

The Native-Migrant Gap in the Progression into and through Upper-Secondary Education

Stefan C. Wolter, Maria Zumbuehl



Impressum:

CESifo Working Papers ISSN 2364-1428 (electronic version) Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute Poschingerstr. 5, 81679 Munich, Germany Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email <u>office@cesifo.de</u> Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl www.cesifo-group.org/wp

An electronic version of the paper may be downloaded

- · from the SSRN website: <u>www.SSRN.com</u>
- from the RePEc website: <u>www.RePEc.org</u>
- from the CESifo website: <u>www.CESifo-group.org/wp</u>

The Native-Migrant Gap in the Progression into and through Upper-Secondary Education

Abstract

In this paper we follow the students that took the PISA 2012 test in Switzerland and analyze their transition into and progress in upper-secondary education. We observe a substantive difference in the rate of progress between natives and students with a migration background. One year after leaving compulsory school, the gap between the natives and migrants that are on-track - entering the second year of upper-secondary education - is 15 percentage points. Observable differences in cognitive and non-cognitive skills can explain the gap in the success rate within upper-secondary education, but cannot fully explain the difference in the transition rate into upper-secondary education. More refined analyses present results that are consistent with the hypotheses of differences in tastes, aspirations and incomplete or inaccurate information about the education system explaining the gap in the transition into post-compulsory education.

JEL-Codes: I240, J150, J240, J620, J710.

Keywords: education, migration, occupational choice.

Stefan C. Wolter University of Bern Department of Economics Schanzeneckstrasse 1 Switzerland – 3001 Bern stefan.wolter@vwi.unibe.ch Maria Zumbuehl* University of Bern Department of Economics Schanzeneckstrasse 1 Switzerland – 3001 Bern maria.zumbuehl@vwi.unibe.ch

*corresponding author

November 30, 2017

We thank Aurelién Abrassart and Martina Viarenga as well as the participants in several workshops for helpful comments. The funding by the Swiss Leading House on Economics of Education is gratefully acknowledged.

1 Introduction

The transition into post-compulsory education is a crucial step for students' further education and success in the labor market. While some delays and drop-outs cannot be avoided in an environment with uncertainty (Manski, 1989), educational delays create costs for the students individually and to the society in general. On the individual level, delays decrease the personal return to education which could lead to a lower demand for further education. On the societal level, delays create additional education costs and the risk that because of the delay and negative experiences associated with grade repetition and dropping out, certain students will not succeed in obtaining a final upper-secondary education degree (see e.g. Goux et al., 2017). Flisi et al. (2016) show that migrants in many countries are a particularly vulnerable group, in terms of educational outcomes at the end of their lower secondary education. Lüdemann and Schwerdt (2013) suggest that in addition to differences in skills, migrants might additionally suffer from less favorable evaluations and recommendations from their teachers. This study investigates how the gap between migrants and natives extends into upper-secondary education.

Using a novel Swiss panel data set¹ that starts with students on the verge of transitioning from compulsory to upper-secondary education, we observe a significant native-migrant gap in the successful transition into upper-secondary education. This study investigates the extent to which this gap can be explained by the differences in skills between native and migrant students. We further investigate possible reasons for the gap that remains after controlling for skills. We examine both, the transition and the successful passage through the first year of upper-secondary education. We find that while the differences in skills explain much of the gap that emerges through failure during the first year of upper-secondary education, the gap in the successful transition remains, although reduced, even after controlling for skills. Migrants, compared with natives, have a more difficult time directly transitioning into post-compulsory education.

In the economic literature on time to degree and drop-out, much of the focus has been placed on tertiary education, with studies from college

¹SEATS (Swiss Educational Attainment and Transition Study). We are grateful to Markus Schwyn, Jacques Babel, and other staff of the Swiss Federal Statistical Office for the provision of the register data and their support.

and universities.² As a stepping stone into the labor market or a tertiary education, successfully transitioning into and finishing upper-secondary education is at least as crucial, but has received less attention in the economic literature.³ However, there are several recent studies that investigate the transition into upper-secondary education and the students' success in their chosen education. While Jaik and Wolter (2016) and Kunz and Staub (2016) investigate the influence of personality and beliefs on the transition into upper-secondary education, Goux et al. (2017) and Boockmann and Nielen (2016) use field experiments to investigate the effect of information on the success in transition and completion of vocational programs for students at the lower end of the skills distribution.

Administrative data from Switzerland confirm the sizable native-migrant gap in the transition into upper-secondary education (Swiss Federal Statistical Office, 2017). Studies based on an older cohort of Swiss school-leavers (TREE panel study, based on PISA 2000) have also found a significant gap in transition for migrants (e.g. Hupka-Brunner et al., 2010, Laganà et al., 2014 or Mueller and Wolter, 2014). For this study, we use the PISA 2012 test and survey, linked to administrative data from the Swiss statistical office (FSO). This gives us the advantage of observing the transition for a large sample of students without attrition. We use the detailed migration information from the PISA study to investigate the origins of the gap, while controlling for cognitive and non-cognitive skills. Although our results are mainly of a descriptive nature, they allow us to illuminate potential mechanisms that could lead to the observed native-migrant gap. In particular, we consider three mechanisms: 1) discrimination by the training firms when assessing applicants for an apprenticeship, 2) the differences in tastes and aspirations between migrants and natives and 3) a gap in information about the educational system and the perspectives of the available tracks. The results of our analyses support differences in tastes and aspirations, and in information as possible mechanisms for the native-migrant gap, whereas we find little support for the channel of discrimination.

 $^{^{2}}$ See, for example, Brunello and Winter-Ebmer (2003) and Garibaldi et al. (2011) for monetary and macroeconomic impacts on time to degree and drop-out, Vignoles and Powdthavee (2009) for individual characteristics, and Bettinger and Baker (2014) and Himmler et al. (2017) for behavioral approaches to reduce delays.

³An exception is the literature on high-school drop-outs, see, for example, Heckman and LaFontaine (2010).

The remainder of this paper proceeds as follows. In the next section, we provide a brief overview of the relevant part of the Swiss educational system. In section 3, we discuss the linked PISA 2012–FSO data. Section 4 presents the results of the decomposition of the gap in delay, and the results of two analyses based on more detailed classifications of migration. In section 5, we discuss possible mechanisms. Section 6 concludes.

2 Swiss education system

The compulsory education in Switzerland spans 9 years: 5 to 6 years of primary education and 3 to 4 years of lower secondary education, in which students are tracked by ability. The exact education system differs among the federal regions (cantons). Most cantons additionally have 2 mandatory years of preschool. At age 15 or 16, students finish compulsory school and transition into upper-secondary education.

We observe three possible choices at the end of the ninth and final year of compulsory education. 1) General education (GE): This category includes baccalaureate schools $(24\%^4)$ and upper-secondary specialized schools (5%), which prepare students for tertiary education. 2) Vocational education (VET): Most of the students who choose this educational track enter a dual VET with a duration of 3 to 4 years (46%).⁵ They split their time between a vocational school and a work-based apprenticeship in a company. However, a minority of students attend a full-time school-based vocational education with a mandatory internship. Because the diploma is the same for both types of educational paths, we do not distinguish between the two. 3) Gap year: Most cantons offer interim solutions for students who do not manage to transition into post-compulsory education or have not yet made up their mind about which educational path to follow (11%); this usually entails one year of bridge courses.⁶ Further, students in some cantons can also repeat their last year of compulsory education. This option is predominantly availed by students planning to enroll in a baccalaureate program, but who did not

⁴This number is based on our sample of PISA participants in 2012.

⁵The duration of the vocational education depends on the chosen occupation. A small share of students complete a shorter, 2-year vocational education, which leads to a different type of vocational certificate.

 $^{^{6}\}mathrm{The}$ availability and type of such interim solutions is determined on a regional level by each canton.

fulfill the requirements to matriculate in such at the end of their compulsory education (5%). Finally, there are students who do not enroll in any type of educational institution in Switzerland for the 2012/2013 school year (8%). Although a small fraction of students truly drop out of the education system, most of the students who are not enrolled in any educational institution in 2012 reappear in the educational system at a later date.⁷ In this study, we do not distinguish between the types of gap years, because our main focus is the incidence of a delay in general.

3 Data

We use the SEATS data, based on the national PISA 2012 sample of ninth graders in Switzerland, linked with register data on student enrollment in the Swiss educational system. This sample allows us to follow the PISA participants' transition into upper-secondary education and their success within their chosen educational path. The register data originate from the LABB program.⁸ They are provided by the Statistical Office Switzerland (FSO) and contain yearly information on all students enrolled in any type of educational institution. This study focuses on the two years after graduation from compulsory school. In the first year, the transition itself is captured, the observed students decide between a direct transition or a gap year. Data on enrollment at the beginning of the second year capture whether the students passed the first year of their chosen type of education without delay. In particular, the students that enter GE with the goal of earning a baccalaureate degree are most prone to dropping out in the first year of their education and, hence, this is indicative of their overall success in their chosen education.

We construct two dependent variables from the register data at two different points in time where we observe the students. The first variable captures the direct transition into upper-secondary education in a binary variable that takes the value 1 if the student does not enroll in a certifying

⁷Out of the 1115 students not enrolled in 2012, 734 students are enrolled in some kind of education in 2013; 645 of the reappearing students enter a vocational education.

⁸The LABB (Längsschnittanalysen im Bildungsbereich) program integrates several sources of register data on the topic of education. For more information see www.labb.bfs.admin.ch.

education directly after compulsory school (gap year). The second dependent variable captures a delay within upper-secondary education during the first year of the chosen education. The cause of the delay can either be repeating a year or dropping out of the chosen education. We summarize both types of delay in a binary variable that takes the value 1 if the student either repeats or drops out (delay/drop-out).

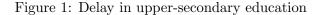
Because of the 2012 PISA study's regional oversampling of students in the last year of compulsory school, we observe a large sample of 13'152 school leavers. Three-quarters of these students transition directly into uppersecondary education. Figure 1 displays how many students progress without delay to their second year of education by migration status. We observe a large native-migrant gap in being on-track⁹ after 1 year: 15 percentage points in the raw data. The variable capturing migration background is from the PISA student survey and indicates if the student has either been born abroad or has non-native parents.¹⁰ We impute the values of missing migration status by using information on the student's nationality from the FSO data. For the second part of our analysis, we also use the information on if the student has been born in Switzerland to distinguish between the first- and second-generation migrants, as well as information on the birth place of both parents to capture students who are Swiss natives, but have parents with a migration background. Additionally we create indicators for migrants from different immigration waves using the country of birth of the mother of the migrant students.

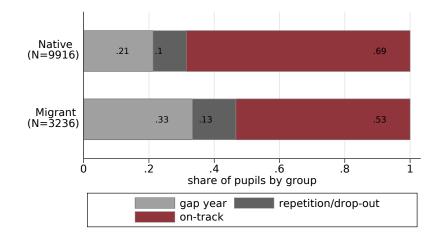
The PISA dataset further provides data on the students' achievement scores in mathematics, language, and science, which we use as proxies for cognitive skills. The focus of the 2012 PISA test was mathematics; therefore, the math scores are the most precisely measured test scores. The PISA student survey elicits if the students have been late for class during the weeks preceding the test. We code the answer as a binary variable, 1 if never late to class, and use this punctuality variable as a proxy for non-cognitive skills.¹¹ We also include a number of demographic and regional control variables. Most of the demographic variables are from the PISA test. Home language

⁹Being on-track means that the student does not face any delay at any time during the observed period.

¹⁰The group of natives captures all students who have at least one Swiss native parent.

¹¹Punctuality is a facet of conscientiousness, a personality trait that is highly predictive for education and labor market outcomes (see e.g. Almlund et al., 2011).





is a binary variable that captures if the language the student speaks at home matches with the language of the PISA test. A dummy variable captures missing values. The variable parents' education reports the years of education of parent that has the highest education within the household. The highest socioeconomic status (HISEI index) captures the socioeconomic status of the parent with the higher-ranking occupation. For the regional controls we use additional information from the FSO. We include an indicator for the regional share of students in baccalaureate schools and the share of students in VETs as an indicator for potential supply side effects.¹² Finally we control for the language region with a dummy that equals 1 for the German-speaking part of Switzerland.

Table 1 reports the summary statistics for the important variables for natives and migrants of the initial sample before transition. We can observe that the students in the migrant sample have a lower mean in all skills measures¹³ and the measures of the socioeconomic background.

For the students who start an apprenticeship, we create an additional variable that captures the academic requirements of the chosen vocational education (VE level). The data on the difficulty level of the apprenticeship

 $^{^{12}{\}rm Missing}$ information on these two shares are controlled for by a dummy variable for the particular region.

 $^{^{13}}$ For a discussion on the differences in skills see, for example, Kunz (2016).

		Natives			Migran	ts
VARIABLES	mean	sd	Ν	mean	sd	Ν
math score	538.7	78.75	9.916	490.2	79.74	3,236
language score	514.8	76.95	9,916	471.8	80.99	3,236
science score	520.3	73.60	9,916	466.2	76.43	3,236
punctuality	0.755	0.430	9,801	0.674	0.469	3,208
female	0.507	0.500	9,916	0.504	0.500	3,236
age	15.88	0.587	9,916	15.98	0.703	3,236
home language	0.952	0.215	9,204	0.456	0.498	$2,\!853$
parents' edu	14.51	2.448	$9,\!682$	12.94	3.748	$3,\!118$
SES	56.32	17.90	9,916	49.65	21.56	$3,\!236$
any delay	0.315	0.464	9,916	0.467	0.499	$3,\!236$
gap year	0.212	0.409	9,916	0.333	0.471	$3,\!236$
delay in 1. year	0.130	0.337	$7,\!812$	0.201	0.401	$2,\!159$

Table 1: Descriptive statistics: natives and migrants

Note: Raw data; for the regressions we add dummy variables for missing values in control variables.

were gathered on behalf of the Swiss Conference of Cantonal Education Ministers and the Swiss Trades and Crafts Association.¹⁴ For this purpose, almost every occupation available through vocational training was evaluated by experts. These experts assigned values from 1–100 for the cognitive difficulty level in math, school language, natural sciences, and a first foreign language for each of the apprenticeships.

4 Results

We split the total delay into two steps, that is, gap year and repetition-dropout, and analyze them separately. Figure 1 shows a native-migrant gap in both stages; however, the drivers behind the gap could differ between these two cases.

 $^{^{14}\}mathrm{See}$ www.anforderungsprofile.ch. We are grateful to Walter Goetze for the provision of the detailed information about the intellectual demand levels of most of the occupations used in this paper.

4.1 Decomposing the total delay

We start by investigating the probability of a delay in the direct transition to upper-secondary education (gap year). Columns (1) and (2) in Table 2 display the average marginal effects on the probability of a gap year from probit regressions. In Column(1), we observe a significant marginal effect for the migration status of the student on the probability to transition with a delay of at least 1 year after controlling for the socioeconomic background of the student, demographics, and regional indicators. All standard errors are clustered at the regional level.

In Column(2), we add variables that capture cognitive and non-cognitive skills in the model. The average marginal effect of migration decreases to half its previous size after controlling for skills, but stays statistically and economically significant. Panel a) of Figure 2 shows the marginal effects of the migration status along the distribution of math skills.¹⁵ In Panel b) of Figure 2, we additionally interact the migrant indicator with the math score to allow for heterogeneous effects in skills.¹⁶

In both specifications, we observe that the marginal effect of a migration background on the probability of a gap year is greater for students at the lower end of the skills distribution. If we allow for interaction effects between migration and skills, the marginal effect on the probability of a gap year becomes insignificant for students that reach level 4 or higher in the PISA math test.¹⁷ Using a nonlinear Oaxaca–Blinder type decomposition method proposed by Fairlie (2005), we find that the two groups' different skills endowments explains approximately 61% of the native–migrant gap in delayed transition. The differences in demographics and socioeconomic background of the students explains an additional 16% of the difference. Regional characteristics, however, appear to attenuate the gap in delayed transition. Table A1 in the appendix displays the full results of the decomposition.¹⁸

In the second stage of our investigation of delays in upper-secondary

¹⁵The MEs are based on the same probit regression as in Column(2) of Table 2, but exclude the PISA scores for science and reading, because they are highly correlated with math scores.

¹⁶See, for example, Aeberhardt et al., 2017 for evidence of such heterogeneous effects in employability.

¹⁷Level 4 in math skills on the 2012 PISA test relates to a minimal test score of 544.7. At least a level 4 is suggested to successfully complete a baccalaureate school's curriculum.

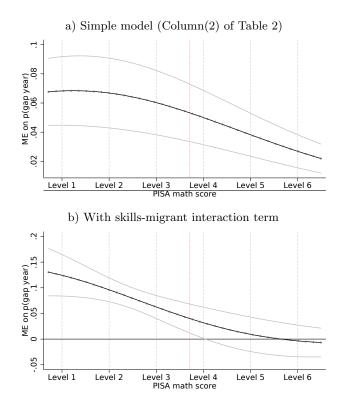
¹⁸We use the coefficients from the pooled model and randomly rotate the order of the variables. The results are based on 1000 replications.

	Gap	year	Re	epeat/drop o	out
	(1)	(2)	(3)	(4)	(5)
migrant	0.098***	0.051***	0.037***	0.021**	0.011
	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)
punctuality		-0.021***		-0.041***	-0.037***
		(0.007)		(0.008)	(0.008)
math score		-0.105***		-0.026**	-0.034***
		(0.013)		(0.011)	(0.011)
language score		-0.002		0.009	-0.002
		(0.008)		(0.007)	(0.007)
science score		-0.003		-0.023**	-0.028***
		(0.016)		(0.011)	(0.010)
home language	-0.022	-0.006	-0.017	-0.011	-0.006
0 0	(0.016)	(0.016)	(0.014)	(0.014)	(0.014)
female	0.080***	0.059***	-0.018***	-0.027***	-0.046***
	(0.013)	(0.014)	(0.005)	(0.008)	(0.007)
age	0.021	-0.020	0.018**	0.003	0.007
0	(0.017)	(0.018)	(0.009)	(0.006)	(0.006)
parents' edu	-0.038***	-0.018*	0.007	0.014**	0.006
1	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)
HISEI	-0.001**	-0.000	0.001***	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
share GE	-0.017***	-0.019***	0.004	0.002	0.001
	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
share VE	-0.006*	-0.006	-0.001	-0.001	-0.001
	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)
German-speaking	-0.100**	-0.078	-0.089***	-0.077***	-0.069***
1 0	(0.051)	(0.057)	(0.016)	(0.018)	(0.019)
bacc school	× /	× /	× /	· /	0.124***
					(0.020)
other GE					0.142***
					(0.033)
Observations	$13,\!152$	$13,\!152$	$9,\!971$	9,971	9,971
Pseudo R-squared	0.040	0.095	0.064	0.081	0.103

Table 2: Average marginal effects on delay in 2 stages

Note: Average marginal effects from probit regressions. We additionally control for missing values in punctuality, home language, parental education and socioeconomic background, as well as in regional shares. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

education, we focus on the successful completion of the first year of uppersecondary education. In the raw data, we also observe a significant native– migrant gap also in this second stage of the transition. Controlling for



demographics, socioeconomic background, and regional characteristics, the average marginal effect of the migration status on the probability of repetition or dropping out is smaller than on the probability to delay the transition altogether, but is still significant, as displayed in Column(3) of Table 2. The regression sample of this second stage is smaller because we observe the success in the first year of upper-secondary education only for the students who transitioned directly. In separate analyses, we run similar regressions on the first year of upper-secondary education including students who took one gap year. The results do not change significantly. Adding controls for cognitive and non-cognitive skills reduces the effect of the migration status, as Column(4) shows. The effect is, however, still significant at the 5% level. If we now use the information on the chosen type of education, the effect of the migration status decreases again and becomes statistically insignificant. If we run the regressions for the students in GE and VET separately, the effect of the migration status remains insignificant for both subsamples. The initial gap in progress can be explained by a different selection of the more demanding (especially GE) tracks. Table A2 demonstrates that migrants are more likely than natives to enter general education (25% at the sample mean), and even more so to enter baccalaureate schools (29%).¹⁹ This holds for both groups in equal measures: students with a too-low skills level for baccalaureate schools and for those with a sufficiently high math level. The results of the decomposition, reported in Table A1, demonstrate that educational choice explains approximately 6% of the gap, and differences in skills explain approximately 58%. Contrary to the effects for the gap in the probability of a gap year, regional characteristics now increase the native–migrant gap; regional differences explain 21% of the gap in progress.²⁰

4.2 Disentangling types of migration

To better understand the native-migrant gap in transition, we extend our analysis by dividing the large and heterogeneous group of migrants into more homogeneous subgroups. As we show in this subsection, a substantial heterogeneity exists between the migrant groups in their educational choices and progress towards the completion of their chosen education. We will refer to the results of this subsection to discuss mechanisms that could lead to the observed native-migrant gap in section 5. We consider two dimensions for splitting the migration indicator: 1) The migration history, i.e. the timing of the migration. We distinguish between first- and second-generation migrants and children with only one migrant parent. 2) We group the migrants by clusters of countries of origin.

Migration history

We split the group of migrants in our sample into two groups: secondgeneration migrants, who were born in Switzerland but have parents not born in Switzerland, and first-generation migrants, who were born abroad to foreign parents. Additionally, we more closely examine students with only one migrant parent. Henceforth, this paper will refer to the children with

 $^{^{19}}$ The transition probability for natives at the sample mean to enter general education and a baccalaureate school is 36% and 30%, respectively.

²⁰The reason for this change is that some regions allow for a relatively easy transition into baccalaureate schools, but have a large dropout or repetition rate at the end of the first year. The migration rate in these regions is somewhat higher than in the regions with stricter entrance regulations for baccalaureate schools.

	(1)	(2)	(2)	(1)
	(1)	(2)	(3)	(4)
VARIABLES	p(Gap year)	p(delay)	p(Bacc)	VE level
1st generation migrant	0.125^{***}	0.043***	0.056^{**}	1.018
	(0.024)	(0.016)	(0.027)	(0.723)
2nd generation migrant	0.048***	0.010	0.113***	2.080^{***}
	(0.013)	(0.010)	(0.010)	(0.361)
migrant mother	0.082***	0.024**	0.045***	0.827**
	(0.011)	(0.010)	(0.011)	(0.373)
migrant father	0.031^{**}	0.008	0.045^{***}	0.131
	(0.016)	(0.008)	(0.015)	(0.532)
Observations	13,152	9.971	9.971	$5,\!620$
R-squared	10,102	0,011	0,011	0.206
Pseudo R-squared	0.100	0.103	0.353	

Table 3: Different types of migration status

Note: Columns (1) - (3): Average marginal effects from probit regressions, Column(4) coefficients from OLS regression. Migrant mother captures pupils with a migrant mother and a Swiss native father, migrant fathers the opposite. We also include dummies for missing migration information on the pupil or one or both of the parents. We interact all migration variables with the PISA math score and add control variables on demographics and socioeconomic background control and regional controls, as explained in Table 2. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

one each native- and migrant-born parent as having either a migrant mother, or father (implying that the other parent is Swiss). Until now, these students were included in the native group. Hence, in this approach, students with two native Swiss parents are the base group.²¹ We interact all migration dummies with the PISA math score to allow the coefficients of the migration variables to differ along the skills distribution. We also control for non-cognitive skills, demographics, and regional variables: punctuality, language spoken at home, gender, age, the parents' highest education, the HISEI, the regional rate of students that enter gymnasium, the regional rate of students that start an apprenticeship, an indicator for the German-speaking part of Switzerland, and the dummy variables for missing values in the control variables.²²

Table 3 shows the results for the first approach. Column(1) reports the average marginal effects of migration status on the probability to take a gap

²¹Additionally, we add two binary variables to control for migrant students with missing information on place of birth and for native students with only one parent.

 $^{^{22}}$ Because of the high correlation between math scores and the other PISA test scores, we do not include reading and science in the control variables.

year.²³ Column(2) presents the average marginal effects of migration status on the probability to repeat or drop-out of upper-secondary education during the first year. To gain insight into the choice behavior among the groups of students, we display the average marginal effects on the probability to enter a baccalaureate school in Column(3).The coefficients of migration status on the academic difficulty level of the apprenticeship, for those students who directly transitioned into VET, are in Column(4). We control for cognitive and non-cognitive skills in all four specifications. Columns(1–3) are based on probit models. Column(4) is based on an OLS regression.²⁴

Figure A1 displays significant differences in the distribution of math skills among the migrant groups by type of migration status. One in five first- or second-generation migrants has a math level below 2, but less than 10% of natives are below this level. Therefore, the marginal effects of the migration variables at different skill levels are informative.

Figure 3 illustrates the marginal effects of the different migration backgrounds along the math skills distribution for the probability to transition directly into upper-secondary education. The underlying estimation is based on the estimation in Table 3, Column(1). We observe that at the bottom of the skills distribution the probability of a gap year is significantly larger for any type of migration background than for natives.

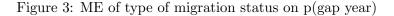
Country of origin

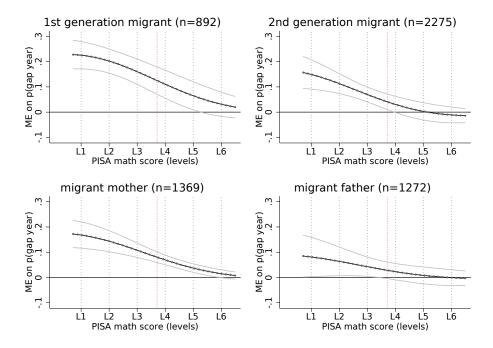
In a second analysis, we investigate the native-migrant gap by examining the migrants' countries of origin. We focus on four groups of origin countries that constitute the major waves of immigration to Switzerland.²⁵ The first wave of immigrants comes from Italy. The immigrants from the Balkan countries²⁶ and Portugal comprise the second wave. The third wave of immigrants are those from neighboring countries other than Italy, that is, Germany, France, and Austria. The information on the migrant's origin is based on the

²³Table 3 displays the marginal effects of the control variables.

²⁴We report the marginal effects also for the OLS model. Hence the reported migration coefficients incorporate the interaction effects with PISA test scores at the average level.

²⁵See Fibbi et al. (2015) for a discussion of Switzerland's different groups of immigrants. ²⁶Our results are robust to adding migrants from Turkey to this group of second wave immigrants, as Schnell and Fibbi (2016) do.





Note: All figures are based on the specification displayed in Column(1) of Table 3 with additional interaction terms between math skill and types of migration status.

mother's country of origin.²⁷ We further include a group of other migrants and a group of migrants for whom we have missing information. In this second part of the analysis, the base group is all Swiss students, including including those with one migrant parent. We apply the same estimation strategy, interacting the migration variables with the PISA math score and using the same control variables on non-cognitive skills and demographic and regional characteristics. Table 4 displays the average marginal effects of these groups of migrants on the probability to transition with a delay, to repeat or drop-out of the chosen education, the probability to choose a baccalaureate school, and the academic difficulty level of the VET, if one is chosen.

The cumulative distribution function of math skills by group in Figure A2 demonstrates that students from the first and second waves of migration

²⁷Students captured in any of the migrant groups have no Swiss-native parentage.

	(1)	(0)	(2)	(4)
	(1)	(2)	(3)	(4)
VARIABLES	p(Gap year)	p(delay)	p(Bacc)	VE level
1. wave: Italy	0.019	0.051^{*}	0.026	1.319
	(0.027)	(0.028)	(0.038)	(1.527)
2. wave: Balkan	0.016	0.011	0.075^{***}	2.184^{***}
	(0.014)	(0.019)	(0.010)	(0.428)
2. wave: Portugal	0.044^{**}	-0.011	0.061^{**}	1.900^{***}
	(0.022)	(0.016)	(0.024)	(0.568)
3. wave: Neighboring countries	0.107^{***}	0.025	0.056^{**}	-0.974
	(0.033)	(0.031)	(0.025)	(0.749)
Observations	13.152	9.971	9.971	5,620
	15,152	9,971	9,971	,
R-squared				0.208
Pseudo R-squared	0.0976	0.0828	0.352	

Table 4: Immigration wave

Note: Columns (1) - (3): Average marginal effects from probit regressions, Column(4) coefficients from OLS regression. Immigration origin is determined by the mother's birth country if both parents are migrants. We also include dummies for other countries of origin and country of origin missing. We interact all migration variables with the PISA math score and add control variables on demographics and socioeconomic background control and regional controls, as explained in Table 2. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

have lower math skills than migrants of the third wave and natives.²⁸

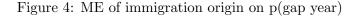
Figure 4 shows the marginal effects of the four principal immigration groups on the probability to delay transition into upper-secondary education along the skills distribution. The figures are based on a probit model displayed in Table 4, Column(1). Figure A3 displays similar results, but allowing the marginal effects of migration origin to differ for students with parents who have either a tertiary or non-tertiary education.

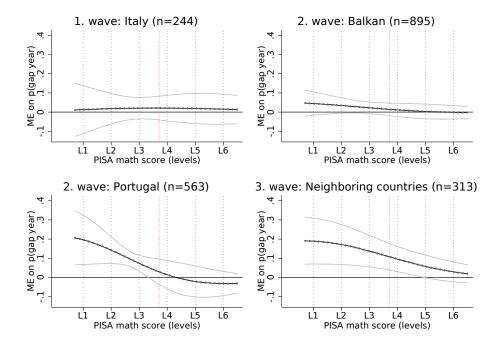
Section 5 will discuss the results of both approaches, with respect to their meaning for the three proposed mechanisms.

5 Discussion of mechanisms

We consider three possible mechanisms that could lead to the observed native-migrant gap, in particular in the transition into upper-secondary education: discrimination against migrants, an information gap between

 $^{^{28}}$ The average math score by group is in Level 3 of the PISA math scores for all groups, with an average math score of 488 for migrants of the first wave, 475 for migrants from the Balkan region, 485 for Portuguese immigrants, 531 for migrants of the third wave, and 539 for natives.





Note: All figures are based on the specification displayed in Column(1) of Table 4 with additional interaction terms between math skill and types of migration status.

natives and migrants, and their differences in tastes and aspirations.

5.1 Discrimination

To enroll in dual vocational education, the students must make an apprenticeship contract with a private or public firm, which may be more difficult to attain for migrants.²⁹ By contrast, admission into general education is more directly based on school grades and entry examinations and has, therefore, less potential for discrimination. Following the literature on discrimination in the labor market (see Lang et al., 2012 for an overview on models of discrimination), we expect to observe the following in our data if discrimination is a primary mechanism for the gap: 1) Students with a migration background

²⁹Imdorf (2006) finds qualitative evidence for discrimination against migrant applicants by training firms.

should have a higher propensity to enter GE if they qualify.³⁰ 2) If GE is not an option because of low school grades, we expect the migrants to either accept apprenticeships below their skill level in terms of academic difficulty, or to take a gap year.

We start with the analysis of the different types of migration status. In the case of strong (name-based)³¹ discrimination, we expect that students with a migrant father and a Swiss mother have a harder time transitioning into upper-secondary education than students with a migrant mother and a Swiss father, because most students receive their family name from their fathers. As aforementioned, we further expect that the migrants and children of migrant parents that do start a VET, start their education below their actual skill level if they are discriminated against.

The results in Table 3 do not support the predictions that are based on discrimination as a mechanism for the native-migrant gap. Comparing the marginal effects of having a migrant mother to having a migrant father indicates that name-based discrimination is unlikely to be the reason for the differences between natives and migrants. Pupils with a migrant mother are more likely to have a Swiss name, but have a significantly higher probability of taking a gap year. Their probability to take a gap year is also higher than for the second-generation migrants. Given an average skill level, students with migrant mothers have a higher propensity to matriculate to a baccalaureate school than the natives (Column 3). If they choose a VET, they enter professions with higher academic demands (Column 4). Even after controlling for the chosen education type, the students with migrant mothers are more likely to be delayed during their first year of education, which can be explained by them choosing more difficult tracks than natives.

More evidence against discrimination as a dominant mechanism for the gap comes from the second subgroup analysis. Evidence from previous research, for example, Booth et al. (2012), suggests that the probability and severity of facing discrimination depends on the migrant's country of origin. Among the four groups of origin countries that we consider, migrants

³⁰The higher propensity to choose general education can either be because of easier (discrimination-free) access or because migrants expect discrimination along the way and acquire a better education as a signal to counteract future discrimination (Lang and Manove, 2011).

³¹See Bartoš et al. (2016) or Bertrand and Mullainathan (2004) for studies of name-based discrimination in the labor market in general, and Fibbi et al. (2006) for the case of name-based discrimination in the transition into vocational education in Switzerland.

from the Balkan region are the most likely to be discriminated against (see Fibbi et al., 2006). However, in at Figure 4, we observe that the difference between natives and migrants from the Balkan region is small and statistically insignificant for students of an average skill level in math. Furthermore, we observe that the students of the third migration wave, from neighboring countries, are significantly more likely to delay transition than the natives, on all but the highest skills level. These students, however, are less likely to be discriminated against than those from the Balkan region.

5.2 Information differences

The Swiss educational system, which strongly relies on dual vocational education, may be difficult to completely understand for immigrants from countries that have very different upper-secondary educational systems. Firstly, the merits of a vocational education might be underestimated, as well as the opportunities for tertiary education that are open to students with a vocational degree. Secondly, the system is more difficult for migrant parents to understand, especially if they do not speak the native language. As a result, these parents are more likely to be inadequately informed about all the vocational options their children have and unable to support them in finding an adequate training position. In case of information differences as an mechanism that leads to the observed native-migrant transition gap, we expect that recent immigrants and those with a different cultural and language background will have a larger gap. We expect these students to enter GE with a larger propensity and to take a gap year more frequently. However, we do not expect the students to choose more demanding vocational education tracks than the natives, if they do choose VET. Finally, if the migrant students must make decisions based on less information than the natives, we expect them to make more errors in their decisions and, thus, have a higher rate of dropping out or repetition than the natives or better informed migrants. Goux et al. (2017) provide evidence for such an effect in an experimental study with low-performing youth with a migration background in France. They show that an information treatment reduces the number of students who drop out of their track, in particular, and from the education system, in general.

The results in Table 3 support the hypothesis of differences in information. First-generation migrants are more likely than any other group to delay their transition into upper-secondary education, and they are also more likely to encounter delays within their chosen education if they transition.³² These results suggest that first-generation migrants are more likely than any other group to choose an education not suitable to them.

The information on which language the students speak at home is also useful to further investigate the hypothesis of information differences. Students who speak their school's language at home might have an advantage in retrieving information because of their and their parents' language knowledge. Two-thirds of the first-generation migrants speak a language other than their school's language at home. We observe that much of the increase in delay within upper-secondary education comes from these first-generation migrants who speak a different language at home (see Table A5). Looking at the difference in transitioning along the skills distribution (see Figure A4), we find that first-generation migrants who speak a different language at home have a higher propensity of not transitioning if their skills level is below the threshold level 4 that is suggested as a minimal requirement to enter a baccalaureate school. Students above this threshold, however, show no statistically significant increase in probability to delay. Given that the information on GE is easier to receive and process—in part because the options are more limited—this finding supports our hypothesis of an information gap.

Students who do speak the school language at home show a different pattern, with a slightly increased probability to take a gap year independent of the skills level. These results are similar to the results we observe for migrants of the third wave of immigration from neighboring countries, for whom there is a similar pattern in terms of an increased delay in transition (Figure 4), but not in delays within upper-secondary education. Table A6 and Figure A5 provide the results for the waves of immigration by language spoken at home. We observe that immigrants of the third wave who do not speak the school language at home have a larger propensity to take a gap year than their fellow third-wave migrants who do speak the school language

 $^{^{32}}$ We can alternatively compare first generation migrants that have spent their entire school career in Switzerland to migrants who arrived after age 6. Late arriving migrants are significantly more likely to take a gap year (AME of 0.134 for late-arriving migrants versus 0.099 for migrants who arrive before age 6). The difference in repetition or drop-out rates of upper-secondary education is not statistically significant between these two groups of first-generation migrants.

at home.

In general, our results suggest that if migrants do not encounter language barriers, the reasons for the delay should be less due to information deficits.

5.3 Differences in tastes and aspirations

Differences in tastes and educational aspirations may also lead to the observed native-migrant gap in the transition into upper-secondary education. This difference can either be a direct preference for a gap year,³³ preferences for the more competitive educational tracks, or different educational aspirations conditional on the student's skills. In Switzerland VET is well established and also attractive for high-ability students. By contrast, in most of the migrants' home countries VET is likely to be valued significantly lower than in Switzerland. Abrassart et al. (2017) show that most migrants living in Switzerland value VET less than Swiss natives do, except for migrants from Southern European countries. Hence, we expect an increased preference for GE if the migrants consider returning to their country of origin or are concerned about the reputation of VET in their country of origin. Even without ties to their country of origin, migrants can have different preferences that are culturally shaped (see e.g. Fernandez and Fogli, 2009). The longer the migrants live in Switzerland, the less important the strategic reasons become, in regard to their choice of education. Thus, we expect the similarity to the natives, in terms of educational choices, to increase with the generation of migration and earlier waves of immigration.

The results of our analyses of the transition into upper-secondary education are in-line with our assumptions. We find that the native migrant gap disappears for the early waves of immigration and that this gap is larger for first-generation migrants than for second-generation migrants. We further observe a significantly different educational choice pattern for migrants that is largely consistent with the hypothesis of differences in tastes and aspirations. Recent migrants have a strong preference for GE; if they choose VET, however, they make a choice similar to the natives or choose slightly more demanding tracks. The strong preference for GE among the secondgeneration migrants and, in particular, the migrants of the second wave (Balkan countries and Portugal) is accompanied by a preference for more

 $^{^{33}}$ See Greenspon (2017).

demanding VET.³⁴ This points to earlier studies that have found a strong preference for upward mobility among young migrants of this group, see, for example, Schnell and Fibbi (2016) and Jonsson and Rudolphi (2011),³⁵ and a larger intergenerational mobility for migrants in general (Bauer and Riphahn, 2007).

6 Conclusion

This study investigates the significant native-migrant gap of 15 percentage points in the successful transition from compulsory school to upper-secondary education. We find that most of the difference in the drop-out and repetition rates during the first period of upper-secondary education are explained by the differences in skills and educational choices. However, the gap in the direct transition into upper-secondary education remains significant after also controlling for skills. When focusing on potential mechanisms for this gap, we find patterns consistent with differences in taste and aspirations or an information gap between migrants and natives and that exclude discrimination as a primary mechanism for the gap in educational progress between the natives and migrants.

From a policy perspective, these results mean that to reduce the nativemigrant gap in the transition into post-compulsory education, it is crucial to understand where the differences in tastes and aspirations originate and if they can be influenced by more or better information on the chances and options in the education system. Given the growing share of students with a migration background in many developed countries, this is a problem of growing importance for educational policy making and overcoming these issues should lead to an increased allocative and productive efficiency of the educational system.

³⁴Pupils with only one migrant parent are, in most respects, "in between" migrants and natives, with students with a migrant mother and a Swiss father being more like migrants than students with a migrant father and a Swiss mother. The results in Table A4 demonstrate that mothers appear to be more important for the formation of school related attitudes than fathers. This finding could partially explain why students with migrant mothers are more like migrants in their educational choices.

³⁵The literature on ethnic choice patterns predicts a strong preference of general education over vocational education (see Tjaden and Hunkler (2017) and Tjaden and Scharenberg (2017) for a discussion of ethnic choice effects in a country with a strong vocational educational system), which we find for first-generation migrants. Second-generation migrants, however, depart from this pattern by displaying an overall higher level of educational aspirations, independent of the type of education.

References

- Abrassart, A., Busemeyer, M. R., Cattaneo, M. A., and Wolter, S. C. (2017). Do migrants prefer academic to vocational education? The role of rational factors vs. social status considerations in the formation of attitudes toward a particular type of education in Switzerland. Economics of Education Working Paper Series 0128.
- Aeberhardt, R., Coudin, É., and Rathelot, R. (2017). The heterogeneity of ethnic employment gaps. *Journal of Population Economics*, 30(1):307–337.
- Almlund, M., Duckworth, A. L., Heckman, J., and Kautz, T. (2011). Personality psychology and economics. *Handbook of the Economics of Education*, 4(1):1–181.
- Bartoš, V., Bauer, M., Chytilová, J., and Matějka, F. (2016). Attention discrimination: Theory and field experiments with monitoring information acquisition. *American Economic Review*, 106(6):1437–1475.
- Bauer, P. and Riphahn, R. T. (2007). Heterogeneity in the intergenerational transmission of educational attainment: evidence from switzerland on natives and second-generation immigrants. *Journal of Population Economics*, 20(1):121–148.
- Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review*, 94(4):991–1013.
- Bettinger, E. P. and Baker, R. B. (2014). The effects of student coaching. Educational Evaluation and Policy Analysis, 36(1):3–19.
- Boockmann, B. and Nielen, S. (2016). Mentoring disadavantaged youths during school-to-work transition: Evidence from Germany. IAW Discussion Papers 123.
- Booth, A. L., Leigh, A., and Varganova, E. (2012). Does ethnic discrimination vary across minority groups? Evidence from a field experiment. Oxford Bulletin of Economics and Statistics, 74(4):547–573.

- Brunello, G. and Winter-Ebmer, R. (2003). Why do students expect to stay longer in college? Evidence from Europe. *Economics Letters*, 80(2):247– 253.
- Fairlie, R. W. (2005). An extension of the Blinder-Oaxaca decomposition technique to logit and probit models. *Journal of Economic and Social Measurement*, 30(4):305–316.
- Fernandez, R. and Fogli, A. (2009). Culture: An empirical investigation of beliefs, work, and fertility. *American Economic Journal: Macroeconomics*, 1(1):146–177.
- Fibbi, R., Lerch, M., and Wanner, P. (2006). Unemployment and discrimination against youth of immigrant origin in Switzerland: When the name makes the difference. *Journal of International Migration and Integration*, 7(3):351–366.
- Fibbi, R., Topgül, C., and Ugrina, D. (2015). The New Second Generation in Switzerland: Youth of Turkish and Former Yugoslav Descent in Zurich and Basel. Amsterdam University Press.
- Flisi, S., Meroni, E. C., and Vera-Toscano, E. (2016). Educational outcomes and immigrant background. JRC Working Papers JRC102629.
- Garibaldi, P., Giavazzi, F., Ichino, A., and Rettore, E. (2011). College cost and time to complete a degree: Evidence from tuition discontinuities. *Review of Economics and Statistics*, 94(3):699–711.
- Goux, D., Gurgand, M., and Maurin, E. (2017). Adjusting your dreams? High school plans and dropout behaviour. *The Economic Journal*, 127(602):1025– 1046.
- Greenspon, J. (2017). The Gap Year: An Overview of the Issues. CSLS Research Reports 2017-01.
- Heckman, J. J. and LaFontaine, P. A. (2010). The American high school graduation rate: Trends and levels. *The Review of Economics and Statistics*, 92(2):244–262.
- Himmler, O., Jaeckle, R., and Weinschenk, P. (2017). Soft commitments, reminders and academic performance. MPRA Paper 76832.

- Hupka-Brunner, S., Sacchi, S., and Stalder, B. E. (2010). Social origin and access to upper secondary education in Switzerland: A comparison of company-based apprenticeship and exclusively school-based programmes. Swiss Journal of Sociology, 36(1):11–31.
- Imdorf, C. (2006). The selection of trainees in small and medium-sized enterprises. Integration and exclusion of immigrant youth at the transitional stage between school and vocational training in Switzerland. In Working Paper presented at the XVI ISA World Congress of Sociology.
- Jaik, K. and Wolter, S. C. (2016). Lost in transition: The influence of locus of control on delaying educational decisions. IZA Discussion Paper 10191.
- Jonsson, J. O. and Rudolphi, F. (2011). Weak performance strong determination: School achievement and educational choice among children of immigrants in Sweden. *European Sociological Review*, 27(4):487.
- Kunz, J. S. (2016). Analyzing educational achievement differences between second-generation immigrants: Comparing Germany and German-speaking Switzerland. *German Economic Review*, 17(1):61–91.
- Kunz, J. S. and Staub, K. E. (2016). Subjective completion beliefs and the demand for post-secondary education. IZA Discussion Paper 10344.
- Laganà, F., Chevillard, J., and Gauthier, J.-A. (2014). Socio-economic background and early post-compulsory education pathways: A comparison between natives and second-generation immigrants in Switzerland. *European Sociological Review*, 30(1):18–34.
- Lang, K., Lehmann, J., and Yeon, K. (2012). Racial discrimination in the labor market: Theory and empirics. *Journal of Economic Literature*, 50(4):959–1006.
- Lang, K. and Manove, M. (2011). Education and labor market discrimination. The American Economic Review, 101(4):1467–1496.
- Lüdemann, E. and Schwerdt, G. (2013). Migration background and educational tracking. Journal of Population Economics, 26(2):455–481.
- Manski, C. F. (1989). Schooling as experimentation: A reappraisal of the postsecondary dropout phenomenon. *Economics of Education Review*, 8(4):305 – 312.

- Mueller, B. and Wolter, S. C. (2014). The role of hard-to-obtain information on ability for the school-to-work transition. *Empirical Economics*, 46(4):1447–1471.
- Schnell, P. and Fibbi, R. (2016). Getting ahead: Educational and occupational trajectories of the 'new' second-generation in Switzerland. Journal of International Migration and Integration, 17(4):1085–1107.
- Swiss Federal Statistical Office (2017). Statistischer Bericht zur Integration der Bevölkerung mit Migrationshintergrund 2017. FSO-Nr. 1722-1700-05.
- Tjaden, J. D. and Hunkler, C. (2017). The optimism trap: Migrants' educational choices in stratified education systems. *Social Science Research*, 67:213 228.
- Tjaden, J. D. and Scharenberg, K. (2017). Ethnic choice effects at the transition into upper-secondary education in Switzerland. Acta Sociologica, 60(4):309–324.
- Vignoles, A. F. and Powdthavee, N. (2009). The socioeconomic gap in university dropouts. The BE Journal of Economic Analysis & Policy, 9(1):1–34.

	(Gap year		Rep	eat/drop	out
	Coef	p value	%	Coef	p value	%
D(dalaa)ti	0.919			0 1 2 0		
P(delay) natives	0.212			0.130		
P(delay) migrant	0.333			0.201		
Difference	-0.121			-0.070		
Total explained	-0.086		71.2	-0.062		87.7
skills	-0.074	0.000	60.9	-0.041	0.000	57.6
demographics	-0.019	0.000	16.0	-0.002	0.621	3.3
regions	0.007	0.000	-5.8	-0.015	0.000	21.2
educational choice				-0.004	0.007	5.9
N of obs	13152			9971		
N natives	9916			7812		
N migrants	3236			2159		

Table A1: Decomposition of the gap

Note: Fairlie decomposition; Coefficients are from the pooled model and the order of the variables is randomly rotated. The results are based on 1000 replications.

(1)	(2)	(3)	(4)
		low skill	high skill
p(GE)	p(Bacc)	p(Bacc)	p(Bacc)
			0.145***
			(0.028)
-0.039***	-0.041^{***}		-0.078***
(0.009)	(0.014)	(0.010)	(0.023)
0.069^{***}	0.086^{***}	0.055^{***}	0.109^{***}
(0.015)	(0.017)	(0.016)	(0.035)
0.106^{***}	0.095^{***}	0.061^{***}	0.138^{***}
(0.020)	(0.023)	(0.015)	(0.040)
0.047**	0.057***	0.042***	0.074^{*}
(0.019)	(0.022)	(0.015)	(0.039)
-0.046***		-0.033**	-0.065**
			(0.028)
			0.125***
			(0.030)
			-0.033
			(0.025)
			0.080***
			(0.014)
	0.003***		0.004***
			(0.001)
· · · ·			0.018*
			(0.010)
	. ,		-0.003
			(0.005)
		· /	-0.028
(0.029)	(0.043)	(0.043)	(0.050)
9.971	9.971	5.196	4,775
	p(GE) 0.091*** (0.017) -0.039*** (0.009) 0.069*** (0.015) 0.106*** (0.020) 0.047** (0.019)	$\begin{array}{c cccc} p(GE) & p(Bacc) \\ \hline 0.091^{***} & 0.086^{***} \\ (0.017) & (0.014) \\ -0.039^{***} & -0.041^{***} \\ (0.009) & (0.014) \\ 0.069^{***} & 0.086^{***} \\ (0.015) & (0.017) \\ 0.106^{***} & 0.095^{***} \\ (0.020) & (0.023) \\ 0.047^{**} & 0.057^{***} \\ (0.019) & (0.022) \\ -0.046^{***} & -0.048^{***} \\ (0.015) & (0.012) \\ 0.160^{***} & 0.087^{***} \\ (0.030) & (0.015) \\ -0.031^{**} & -0.032^{*} \\ (0.014) & (0.019) \\ 0.062^{***} & 0.067^{***} \\ (0.008) & (0.010) \\ 0.003^{***} & 0.003^{***} \\ (0.000) & (0.000) \\ 0.007 & 0.017^{**} \\ (0.005) & (0.008) \\ -0.007^{**} & -0.001 \\ (0.003) & (0.004) \\ -0.098^{***} & -0.037 \\ (0.029) & (0.045) \\ \hline \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

Table A2: Choice of education on upper-secondary level

Note: Average marginal effects from probit regressions. We additionally control for missing values in punctuality, home language, parental education and socioeconomic background, as well as in regional shares. The standard errors are clustered by region, *significant at 10%; **significant at 5%; ***significant at 1%.



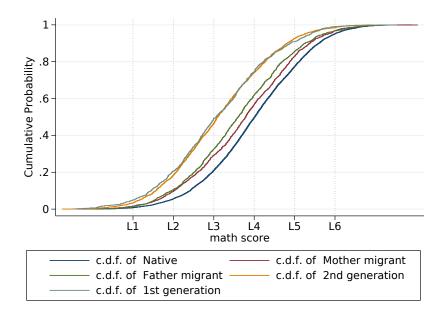
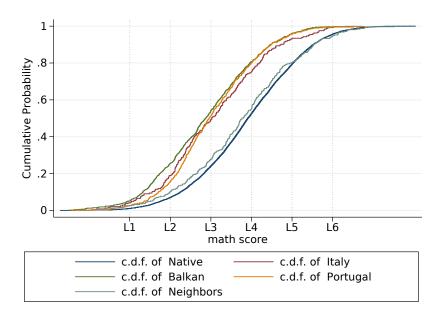


Figure A2: Cumulative distribution of math skills by migration origin



1st generation migrant 2nd generation migrant migrant mother migrant father	$\begin{array}{c} p(\text{Gap year}) \\ \hline 0.125^{***} \\ (0.024) \\ 0.048^{***} \\ (0.013) \\ 0.082^{***} \\ (0.011) \end{array}$	p(delay) 0.043*** (0.016) 0.010 (0.010)	p(Bacc) 0.056** (0.027) 0.113*** (0.010)	VE level 1.018 (0.723) 2.080***
2nd generation migrant migrant mother migrant father	(0.024) 0.048^{***} (0.013) 0.082^{***}	$(0.016) \\ 0.010 \\ (0.010)$	(0.027) 0.113^{***}	(0.723)
2nd generation migrant migrant mother migrant father	(0.024) 0.048^{***} (0.013) 0.082^{***}	$(0.016) \\ 0.010 \\ (0.010)$	(0.027) 0.113^{***}	(0.723)
migrant mother migrant father	0.048*** (0.013) 0.082***	0.010 (0.010)	0.113***	
migrant mother migrant father	(0.013) 0.082^{***}	(0.010)		2.080^{***}
migrant father	0.082***		(0, 0, 1, 0)	
migrant father			(0.010)	(0.361)
-	(0.011)	0.024^{**}	0.045^{***}	0.827^{**}
-		(0.010)	(0.011)	(0.373)
	0.031^{**}	0.008	0.045^{***}	0.131
	(0.016)	(0.008)	(0.015)	(0.532)
migrant, no info	-0.014	-0.009	0.090^{***}	-0.791
	(0.026)	(0.023)	(0.033)	(1.481)
native, one parent	-0.013	0.009	0.004	0.117
	(0.025)	(0.039)	(0.046)	(1.245)
math score	-0.001***	-0.001***	0.003^{***}	0.048^{***}
	(0.000)	(0.000)	(0.000)	(0.003)
home language	0.006	-0.003	-0.045***	-1.179***
	(0.015)	(0.014)	(0.011)	(0.389)
female	0.057***	-0.049***	0.146***	3.354***
	(0.014)	(0.006)	(0.010)	(0.223)
age	-0.022	0.006	-0.033*	-1.290***
-	(0.017)	(0.006)	(0.019)	(0.301)
parents' edu	-0.021**	0.002	0.077***	1.155***
-	(0.009)	(0.007)	(0.011)	(0.209)
HISEI	-0.000	0.000*	0.003***	0.037***
	(0.000)	(0.000)	(0.000)	(0.009)
share GE	-0.019***	0.001	0.015^{*}	0.217
	(0.006)	(0.004)	(0.008)	(0.163)
share VE	-0.006	-0.000	-0.003	-0.043
	(0.004)	(0.001)	(0.004)	(0.108)
German-speaking	-0.075	-0.072***	-0.030	-0.257
I G	(0.058)	(0.019)	(0.044)	(0.879)
Observations	13,152	9,971	9,971	$5,\!620$

Table A3: Different types of migration status

Note: Columns (1) - (3): Average marginal effects from probit regressions, Column(4) coefficients from OLS regression. Migrant mother captures pupils with a migrant mother and a Swiss native father, migrant fathers the opposite. All migration variables are interacted with the PISA math score. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

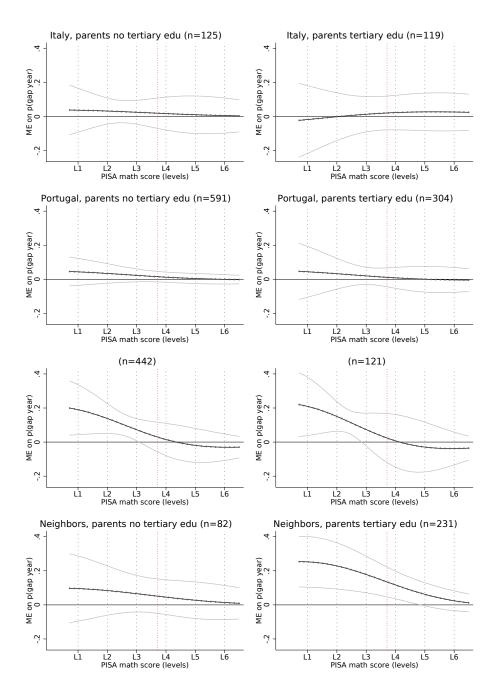


Figure A3: ME of immigration origin on p(gap year)

× × × × × × × ×		$\begin{array}{c} 0.101^{***} \\ 0.027) \\ 0.057^{***} \\ 0.057^{***} \\ 0.013) \\ 0.042^{**} \\ 0.015 \\ 0.042^{**} \\ 0.016) \\ -0.012 \\ 0.046) \\ 0.012 \\ 0.046) \\ 0.012 \\ 0.046) \\ 0.014) \\ 0.048^{***} \\ 0.014) \\ -0.020 \\ 0.016) \\ -0.020 \\ 0.016) \\ -0.149^{***} \end{array}$	$\begin{array}{c} 0.060^{**}\\ 0.023)\\ 0.023)\\ 0.023)\\ 0.020\\ 0.022\\ 0.020\\ 0.022\\ 0.015\\ 0.015\\ 0.013\\ 0.013\\ 0.013\\ 0.013\\ 0.013\\ 0.013\\ 0.011)\\ 0.017^{***}\\ (0.011)\\ 0.047^{***}\\ (0.011)\\ 0.143^{***}\\ (0.012)\\ 0.047^{***}\\ (0.012)\\ 0.015)\end{array}$	$\begin{array}{c} 0.038 \\ 0.038 \\ (0.022) \\ 0.055 \\ (0.015) \\ -0.004 \\ (0.017) \\ -0.001 \\ (0.017) \\ -0.002 \\ (0.012) \\ 0.029 \\ (0.012) \\ 0.022 \\ (0.012) \\ 0.012 \\ 0.012 \\ 0.002 \\ (0.019) \\ -0.035 \\ ** \end{array}$
eration migrant 0.221^{***} 0.248^{***} 0.255^{***} acration migrant 0.040 0.040 0.047 acration migrant 0.027 0.040 0.047 acration migrant 0.213^{***} 0.257^{***} 0.18^{***} 0.027 0.021 0.023 0.043^{*} 0.029^{*} t father 0.021 0.021 0.018^{*} 0.029^{*} t father 0.021 0.021 0.023^{*} 0.023^{*} t n/a 0.021 0.021 0.031^{*} 0.023^{*} t n/a 0.174^{**} 0.206^{***} 0.103^{*} 0.023^{*} t n/a 0.021 0.021 0.031^{*} 0.033^{*} t n/a 0.257^{***} 0.233^{***} 0.233^{***} 0.034^{*} t n/a 0.0221 0.031^{*} 0.033^{*} 0.034^{*} t n/a 0.023^{*} 0.023^{*} 0.034^{*} 0.032^{*} t n/a 0.023^{*} 0.023^{*}		0.101^{***} (0.027) 0.057^{***} (0.013) 0.042^{**} (0.018) -0.015 (0.018) -0.012 (0.020) 0.042^{***} (0.011) 0.069^{***} (0.014) -0.022) 0.061^{****} (0.014) -0.020 0.0149^{****} (0.016) -0.149^{***}	$\begin{array}{c} 0.060^{**} \\ (0.023) \\ 0.089^{***} \\ (0.020) \\ 0.022 \\ (0.015) \\ 0.013 \\ (0.013) \\ 0.013 \\ (0.013) \\ 0.013 \\ (0.013) \\ 0.015 \\ 0.011) \\ 0.047^{***} \\ (0.011) \\ 0.143^{***} \\ (0.012) \\ 0.015 \\ 0.015 \\ 0.015 \\ \end{array}$	$\begin{array}{c} 0.038*\\ (0.022)\\ 0.055***\\ (0.015)\\ -0.004\\ (0.017)\\ -0.001\\ (0.017)\\ -0.002\\ (0.012)\\ 0.029\\ (0.012)\\ 0.002\\ (0.012)\\ 0.012\\ 0.012\\ (0.019)\\ -0.035**\\ (0.016) \end{array}$
acration migrant (0.039) (0.040) (0.047) acration migrant 0.213^{***} 0.257^{***} 0.118^{***} (0.027) (0.023) (0.029) (0.029) t father 0.073^{***} 0.043^{*} 0.029^{***} (1024) 0.021 (0.029) (0.029) t n/a 0.031 0.031 0.015^{*} (1025) (0.021) (0.023) (0.026) (1020) 0.031 0.031 0.032^{*} (1020) 0.071^{*} 0.031^{*} 0.032^{*} (1020) 0.021^{*} 0.031^{*} 0.032^{*} (1020) 0.021^{*} 0.033^{*} 0.033^{*} (1020) 0.021^{*} 0.033^{*} 0.033^{*} (1020) 0.022^{**} 0.033^{*} 0.033^{*} (1020) 0.023^{*} 0.033^{*} 0.033^{*} (1020) 0.023^{*} 0.033^{*} 0.033^{*} $(10011)^{***}$ 0.023^{*} <		(0.027) 0.057*** (0.013) $0.042^{*}*$ (0.018) -0.015 (0.013) -0.012 (0.012) (0.011) $0.069^{*}**$ (0.011) $0.069^{*}**$ (0.011) $0.061^{*}**$ (0.014) -0.020 (0.014) -0.020 (0.016) $-0.149^{*}**$	(0.023) 0.089*** (0.020) 0.022 (0.015) -0.029 (0.013) (0.013) 0.013 (0.013) 0.0117*** (0.010) 0.047*** (0.011) 0.047*** (0.011) 0.143*** (0.015) -0.021) -0.021)	$\begin{array}{c} (0.022)\\ 0.055***\\ (0.015)\\ -0.004\\ (0.017)\\ -0.001\\ (0.017)\\ -0.002\\ (0.012)\\ 0.002\\ (0.012)\\ 0.002\\ (0.017)\\ 0.0135**\\ (0.016)\\ (0.016) \end{array}$
acration migrant 0.213^{***} 0.257^{***} 0.118^{***} it mother 0.073^{***} 0.024 0.023 0.029 it mother 0.073^{***} 0.043^{**} 0.023 0.029^{***} it father 0.071 0.024 0.021 0.029^{***} 0.015^{***} it mother 0.031 0.031 0.031 0.015^{***} 0.015^{***} it m/a 0.174^{**} 0.206^{****} 0.032^{**} 0.032^{***} 0.032^{***} ality 0.020^{***} 0.206^{****} 0.033^{***} 0.033^{***} 0.033^{****} ality 0.020^{***} 0.021^{***} 0.033^{****} 0.033^{****} core 0.020^{****} 0.023^{****} 0.033^{****} 0.033^{*****} ge score 0.049^{*} 0.023^{****} 0.033^{****} 0.033^{****} score 0.041^{*} 0.023^{*} 0.033^{*} 0.033^{*} score 0.041^{*} 0.033^{*} 0.033^{*} 0.033^{*} </td <td></td> <td>0.057*** (0.013) 0.042^{**} (0.018) -0.015 (0.018) -0.015 (0.012) 0.069^{***} (0.011) 0.069^{***} (0.011) 0.061^{***} (0.014) -0.020 0.061^{***} (0.014) -0.020 (0.016) -0.149^{***}</td> <td>0.089*** (0.020) 0.022 (0.015) -0.029 (0.019) 0.013 (0.013) 0.0117*** (0.010) 0.047*** (0.011) 0.047*** (0.011) 0.143*** (0.011) 0.143*** (0.015) -0.100***</td> <td>0.055*** (0.015) -0.004 (0.017) -0.001 (0.015) -0.002 (0.012) 0.002 (0.012) 0.017) 0.0135*** (0.016) (0.016)</td>		0.057*** (0.013) 0.042^{**} (0.018) -0.015 (0.018) -0.015 (0.012) 0.069^{***} (0.011) 0.069^{***} (0.011) 0.061^{***} (0.014) -0.020 0.061^{***} (0.014) -0.020 (0.016) -0.149^{***}	0.089*** (0.020) 0.022 (0.015) -0.029 (0.019) 0.013 (0.013) 0.0117*** (0.010) 0.047*** (0.011) 0.047*** (0.011) 0.143*** (0.011) 0.143*** (0.015) -0.100***	0.055*** (0.015) -0.004 (0.017) -0.001 (0.015) -0.002 (0.012) 0.002 (0.012) 0.017) 0.0135*** (0.016) (0.016)
t mother (0.027) (0.023) (0.029) t father 0.073^{***} 0.043^{*} 0.062^{***} (0.024) (0.021) $(0.015)(1.018)$ 0.031 0.031 0.031 $0.032)(1.018)$ (0.025) (0.031) $(0.032)(1.014^{**}) 0.031 0.032)ality (0.022) (0.071) (0.058)ality (0.020) (0.071) (0.058)(0.020)$ (0.071) $(0.058)(0.021)$ $(0.026)core (0.049) (0.021) (0.026)(0.034)$ $(0.034)ge score (0.041) (0.021) (0.026)(0.033)$ (0.033) $(0.033)(0.033)$ (0.033) $(0.033)anguage (0.041) (0.022) (0.030)0.065^{***} -0.145^{***} -0.133^{****}(0.013)$ (0.023) $(0.033)(0.033)$ (0.033) $(0.033)(0.033)$ (0.033) $(0.032)-0.039anguage (0.018) (0.023) (0.032)(0.018)$ (0.023) $(0.032)(0.018)$ (0.019) $(0.020)(0.018)$ (0.019) $(0.020)(0.010)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ (0.000) (0.000) $(0.000)(0.000)$ (0.000) (0.000) (0.000)		$\begin{array}{c} (0.013)\\ 0.042^{**}\\ (0.018)\\ -0.015\\ 0.020)\\ -0.012\\ (0.020)\\ 0.069^{***}\\ (0.011)\\ 0.046^{***}\\ (0.011)\\ 0.048^{***}\\ (0.014)\\ -0.020\\ -0.020\\ (0.016)\\ -0.149^{***}\\ \end{array}$	(0.020) 0.022 (0.015) -0.029 (0.019) 0.013 (0.010) 0.017 *** (0.010) 0.047 *** (0.011) 0.047 *** (0.011) 0.143 *** (0.012) -0.100 *** (0.015)	$\begin{array}{c} (0.015)\\ -0.004\\ (0.017)\\ -0.001\\ (0.015)\\ -0.002\\ (0.029)\\ 0.079^{***}\\ (0.012)\\ 0.002\\ (0.017)\\ 0.135^{***}\\ (0.019)\\ -0.035^{**}\\ (0.016) \end{array}$
t mother 0.73^{***} 0.043^{*} 0.062^{***} t father 0.031 0.031 0.015 t father 0.031 0.031 0.015 t n/a 0.174^{**} 0.206^{****} 0.089 ality 0.062^{**} 0.071^{**} 0.089 0.174^{***} 0.208^{****} 0.178^{****} 0.020^{***} 0.071^{***} 0.089 core 0.049^{***} 0.021^{***} 0.178^{****} 0.023^{***} 0.026^{****} 0.178^{****} 0.049^{***} 0.021^{***} 0.026^{****} 0.049^{***} 0.021^{***} 0.033^{*} core 0.049^{***} 0.021^{***} 0.033^{*} 0.049^{***} 0.021^{****} 0.033^{****} 0.041^{***} 0.023^{****} 0.033^{****} 0.033^{***} 0.033^{****} 0.033^{****} 0.041^{***} 0.022^{***} 0.033^{****} 0.033^{****} 0.041^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.019^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.010^{***} 0.003^{****} 0.033^{****} 0.033^{****} 0.033^{****} 0.019^{****} 0.019^{****} 0.019^{****} 0.012^{****} 0.000^{****} 0.000^{****} 0.012^{****} 0.000^{****} 0.012^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{*****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{*} 0.000^{****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{*****} 0.000^{******} 0.000^{******} $0.000^{*******}$ $0.000^{*******}$ 0.000		0.042^{**} (0.018) -0.015 (0.020) -0.012 (0.046) 0.069^{***} (0.011) 0.148^{***} (0.014) -0.022 0.061^{***} (0.014) -0.020 (0.016) -0.149^{***}	$\begin{array}{c} 0.022\\ (0.015)\\ -0.029\\ (0.019)\\ 0.013\\ (0.015)\\ 0.117^{***}\\ (0.010)\\ 0.047^{***}\\ (0.011)\\ 0.143^{****}\\ (0.011)\\ 0.143^{****}\\ (0.015)\\ -0.100^{****}\end{array}$	-0.004 (0.017) -0.001 (0.015) -0.002 (0.029) 0.079^{***} (0.012) 0.079^{***} (0.012) 0.0135^{***} (0.016) (0.016)
t father (0.024) (0.021) (0.015) t father 0.031 0.031 0.031 0.015 t n/a 0.174^{**} 0.206^{***} $0.032)$ ality (0.020) (0.071) (0.058) 0.178^{***} 0.069^{***} 0.178^{***} (0.020) (0.021) $(0.056)core 0.363^{***} 0.221^{***} 0.178^{***}0.049)$ (0.021) $(0.026)0.040)$ (0.021) $(0.026)0.040)$ (0.021) $(0.033)score 0.363^{***} 0.221^{***} 0.178^{***}0.041)$ (0.023) $(0.033)0.041)$ (0.022) $(0.033)0.041)$ (0.022) $(0.033)0.029)$ $(0.033)0.041)$ (0.022) $(0.033)0.029)$ (0.023) $(0.033)0.029)$ (0.029) $(0.029)0.018)$ (0.023) $(0.029)0.024^{*} 0.000 (0.0019) (0.020)0.0013$ (0.019) $(0.012)0.024^{***} 0.000 (0.000)0.000$ $0.0020.000$ 0.0000 $(0.000)0.0000$ $0.00020.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 $0.00000.0000$ 0.0000 0.0000 $0.00000.0000$ 0.0000 0.0000 $0.00000.0000$ 0.0000 0.0000 0.0000 0.0000		(0.018) - 0.015 (0.020) - 0.012 (0.046) (0.046) (0.014) (0.014) (0.014) (0.014) (0.014) (0.014) (0.021) -0.020 (0.016) (0.016)	(0.015) -0.029 (0.019) 0.013 (0.015) 0.117*** (0.015) 0.117*** (0.011) 0.047*** (0.011) 0.143*** (0.011) 0.143*** (0.011) 0.015) (0.015) (0.015)	$\begin{array}{c} (0.017)\\ -0.001\\ (0.015)\\ -0.002\\ (0.029)\\ 0.079^{***}\\ (0.012)\\ 0.02\\ 0.012\\ 0.012\\ 0.0135^{***}\\ (0.016)\\ (0.016)\end{array}$
t father 0.031 0.031 0.031 -0.015 t n/a 0.174^{**} 0.206^{***} 0.032 0.174^{**} 0.206^{***} 0.089 ality 0.020 0.071 0.058 0.020 0.071 $0.0580.020$ 0.021 $0.026core 0.363^{***} 0.221^{***} 0.178^{***}0.033core 0.049 0.021 0.021 0.0260.034$ $0.034g score 0.363^{***} 0.221^{***} 0.158^{***}0.040$ 0.023 $0.0330.039$ 0.033 $0.0330.039$ 0.033 $0.0340.033score 0.041 0.022 0.0330.039$ $0.0330.039$ $0.0330.039$ $0.0330.039$ $0.0330.039$ $0.0330.0320.033$ $0.0330.0320.0320.0320.0330.0330.0330.0330.0320.0320.0320.0320.0320.0320.0320.0330.0330.0330.0330.0330.0330.0330.0330.0330.0330.0320.0030.0030.0000.$		-0.015 (0.020) -0.012 (0.046) 0.069*** (0.011) 0.148*** (0.011) 0.061*** (0.014) -0.020 (0.016) -0.149***	-0.029 (0.019) 0.013 (0.015) 0.117*** (0.010) 0.047*** (0.011) 0.047*** (0.011) 0.143*** (0.011) 0.143*** (0.015) -0.0321) -0.032***	-0.001 (0.015) -0.002 (0.029) 0.079*** (0.012) 0.002 (0.012) 0.135^{***} (0.019) -0.035^{**} (0.016)
t n/a (0.025) (0.031) (0.032) t n/a (0.052) (0.071) (0.058) ality (0.062) (0.071) (0.058) (0.050) (0.021) (0.056) core (0.049) (0.021) (0.026) core (0.049) (0.046) (0.034) ge score (0.049) (0.046) (0.034) -0.152^{***} (0.046) (0.033) (0.039) (0.033) (0.038) -0.041 (0.033) (0.038) -0.041 (0.022) (0.030) 0.039 (0.033) (0.039) -0.041 (0.022) (0.030) -0.041 (0.022) (0.039) -0.041 (0.022) (0.039) -0.041 (0.022) (0.030) -0.033 (0.032) -0.044 (0.019) (0.029) -0.018 (0.019) (0.029) -0.000 (0.0019) (0.020) -0.000 (0.0010) (0.000) -0.000 (0.000) (0.000) (0.000) -0.000 (0.000) (0.000) (0.000) -0.000 (0.000) (0.000) (0.000) (0.000) -0.000 (0.000) (0.0		(0.020) -0.012 (0.046) (0.046) (0.011) (0.011) (0.014) (0.014) (0.014) (0.014) (0.016) (0.016) (0.016)	(0.019) 0.013 (0.015) 0.117*** (0.010) 0.047*** (0.011) 0.143*** (0.011) 0.143*** (0.021) -0.100*** (0.015)	$\begin{array}{c} (0.015)\\ -0.002\\ (0.029)\\ 0.079^{***}\\ (0.012)\\ 0.002\\ (0.012)\\ 0.135^{***}\\ (0.019)\\ -0.035^{**}\\ (0.016) \end{array}$
t n/a 0.174^{**} 0.206^{***} 0.089 ality 0.062 (0.071) (0.058) 0.062^{***} 0.069^{***} 0.178^{***} core 0.209^{***} 0.026^{*} 0.178^{***} 0.178^{***} core 0.363^{***} 0.221^{***} 0.178^{***} 0.034^{*} ge score 0.363^{***} 0.221^{***} 0.533^{***} 0.049^{*} (0.046^{*}) (0.034^{*}) (0.034^{*}) score 0.033^{*} (0.033) (0.033) (0.038^{*}) 0.041^{*} (0.033) (0.033) (0.038^{*}) anguage -0.043^{*} 0.191^{***} -0.145^{***} -0.145^{***} 0.011^{*} (0.022) (0.029) (0.029) anguage -0.062^{**} -0.053^{*} -0.194^{***} -0.194^{***} 0.018^{*} (0.019) (0.022) (0.029) 0.024^{*} 0.030^{*} 0.019^{*} (0.012^{*}) 0.000^{*} -0.000^{**} -0.000^{**} 0.000^{*} -0.000^{**} -0.000^{**} -0.000^{**}		-0.012 (0.046) (0.046) (0.011) (0.011) (0.014) (0.014) (0.014) (0.014) (0.021) (0.021) (0.016) (0.016) (0.016)	$\begin{array}{c} 0.013\\ (0.015)\\ 0.117^{***}\\ (0.010)\\ 0.047^{***}\\ (0.011)\\ 0.143^{****}\\ (0.021)\\ -0.100^{****}\\ (0.015)\\ -0.032^{****}\end{array}$	-0.002 (0.029) 0.079^{***} (0.012) 0.002 (0.012) 0.135^{***} (0.019) -0.035^{**} (0.016)
ality (0.062) (0.071) (0.058) ality (0.200) (0.021) (0.058) core (0.200) (0.021) (0.026) (0.020) (0.021) $(0.026)ge score (0.049) (0.046) (0.034)= 0.152^{***} -0.154^{***} -0.263^{***} -0.133)score (0.041) (0.033) (0.033) (0.033)= 0.041)$ (0.022) (0.033) $(0.033)anguage -0.062^{**} -0.191^{***} -0.145^{***} -0.139= 0.041)$ (0.022) $(0.030)= 0.041)$ (0.022) $(0.030)= 0.041)$ (0.022) $(0.030)= 0.033)$ (0.033) $(0.033)= 0.030$ $(0.033)= 0.030$ $(0.032)= 0.030$ (0.023) $(0.032)= 0.030$ $(0.032)= 0.030$ $(0.032)= 0.019$ $(0.023)(0.019)$ $(0.020)= 0.000$ (0.000) $(0.000)= 0.000$ (0.000) $(0.000)= 0.000$ (0.000) (0.000) $(0.000)= 0.000$ (0.000) (0.000) $(0.000)= 0.000$ (0.000) (0.000) (0.000) $(0.000)= 0.000$ (0.000) (0.000) (0.000) $(0.000)= 0.002$ (0.000) (0.000) (0.000) (0.000) (0.000) (0.000) $(0.000)= 0.002$ (0.000) $(0$		(0.046) 0.069*** (0.011) 0.148*** (0.012) 0.061*** (0.014) -0.094*** (0.021) -0.020 (0.016) -0.149***	(0.015) 0.117*** (0.010) 0.047*** (0.011) 0.143*** (0.013) 0.143*** (0.021) -0.100***	$\begin{array}{c} (0.029)\\ 0.079^{***}\\ (0.012)\\ 0.002\\ (0.017)\\ 0.135^{***}\\ (0.019)\\ -0.035^{**}\\ (0.016)\end{array}$
ality 0.209^{***} 0.069^{***} 0.178^{***} 0.78^{***} 0.020) (0.021) (0.026) core 0.363^{***} 0.221^{****} 0.533^{***} 0.533^{***} 0.333 ge score 0.363^{***} 0.146) (0.034) (0.034) ge score 0.049) (0.046) (0.033) (0.033) score 0.041) (0.033) (0.033) (0.038) anguage 0.041) (0.022) (0.030) 0.041) (0.022) $(0.030)anguage -0.062^{**} -0.191^{***} -0.145^{***} -0.133(0.030)anguage 0.062^{**} -0.239^{***} -0.194^{***} -0.039(0.029)$ (0.029) $(0.029)0.067^{***} 0.030 0.084^{***} -0.194^{***} -0.0320.067^{***} 0.030 0.084^{***} -0.1020.000 0.002^{***} -0.0000.000 0.002^{***} -0.0000.000$ 0.0000 0.0000 $-0.0000.000$ 0.0000 0.0000 $-0.0000.0000$ 0.0000 0.0000 0.0000 -0.000		0.069^{***} (0.011) 0.148^{***} (0.022) 0.061^{***} (0.014) -0.094^{***} (0.021) -0.020 (0.016) -0.149^{***}	$\begin{array}{c} 0.117^{***} \\ (0.010) \\ 0.047^{***} \\ (0.011) \\ 0.143^{***} \\ (0.021) \\ -0.100^{***} \\ (0.015) \\ -0.032^{***} \end{array}$	$\begin{array}{c} 0.079^{***} \\ (0.012) \\ 0.002 \\ (0.017) \\ 0.135^{***} \\ (0.019) \\ -0.035^{**} \end{array}$
core (0.020) (0.021) (0.025) core $0.363***$ $0.221***$ $0.533***$ $0.533***$ ge score 0.049 (0.046) (0.034) 0.034 ge score $0.152***$ $-0.154***$ $0.533***$ 0.034 score 0.043 0.041 (0.033) 0.033 score 0.041 0.033 0.033 0.038 anguage 0.041 (0.022) (0.033) 0.033 anguage 0.041 (0.022) (0.033) 0.033 anguage 0.041 (0.022) (0.033) 0.033 anguage $-0.062**$ -0.039 (0.039) 0.030 0.018 (0.023) (0.024) (0.024) 0.032 0.018 (0.019) (0.021) (0.020) (0.020) 0.021 0.0223 (0.024) (0.020) (0.020) 0.018 (0.019) (0.023) (0.020) $(0.$		$\begin{array}{c} (0.011)\\ 0.148^{***}\\ (0.022)\\ 0.061^{***}\\ (0.014)\\ -0.094^{***}\\ (0.021)\\ -0.020\\ (0.016)\\ -0.149^{***}\end{array}$	(0.010) 0.047*** (0.011) 0.143*** (0.021) -0.100*** (0.015)	$\begin{array}{c} (0.012)\\ 0.002\\ (0.017)\\ 0.135**\\ (0.019)\\ -0.035**\\ (0.016)\end{array}$
core 0.363^{***} 0.221^{***} 0.533^{***} 0.533^{***} 0.533^{***} 0.046 (0.046) (0.034) ge score 0.152^{***} -0.154^{***} 0.263^{****} -0.263^{****} -0.046 (0.033) (0.038) score 0.0413 0.191^{****} -0.263^{****} -0.145^{****} -0.039 anguage 0.0411 (0.022) (0.030) 0.0411 (0.022) (0.039) $(0.039)0.0110^{***} -0.053^{**} -0.145^{****} -0.194^{****} -0.110^{****} -0.123^{****} -0.194^{****} -0.110^{****} -0.239^{****} -0.194^{****} -0.012 (0.029) 0.024^{**} 0.019) (0.020) (0.020)0.024^{**} 0.030 0.024^{****} -0.000 0.024^{****} -0.000 0.024^{****} -0.000 0.022^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.002^{****} -0.000 0.000^{****} -0.000 0.000^{****} -0.000 0.000^{****} -0.000^{*****} -0.000^{******} -0.000^{******} -0.000^{*****} -0.000^{******}$		$\begin{array}{c} 0.148^{***} \\ (0.022) \\ 0.061^{***} \\ (0.014) \\ -0.094^{***} \\ (0.021) \\ -0.020 \\ (0.016) \\ -0.149^{***} \end{array}$	0.047*** (0.011) 0.143*** (0.021) -0.100*** (0.015) -0.032***	$\begin{array}{c} 0.002 \\ (0.017) \\ 0.135^{***} \\ (0.019) \\ -0.035^{**} \end{array}$
ge score (0.049) (0.046) (0.034) ge score -0.152^{***} -0.154^{***} -0.263^{***} -0.263^{***} score (0.039) (0.033) (0.038) 0.041) (0.022) $(0.030)0.0411)$ (0.022) $(0.030)0.029)$ (0.022) $(0.030)0.029)$ (0.029) $(0.029)-0.110^{***} -0.239^{***} -0.194^{***}(0.018)$ (0.023) $(0.029)0.018)$ (0.023) $(0.029)0.024^{*} 0.030 0.084^{***}(0.018)$ (0.019) $(0.020)0.024^{*} 0.080^{***} 0.012(0.018)$ (0.019) $(0.020)0.000 0.002^{***} -0.0000.000 0.002^{***} -0.0000.000 0.002^{***} -0.0000.000 0.002^{***} -0.0000.000 0.0002^{***} -0.0000.000 0.0002^{***} -0.000$		(0.022) 0.061^{***} (0.014) -0.094^{***} (0.021) -0.020 (0.016) -0.149^{***}	(0.011) 0.143*** (0.021) -0.100*** (0.015) -0.032***	(0.017) 0.135*** (0.019) -0.035** (0.016)
ge score $-0.152^{***} -0.154^{***} -0.263^{***} -0.263^{***}$ score $0.043 0.191^{***} -0.263^{***} -0.145^{***} -0.043 0.033 (0.038)$ score $0.041 0.022 (0.033) (0.030)$ anguage $-0.062^{**} -0.053^{*} -0.039 (0.039) (0.029) (0.029) (0.029) (0.029) (0.029) (0.029) (0.029) (0.018) (0.018) (0.029) (0.029) (0.020) (0.020) (0.018) (0.019) (0.020) (0.020) (0.020) (0.012) (0.018) (0.019) (0.020) (0.020) (0.020) (0.012) (0.013) (0.012) (0.013) (0.020) (0.020) (0.000) (0$		0.061*** (0.014) -0.094^{***} (0.021) -0.020 (0.016) -0.149^{***}	$\begin{array}{c} 0.143^{***} \\ (0.021) \\ -0.100^{***} \\ (0.015) \\ -0.032^{***} \end{array}$	0.135^{***} (0.019) -0.035^{**} (0.016)
score (0.039) (0.033) (0.033) score -0.043 $0.191***$ $-0.145***$ $-0.145***$ -0.043 $0.041)$ (0.022) (0.030) anguage $-0.062**$ $-0.053*$ -0.039 (0.039) (0.029) (0.029) (0.029) $-0.039-0.110**** -0.239**** -0.194*** -0.194*** -0.104** -0.239**** -0.194*** -0.124** 0.012 (0.012) (0.020) (0.020) 0.024^{*} 0.012 (0.012) (0.020) 0.024^{*} 0.012 (0.012) (0.012) 0.020 0.024^{*} -0.000 0.024^{*} -0.000 0.022 (0.012) -0.012 (0.013) 0.0012 (0.013) (0.015) (0.018) (0.012) 0.012 -0.000 0.002 *** -0.000 0.002 *** -0.000 0.002 *** -0.000 0.000 \times *** -0.000 0.000$		(0.014) - 0.094^{***} (0.021) - 0.020 (0.016) - 0.149^{***}	(0.021) -0.100*** (0.015) -0.032***	(0.019) -0.035** (0.016)
score -0.043 0.191^{***} -0.145^{***} -0.145^{***} -0.0622^{**} 0.030^{*} 0.030^{*} 0.030^{*} 0.030^{*} 0.029^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.039^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.029^{*} 0.020^{*} 0.020^{*} 0.020^{*} 0.020^{*} 0.020^{*} 0.020^{*} 0.020^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.012^{*} 0.000^{*} $0.$		-0.094^{***} (0.021) -0.020 (0.016) -0.149^{***}	-0.100*** (0.015) -0.032***	-0.035^{**} (0.016)
anguage (0.041) (0.022) (0.030) -0.062^{**} -0.053^{*} -0.039 (0.029) (0.026) $(0.029)-0.110^{***} -0.239^{***} -0.194^{***}(0.018)$ (0.023) $(0.032)(0.032)0.067^{***} 0.030 0.084^{***}(0.013)$ (0.019) $(0.020)(0.013)$ (0.019) $(0.020)(0.013)$ (0.015) $(0.018)(0.013)$ (0.015) $(0.018)(0.013)$ (0.015) $(0.018)(0.013)$ (0.015) $(0.018)(0.013)$ (0.015) $(0.018)(0.000)$ $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ $(0.000)(0.000)$ $(0.000)(0.000)$ $(0.000)($	·	(0.021) -0.020 (0.016) -0.149***	(0.015) -0.032***	(0.016)
anguage -0.062^{**} -0.053^{*} -0.039 0.029 (0.026) $(0.029)-0.110^{***} -0.239^{***} -0.194^{****}(0.018)$ (0.023) $(0.023)0.067^{***} 0.030 0.032^{****}(0.018)$ (0.023) $(0.020)0.024^{**} 0.030 (0.020)(0.013)$ (0.019) $(0.020)0.024^{***} 0.030^{****} 0.012(0.013)$ (0.015) $(0.018)0.000 0.002^{****} -0.000(0.000)$ $(0.000)(0.000)$ (0.000) $(0.000)(0.000)$ $(0.000)TE$ -0.002 $-0.012(0.003)$ (0.008) $(0.009)TE$ -0.000 -0.002 -0.012	·	-0.020 (0.016) -0.149^{***}	-0.032^{***}	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	·	(0.016) -0.149***		-0.033^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		-0.149^{***}	(0.010)	(0.011)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			0.052^{***}	-0.049^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.019)	(0.014)	(0.012)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		0.013	0.008	0.005
s' edu 0.024^* 0.080^{***} 0.012 (0.013) (0.015) $(0.018)0.000 0.002^{****} -0.0003.E$ -0.003 -0.002 $-0.012(0.008)$ (0.008) $(0.009)0.003$ -0.002 $-0.0120.000$ -0.002 -0.003	(0.020) (0.017)	(0.010)	(0.001)	(0.010)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.012 -0.007	-0.035***	0.024	-0.001
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	(0.018) (0.018)	(0.008)	(0.015)	(0.010)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.000 -0.001**	-0.001^{**}	-0.001^{***}	-0.000
$\begin{array}{rcrc} -0.003 & -0.002 & -0.012 \\ (0.008) & (0.008) & (0.009) \\ -0.000 & -0.003 & -0.003 \end{array}$	(0.000) (0.001)	(0.00)	(0.00)	(0.000)
(0.008) (0.008) $(0.009)-0.000 -0.003 -0.003$	-0.012 -0.012	-0.005	-0.007*	-0.006**
	(0.009) (0.008)	(0.006)	(0.003)	(0.003)
	-0.003 -0.002	-0.001	-0.003^{*}	-0.002
(0.005) (0.005)		(0.003)	(0.002)	(0.002)
German-speaking 0.126*** -0.014 -0.152*** -0.179 ³	152*** -0.179***	-0.010	-0.033^{**}	0.041^{***}
(0.038) (0.031)		(0.025)	(0.014)	(0.012)
Constant $1.931^{***} 3.110^{***} 1.404^{**} 2.776^{**}$	$.404^{**}$ 2.776^{***}	3.150^{***}	3.430^{***}	3.305^{***}
(0.395) (0.547) (0.577) (0.53)	(0.577) (0.533)	(0.279)	(0.195)	(0.174)
Observations 8.552 8.510 8.538 8.56	8.538 8.563	8.474	8.406	8.434
		0.005	0.001	0.077
IX-squared 0.128 0.173 0.1749 0.085 0.091 0.077	0.173 0.149	0.000	160.0	0.011

Table A4: Pupils' attitudes towards math and school

(1)	(2)	(3)	(4)
p(Gap year)	p(delay)	p(Bacc)	VE level
0.127^{***}	0.061^{**}	0.017	1.760
(0.043)	(0.025)	(0.045)	(1.560)
0.119^{***}	0.046	0.028	-0.356
(0.034)	(0.034)	(0.031)	(0.694)
0.063	0.033	0.042	2.746^{**}
(0.043)	(0.028)	(0.030)	(1.184)
0.051^{***}	0.022	0.130^{***}	1.676^{***}
(0.017)	(0.014)	(0.016)	(0.485)
0.155^{***}	0.087	-0.010	-0.616
(0.048)	(0.054)	(0.039)	(1.651)
0.073^{***}	0.027^{**}	0.046^{***}	0.997^{**}
(0.014)	(0.011)	(0.010)	(0.375)
0.069^{**}	0.024	-0.012	1.074
(0.033)	(0.047)	(0.034)	(1.667)
0.028^{*}	0.011	0.050^{***}	0.040
(0.017)	(0.008)	(0.017)	(0.540)
$13,\!152$	$9,\!971$	9,971	$5,\!620$
			0.208
0.102	0.106	0.354	
	$\begin{array}{c} p(\text{Gap year})\\ \hline 0.127^{***}\\ (0.043)\\ 0.119^{***}\\ (0.034)\\ 0.063\\ (0.043)\\ 0.051^{***}\\ (0.017)\\ 0.155^{***}\\ (0.014)\\ 0.069^{**}\\ (0.014)\\ 0.069^{**}\\ (0.033)\\ 0.028^{*}\\ (0.017)\\ 13,152\\ 0.102\\ \end{array}$	$\begin{array}{c cccc} p(Gap \ year) & p(delay) \\ \hline p(Gap \ year) & p(delay) \\ \hline 0.127^{***} & 0.061^{**} \\ \hline (0.043) & (0.025) \\ \hline 0.119^{***} & 0.046 \\ \hline (0.034) & (0.034) \\ \hline 0.063 & 0.033 \\ \hline (0.043) & (0.028) \\ \hline 0.051^{***} & 0.022 \\ \hline (0.017) & (0.014) \\ \hline 0.155^{***} & 0.087 \\ \hline (0.048) & (0.054) \\ \hline 0.073^{***} & 0.027^{**} \\ \hline (0.014) & (0.011) \\ \hline 0.069^{**} & 0.024 \\ \hline (0.033) & (0.047) \\ \hline 0.028^{*} & 0.011 \\ \hline (0.017) & (0.008) \\ \hline 13,152 & 9,971 \\ \hline \end{array}$	$\begin{array}{c cccccc} p(Gap \ year) & p(delay) & p(Bacc) \\ \hline p(Gap \ year) & p(delay) & p(Bacc) \\ \hline 0.127^{***} & 0.061^{**} & 0.017 \\ \hline (0.043) & (0.025) & (0.045) \\ 0.119^{***} & 0.046 & 0.028 \\ \hline (0.034) & (0.034) & (0.031) \\ 0.063 & 0.033 & 0.042 \\ \hline (0.043) & (0.028) & (0.030) \\ 0.051^{***} & 0.022 & 0.130^{***} \\ \hline (0.017) & (0.014) & (0.016) \\ 0.155^{***} & 0.087 & -0.010 \\ \hline (0.048) & (0.054) & (0.039) \\ 0.073^{***} & 0.027^{**} & 0.046^{***} \\ \hline (0.014) & (0.011) & (0.010) \\ 0.069^{**} & 0.024 & -0.012 \\ \hline (0.033) & (0.047) & (0.034) \\ 0.028^{*} & 0.011 & 0.050^{***} \\ \hline (0.017) & (0.008) & (0.017) \\ \hline 13,152 & 9,971 & 9,971 \\ \hline 0.102 & 0.106 & 0.354 \\ \hline \end{array}$

Table A5: AME of migration by status and language spoken at home

Note: Columns (1) - (3): Average marginal effects from probit regressions, Column(4) coefficients from OLS regression. Same language denotes that the pupil speaks the school language at home, other language that a different language is spoken. Migrant mother captures pupils with a migrant mother and a Swiss native father, migrant fathers the opposite. We also include dummies for missing migration information on the pupil or one or both of the parents. We interact all migration variables with the PISA math score and add control variables on demographics and socioeconomic background control and regional controls, as explained in Table 2. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

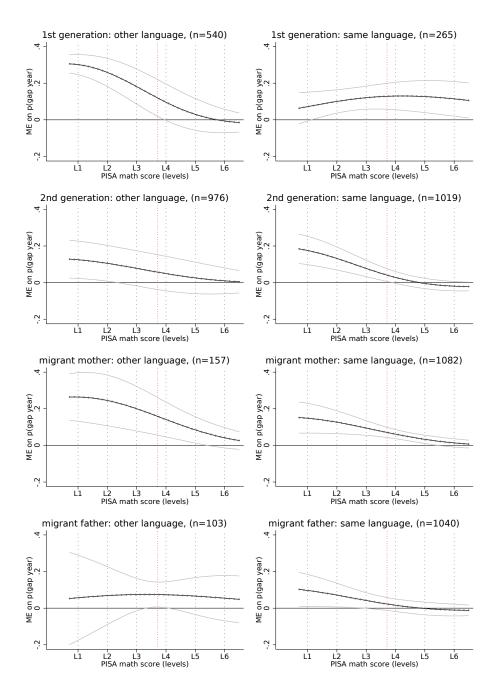


Figure A4: ME of migration by status and language spoken at home

VARIABLES $p(Gap year)$ $p(delay)$ $p(Bacc)$ VE level1. wave; other language-0.0110.0010.041 3.610^{***} (0.065)(0.038)(0.031)(1.272)1. wave; same language0.0250.071^{**}0.014-0.169(0.038)(0.029)(0.044)(1.572)2. wave Balkan; other language0.0260.0230.019 2.344^{***} (0.025)(0.029)(0.023)(0.741)2. wave Balkan; same language0.0080.0250.168^{***} 2.570^{***} (0.021)(0.027)(0.021)(0.677)2. wave Portugal; other language0.032-0.000-0.003 2.180 (0.035)(0.019)(0.029)(1.425)2. wave Portugal; same language0.058^{***}-0.0180.117^{***} 2.301^{**} (0.022)(0.017)(0.030)(0.973)3. wave; other language0.125^{**}0.0220.0540.711(0.063)(0.038)(0.043)(0.956)3. wave; same language0.086*0.0240.039-1.680(0.050)(0.032)(0.041)(1.118)		(1)	(2)	(3)	(4)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	VARIABLES	p(Gap year)	p(delay)	p(Bacc)	VE level
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$					
1. wave; same language 0.025 0.071^{**} 0.014 -0.169 (0.038)(0.029)(0.044)(1.572)2. wave Balkan; other language 0.026 0.023 0.019 2.344^{***} (0.025)(0.029)(0.023)(0.741)2. wave Balkan; same language 0.008 0.025 0.168^{***} 2.570^{***} (0.021)(0.027)(0.021)(0.677)2. wave Portugal; other language 0.032 -0.000 -0.003 2.180 (0.035)(0.019)(0.029)(1.425)2. wave Portugal; same language 0.058^{***} -0.018 0.117^{***} 2.301^{**} (0.022)(0.017)(0.030)(0.973)3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063)(0.038)(0.043)(0.956)3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050)(0.050)(0.032)(0.041)(1.118)	1. wave; other language	-0.011	0.001	0.041	3.610^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.065)	(0.038)	(0.031)	(1.272)
2. wave Balkan; other language 0.026 0.023 0.019 2.344^{***} (0.025) (0.029) (0.023) (0.741) 2. wave Balkan; same language 0.008 0.025 0.168^{***} 2.570^{***} (0.021) (0.027) (0.021) (0.677) 2. wave Portugal; other language 0.032 -0.000 -0.003 2.180 (0.035) (0.019) (0.029) (1.425) 2. wave Portugal; same language 0.058^{***} -0.018 0.117^{***} 2.301^{**} (0.022) (0.017) (0.030) (0.973) 3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063) (0.038) (0.043) (0.956) 3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050) (0.032) (0.041) (1.118)	1. wave; same language	0.025	0.071^{**}	0.014	-0.169
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.038)	(0.029)	(0.044)	(1.572)
2. wave Balkan; same language 0.008 0.025 0.168^{***} 2.570^{***} (0.021) (0.027) (0.021) (0.677) 2. wave Portugal; other language 0.032 -0.000 -0.003 2.180 (0.035) (0.019) (0.029) (1.425) 2. wave Portugal; same language 0.058^{***} -0.018 0.117^{***} 2.301^{**} (0.022) (0.017) (0.030) (0.973) 3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063) (0.038) (0.043) (0.956) 3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050) (0.032) (0.041) (1.118)	2. wave Balkan; other language	0.026	0.023	0.019	2.344^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.025)	(0.029)	(0.023)	(0.741)
2. wave Portugal; other language 0.032 -0.000 -0.003 2.180 (0.035)(0.019)(0.029) (1.425) 2. wave Portugal; same language 0.058^{***} -0.018 0.117^{***} 2.301^{**} (0.022)(0.017)(0.030)(0.973)3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063)(0.038)(0.043)(0.956)3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050)(0.032)(0.041)(1.118)	2. wave Balkan; same language	0.008	0.025	0.168^{***}	2.570^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.021)	(0.027)	(0.021)	(0.677)
2. wave Portugal; same language 0.058^{***} -0.018 0.117^{***} 2.301^{**} (0.022) (0.017) (0.030) (0.973) 3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063) (0.038) (0.043) (0.956) 3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050) (0.032) (0.041) (1.118)	2. wave Portugal; other language	0.032	-0.000	-0.003	2.180
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.035)	(0.019)	(0.029)	(1.425)
3. wave; other language 0.125^{**} 0.022 0.054 0.711 (0.063) (0.038) (0.043) (0.956) 3. wave; same language 0.086^{*} 0.024 0.039 -1.680 (0.050) (0.050) (0.032) (0.041) (1.118)	2. wave Portugal; same language	0.058^{***}	-0.018	0.117^{***}	2.301^{**}
(0.063) (0.038) (0.043) (0.956) (0.086^*) (0.024) (0.039) (-1.680) (0.050) (0.032) (0.041) (1.118)		(0.022)	(0.017)	(0.030)	(0.973)
3. wave; same language 0.086^* 0.024 0.039 -1.680 (0.050) (0.032) (0.041) (1.118)	3. wave; other language	0.125^{**}	0.022	0.054	0.711
(0.050) (0.032) (0.041) (1.118)		(0.063)	(0.038)	(0.043)	(0.956)
	3. wave; same language	0.086^{*}	0.024	0.039	-1.680
Observations 12,152 0,071 0,071 5,620		(0.050)	(0.032)	(0.041)	(1.118)
Observations $15,152$ $9,971$ $9,971$ $5,020$	Observations	13,152	9,971	9,971	5,620
R-squared 0.211	R-squared		·	,	,
Pseudo R-squared 0.0985 0.0847 0.356	Pseudo R-squared	0.0985	0.0847	0.356	

Table A6: AME of migration wave and language spoken at home

Note: Columns (1) - (3): Average marginal effects from probit regressions, Column(4) coefficients from OLS regression. Same language denotes that the pupil speaks the school language at home, other language that a different language is spoken. Migrant mother captures pupils with a migrant mother and a Swiss native father, migrant fathers the opposite. We also include dummies for other countries of origin and country of origin missing. We interact all migration variables with the PISA math score and add control variables on demographics and socioeconomic background control and regional controls, as explained in Table 2. The standard errors are clustered by region, * significant at 10%; **significant at 5%; ***significant at 1%.

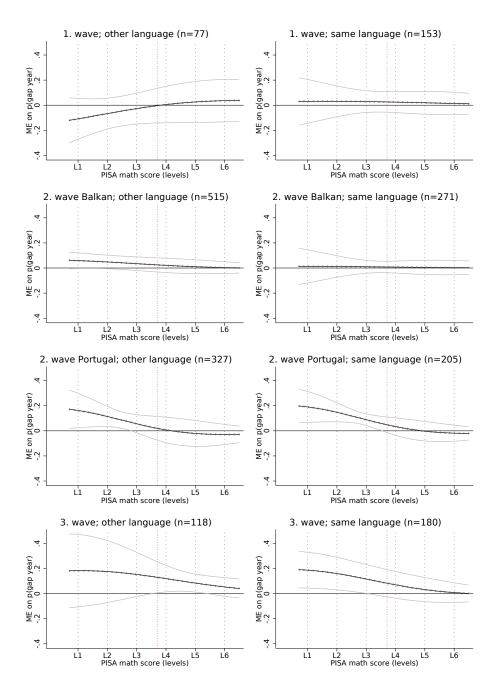


Figure A5: ME of migration wave and language spoken at home