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Immigrant background and expected early school leaving in Europe: evidence from PISA

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Note

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Executive summary

This technical brief analyses the relationship between immigrant status and educational expectations in PISA. Migration flows from outside and within the EU have increased in recent years, and this has raised the attention of policy makers and the general public, with special interests on the implications that those flows can have on, among other, the education system and the labour markets. At the same time, the EU has set the Europe 2020 headline target of reducing the share of early school leavers to 10 % within the EU. Early school leavers become generally disadvantaged socially and economically in later stages in life, so that it is important to better understand the motivations for leaving school and provide adequate policy solutions. The European Commission (2016, p. 3) indicates that early school leavers are more likely to come from immigrant student groups, as their "early school leaving rates are nearly twice as high as for the native population". Yet it also emphasises that there is still a lack of evidence pointing to the underlying reasons. In particular, it is not clear whether, among early school leavers, immigrants students are more frequent due to specific reasons related to the status of immigrants or whether they are more frequent because immigrant students are more likely to possess the set of characteristics that are normally associated to early school leaving behaviour (such as belonging to low socio economic status).

This study analyses the factors that are most strongly related to the probability to leave school early, putting special attention to immigrant status (by differentiating among first and second generation immigrants and, where possible, among EU and non-EU immigrants). To this end, we use OECD's PISA data, which are the most widely employed data on international student assessment. Since early school leavers cannot directly be considered with these data, we focus on educational expectations, including the expectation to dropout early from school. As the related literature emphasises, these expectations are very closely linked to actually realised educational career patterns. Therefore, we can use expectations to gain insights on the factors influencing early school leaving. In addition, we also employ data from Eurostat to complement the picture on early school leavers and immigrants.

First, we provide a range of descriptive data on immigrants and expected early school leavers. Second, we run a number of two-level logit regression models, including a range of student- and school-level variables. In particular, we consider all (available) EU Member States together, before providing results for each MS individually. Finally, we also distinguish more specifically between EU and non-EU immigrants in our regression models.

The results show that, when controlling for individual and school characteristics, immigrant students do not structurally differ in their expected early dropout probability from natives across Europe. In other words, the reasons why students expect to leave school early are the same for both immigrant students and natives. This finding implies that it is more important to focus on the common factors that are associated with expected early school leaving. In particular, our results suggest that these are, at the students' level, the socio-economic background of students, their epistemological beliefs and grade repetition, while, at the school level, the most consistent factor is the school's mean expected early school leavers rate. The school-environment thus appears to play a key role in shaping educational expectations. Among the student-related factors, grade repetition is the most amenable by policy, so that grade repetition practices may be reconsidered by national policy makers.

1 Introduction

This brief pertains to EAC's strategic area of *Fighting inequalities, promoting social inclusion and investment in young people, common EU values and Solidarity Corps,* and in particular addresses the need to better understand the educational expectations of both first and second generation immigrants, in an attempt to obtain greater insights on the increased risk of early dropouts for this group of individuals. It is also related to the CRELL IX Technical Report on Civic and Citizenship Education.

Achieving equity and improving educational levels of young people is a policy priority for the EU.¹ As a consequence, the Europe 2020 headline targets in education sets as goals that at least 40 % of 30-34 year-olds complete tertiary education and that the rates of early school leaving are reduced to below 10 % in the EU28. Recently, the European Commission has also suggested to lower the latter benchmark for early school leaving to 5 % by 2025 (European Commission, 2017). Early school leaving is a crucial issue as it "is an obstacle to economic growth and employment. It hampers productivity and competitiveness, and fuels poverty and social exclusion" (European Commission, 2016, p. 1). However, early school leaver (ESL) rates vary substantially among Member States (MS) (see Figure 1). In the EU, Malta has the highest ESL rate (20 %) in 2016, while Croatia has the lowest one (3 %).

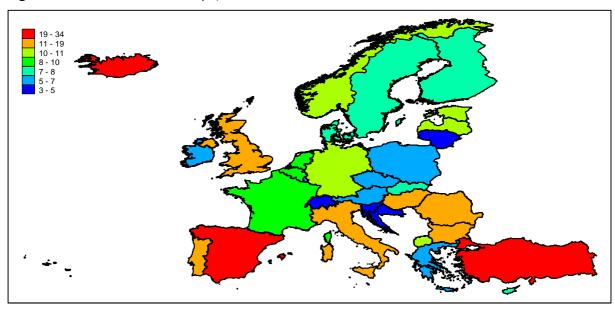


Figure 1. Shares of ESL in Europe, 2016

Note: 7 classes automatically defined. Shares given in percent. Only those European (i.e., EU and non-EU) countries for which Eurostat provides data are shown in the map.

Source: Eurostat (2017b). Background map: © EuroGeographics for the administrative boundaries.

Early school leaving is a complex issue and a concern for policy makers as empirical evidence also shows that dropping out from school is connected with several forms of individual and social disadvantages, with significant negative consequences for job, wages and life satisfaction (e.g., European Commission, EACEA, Eurydice, & Cedefop, 2014). In particular, immigrant students "are largely over-represented among the early leavers from education and training in many European countries" (European Commission et al., 2014, p. 38).

Persisting disparities between immigrants² and natives in educational (and labour market) outcomes in MS are a source of inequality and social exclusion (see Flisi, Meroni,

1

¹ For more information on equity in education related issues, see Hippe, Araújo, & Dinis da Costa (Hippe, Araújo, & Dinis da Costa, 2016).

² In this brief, the terms immigrants and migrants are used synonymously.

& Vera-Toscano, 2016; Rodrigues, 2018). Therefore, comparing educational expectations between immigrants and natives, at an early age, is particularly important if policy makers intend to counteract disparities in educational achievement that later in life lead to social and economic inequalities.

The recent wave of large-scale refugee intake by MS has increased the challenges associated with the integration of immigrants in the host countries (European Commission, 2016). In this context, education is key to successful integration and employability (OECD, 2016c). At the same time, the free movement of persons among MS has led to significant worker and student mobility within the EU. In consequence, it is useful to distinguish immigrants not only by their time of arrival in a MS (first or second generation) but also by their place of origin (we distinguish between EU- or non-EU origin).

Our objective is to better understand inequalities in (expected) early school leaving within and across MS. In addition, we analyse the factors that are most strongly related to disparities in the probability to leave school early, putting special attention to immigrant status (by differentiating among first and second generation immigrants and, where possible, among EU and non-EU immigrants).

To achieve this task, this technical brief uses data from OECD's Program for International Student Assessment (PISA).³ As PISA 2015 includes a broader set of variables than previous rounds, we are able to consider a large range of possible relevant factors that may be related to early school leaving (and immigrant status). However, ESL rates cannot be measured directly in international student assessment data like PISA. Thus, it is only possible to consider students' expectations. Still, expected educational levels provide useful information on potential future educational attainment. In fact, the relationship between expectations and (later) achievement is well established in the social sciences (Portes et al. 2010). Therefore, we can use these expectations to gain insights on the factors influencing early school leaving. Furthermore, we also use complementary data from Eurostat on migrant populations in Europe.

While PISA 2015 includes data on students with immigrant background in all MS, for some MS the number of migrants in the sample is too low and so we cannot include them in our analysis. In addition, for a few MS there is no information on educational expectations of students in PISA, which further reduces the sample. For these reasons, we analyse the expected educational level in accordance with these sample size limitations.

We analyse educational expectations first by computing descriptive statistics and then by running a range of regression models for all MS together and for each MS separately. More specifically, we use two-level logit regression models that include both the student and the school level to explore the factors that are significantly correlated with the probability to expect leaving school early. In a final step, we also distinguish among EU and non-EU immigrants in further regression models, by comparing each group to natives and by comparing directly both groups to each other.

The results for all MS together indicate that there are no inherent differences between natives and immigrants in Europe in the factors that influence the probability of expected early school leaving. This finding implies that instead of focussing on immigrant-specific measures, it may be more appropriate to consider policy measures that deal with the underlying issues leading to expecting early school leaving that are common to both natives and immigrant students. In fact, our regressions show that these underlying factors are both related to students and to schools. At the student level, the most relevant factors are socio-economic background of students, epistemological beliefs and grade repetition. At the school level, it is the school's mean expected early school leavers' rate.

³ PISA data are described more in detail in section 3. For more information see also the official OECD PISA website: http://www.oecd.org/pisa/.

These findings are largely confirmed by our country-by-country multilevel regressions. Interestingly, the only significant factor across all MS is the school's mean expected early school leavers rate, confirming that the school-environment plays a crucial role in shaping educational expectations. All other factors, both at the student and school level, are to varying degrees consistent across MS, but the student-related factors that are mostly relevant in the regressions for the entire EU are also mostly important in the country-by-country design. The detailed results for each MS and the distinction between EU and non-EU immigrants show some specific features that are characteristic of each MS's education system and immigrant population, which may provide useful information for MS.

The technical brief is divided as follows. First, we review the literature on immigrant student populations and educational expectations. The data and methodology are presented in the following section, which is followed by the empirical analysis. Finally, the conclusion sums up the results of the technical brief, provides policy recommendations and indicates future research avenues.

2 Literature review

2.1 Immigrant students in Europe

The integration of immigrants across European educational systems is a priority for policymakers in the European Union (Hippe et al., 2016). Similarly, the OECD (2016c, p. 243) stresses that "[m]igration puts enormous strains on both host communities and immigrants themselves; but it can also provide new opportunities for countries that face ageing native-born populations and the threat of labour and skill shortages". In general, the educational achievement of immigrants lags behind that of native students in almost all MS. In most MS immigrant students come from less favourable backgrounds as their parents have, on average, lower levels of education than native individuals. In fact, evidence shows that socio-economic status or family background are more strongly associated to students' performance than immigrant background (Blanden & McNally, 2015; Dustmann, Frattini, & Lanzara, 2012; OECD, 2016c; Schnepf, 2007). Clearly, it should be a priority for policy makers to support and raise achievement of low performing students, namely, students with socio-economically disadvantaged backgrounds, immigrant students and students from diverse ethnic minorities in order to reduce the impact of socio-economic background on education outcomes.

Another factor that influences school performance is how long immigrant students have resided in the host country. Studies indicate that native students outperform immigrants, including those that arrived in the host country during their childhood (Dustmann & Theodoropoulos, 2010; Murat, 2011; OECD & European Union, 2015). In addition, there is also evidence of the high relevance of host country language knowledge, together with family background, as a driver of the immigrant-native gaps in many countries (Dustmann et al., 2012; OECD, 2016c). Specifically, language knowledge can help to reduce the immigrant-native educational gap.

In what regards the influence of early tracking, Hanushek & Wößmann (2006) show that, in general, early tracking⁵ of students in secondary schools based on their academic skills increases educational inequality. This in in line with a recent study from Jakubowski & Pokropek (2015) that finds that while an early tracking policy might not be harmful for the best students, it can lower the performance development of the weakest students, such as immigrants. There is also evidence that tracking at later stages does not always reduce score gaps between immigrant and native students, although it can contribute to improve educational opportunities of students lacking proficiency in the language of instruction (Ruhose & Schwerdt, 2016). In addition, in some EU Member States early

⁴ Hippe et al. (2016) has been used for the following review of the literature on immigrant students.

⁵ Tracking in this context is the differentiation of school curricula into vocational and academic tracks.

tracking systems are viewed as an obstacle for the integration of immigrants as, in general, the selection into tracks occurs before children become skilled in the host country language (De Paola & Brunello, 2016; Lüdemann & Schwerdt, 2010). Consequently, Ruhose & Schwerdt (2016) suggest that action must be taken to improve the educational opportunities of children from less integrated families calling for a more comprehensive school system that contributes to the integration of immigrant students.

The recent literature has also pointed out the importance of class and school composition in fostering immigrants' integration. Having a high share of immigrants in the class or school has a negative effect on immigrants' performance⁶ (De Paola & Brunello, 2016). These results indicate that introducing a limit in the share of immigrant students in the classroom is a supportive policy that might reduce immigrants' educational gap (similar policies have been introduced in Denmark and Belgium; see De Paola & Brunello, 2016). Additionally, retaining and attracting more advantaged students in schools that also host immigrant students could be a supportive policy to improve immigrants' educational opportunities (OECD, 2015b). In contrast, PISA 2015 results do not show a negative influence of immigrant concentration in schools on science scores, after controlling for the school's socio-economic composition (OECD, 2016c).

The literature also reveals that free pre-school programmes for immigrants can help to increase equity for students with an immigrant background (De Paola & Brunello, 2016). Several recent system-level reforms have also been adopted to design more inclusive education systems, through structural changes to education systems or more targeted approaches, such as reducing grade repetition or raising the age of early tracking.⁷

In sum, the evidence shows that there are many factors influencing immigrants' integration and success at school and that, while some may be common across MS, others are country specific.

2.2 Early school leaving and educational expectations

Early school leaving is an important and policy-relevant issue, as it produces high costs for the individual and society (Brunello & De Paola, 2013). ESL miss out on additional years at school, which is costly because "an additional year of schooling can increase individual lifetime earnings by between 4% and 10%" (European Commission, 2013b, p. 11). Thus, individuals cannot reap the benefits of further educational studies although these advantages are manifold, not only in economic terms, but also in other areas. For example, on average, individuals who stay longer in education have higher job satisfaction, take better informed decisions for health, social life, etc. and increase their non-cognitive skills. On the other hand, the state also faces higher costs for its finances (e.g., potentially higher unemployment benefit payments) and its social welfare, as early school leaving has detrimental impacts on crime rates, and on attitudes towards immigrants and other minority groups, etc. (Brunello & De Paola, 2013).

The European Commission et al. (2014) names a number of factors that are most closely related to early school leaving, such as low socio-economic background, being an immigrant student and being male. In particular, early school leaving is particularly widespread among immigrant groups.⁸ However, the most important determinant of

⁶ Schneeweis (2015) shows that, in terms of grade repetition and track attendance of students with an immigrant background, there is a negative association with high share of immigrants, particularly for students of the same ethnic group.

⁷ Table 5 (in appendix) shows that some MS, like DE, FI, IE and SI, have recently implemented educational reforms, strategies or policies aimed at providing equal opportunities in education for disadvantaged students.

⁸ According to the European Commission et al. (2014, p. 39), "[t]he proportion of foreign-born compared to those born in the reporting country is nearly three to five times as high in Greece, Slovenia, Croatia, Austria and Switzerland. In Belgium, Spain, France, Italy, Cyprus, Finland and Sweden, the rates of early leavers among foreign-born students are still around twice as high. [...] In Denmark, Ireland, Malta, the Netherlands and Portugal, the differences between the two groups are relatively lower, even though in

early school leaving is not the immigrant status per se, but the often associated low socio-economic background.

However, in many international student assessments like PISA it is most often not possible to measure the accomplished educational level of students but only their 'expected' level, as the students are not followed through their subsequent educational career once they have completed the assessment. That is, one cannot check whether 'expected' educational levels are identical with future 'realised' educational levels. In principle there may be differences between the expected and the actually realised level, which may be influenced by personal ability, socio-economic status (e.g., due to financial issues) and cultural values (which may be different between natives and (among different) migrant groups). Nevertheless, the literature emphasises that overall expected education levels correlate very highly with those actually realised. The analysis of expectations was first introduced about 50 years ago by Sewell & Shah (1968), Sewell, Haller, & Ohlendorf (1970) and Sewell & Hauser (1972). These authors found in their models that parents' and students' educational expectations were predicting educational achievement quite well (see Gutierrez & Lopez-Agudo, 2016; Minello, 2014). This association has become quite established in the literature. In fact, authors such as Portes, Aparicio, Haller, & Vickstrom (2010, p. 793) state that the "relationship between expectations and achievement is arguably one of the best established facts in social science. The rationale is obvious: if a young person aims at some lofty goal, she may not achieve it; but if she does not aim high in the first place, she will surely not get there. Stated in this form, ambition becomes a prerequisite - a necessary condition - for achievement". The OECD confirms these findings, indicating that "[e]xpectations for higher education and careers are often self-fulfilling prophecies: students who hold ambitious - but realistic - expectations for their future are more likely to put greater effort into their learning and make better use of the education opportunities available to them" (OECD, 2015a, p. 18).

At the same time, immigrant students may have differing educational goals and expectations than their native counterparts. Their parents' migration decision was often motivated by the search for better work and education opportunities for themselves and their children (Goldenberg, Gallimore, Reese, & Garnier, 2001; Kao & Tienda, 1995; Phalet, Andriessen, & Lens, 2004). While work opportunities may sometimes be more important than educational prospects (Hagelskamp, Suárez-Orozco, & Hughes, 2010; Massey & Taylor, 2004), a very good education for their children is often a key motivating factors for immigrant parents (Dustmann & Glitz, 2011; OECD, 2017b). In consequence, the different backgrounds and the different reasons behind the migration decision may potentially induce immigrant students to have specific educational expectations. This is one of the reasons why this issue has recently received more attention by researchers (Feliciano, 2006; Minello, 2014; Minello & Barban, 2012). For example, educational expectations of various immigrant groups tend to be high in a number of MS (Brinbaum & Cebolla-Boado, 2007; Jonsson & Rudolphi, 2010; Kristen & Dollmann, 2010; Relikowski, Yilmaz, & Blossfeld, 2012; Salikutluk, 2016; Teney, Devleeshouwer, & Hanquinet, 2013).

This finding can theoretically be explained in four different ways (see Salikutluk, 2016). The first is the immigrant optimism approach. Even if the parents were not successful and find themselves in the lower strata in the destination country, their children may continue the pursuit of their parents' goals, for which education is a key factor (Heath, Rothon, & Kilpi, 2008; Tjaden & Hunkler, 2017). Second, immigrants may positively react to difficulties in the destination country by trying to overcome these hurdles, as summarised in the blocked opportunities assumption (e.g., Heath & Brinbaum, 2007). Third, it is possible that immigrant parents do not have sufficient information about the educational system of the country they have migrated to, so that they underestimate the

some of these countries, high rates of migrants exist. Finally, one country stands out as an exception: the United Kingdom has a slightly higher rate of students leaving education and training early among those born in the country".

requirements and standards in order to attain high educational attainment (Kao & Tienda, 1995). Finally, the so-called 'influence of significant others' hypothesis states that close relationships within and outside the family (parents, siblings, peers, friends, etc.) may have various positive and negative influences on the expectations of students, and immigrant students in particular (e.g., Gabay-Egozi, Shavit, & Yaish, 2014; Nauck & Kohlmann, 1999).

However, expectations of immigrant students are importantly influenced also by their origin countries and the level of resources that is available to the origin population and the socio-economic status of immigrants in their home (Blasko, Pokropek, & Sikora, 2017). Salikutluk (2016) shows that students with Turkish origins have higher educational expectations than the native population in Germany, while this is not the case for students coming from countries of the former Soviet Union. Upward mobility seems to be driving the high educational ambitions of the Turkish students. Therefore, it is relevant to distinguish immigrant populations according to their country of origin. Differences between EU and non-EU immigrants may be especially interesting in this context.

In addition, many other factors may be related to educational expectations. For example, the OECD notes that "[s]tudents' expectations of further education are influenced by education policy, particularly the degree of sorting students into different education tracks" (OECD, 2017b, p. 104). Thus, in our following analyses we will also assess various ways by which education policy is related to educational expectations.

3 Data and methodology

3.1 Variables included in this study

For the purpose of this report, we included most of the variables the OECD reports when presenting and discussing PISA 2012 and 2015 cross-country differences and similarities in the performance and characteristics of students with immigrant background and students' expectations of further education (OECD, 2015a, 2015c, 2016c, 2017b). In addition, we include two variables (epistemological beliefs, truancy) which have been shown to be major predictors of PISA performance in the newest PISA 2015 round (Hippe, Jakubowski, & Araújo, 2017; OECD, 2016c) and which are also susceptible to be relevant drivers of expected dropout rates.

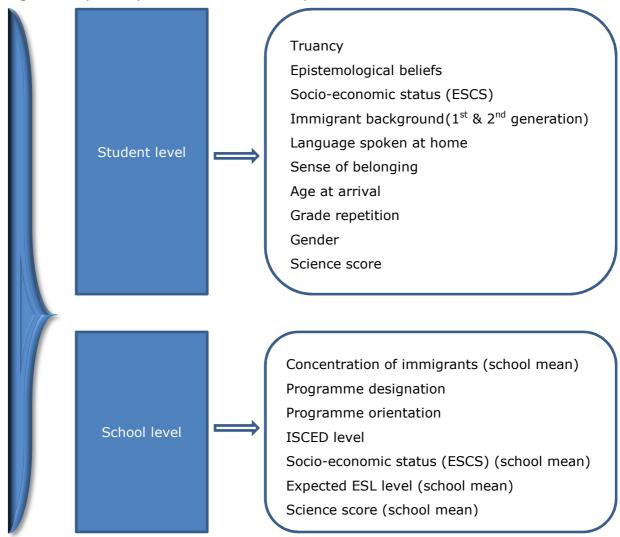
Expected early school leaving is measured via the student responses to the question "Which of the following do you expect to complete?", which allows students to choose among different ISCED levels. For our purposes, we code expected early school leaving in a binary way, this means that leaving school early is either expected (when students choose the category ISCED 2) or not expected (in the cases that students choose a level higher than ISCED 2). The choice of this cut-off point is according to the official EU definition of early school leavers who have ISCED2 as their highest school attainment level.

In addition, the explanatory variables used in this brief can be classified into two groups of predictors: variables that refer to students and variables that relate to schools (see Figure 2). 9

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⁹ See appendix for more details on the included variables.

Figure 2. Explanatory variables used in the analysis



In consequence, at the student level we include the following variables:

Truancy measures whether students are skipping school days, skipping classes, being late at school. In fact, students were asked several questions about truancy. We used their responses to estimate an index of truancy using the principal component analysis based on polychoric correlations for ordinal responses (Kolenikov & Ángeles, 2004). The intuition is that skipping classes may have a negative association with performance and thus a positive one with the expectation of dropping out early.

Epistemological beliefs reflect how students see science and scientific enquiry. Students who score higher in the PISA index of epistemological beliefs argue that "scientific knowledge is tentative" (to the extent that students recognise that scientific theories are not absolute truths, but evolve over time) and adhere "to beliefs about the validity and limitations of empirical methods of enquiry as a source of knowing" (OECD, 2016c, pp. 99–100). The index is standardised to have a mean of 0 and a standard deviation of 1 across OECD countries (weighting each country equally).

Economic, Social and Cultural Status (ESCS) is an OECD index measuring student socio-economic background. PISA measures ESCS with an extensive set of questions related to parent occupation, education and household cultural, educational and economic resources. It is usually positively associated with PISA scores. The index is standardised to have mean of 0 and standard deviation of 1 across OECD countries (weighting each country equally). A lower socio-economic background of students generally increases

early dropout rates, as has been shown by a multitude of studies on this subject (European Commission et al., 2014).

Immigrant background refers to first or second generation immigrant students. As first and second generation students have different immigration backgrounds, the results may in many cases vary according to each group. In consequence, we include this distinction among immigrant students.

Language spoken at home controls for the fact that the language taught at school and the language spoken at home may be different. In consequence, a student may have more difficulty in the subjects at school and in socialising with schoolmates when the same language is not practiced in both home and school environments. Thus, not speaking the language at home has also been shown to be negatively associated with PISA scores. In MS such as Czech republic, Finland, Slovenia and Sweden, the share of first generation students who do not speak the same language at home as in school is more than 80 %, while in Croatia this is true only for less than 10 % (OECD, 2015a).

Sense of belonging shows how psychologically well students feel integrated and belonging to the school they attend. This is an important measure of the social integration of immigrant students. The OECD concludes that the sense of belonging varies widely among EU MS. For example, in the UK newly arriving (first generation) immigrant students have a higher feeling of belonging than natives and second generation students. Both of the latter two groups have a similar level of belonging. Second, e.g. in France second generation students have the lowest sense of belonging of all groups. In contrast, integration is more progressive in Italy, Spain and Sweden. In these MS, second generation students have similar (high) values to natives, while first generation students have lower values (OECD, 2015a).

Age at arrival provides information on when an immigrant student has arrived in the destination country in which she took the PISA test. The intuition for including this variable is that it is easier for a student to learn and integrate into a new cultural and linguistic environment the younger she is (OECD, 2016c). More specifically, the OECD calls this also the 'late-arrival penalty': "[i]n most OECD countries, immigrant students who arrived at the age of 12 or older – and have spent at most four years in their new country – lag farther behind students in the same grade in reading proficiency than immigrants who arrived at younger ages" (OECD, 2015a, p. 10).

Grade repetition is a policy that is common in some European countries and has been shown to influence school leaving negatively (European Commission et al., 2014). In addition, previous research with PISA data suggests that repeating a grade is not associated with improved student performance and shows a negative association with student attitudes (Ikeda & García, 2014). At the same time, this policy is very costly (Benhenda & Grenet, 2015). In PISA 2015, and in line with findings from previous PISA rounds, students who have repeated a grade at least once score lower (OECD, 2016c).

Finally, gender is a dummy variable, taking one for female students. Research has shown that girls may have different educational expectations than boys (e.g., Sikora & Biddle, 2015). For example, girls' educational expectations are much higher in Italy (Minello, 2014). In general, girls also have lower realised early dropout rates than boys at the European level (European Commission, 2016; European Commission et al., 2014).

In some specifications, we also include students' science scores. ¹⁰ In fact, science achievement is the main domain in PISA 2015. This means that science was measured with the highest possible precision and every student taking the 2015 PISA test answered a number of science-related test items. While reading and mathematics were also

Student achievement is reflected by a set of the so-called plausible values that reflect student outcomes and allow for estimating measurement error. In PISA 2015, ten plausible values are provided in the datasets and the analysis should replicate every estimation ten times with each plausible value. The results averaged across ten replications provide unbiased estimates of student achievement. In the calculation of standard errors variation across ten replications is included using special formulas that add estimates of measurement error to the estimates of sampling error.

measured in 2015, the number of test items for these domains was smaller and the resulting measurement is less precise. Thus, we decided to include science performance and not reading or mathematics performance. In PISA, science is defined as "the ability to engage with science-related issues, and with the ideas of science, as a reflective citizen. A scientifically literate person is willing to engage in reasoned discourse about science and technology, which requires the competencies to explain phenomena scientifically, evaluate and design scientific enquiry, and interpret data and evidence scientifically" (OECD, 2016b, p. 13). We use this variable to proxy for unobserved ability.

In addition, we consider the following variables at the school level:

Concentration of immigrant students in schools indicates the relative prevalence of immigrant students in schools (averaged for schools). While there can be some advantages of arriving in a school with students from a similar cultural background, in many cases the concentration of immigrants is related to a concentration of socioeconomically disadvantaged students (OECD, 2015a). In PISA 2015, a high concentration of immigrant students in schools is not associated with poorer student performance, while, individually, immigrant students on average show lower performance in EU MS (OECD, 2016c).

We also include *programme designation*, which provides further information on the study programme (general or vocational level giving access to next level, giving direct access to labour market and modular). Similarly, *programme orientation* indicates whether students are enrolled in general, pre-vocational or vocational programmes. It should be noted that in many MS included in this analysis all 15-year-olds are in academic or general schools. Thus, the results should be interpreted cautiously. However, this variable provides interesting insights for some MS with a sufficient number of students in vocational education. Early tracking, before the age of 15, has been shown to increase educational inequality (Ruhose & Schwerdt, 2016). On the other hand, at the country level, MS "with a relatively weak VET system tend to have a higher problem of early leaving, likely due to the lack of sufficiently attractive non-academic programmes" (European Commission et al., 2014, p. 13).

We also control for the *ISCED level*. In fact, PISA uses as criteria the age of students for inclusion in the survey, i.e. only 15 years olds are allowed to participate. As a consequence, some students are already in an ISCED3 year, and many others are still in ISCED2. While this does not mean that they may expect to complete ISCED3, this may potentially influence the results. Therefore, we control for this factor in the regression analysis. 11

Finally, we also include school means for the ESCS, expected early school leaving and science scores. In other words, the student's data were aggregated and averaged for schools to be able to control for further school environment effects.

To get a clear picture, we provide below a summary table of the variables and their descriptions that are used in this brief (see Table 1). To simplify the reading of the regression tables later on, we also include information on the reference category in the multilevel regressions.

Table 1. Description of student-level variables

Variable	Description
Expected early school leaving	Leaving school early (after ISCED 2) is expected or not. Reference category: not
	expecting to leave school early .
Gender	Male or female. Reference category: male
Student's ESCS	Measures student socio-economic background
1st generation	1st generation immigrant or native student. Reference category: native
2nd generation	2 nd generation immigrant or native student. Reference category: native
Language at home	Language taught at school and the language spoken at home are different. Reference

¹¹ See also details on the minimum age during compulsory schooling in the appendix.

	category: languages are not different
Age at arrival	Measures when an immigrant student has arrived in the destination country
Sense of belonging	Measures how well students feel integrated and belonging to the school they attend
Epistemological beliefs	Measures how students see science and scientific enquiry
Truancy	Measures whether students are skipping school days, skipping classes, being late at school (index)
Grade repetition	Student has repeated a grade or not. Reference category: not having repeated a grade.
Science scores	Measures science achievement
(Programme) Designation	Student attends: general programmes designed to give access to the next programme level, or programmes designed to give access to vocational studies at the next programme level, or giving direct access to labour market, or modular. Reference
	category: general programmes
(Programme) Orientation	Student attends: general, pre-vocational or vocational programmes (and in Luxembourg, also modular programmes). Reference category: general
ISCED Level	Student attends: ISCED2 or ISCED3. Reference category: ISCED2

3.2 Sample sizes

Given the varying distribution of immigrants in the MS, we can expect that immigrant student populations have quite different sample sizes and characteristics in the MS in the PISA dataset. In addition, the large variance found in the data indicates that it may be worth considering the difference between EU and non-EU immigrants. However, the low shares of immigrants in general, and EU migrants in particular, may lead to very low sample sizes, which may not allow an in-depth analysis for some MS.

To define minimum threshold sizes for the inclusion of countries in our regressions, we follow the recommendations set up by the OECD (see e.g., OECD, 2011, p. 179), which is at least 30 students from at least 5 schools. The details on the sample sizes in our study can be seen in Table 2. More specifically, immigrants can be considered for all MS except PL and RO, while both first and second generation immigrants can be included for all MS except BG, PL and RO.

In this brief, our aim is also to characterise the immigrant populations according to the distinction EU-/non-EU origin country. Given the low sample sizes in most MS, this more detailed differentiation can only be done for AT, BE, CY, CZ, DE, FI, IE, IT, LU, MT, PT and the UK (the differenciation between first or second generation would only be possible for fewer MS) in the regression models. In contrast, non-EU immigrant populations are generally more numerous, so that non-EU immigrants can be analysed in all MS apart from CY, PL and RO.

Table 2. Samp	le size by	immigrant	status
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		То	tal	Immigrants		EU migrants		Non-EU immigrants			
MS	Total	Natives	Migrants	1 st gen.	2 nd gen.	Total	1 st gen.	2 nd gen.	Total	1 st gen.	2 nd gen.
AT	6928	5609	1319	477	842	237	141	96	1082	336	746
BE	9363	7812	1551	773	778	467	355	112	1084	418	666
BG	5707	5650	57	28	29	0	0	0	57	28	29
CY	4942	4712	230	167	63	230	167	63	0	0	0
CZ	6788	6562	226	109	117	48	24	24	178	85	93
DE	5691	4724	967	215	752	135	42	93	832	173	659
DK	6967	5281	1686	368	1318	2	1	1	1684	367	1317
EE	5459	4899	560	37	523	0	0	0	560	37	523

EL	5420	4893	527	170	357	0	0	0	527	170	357
ES	6577	5896	681	556	125	0	0	0	681	556	125
FI	5794	5564	230	126	104	38	33	5	192	93	99
FR	5946	5184	762	252	510	0	0	0	762	252	510
HR	5621	5016	605	100	505	0	0	0	605	100	505
HU	5566	5419	147	57	90	0	0	0	147	57	90
IE	5495	4735	760	581	179	157	95	62	603	486	117
IT	11232	10333	899	526	373	226	161	65	673	365	308
LT	6260	6039	221	36	185	0	0	0	221	36	185
LU	5170	2498	2672	1093	1579	1918	780	1138	754	313	441
LV	4797	4554	243	43	200	0	0	0	243	43	200
MT	3489	3314	175	123	52	70	61	9	105	62	43
NL	5209	4649	560	114	446	22	18	4	538	96	442
PL	4428	4417	11	7	4	0	0	0	11	7	4
PT	7179	6757	422	236	186	60	34	26	362	202	160
RO	4818	4799	19	7	12	0	0	0	19	7	12
SE	5283	4385	898	395	503	0	0	0	898	395	503
SI	6297	5779	518	223	295	13	8	5	505	215	290
SK	6165	6095	70	35	35	25	16	9	45	19	26
UK	13391	11679	1712	1086	626	482	441	41	1230	645	585
EU28	175982	157254	18728	7940	10788	4130	2377	1753	14598	5563	9035

Note: gen. = generation; orange = insufficient number of observations.

3.3 Econometric model

Multilevel regression models are well-suited to the analysis of large scale international student assessment surveys because they recognize the hierarchical structure of the data with students nested in schools. Accordingly, in our analysis the two-level model reflects that students are nested in schools. The associations between performance and student-level or school-level factors can also be decomposed into within-school and between-school associations. Thus, with these models it is possible to analyse how differences in key policy-relevant variables are associated with student and school characteristics. ¹²

The basic two-level model with random effects can be described by two equations. The first equation describes the model for the student-level where i is an index for students and j is an index for schools:

$$Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + e_{ij}.$$

In this equation, Y_{ij} is the outcome variable, in this case expected early school leaving. This implies that we are using a multilevel binary logistic model. In other words, the outcome variable is binary, that is it can only take the value 0 (i.e., early school leaving is not expected) or 1 (i.e., early school leaving is expected). Thus, we are analysing the factors that affect the probability of expecting to leave school early in these models. In addition, X_{ij} is a vector of student-level characteristics and e_{ij} is a student-level error.

The second level equation describes school level intercepts:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j},$$

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¹² For more information on missing data imputation and weights, see appendix.

where W_j is a school-level predictor (or a set of predictors) and u_{0j} is a random error component at the school-level.

In our multilevel logit regression analysis (see section 4.2), we first consider the entire EU, controlling for country fixed effects and including a number of variables that are specifically addressing (the characteristics of) immigrant students. In this model, we weight all countries by their population size and we adjust school-level weights to obtain proper estimates of between-school variance (see Rabe-Hesketh & Skrondal, 2006). In a second step, we analyse each MS individually. Finally, we also distinguish between EU and non-EU immigrants.

4 Empirical analysis

4.1 Descriptives

4.1.1 Characteristics of students with immigration background

Before analysing immigrant students in PISA 2015 data in more detail, we begin by showing the distribution of the actual total immigrant population in the European countries. Eurostat (2017c) data show for 2016 that the share of immigrants (defined as individuals not residing in their country of birth) within the total population varies substantially among MS. The highest rates of immigrants are recorded in LU (45 %), while the lowest are to be found in many new MS in Eastern Europe.

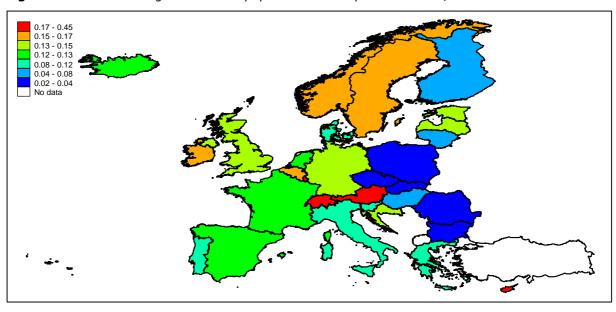


Figure 3. Share of immigrants in total population in European countries, 2016

Note: 7 classes automatically defined. An immigrant is defined as a person not born in the country he is a resident in. Only those countries are shown in the map for which Eurostat provides data.

Source: calculated from data by Eurostat (2017c). Background map: © EuroGeographics for the administrative boundaries.

An interesting aspect is to differentiate between immigrants born in another MS and immigrants born outside the EU. EU migrants make up a high share of all immigrants in SK (83 %), LU (75 %) and IE (69 %), while particularly in the Baltic MS, HR and PT most immigrants come from countries outside of the EU (EE having the lowest share of EU migrants with only 10 %). The low shares could be explained by the specific historical and cultural relationships of these countries to various non-EU countries (the Baltics with

Russia, HR with other former parts of Yugoslavia, PT with its former colonies, in particular Brazil).

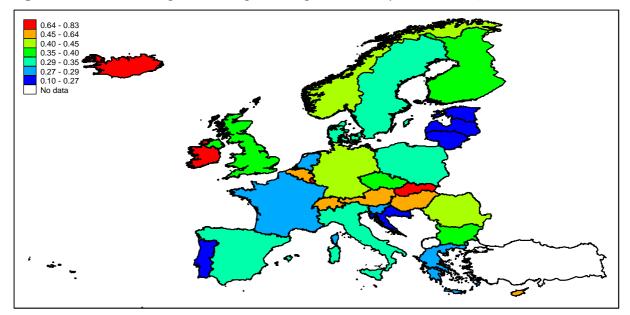


Figure 4. Share of EU migrants among all immigrants in European countries, 2016

Note: 7 classes automatically defined. An immigrant is defined as a person not born in the country he is a resident in. Only those countries are shown in the map for which Eurostat provides data.

Source: calculated from data by Eurostat (2017c). Background map: © EuroGeographics for the administrative boundaries.

After this first impression on the total immigrant population in Europe, we now turn to the immigrant students' data in PISA 2015. Across all EU MS, 11 % of students in the PISA 2015 sample have an immigrant background (see Figure 5). The share is equally divided among first (5 %) and second (6 %) generation students. Most of the immigrants come from outside the EU, with a higher incidence of second generation immigrants. LU has by far the highest share, with more than 50 % of students having an immigrant background, followed by DK and AT, where almost a quarter and a fifth of students respectively are immigrants. Very low shares of immigrants are included in many new MS (e.g., BG, CY, CZ, HU and SK, in addition to PL and RO where the immigrant numbers are even too low to be presented here).

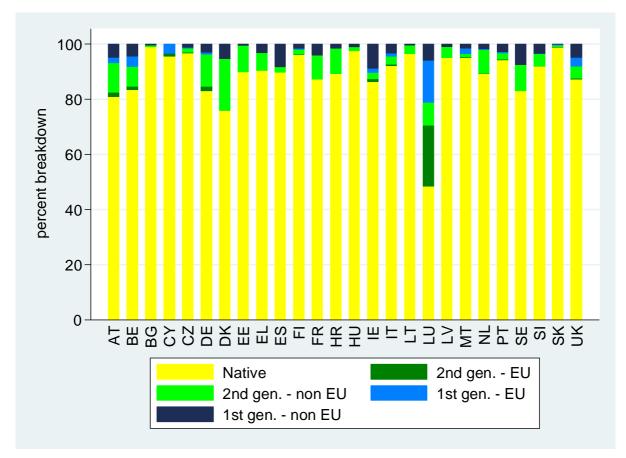


Figure 5. Share of immigrant students in PISA 2015

Note: Shares are calculated with regard to the total number of students. Shares not presented for MS with insufficient number of observations.

Out of all immigrants, 42 % are first generation students (see Figure 6). The MS with a rather massive recent immigration are e.g., CY, ES, IE, MT and UK, while new arrivals are a small minority among immigrants in EE, HR, LT and LV.

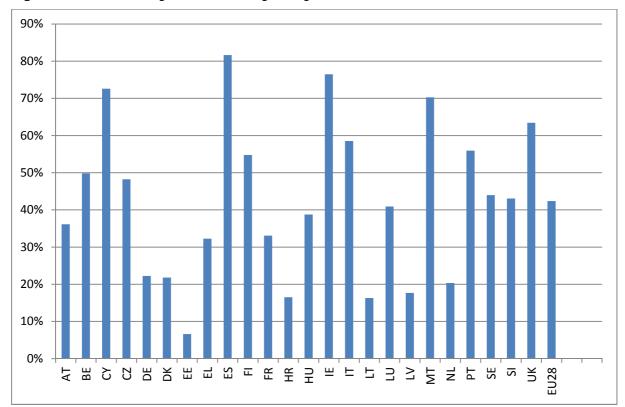


Figure 6. Share of first generation among immigrant students in PISA 2015

Note: Shares are calculated with regard to the total number of students with immigrant background. Shares not presented for MS with insufficient number of observations.

Among the immigrant student population, only about one out of five is an EU migrant, while most immigrant students come from countries outside the EU (see Figure 7). However, EU migrants are unequally distributed among MS. In particular, the highest share of EU migrant students is in CY, where all immigrant students come from other MS. In addition, LU has a very high share with more than 70 % of migrant students coming from another MS. We can see from these figures that LU has a very specific migrant population, which is very high in comparison to other MS, but also more European (more exactly, from other MS) than it is the case for other MS. High shares of EU migrants among all immigrants are also present in MT (40 %), SK, BE and UK (around 30 %).

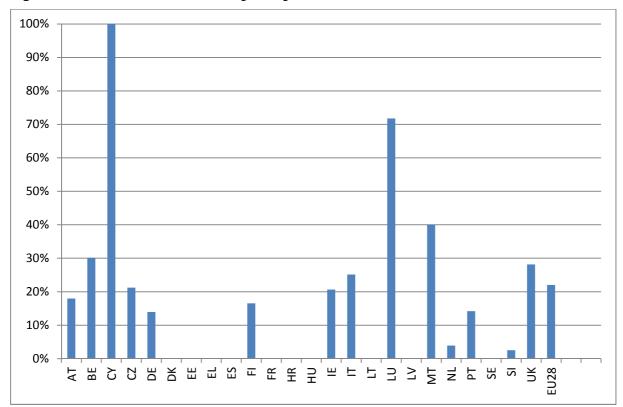


Figure 7. Share of EU students among immigrant students in PISA 2015

Note: Shares are calculated with regard to the total number of students with immigrant background. Shares not presented for MS with insufficient number of observations.

The number of immigrants has also evolved over time. Compared to 2006, there has been an increase in immigrant numbers in most MS, while in some new MS immigrant numbers have decreased in the last decade (see Figure 8). The outstanding numbers for LU are to an important extent due to immigrants entering the school system rather recently (first generation). This fact shows the attraction that LU exerts among other countries, and as we know from the figures above, particularly among other MS. The reverse case we can see in IE und UK, which have the second and third highest overall change in student numbers, respectively. In these MS, it is the second generation of migrants that prevails in number. In addition, in AT, the subsequent MS in fourth position, the percentage changes are driven by recent arrivals from the first generation, while the changes in the second generation are not even statistically significant.

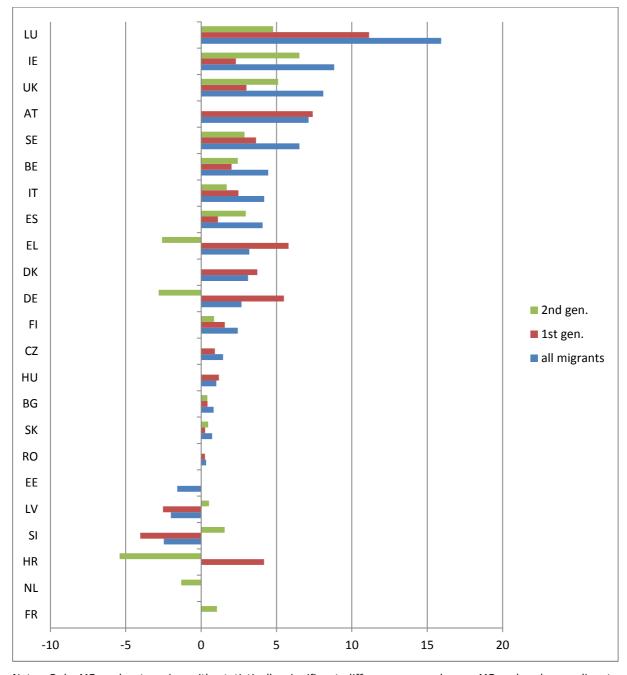


Figure 8. Percentage change in number of immigrants between 2006 and 2015

Note: Only MS and categories with statistically significant differences are shown. MS ordered according to change in all immigrants.

Source: based on OECD (2016c).

In addition, Figure 9 shows the share of immigrants participating in PISA 2015 as well as the gap (and its change between 2006 and 2015) in science scores between natives and migrant students. In most MS natives have a significantly higher score than migrants, even after accounting for socio-economic status and language spoken at home. The largest gap exists in BG, followed by SE, SK, DK and FI, all with a gap corresponding to about one year difference of schooling and more. Comparing 2006 to 2015 results also mostly indicates that there have been no statistically significant changes in these gaps in most MS, apart from a few MS in which the gap has become smaller. This is the case in BE, ES, IT, LU and PT.

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¹³ See similar interpretations of score point differences in OECD (2010, p. 30) and OECD (2016e, p. 7).

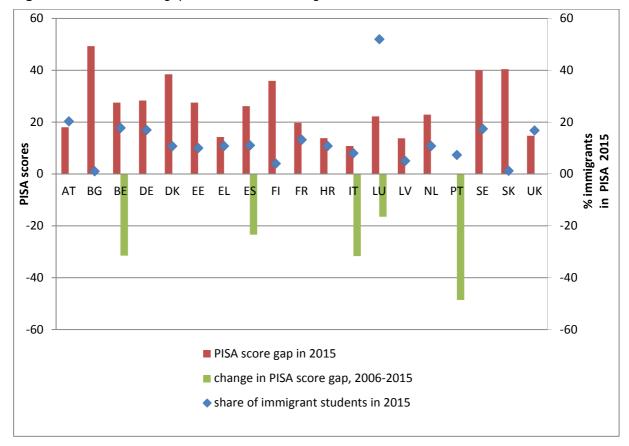


Figure 9. Science score gaps and shares of immigrants in PISA

Note: PISA score gaps in science shown are between natives and immigrant students, after accounting for socio-economic status and language spoken at home. Only significant values are shown. Source: based on OECD (2016c).

Science score results also vary substantially among MS, even if the origin countries of migrants are the same. For example, Figure 10 shows that it makes an important difference whether an Arabic-speaking student, both in the first or second generation, goes to school in NL, FI or DK. In fact, in NL these students score always higher than in their Nordic counterparts. A similar observation can be made for Turkish students, who always perform best in NL, and worst in DE (first generation) and DK (second generation). In comparison to these observations, the differences among Polish students in DE, AT and UK are rather minor.

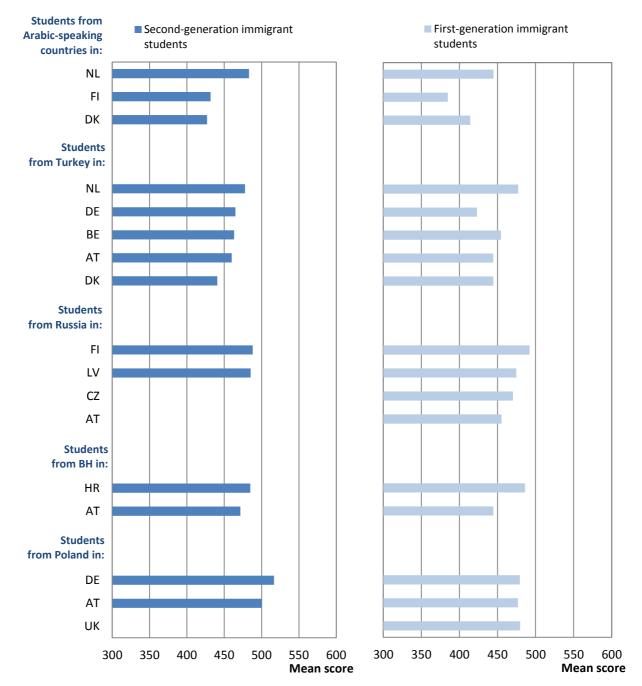


Figure 10. PISA 2015 science scores for students from various origin countries

Note: BH = Bosnia-Herzegovina. Source: adapted from OECD (2016c).

4.1.2 The intersection of immigrants and educational expectations

After these general observations about the characteristics of immigrant students and their performance, let us now turn to the more specific question of this brief. That is, the relationship between immigrant status and educational attainment, in particular expected early school leaving. We will present results only for those MS with a sufficient high number of migrants and where expected dropout rates are available.

Considering Figure 11, we can see that in most MS the shares of both natives and immigrants expecting to leave school earlier (i.e., the shares of those who plan to finish

education at ISCED 2) are quite low. High shares of expected ESL exist in systems with relatively important shares of vocational education, that is DE, DK, FI and NL (see also appendix). But also in MS like ES, FR and PT we can see relevant expected ESL shares.

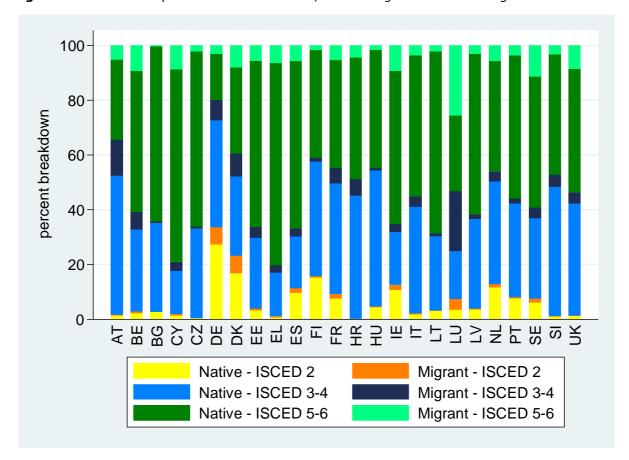


Figure 11. Shares of expected educational levels, considering natives and immigrants

Note: Shares not calculated for MS with insufficient number of observations or lacking information on educational expectations.

In addition to simple shares, it is also interesting to consider whether students that have low educational expectations also perform worse than others. In fact, one would expect a lower performance, i.e. lower PISA scores, for expected ESL as they do not have an incentive to stay longer in school, and often have had difficulties in school. To understand this issue better, we compute separate scores for ESL and non-ESL, for natives and immigrants (distinguishing also first and second level generations). In many cases, sample size is insufficient for constructing scores for all categories (i.e., separately for natives, first and second generation). As expected, we find that – where all categories can be computed – ESL have a lower performance than non-ESL in all cases (i.e. the score point differences are always positive; see Figure 12). These differences amount to more than one year of schooling, in many cases even more than two years of schooling. The differences are in some MS largest among natives, such as DE and FR. In contrast, differences are largest among first generation migrants in DK and LU, while they are never largest among second generation students.

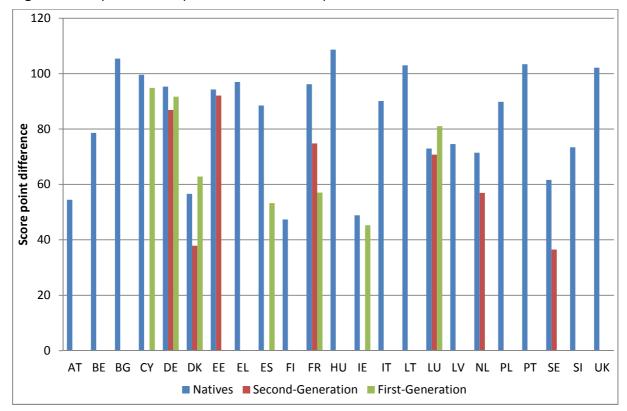


Figure 12. Gap between expected non-ESL and expected ESL in PISA 2015

In a next step, we consider only expected non-ESL, and distinguish among natives and the various immigrant groups (see Figure 13). Among expected non-ESL, we find large gaps between natives and first- and second-generation immigrants in many MS, while they are in many cases not as large as in the previous case. Still, they can be up to around 90 score points or more than two years of schooling (in SE and SI). Apart from a few cases, in which second generation students (in CY, CZ, HU and LT) or first generation students (HU) have higher scores than natives among expected non-ESL, natives always outperform immigrants. The tendency is also that the gap between natives and second-generation immigrants is smaller than between natives and first-generation migrants. This is intuitive as second-generation immigrants have less difficulty in integrating into the host country and learning a new language, as they were born in the same country. The reverse case is notably present in DK, and to a smaller extent in BE, IE and LU.

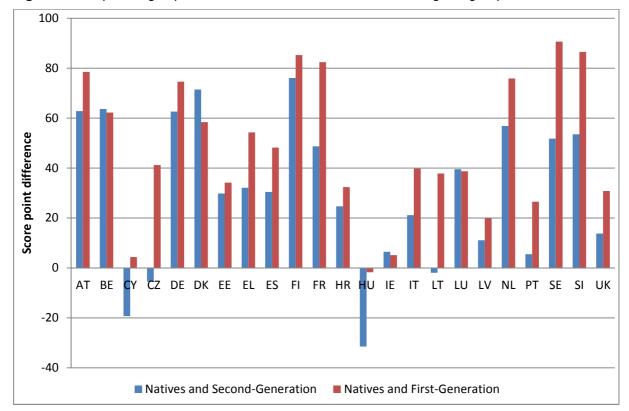


Figure 13. Gap among expected non-ESL between natives and immigrant groups

Figure 14 provides the same analysis, but this time looking at the differences between natives and immigrant groups among expected ESL. Interestingly, the score point differences are mostly in favour of natives, particularly in DE and DK. In contrast, very small differences exist in CY and IE. In the four MS where we have enough observations for expected ESL among both first and second generation immigrants (i.e., in DE, DK, FR, and LU), we always find that second generation students have lower score point differences (compared to first generation ones), confirming the previous results.

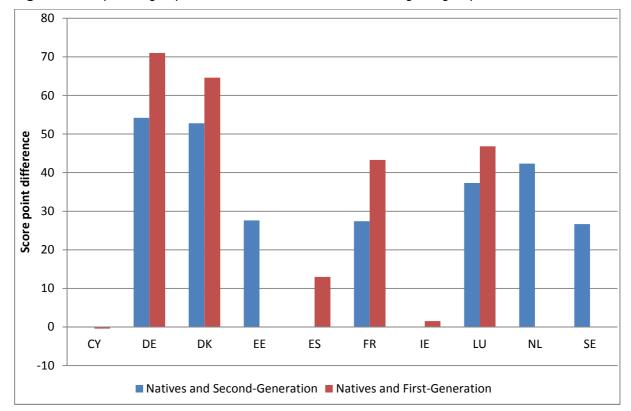


Figure 14. Gap among expected ESL between natives and immigrant groups

Finally, we also consider the differences between natives, EU migrants and non-EU migrants. For this reason, we repeat the same procedure as for the previous graphs, but instead of distinguishing between first and second generation migrants, we now distinguish between EU migrants and non-EU immigrants (where sample size is sufficiently high). Thus, in fact, only in LU we can compare all three categories. In this MS, we find that natives and EU migrants have almost the same score point difference among expected non-ESL and ESL, while in the case of non-EU immigrants it is a bit lower. In general, we find that expected ESL have a lower performance than non-ESL in all cases (see Figure 15), confirming our previous results. Differences among non-EU immigrants are usually lower than among natives, except for FI. In contrast, the differences among EU migrants are about an entire year of schooling higher than for natives in DE, the only MS where we can compare these categories.

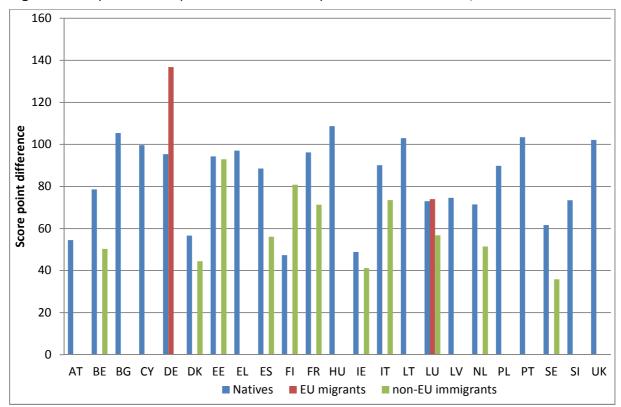


Figure 15. Gap between expected non-ESL and expected ESL in PISA 2015, EU and non-EU

Second, we now consider only expected non-ESL (see Figure 16). Among expected non-ESL, we find large gaps between natives and EU and non-EU immigrants in many MS. They are up to 80 score points or around two years of schooling (in FI). In a few cases, EU migrant students (in CY, IE and, most strikingly, PT) or non-EU immigrant students (HU) have higher scores than natives among expected non-ESL. However, in most cases natives outperform immigrants. The gap between natives and EU migrants appears to be smaller than the gap between natives and non-EU immigrants. This is an intuitive result as EU migrants may have on average a higher socio-economic background than non-EU immigrants. Nevertheless, we find the opposite situation in LU, and to a smaller extent also in CZ and UK.

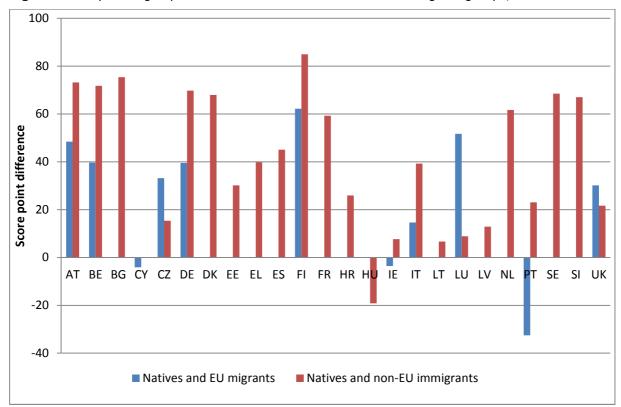


Figure 16. Gap among expected non-ESL between natives and immigrant groups, EU and non-EU

Figure 17 considers the differences between natives and immigrant groups among expected ESL. In most cases, the score point differences are high in favour of natives, particularly again in FI (compared to non-EU immigrants, it is almost three years of schooling). However, only small differences exist in ES and IE (in the latter MS, the difference with non-EU immigrants is virtually zero). Only in DE and LU we are able to compare expected ESL among both EU and non-EU immigrants. We find in both MS that EU migrant students have a score point difference (with respect to natives) higher than the one for non-EU immigrant students. Interestingly, however, non-EU immigrants have higher scores than natives among expected ESL in LU.

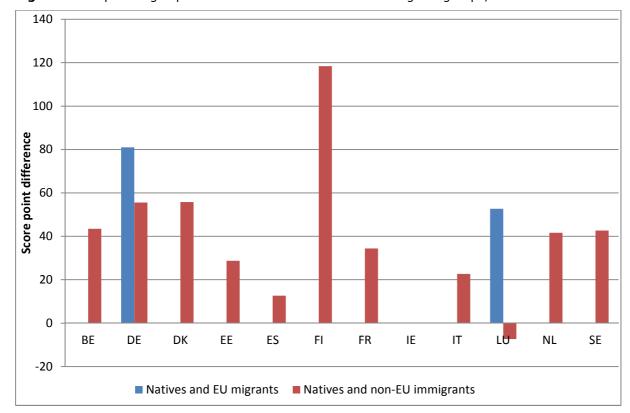


Figure 17. Gap among expected ESL between natives and immigrant groups, EU and non-EU

4.1.3 Summary descriptives of variables

Table 3 below provides descriptive statistics and sample size for the variables used in the multilevel model. As we are looking at country-level data, we have more than 120,000 observations for all MS included.

At the student level, expected dropout varies significantly – that is, while the mean value of expected dropout is 2.35, its standard deviation is 14.66.

Table 3. Descriptive statistics for the variables included in	this study
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Variable	Mean	SD	N
Expected early school leaving	2.35	14.66	124932
Gender	0.50	0.50	127020
Student's ESCS	-0.01	0.95	123713
1st generation	0.53	2.01	126834
2nd generation	0.55	2.01	126834
Language at home	0.57	6.66	124971
Age at arrival	1.70	11.04	124884
Sense of belonging	5.59	22.66	126684
Epistemological beliefs	16.83	37.17	126271
Truancy	-0.20	0.81	124317
Grade repetition	0.56	1.86	126885
(Programme) Designation	1.46	0.79	127020
(Programme) Orientation	1.30	0.70	127020
ISCED Level	2.56	0.50	127020

The explanatory variables also vary significantly, which provides a basis for analyzing school differences in expected student dropouts using this set of explanatory variables. The majority of the variables have no missing data.

4.2 Multilevel regression analysis

4.2.1 For the entire EU

Multilevel regression models are well-suited to the analysis of educational data. They recognize the hierarchical structure of the data with students nested in schools and countries. In this analysis, the two-level model reflects that students are nested in schools. The associations between educational expectations and student-level or school-level factors can be decomposed into within-school and between-school associations. Thus, with these models it is possible to analyse how differences in key policy-relevant variables are associated with student educational expectations.

Table 4 shows the results from the two-level logit regression with school random effects and students being nested in schools, including the variables that we have discussed in the previous section. The model estimates the probability of having lower expectations (finishing school at ISCED 2) as a function of a set of student- and school-level factors. The model is representative of the whole population of 15-year-olds in MS with a sufficient number of immigrant students. As mentioned before, using the criterion for PISA data developed by the OECD, MS with less than 30 immigrant students or with immigrant students sampled from less than 5 schools are excluded from the analysis. As a result, we disregard Poland and Romania. In addition, data from Malta and Slovakia are not analysed as these countries did not provide information on student educational expectations.

Column (1) presents the model with the full set of predictors without the science scores for students and schools. Column (2) presents a similar model but with student science scores and school average science scores added. Thus, the results in column (2) provide coefficients after controlling for the actual student and school performance in science. In general, both sets of results provide similar insights. In both models, country fixed effects are included. Except for the immigrant variables, here we focus on presenting only significant associations.

As the main focus of our study is on *immigrant* students, we begin with the discussion of the variables that are specifically related to this group (i.e., language at home, age at arrival, first generation, second generation). Interestingly, we do not find that these variables are significant. At the lower end of the regression table we have also included a number of interaction terms between immigrant status and other variables, which are also all insignificant. Thus, it appears that immigrants may not be 'special' or inherently different in their expected dropout behaviour with regard to natives. Both immigrants and natives behave in the same way when forming their educational expectations, influenced by a number of common factors that we control for.

The variable reflecting *student socio-economic background* included in our models is typically used in the analysis of PISA data and the estimated coefficients are also in line with other research. Student socio-economic background as measured by the PISA ESCS index is negatively related to expected early dropout at the student level (but not at the school level). This result reflects the strong association between socio-economic background and educational expectations that is observed across many countries.

The results from the multilevel model also suggest that *epistemological beliefs* are negatively related to the lower educational expectations. However, their strong relationship with scores leads to the fact that the effect disappears once students' scores are included. Still, these results seem to directly refer to policies that aim at changing the

way scientific knowledge is presented to students. Stipulating better understanding of scientific knowledge might affect expectation levels and should hence be considered as a policy option in reforming curricula and the way science is taught in schools.

In our multilevel model, grade repetition is associated with higher expected dropout probability, which can be explained by the fact that students repeating a grade are those who in fact struggle with learning more than their peers, and thus are more susceptible to leave school early. In some MS, however, grade repetition is rare despite that these MS might face similar challenges in terms of students' low performance or socioeconomic background. This makes us think that there might be room for rethinking grade repetition practices in some MS.

A school's expected ESL level is positively significantly related to expected early school leaving at the student level. This finding implies that compositional effects at the school level play a role. In other words, there may be peer effects of many students wanting to leave school early in a particular school.¹⁴ Another possibility is segregation if in certain schools there is a higher proportion of low achievers.

Finally, if a student is already in ISCED3, the odds of early dropout (i.e. finishing after ISCED2) are lower than for ISCED2 students. This result is intuitive, as such a student is already attending a higher school level.

Comparing the two models in columns (1) and (2), we see that the overall results remain intact no matter if science scores at the student and the school level are included. However, these two variables themselves are both significant negative predictors of expected early school dropout. These results indicate the plausible relationship between having a higher (science) score and the willingness to study further, or in other words that students that score lower have a higher probability to expect to leave school early.

Overall, one important conclusion is that both individual (e.g. epistemological beliefs, a student's ESCS) and compositional effects (a school's expected early dropout rate and average science score) play an important role, so that also segregation of students increases dropout probability. The fact that most of the migrant-related variables are insignificant is in line with other research, which indicates that being a migrant is not the driving force behind the probability to leave school early (e.g., European Commission et al., 2014). Instead, a key factor seems rather to be the situation that a student and a student's family are in and the effects of schools characteristics on students' expectations.

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¹⁴ As for the programme orientation, students in pre-vocational education have on average a lower expected early school leaving probability than students in general education. However, one has to bear in mind that it is a country-specific variable as it is coded this way only in few MS. Thus, we do not discuss it here but only when we consider individual MS in the next subchapter.

Table 4. Multilevel regressions on expected early school leaving for the entire EU

_		-
	(1)	(2)
Gender	0.055	-0.060
Gender	(0.101)	(0.091)
Student's ESCS	-0.404***	
Student's ESCS	(0.049)	(0.048)
1st generation	-0.317	-0.342
13t generation	(0.340)	
2nd generation	-0.176	-0.325
- na generation	(0.190)	
Language at home	0.161	
	(0.127)	(0.147)
Age at arrival	0.052	
S	(0.036)	(0.038)
Sense of belonging	-0.016	-0.023
	(0.044)	(0.043)
Epist. beliefs	-0.163***	-0.066
	(0.039)	(0.036)
Truancy	0.033	-0.030
	(0.043)	(0.044)
Grade repetition	1.035***	0.767***
	(0.101)	(0.100)
ISCED level: 3	-0.646***	-0.644***
	(0.167)	(0.176)
Designation: B	0.364	0.264
	(0.237)	(0.260)
Designation: C	0.728*	0.596
	(0.367)	
Orientation: Pre-Voc.	-0.436	-0.669*
	(0.245)	(0.275)
Orientation: Voc.	0.153	0.081
	(0.212)	(0.219)
Orientation: Modular	0.885***	0.431*
	(0.222)	(0.214)
I: Immig. x Lang. at home	-0.441	-0.335
	(0.242)	
I: Immig. x Sense of belong.	0.058	
Caba alla ECCC	(0.105)	
School's ESCS	-0.138* (0.063)	
School's conc. of mig.	0.061	
School's colle. Of filig.	(0.165)	
School's exp. ESL level		5.656***
School's exp. Est level	(0.176)	
School's science score	(0.170)	-0.003***
School 3 science score		(.)
Student's science score		-0.007***
Stadent 3 Solenice Score		(0.001)
Constant	-3.774***	
	(0.269)	(0.528)
	(3.203)	(0.320)

Note: Significance level: * p<0.05, ** p<0.01, *** p<0.001. Results from multilevel regression with random effects. Estimates over ten imputed datasets after multiple imputation of missing data for each dataset containing one of the ten plausible values of student achievement. The variables starting with 'I:' indicate

interaction terms. The variable 'Designation' has the following categories: "A" (general programmes designed to give access to the next programme level); "B" (programmes designed to give access to vocational studies at the next programme level); "C" (programmes designed to give direct access to the labour market). For more detailed information on all variables, see appendix. For the reference categories, see Table 1.

4.2.2 Country by country

In a second step, we analyse whether there exist relevant differences among MS that are hidden in the overall results for the entire EU. Therefore, we run the same multilevel regressions at the country level for each MS, once without students' and schools' science scores (indicated by the ending "_", e.g., "AT_" for Austria) and once with these scores (ending in "_pv", e.g. "AT_pv"). In addition, we also include standard logit regressions (indicated by "_logit", e.g. "AT_logit") to provide an additional robustness check for our results. We only provide a brief summary here, but the details on the country regressions can be found in the appendix in Table 7.

Overall, the results for these multilevel regressions confirm our multilevel models for the entire EU, in the sense that similar variables are significantly related to outcomes. In the country-level regressions, the student-level variables "ESCS", "epistemological beliefs", "grade repetition" and "science score", and the school-level variable "expected ESL level" turn out to be often significantly and with the same signs found in the overall sample. In fact, the only variable that is always significant in all MS and across all specifications (including logit models) is the school's expected ESL level. That is, it is always positively related to a student's expected ESL probability. This finding appears to indicate that there are relevant school or peer factors within schools that have a major influence on the expected early dropout behaviour of students. Thus, there seems to be interdependence between the expectations of individual students and those of the other students within the same school.

The inclusion of the student's science score in the "_pv" models has as a consequence that the coefficients of other variables are less often significant, showing the relevance of this factor. This is e.g. the case for epistemological beliefs but also for grade repetition – not a surprising result, given that these factors have been found to be significantly associated to science performance in other related research on PISA 2015 (Hippe et al., 2017; OECD, 2016c). Also, it is not surprising that lower science performance is associated with lower educational expectations. It only shows that students rationally evaluate their own capabilities and that motivation is intrinsically connected with science results

In addition, in the models with student scores included, the regressions show that immigrant status does matter in only in few MS. In other words, the coefficients for being a first generation and being a second generation immigrant student are negatively significant in 4 MS (out of the 23 MS included). It is a minority of MS, which may explain why it is not a significant factor in the regressions for the entire EU. Furthermore, the effect of being a first or second generation immigrant student changes across MS: in some cases it is positive while in most it is negative. This appears to be in line with our descriptive results earlier on, which emphasise the varying score point differences in the various MS.

Moreover, students' sense of belonging to a school is negatively related to expected dropout probability in a relevant number of MS. This finding indicates that the feeling of being integrated and accepted by school mates and a student's identification with its learning environment is a relevant factor in some MS.

Of course, the picture is even more complex when considering all variables for all MS, but this detailed analysis goes beyond the limits of this technical brief. We provide, however, some additional insights in the appendix. Those results indicate that in each MS there are different variables that have an additional important role in relation to expected early dropout. This shows the diversity of the European education systems and also of

immigrant populations in the MS. Further research would be needed to better understand the cross-country differences and their relationship with MS specificities.

4.2.3 Distinction among EU and non-EU immigrants

Comparison of EU and non-EU immigrants to natives

In this section we explore whether there are relevant differences in the early dropout probabilities when separately comparing EU and non-EU immigrant students to native students. Thus, we run the same set of regressions for these two different immigrant groups with native students as the baseline category.

Looking at all MS together (see Table 8 in the appendix), we find that both first and second generation EU migrants do not have a different early dropout probability than natives. The same is also true for non-EU immigrants (see Table 9 in the appendix).

Similar to previous results, the significant negative coefficient on epistemological beliefs (as compared to natives) disappears once students' science scores are included (compare columns 1 and 2 in Table 8 and Table 9). Our results suggest that the school's concentration of immigrants leads to higher early dropout probability for EU migrants, while not for non-EU immigrants.

Moreover, the average science score of the school level (and thus the school background) matters for both EU and non-EU immigrants as we find a significant negative effect of a school's science score. Thus, it seems that school composition (or peer effects) shapes educational expectations. The additional detailed country-by-country results can be found in the appendix (see Table 10 and Table 11).

Direct comparison of EU to non-EU immigrants

In a final step, we directly compare EU and non-EU immigrants and the factors that lead to different expected early dropout probabilities for these two groups (i.e. we drop all native students from the regressions; see also detailed explanations in the appendix). In other words, we want to know whether there are differences in the factors associated to expected early school leaving between EU migrants and non-EU immigrants. Evidently, sample sizes are small, so results should be taken with caution. For all EU MS together (see appendix, Table 12), after controlling for students' science scores and taking EU migrants as the reference category, we find that the sense of belonging is negatively significant, indicating that the sense of belonging lowers significantly the early dropout probability for EU migrant students. This confirms earlier results from comparisons between native students and EU migrants.

We also find that grade repetition is positively significantly related to expected early dropout in the case of EU migrants. This finding shows again that grade repetition practices are particularly affecting the early dropout expectations of EU migrants. We didn't find any other significant differences between EU and non-EU migrants in the sample with pooled data from all MS. Further regression analysis conducted separately for each MS can be found in the appendix (see appendix, Table 13).

5 Conclusions

This technical brief has considered educational expectations among various student populations in Europe, in particular distinguishing between native and immigrant students. Educational and skills differences are seen in the literature as fundamental factors for economic divides (Hanushek & Wößmann, 2015). Understanding better educational divergences in a European perspective and subsequently improving educational attainment may help in countering widening divides within and across MS.

The recent refugee crisis has put even more to the forefront the issue of immigrants in the EU agenda (European Commission, 2016), while migration patterns among EU MS have led to discussions in both origin and destination countries. At the same time, the Europe 2020 headline target of achieving less than 10 % early school dropouts shows the importance that policy makers give to the reduction in ESL. ESL reflects and reinforces a range of individual and social disadvantages, which have negative consequences for students, the society and the state.

In this study, we have used OECD's PISA 2015 data to explore the importance of immigrant status – together with other factors measured at the school and individual level – in accounting for the probability of early school leaving. PISA provides the most employed data in the field of educational achievement. In particular, PISA 2015 data have the advantage that they include more variables than previous rounds. PISA data on migrants (irrespective from their origin within or outside the EU) are available for the majority of MS, but not for all. Similarly, there is no information included on educational expectations of students for a few MS, further reducing the usable sample. In addition, we also employ data from Eurostat to complement the picture on early school leavers and immigrants.

We analyse expected early school leaving in PISA in various ways. First, we present some descriptive statistics to get a better intuition for the data. Then, we run two-level multilevel models including both the student and the school level. The employed explanatory variables follow the standard methodology by the OECD and include new relevant variables that are introduced in PISA 2015 for the first time. In addition, we also constructed a new variable on truancy from PISA responses.

Overall, in various settings we find that, once we control for individual and school characteristics, immigrant status does not have a significant effect on the expected probability of early school leaving. The latter depends rather on other factors, that are unequally distributed between migrants and natives (socio-economic status in particular), but that affect similarly both groups. In particular, our analyses indicate that the most relevant factors that decrease the likelihood of expected early school leaving are the ESCS of students and their epistemological beliefs, while grade repetition increases it. However, the importance of these student factors varies to various degrees among MS. Interestingly, consistent among all MS is the positive association of a student's expected ESL and the share of expected early school leavers at the school level. This result implies that the school environment and peer effects are strong and have a significant impact on the dropout decisions of students, independent of whether they are native or immigrant.

In particular, there might be space to revise grade repetition practices in MS, and our results give further emphasis to the specific recommendation related to grade repetition by the Thematic Workgroup on Early School Leaving (European Commission, 2016). Moreover, our results are in line with the literature as concerns the socio-economic background (ESCS). The ESCS is a major predictor of expected early school leaving. This means that students with a low socio-economic background have the tendency to expect to leave school earlier than those who come from higher socio-economic strata. Therefore, it is important that education policy aim at equalising opportunities across the different layers of society.

While males have usually higher ESL rates, we do not find that gender is a significant factor across Europe when a whole set of explanatory variables is included. Even at the country level, gender is only rarely significant, and the direction of the effect does vary (i.e., it is in part positive or negative). Thus, our study suggests that there may be differences between boys and girls but these are related to other factors that are common to both sexes.

On the other hand, it would be advisable to analyse for each school what leads to the dropout decisions of students, and how this can be improved. For example, providing more information for students about possible future educational and career opportunities may be a potential useful policy to tackle low educational expectations. As the OECD

(2017b, p. 111) notes, "[s]chools should provide academic and career counselling to all students so that they develop ambitious – yet realistic – expectations about their education and career prospects". In addition, our country-by-country results also emphasise the relevance of the sense of belonging of students. The relevance of students' sense of belonging to a school in a number of MS gives further credence to the importance of helping students, with native or immigrant background, to provide a learning-conducive environment and to take into account the specific needs of each student (see also European Commission, 2013b). In consequence, measures that aim at improving the school climate could be useful in this regard.

Policy makers can take away a number of further messages from this study. In fact, the most important limitation of this study is sample size. Data on immigrant students are quite limited for many MS. This is even more the case when distinguishing among various immigrant subpopulations (i.e., first generation and second generation, as well as EU and non-EU immigrants). The same lack of information exists for early school leavers. More generally, this fact has already been indicated, particularly for the latter group, by the European Commission (2016, p. 4), stating that "with some notable exceptions, Member States lack detailed information on the background of early school leavers and analyses of the causes and incidence of early school leaving. Only a few countries take a systematic approach to collecting, monitoring and analysing data on early school leaving". This study aims to reduce the knowledge gap and better understand the characteristics of (expected) early school leavers. PISA provides the information that we have exploited in a comparable way across MS, providing a European and international perspective on these issues. Nevertheless, evidence-based policy making is still lacking for many MS. More data collection and analysis is needed for the design and implementation of more efficient policies. Therefore, more data on these student subpopulations need also to be collected in future PISA rounds, as our analyses clearly show the limitations of the available data.

Similarly, a holistic approach to the challenge of early school leavers and the successful integration of immigrant students in schools and society is needed to create efficient education policies in this area. This holistic approach would not only consider the specific groups at stake, but include a larger set of stakeholders at the local and regional level and take into account all parts of the education system in a comprehensive strategy (see also recommendations by European Commission 2013b, 2016). In many MS, such a national strategy is still not designed (European Commission, 2016).

Finally, the results of this and other (e.g., Hippe et al., 2017) studies indicate that in the future it may be worth studying more in detail how epistemological beliefs are created, as this is a new item in PISA 2015 and highly related to early school leaving and PISA scores. In other words, what are the factors that shape epistemological beliefs and how can these factors be influenced by policy? Understanding these issues better could be very useful in improving both educational attainment and educational achievement rates in the MS.

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List of abbreviations and definitions

EU MS abbreviations

Code	MS name	
AT	Austria	
BE	Belgium	
BG	Bulgaria	
CY	Cyprus	
CZ	Czechia	
DE	Germany	
DK	Denmark	
EE	Estonia	
EL	Greece	
ES	Spain	
FI	Finland	
FR	France	
HR	Croatia	
HU	Hungary	
ΙΕ	Ireland	
IT	Italy	
LT	Lithuania	
LU	Luxembourg	
LV	Latvia	
MT	Malta	
NL	The Netherlands	
PL	Poland	
PT	Portugal	
RO	Romania	
SE	Sweden	
SI	Slovenia	
SK	Slovakia	
UK	United Kingdom	

Non-EU country abbreviations

Code	Country name
AL	Albania
BH	Bosnia-Herzegovina
CH	Switzerland
GE	Georgia
IS	Iceland
KS	Kosovo
MD	Moldova
ME	Montenegro
MK	FYROM
NO	Norway
RS	Republic of Serbia
RU	Russian Federation
TR	Turkey

Other abbreviations

Abbreviation	Description
Coef.	Coefficient
ESCS	Economic, Social and Cultural Status
ESL	Early school leaver(s)
EU	European Union
GDP	Gross Domestic Product
Gen.	Generation
IRT	Items Response Theory
ISCED	International Standard Classification of Education
MS	Member States
OECD	Organisation for Economic Co-operation and Development
PISA	Programme for International Student Assessment
S.E.	Standard Errors

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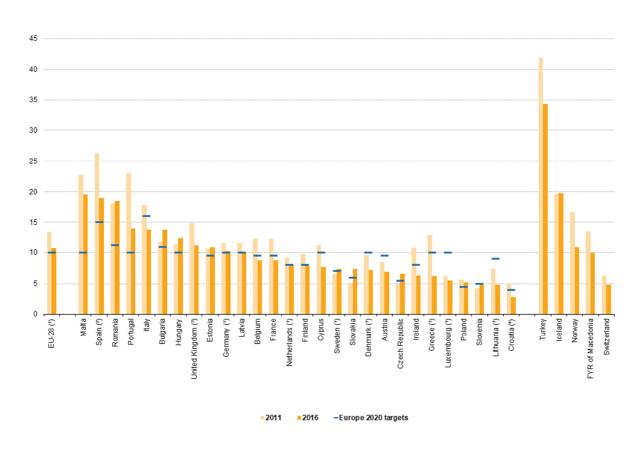
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Appendix

Annex 1. Europe 2020 targets for early school leaving

Figure 18. Europe 2020 targets for early school leaving and current rates



(*) For the target to be achieved, the share of early leavers from education and training should be below the target value.
(*) Europe 2020 target is defined as the school drop-out rate.

(*) No Europe 2020 target. (*) 2016: low reliability. Source: Eurostat (online data code: edat_lfse_14)

Source: Eurostat (2017d).

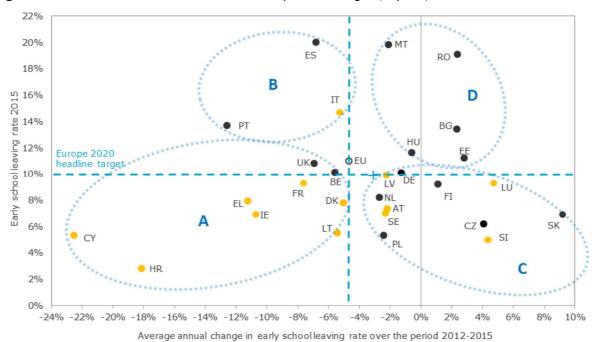
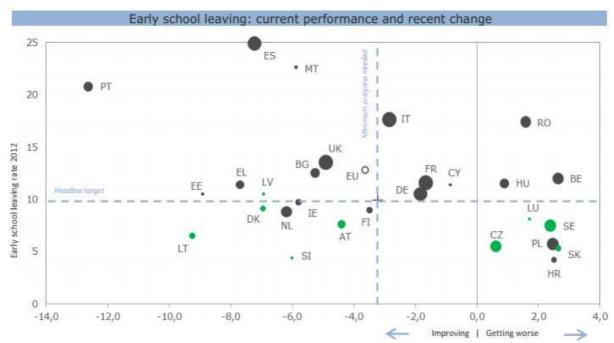


Figure 19. Evolution of ESL rates towards Europe 2020 targets, by MS, 2012-2015

Source: European Commission (2016, p. 3).

Note: European Commission (2016, p. 3) explains the MS groupings: "A. Countries that have early school leaving rates below or just above 10% and are nonetheless still making progress. These countries have also reached their national targets, with the exception of Belgium (the UK did not set a national target). B. Countries that have early school leaving rates above 10% but are nevertheless making significant progress. This is a diverse group of countries, with Spain standing out as the Member State with the highest early school leaving rate and Portugal among the fastest-progressing Member States in recent years. C. Countries that have early school leaving rates below 10% but are making little or no progress. Early school leaving rates have been increasing in Finland, Czech Republic, Slovenia, Luxembourg and most notably Slovakia, while they declined marginally in Germany, Latvia, The Netherlands, Austria, Sweden and Poland. D. Finally, the situation is worst for the five countries in Group D, combining early school leaving rates above 10% with insufficient progress between 2012 and 2015".

Figure 20. Evolution of ESL rates towards Europe 2020 targets, by MS, 2009-2012



Average annual change in early school leaving rate (%) over the period 2009-2012

Source: JRC-CRELL and DG EAC calculations based on Eurostat (LFS) data. Member States having already achieved their national targets are marked in green. Countries are shown according to their 18-24 cohort size, with five categories. Further notes: the average annual change rate is artificial for countries with a break in series, i.e. NL (2010) and LV (2011).

Source: European Commission (2013b).

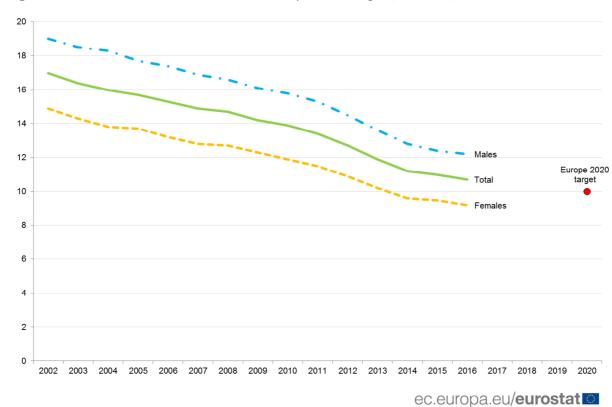


Figure 21. Evolution of ESL rates towards Europe 2020 targets, EU level, 2002-2016

Source: Eurostat (2017a).

Annex 2. Compulsory schooling in Europe

Figure 22. Duration of compulsory schooling in Europe

Student's age-groups and duration of compulsory education, 2014/15

	Full-time education/schooling					Additional compulsory part-time				
	4	Startir 5	ng age 6	7	14 15	Ending a	ge 17	18	Duration (in years)	Ending age
BE fr			6		15				9	18
BE de			6		15				9	18
BE nl			6		15				9	18
BG	1			7		16			9	na
CZ			6		15				9	na
DK	1		6			16			10	na
DE (12 Länder)	1		6		15				9	18
DE (5 Länder)			6		10	16			10	19
EE	l			7		16			9	na
IE .			6			16			10	na
EL		5	6		15	10			10	na
ES		9	6		10	16			10	na
FR			6			16			10	na
HR		5	6		14	10			9	na
IT		J	6		14	16			10	na
CY		ars +	5 ye	ears +	15	10			10 years + 4 months	na
LV	O III	5	O II	7	6	16			11	na
LT		J		7	5	16			9	na
LU	4		6		-	16			12	na
HU		5	6			16		(18)	11 (13)	na
MT	ļ i	5	O			16		(10)	11 (13)	na
NL.	1	5	6			10		18	13	na
AT	<u> </u>	•	6		15			10	9	na
PL		5	6		10	15			10	18
PT		J	6			10		18	12	na
RO		<i>,</i>	6	-		17		10	11	na
SI) 	6		15	1.7			9	na
SK)	6)	13	16			10	na
FI)	U	7		16			9	na
SE	ļ		i c	7	8	16			9	na
UK-ENG		5		- 1		16			11	17
UK-WLS		5		-		16			11	na na
UK-NIR	4	J		-		16			12	na
UK-SCT	() () () () () () () () () ()	5		-		16			11	na
BA		5	6			15			10	na
IS		J	6			16			10	na
LI	-	·	6		15	10			9	na
ME			6		15				9	na
MK*	1000	ars +	U		15	16	17	18	11/12/ 13	na
NO	/ m	onths	6	X		16			10	na
NO RS		ars +	6 ye	ears +	15	10			9 years + 6 months	na na
TR	1000000	**********	100/02/	MANAGEST.	17 years + 6 months				12	na
***	5 years + 6 months			I / years + 0 months				12	na	

^{*} Former Yugoslav Republic of Macedonia: ISO code 3166. Provisional code which does not prejudge in any way the definitive nomenclature for this country, which will be agreed following the conclusion of negotiations currently taking place on this subject at the United Nations.

Source: Eurydice (2015).

Annex 3. Definitions of immigrant background

Non-immigrant (native): born in the country of assessment/survey, or with at least one parent born in that country; born abroad with at least one parent born in the country of assessment/survey.

Second-generation immigrants: born in the country of assessment/survey, but whose parents were born in another country. In this case, it is not the individuals who move, but their parents (definition based on previous generation's move).

First-generation immigrants: born outside the country of assessment/survey and whose parents were also born in another country.

EU migrant: born in an EU country outside the country of assessment/survey (first generation) or whose parents were born in another EU country while she/he was born in the country of assessment/survey (second generation).

Non-EU immigrant: born in a non-EU country outside the country of assessment/survey (first generation) or whose parents were born in another non-EU country while she/he was born in the country of assessment/survey (second generation).

Annex 4. Recent immigration policies in MS

Table 5. Immigration policies in EU Member States, 2008-2016

MS	Policy name	Description
Finland	National Core Curriculum for Instruction Preparing Immigrants for Basic Education	In 2009, Finland introduced a reform to support
	Education and Research	A plan to increase the participation of students with immigrant background in preparatory education between 2011 and 2016 with the aim of improving their opportunity to be enrolled in upper secondary education. In particular, in 2014 one year of preparatory education was created for students to integrate general upper secondary education.
	The Action Programme for Equal Opportunity in Education	The reform was initiated in 2013 and aimed at improving the situation of disadvantaged groups at all levels of education.
		The national core curricula for VET implemented in Finland includes educational arrangements for immigrants.
Ireland	Intercultural Education Strategy	Between 2010 and 2015, Ireland implemented a reform aiming at promoting "inclusive and intercultural learning environments for migrant students by developing leadership and teaching quality, instructional language knowledge, mainstreaming, rights and responsibilities and setting high expectations, among other features" (OECD, 2015a, p. 54).
Germany	National Action Plan on Integration (NAP-I)	In 2011, in Germany there was plan that "sets goals in education, training and continued education to increase the participation and success of students from immigrant backgrounds" (OECD, 2015a, p. 54).
Slovenia	(Popestrimo šolo, 2011) Program of Education for Professionals' Skills Improvement	in primary and secondary education.
	Measures and Guidelines for the integration of immigrant children in kindergartens and schools (2009 and 2012)	2012 aiming at supporting children before the start
	Project raising the social and cultural capital in areas inhabited by members of Roma Community	
	Projects for the Successful	Between 2008 and 2016, Slovenia implemented a

Integration Schools	of Roma	Students i	'
Schools			teaching among kindergartens and schools and teachers in areas with little or no such experience. Specifically, between 2013 and 2015, this programme provides educational activities for immigrant students and training for teaching staff to promote interculturalism in schools. Results of this project carried out "by the end of 2010 included higher attendance of Roma children in educational institutions, improved co-operation between Roma parents and educational
			institutions, increased awareness among Roma of the importance of learning and education, and more successful co-operation between teaching assistants, teachers and Roma parents in the education of Roma children" (OECD, 2016a, p. 8)

Source: Hippe et al. (2016, pp. 26–28).

Annex 5. Background on PISA

The OECD has been running this international large assessment of 15 year old students' skills in Mathematics, Science and Reading every three years since 2000. Each PISA assessment cycle has a major domain, which in 2015 was science. The fact that each cycle targets student performance in a particular subject means that domain-specific questions appear in the student, school and teacher questionnaires.

PISA assesses students' performance in science through questions related to contexts, knowledge, competencies and attitudes. In addition to cognitive data, PISA gathers contextual information through the application of the questionnaires¹⁵ and this information can be linked to student performance (OECD, 2016b, p. 15). More specifically, as defined by the OECD, the questionnaires cover the following aspects:

- "Aspects of students' lives, such as their attitudes towards learning, their habits and life in and outside of school, and their family environment."
- "Aspects of schools, such as the quality of the schools' human and material resources, public and private management and funding, decision-making processes, staffing practices and the school's curricular emphasis and extracurricular activities offered."
- "Context of instruction, including institutional structures and types, class size, classroom and school climate, and reading activities in class."
- "Aspects of learning, including students' interest, motivation and engagement."

Finally, in PISA, students' test scores in Mathematics, Science and Reading are computed according to Item Response Theory (IRT). In 2015 the mean was established at 493, which means that "approximately two-thirds of all students in OECD countries scored between 393 and 593 (i.e., within one standard deviation of the average) on this PISA 2015 assessment" (CMEC, 2016, p. 19).

PISA 2015 counted with the participation of all 28 MS out of a total of 72 countries. The results show the differences and similarities among education systems and how student outcomes are related to education practices and policies.

-

¹⁵ Four additional were offered in PISA as optional: a computer familiarity questionnaire, an educational career questionnaire, a parent questionnaire, and a teacher questionnaire.

Annex 6. Missing data imputation

PISA 2015 data contain information for all students about their science performance. However, additional background information from students and school principals have gaps due to missing responses. Data imputation techniques are necessary to address this issue and they can be applied as the amount of missing data per variable is relatively small. In consequence, sample sizes for the original data vary, while for the imputed dataset there is no missing data so full sample size is available. It is worth noting that while there is substantial variation across students in these variables, descriptive statistics for the original and imputed datasets are very close. In our case we used multiple imputation with chained equations that can deal with different data types (continuous, ordered and nominal) (see Royston, 2009).

Annex 7. Details on the questions asked in PISA to construct the variables

In the following we provide additional information on the variables included in this study, directly taken from and as presented by OECD sources (2017a, 2017c), except for truancy which we constructed ourselves (see main text for more details).

Expected school leaving

ST111Q01TA	Which of the following do you expect to complete?
1	<isced 2="" level=""></isced>
2	<isced 3b="" c="" level="" or=""></isced>
3	<isced 3a="" level=""></isced>
4	<isced 4="" level=""></isced>
5	<isced 5b="" level=""></isced>
6	<isced 5a="" 6="" level="" or=""></isced>

Immigration background

The PISA database contains three country-specific variables relating to the students' country of birth, their mother and father (COBN_S, COBN_M, and COBN_F). The items ST019Q01TA, ST019Q01TB and ST019Q01TC were recoded into the following categories: (1) country of birth is the same as country of assessment and (2) other. The index of immigrant background (IMMIG) was calculated from these variables with the following categories: native students (those students who had at least one parent born in the country), (2) second generation students (those born in the country of assessment but whose parent(s) were born in another country) and (3) first-generation students (those students born outside the country of assessment and whose parents were also born in another country). Students with missing responses for either the student or for both parents were assigned missing values for this variable.

COBN_F	Country of Birth National Categories- Father
COBN_M	Country of Birth National Categories- Mother
COBN_S	Country of Birth National Categories- Self

IMMIG	Index Immigration status
1	Native
2	Second-Generation
3	First-Generation

Truancy

An index which we constructed using the responses to the test questions below:

Item	In the last two full weeks of school, how often did the following things occur?
ST062Q01TA	In the last two full weeks of school, how often: I <skipped> a whole school day</skipped>
ST062Q02TA	In the last two full weeks of school, how often: I <skipped> some classes</skipped>
ST062Q03TA	In the last two full weeks of school, how often: I arrived late for school

Epistemological beliefs

Epistemological beliefs about science were measured with a new question about students' views on scientific approaches (ST131). Students answered on a four-point Likert scale with the answering categories "strongly agree", "agree", "disagree", and "strongly disagree". The derived variable EPIST was scaled using the IRT scaling model described above. [The table below] shows the item wording, international item parameters and item fit for EPIST.

Item	How much do you disagree or agree with the statements below?
ST131Q01NA	A good way to know if something is true is to do an experiment.
ST131Q03NA	Ideas in broad science> sometimes change.
ST131Q04NA	Good answers are based on evidence from many different experiments.
ST131Q06NA	It is good to try experiments more than once to make sure of your findings.
ST131Q08NA	Sometimes broad science> scientists change their minds about what is true in science.
ST131Q11NA	The ideas in broad science> science books sometimes change.

Grade repetition

The grade repetition variable (REPEAT) was computed by recoding variables ST127Q01TA, ST127Q02TA, and ST127Q03TA. REPEAT took the value of "1" if the student had repeated a grade in at least one ISCED level and the value of "0" if "no, never" was chosen at least once, given that none of the repeated grade categories were chosen. The index is assigned a missing value if none of the three categories were ticked in any levels.

ST127Q01TA	Have you ever repeated a <grade>? At <isced 1=""></isced></grade>
ST127Q02TA	Have you ever repeated a <grade>? At <isced 2=""></isced></grade>
ST127Q03TA	Have you ever repeated a <grade>? At <isced 3=""></isced></grade>

Programme orientation

Programme orientation (ISCEDO) indicates whether the programme's curricular content was general, pre-vocational or vocational. Note: in Luxembourg also "modular" existing.

ISCED level

Programme level (ISCEDL) indicates whether students were at the lower or upper secondary level (ISCED 2 or ISCED 3).

Programme designation

Programme designation (ISCEDD) indicates the designation of the study programme: (1) "A" (general programmes designed to give access to the next programme level); (2) "B" (programmes designed to give access to vocational studies at the next programme level); (3) "C" (programmes designed to give direct access to the labour market); or (4) "M" (modular programmes that combine any or all of these characteristics).

Sense of belonging

PISA 2015 asked students about their sense of belonging to school (ST034) using six trend items previously used in PISA 2012 (ID in 2012: ST87). The answering format was a four-point Likert scale with the answering categories "strongly agree", "agree", "disagree", and "strongly disagree"; the derived IRT-Scale is named BELONG. Items

ST034Q02TA, ST034Q03TA and ST034Q05TA were reverse-coded so that higher WLEs and higher difficulty correspond to higher level of sense of belonging on all items.

Age at arrival

ST021Q01TA How old were you when you arrived in <country of="" test="">?</country>		
	1	age 0 - 1
	2	age 1
	3	age 2
	4	age 3
	5	age 4
	6	age 5
	7	age 6
	8	age 7
	9	age 8
	10	age 9
	11	age 10
	12	age 11
	13	age 12
	14	age 13
	15	age 14
	16	age 15
	17	age 16
	95 / .V	Valid Skip
	97 / .N	Not Applicable
	98 / .I	Invalid
	99 / .M	No Response
	SYSTEM MISSING	Missing

Language at home

Students indicated what language they usually speak at home (ST022), and the database includes a derived variable (LANGN) containing a country-specific code for each language. In addition, an internationally comparable variable was derived from this information with the following categories: (1) language at home is the same as the language of assessment for that student and (2) language at home is another language.

Annex 8. Additional descriptive tables and figures

PISA uses as criteria the age of students for inclusion in PISA, i.e. only 15 years olds are allowed to participate. As a consequence, some students are already in an ISCED3 year. While this does not mean that they may expect to complete ISCED3, this may influence the results. Therefore, one should control for this variable, as we do in our study.

Table 6. Number of immigrants in PISA 2015 sample, ISCED 2 students only

		Immigrants			EU migrants	;	Non-EU immigrants			
MS	Total	1 st gen.	2 nd gen.	Total	1 st gen.	2 nd gen.	Total	1st gen.	2 nd gen.	
AT	38	27	11	9	9	0	29	18	11	
BE	280	181	99	72	60	12	208	121	87	
BG	6	4	2	0	0	0	6	4	2	
CZ	123	64	59	29	13	16	94	51	43	
DE	944	212	732	131	41	90	813	171	642	
DK	1673	365	1308	2	1	1	1671	364	1307	
EE	546	35	511	0	0	0	546	35	511	
EL	60	31	29	0	0	0	60	31	29	
ES	681	556	125	0	0	0	681	556	125	
FI	229	126	103	38	33	5	191	93	98	
FR	264	142	122	0	0	0	264	142	122	
HR	4	0	4	0	0	0	4	0	4	
HU	8	6	2	0	0	0	8	6	2	
IE	480	372	108	100	63	37	380	309	71	
IT	57	51	6	10	9	1	47	42	5	
LT	220	36	184	0	0	0	220	36	184	
LU	1588	673	915	1229	527	702	359	146	213	
LV	226	39	187	0	0	0	226	39	187	
MT	2	2	0	0	0	0	2	2	0	
NL	459	107	352	20	18	2	439	89	350	
PL	10	6	4	0	0	0	10	6	4	
PT	213	154	59	31	20	11	182	134	48	
RO	19	7	12	0	0	0	19	7	12	
SE	885	390	495	0	0	0	885	390	495	
SI	23	16	7	0	0	0	23	16	7	
SK	38	19	19	14	10	4	24	9	15	
UK	9	8	1	6	6	0	3	2	1	

Note: orange = insufficient observations for EU migrants; green = sufficient observations for immigrants or EU migrants.

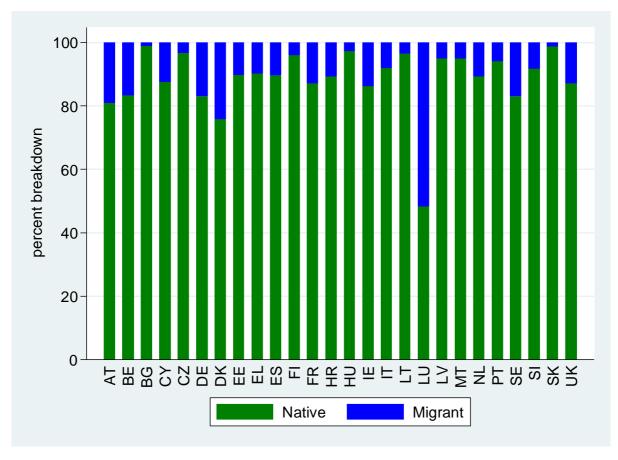
An important aspect, which we also consider in our regression analysis, is the concentration of immigrants in schools. This concentration of immigrants has been seen in the literature to be detrimental to learning and educational outcomes, as the acquisition of language skills may be hampered, but most importantly, because many migrants students come from a lower socio-economic background. The OECD has calculated an index of current concentration, which can be included alongside an index of maximum potential concentration of immigrants. This current concentration of immigrants varies importantly among MS, with the highest shares being in LU, AT, UK and BE (see Figure 23, concentration with at least 50 % immigrants).

% 20 18 16 14 12 10 students in the country/economy 8 Percentage of immigrant 6 4 2 0 52 20 14 17 11 11 11 10 \exists ΑT \vdash Ш \sim BE SE 품 ES Ы Н

Figure 23. Index of current concentration of immigrants in schools

Source: adapted from OECD (2016c).

Figure 24. Shares of immigrants



Note: Shares not calculated for MS with insufficient number of observations or lacking information on educational expectations.

As concerns expected ESL, distinguishing additionally between first and second generation immigrants we find a varied picture (not shown). Still, the tendency is that first generation immigrants have the highest probability to be expected ESL. In a number of MS, such as AT, BE, CZ, DE, DK, EL, ES, FR, SI, UK, there is an upward trend when looking at natives, second generation and first generation immigrants. In other words, the lowest numbers of expected ESL are to be found among natives, and the highest among the more recent first generation arrivals. This finding is intuitive, as more recent arrivals have in many cases to overcome language barriers and cultural differences. Still, the differences are often not very large with regard to second generation students, and in some MS the expected early school dropout rates are even lower for first generation students than for second generation ones (such as IE, IT, LU, NL, SE). Interestingly, the only case where we find the opposite direction, with natives having the highest and first generation students the lowest expected early school leaving rates, is (again) NL. It appears that there is either a specific positive selection of immigrants during the recent decades, or that immigrants that go to NL have high expectations, which are even a bit higher than the ones of locals. In addition, first generation students (but not second generation immigrant students) have also lower expected dropout rates than natives in LU.

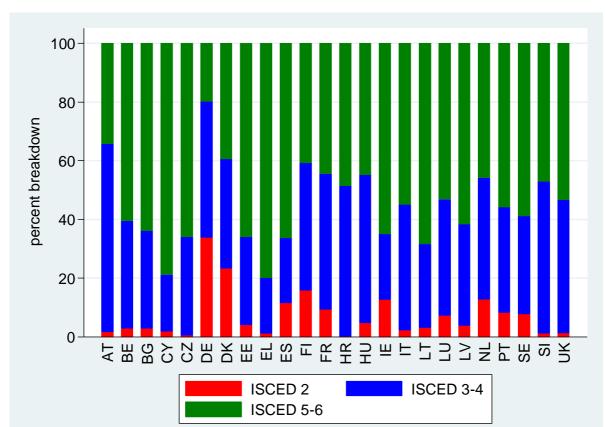


Figure 25. Shares of expected ISCED levels

Note: Shares not calculated for MS with insufficient number of observations or lacking information on educational expectations.

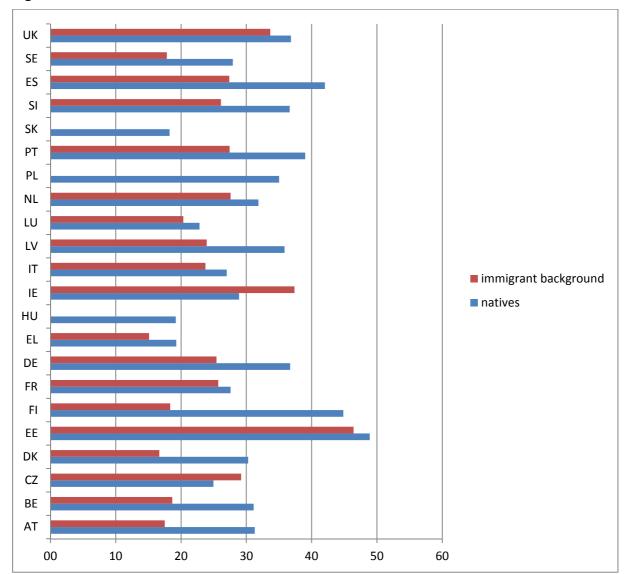


Figure 26. Resilient students in PISA 2015

Source: based on OECD (2016c).

Note: the OECD definition of resilient students is "[a] student is classified as resilient if he or she is in the bottom quarter of the PISA index of economic, social and cultural status (ESCS) in the country/economy of assessment and performs in the top quarter of students among all countries/economies, after accounting for socio-economic status"

Annex 9. Multilevel regressions, country-by-country

Here we consider individual MS, pointing out the relevance of other variables not mentioned in the main text. We only comment on the regression models including science scores and significant positive or negative associations. When there is a significant positive association, it means that the higher this factor is, the higher is expected early school leaving (ESL) probability or, in the case of a categorical variable, the expected ESL probability is significantly higher than in the baseline category. The reverse is the case for negative associations. While in the 'entire EU' specification in the main text the interaction terms were always insignificant, they are relevant only in a number of MS in this set of regressions. More specifically, we interacted immigrant status with various other explanatory variables. The resulting associations can be interpreted as follows: for example, if the coefficient on the interaction between immigrant status and sense of belonging is significantly positive, then it means that the "effect" of sense of belonging is stronger for immigrants than for natives. The detailed regression results can be found below. Given the fact that we have only expectations and not actual outcomes available (i.e., we cannot observe actual school leaving rates), it is possible that in some instances rather non-intuitive results may appear. For example, students may have unrealistically high expectations or ambitions in a specific school form in a MS. However, this is the way students have responded to the PISA questions and we are often facing small sample sizes, which is one limitation of the underlying PISA data. In most cases, however, the findings are in line with intuitions.

We will now comment on each MS individually, and only on those MS where there are relevant changes to what has been said in the main text (and those where the model could be calculated). Full regression results are provided below.

- AT: being a student in programmes designed to give direct access to the labour market is positively associated, while having a pre-vocational programme orientation is negatively associated to expected ESL probability.
- BE: interestingly, we find the reverse case of AT, i.e., being a student in programmes designed to give direct access to the labour market is negatively associated, while having a pre-vocational programme orientation is positively associated to expected ESL probability.
- BG: the school's concentration of immigrants is positively related to expected ESL probability.
- CY: the school's ESCS and the school's concentration of immigrants are positively related to expected ESL probability.
- CZ: Truancy, and being in programmes designed to give direct access to the labour market are positively associated, while having a vocational orientation is negatively associated to expected ESL probability.
- DE: having a different language at home is negatively associated, while being in programmes designed to give access to vocational studies at the next programme level, and having a pre-vocational orientation are positively related to expected ESL probability. The same positive significance has been found for the interaction term between immigrant status and vocational orientation.
- DK: the school's ESCS is positively related to expected ESL probability.
- EE: the time of arrival is negatively, the school's ESCS is positively related to expected ESL probability.
- EL: speaking a different language at home is negatively, while truancy is positively related to expected ESL probability. Similarly, the interaction term of immigrant status and language at home is positive.
- ES: being in a programme designed to give direct access to the labour market is negatively associated to expected ESL probability.

- FI: in contrast to other MS, the school's ESCS is negatively related to expected ESL probability.
- HR: being a female student is negatively associated, while speaking a different language at home is positively associated to expected ESL probability. Similarly, the interaction between immigrant status and language at home is positive, while the interaction between immigrant status and sense of belonging is negative.
- HU: age at arrival is negatively related, while being in a programme designed to give direct access to the labour market is positively associated to expected ESL probability. In addition, the interaction with language at home is negative, while the interaction with senses of belonging and vocational programme orientation is positive.
- IT: Truancy is positively related to expected ESL probability.
- LT: being female and speaking a different language at home are negatively associated to expected ESL probability.
- LU: having a modular programme orientation and the school's science score are positively related to expected ESL probability, as is also the interaction between immigrant status and sense of belonging is positive.
- NL: being female and being in a programme designed to give access to vocational studies at the next programme level as well as the school's ESCS are positively related to expected ESL probability.
- PT: speaking a different language at home and age of arrival are negatively related, while truancy and being in vocational orientation and a school's concentration of immigrants are positively associated to expected ESL probability. In addition, the interaction of immigrant status with speaking a different language at home is positive, while it is negative its interaction with being in vocational orientation.
- SI: being in a programme designed to give access to vocational studies at the next programme level and being in programmes designed to give direct access to the labour market are positively related to expected ESL probability. The same is true for the concentration of immigrants in a school and a school's science score.

Table 7. Multilevel regressions, country-by-country

	AT_logit	AT_	AT_pv	BE_logit	BE_	BE_pv	BG_logit	BG_	BG_pv	CY_logit	CY_	CY_pv
Gender	-0.110	-0.252	-0.407	0.020	-0.121	-0.241	-0.263	0.178	0.203	0.009	0.028	-0.050
Gerraer	(0.236)	(0.265)	(0.286)	(0.183)	(0.238)	(0.239)	(0.260)	(0.299)	(0.297)	(0.274)	(0.274)	(0.269)
Student's ESCS	-0.189	-0.277	-0.282	0.140	0.160	0.200	-0.208	-0.269	-0.239	0.031	0.007	0.047
51446 5 25 65	(0.177)	(0.211)	(0.208)	(0.111)	(0.135)	(0.138)	(0.195)	(0.269)	(0.257)	(0.232)	(0.237)	(0.216)
1st generation	0.112	-0.394	-0.559	0.485	0.044	0.120	0.000	0.000	0.000	0.115	0.011	0.156
150 80.101.011	(0.914)	(1.547)	(1.640)	(0.589)	(0.722)	(0.729)	(.)	(.)	(.)	(0.964)	(0.993)	(0.853)
2nd generation	0.105	0.640	0.595	-0.494	-0.409	-0.483	-2.958	-3.870	-4.505*	-0.661	-0.678	
Zila generation	(0.635)	(1.107)	(1.126)	(0.335)	(0.379)	(0.372)	(2.104)	(2.014)	(1.996)	(0.883)	(0.874)	(0.889)
Language at home	-0.189	-0.876	-0.931	-0.285	-0.691	-0.766	-0.882	-1.003	-1.003	0.102	0.080	0.106
Language at nome	(0.812)	(0.921)	(0.933)	(0.362)	(0.471)	(0.499)	(0.717)	(0.836)	(0.877)	(0.552)	(0.561)	(0.572)
Age at arrival	0.102	0.137	0.129	-0.101	-0.071	-0.093	0.000	0.000	0.000	-0.034	-0.028	-0.032
Age at arrival	(0.077)	(0.093)	(0.103)	(0.055)	(0.064)	(0.067)	(.)	(.)	(.)	(0.080)	(0.082)	(0.070)
Sonso of bolonging		-0.378***	, ,	-0.325*	-0.319*	-0.319*	-0.284*	-0.207	-0.186	-0.230	-0.232	-0.197
Sense of belonging	(0.083)							(0.202)	(0.206)		(0.197)	
Faire ballafa	-0.428***	(0.095)	(0.093)	(0.147) -0.360***	(0.148)	(0.146)	(0.142)		, ,	(0.199)		(0.188)
Epist. beliefs		-0.564**					-0.358*	-0.269	-0.206	-0.263	-0.258	-0.060
T	(0.117)	(0.183)	(0.175)	(0.089)	(0.111)	(0.119)	(0.143)	(0.166)	(0.171)	(0.169)	(0.168)	(0.177)
Truancy	0.166	0.071	0.108	0.128	0.081	0.043	-0.007	-0.107	-0.152	0.276*	0.277*	0.204*
	(0.158)	(0.348)	(0.303)	(0.104)	(0.129)	(0.132)	(0.133)	(0.174)	(0.172)	(0.116)	(0.116)	(0.104)
Grade repetition	1.143***	1.211**	1.000*	1.017***		1.002***			2.589***	1.107*	1.137*	0.872
	(0.285)	(0.399)	(0.406)	(0.198)	(0.261)	(0.276)	(0.572)	(0.669)	(0.695)	(0.496)	(0.497)	(0.493)
ISCED level: 3	2.554	2.629	2.385	-0.753**	-0.775**	-0.596	2.301*	2.172*	2.199*	-1.318	-1.338	
	(2.310)	(1.757)	(1.883)	(0.279)	(0.277)	(0.307)	(0.957)	(0.894)	(0.887)	(0.703)	(0.732)	(0.934)
Designation: B	-0.140	-0.273	-0.269		0.000	0.000				1.705***	1.718***	0.942
	(0.413)	(0.390)	(0.489)		(.)	(.)				(0.477)	(0.483)	(0.730)
Designation: C	7.748**	10.682***	10.626***	-0.492	-0.833*	-0.975**						
	(2.736)	(2.030)	(2.154)	(0.324)	(0.370)	(0.375)						
Orientation: Pre-Voc.	-8.072***	10.877***	10.562***	1.706**	2.237**	2.283**						
	(2.277)	(1.715)	(1.772)	(0.628)	(0.683)	(0.726)						
Orientation: Voc.	0.058	0.154	0.168	-0.097	0.049	0.095	-0.418	-0.367	-0.323	0.000	0.000	0.000
	(0.296)	(0.329)	(0.348)	(0.200)	(0.204)	(0.215)	(0.255)	(0.304)	(0.328)	(.)	(.)	(.)
Orientation: Modular												
I: Immig. x Lang. at home	-0.412	-0.258	-0.507	-0.137	0.460	0.436	0.000	0.000	0.000	-1.934**	-1.840*	-1.847*
	(0.993)	(1.349)	(1.491)	(0.524)	(0.567)	(0.584)	(.)	(.)	(.)	(0.713)	(0.723)	(0.759)
I: Immig. x Sense of belong.	0.196	-0.086	-0.149	-0.376	-0.365	-0.391	3.695*	4.898**		-1.380***		
0 11 11 11 0	(0.178)	(0.368)	(0.411)	(0.227)	(0.232)	(0.231)	(1.502)	(1.612)	(1.618)	(0.341)	(0.343)	(0.364)
School's ESCS	0.509	0.616	0.495	0.641**	0.665*	0.081	-0.341	-0.090	-0.197	0.421	0.436	1.030
	(0.598)	(0.529)	(0.566)	(0.229)	(0.295)	(0.407)	(0.260)	(0.247)	(0.280)	(0.399)	(0.405)	(0.564)
School's conc. of mig.	-0.376	-0.249	-0.002	0.064	0.442	0.676	3.880	8.662	9.904	1.234	1.191	
School's conc. of mig.	(0.686)	(1.113)	(1.204)	(0.508)	(0.590)	(0.605)	(6.164)	(5.395)	(5.277)	(0.774)	(0.802)	(0.848)
School's exp. ESL level	24.362***	, ,	, ,	, ,	, ,	, ,	, ,	, ,	, ,	, ,	9.607***	, ,
Juliout 3 Exp. Lat level	(3.601)	(2.989)	(3.070)	(1.740)	(2.087)	(2.301)	(1.825)	(1.606)	(1.858)	(1.529)	(1.598)	
School's sciones score	(3.001)	(2.303)	-0.000	(1.740)	(2.007)	0.005	(1.023)	(1.000)	0.001	(1.323)	(1.550)	-0.015*
School's science score						(0.004)			(0.003)			
Ctudent's science see			(0.004)						, ,			(0.008)
Student's science score			-0.007**			-0.005**			-0.005			-0.008***
Country	7.005***	7.040***	(0.003)	4 274***	4 240***	(0.002)	7 027***	C 057***	(0.003)	4.050***	4 0 4 4 4 4 4	(0.002)
Constant	-7.805***							-6.957***				1.007
	(2.193)	(1.665)	(2.921)	(0.317)	(0.361)	(1.924)	(0.982)	(0.955)	(1.683)	(0.662)	(0.682)	(2.797)

	CZ_logit	CZ_	CZ_pv	DE_logit	DE_	DE_pv	DK_logit	DK_	DK_pv	EE_logit	EE_	EE_pv
Gender	-1.713*	-1.730*	-1.384	-0.217	0.083	-0.160	0.074	0.221	0.131	-0.738***	-0.724*	-0.866**
	(0.796)	(0.858)	(0.748)	(0.118)	(0.230)	(0.195)	(0.085)	(0.153)	(0.160)	(0.192)	(0.299)	(0.314)
Student's ESCS	-1.469***					-0.539***		. ,	-0.412***		-0.558*	-0.381
	(0.413)	(0.454)	(0.401)	(0.067)	(0.094)	(0.094)	(0.053)	(0.109)	(0.120)	(0.145)	(0.247)	(0.268)
1st generation	-12.387*		-14.889**	-0.385	0.183	-0.006	0.010	0.329	0.062	0.187	0.636	0.324
•	(5.581)	(5.369)	(5.158)	(0.533)	(0.525)	(0.569)	(0.361)	(0.541)	(0.513)	(0.753)	(0.828)	(0.697)
2nd generation	-3.238	-2.470	-3.444	-0.443	-0.630*	-0.866**	0.092	0.214	0.079	0.372	0.568	0.340
•	(3.341)	(3.212)	(3.563)	(0.260)	(0.302)	(0.286)	(0.148)	(0.223)	(0.250)	(0.279)	(0.422)	(0.389)
Language at home	1.507	0.676	1.126	-0.149	-0.098	-0.757*	-0.003	-0.425	-0.507	-0.011	-0.035	-0.427
	(0.901)	(1.049)	(1.013)	(0.317)	(0.309)	(0.316)	(0.313)	(0.438)	(0.418)	(0.489)	(0.839)	(0.889)
Age at arrival	0.584*	0.685*	0.806**	-0.003	-0.062	-0.081	0.013	0.003	0.017	-0.102	-0.105	-0.089
_	(0.268)	(0.281)	(0.264)	(0.066)	(0.074)	(0.073)	(0.038)	(0.052)	(0.050)	(0.057)	(0.070)	(0.092)
Sense of belonging	-0.492	-0.268	-0.121	-0.055	-0.042	-0.076	-0.152***	-0.166**	-0.173**	-0.280*	-0.564**	-0.539**
	(0.400)	(0.479)	(0.424)	(0.063)	(0.073)	(0.077)	(0.041)	(0.051)	(0.053)	(0.137)	(0.183)	(0.190)
Epist. beliefs	-0.454	-0.701	-0.724	-0.180***	-0.154*	0.008	-0.213***	-0.219***	-0.072	-0.353**	-0.345	-0.082
	(0.322)	(0.381)	(0.381)	(0.053)	(0.067)	(0.064)	(0.039)	(0.064)	(0.074)	(0.111)	(0.203)	(0.219)
Truancy	0.407	0.723*	0.666*	0.051	-0.006	-0.110	0.112**	0.159**	0.095	0.206**	0.193	0.024
	(0.306)	(0.330)	(0.307)	(0.077)	(0.094)	(0.097)	(0.038)	(0.050)	(0.056)	(0.074)	(0.101)	(0.110)
Grade repetition	1.727*	2.111*	1.934*	0.724***	0.697***	0.409*	0.306	0.148	-0.205	0.918*	1.153*	0.618
·	(0.744)	(0.857)	(0.812)	(0.147)	(0.178)	(0.184)	(0.224)	(0.338)	(0.345)	(0.358)	(0.547)	(0.578)
ISCED level: 3	0.935	1.301	0.178	14.133***	16.036***	16.810***	0.000	0.000	0.000	0.000	0.000	0.000
	(1.021)	(1.368)	(0.995)	(0.375)	(0.373)	(0.373)	(.)	(.)	(.)	(.)	(.)	(.)
Designation: B		, ,		13.997***	15.900	16.524	.,		• • •	0.000	0.000	0.000
•				(0.534)	(.)	(.)				(.)	(.)	(.)
Designation: C	1.925**	1.257	2.359*	, ,	` ,	.,				.,	` ,	` ,
· ·	(0.725)	(0.842)	(0.941)									
Orientation: Pre-Voc.		, ,		0.918***	1.215***	1.844***						
				(0.199)	(0.242)	(0.374)						
Orientation: Voc.	-2.118*	-2.015	-0.858	0.000	0.000	0.000				0.000	0.000	0.000
	(0.869)	(1.054)	(1.015)	(.)	(.)	(.)				(.)	(.)	(.)
Orientation: Modular	, ,	, ,	, ,	.,	` ,	.,				.,	` ,	` ,
I: Immig. x Lang. at home	0.646	0.489	0.262	-0.239	-0.166	0.283	-0.076	0.162	0.154	-0.297	-0.623	-0.539
	(1.781)	(1.839)	(1.668)	(0.446)	(0.454)	(0.446)	(0.371)	(0.541)	(0.507)	(0.776)	(1.076)	(1.181)
I: Immig. x Sense of belong.	-3.806*	-3.338	-3.869*	0.183	0.193	0.188	0.045	-0.161	-0.149	0.264	0.616*	0.522
	(1.706)	(1.753)	(1.902)	(0.152)	(0.192)	(0.191)	(0.113)	(0.174)	(0.173)	(0.263)	(0.302)	(0.318)
School's ESCS	0.059	0.047	-1.018	-0.386*	-0.207	0.047	0.131*	0.116	0.086	0.588**	0.860**	0.869*
	(0.582)	(0.702)	(0.989)	(0.190)	(0.222)	(0.240)	(0.056)	(0.071)	(0.093)	(0.213)	(0.268)	(0.342)
School's conc. of mig.	-1.375	1.532	4.888	0.254	0.479	0.767*	-0.150	-0.423	-0.208	-0.011	-0.056	0.639
	(4.941)	(3.383)	(3.781)	(0.297)	(0.321)	(0.377)	(0.165)	(0.286)	(0.300)	(0.611)	(0.698)	(0.769)
School's exp. ESL level	43.457***		. ,	5.671***		5.757***		6.192***		14.179***		16.135***
	(4.471)	(4.748)	(8.425)	(0.290)	(0.341)	(0.450)	(0.233)	(0.382)	(0.343)	(1.583)	(1.544)	(1.875)
School's science score	, ,	, ,	0.018	, ,	` ,	-0.005**	, ,	` ,	-0.000	, ,	` ,	-0.000
			(0.009)			(0.002)			(0.001)			(0.003)
Student's science score			-0.009			-0.010***			-0.007***			-0.012***
			(0.009)			(0.002)			(0.001)			(0.002)
Constant	-7.892***	-8.448***	, ,	-3.067***	-3.240***	,	-2.830***	-2.931***	-2.970***	-4.177***	-4.348***	-4.438**
*** *	(0.761)	(0.997)	(5.734)	(0.170)	(0.262)	(1.078)	(0.093)	(0.154)	(0.687)	(0.143)	(0.209)	(1.619)
	(5 52)	(0.007)	, ,	(5.2.0)	(3:-3-)	(=::::0)	(5.550)	(-:)	(5.557)	(5.2.5)	(5.25)	(=:==)

	EL_logit	EL_	EL_pv	ES_logit	ES_	ES_pv	FI_logit	FI_	Fl_pv	FR_logit	FR_	FR_pv
Gender	-0.425	-0.688	-0.728	-0.090	-0.041	-0.191	-0.103	-0.232*	-0.191	0.094	0.143	0.083
	(0.491)	(0.642)	(0.632)	(0.101)	(0.113)	(0.125)	(0.082)	(0.106)	(0.111)	(0.124)	(0.139)	(0.139)
Student's ESCS	0.505	0.920				-0.339***			-0.253**	-0.276**	-0.149	-0.108
	(0.372)	(0.472)	(0.437)	(0.052)	(0.077)	(0.075)	(0.067)	(0.079)	(0.077)	(0.086)	(0.095)	(0.095)
1st generation	-2.663	-1.091	-0.745	-0.308	0.068	-0.041	0.467	1.301	0.530	-0.213	-0.600	
· ·	(2.011)	(2.302)	(2.323)	(0.359)	(0.453)	(0.435)	(0.715)	(0.854)	(0.701)	(0.690)	(0.724)	(0.779)
2nd generation	0.567	0.856	0.797	0.053	-0.251	-0.504	-0.422	-0.272	-0.830	0.624**	0.488	
•	(0.697)	(0.678)	(0.677)	(0.356)	(0.463)	(0.453)	(0.512)	(0.516)	(0.499)	(0.237)	(0.291)	(0.310)
Language at home	1.606	1.441	1.483	0.298*	0.296*	0.246	-0.357	0.030	-0.036	0.600*	0.316	0.183
	(0.981)	(1.140)	(1.105)	(0.135)	(0.150)	(0.142)	(0.304)	(0.445)	(0.470)	(0.298)	(0.333)	(0.369)
Age at arrival	0.202	0.011	-0.046	-0.001	-0.024	-0.041	-0.103	-0.173*	-0.145*	0.101	0.119	0.113
•	(0.129)	(0.228)	(0.212)	(0.043)	(0.049)	(0.048)	(0.066)	(0.080)	(0.073)	(0.072)	(0.066)	(0.070)
Sense of belonging	-0.579*	-0.747**	-0.725**	-0.084	-0.091	-0.095	-0.140**	-0.169**	-0.180**	0.003	0.085	0.090
	(0.268)	(0.267)	(0.249)	(0.045)	(0.049)	(0.048)	(0.048)	(0.055)	(0.056)	(0.092)	(0.106)	(0.102)
Epist. beliefs	-0.041	-0.346	-0.218	-0.218***	-0.232**	-0.053	-0.175***	-0.155**	-0.032	-0.101	-0.091	-0.060
·	(0.186)	(0.259)	(0.240)	(0.052)	(0.080)	(0.076)	(0.047)	(0.047)	(0.049)	(0.062)	(0.066)	(0.065)
Truancy	0.023	-0.372	-0.395	0.101	0.084	0.043	0.062	0.070	0.021	-0.003	-0.056	
,	(0.262)	(0.327)	(0.330)	(0.054)	(0.062)	(0.063)	(0.037)	(0.046)	(0.045)	(0.064)	(0.069)	(0.069)
Grade repetition	1.512	1.288	1.092	1.674***	1.733***	1.156***	0.478*	0.614*	0.243	1.067**	0.924**	0.943**
•	(0.793)	(0.736)	(0.871)	(0.113)	(0.133)	(0.127)	(0.216)	(0.295)	(0.276)	(0.328)	(0.343)	(0.337)
ISCED level: 3	-0.278	-0.456	-0.016	0.000	0.000	0.000	0.000	0.000	0.000	-0.913*	-0.756	-0.492
	(0.995)	(1.006)	(1.032)	(.)	(.)	(.)	(.)	(.)	(.)	(0.434)	(0.420)	(0.463)
Designation: B	` '	, ,	` ,	` '	` '	.,	.,	.,	.,	0.651*	0.430	
· ·										(0.296)	(0.370)	(0.395)
Designation: C	0.278	-0.665	-1.173	-0.883	-1.165*	-1.284**				0.270	0.317	0.021
9	(0.708)	(0.805)	(0.940)	(0.473)	(0.456)	(0.497)				(0.605)	(0.548)	(0.552)
Orientation: Pre-Voc.		, ,		0.000	0.000	0.000				-0.659	-0.538	-0.576
				(.)	(.)	(.)				(0.353)	(0.413)	(0.433)
Orientation: Voc.	0.000	0.000	0.000	` ,	` '	.,				0.000	0.000	0.000
	(.)	(.)	(.)							(.)	(.)	
Orientation: Modular	.,	. ,	` ,							.,	` ,	.,
I: Immig. x Lang. at home	-1.282	-1.295	-1.266	-0.591*	-0.697*	-0.593	0.448	-0.228	0.023	-1.271**	-0.636	-0.526
	(1.290)	(1.177)	(1.297)	(0.272)	(0.324)	(0.359)	(0.631)	(0.862)	(0.842)	(0.458)	(0.518)	(0.557)
I: Immig. x Sense of belong.	-0.211	0.453	0.382	0.034	-0.035	-0.064	0.259	0.293	0.360*	-0.077	-0.047	-0.060
	(0.435)	(0.495)	(0.484)	(0.121)	(0.138)	(0.134)	(0.172)	(0.174)	(0.165)	(0.187)	(0.225)	(0.232)
School's ESCS	-0.271	0.079	0.223	0.092	0.125	0.025	-0.013	-0.139	-0.238	0.152	-0.086	
	(0.489)	(0.468)	(0.509)	(0.074)	(0.082)	(0.094)	(0.092)	(0.120)	(0.134)	(0.180)	(0.150)	(0.185)
School's conc. of mig.	-0.360	0.326	0.094	0.091	0.108	0.473	0.046	0.035	0.475	-0.330	-0.281	-0.198
-	(1.534)	(1.865)	(1.505)	(0.277)	(0.315)	(0.292)	(0.349)	(0.415)	(0.410)	(0.287)	(0.265)	(0.266)
School's exp. ESL level	9.565***	8.662***	8.692***	7.708***	7.715***	8.507***	7.469***	7.061***		4.542***	4.722***	4.844***
	(2.055)	(1.382)	(1.391)	(0.523)	(0.506)	(0.480)	(0.468)	(0.552)	(0.532)	(0.435)	(0.370)	(0.348)
School's science score	` ,	, ,	-0.008	, ,	, ,	0.000	, ,	, ,	0.001	, ,	, ,	-0.003
			(0.007)			(0.001)			(0.001)			(0.002)
Student's science score			-0.007			-0.010***			-0.005***			-0.004***
			(0.005)			(0.001)			(0.001)			(0.001)
Constant	-5.496***	-4.931***		-3.919***	-3.954***	-4.112***	-3.008***	-2.867***		-3.137***	-3.263***	-2.095*
********	(1.017)	(1.058)	(3.034)	(0.117)	(0.123)	(0.776)	(0.114)	(0.141)	(0.594)	(0.413)	(0.405)	(0.874)
	(2.027)	(1.000)	(3.004)	(0.11/)	(0.123)	(0.7.0)	(0.114)	(0.1/1)	(0.004)	(0.125)	(000)	(0.0,4)

	HR_logit	HR_	HR_pv	HU_logit	HU_	HU_pv	IT_logit	IT_	IT_pv
								0.400	0.005
Gender	-0.971	-1.612	-1.801	0.015	0.236	0.192		-0.109	0.006
Student's ESCS	(1.168) 0.667	(1.046) 0.575	(1.085) 0.628	(0.191) -0.191	(0.271) -0.160	(0.278) -0.113	(0.268) -0.332	(0.429) -0.369	(0.416) -0.341
Student's LSCS	(0.512)	(0.523)	(0.522)	(0.151)	(0.236)	(0.245)	(0.171)	(0.273)	(0.288)
1st generation	0.000	0.000	0.000		11.190***	9.772**		-4.819**	-4.833*
13t generation	(.)	(.)	(.)	(3.546)	(3.216)	(3.114)	(1.420)	(1.765)	(1.965)
2nd generation	12.997***			0.133	0.270	0.196		-2.018*	-1.881*
. 0	(0.527)	(1.082)	(0.883)	(0.643)	(0.727)	(0.727)	(0.596)	(0.937)	(0.960)
Language at home	1.988**	2.082**	2.355*	0.548	0.166	-0.008		0.137	0.160
	(0.623)	(0.687)	(0.925)	(0.427)	(0.567)	(0.582)	(0.384)	(0.614)	(0.608)
Age at arrival	0.000	0.000	0.000	-7.669***	-9.962***		0.170	0.280*	0.282*
	(.)	(.)	(.)	(1.981)	(1.864)	(1.834)	(0.115)	(0.121)	(0.137)
Sense of belonging	-0.461	-0.420	-0.516	-0.129	0.077	0.099	-0.223	0.078	0.094
	(0.345)	(0.364)	(0.448)	(0.111)	(0.159)	(0.163)	(0.197)	(0.356)	(0.344)
Epist. beliefs	-0.808	-0.955	-0.764	-0.046	-0.014	0.015	-0.458**	-0.404	-0.411*
	(0.645)	(0.656)	(0.701)	(0.148)	(0.204)	(0.199)	(0.149)	(0.215)	(0.194)
Truancy	0.327	0.267	0.180	0.230*	0.133	0.101	0.335**	0.380*	0.384*
	(0.329)	(0.300)	(0.331)	(0.099)	(0.145)	(0.143)	(0.109)	(0.163)	(0.161)
Grade repetition	2.531	2.704	2.394	0.001	0.002	-0.161		1.432**	1.350*
	(1.399)	(1.451)	(1.553)	(0.368)	(0.448)	(0.484)	(0.270)	(0.527)	(0.589)
ISCED level: 3	0.000	0.000	0.000	-0.853*	-0.989*	-1.094*		2.475	1.980
	(.)	(.)	(.)	(0.388)	(0.435)	(0.435)	(1.072)	(1.456)	(1.399)
Designation: B									
Designation: C	0.247	0.110	-0.422	1.224***	1.442***	1.492***	-0.850	-0.240	-0.236
	(0.739)	(0.655)	(1.047)	(0.316)	(0.352)	(0.382)	(0.537)	(0.532)	(0.528)
Orientation: Pre-Voc.	, ,	, ,	, ,	,	, ,	, ,	,	, ,	, ,
Orientation: Voc.	0.000	0.000	0.000	0.000	0.000	0.000	0.158	-0.119	0.231
	(.)	(.)	(.)	(.)	(.)	(.)	(0.306)	(0.541)	(0.496)
Orientation: Modular									
Ir Immig y Lang at homo	15.546***	10 657	17.966***	0.458	1.735	1.901	-0.139	1.755	1.420
I: Immig. x Lang. at home	(1.133)	(.)	(1.148)	(1.101)	(1.167)	(1.173)	(0.645)	(0.971)	(1.011)
I: Immig. x Sense of belong.	-1.002	-1.431	-1.311	0.079	-0.387	-0.401	-0.684*	-1.059*	-1.238*
i. illillig. A Selise of belong.	(0.746)	(0.825)	(0.897)	(0.266)	(0.340)	(0.324)	(0.282)	(0.425)	(0.488)
School's ESCS	-1.278	-1.896	-1.185	0.038	0.400	0.393		0.419	0.165
3011001 3 2303	(1.729)	(1.890)	(2.021)	(0.192)	(0.215)	(0.208)	(0.272)	(0.404)	(0.432)
School's conc. of mig.	-4.363	-3.693	-5.049	1.619	1.937	2.019		1.646	1.587
Series a series of times	(4.637)	(5.599)	(5.341)	(1.710)	(1.456)	(1.366)	(0.889)	(1.181)	(1.121)
School's exp. ESL level	90.747***			7.741***				16.603***	
	(15.331)	(17.458)	(13.729)	(0.657)	(0.673)	(0.751)	(2.381)	(2.858)	(2.923)
School's science score	7		-0.019	, ,	/	0.000	, - /	,,	0.006
			(0.016)			(0.003)			(0.004)
Student's science score			-0.009			-0.006**			-0.005*
			(0.009)			(0.002)			(0.002)
Constant	-8.903***	-9.695***		-3.736***	-3.652***		-8.750***	-8.088***	10.567***
	(1.209)	(1.384)	(7.752)	(0.360)	(0.386)	(1.268)	(1.119)	(1.684)	(2.539)

Note: The model for IE did not converge, so that IE is not shown here.

	LT_logit	LT_	LT_pv	LU_logit	LU_	LU_pv	LV_logit	LV_	LV_pv	NL_logit	NL_	NL_pv
Gender	-0.725**	-0.741**	-0.838**	0.238	0.238	0.172	-0.583**	-0.474	-0.377	0.262**	0.378***	0.382***
	(0.242)	(0.274)	(0.300)	(0.152)	(0.152)	(0.150)	(0.204)	(0.295)	(0.262)	(0.092)	(0.101)	(0.101)
Student's ESCS	-0.542***	-0.370	. ,	-0.265***	-0.265***	-0.250***	-0.567***	-0.644***	. ,	-0.179*	-0.167*	-0.168*
	(0.135)	(0.193)	(0.205)	(0.076)	(0.076)	(0.076)	(0.120)	(0.167)	(0.177)	(0.078)	(0.085)	(0.084)
1st generation	0.000	0.000	0.000	-1.478*	-1.478*	-1.531*	1.771	0.972	0.213	-2.132*	-2.110	-2.100
· ·	(.)	(.)	(.)	(0.627)	(0.627)	(0.622)	(1.148)	(1.353)	(1.222)	(0.845)	(1.097)	(1.103)
2nd generation	-0.307	-0.652	-0.462	-0.771	-0.771	-0.832	0.807*	0.956*	0.584	-0.376	-0.484	-0.476
G	(0.566)	(0.614)	(0.606)	(0.422)	(0.422)	(0.439)	(0.386)	(0.447)	(0.443)	(0.260)	(0.284)	(0.285)
Language at home	-0.323	-1.078	-0.983	-0.177	-0.177	-0.221	-0.017	-0.010	-0.127	-0.459	-0.595	-0.595
5	(0.411)	(0.612)	(0.596)	(0.375)	(0.375)	(0.372)	(0.309)	(0.372)	(0.327)	(0.376)	(0.398)	(0.397)
Age at arrival	0.000	0.000	0.000	0.026	0.026	. ,		-0.196*		0.221*	0.199	0.199
rige ac ava.	(.)	(.)	(.)	(0.040)	(0.040)	(0.041)	(0.075)	(0.081)	(0.061)	(0.093)	(0.114)	(0.114)
Sense of belonging	-0.168	-0.114		-0.347***	, ,	, ,	-0.317**	-0.405**	-0.359**	-0.041	-0.053	-0.052
Series of Seronging	(0.088)	(0.109)	(0.113)	(0.092)	(0.092)	(0.093)	(0.103)	(0.140)	(0.138)	(0.056)	(0.052)	(0.053)
Epist. beliefs	-0.379***	, ,	-0.364**	-0.180**	-0.180**	-0.126*	-0.167	-0.144	0.013	-0.054	-0.084	-0.088
Lpist. beliefs	(0.102)	(0.125)	(0.134)	(0.063)	(0.063)	(0.064)	(0.106)	(0.127)	(0.128)	(0.064)	(0.068)	(0.074)
Truancy	0.271***	0.278*	. ,	0.211***			0.176*	0.219	0.171	0.032	0.057	0.059
Truancy	(0.077)	(0.108)	(0.117)	(0.057)	(0.057)	(0.056)	(0.088)	(0.116)	(0.121)	(0.068)	(0.072)	(0.073)
Grade repetition	, ,	1.703***	1.201**	0.291*	0.291*	, ,	1.091***	1.276**	0.789	0.125	0.102	0.108
Grade repetition			(0.398)	(0.132)	(0.132)	(0.131)			(0.421)	(0.131)	(0.142)	(0.142)
ISCED level: 3	(0.370) 0.000	(0.409)	, ,	-1.584***	, ,	, ,	(0.331)	(0.426) -0.972	, ,	-3.083***	, ,	, ,
ISCED level: 3							-0.826					
	(.)	(.)	(.)	(0.290)	(0.290)	(0.310)	(0.710)	(0.726)	(0.657)	(0.683)	(0.734)	(0.735)
Designation: B				0.120	0.120	0.053	0.000	0.000		1.204***	1.252***	
				(0.565)	(0.565)	(0.567)	(.)	(.)	(.)	(0.245)	(0.283)	(0.307)
Designation: C				-0.358	-0.358	-0.450				0.223	0.314	0.308
				(0.891)	(0.891)	(0.923)				(0.966)	(0.980)	(1.008)
Orientation: Pre-Voc.										0.129	0.186	0.189
										(0.103)	(0.133)	(0.155)
Orientation: Voc.	0.299	0.088	-0.120	0.291	0.291	0.329	0.000	0.000	0.000	0.000	0.000	0.000
	(0.390)	(0.587)	(0.703)	(0.381)	(0.381)	(0.396)	(.)	(.)	(.)	(.)	(.)	(.)
Orientation: Modular				0.941***	0.941***	0.723**						
				(0.258)	(0.258)	(0.255)						
I: Immig. x Lang. at home	-0.354	0.455	0.229	0.631	0.631	0.574	-0.415	-0.732	-0.313	-0.163	-0.157	-0.160
	(1.190)	(1.258)	(1.239)	(0.466)	(0.466)	(0.474)	(0.949)	(1.099)	(1.070)	(0.516)	(0.583)	(0.582)
I: Immig. x Sense of belong.	-0.327	-0.411	-0.535	0.267**	0.267**	0.286**	0.317	0.356	0.368	0.283	0.328	0.328
	(0.289)	(0.354)	(0.367)	(0.102)	(0.102)	(0.103)	(0.436)	(0.393)	(0.362)	(0.157)	(0.167)	(0.167)
School's ESCS	0.064	0.309	0.262	0.600**	0.600**	-0.047	0.307	0.364	0.103	0.183	0.265	0.281*
	(0.219)	(0.208)	(0.293)	(0.187)	(0.187)	(0.241)	(0.159)	(0.186)	(0.263)	(0.129)	(0.149)	(0.126)
School's conc. of mig.	1.089	-0.265	-0.505	0.667*	0.667*	0.795*	-0.269	-0.379	0.175	0.542	0.614*	0.605*
-	(0.714)	(1.418)	(1.452)	(0.336)	(0.336)	(0.315)	(0.941)	(1.204)	(1.139)	(0.281)	(0.278)	(0.283)
School's exp. ESL level	17.604***	18.154***	18.084***	9.201***	9.201***	11.571***	18.660***	17.451***	19.267***	5.866***	5.748***	5.735***
·	(1.792)	(1.643)	(1.739)	(1.103)	(1.103)	(1.274)	(1.598)	(1.786)	(2.078)	(0.273)	(0.299)	(0.291)
School's science score	, - - /	,7	-0.001	,,	/	0.007**	,/	,,	0.003	,	,,	-0.000
			(0.003)			(0.002)			(0.003)			(0.001)
Student's science score			-0.010***			-0.004***			-0.015***			0.000
			(0.002)			(0.001)			(0.002)			(0.001)
Constant	-4 815***	-4.699***	. ,	-3 379***	-3 379***	-6.669***	-4 504***	-4 613***	. ,	-4 057***	-4 158***	
Constant	(0.171)	(0.193)	(1.463)	(0.422)	(0.422)	(1.190)	(0.180)	(0.257)	(1.791)	(0.239)	(0.276)	(0.751)
	(0.1/1)	(0.133)	(1.403)	(0.422)	(0.422)	(1.130)	(0.100)	(0.237)	(1./91)	(0.233)	(0.270)	(0.751)

	DT last	DT	DT	CE :+	CE	CE	CL last	CI	Cl. m.
	PT_logit	PT_	PT_pv	SE_logit	SE_	SE_pv	SI_logit	SI_	SI_pv
Gender	-0.367*	-0.126	-0.189	-0.169	-0.413*	-0.438**	-0.043	-0.087	0.086
Gender	(0.144)	(0.260)	(0.299)	(0.136)	(0.168)	(0.170)	(0.388)	(0.511)	(0.508)
Student's ESCS	-0.533***	-0.468*	-0.413*	-0.296**	-0.327**	-0.233*		-	-0.458
Student's LSCS	(0.104)	(0.197)	(0.200)	(0.092)	(0.109)	(0.108)	(0.333)	(0.519)	(0.540)
1st gonoration	0.443	0.197)	1.068	-0.016	-0.099	-0.067			-1.578
1st generation	(0.568)	(0.754)	(0.738)	(0.678)	(0.678)	(0.619)	(1.727)	(1.875)	(1.897)
2nd generation	-0.057	0.593	0.512	0.395	0.417	0.204			0.607
Ziid generation	(0.478)	(0.597)	(0.657)	(0.334)	(0.382)	(0.396)	(1.090)	(1.268)	(1.252)
Languago at homo		-2.883***		0.759**	0.645*	0.531		-	1.060
Language at home									(1.682)
Ago at arrival	(0.594) -0.164*	(0.735) -0.289	(0.762) -0.279	(0.268) 0.040	(0.305) 0.051	(0.317) 0.007	(1.002) 0.162	(1.553) 0.049	0.107
Age at arrival									
Canas of halansina	(0.082)	(0.157)	(0.149)	(0.071)	(0.083)	(0.072)	(0.127)	(0.177)	(0.187)
Sense of belonging	-0.091	-0.044	-0.004	-0.111	-0.042			-1.046***	
Fortable Baltafa	(0.070)	(0.071)	(0.070)	(0.057)	(0.084)	(0.078)	(0.171)	(0.295)	(0.311)
Epist. beliefs	-0.156*	-0.156		-0.237***		-0.202**		-0.010	-0.086
_	(0.073)	(0.082)	(0.084)	(0.052)	(0.063)	(0.070)	(0.231)	(0.341)	(0.332)
Truancy	0.177**	0.196*	0.161	0.079	-0.051	-0.120		-0.115	-0.152
	(0.064)	(0.097)	(0.103)	(0.081)	(0.108)	(0.110)	(0.192)	(0.347)	(0.355)
Grade repetition	0.240	0.370	0.215	-0.057	-0.019	-0.145		1.647*	2.284**
	(0.360)	(0.564)	(0.605)	(0.341)	(0.524)	(0.503)	(0.623)	(0.696)	(0.870)
ISCED level: 3		-3.882***		0.000	0.000	0.000		-3.034***	
	(0.832)	(1.079)	(0.991)	(.)	(.)	(.)	(0.788)	(0.711)	(0.862)
Designation: B	1.918***	1.741**	1.920**				1.854*	2.438**	3.495**
	(0.566)	(0.636)	(0.587)				(0.742)	(0.877)	(1.117)
Designation: C	0.000	0.000	0.000	0.000	0.000	0.000	2.894***	3.697***	5.844***
	(.)	(.)	(.)	(.)	(.)	(.)	(0.853)	(1.065)	(1.658)
Orientation: Pre-Voc.	-0.218	-0.197	-0.402						
	(0.306)	(0.407)	(0.416)						
Orientation: Voc.	3.179***	2.967***	2.952***	0.000	0.000	0.000	0.000	0.000	0.000
	(0.560)	(0.582)	(0.558)	(.)	(.)	(.)	(.)	(.)	(.)
Orientation: Modular									
I: Immig. x Lang. at home	2.452**	3.781***	3.617***	-1.249**	-1.115*	-0.926	-0.077	-0.431	-1.033
	(0.855)	(1.062)	(1.062)	(0.447)	(0.492)	(0.520)	(1.508)	(1.790)	(1.966)
I: Immig. x Sense of belong.	0.346	0.128	0.063	0.173	-0.051	-0.087	-0.321	-0.381	-0.404
	(0.383)	(0.458)	(0.488)	(0.153)	(0.187)	(0.186)	(0.409)	(0.598)	(0.585)
School's ESCS	0.177	-0.029	-0.330	-0.131	0.007	-0.294	1.717**	2.590**	2.232**
	(0.142)	(0.196)	(0.207)	(0.144)	(0.178)	(0.215)	(0.567)	(0.903)	(0.822)
School's conc. of mig.	-0.521	0.149	0.407	0.149	0.449	0.957*	0.103	1.639	3.178
-	(0.492)	(0.477)	(0.471)	(0.355)	(0.387)	(0.395)	(1.491)	(2.070)	(2.746)
School's exp. ESL level		7.639***				9.534***	11.433***	13.203***	
•	(0.923)	(0.999)	(1.256)	(0.955)	(0.941)	(1.005)	(1.537)	(2.453)	(2.841)
School's science score	, ,	,	0.004	,	,	0.003	, ,	, ,	0.016*
			(0.003)			(0.002)			(0.007)
Student's science score			-0.005*			-0.006***			0.001
			(0.002)			(0.001)			(0.006)
Constant	-2.799***	-3.341***		-3.478***	-3.398***		-5.177***	-5.681***	
	(0.355)	(0.539)	(1.743)	(0.141)	(0.162)	(0.872)	(0.622)	(0.842)	(4.130)
	(0.555)	(0.333)	(4.743)	(0.141)	(0.102)	(0.072)	(0.022)	(0.042)	(4.130)

Note: The model for the UK did not converge, so that it is not shown here.

Annex 10. Multilevel regressions, distinction among EU and non-EU migrants

A. Comparison of EU and non-EU immigrants to natives

These regressions compare separately EU and non-EU migrants to natives. The baseline category are natives.

The column prefix "eu" means that EU migrant students are considered, while "neu" means that non-EU migrant students are considered. As in the other multilevel regressions, the comparison group are native students. The identical strategy as in the other regressions is used. Columns (1) and (2) indicate regressions including all available MS, as in the main text.

1. <u>All MS</u>

Table 8. Multilevel regressions, all MS, for EU migrants

	(1)	(2)
Gender	0.067	-0.069
	(0.106)	(0.093)
Student's ESCS	-0.435***	-0.364***
	(0.052)	(0.052)
1st generation	-1.473	-1.473
	(0.985)	(1.002)
2nd generation	-0.663	-0.543
	(0.631)	(0.578)
Language at home	0.149	-0.009
	(0.128)	(0.151)
Age at arrival	0.123	0.11
	(0.116)	(0.113)
Sense of belonging	-0.031	-0.039
	(0.043)	(0.042)
Epist. beliefs	-0.145**	-0.035
	(0.044)	(0.041)
Truancy	0.055	-0.013
	(0.046)	(0.047)
Grade repetition	1.053***	0.752***
	(0.115)	(0.115)
ISCED level: 3	-0.541**	-0.534**
	(0.178)	(0.192)
Designation: B	0.262	0.144
	(0.247)	(0.271)
Designation: C	0.465	0.316
	(0.368)	(0.364)
Orientation: Pre-Voc.	-0.322	-0.568*
	(0.253)	(0.285)
Orientation: Voc.	0.176	0.089
	(0.233)	(0.24)
Orientation: Modular	1.021***	0.538*
	(0.261)	(0.257)
I: Immig. x Lang. at home	-1.13	-1.383
	(0.727)	,
I: Immig. x Sense of belong.	-0.611	
	(0.386)	, ,
School's ESCS	-0.129	-0.066
	(0.067)	(0.079)
School's conc. of mig.	2.792***	3.071***
	(0.843)	(0.9)
School's exp. ESL level	5.885***	6.021***
	(0.2)	(0.23)
School's science score		-0.003**
		(0.001)
Student's science score		-0.008***
		(0.001)
Constant	-4.137***	-2.320***
	(0.328)	(0.586)

Table 9. Multilevel regressions, all MS, for non-EU migrants

	(1)	(2)
Condor	0.034	0.005
Gender	0.031	-0.085 (0.09)
Student's ESCS	(0.1) -0.401***	-0.342***
Students ESCS	(0.048)	(0.048)
1st generation	-0.267	-0.299
13t generation	(0.351)	(0.378)
2nd generation	-0.131	-0.298
Zila generaten	(0.195)	(0.199)
Language at home	0.168	-0.001
	(0.126)	(0.146)
Age at arrival	0.049	0.025
	(0.038)	(0.04)
Sense of belonging	-0.021	-0.027
	(0.043)	(0.042)
Epist. beliefs	-0.167***	-0.07
	(0.039)	(0.036)
Truancy	0.025	-0.038
	(0.041)	(0.042)
Grade repetition	1.046***	0.765***
	(0.1)	(0.1)
ISCED level: 3	-0.669***	-0.662***
	(0.17)	(0.179)
Designation: B	0.379	0.269
	(0.249)	(0.269)
Designation: C	0.792	0.637
	(0.411)	(0.417)
Orientation: Pre-Voc.	-0.46	-0.691*
Orientafana Va	(0.256)	(0.282)
Orientation: Voc.	0.138	0.057
Orientation: Madular	(0.215)	(0.223) 0.105
Orientation: Modular	0.557** (0.213)	(0.202)
I: Immig. x Lang. at home	-0.427	-0.304
i. inlinig. X Lang. at nome	(0.252)	(0.273)
I: Immig. x Sense of belong.	0.104	0.094
i. ining. X conce or solong.	(0.109)	(0.11)
School's ESCS	-0.159*	-0.073
	(0.063)	(0.074)
School's conc. of mig.	0.002	0.195
ŭ	(0.166)	(0.185)
School's exp. ESL level	5.585***	5.669***
	(0.178)	(0.207)
School's science score		-0.003***
		(0.001)
Student's science score		-0.007***
		(0.001)
Constant	-3.811***	-2.012***
	(0.281)	(0.529)

2. <u>Country-by-country</u>

Table 10. Multilevel regressions, country-by-country, for EU migrants

	eu_AT_logit	eu_AT_	eu_AT_pv	eu_BE_logit	eu_BE_	eu_BE_pv	eu_CZ_logit	eu_CZ_	eu_CZ_pv
Gender	0.004	-0.072	-0.22	-0.131	-0.32	-0.449	-1.316	-1.32	-1.296
	(0.27)	(0.291)	(0.299)	(0.198)	(0.245)	(0.243)	(0.709)	(0.762)	(0.766)
Student's ESCS	-0.058	-0.21	-0.221	0.035	0.003	0.046	-1.487***	-1.408**	-1.283**
	(0.22)	(0.348)	(0.359)	(0.124)	(0.149)	(0.151)	(0.431)	(0.484)	(0.447)
1st generation	0.415	0.512	0.412	-0.493	-1.158	-1.14	-53.641	-29.125	-31.647
	(1.263)	(1.146)	(1.28)	(0.973)	(0.95)	(0.969)	(.)	(37.03)	(.)
2nd generation	0.487	-0.262	-0.192	-0.723	-0.944	-1.027	0	0	0
	(0.751)	(1.067)	(1.033)	(0.971)	(1.099)	(1.119)	(.)	(.)	(.)
Language at home	-0.354	-1.055	-1.107	-0.277	-0.602	-0.673	1.617	0.859	1.264
	(0.878)	(1.045)	(1.07)	(0.356)	(0.449)	(0.478)	(0.888)	(1.034)	(0.984)
Age at arrival	0.116	0.058	0.06	-0.098	-0.052	-0.055	0.745	0.014	-0.085
	(0.096)	(0.078)	(80.0)	(0.095)	(0.081)	(0.082)	(.)	(0.953)	(.)
Sense of belonging	-0.403***	-0.438***	-0.445***	-0.320*	-0.309*	-0.311*	-0.48	-0.246	-0.091
	(0.089)	(0.115)	(0.117)	(0.141)	(0.139)	(0.137)	(0.439)	(0.516)	(0.463)
Epist. beliefs	-0.441***	-0.417*	-0.294	-0.317**	-0.328*	-0.26	-0.576	-0.794*	-0.843*
	(0.134)	(0.19)	(0.188)	(0.1)	(0.136)	(0.144)	(0.307)	(0.374)	(0.368)
Truancy	0.351*	0.523**	0.526**	0.178	0.147	0.112	0.546	0.876**	0.829**
	(0.141)	(0.174)	(0.175)	(0.104)	(0.135)	(0.137)	(0.283)	(0.324)	(0.291)
Grade repetition	1.216***	1.144*	0.986*	1.038***	1.167***	1.024***	1.754*	2.112*	2.019*
	(0.326)	(0.454)	(0.486)	(0.204)	(0.274)	(0.288)	(0.789)	(0.915)	(0.853)
ISCED level: 3	-0.157	0.849	0.987	-0.684*	-0.661*	-0.448	1.418	1.696	0.292
	(0.865)	(1.089)	(1.091)	(0.336)	(0.315)	(0.362)	(0.983)	(1.272)	(0.886)
Designation: B	-0.677	-0.913*	-0.751		0	0			
D : " O	(0.347)	(0.396)	(0.469)	0.057	(.)	(.)	10010***	40.070***	40 457***
Designation: C	11.681***	13.059***	12.541***	-0.357	-0.67	-0.868*	12.040***	10.873***	16.157***
0:45 8 4	(1.489)	(1.767)	(1.712)	(0.343)	(0.41)	(0.424)	(0.697)	(0.812)	(1.5)
Orientation: Pre-Voc.	-12.958***	-15.027***	-13.938***	1.600*	1.883**	1.808*			
0: (")/	(1.271)	(1.383)	(1.48)	(0.666)	(0.728)	(0.786)	40 550+++	44.004***	44.000***
Orientation: Voc.	0.147	0.374	0.371	-0.098	-0.021	0.012	-12.559***	-11.801***	-14.332***
Orientafana Madadan	(0.33)	(0.384)	(0.392)	(0.207)	(0.201)	(0.218)	(0.801)	(0.887)	(0.99)
Orientation: Modular									
I: Immig. x Lang. at home	0.39	2.194	2.015	1.008	1.338	1.295	0	0	0
	(1.006)	(1.21)	(1.245)	(1.023)	(1.123)	(1.169)	(.)	(.)	(.)
I: Immig. x Sense of belong.	0.161	0.079	0.154	-0.62	-0.828	-0.821	-38.904	-20.603	-20.866
	(0.166)	(0.245)	(0.259)	(0.393)	(0.479)	(0.498)	(.)	(34.999)	(.)
School's ESCS	0.028	0.332	-0.03	0.781**	0.779*	0.063	-0.253	-0.033	-1.35
	(0.46)	(0.528)	(0.547)	(0.255)	(0.324)	(0.507)	(0.641)	(0.761)	(0.941)
School's conc. of mig.	-1.119	-0.257	-0.035	1.285	2.136**	2.321**	-2.123	2.876	12.079
	(1.218)	(1.323)	(1.305)	(0.767)	(0.652)	(0.725)	(8.167)	(6.845)	(8.584)
School's exp. ESL level	30.727***	33.797***	34.522***	17.996***	15.382***	17.682***	42.459***	43.601***	50.769***
	(2.637)	(2.997)	(3.331)	(1.875)	(2.366)	(2.515)	(4.343)	(5.137)	(8.042)
School's science score		,	0.003		,	0.005	,	,	0.021*
			(0.005)			(0.004)			(0.009)
Student's science score			-0.007*			-0.005**			-0.006
			(0.003)			(0.002)			(0.009)
Constant	-5.290***	-6.550***	-8.110**	-4.451***	-4.385***	-7.011**	-8.307***	-8.782***	-19.530***
	(0.791)	(1.042)	(2.746)	(0.359)	(0.392)	(2.132)	(0.843)	(1.082)	(5.614)

	eu_FI_logit	eu_FI_	eu_FI_pv	eu_IE_logit	eu_IE_	eu_IE_pv	eu_IT_logit	eu_IT_	eu_IT_pv	eu_LU_logit	eu_LU_	eu_LU_pv
Gender	-0.082	-0.203	-0.171	0.210*	0.179	0.145	0.039	-0.068	0.052	0.242	0.242	0.177
	(0.085)	(0.106)	(0.111)	(0.097)	(0.125)	(0.124)	(0.298)	(0.466)	(0.469)	(0.173)	(0.173)	(0.17)
Student's ESCS	-0.453***	-0.358***	-0.253**	-0.381***	-0.437***	-0.298***	-0.272	-0.368	-0.351	-0.224**	-0.224**	-0.210**
	(0.069)	(0.082)	(0.08)	(0.072)	(0.077)	(0.082)	(0.193)	(0.315)	(0.326)	(80.0)	(0.08)	(0.08)
1st generation	-1.697	-2.014	-2.085	-0.5	-0.454	-0.539	-11.024	-27.867*	-29.192*	-1.533*	-1.533*	-1.620*
3	(1.833)	(1.825)	(1.841)	(0.543)	(0.63)	(0.578)	(6.676)	(11.502)	(12.945)	(0.667)	(0.667)	(0.656)
2nd generation	-0.176	0.027	-0.319	-0.057	-0.39	-0.532	-6.356	-12.271***	-12.418***	-0.886	-0.886	-0.941*
3	(0.879)	(0.843)	(0.98)	(0.486)	(0.538)	(0.544)	(3.31)	(2.407)	(2.454)	(0.464)	(0.464)	(0.476)
Language at home	-0.354	0.035	-0.014	-12.241***	-14.460***	-15.131***	0.416	0.202	0.214	-0.193	-0.193	-0.247
3.13.11	(0.305)	(0.446)	(0.47)	(0.416)	(0.46)	(0.562)	(0.371)	(0.614)	(0.609)	(0.381)	(0.381)	(0.378)
Age at arrival	-0.042	-0.008	-0.026	0.109	0.111	0.139	0.807	1.765**	1.847*	0.022	0.022	0.027
3	(0.119)	(0.123)	(0.124)	(0.075)	(0.085)	(0.083)	(0.415)	(0.638)	(0.717)	(0.038)	(0.038)	(0.036)
Sense of belonging	-0.139**	-0.168**	-0.178**	-0.012	-0.015	-0.061	-0.254	0.007	0.012	-0.346***	-0.346***	-0.352***
3 3	(0.048)	(0.054)	(0.056)	(0.048)	(0.054)	(0.059)	(0.189)	(0.379)	(0.375)	(0.092)	(0.092)	(0.092)
Epist beliefs	-0.176***	-0.170***	-0.046	-0.208***	-0.237**	-0.052	-0.447**	-0.339	-0.351	-0.181**	-0.181**	-0.128
	(0.047)	(0.05)	(0.052)	(0.063)	(0.088)	(80.0)	(0.169)	(0.258)	(0.237)	(0.068)	(0.068)	(0.068)
Truancy	0.051	0.059	0.017	0.133*	0.192*	0.141	0.268*	0.286	0.29	0.240***	0.240***	0.227***
,	(0.039)	(0.05)	(0.047)	(0.065)	(0.081)	(0.083)	(0.118)	(0.174)	(0.17)	(0.063)	(0.063)	(0.062)
Grade repetition	0.558*	0.698*	0.312	-0.146	-0.185	-0.323	1.030***	1.448*	1.398*	0.275	0.275	0.198
·	(0.227)	(0.309)	(0.296)	(0.19)	(0.193)	(0.182)	(0.306)	(0.608)	(0.663)	(0.144)	(0.144)	(0.143)
ISCED level: 3	Ó	0	0	-3.479***	-3.427***	-3.427***	2.087	1.75	1.296	-1.637***	-1.637***	-1.495***
	(.)	(.)	(.)	(0.591)	(0.575)	(0.581)	(1.707)	(1.236)	(1.308)	(0.288)	(0.288)	(0.302)
Designation: B	()	()	()	(,	(/	(,	(' '	(/	(,	0.373	0.373	0.299
3										(0.572)	(0.572)	(0.563)
Designation: C				0.339	0.337	0.347	-0.778	-0.491	-0.527	-0.152	-0.152	-0.268
3				(0.674)	(0.675)	(0.68)	(0.599)	(0.636)	(0.61)	(0.913)	(0.913)	(0.932)
Orientation: Pre-Voc.				1.387	0.802	0.46	(/	(/	(/	(/	(/	(/
				(0.899)	(1.001)	(0.991)						
Orientation: Voc.				(/	(/	(,	0.305	-0.106	0.235	0.194	0.194	0.208
							(0.333)	(0.577)	(0.544)	(0.433)	(0.433)	(0.442)
Orientation: Modular							(3.230)	(/	()	1.053***	1.053***	0.824**
										(0.259)	(0.259)	(0.252)
I: Immig. x Lang. at home	2.33	2.089	2.189	13.601***	13.864***	14.644***	-1.602	0.675	0.172	0.791	0.791	0.719
J . J	(1.303)	(1.492)	(1.513)	(2.3)	(2.266)	(2.389)	(1.456)	(1.726)	(1.781)	(0.538)	(0.538)	(0.544)
I: Immig. x Sense of belong.	0.362	0.214	0.327	0.34	0.364	0.255	-2.010*	-2.944*	-3.475*	0.263**	0.263**	0.283**
J	(0.517)	(0.581)	(0.62)	(0.267)	(0.357)	(0.363)	(0.862)	(1.276)	(1.595)	(0.097)	(0.097)	(0.098)
School's ESCS	-0.04	-0.154	-0.266*	0.03	0.153	0.159	0.589	0.221	0.01	0.582**	0.582**	-0.029
	(0.092)	(0.12)	(0.135)	(0.108)	(0.14)	(0.186)	(0.315)	(0.462)	(0.486)	(0.202)	(0.202)	(0.217)
School's conc. of mig.	1.89	1.986	3.174*	0.927	0.308	0.622	4.098*	5.962*	6.127**	0.49	0.49	0.52
	(0.975)	(1.232)	(1.46)	(1.147)	(1.658)	(1.62)	(2.041)	(2.316)	(2.258)	(0.385)	(0.385)	(0.364)
School's exp. ESL level	7.349***	6.933***	7.274***	8.395***	7.970***	8.398***	18.912***	16.273***	17.775***	8.773***	8.773***	10.917***
230.0 onp. 202 10101	(0.436)	(0.533)	(0.501)	(0.547)	(0.656)	(0.604)	(2.658)	(2.829)	(3.032)	(1.035)	(1.035)	(1.293)
School's science score	(21.50)	(====0)	0.001	(/	()	-0.001	(=:::0)	(=:==0)	0.005	()	()	0.006**
232 3 00000 000.0			(0.001)			(0.002)			(0.004)			(0.002)
Student's science score			-0.005***			-0.007***			-0.004*			-0.004***
5.2.5			(0.001)			(0.001)			(0.002)			(0.001)
Constant	-3.002***	-2.865***	-3.587***	-2.722***	-2.624***	-2.202**	-7.942***	-7.390***	-9.862***	-3.213***	-3.213***	-5.975***
Conduit	(0.107)	(0.135)	(0.622)	(0.109)	(0.143)	(0.835)	(1.744)	(1.332)	(2.646)	(0.433)	(0.433)	(1.067)
	(0.107)	(0.155)	(0.022)	(0.109)	(0.143)	(0.000)	(1.744)	(1.002)	(2.040)	(0.400)	(0.400)	(1.007)

	eu_PT_logit	eu_PT_	eu_PT_pv
Gender	-0.364*	-0.235	-0.371*
Chidanila FCCC	(0.148)	(0.178)	(0.184)
Student's ESCS	-0.572***	-0.702***	-0.647***
1st generation	(0.099) 9.194***	(0.123) 13.794***	(0.119) 14.058***
rst generation	(1.718)	(1.992)	(2.076)
2nd generation	0.595	0.77	0.924
zna gonoraton	(0.717)	(0.858)	(0.853)
Language at home	-1.441*	-2.801***	-2.823***
	(0.596)	(0.736)	(0.759)
Age at arrival	-6.562***	-10.220***	-10.497** [*]
	(1.564)	(1.762)	(1.828)
Sense of belonging	-0.087	-0.033	0.022
	(0.07)	(0.076)	(0.082)
Epist. beliefs	-0.156*	-0.195*	-0.149
	(0.075)	(0.096)	(0.103)
Truancy	0.175**	0.254**	0.230**
0 1 ""	(0.068)	(0.079)	(0.085)
Grade repetition	0.159	0.085	-0.158
ICCED levels 2	(0.374)	(0.499)	(0.503)
ISCED level: 3	-4.591*** (0.922)	-4.776***	-5.079*** (4.031)
Designation: P	(0.823) 2.214***	(1.02) 2.468***	(1.031) 2.833***
Designation: B	(0.536)	(0.591)	(0.59)
Designation: C	(0.550)	(0.591)	(0.59)
Designation. O	(.)	(.)	(.)
Orientation: Pre-Voc.	-0.183	-0.242	-0.558
	(0.299)	(0.402)	(0.393)
Orientation: Voc.	3.478***	3.573***	3.651***
	(0.534)	(0.582)	(0.601)
Orientation: Modular	, ,	, ,	,
I: Immig. x Lang. at home	0.018	1.488	1.077
	, ,	(1.496)	, ,
I: Immig. x Sense of belong.	0.281		
	(0.342)		. ,
School's ESCS	0.088		
Och cells come of sign	, ,	(0.19)	. ,
School's conc. of mig.	0.5		
Cabacila ava ESI laval		(4.356) 7.329***	(3.886) 8.248***
School's exp. ESL level	(0.926)		6.246 (1.107)
School's science score	(0.320)	(0.341)	0.004
23.13313 33.01100 30010			(0.003)
Student's science score			-0.007***
2.			(0.001)
Constant	-2.822***	-3.265***	, ,
·	(0.341)	(0.455)	(1.482)

Note: Only those MS are shown for which the models converged.

Table 11. Multilevel regressions, country-by-country, for non-EU migrants

	neu_BE_logit	neu_BE_	neu_BE_pv
Gender	0.023	-0.143	-0.25
35.146.	(0.191)	(0.248)	(0.245)
Student's ESCS	0.154	0.188	0.223
	(0.113)	(0.14)	(0.142)
1st generation	1.154	0.667	0.755
	(0.79)	(1.028)	(1.035)
2nd generation	-0.297	-0.132	-0.225
	(0.33)	(0.368)	(0.358)
Language at home	-0.252	-0.624	-0.702
	(0.357)	(0.457)	(0.483)
Age at arrival	-0.103	-0.08	-0.111
	(0.079)	(0.1)	(0.104)
Sense of belonging	-0.327*	-0.319*	-0.318*
	(0.147)	(0.15)	(0.148)
Epist. beliefs	-0.361***	-0.388***	-0.329**
_	(0.092)	(0.116)	(0.124)
Truancy	0.147	0.095	0.059
.	(0.111)	(0.138)	(0.14)
Grade repetition	0.982***	1.093***	0.984***
100501 10	(0.203)	(0.266)	(0.284)
ISCED level: 3	-0.889**	-0.897**	-0.727*
D : 1 D	(0.294)	(0.285)	(0.313)
Designation: B		0	0
Desires for O	0.470	(.)	(.)
Designation: C	-0.478	-0.821*	-0.961*
Orientation, Dra Ves	(0.336) 1.451*	(0.386) 2.193**	(0.391) 2.244**
Orientation: Pre-Voc.	(0.639)	(0.705)	
Orientation: Voc.	-0.024	0.149	(0.756) 0.179
Orientation: voc.	(0.205)	(0.217)	(0.234)
Orientation: Modular	(0.203)	(0.217)	(0.234)
Offernation: Modular			
I: Immig. x Lang. at home	-0.696	0.071	0.084
i. minig. X Lang. at nome	(0.556)	(0.589)	
I: Immig. x Sense of belong.	-0.281	-0.235	, ,
g. x conce or seeing.	(0.268)	(0.27)	
School's ESCS	0.644*	0.62	0.154
	(0.258)		
School's conc. of mig.	-0.485		, ,
3	(0.568)		
School's exp. ESL level	18.434***		17.352***
	(1.901)	(2.195)	(2.265)
School's science score	, ,	` ,	0.003
			(0.004)
Student's science score			-0.004**
			(0.002)
Constant	-4.230***	-4.160***	-5.931**
	(0.351)	(0.378)	(1.941)

	neu_FI_logit	neu_FI_	neu_FI_pv ı	neu_IT_logit	neu_IT_	neu_IT_pv n	eu_LU_logit	neu_LU_	neu_LU_pv
Gender	-0.106	-0.233*	-0.195	-0.122	-0.106	0.004	0.376*	0.376*	0.303
3333.	(0.082)	(0.105)	(0.11)	(0.272)	(0.424)	(0.411)	(0.178)	(0.178)	(0.183)
Student's ESCS	-0.442***	-0.365***	-0.254***	-0.312	-0.369	-0.348	-0.387**	-0.387**	-0.361**
	(0.066)	(0.078)	(0.076)	(0.177)	(0.276)	(0.289)	(0.118)	(0.118)	(0.12)
1st generation	0.772	1.767	0.88	-0.852	-3.032*	-3.241	-1.704	-1.704	-1.624
•	(0.794)	(0.903)	(0.77)	(1.407)	(1.533)	(1.694)	(1.221)	(1.221)	(1.225)
2nd generation	-0.307	-0.202	-0.766	0.646	-0.714	-0.87	-0.592	-0.592	-0.665
-	(0.536)	(0.517)	(0.515)	(0.575)	(0.857)	(0.869)	(0.615)	(0.615)	(0.63)
Language at home	-0.359	0.029	-0.039	0.368	0.126	0.146	-0.21	-0.21	-0.254
	(0.304)	(0.446)	(0.47)	(0.38)	(0.601)	(0.594)	(0.378)	(0.378)	(0.372)
Age at arrival	-0.126	-0.243*	-0.204*	0.135	0.227	0.229	0.057	0.057	0.041
	(0.092)	(0.107)	(0.097)	(0.122)	(0.134)	(0.143)	(0.118)	(0.118)	(0.125)
Sense of belonging	-0.140**	-0.169**	-0.180**	-0.224	0.068	0.084	-0.351***	-0.351***	-0.358***
	(0.048)	(0.055)	(0.056)	(0.196)	(0.358)	(0.346)	(0.097)	(0.097)	(0.097)
Epist beliefs	-0.174***	-0.157**	-0.033	-0.461**	-0.384	-0.397	-0.159	-0.159	-0.107
	(0.048)	(0.048)	(0.049)	(0.151)	(0.225)	(0.206)	(0.093)	(0.093)	(0.091)
Truancy	0.066	0.071	0.023	0.302**	0.345*	0.357*	0.145	0.145	0.139
	(0.038)	(0.048)	(0.046)	(0.107)	(0.162)	(0.158)	(0.082)	(0.082)	(0.082)
Grade repetition	0.471*	0.614*	0.248	0.873**	1.379*	1.313*	0.329	0.329	0.278
	(0.218)	(0.298)	(0.281)	(0.28)	(0.537)	(0.597)	(0.236)	(0.236)	(0.238)
ISCED level: 3	0	0	0	2.400*	1.1	0.58	-1.629***	-1.629***	-1.552***
	(.)	(.)	(.)	(1.221)	(1.568)	(1.539)	(0.311)	(0.311)	(0.321)
Designation: B							-0.502	-0.502	-0.524
D : " O				0.500	0.457	0.400	(1.014)	(1.014)	(1.01)
Designation: C				-0.598	0.157	0.136	-0.002	-0.002	-0.099
Orientation Dec Voc				(0.644)	(0.567)	(0.561)	(0.916)	(0.916)	(0.953)
Orientation: Pre-Voc.									
Orientation: Voc.				0.235	0.091	0.426	0.526	0.526	0.564
Orientation, voc.				(0.324)	(0.535)	(0.426	(0.435)	(0.435)	(0.448)
Orientation: Modular				(0.324)	(0.555)	(0.430)	0.541*	0.541*	0.366
Offernation: Modular							(0.251)	(0.251)	(0.245)
I: Immig. x Lang. at home	0.221	-0.396	-0.14	-0.344	0.954	0.861	0.275	0.275	0.26
i. illing. X Lang. at home	(0.655)	(0.853)	(0.848)	(0.668)	(0.979)	(1.004)	(0.625)	(0.625)	(0.633)
I: Immig. x Sense of belong.	0.257	0.281	0.37	-0.773*	-1.116*	-1.157*	0.346	0.346	0.354
i. iiiiiig. A conce of bolong.	(0.216)	(0.228)	(0.21)	(0.352)	(0.52)	(0.576)	(0.268)	(0.268)	(0.278)
School's ESCS	-0.004	-0.134	-0.225	0.589*	0.375	0.136	0.484*	0.484*	-0.275
	(0.093)	(0.12)	(0.135)	(0.296)	(0.437)	(0.462)	(0.194)	(0.194)	(0.319)
School's conc. of mig.	0.034	0.038	0.462	0.807	-0.224	-0.327	0.907*	0.907*	1.077*
3	(0.395)	(0.455)	(0.442)	(1.046)	(1.446)	(1.46)	(0.44)	(0.44)	(0.437)
School's exp. ESL level	7.466***	7.045***	7.290***	19.125***	14.809***	16.200***	11.671***	11.671***	14.327***
	(0.473)	(0.555)	(0.537)	(2.462)	(3)	(3.155)	(1.729)	(1.729)	(1.95)
School's science score	, ,	. ,	0.001	, ,	` '	0.006	, ,	, ,,	0.008*
			(0.001)			(0.004)			(0.004)
Student's science score			-0.005***			-0.005*			-0.003**
			(0.001)			(0.002)			(0.001)
Constant	-3.008***	-2.865***	-3.331***	-8.079***	-6.590***	-9.046***	-3.473***	-3.473***	-7.407***
	(0.116)	(0.141)	(0.604)	(1.2)	(1.731)	(2.624)	(0.393)	(0.393)	(1.955)

	neu_PT_logit	neu_PT_	neu_PT_pv 1	eu_UK_logit
Gender	-0.374**	-0.128	-0.188	-0.205
	(0.144)	(0.254)	(0.29)	(0.319)
Student's ESCS	-0.536***	-0.470*	-0.414*	-0.629***
	(0.105)	(0.197)	(0.2)	(0.189)
1st generation	0.098	0.138	0.301	-0.613
Ondonosta	(0.704)	(0.826)	(0.821)	(0.734)
2nd generation	-0.095	0.589	0.507	-0.872
Language at home	(0.541) -1.455*	(0.64) -2.881***	(0.706) -2.834***	(1.067) 1.801**
Language at home	(0.594)	(0.736)	-2.034 (0.764)	(0.589)
Age at arrival	-0.141	-0.217	-0.213	0.041
Age at arrivar	(0.084)	(0.152)	(0.145)	(0.067)
Sense of belonging	-0.092	-0.047	-0.008	-0.573**
cerise of belonging	(0.07)	(0.071)	(0.07)	(0.221)
Epist. beliefs	-0.151*	-0.144	-0.109	-0.254
Epide Bollolo	(0.073)	(0.082)	(0.084)	(0.163)
Truancy	0.169**	0.174	0.142	0.26
,	(0.065)	(0.1)	(0.107)	(0.166)
Grade repetition	0.226	0.391	0.234	0.128
•	(0.365)	(0.587)	(0.625)	(0.473)
ISCED level: 3	-4.272***	-3.911***	-4.137** [*]	-13.305***
	(0.828)	(1.101)	(0.995)	(0.921)
Designation: B	1.958***	1.773**	1.985***	Ó
	(0.559)	(0.639)	(0.585)	(.)
Designation: C	0	0	0	12.066***
	(.)	(.)	(.)	(0.306)
Orientation: Pre-Voc.	-0.219	-0.153	-0.357	
	(0.312)	(0.408)	(0.417)	
Orientation: Voc.	3.227***	3.020***	3.047***	-0.131
	(0.552)	(0.586)	(0.554)	(0.483)
Orientation: Modular				
I: Immig. x Lang. at home	2.944**	4.347***	4.077***	-0.804
a managa na Earrigh a a manana	(0.928)	(1.143)		(0.866)
I: Immig. x Sense of belong.	0.427	0.278	, ,	0.144
0	(0.438)	(0.513)	(0.548)	(0.342)
School's ESCS	0.185	-0.015	, ,	0.053
	(0.143)	(0.197)	(0.211)	(0.328)
School's conc. of mig.	-0.558	0.261	0.528	0.748
	(0.501)	(0.5)		(0.751)
School's exp. ESL level	8.278***	7.587***	8.502***	30.993***
	(0.931)	(1.01)	(1.279)	(4.261)
School's science score			0.005	
			(0.003)	
Student's science score			-0.005*	
	0 ==0	0.64=	(0.002)	4 -0-
Constant	-2.773***	-3.347***	-5.737**	-4.727***
	(0.356)	(0.553)	(1.834)	(0.913)

B. Direct comparison of EU to non-EU immigrants

These regressions do not consider natives, but compare directly EU migrants to non-EU immigrants. The baseline category are EU migrants. Thus, if there is a significant coefficient, it means that there is a significant difference between non-EU immigrants to the baseline category which are EU migrants. Otherwise, the regressions follow the same specifications as the previous ones. Note that we do not show regressions for those MS for which the models did not achieve convergence (usually due to relatively small sample size and small variation in the variables).

Table 12. Multilevel regressions, all MS, baseline category: EU migrants

Gender			
Student's ESCS -0.252* -0.252* -0.225 (0.125) (0.124) 1st generation -0.474 -0.440 (0.452) (0.470) 2nd generation 0.000 -0.000 (1.) (.) Language at home -0.120 -0.292 (0.441) (0.459) Age at arrival 0.045 -0.25 (0.041) (0.042) Sense of belonging -0.696* -0.834* (0.307) (0.334) Epist beliefs -0.247** -0.162 Fixed repetition (0.992) (0.099) Truancy -0.065 -0.102 (0.100) (0.097) Grade repetition 0.940*** 0.769** (0.265) (0.270) (0.265) (0.270) ISCED level: 3 -0.146 -0.388 (0.350) (0.351) Designation: B 0.011 -0.048 (0.500) (0.512) Orientation: Pre-Voc. -0.413 -0.695 (0.514) Orientation: Voc. 0.255 (0.370) (0.553) Orientation: Modular 1.013** (0.508) (0.514) Orientation: Modular 1.013** (0.367) (0.382) (0.392) (0.392) (0.392) I: Immig. x Lang. at home 0.336 (0.344) (0.430) (0.392) (0.392) (0.394) S		(1)	(2)
Student's ESCS -0.252* -0.252* -0.225 (0.125) (0.124) 1st generation -0.474 -0.440 (0.452) (0.470) 2nd generation 0.000 -0.000 (1.) (.) Language at home -0.120 -0.292 (0.441) (0.459) Age at arrival 0.045 -0.25 (0.041) (0.042) Sense of belonging -0.696* -0.834* (0.307) (0.334) Epist beliefs -0.247** -0.162 Fixed repetition (0.992) (0.099) Truancy -0.065 -0.102 (0.100) (0.097) Grade repetition 0.940*** 0.769** (0.265) (0.270) (0.265) (0.270) ISCED level: 3 -0.146 -0.388 (0.350) (0.351) Designation: B 0.011 -0.048 (0.500) (0.512) Orientation: Pre-Voc. -0.413 -0.695 (0.514) Orientation: Voc. 0.255 (0.370) (0.553) Orientation: Modular 1.013** (0.508) (0.514) Orientation: Modular 1.013** (0.367) (0.382) (0.392) (0.392) (0.392) I: Immig. x Lang. at home 0.336 (0.344) (0.430) (0.392) (0.392) (0.394) S	Gondor	0 120	0.214
Student's ESCS	Gender		
1st generation	Students ESCS	, ,	, ,
St generation	Sudents ESCS		
(0.452) (0.470) (0.000 (0.000) (0.000) (0.000) (0.000) (0.000) (0.000) (0.000) (0.000) (0.441) (0.459) (0.441) (0.459) (0.041) (0.042) (0.041) (0.042) (0.041) (0.042) (0.307) (0.334) (0.307) (0.334) (0.307) (0.334) (0.092) (0.099) (0.0992) (0.099) (0.0992) (0.099) (0.100) (0.097) (0.100) (0.097) (0.100) (0.097) (0.265) (0.270) (0.265) (0.270) (0.265) (0.270) (0.350) (0.351) (0.350) (0.351) (0.350) (0.351) (0.500) (0.512) (0.500) (0.512) (0.500) (0.512) (0.500) (0.512) (0.519) (0.553) (0.514) (0.509) (0.553) (0.514) (0.500) (0.514) (0.508) (0.514) (0.508) (0.514) (0.367) (0.382) (0.367) (0.382) (0.348) (0.448) (0.484) (0.475) (0.484) (0.475) (0.347) (0.302) (0.347) (0.506) (0.604) (0.591) (0.5091) (0.5091) (0.5091) (0.5091) (0.5091) (0.5091) (0.5091) (0.5091) (0.5001) (0.604) (0.591) (0.5001) (0.604) (0.591) (0.5001) (0.604) (0.591) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.505) (0.604) (0.5	1st generation	, ,	. ,
2nd generation	13t generation		
(.) (.) Language at home	2nd generation	, ,	, ,
Language at home	zna generaten		
Age at arrival	Language at home		
Age at arrival 0.045 0.025 (0.041) (0.042) Sense of belonging -0.696* -0.834* (0.307) (0.334) Epist beliefs -0.247** -0.162 (0.092) (0.099) Truancy -0.065 -0.102 (0.100) (0.097) Grade repetition 0.940*** 0.769** (0.265) (0.270) ISCED level: 3 -0.146 -0.388 (0.350) (0.351) Designation: B 0.011 -0.048 (0.500) (0.512) Designation: C 0.587 0.558 (0.741) (0.725) Orientation: Pre-Voc0.413 -0.695 (0.519) (0.553) Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's science score 0.001 Student's science score -0.002 Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***			
Sense of belonging	Age at arrival	, ,	, ,
Sense of belonging	3		
Co.307 Co.334	Sense of belonging	, ,	. ,
Epist beliefs	3 3	(0.307)	(0.334)
Truancy	Epist. beliefs		, ,
Grade repetition 0.940**** 0.769** 0.769** 0.270) ISCED level: 3 -0.146 -0.388 (0.350) (0.351) Designation: B 0.011 -0.048 (0.500) (0.512) Designation: C 0.587 0.558 (0.741) (0.725) Orientation: Pre-Voc0.413 -0.695 (0.519) (0.553) Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013*** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's science score 0.001 School's science score -0.008*** (0.002) Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***		(0.092)	(0.099)
Grade repetition 0.940*** 0.769** (0.265) (0.270) ISCED level: 3 -0.146 -0.388 (0.350) (0.351) Designation: B 0.011 -0.048 (0.500) (0.512) Designation: C 0.587 0.558 (0.741) (0.725) Orientation: Pre-Voc. -0.413 -0.695 (0.519) (0.553) Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013*** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's science score 0.001 School's science score 0.001 (0.002) 0.008*** -0.008**	Truancy	-0.065	-0.102
SCED level: 3		(0.100)	(0.097)
SCED level: 3	Grade repetition	0.940***	0.769**
Designation: B		(0.265)	(0.270)
Designation: B 0.011 -0.048 (0.500) (0.512) Designation: C 0.587 0.558 (0.741) (0.725) Orientation: Pre-Voc. -0.413 -0.695 (0.519) (0.553) Orientation: Woc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887*** 7.487*** (0.002) Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***	ISCED level: 3	-0.146	-0.388
Designation: C			(0.351)
Designation: C 0.587 0.558 (0.741) (0.725) Orientation: Pre-Voc. -0.413 -0.695 (0.519) (0.553) Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013*** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903*** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887*** 7.487*** (0.002) 0.001 0.002 Student's science score -0.008*** (0.002) -0.008*** -4.308*** -4.308*** -4.255***	Designation: B	0.011	-0.048
Orientation: Pre-Voc. Orientation: Voc. Orientation: Voc. Orientation: Modular Orientation: Voc. Orientation: Orientation Orientation: Voc. Orientation: Orientation Orientation: Orientation Orientation: Voc. Orientation: Orientation Orientation: Orient		, ,	, ,
Orientation: Pre-Voc. -0.413 -0.695 (0.519) (0.553) Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487**** (0.374) (0.430) School's science score 0.001 (0.002) -0.008*** Student's science score -0.008*** (0.002) -0.008***	Designation: C		
Orientation: Voc. (0.519) (0.553) Orientation: Wodular (0.508) (0.514) Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487**** (0.374) (0.430) School's science score 0.001 Student's science score -0.008*** Constant -4.308*** -4.255***		, ,	, ,
Orientation: Voc. 0.255 0.418 (0.508) (0.514) Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903*** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887*** 7.487*** (0.374) (0.430) School's science score 0.001 (0.002) -0.008*** Student's science score -0.008*** (0.002) -4.308*** -4.255***	Orientation: Pre-Voc.		
Orientation: Modular Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887*** 7.487*** (0.374) (0.430) School's science score 0.001 (0.002) Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***		, ,	, ,
Orientation: Modular 1.013** 0.586 (0.367) (0.382) I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487**** (0.374) (0.430) School's science score 0.001 Student's science score -0.008*** Constant -4.308*** -4.255***	Orientation: Voc.		
Company Comp		, ,	. ,
I: Immig. x Lang. at home 0.336 0.448 (0.484) (0.475) I: Immig. x Sense of belong. 0.785* 0.903*** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487*** (0.374) (0.430) School's science score 0.001 Student's science score -0.008*** Constant -4.308*** -4.255****	Orientation: Modular		
Constant		, ,	
I: Immig. x Sense of belong. 0.785* 0.903*** (0.322) (0.347) School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487**** (0.374) (0.430) School's science score 0.001 Student's science score -0.008**** Constant -4.308*** -4.255****	I: Immig. x Lang. at home		
(0.322) (0.347) School's ESCS	la lassación de Octobra estáblica es	, ,	, ,
School's ESCS -0.217 -0.245 (0.149) (0.146) School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887**** 7.487**** (0.374) (0.430) School's science score 0.001 (0.002) -0.008*** Constant -4.308*** -4.255****	i: immig. x Sense or belong.		
(0.149) (0.146)	Cabaalla ESCS	, ,	,
School's conc. of mig. 0.207 0.026 (0.604) (0.591) School's exp. ESL level 6.887*** 7.487*** (0.374) (0.430) School's science score 0.001 (0.002) -0.008*** Constant -4.308*** -4.255***	SC10018 ESCS		
(0.604) (0.591) School's exp. ESL level	School's conc. of mig	,	,
School's exp. ESL level 6.887*** 7.487*** (0.374) (0.430) School's science score 0.001 (0.002) -0.008*** (0.002) (0.002) Constant -4.308*** -4.255***	School's conc. of mig.		
(0.374) (0.430) School's science score	School's exp. FSI level	, ,	
School's science score 0.001 (0.002) (0.002) Student's science score -0.008**** (0.002) (0.002) Constant -4.308**** -4.255****	CONCORD CAP. LOL ICVOI		
(0.002) Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***	School's science score	(0.07 1)	, ,
Student's science score -0.008*** (0.002) Constant -4.308*** -4.255***			
(0.002) Constant -4.308*** -4.255***	Student's science score		, ,
Constant -4.308*** -4.255***			
	Constant	-4.308***	, ,
(0.700) (1.101)		(0.796)	(1.181)

Table 13. Multilevel regressions, country-by-country, baseline category: EU migrants

	_AT_logit	_AT_	_AT_pv	_BE_logit	_BE_	_BE_pv	_DE_logit	_DE_	_DE_pv	_FI_logit	_FI_	_FI_pv
Gender	-1.378	-2.137	-2.760	0.708	0.606	0.576	0.254	0.294	0.179	-0.087	-0.369	-0.216
	(0.820)	(1.300)	(1.699)	(0.644)	(0.708)	(0.705)	(0.299)	(0.397)	(0.409)	(0.527)	(0.533)	(0.504)
Student's ESCS	-0.443	-0.680	-0.242	0.579	0.821*	0.883*	-0.544**	-0.676***	-0.692***	-0.403	-0.567	-0.272
	(0.485)	(0.867)	(0.927)	(0.331)	(0.365)	(0.377)	(0.173)	(0.192)	(0.175)	(0.314)	(0.326)	(0.358)
1st generation	0.355	-0.015	0.143	1.238	0.924	1.075	0.042	0.787	0.850	0.589	0.427	0.084
ŭ	(1.153)	(1.835)	(1.976)	(0.703)	(0.823)	(0.769)	(0.756)	(0.761)	(0.735)	(0.748)	(0.768)	(0.808)
2nd generation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
•	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Language at home	0.502	1.457	1.255	0.183	0.257	0.143	-0.209	-0.159	-0.543	-0.726	-0.033	0.349
	(1.121)	(1.867)	(2.425)	(0.761)	(0.802)	(0.804)	(0.515)	(0.509)	(0.663)	(1.027)	(1.003)	(1.223)
Age at arrival	0.021	-0.057	-0.107	-0.185	-0.192	-0.209	-0.029	-0.130	-0.162	-0.067	-0.067	-0.049
·	(0.072)	(880.0)	(0.156)	(0.109)	(0.132)	(0.126)	(0.094)	(0.093)	(0.083)	(0.074)	(0.091)	(0.097)
Sense of belonging	-0.188	-0.325	-0.234	-0.491	-0.685	-0.756	-0.466	-0.766	-0.988*	-0.113	-0.018	0.234
• •	(0.301)	(0.713)	(0.476)	(0.451)	(0.543)	(0.575)	(0.307)	(0.413)	(0.480)	(0.285)	(0.285)	(0.387)
Epist beliefs	-0.704	-1.222	-1.152	-0.569**	-0.703**	-0.555*	-0.241	-0.231	-0.029	0.044	0.174	0.410
	(0.400)	(0.746)	(0.740)	(0.202)	(0.239)	(0.249)	(0.127)	(0.138)	(0.170)	(0.275)	(0.284)	(0.341)
Truancy	-0.689	-1.229	-1.107	-0.136	-0.290	-0.351	0.119	0.244	0.174	0.084	0.030	-0.010
	(0.464)	(0.815)	(0.686)	(0.239)	(0.319)	(0.339)	(0.143)	(0.174)	(0.198)	(0.274)	(0.270)	(0.285)
Grade repetition	1.559*	2.241	2.064	1.649*	1.479*	1.432	0.401	0.469	0.197	-0.738	-0.862	-1.201
	(0.749)	(1.410)	(1.318)	(0.733)	(0.734)	(0.784)	(0.330)	(0.372)	(0.326)	(1.056)	(1.208)	(1.268)
ISCED level: 3	-1.492	-2.677	-2.203	-0.355	-0.520	-0.133	-11.920***	-12.455***	-12.516***	0.000	0.000	0.000
	(0.961)	(1.509)	(1.889)	(0.594)	(0.617)	(0.585)	(0.707)	(0.714)	(0.878)	(.)	(.)	(.)
Designation: B	0.284	-0.140	-1.301		0.000	0.000	12.330***	12.845***	12.816***			
	(0.685)	(1.040)	(1.434)		(.)	(.)	(0.742)	(0.772)	(0.934)			
Designation: C	14.419***	15.384***	13.347***	-2.854**	-4.819***	-5.048***						
	(1.402)	(1.613)	(1.690)	(1.067)	(1.037)	(1.103)						
Orientation: Pre-Voc.	-14.481***	-15.049***	-15.712***	2.207	2.192	2.210		0.000	0.000			
	(1.340)	(1.792)	(1.523)	(1.182)	(1.326)	(1.471)		(.)	(.)			
Orientation: Voc.	0.591	1.264	0.287	-0.007	0.369	0.157	0.000	0.000	0.000			
	(0.931)	(1.355)	(1.195)	(0.632)	(0.643)	(0.604)	(.)	(.)	(.)			
Orientation: Modular												
I: Immig. x Lang. at home	-1.754	-4.059	-4.557	-1.503	-1.466	-1.392	0.358	0.439	0.612	0.858	0.464	0.035
3 3 3 3 4 4 4	(1.099)	(2.123)	(2.515)	(0.968)	(1.123)	(1.117)	(0.604)	(0.606)	(0.680)	(1.076)	(1.014)	(1.035)
I: Immig. x Sense of belong.	0.250	0.292	0.105	-0.278	0.013	0.150	0.459	0.844	1.027*	0.673	0.578	0.291
gg.	(0.414)	(0.881)	(0.616)	(0.517)	(0.575)	(0.613)	(0.336)	(0.446)	(0.487)	(0.442)	(0.413)	(0.455)
School's ESCS	-0.148	-0.171	0.565	0.082	-0.050	0.152	-0.099	0.032	0.143	0.405	0.399	0.651*
	(0.584)	(0.893)	(1.264)	(0.325)	(0.383)	(0.419)	(0.294)	(0.372)	(0.334)	(0.261)	(0.303)	(0.285)
School's conc. of mig.	0.088	0.725	1.022	0.461	0.278	0.127	0.611	0.094	-0.172	-2.114*	-2.083*	-1.745
g-	(0.746)	(1.164)	(1.781)	(0.751)	(0.876)	(0.893)	(0.590)	(0.704)	(0.682)	(0.962)	(0.921)	(0.894)
School's exp. ESL level	13.507***	18.737***	20.211**	17.986***	15.889***	16.211***	6.592***	7.000***	8.123***	9.087***	9.233***	9.292***
	(2.039)	(5.151)	(7.004)	(2.801)	(2.913)	(3.079)	(0.497)	(0.730)	(0.907)	(1.326)	(1.263)	(1.691)
	(2.000)	(551)	-0.019	(2.001)	(2.0.0)	-0.006	(001)	(330)	0.001	()	(200)	-0.004
School's science score												
School's science score						(0.007)			(0.003)			(0.004)
			(0.012)			(0.007)			(0.003) -0.011**			(0.004) -0.008*
School's science score Student's science score			(0.012) -0.017			-0.004			-0.011**			-0.008*
	-4.647***	-5.181*	(0.012)	-6.336***	-5.762***		-4.421***	-4.301***		-2.294***	-2.442***	

	_LU_logit	_LU_	_LU_pv	_UK_logit	_UK_	_UK_pv
			·			
Gender	0.134	0.134	0.087	0.151	0.459	0.875
0	(0.145)	(0.145)	(0.139)	(0.868)	(1.245)	(1.204)
Student's ESCS	-0.218*	-0.218*	-0.218*	0.070	1.091	1.307
	(0.097)	(0.097)	(0.100)	(0.777)	(0.661)	(0.832)
1st generation	-0.736	-0.736	-0.730	0.963	-0.133	-0.635
and concretion	(0.410)	(0.410)	(0.409)	(1.220)	(2.314)	(2.055)
2nd generation	0.000	0.000	0.000	0.000	0.000	0.000
Language et home	(.) 0.597	(.) 0.597	(.) 0.464	(.) -0.057	(.) 0.557	(.) -0.537
Language at home						
Age at arrival	(0.381) 0.030	(0.381) 0.030	(0.376) 0.034	(1.020) -0.215	(1.403) -0.217	(2.043) -0.239
Age at arrival	(0.039)	(0.039)	(0.038)	(0.118)	(0.249)	(0.213)
Sense of belonging	-0.078	-0.078	-0.063	1.056*	0.707	1.137
Serise of belonging	(0.092)	(0.092)	(0.093)	(0.453)	(0.729)	(2.012)
Epist. beliefs	-0.214*	-0.214*	-0.166	-0.483	0.056	0.176
Epide Dollow	(0.099)	(0.099)	(0.112)	(0.389)	(0.550)	(0.680)
Truancy	0.213**	0.213**	0.192**	0.079	-0.472	-0.468
riddioy	(0.076)	(0.076)	(0.073)	(0.286)	(0.312)	(0.385)
Grade repetition	0.286	0.286	0.209	3.165	4.174	5.018*
Grade repositori	(0.173)	(0.173)	(0.167)	(1.691)	(2.291)	(1.977)
ISCED level: 3	-1.486**	-1.486**	-1.381**	15.393***	20.917***	16.917***
	(0.485)	(0.485)	(0.499)	(2.264)	(2.330)	(1.809)
Designation: B	0.091	0.091	-0.034	-14.854***	-20.126***	-17.610***
3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3	(0.830)	(0.830)	(0.812)	(2.179)	(2.386)	(2.371)
Designation: C	0.000	0.000	0.000	0.000	0.000	0.000
Ç	(.)	(.)	(.)	(.)	(.)	(.)
Orientation: Pre-Voc.	()	· · ·	· · ·	-3.879***	-3.513**	-3.711*
				(0.937)	(1.151)	(1.511)
Orientation: Voc.	0.216	0.216	0.339	-12.357***	-17.338	-13.993
	(0.610)	(0.610)	(0.612)	(1.440)	(.)	(.)
Orientation: Modular	1.010**	1.010**	0.797*			
	(0.377)	(0.377)	(0.393)			
I: Immig. x Lang. at home	-0.148	-0.148	-0.138	2.388	2.760	4.644*
	(0.257)	(0.257)	(0.253)	(1.456)	(1.758)	(1.876)
I: Immig. x Sense of belong.	0.062	0.062	0.048	-0.704	0.131	0.081
	(0.228)	(0.228)	(0.232)	(0.767)	(0.867)	(1.954)
School's ESCS	0.941***	0.941***	0.480	0.526	-0.319	-1.701
	(0.274)	(0.274)	(0.307)	(0.474)	(0.880)	(1.293)
School's conc. of mig.	-1.181	-1.181	-1.060	0.577	0.159	0.951
	(0.989)	(0.989)	(1.019)	(1.311)	(1.420)	(1.673)
School's exp. ESL level	10.628***	10.628***	12.056***	12.432***	12.263***	16.969***
	(1.281)	(1.281)	(1.292)	(2.092)	(1.849)	(3.997)
School's science score			0.004*			0.031*
Chidanda asianaa			(0.002)			(0.014)
Student's science score			-0.005**			-0.004
Constant	2 057***	2 257***	(0.001)	7.005**	0 770**	(0.009)
Constant	-3.257***	-3.257***	-5.213***	-7.685** (2.736)	-8.773** (2.470)	-26.121**
	(0.441)	(0.441)	(1.183)	(2.736)	(3.179)	(9.408)

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