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THE EFFECTS OF KINDERGARTEN ENTRY AGE ON EDUCATIONAL MOBILITY IN SWITZERLAND

Comparing Effects on Natives and Immigrants

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ABSTRACT

Kilian Goffinet: The Effects of Kindergarten Entry Age on Educational Mobility in Switzerland: Comparing Effects on Natives and Immigrants
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Social and educational immobility are well-known issues that many researchers from different fields tried to address. Public schools can play an important role to reduce inequalities in society. The objective of this paper is to measure the importance of the age of entry in kindergarten on educational mobility in Switzerland, with a special focus on immigrants. To investigate this topic, I used a multiple linear regression model and the COFO-Suisse database. The latter gathers test scores in reading and multiple personal characteristics on about 20'000 Swiss children at the end of eighth grade in 2017. I could also take advantage of the cantonal heterogeneities in terms of age of entry in kindergarten in the period 2008-2010, which contributed to creating a well-dispersed sample.

There are three main conclusions to draw. Firstly, the parental level of education significantly impacts the test scores in reading of all the children, confirming the expected pattern of intergenerational educational transmission.

Secondly, the ideal age of entry in kindergarten seems to be five years old. The children who entered at that age perform significantly better than any other child.

Finally, frequenting kindergarten at any age does not significantly reduce the effect of the parental level of education on children's test scores. Thus, the age of entry is not of major importance to improve educational mobility, though the tendency is globally positive. The impact is more pronounced for natives than for immigrants.

Keywords: educational mobility, kindergarten, age of entry, immigrants, ECEC

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Summary

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List of Abbreviations

BLUE — "Best Linear Unbiased Estimator". According to the Gauss-Markov theorem, the OLS (ordinary least squares) model is the best linear unbiased estimator if some specific conditions presented in this paper are satisfied.

COFO-Suisse — This is the French name of the program of evaluation of the core competencies of Swiss pupils of the Swiss Conference of Cantonal Ministers of Education (EDK). COFO is the abbreviation of "compétences fondamentales" (my traduction: core competencies). ÜGK in German.

ECEC — Early Childhood Education and Care. Sometimes also referred ECCE, Early Childhood Care and Education, this abbreviation refers to any care or educational program for children from birth to eight years old (UNESCO, 2010).

PISA — Program for International Student Assessment conducted by the OECD to evaluate educational systems around the world.

SES — Socioeconomic status

X — Vector of explanatory and control variables sometimes used to simplify the lecture of the document

Introduction

Education is a major factor for the well-being and the equity of a society. It represents also generally a big part of the budget in a nation. It is necessary to improve the efficiency of the resources to allow social mobility and give everyone a good start in life, no matter the socioeconomic status of the parents.

The concept of social mobility, related to social classes is wide and historically very diverse. Economists and sociologists have been working on the subject for many decades.

The starting point of the thesis was the PISA 2018 ranking. Switzerland is a well-known country in terms of tertiary education, but the scores of the overall population of fifteen years old are not as impressive.

In the 2018 PISA study (The Federal Council, 2019), Swiss teenagers were, as in the previous reports, very good at mathematics, but around the OECD average for sciences and reading. The latter worsened between 2015 and 2018 and needs to be improved, according to Swiss cantons and teachers (ATS, 2019). Part of the response for these unsatisfactory scores may be the large number of immigrants in Switzerland, as their scores are poorer than natives'.

The strategy is to measure the effect of the parental level of education and the age of entry in kindergarten on the test scores of the children in Switzerland in a first step. Then, I will evaluate the mutual dependency of these factors to see if the age of entry is a key element to improve educational mobility. The identification strategy relies on multiple linear regressions with and without interaction terms.

To reach this objective, I used the database of COFO-Suisse 2017. COFO-Suisse carried out a study to evaluate the performance of Swiss pupils of HarmoS eighth grade (about twelve years old) in reading and other language-related subjects. The children were chosen randomly following a strict procedure to create a reliable and representative sample of the population for every region. The database of 2017 contains many individual, cantonal and outcome variables that allow a strong validity of the model.

In the first part of this paper, we will start with a brief presentation of the Swiss educational context and a literature review. Through the latter, I will first describe what seems to be the main determinants of the effectiveness of ECEC institutions, with a special focus on disadvantaged children. Then, I will determine what the role of the age of entry is on the efficiency of such programs. Finally, I will connect these factors specifically to educational mobility.

In the second part, I will expose my identification strategy, namely the models that I used to identify the causal effects of the parental level of education and the age of entry on test scores and educational mobility.

The data used in the different regressions and some descriptive statistics are developed in the third section while the fourth and last part gathers the tables and interpretations of the empirical results.

1 Context and Literature Review

The school system in Switzerland is delegated to the cantons and municipalities, which tends to some disparities between them like the age of entry in an elementary educational institution. Approved in 2006 and implemented progressively in some cantons from 2009, the HarmoS concordat planned to harmonize the age of entry and the duration of kindergarten. This is currently ongoing but as the COFO-Suisse database includes children of HarmoS eighth grade, these children began kindergarten approximately between 2008-2010. In this period, there were still important disparities in the preschool organization across cantons. This heterogeneity represents a good opportunity to evaluate the impact of age of entry on educational mobility.

The literature on this specific subject is not very broad. However, there exists much literature on the effects of ECEC programs and the age of entry in such institutions on educational outcomes. Much information has been found in the meta-analysis of van Huizen & Plantenga (2018).

ECEC can concern any program of education and/or care for children aged between zero and eight years old. It is not always referring to the exact same kind of institution as kindergarten in Switzerland. However, this will be helpful to have an overview of what seems to work or not in terms of education for those kids, with a special focus on disadvantaged children.

1.1 Impacts of ECEC on Educational Outcomes

Intuitively, we could expect that any education program should serve educational interests. Thus ECEC should be beneficial to the children that frequent it in terms of schooling achievements.

Doyle, Harmon, Heckman & Tremblay (2009) and Attanasio (2015) demonstrated that the early years of life are very important for the development of the child. The earlier we stimulate the brain of the child, the better outcomes we should observe.

This intuition and neuroscientific arguments are also empirically confirmed. First of all, some studies demonstrated the effects in the short run. For example, Bartik (2013) found statistically significant effects of a half-day pre-kindergarten program on kindergarten test scores in Michigan, USA. The results are very high in mathematics but smaller in languages. Magnuson, Lahaie & Waldfogel (2006) found that attending preschool was beneficial in maths and reading test scores later in school. Melhuish et al. (2015), Ulferts & Anders (2016) and Pagnosin, Armi & Matei (2016) found similar results.

In the long term, Fessler & Schneebaum (2019) recognize ECEC as a key ingredient for later economic success. Through their study, they show strong and positive impacts of preschool attendance on later educational attainments. Delalibera & Ferreira (2018) show also a positive significant relation between ECEC and higher educational attainments. Carneiro & Ginja (2014), Deming (2009), Ludwig & Miller (2007), McCoy et al. (2017) draw similar conclusions.

Some other authors observe an attenuation (Elango et al. (2015), Camilli et al. (2010), Leak et al. (2010)) or disappearance of the effects (Puma, Bell, Cook, & Heid (2010, 2012)). For example, Cornelissen & Dustmann (2019) estimated the effects of additional schooling before age five. They found significant positive results at ages five and seven, particularly for the ones with a disadvantaged parental background. But the impact on cognitive outcomes is no longer observed at age eleven. Only noncognitive impacts stay present. Duncan & Magnuson (2013) show also a boost in cognitive ability in the short run but no longer in the long-term.

In their meta-analysis, van Huizen & Plantenga (2018) showed that a third of all the studies that they observed were positively significant, half were insignificant and one out of six were negative. They also concluded that the main factors explaining disparities are the quality and the autonomy of ECEC institutions.

1.2 Effects of ECEC on Educational Outcomes for Disadvantaged Children

The children who benefit from a good stimulating environment have few things to gain, switching a high-quality environment for another high-quality environment. In contrast, disadvantaged children face usually a less adapted situation at home. Thus, if everyone frequents kindergarten, they should benefit more from ECEC institutions than others.

van Huizen & Plantenga (2018) confirm this intuition. They mentioned several authors in their meta-analysis who support it empirically like Cascio (2015), Cascio & Schanzenbach (2013, 2014), Drange & Havnes (2015) and Felfe, Nollenberger & Rodríguez-Planas (2015). We can also mention Cornelissen & Dustmann (2019) (described above) and Rossin-Slater & Wust (2020).

Magnuson, Lahaie & Waldfogel (2006) found that attending preschool was beneficial in maths and reading for natives and immigrants in the same proportion. Equity of enrollment would help to reduce inequalities as both groups could beneficiate from the same support.

1.3 Effects of Age of Entry in ECEC Institution on Educational Outcomes

With the same mechanisms as about the impacts of ECEC on educational outcomes, we could expect that earlier age of entry should improve cognitive skills. As you frequent a stimulating environment earlier or longer, you should beneficiate from better preparation before entering primary school. Once more, the effect should be larger for disadvantaged children, who usually do not beneficiate from an adapted educational environment at home. The gaps between natives and immigrants or low-SES children should be positively correlated with a decrease in the age of entry.

Already mentioned above, Doyle, Harmon, Heckman & Tremblay (2009) and Attanasio (2015) demonstrated that the early years of life were very important for the development of the child. We should thus stimulate the children as early as possible.

Empirical studies support this intuition like Leak & al (2010) who concluded, not significantly, that ECEC programs before age three were beneficial to the kids. Cornelissen & Dustmann (2019) that I already mentioned twice, could also demonstrate that one additional year of schooling before age five increased cognitive outcomes in the short term.

However, I found more studies that proved the inverse. Barnett (2011) and Melhuish et al. (2015) showed that entering before three was not effective. Skirbekk (2006) did not find any improvement of one additional year of schooling (including kindergarten) in Switzerland on cognitive skills.

van Huizen & Plantenga (2018) demonstrated through their meta-analysis that the age of entry was not of major importance to explain the effectiveness of the ECEC programs.

1.4 Educational Mobility

Studies from regions all around the world have been published with various impacts using different variables. Sociologists like Bourdieu & Passeron in their famous publication of "Les Héritiers" in French (my traduction: "The Heirs"), led studies on the effects of the social classes on educational outcomes already in 1964. Some criticized the way of conducting the study but, figures at hand, could anyway demonstrate the correlation between the social class of the children and their educational achievements. They could also justify these differences by the valorization at school of the same culture and vocabulary of high social classes. This creates discrimination for the children, depending on their socioeconomic background pursuing them during their whole curriculum. The objective of the school to reduce entirely inequalities by giving the same chances to every child, no matter the level of education of his parents, is still not resolved and authors keep publishing works on it.

1.5 Effects of ECEC Age of Entry on Educational Mobility

There are not many studies evaluating precisely the effects of the age of entry in ECEC on educational mobility. However, Bauer & Riphahn are two authors that have been studying ways to reduce intergenerational educational transmission. In the early 2000s, they published several papers related to that subject in Switzerland.

Their most comparable analysis has been published in 2013. Using the Swiss Census data of 2000, they first evaluated the impact of the level of education of the parents on the attended post-secondary track of 17 years old teenagers with a multiple linear regression. As expected, they found a significant effect of the parental level of education.

After that, they used the heterogeneity of the school systems across Swiss cantons to check whether the age of entry in kindergarten impacted educational mobility for natives and/or immigrants. The results confirmed the expected patterns, saying that a higher share of four years old in kindergarten seems to lower educational mobility. The effect is positive in both groups, but it is larger and significant only for immigrants. In conclusion, lowering the age of entry seems beneficial to reduce the impact of the parental level of education, especially for immigrants.

They found however intriguing results for the age of entry in primary school for immigrants, saying that a lower age of entry in this institution reduces significantly educational mobility.

1.6 ECEC in Switzerland

This is difficult for a government, at least in Switzerland, to impact education before the legal age of schooling, due to the limitation of public intervention before that age. The most efficient way seems to be the kindergarten. These public institutions may help all the children from any socio-economic background to begin their primary school with more equitable chances of achievement and thus reduce inequalities.

However, Fuentes (2011) and Dutu (2016) underlined the lack of Switzerland in terms of ECEC institutions. He thinks that the country should improve these latter to allow children with an immigrant or low-SES background to perform better at school. van Huizen & Plantenga (2018) also insisted on the importance of the quality of these institutions.

1.7 Expected Patterns

Firstly, we should undoubtedly find a statistically significant impact of the parental level of education on reading test scores for any group of children as this effect is well-recognized and proved by many studies.

Secondly, we can intuitively expect higher test scores as the age of entry in an ECEC institution is lower. Indeed, mechanically, the more time the children spend in a professional and stimulating environment, the better they should be prepared, in terms of language, culture and other factors, to the primary school. Moreover, the effect should be higher for children with a disadvantaged socioeconomic background because their environment at home is usually less in accordance with the expectations of the Swiss educational system. However, some studies demonstrated that the age of entry was not of major importance for the success of ECEC programs (van Huizen & Plantenga, 2018). This point stays a discussion topic and it is difficult to predict any effect for the actual study.

Finally, we can expect that a lower age of entry in kindergarten would help to reduce the effect of the parental level of education. Effectively, as every child would have more time to accommodate himself with the educational system, no matter his individual characteristics, the gaps should become smaller between natives and immigrants.

2 Empirical Model

The choice of the model depends on the available data. In this case, the COFO-Suisse database of 2017 is a Census of children of HarmoS eighth grade in Switzerland. As these are simple cross-sectional data, any longitudinal study like difference-in-differences is not possible.

I have access to a wide range of interest and control variables, I can run a multiple linear regression model with the OLS (ordinary least squares) estimation method. The goal is to ensure a strong validity by including enough relevant control variables. The model is similar to the one that Bauer & Riphahn used with the Federal Swiss Census 2000 in 2013.

I will use the software R to run my regressions.

2.1 Multiple Linear Regression Model

$$y = \beta_0 + \beta_1 \boldsymbol{X} + \beta_2 PE + \beta_3 AE + u \tag{1}$$

Firstly, I will use this model (1) to control if the expected patterns listed in the last section are respected or not. The dependent variable *y* refers to the test scores in reading in the main language learned at school. β_0 is a constant term while other bêta coefficients represent the effects of the parental level of education PE, the age of entry in kindergarten AE and other covariates, represented by the vector **X**. *u* is the error term.

I will run this model three times: once for the whole sample, once for natives and once for children with an immigrant background. This way, I will be able to check if the effects differ across those groups.

$$y = \beta_0 + \beta_1 \boldsymbol{X} + \beta_2 PE + \beta_3 AE + \beta_4 (PE \cdot AE) + u \qquad (2)$$

In the second model (2), the coefficient β_4 represents the mutual effects of the age of entry and the parental level of education. It will allow me to determine if and how the age of entry in kindergarten influences educational mobility. I will run this model three times as well with the same subsamples.

2.2 Identification of the Causal Effect – 5 MLR Assumptions

The multiple linear regression model based on OLS is the Best Linear Unbiased Estimator (BLUE) if it respects the five Gauss-Markov MLR assumptions (Wooldridge, 2012). The four first assumptions are necessary for the multiple regression model to be unbiased. The fifth, homoscedasticity, ensures the lowest sampling variance within all linear unbiased estimators.

2.2.1 MLR 1 – Linearity in Parameters

The model shows a linear dependence of the outcome variable with the independent variables. The coefficients have to show the linear impact of a change in the affected variable on the outcome. For example, what is the average impact of being one year older on reading test scores. The relationship between those variables is defined by a coefficient that should not depend on the size of the variable to be interpreted effectively. However, the model is flexible as we can add logarithms and squared terms. We can check for such linearity by interacting variables with each other, in case of uncertainty and need.

2.2.2 MLR 2 – Random Sampling

The sample has to be randomized to assume that residuals are normally distributed. As it is developed in section 3 "Data", the COFO-Suisse study has been coordinated by reliable Swiss institutions, respecting a strict randomization procedure. A paper has been published by the University of Zürich to show how the children have been selected across regions and schools (Verner & Helbling, 2019).

Looking at the strong reliability of the institutions mandated and the strict randomization process used to create the database, I assume the MLR 2 to be satisfied.

2.2.3 MLR 3 – No Perfect Collinearity

The MLR 3 requires no perfect collinearity between all independent variables. Selecting carefully all my variables, I could already check for any possible perfect collinearity. Moreover, the software R usually drops automatically any variable that respects this condition. Thus, this problem should not occur in our regression.

However, a problem of almost perfect collinearity or very high collinearity could occur and would not be detected by the software R. This could induce errors in the regression by affecting the coefficients of the highly correlated variables. The impacts on the sign, the size and the significance can be very large and affect the coefficients of other interest variables. This needs to be controlled for. The robustness checks for the present model are developed later in that chapter.

2.2.4 MLR 4 – Zero Conditional Mean

The zero conditional mean can be mathematically written as $E(u|x_1, x_2, \ldots, x_K) = 0$. This means that, conditioning on all independent variables, the mean of the error terms should be equal to 0. In other words, the expected value of *u* is the same for any combination of $x_1, x_2, \ldots, x_K$. Thus, any difference in the outcome is explained only by the independent variables that have been listed. This implies that there is no omitted variable bias and no measurement error in the different covariates. This is a strong and very important assumption for the validity of the model. However, it is not possible to ensure that it respects that condition. It is necessary to evaluate in advance what could have been omitted or wrongly measured and try to correct the problems upstream. This is not always possible because we may not have access to some information or we may not be able to measure some variables with total accuracy.

If not enough attention is paid to avoid such violation of MLR 4, we could end up with very different results, far from the reality, and lead to decisions that are inefficient or counterproductive.

2.2.5 MLR 5 – Homoscedasticity

The variances of the variables should be homoscedastic for the regression to be the Best Linear Unbiased Estimator (BLUE). To evaluate the validity of this assumption, we can run a Breusch-Pagan test, which evaluates the nature of the variance of the error term. The null hypothesis assumes that the variance is constant and that the model is homoscedastic.

2.3 Further Assumption

Swiss cantons have much independence to organize their school systems, inducing heterogeneities across them. However, they also have a lasting tradition of harmonization of their school systems. Effectively, they signed a concordat in 1970 defining the main structural characteristics of elementary school. The "new" HarmoS concordat has been approved by the Swiss Folk in 2006, increasing the harmonization across cantons and determined a common age of enrollment - four years old on the 31st of July (HarmoS Agreement, 2007). We can also say that they all must refer to the article 62 of the Federal Constitution of the Swiss Confederation mentioning dispositions for public education.

For those reasons, I will assume a common quality of educational institutions in Switzerland and use the heterogeneities to conduct my study.

2.4 Validity of the Model

2.4.1 Potential Endogeneity Problems

Paying enough attention, MLR 1, 2, 3 and 5 should be more or less preventable. At least, some tools can help to reduce potential disrespect of these conditions. This is more difficult with MLR 4. We can hardly see if a key omitted variable biases the model or if any measurement error has occurred. Here is a list of potential problems that can affect the validity of the results of the present paper.

Firstly, some information is not available in the actual database like the participation in any pre-kindergarten program or the alternative methods of education of children who did not frequent kindergarten. The variable "number of siblings" is also missing. This may be considered as a key omitted variable, as some authors demonstrated its significant effects on educational mobility (Blake, 1985).

Secondly, there are always variables that are hardly estimable like innate ability, motivation or other characteristics proper to each individual and context. Endogeneity may occur if we do not include them in the model. We can sometimes try to limit this bias by creating proxy variables. However, this is not always possible and many potential measurement errors can occur during the process.

In our model, we can mention that such measurement error problems could appear with the following variables for example: test motivation (TestMot_M), pressure of the parents (press_M), emotional integration (EmoInt_M) and social integration (SocInt_M), as the answers come from the own interpretation of the children through a quantitative questionnaire.

2.4.2 *Robustness checks*

All regressions have been run at least a second time without all the control variables to see if the coefficients of interest changed significantly or not. The same procedure has been used to control for potential high multicollinearity problems while selecting the variables. I detail that in the next chapter.

I ran Breusch-Pagan tests after every regression and I never had to reject the null hypothesis, assuming the models to be homoscedastic. The results of these tests are available in Appendix A.

3 Data

The data come from the database of COFO-Suisse created for the evaluation of the core competencies that Swiss children should acquire at elementary school. This study has been conducted between April and June 2017 in classes of the HarmoS eighth grade to measure the achievements in the languages of Swiss pupils. The study has been coordinated by the Interfaculty Centre for Educational Research (ICER) of the University of Bern, which is devoted to such tasks. This corporation works with many other institutions of all regions to conduct the study with the professionalism that can be expected for such a project.

The tests have been standardized to ensure the comparison of educational achievements across regions. Besides their cognitive skills, the children had to fulfill a questionnaire about their individual characteristics and other relevant aspects that could influence their scores in languages.

The sample has been randomized respecting a strict procedure to be representative of a major part of the population. This objective is partially achieved. Effectively, children frequenting educational institutions in other languages (international schools) and children with too many cognitive or language problems have been excluded. Moreover, the participation rate is never 100% due to absences, refusals or technical problems. It varies between 95% and 99% depending on the cantons. This means that my results can be extrapolated to a major part of the population, but not entirely. The whole details about the study are available in the different documents published by the COFO Consortium, listed in the references at the end of this document.

Besides the exclusion of a part of the society by the authors of the database, I also decided to proceed to new filtering. My objective being the evaluation of the impact of the age of entry in kindergarten, I wanted all institutions to be of comparable quality. Thus, I decided to keep only the children who frequented kindergarten in Switzerland by selecting only the individuals who arrived in the country before three years old. After filtering, we end up with a sample of 18'338 children.

The different variables that I used to conduct my study are developed later in that section, as well as descriptive statistics. Their selection was inspired by other studies and depended on their availability in the database.

3.1 Variables

The variables are divided into six parts. Firstly, we will see the dependent variable, namely the test scores in reading, then the parental levels of education and the different ages of entry, which are the two main independent variables. Sections three and four present the other individual and cantonal covariates. The last one outlines the interaction terms between the age of entry and the parental level of education.

3.1.1 *Dependent Variable – Test Score in Reading*

Table 3-1 - **Dependent Variable - Test Scores in Reading**

Variable	Description
PVR_SL_M	Test score in reading in the main language learned at school (German, French or Italian depending on the region). Obtained by averaging the 20 plausible variables measured by the authors of the database

Source: COFO-Suisse database. Creation of the variable in R.

3.1.2 *Parental Level of Education*

Table 3-2 - **Parental Level of Education**

Variable	Description
HISCED**	Highest parental level of education. Ordinal variable with 1 = obligatory, 2 = secondary, 3 = tertiary
PE1*	Takes 1 if the highest parental level of education (HISCED) is "obligatory" (HISCED = 1)
PE2	Takes 1 if the highest parental level of education (HISCED) is "secondary" (HISCED = 2)
PE3	Takes 1 if the highest parental level of education (HISCED) is "tertiary" (HISCED = 3)

** = Reference group, not included in the regression. ** = only used to create dummy variables, not included in the regression. Source: COFO-Suisse database and creation of new variables in R.*

3.1.3 *Age of Entry*

Table 3-3 - **Kindergarten Age of Entry**

Variable	Description
B01**	How old when the child started kindergarten. Ordinal variable with 1 = 3 years old, 2 = 4 years old, 3 = 5 years old, 4 = 6 years old, 5 = did not frequent
AE1	Takes 1 if the child started kindergarten at 3 years old (B01 = 1)
AE2	Takes 1 if the child started kindergarten at 4 years old (B01 = 2)
AE3	Takes 1 if the child started kindergarten at 5 years old (B01 = 3)
AE4	Takes 1 if the child started kindergarten at 6 years old (B01 = 4)
AE5*	Takes 1 if the child did not frequent kindergarten (B01 = 5)

** = Reference group, not included in the regression. ** = only used to create dummy variables, not included in the regression. Source: COFO-Suisse database and creation of new variables in R.*

3.1.4 *Individual Control Variables*

Table 3-4 - **Individual Control Variables**

Variable	Description
Age	Age in years (continuous) in the period of testing. Reference date: End of May 2017. Variable created in R with *st_byear* and *st_bmonth*.
st-female	Dummy variable whether the individual is a woman or not
testMot_M	Test motivation mean score
famstruc1*	Takes 1 if the family structure is a single parent
famstruc2	Takes 1 if the family structure is nuclear
famstruc3	Takes 1 if the family structure is mixed
famstruc4	Takes 1 if the family structure is other than single parent, nuclear or mixed
mothemp1*	Takes 1 if the mother is full-time employed
mothemp2	Takes 1 if the mother is part-time employed
mothemp3	Takes 1 if the mother is unemployed
fathemp1*	Takes 1 if the father is full-time employed
fathemp2	Takes 1 if the father is part-time employed
fathemp3	Takes 1 if the father is unemployed
immig_pisa1*	Takes 1 if the immigrant status is native

immig_pisa2	Takes 1 if the immigrant status is second-generation immigrant
immig_pisa3	Takes 1 if the immigrant status is first-generation immigrant
A11	Age in years (discrete) when the individual arrived in Switzerland (takes 0 if born in Switzerland)
homelang1	Takes 1 if the main language spoken at home is the school language
wealth_M	Wealth index mean score
cultpos_M	Cultural possession mean score
EmoInt_M	Emotional integration mean score
SocInt_M	Social integration mean score
famedsup_M	Family education support mean score
press_M	Pressure of the parents mean score
HISEI	Highest parental ISEI (International Socio-Economic Index of the parents)
nbooks0*	Takes 1 if the child has between 0-10 books at home
nbooks1	Takes 1 if the child has between 11-50 books at home
nbooks2	Takes 1 if the child has between 51-100 books at home
nbooks3	Takes 1 if the child has between 101-250 books at home
nbooks4	Takes 1 if the child has more than 250 books at home

** = Reference group, not included in the regression. Source: COFO-Suisse database and creation of the variable "Age" in R.*

3.1.5 Cantonal Control Variables

Table 3-5 - **Cantonal Control Variables**

Variable	**Description**
id_region1*	Takes 1 if the language region is German
id_region2	Takes 1 if the language region is French
id_region3	Takes 1 if the language region is Italian
cantlev_htotprim	Number of lessons taught (all subjects) in primary school grades 1-6 in the canton of residence of the individual
cantlev_stuteachprim	Number of students per teacher (full-time equivalent) in primary stage in the canton of residence of the individual in 2015
cantlev_teachage29*	Proportion of teachers with age 29 and lower (obligatory school, 2015/16) in the canton of residence of the individual

cantlev_teachage30to49	Proportion of teachers with age between 30 and 49 (obligatory school, 2015/16) in the canton of residence of the individual
cantlev_teachage50	Proportion of teachers with age 50 and older (obligatory school, 2015/16) in the canton of residence of the individual
cantlev_femteach	Proportion of female teacher in obligatory schools in the canton of residence of the individual in 2015/16
cantlev_urbanpop	Proportion of population living in urban communities in the canton of residence of the individual in 2015 (based on Gemeindetypologie 2012)
cantlev_noconfess	Proportion of confessionless population in the canton of residence of the individual in 2015
cantlev_unemployed	Unemployment rate in the canton of residence of the individual in 2016
cantlev_gcppp	Gross cantonal product per person in Swiss Francs in the canton of residence of the individual in 2015
cantlev_gradpop	Proportion of graduate population in the canton of residence of the individual in 2015
cantlev_welfare	Proportion of population needing social help in the canton of residence of the individual in 2015
cantlev_3rdsector	Proportion of employed population working in 3rd sector in the canton of residence of the individual in 2015 (values concentrated between 0 and 1, against 0-100 for other variables with proportions)

** = Reference group, not included in the regression. Source: COFO-Suisse database*

3.1.6 Interaction Terms AE – PE

The following interaction terms will allow us to check whether frequenting kindergarten has an impact on educational mobility and whether particular ages of entry affect the coefficients of the parental levels of education. The reference group being "AE5 – did not frequent kindergarten" and "PE1 – highest parental level of education = obligatory", I will integrate new variables for all possible interactions that could occur between AE1/AE2/AE3/AE4 and PE2 / PE3.

3.2 Descriptive Statistics

3.2.1 Distribution of the Sample by Immigrant Status

The sample counts about one-fourth of children with an immigrant background and three-fourth of natives.

Table 3-6 - **Distribution of the Sample by Immigrant Status**

Native	2nd Gen. Immigrant	1st Gen. Immigrant	Total
13627	3952	759	18338
74%	22%	4%	100%

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Word to create the table

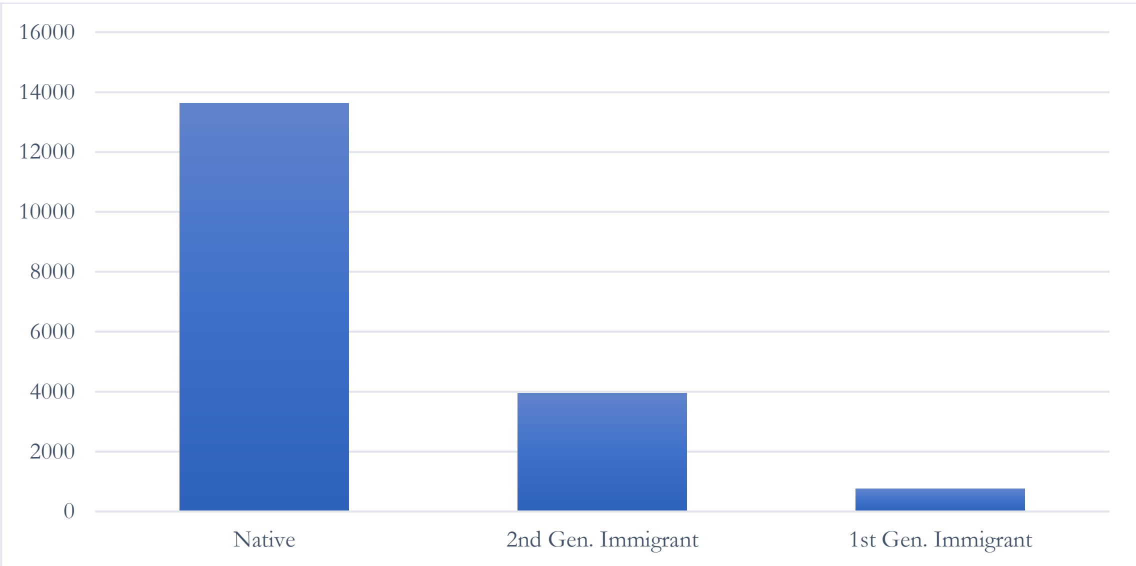

Figure 3-1 - **Distribution of the Sample by Immigrant Status**

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Excel to create the graph.

The small number of first-generation immigrants is partly due to the filtering of the data. I chose to keep only the children who frequented kindergarten in Switzerland. This way, 1479 children of first-generation immigrants are not included in the sample.

3.2.2 Distribution of Age

The children are mainly aged between twelve and thirteen years old. Older children often repeated classes.

Table 3-7 - **Distribution of Age**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
10.5	12.17	12.5	12.55	12.83	16.25

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Word to create the table

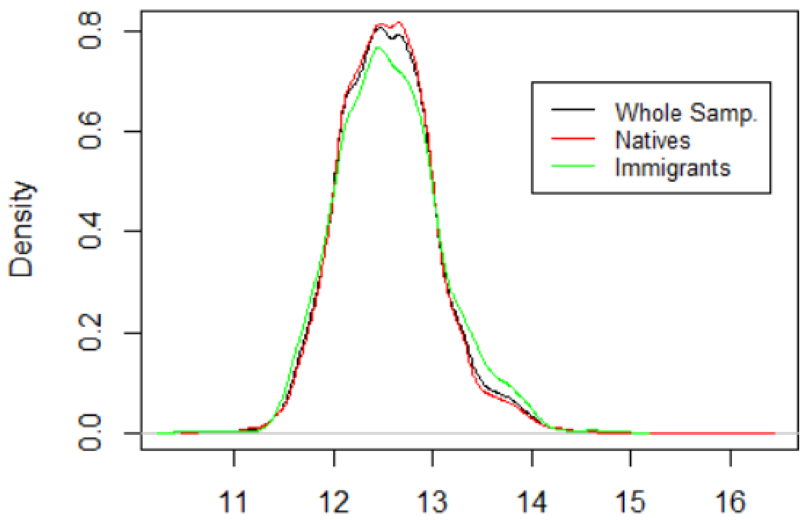

Figure 3-2 - **Distribution of Age**

Source: COFO-Suisse database. Graph created on R.

3.2.3 *Distribution of Test Scores*

The test scores of any subset of the population seem to follow a normal distribution around zero. We can already observe that the natives seem to slightly obtain better scores than immigrants.

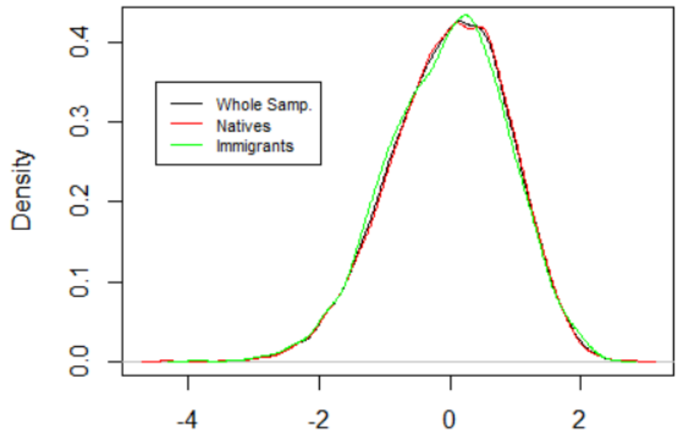

Figure 3-3 - **Distribution of Test Scores**

Source: COFO-Suisse database. Graph created on R.

3.2.4 *Distribution of Parental Levels of Education*

The parents of natives are on average more qualified than the parents of immigrants.

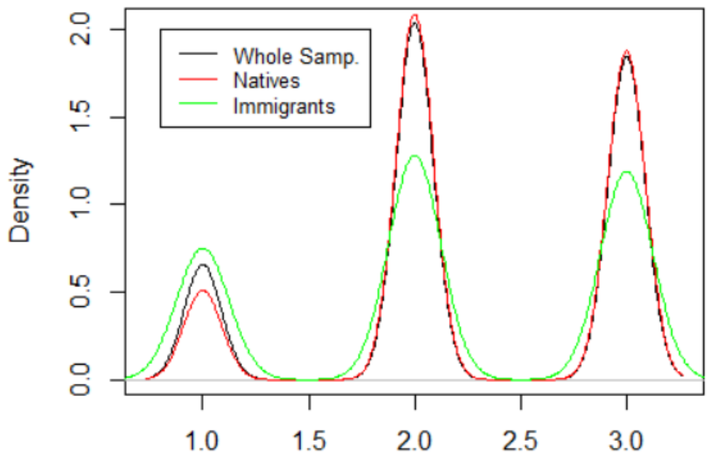

Figure 3-4 - **Distribution of Parental Levels of Education**

Source: COFO-Suisse database. Graph created on R.

3.2.5 Distribution of Ages of Entry in Kindergarten

Only a few children did not frequent kindergarten. A majority entered in this institution at four or five years old.

Table 3-8 - **Distribution of Ages of Entry in Kindergarten**

3 years old	4 years old	5 years old	6 years old	Did not frequent
1781	8288	6467	1606	174
10%	45%	35%	9%	1%

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Excel to create the table.

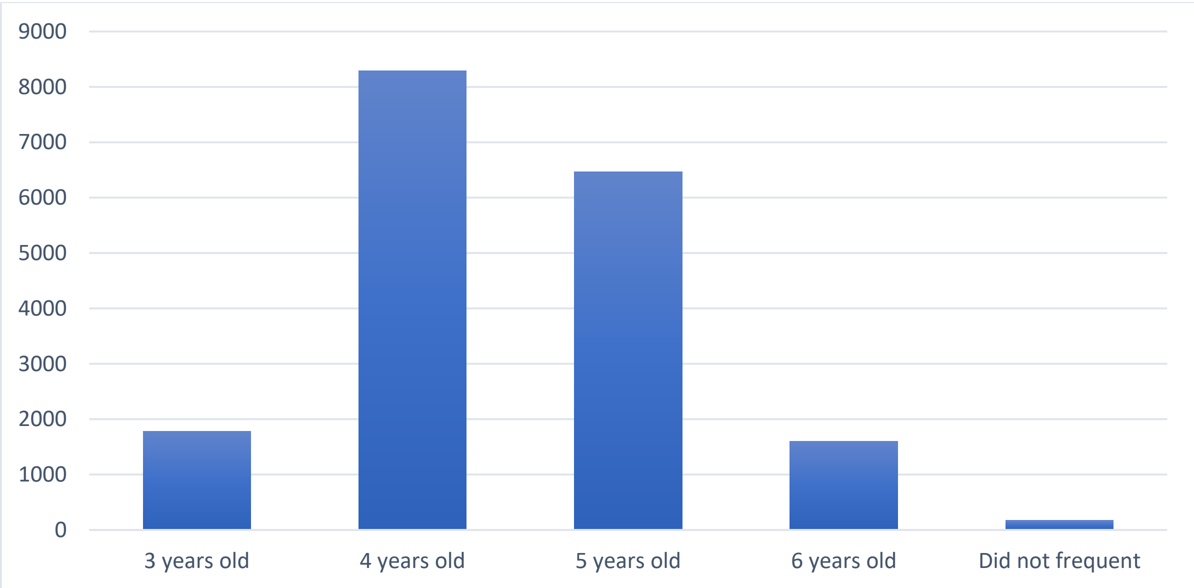

Figure 3-5 - **Distribution of Ages of Entry in Kindergarten**

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Excel to create the graph.

3.2.6 Average Test Scores by Parental Level of Education

The expected patterns of educational transmission seem to be confirmed for all samples and subsamples. Effectively, the more the parental level of education is high, the better are the test scores of the children.

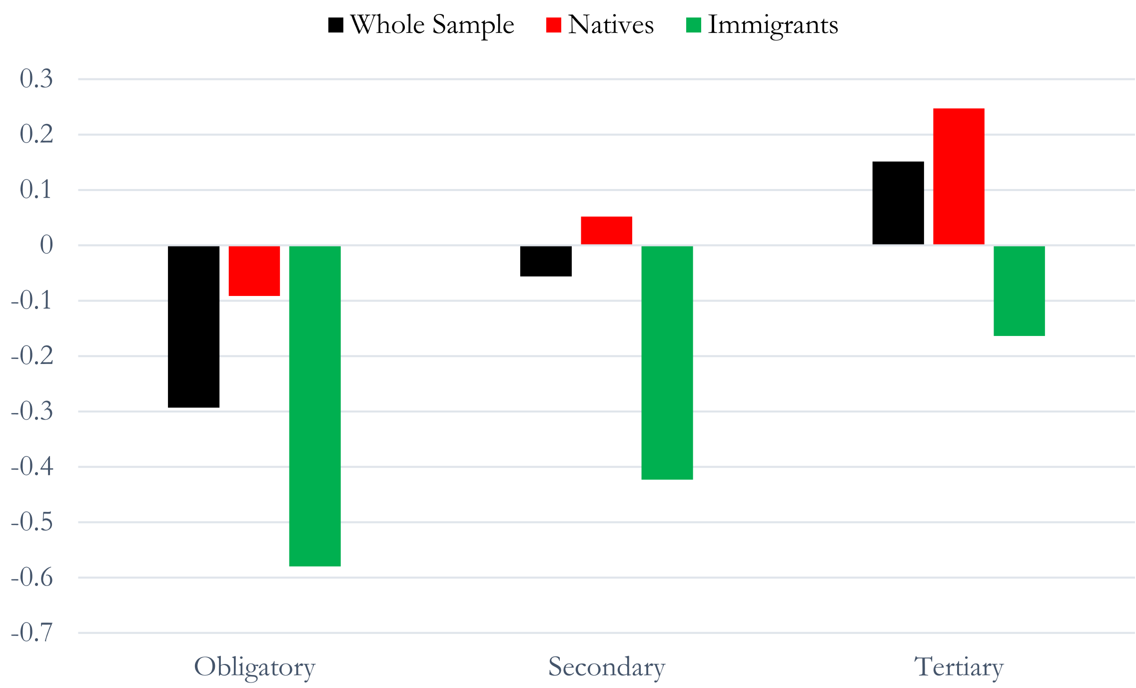

Figure 3-6 - **Average Test Scores by Parental Level of Education**

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Excel to create the graph.

3.2.7 Average Test Scores by Ages of Entry in Kindergarten

We remark that a lower age of entry seems to be more valuable for children with an immigrant background than for natives. The best age of entry in kindergarten seems to be four for all samples and subsamples.

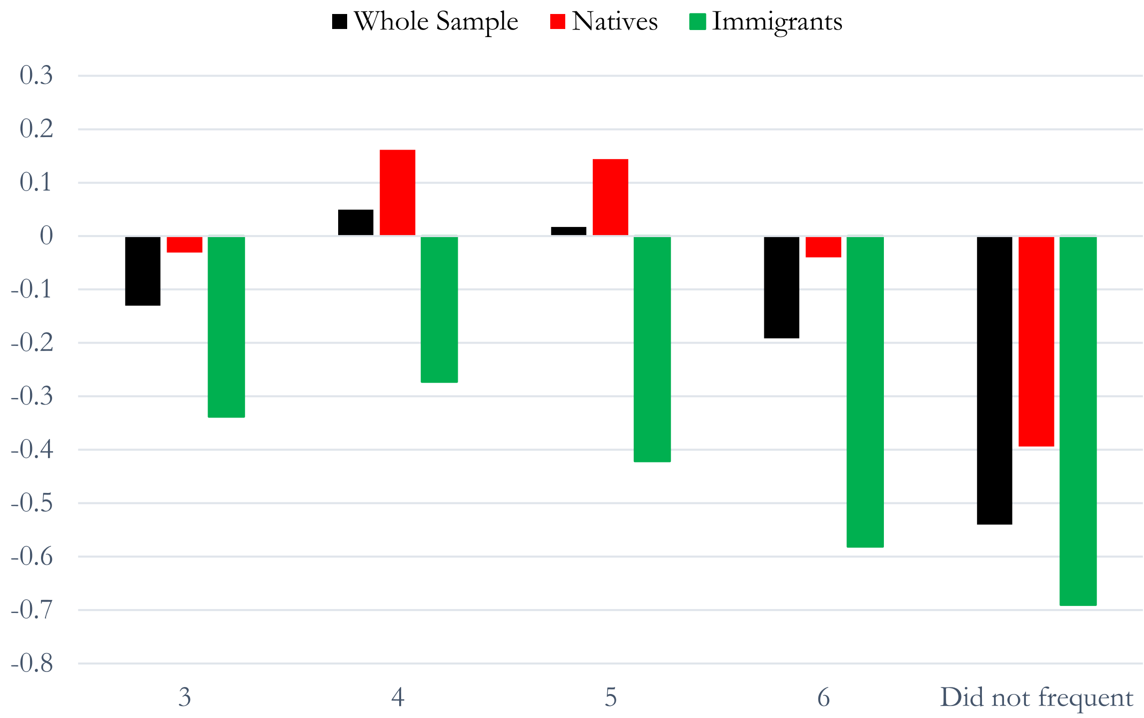

Figure 3-7 - **Average Test Scores by Age of Entry in Kindergarten**

Source: COFO-Suisse database. Figures reported from R to Microsoft Office Excel to create the graph.

3.3 Variables Unused in the Regression

There were several interrogations about which variables to include or not to finalize the model. Thus, choices had to be made to get, hopefully, the strongest possible model with the data at hand. I will describe my choices related to some variables that I decided not to take into account for different reasons. The details of the different regressions are available in Appendix B.

Table 3-9 - **Variables Unused in the Regression**

SES	Socioeconomic status. This variable is generated by the mean of three variables that are already included in the regression, namely *HISEI*, *HISCED* and *nbooks* (Pham & al., 2019). Thus, there is a potential problem of perfect multicollinearity. After regressing the model twice, with or without the variable, I could observe a total transformation of many coefficients, inducing several incoherent results. The most shining example is the higher parental levels of education becoming negative.
B04acoachlang1	The variables *B04acoachlang1, famedsup_M* and *press_M* represent respectively the eventual specialized paid help received by the child in the main language learned at school, the family educational support and the pressure of the parents at home. The nature of these factors is ambiguous as they could either be outcome or control variables. After controlling for their effects in the model, I decided to include *famedsup_M* and *press_M,* and to exclude *B04alang1*.
id_canton	Including the variable *id_canton* in addition to the numerous cantonal control variables induces problems in the regression as R attributes the value NA to the last included control variables. There may a problem of redundancy of information. Thus, I decided to remove it, even if it would have been useful to check for eventual further cantonal fixed effects.
cantlev_age	Including too many cantonal control variables induced problems of too high correlation, as with the variable id_canton. As this category of variables split into *cantlev_age20, cantlev_age20to64* and *cantlev_age65* was less significant than others, I chose to remove it from my regressions.

Source: COFO-Suisse database

3.3.1 *Missing Values*

There were 22 missing observations for the age of the children. I decided to drop them as there were only a few missing values.

I also remarked implausible values in two variables that I could have potentially used in the regression. The average staff costs per student and the number of first language lessons taught in primary school took the value -999 in some cantons. I thus transformed the implausible values to NAs at first. Then, instead of dropping more than 4'000 observations or create a new missing dummy, I replaced them with other "clean" variables that shared enough dependency to be used instead (see Appendix B). I finally used the average number of students per teacher instead of the average staff costs per student and the total amount of lessons taught in primary school instead of the total number of first language lessons taught in primary school.

4 Empirical Results

This section will summarize the results found for the different observed groups. There are three major conclusions to draw.

Firstly, a higher parental level of education affects positively and significantly the test scores of the children of all groups. This confirms the problem of educational immobility.

Secondly, frequenting kindergarten at any observed age impacts positively the test scores. The coefficients are significantly higher for an entry at five years old. A too low age of entry is indeed counterproductive and the benefits of kindergarten are also lower if the children enter too late. The effect of kindergarten is larger for natives than for immigrants.

Finally, frequenting kindergarten at any age does not significantly improve educational mobility. We can however underline that the tendency is positive, as a majority of coefficients of interaction terms are negative. The results are less pronounced for immigrants than for natives.

The coefficients on immigrants may sometimes be smaller in the following tables because of the smaller sample size inducing a higher variance.

4.1 Impact of Age of Entry and Parental Level of Education on Test Scores

Table 4-1 - **Impact of AE and PE on Test Scores**

	Whole Sample	Natives	Immigrants
(Intercept)	-0.75	-0.99	0.68
Parental Education = Secondary	0.07 ***	0.08 ***	0.08 *
Parental Education = Tertiary	0.1 ***	0.11 ***	0.07 *
Age of Entry = 3 years old	0.1	0.17 *	0.04
Age of Entry = 4 years old	0.26 ***	0.33 ***	0.2 *
Age of Entry = 5 years old	0.31 ***	0.39 ***	0.2 *
Age of Entry = 6 years old	0.21 ***	0.3 ***	0.09

*Reference group = AE5-did not enter kindergarten and PE1-highest parental level of education = obligatory. Source : COFO-Suisse database. Significance levels : *** = 0.1%, ** = 1%, * = 5%, . = 10%*

A higher parental level of education impacts positively and significantly the test scores of the children. Unsurprisingly, educational transmission across generations is confirmed. We can also mention that parents with a secondary level of education seem to be more beneficial to immigrant children than parents with a tertiary level of education. The difference is marginal but still goes against the odds.

All coefficients of having frequented kindergarten are positive, which also confirm the expected patterns. Globally, we can observe that the benefits of the age of entry in kindergarten are not linear. Beginning kindergarten at three is less beneficial than beginning at four or five, which can be counterintuitive. van Huizen & Plantenga (2018) mentioned that the age of entry was not of major importance but our results seem to show off an ideal age of five years old to enter kindergarten in Switzerland. Changing the reference group to five years old gives significant differences with all other ages of entry. The most important conclusion about these coefficients is that entering kindergarten too early can be counterproductive in terms of cognitive skills. One possible explanation may be inspired by Bowlby (1969) or Jacob (2009) who showed that the children need their home references until some age and that entering too early into an institution can generate insecurity, anxiety and stress. I think that possible solutions may be a more adapted program like pre-kindergarten for very young children, part-time schooling or personalized early intervention at home for those with difficulties.

We can also observe that the benefits of kindergarten are lower and less significant for immigrants than for natives. The significance is certainly due to the smaller sample but the lower coefficient is mainly counterintuitive as disadvantaged children should usually beneficiate more from having access to public institutions than others. May the programs not be adapted to ensure every child the same chances of achievement without promoting one or another category of children. Fuentes (2011) and Dutu (2016) underlined that Switzerland should improve the quality of actual preschool programs and increase the supply of pre-kindergarten institutions to allow disadvantaged children to fill their gaps. This may be the premise of a solution to reduce inequalities. The challenge is to help disadvantaged children without altering the benefits of the institutions for the more fortunate ones.

4.2 Impact of Other Covariates on Test Scores

4.2.1 Individual Control Variables

Many coefficients are significant in this section and there are several interesting conclusions to draw. One of the most valuable may be the difference of the impact of the unusual family structure between natives and immigrants. These latter seem to suffer more from a difficult family context.

Table 4-2 - **Impacts of Other Individual Control Variables on Test Scores**

	Whole Sample	Natives	Immigrants
Age	-0.23 ***	-0.22 ***	-0.26 ***
Female	0.09 ***	0.08 ***	0.1 ***
Nuclear Family	0.04 *	0.05 **	-0.01
Mixed Family	0.01	0.02	0.01
Other Family Structure	-0.14 **	-0.07	-0.39 ***
Mother Part-time employed	0.11 ***	0.12 ***	0.08 **
Mother unemployed	0.05 **	0.08 ***	-0.01
Father part-time employed	-0.02	-0.02	-0.05
Father unemployed	-0.1 ***	-0.11 ***	-0.07 .

2nd gen immigrant	-0.1 ***	0	0
1st gen immigrant	-0.19 ***	0	-0.11 **
Age of arrival in CH	0.07 **	0	0.11 ***
Home lang. is school lang.	0.19 ***	0.16 ***	0.21 ***
Test Motivation	0.03 **	0.04 ***	-0.01
Wealth M	0	0.01	-0.01
Cultural possessions M	-0.03	-0.05 *	0.04
Emotional integration M	0.1 ***	0.11 ***	0.06 **
Social integration M	0.04 ***	0.03 *	0.05 *
Family educational support M	-0.1 ***	-0.09 ***	-0.11 ***
Pressure of the parents M	-0.06 ***	-0.08 ***	-0.02
HISEI	0.01 ***	0.01 ***	0 ***
11-50 books at home	0.27 ***	0.3 ***	0.24 ***
51-100 books at home	0.42 ***	0.43 ***	0.43 ***
101-250 books at home	0.6 ***	0.62 ***	0.54 ***
More than 250 books at home	0.7 ***	0.71 ***	0.71 ***

*Reference group : see the section "Data". Source : COFO-Suisse database. Significance levels : *** = 0.1%, ** = 1%, * = 5%, . = 10%*

We can observe a counterintuitive result for age. As demonstrated by several authors (Givord, 2020; Pehkonen, 2015; Ponzo & Scoppa, 2013), the relative age of entry into school can be an important factor explaining cognitive differences between children. However, here we have differences of age in years, while the authors focused on the differences in months relative to the cut-off date. In the actual study, older pupils are usually older because they repeated a class. The correlation between the variable *age* and *B03a* which represents the number of times the child repeated a class is 0.5. As this fact concerns only the children who have difficulties, the probability of the age being correlated with lower test scores is high and confirmed here in all groups.

Less evident to explain, there is a highly significant difference between girls and boys in all groups, girls doing better than boys. Marks (2008) mentions such a result has been observed in several countries. The gaps are usually more pronounced in reading in favor of girls than mathematics for example. This can depend on multiple things like “school system organization, student's expectations and macro-societal factors". I do not see any further justification with the data at hand. This would deserve further investigation.

Living in a conventional nuclear family seems only beneficial for the natives. The coefficient is surprisingly slightly negative for immigrants. But the most important gap here is the non-conventional family structure (neither single parent, nuclear or mixed) which impacts very significantly the test scores of immigrants. These latter seem to suffer hardly from that kind of situation. It is known that difficult situations alter the concentration of children at school but the large gap between both groups is not obvious. Immigrants may be more concerned by this kind of problem and alternative solutions are sometimes more radical than for natives who can easier get the support of family and friends.

A mother who works part-time seems to be the most beneficial professional status that she can have for her children. Maybe keeping a foot in the professional world while also having time for the kids is a perfect balance. Not working at all is better than a full-time job for natives. There is no significant difference for immigrants.

Curiously, the impact is the opposite for the fathers. A father working full-time is more beneficial to the child than an unemployed father. This may be explained by the historic and still present picture of the father working and the mother at home. The situation of unemployment may affect more the mental health of the fathers than the mothers. Moreover, the relation of a father with his children is undoubtedly not the same as with a mother. A child having more time with his father seems less valuable than with his mother on average.

Looking at the whole sample and despite all the control variables, we remark that the immigrant status still impacts negatively and significantly the test scores of the children. This means that we miss some unobserved characteristics in our model to fully explain these differences between natives and immigrants.

Only looking at the immigrant column, we observe a significant difference between first and second-generation immigrants. This may be because integration takes time. After one generation, the children are better integrated and count fewer gaps with the natives than the first-generation immigrants, all things being equal. They could accommodate the culture and the language for example, facilitating their integration into the school system. We can also mention that the migration policy evolved throughout the years in Switzerland, which could have induced a significant difference in the individual characteristics of the "new" immigrants. Cattaneo & Wolter (2015) explained that immigrants were always more qualified and had better PISA scores thanks to the higher qualifications of the parents. It would be interesting to compare the evolution of these coefficients through time and see if the evolution of the scores of immigrants and the gaps with natives increase or decrease across time.

It is confusing to see that arriving later (between one and three years old) in Switzerland improves significantly the reading test scores of the immigrants. Delaying the migration may allow the children to benefit from a more stable situation in their first years of life, which can be valuable for later learnings.

The home language being the same as the school language helps unsurprisingly all groups of children. The coefficients are highly significant.

A higher motivation during the test increases the scores of the natives. This is highly significant. The coefficient is curiously slightly negative but insignificant for immigrants.

Unexpectedly, more cultural possessions conduct to poorer test scores for the natives. The result is significant at the 5% level, which is hardly explainable. This may be due to the low reliability of the measures, as warned by COFO-Suisse, or to the fact that some collinearity occurs with the number of books at home. The opposite appears for the immigrants who beneficiate from more cultural possessions, but not significantly.

Emotional and social integrations are positively correlated with the test scores. This is intuitive and significant for all groups.

The coefficients of the two variables that we could also have considered as outcomes, namely famedsup_M and press_M are negative and highly significant in most cases. This means that having support and pressure at home is negative for the educational achievements of the child, which can be counterintuitive. A first hypothesis would be to imagine that there are at least some reciprocal effects of the control variables with the outcome as we feared by including them in the regression. The children who have lower test scores may face more pressure and educational support at home. A second hypothesis for the family educational support would be that the child loses autonomy as the parents help him too often. Once the child is alone, he faces more difficulties than his peers. An alternative hypothesis about the pressure of the parents could be that the child works for his parents and not for him anymore, which reduces the sense of doing things. The coefficient of the pressure of the parents is not significant for children with an immigrant background.

Interesting but not surprising, a higher socioeconomic index increases significantly the test scores for all groups. The same observation can be made for cultural possessions measured by the number of books, confirming the importance of such a factor as described by Bourdieu & Passeron (1964).

4.2.2 Cantonal Control Variables

About half of the cantonal control variables are significant. The results are different for immigrants and natives on several points.

Table 4-3 - **Impact of Cantonal Control Variables on Test Scores**

	Whole Sample	Natives	Immigrants
French speaking region	0.12 ***	0.09 **	0.27 ***
Italian speaking region	-0.06	-0.11 *	0.13 .
Number of all lessons taught M	0	0	0
Number of students per teacher M	0	0	0
Proportion of teachers aged 30to49	0.02 ***	0.02 ***	0.02 *
Proportion of teachers aged >50	0.02 ***	0.02 ***	0.02 .
Proportion of female teachers	0.01 ***	0.01 ***	0.01
Proportion of urban population	0	0	0
Proportion of population with no confession	-0.01 ***	-0.01 ***	0
Proportion of unemployed population	0.04 **	0.06 ***	-0.03
Gross cantonal product per capita M	0 *	0 *	0
Proportion of population graduated	0	0	0
Proportion of population needing social welfare	-0.03 **	-0.04 **	-0.02
Proportion of population working in 3rd sector	-0.17	-0.08	-0.55 *

*Reference group: see the section "Data". Source : COFO-Suisse database. Significance levels : *** = 0.1%, ** = 1%, * = 5%, . = 10%*

All groups benefit from frequenting school in the French-speaking region instead of the German one. The coefficients about the Italian part are strange as it shows opposition to the results between natives and immigrants. Effectively, the natives face lower test scores in this region while immigrants have higher test scores than in the German part, both significant respectively at the 5% and 10% levels. The main conclusion here is that the immigrants seem to beneficiate more from living in a Latin language-speaking part of Switzerland than in the German part. Depending on the origin of the immigrants, their home language may be more similar to French or Italian than German. Or may these languages be easier to learn for reading. This difference is hardly explainable with the data at hand. This would deserve further investigation.

It is somewhat surprising to see that the variables related to school organization, namely the number of lessons taught and the number of students per teacher, do not affect test scores in reading.

Conversely, the age of the teachers is positively and significantly correlated with reading test scores for all groups. The pupils of teachers aged over 30 years seem to perform better than pupils of teachers aged below this threshold. I see three potential pieces of explanation. Firstly, we may conclude that experience is more important than youth energy. Secondly, this difference of age may also increase the legitimacy and the respect of pupils and parents for the teacher. Finally, older teachers have higher probabilities to be parents, allowing them to understand the problems of children from a different perspective. These are obviously just premises of solutions that deserve to be deepened by further investigation.

More female teachers also increase significantly the average test scores of the students. The coefficient is positive for the natives and the whole sample, but not for immigrants.

The proportions of the urban and/or graduated population do not affect the test scores. Conversely, the proportions of the population with no confession and needing social welfare to affect negatively and significantly the test scores of the whole sample and the natives.

The proportion of unemployed population increases the test scores of the natives, which can look counterintuitive at the first glance. However, this means that these people have more time at home to take care of their children, which can be beneficial to them. The inverse observation, although insignificant, can be made for immigrants who suffer from a higher unemployment rate. Parents with an immigrant background may suffer more from this kind of situation and thus take less advantage of their free time to be valuable for their children. The fear of not finding a job may deteriorate more the mental health of immigrants than natives because of their lower probabilities to get hired. Moreover, the abilities to help the child may also be lower as they are less aware of the Swiss educational system.

Unsurprisingly, even if the coefficient rounded at to decimal points shows zero in the table, living in a richer canton significantly increases the test scores of the natives. The coefficient is also positive but not significant for immigrants.

Finally, we can notice that a higher proportion of the population working in the third sector impacts negatively the reading test scores. The coefficient is significant for the children with an immigration background. This may be because their parents have on average fewer job opportunities in this sector, inducing a less favorable situation.

4.3 Effects of Age of Entry on Educational Mobility

We can observe in the following table that none of the interaction terms is significant, saying that the age of entry in kindergarten seems not to be a valid solution to increase educational mobility.

Table 4-4 – **Impact of Age of Entry on Educational Mobility**

	Whole sample	Natives	Immigrants
(Intercept)	-0.84	-1.13 .	0.69
Parental Education = Secondary	0.12	0.21	0.01
Parental Education = Tertiary	0.24	0.29	0.21
Age of Entry = 3 years old	0.12	0.2	0.05
Age of Entry = 4 years old	0.32 *	0.46 **	0.18
Age of Entry = 5 years old	0.38 **	0.52 **	0.25
Age of Entry = 6 years old	0.32 *	0.45 *	0.19
Impact of AE 3 years old on PE «Secondary»	-0.04	-0.06	0.01
Impact of AE 3 years old on PE «Tertiary»	-0.05	-0.05	-0.07
Impact of AE 4 years old on PE «Secondary»	-0.04	-0.15	0.12
Impact of AE 4 years old on PE «Tertiary»	-0.13	-0.19	-0.08
Impact of AE 5 years old on PE «Secondary»	-0.05	-0.14	0.06
Impact of AE 5 years old on PE «Tertiary»	-0.15	-0.19	-0.21
Impact of AE 6 years old on PE «Secondary»	-0.09	-0.16	0
Impact of AE 6 years old on PE «Tertiary»	-0.21	-0.21	-0.33
Mean of interaction term coefficients	**-0.09**	**-0.14**	**-0.06**

*Reference group = AE5-did not enter kindergarten and PE1-highest parental level of education = obligatory. Control variables included in the regression but not presented here. Source: COFO-Suisse database. Significance levels : *** = 0.1%, ** = 1%, * = 5%, . = 10%*

As mentioned above, none of the coefficients is significant. However, we can observe that they are, on average, negative in all groups, meaning that the benefits of kindergarten at any age are lower for the children of more educated parents. The effects are also more pronounced for "PE Tertiary" than "PE Secondary", showing a kind of linearity in the coefficients. Thus, the tendency seems to show an improvement of educational mobility while frequenting kindergarten for the whole sample, which follows the expected patterns.

Nevertheless, the coefficients are surprisingly less pronounced for immigrants than for natives, which is the opposite result that Bauer & Riphahn found in 2013. The regression on immigrants shows even slightly positive coefficients when the parental level of education is secondary, saying that the benefits of kindergarten are higher for them than for the children with low-educated parents. One hypothesis would be that cumulating an immigrant status and a low parental level of education prevent the children to fully benefit from the institutions. The school helps children to acquire some knowledge and skills but there is a sort of continuity of school at home with exercises and learnings. The low-educated parents with an immigrant background may not be able to bring the necessary support to their children to benefit from the school system as much as other children. In this kind of situation, the school system may not be adapted enough to children cumulating disadvantages.

One other possible explanation may be taken out of the theory presented by Bader & Fibbi (2012). The authors show five educational inputs that can determine the success of immigrant children. One part of these inputs is the reason to come to Switzerland. Some immigrants come with the hope of better socioeconomic perspectives while others just escaped from their country because of political issues for example. The implication and the motivation of the parents to integrate into the society may be correlated with their level of education, which could explain some differences between groups.

I think that many other factors could explain such results but that the significance of the results presented here does not allow a strong enough reliability of our hypotheses. The problem would need a more solid foundation and further investigation.

Conclusion

Are we able through our public educational institutions to enable any child to beneficiate from equitable chances of achievement, no matter his background? The objective of this paper has been to give a piece of answer to this broad question while focusing on the effects of kindergarten in Switzerland on educational mobility.

We could firstly confirm that the parental level of education had a significant impact on cognitive skills for any subset of children. Then, we understood the positive effects of frequenting kindergarten and we defined an ideal age of entry in such an institution at five years old. We could finally evaluate the dependency of both variables to check whether a specific age of start could help to improve educational mobility. We observed a positive tendency, however insignificant, which does not allow us to affirm that any age of entry is beneficial to reduce intergenerational educational transmission.

Universal kindergarten as it is offered in Switzerland seems not to be sufficient to reduce inequalities noticeably between social classes. Fuentes (2011) and Dutu (2016) already mentioned the lack of Switzerland in terms of early childhood education and care. The new HarmoS concordat was not as developed as today twelve years ago, when the children evaluated in this paper started kindergarten. It would be interesting to see how it has evolved since that period and what the impacts on educational mobility are to this day.

Many other options than kindergarten are possible in Switzerland. It would be interesting to have further information on childcare facilities and programs to strengthen the current model and see the impacts of such institutions in Switzerland.

Appendix A – Breusch-Pagan Tests

The different Breusch-Pagan tests show that we can never reject the hypothesis H_0, considering the different regressions to be homoscedastic. Thus, we can consider the models as BLUE.

```
#Whole sample without interaction
terms

> bptest(reg1)

studentized Breusch-Pagan test

data:  reg1
BP = 394.86, df = 45,
p-value < 2.2e-16
```

```
#Whole sample with interaction
terms

> bptest(reg2)

studentized Breusch-Pagan test

data:  reg2
BP = 406.36, df = 53,
p-value < 2.2e-16
```

```
#Natives without interaction
terms

> bptest(regnative1)

studentized Breusch-Pagan test

data:  regnative1
BP = 284.49, df = 43,
p-value < 2.2e-16
```

```
#Natives with interaction
terms

> bptest(regnative2)

studentized Breusch-Pagan test

data:  regnative2
BP = 290.34, df = 51,
p-value < 2.2e-16
```

```
#Immigrants without interaction
terms

> bptest(regimmig1)

studentized Breusch-Pagan test

data:  regimmig1
BP = 140.66, df = 44,
p-value = 4.872e-12
```

```
#Immigrants with interaction
terms

> bptest(regimmig2)

studentized Breusch-Pagan test

data:  regimmig2
BP = 159.64, df = 52,
p-value = 7.185e-13
```

Appendix B - Choice of the variables

Variable SES

```
Regression without SES
> summary(reg1noSES)
Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+X)
Coefficients:
                        Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)           -7.451e-01   5.518e-01   -1.350  0.176938
PE2TRUE                7.463e-02   1.752e-02    4.261  2.05e-05 ***
PE3TRUE                1.027e-01   1.842e-02    5.575  2.52e-08 ***
AE1TRUE                9.858e-02   6.189e-02    1.593  0.111177
AE2TRUE                2.556e-01   5.940e-02    4.303  1.69e-05 ***
AE3TRUE                3.067e-01   5.953e-02    5.151  2.61e-07 ***
AE4TRUE                2.056e-01   6.173e-02    3.331  0.000868 ***
HISEI                  6.429e-03   3.038e-04   21.162  < 2e-16 ***
nbooks1TRUE            2.721e-01   2.137e-02   12.735  < 2e-16 ***
nbooks2TRUE            4.200e-01   2.217e-02   18.946  < 2e-16 ***
nbooks3TRUE            5.984e-01   2.316e-02   25.839  < 2e-16 ***
nbooks4TRUE            6.998e-01   2.296e-02   30.475  < 2e-16 ***
X                          -           -          -         -
```

```
Regression with SES
> summary(reg1SES)
Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+SES+X)
Coefficients: (1 not defined because of singularities)
                        Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)            6.901e-01   5.518e-01    1.251  0.211050
PE2TRUE               -2.587e-01   2.098e-02  -12.330  < 2e-16 ***
PE3TRUE               -5.640e-01   2.958e-02  -19.067  < 2e-16 ***
AE1TRUE                9.858e-02   6.189e-02    1.593  0.111177
AE2TRUE                2.556e-01   5.940e-02    4.303  1.69e-05 ***
AE3TRUE                3.067e-01   5.953e-02    5.151  2.61e-07 ***
AE4TRUE                2.056e-01   6.173e-02    3.331  0.000868 ***
HISEI                 -4.701e-03   5.052e-04   -9.305  < 2e-16 ***
SES                    5.249e-01   1.722e-02   30.475  < 2e-16 ***
nbooks1TRUE            9.718e-02   1.802e-02    5.394  6.97e-08 ***
nbooks2TRUE            7.016e-02   1.616e-02    4.342  1.42e-05 ***
nbooks3TRUE            7.354e-02   1.611e-02    4.564  5.05e-06 ***
nbooks4TRUE                   NA          NA       NA        NA
X                          -           -          -         -
---
```

The coefficients and p-values change drastically due to the perfect collinearity. The software removes also automatically the last value because of too high correlation between independent variables. This is the reason why I decided not to include the variable SES.

Variables b04acoachlang1, famedsup_M, press_M

```
##Regression with all the variables
```

```
> summary(reg1all)

Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+B04acoachlang1+famedsup_M+pre
ss_M X)

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)          -2.939e+00  5.246e-01  -5.603 2.13e-08 ***
PE2TRUE               7.464e-02  1.728e-02   4.319 1.57e-05 ***
PE3TRUE               1.134e-01  1.816e-02   6.244 4.37e-10 ***
AE1TRUE               1.173e-01  6.100e-02   1.922 0.054570 .
AE2TRUE               2.474e-01  5.858e-02   4.223 2.42e-05 ***
AE3TRUE               2.567e-01  5.877e-02   4.368 1.26e-05 ***
AE4TRUE               1.498e-01  6.093e-02   2.459 0.013945 *
B04acoachlang1       -2.983e-01  1.032e-02 -28.909  < 2e-16 ***
famedsup_M           -9.328e-02  5.319e-03 -17.539  < 2e-16 ***
press_M              -5.879e-02  8.617e-03  -6.823 9.23e-12 ***
X                          -          -          -        -
```

```
##Regression without the variables B04acoachlang1, famedsup_m and press_M
```

```
> summary(reg1nocoachnofamedsup_Mnopress_M)

Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+X)

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)          -3.647e+00  5.424e-01  -6.724 1.82e-11 ***
PE2TRUE               7.917e-02  1.788e-02   4.428 9.56e-06 ***
PE3TRUE               1.137e-01  1.880e-02   6.050 1.48e-09 ***
AE1TRUE               1.635e-01  6.311e-02   2.591 0.009586 **
AE2TRUE               3.128e-01  6.058e-02   5.163 2.46e-07 ***
AE3TRUE               3.316e-01  6.078e-02   5.457 4.92e-08 ***
AE4TRUE               2.097e-01  6.303e-02   3.327 0.000880 ***
X                          -          -          -        -
```

The coefficients of the variables are significant but others do not change drastically with or without these variables. Thus I decided to choose the variables myself and remove only the paid specialized help. I think that this variable has more chances to be considered as an outcome variable. The family educational support and the pressure of the parents can be related to the culture of the family and the importance attached to school. Paid specialized help is often provided or advised by schools.

Variable id_canton

```
##Regression with id_canton
```

```
> summary(regidcanton)

Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+id_canton+X)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.2607 -0.4980  0.0538  0.5374  2.6776 

Coefficients: (12 not defined because of singularities)
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -6.151e+10  7.671e+10  -0.802 0.422636    
PE2TRUE                 8.186e-02  1.769e-02   4.629 3.70e-06 ***
PE3TRUE                 1.162e-01  1.858e-02   6.256 4.03e-10 ***
AE1TRUE                 1.504e-01  6.237e-02   2.411 0.015921 *  
AE2TRUE                 3.048e-01  5.985e-02   5.092 3.58e-07 ***
AE3TRUE                 3.191e-01  6.004e-02   5.314 1.08e-07 ***
AE4TRUE                 1.895e-01  6.226e-02   3.043 0.002346 ** 
id_cantonAI             5.286e+09  6.592e+09   0.802 0.422636    
id_cantonAR             4.776e+09  5.955e+09   0.802 0.422636    
Other id_canton             -          -          -      -
id_cantonZG             2.169e+09  2.705e+09   0.802 0.422636    
id_cantonZH             1.807e+07  2.253e+07   0.802 0.422636    
id_region2TRUE                 NA         NA      NA       NA    
id_region3TRUE          9.745e-02  9.522e-02   1.023 0.306132    
cantlev_htotprim               NA         NA      NA       NA    
cantlev_stuteachprim           NA         NA      NA       NA    
cantlev_teachage30to49         NA         NA      NA       NA    
cantlev_teachage50             NA         NA      NA       NA    
cantlev_femteach        8.168e+08  1.019e+09   0.802 0.422636    
cantlev_urbanpop               NA         NA      NA       NA    
cantlev_noconfess              NA         NA      NA       NA    
cantlev_unemployed             NA         NA      NA       NA    
cantlev_gcppp                  NA         NA      NA       NA    
cantlev_gradpop                NA         NA      NA       NA    
cantlev_welfare                NA         NA      NA       NA    
cantlev_3rdsector              NA         NA      NA       NA    
X                            -          -          -        -
```

The software does not calculate the last cantonal control variables because of a too strong correlation between independent variables. This is the reason why I decided to remove the variable *id_canton*.

Variable cantlev_age

```
##Regression with cantlev_age
```

```
> summary(regcantlevage)

Call:
lm(formula=PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+cantlev_age20+cantlev_age20to
64+cantlev_age65+X)

Coefficients: (1 not defined because of singularities)
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)             -5.624e+00  8.480e-01  -6.632 3.39e-11 ***
PE2TRUE                  8.180e-02  1.767e-02   4.629 3.69e-06 ***
PE3TRUE                  1.157e-01  1.857e-02   6.233 4.66e-10 ***
AE1TRUE                  1.548e-01  6.235e-02   2.483 0.013027 *
AE2TRUE                  3.044e-01  5.984e-02   5.087 3.68e-07 ***
AE3TRUE                  3.215e-01  6.004e-02   5.356 8.62e-08 ***
AE4TRUE                  1.980e-01  6.226e-02   3.180 0.001477 **
cantlev_age20            1.164e-02  1.023e-02   1.138 0.255343
cantlev_age20to64        4.083e-02  1.438e-02   2.840 0.004523 **
cantlev_age65                   NA         NA      NA       NA
X                            -           -         -        -
```

As for id_canton, the software does not calculate the last cantonal control variables because of a too strong correlation between independent variables. I thus had to remove some covariates. Due to the small significance of the coefficients compared to others, I chose to remove the variables *cantlev_age*.

Appendix C - Replacement of Variables with Missings

```
#Number of First Language Lessons Taught
```

```
> summary(lm(cantlev_hL1prim~cantlev_htotprim))

Call:
lm(formula = cantlev_hL1prim ~ cantlev_htotprim)

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)      -8.567e+02  3.299e+01  -25.97   <2e-16 ***
cantlev_htotprim  3.994e-01  6.695e-03   59.66   <2e-16 ***
---


> cor(cantlev_hL1prim,cantlev_htotprim, use = "pairwise.complete.obs")
[1] 0.4446661
```

```
#Average Staff Costs per Student
```

```
> summary(lm(cantlev_staffcosts~cantlev_stuteachprim))

Call:
lm(formula = cantlev_staffcosts ~ cantlev_stuteachprim)

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          20561.74     178.37  115.28   <2e-16 ***
cantlev_stuteachprim  -493.27      11.79  -41.84   <2e-16 ***
---


> cor(cantlev_staffcosts,cantlev_stuteachprim, use = "pairwise.complete.o
bs")
[1] -0.3092933
```

Script

```
#Download of the libraries

library(foreign) # Read Data Stored by other programs
library(sandwich) #model-robust covariance matrix estimators
library(lmtest)
library(mfx) # Marginal Effects, Odds Ratios and Incidence Rate Ratios
for GLMs
library(histogram)
library(descr) #litting, applying and combining data
library(censReg) # for Tobit
library(plyr) #to call ddply function. "Tools for splitting, applying and
combining data"
library(memisc) #build a table comparing several models
library(dplyr)
library(lmtest)
library(ggplot2)

#Preparation of the database

load("C:/Users/Kilian/Desktop/Files Master's
Thesis/UEGK_2017__IMPDATA20.Rdata")

#Addition to the database of the 20 plausible values of reading test
scores of the children from the Microsoft Excel raw database
datPVR_SL<-read.csv2("C:/Users/Kilian/Desktop/Files Master's
Thesis/Data_Raw_WithMissings_v1PVR_SL1-20.csv",header=TRUE)

datcomplete<-merge(dat, datPVR_SL, by ="id_student")
attach(datcomplete)

#Filter to consider only children who followed kindergarten in
Switzerland
filterdat<-filter(datcomplete,A11<3)

#Recode implausible variables
filterdatNA<-filterdat
filterdatNA<-replace(filterdat,filterdat==-999,NA)
attach(filterdatNA)

#Create a variable for age at test in years (reference test date end of
May 2017)
age<-(2017 + (5/12)) - (st_byear+(st_bmonth/12))
```

```r
#Drop 22 observations with age NAs
dat2<-filter(filterdatNA,!is.na(age))
attach(dat2)

#Reload age without NAs
age<-(2017 + (5/12)) - (st_byear+(st_bmonth/12))

#Create a variable for the average test score in reading
PVR_SL_M<-
((PVR_SL_1+PVR_SL_2+PVR_SL_3+PVR_SL_4+PVR_SL_5+PVR_SL_6+PVR_SL_7+PVR_SL_8
+PVR_SL_9+PVR_SL_10+PVR_SL_11+PVR_SL_12+PVR_SL_13+PVR_SL_14+PVR_SL_15+PVR
_SL_16+PVR_SL_17+PVR_SL_18+PVR_SL_19+PVR_SL_20)/20)

#Creation of missing dummy variables
famstruc1<-famstruc==1
famstruc2<-famstruc==2
famstruc3<-famstruc==3
famstruc4<-famstruc==4

mothemp1<-A02==1
mothemp2<-A02==2
mothemp3<-A02==3

fathemp1<-A03==1
fathemp2<-A03==2
fathemp3<-A03==3

immig_pisa1<-immig_pisa==1
immig_pisa2<-immig_pisa==2
immig_pisa3<-immig_pisa==3

nbooks0<-nbooks==0
nbooks1<-nbooks==1
nbooks2<-nbooks==2
nbooks3<-nbooks==3
nbooks4<-nbooks==4

id_region1<-id_region==1
id_region2<-id_region==2
id_region3<-id_region==3

PE1<-HISCED==1
PE2<-HISCED==2
PE3<-HISCED==3

AE1<-B01==1
AE2<-B01==2
AE3<-B01==3
AE4<-B01==4
AE5<-B01==5
```

```r
#Descriptive Statistics
##Distribution of the Sample by Immigration Status
table(immig_pisa)

#Distribution of Age
summary(age)
plot(density(age))
lines(density(age[immig_pisa==1]),col='red')
lines(density(age[immig_pisa>1]),col='green')
legend(14, 0.7, legend=c("Whole Samp.",
"Natives","Immigrants"),col=c("black","red", "green"),lty=1,cex=0.8)

##Distribution of Test Scores
plot(density(PVR_SL_M))
lines(density(PVR_SL_M[immig_pisa==1]),col='red')
lines(density(PVR_SL_M[immig_pisa>1]),col='green')
legend(-4.5, 0.35, legend=c("Whole Samp.",
"Natives","Immigrants"),col=c("black","red", "green"),lty=1,cex=0.7)

##Distribution of the Parental Levels of Education
plot(density(HISCED))
lines(density(HISCED[immig_pisa==1]),col='red')
lines(density(HISCED[immig_pisa>1]),col='green')
legend(0.8, 2, legend=c("Whole Samp.",
"Natives","Immigrants"),col=c("black","red", "green"),lty=1,cex=0.8)

#Distribution of Ages of Entry in Kindergarten
table(B01)

##Average Test Scores by Parental Levels of Education
aggregate(PVR_SL_M,list(HISCED=HISCED),mean)
aggregate(PVR_SL_M[immig_pisa==1],list(HISCED=HISCED[immig_pisa==1]),mean
)
aggregate(PVR_SL_M[immig_pisa>1],list(HISCED=HISCED[immig_pisa>1]),mean)

##Average Test Scores by Age of Entry in Kindergarten
aggregate(PVR_SL_M,list(B01=B01),mean)
aggregate(PVR_SL_M[immig_pisa==1],list(B01=B01[immig_pisa==1]),mean)
aggregate(PVR_SL_M[immig_pisa>1],list(B01=B01[immig_pisa>1]),mean)
```

```
#Robustness checks
##test SES
reg1SES<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pi
sa3+A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M
+HISEI+SES+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_
htotprim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+c
antlev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+can
tlev_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
reg1noSES<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pi
sa3+A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M
+HISEI+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htot
prim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantl
ev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev
_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(reg1noSES)
summary(reg1SES)


#Test with or without B04acoachlang1, famedsup_M and press_M
##Reference regression with all variables
reg1all<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+st_female+TestMot_M+famstruc2+famstru
c3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pisa3+
A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+B04acoachlang1+famedsu
p_M+press_M+HISEI+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+c
antlev_htotprim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teach
age50+cantlev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemplo
yed+cantlev_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(reg1all)

##Regression without B04acoachlang1, famedsup_M and press_M
reg1nocoachnofamedsup_Mnopress_M<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+st_female+TestMot_M+famstruc2+famstru
c3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pisa3+
A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+HISEI+nbooks1+nbooks2+
nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim+cantlev_stuteachpr
im+cantlev_teachage30to49+cantlev_teachage50+cantlev_femteach+cantlev_urb
anpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+cantlev_gradpop+
cantlev_welfare+cantlev_3rdsector)
summary(reg1nocoachnofamedsup_Mnopress_M)

#Regression with id_canton
regidcanton<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+st_female+TestMot_M+famstruc2+famstru
c3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pisa3+
A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HIS
EI+nbooks1+nbooks2+nbooks3+nbooks4+id_canton+id_region2+id_region3+cantle
v_htotprim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50
```

```
+cantlev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+c
antlev_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(regidcanton)

#Regression with cantlev_age
regcantlevage<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+st_female+TestMot_M+famstruc2+famstru
c3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pisa3+
A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HIS
EI+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim
+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantlev_f
emteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcp
pp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector+cantlev_age20+cantle
v_age20to64+cantlev_age65)
summary(regcantlevage)

#Replacement of average staffcosts per student and number of first
language lessons taught
cor(cantlev_staffcosts,cantlev_stuteachprim,use = "complete.obs")
summary(lm(cantlev_staffcosts~cantlev_stuteachprim))
cor(cantlev_hL1prim,cantlev_htotprim,use = "complete.obs")
summary(lm(cantlev_hL1prim~cantlev_htotprim))



#Empirical Results
##Regressions on the Entire Population
###impact of AE, PE and other covariates
reg1<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pi
sa3+A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M
+HISEI+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htot
prim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantl
ev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev
_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(reg1)
bptest(reg1)

###Impact of AE on PE
reg2<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+AE1*PE2+AE1*PE3+AE2*PE2+AE2*PE3+AE3*P
E2+AE3*PE3+AE4*PE2+AE4*PE3+age+st_female+TestMot_M+famstruc2+famstruc3+fa
mstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immig_pisa3+A11+h
omelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nb
ooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim+cant
lev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantlev_femtea
ch+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+ca
ntlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(reg2)
bptest(reg2)
```

```
##Regressions for Natives (reload the created variables after attaching
the new database!)
nativedat<-filter(dat2,immig_pisa==1)
attach(nativedat)
  #[Reload variables]#
###Impact of AE, PE and Other Covariates
regnative1<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+A11+homelang1+wealth
_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nbooks1+nbooks2+n
books3+nbooks4+id_region2+id_region3+cantlev_htotprim+cantlev_stuteachpri
m+cantlev_teachage30to49+cantlev_teachage50+cantlev_femteach+cantlev_urba
npop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+cantlev_gradpop+c
antlev_welfare+cantlev_3rdsector)
summary(regnative1)
bptest(regnative1)

###Impact of AE on PE
regnative2<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+AE1*PE2+AE1*PE3+AE2*PE2+AE2*PE3+AE3*P
E2+AE3*PE3+AE4*PE2+AE4*PE3+age+st_female+TestMot_M+famstruc2+famstruc3+fa
mstruc4+mothemp2+mothemp3+fathemp2+fathemp3+A11+homelang1+wealth_M+cultpo
s_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nbooks1+nbooks2+nbooks3+nb
ooks4+id_region2+id_region3+cantlev_htotprim+cantlev_stuteachprim+cantlev
_teachage30to49+cantlev_teachage50+cantlev_femteach+cantlev_urbanpop+cant
lev_noconfess+cantlev_unemployed+cantlev_gcppp+cantlev_gradpop+cantlev_we
lfare+cantlev_3rdsector)
summary(regnative2)
bptest(regnative2)


##Regressions for Immigrants
immigdat<-filter(dat2,immig_pisa>1)
attach(immigdat)
  #[Reload variables]#
####Impact of AE and PE and other Covariates
regimmig1<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa3+A11+home
lang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nbook
s1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim+cantlev
_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantlev_femteach+
cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+cantl
ev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(regimmig1)
bptest(regimmig1)

####Impact of AE on PE
regimmig2<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE3+AE4+AE1*PE2+AE1*PE3+AE2*PE2+AE2*PE3+AE3*P
E2+AE3*PE3+AE4*PE2+AE4*PE3+age+st_female+TestMot_M+famstruc2+famstruc3+fa
mstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa3+A11+homelang1+wea
lth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nbooks1+nbooks
```

```
2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim+cantlev_stuteach
prim+cantlev_teachage30to49+cantlev_teachage50+cantlev_femteach+cantlev_u
rbanpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+cantlev_gradpo
p+cantlev_welfare+cantlev_3rdsector)
summary(regimmig2)
bptest(regimmig2)


#Interpretation of results
##The children who entered at five years old do significantly better than
others
regAE3<-
lm(PVR_SL_M~PE2+PE3+AE1+AE2+AE4+AE5+age+st_female+TestMot_M+famstruc2+fam
struc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa3+A11+home
lang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+press_M+HISEI+nbook
s1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_htotprim+cantlev
_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+cantlev_femteach+
cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+cantlev_gcppp+cantl
ev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(regAE3)

##Older children are older because they repeated classes
summary(lm(B03a~age))
cor(age,B03a)

##Frequenting Kindergarten improves educational mobility
regAE5<-
lm(PVR_SL_M~PE2+PE3+AE5+AE5*PE2+AE5*PE3+age+st_female+TestMot_M+famstruc2
+famstruc3+famstruc4+mothemp2+mothemp3+fathemp2+fathemp3+immig_pisa2+immi
g_pisa3+A11+homelang1+wealth_M+cultpos_M+EmoInt_M+SocInt_M+famedsup_M+pre
ss_M+HISEI+nbooks1+nbooks2+nbooks3+nbooks4+id_region2+id_region3+cantlev_
htotprim+cantlev_stuteachprim+cantlev_teachage30to49+cantlev_teachage50+c
antlev_femteach+cantlev_urbanpop+cantlev_noconfess+cantlev_unemployed+can
tlev_gcppp+cantlev_gradpop+cantlev_welfare+cantlev_3rdsector)
summary(regAE5)
```

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