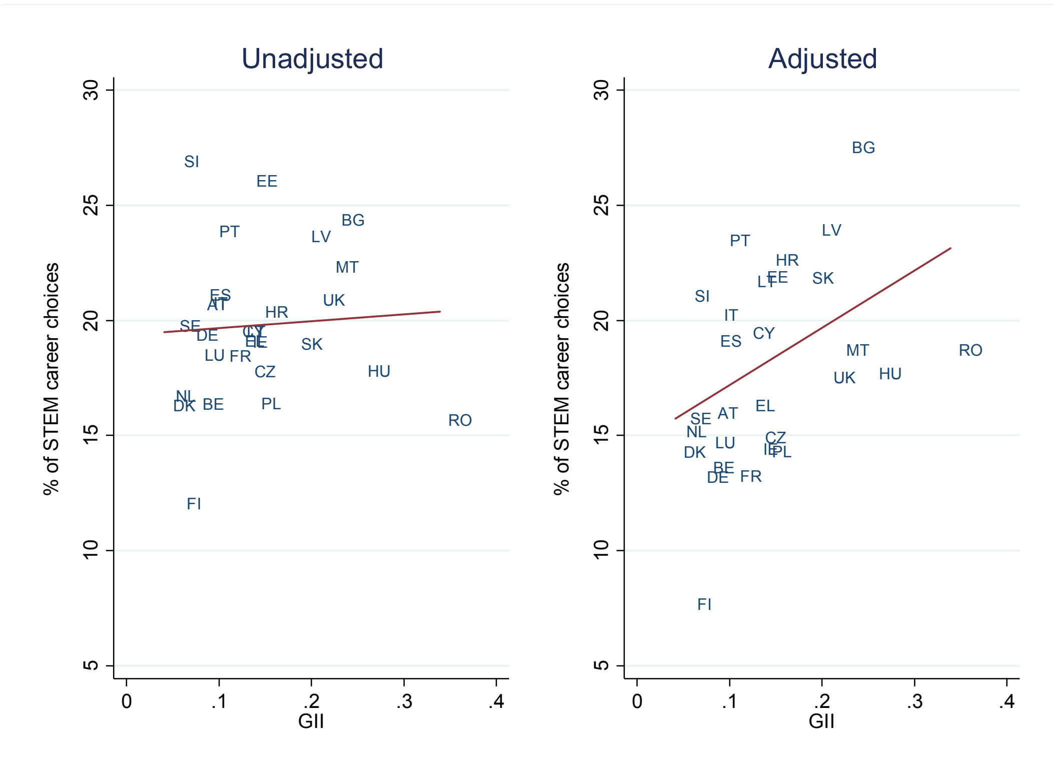
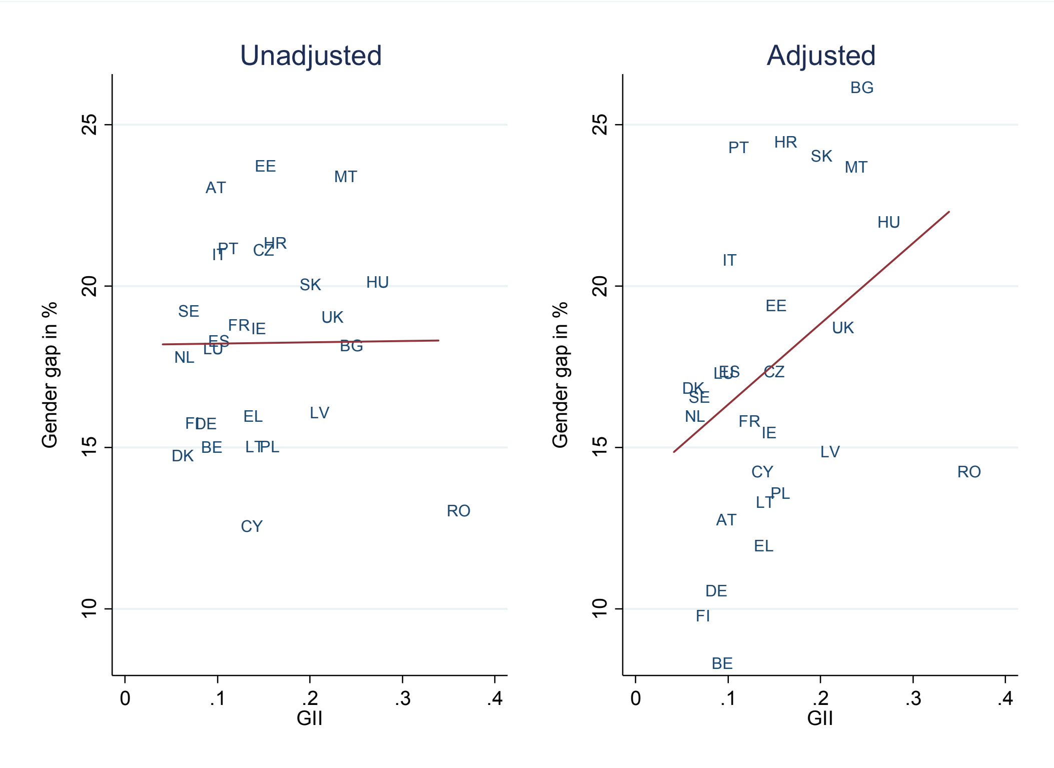


Figure 5.17. Relation between STEM level and GII (note that Slovenia is excluded as an outlier).



5.6 Summary

Our results have shown that factors that correlate with the overall level of students' interest in STEM occupations are not the same as factors linked to the gender gap in this interest. In our analysis, we identified more factors related to the first issue than to the second. In fact, individual dispositions, but also educational approaches that seem to matter in promoting students' motivations for STEM, are likely to boost both males' and females' interest to a similar extent (with no effects on the gap), or even to be less efficient in motivating females than males (increasing the gap).

Clearly, an increased understanding of science is also linked to an increased level of interest in related careers. The more a school can promote students' capacity to understand scientific concepts and ideas, the more students will consider entering an occupation in this field. However, males are likely to be more responsive to this approach than females, who – as their understanding improves – will probably turn rather to medical professions.

Above cognitive understanding, non-cognitive attitudes towards science, in particular enjoyment of science learning, are also important. Students who enjoy science learning more are also more likely to plan a STEM career. Although European-level analysis reveals no gender difference in this pattern, there are in fact notable cultural variations in the effect of science enjoyment. While in the majority of the post-socialist Member States enjoyment does not matter or matters only for females, boosting the enjoyment of science in the rest of Europe is again an approach that can affect males more than females (increasing the gap).

Schools can be more or less well equipped to teach sciences and they can also offer different opportunities to participate in science outside compulsory lessons. In general, however, neither the resources available for science teaching nor the provision of science clubs in school can directly be linked to students' plans for a STEM career. Science competitions, however, seem to have some marginal effect on this decision, although more so for males than for females. Thus, again, offering competitions for students to test their science competencies may increase the tendency towards segregation.

As expected, students also develop their career plans differently across the different educational systems in Europe. Although system stratification (as measured either by age at first selection or by number of programmes offered at age 15) was not significantly correlated to STEM outcomes at the country level, indirect evidence as well as the importance of vocationality – which is highly correlated with stratification – suggest that these dimensions of the education system can still have a notable effect on students' STEM-related career plans.

In most countries, students who are on a vocational track at the age of 15 are increasingly interested in choosing a STEM job. This overall pattern also appears in the country-level model, where system vocationality maintains its positive impact on STEM interest after all the other factors are controlled for. Between-country comparisons further reveal that this influence is particularly strong and positive in countries where upper secondary vocational programmes offer a relatively smooth transition to the higher education system.

Although the multivariate analysis has not revealed any significant association between characteristics of the education systems and the gender segregation in students' vocational interest, there is some qualitative evidence that, in certain types of education systems, differences between schools can further contribute to the segregative processes. We have found that the elimination of the differences in school-level factors in Austria, Croatia, Italy and Slovenia, and also to a lesser extent in Bulgaria and Slovakia, would bring females' vocational interest in STEM much closer to that of males. With no exceptions, these are all countries with relatively early first tracking (from age 10 in Austria to age 14 Croatia, Italy and Slovenia), and a high proportion of 15-year-old students in vocational programmes (from 43% in Slovakia to 70% in Austria). The school characteristic that contributes most to the STEM gender gap (as well as to the variation in STEM vocational interest) in these countries is inarguably the share of females in the school, but in some cases the (unequal) availability of science competitions, the occurrence of grade repetition and differences in average school science performance also contribute to the situation. A high concentration of female students in certain, presumably non-STEM-related, schools could be one reason for the gender segregation of vocational interest in all of these countries. This might happen because early selection is often associated with the concentration of females in education programmes that promote different – non-STEM-related – interests and careers. Examples are vocational schools oriented towards traditionally female-dominated employment, such as healthcare or certain types of services, but also general schools that offer the opportunity to specialise, for instance, in the human sciences. At the same time, the provision of science competitions further contributes to the gap in Croatia, Slovakia and Slovenia, while females' reduced motivation in academically strong school environments is a further contributing factor in Austria, Bulgaria and Slovenia. Moreover, in four of these countries (Austria, Bulgaria, Croatia and Slovenia) males – relative to females – may be slightly more encouraged to choose a STEM career in academically strong environments, i.e. where the average science performance of the students is high. Therefore, instead of converging, males' and females' career plans may further diverge when overall academic performance is high in the education systems with early selection.

Notwithstanding the notable school effects in these six countries, our analysis has generally been more successful in identifying factors that lead to increasing the overall number of students planning a science career than in identifying factors that lead to reducing the existing gender segregation. The gender gap explored remained by and large unaffected by the various individual- and school-level characteristics that we included in the analysis, and the country-level factors did not account for much of this gender difference. These findings underline the importance of the universal cultural patterns that maintain gendered career choices of adolescents across very different countries, and that further contribute to segregation both in higher education and in the labour market.

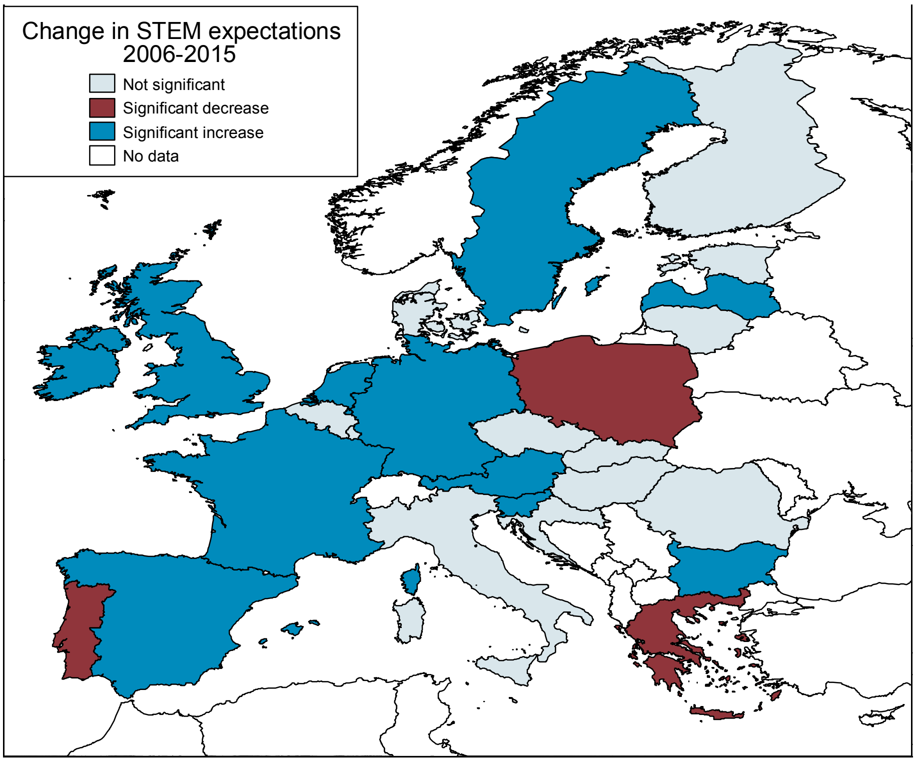
6 Changes in STEM career plans, 2006–2015

Promoting students' interest in STEM careers and reducing the gender gap in STEM areas have been considered two important goals in several individual Member States but also at the European level. In this chapter, we will consider the 10-year period from 2006 to 2015 and explore the major tendencies in these domains across Europe. After describing the changes that occurred in the various countries, we will try to identify the main driving forces behind them, again taking into account possible factors at the individual, the school and the country level. As in the previous chapters, we will also try to shed light on the differences and similarities between the processes that shape levels of interest in STEM professions on the one hand and the gender segregation in this interest on the other.

6.1 Changes in STEM career plans ([27])

As is apparent both from Table 6.1 and Figure 6.1, the 2006–2015 period was not characterised by a uniform European trend in students' STEM-related career plans. Although on average a small positive change occurred, with an overall increase of 3 percentage points, variations between countries were remarkable. In particular, a significant positive change took place only in 10 Member States, while in 13 Member States no statistically significant change could be identified, and in the remaining three some decline was registered.

Figure 6.1. Change in STEM career expectations between 2006 and 2015.



The greatest increase in the number of students considering a STEM occupation occurred in Bulgaria (9 percentage points), followed by the United Kingdom (8 percentage points), the Netherlands (6), Austria, Estonia and Latvia (5), Germany, Ireland and Slovenia (4), France (3), and finally Sweden (2). On the other hand, the greatest decrease was revealed in Poland (7 percentage points), followed by Portugal (4 percentage points) and Greece (3 percentage points). As a general pattern, we can conclude that an increase was more likely to occur in the

([27]) In the first part of this chapter descriptive statistics similar to the those presented in chapter 4 are given. Slight differences in the figures might occur because data were presented before the imputation in chapter 4.

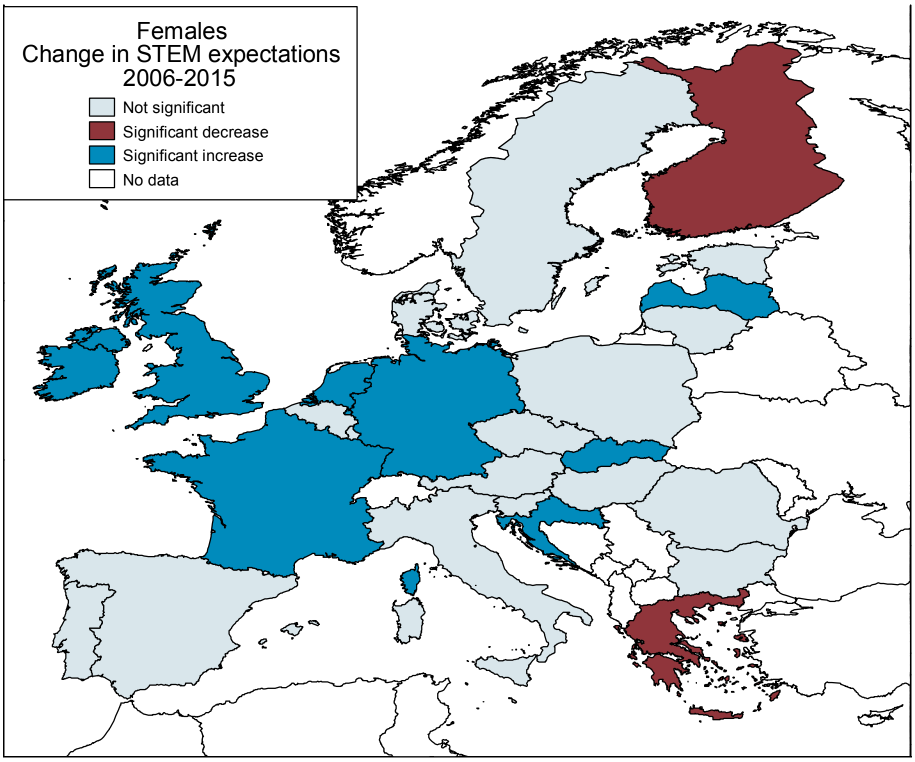
western parts of Europe, while in the eastern regions no significant change, or even some decrease in the level of interest in STEM careers, could typically be found.

Table 6.1. Levels of STEM career expectations in 2015 and 2006. Proportions and Standard errors

	STEM in 2015		STEM in 2006		Change	
Country	Prop.	Std. error	Prop.	Std. error	Change	Std. error
Austria	**0.207**	(0.010)	**0.160**	(0.012)	**0.047**	(0.016)
Belgium	**0.164**	(0.008)	**0.172**	(0.009)	0.008	(0.012)
Bulgaria	**0.244**	(0.014)	**0.155**	(0.007)	**0.089**	(0.015)
Czech Republic	**0.178**	(0.008)	**0.189**	(0.015)	−0.011	(0.017)
Germany	**0.194**	(0.006)	**0.158**	(0.008)	**0.036**	(0.010)
Denmark	**0.163**	(0.006)	**0.148**	(0.006)	0.015	(0.009)
Estonia	**0.261**	(0.007)	**0.208**	(0.009)	**0.053**	(0.011)
Greece	**0.191**	(0.007)	**0.223**	(0.008)	**−0.031**	(0.011)
Spain	**0.211**	(0.006)	**0.203**	(0.006)	0.008	(0.009)
Finland	**0.121**	(0.006)	**0.117**	(0.005)	0.003	(0.008)
France	**0.185**	(0.007)	**0.160**	(0.008)	**0.025**	(0.011)
Croatia	**0.204**	(0.012)	**0.188**	(0.015)	0.016	(0.019)
Hungary	**0.178**	(0.009)	**0.164**	(0.011)	0.014	(0.015)
Ireland	**0.191**	(0.005)	**0.147**	(0.006)	**0.044**	(0.008)
Italy	**0.208**	(0.012)	**0.198**	(0.009)	0.010	(0.015)
Lithuania	**0.195**	(0.006)	**0.185**	(0.006)	0.010	(0.009)
Luxembourg	**0.185**	(0.006)	**0.172**	(0.005)	0.013	(0.008)
Latvia	**0.237**	(0.007)	**0.182**	(0.008)	**0.054**	(0.011)
Netherlands	**0.167**	(0.006)	**0.106**	(0.006)	**0.061**	(0.008)
Poland	**0.164**	(0.006)	**0.234**	(0.007)	**−0.070**	(0.009)
Portugal	**0.239**	(0.007)	**0.279**	(0.009)	**−0.040**	(0.012)
Romania	**0.157**	(0.009)	**0.150**	(0.010)	0.007	(0.013)
Sweden	**0.198**	(0.007)	**0.176**	(0.008)	**0.021**	(0.010)
Slovenia	**0.269**	(0.006)	**0.228**	(0.007)	**0.041**	(0.009)
Slovakia	**0.190**	(0.009)	**0.164**	(0.011)	0.025	(0.014)
United Kingdom	**0.209**	(0.006)	**0.130**	(0.005)	**0.079**	(0.007)
EU-26	**0.196**	(0.002)	**0.168**	(0.003)	**0.029**	(0.002)

As it could be expected, the changes of the career plans did not equally affect males and females in the different countries (Table 6.2 and Figure 6.2.) thus in Member States also the size of the gender gap was affected. In a number of countries, an increase in the level of interest occurred among male students only – to this group belong Austria, Bulgaria, Estonia, Sweden, and also Slovenia. In some other places, females experienced a more moderate increase than males did. This was the case in the United Kingdom, the Netherlands and to some extent also in Latvia. Conversely, positive tendencies of comparable magnitude among males and females were found in Germany and Ireland only, while in three other countries (France, Croatia and Slovakia) only females' expectations grew. Finally, where a significant decrease occurred, it either affected males (Poland and Portugal) or females (Greece, Finland) only, but never both genders at the same time.

Figure 6.2. Change in STEM career expectations between 2006 and 2015 by gender.



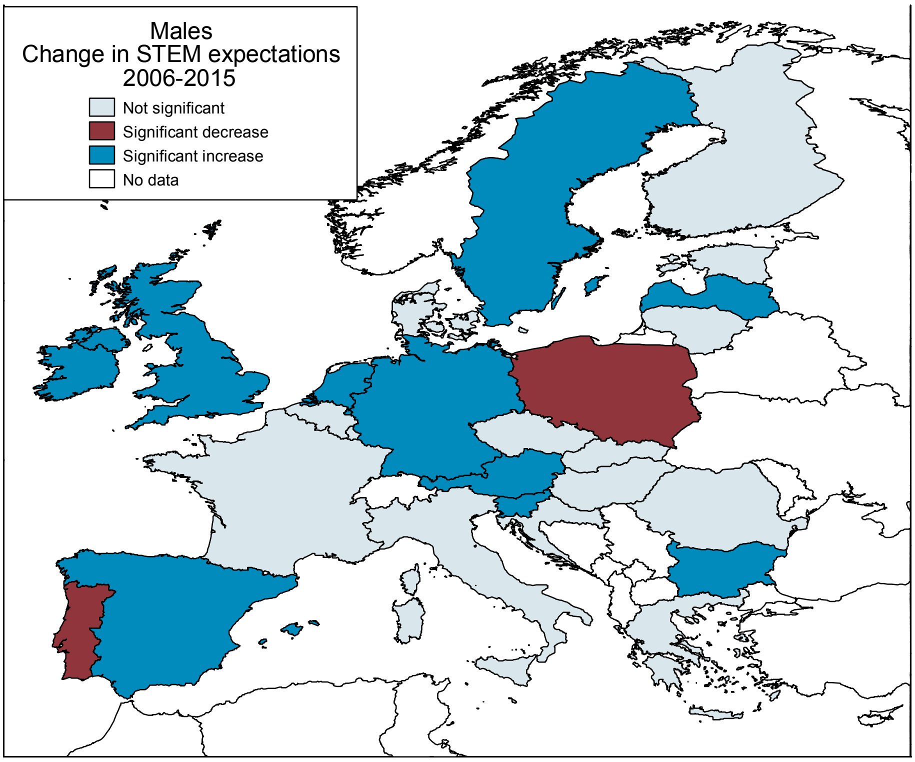


Table 6.2. Change in STEM career expectations between 2006 and 2015 among females and males. Proportions, Standard Errors and Changes

	Females						Males					
Country	Prop. in 2015	Std. error	Prop. in 2006	Std. error	Change	SE	Prop. in 2015	Std. error	Prop. in 2006	Std. error	Change	Std. error
Austria	**0.091**	(0.006)	**0.072**	(0.008)	0.018	(0.010)	**0.321**	(0.018)	**0.245**	(0.018)	**0.076**	(0.025)
Belgium	**0.087**	(0.009)	**0.082**	(0.009)	0.005	(0.012)	**0.238**	(0.014)	**0.256**	(0.015)	−0.019	(0.021)
Bulgaria	**0.148**	(0.012)	**0.148**	(0.009)	0.000	(0.015)	**0.330**	(0.018)	**0.161**	(0.010)	**0.169**	(0.021)
Czech Republic	**0.069**	(0.005)	**0.087**	(0.011)	−0.018	(0.013)	**0.281**	(0.013)	**0.267**	(0.020)	0.014	(0.024)
Germany	**0.114**	(0.006)	**0.077**	(0.006)	**0.037**	(0.009)	**0.271**	(0.010)	**0.234**	(0.015)	**0.037**	(0.018)
Denmark	**0.089**	(0.008)	**0.077**	(0.007)	0.013	(0.010)	**0.237**	(0.010)	**0.220**	(0.011)	0.016	(0.014)
Estonia	**0.140**	(0.008)	**0.149**	(0.009)	−0.009	(0.012)	**0.377**	(0.010)	**0.263**	(0.015)	**0.114**	(0.018)
Greece	**0.108**	(0.007)	**0.159**	(0.010)	**−0.050**	(0.012)	**0.268**	(0.011)	**0.286**	(0.012)	−0.018	(0.016)
Spain	**0.120**	(0.007)	**0.105**	(0.005)	0.015	(0.009)	**0.303**	(0.009)	**0.298**	(0.010)	0.005	(0.013)
Finland	**0.039**	(0.005)	**0.059**	(0.005)	**−0.020**	(0.007)	**0.197**	(0.010)	**0.177**	(0.008)	0.020	(0.013)
France	**0.091**	(0.007)	**0.071**	(0.007)	**0.020**	(0.010)	**0.279**	(0.011)	**0.254**	(0.013)	0.026	(0.017)
Croatia	**0.101**	(0.010)	**0.070**	(0.007)	**0.031**	(0.012)	**0.314**	(0.018)	**0.307**	(0.020)	0.008	(0.027)
Hungary	**0.077**	(0.006)	**0.069**	(0.007)	0.008	(0.009)	**0.279**	(0.016)	**0.252**	(0.017)	0.027	(0.023)
Ireland	**0.095**	(0.006)	**0.056**	(0.006)	**0.038**	(0.009)	**0.282**	(0.009)	**0.240**	(0.011)	**0.042**	(0.014)
Italy	**0.103**	(0.008)	**0.097**	(0.006)	0.007	(0.010)	**0.314**	(0.015)	**0.301**	(0.013)	0.013	(0.020)
Lithuania	**0.119**	(0.006)	**0.112**	(0.008)	0.007	(0.010)	**0.269**	(0.010)	**0.255**	(0.010)	0.014	(0.014)
Luxembourg	**0.095**	(0.006)	**0.086**	(0.006)	0.009	(0.009)	**0.276**	(0.009)	**0.255**	(0.009)	0.021	(0.013)
Latvia	**0.156**	(0.008)	**0.116**	(0.008)	**0.040**	(0.011)	**0.317**	(0.011)	**0.252**	(0.014)	**0.065**	(0.018)
Netherlands	**0.078**	(0.005)	**0.046**	(0.005)	**0.032**	(0.007)	**0.257**	(0.011)	**0.164**	(0.010)	**0.093**	(0.015)
Poland	**0.087**	(0.007)	**0.101**	(0.006)	−0.014	(0.009)	**0.238**	(0.010)	**0.368**	(0.012)	**−0.130**	(0.015)
Portugal	**0.132**	(0.008)	**0.152**	(0.008)	−0.020	(0.011)	**0.344**	(0.012)	**0.414**	(0.015)	**−0.070**	(0.020)
Romania	**0.092**	(0.008)	**0.085**	(0.008)	0.007	(0.011)	**0.222**	(0.015)	**0.215**	(0.013)	0.007	(0.020)
Sweden	**0.101**	(0.007)	**0.100**	(0.008)	0.001	(0.010)	**0.293**	(0.011)	**0.249**	(0.014)	**0.044**	(0.018)
Slovenia	**0.108**	(0.007)	**0.095**	(0.007)	0.013	(0.010)	**0.420**	(0.010)	**0.362**	(0.010)	**0.058**	(0.015)
Slovakia	**0.087**	(0.008)	**0.056**	(0.007)	**0.030**	(0.011)	**0.287**	(0.012)	**0.267**	(0.017)	0.021	(0.021)
United Kingdom	**0.112**	(0.006)	**0.070**	(0.005)	**0.042**	(0.008)	**0.303**	(0.009)	**0.191**	(0.007)	**0.111**	(0.011)
EU-26	**0.102**	(0.001)	**0.168**	(0.003)	**−0.066**	(0.002)	**0.289**	(0.002)	**0.168**	(0.003)	**0.122**	(0.004)

6.2 Changes in the gender gap

As was shown in the previous section, and as with the level of overall interest, gender segregation in STEM career plans also did not change uniformly across the Member States, and even when the direction of the change was similar, it was driven by different processes across the Member States.

Data provided in Table 6.3 show that, in the EU-26, the overall size of the gender gap grew by 2 percentage points between 2006 and 2015. This was mostly due to a massive increase in Bulgaria (17 percentage points) and more modest increases in Estonia (12 percentage points), the United Kingdom (7 percentage points), Austria and the Netherlands (6 percentage points), Slovenia (5 percentage points), and Sweden and Finland (4 percentage points). In the other countries, the size of the gender gap remained unaffected or even decreased. In Poland, the gap decreased by 12 percentage points, and in Portugal by 5 percentage points.

Table 6.3. Change in STEM gender gap expectations between 2006 and 2015. Difference in proportions (Gap) and Standard error.

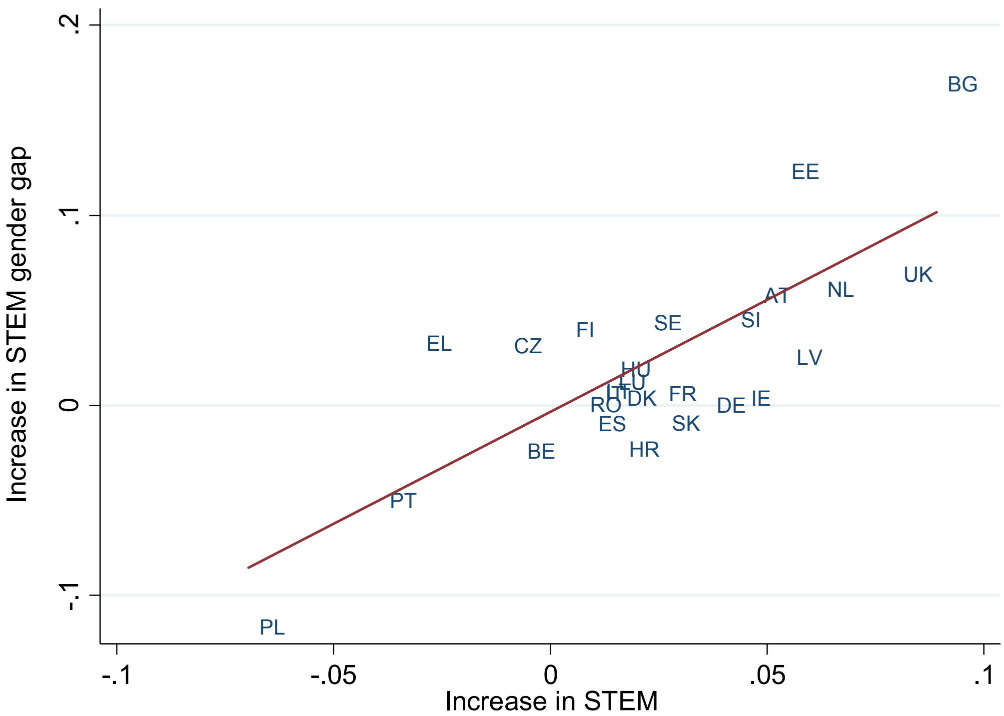
Country	Gap 2015	Std.error	Gap 2006	Std.error	Gap change	Std.error
Austria	**0.231**	(0.019)	**0.173**	(0.020)	**0.058**	(0.027)
Belgium	**0.150**	(0.017)	**0.174**	(0.017)	−0.024	(0.024)
Bulgaria	**0.182**	(0.022)	0.013	(0.014)	**0.169**	(0.026)
Czech Republic	**0.211**	(0.014)	**0.180**	(0.023)	0.031	(0.027)
Germany	**0.158**	(0.012)	**0.158**	(0.016)	0.000	(0.020)
Denmark	**0.148**	(0.012)	**0.144**	(0.012)	0.004	(0.018)
Estonia	**0.237**	(0.013)	**0.114**	(0.017)	**0.123**	(0.021)
Greece	**0.160**	(0.013)	**0.127**	(0.015)	0.033	(0.020)
Spain	**0.183**	(0.011)	**0.193**	(0.011)	−0.010	(0.016)
Finland	**0.158**	(0.011)	**0.118**	(0.009)	**0.040**	(0.014)
France	**0.188**	(0.013)	**0.182**	(0.015)	0.006	(0.020)
Croatia	**0.213**	(0.020)	**0.237**	(0.021)	−0.023	(0.029)
Hungary	**0.201**	(0.017)	**0.183**	(0.018)	0.019	(0.025)
Ireland	**0.187**	(0.011)	**0.183**	(0.013)	0.004	(0.017)
Italy	**0.210**	(0.017)	**0.204**	(0.014)	0.006	(0.022)
Lithuania	**0.150**	(0.012)	**0.143**	(0.013)	0.007	(0.018)
Luxembourg	**0.181**	(0.011)	**0.169**	(0.011)	0.012	(0.015)
Latvia	**0.161**	(0.014)	**0.136**	(0.016)	0.025	(0.021)
Netherlands	**0.178**	(0.012)	**0.117**	(0.011)	**0.061**	(0.016)
Poland	**0.150**	(0.012)	**0.267**	(0.013)	**−0.117**	(0.018)
Portugal	**0.212**	(0.014)	**0.262**	(0.017)	**−0.050**	(0.023)
Romania	**0.131**	(0.017)	**0.130**	(0.016)	0.000	(0.023)
Sweden	**0.193**	(0.013)	**0.149**	(0.016)	**0.043**	(0.021)
Slovenia	**0.311**	(0.012)	**0.266**	(0.013)	**0.045**	(0.018)
Slovakia	**0.201**	(0.015)	**0.210**	(0.018)	−0.009	(0.023)
United Kingdom	**0.191**	(0.011)	**0.121**	(0.009)	**0.069**	(0.014)
EU-26	**0.188**	(0.003)	**0.168**	(0.003)	**0.020**	(0.004)

Figure 6.3 plots the changes in the level of STEM career plans against the size of the gender gap by country. It reveals a clear positive relation between the two, suggesting that in most of

the countries where an increase in the level of students' interest in STEM was achieved, this happened at the cost of an increased gender gap. In particular, in Bulgaria, Estonia, the United Kingdom, the Netherlands, Austria, Sweden and Slovenia, the considerable growth in interest was accompanied by an increase in the level of gender segregation. This is because, in these countries, the growth either affected males only, or it affected males to a considerably higher extent than females. In Finland, on the other hand, the increased gender gap is a consequence of female students' decreasing motivation to enter a STEM occupation.

It is important to note that in Germany, Ireland and Latvia some improvement in the overall interest was achieved without increasing gender segregation. In these three countries, the proportion of STEM-oriented students grew by 4 to 5 percentage points, and this growth was more or less equally distributed across the genders – leaving the size of the gender gap unaffected. On the other hand, in none of the Member States did the size of the gender gap decrease, unless – as in Poland and Portugal – significantly fewer male students expressed an interest in STEM occupations in 2015 than in 2006.

Figure 6.3. Relation between changes in STEM and changes in STEM gender gap.



6.3 Explaining the change

6.3.1 Students and their schools

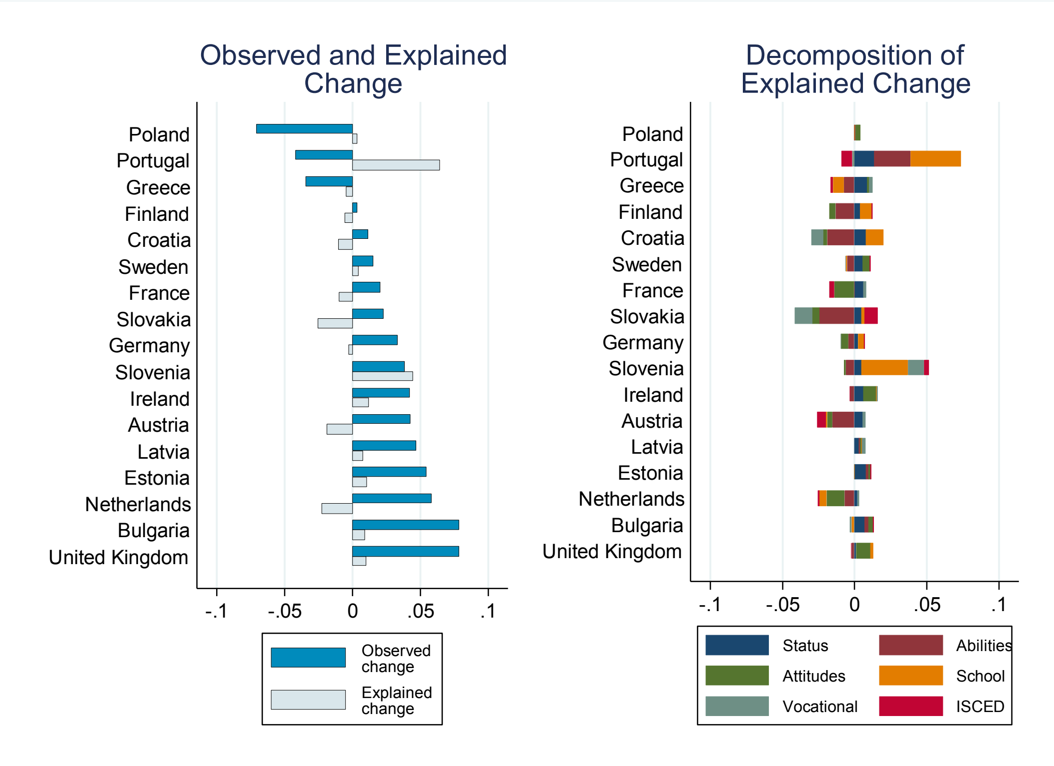
One potential explanation for changes between 2006 and 2015 is the changes in student- and school-related factors over this period. For instance, as we know, science abilities are strongly related to choosing STEM occupations, and therefore with an increase of abilities in one country we would expect an increase of interest in STEM careers. Similarly, an increase can be expected if the share of students with a parent in STEM employment, the overall level of enjoyment of science or the share of students in vocational schools has increased. In this section, we present an analysis that decomposes the change in STEM career expectations between 2006 and 2015, using the changes in the distribution of variables studied in chapter 5 (excluding grade repetition, which was not available for the year 2006, and compositional variables, which are functionally related to individual-level variables). The Oaxaca decomposition model was applied (see chapter 3 for more details).

Results of Oaxaca decomposition are shown in Figure 6.4. for countries where, between 2006 and 2015, a significant change in the level of STEM expectations occurred – either overall or in one of the gender groups (see Tables 6.1 and 6.2). In the left panel of the figure, we present the observed changes in STEM expectations – as reported in PISA data (dark blue bars) – against explained changes (light blue bars), that is, the changes that we could expect considering the changes in the distribution of explanatory variables (similar information is represented for males and females separately in Figure 6.5). Results presented in the graphs were sorted by the size of observed change.

As one can see, the explained change in most cases does not fully account for the observed change (i.e. the light blue bar is shorter than the respective dark blue bar), suggesting that the observed change was greater than one would expect on the basis of the changes observed in our explanatory variables. Nevertheless, if the explained changes point in the same direction as observed changes do, we assume that explained change accounts for the observed change. Thus explained change represents the part of the observed change related to changes in population characteristics, while the difference between the observed and the explained change is what we call unexplained change. In the United Kingdom, for example, an increase of 8 percentage points was observed in the share of STEM-oriented students, but of this, only 1 percentage point can be explained, leaving 7 percentage points unexplained. Only in Slovenia did the explained change account for the full observed change. In this case, the explained component even exceeds the observed change, suggesting that on the basis of changes in the explanatory variables one would expect even greater increase in the number of students interested in STEM in Slovenia.

Notably, the direction of the explained changes are not always aligned with the direction of the observed changes. In such situations, we can assume that some other factors (unmeasured student-, school- and/or country-related factors, and/or world culture factors) were interfering in the opposite direction and altered the effects of changes in the distributions of explanatory variables used in our analyses. One remarkable example is Portugal, where students' interest in STEM decreased despite some favourable changes in the factors observed in this study.

Figure 6.4. Observed and explained changes, and results from Oaxaca decomposition for countries where a significant change in the level of STEM expectations occurred (either overall or in one of the gender groups).



The right panel of Figure 6.4 (as well as the set of two panels in Figure 6.6) then show the decomposition of the explained change, showing how changes in the various sets of factors between 2006 and 2015 could have contributed to the level of students' interest in undertaking a STEM career. Here we grouped the various contributing factors into six categories: 'status' refers to the composition of the student body in terms of parental socio-economic status, number of students with a parent in STEM employment and migrant status; 'abilities' denotes science test scores; 'attitudes' represents enjoyment of science and science self-efficacy; 'school' refers to the level of school autonomy, the existence of science clubs and the average students' science abilities in the school; 'vocational' reflects whether or not the student is in a vocational programme; and 'ISCED' stands for the ISCED level at which they are studying. As discussed above, on the basis of changes in the distributions of explanatory variables, for instance in Portugal, we would expect an increase in STEM interest. Changes in the school-level factors by themselves could have resulted in a 4-percentage-point increase in the level of STEM vocational interest, and the increase in students' abilities could have contributed by another 2.5 percentage points. The negative change occurred despite all these favourable tendencies, for reasons that we cannot identify using our models.

Generally, we can see that our explanatory variables have not been successful in explaining a decrease in the overall levels of interest in any of the three countries where such a decline occurred. Besides Portugal, this is also the case for Poland and Greece. Moreover, the contribution of factors we control for also seems to be limited to the more positive changes in the other countries. Among the places where the greatest growth in the level of interest was registered, in the United Kingdom this can mostly be related to students' growing enjoyment of science (this explains 1 percentage point of the improvement), but in Bulgaria, Estonia and Latvia it can be related more to an increase in parents' socio-economic status. In Latvia, an increase in the share of students in vocational programmes may also have contributed slightly to the increase in the level of students' STEM aspirations.

As we have seen, Germany and Ireland were the two countries most successful in increasing the number of students considering a STEM career without widening the gender gap in STEM (see Table 6.2, Table 6.3 and Figure 6.5). In the case of Germany, unfortunately, our data tell us very little about the factors driving this change (Figure 6.6). For Ireland, though, it seems that – besides the increased share of immigrant students in classrooms – more enjoyment of science also contributed to this improvement, but mostly for males (Figure 6.6).

Finally, Slovenia represents an interesting case, as here we can obtain a reasonably good understanding of the different tendencies that contributed to the overall 4-percentage-point increase in students' – mainly males' – interest in STEM occupations. As can be seen from Figure 6.4., all the change observed in this country can be attributed to the factors we have controlled for (moreover, based on these factors, an even greater increase in the level of interest might have occurred). Although, overall, change in the number of science clubs, the increased share of students in the vocational track, and also, to a lesser extent, a growth in parents' status and students' self-efficacy had contributed to the change, looking at gender differences also shows that, for males, increased vocationality and science competitions were particularly important (see Tables A6.2, A6.3 and A6.4 in the appendix).

Figure 6.5. Observed and explained changes for countries where a significant change in the level of STEM expectations occurred, by gender.

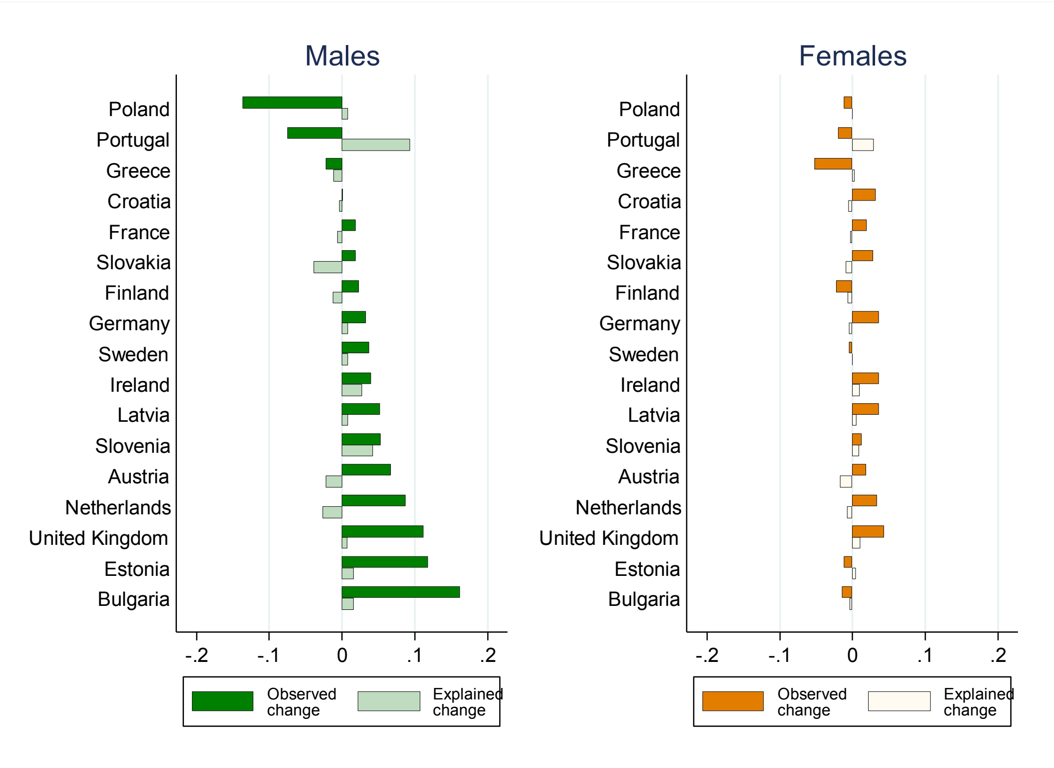
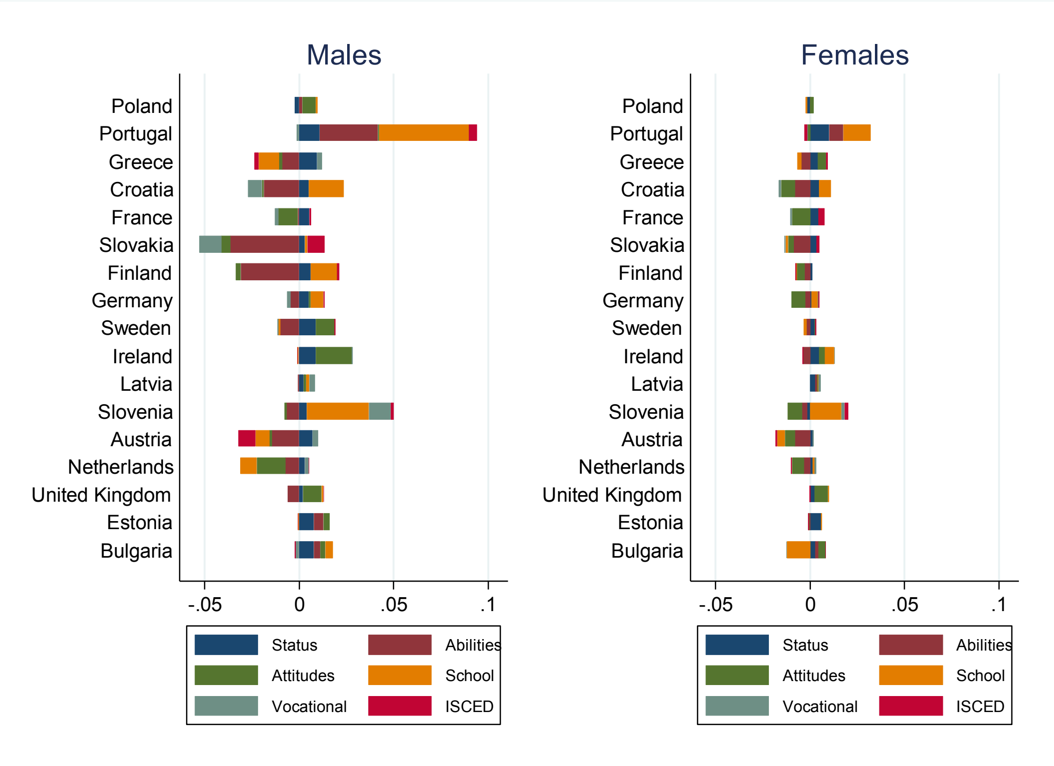


Figure 6.6. Results of Oaxaca decomposition for countries where a significant change in average STEM expectations occurred, by gender.



6.3.2 Country-level factors

Finally, we move on to country-level factors. We used country-level variables as explanatory variables in a multilevel model to explain the overall level of STEM expectations, as well as the gender gap in the two cohorts, using the pooled sample of countries that participated in both PISA 2006 and 2015 ([28]). In the model, we included country-level variables that were significantly related to career expectations in 2015 (see chapter 5) and for which we have reliable information both for 2006 and 2015. The following variables met these criteria: HDI, GII and vocational orientation (VOCAT). Similar to the models in chapter 5, individual- and school-level variables were introduced as control variables. The additional variable describing time (TIME) was coded as a dummy variable (0 for 2006 and 1 for 2015). TIME coefficient (main effect) describes the difference between 2006 and 2015 in the STEM level, a general trend that was similar across the various countries. We also specified interactions between time dummy and country-level variables (for instance, TIME*HDI). Coefficients of such interaction variables show whether or not countries with higher levels in the country-level variables (such as HDI) experienced stronger increase in STEM career interests. This might be understood as a difference in differences (DiD) approach, where treatment variables such as HDI reflect the intensity of treatment effect rather than the binary fact of treatment occurrence (Acemoglu et al., 2004). In other words, we could explore whether or not changes in STEM expectations and changes in the size of the gender gap might be related to changes in the level of country-level explanatory variables (Angrist and Pischke, 2009; Murnane and Willett, 2010). This approach is closer to the causal inferences than simple regression modelling, and should provide more robust information. We retain individual-level variables as controls for the analysis but do not report their effects, as the full analysis is presented in chapter 5.

In Tables 6.4 and 6.5, the main effects of the country-level variables (HDI, vocational orientation and GII) on overall level of STEM (gender gap) are presented, together with the time effect and the interaction effects between TIME and the respective country-level variables. The main effects of the country-level variables might be interpreted as the general

([28]) Here we present results from LPM, as they are easier to interpret, especially in the presence of interaction terms. We also tested a multilevel logistic model, and the results of both approaches bring the same conclusions.

relation between interest in STEM (gender gap) and HDI (vocational orientation or GII). At the same time, the interaction terms HDI*TIME (GII*TIME) indicate whether or not the country-level changes in students' interest in STEM (gender gap) can be attributed to country-level changes in HDI (vocational orientation or GII) (Angrist and Pischke, 2009; Murnane and Willett, 2010).

Table 6.4. Country-level effects of final multilevel LPM specification with HDI.

	Model A1		Model A2	
	Estimate	*P*-value	Estimate	*P*-value
Level of STEM (intercept) on				
HDI	−0.562	0.002	−0.559	0.099
HDI*TIME	0.116	0.577	0.110	0.768
VOCAT	−0.006	0.840	0.025	0.571
VOCAT*TIME	0.064	0.094	0.078	0.195
TIME	0.035	0.000	0.043	0.001
Gender gap (female slope)				
HDI			−0.013	0.972
HDI*TIME			0.022	0.954
VOCAT			−0.029	0.595
VOCAT*TIME			−0.063	0.117
TIME			−0.017	0.089

Coefficients of the TIME variable across all the countries indicate an increase of 4% in the overall level of interest in STEM between 2006 and 2015 that was irrespective of the other factors we account for. At the same time, the gender gap also decreased slightly – although here the statistical significance is not very high (*p*-value 0.089).

Considering HDI and GII we find no significant DiD estimates bound either to changes in students' overall interest in STEM or to changes in the size of the gender gap. Increase of HDI was positively related to increase of STEM expectations (HDI*TIME), but the relation was not statistically significant ($p = 0.577$ in model A1 and $p = 0.768$ in model A2). This means that there is some tendency for an increase of overall interest in STEM when a country's HDI is increasing, but this tendency is statistically rather weak. The situation is similar with GII – there is slight positive effect in DiD estimates but it is not significant.

The only statistically significant DiD estimate here is that change in the proportion of students enrolled in vocational programmes is positively related to changes in students' interest in STEM occupations (coefficient for VOCAT*TIME). This finding is notable even though the coefficient is only significant at the 0.1 level in the specification that includes HDI, and loses its significance when the female slope is also taken into account (Table 6.4). However, given the relatively small case numbers (number of countries) in the models, we can consider this as reasonable evidence that in countries where the vocational upper secondary education sector was developed, an increase also occurred in the number of students who are planning a STEM career.

Table 6.5. Country-level effects of final LPM multilevel specification with GII.

	Model A1		Model A2	
	Estimate	*P*-value	Estimate	*P*-value
Level of STEM (intercept) on				
GII	0.168	0.194	0.079	0.659
GII*TIME	0.021	0.890	0.105	0.607
VOCAT	0.014	0.611	0.043	0.316
VOCAT*TIME	0.061	0.108	0.077	0.178
TIME	0.028	0.015	0.034	0.038
Gender gap (female slope)				
GII			0.177	0.233
GII*TIME			–0.169	0.321
VOCAT			–0.057	0.161
VOCAT*TIME			–0.034	0.515
TIME			–0.012	0.331

6.4 Summary

In this chapter, we have provided a descriptive analysis of the changes observed in the EU Member States between 2006 and 2015 in the share of 15-year-old students who expressed an interest in working in STEM areas. Moreover, we also looked at how these changes affected the size of the gender gap in this interest across the various countries. Finally, we made an attempt to relate these changes to changes in the various individual-, school- and country-level factors that we could account for in our analysis.

Our results have shown that the various Member States have been going through different paths in the 10-year period discussed here. While in a number of Member States a more substantial increase in the level of males’ interest was achieved, with or without a small increase in females’ STEM aspirations, only in Germany and Ireland did a more or less gender-neutral growth in interest in STEM occupations occur. From the data PISA provides it is hard to identify the processes guiding these changes, and it is not possible to point to any consistent pattern across the countries related to the changes. In fact, the lack of explanatory power in our variables is more helpful in discounting than in providing explanations for the tendencies described in the various countries. The most important finding from the multilevel analysis points (again) at the relevance of vocationality, as it shows that an increase in the share of students interested in STEM occupations was most likely to occur in countries where the number of students in the vocational upper secondary programmes has also increased.

7 Conclusions and policy implications

7.1 STEM career expectations matter

European labour markets require substantial science, technology, engineering and mathematics (STEM) workforce equipped with upper secondary and tertiary credentials. As STEM workers can be found in the technologically most advanced and potentially most productive sectors of the labour market, meeting the labour force demand for STEM skills is considered a high priority in the EU. In fact, the prospect of shortages in STEM-skilled labour has been named one of the main barriers to economic growth in the first half of 21st century (Caprile et al., 2015, p. 12). There is widespread concern that lack of sufficient STEM labour supply may hinder future economic development and reduce economic competitiveness across the EU (European Commission et al., 2015). The European Commission has listed science and engineering professionals in second place in its list of the 10 occupations that are most difficult to fill, with ICT professionals following in third, and science and engineering associate professionals in seventh place (Attström et al., 2014).

The shortage of STEM skills can arguably be addressed by increasing the participation in STEM of groups that are currently underrepresented – predominantly women (Gonzalez and Kuenzi, 2012; Caprile et al., 2015). Attracting more females into STEM education and consequently into STEM employment is seen as a suitable response to the challenge of low supply. This will broaden the pool of applicants and potential recruits (Gonzalez and Kuenzi, 2012; ICF and Cedefop, 2014; European Commission, 2017), as well as reduce gender segregation in the labour market (Burchell et al., 2014).

Although not all STEM graduates enter STEM occupations, a strong pathway dependency exists between STEM education and employment. In secondary schooling, individual field-of-study specialisation and ability streaming create path dependencies that determine later entry into tertiary education and the labour market. Teenagers' career plans are indicative of their future educational careers as well as their employment, even as far as specific professional choices are concerned (Tai et al., 2006; Sikora, 2014). Therefore, any analysis of the supply and demand factors that affect the availability of STEM skills needs to recognise the implications that early education and vocational orientations of youth have for their later ability and willingness to undertake STEM training and work.

In our report, we have systematically explored a range of potential influences on young people's career plans, starting from individual characteristics, then moving through school-level factors to interventions at the national level. For the analysis, we used the PISA data from 2006 and 2015 for each of the EU Member States. We attempted to explain as well as identify changes in science-related occupational expectations that occurred during this 10-year period.

The level of interest in STEM occupations among adolescents remained stable or even increased in many European countries over the decade, yet we have also noted the persistent gap between males and females across the whole of Europe. We have considered possible motives that may lead young people to consider the pursuit of a STEM career, including factors related to their families, school environments and country of residence.

7.2 Main findings and their policy implications

7.2.1 STEM career expectations vary between countries and by gender

In 2015, on average, 20 in every 100 15-year-old students in Europe planned to pursue a science-related career. However, considerable differences exist across countries. In Finland, for instance, only 12 in every 100 students are interested in STEM careers, in Sweden 20 students (which is closest to the EU average), and in Slovenia 27 in every 100 students expect such careers.

Expectations of STEM career plans are also strongly differentiated by gender. On average, in Europe, only 10 out of every 100 females are interested in STEM careers, while the number of males expecting a similar career is nearly three times higher. Between-country differences in this gender divide are also considerable. In Finland, only 4 out of every 100 female students want to engage in STEM, while in Latvia the number of females that see their future in STEM occupations is 4 times higher, as 16 out of every 100 adolescent females expect to work in STEM occupations.

The past 10 years have not brought about major changes in European students' career orientations towards STEM. The share of 15-year-olds considering such an occupation increased only marginally – and rather unevenly – across the Member States, while gender segregation remained deep, showing a tendency to persist across EU Member States. Notably, in most countries that experienced a significant increase in the overall level of students' interest in STEM, an increase in the size of the gender gap also occurred. This suggests that, over time, what is growing is mostly the proportion of males – not females – who are interested in STEM.

7.2.2 Students expecting an STEM career are good at science and sometimes enjoy science

First, improving students' abilities in the sciences is undoubtedly key to raising young people's interest in related occupations. The more schools can promote students' capacity to understand scientific concepts and ideas, the more students will consider entering an occupation in this field. However, the relationship between academic performance in science and the development of an occupational interest in science is stronger for males than females. In fact, the vocational expectations gap between males and females is greater between top achievers than between students who are average or below average. Although females with outstanding science abilities who do not choose a STEM career might be considered to have wasted an opportunity, we have shown in this report that their talent it is likely to be utilised in health-related professions.

Enjoyment of science is positively and significantly related to students' expectations of pursuing a science career. But, again, gender differences exist. On average, females enjoy science less than males; moreover, the relation between science enjoyment and interest in STEM occupations is weaker for females than for males. Therefore, there is scope for raising the level of enjoyment of science and strengthening the link between positive attitudes toward science and science career choices among females, in the hope that this greater enjoyment will lead them to consider a future in science. As long as males continue to enjoy science more than females, growth in the proportions of students who become interested in science careers, because of enjoyment of the field, will occur at the price of increasing gender segregation. Thus, creating more interesting and enjoyable science lessons that appeal to males without recognising the gendered differences in attitudes to science and science interests might increase the number of future STEM employees but without the beneficial effect of reducing the level of gender segregation.

It also needs to be emphasised that the effects of enjoyment in science on science career aspirations are context dependent. Our analysis suggests that reliance on increasing enjoyment of science can lead to different consequences in different cultural environments and educational systems. While in European countries without a socialist past enjoyment in science is significantly related to STEM career choice, in most post-socialist countries students' STEM career choice is unrelated to whether or not they enjoy learning science. In these countries, the motivation to choose STEM careers seems to be more instrumental, and therefore efforts to increase science enjoyment of students may be desirable in their own right, rather than on the basis of the relationship between enjoyment and occupational expectations.

7.2.3 Potential parental role modelling

We also find that, of the students' family background characteristics, the factor that comes across as most influential is parental employment in STEM. All in all, parental role models contribute to adolescent vocational goal forming. This effect does not negate the possibility that parents employed in non-science occupations can actively encourage science orientation in their children. Rather, it suggests that parents who work in the science sector are more successful in influencing their children than other parents, regardless of whether or not they make a conscious effort in this direction. Our analysis indicates that sons are more receptive to modelling their occupational interests in alignment with parental employment in STEM. This is mostly because males are more influenced by their fathers' STEM employment than females. Mothers also serve as role models for STEM occupations and they influence daughters and sons to a similar extent, which may be interpreted as an indicator that more gender-neutral parental role modelling will be the thing of the future. However, it has to be borne in mind that so far the proportions of mothers employed in STEM are relatively low. Nevertheless, clearly the potential exists to popularise female role models, particularly mothers, among female adolescents. Fathers are already influential role models, but there is a scope to strengthen the influence of mothers and to broaden the visibility of those mothers who work in STEM. Another potential way of popularising STEM occupations is to encourage females to consider STEM jobs held by their fathers as attractive choices.

7.2.4 Migrant students choose STEM

Migrants show a greater interest in science careers than other students who are comparable with respect to their science performance, attitudes, and parental cultural and socio-economic background. This might be connected with the fact that, for at least some of the STEM occupations, language skills may be of lesser importance, while other competencies matter more. STEM occupations therefore seem to be an attractive choice for students that want to pursue professional careers in their new country.

A closer look at migrants' career choices provide further insights, revealing that the greater interest in STEM in migrant populations comes mostly from males. Although the pattern is not universal, it is the migrant males that plan to pursue STEM careers more often than the rest of the student population, while migrant females are much closer to native females.

As in general migrant students show a greater interest in science careers than other students, and as STEM occupations seem to be attractive choices for students who want to pursue professional careers in their new country, science education might be considered an attractive tool for promoting the integration of migrants.

7.2.5 School practices make a difference

Schools can be more or less well equipped to teach sciences and they can also offer different opportunities to engage in science outside compulsory classes. However, we have found that neither the resources available for science teaching nor the provision of science clubs in schools can be directly linked to students' plans for a STEM career. Science competitions, however, have a marginal positive association with the level of interest in STEM occupations, although this is the case more for males than for females. Given the literature that suggests that males prefer competition while females prefer cooperative activities, the practice of offering science competitions to students to evaluate their science competencies may need to be balanced out by more cooperative science activities that rely on teamwork rather than competition, to make sure that the tendency towards segregation is not strengthened.

7.2.6 School practices make a difference, particularly in education systems with early selection and high levels of vocationality

Students develop their career plans differently in different educational systems across Europe. One key factor is the timing of sorting into vocational versus academic tracks. In most countries, students who are on a vocational track by the age of 15 are more interested in choosing a STEM job than other students. This is also evident in the country-level analysis, where system vocationality has a positive relationship with vocational interest in STEM, after controlling for many other factors. Between-country comparisons reveal that this positive influence is strong in education systems where upper secondary vocational programmes offer a smooth transition to tertiary education. However, none of the examined characteristics of the national education systems made any significant difference for bridging the gap between males' and females' STEM expectations, either in the pooled sample or in country-by-country analysis.

Although we have not found any statistically significant, systematic associations between the characteristics of the education system and gender differences in students' vocational choices, it is still plausible to assume that certain educational system characteristics are relevant to the gender divide in STEM. For instance, in six Member States (Austria, Bulgaria, Croatia, Italy, Slovakia and Slovenia), school-level factors are likely to be linked to students' vocational interests in STEM as well as to the size of the gender-related gap. If 15-year-olds attended more similar schools in these countries, males and females would make more similar occupational choices, at least as far as STEM careers are concerned. In these Member States, students go through the first educational sorting before the age of 15, and a large number of them are already on a vocational track. From this we might conclude that early selection and a high level of vocationality foster gender divides. Most importantly, the share of females in a school is positively correlated with smaller STEM-related gender differences, implying that, with less gender segregation between schools, more gender-balanced occupational choices are possible. One possible explanation is that, in these countries, early selection is associated with females' concentration in education programmes that promote interests and careers unrelated to STEM. Examples might be vocational schools with an orientation towards traditionally female-dominated employment such as healthcare, but also non-vocational schools that offer the opportunity to specialise in the human sciences. Moreover, in Austria, Bulgaria, Croatia and Slovenia, males – relative to females – may be more inclined to choose a STEM career when they find themselves in academically strong environments, i.e. where the average science performance of students reaches a higher level. Therefore, instead of converging, males' and females' career plans may diverge in education systems with early selection of students where overall academic science performance is strong.

7.2.7 National educational policies may matter

To expand our analysis beyond the distinctions between stratification, vocationality and standardisation, as key features of educational systems, in this study we explored the potential influences of a range of educational approaches and policies that are typically initiated at the national level. With this intention, several groups of indicators were collated, mostly from Eurydice's reports on science and mathematics teaching (Eurydice, 2011a, 2011b). They were indicators of (1) national activities for promoting STEM education, (2) the contextual information included in science teaching, (3) ability grouping in science and mathematics teaching and (4) directly addressing the gender issue in mathematics teaching. Our analysis shows that the key factor that encourages males and females to consider a STEM-related career is having compulsory mathematics exams at the end of upper secondary education. None of the other education policy-related characteristics is related to adolescents' vocational interest in STEM.

Our findings suggest a significant positive association between compulsory national examination in maths and students' plans to enter a STEM occupation. Although the association was not confirmed in all statistical tests, it indicates that the existence of standardised maths tests at the end of upper secondary education may promote students' career expectations in STEM. A possible mechanism behind the positive association we have identified is that facing a compulsory maths exam at the end of secondary education may force students to continue studying this subject even if, in a less standardised system, they might have dropped or at least neglected this area of study. It needs to be emphasised that these findings are not in line with previous studies that focused on examinations. So far, research on the topic has been limited to one study (Han, 2016), which revealed a significant negative relationship between the existence of standards-based external exams in science and students' plans to work in STEM across 55 PISA countries in 2006. The association explored was consistent across gender and also students' level of science performance. Han argued that the negative influence was possibly generated by overly standardised exam-preparatory teaching practices, which cooled students' attitudes towards science. Alternatively, it seems that, in Europe, the necessity of preparing for standardised external testing provides a context in which a number of students find an opportunity to consider STEM as a future career, and students' career expectations become more realistic, by being more strongly associated with school performance.

7.3 Further policy recommendations

In terms of policy measures designed to mitigate the gender gap in the supply of young people available to train for employment in the STEM sector, the patterns presented in this report indicate an urgent need to develop more effective methods to encourage females to consider STEM employment as a viable option for their own future. It is important to note that the distribution of teenage expectations presented here does not necessarily imply that the policies used to encourage youth to take interest in STEM have been unsuccessful. It is possible that the cultural contexts and economic incentives in European economies are conducive to strengthening gender segregation in youth occupational expectations over time, and that the educational policy designed to counteract these tendencies has been successful in keeping segregative tendencies in check over time. But more research is needed to directly address this issue.

The results presented in this report indicate that the interventions capable of positively influencing the overall level of students' interest in STEM occupations are not necessarily the same as those that can be efficient in decreasing gender segregation. This implies that pedagogical approaches and policy tools need to be selected with great care, taking into account potential influences not only on the STEM labour supply in general but also on gender segregation in STEM in particular. Further, initiatives that aim to influence interest in STEM in a gender-balanced way are possible at various levels of potential policy intervention, from school-level policies to country-level education policies, and can be extended to take advantage of the collaborative efforts of all Member States.

If an increased supply of STEM workers is the key policy target, schools should be supported by educational policies in promoting maths and science competencies, enjoyment of science, and interest in science. Most importantly, improving students' abilities in sciences is a key tool for raising young people's interest in related occupations. Well designed curricula with good implementation of school teaching will result in larger numbers of students considering a science occupation. As our results suggest, good science curricula should be paired with proper assessment systems for science and maths competencies. As we can see, maintaining compulsory examinations in mathematics seems a good idea to give students an opportunity to contemplate and therefore discover an interest in STEM careers. Properly designed examinations and assessment systems could increase motivation for learning maths and science, and provide objective information about individual abilities. Developing a willingness to enter a science occupation and providing access to good information on individual students' science ability should be supported by tailored vocational counselling systems that will minimise rates of talent loss in science.

Additional recommendations for school-level policies include promoting science and enjoyment of science in a gender-sensitive way. Clearly, there is still room to creatively design curriculum activities that popularise science and STEM occupations. Up to now, most school-level science-promoting programmes and actions have showed rather marginal effect on students' vocational interest in STEM. The initiatives already in existence seem to appeal more to males than females, so the remaining challenge is to design curriculum activities that are at least as effective for females as for males.

Effective school and educational policies should target not only students but also parents, who can support children in the process of developing their career plans. Clearly, there is room for educating parents to assist in overcoming gender bias. This bias may pervade not only parental perceptions and values but also the environment in which young people grow up. Parents can be effective role models for STEM education or work, and effective mentors in orienting their children towards science. For this, parents and their children should receive reliable information about their children's achievements through the assessment system, as well as information on realistic vocational perspectives that takes into account both the level of abilities and the personal interest of children.

STEM education and career plans have provided the main foci of this report, but effective policy should also foster other science-related careers – for instance, careers in the health sector. As European societies age, health-related occupations will be in high demand. With the passage of time it is also highly probable that the progressive digitalisation of health services will bring the tasks performed in these occupations closer to the content of STEM jobs.

We have seen considerable interest in most EU Member States in promoting science careers, reflected in the fact that, at the national level, most Member States undertake some initiatives to promote science and maths. The European Commission could undertake action to coordinate exchange of best practices between Member States, with a view to promoting STEM careers in a gender-sensitive way. Moreover, the European Commission might suggest some standardised tools for monitoring and evaluation of practices promoting STEM education at school and country levels. From a broader perspective, the European Commission could coordinate work and information exchange on vocational counselling. A system that took as an input the interests and abilities of students on the one hand and the labour market situation on the other, as well as providing vocational guidance, might be of great value. Such a system might be built as an interactive web-based tool to facilitate country-level and school-level vocational counselling and science popularisation activities.

7.4 Limitations of the study and recommendations for further research

PISA is the only source of internationally comparable data on teenage career expectations that contains verbatim information about occupational titles nominated by adolescents as their future jobs. It is also the only source of such data collected at different points in time, and allows for detailed cross-country, cross-time analysis. Still, it is not without limitations. First, focusing on cross-country and cross-time comparability, it does not provide experimental data or tools for a quasi-experimental approach (Pokropek, 2016). Instead, with PISA data we are looking at various kinds of associations and conditional associations. It does not mean that causal inference is not possible with such data. If the temporal precedence is correctly specified, association is statistically significant and all plausible alternative explanations for an observed relationship are excluded, the causal claims may still be valid (Shadish, 2010; Shadish and Sullivan, 2012; Preacher, 2015), although the internal validity will always be weaker than that of properly designed experiments. Limitations of cross-country comparability also need to be kept in mind, as indicators and questions may not all have perfectly equivalent meanings in all of the countries and at all time points, because of cultural and language differences. Although PISA questionnaires were specially designed and checked to maintain comparability, in some situations this may still be an issue (Pokropek et al., 2017).

PISA data for 2006 and 2015 provide only a limited number of additional variables that are related to future career choices. While they provide ample opportunities to explore students' abilities and attitudes towards general science, they do not allow consideration in detail of dispositions towards other subjects relevant to STEM areas, most importantly mathematics and computing (ICT). Although analysis of PISA data has confirmed high levels of correlation between students' achievements in science and maths (OECD, 2017), little is known about how students who enjoy one subject feel about the other, or whether or not their level of confidence regarding the various subjects is also correlated. It is possible, for example, that for choosing a STEM career, enjoyment of ICT or mathematics is more important than science enjoyment or science self-efficacy. Consequently, further research should find ways of relating STEM career choices to attitudes towards mathematics and digital technology, rather than solely those towards general science. Including a survey question on students' career expectations in each PISA cycle, irrespective of the competency focus of the study, would significantly broaden the opportunities for explaining adolescents' career plans.

The other limitation of this analysis relates to the country-level data. The number of countries analysed in this report is very small, and, combined with small variations for most policy-relevant variables (most initiatives were introduced in most of the countries or not introduced at all), this does not provide high statistical power. In this situation, small and even medium effects may not be detected by the statistical analysis. Moreover, the measurement of most of the policy-relevant variables is prone to some imprecision and arbitrariness. In most cases, we do have information on whether or not a certain type of policy was implemented, but we do not have details about implementation (e.g. percentage of coverage, intensity of impacts, etc.). In addition, individual interventions are often broadly defined and thus may have very different meanings in different countries. Therefore, our analysis could provide only a broad picture of the relations between STEM expectations and policy-relevant variables, and the lack of associations found here certainly does not imply that none of the initiatives considered has had any impact. Much additional work needs to be done concerning country-level (but potentially also regional- and school-level) policy-relevant variables. The sources that currently exist are not very comprehensive, and a detailed catalogue of policy practices, coupled with information about the degree of implementation, might push further policy-oriented cross-country research forward.

Even though our study provides many insights on the topic, there is still work to be done. The conclusions drawn from PISA data should be explored and tested in more detail, using different approaches to confirm or refute our findings, and also to provide more tailored answers to policy-relevant questions. For instance, future research should explore and test a more specific hypothesis about parental role models and their involvement in shaping career expectations, but also answer the question of whether or not positive role modelling operates similarly outside the family circle. More research is also needed to explore migrant students' increased motivations for STEM careers. We could not go into detail on this issue here, as migrant students' STEM choices are country dependent and also conditioned by type of migration inflow, which could not be examined properly in this analysis because of sample size restrictions. Our country-specific findings concerning enjoyment of science also deserve more consideration in future, to better understand detailed mechanisms and context specificity related to the link between enjoyment of science and career expectations.

In the report, we have explained the persistence of gender segregation despite growth in the overall level of interest in STEM occupations. However, the level of interest in STEM and the extent of gender segregation varies country by country. We have shown that some aspects of the cross-country differences can be explained by the features of educational systems, such as the level of vocationality or the presence of compulsory maths examinations. We believe that more research on the relevant aspects of educational systems, at both country and regional levels, should be undertaken to follow up, test and enrich the results presented in this report.

References

Acemoglu, D., Autor, D. H., & Lyle, D. (2004). Women, war, and wages: the effect of female labor supply on the wage structure at midcentury. *Journal of Political Economy*, *112*(3), 497–551.

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, *80*(1), 123–129.

Alexander, K., Bozick, R., & Entwisle, D. (2008). Warming up, cooling out, or holding steady? Persistence and change in educational expectations after high school. Sociology of Education, 81(4), 371–396. https://doi.org/10.1177/003804070808100403

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion* (1st edition). Princeton: Princeton University Press.

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2010). "Doing" science versus "being" a scientist: Examining 10/11-year-old schoolchildren's constructions of science through the lens of identity. Science Education, 94(4), 617–639.

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2013). Not girly, not sexy, not glamorous': Primary school girls' and parents' constructions of science aspirations. Pedagogy, Culture and Society, 21(1), 171–194. https://doi.org/10.1080/14681366.2012.748676

Ashby, J., & Schoon, I. (2010). The role of aspirations, ambition and gender in predicting adult social status and earnings. *Journal of Vocational Behavior 77*(3), 350–360.

Attström, K., Niedlich, S., Sandvliet, K., Kuhn, H.-M., & Beavor, E. (2014). *Mapping and Analysing Bottleneck Vacancies in EU Labour Markets*. Brussels: European Commission. Retrieved from https://ec.europa.eu/eures/downloadSectionFile.do?fileId=8010

Baird, C. L., Burge, S. W., & Reynolds, J. R. (2008). Absurdly ambitious? Teenagers' expectations for the future and the realities of social structure. Sociology Compass, 2(3), 944–962.

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: early identification and effective interventions. *Educational Psychologist*, *42*(4), 223–235.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215.

Bandura, A. (1999). Social cognitive theory: an agentic perspective. *Asian Journal of Social Psychology*, *52*, 21–41.

Barone, C. (2011). Some things never change: gender segregation in higher education across eight nations and three decades. *Sociology of Education*, *84*(2), 157–176. https://doi.org/10.1177/0038040711402099

Becker, B. J. (1989). Gender and science achievement: A reanalysis of studies from two meta-analyses. *Journal of Research in Science Teaching*, *26*(2), 141-169.

Bedard, K., & Cho, I. (2010). Early gender test score gaps across OECD countries. *Economics of Education Review*, *29*(3), 348–363. https://doi.org/10.1016/j.econedurev.2009.10.015

Beede, D. N., Julian, T. A., Langdon, D., McKittrick, G., Khan, B., & Doms, M. E. (2011). Women in STEM: a gender gap to innovation. *Economics and Statistics Administration Issue Brief*, *4*(11). Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1964782

Benbow, C. P., and Stanley, J. C. (1980). Sex Differences in Mathematical Ability: Fact or Artifact? Science, (4475), 1262–1264.

Bleeker, M. M., & Jacobs, J. E. (2004). Achievement in math and science: do mothers' beliefs matter 12 years later? *Journal of Educational Psychology*, *96*(1), 97.

Bol, T., & Van de Werfhorst, H. G. (2013). *The Measurement of Tracking, Vocational Orientation, and Standardization of Educational Systems: A Comparative Approach*. Gini Discussion Paper 81. Retrieved from http://www.gini-research.org/system/uploads/532/original/81.pdf?1380554366

Böttcher, L., Araújo, N. A., Nagler, J., Mendes, J. F., Helbing, D., & Herrmann, H. J. (2016). Gender gap in the ERASMUS mobility program. PloS One, 11(2), e0149514. https://doi.org/10.1371/journal.pone.0149514

Buchmann, C., & Dalton, B. (2002). Interpersonal influences and educational aspirations in 12 countries: the importance of institutional context. *Sociology of Education*, *75*(2), 99. https://doi.org/10.2307/3090287

Buchmann, C., & Park, H. (2009). Stratification and the formation of expectations in highly differentiated educational systems. *Research in Social Stratification and Mobility*, *27*(4), 245–267. https://doi.org/10.1016/j.rssm.2009.10.003

Buchmann, C., & Parrado, E. A. (2006). Educational achievement of immigrant-origin and native students: a comparative analysis informed by institutional theory. In D. P. Baker & A. W. Wiseman (eds), *International Perspectives on Education and Society Volume 7* (pp. 335–366). Bingley: Emerald. https://doi.org/10.1016/S1479-3679(06)07014-9

Burchell, B., Hardy, V., Rubery, J., & Smith, M. (2014). *New Method to Understand Occupational Gender Segregation in European Labour Markets*. Luxembourg: Publications Office of the European Union. Retrieved from http://bookshop.europa.eu/uri?target=EUB:NOTICE:DS0514172:EN:HTML

Bytchkova, A., & Salvi del Pero, A. (2013). *A Bird's Eye View of Gender Differences in Education in OECD countries*. OECD Social, Employment and Migration Working Papers No 149. Paris: Organisation for Economic Co-operation and Development. https://doi.org/10.1787/5k40k706tmtb-en

Caprile, M., Rachel, P., Pablo, S., & Giancarlo, D. (2015). *Encouraging STEM Studies for the Labour Market*. Brussels: European Parliament. Retrieved from http://www.europarl.europa.eu/RegData/etudes/STUD/2015/542199/IPOL_STU(2015)542199_EN.pdf

Carle, A. C. (2009). Fitting multilevel models in complex survey data with design weights: recommendations. *BMC Medical Research Methodology*, *9*(1), 49.

Ceci, S. J., Williams, W. M., & Barnett, S. M. (2009). Women's Underrepresentation in Science: Sociocultural and Biological Considerations. Psychological Bulletin, 135(2), 218–261.

Cedefop (2016). *Skills Shortage and Surplus Occupations in Europe*. Thessaloniki: European Centre for the Development of Vocational Training. Retrieved from http://www.cedefop.europa.eu/en/publications-and-resources/publications/9115

Charles, M. (2003). Deciphering sex segregation vertical and horizontal inequalities in ten national labor markets. *Acta Sociologica*, *46*(4), 267–287.

Charles, M. (2011). What Gender is Science? Context, Spring, http://contexts.org/articles/spring-2011/what-gender-is-science/.

Charles, M. (2017). Venus, Mars, and math: gender, societal affluence, and eighth graders' aspirations for STEM. *Socius*, *3*, 1–16.

Charles, M., & Bradley, K. (2002). Equal but separate? A cross-national study of sex segregation in higher education. *American Sociological Review*, *67*, 573–599.

Charles, M., & Bradley, K. (2009). Indulging our gendered selves? Sex segregation by field of study in 44 countries. *American Journal of Sociology*, *114*(4), 924–976. https://doi.org/10.1086/595942

Charles, M., Harr, B., Cech, E., & Hendley, A. (2014). Who Likes Math Where? Gender Differences in Eighth-Graders' Attitudes around the World. International Studies in Sociology of Education, 24(1), 85–112.

Cheryan, S. (2012). Understanding the paradox in math-related fields: why do some gender gaps remain while others do not? *Sex Roles*, *66*(3–4), 184–190. https://doi.org/10.1007/s11199-011-0060-z

Cochran, D. B., Wang, E. W., Stevenson, S. J., Johnson, L. E., & Crews, C. (2011). Adolescent occupational aspirations: Test of Gottfredson's theory of circumscription and compromise. Career Development Quarterly, 59(5), 412–427.

Correll, S. J. (2001). Gender and the career choice process: the role of biased self-assessments. *American Journal of Sociology*, *106*(6), 1691–1730. https://doi.org/10.1086/321299

Craig, E., Thomas, R., Hou, C., & Mathur, S. (2011). *No Shortage of Talent: How the Global Market Is Producing the STEM Skills Needed for Growth*. Boston: Accenture Institute for High Performance*.* Retrieved from http://www.holconsultingservices.com/wp-content/uploads/2014/07/Accenture-No-Shortage-of-Talent.pdf

Croll, P. (2008). Occupational choice, socio-economic status and educational attainment: a study of the occupational choices and destinations of young people in the British Household Panel Survey. *Research Papers in Education*, *23*(3), 243–268.

Crosnoe, R., Riegle-Crumb, C., Field, S., Frank, K., & Muller, C. (2008). Peer group contexts of females' and males' academic experiences. *Child Development*, *79*(1), 139–155. https://doi.org/10.1111/j.1467-8624.2007.01116.x

Crowley, K., Callanan, M. A., Tenenbaum, H. R., & Allen, E. (2001). Parents explain more often to males than to females during shared scientific thinking. *Psychological Science*, *12*, 258–261.

Demnati, A., & Rao, J. N. K. (2004). Linearization variance estimators for survey data. *Survey Methodology*, *30*(1), 17–26.

Diekman, A. B., Brown, E. R., Johnston, A. M., & Clark, E. K. (2010). Seeking congruity between goals and roles: a new look at why women opt out of science, technology, engineering, and mathematics careers. *Psychological Science*, *21*(8), 1051–1057. https://doi.org/10.1177/0956797610377342

Dronkers, J., Levels, M., & de Heus, M. (2014). Migrant pupils' scientific performance: the influence of educational system features of origin and destination countries. *Large-Scale Assessments in Education*, *2*(1), 3.

Dryler, H. (1998). Parental role models, gender and educational choice. *British Journal of Sociology*, *49*(3), 375–398.

Eccles, J. (2011). Gendered Educational and Occupational Choices: Applying the Eccles et al. Model of Achievement-Related Choices. International Journal of Behavioral Development, 35(3), 195–201.

Eccles, J. S. (1994). Understanding women's educational and occupational choices. *Psychology of Women Quarterly*, *18*(4), 585–609.

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist*, *44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S., Barber, B. L., Updegraff, K., & O'Brian, K. M. (1998). An expectancy–value model of achievement choices: the role of ability self-concepts, perceived task utility and interest in predicting activity choice and course enrollment. In *Interest and Learning: Proceedings of the Seeon Conference on Interest and Gender* (pp. 267–280). Kiel: IPN.

Eccles, J. S., Jacobs, J., & Harold, R. (1990). Gender role stereotypes, expectancy effects, and parents' socialization of gender differences. *Journal of Social Issues*, *46*(2.), 183–201.

Eccles, J., Jacobs, J., Harold, R., Yoon, K. S., Arbreton, A., & Freedman-Don, C. (1993). Parents and gender-role socialization during the middle-childhood and adolescent years. In S. Oskamp & M. Costanzo (eds), *Gender Issues in Contemporary Society* (pp. 59–83). Newbury Park, CA: SAGE.

Enders, C. K. (2010). *Applied Missing Data Analysis*. New York: Guilford Press.

Estévez-Abe, M. (2005). Gender Bias in Skills and Social Policies: The Varieties of Capitalism Perspective on Sex Segregation. Social Politics: International Studies in Gender, State and Society, 12(2), 180–215. https://doi.org/10.1093/sp/jxi011

European Centre for the Development of Vocational Training (2014). *On the Way to 2020: Data for Vocational Education and Training Policies – Country Statistical Overviews (Update 2013)*. Luxembourg: Publications Office of the European Union.

European Commission (2012). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. 'Rethinking education: investing in skills for better socio-economic outcomes'. COM(201) 669 final of 20 November 2012. Retrieved from http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52012DC0669&from=EN

European Commission (2017). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. 'Strengthening European identity through education and culture: the European Commission's contribution to the Leaders' meeting in Gothenburg'. COM(201) 673 final of 14 November 2017. Retrieved from https://ec.europa.eu/commission/sites/beta-political/files/communication-strengthening-european-identity-education-culture_en.pdf

European Commission, Directorate-General for Education and Culture, Dansk Teknologisk Institut, Technopolis Limited (Brighton), 3s Unternehmensberatung GmbH, & ICF Consulting Services (2015). *Does the EU Need More STEM Graduates? Final Report.* Luxembourg: Publications Office of the European Union. Retrieved from http://bookshop.europa.eu/uri?target=EUB:NOTICE:NC0416008:EN:HTML

European Parliament (2014). *Report on Creating a Competitive EU Labour Market for the 21st Century: Matching Skills and Qualifications with Demand and Job Opportunities – A Way to Recover from the Crisis*. Brussels: European Parliament. Retrieved from http://www.europarl.europa.eu/sides/getDoc.do?pubRef=-//EP//NONSGML+REPORT+A8-2015-0222+0+DOC+PDF+V0//EN

Eurydice (2011a). *Mathematics Education in Europe: Common Challenges and National Policies*. Brussels: Education, Audiovisual and Culture Executive Agency.

Eurydice (2011b). *Science Education in Europe: National Policies, Practices and Research*. Brussels: Education, Audiovisual and Culture Executive Agency.

Fisi, S., Meroni, E., & Vera-Toscano, E. (2016). *Educational Outcomes and Immigrant Background*. Ispra: European Commission, Joint Research Centre.

Frank, K. A., Muller, C., Schiller, K. S., Riegle-Crumb, C., Mueller, A. S., Crosnoe, R., & Pearson, J. (2008). The social dynamics of mathematics coursetaking in high school. *American Journal of Sociology*, *113*(6), 1645–1696. https://doi.org/10.1086/587153

Frenzel, A. C., Goetz, T., Pekrun, R., & Watt, H. M. G. (2010). Development of mathematics interest in adolescence: influences of gender, family, and school context. *Journal of Research on Adolescence*, *20*(2), 507–537. https://doi.org/10.1111/j.1532-7795.2010.00645.x

Fuchs, T., & Wössmann, L. (2004). *What Accounts for International Differences in Student Performance?* CESifo working paper. Munich: CESifo Group. Retrieved from https://www.econstor.eu/handle/10419/18874

Fuller, W. A. (2011). *Sampling Statistics*. Hoboken, NJ: John Wiley & Sons.

Ganzeboom, H., & Treiman, D. (2015). *International Stratification and Mobility File: Conversion Tools.* Amsterdam: Department of Social Research Methodology. Retrieved from http://www.harryganzeboom.nl/ismf/index.htm

Gerber, T. P., & Cheung, S. Y. (2008). Horizontal Stratification in Postsecondary Education: Forms, Explanations, and Implications. Annual Review of Sociology, 34, 299–318.

Gonzalez, H. B., & Kuenzi, J. J. (2012). *Science, Technology, Engineering, and Mathematics (STEM) Education: A Primer*. Washington, DC: Congressional Research Service, Library of Congress. Retrieved from https://fas.org/sgp/crs/misc/R42642.pdf

Goos, M., Hathaway, I., Konings, J., & Vandeweyer, M. (2013). *High-Technology Employment in the European Union*. Leuven: VIVES. Retrieved from https://lirias.kuleuven.be/handle/123456789/445755

Han, S. W. (2015). Curriculum standardization, stratification, and students' STEM-related occupational expectations: evidence from PISA 2006. *International Journal of Educational Research*, *72*, 103–115. https://doi.org/10.1016/j.ijer.2015.04.012

Han, S. W. (2016a). National education systems and gender gaps in STEM occupational expectations. *International Journal of Educational Development*, *49*, 175–187. https://doi.org/10.1016/j.ijedudev.2016.03.004

Han, S. W. (2016b). Standards-based external exams and students' science-related career expectations: an international perspective. *Educational Research and Evaluation*, *22*(7–8), 374–401. https://doi.org/10.1080/13803611.2016.1257946

Han, S. W. (2017). What motivates high-school students to pursue STEM careers? The influence of public attitudes towards science and technology in comparative perspective. *Journal of Education and Work*, *30*(6), 632–652. https://doi.org/10.1080/13639080.2017.1329584

Hardie, J. H. (2014). The consequences of unrealized occupational goals in the transition to adulthood. Social Science Research, 48, 196–211. https://doi.org/10.1016/j.ssresearch.2014.06.006

Hattie, J. (2008). *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement*. Abingdon: Routledge.

Hellevik, O. (2009). Linear versus logistic regression when the dependent variable is a dichotomy. *Quality & Quantity*, *43*(1), 59–74.

Helwig, A. A. (2008). From Childhood to Adulthood: A 15-Year Longitudinal Career Development Study. The Career Development Quarterly, 57(1), 38.

Hidden Half (2015). *Methodology*. Retrieved from http://changetheequation.org/hidden-half-methodology

Hillmert, S. (2015). Gender segregation in occupational expectations and in the labour market: international variation and the role of education and training systems. In C. Imdorf, K. Hegna, & L. Reisel (eds), *Comparative Social Research Volume 31* (pp. 123–148). Bingley: Emerald. Retrieved from http://www.emeraldinsight.com/doi/10.1108/S0195-631020150000031005

Holmes, C. T., & Matthews, K. M. (1984). The effects of nonpromotion on elementary and junior high school pupils: a meta-analysis. *Review of Educational Research*, *54*(2), 225–236. https://doi.org/10.3102/00346543054002225

Hughes, J. N., Kowk, O., & Im, M. (2013). Effect of retention in first grade on parents' educational expectations and children's academic outcomes. *American Educational Research Journal*, *50*(6), 1336–1359. https://doi.org/10.3102/0002831213490784

ICF & Cedefop (2014). *EU Skills Panorama (2014) STEM Skills Analytical Highlight*. Brussels: European Commission. Retrieved from http://skillspanorama.cedefop.europa.eu/sites/default/files/EUSP_AH_STEM_0.pdf

ILO (2012). *International Standard Classification of Occupations*. Geneva: International Labour Office. Retrieved from http://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_172572.pdf

ILO (n.d.). *International Standard Classification of Occupations*. ISCO-08 Part 3: Gropu Definitions. Geneva: International Labour Office. Retrieved 21 November 2016 from http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm

ILO. (1990). International standard classification of occupations : ISCO-88. Geneva: International Labour Office.

Jarman, J., Blackburn, R. M., & Racko, G. (2012). The dimensions of occupational gender segregation in industrial countries. *Sociology*, *46*(6), 1003–1019.

Kao, G., & Tienda, M. (1995). Optimism and Achievement: The Educational Performance of Immigrant Youth. Social Science Quarterly, 76(1).

Keller, C. (2001). Effect of teachers' stereotyping on students' stereotyping of mathematics as a male domain. *The Journal of Social Psychology*, *141*(2), 165–173. https://doi.org/10.1080/00224540109600544

Koller, O., Baumert, J., & Schnabel, K. (2001). Does interest matter? The relationship between academic interest and achievement in mathematics. *Journal for Research in Mathematics Education*, *32*(5), 448. https://doi.org/10.2307/749801

Koonce, D. A., Zhou, J., Anderson, C. D., Hening, D. A., & Conley, V. M. (2011). *What is STEM?* Athens, OH: Ohio University. Retrieved from http://www.asee.org/file_server/papers/attachment/file/0001/0726/What_is_STEM_-_Final.pdf

Law, H., & Kim, D. H. (2011). Single-Sex Schooling and Mathematics Performance: Comparison of Sixteen Countries in PISA 2006. Social Transformations in Chinese Societies, 7(2), 233–272.

Lee, J., & Zhou, M. (2015). The Asian American Achievement Paradox. Russell Sage Foundation.

Lee, J., & Zhou, M. (2015). *The Asian American Achievement Paradox*. New York: Russell Sage Foundation.

Legewie, J., & DiPrete, T. A. (2014). The high school environment and the gender gap in science and engineering. *Sociology of Education*, *87*(4), 259–280. https://doi.org/10.1177/0038040714547770

Lesko, A. C., & Corpus, J. H. (2006). Discounting the difficult: how high math-identified women respond to stereotype threat. *Sex Roles*, *54*(1–2), 113–125. https://doi.org/10.1007/s11199-005-8873-2

Little, A. (1978). The Occupational and Educational Expectations of Students in Developed and Less-Developed Countries (No. Education Report 3). Sussex: Sussex University, Institute of Development Studies.

Looker, E. D., & Magee, P. A. (2000). Gender and work: The occupational expectations of young women and men in the 1990s. Gender Issues, 18(2), 74–88. https://doi.org/10.1007/s12147-000-0012-3

Mann, A., & DiPrete, T. (2016). The consequences of the national math and science performance environment for gender differences in STEM aspiration. *Sociological Science*, *3*, 568–603. https://doi.org/10.15195/v3.a25

Mann, A., & DiPrete, T. A. (2013). Trends in gender segregation in the choice of science and engineering majors. *Social Science Research*, *42*(6), 1519–1541. https://doi.org/10.1016/j.ssresearch.2013.07.002

Mann, A., Legewie, J., & DiPrete, T. A. (2015). The role of school performance in narrowing gender gaps in the formation of STEM aspirations: a cross-national study. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00171

Marks, G. N. (2010). Meritocracy, modernization and students' occupational expectations: Cross-national evidence. Research in Social Stratification and Mobility, 28(3), 275–289. https://doi.org/10.1016/j.rssm.2010.06.002

Marks, G.M. (2013): Education, Social Background and Cognitive Ability. The decline of the social. New York, Routledge

Marsh, H. W., & Hau, K.-T. (2003). Big-Fish–Little-Pond effect on academic self-concept: a cross-cultural (26-country) test of the negative effects of academically selective schools. *American Psychologist*, *58*(5), 364–376. https://doi.org/10.1037/0003-066X.58.5.364

Marx, D. M., & Roman, J. S. (2002). Female role models: protecting women's math test performance. *Personality and Social Psychology Bulletin*, *28*(9), 1183–1193.

McIntyre, R. B., Paulson, R. M., & Lord, C. G. (2003). Alleviating women's mathematics stereotype threat through salience of group achievements. *Journal of Experimental Social Psychology*, *39*(1), 83–90.

Mood, C. (2010). Logistic regression: why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67–82.

Morgan, S. L., Gelbgiser, D., & Weeden, K. A. (2013). Feeding the pipeline: gender, occupational plans, and college major selection. *Social Science Research*, *42*(4), 989–1005. https://doi.org/10.1016/j.ssresearch.2013.03.008

Murnane, R. J., & Willett, J. B. (2010). *Methods Matter: Improving Causal Inference in Educational and Social Science Research* (1st edition). Oxford : Oxford University Press.

Nagy, G., Watt, H. M. G., Eccles, J. S., Trautwein, U., Lüdtke, O., and Baumert, J. (2010). The Development of Students' Mathematics Self-Concept in Relation to Gender: Different Countries, Different Trajectories? Journal of Research on Adolescence, 20(2), 482–506.

Newman, D. A. (2014). Missing data: five practical guidelines. *Organizational Research Methods*, *17*(4), 372–411.

Noyes, A., & Adkins, M. (2016). Studying advanced mathematics in England: findings from a survey of student choices and attitudes. Research in Mathematics Education, 18(3), 231–248. https://doi.org/10.1080/14794802.2016.1188139

OECD (2007). *PISA 2006 Science Competencies for Tomorrow's World. Volume 1 – Analysis*. Paris: Organisation for Economic Co-operation and Development.

OECD (2009). *PISA 2006 Technical Report*. Paris: Organisation for Economic Co-operation and Development.

OECD (2010). *Measuring Innovation*. Paris: Organisation for Economic Co-operation and Development. Retrieved from http://www.oecd-ilibrary.org/science-and-technology/measuring-innovation_9789264059474-en

OECD (2013). *PISA 2012 Results: What Makes Schools Successful (Volume IV)*. Paris: Organisation for Economic Co-operation and Development. https://doi.org/10.1787/9789264201156-en

OECD (2015a). *Indicators of Immigrant Integration 2015*. Paris: Organisation for Economic Co-operation and Development. https://doi.org/10.1787/9789264234024-en

OECD (2015b). *The ABC of Gender Equality in Education*. Paris: Organisation for Economic Co-operation and Development. Retrieved from http://www.oecd-ilibrary.org/education/the-abc-of-gender-equality-in-education_9789264229945-en

OECD (2016a). *Education at a Glance 2016: OECD Indicators*. Paris: Organisation for Economic Co-operation and Development. http://www.oecd.org/education/skills-beyond-school/education-at-a-glance-2016-indicators.htm

OECD (2016b). *PISA 2015 Results (Volume I)*. Paris: Organisation for Economic Co-operation and Development. https://doi.org/10.1787/9789264266490-en

OECD (2016c). *PISA 2015 Results (Volume II): Policies and Practices for Successful Schools*. Paris: Organisation for Economic Co-operation and Development.

OECD (2017). *PISA 2015 Technical Report*. Paris: Organisation for Economic Co-operation and Development. http://www.oecd.org/pisa/sitedocument/PISA-2015-technical-report-final.pdf

OECD. (2006). Women in Scientific Careers: Unleashing the Potential. Paris: OECD Publishing.

Osborne, J., & Dillon, J. (2008). Science education in Europe: Critical reflections (Vol. 13). London: The Nuffield Foundation. Retrieved from http://efepereth.wdfiles.com/local--files/science-education/Sci_Ed_in_Europe_Report_Final.pdf

Osborne, J., Simon, S., & Collins, S. (2003). Attitudes towards science: a review of the literature and its implications. International Journal of Science Education, 25(9), 1049–1079.

Page, S. E. (2008). *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton University Press.

Patton, W., & Creed, P. (2007). Occupational Aspirations and Expectations for Australian Adolescents. Australian Journal of Career Development, 16(1), 46–58.

Pokropek, A. (2016). Introduction to instrumental variables and their application to large-scale assessment data. *Large-Scale Assessments in Education*, *4*(1), 4.

Pokropek, A., Borgonovi, F., & McCormick, C. (2017). On the cross-country comparability of indicators of socioeconomic resources in PISA. *Applied Measurement in Education*, *30*(4), 243–258. https://doi.org/10.1080/08957347.2017.1353985

Preacher, K. J. (2015). Advances in mediation analysis: a survey and synthesis of new developments. Annual Review of Psychology, 66, 825–852. https://doi.org/10.1146/annurev-psych-010814-015258

Preacher, K. J. (2015). Advances in mediation analysis: a survey and synthesis of new developments. *Annual Review of Psychology*, *66*, 825–852. https://doi.org/10.1146/annurev-psych-010814-015258

Raudenbush, S. W., & Bryk, A. S. (2001). *Hierarchical Linear Models: Applications and Data Analysis Methods* (2nd edition). Thousand Oaks, CA: SAGE.

Reisel, L., Hegna, K., & Imdorf, C. (2015). Gender Segregation in Vocational Education: Introduction. In C. Imdorf, K. Hegna, & L. Reisel (Eds.), Gender Segregation in Vocational Education (Vol. 31, pp. 1–22). Bingley, UK: Emerald.

Reynolds, J., Stewart, M., MacDonald, R., & Sischo, L. (2006). Have Adolescents Become Too Ambitious? High School Seniors' Educational and Occupational Plans 1976 to 2000. Social Problems, 53(2), 186–206.

Riegle-Crumb, C., King, B., Grodsky, E., & Muller, C. (2012). The more things change, the more they stay the same? Prior achievement fails to explain gender inequality in entry into STEM college majors over time. *American Educational Research Journal*, *49*(6), 1048-1073.

Riegle-Crumb, C., Moore, C., & Ramos-Wada, A. (2011). Who wants to have a career in science or math? Exploring adolescents' future aspirations by gender and race/ethnicity. *Science Education*, *95*(3), 458–476. https://doi.org/10.1002/sce.20431

Rindfuss, R. R., Cooksey, E. C., & Sutterlin, R. L. (1999). Young Adult Occupational Achievement. Early Expectations Versus Behaviour Reality. Work and Occupations, 26(2), 220–263.

Royston, P. & Sauerbrei, W. (2008): Multivariable Model-Building: A pragmatic approach to regression analysis based on fractional polynomials for modelling continuous variables. John Wiley and Sons, Ltd

Royston, P. (2004). Multiple imputation of missing values. Stata Journal, 4(3), 227–41.

Rozi, S., Mahmud, S., Lancaster, G., Hadden, W., & Pappas, G. (2017). Multilevel modeling of binary outcomes with three-level complex health survey data. *Open Journal of Epidemiology*, *7*, 27–43.

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. Science Education, 96(3), 411–427. https://doi.org/10.1002/sce.21007

Saha, L. J. (1982). National Development and the Revolution of Rising Expectations: Determinants of Career Orientations Among School Students in Comparative Perspective. In M. A. Archer (Ed.), The Sociology of Educational Expansion: Take-Off, Growth and Inflation in Educational Systems (p. 241–264.). London: Sage Publishers.

Schafer, J. L., & Graham, J. W. (2002). Missing data: our view of the state of the art. *Psychological Methods*, *7*(2), 147–177.

Schneeweis, N., & Zweimüller, M. (2012). Females, females, females: gender composition and female school choice. *Economics of Education Review*, *31*(4), 482–500. https://doi.org/10.1016/j.econedurev.2011.11.002

Schneider, B. L., & Stevenson, D. (2000). The ambitious generation: America’s teenagers, motivated but directionless. Yale University Press.

Schoon, I., Martin, P., & Ross, A. (2007). Career transitions in times of social change: his and her story. *Journal of Vocational Behavior*, *70*(1), 78–96. https://doi.org/10.1016/j.jvb.2006.04.009

Scott Long, J. (1997). *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: SAGE.

Shadish, W. R. (2010). Campbell and Rubin: a primer and comparison of their approaches to causal inference in field settings. *Psychological Methods*, *15*(1), 3.

Shadish, W. R., & Sullivan, K. J. (2012). Theories of causation in psychological science.

Shadish, W. R., & Sullivan, K. J. (2012). Theories of causation in psychological science. In H. M. Cooper (ed), *APA Handbook of Research Methods in Psychology* (pp. 23–52). Washington, DC: American Psychological Association.

Shavit, Y., & Blossfeld, H.-P. (1993). *Persistent Inequality: Changing Educational Attainment in Thirteen Countries.* New York: Avalon.

Sheldon, K. M., & Biddle, B. J. (1998). Standards, accountability, and school reform: perils and pitfalls. *Teachers College Record*, *100*, 164–180.

Sikora, J. (2014). *Gendered Pathways into the Post-secondary Study of Science*. NCVER Occasional Paper. Adelaide: National Centre for Vocational Education Research.

Sikora, J. (2015). Gender Segregation in Australian Science Education: Contrasting Post-Secondary VET with University. In Gender Segregation in Vocational Education (pp. 263–289). Emerald Group Publishing Limited. Retrieved from http://www.emeraldinsight.com/doi/abs/10.1108/S0195-631020150000031009

Sikora, J., & Pokropek, A. (2011). *Gendered Career Expectations of Students*. OECD Education Working Papers No 57. Paris: Organisation for Economic Co-operation and Development. Retrieved from http://www.oecd-ilibrary.org/education/gendered-career-expectations-of-students_5kghw6891gms-en

Sikora, J., & Pokropek, A. (2012a). Gender segregation of adolescent science career plans in 50 countries. *Science Education*, *96*(2), 234–264.

Sikora, J., & Pokropek, A. (2012b). Intergenerational transfers of preferences for science careers in comparative perspective. *International Journal of Science Education*, *34*(16), 2501–2527.

Sikora, J., & Saha, L. J. (2009). Gender and Professional Career Plans of High School Students in Comparative Perspective. Educational Research and Evaluation, 15(4), 387–405.

Sikora, J., Saha, L. J., & National Centre for Vocational Education Research (2011). *Lost Talent? The Occupational Ambitions and Attainments of Young Australians.* Adelaide: National Centre for Vocational Education Research.

Sjoberg, S., & Schreiner, C. (2005). How do learners in different cultures relate to science and technology? Results and perspectives from the project ROSE (the Relevance of Science Education). Asia-Pacific Forum on Science Learning and Teaching, 6(2).

Sjøberg, S., & Schreiner, C. (2010). *The ROSE Project: An Overview and Key Findings*. Oslo: University of Oslo.

Smyth, E. (2010). Single-Sex Education: What Does Research Tell Us? Revue Française de Pédagogie, 171, 47–55.

Smyth, E., & Steinmetz, S. (2008). Field of study and gender segregation in European labour markets. *International Journal of Comparative Sociology*, *49*(4–5), 257–281. https://doi.org/10.1177/0020715208093077

Smyth, E., & Steinmetz, S. (2015). Vocational Training and Gender Segregation Across Europe. In Gender Segregation in Vocational Education (pp. 53–81). Emerald Group Publishing Limited.

Steele, C. M., Spencer, S. J., & Aronson, J. (2002). Contending with group image: the psychology of stereotype and social identity threat. *Advances in Experimental Social Psychology*, *34*, 379–440.

Tai, R. H., Liu, C. Q., Maltese, A. V., & Fan, X. (2006). Planning early for careers in science. *Science*, *312*(5777), 1143–1144.

Tiedmann, J. (2000). Parents' gender stereotypes and teachers' beliefs as predictors of children's concept of their mathematical ability in elementary school. *Journal of Educational Psychology*, *92*(1), 144–151.

UIS, U. S. I. (2006). International Standard Classification of Education ISCED 1997. Montreal: UNESCO Statistical Institute. Retrieved from http://www.uis.unesco.org/Education/Pages/international-standard-classification-of-education.aspx

UKCES (2011). *The Supply of and Demand for High Level STEM Skills*. Briefing paper. London: UK Commission for Employment and Skills.

van Langen, A., Bosker, R., & Dekkers, H. (2006). Exploring cross-national differences in gender gaps in education. *Educational Research and Evaluation*, *12*(2), 155–177. https://doi.org/10.1080/13803610600587016

Wang, M.-T., & Degol, J. (2013). Motivational pathways to STEM career choices: using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review*, *33*(4), 304–340. https://doi.org/10.1016/j.dr.2013.08.001

Ware, N. C., Steckler, N. A., & Leserman, J. (1985). Undergraduate women: who chooses a science major? *The Journal of Higher Education*, *56*(1), 73. https://doi.org/10.2307/1981723

Xie, Y., & Shauman, K. A. (2003). Women in Science: Career Processes and Outcomes. Cambridge, Massachusetts; London, England: Harvard University Press.

Xie, Y., & Shauman, K. A., (2003). *Women in Science: Career Processes and Outcomes*, *Volume 26*. Cambridge, MA: Harvard University Press. Retrieved from http://personal.psc.isr.umich.edu/yuxie-web/files/women/women-2001/cover.pdf

Yazilitas, D., Svensson, J., de Vries, G., & Saharso, S. (2013). Gendered study choice: a literature review: a review of theory and research into the unequal representation of male and female students in mathematics, science, and technology. *Educational Research and Evaluation*, *19*(6), 525–545. https://doi.org/10.1080/13803611.2013.803931

List of abbreviations and definitions

Country codes

AT – Austria

BE - Belgium

BG - Bulgaria

CY - Croatia

CZ - Czech Republic

DE - Germany

DK - Denmark

EE - Estonia

EL - Greece

ES - Spain

FI - Finland

FR - France

HR - Croatia

HU - Hungary

IE - Ireland

IT - Italy

LT – Lithuania

LU - Luxembourg

LV - Latvia

MT - Malta

NL – The Netherlands

PL - Poland

PT - Portugal

SE - Sweden

SK - Slovakia

UK – United Kingdom

EU – European Union

Abbreviations

DiD – Difference in Difference

ESCS – Economic, Social and Cultural Status

GII - Gender Inequality Index

GPG – Gender Pay Gap

HDI – Human Development Index

ILO – International Labour Organisation

IRT – Item Response Theory

ISCED – International Standard Classification of Education

ISCO – International Standard Classification of Occupations

ISEI – International Socio-Economic Index of Social Status

LPM – Linear Probability Model

OECD - Organisation for Economic Co-operation and Development

OLS – Ordinary Least Square

PISA - Programme for International Student Assessment

STEM - Science, Technology, Engineering and Mathematics

TIMSS – Trends in International Mathematics and Science Study

List of figures

List of tables

Appendix

Table A3.1 Discrepancies between STEM ISCO categories 21, 31, 25, 35 in ISCO-88 and ISCO-08 schemes.

STEM occupations in ISCO-08 category 21 (but not STEM in ISCO-88):
Decorators and Commercial Designers, Decorators and Commercial Designer
STEM occupations in ISCO-08 category 31 (but not STEM in ISCO-88):
Miners and Quarry Workers, Mining-plant Operators, Automated-assembly-line Operators, Industrial-robot Operators, Machine-tool Operators, Pharmaceutical- and Toiletry-products Machine Operators, Ammunition- and Explosive-products Machine Operators, Metal Finishing-, Plating- and Coating-machine Operators, Chemical-products Machine Operators Not Elsewhere Classified, Rubber-products Machine Operators, Plastic-products Machine Operators, Wood-products Machine Operators, Printing-machine Operators, Bookbinding-machine Operators, Paper-products Machine Operators, Fibre-preparing-, Spinning- and Winding-machine Operators, Weaving- and Knitting-machine Operators, Sewing-machine Operators, Bleaching-, Dyeing- and Cleaning-machine Operators, Fur- and Leather-preparing-machine Operators, Shoemaking- and Related Machine Operators, Textile-, Fur- and Leather-products Machine Operators Not Elsewhere Classified, Meat- and Fish-processing-machine Operators, Dairy-products Machine Operators, Grain- and Spice-milling-machine Operators, Baked-goods, Cereal and Chocolate-products Machine Operators, Fruit-, Vegetable- and Nut-processing-machine Operators, Sugar Production Machine Operators, Tea-, Coffee-, and Cocoa-processing-machine Operators, Brewers-, Wine and Other Beverage Machine Operators, Tobacco Production Machine Operators, Mechanical-machinery Assemblers, Electrical-equipment Assemblers, Electronic-equipment Assemblers, Metal-, Rubber- and Plastic-products Assemblers, Wood and Related Products Assemblers, Paperboard, Textile and Related Products Assemblers, Other Machine Operators and Assemblers, Production and Operations Department Managers in Construction, Building Frame and Related Trades Workers Not Elsewhere Classified, Power-production Plant Operators, Incinerator, Water-treatment and Related Plant Operators, Chemical-heat-treating-plant Operators, Chemical-filtering- and Separating-equipment Operators, Chemical-still and Reactor Operators (except Petroleum and Natural Gas), Chemical-processing-plant Operators Not Elsewhere Classified, Petroleum- and Natural-gas-refining-plant Operators, Ore and Metal Furnace Operators, Metal Melters, Casters and Rolling-mill Operators, Metal-heat-treating-plant Operators, Metal Drawers and Extruders, Paper-pulp Plant Operators, Papermaking-plant Operators, Automated-assembly-line Operators, Industrial-robot Operators, Life Science Technicians, Agronomy and Forestry Technicians, Agronomy and Forestry Technicians
STEM occupations in ISCO-88 category 21 (but not STEM in ISCO-08):
Industrial pharmacists, pharmaceutical chemists (ISCO-88 2113; transformed into Pharmacists ISCO-08 2262);
STEM occupations in ISCO-88 category 31 (but not STEM in ISCO-08):
Medical Equipment operators, Safety, Health and Quality Inspectors, Sanitarians (formerly groups 31)
Remaining in STEM: ISCO-88 category 21 moved to ISCO-08 category 25:
Computer Systems Designers and Analysts, Computer Systems Designers and Analysts, Computer Systems Designers and Analysts, Computer Programmers, Computing Professionals Not Elsewhere Classified, Computer Programmers, Computer Systems Designers and Analysts, Computer Programmers, Computing Professionals Not Elsewhere Classified, Computer Systems Designers and Analysts, Computer Systems Designers and Analysts, Computer Systems Designers and Analysts, Computer Programmers, Computing Professionals Not Elsewhere Classified
Remaining in STEM: ISCO-88 category 31 moved to ISCO-08 category 35:
Computer Equipment Operators, Computer Assistants, Computer Assistants, Computer Assistants, Photographers and Image and Sound Recording Equipment Operators, Broadcasting and Telecommunications Equipment Operators, Electronics and Telecommunications Engineering Technicians, Broadcasting and Telecommunications Equipment Operators, Telecommunications equipment operators

Table A3.2. STEM descriptive statistics before and after imputations. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of	Raw data		After imputation		Prop. of
	Mean	SD	Mean	SD	missing	Mean	SD	Mean	SD	missing
Austria	0.206	0.404	0.207	0.405	0.228	0.159	0.366	0.161	0.368	0.332
Belgium	0.166	0.372	0.163	0.369	0.187	0.171	0.376	0.173	0.378	0.215
Bulgaria	0.247	0.431	0.243	0.429	0.248	0.153	0.360	0.157	0.364	0.300
Cyprus	0.197	0.398	0.196	0.397	0.114	NA	NA	NA	NA	NA
Czech Republic	0.178	0.382	0.176	0.380	0.247	0.196	0.397	0.187	0.390	0.326
Germany	0.202	0.402	0.196	0.397	0.341	0.162	0.369	0.161	0.367	0.338
Denmark	0.159	0.366	0.161	0.368	0.515	0.150	0.357	0.149	0.357	0.226
Estonia	0.258	0.438	0.263	0.440	0.160	0.209	0.407	0.207	0.405	0.261
Greece	0.190	0.392	0.191	0.393	0.114	0.229	0.420	0.226	0.418	0.268
Spain	0.211	0.408	0.212	0.408	0.110	0.203	0.402	0.202	0.402	0.263
Finland	0.118	0.322	0.121	0.326	0.254	0.110	0.312	0.117	0.321	0.253
France	0.187	0.390	0.185	0.388	0.208	0.161	0.368	0.165	0.371	0.244
Croatia	0.200	0.400	0.202	0.401	0.166	0.188	0.391	0.190	0.392	0.343
Hungary	0.182	0.386	0.181	0.385	0.226	0.166	0.372	0.169	0.375	0.321
Ireland	0.191	0.393	0.190	0.392	0.134	0.148	0.355	0.149	0.356	0.172
Italy	0.211	0.408	0.208	0.406	0.190	0.200	0.400	0.199	0.399	0.157
Lithuania	0.194	0.396	0.196	0.397	0.221	0.193	0.394	0.192	0.394	0.263
Luxembourg	0.183	0.386	0.184	0.388	0.181	0.170	0.376	0.172	0.377	0.213
Latvia	0.233	0.423	0.237	0.425	0.189	0.183	0.387	0.190	0.393	0.255
Malta	0.225	0.418	0.226	0.418	0.110	NA	NA	NA	NA	NA
Netherlands	0.166	0.372	0.168	0.374	0.216	0.105	0.307	0.109	0.311	0.132
Poland	0.161	0.368	0.161	0.368	0.135	0.236	0.425	0.231	0.422	0.209
Portugal	0.241	0.428	0.237	0.425	0.180	0.275	0.447	0.279	0.449	0.207
Romania	0.156	0.363	0.156	0.363	0.202	0.153	0.360	0.151	0.358	0.111
Sweden	0.199	0.399	0.197	0.398	0.213	0.176	0.381	0.181	0.385	0.193
Slovenia	0.273	0.445	0.270	0.444	0.177	0.224	0.417	0.232	0.422	0.238
Slovakia	0.191	0.393	0.188	0.391	0.240	0.168	0.374	0.165	0.371	0.252
United Kingdom	0.208	0.406	0.209	0.407	0.181	0.131	0.338	0.132	0.338	0.146
Average	0.198	0.396	0.196	0.395	0.203	0.178	0.379	0.179	0.380	0.240

Table A3.3. Descriptive statistics of students' characteristics: Science literacy and gender. PISA 2015 and 2006*.

Country	PISA 2006				PISA 2015			
	Science literacy		Share of females		Science literacy		Share of females	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Austria	0.080	0.990	0.495	0.500	0.153	0.999	0.491	0.500
Belgium	-0.015	0.974	0.492	0.500	-0.100	1.052	0.486	0.500
Bulgaria	-0.421	1.033	0.472	0.499	-0.631	1.089	0.482	0.500
Cyprus	-0.555	0.944	0.502	0.500	NA	NA	NA	NA
Czech Republic	0.057	0.969	0.487	0.500	0.173	1.005	0.434	0.496
Germany	0.223	1.010	0.491	0.500	0.202	1.020	0.484	0.500
Denmark	0.150	0.918	0.498	0.500	0.000	0.950	0.503	0.500
Estonia	0.478	0.904	0.490	0.500	0.363	0.854	0.488	0.500
Greece	-0.329	0.935	0.480	0.500	-0.230	0.941	0.497	0.500
Spain	0.057	0.895	0.501	0.500	-0.076	0.924	0.494	0.500
Finland	0.442	0.978	0.482	0.500	0.688	0.874	0.504	0.500
France	0.079	1.037	0.504	0.500	-0.007	1.037	0.515	0.500
Croatia	-0.120	0.908	0.519	0.500	-0.027	0.875	0.500	0.500
Hungary	-0.106	0.980	0.499	0.500	0.082	0.900	0.479	0.500
Ireland	0.157	0.904	0.487	0.500	0.127	0.963	0.506	0.500
Italy	-0.068	0.930	0.503	0.500	-0.209	0.975	0.504	0.500
Lithuania	-0.120	0.925	0.493	0.500	-0.081	0.919	0.491	0.500
Luxembourg	-0.045	1.021	0.503	0.500	-0.097	0.988	0.494	0.500
Latvia	0.031	0.836	0.499	0.500	-0.065	0.861	0.514	0.500
Malta	-0.228	1.196	0.492	0.500	NA	NA	NA	NA
Netherlands	0.218	1.027	0.502	0.500	0.296	0.976	0.491	0.500
Poland	0.145	0.923	0.491	0.500	0.020	0.917	0.503	0.500
Portugal	0.142	0.934	0.495	0.500	-0.220	0.904	0.517	0.500
Romania	-0.532	0.805	0.502	0.500	-0.791	0.828	0.502	0.500
Sweden	0.063	1.042	0.495	0.500	0.076	0.961	0.487	0.500
Slovenia	0.261	0.968	0.483	0.500	0.234	1.002	0.502	0.500
Slovakia	-0.269	1.006	0.485	0.500	-0.076	0.951	0.486	0.500
United Kingdom	0.224	1.013	0.492	0.500	0.193	1.090	0.505	0.500
Average	0.000	0.965	0.494	0.500	0.000	0.956	0.495	0.500

* Standardized among EU countries; no missing data

Table A3.4. Descriptive statistics of ESCS index. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of	Raw data		After imputation		Prop. of
	Mean	SD	Mean	SD	missing	Mean	SD	Mean	SD	missing
Austria	0.145	0.900	0.091	0.852	0.010	0.217	0.879	-0.115	0.849	0.003
Belgium	0.126	0.982	0.068	0.930	0.020	0.145	0.980	-0.086	0.987	0.013
Bulgaria	-0.037	1.054	-0.087	0.997	0.023	-0.212	1.069	-0.627	1.047	0.023
Cyprus	0.255	0.981	0.193	0.928	0.018	NA	NA	NA	NA	NA
Czech Republic	-0.170	0.843	-0.210	0.797	0.015	0.040	0.805	-0.363	0.785	0.005
Germany	0.175	1.000	0.077	0.944	0.134	0.319	0.983	0.025	0.954	0.042
Denmark	0.674	0.916	0.588	0.868	0.025	0.336	0.942	0.299	0.859	0.008
Estonia	0.099	0.813	0.046	0.768	0.016	0.158	0.857	-0.281	0.815	0.002
Greece	-0.035	1.016	-0.081	0.962	0.007	-0.152	1.024	-0.394	0.992	0.002
Spain	-0.492	1.259	-0.514	1.192	0.009	-0.318	1.126	-0.327	1.339	0.005
Finland	0.316	0.795	0.252	0.752	0.012	0.279	0.831	0.067	0.791	0.004
France	-0.097	0.845	-0.149	0.801	0.027	-0.086	0.907	-0.442	0.906	0.023
Croatia	-0.206	0.871	-0.241	0.824	0.014	-0.105	0.919	-0.493	0.864	0.002
Hungary	-0.191	1.013	-0.228	0.959	0.016	-0.080	0.973	-0.471	0.900	0.004
Ireland	0.217	0.890	0.157	0.842	0.013	-0.007	0.902	-0.054	0.942	0.018
Italy	-0.022	1.005	-0.071	0.951	0.022	-0.064	1.031	-0.466	0.993	0.004
Lithuania	-0.020	0.917	-0.067	0.867	0.029	0.047	0.968	-0.440	0.906	0.005
Luxembourg	0.127	1.170	0.069	1.106	0.022	0.103	1.159	-0.138	1.154	0.017
Latvia	-0.413	0.971	-0.437	0.918	0.011	-0.013	0.951	-0.497	0.847	0.006
Malta	-0.006	1.004	-0.054	0.950	0.009	NA	NA	NA	NA	NA
Netherlands	0.218	0.805	0.158	0.762	0.011	0.276	0.941	0.078	0.873	0.007
Poland	-0.368	0.870	-0.396	0.824	0.007	-0.307	0.912	-0.747	0.848	0.005
Portugal	-0.363	1.216	-0.395	1.150	0.014	-0.641	1.345	-0.980	1.282	0.004
Romania	-0.568	0.917	-0.583	0.868	0.001	-0.382	1.005	-0.827	0.915	0.002
Sweden	0.401	0.863	0.328	0.817	0.027	0.259	0.832	0.164	0.825	0.011
Slovenia	0.081	0.864	0.028	0.818	0.010	0.146	0.921	-0.272	0.867	0.006
Slovakia	-0.066	1.004	-0.114	0.951	0.015	-0.147	0.957	-0.408	0.898	0.002
United Kingdom	0.270	0.910	0.203	0.861	0.045	0.211	0.858	-0.073	0.853	0.026
Average	0.002	0.953	-0.058	0.899	0.021	0.001	0.964	-0.303	0.934	0.010

Table A3.5. Descriptive statistics of Parents in STEM. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of missing	Raw data		After imputation		Prop. of missing
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Austria	NA	NA	NA	NA	NA	0.075	0.263	0.075	0.263	0.016
Belgium	0.109	0.311	0.114	0.317	0.051	0.117	0.322	0.118	0.322	0.018
Bulgaria	0.121	0.326	0.123	0.328	0.115	0.111	0.314	0.111	0.315	0.034
Cyprus	0.131	0.337	0.132	0.339	0.050	NA	NA	NA	NA	NA
Czech Republic	0.154	0.361	0.155	0.362	0.052	0.136	0.343	0.136	0.343	0.017
Germany	0.124	0.329	0.124	0.330	0.003	0.121	0.326	0.121	0.326	0.040
Denmark	0.123	0.328	0.122	0.327	0.080	0.123	0.328	0.124	0.329	0.042
Estonia	0.129	0.336	0.129	0.335	0.013	0.081	0.272	0.081	0.273	0.010
Greece	0.096	0.295	0.098	0.297	0.048	0.091	0.287	0.092	0.289	0.014
Spain	0.088	0.283	0.087	0.283	0.025	0.063	0.242	0.062	0.242	0.008
Finland	0.149	0.356	0.149	0.356	0.030	0.116	0.320	0.117	0.321	0.021
France	0.132	0.339	0.132	0.339	0.007	0.105	0.307	0.106	0.308	0.027
Croatia	0.130	0.336	0.130	0.336	0.034	0.139	0.346	0.140	0.347	0.014
Hungary	0.118	0.322	0.120	0.325	0.063	0.088	0.283	0.091	0.287	0.035
Ireland	0.115	0.319	0.116	0.320	0.039	0.093	0.290	0.093	0.290	0.016
Italy	0.116	0.320	0.116	0.320	0.025	0.082	0.274	0.082	0.274	0.008
Lithuania	0.072	0.258	0.073	0.260	0.090	0.053	0.225	0.055	0.227	0.023
Luxembourg	0.112	0.316	0.115	0.318	0.081	0.098	0.298	0.100	0.300	0.029
Latvia	0.089	0.285	0.093	0.291	0.067	0.070	0.256	0.073	0.260	0.033
Malta	0.094	0.292	0.095	0.293	0.050	NA	NA	NA	NA	NA
Netherlands	0.138	0.345	0.139	0.346	0.044	0.103	0.304	0.104	0.305	0.015
Poland	0.073	0.260	0.074	0.263	0.038	0.121	0.326	0.121	0.326	0.011
Portugal	0.109	0.311	0.108	0.311	0.028	0.071	0.256	0.072	0.258	0.012
Romania	0.078	0.269	0.079	0.270	0.023	0.078	0.268	0.078	0.268	0.013
Sweden	0.185	0.388	0.183	0.387	0.059	0.128	0.334	0.129	0.335	0.010
Slovenia	0.168	0.374	0.168	0.374	0.045	0.179	0.383	0.179	0.383	0.021
Slovakia	0.116	0.320	0.117	0.322	0.067	0.103	0.304	0.103	0.305	0.016
United Kingdom	0.105	0.307	0.105	0.306	0.079	0.102	0.302	0.102	0.302	0.033
Average	0.118	0.319	0.119	0.321	0.082	0.102	0.299	0.104	0.301	0.021

Table A3.6. Descriptive statistics of migrant indicator. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of	Raw data		After imputation		Prop. of
	Mean	SD	Mean	SD	missing	Mean	SD	Mean	SD	missing
Austria	0.403	0.203	0.402	0.204	0.403	0.215	0.411	0.219	0.413	0.017
Belgium	0.416	0.222	0.416	0.224	0.417	0.002	0.046	0.005	0.071	0.046
Bulgaria	0.102	0.010	0.101	0.012	0.110	NA	NA	NA	NA	NA
Cyprus	0.316	0.113	0.316	0.115	0.320	0.019	0.137	0.020	0.139	0.008
Czech Republic	0.181	0.034	0.181	0.035	0.183	0.142	0.349	0.149	0.356	0.059
Germany	0.374	0.169	0.375	0.179	0.383	0.076	0.265	0.077	0.266	0.009
Denmark	0.309	0.107	0.309	0.110	0.313	0.116	0.320	0.117	0.322	0.022
Estonia	0.301	0.100	0.300	0.101	0.302	0.076	0.264	0.077	0.266	0.016
Greece	0.310	0.108	0.310	0.109	0.312	0.069	0.254	0.070	0.255	0.012
Spain	0.313	0.110	0.313	0.111	0.314	0.015	0.123	0.016	0.125	0.009
Finland	0.195	0.040	0.195	0.040	0.197	0.130	0.336	0.132	0.339	0.030
France	0.338	0.132	0.338	0.135	0.342	0.120	0.325	0.122	0.327	0.015
Croatia	0.310	0.108	0.310	0.110	0.313	0.017	0.128	0.018	0.132	0.008
Hungary	0.162	0.027	0.162	0.027	0.162	0.056	0.229	0.058	0.235	0.031
Ireland	0.351	0.144	0.351	0.145	0.352	0.038	0.191	0.039	0.194	0.024
Italy	0.272	0.080	0.271	0.081	0.273	0.021	0.142	0.022	0.147	0.024
Lithuania	0.131	0.018	0.131	0.020	0.139	0.361	0.480	0.363	0.481	0.017
Luxembourg	0.500	0.520	0.500	0.519	0.500	0.071	0.256	0.073	0.260	0.026
Latvia	0.219	0.050	0.219	0.051	0.221	NA	NA	NA	NA	NA
Malta	0.217	0.050	0.217	0.052	0.221	0.113	0.316	0.114	0.318	0.017
Netherlands	0.310	0.107	0.310	0.111	0.314	0.002	0.043	0.002	0.050	0.018
Poland	0.051	0.003	0.051	0.003	0.055	0.059	0.236	0.061	0.239	0.011
Portugal	0.262	0.073	0.261	0.074	0.261	0.001	0.023	0.001	0.024	0.001
Romania	0.061	0.004	0.062	0.004	0.064	0.108	0.311	0.111	0.315	0.018
Sweden	0.379	0.174	0.379	0.176	0.381	0.103	0.304	0.103	0.304	0.017
Slovenia	0.268	0.078	0.268	0.079	0.270	0.005	0.068	0.006	0.074	0.010
Slovakia	0.109	0.012	0.109	0.013	0.115	0.086	0.281	0.086	0.280	0.030
United Kingdom	0.373	0.167	0.373	0.167	0.373	0.083	0.238	0.084	0.241	0.019
Average	0.269	0.106	0.269	0.109	0.272	0.215	0.411	0.219	0.413	0.017

Table A3.7. Descriptive statistics of Self-efficacy indicator. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation (comparable across time)		Prop. of missing	Raw data		After imputation (comparable across time)		Prop. of missing
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Austria	-0.160	1.047	20.898	5.581	0.124	-0.102	1.011	21.413	4.673	0.009
Belgium	-0.165	0.958	20.747	5.276	0.173	-0.076	0.968	21.495	4.515	0.018
Bulgaria	0.303	1.051	23.452	5.052	0.211	-0.035	1.099	21.593	4.898	0.048
Cyprus	-0.056	1.107	21.473	5.708	0.110	NA	NA	NA	NA	NA
Czech Republic	0.064	0.931	22.236	4.928	0.065	0.163	0.945	22.607	4.280	0.023
Germany	-0.031	0.975	21.520	5.317	0.482	0.077	1.031	22.157	4.630	0.064
Denmark	0.045	1.015	22.075	5.421	0.154	-0.073	1.071	21.468	4.995	0.011
Estonia	-0.050	0.910	21.631	4.959	0.033	0.041	0.892	22.081	4.235	0.003
Greece	-0.051	1.031	21.436	5.505	0.054	-0.120	0.982	21.251	4.614	0.004
Spain	-0.135	1.066	21.046	5.775	0.078	-0.060	1.105	21.573	5.082	0.004
Finland	-0.053	0.968	21.556	5.208	0.070	0.037	0.970	22.067	4.450	0.004
France	-0.128	1.034	20.971	5.540	0.129	-0.046	0.983	21.658	4.581	0.018
Croatia	0.061	1.019	22.221	5.256	0.056	0.161	0.943	22.696	4.357	0.004
Hungary	-0.062	1.010	21.486	5.276	0.123	-0.047	0.891	21.684	4.198	0.005
Ireland	0.032	0.981	22.126	5.326	0.040	0.022	1.090	21.949	4.951	0.019
Italy	0.088	0.950	22.301	5.044	0.070	-0.201	0.813	20.961	3.920	0.007
Lithuania	0.192	0.954	22.991	4.855	0.076	0.021	0.847	22.062	4.009	0.004
Luxembourg	-0.042	1.082	21.490	5.610	0.136	-0.128	1.096	21.266	4.820	0.008
Latvia	-0.023	0.824	21.792	4.610	0.046	-0.006	0.860	21.876	4.065	0.005
Malta	-0.089	1.050	21.271	5.681	0.040	NA	NA	NA	NA	NA
Netherlands	-0.080	1.037	21.479	5.565	0.061	0.042	1.030	22.048	4.689	0.023
Poland	0.114	0.910	22.578	4.848	0.021	0.284	0.974	23.263	4.262	0.005
Portugal	0.202	1.024	22.979	5.283	0.045	0.227	0.967	22.965	4.404	0.004
Romania	-0.181	0.808	20.891	4.669	0.005	-0.351	1.066	20.138	4.923	0.004
Sweden	0.026	1.059	21.866	5.557	0.140	-0.057	1.076	21.611	4.830	0.012
Slovenia	0.042	0.902	22.126	4.878	0.074	-0.097	0.957	21.366	4.542	0.036
Slovakia	-0.070	1.069	21.391	5.563	0.098	0.124	0.901	22.467	4.176	0.011
United Kingdom	0.205	1.000	22.887	5.249	0.101	0.208	1.099	22.742	4.795	0.015
Average	0.000	0.992	21.853	5.236	0.101	0.000	0.987	21.864	4.534	0.014

Table A3.8. Descriptive statistics of Enjoyment of science indicator. PISA 2015 and 2006.

Country	PISA 2006					PISA 2015				
	Raw data		After imputation (comparable across time)		Prop. of missing	Raw data		After imputation (comparable across time)		Prop. of missing
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Austria	-0.293	1.131	11.711	4.607	0.077	-0.248	1.162	12.240	4.067	0.003
Belgium	0.101	1.020	13.336	4.111	0.105	0.121	1.037	13.574	3.571	0.004
Bulgaria	0.249	0.915	13.980	3.570	0.171	0.388	0.857	14.506	2.898	0.026
Cyprus	0.132	1.024	13.449	4.056	0.093	NA	NA	NA	NA	NA
Czech Republic	-0.307	0.886	11.815	3.678	0.040	-0.083	0.927	12.903	3.205	0.003
Germany	-0.162	1.099	12.205	4.468	0.376	-0.116	1.152	12.686	4.005	0.035
Denmark	0.105	1.035	13.402	4.077	0.078	-0.102	1.031	12.801	3.565	0.009
Estonia	0.144	0.924	13.628	3.623	0.027	-0.004	0.902	13.174	3.103	0.002
Greece	0.117	1.015	13.398	4.043	0.043	0.060	1.073	13.348	3.678	0.003
Spain	0.026	1.030	13.074	4.144	0.061	-0.167	1.009	12.581	3.528	0.004
Finland	-0.070	0.913	12.779	3.632	0.048	0.095	0.939	13.495	3.207	0.002
France	-0.030	1.010	12.786	4.108	0.092	0.124	1.039	13.577	3.583	0.015
Croatia	-0.101	0.977	12.612	3.947	0.040	0.081	0.944	13.462	3.228	0.002
Hungary	-0.207	0.972	12.171	3.952	0.101	0.180	0.950	13.792	3.233	0.002
Ireland	0.178	0.998	13.710	3.941	0.031	-0.211	1.080	12.394	3.782	0.020
Italy	-0.005	0.923	13.021	3.716	0.051	0.102	0.899	13.527	3.084	0.005
Lithuania	0.329	1.056	14.194	4.107	0.065	0.194	0.856	13.866	2.903	0.002
Luxembourg	0.088	1.106	13.220	4.405	0.091	-0.062	1.166	12.894	4.042	0.004
Latvia	0.082	0.864	13.451	3.436	0.030	-0.026	0.723	13.158	2.493	0.004
Malta	0.157	1.029	13.572	4.091	0.032	NA	NA	NA	NA	NA
Netherlands	-0.474	0.970	11.043	4.043	0.043	-0.363	0.974	11.879	3.431	0.002
Poland	0.014	0.885	13.164	3.492	0.018	-0.288	0.982	12.154	3.426	0.004
Portugal	0.285	0.904	14.153	3.522	0.036	0.308	0.829	14.256	2.793	0.003
Romania	-0.026	0.763	13.000	3.098	0.003	0.455	0.834	14.723	2.787	0.003
Sweden	0.069	1.143	13.111	4.509	0.106	-0.129	1.095	12.683	3.797	0.011
Slovenia	-0.333	0.956	11.676	3.949	0.035	-0.162	1.034	12.586	3.591	0.003
Slovakia	-0.223	0.917	12.127	3.774	0.076	-0.033	0.874	13.090	3.003	0.001
United Kingdom	0.130	0.966	13.536	3.827	0.076	-0.111	0.962	12.782	3.347	0.013
Average	-0.001	0.980	12.935	3.915	0.073	0.000	0.974	13.159	3.360	0.007

Table A3.9. Descriptive statistics of science clubs. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of	Raw data		After imputation		Prop. of
	Mean	SD	Mean	SD	missing	Mean	SD	Mean	SD	missing
Austria	0.050	0.218	0.053	0.224	0.049	0.269	0.444	0.268	0.443	0.044
Belgium	0.044	0.205	0.055	0.228	0.152	0.061	0.240	0.064	0.245	0.042
Bulgaria	0.609	0.488	0.602	0.490	0.047	NA	NA	NA	NA	NA
Cyprus	0.746	0.435	0.738	0.440	0.048	NA	NA	NA	NA	NA
Czech Republic	0.471	0.499	0.467	0.499	0.068	0.469	0.499	0.469	0.499	0.025
Germany	0.484	0.500	0.501	0.499	0.276	0.471	0.499	0.468	0.499	0.047
Denmark	0.089	0.284	0.109	0.310	0.252	0.032	0.175	0.062	0.242	0.176
Estonia	0.425	0.494	0.425	0.494	0.062	0.499	0.500	0.498	0.500	0.014
Greece	0.185	0.389	0.185	0.388	0.140	0.107	0.309	0.110	0.313	0.046
Spain	0.157	0.363	0.159	0.366	0.062	0.693	0.461	0.690	0.462	0.026
Finland	0.129	0.335	0.134	0.341	0.065	0.090	0.287	0.090	0.287	0.000
France	0.243	0.429	0.265	0.441	0.197	NA	NA	NA	NA	NA
Croatia	0.520	0.500	0.518	0.500	0.036	0.213	0.409	0.216	0.411	0.031
Hungary	0.520	0.500	0.518	0.500	0.091	0.725	0.447	0.724	0.447	0.024
Ireland	0.346	0.476	0.344	0.475	0.144	0.209	0.407	0.216	0.411	0.069
Italy	0.457	0.498	0.432	0.495	0.313	0.391	0.488	0.383	0.486	0.076
Lithuania	0.345	0.475	0.341	0.474	0.059	0.797	0.403	0.795	0.404	0.010
Luxembourg	0.325	0.468	0.326	0.469	0.075	0.329	0.470	0.329	0.470	0.003
Latvia	0.454	0.498	0.451	0.498	0.039	0.141	0.348	0.144	0.351	0.028
Malta	0.658	0.475	0.648	0.478	0.065	NA	NA	NA	NA	NA
Netherlands	0.182	0.386	0.233	0.422	0.365	0.080	0.271	0.080	0.272	0.006
Poland	0.794	0.404	0.787	0.409	0.053	0.781	0.413	0.781	0.413	0.021
Portugal	0.566	0.496	0.540	0.498	0.224	0.644	0.479	0.644	0.479	0.003
Romania	0.734	0.442	0.734	0.442	0.000	0.714	0.452	0.709	0.454	0.030
Sweden	0.071	0.256	0.072	0.258	0.034	0.072	0.259	0.074	0.262	0.014
Slovenia	0.521	0.500	0.510	0.500	0.112	0.918	0.275	0.917	0.275	0.011
Slovakia	0.602	0.489	0.593	0.491	0.071	0.776	0.417	0.773	0.419	0.021
United Kingdom	0.793	0.405	0.736	0.441	0.249	0.731	0.443	0.703	0.457	0.085
Average	0.411	0.425	0.388	0.429	0.120	0.425	0.391	0.425	0.396	0.038

Table A3.10. Descriptive statistics of science competitions. PISA 2015 and 2006.

Country	PISA 2015					PISA 2006				
	Raw data		After imputation		Prop. of	Raw data		After imputation		Prop. of
	Mean	SD	Mean	SD	missing	Mean	SD	Mean	SD	missing
Austria	0.309	0.462	0.312	0.463	0.048	0.351	0.477	0.349	0.477	0.038
Belgium	0.601	0.490	0.597	0.490	0.114	0.448	0.497	0.453	0.498	0.042
Bulgaria	0.832	0.374	0.824	0.380	0.037	0.785	0.411	0.785	0.411	0.034
Cyprus	0.870	0.336	0.869	0.337	0.031	NA	NA	NA	NA	NA
Czech Republic	0.849	0.358	0.844	0.363	0.036	0.784	0.412	0.783	0.412	0.025
Germany	0.589	0.492	0.601	0.489	0.258	0.434	0.496	0.439	0.496	0.061
Denmark	0.332	0.471	0.320	0.466	0.252	0.104	0.305	0.132	0.338	0.171
Estonia	0.945	0.228	0.944	0.231	0.017	0.883	0.322	0.883	0.322	0.000
Greece	0.708	0.455	0.685	0.464	0.085	0.672	0.469	0.672	0.469	0.028
Spain	0.656	0.475	0.653	0.476	0.019	0.369	0.483	0.367	0.482	0.041
Finland	0.860	0.347	0.854	0.353	0.026	0.372	0.483	0.372	0.483	0.006
France	0.671	0.470	0.653	0.476	0.158	NA	NA	NA	NA	NA
Croatia	0.815	0.388	0.811	0.391	0.029	0.749	0.434	0.748	0.434	0.012
Hungary	0.927	0.260	0.914	0.280	0.069	0.835	0.371	0.832	0.374	0.024
Ireland	0.653	0.476	0.633	0.482	0.109	0.539	0.499	0.542	0.498	0.035
Italy	0.659	0.474	0.664	0.472	0.312	0.344	0.475	0.339	0.473	0.098
Lithuania	0.922	0.269	0.921	0.270	0.015	0.912	0.284	0.911	0.285	0.004
Luxembourg	0.808	0.394	0.806	0.396	0.031	0.406	0.491	0.406	0.491	0.003
Latvia	0.852	0.355	0.845	0.362	0.023	0.913	0.281	0.912	0.284	0.013
Malta	0.747	0.435	0.735	0.441	0.055	NA	NA	NA	NA	NA
Netherlands	0.507	0.500	0.540	0.498	0.371	0.350	0.477	0.351	0.477	0.023
Poland	0.949	0.219	0.943	0.231	0.032	1.000	0.000	1.000	0.000	0.006
Portugal	0.886	0.318	0.852	0.355	0.184	0.623	0.485	0.623	0.485	0.024
Romania	0.372	0.483	0.372	0.483	0.013	0.919	0.274	0.916	0.278	0.011
Sweden	0.610	0.488	0.609	0.488	0.021	0.561	0.496	0.561	0.496	0.013
Slovenia	0.873	0.333	0.870	0.337	0.081	0.805	0.396	0.804	0.397	0.016
Slovakia	0.806	0.396	0.796	0.403	0.040	0.808	0.394	0.805	0.396	0.025
United Kingdom	0.721	0.449	0.722	0.447	0.252	0.716	0.451	0.714	0.452	0.103
Average	0.726	0.400	0.715	0.406	0.120	0.627	0.406	0.628	0.408	0.037

Table A3.11. Descriptive statistics of gender composition and school performance. PISA 2015 and 2006.

Country	PISA 2015				PISA 2006			
	School performance		Female composition		School performance		Female composition	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Austria	0.499	0.303	0.499	0.303	0.492	0.311	0.492	0.311
Belgium	0.492	0.164	0.492	0.164	0.483	0.220	0.483	0.220
Bulgaria	0.475	0.197	0.475	0.197	0.481	0.242	0.481	0.242
Cyprus	0.502	0.146	0.502	0.146	NA	NA	NA	NA
Czech Republic	0.484	0.217	0.484	0.217	0.434	0.254	0.434	0.254
Germany	0.490	0.131	0.490	0.131	0.487	0.153	0.487	0.153
Denmark	0.499	0.106	0.499	0.106	0.511	0.130	0.511	0.130
Estonia	0.493	0.118	0.493	0.118	0.490	0.116	0.490	0.116
Greece	0.476	0.145	0.476	0.145	0.496	0.160	0.496	0.160
Spain	0.503	0.097	0.503	0.097	0.503	0.124	0.503	0.124
Finland	0.485	0.083	0.485	0.083	0.506	0.094	0.506	0.094
France	0.506	0.164	0.506	0.164	0.514	0.171	0.514	0.171
Croatia	0.517	0.249	0.517	0.249	0.500	0.259	0.500	0.259
Hungary	0.498	0.234	0.498	0.234	0.480	0.235	0.480	0.235
Ireland	0.492	0.322	0.492	0.322	0.506	0.349	0.506	0.349
Italy	0.503	0.243	0.503	0.243	0.508	0.259	0.508	0.259
Lithuania	0.491	0.122	0.491	0.122	0.493	0.125	0.493	0.125
Luxembourg	0.506	0.182	0.506	0.182	0.494	0.186	0.494	0.186
Latvia	0.498	0.137	0.498	0.137	0.517	0.099	0.517	0.099
Malta	0.492	0.479	0.492	0.479	NA	NA	NA	NA
Netherlands	0.502	0.087	0.502	0.087	0.491	0.125	0.491	0.125
Poland	0.493	0.096	0.493	0.096	0.509	0.100	0.509	0.100
Portugal	0.497	0.079	0.497	0.079	0.520	0.111	0.520	0.111
Romania	0.502	0.140	0.502	0.140	0.501	0.187	0.501	0.187
Sweden	0.499	0.102	0.499	0.102	0.487	0.111	0.487	0.111
Slovenia	0.484	0.295	0.484	0.295	0.505	0.288	0.505	0.288
Slovakia	0.483	0.232	0.483	0.232	0.487	0.223	0.487	0.223
United Kingdom	0.492	0.183	0.492	0.183	0.505	0.199	0.505	0.199
Average	0.495	0.180	0.495	0.180	0.496	0.186	0.496	0.186

Table A3.12. Descriptive statistics of Institutional factors: Educational level and Vocational track orientation. PISA 2015 and 2006.

Country	PISA 2015				PISA 2006			
	ISCED 3		Vocational		ISCED 3		Vocational	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Austria	0.979	0.143	0.714	0.452	0.933	0.250	0.704	0.456
Belgium	0.844	0.363	0.278	0.448	0.897	0.303	0.387	0.487
Bulgaria	0.969	0.173	0.462	0.499	0.926	0.262	0.471	0.499
Croatia	0.998	0.046	0.673	0.469	0.996	0.059	0.722	0.448
Cyprus	0.939	0.240	0.119	0.324	NA	NA	NA	NA
Czech Republic	0.456	0.498	0.333	0.471	0.496	0.500	0.412	0.492
Denmark	0.007	0.082	0.000	0.000	0.011	0.106	0.000	0.000
Estonia	0.013	0.114	0.003	0.053	0.018	0.131	0.000	0.000
Finland	0.002	0.049	0.000	0.000	0.000	0.014	0.000	0.000
France	0.759	0.428	0.187	0.390	0.600	0.490	0.093	0.291
Germany	0.038	0.192	0.027	0.163	0.027	0.163	0.024	0.154
Greece	0.953	0.212	0.164	0.370	0.920	0.271	0.137	0.344
Hungary	0.898	0.303	0.159	0.366	0.923	0.266	0.570	0.495
Ireland	0.376	0.484	0.008	0.088	0.387	0.487	0.013	0.112
Italy	0.989	0.104	0.497	0.500	0.983	0.130	0.560	0.496
Latvia	0.037	0.189	0.008	0.090	0.034	0.180	0.034	0.180
Lithuania	0.000	0.015	0.015	0.121	0.000	0.016	0.002	0.048
Luxembourg	0.435	0.496	0.223	0.416	0.358	0.479	0.130	0.336
Malta	0.997	0.055	0.000	0.000	NA	NA	NA	NA
Netherlands	0.295	0.456	0.261	0.439	0.265	0.441	0.306	0.461
Poland	0.006	0.079	0.001	0.029	0.006	0.074	0.000	0.000
Portugal	0.653	0.476	0.131	0.338	0.498	0.500	0.140	0.347
Romania	0.000	0.000	0.000	0.000	0.000	0.000	0.234	0.424
Slovakia	0.526	0.499	0.326	0.469	0.614	0.487	0.431	0.495
Slovenia	0.949	0.220	0.574	0.495	0.963	0.188	0.521	0.500
Spain	0.001	0.030	0.009	0.095	0.000	0.019	0.000	0.000
Sweden	0.019	0.136	0.001	0.037	0.022	0.148	0.008	0.087
United Kingdom	0.998	0.046	0.008	0.087	0.995	0.067	0.000	0.000
Average	0.505	0.219	0.185	0.257	0.457	0.232	0.227	0.275

Table A3.13. Descriptive statistics of school science resources, grade repetition and school autonomy indicator (for school autonomy no missing data) Data available only for PISA 2015.

Country	School science resources					Grade repetition					Autonomy	
	Raw data		After imputation		Prop. of missing	Raw data		After imputation		Prop. of missing	Mean	SD
	Mean	SD	Mean	SD		Mean	SD	Mean	SD			
Austria	-0.441	1.139	-0.461	1.142	0.048	0.152	0.359	0.155	0.362	0.008	-0.279	0.576
Belgium	-0.028	0.831	-0.080	0.846	0.095	0.458	0.498	0.477	0.499	0.043	-0.483	0.924
Bulgaria	-0.266	0.925	-0.265	0.927	0.026	0.048	0.214	0.051	0.220	0.029	0.516	0.562
Cyprus	0.363	0.728	0.362	0.728	0.001	0.047	0.212	0.049	0.215	0.024	-1.142	1.108
Czech Republic	-0.281	1.041	-0.271	1.046	0.027	0.048	0.214	0.056	0.229	0.022	0.981	0.503
Germany	-0.178	0.905	-0.258	0.919	0.226	0.181	0.385	0.194	0.395	0.124	-0.614	0.973
Denmark	-0.196	0.737	-0.228	0.747	0.210	0.034	0.181	0.036	0.187	0.067	0.034	1.224
Estonia	-0.429	0.892	-0.432	0.893	0.009	0.040	0.196	0.041	0.198	0.015	0.759	0.519
Greece	-0.150	0.922	-0.150	0.921	0.034	0.050	0.217	0.050	0.219	0.008	-1.388	0.543
Spain	-0.190	0.930	-0.191	0.930	0.004	0.313	0.464	0.314	0.464	0.005	-0.308	0.640
Finland	-0.525	0.743	-0.539	0.752	0.012	0.030	0.169	0.032	0.177	0.018	0.275	0.598
France	0.102	0.829	0.078	0.833	0.083	0.221	0.415	0.230	0.421	0.028	-0.407	0.840
Croatia	-0.516	1.199	-0.539	1.206	0.025	0.016	0.124	0.016	0.126	0.015	-0.096	0.542
Hungary	-0.924	1.051	-0.948	1.055	0.067	0.095	0.293	0.096	0.295	0.013	-0.230	0.880
Ireland	0.474	0.785	0.471	0.787	0.062	0.072	0.258	0.073	0.260	0.011	0.146	0.769
Italy	-0.003	0.868	0.005	0.856	0.290	0.151	0.358	0.152	0.359	0.022	-0.804	0.983
Lithuania	-0.179	0.843	-0.179	0.843	0.000	0.025	0.156	0.026	0.159	0.025	0.860	0.401
Luxembourg	0.750	0.640	0.742	0.645	0.016	0.309	0.462	0.310	0.463	0.013	0.047	0.569
Latvia	0.444	0.964	0.435	0.976	0.018	0.050	0.218	0.051	0.219	0.010	0.607	0.633
Malta	1.000	0.656	0.999	0.656	0.007	0.070	0.255	0.071	0.256	0.010	-0.474	0.882
Netherlands	0.027	1.019	-0.006	1.023	0.350	0.201	0.401	0.208	0.406	0.037	-0.162	1.612
Poland	-0.026	0.924	-0.022	0.927	0.016	0.053	0.223	0.053	0.224	0.002	0.397	0.555
Portugal	0.499	0.730	0.491	0.734	0.018	0.312	0.464	0.316	0.465	0.015	-0.186	0.606
Romania	0.517	0.828	0.517	0.828	0.000	0.059	0.235	0.059	0.235	0.001	0.066	0.529
Sweden	-0.252	0.795	-0.252	0.795	0.000	0.040	0.197	0.043	0.202	0.023	0.741	0.427
Slovenia	0.338	0.935	0.289	0.962	0.088	0.019	0.136	0.020	0.140	0.029	0.200	0.801
Slovakia	-0.423	1.092	-0.423	1.092	0.000	0.065	0.247	0.077	0.267	0.031	0.766	0.468
United Kingdom	0.531	0.853	0.416	0.883	0.234	0.028	0.164	0.028	0.166	0.026	0.181	1.446
Average	0.001	0.886	-0.069	0.906	0.070	0.114	0.275	0.122	0.283	0.024	0.000	0.754

Table A3.14. Valid and missing response for the career expectation question sorted by number of valid responses in 2015.

Country	2015								2006							
	Males				Females				Males				Females			
	Expectations	Invalid	Do not know	Missing/NA	Expectations	Invalid	Do not know	Missing/NA	Expectations	Invalid	Do not know	Missing/NA	Expectations	Invalid	Do not know	Missing/NA
Austria	77.0	14.1	0.0	8.9	77.8	13.0	0.0	9.2	65.2	6.4	6.3	22.0	69.0	9.4	8.9	12.6
Belgium	78.8	1.6	6.7	12.9	84.5	0.9	5.5	9.1	80.0	2.6	7.6	9.8	81.3	3.3	8.8	6.7
Bulgaria	72.6	11.7	3.9	11.7	79.8	6.4	3.7	10.1	69.3	1.7	8.5	20.6	72.8	1.7	7.4	18.1
Cyprus	87.3	3.5	3.7	5.6	93.1	0.5	3.7	2.8	NA	NA	NA	NA	NA	NA	NA	NA
Czech Republic	74.1	9.9	7.2	8.8	78.6	6.9	6.3	8.1	63.1	3.8	8.2	24.9	70.7	3.0	11.0	15.3
Germany	91.3	1.6	6.8	0.3	91.6	1.9	6.4	0.2	66.1	8.9	4.9	20.0	72.2	6.2	5.8	15.9
Denmark	51.1	27.1	11.0	10.8	55.0	20.7	13.5	10.8	78.8	9.6	5.1	6.5	75.8	12.2	6.1	5.9
Estonia	87.2	0.0	0.0	12.8	91.7	0.0	0.0	8.3	72.5	4.9	7.1	15.5	75.5	3.5	8.2	12.9
Greece	84.8	3.9	3.6	7.7	89.7	1.6	4.2	4.5	66.2	3.1	3.1	27.5	80.0	2.3	4.3	13.4
Spain	88.3	2.4	4.8	4.4	90.5	1.9	3.4	4.3	69.0	1.2	4.9	24.9	79.0	1.2	5.2	14.6
Finland	72.0	10.3	8.5	9.2	78.5	8.2	5.6	7.7	69.3	12.8	5.5	12.4	80.3	6.4	6.8	6.6
France	90.4	4.0	4.8	0.7	92.7	2.1	5.0	0.3	72.4	2.7	0.2	24.8	80.6	2.4	0.2	16.8
Croatia	84.0	5.3	4.5	6.2	86.5	2.9	3.8	6.8	64.2	3.1	16.0	16.8	67.1	2.4	22.4	8.1
Hungary	79.3	7.1	6.2	7.4	77.3	6.2	6.2	10.3	65.3	5.7	6.9	22.2	70.6	5.8	9.7	13.9
Ireland	85.0	3.1	3.5	8.4	88.7	3.4	2.8	5.1	82.3	2.9	3.3	11.6	86.4	3.5	4.0	6.1
Italy	81.5	4.1	4.8	9.5	84.4	1.7	6.1	7.8	84.6	0.7	6.0	8.6	85.4	1.0	6.4	7.2
Lithuania	77.5	4.8	9.4	8.4	83.5	2.4	7.4	6.7	71.6	2.1	11.4	14.9	76.1	1.3	12.9	9.7
Luxembourg	78.5	6.2	5.8	9.5	85.9	1.5	5.0	7.7	75.6	5.0	8.6	10.8	82.3	4.5	9.6	3.7
Latvia	79.3	10.0	4.8	5.9	84.4	5.4	4.8	5.4	67.8	6.5	3.6	22.0	79.9	4.4	4.6	11.1
Malta	87.4	5.7	0.7	6.2	90.9	4.9	1.4	2.8	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	77.0	4.5	8.9	9.6	81.5	3.3	8.2	7.0	85.4	2.6	7.6	4.3	88.2	1.4	7.6	2.8
Poland	87.5	1.9	5.5	5.1	88.5	1.2	4.8	5.4	77.7	1.3	6.4	14.6	80.1	1.1	8.3	10.6
Portugal	82.9	3.5	4.9	8.6	82.8	3.2	5.3	8.8	76.9	12.1	7.2	3.7	81.6	6.8	7.6	4.0
Romania	90.6	2.7	2.7	4.1	91.5	1.5	3.5	3.5	88.7	0.3	5.9	5.2	90.1	0.3	5.7	3.9
Sweden	80.5	6.5	6.5	6.5	79.0	6.9	7.4	6.6	79.3	4.1	6.8	9.8	83.3	2.8	7.9	6.0
Slovenia	82.9	3.6	5.5	8.0	85.1	2.5	5.3	7.0	75.1	1.9	5.2	17.8	80.7	1.2	6.9	11.2
Slovakia	74.9	8.2	8.4	8.5	80.4	4.7	7.0	7.9	72.2	2.6	8.8	16.4	76.6	3.3	11.1	8.9
United Kingdom	81.3	2.3	4.6	11.8	86.5	1.4	4.2	7.9	84.4	3.9	4.4	7.4	86.8	4.8	4.5	3.9
Average	80.4	6.2	5.5	7.9	83.7	4.3	5.2	6.8	74.0	4.3	6.5	15.2	78.9	3.7	7.8	9.6

Table A4.1. Percentage of students with career expectation in managerial, professional and associate professional occupations.

Country	2015						2006					
	Fem			Males			Fem			Males		
	Managers	Professionals	Associate Prof.	Managers	Professionals	Associate Prof.	Managers	Professionals	Associate Prof.	Managers	Professionals	Associate Prof.
Austria	4.1	54.6	14.4	5.8	43.6	13.3	9.9	38.7	18.4	7.5	24.5	21.4
Belgium	2.4	61.4	17.0	3.5	49.1	14.0	4.3	68.6	5.7	6.8	50.3	8.3
Bulgaria	4.6	69.5	11.3	3.9	48.0	20.5	8.2	66.9	5.8	8.8	59.7	8.1
Cyprus	2.7	76.6	10.3	4.1	48.5	19.1	0.0	0.0	0.0	0.0	0.0	0.0
Czech Republic	2.8	50.6	16.4	3.2	33.2	21.5	8.4	44.2	12.9	13.1	29.7	15.8
Germany	2.7	44.6	21.9	3.2	39.3	14.8	2.7	38.9	22.0	5.5	31.6	22.7
Denmark	4.0	68.4	11.4	6.9	44.2	18.9	2.6	51.3	20.7	8.3	34.8	17.6
Estonia	6.5	63.1	12.9	10.2	47.4	15.7	5.7	57.3	15.0	12.4	33.7	15.5
Greece	1.2	76.1	6.0	1.8	48.8	19.5	5.7	71.2	9.9	7.6	45.9	22.2
Spain	4.3	73.4	9.4	4.9	55.5	11.2	3.4	71.2	9.1	6.6	51.3	12.3
Finland	1.2	54.5	15.8	2.5	35.3	15.2	3.1	50.3	10.9	7.5	28.8	12.3
France	4.0	52.2	19.5	3.7	44.2	15.4	4.3	42.7	33.4	4.4	40.1	22.5
Croatia	3.1	56.4	15.5	4.1	34.5	23.4	2.5	55.8	15.6	4.2	24.2	31.5
Hungary	3.2	46.5	13.7	5.3	39.4	13.1	4.8	47.8	7.0	5.2	38.3	10.9
Ireland	2.6	74.2	8.4	4.4	57.1	16.7	4.2	67.0	8.8	6.4	52.6	10.3
Italy	3.5	63.0	8.9	5.2	41.6	23.6	4.6	65.6	11.1	8.1	46.7	20.0
Lithuania	6.2	63.5	13.0	11.8	42.0	11.0	12.1	55.3	16.2	19.8	39.9	11.5
Luxembourg	1.5	58.1	13.5	2.4	47.9	16.6	2.6	69.0	8.3	5.3	46.6	15.2
Latvia	9.8	61.9	12.5	8.7	36.6	20.0	15.5	46.0	17.0	18.7	34.3	12.1
Malta	4.2	64.9	9.8	5.3	56.3	20.3	0.0	0.0	0.0	0.0	0.0	0.0
Netherlands	8.6	44.9	21.4	10.8	39.1	20.1	8.1	43.1	24.8	18.5	29.3	22.1
Poland	2.2	58.1	11.2	3.4	27.8	20.4	2.0	67.0	8.0	5.7	41.3	25.8
Portugal	5.7	72.0	7.2	7.5	49.7	22.4	1.4	76.3	8.7	2.0	53.9	24.3
Romania	2.5	61.6	6.4	2.0	46.8	4.8	4.3	62.5	9.7	7.1	38.6	15.7
Sweden	2.0	60.5	16.5	3.1	37.8	27.6	5.4	47.0	22.2	7.1	31.4	27.4
Slovenia	2.1	64.0	15.3	4.2	36.2	32.9	2.4	65.1	12.6	5.6	44.6	22.7
Slovakia	11.6	51.8	11.5	10.0	30.0	23.2	11.1	50.1	14.7	11.5	38.5	17.1
United Kingdom	3.9	74.7	9.2	8.2	56.6	14.0	3.5	58.6	15.4	8.0	42.7	18.7
Average	4.1	60.7	13.1	5.4	42.8	18.1	5.5	56.8	14.0	8.5	39.7	17.8

Table A4.2. Percentage of students with career expectation in managerial, professional and associate professional STEM occupations.

Country	2015 Fem STEM Prof.	2015 Fem STEM Associate Prof.	2015 Males STEM Prof.	2015 Males STEM Associate Prof.	2006 Fem STEM Prof.	2006 Fem STEM Associate Prof.	2006 Males STEM Prof.	2006 Males STEM Associate Prof.
Austria	8.1	0.7	26.7	5.6	5.1	2.3	11.7	13.0
Belgium	8.2	0.5	22.8	1.8	6.2	1.8	21.8	4.0
Bulgaria	14.1	0.7	28.0	6.5	14.0	0.6	14.5	1.5
Cyprus	12.8	0.5	23.9	2.8	0.0	0.0	0.0	0.0
Czech Republic	5.8	1.1	16.0	12.7	7.8	1.5	18.0	10.4
Germany	9.9	1.9	23.4	5.6	5.4	2.3	14.7	10.2
Denmark	8.1	1.0	16.0	7.1	5.2	2.6	14.0	7.9
Estonia	13.0	0.9	30.8	7.2	12.2	2.9	21.5	5.3
Greece	9.5	1.2	19.2	7.8	14.9	1.3	23.1	7.9
Spain	10.5	1.3	27.1	3.6	9.9	0.8	26.3	4.7
Finland	2.8	1.0	13.7	6.1	3.7	2.1	11.9	5.2
France	8.2	0.8	24.6	4.3	4.4	2.8	17.9	8.7
Croatia	8.0	2.0	17.2	13.8	4.2	2.3	9.1	22.5
Hungary	7.1	0.7	25.5	2.8	6.3	0.9	20.1	5.9
Ireland	7.9	1.5	23.2	5.5	4.8	0.9	20.6	4.0
Italy	8.6	1.8	20.2	12.0	8.4	1.4	24.0	6.6
Lithuania	11.2	0.8	24.9	2.4	11.2	0.6	24.7	2.2
Luxembourg	8.4	1.1	23.2	4.8	7.1	1.6	19.0	6.9
Latvia	14.6	0.9	22.5	9.2	11.2	0.8	22.1	4.3
Malta	8.9	1.7	25.9	8.6	0.0	0.0	0.0	0.0
Netherlands	5.2	2.5	16.2	9.9	2.8	1.7	8.4	8.2
Poland	7.1	1.5	11.3	12.3	9.3	1.1	21.9	15.5
Portugal	12.7	0.5	26.6	8.1	11.0	4.0	28.5	13.2
Romania	8.3	0.9	19.9	2.4	6.1	2.6	18.0	4.0
Sweden	7.4	2.4	17.5	12.0	4.7	5.2	11.3	13.9
Slovenia	7.1	3.6	18.9	24.3	8.1	1.2	24.4	12.2
Slovakia	6.6	2.0	14.6	15.0	5.3	0.6	21.7	6.2
United Kingdom	10.7	0.5	27.0	3.5	5.5	1.7	15.4	3.9
Average	8.8	1.3	21.4	7.9	7.5	1.8	18.6	8.0

Table A4.3. Percentage of students with career expectation in managerial, professional and associate professional health occupations.

Country	2015				2006			
	Fem		Males		Fem		Males	
	Health Prof.	Health Associate Prof.	Health Prof.	Health Associate Prof.	Health Prof.	Health Associate Prof.	Health Prof.	Health Associate Prof.
Austria	15.8	7.3	5.6	1.3	10.0	11.0	3.4	1.1
Belgium	20.7	6.7	8.6	0.5	19.1	0.8	6.8	0.1
Bulgaria	22.5	0.3	8.9	0.1	20.1	0.3	17.2	0.3
Cyprus	23.2	0.0	11.2	0.3	0.0	0.0	0.0	0.0
Czech Republic	13.6	8.1	5.2	1.3	8.1	3.3	2.3	0.4
Germany	9.9	9.6	3.6	1.4	8.7	7.4	3.6	1.3
Denmark	26.1	2.6	7.9	0.3	13.9	6.5	5.3	0.3
Estonia	15.0	1.1	4.2	0.3	10.0	0.2	1.6	0.2
Greece	18.0	0.8	9.2	0.3	10.6	2.5	6.8	0.8
Spain	22.0	1.1	7.8	0.3	19.3	2.3	7.0	0.5
Finland	21.2	9.5	7.3	2.0	12.1	3.7	4.3	0.5
France	16.5	10.3	6.8	2.2	12.0	15.7	5.9	3.5
Croatia	18.0	8.8	7.5	2.0	11.5	4.7	4.2	1.8
Hungary	10.8	2.7	3.3	0.3	9.4	2.7	3.7	0.2
Ireland	22.7	2.2	9.2	0.7	21.5	2.6	9.3	0.2
Italy	16.9	2.1	7.4	0.9	15.8	0.8	7.6	1.1
Lithuania	20.9	3.3	5.2	0.4	10.8	1.2	3.3	0.4
Luxembourg	13.6	6.6	6.7	1.8	14.9	2.6	6.0	0.8
Latvia	18.8	1.0	3.8	0.2	7.7	1.0	2.5	0.0
Malta	14.8	0.6	8.3	0.4	0.0	0.0	0.0	0.0
Netherlands	13.5	10.5	5.8	0.8	12.4	13.0	5.1	1.0
Poland	23.1	1.5	5.5	0.4	15.6	1.2	5.1	0.7
Portugal	25.8	1.1	7.8	0.2	28.5	1.0	10.5	0.7
Romania	19.9	3.5	8.9	1.3	11.1	2.7	3.6	0.5
Sweden	17.5	1.2	5.1	0.1	12.6	3.3	4.4	0.2
Slovenia	22.7	5.8	6.9	2.1	17.9	5.5	7.1	1.3
Slovakia	18.8	3.5	6.1	0.5	9.2	2.9	3.0	0.4
United Kingdom	24.3	1.6	8.4	0.4	14.1	4.1	7.2	0.7
Average	18.8	4.4	6.6	0.9	13.7	4.0	5.6	0.7

Table A5.1. Regression coefficients for models M3i (see Table 5.2 for references).

Country	Female	Science literacy	ESCS	Parents in STEM	Migrant	Self-efficacy	Enjoyment of science	Interaction terms Female X … Science literacy	ESCS	Parents in STEM	Migrant	Self-efficacy	Enjoyment of science	R2
Austria	**-0.221**	**0.107**	**-0.033**		0.018	-0.012	**0.026**	**-0.072**	**0.047**		0.011	0.010	-0.011	**0.124**
Belgium	**-0.126**	**0.120**	-0.006	0.045	0.056	-0.001	**0.039**	**-0.096**	0.008	-0.029	-0.033	0.010	-0.024	**0.116**
Bulgaria	**-0.211**	**0.116**	0.013	**0.156**	**-0.142**	0.014	-0.007	**-0.069**	0.000	-0.054	0.133	-0.012	-0.022	**0.121**
Croatia	**-0.200**	**0.119**	0.005	**0.096**	-0.011	0.005	0.001	**-0.080**	0.023	-0.066	-0.001	-0.012	**0.029**	**0.128**
Cyprus	**-0.145**	**0.080**	-0.004	**0.124**	-0.015	0.015	**0.030**	**-0.044**	0.003	**-0.081**	-0.026	-0.020	-0.006	**0.070**
Czech Republic	**-0.187**	**0.123**	-0.003	**0.075**	-0.026	-0.001	0.018	**-0.104**	0.000	-0.060	0.012	0.012	0.015	**0.147**
Denmark	**-0.144**	**0.051**	-0.026	**0.168**	0.012	0.012	**0.034**	-0.019	0.032	-0.110	-0.016	-0.010	-0.007	**0.083**
Estonia	**-0.181**	**0.092**	0.001	**0.147**	0.061	-0.011	-0.001	**-0.067**	-0.003	**-0.100**	**-0.130**	0.021	**0.037**	**0.107**
Finland	**-0.125**	**0.075**	0.001	**0.078**	**0.119**	0.007	**0.025**	**-0.062**	0.000	**-0.068**	-0.084	-0.007	-0.013	**0.105**
France	**-0.154**	**0.085**	0.000	**0.136**	**0.087**	-0.005	**0.074**	**-0.053**	0.014	**-0.094**	-0.046	0.003	**-0.039**	**0.146**
Germany	**-0.102**	**0.108**	0.017	**0.138**	**0.095**	-0.014	**0.052**	**-0.073**	0.000	**-0.078**	-0.068	0.009	-0.018	**0.134**
Greece	**-0.149**	0.022	0.002	**0.173**	-0.002	0.003	**0.041**	0.003	-0.004	**-0.101**	-0.005	0.003	0.015	**0.077**
Hungary	**-0.193**	**0.135**	0.000	**0.204**	-0.055	-0.008	**0.030**	**-0.089**	-0.007	**-0.170**	0.086	0.016	-0.006	**0.175**
Ireland	**-0.159**	**0.075**	-0.014	**0.078**	**0.137**	0.003	**0.048**	-0.024	0.008	-0.008	**-0.080**	-0.003	**-0.029**	**0.112**
Italy	**-0.180**	**0.079**	-0.018	**0.095**	0.032	0.013	**0.062**	**-0.043**	0.009	**-0.084**	-0.023	-0.016	-0.019	**0.112**
Latvia	**-0.162**	**0.128**	0.005	**0.112**	-0.043	0.009	-0.002	**-0.104**	0.015	-0.025	0.055	-0.026	0.013	**0.082**
Lithuania	**-0.161**	**0.119**	0.019	0.083	-0.008	-0.009	**0.019**	**-0.095**	0.004	-0.019	-0.031	0.007	-0.020	**0.095**
Luxembourg	**-0.162**	**0.091**	-0.001	**0.120**	0.024	0.015	**0.023**	**-0.049**	0.012	**-0.098**	-0.002	-0.008	-0.014	**0.115**
Malta	**-0.234**	**0.054**	-0.001	**0.127**	0.008	**-0.034**	**0.071**	**-0.029**	0.003	-0.038	0.001	**0.032**	-0.025	**0.133**
Netherlands	**-0.165**	**0.057**	0.007	**0.132**	0.014	-0.001	**0.078**	**-0.027**	0.002	**-0.119**	0.007	0.007	**-0.046**	**0.124**
Poland	**-0.146**	**0.106**	**0.033**	0.071	0.124	0.014	0.013	**-0.062**	**-0.037**	-0.043	-0.192	-0.012	-0.014	**0.103**
Portugal	**-0.191**	**0.116**	0.017	0.061	-0.037	-0.009	**0.045**	**-0.077**	-0.007	-0.039	**0.092**	0.000	-0.014	**0.124**
Romania	**-0.186**	**0.112**	**0.060**	**0.126**	-0.076	0.021	0.006	**-0.053**	**-0.044**	-0.078	0.221	-0.017	-0.012	**0.116**
Slovakia	**-0.217**	**0.101**	0.003	**0.080**	-0.105	0.002	0.007	**-0.063**	0.006	-0.049	**0.271**	0.000	0.000	**0.118**
Slovenia	**-0.279**	**0.100**	**-0.032**	**0.093**	-0.047	0.000	-0.005	**-0.089**	0.019	-0.018	0.027	0.022	**0.037**	**0.156**
Spain	**-0.161**	**0.133**	0.005	**0.079**	**0.086**	0.002	**0.042**	**-0.076**	0.005	-0.009	-0.057	-0.003	-0.013	**0.136**
Sweden	**-0.157**	**0.094**	0.006	**0.105**	**0.072**	0.003	**0.034**	**-0.064**	-0.010	-0.068	-0.071	0.006	-0.010	**0.125**
United Kingdom	**-0.176**	**0.064**	-0.010	0.063	0.030	0.011	**0.049**	**-0.025**	0.017	-0.019	0.003	-0.004	-0.022	**0.097**
EU28	**-0.172**	**0.095**	0.003	**0.110**	0.014	0.002	**0.031**	**-0.061**	0.002	**-0.064**	0.002	0.000	**-0.008**	**0.117**

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table A5.2 Coefficients of the M5i linear probability model (model with interactions). Main effects

Country	Female	Science literacy	ESCS	Parents in STEM	Migrant	Self-efficacy	Enjoyment of science	Science res.	Scie. clubs	Scie. comp.	% of females	School auto-nomy	Grade repeti-tion	School perfor.	R2
Austria	**-0.092**	**0.052**	**-0.015**		0.023	-0.008	**0.021**	**0.027**	-0.058	0.021	**-0.063**	-0.007	**0.036**	**0.046**	**0.174**
Belgium	**-0.150**	**0.077**	-0.004	0.030	**0.037**	0.005	**0.029**	**-0.035**	0.001	0.027	**0.022**	0.007	0.003	0.001	**0.108**
Bulgaria	**-0.150**	**0.073**	0.012	**0.120**	-0.091	0.008	-0.015	-0.017	0.010	0.015	**-0.072**	-0.006	**-0.065**	**0.046**	**0.135**
Croatia	**-0.119**	**0.082**	**0.021**	**0.055**	-0.005	-0.006	**0.016**	0.023	0.012	**0.061**	**-0.070**	**0.041**	0.045	0.009	**0.177**
Cyprus	**-0.137**	**0.068**	0.001	**0.085**	-0.029	0.005	**0.024**	-0.003	0.011	-0.022	0.013	-0.009	0.006	-0.021	**0.066**
Czech Republic	**-0.179**	**0.077**	-0.006	**0.050**	-0.022	0.005	**0.025**	-0.014	0.028	0.035	**-0.029**	0.019	-0.044	0.001	**0.139**
Denmark	**-0.139**	**0.046**	-0.010	**0.114**	0.001	0.008	**0.030**	-0.006	0.005	-0.003	-0.006	-0.002	0.035	-0.013	**0.080**
Estonia	**-0.242**	**0.068**	0.000	**0.095**	0.004	-0.002	**0.017**	**0.015**	0.004	-0.007	0.025	-0.004	-0.058	**-0.044**	**0.103**
Finland	**-0.162**	**0.050**	0.002	**0.041**	**0.088**	0.002	**0.020**	-0.006	-0.005	0.009	-0.034	0.007	-0.018	-0.017	**0.095**
France	**-0.166**	**0.071**	0.010	**0.086**	**0.067**	-0.004	**0.055**	0.005	-0.007	-0.009	-0.015	-0.010	-0.012	-0.019	**0.136**
Germany	**-0.134**	**0.070**	0.014	**0.103**	**0.060**	-0.008	**0.045**	**-0.013**	-0.023	0.026	-0.007	0.000	**0.036**	0.017	**0.126**
Greece	**-0.138**	**0.040**	0.005	**0.119**	-0.007	0.004	**0.049**	-0.003	0.020	-0.002	**-0.042**	-0.012	-0.004	-0.024	**0.083**
Hungary	**-0.176**	**0.062**	**-0.018**	**0.121**	-0.019	-0.001	**0.025**	0.011	0.020	**-0.070**	**-0.034**	-0.006	0.005	**0.071**	**0.171**
Ireland	**-0.206**	**0.069**	-0.011	**0.073**	**0.098**	0.001	**0.034**	0.005	0.012	-0.007	**0.012**	0.003	-0.010	-0.024	**0.110**
Italy	**-0.106**	**0.045**	-0.008	**0.045**	0.017	0.006	**0.044**	0.014	-0.006	0.016	**-0.071**	-0.001	-0.015	0.020	**0.146**
Latvia	**-0.169**	**0.079**	0.012	**0.099**	-0.013	-0.004	0.008	-0.002	-0.002	0.024	-0.004	-0.004	**-0.058**	-0.013	**0.072**
Lithuania	**-0.159**	**0.073**	**0.017**	**0.077**	-0.016	-0.006	0.010	-0.005	0.017	-0.001	0.005	-0.023	0.009	0.011	**0.082**
Luxembourg	**-0.173**	**0.067**	0.000	**0.075**	0.015	0.012	**0.017**	0.008	-0.010	0.013	-0.002	**0.033**	-0.001	0.002	**0.110**
Malta	**-0.275**	**0.040**	0.001	**0.104**	0.019	**-0.022**	**0.061**	0.014	**0.040**	-0.022	0.008	-0.002	-0.038	0.002	**0.133**
Netherlands	**-0.169**	**0.048**	0.010	**0.069**	0.016	0.001	**0.057**	-0.006	-0.001	0.009	0.031	0.008	-0.003	-0.012	**0.117**
Poland	**-0.144**	**0.078**	0.012	0.050	0.029	0.009	0.004	0.010	0.007	-0.019	-0.020	-0.008	-0.030	-0.008	**0.091**
Portugal	**-0.204**	**0.079**	0.010	**0.047**	0.012	-0.010	**0.039**	-0.009	0.018	0.025	0.020	0.021	-0.013	-0.006	**0.116**
Romania	**-0.135**	**0.074**	**0.035**	**0.082**	0.006	0.013	0.001	0.010	-0.027	-0.009	-0.006	-0.019	-0.016	0.035	**0.106**
Slovakia	**-0.161**	**0.079**	0.003	**0.057**	-0.003	0.000	0.008	-0.004	0.010	**0.052**	**-0.040**	-0.009	**-0.061**	-0.019	**0.124**
Slovenia	**-0.129**	**0.051**	**-0.017**	**0.070**	-0.011	0.009	**0.019**	**0.016**	**-0.046**	**0.039**	**-0.110**	**0.016**	0.015	**0.051**	**0.240**
Spain	**-0.178**	**0.091**	0.005	**0.075**	**0.058**	0.001	**0.035**	0.001	0.003	0.002	0.004	0.002	**-0.034**	-0.011	**0.129**
Sweden	**-0.186**	**0.072**	0.002	**0.071**	0.037	0.005	**0.029**	0.000	0.001	-0.010	-0.017	-0.009	-0.010	-0.030	**0.116**
United Kingdom	**-0.184**	**0.061**	0.002	**0.054**	0.031	0.008	**0.037**	-0.004	0.009	0.008	0.002	-0.003	-0.015	**-0.036**	**0.097**
EU28	**-0.166**	**0.066**	**0.004**	**0.077**	0.014	0.001	**0.027**	0.000	0.004	0.007	**-0.016**	0.001	**-0.013**	-0.001	**0.119**

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table A5.3. Coefficients of the M5i linear probability model (model with interactions). Main effects

Country	Interaction terms Female X …												
	Science literacy	ESCS	Parents in STEM	Migrant	Self-efficacy	Enjoyment of science	Science res.	Scie. clubs	Scie. comp.	% of females	School auto-nomy	Grade repeti-tion	School perfor.
Austria	**-0.046**	**0.033**		-0.037	0.007	-0.012	**-0.045**	0.045	-0.021	**0.048**	0.052	-0.068	**-0.071**
Belgium	**-0.099**	0.006	-0.034	-0.027	0.010	-0.022	0.017	0.036	-0.020	-0.016	-0.006	0.004	0.024
Bulgaria	**-0.053**	-0.002	-0.041	0.104	-0.011	-0.024	-0.011	-0.037	-0.050	0.018	0.029	0.097	-0.023
Croatia	**-0.065**	0.019	-0.055	-0.001	-0.013	**0.026**	0.031	-0.036	**-0.133**	**0.055**	0.014	0.050	**-0.099**
Cyprus	**-0.040**	0.002	**-0.087**	-0.035	**-0.022**	-0.004	0.006	-0.008	-0.021	**-0.084**	0.003	0.060	0.019
Czech Republic	**-0.110**	-0.007	**-0.063**	-0.006	0.011	0.013	0.012	-0.020	**-0.118**	0.028	-0.026	0.030	0.033
Denmark	-0.026	0.029	-0.108	-0.009	-0.009	-0.006	-0.005	-0.006	-0.015	-0.021	0.015	0.034	0.043
Estonia	**-0.072**	-0.004	**-0.099**	**-0.117**	0.020	**0.037**	-0.006	-0.030	-0.118	-0.027	-0.020	0.117	0.073
Finland	**-0.064**	-0.004	**-0.067**	-0.095	-0.006	-0.014	0.018	0.012	-0.027	0.047	-0.002	0.056	0.029
France	**-0.064**	0.009	**-0.089**	-0.058	0.002	**-0.037**	-0.022	-0.040	-0.008	**0.059**	0.022	-0.036	-0.009
Germany	**-0.076**	0.000	-0.077	-0.070	0.010	-0.020	0.003	-0.002	-0.017	0.004	-0.024	-0.027	0.003
Greece	-0.034	-0.016	**-0.100**	-0.001	0.005	0.013	-0.003	0.030	-0.053	0.052	0.014	-0.017	**0.063**
Hungary	-0.032	0.009	**-0.165**	0.106	0.013	-0.008	-0.011	-0.040	-0.019	0.011	-0.003	-0.097	**-0.123**
Ireland	**-0.033**	0.005	-0.011	**-0.077**	-0.004	**-0.026**	-0.017	0.028	0.001	**-0.038**	-0.007	-0.002	0.033
Italy	-0.036	-0.007	**-0.077**	-0.023	-0.018	-0.017	**-0.031**	0.003	-0.055	**0.038**	-0.014	0.036	0.006
Latvia	**-0.106**	0.015	-0.024	0.052	-0.024	0.013	-0.011	0.000	0.040	0.006	0.009	0.001	0.006
Lithuania	**-0.089**	0.003	-0.021	-0.039	0.007	-0.020	0.020	-0.035	-0.011	-0.020	-0.038	**0.155**	0.006
Luxembourg	**-0.066**	0.002	**-0.096**	-0.003	-0.008	-0.015	0.028	0.004	-0.024	-0.028	-0.042	0.020	**0.086**
Malta	-0.024	-0.004	-0.029	-0.003	**0.032**	-0.023	0.003	-0.006	-0.016	-0.019	0.035	0.112	-0.008
Netherlands	-0.028	0.001	**-0.121**	0.006	0.009	**-0.048**	0.001	0.013	0.014	-0.020	-0.007	**0.064**	0.012
Poland	**-0.064**	**-0.038**	-0.045	-0.187	-0.012	-0.014	-0.006	-0.034	0.042	0.010	-0.021	0.005	0.013
Portugal	**-0.072**	-0.007	-0.037	0.091	-0.001	-0.013	0.037	-0.019	-0.070	-0.042	-0.020	0.032	0.030
Romania	-0.039	**-0.037**	-0.076	0.229	-0.016	-0.012	**-0.040**	**0.077**	-0.027	**-0.064**	0.053	-0.011	-0.012
Slovakia	**-0.068**	0.010	-0.042	**0.231**	-0.002	-0.002	-0.010	-0.025	**-0.065**	0.003	0.006	**0.083**	0.035
Slovenia	**-0.045**	0.006	0.009	-0.034	0.015	0.022	0.017	-0.044	-0.051	**0.074**	-0.014	-0.070	**-0.188**
Spain	**-0.070**	0.005	-0.009	-0.060	-0.003	-0.013	0.001	-0.011	0.003	0.002	0.008	0.035	0.022
Sweden	**-0.072**	-0.013	-0.073	-0.063	0.008	-0.010	0.010	-0.039	0.021	0.011	-0.023	0.007	0.052
United Kingdom	**-0.040**	0.008	-0.019	0.005	-0.004	-0.020	0.010	-0.017	-0.015	0.005	0.002	-0.060	**0.067**
EU28	**-0.059**	0.000	**-0.061**	-0.003	0.000	**-0.009**	0.001	-0.009	**-0.030**	0.002	-0.002	**0.025**	0.007

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table A5.4 Pairwise correlations between country level variables. Lower diagonal absolute value upper diagonal sign

	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	D1	D2	D3	D4	D5	E1	E2	E3	F1	F2	F3	F4
A1	**1.0**	−	−	−	−	+	+	+	+	+	+	+	+	−	+	+	−	+	+	+	+	+	−	−	+	−	+	+	−	−	−	−
A2	**0.6**	**1.0**	+	+	+	−	−	−	+	−	−	−	−	−	−	−	−	−	−	−	−	−	−	−	−	−	−	−	+	−	+	+
A3	**0.6**	0.3	**1.0**	+	+	+	−	−	−	+	−	+	+	+	−	−	−	−	−	−	−	−	+	+	+	+	−	−	−	−	−	−
A4	0.2	0.2	0.2	**1.0**	+	−	+	−	+	−	−	−	−	−	−	−	−	−	−	−	+	+	+	+	+	+	+	+	−	+	+	−
A5	0.3	0.2	0.2	0.1	**1.0**	+	+	+	+	+	−	−	−	−	+	+	−	+	−	−	−	−	−	−	−	+	−	+	−	+	+	+
B1	0.2	0.1	0.1	0.2	0.1	**1.0**	+	+	+	+	−	+	+	+	+	+	+	−	+	+	−	−	−	−	−	+	+	+	−	−	+	+
B2	0.1	0.1	0.1	0.1	0.1	0.2	**1.0**	−	+	+	+	−	−	−	+	−	+	−	−	−	−	−	−	−	+	+	+	−	+	+	+	−
B3	**0.4**	0.2	0.1	0.2	0.1	0.3	**0.4**	**1.0**	+	+	−	+	+	+	−	+	−	−	−	−	+	+	−	−	+	+	+	+	+	−	+	+
B4	0.3	0.1	0.1	0.1	0.3	**0.4**	0.1	0.2	**1.0**	+	−	−	−	−	+	+	−	−	+	−	−	−	−	−	−	+	+	+	+	−	−	−
B5	0.3	0.1	0.0	0.1	0.2	**0.8**	0.1	**0.5**	**0.7**	**1.0**	−	−	+	+	+	+	−	−	+	+	−	−	−	−	−	+	+	+	+	−	+	+
C1	0.1	0.3	0.2	0.1	0.0	0.1	0.3	0.1	**0.3**	0.2	**1.0**	+	−	+	+	−	−	+	+	+	−	+	+	+	+	+	−	−	−	+	+	+
C2	0.0	0.1	0.2	0.3	**0.4**	0.2	0.2	0.0	**0.3**	0.1	0.0	**1.0**	+	+	+	+	+	+	+	+	−	+	+	−	−	+	−	−	−	+	+	+
C3	0.0	0.2	0.2	0.2	**0.3**	0.2	0.1	0.0	0.0	0.0	0.1	**0.4**	**1.0**	+	+	+	+	+	+	+	+	+	+	+	−	−	−	−	+	−	−	+
C4	0.0	0.2	0.2	0.3	0.1	**0.3**	0.2	0.1	0.0	0.2	0.2	0.2	**0.6**	**1.0**	+	+	+	+	+	+	+	+	+	+	−	+	−	−	+	−	−	+
C5	**0.4**	**0.4**	0.3	**0.4**	0.2	**0.4**	0.1	0.1	0.1	0.2	0.2	**0.3**	0.2	**0.4**	**1.0**	+	+	+	+	+	+	+	+	−	−	−	−	−	−	−	+	+
C6	0.1	0.0	0.1	0.1	0.0	**0.6**	0.1	0.0	0.1	**0.3**	0.0	**0.6**	0.2	0.1	**0.4**	**1.0**	+	+	+	+	−	−	−	−	−	+	+	+	−	−	+	+
C7	0.0	0.1	0.0	0.1	0.1	0.1	0.2	0.2	0.0	0.0	0.2	**0.3**	**0.6**	0.2	**0.3**	**0.5**	**1.0**	+	+	+	+	+	+	−	−	−	−	−	−	+	+	+
C8	0.2	**0.4**	**0.3**	0.1	0.0	0.2	0.0	0.1	**0.3**	0.3	0.3	0.2	0.3	**0.4**	**0.4**	0.2	**0.5**	**1.0**	+	+	+	+	+	+	+	−	+	−	−	+	+	+
C9	0.2	0.2	0.0	0.2	0.0	**0.4**	0.0	0.1	0.2	0.2	0.1	**0.4**	**0.5**	**0.4**	**0.6**	**0.6**	**0.5**	**0.4**	**1.0**	+	+	+	+	−	−	−	−	−	+	−	+	+
C10	0.2	**0.3**	0.0	**0.3**	0.2	**0.3**	0.0	0.0	0.1	0.1	0.2	**0.6**	**0.6**	**0.6**	**0.7**	**0.7**	**0.7**	**0.6**	**0.8**	**1.0**	+	+	+	−	−	−	−	−	−	−	+	+
D1	**0.4**	0.2	0.3	0.1	**0.4**	**0.4**	0.2	0.1	0.1	**0.3**	0.1	0.1	0.2	0.0	0.1	0.2	0.1	**0.4**	0.1	0.1	**1.0**	+	+	+	+	−	+	+	+	−	−	−
D2	**0.4**	0.1	0.2	0.1	**0.4**	**0.4**	0.3	0.1	0.1	0.3	0.0	0.1	0.1	0.0	0.2	0.2	0.1	**0.3**	0.0	0.1	**0.8**	**1.0**	+	+	+	−	+	+	+	+	−	−
D3	0.2	0.1	0.3	0.1	0.0	0.2	0.2	0.1	0.2	**0.4**	0.3	0.0	0.3	0.1	0.1	0.2	0.2	0.1	0.1	0.2	**0.4**	0.3	**1.0**	+	+	+	+	−	+	−	+	+
D4	0.0	0.1	0.2	0.2	0.1	0.2	0.1	0.1	**0.3**	**0.4**	**0.3**	0.1	0.1	0.0	0.0	0.2	0.0	0.0	0.0	0.0	**0.5**	**0.3**	**0.8**	**1.0**	+	−	+	+	−	+	−	−
D5	0.0	0.1	0.2	0.2	0.2	**0.4**	0.2	0.0	**0.3**	**0.4**	0.1	0.1	0.1	0.1	0.0	**0.3**	0.0	0.1	0.1	0.1	**0.5**	**0.7**	**0.7**	**0.8**	**1.0**	+	+	+	+	+	−	−
E1	0.1	0.1	0.2	0.1	0.0	0.1	**0.3**	**0.3**	0.1	0.2	0.1	0.2	0.1	0.0	0.2	0.0	0.1	0.0	0.1	0.0	0.2	0.0	0.0	0.1	0.1	**1.0**	+	+	+	−	+	+
E2	0.1	0.1	0.0	0.1	0.1	**0.3**	0.2	**0.4**	0.0	0.3	0.1	0.1	0.2	0.0	0.1	0.3	0.0	0.0	0.2	0.1	0.1	0.1	0.0	0.3	0.3	**0.3**	**1.0**	+	+	−	+	+
E3	0.2	0.2	0.1	0.1	0.0	**0.4**	0.3	**0.4**	0.2	**0.4**	0.0	0.2	0.3	0.1	0.2	0.1	0.2	0.1	0.2	0.2	0.0	0.0	0.0	0.2	0.2	**0.5**	**0.9**	**1.0**	+	−	+	+
F1	0.0	0.1	0.1	0.2	0.0	0.1	0.1	**0.3**	0.1	0.1	0.2	0.0	0.3	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.2	0.2	**1.0**	−	+	+
F2	0.0	0.1	0.1	0.2	0.1	0.1	0.2	0.3	0.1	0.3	0.2	0.0	0.0	0.3	0.1	0.2	0.0	0.1	0.3	0.1	0.1	0.0	0.0	0.1	0.1	0.1	0.0	0.0	**0.7**	**1.0**	−	−
F3	0.1	0.1	0.2	0.0	0.2	**0.4**	0.2	0.3	0.1	0.2	0.2	0.1	0.1	0.0	0.1	**0.5**	**0.3**	0.1	0.2	0.2	0.2	0.2	0.0	0.0	0.1	0.0	**0.3**	0.3	0.2	0.1	**1.0**	+
F4	0.0	0.1	0.2	**0.4**	0.2	0.2	0.1	0.1	0.2	0.0	**0.4**	0.2	0.2	0.2	**0.3**	**0.5**	0.2	0.2	**0.4**	**0.4**	0.3	0.3	0.1	0.0	0.2	0.1	0.1	0.0	**0.4**	**0.3**	**0.6**	**1.0**

Table A6.1. Real and predicted change form Oaxaca decomposition.

	All				Males				Females			
	Real change		Predicted change		Real change		Predicted change		Real change		Predicted change	
Country	est.	se	est.	se	est.	se	est.	se	est.	se	est.	se
Austria	**0.043**	(0.015)	-0.019	(0.011)	**0.068**	(0.024)	-0.022	(0.016)	0.018	(0.012)	-0.017	(0.008)
Bulgaria	**0.079**	(0.014)	0.009	(0.016)	**0.162**	(0.020)	0.015	(0.023)	-0.014	(0.015)	-0.004	(0.016)
Croatia	0.012	(0.019)	-0.010	(0.012)	0.000	(0.027)	-0.003	(0.018)	**0.031**	(0.012)	-0.005	(0.009)
Estonia	**0.054**	(0.010)	**0.011**	(0.005)	**0.118**	(0.016)	**0.016**	(0.007)	-0.012	(0.013)	0.005	(0.006)
Finland	0.004	(0.008)	-0.006	(0.008)	0.023	(0.013)	-0.012	(0.013)	-0.022	(0.008)	-0.007	(0.005)
France	0.021	(0.011)	-0.010	(0.005)	0.018	(0.017)	-0.006	(0.009)	**0.020**	(0.010)	-0.003	(0.003)
Germany	**0.033**	(0.011)	-0.003	(0.005)	0.033	(0.018)	0.007	(0.009)	**0.035**	(0.011)	-0.005	(0.004)
Greece	-0.034	(0.010)	-0.005	(0.006)	-0.022	(0.016)	-0.011	(0.008)	-0.052	(0.012)	0.003	(0.007)
Ireland	**0.042**	(0.008)	**0.012**	(0.005)	**0.041**	(0.013)	**0.027**	(0.008)	**0.036**	(0.009)	**0.009**	(0.005)
Latvia	**0.047**	(0.011)	0.007	(0.008)	**0.053**	(0.020)	0.008	(0.012)	**0.036**	(0.010)	0.006	(0.008)
Netherlands	**0.058**	(0.007)	-0.023	(0.005)	**0.087**	(0.015)	-0.026	(0.010)	**0.033**	(0.008)	-0.007	(0.003)
Poland	-0.071	(0.009)	0.003	(0.005)	-0.136	(0.015)	0.008	(0.007)	-0.012	(0.008)	0.000	(0.005)
Portugal	-0.042	(0.011)	**0.065**	(0.016)	-0.075	(0.018)	**0.093**	(0.023)	-0.019	(0.013)	**0.029**	(0.014)
Slovakia	0.023	(0.014)	-0.025	(0.008)	0.019	(0.017)	-0.039	(0.012)	**0.028**	(0.011)	-0.009	(0.006)
Slovenia	**0.038**	(0.009)	**0.044**	(0.007)	**0.053**	(0.014)	**0.043**	(0.015)	0.012	(0.012)	0.009	(0.007)
Sweden	0.015	(0.009)	0.004	(0.003)	**0.037**	(0.014)	0.008	(0.006)	-0.004	(0.012)	0.000	(0.003)
United Kingdom	**0.079**	(0.007)	**0.010**	(0.004)	**0.112**	(0.011)	0.007	(0.005)	**0.043**	(0.008)	**0.010**	(0.004)

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table A6.2. Results of Oaxaca decomposition predicted changes attributed to the variables for total population.

	Parents in STEM	Abilities	ESCS	Migrants	Joyscie	Scieeff	Auto-nomy	Sclub	Scomp	Vocat track	Isced3
Austria		-0.015	0.002	**0.004**	-0.004	0.000	0.004	0.000	-0.005	0.001	-0.006
Bulgaria	0.001	0.003	**0.007**	0.000	0.001	0.002	-0.003	NA	0.001	-0.002	0.000
Croatia	-0.001	-0.019	**0.008**	0.000	-0.003	-0.001	0.002	0.001	0.008	-0.008	NA
Estonia	**0.003**	0.002	0.005	0.000	**0.002**	-0.001	0.000	0.000	0.000	NA	0.000
Finland	**0.002**	-0.013	0.001	**0.001**	-0.003	-0.001	0.002	0.000	0.006	0.000	0.000
France	**0.002**	0.000	**0.005**	0.000	-0.013	-0.001	NA	NA	NA	0.002	-0.004
Germany	0.000	-0.004	0.001	**0.002**	-0.006	0.001	0.000	0.000	0.004	0.000	0.000
Greece	0.001	-0.007	**0.007**	0.001	0.001	0.000	-0.007	-0.001	0.000	0.002	-0.002
Ireland	**0.001**	-0.003	-0.001	**0.006**	**0.008**	0.000	0.000	0.001	-0.001	0.000	0.000
Latvia	**0.002**	0.001	0.001	0.000	0.001	0.000	-0.001	0.002	0.000	**0.002**	NA
Netherlands	**0.002**	-0.007	0.000	0.000	-0.012	-0.001	-0.002	-0.002	-0.001	0.001	-0.001
Poland	-0.002	0.001	0.002	0.000	0.002	0.001	0.000	0.000	0.000	NA	NA
Portugal	**0.003**	**0.025**	**0.011**	0.000	-0.001	0.000	**0.040**	-0.002	-0.003	-0.001	-0.007
Slovakia	0.001	-0.025	0.004	0.000	-0.002	-0.002	0.003	-0.001	0.000	-0.012	**0.009**
Slovenia	-0.001	-0.006	**0.005**	0.000	-0.003	**0.002**	-0.001	**0.025**	**0.007**	**0.011**	**0.003**
Sweden	**0.003**	-0.005	0.001	0.002	**0.004**	0.001	0.000	0.000	-0.001	0.000	0.000
United Kingdom	0.000	-0.002	0.000	0.002	**0.010**	0.000	0.001	0.000	0.000	NA	0.000

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table 6.3. Results of Oaxaca decomposition predicted changes attributed to the variables for males.

	Parents in STEM	Abilities	ESCS	Migrants	Joyscie	Scieeff	Autonomy	Sclub	Scomp	Vocat track	Isced3
Austria		-0.014	0.001	**0.006**	-0.001	0.000	-0.008	0.005	-0.004	0.003	-0.009
Bulgaria	0.001	0.003	0.008	-0.001	0.000	0.003	0.001	NA	0.002	-0.002	0.000
Croatia	0.000	-0.019	0.005	0.000	-0.001	0.000	-0.005	0.006	0.017	-0.008	NA
Estonia	**0.005**	0.005	0.003	0.000	0.004	0.000	0.000	0.000	0.000	NA	0.000
Finland	**0.002**	-0.031	0.002	**0.002**	-0.003	0.000	0.001	-0.001	0.013	0.000	0.001
France	0.002	0.000	0.004	0.000	-0.010	0.000	NA	NA	NA	-0.002	0.001
Germany	0.001	-0.005	0.000	**0.004**	0.001	0.000	0.001	-0.001	0.007	-0.002	0.000
Greece	0.000	-0.009	**0.008**	0.001	-0.002	0.000	-0.010	-0.001	0.000	0.003	-0.002
Ireland	0.001	0.000	-0.001	**0.009**	**0.019**	0.000	0.000	0.002	-0.002	0.000	0.000
Latvia	0.001	-0.001	0.000	0.001	0.001	0.000	-0.001	0.004	-0.001	0.003	NA
Netherlands	0.003	-0.007	0.000	0.000	-0.015	0.000	-0.004	-0.003	-0.002	0.002	0.000
Poland	-0.003	0.002	0.001	0.000	**0.007**	0.000	0.001	0.000	0.000	NA	NA
Portugal	**0.002**	**0.031**	**0.009**	0.000	0.001	0.000	**0.053**	-0.002	-0.003	-0.001	0.004
Slovakia	0.000	-0.036	0.004	-0.001	-0.003	-0.002	0.002	0.000	-0.001	-0.012	**0.009**
Slovenia	0.001	-0.007	0.002	0.001	-0.002	0.001	0.000	0.020	**0.013**	**0.011**	0.002
Sweden	**0.005**	-0.010	0.000	**0.004**	**0.011**	-0.001	0.000	0.000	-0.001	0.000	0.000
United Kingdom	0.001	-0.006	-0.001	0.002	**0.010**	0.000	0.001	0.000	0.000	NA	0.000

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table 6.4. Results of Oaxaca decomposition predicted changes attributed to the variables for total females.

	Parents in STEM	Abilities	ESCS	Migrants	Joyscie	Scieeff	Autonomy	Sclub	Scomp	Vocat track	Isced3
Austria	NA	-0.008	0.001	0.001	-0.004	-0.001	**0.006**	-0.007	-0.003	0.000	-0.001
Bulgaria	0.000	0.002	0.003	0.000	0.001	0.002	-0.012	NA	0.000	0.000	0.000
Croatia	-0.001	-0.008	**0.006**	0.000	-0.007	0.000	0.004	0.001	0.002	-0.001	NA
Estonia	0.002	0.000	0.002	0.001	0.001	-0.002	0.000	0.000	0.000	NA	0.000
Finland	0.001	-0.003	0.000	0.000	-0.003	-0.001	0.002	0.000	-0.002	0.000	0.000
France	0.001	0.000	**0.004**	0.000	-0.010	0.000	NA	NA	NA	-0.001	0.003
Germany	0.000	-0.003	0.000	0.000	-0.009	0.002	0.000	0.000	0.004	0.000	0.000
Greece	0.001	-0.005	0.003	0.000	0.004	0.000	-0.002	0.000	0.000	0.000	0.001
Ireland	**0.002**	-0.004	0.000	**0.003**	**0.003**	0.000	0.004	0.002	-0.001	**0.000**	0.000
Latvia	0.001	0.001	0.001	0.000	0.000	0.000	-0.001	0.001	0.000	0.001	NA
Netherlands	0.001	-0.003	0.001	0.000	-0.005	-0.001	-0.001	0.000	0.002	0.001	-0.001
Poland	-0.001	0.000	0.000	0.000	0.002	0.000	-0.001	0.000	0.000	NA	NA
Portugal	0.002	**0.008**	**0.008**	0.000	-0.002	0.000	0.017	-0.001	-0.003	0.000	-0.001
Slovakia	0.001	-0.009	0.002	0.001	-0.003	0.000	-0.001	0.000	0.000	-0.001	0.002
Slovenia	-0.001	-0.003	0.000	0.000	-0.009	0.001	0.000	**0.016**	0.001	**0.002**	0.002
Sweden	0.002	-0.002	0.001	0.000	0.001	0.000	-0.001	0.000	0.000	0.000	0.000
United Kingdom	-0.001	0.000	0.001	0.002	**0.007**	0.000	0.001	0.000	0.000	NA	0.000

Note: results in **bold** are statistically significant (different from zero) at p<=0.05

Table A6.5. Proportion of 15-old students in vocational tracks for PISA 2015 and 2006 by gender.

Country	2015				2006			
	Females		Males		Females		Males	
	prop.	se	prop.	se	prop.	se	prop.	se
Austria	0.676	(0.016)	0.752	(0.016)	0.673	(0.018)	0.735	(0.020)
Belgium	0.250	(0.025)	0.304	(0.030)	0.333	(0.029)	0.437	(0.039)
Bulgaria	0.386	(0.025)	0.530	(0.022)	0.386	(0.032)	0.551	(0.032)
Cyprus	0.048	(0.001)	0.191	(0.002)	NA	NA	NA	NA
Czech Republic	0.355	(0.018)	0.311	(0.017)	0.349	(0.030)	0.461	(0.026)
Germany	0.025	(0.008)	0.029	(0.010)	0.030	(0.008)	0.019	(0.003)
Denmark	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Estonia	0.003	(0.001)	0.003	(0.003)	0.000	(0.000)	0.000	(0.000)
Greece	0.096	(0.019)	0.227	(0.032)	0.085	(0.014)	0.190	(0.024)
Spain	0.006	(0.002)	0.012	(0.002)	0.000	(0.000)	0.000	(0.000)
Finland	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
France	0.155	(0.015)	0.221	(0.016)	0.086	(0.012)	0.100	(0.012)
Croatia	0.598	(0.015)	0.755	(0.011)	0.637	(0.017)	0.806	(0.011)
Hungary	0.111	(0.012)	0.207	(0.013)	0.526	(0.024)	0.610	(0.022)
Ireland	0.004	(0.001)	0.011	(0.004)	0.010	(0.002)	0.015	(0.003)
Italy	0.386	(0.017)	0.610	(0.016)	0.452	(0.016)	0.671	(0.012)
Lithuania	0.008	(0.004)	0.021	(0.010)	0.000	(0.000)	0.004	(0.003)
Luxembourg	0.210	(0.003)	0.237	(0.003)	0.130	(0.006)	0.129	(0.005)
Latvia	0.012	(0.007)	0.004	(0.004)	0.040	(0.005)	0.027	(0.005)
Malta	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	0.238	(0.010)	0.283	(0.012)	0.293	(0.015)	0.319	(0.017)
Poland	0.001	(0.001)	0.001	(0.001)	0.000	(0.000)	0.000	(0.000)
Portugal	0.110	(0.012)	0.153	(0.012)	0.117	(0.010)	0.165	(0.015)
Romania	NA	NA	NA	NA	0.181	(0.030)	0.288	(0.024)
Sweden	0.003	(0.002)	0.000	(0.000)	0.008	(0.002)	0.008	(0.004)
Slovenia	0.491	(0.004)	0.651	(0.005)	0.440	(0.006)	0.602	(0.008)
Slovakia	0.296	(0.020)	0.354	(0.019)	0.409	(0.031)	0.451	(0.028)
United Kingdom	0.007	(0.002)	0.009	(0.003)	0.000	(0.000)	0.000	(0.000)
Average	0.172	(0.012)	0.226	(0.013)	0.200	(0.016)	0.253	(0.017)

Table A6.6. Science literacy PISA 2015 and 2006 by gender.

Country	Females 2015				Males 2015				Females 2006				Males 2006			
	mean		sd		mean		sd		mean		sd		mean		sd	
	est	se	est	se	est	se	est	se	est	se	est	se	est	se	est	se
Austria	485.5	(3.1)	93.1	(1.7)	504.4	(3.6)	100.4	(1.6)	507.0	(4.9)	98.0	(3.7)	514.5	(4.2)	97.6	(2.1)
Belgium	480.2	(4.7)	93.3	(2.1)	491.1	(5.6)	97.9	(2.0)	487.8	(5.3)	99.3	(3.4)	484.5	(5.5)	106.5	(3.5)
Bulgaria	453.9	(4.4)	98.5	(2.5)	438.5	(5.3)	103.6	(2.4)	442.9	(6.9)	103.3	(3.3)	425.9	(6.6)	109.2	(3.7)
Cyprus	440.9	(1.9)	86.7	(1.6)	424.1	(1.7)	97.9	(1.6)	NA	NA	NA	NA	NA	NA	NA	NA
Czech Republic	488.4	(2.5)	90.2	(1.9)	497.0	(3.3)	99.6	(1.8)	510.1	(4.8)	100.7	(3.0)	515.0	(4.2)	96.6	(1.9)
Germany	503.8	(2.8)	96.7	(1.6)	514.3	(3.2)	101.5	(1.9)	512.0	(3.8)	96.8	(2.0)	519.1	(4.6)	102.7	(2.5)
Denmark	498.9	(3.2)	87.2	(1.4)	504.9	(2.6)	93.2	(1.6)	491.5	(3.4)	91.6	(1.8)	500.4	(3.6)	94.5	(1.7)
Estonia	532.5	(2.3)	84.6	(1.4)	535.8	(2.7)	92.8	(1.5)	533.3	(2.9)	80.6	(1.5)	529.6	(3.1)	86.4	(1.4)
Greece	459.4	(3.9)	88.3	(2.1)	450.6	(4.6)	95.0	(2.1)	479.1	(3.4)	85.3	(2.2)	467.7	(4.5)	98.2	(2.7)
Spain	489.5	(2.5)	84.3	(1.4)	496.1	(2.5)	91.4	(1.5)	486.2	(2.7)	87.4	(1.4)	490.6	(2.9)	93.5	(1.3)
Finland	540.5	(2.6)	90.6	(1.7)	521.5	(2.7)	100.2	(1.6)	564.9	(2.4)	81.6	(1.4)	561.8	(2.6)	89.5	(1.4)
France	494.0	(2.7)	97.2	(1.6)	495.9	(2.7)	106.6	(1.9)	493.9	(3.6)	97.2	(2.4)	496.6	(4.3)	106.0	(2.6)
Croatia	472.6	(2.8)	85.5	(1.6)	478.4	(3.2)	93.2	(1.6)	494.4	(3.1)	82.8	(1.7)	492.0	(3.3)	88.6	(1.7)
Hungary	475.2	(2.9)	94.5	(1.9)	478.2	(3.4)	98.1	(1.8)	500.6	(3.5)	83.6	(2.0)	507.0	(3.3)	92.1	(2.2)
Ireland	497.2	(2.6)	82.9	(1.4)	507.7	(3.2)	93.9	(1.8)	508.5	(3.3)	90.8	(1.8)	508.1	(4.3)	97.9	(1.9)
Italy	472.1	(3.6)	88.9	(1.8)	489.1	(3.1)	93.2	(1.5)	473.9	(2.5)	91.0	(1.4)	476.9	(2.8)	100.0	(1.9)
Lithuania	479.2	(2.8)	87.9	(1.5)	471.8	(3.3)	93.6	(1.8)	492.7	(3.1)	88.7	(1.7)	483.4	(3.1)	91.0	(1.9)
Luxembourg	479.0	(1.5)	96.5	(1.4)	486.7	(1.7)	104.0	(1.3)	481.6	(1.8)	92.2	(1.4)	490.9	(1.8)	100.9	(1.5)
Latvia	495.6	(2.2)	78.9	(1.5)	484.9	(2.0)	85.1	(1.4)	493.0	(3.2)	82.6	(1.6)	485.9	(3.5)	85.9	(1.8)
Malta	470.2	(2.2)	114.9	(2.4)	459.5	(2.5)	120.0	(1.7)	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	506.5	(2.5)	97.3	(1.7)	510.6	(2.9)	104.4	(1.8)	521.2	(3.1)	94.1	(2.1)	528.4	(3.2)	96.9	(1.9)
Poland	498.3	(2.8)	86.9	(1.7)	504.5	(2.9)	94.3	(1.8)	496.1	(2.6)	86.3	(1.4)	499.5	(2.7)	93.3	(1.4)
Portugal	496.1	(2.6)	87.1	(1.4)	506.1	(2.9)	96.0	(1.3)	471.9	(3.2)	86.1	(1.9)	476.9	(3.7)	91.0	(2.1)
Romania	437.9	(3.4)	78.2	(1.8)	431.9	(3.7)	79.9	(2.1)	419.5	(4.8)	76.9	(2.9)	417.3	(4.1)	85.2	(2.4)
Sweden	495.7	(3.7)	98.2	(1.7)	491.2	(4.1)	106.5	(1.7)	502.7	(2.9)	91.6	(2.1)	504.0	(2.7)	96.6	(1.9)
Slovenia	515.8	(1.9)	93.0	(1.6)	510.1	(1.9)	97.1	(1.5)	522.7	(1.9)	95.7	(1.7)	514.9	(2.0)	100.4	(1.5)
Slovakia	461.2	(3.3)	96.2	(2.0)	460.4	(3.0)	101.5	(1.7)	485.2	(3.0)	89.9	(1.9)	491.5	(3.9)	96.0	(2.6)
United Kingdom	508.8	(3.3)	98.0	(1.5)	509.6	(2.9)	101.2	(1.4)	509.8	(2.8)	101.9	(1.8)	519.9	(3.0)	111.3	(2.0)
Average	486.8	(3.0)	91.3	(1.7)	487.7	(3.2)	97.9	(1.7)	495.5	(3.6)	90.6	(2.2)	496.2	(3.7)	96.5	(2.1)

KJ-NA-28878-EN-N

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub

Publications Office

doi:10.2760/251627
ISBN 978-92-79-76475-2